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**Intelligent Consensus
Systems in Group
Decision-Making based on
Behavioural Analysis**

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Ahora, retomando el tema de los agradecimientos... ha llegado el día de exponer en una página lo que han sido estos años de tesis doctoral. Tenemos que admitirlo, “ningún gitano quiere buenos principios para su hijo”, y obviamente, yo no iba a ser menos. Después de un primer año, curso 2019-2020, donde comencé en medio de una pandemia mundial y un curso express sobre cómo no deben tratarse a los doctorandos, aunque nunca olvidaré a Alberto que me hizo de escudo, gracias por ser mi apoyo ese año. Fui recogido como un perro abandonado y destrozado, por Enrique, Juanan y Javi. Gracias por confiar en mí.

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Podría alargar esto un poco más, hablando de lo que es una tesis doctoral que no se limita a estos artículos que se van a ver, pero en verdad ha sido una vida donde la formación ha sido la punta de lanza de la tesis, pero no ha sido mas que eso, ha habido política, amor, deporte, idiomas, viajes, proyectos, artículos de tesis y también artículos de congreso. Espero que se vean esta tesis con los ojos de que es una vida de casi cinco años.

Resumen

En la actualidad, la toma de decisiones en diversos ámbitos, como el empresarial, desempeña un papel fundamental en la determinación del éxito o fracaso de una empresa o proyecto. Los algoritmos orientados a la toma de decisiones son herramientas esenciales para elegir la mejor solución entre un conjunto de alternativas y maximizar así la satisfacción del grupo involucrado. Sin embargo, la ausencia de medidas exhaustivas para analizar el debate entre expertos puede ocasionar la pérdida de información crucial que incide directamente en la elección de la solución óptima. Por lo tanto, resulta imperativo desarrollar nuevos métodos que capturen y analicen la información generada durante estos debates. Dado que estos intercambios a menudo se dan en forma de comentarios escritos, el análisis de sentimientos, una disciplina dentro del procesamiento del lenguaje natural, surge como una herramienta eficaz para extraer información sobre el estado emocional de los individuos al expresar opiniones específicas. En nuestra investigación, nos propusimos examinar el comportamiento de los expertos a través de los comentarios generados durante estos debates.

Durante los debates, los expertos aprovechan el escenario para intercambiar puntos de vista, experiencias y preferencias. Sin embargo, la dinámica y el comportamiento de los individuos durante estos intercambios pueden influir notablemente en la facilidad o dificultad para llegar a un consenso satisfactorio. Es evidente que la forma en que los participantes se expresan y comunican, así como el tono emocional y la naturaleza de sus comentarios, pueden tener un impacto sustancial en la atmósfera del debate y, en última instancia, en la capacidad del grupo para llegar a un acuerdo.

En este contexto, resulta esencial analizar a fondo los comentarios generados durante el debate por los expertos. Este análisis permite identificar patrones de comportamiento, tendencias en la expresión emocional e inclinación hacia determinados tipos de argumentos o posturas. Por ejemplo, un experto que tiende a generar comentarios agradables y constructivos puede contribuir positivamente a la creación de una atmósfera propicia al consenso, fomentando el respeto mutuo y la apertura a las ideas de los demás. Por el contrario, un experto cuyos comentarios sean críticos, conflictivos o negativos puede entorpecer el proceso de consenso, generando tensiones y

obstáculos que dificulten la búsqueda de un terreno común. En este sentido, el análisis de los comentarios resulta esencial para comprender cómo influyen los comportamientos individuales en la dinámica del grupo y en la capacidad de alcanzar acuerdos satisfactorios.

Por tanto, nuestra tesis doctoral se enfoca en explorar los avances en la toma de decisiones grupales, desde los fundamentos teóricos más profundos hasta la aplicación práctica y la validación empírica de los conceptos desarrollados. Este trayecto, marcado por la curiosidad intelectual y la búsqueda incansable de soluciones efectivas, representa un compromiso constante con la mejora continua y la innovación en el área de la toma de decisiones en grupo.

El primer hito en esta investigación consiste en una inmersión completa en los conceptos de la teoría y la investigación, tal como se describe en el artículo “*Theorem Verification of the Quantifier-Guided Dominance Degree with the Mean Operator for Additive Preference Relations*”. Aquí, se lleva a cabo una meticulosa verificación de un teorema que proporciona una base sólida y fundamentada para comprender las complejidades de las relaciones de preferencia en contextos de toma de decisiones en grupo. Este enfoque teórico riguroso, respaldado por una exhaustiva revisión de la literatura existente, establece los cimientos necesarios para abordar de manera efectiva los desafíos que se presentan en el proceso de toma de decisiones.

Después de haber asentado una base teórica sólida, nuestra investigación continúa con la exploración de aplicaciones prácticas, como se describe en el artículo “*A Large Scale Group Decision Making System Based on Sentiment Analysis Cluster*”. Aquí, presentamos un sistema innovador de toma de decisiones grupales que utiliza técnicas de análisis de sentimientos para comprender mejor las emociones y actitudes de los miembros del grupo. Esta aproximación práctica ofrece una perspectiva fascinante sobre cómo la tecnología puede ser utilizada para mejorar la toma de decisiones en entornos grupales a gran escala, combinando principios teóricos con aplicaciones prácticas. Sin embargo, la verdadera prueba de la efectividad de estos enfoques surge en el artículo “*A Group Decision-Making Method Based on the Experts’ Behavior During the Debate*”. Aquí, se realiza una investigación empírica y experimental para analizar en profundidad el comportamiento de los expertos durante los debates grupales. Al aprovechar datos empíricos reales y técnicas de aprendizaje automático, este enfoque práctico proporciona una comprensión valiosa de las dinámicas de grupo y su impacto en el proceso de toma de decisiones.

Finalmente, nuestro trabajo destaca la importancia de analizar el comportamiento de los expertos durante los debates grupales para mejorar el proceso de toma de decisiones. Hemos demostrado cómo el análisis de sentimientos puede proporcionar información valiosa sobre las emociones y actitudes de los participantes, lo que influye significativamente en la dinámica del debate y en la capacidad del grupo para llegar a un consenso satis-

factorio. Además, hemos desarrollado un enfoque teórico sólido respaldado por una exhaustiva revisión de la literatura y hemos explorado aplicaciones prácticas utilizando técnicas innovadoras como el aprendizaje automático. Nuestra investigación representa un paso adelante en la comprensión de los procesos de toma de decisiones grupales y ofrece perspectivas valiosas para mejorar la eficacia y la eficiencia de estos procesos en una variedad de contextos. En última instancia, esperamos que nuestros hallazgos contribuyan al desarrollo de herramientas y metodologías más sofisticadas que faciliten la toma de decisiones colaborativa y conduzcan a resultados más satisfactorios para todos los involucrados.

Abstract

Nowadays, decision-making in various fields, such as business, plays a key role in determining the success or failure of a company or project. Decision-oriented algorithms are essential tools for choosing the best solution from a set of alternatives to maximise the satisfaction of the group involved. However, the absence of comprehensive measures to analyse the debate among experts can result in the loss of crucial information that directly affects the choice of the optimal solution. It is therefore imperative to develop new methods that capture and analyse the information generated during these discussions. Since these exchanges often take the form of written comments, sentiment analysis, a discipline within natural language processing, emerges as an effective tool to extract information about the emotional state of individuals when expressing specific opinions. In our research, we set out to examine the behaviour of experts through the comments generated during these discussions.

During the debate, experts use the stage to exchange views, experiences and preferences. Nevertheless, the dynamics and behaviour of individuals during these exchanges can have a significant impact on the ease or difficulty of reaching a satisfactory consensus. It is clear that how participants express themselves and communicate, as well as the emotional tone and nature of their comments, can have a substantial impact on the atmosphere of the debate and, ultimately, on the group's ability to reach agreement.

In this context, it is essential to analyse in depth the comments generated during the debate by the experts. This analysis can identify patterns of behaviour, tendencies in emotional expression and inclination towards certain types of arguments or positions. For example, an expert who tends to generate pleasant and constructive comments may contribute positively to the creation of an atmosphere conducive to consensus, fostering mutual respect and openness to the ideas of others. Conversely, an expert whose comments are critical, confrontational or negative can hinder the consensus process, creating tensions and obstacles that make it difficult to find common ground. In this sense, the analysis of comments is essential to understanding how individual behaviour influences group dynamics and the ability to reach satisfactory agreements.

Therefore, our doctoral thesis focuses on exploring advances in group decision-making, from the deepest theoretical foundations to the practical application and empirical validation of the concepts developed. This journey, marked by intellectual curiosity and a relentless search for effective solutions, represents an ongoing commitment to continuous improvement and innovation in the area of group decision-making.

The first milestone in this research consists of a full immersion in the concepts of theory and research, as described in the article “*Theorem Verification of the Quantifier-Guided Dominance Degree with the Mean Operator for Additive Preference Relationships*”. Here, a meticulous verification of a theorem is carried out that provides a solid and well-founded basis for understanding the complexities of preference relations in group decision-making contexts. This rigorous theoretical approach, supported by a thorough review of the existing literature, lays the necessary foundation for effectively addressing the challenges faced in the decision-making process.

Having laid a solid theoretical foundation, our research continues with the exploration of practical applications, as described in the article “*A Large Scale Group Decision Making System Based on Sentiment Analysis Cluster*”. Here, we present an innovative group decision-making system that uses sentiment analysis techniques to better understand the emotions and attitudes of group members. This practical approach offers a fascinating perspective on how technology can be used to improve decision-making in large-scale group settings, combining theoretical principles with practical applications. Nonetheless, the real test of the effectiveness of these approaches comes in the article “*A Group Decision-Making Method Based on the Experts’ Behaviour During the Debate*”. Here, empirical and experimental research is conducted to analyse in-depth the behaviour of experts during group discussions. By leveraging real empirical data and machine learning techniques, this practical approach provides valuable insights into group dynamics and their impact on the decision-making process.

Finally, our work highlights the importance of analysing experts’ behaviour during group discussions to improve the decision-making process. We have shown how sentiment analysis can provide valuable information about participants’ emotions and attitudes, which significantly influences the dynamics of the discussion and the group’s ability to reach a successful consensus. Moreover, we have developed a sound theoretical approach supported by a comprehensive literature review and explored practical applications using innovative techniques such as machine learning. Our research represents a step forward in the understanding of group decision-making processes and offers valuable insights for improving the effectiveness and efficiency of these processes in a variety of contexts. Ultimately, we hope that our findings will contribute to the development of more sophisticated tools and methodologies that facilitate collaborative decision-making and lead to more satisfying outcomes for all involved.

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Capítulo 1

PhD dissertation

“Se muere con las botas puestas”. Refrán popular

1.1. Introduction

Currently, decision-making in various fields, such as business, can determine the success or failure of a company or project. Algorithms based on decision-making are crucial tools for selecting the best solution from a set of alternatives and maximising group satisfaction [34, 65]. Nonetheless, the lack of comprehensive measures to analyse the debate among experts may result in the loss of crucial information affecting the choice of the optimal solution [58, 6]. It is therefore imperative to develop new methods that capture and analyse the information generated during the debate. Since these debates often take place in the form of written comments, sentiment analysis, a discipline of natural language processing, emerges as an effective tool to extract information about the emotional state of individuals when expressing specific opinions. In our research, we set out to analyse the experts' behaviour through the comments generated during the debate [20, 100].

It is important to note that effective decision-making depends on the quality of the alternatives considered and the interpersonal dynamics and interaction among participants [92, 68]. Written comments during the discussion can reveal individual preferences and group dynamics, including conflicts, mutual influences and persuasion strategies. Therefore, analysing expert behaviour through these comments can provide a more complete picture of group decision-making processes [42].

Moreover, sentiment analysis can go beyond simply identifying positive or negative emotions in comments [53, 84]. It can also reveal emotional nuances, such as uncertainty, ambiguity or apathy, which can influence how different alternatives are perceived and evaluated. Integrating this level of emotional analysis into group decision-making methods can help improve the understanding and management of emotions in the decision-making process, which in turn can lead to more informed and effective decisions [27, 73].

Typically, in the complex web of group decision-making, two primary processes loom large: the consensus process and the selection process [13, 5]. The first, the consensus process, is not simply a series of superficial interactions [23], but rather a dialectical journey involving multiple rounds of debate and deliberation among experts. In this process, each participant makes their case, justifies their views and listens to the perspectives of others with the ultimate goal of reaching a shared understanding and a high level of agreement [87]. This dynamic of constant exchange of ideas and opinions not only seeks to eliminate superficial disagreements but aims to reach a deep consensus that reflects mutual understanding and a solid basis for the final decision [51].

On the other hand, the selection process moves into the realm of evaluating and choosing the best solution among the available alternatives [16].

This process involves a thorough and objective analysis of all the options on the table, taking into account various criteria such as feasibility, effectiveness and possible long-term implications. Here, decision-making is underpinned by a pragmatic and evidence-based approach, where expert opinions and relevant data are carefully weighed to identify the most favourable option [64].

Importantly, while the consensus process is not always an absolute requirement, achieving consensus has many benefits [102]. Reaching a high degree of agreement promotes cohesion and collaboration within the group, strengthening the final decision's legitimacy and acceptance [32]. Furthermore, the consensus process fosters the building of trusting relationships and the development of communication and conflict-resolution skills among participants.

It is important to recognise that individual opinions can influence both the sender and the preferences of other participants in the discussion. According to Lawrence Kohlberg [45, 44], in his theory of moral development, at the Conventional level, humans tend to adjust their preferences to please others when making group decisions. Therefore, the analysis of expert comments may provide a solution within the set of alternatives, and may also reflect the degree of consensus reached by the group [35].

Nevertheless, an expert's willingness to change his or her opinion may be influenced by how he or she feels emotionally in response to others' comments or the topic under discussion. Therefore, assessing the behaviour of experts may reveal who is more open to changing their perspective and who sticks to their pre-existing views [84].

The analysis of individual commentary behaviour is an emerging field that is experiencing remarkable growth in interest and relevance. Until recently, this field lacked adequate datasets to allow for a comprehensive and systematic study. Nevertheless, in recent years, we have witnessed a significant increase in research efforts aimed at addressing this gap [61].

A crucial milestone in the development of this field was Xu's 2012 dataset of aggressive Twitter comments created by Xu's [95]. This initiative provided a solid foundation for research in online behaviour analysis, especially concerning detecting and understanding aggressive and hostile expressions in social media comments [14]. From this starting point, it has triggered a wave of further research and the creation of various datasets by researchers around the world [74].

While Twitter's aggressive comments dataset marked a turning point in the field, it is important to recognise that there are still many challenges ahead [48]. For example, the diversity of online platforms and contexts raises the need to develop specific datasets that address a wide range of behaviours

and expressions. Moreover, the constant evolution of social and technological dynamics requires an adaptive and responsive approach to capture and analyse the complexity of human behaviour online adequately [78].

In response to these challenges, many researchers have undertaken the task of developing their datasets to address specific aspects of individual commentary behaviour. These datasets may vary in terms of size, scope and focus, but all share the common goal of providing valuable resources for advancing the understanding and analysis of online behaviour [74].

Detecting the behaviour of a comment is a complex process that requires advanced text analysis and machine-learning techniques [80]. One of the most effective approaches to accomplish this task is through the use of classifiers, which are algorithms capable of learning relevant patterns and features in the data to make predictions about the emotional or sentimental behaviour of a comment [1].

To be able to apply these classifiers, it is first necessary to convert the comments into numerical representations that the algorithms can process. This process, known as vectorisation, involves dividing the comments into groups of words, or even individual words, and then assigning each word a numerical value that reflects its relative importance in the comment [47].

Nonetheless, not all words contribute equally to the expression of feeling in a comment. Therefore, it is crucial to eliminate irrelevant elements that do not provide useful information for the detection of emotional behaviour [75]. This may include common words, grammatical connectors or context-specific terms that do not have a significant impact on the interpretation of the comment.

Once this pre-processing has been done, a meaningful set of features representing each comment is obtained in the form of numerical vectors [82]. These numerical vectors can then be used as input for the classifiers, which will learn to associate specific patterns in the vectors with the different emotional behaviours they wish to detect, such as positive, negative or neutral [72].

It is essential to understand that written comments can encompass a wide range of emotional tones and nuances, from expressions of joy and satisfaction to expressions of irritation or discontent, and even a neutral tone that lacks any obvious emotional charge. This diversity of emotions and attitudes can significantly influence the perception and interpretation of comments, which in turn can affect the dynamics and outcomes of group decision-making [37].

In this regard, it is essential to classify comments that reflect their predominant emotional tone [2]. Comments can be labelled as positive if they convey feelings of happiness, satisfaction or appreciation, while they are

considered negative if they express emotions such as irritation, disgust or displeasure. On the other hand, neutral comments lack a clear emotional charge and are usually objective or descriptive in content.

Furthermore to classification based on emotional tone, other aspects of comment behaviour can also be considered to assess their impact on group decision-making [52]. For example, the use of emoticons or emojis may provide additional clues about the emotional state of the commenter, while offensive or aggressive language may indicate a level of tension or conflict in the interaction.

In our research, we aim to develop group decision-making methods that take into account the behaviour of comments made by experts. We recognise that experts' preferences and perceptions can be influenced by the emotional nature of the comments they are exposed to. It is therefore critical to understand how different types of comments can affect decision-making and the degree of consensus reached within the group [21].

By considering the behaviour of comments in the decision-making process, we hope to identify patterns and trends that will help us better understand how emotional interactions influence group dynamics and the quality of decisions made. This, in turn, will allow us to develop more effective strategies and tools to facilitate collaboration and improve outcomes in group decision-making environments [101].

1.2. Preliminaries

In this section, we provide an overview of the foundational concepts essential for comprehending the GDM (Group Decision Making) method formulated within this research. Section 1.2.1 delves into the realm of sentiment analysis, elucidating the intricate steps involved in constructing a classifier tailored to this purpose. Herein, we explore the methodologies and techniques pivotal in discerning and categorizing sentiments expressed within textual data. Additionally, Section 1.2.2 is dedicated to acquainting the reader with fundamental principles underpinning GDM problems. Within this section, we expound upon key concepts, methodologies, and theoretical frameworks pertinent to the field of Group Decision Making, laying a robust foundation for understanding the subsequent discussions and analyses presented in this study.

1.2.1. Sentiment Analysis

Sentiment analysis, a key discipline in natural language processing (NLP), is concerned with understanding the emotions, opinions and attitudes expressed in text [67, 39] (see Figure 1.1)¹. Nonetheless, before meaningful information can be extracted from textual data, it needs to undergo a pre-processing process to clean and prepare it properly. This pre-processing is essential, as textual data is often messy, contains noise and has linguistic variations that can make the task of analysis difficult [31].

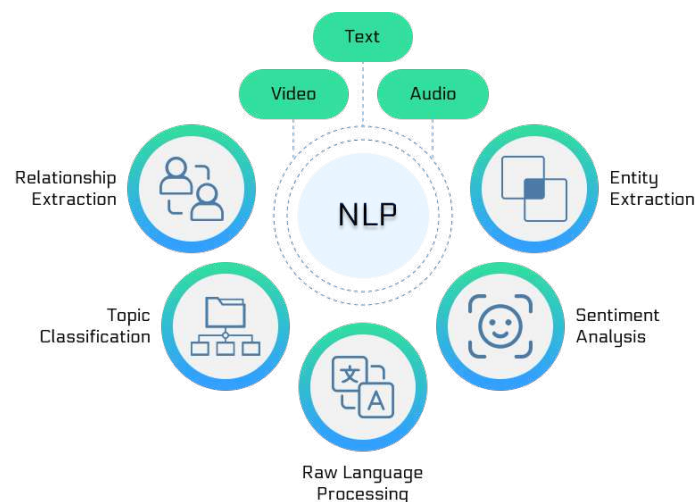


Figura 1.1: General diagram of NLP

¹Imagen extraída de <https://amazon.com/insights/what-is-nlp-and-how-it-is-implemented-in-our-lives/>

In the pre-processing stage, several tasks are performed to prepare the data optimally. One of the first actions is tokenisation, which involves breaking the text into smaller units, such as words or phrases. This facilitates further manipulation and analysis [7]. Then, special characters such as punctuation marks, numbers and other symbols that do not contribute to sentiment analysis are removed. Furthermore, all text is converted to lowercase to ensure uniformity in the analysis and to avoid duplication of words due to differences in capitalisation [28].

Another important step is the elimination of stop words, which are words that are very common but lack contextual meaning in sentiment analysis, such as “the”, “of”, etc [12]. By removing these words, noise in the data is reduced and the performance of the analysis is optimised. Subsequently, stemming or lemmatisation is applied to reduce words to their base form, which facilitates the comparison and grouping of words with similar meanings [36].

Moreover to these actions, pre-processing also corrects misspellings and removes elements that are not relevant for sentiment analysis, such as URLs or user mentions in social networks [86]. This helps to focus on the text’s substantive content and improve the analysis’s accuracy.

Once the preprocessing phase is completed, data processing begins. Here, relevant text features are extracted that may be useful for predicting sentiment. These features may include the frequency of words, the presence of certain linguistic patterns or the grammatical structure of sentences. Machine learning algorithms or NLP techniques are then used to analyse these features and predict the sentiment associated with the text [63].

The pre-processing of supplied comments is essential to convert them into a format that is both useful and effective for the classifier [30]. Moreover, this step is crucial to fit the raw data from the training and test sets, which are used in the construction of the classifier.

Various pre-processing techniques are employed, from which we have selected the following for their ability to segment comments, identify the type of words present and optimise the generation of the bag of words [38] 1.2)²:

- **Tokenization:** This initial step segments the comments into individual words or sets of words. Additionally, it separates words and removes punctuation, thereby breaking down the text into its basic units for easier processing [76].
- **Stemming and Lemmatization:** Following tokenization, stemming

²Imagen extraída de <https://hp-analytics.medium.com/sentiment-analysis-solutions-and-applications-survey-9e52d3ea2ac7>



- **Removal of Stop Words** [24]: Stop words, which are commonly used but contribute little to the overall meaning of the text, are eliminated. This helps to reduce noise in the data and streamline subsequent analyses.
- **Part-of-speech tagging (POS-tagging)** [17]: This step involves assigning parts of speech to each word in the text, such as identifying whether a word is a noun, verb, adjective, etc. POS tagging provides valuable contextual information that aids in understanding the syntactic structure of the text.

The preprocessing procedure outlined above consists of five distinct steps, each playing a crucial role in preparing the textual data for further analysis and modelling. Through meticulous preprocessing, the foundation is laid for robust and effective natural language processing applications.

1. **Simplify:** This step involves reducing words to their root form and eliminating redundant elements that do not contribute valuable information. Specifically, non-relevant words, numbers, and excessive whi-

tespace are removed. Techniques such as stemming, lemmatization, and the removal of stop words are employed to achieve this [15].

2. **Segment:** In this stage, comments are disassembled into n-grams, breaking them down into individual words or sets of words. This segmentation process is facilitated through tokenization, allowing for a structured analysis of the textual data [81].
3. **Extract Linguistic Features:** This phase entails enriching the comments with additional linguistic attributes to enhance their interpretability. Specifically, selected linguistic features are applied based on extensive experimentation, demonstrating their effectiveness in comment classification [25]:

- **Length of Comments:** The length of a comment, measured by the number of words it comprises, offers crucial insights into the commenter's communication style and intent. Longer comments may indicate a more detailed expression of thoughts or emotions, potentially reflecting a heightened level of engagement or investment in the topic at hand. Conversely, shorter comments might suggest brevity or succinctness, which could be indicative of a direct and assertive communication style commonly associated with aggressive behaviour. By analyzing the length of comments, we gain valuable context for understanding the underlying motivations and emotional nuances conveyed within them.
- **Number of Characters:** Beyond word count, the number of characters in a comment provides additional granularity in assessing its complexity and expressive depth. Comments with a high character count may contain elaborate arguments, detailed explanations, or emotionally charged language, all of which could signify a heightened level of involvement or intensity. Conversely, comments with fewer characters but dense content may convey a sense of urgency or terseness, potentially signalling aggression or impatience. By considering both word and character counts, we gain a more comprehensive understanding of the linguistic features and emotional dynamics inherent in the comments.
- **Number of Negative, Neutral, and Positive Emojis:** Emojis serve as powerful visual cues that complement textual communication by conveying emotions and attitudes with immediacy and clarity. The presence of negative emojis, such as frowns or angry faces, may indicate discontent, frustration, or hostility, suggesting a potentially aggressive tone in the comment. Conversely, an abundance of neutral or positive emojis, such as smiles or

hearts, could signify a more amicable or positive sentiment, indicating a non-aggressive stance. By categorizing emojis based on their predominant sentiment, we can discern subtle shifts in emotional tone and better interpret the underlying sentiments conveyed within the comments [66].

- **Number of Emojis:** The overall frequency of emojis within comments offers valuable insights into the commenter’s emotive expression and engagement level. Emojis serve as non-verbal signals that supplement textual content, providing cues about the commenter’s mood, attitude, and communicative style. A comment devoid of emojis may suggest a more formal or reserved tone, while an abundance of emojis could indicate a more informal or expressive communication style. By examining the prevalence of emojis, we can gauge the commenter’s emotional involvement and the overall affective tone of the comments.
- **Number of Negative, Neutral, and Positive Words:** Delving deeper into the textual content of comments, we analyze the occurrence of words categorized by their sentiment values to discern underlying emotional nuances. A high frequency of negative words, such as “hate” or “angry,” may signal aggression or dissatisfaction, while an abundance of neutral or positive words, such as “love” or “happy,” may suggest a non-aggressive or positive tone. By quantifying the distribution of sentiment-laden words, we gain insights into the emotional valence and affective disposition conveyed within the comments, enabling more accurate classification and interpretation [43].
- **Number of Words with Repeated Characters:** Words containing consecutive repeated characters, such as “sooo” or “loooo-ve”, often convey emphasis, intensity, or exaggeration in expression. The presence of such words within comments may indicate heightened emotionality or emphasis, potentially reflecting a passionate or emphatic stance on the part of the commenter. By identifying and quantifying words with repeated characters, we gain insights into the stylistic nuances and emotional intensity embedded within the comments, facilitating a more nuanced understanding of the underlying sentiments conveyed.
- **Number of Consecutive Repeated Words:** Similarly, the occurrence of consecutively repeated words within comments offers valuable insights into the commenter’s linguistic style and expressive tendencies. In formal discourse, such repetitions are typically minimized to maintain clarity and coherence. Nevertheless, in informal or emotionally charged contexts, the deliberate repetition of words may serve rhetorical or expressive purposes, emphasizing

key points or sentiments. By quantifying the frequency of consecutive word repetitions, we can discern patterns of emphasis, intensity, or emotional engagement within the comments, enriching our understanding of the commenter's communicative intent and emotional state.

- **Number of Repeated Exclamations:** Exclamation marks serve as punctuation marks that denote emphasis, excitement, or strong emotion in written communication. The repetition of exclamation marks within comments intensifies the emotional tone and urgency of the message, conveying heightened enthusiasm, urgency, or intensity. By quantifying the frequency of repeated exclamations, we gain insights into the commenter's emotional arousal, expressive style, and communicative intent. A higher frequency of repeated exclamations may indicate heightened emotional engagement or emphasis, potentially signalling aggression, enthusiasm, or urgency depending on the context and content of the comments.
- **Number of Negative and Positive Classic Emoticons:** While emojis offer a diverse range of visual expressions, classic emoticons consisting of punctuation marks retain their significance in digital communication. Categorized based on their sentiment values, the occurrence of negative and positive classic emoticons provides additional cues about the emotional tone and affective disposition of comments. Negative emoticons, such as “:(” or “:/”, may convey dissatisfaction, sadness, or disapproval, while positive emoticons, such as “:)” or “:D”, may signify happiness, approval, or excitement. By analyzing the frequency and distribution of classic emoticons, we gain insights into the emotional valence and affective stance conveyed within the comments, enabling more nuanced interpretation and classification [59].
- **Number of Complete Words in Capital Letters:** Capitalization serves as a stylistic device to convey emphasis, urgency, or intensity in written communication. Words entirely capitalized within comments often denote heightened emotionality, emphasis, or assertiveness. By identifying and quantifying words in all capital letters, we can discern instances of heightened intensity, emphasis, or emotional engagement within the comments. Comments with a higher frequency of fully capitalized words may signal strong opinions, passionate expression, or potential aggression, warranting closer scrutiny for contextual interpretation.
- **Number of Insults:** Insults represent a direct form of verbal aggression, intended to demean, offend, or provoke others. By quantifying the occurrence of insults within comments, we gain

insights into the level of hostility, antagonism, or disrespect conveyed by the commenter. A higher frequency of insults may indicate a more confrontational or aggressive stance, reflecting the contentious nature of the discourse and the commenter's communicative style. Analyzing the presence and distribution of insults enables us to identify and interpret instances of aggression, hostility, or verbal abuse within the comments, facilitating more accurate classification and assessment of their emotional tone and affective content.

- **Part-of-Speech Tagging (POS-tagging):** This linguistic analysis technique assigns grammatical categories or tags to each word within comments, providing valuable contextual information about their syntactic structure and semantic role. By discerning the part of speech of each word—whether it functions as a noun, verb, adjective, or adverb—we gain deeper insights into the linguistic patterns, syntactic structures, and semantic relationships present in the comments. POS-tagging enables us to identify and analyze linguistic features such as sentence structure, word usage, and grammatical patterns, enhancing our understanding of the linguistic complexity and expressive richness inherent in the comments. Additionally, POS-tagging facilitates more accurate interpretation and classification of comments by providing contextual information about the syntactic roles and semantic functions of words within the text. By leveraging POS-tagging, we can extract valuable linguistic features and syntactic structures from comments, enabling more nuanced analysis and interpretation of their linguistic content and communicative intent [17].
4. **Digitization:** It is the process of converting the set of n-grams into a numeric matrix, facilitating computational analysis. This step is crucial for transforming textual data into a format that algorithms can effectively process. There are three distinct methods available to accomplish this transformation:
- **Binary Frequency of Terms:** This method lays the groundwork for the digitization process by simplifying the textual data into a binary representation. While it efficiently captures the presence or absence of specific terms within each comment, it may overlook the frequency of term occurrences, potentially missing out on nuanced insights. Nonetheless, it provides a straightforward and easy-to-understand representation, making it suitable for initial exploratory analysis and basic classification tasks. Additionally, it serves as a useful baseline for comparison with more advanced digitization techniques [60].

- **Frequency of Terms** [98]: Building upon the binary frequency approach, this method offers a more detailed perspective by considering the frequency of term occurrences within each comment. By quantifying the number of times each term appears, this approach generates a numeric matrix that reflects the varying importance and prevalence of terms across the dataset. This richer representation enables a deeper understanding of the linguistic patterns and recurring themes within the comments. Furthermore, it allows for the identification of frequently used terms or phrases that may carry specific sentiments or thematic relevance, providing valuable insights for further analysis and interpretation.
 - **Term Frequency-Inverse Document Frequency (TF-IDF)**: TF-IDF represents a sophisticated technique for assessing the significance of terms within individual comments relative to their occurrence across the entire dataset. By combining term frequency (TF) with inverse document frequency (IDF), TF-IDF assigns higher weights to terms that are frequent within a comment but rare across the dataset. This method effectively captures the unique linguistic characteristics of each comment, highlighting terms that are both informative and distinctive within the broader context of the dataset. As a result, TF-IDF facilitates the identification of key terms that contribute significantly to the overall content and meaning of each comment, enabling more nuanced analysis and interpretation [4].
5. **Aggregation**: Once the numeric matrix representing the linguistic characteristics of each comment has been generated using one of the aforementioned methods, the next critical step is integration into the dataset. Each characteristic, whether binary frequency, term frequency, or TF-IDF score, is added as a separate column in the matrix, expanding the dataset to include quantitative representations of the linguistic features present in each comment. This transformation enhances the dataset's richness and complexity, enabling more comprehensive analysis and modelling. Moreover, to support the classification task, an additional column is appended to the matrix to indicate whether each comment is classified as aggressive (assigned a value of "1") or non-aggressive (assigned a value of "0"). This binary classification serves as the ground truth for training and evaluating classification algorithms. By combining quantitative linguistic features with binary classification labels, the dataset becomes a valuable resource for developing robust and accurate models for detecting and addressing aggressive behaviour in online discourse.

Several machine learning algorithms can be used to build a classifier

based on supervised learning in terms of sentiment analysis processing [8]. In this doctoral thesis, we have specifically selected algorithms that are not based on deep learning. This choice is based on the need for models that allow for faster and more efficient training, without compromising the quality of the results.

Among the chosen algorithms, we highlight those that have proven to be effective in sentiment analysis tasks and that present advantages in terms of training speed and performance. Some of these algorithms include:

- **Support Vector Machine (SVM)** [18]: SVM is a supervised learning technique used for classification and regression. Its main objective is to find the optimal hyperplane that best separates classes in a multidimensional space. When doing this, SVM seeks to maximise the margin, which is the distance between the closest data points of different classes. This approach not only helps to classify the data but also provides good generalisation through a class separation with a maximum margin. In addition, SVM can handle non-linear datasets through the use of kernel functions, which allow mapping the data to a higher dimensional space where linear separation is possible. This makes SVM very versatile and suitable for a wide range of applications, including sentiment analysis.
- **Naïve Bayes** [22]: Naïve Bayes is a probabilistic classification algorithm that is based on Bayes' theorem with a "naïve" assumption of conditional independence between features. Although this assumption may be unrealistic in practice, Naïve Bayes remains a simple but powerful method for classification. It works by calculating the conditional probability of a class given a feature and then combining these probabilities using Bayes' theorem. Despite its simplicity, Naïve Bayes has proven to be surprisingly effective in a variety of classification problems, including sentiment analysis. It is also computationally efficient and can handle large volumes of data with ease, making it suitable for applications where speed and scalability are a priority.
- **K-Nearest Neighbors (KNN)** [19]: KNN is a supervised learning algorithm based on the principle that similar instances tend to belong to the same class. It works by calculating the distance between the unlabelled data point and all labelled data points in the training set and then assigning the data point the most common class among its k nearest neighbours. KNN is intuitive and easy to understand, as it does not require any explicit assumptions about the distribution of the data. Nevertheless, its main disadvantage lies in its need to store all training data in memory, which can be computationally expensive on large data sets. Furthermore, KNN can be sensitive to the choice of

distance metric and the value of K , which requires careful tuning and validation of the parameters.

These algorithms provide a robust set of tools to address sentiment analysis in this research. By choosing algorithms that do not rely on deep learning, faster and more efficient training is prioritised, allowing for more agile iteration in the research process. Furthermore, the combination of SVM, Naïve Bayes and KNN offers a variety of approaches that can complement each other to improve the accuracy and robustness of the sentiment analysis classifier.

1.2.2. Group Decision Making

A Group Decision Making (GDM) challenge arises when a diverse panel of experts is tasked with reaching a unified decision [99, 10]. In this scenario, it becomes imperative to delineate a group of m experts, denoted as E , who must collaboratively choose from a set of n alternatives, labelled as X , utilizing individual preference sets P_s , where s ranges from 1 to m [9].

In contemporary literature, a variety of methodologies are evident for representing expert evaluations, with one prominent approach being the utilization of preference relations [46]. These relations play a pivotal role in GDM problems as they enable comparative analysis and subsequent consistency checks of the experts' preferences. This preference comparison is facilitated through a function $\mu_s : X \times X \rightarrow [0, 1]$, which signifies the degree of preference between alternatives. The preference matrix $P_s = (p_s^{ij}; i \neq j = 1, \dots, n)$, where $p_s^{ij} = \mu_s(x_i, x_j); \forall x_i, x_j \in X$, is employed to represent these preferences, possessing dimensions $n \times n$ [11].

Preference relations serve as a cornerstone in GDM as they provide a structured framework for understanding the diverse perspectives of individual experts within the group [85, 104]. These relations encapsulate the nuances of preferences between different alternatives, enabling a nuanced analysis of their relative merits. By employing preference matrices, which systematically capture the pairwise preferences of experts for each alternative, GDM frameworks can effectively navigate the complexities inherent in decision-making scenarios involving multiple stakeholders.

One notable aspect of preference relations is their role in fostering consensus and coherence within the decision-making process [91]. Through comparative analysis facilitated by preference functions, decision-makers can identify areas of agreement and divergence among experts' viewpoints [79]. This not only aids in reaching a unified decision but also allows for the exploration of trade-offs and compromises that may be necessary to accommodate varying preferences within the group.

Furthermore, preference relations offer a means of evaluating the robustness and reliability of decision outcomes. By subjecting preference matrices to consistency checks and validation measures, decision-makers can assess the stability of the chosen alternatives and identify potential sources of disagreement or uncertainty [3]. This proactive approach to quality assurance enhances the credibility and trustworthiness of the decision-making process, particularly in contexts where the stakes are high or the consequences of suboptimal choices are significant [49].

In practical applications, the utilization of preference relations extends beyond traditional decision-making contexts to encompass a wide range of domains, including strategic planning, resource allocation, and policy formulation [62, 40]. Whether in business settings, governmental institutions, or academic research, the ability to effectively synthesize and reconcile diverse preferences is paramount for achieving outcomes that reflect the collective wisdom of the group [57]:

- **Expressing Expert Opinions:** The initial stage of providing opinions serves as a crucial foundation for the entire decision-making process [70]. Through a structured debate, experts engage in an exchange of perspectives and insights on the available alternatives [93]. This phase fosters a comprehensive understanding of the strengths, weaknesses, and unique considerations associated with each option. By articulating their preferences via the preference relation matrix, experts contribute valuable input that informs subsequent stages of the decision-making process.
- **Consensus Analysis:** The evaluation of consensus among experts represents a pivotal step in ensuring the robustness and validity of the decision outcomes [94]. This phase involves a thorough analysis of the level of agreement or divergence among expert opinions, both within individual groups and across the entire panel. A higher consensus value indicates a greater convergence of viewpoints, signalling a stronger collective endorsement of the chosen option [71]. However, establishing the threshold for acceptable consensus involves careful consideration of various factors, including the complexity of the decision context and the diversity of expert perspectives. Through iterative assessments and adjustments, decision-makers strive to strike a balance between achieving consensus and accommodating diverse viewpoints.
- **Aggregating Information:** The aggregation of information marks a critical juncture where individual preferences are synthesized into a unified representation of collective opinion. The creation of the collective preference relation matrix, denoted as C_G , consolidates the diverse array of expert perspectives into a comprehensive framework

for decision-making [69]. This process often involves the application of aggregation operators, which weigh and combine individual preferences to derive a holistic assessment of each alternative [77]. By leveraging aggregation techniques, decision-makers can distil complex and multi-dimensional input into actionable insights that inform the subsequent ranking of alternatives.

- **Ranking of Alternatives:** The final stage entails the derivation of a ranked list of alternatives based on the aggregated preferences captured in the matrix C_G [50]. This ranking serves as a valuable tool for decision-makers in identifying the most preferred options and guiding subsequent actions or interventions. Various methodologies, such as the Quantifier Guided Dominance Degree (QGDD) [33] and Quantifier Guided Non-dominance Degree (QGNDD) [103], offer systematic approaches for prioritizing alternatives based on different criteria and preferences. By integrating multiple measures and perspectives, decision-makers can arrive at a comprehensive ranking that reflects the collective priorities and preferences of the expert panel.

Currently, the realm of GDM is witnessing a surge in research endeavours, with numerous papers offering innovative solutions to address its inherent challenges. In [55], an in-depth exploration of social network dynamics is undertaken to unveil conflicts within GDM processes. Through the lens of a trust relationship model, this research delves into the intricacies of trust propagation, conflict detection, and resolution mechanisms. By integrating these components into a cohesive framework, the study offers valuable insights into mitigating conflicts and enhancing decision-making outcomes in large-scale group settings. Building on this, [97] introduces a novel approach to identifying opinion leaders within GDM contexts. By leveraging a cluster-based consensus model and employing k-core decomposition techniques, this research provides a systematic methodology for identifying influential individuals whose opinions carry significant weight in group decision-making processes. This nuanced understanding of opinion dynamics enables decision-makers to effectively leverage key influencers to drive consensus and facilitate informed decision outcomes. Additionally, [56] presents a comprehensive two-stage composite method tailored to support the consensus elicitation process in large-scale multi-attribute group decision-making scenarios. By integrating diverse decision criteria and eliciting consensus iteratively, this method offers a robust framework for navigating the complexities inherent in large-scale decision-making contexts. Through empirical validation and practical applications, this research contributes valuable tools and techniques for enhancing decision quality and fostering stakeholder satisfaction. Moreover, in [26], a pioneering model is proposed to address hesitant GDM problems, where decision-makers express their preferences using hesitant

fuzzy preference relations. This model offers a systematic approach to handling uncertainty and ambiguity in group decision-making processes by leveraging advanced mathematical frameworks and innovative algorithms. This research not only advances theoretical understanding but also provides practical tools for decision-makers to navigate real-world decision challenges effectively. Furthermore, [96] introduces a consensus-based GDM model to analyse experts' non-cooperative behaviours. Through the establishment of a collective decision-making setting and the assessment of rationality levels, this model offers insights into the underlying dynamics of group decision processes. By identifying and addressing non-cooperative behaviours, decision-makers can foster a collaborative environment conducive to achieving consensus and driving effective decision outcomes. Finally, [83] presents an innovative GDM model that integrates imprecise information provided by users into the decision-making process. This model offers a flexible framework for handling diverse data sources and accommodating uncertainty in decision-making contexts by employing probabilistic terms and advanced computational techniques. This research contributes to expanding the scope of GDM methodologies by embracing the complexities of real-world decision scenarios and offering practical solutions for decision-makers to navigate them effectively.

1.3. Justification

Experts, when participating in debates, use this setting to exchange their views, experiences and preferences. Nonetheless, the dynamics and behaviour of individuals during these discussions can have a significant impact on the ease or difficulty of reaching a satisfactory consensus. It is clear that how participants express themselves and communicate, as well as the emotional tone and nature of their comments, can substantially influence the atmosphere of the debate and, ultimately, the group's ability to reach an agreement.

In this sense, it is imperative to thoroughly analyse the comments generated during the discussion by the experts. This analysis allows for the identification of patterns of behaviour, tendencies in emotional expression and inclination towards certain types of arguments or positions. For example, an expert who tends to generate pleasant and constructive comments may contribute positively to the creation of an atmosphere conducive to consensus, fostering mutual respect and openness to the ideas of others.

Conversely, an expert whose comments are critical, confrontational or negative can hinder the consensus process, generating tensions and obstacles that make it difficult to find common ground. In this sense, the analysis of comments becomes essential to understanding how individual behaviours influence group dynamics and the ability to reach satisfactory agreements.

An important aspect to consider is that comments not only convey explicit information about the experts' opinions and positions but also reflect their attitude and disposition towards the process of discussion and collaboration. Therefore, by analysing the comments, we can obtain a more complete and nuanced view of the interactions within the group, which allows us to identify opportunities to improve communication, manage conflicts and promote a more collaborative and productive work environment.

Within the framework of this thesis, our attention will be specifically directed towards the in-depth analysis of the information generated by individuals during the debates. We will embark on a detailed study of the comments made, employing advanced sentiment analysis tools to unravel the complexities of human behaviour in this context. Our primary goal is to create measures that allow us to understand and categorise these behaviours accurately and comprehensively.

Sentiment analysis proves to be an invaluable tool in our research, as it provides us with the ability to delve into the emotional and subjective essence of the comments made during the debate. By breaking down and examining the emotional nuances present in the language used by participants, we can more accurately capture the essence and underlying tone of

their expressions. This, in turn, provides us with a unique insight into their attitudes, perceptions and motivations during the exchange of ideas.

We aim, then, to create more robust measures of consensus that holistically integrate the complex emotional and cognitive interactions that take place in the context of debate. By better understanding individual behaviours and their influence on the group decision-making process, we hope to develop tools and strategies that promote stronger and more genuine consensus among participants.

Through a rigorous, interdisciplinary approach, we will delve into the analysis of large volumes of data, exploring the many facets of human behaviour in debate settings. With a combination of natural language processing, data mining and machine learning techniques, we seek to uncover meaningful patterns and trends that shed light on the underlying dynamics that shape the group decision-making process.

Ultimately, we aim to contribute to the advancement of knowledge in this emerging field by providing valuable insights and practical tools that can be applied in a wide range of contexts, from academia to business and beyond. Our research is positioned as a comprehensive, multidisciplinary effort aimed at unravelling the complex webs of human behaviour in the process of collective decision-making.

Precisely, at the core of our research proposal, we propose the adoption and application of advanced group decision-making techniques in conjunction with the detection and analysis of the behaviours manifested in the comments made by the experts during the discussion process. This synergistic combination of approaches will allow us to explore and understand in depth the complexities and dynamics underlying the exchange of ideas and opinions within the group.

To accomplish this task, we will rely on the use of sentiment analysis techniques, a field of study that has undergone rapid development in recent years. By using specialised tools and algorithms, such as those described by [54, 29], we will be able to unravel the emotional and subjective nuances present in the experts' comments.

These techniques will allow us to accurately identify and categorise the emotions, attitudes and tones expressed by participants during the debate. From expressions of enthusiasm and support to expressions of dissatisfaction or scepticism, we aim to capture and fully understand the emotional and cognitive richness present in the comments.

By combining this detailed analysis of behaviours with proven approaches to group decision-making, we will be in a unique position to assess how verbal and emotional interactions influence the decision-making process. This will allow us not only to identify significant patterns and trends

in expert behaviour but also to understand how these behaviours impact the quality and degree of consensus reached by the group.

Our research is positioned at the forefront of this emerging field, fusing traditional and cutting-edge methods to provide a comprehensive understanding of group decision-making processes. In doing so, we aim to generate valuable and applicable knowledge that can inform and improve practice in a wide range of contexts, from business and organisational settings to academia and beyond.

Transforming written commentary into a format that can be understood by a computer is a fundamental process in text analytics and machine learning. One of the most common techniques to achieve this is the representation of the comment as a numerical vector. This process begins by breaking the comment into individual words or groups of words, known as n-grams. These n-grams capture the structure and meaning of the comment in a more granular way, allowing for a more detailed representation of the comment.

Once the n-grams have been obtained, it is crucial to perform a filtering process to remove words or groups of words that do not provide relevant information for the analysis. This may involve the elimination of common words, grammatical connectors or context-specific terms that do not contribute to the meaning of the comment. In addition, dimensionality reduction techniques can be applied to simplify the set of words and improve the efficiency of the process.

When the set of relevant n-grams has been obtained, various measures can be used to generate a numerical vector that represents the comment compactly and effectively. These measures may include the frequency of occurrence of each word in the comment, the presence of certain key terms or the length of the comment, among others. In addition, more advanced measures can be considered, such as the number of repeated words or similarity to previously analysed comments.

Once the numerical vector has been generated for each comment, machine learning-based classification techniques can be used to assign a label or category to each comment, based on its content and context. This allows comments to be automatically classified into different categories, such as positive, negative or neutral, based on emotional tone or communicative intent.

Nevertheless, until now, most methods have mainly focused on the analysis of the preferences provided by the experts to the system, without taking into account the experts' behaviour during the debate. In this thesis, we propose new decision-making and consensus methods that take into account the experts' behaviour during the debate by analysing their comments. This

will allow us to gain a more complete and accurate understanding of group decision-making processes, and to develop more effective tools and strategies to facilitate collaboration and improve outcomes in debate and deliberation environments.

1.4. Objectives

The proposal is distinguished by its holistic and advanced approach to analysing the dynamics of the debate and its impact on group decision-making. In essence, it seeks to go beyond the mere observation of the opinions expressed by the experts and delve into the study of their underlying behaviours, emotions and attitudes as reflected in their comments during the discussion process.

The proposed model aims to identify significant patterns in the way experts interact and communicate with each other during the debate. It seeks to distinguish between those who show an openness to change and are willing to consider and adapt their views in the light of the arguments presented, and those who cling tenaciously to their perspectives, showing less flexibility and openness to dialogue.

To achieve this detailed analysis, advanced sentiment analysis techniques will be applied to the comments written by the experts. These techniques will allow us to unravel the emotional and subjective nuances present in the language used by the participants, identifying the emotions, attitudes and tones expressed in their comments with great precision and detail.

The value of this approach lies in its ability to provide relevant and useful information that can be used in the group decision-making process. By better understanding experts' behaviours and attitudes during the debate, a new decision-making model can be designed that takes these key variables into account, thus optimising the deliberation process and arriving at more informed and consensual decisions.

Ultimately, this innovative model holds the promise of substantially enhancing the quality and efficacy of outcomes in group decision-making contexts. By integrating a more comprehensive analysis of the behaviours and emotions exhibited by participants during discussions, it aims to foster increased receptiveness to dialogue, improved collaboration, and more thoughtful and well-informed decision-making processes. As for the specific objectives, the following have been delineated:

- **Comprehensive Review of the State-of-the-Art:** Conducting an exhaustive examination of existing literature on consensus models, decision-making frameworks, and behaviour detection through sentiment analysis. This entails critically analyzing relevant research, methodologies, techniques, and tools employed in these domains to inform the development of the proposed model.
- **Implementation of a Machine Learning Algorithm:** Designing and deploying a robust machine learning algorithm capable of accurately detecting and categorizing behavioural patterns within comments

made by participants during discussions. This algorithm will be trained using labelled datasets and optimized to achieve optimal performance in identifying relevant behavioural cues.

- **Application of Behavior Detection to Expert Discussions:** Leveraging the developed algorithm to analyze discussions among experts, extracting insights into various behavioural tendencies such as openness to change, resistance, or influence on group decision-making dynamics. These insights will serve as foundational elements for the creation of a group decision-making and consensus model that integrates the extracted information.
- **The proposition of Novel Measures to Enhance Decision-making:** Developing and proposing novel metrics and methodologies that incorporate insights gleaned from the analysis of expert behaviour during discussions. These measures will be designed to augment the quality and efficiency of group decision-making processes, facilitating consensus-building and conflict resolution.
- **Dissemination of Findings through Scholarly Publications:** Authoring and disseminating research articles in peer-reviewed journals and presenting findings at conferences and symposiums. This dissemination strategy aims to share research outcomes, contribute to the advancement of knowledge in the field, and facilitate the practical application of research findings across various contexts.

1.5. Methodology

The previously outlined objectives can be achieved through the implementation of a rigorous methodological sequence within the framework of scientific research. This sequencing, which is deployed in a systematic and organised manner, is an essential process to address each of the objectives effectively and efficiently. How this sequencing is developed is detailed below:

- **Exhaustive Review of the State of the Art:** This stage involves conducting a detailed and exhaustive review of the existing scientific literature related to the proposed line of research. A thorough study of scientific articles, doctoral theses and other relevant academic works will be carried out. This review will provide an in-depth understanding of the current landscape concerning consensus models, decision making and sentiment analysis. It will also serve as a basis for the detailed modelling and design of the research plan.
- **Theoretical Design of the Models:** Based on the findings and conclusions derived from the state-of-the-art review, new theoretical models will be proposed. These models will be aimed at addressing the challenges and problems identified in the research. Models will be designed both for group decision-making and for sentiment analysis in the expert comments during the discussion. This theoretical design will constitute the conceptual and methodological framework on which the empirical work will be developed.
- **Implementation of the Theoretical Models:** Once the theoretical models have been defined, we will proceed to their practical implementation by programming algorithms in an appropriate programming language. This process will involve the translation of the conceptual models into functional computational algorithms. Tests and adjustments will be carried out to ensure the validity and effectiveness of the implemented algorithms in behaviour detection and group decision-making.
- **Dissemination of Results Obtained:** The results obtained from the implementation and application of the theoretical models will be documented and presented in the form of scientific articles. They will be written and submitted to reputable scientific journals for peer review and possible publication. In addition, presentations will be prepared for presentation at relevant academic congresses and conferences. This dissemination of results will contribute to the sharing of research findings and promote discussion and collaboration in the scientific field.

1.6. Resumen (Summary)

En el contexto de una tesis doctoral dedicada a explorar los avances en la toma de decisiones grupales, se emprende una investigación que abarca desde los fundamentos teóricos más profundos hasta la aplicación práctica y la validación empírica de los conceptos desarrollados. Este trayecto, marcado por la curiosidad intelectual y la búsqueda incansable de soluciones efectivas, representa un compromiso constante con la mejora continua y la innovación en el área de la toma de decisiones en grupo.

El primer hito en esta investigación es la inmersión completa en los conceptos de la teoría y la investigación en el artículo “*Theorem Verification of the Quantifier-Guided Dominance Degree with the Mean Operator for Additive Preference Relations*” [88]. Aquí, se lleva a cabo una meticulosa verificación de un teorema que proporciona una base sólida y fundamentada para comprender las complejidades de las relaciones de preferencia en contextos de toma de decisiones en grupo. Este enfoque teórico riguroso, respaldado por una exhaustiva revisión de la literatura existente, establece los cimientos necesarios para abordar de manera efectiva los desafíos que se presentan en el proceso de toma de decisiones.

Después de haber asentado una base teórica sólida, la investigación continúa con la exploración de aplicaciones prácticas en el artículo “*A Large Scale Group Decision Making System Based on Sentiment Analysis Cluster*” [90]. Aquí, se presenta un sistema innovador de toma de decisiones grupales que utiliza técnicas de análisis de sentimientos para comprender mejor las emociones y actitudes de los miembros del grupo. Esta aproximación pseudopráctica ofrece una perspectiva fascinante sobre cómo la tecnología puede ser utilizada para mejorar la toma de decisiones en entornos grupales a gran escala, combinando principios teóricos con aplicaciones prácticas.

Sin embargo, la verdadera prueba de la efectividad de estos enfoques surge en el artículo “*A Group Decision-Making Method Based on the Experts’ Behavior During the Debate*” [89]. Aquí, se realiza una investigación empírica y experimental para analizar en profundidad el comportamiento de los expertos durante los debates grupales. Al aprovechar datos empíricos reales y técnicas de aprendizaje automático, este enfoque práctico proporciona una comprensión valiosa de las dinámicas de grupo y su impacto en el proceso de toma de decisiones.

1.6.1. Theorem Verification of the Quantifier-Guided Dominance Degree with the Mean Operator for Additive Preference Relations

En este minucioso y detallado análisis, nos embarcamos en la formulación de un teorema de una magnitud sin precedentes, con el propósito fundamental de erigir una estructura robusta y confiable que asegure la integridad y precisión de todos los procesos y cálculos realizados en el ámbito científico y tecnológico contemporáneo. En una era caracterizada por la creciente complejidad y sofisticación de los algoritmos y métodos computacionales, la certeza de la ausencia de fallos lógicos en su programación se torna esencial, siendo esta empresa no solo un desafío técnico, sino también un imperativo ético y epistemológico de la más alta relevancia.

El fundamento de nuestro teorema se cimienta en un profundo y exhaustivo análisis de la vasta literatura existente, donde se revela una preocupante carencia: la ausencia de un mecanismo efectivo para certificar la exactitud y la validez de los cálculos presentados en los diversos artículos de investigación. Esta falta de verificación y validación no solo plantea interrogantes sobre la confiabilidad y la credibilidad de los resultados científicos, sino que también suscita serias dudas sobre la reproducibilidad y la transparencia de los procesos científicos en sí mismos. En respuesta a esta apremiante necesidad, nos proponemos desarrollar una solución matemática que no solo proporcione un método riguroso y sistemático de validación, sino que también permita a los expertos y científicos afirmar con confianza la inexistencia de errores en los procedimientos computacionales empleados, sentando así las bases para una nueva era de confianza y seguridad en el conocimiento científico.

La envergadura y profundidad de nuestro teorema trasciende los límites disciplinarios convencionales, abarcando un amplio espectro de campos de estudio y aplicaciones. Desde la inteligencia artificial y la computación cuántica hasta la biología computacional y la astrofísica, cada área del conocimiento se beneficia de la solidez y la fiabilidad que nuestra propuesta promete ofrecer. Nuestra ambición es proporcionar un marco teórico robusto y universal que sirva como cimiento para futuros avances científicos y tecnológicos, mitigando así la incertidumbre y el escepticismo que a menudo rodean los descubrimientos y desarrollos más innovadores.

Como se destaca y demuestra de manera inequívoca en la Figura 1.3, la relevancia y la trascendencia de nuestro teorema se hacen patentes en múltiples niveles y etapas del proceso de toma de decisiones y de la investigación científica en general. Desde la fase inicial de modelización de las opiniones de los expertos hasta la etapa final de evaluación y clasificación de las alternativas disponibles, cada paso se ve beneficiado por la rigurosidad y

la precisión que nuestra propuesta garantiza, consolidando así la confianza y la credibilidad en el proceso científico en su conjunto. La demostración y aplicación de este teorema no solo verificará la corrección del proceso GDM propuesto, sino que también sentará las bases para una nueva era de avance y progreso científico, donde la certeza y la confianza en la validez de los resultados son pilares fundamentales.

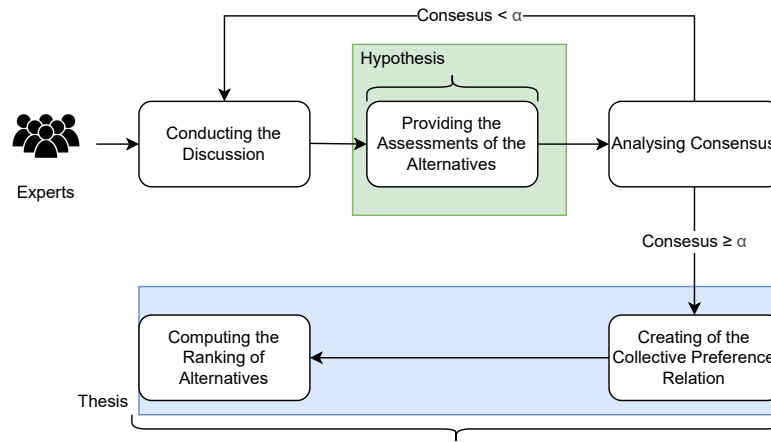


Figura 1.3: Secciones afectadas por la hipótesis y la tesis dentro del esquema básico de un sistema GDM.

Seguidamente, se va desarrollar el teorema que hemos desarrollado con el propósito de establecer un robusto marco de validación para los procesos y cálculos en el ámbito científico y tecnológico. Este teorema representa un hito significativo en la búsqueda de una solución matemática que garantice la integridad y la precisión de los resultados obtenidos, abordando así una necesidad apremiante en el panorama actual de la investigación y el desarrollo. Sin más dilación, procedamos a la enunciación del teorema [88].

Para un proceso de toma de decisiones, sea $E = \{e_1, \dots, e_b\}$, $b \in \mathbb{N}$, el conjunto de expertos con pesos no negativos, $W = \{w_{e_1}, \dots, w_{e_b}\}$, verificando $\sum_{q=1}^b w_{e_q} = 1$. Sea $A = \{A_1, \dots, A_n\}$, $n \in \mathbb{N} \setminus \{1\}$, el conjunto de alternativas. Sea $\{M_{e_q} = (m_{tk}^q), q = 1, \dots, b; t, k = 1, \dots, n\}$ el conjunto de matrices aditivas que representan las preferencias del conjunto de expertos sobre el conjunto de alternativas. Entonces, se verifica la siguiente

expresión:

$$\sum_{p=1}^n QGDD_{A_p} = \frac{U \cdot n}{2}, \quad (1.1)$$

donde $QGDD_{A_p}$ es el $QGDD$ de la alternativa A_p , n es el número de alternativas, y $U \in \mathbb{N}$.

1.6.2. A Large Scale Group Decision Making System Based on Sentiment Analysis Cluster

En esta sección, se expone detalladamente el método innovador desarrollado para abordar los desafíos asociados con la Toma de Decisiones en Grupo a Gran Escala (LSGDM, por sus siglas en inglés). Nuestra propuesta se centra en la detección y análisis de la agresividad y positividad manifestadas por los expertos a través de los comentarios que emiten durante el debate. Para lograr este objetivo, empleamos técnicas avanzadas de análisis de sentimientos, lo que nos permite discernir el grado de positividad y agresividad presentes en las contribuciones de los participantes.

En primer lugar, nuestro método aprovecha el enfoque de la “bolsa de palabras” para clasificar los comentarios de los expertos en función de su tono emocional, diferenciando entre expresiones agresivas y positivas. Este enfoque nos permite capturar tanto el contenido semántico como el contexto emocional de las interacciones, proporcionando así una visión más completa de la dinámica del debate.

Posteriormente, los expertos son agrupados en función de las frases que proporcionan al sistema, lo que facilita un análisis más granular y personalizado de sus contribuciones. Esta segmentación permite identificar patrones de comportamiento y preferencias individuales, lo que a su vez enriquece la comprensión del proceso de toma de decisiones grupales.

El método LSGDM, representado de manera esquemática en la figura 1.4, consta de los siguientes pasos:

- **Detección del comportamiento en los comentarios:** Nuestro método se inicia con la identificación de los comentarios generados por los expertos, los cuales son sometidos a un análisis exhaustivo para evaluar tanto su grado de agresividad como de positividad. Esta fase se desglosa en dos pasos fundamentales:
 - **Eliminación y simplificación de palabras:** En este primer paso, se procede a depurar los comentarios eliminando aquellas palabras que no aportan información relevante al análisis. Posteriormente, se simplifican todas las palabras restantes a su forma raíz, lo que permite reducir la complejidad y la dimensionalidad

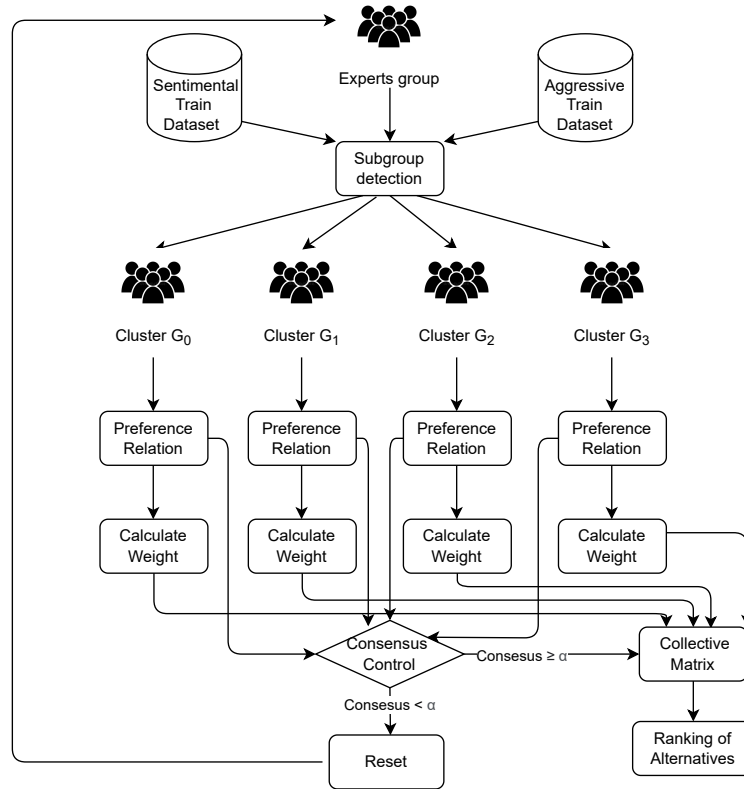


Figura 1.4: Esquema gráfico del método propuesto

del conjunto de palabras. Este proceso resulta en un conjunto más conciso y manejable de términos por comentario, lo que contribuye a mejorar la eficacia general del método.

- Creación de bolsas de palabras y cálculo del grado de pertenencia:** En esta etapa, los textos depurados se desglosan en palabras individuales, y a partir de las clases asociadas a cada comentario se construyen bolsas de palabras correspondientes a distintas categorías de sentimientos. Concretamente, se generan cuatro bolsas de palabras distintas: dos para expresiones positivas y negativas respectivamente, y otras dos para expresiones agresivas y no agresivas. Una vez constituidas estas bolsas, se eliminan las palabras que se encuentran en ambas bolsas dentro de la misma categoría de sentimiento. Finalmente, se calcula el grado de agresividad y positividad de cada comentario en base a la proporción de palabras que pertenecen a las respectivas bolsas.

Este enfoque meticuloso y estructurado garantiza una evaluación precisa y detallada del tono emocional de los comentarios de los expertos, permitiendo así una comprensión más profunda de sus actitudes y perspectivas. Además, la utilización de bolsas de palabras específicamente diseñadas para cada categoría de sentimientos contribuye a mejorar la precisión y la fiabilidad del análisis, lo que facilita la posterior clasificación y valoración de los comentarios.

- **Aportación de opiniones:** Tras el intercambio de opiniones y el debate entre los expertos, cada uno contribuye con sus preferencias a través de relaciones de preferencia. Estas relaciones sirven como un medio para expresar de manera formal y estructurada las inclinaciones individuales hacia las diversas alternativas o soluciones en consideración. Al representar las preferencias de esta manera, se facilita la comprensión y el análisis de las distintas perspectivas dentro del grupo, lo que permite identificar áreas de consenso y discrepancia. Esta representación también establece una base sólida para la toma de decisiones colectivas, al proporcionar un marco común para evaluar y comparar las opciones disponibles. En última instancia, el uso de relaciones de preferencia promueve un proceso de toma de decisiones más transparente y colaborativo, en el cual se pueden alcanzar soluciones que sean aceptables y beneficiosas para todos los involucrados.
- **Creación de los grupos de expertos:** Después de examinar detenidamente los comentarios de los expertos y evaluar sus niveles de agresividad y positividad, se procede a agruparlos en cuatro categorías distintas, a saber:
 - Grupo Agresivo - Positivo
 - Grupo Agresivo - Negativo
 - Grupo No Agresivo - Positivo
 - Grupo No Agresivo - Negativo

Estos grupos representan combinaciones únicas de tonos emocionales, lo que permite una segmentación más precisa y detallada de los expertos según sus características individuales. Una vez completada la agrupación, se calculan cuatro relaciones de preferencia, una para cada grupo. Este cálculo se realiza mediante la agregación de las matrices de relaciones de preferencia de los expertos que pertenecen a cada grupo. En esta etapa, todas las relaciones de preferencia se ponderan igualmente, asegurando así una consideración justa y equilibrada de las opiniones de los expertos en cada grupo. Esto permite capturar de manera efectiva las preferencias y tendencias comunes dentro de cada categoría de expertos, lo que facilita la identificación de patrones y

la toma de decisiones informada en cada grupo específico. Además, al asignar igual peso a todas las relaciones de preferencia, se promueve un análisis imparcial y equitativo, lo que contribuye a la objetividad y transparencia del proceso de toma de decisiones en su conjunto.

- **Cálculo de los pesos de los grupos:** Una vez obtenida una única matriz de relaciones de preferencia para cada grupo, se procede a asignar distintos pesos a cada uno de ellos, tomando en cuenta diversos criterios significativos:
 - **Consolidación del consenso dentro del grupo:** Se otorga mayor peso a aquellos grupos cuyos expertos muestran un alto grado de acuerdo en sus preferencias. Esta medida refleja la cohesión interna del grupo y su capacidad para llegar a un consenso unificado.
 - **Tamaño del grupo de expertos:** Los grupos con un mayor número de miembros pueden tener un impacto más significativo en la toma de decisiones. Por lo tanto, se asignan pesos proporcionales al tamaño de cada grupo, reconociendo así la influencia potencial que estos pueden tener en el resultado final.
 - **Nivel de agresividad:** Se considera el grado de agresividad manifestado por los expertos dentro de cada grupo como un factor relevante. Aquellos grupos que presentan un tono más colaborativo y respetuoso pueden recibir una ponderación adicional, promoviendo así un ambiente de discusión constructiva y productiva.
 - **Nivel de positividad:** De manera complementaria, se evalúa el nivel de positividad expresado por los expertos en sus interacciones grupales. Los grupos que fomentan un ambiente de apoyo mutuo y consideración pueden ser reconocidos con un peso mayor, ya que esto puede contribuir a un proceso de toma de decisiones más armonioso y satisfactorio.

Al considerar estos criterios en la asignación de pesos a cada grupo, se busca garantizar una representación equitativa y balanceada de las diversas dinámicas y características presentes en el proceso de toma de decisiones en grupo. Esto permite una evaluación más completa y precisa de las preferencias y opiniones de los expertos, facilitando así la selección de la mejor opción posible.

- **Análisis del consenso:** Esta etapa despliega un análisis minucioso del grado de consenso tanto dentro de los grupos individuales como entre ellos, con el objetivo de evaluar la cohesión general del conjunto. Este proceso permite discernir si existen discrepancias notables de opinión entre los diferentes grupos y si hay tendencias de pensamiento

específicas asociadas a cada uno de ellos. En esencia, este paso nos brinda una visión detallada de cómo se desenvuelve cada grupo en términos de acuerdo o disensión interna, lo que proporciona una comprensión más profunda de sus dinámicas y comportamientos individuales.

- **Cálculo de la relación de preferencias colectiva:** En esta fase, se emplean las relaciones de preferencia individuales de cada miembro del grupo, junto con los respectivos pesos asignados a cada experto, con el fin de derivar una relación de preferencia colectiva. Este proceso de agregación requiere la utilización de operadores específicos diseñados para combinar las preferencias individuales en una visión colectiva unificada. Estos operadores actúan como herramientas fundamentales para sintetizar las múltiples perspectivas presentes en el grupo y llegar a una decisión consensuada.
- **Creación de la ranking de alternativas:** La etapa final del proceso, la creación del ranking de alternativas, desempeña un papel crucial en la selección de la opción óptima que satisfaga las necesidades y preferencias del grupo de expertos. En esta fase, se integran dos operadores fundamentales: el QGDD (Quantitative Group Decision Making with Decision Degree) y el QGNDD (Quantitative Group Non-Dominance Decision Making). El operador QGDD se encarga de evaluar cuantitativamente cada alternativa en función de la contribución individual de los expertos y sus respectivos pesos asignados. Este enfoque permite asignar una puntuación numérica a cada opción, reflejando así su grado de preferencia dentro del grupo. Al combinar las evaluaciones individuales y los pesos respectivos, se obtiene una medida objetiva de la utilidad y viabilidad de cada alternativa, lo que facilita la comparación y clasificación final.

1.6.3. A Group Decision-Making Method Based on the Experts' Behavior During the Debate

En esta sección, se presenta una vanguardista aproximación destinada a resolver los desafíos inherentes a la GDM. Este enfoque innovador no solo considera los argumentos racionales, sino que también integra el análisis del comportamiento y las emociones de los expertos durante las etapas de debate dentro del proceso de toma de decisiones.

El núcleo del método pionero radica en la utilización de técnicas avanzadas de análisis de sentimientos, las cuales permiten descifrar las emociones expresadas por los expertos a lo largo del debate. Al examinar sus comentarios, podemos desentrañar sus actitudes, sentimientos y percepciones, lo que nos brinda una comprensión más profunda de cómo las decisiones bajo consideración impactan en ellos.

Para fortalecer aún más su robustez y aplicabilidad, el algoritmo subyacente se nutre de datos auténticos extraídos de plataformas de redes sociales de renombre como Facebook y Twitter. Estos datos, meticulosamente clasificados por expertos en términos de agresividad y tono emocional, garantizan la integridad y confiabilidad del proceso. Así, el ejemplo utilizado se arraiga en la realidad, lo que lo convierte en un instrumento directamente transferible a una diversidad de contextos cotidianos.

Este método disruptivo de GDM incorpora un sofisticado clasificador de análisis de sentimientos diseñado específicamente para identificar el uso de un lenguaje agresivo durante las interacciones entre expertos durante el debate. Su proceso se desglosa meticulosamente en las siguientes etapas (consultar Figura 1.5):

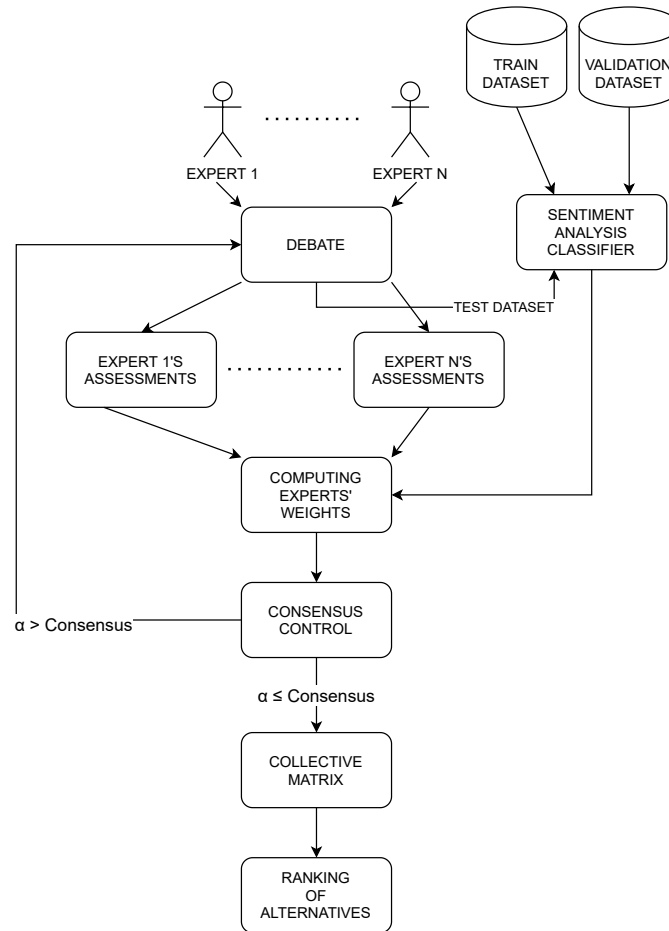


Figura 1.5: Esquema general del método GDM propuesto

- **Detección de lenguaje agresivo durante el debate:** Esta etapa implica el uso de algoritmos de NLP para analizar los comentarios y

contribuciones de los expertos durante el debate. Se aplican técnicas de análisis de sentimientos para identificar expresiones lingüísticas que denoten agresión, como insultos, menosprecios o tono confrontativo. El algoritmo puede estar entrenado para reconocer patrones específicos de lenguaje asociados con la agresión, permitiendo así una identificación precisa y automatizada de este tipo de comportamiento.

- **Aporte de evaluaciones:** Una vez detectado el lenguaje agresivo, se procede a recopilar y analizar las evaluaciones individuales proporcionadas por los expertos durante el debate. Estas evaluaciones pueden incluir opiniones, valoraciones o argumentos a favor o en contra de las diferentes alternativas en consideración. Es importante tener en cuenta tanto el contenido de las evaluaciones como el tono emocional en el que están expresadas, ya que esto puede influir en la percepción y aceptación de las ideas por parte del grupo.
- **Cálculo del peso de los expertos:** En esta etapa, se asigna un peso a cada experto en función de la calidad y relevancia de sus contribuciones durante el debate. Este peso puede determinarse utilizando diferentes criterios, como la experiencia, el conocimiento técnico o la consistencia en sus argumentos. Además, el análisis de sentimientos puede tener en cuenta la actitud y comportamiento de los expertos, otorgando mayor peso a aquellos que mantienen un tono constructivo y respetuoso en sus intervenciones, mientras que se puede restar peso a aquellos que recurren a la agresión o la confrontación.
- **Análisis del consenso:** Una vez que se han recopilado las evaluaciones individuales y se han calculado los pesos de los expertos, se procede a realizar un análisis del consenso entre los miembros del grupo. Esto implica identificar áreas de acuerdo y desacuerdo, así como evaluar la coherencia y consistencia de las opiniones expresadas. El análisis del consenso puede revelar tendencias o patrones en las preferencias de los expertos, así como identificar posibles puntos de conflicto que requieran una mayor atención y discusión.
- **Determinación de una evaluación colectiva:** Con base en el análisis del consenso, se busca alcanzar una evaluación colectiva que refleje la opinión general del grupo sobre las alternativas en consideración. Esta evaluación puede obtenerse mediante técnicas de agregación de opiniones, como la media ponderada de las evaluaciones individuales, teniendo en cuenta los pesos asignados a cada experto. La evaluación colectiva proporciona una guía para la toma de decisiones, al ofrecer una visión integrada y consensuada de las preferencias del grupo.
- **Clasificación de las alternativas:** Finalmente, se procede a clasificar las alternativas en función de la evaluación colectiva obtenida

en la etapa anterior. Las alternativas se pueden ordenar de acuerdo con su grado de preferencia o utilidad para el grupo, lo que facilita la identificación de la opción más favorable. Esta clasificación puede servir como base para la toma de decisiones finales, proporcionando una estructura clara y objetiva para evaluar y comparar las diferentes opciones disponibles.

Este enfoque innovador no solo mejora la calidad de las decisiones grupales al considerar aspectos emocionales y conductuales de los expertos, sino que también puede aplicarse en una variedad de contextos, como reuniones de inversores, interacciones entre expertos o dinámicas de equipo en entornos laborales.

1.7. Discusión de los resultados (Discussion of results)

En esta parte, analizaremos los resultados obtenidos de cada uno de los artículos mencionados anteriormente. En la Sección 1.7.1 se va discutir los resultados obtenidos del paper *Theorem Verification of the Quantifier-Guided Dominance Degree with the Mean Operator for Additive Preference Relations*. En la Sección 1.7.2 se va a analizar los resultados obtenidos en el paper *A Large Scale Group Decision Making System Based on Sentiment Analysis Cluster*. Finalmente, en la Sección 1.7.3, se van a analizar las ventajas y desventajas obtenidas en el paper *A Group Decision-Making Method Based on the Experts' Behavior During the Debate*. En esta sección, nos adentraremos en el análisis exhaustivo de los resultados obtenidos de cada uno de los artículos mencionados previamente. Comenzaremos abordando en detalle los hallazgos del estudio titulado “*Theorem Verification of the Quantifier-Guided Dominance Degree with the Mean Operator for Additive Preference Relations*”, detallado en la Sección 1.7.1. Exploraremos minuciosamente cada aspecto investigado, desde la metodología empleada hasta las conclusiones alcanzadas, con el propósito de extraer un entendimiento profundo de los resultados y su relevancia en el campo de estudio. A continuación, en la Sección 1.7.2, nos sumergiremos en el análisis exhaustivo de los resultados extraídos del artículo “*A Large Scale Group Decision Making System Based on Sentiment Analysis Cluster*”. Nos detendremos en cada componente del proceso de investigación, desde la recopilación y análisis de datos hasta la implementación y evaluación del sistema propuesto. Será crucial examinar cómo estos resultados contribuyen al avance del conocimiento en el área de la toma de decisiones grupales y la aplicación de técnicas de análisis de sentimientos. Finalmente, en la Sección 1.7.3, exploraremos en profundidad las ventajas y desventajas identificadas en el estudio titulado “*A Group Decision-Making Method Based on the Experts' Behavior During the Debate*”. Nos sumergiremos en un análisis detallado de las diferentes perspectivas presentadas por los expertos, evaluando la efectividad del método propuesto en diferentes contextos y situaciones. Además, examinaremos las implicaciones prácticas de estos hallazgos y discutiremos posibles áreas de mejora para futuras Investigaciones.

1.7.1. Theorem Verification of the Quantifier-Guided Dominance Degree with the Mean Operator for Additive Preference Relations

El teorema presentado en este estudio constituye un avance notable en el ámbito de los sistemas de Toma de Decisiones en Grupo (GDM), al ofrecer una demostración sólida de que estos sistemas pueden ser sometidos a

una verificación exhaustiva de manera eficiente y expedita. Esta capacidad de verificación no solo confiere a los programadores la tranquilidad de una implementación correcta, sino que también les otorga la capacidad de identificar y subsanar cualquier fallo lógico potencial. Además, proporciona a los expertos una herramienta poderosa para evaluar la fiabilidad y la solidez de las soluciones propuestas por el sistema, asegurando que las decisiones tomadas estén respaldadas por evaluaciones rigurosas y fundamentadas. Las ventajas específicas derivadas de este teorema son numerosas y significativas:

- **Verificación exhaustiva de errores:** La demostración del teorema permite llevar a cabo una verificación minuciosa y rigurosa del proceso de Toma de Decisiones, garantizando que se haya ejecutado de manera precisa y que no existan errores al aplicarlo a problemas específicos dentro del ámbito de la Toma de Decisiones. Esta capacidad de verificación se revela especialmente útil y valiosa en los procesos de programación, donde la exactitud y la integridad son esenciales para el éxito del sistema.
- **Aplicabilidad flexible sin necesidad de asignación de pesos:** El teorema puede aplicarse de manera flexible y adaptable sin la necesidad de asignar pesos específicos a los expertos, utilizando en su lugar la media aritmética como un caso especial del operador OWA. Esta flexibilidad en la aplicación del teorema facilita su implementación en una amplia variedad de contextos y situaciones de toma de decisiones, lo que lo convierte en una herramienta versátil y altamente aplicable en diferentes escenarios.
- **Amplia aplicabilidad a diversas áreas de estudio:** La versatilidad y la robustez del teorema permiten su extensión a una amplia gama de áreas dentro del campo de la Toma de Decisiones, incluyendo procesos de GDM, decisiones a gran escala, entornos multi-granulares y criterios múltiples. Esta capacidad de adaptación y aplicación lo convierte en una herramienta valiosa y ampliamente utilizada tanto en la investigación como en la práctica de la Toma de Decisiones.
- **Fundamentación matemática sólida y rigurosa:** Al tratarse de un teorema demostrado y respaldado por una fundamentación matemática sólida y rigurosa, sin contraejemplos que lo invaliden, proporciona a los investigadores una base sólida y confiable para respaldar sus hallazgos y conclusiones. Esto contribuye significativamente a la credibilidad y la confianza en los resultados obtenidos, aumentando así la relevancia y el impacto del estudio realizado en el campo de la Toma de Decisiones en Grupo.

Las ventajas inherentes al teorema propuesto son sin duda notables, pero como cualquier herramienta analítica, su efectividad está condicionada

por el cumplimiento de la hipótesis que lo sustenta. Es en esta hipótesis donde encontramos el principal punto de atención y, por consiguiente, la limitación principal en su aplicación práctica. Sin embargo, es fundamental destacar que, si el sistema en cuestión satisface los requisitos establecidos por esta hipótesis, entonces el teorema puede ser implementado de manera exitosa, sin importar el dominio específico al que pertenezca dicho sistema. Esta flexibilidad representa un aspecto clave en términos de aplicabilidad y utilidad práctica, ya que libera al teorema de las restricciones impuestas por un ámbito de aplicación particular.

En cuanto a la relevancia práctica de la solución propuesta, se vuelve imperativo resaltar el impacto potencial que puede tener en diversos contextos de toma de decisiones. Específicamente, en aquellos escenarios donde se emplean sistemas basados en matrices aditivas y se recurre al QGDD para la ordenación de alternativas, la aplicación de este teorema emerge como un recurso valioso. Esto se debe a que el teorema proporciona una sólida garantía de la fiabilidad del orden establecido por el QGDD, asegurando la equidad en la evaluación de las diferentes opciones disponibles. Además, al incorporar un enfoque matemático riguroso en el proceso de toma de decisiones, se mejora significativamente la confiabilidad del método utilizado. Esta mejora en la fiabilidad no solo contribuye a la eficacia del proceso en sí, sino que también fortalece la percepción de los usuarios sobre la validez y la solidez de las decisiones tomadas por el sistema.

1.7.2. A Large Scale Group Decision Making System Based on Sentiment Analysis Cluster

El enfoque descrito en este artículo representa una innovación significativa en el campo, dado que aborda la evaluación de la agresividad y positividad de los expertos mediante el uso del Procesamiento del Lenguaje Natural (PLN) para crear un sistema de clasificación basado en sus comentarios. El PLN emerge como un pilar fundamental en todo el proceso, siendo inseparable del modelo presentado en este estudio. Esta interdependencia se sustenta en múltiples razones de peso: En primer lugar, el lenguaje natural desempeña un papel crucial en la agrupación de expertos, lo que conduce a la formación de los cuatro grupos distintos delineados en el estudio. Esta clasificación, generada a partir del análisis del lenguaje empleado por los expertos, constituye el punto de partida esencial para el desarrollo del modelo propuesto. En segundo lugar, el grado medio de agresividad y positividad expresado por los expertos durante la discusión influye de manera significativa en la determinación de los pesos asignados a los diferentes conglomerados. La capacidad del PLN para capturar y cuantificar estas dimensiones emocionales permite una asignación más precisa y equitativa de los pesos, lo que mejora la robustez y la eficacia del modelo en su conjunto. Por último, pero

no menos importante, eliminar el componente de PLN tendría repercusiones devastadoras en la viabilidad del modelo. La ausencia de esta herramienta impediría la formación adecuada de los clusters y dificultaría enormemente el ajuste preciso de sus pesos. En consecuencia, el modelo perdería su coherencia y su capacidad para ser comparado con enfoques de consenso más tradicionales. Es esencial destacar que gran parte de la fórmula de ajuste del peso de cada conglomerado depende directamente de los comentarios expresados por los expertos durante la discusión, lo que subraya la importancia crítica del PLN en todo el process.

El enfoque delineado en este artículo se apoya en el uso de bolsas de palabras, una técnica ampliamente reconocida dentro del ámbito del PLN, se distingue por la implementación de bolsas de palabras que contienen términos específicos de cada clase. Esta estrategia resulta en la generación de bolsas de palabras con un conjunto de términos únicos, agilizando así el proceso de asignación a una clase en comparación con el uso de todas las palabras presentes en las frases de cada clase. Esta singularidad del enfoque contribuye a una ejecución más eficiente y precisa del sistema de clasificación. Por otro lado, la aplicación del PLN conlleva una contribución especial al proceso de toma de decisiones en grupo, al integrar los comentarios expresados por los expertos durante el debate en el sistema. Este aspecto otorga un mayor peso al debate en el proceso de toma de decisiones, ya que los comentarios de los expertos no solo se consideran como aportaciones individuales, sino que también influyen en el desarrollo global del proceso. La manera en que estos comentarios son expresados durante el debate repercute significativamente en la dinámica y en las decisiones finales del grupo.

Por consiguiente, el debate adquiere una relevancia aún mayor en el proceso de toma de decisiones, ya que no solo permite a los expertos expresar sus opiniones individualmente, sino que también moldea el curso y los resultados del proceso en su totalidad. Es importante resaltar que, además de las opiniones vertidas al término del debate, la forma en que estas opiniones son expresadas influye de manera significativa en el resto del proceso de toma de decisiones, enfatizando así la importancia del PLN en la mejora de la dinámica y la efectividad del debate en el contexto de la toma de decisiones grupales.

1.7.3. A Group Decision-Making Method Based on the Experts' Behavior During the Debate

En el contexto de este estudio, hemos desarrollado un método revolucionario para GDM, que se fundamenta en el análisis detallado del comportamiento de los expertos durante la fase crucial del debate previa a la emisión de valoraciones. Es esencial resaltar que, tradicionalmente, los méto-

dos GDM no suelen considerar ni aprovechar el valioso flujo de información generado durante este proceso de interacción entre los participantes, lo que resulta en una pérdida potencial de datos relevantes y perspectivas significativas. Sin embargo, nuestra aproximación innovadora incorpora un sofisticado clasificador, basado en técnicas avanzadas de análisis de sentimientos, que tiene la capacidad única de capturar y procesar esta información adicional generada durante el debate entre los expertos.

Este enfoque, que aprovecha eficazmente el comportamiento observado de los expertos, ha dado lugar al desarrollo de dos procedimientos pioneros para la asignación de pesos a los participantes y ha propuesto dos nuevas medidas de consenso. Estas medidas, diseñadas específicamente para reflejar la dinámica única del debate y la interacción entre los expertos, representan una valiosa adición al arsenal de herramientas disponibles para el proceso de toma de decisiones en grupo. Al proporcionar una visión más completa y detallada del proceso, estas medidas enriquecen significativamente la calidad y la fiabilidad de las decisiones tomadas. Sin embargo, en el ámbito de la comparación entre diferentes modelos de GDM, se presentan desafíos significativos. Cada modelo aborda aspectos particulares del proceso de toma de decisiones, y las características consideradas varían ampliamente entre ellos. Esta diversidad de enfoques dificulta una comparación directa y cuantitativa de los resultados obtenidos. No obstante, a pesar de estas complejidades, es fundamental analizar en detalle algunas de las ventajas y desventajas asociadas con nuestro enfoque innovador.

Por otro lado, podemos tener las siguientes características:

- Mediante la integración de un clasificador, que utiliza técnicas avanzadas de análisis del sentimiento y aprovecha diversas características lingüísticas, el modelo propuesto categoriza hábilmente el comportamiento exhibido por los expertos durante la fase crucial del debate. Esto representa un notable avance respecto a los métodos existentes basados en técnicas de análisis de sentimientos, como se ha puesto de manifiesto en estudios relacionados que analizan los debates de expertos. En particular, la investigación ha dilucidado que el uso de un lenguaje agresivo no sólo socava la fiabilidad y credibilidad del orador, sino que también precipita una disminución de la calidad de la dinámica del debate. Dado que la consecución del consenso se erige como el objetivo primordial en los procesos de GDM, ambos escenarios deben ser inequívocamente evitados. Por lo tanto, el modelo propuesto aquí, al aprovechar los conocimientos derivados del clasificador de análisis de sentimientos, mejora la fidelidad del proceso de creación de consenso inherente a los procedimientos de GDM. Este aumento se deriva de su capacidad para discernir patrones de comportamiento matizados durante los debates, lo que facilita una comprensión más matizada de

la dinámica subyacente en juego. Al reconocer y mitigar el impacto nocivo del lenguaje agresivo y fomentar el discurso constructivo, el modelo propuesto sirve como herramienta fundamental para fomentar el diálogo productivo y, en última instancia, avanzar en la consecución del consenso en los marcos de GDM.

- En línea con la ventaja previamente señalada, este estudio introduce dos nuevos procedimientos que asignan pesos a los expertos según su comportamiento durante el debate en la fase de GDM, enriqueciendo así el análisis del consenso y la valoración colectiva. Estos procedimientos permiten considerar más exhaustivamente el comportamiento de los expertos a lo largo de todo el proceso de GDM, especialmente en la evaluación del consenso, donde se examina la convergencia de las valoraciones de los expertos, y en el cálculo de la valoración colectiva, que implica la agregación de las valoraciones individuales. Por un lado, el método de cálculo de la ponderación global promedia los comentarios agresivos de un experto, ofreciendo la ventaja de compensar el peso del experto en rondas posteriores incluso si todos los comentarios son agresivos en una ronda. Sin embargo, su enfoque general impide analizar el comportamiento del experto en cada ronda específica. Por otro lado, el método de cálculo del peso iterativo ajusta el peso del experto en función de su comportamiento en la ronda anterior, lo que brinda una mayor precisión en el análisis, aunque es más estricto al asignar un peso nulo a un experto si todos sus comentarios en una ronda son agresivos. Utilizando estos procedimientos, se proponen dos nuevas medidas de consenso y dos métodos adicionales para calcular la valoración colectiva, mejorando así la capacidad del proceso de GDM para reflejar con precisión la interacción y el comportamiento de los expertos y fortaleciendo la calidad de las decisiones alcanzadas en el contexto del consenso grupal.
- El clasificador basado en técnicas de análisis de sentimiento se apoya en diversas características lingüísticas que proveen información crucial para la clasificación de los comentarios, destacando una serie de ventajas significativas. En primer lugar, este enfoque tiene la capacidad de detectar comentarios agresivos mediante la incorporación de una variedad de características lingüísticas que enriquecen el proceso de preprocesamiento. Si bien algunas de estas características, como el uso de POS-tagging, han sido previamente empleadas, otras son innovadoras, como la medición del número de palabras completas escritas en mayúsculas o la identificación de secuencias consecutivas de exclamaciones repetidas, entre otros ejemplos. Esta diversidad de características permite una detección más precisa y exhaustiva de la agresividad en los comentarios. En segundo lugar, el clasificador utili-

za una matriz de preprocesamiento optimizada, desarrollada a través de diversos métodos, para filtrar palabras que no aportan información relevante y reducir las palabras a sus formas base, lo que contribuye a disminuir el número de elementos en la bolsa de palabras. Sin embargo, es importante señalar que una limitación de este enfoque radica en su incapacidad para identificar todas las características lingüísticas presentes en los comentarios. Esta limitación puede resultar en una matriz numérica menos completa, lo que podría conducir a la clasificación errónea de algunos comentarios agresivos como no agresivos, generando así falsos negativos en el proceso de clasificación.

- Las medidas de consenso desempeñan un papel crucial en la evaluación del proceso GDM. Tradicionalmente, el consenso se ha definido simplemente como la diferencia entre las evaluaciones individuales de los expertos. Sin embargo, esta definición resulta incompleta, ya que el comportamiento exhibido por los expertos durante el proceso de deliberación puede ser igualmente relevante. Por ejemplo, dos expertos pueden coincidir en que una alternativa específica es preferible a otra, pero sus fundamentos subyacentes para tal conclusión pueden ser distintos. En este escenario, ambos expertos comparten la misma opinión final, pero sus argumentos divergen. En consecuencia, es esencial que las medidas de consenso no solo consideren las evaluaciones numéricas, sino también el comportamiento exhibido por los expertos para llegar a estas evaluaciones. Este enfoque más holístico y completo permite una comprensión más profunda del grado de acuerdo alcanzado dentro del grupo de expertos. Por lo tanto, las medidas de consenso propuestas en este estudio representan una mejora significativa sobre los enfoques convencionales, ya que capturan tanto la dimensión cuantitativa como cualitativa del consenso, proporcionando una evaluación más precisa y completa del proceso de toma de decisiones en grupo.

1.8. Conclusions

In this section, we present the main conclusions derived from each of the aspects addressed in this doctoral thesis, where our main objective has been the construction of new models and the enrichment of the theory related to GDM problems in real contexts. Our research has resulted in the development of innovative models that address key aspects of GDM problems, demonstrating their effectiveness in business management, urban planning and governmental decision-making. Extensive evaluation of these models, both with simulated and real data, has confirmed their ability to provide accurate and reliable solutions. Moreover, we have identified promising areas of research for future work, opening up new opportunities to advance the field of Group Decision Making and its application in real-world environments. We will now draw some conclusions from the published articles:

The first conclusion addressed in this study was the comprehensive development of the theoretical framework associated with GDM. This endeavour culminated in the formulation of a robust theorem meticulously crafted to scrutinize and validate the integrity of the decision-making process. By rigorously verifying the absence of errors, this theorem serves as a foundational cornerstone, providing assurance and confidence in the reliability of decision-making systems. Notably, its applicability transcends a myriad of decision-making methods, with a particular emphasis on those entrenched within the realm of GDM. Specifically, the theorem elucidates the intricate architecture of the collective preference relation, showcasing its manifestation as an additive matrix, meticulously crafted through the weighted aggregation of individual preferences. Moreover, it unveils a compelling insight, demonstrating that the summation of values derived from the QGDD equates to precisely half the number of available alternatives. This inherent adaptability and versatility extend beyond traditional GDM frameworks, encompassing multi-granular, large-scale, and multi-criteria decision-making systems, among others, wherein additive matrices serve as linchpins in the decision-making process. Nonetheless, it is imperative to acknowledge the inherent limitation of this theorem, necessitating strict adherence to the underlying hypothesis for its successful application. Any deviation from the prescribed conditions renders the theorem inapplicable, underscoring the critical importance of maintaining the integrity of the foundational assumptions.

The second conclusion of great relevance drawn from the analysis of the second paper lies in the system's ability to classify the different shades of sentiment expressed by the experts. This finding marks a significant advance in the understanding and analysis of the emotional dimension in group decision-making processes. Nevertheless, it is crucial to highlight that, while this approach is effective in classifying two different emotional states, there is still further potential to be explored. As suggested in the third paper, it

is plausible to extend this analysis to encompass a wider range of feelings, provided that a balanced set of emotional polarities, such as positive and negative, is available. In this sense, the consideration of a broader spectrum of emotions could greatly enrich the understanding of emotional dynamics in the group decision-making process. Nonetheless, it is important to keep in mind that complexity increases with the number of classes in the clustering, commonly being a power of 2. Hence, the incorporation of a third sentiment could lead to an expansion of the number of classes up to 8, which poses additional challenges in terms of defining categories and managing the complexity of the model. Consequently, a careful and systematic approach is required to determine the optimal number of classes for an accurate and meaningful categorisation of experts' emotional expressions. This thorough and detailed analysis is essential to ensure the effectiveness and relevance of the classification system in assessing the behaviour of participants in the group decision-making process.

The third conclusion of great relevance and potential impact lies in the application of machine learning, specifically supervised learning, within the context of decision-making. In this aspect, an innovative process has been carried out, where an algorithm has been trained using a competitive training dataset. This meticulously crafted dataset allows the algorithm to learn from patterns and relationships present in the data, thus providing the ability to make predictions and decisions autonomously. Furthermore, it is important to note that this training process has been complemented by rigorous evaluation of the algorithm, using verification and test data sets to validate its performance and accuracy. While the application of machine learning in decision-making is not a new concept in itself, what distinguishes this study is the innovative way in which this approach has been implemented. Specifically, advanced techniques have been developed and applied to adjust the weights on a case-by-case basis, allowing a differentiated weight to be assigned to each expert based on their input and feedback. This capacity for personalisation and adaptability represents a significant advance in the optimisation of the group decision-making process, as it allows for greater precision and relevance in the weighting of participants' opinions. Furthermore, this application of machine learning opens up new perspectives and possibilities to further improve the efficiency and effectiveness of decision-making systems, while offering a more dynamic and agile approach to address complex challenges that arise in business and organisational environments. In this sense, the potential of this application is considerable, and its impact could be significant in the future development of decision-making in various areas and sectors.

Finally, it is important to highlight that the validity and feasibility of all theorem and group decision-making methods proposed in this thesis are supported by comprehensive theoretical examples. These examples are fun-

damental to illustrate the practical application of the developed approaches, allowing a clear understanding of their operation and their potential impact on decision-making in diverse environments.

1.9. Future Work

Future work in sentiment analysis decision-making promises several significant advances, with the potential to radically transform the way this process is carried out. Key developments include the integration of large language models (LLMs) and the adoption of objective measures to evaluate the ranking of alternatives.

First, large language models, such as Transformers, are highly effective in a wide range of NLP-related tasks, including context understanding and coherent text generation. These models have the potential to significantly improve sentiment analysis in the context of decision-making by more accurately and completely capturing the emotional and semantic nuance present in the language used by experts. By harnessing the ability of LLMs to understand and generate text in a more contextualised way, sentiment analysis systems could provide more accurate and detailed assessments of the opinions and attitudes expressed in textual data, which in turn could improve the quality of decisions made based on these assessments.

Furthermore, the development and adoption of objective measures to assess the ranking of alternatives in the context of sentiment analysis decision-making is expected to be an important growth area in the future. These objective measures can be based on various metrics, such as semantic coherence, contextual relevance and emotional congruence between the evaluated alternatives. By incorporating these objective measures into the decision-making process, decision-makers can obtain a more rigorous and systematic evaluation of the available options, allowing them to make more informed and informed decisions.

On the other hand, by integrating large-scale language models and developing objective measures to evaluate the ranking of alternatives, the future of sentiment analysis decision-making could also include the following advances:

- **Personalisation and Adaptation:** Sentiment analysis systems are expected to evolve to offer greater personalisation and adaptation to the specific needs of users and organisations. This could involve the incorporation of machine learning algorithms and natural language processing techniques that dynamically adapt to users' preferences and linguistic peculiarities, as well as to the specific characteristics of the domain in which the sentiment analysis is applied.
- **Integration of Multiple Data Sources:** Advances in information and communication technology are enabling greater integration of multiple data sources into decision-making processes. In the future, sentiment analysis systems are expected to benefit from this trend by

integrating textual data from a variety of sources, such as social media, customer feedback, online reviews and customer service call transcripts. This integration of multiple data sources could provide a more complete and holistic view of stakeholder opinions and attitudes, thus enriching sentiment analysis and improving the quality of decisions made based on this analysis.

- **Improved Human-Computer Interaction:** Advances in artificial intelligence and affective computing are expected to lead to more natural and fluid interaction between humans and sentiment analysis systems. Systems could incorporate emotional and contextual understanding capabilities, allowing them to interpret not only textual content but also emotional tone, situational context and other non-verbal cues present in human language. This could lead to greater trust and acceptance of sentiment analysis systems by users, as well as more effective interpretation and application of sentiment analysis results in the decision-making process.
- **Ethics and Accountability:** As sentiment analysis becomes more ubiquitous and powerful, it is also important to address the ethical and accountability issues associated with its use. This includes concerns about data privacy, fairness and transparency in sentiment analysis algorithms, and the ethical use of sentiment analysis results in decision-making. In the future, it is expected that there will be a greater focus on developing ethical frameworks and regulations to guide the responsible use of sentiment analysis in various applications and contexts.

Finally, the future of decision-making with sentiment analysis is characterised by increased personalisation and customisation, integration of multiple data sources, improved human-computer interaction, and a renewed focus on ethical and liability issues. These advances have the potential to significantly improve the quality and efficiency of decision-making across a wide range of applications and sectors.

Capítulo 2

Published Papers

“En el laboratorio de la ciencia, la bata se convierte en el uniforme del conocimiento, el escudo que nos protege en la búsqueda de la verdad. En este noble empeño, servimos a nuestra patria con la convicción de que el progreso científico es el motor que impulsa el desarrollo y la prosperidad.”

- Santiago Ramón y Cajal

2.1. Theorem Verification of the Quantifier-Guided Dominance Degree with the Mean Operator for Additive Preference Relations



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Article

Theorem Verification of the Quantifier-Guided Dominance Degree with the Mean Operator for Additive Preference Relations

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Abstract: Deciding which film is the best or which portfolio is the best for investment are examples of decisions made by people every day. Decision-Making systems aim to help people make such choices. In general, a Decision-Making system processes and analyses the available information to arrive at the best alternative solution of the problem of interest. In the preference modelling framework, Decision-Making systems select the best alternative(s) by maximising a score or choice function defined on the decision makers' expressed preferences on the set of feasible alternatives. Nevertheless, Decision-Making systems may have logical errors that cannot be appreciated by developers. The main contribution of this paper is the provision of a verification theorem of the score function based on the Quantifier-Guided Dominance Degree (QGDD) with the mean operator in the context of additive preference relations. The provided theorem has several benefits because it can be applied to verify that the result obtained is correct and that there are no problems in the programming of the corresponding Decision-Making systems, thus improving their reliability. Moreover, this theorem acts on different parts of such systems, since not only does the theorem verify that the order of alternatives is correct, but it also verifies that the creation of the global preference relation is correct.

Keywords: quantifier-guided dominance degree; verification; additive matrix; decision-making system; selection process

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1. Introduction

From which mobile phone to buy to which road map a company should follow, decisions are part of people's everyday activities. We make some decisions without difficulty, others though are difficult and are the reason why Decision-Making systems exist [1]. There are many different systems developed to help experts make decisions based on their opinions or preferences [2–4]. In any case, systems can fail and there can be errors, called logical errors, which do not affect the functioning of the system but do affect the final result [5], and that may have enormous negative repercussions in financial terms because the systems are supposed to provide a good support to the decision makers.

In order to avoid logical errors in decision making systems, specifically in Group Decision-Making (GDM) systems [6–9], it is necessary to apply theories that can be demonstrated mathematically. Consequently, reliable programmes must be obtained and supported by mathematical theorems proving their correct functioning.

A theorem is a proposition that can be proved mathematically and lacks a contradictory case that would allow its invalidation [10]. Every mathematical theorem starts from an assumption, called a hypothesis, and a rationale called a thesis [11]. Consequently, this study proposes a mathematical theorem to verify that the GDM system works correctly when it selects the best alternative(s) by maximising the Quantifier-Guided Dominance Degree (QGDD) with the mean operator [12–14].

The QGDD is a concept used to define a score or choice function, based on the information provided by the decision makers (experts or users), that is used to provide an ordering of the alternatives, which is performed at the last step of a GDM system [15,16]. Since the application of a choice function is performed at the last step of the GDM process, the system must have worked correctly up to that point; otherwise, in case of any logical error, the QGDD could provide an incorrect ordering of the alternatives, and the wrong solution to the problem would be obtained. Nevertheless, the theorem provided in this study will allow both experts and researchers to mathematically verify that the result provided by the GDM system is reliable [17].

Logical errors have been analysed in existent literature [18]. For example, in [19] and [20], the authors focus on the logical errors produced by the experts but not on the errors that the developed system may be exhibiting, which may lead to incorrect ranking of the alternatives. In contrast, this article focuses on the logical errors produced by the formal processes implemented by developers in the system but not on the logical errors produced by the experts. For this reason, an advantage of this theorem is that it effectively verifies that the program obtains consistent results and that the programmers have not made mistakes. The theorem has also limitations on its applicability since it can only be applied when its supporting hypothesis is verified. Consequently, although it can be applied to any area that uses a Decision-Making system, it is also restricted to the set of systems that use additive preference relations.

2. Preliminaries

2.1. Group Decision-Making System

A GDM system is characterised by a set of experts, $E = \{e_q; q = 1, \dots, b\}; b \in \mathbb{N}$, who aim to jointly choose the best alternative(s) from a previously defined set of feasible alternatives, $A = \{A_t; t = 1, \dots, n\}; n \in \mathbb{N} \setminus \{1\}$. This article deals with systems that aim to create an ordering of the alternatives, from best to worst, from which the best alternative solution(s) to the problem is chosen [21,22]. The final ranking of the alternatives is derived from the evaluations on the set of alternatives that each expert involved in the GDM problem provides [23,24]. This article restricts to GDM problems with assessments on pairs of alternatives, which is known as the preferences of one alternative over another [25]. In order to carry out a solution to the problem, this study applies a fuzzy set theory methodology since it assumes that the preference degree of one alternative over another is not restricted to be in a binary set ($\{0, 1\}$) but in a continuum set ($[0, 1]$ or $[0, U]$, $U \in \mathbb{N}$) [26].

A GDM system consists of a series of steps or processes: discussion between the different experts involved to identify the set of alternatives and preference representation format; experts' provision of their evaluations on the alternatives; ranking of the alternatives is obtained, which is the solution provided by the system to the problem [14]. In the following, each step is described in more detail (see Figure 1):

- Conducting the discussion among the experts. The problem is analysed by the experts, a feasible set of alternatives is established, and a preference representation structure is agreed to be used [27].
- Providing the assessments of the alternatives. Using the agreed preference representation structure, the experts provide their corresponding preferences (preference relation) on the set of feasible alternatives [25].
- Analysing consensus. This step is optional in a GDM process, but it is often used to ensure that the decision to be taken is agreed upon by the experts [28]. To do this, a

group consensus value is defined and computed. If the group consensus is not below a previously established threshold value, denoted by $\alpha \in \mathbb{R}_0^+$ [29], then the system continues processing the experts' preferences to derive a ranking of the alternatives; otherwise, a feedback mechanism is activated to support the experts in reaching the consensus threshold [30].

- Creating the collective preference relation. The experts' preference relations are aggregated into a single collective preference relation [31]: $G = (g_{tk}; t \neq k; t, k = 1, \dots, n)$ with $g_{tk} \in \mathbb{R}$ being the preference of alternative A_t over alternative A_k for the group of experts. Many aggregation operators could be used to derive the collective preference relation, being the weighed average (WA) operator usually implemented in GDM systems [32], with each expert being associated a corresponding weighting/importance.
- Computing the ranking of alternatives. Using the collective preference relation, a score/choice function is defined to produce the final (consensus) ranking of the alternatives, which is a solution to the problem offered by the GDM system [33]. This study assumes that the QGDD is the score/choice function [12–14].

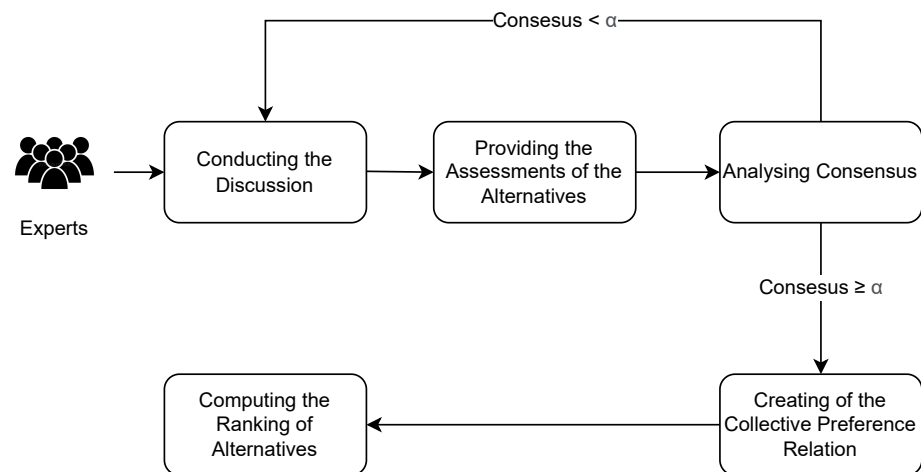


Figure 1. Basic diagram of a GDM system.

2.2. The Quantifier-Guided Dominance Degree

Orlovsky proposed the concept of dominance degree of one alternative over the rest of alternatives (all other alternatives) [34,35] by modelling the concept “all” with the application of the fuzzy set theory based minimum operator. This approach was later generalized with the OWA operator [36], which has the minimum operators as a particular case. The range of OWA operators is extensive. One of them is the usual average/mean operator, which treats with the same importance all the alternatives that are compared [37]. This is the operator used in this study.

The QGDD with the mean operator computes the average dominance of an alternative over the rest of alternatives. Using the collective preference relation, G , the QGDD with the mean operator of alternatives A_t ($t = 1, \dots, n$) is:

$$QGDD_{A_t} = \frac{1}{n-1} \sum_{k=1; k \neq t}^n g_{tk}, \quad (1)$$

with n the number of alternatives, and g_{kt} of row k and column t belonging to the matrix G .

From (1), the ordering of the alternatives is produced from more dominance to less dominance degree. The solution alternative(s) of the GDM problem is therefore defined as follows:

$$X^{QGDD} = \{A_s \in A \mid QGDD_{A_s} = \sup_{A_t \in A} QGDD_{A_t}\}, \quad (2)$$

with A being the set of alternatives.

3. Theorem Verification of the Quantifier-Guided Dominance Degree with the Mean Operator

As it can be seen in Figure 2, the hypothesis of the theorem affects the second step of the GDM process, since the experts' opinions are to be modelled as additive preference matrices, while the thesis of the theorem affects the last two steps of a GDM process, in which the collective preference relation and the ranking of alternatives are calculated. Consequently, the proof of the theorem will verify that the proposed GDM process is correct.

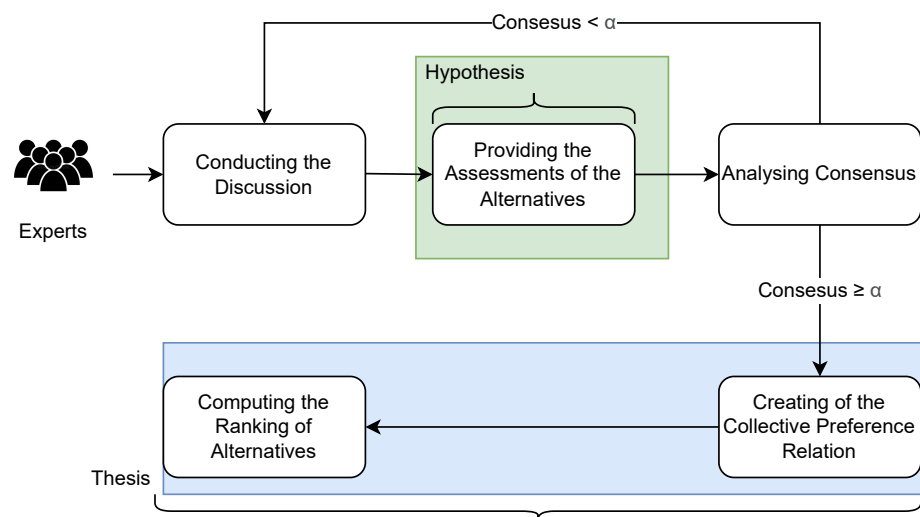


Figure 2. Sections affected by the hypothesis and thesis within the basic outline of a GDM system.

The below two definitions are necessary for the understanding of the theorem and its proof.

Definition 1 (Triangular number). *The following sum*

$$\sum_{i=1}^n i = \frac{n \cdot (n + 1)}{2}; n \in \mathbb{N} \quad (3)$$

*is called a **triangular number**.*

Geometrically, a triangular number coincides with the number of points of the triangular arrangement with n points (shown in Figure 3).

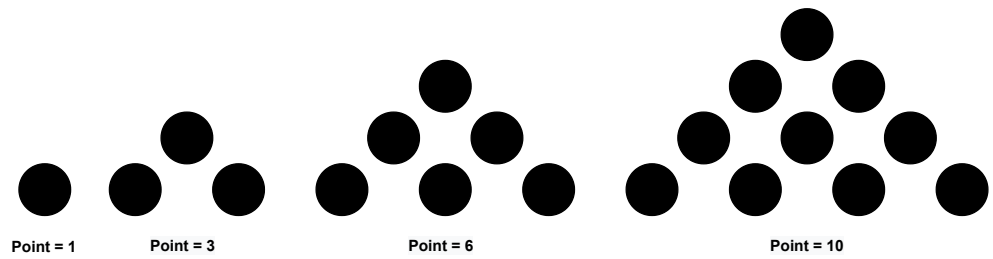


Figure 3. Examples of the triangular number.

Definition 2 (Additive matrix). A matrix $M = (m_{tk}; t, k = 1, \dots, n)$, where m_{tk} is the element of row t and column k belonging to the matrix M of dimension $n \times n$ with $n \in \mathbb{N} \setminus \{1\}$, is called additive when the main diagonal element is empty and the rest of elements satisfy:

$$m_{tk}^q + m_{kt}^q = U; t \neq k; t, k = 1, \dots, n; U \in \mathbb{N}. \quad (4)$$

With these two definitions in place, we can proceed to state the verification theorem proposed in this study. 127
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Theorem 1. For a Decision-Making process, let $E = \{e_1, \dots, e_b\}$, $b \in \mathbb{N}$, be the set of experts with non-negative weights, $W = \{w_{e_1}, \dots, w_{e_b}\}$, verifying $\sum_{q=1}^b w_{e_q} = 1$. Let $A = \{A_1, \dots, A_n\}$, $n \in \mathbb{N} \setminus \{1\}$, be the set of alternatives. Let $\{M_{e_q} = (m_{tk}^q), q = 1, \dots, b; t, k = 1, \dots, n\}$ be the set of additive matrices representing the preferences of the set of experts on the set of alternatives. Then, the following expression is verified:

$$\sum_{p=1}^n QGDD_{A_p} = \frac{U \cdot n}{2}, \quad (5)$$

where $QGDD_{A_p}$ is the QGDD of alternative A_p , n is the number of alternatives, and $U \in \mathbb{N}$. 129

Proof. The collective preference matrix $G = (g_{tk}; t, k = 1, \dots, n)$ where

$$g_{tk} = \sum_{q=1}^b w_{e_q} \cdot m_{tk}^q; w_{e_q} \in W, m_{tk}^q \in M_{e_q} \quad (6)$$

is an additive matrix. Let $t \neq k$; since $\{M_{e_q}; q = 1, \dots, b\}$ are additive matrices, it holds that:

$$g_{kt} = \sum_{q=1}^b w_{e_q} \cdot m_{kt}^q = \sum_{q=1}^b w_{e_q} \cdot (U - m_{tk}^q) = U - \sum_{q=1}^b w_{e_q} \cdot m_{tk}^q.$$

Therefore, we conclude that:

$$g_{tk} + g_{kt} = \sum_{q=1}^b w_{e_q} \cdot m_{tk}^q + U - \sum_{q=1}^b w_{e_q} \cdot m_{tk}^q = U.$$

The mean QGDD of alternative A_p is:

$$QGDD_{A_p} = \frac{\sum_{j=1; p \neq j}^n g_{pj}}{n-1}. \quad (7)$$

Therefore, it holds that:

$$\sum_{p=1}^n QGDD_{A_p} = \frac{\sum_{p=1}^n \sum_{j=1; p \neq j}^n g_{pj}}{n-1}.$$

Since $g_{pj} + g_{jp} = U$, the following algebraic manipulation yields:

$$\begin{aligned} \frac{\sum_{p=1}^n \sum_{j=1; p \neq j}^n g_{pj}}{n-1} &= \frac{\sum_{p=1}^n \sum_{j=p+1}^n [g_{pj} + g_{jp}]}{n-1} = \frac{\sum_{p=1}^n \sum_{j=p+1}^n U}{n-1} = \frac{U \cdot \sum_{p=1}^n \sum_{j=p+1}^n 1}{n-1} = \frac{U \cdot \sum_{p=1}^n (n-p)}{n-1} \\ &= \frac{U \cdot \sum_{r=0}^{n-1} r}{n-1} = \frac{U \cdot (n-1) \cdot (n+1-1)}{2 \cdot (n-1)} = \frac{U \cdot n}{2}. \end{aligned}$$

Summarising, it is proved that

$$\sum_{p=1}^n QGDD_{A_p} = \frac{U \cdot n}{2},$$

when n is the number of alternatives. $\square$

4. Illustrative Example

In this section, we present a GDM problem where four experts, $E = \{e_1, e_2, e_3, e_4\}$, have to choose where to invest money to make improvements in a city. They have four options: to improve (A_1) gardens, to improve pavements (A_2), to improve healthcare (A_3), and to renovate old buildings (A_4).

The experts start debating and, once the debate is over, they express their preferences by using numeric values in the $[0, 1]$ interval, that is, by using fuzzy preference relations [34,39]. Concretely, the fuzzy preference relations given by each expert are as follows:

$$\begin{aligned} M_{e_1} &= \begin{bmatrix} - & 0.5 & 0.0 & 0.5 \\ 0.5 & - & 0.1 & 0.5 \\ 1.0 & 0.9 & - & 0.8 \\ 0.5 & 0.5 & 0.2 & - \end{bmatrix} & M_{e_2} &= \begin{bmatrix} - & 0.4 & 0.1 & 0.8 \\ 0.6 & - & 0.1 & 0.5 \\ 0.9 & 0.9 & - & 0.9 \\ 0.2 & 0.5 & 0.1 & - \end{bmatrix} \\ M_{e_3} &= \begin{bmatrix} - & 0.5 & 0.2 & 0.7 \\ 0.5 & - & 0.2 & 0.9 \\ 0.8 & 0.8 & - & 0.9 \\ 0.3 & 0.1 & 0.1 & - \end{bmatrix} & M_{e_4} &= \begin{bmatrix} - & 0.4 & 0.1 & 0.4 \\ 0.6 & - & 0.0 & 0.5 \\ 0.9 & 1.0 & - & 1.0 \\ 0.6 & 0.5 & 0.0 & - \end{bmatrix} \end{aligned}$$

Applying the theorem developed in Section 3, we proceed to see that the hypothesis is satisfied because all preference relations are additive matrices. Therefore, since all matrices satisfy that hypothesis, the verification theorem can be applied.

Once the experts have provided their preference relations, the consensus achieved should be calculated. However, in this example, as our objective is to show the applicability of the proposed theorem, we suppose that the group consensus is not below the consensus threshold value and we proceed to the following step, i.e., the calculation of the collective preference relation.

To calculate the collective preference relation, each expert has to be assigned a weight. In this illustrative example, the WA operator will be used and all experts will have the same weight, i.e., $w_{e_q} = 0.25$; $q = 1, \dots, b$. The following collective preference relation:

$$G = \begin{bmatrix} - & 0.45 & 0.1 & 0.6 \\ 0.55 & - & 0.1 & 0.6 \\ 0.9 & 0.9 & - & \mathbf{0.9} \\ 0.4 & 0.4 & \mathbf{0.2} & - \end{bmatrix}$$

would be detected to be erroneous by the verification theorem, since it is not an additive matrix, and it would be corrected to become:

$$G = \begin{bmatrix} - & 0.45 & 0.1 & 0.6 \\ 0.55 & - & 0.1 & 0.6 \\ 0.9 & 0.9 & - & \mathbf{0.9} \\ 0.4 & 0.4 & \mathbf{0.1} & - \end{bmatrix}.$$

The mean QGDD of alternatives from G are obtained:

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Table 1. Mean QGDD of each of the alternatives

Values\Alternatives	A_1	A_2	A_3	A_4
QGDD	0.38	0.42	0.9	0.3

To verify that the results obtained are correct, it is necessary to show that the thesis of the verification theorem is verified:

$$0.38 + 0.42 + 0.9 + 0.3 = 2 = \frac{1 \cdot 4}{2} = 2$$

Consequently, we obtain that the order of preference of the alternatives is $A_3 \succ A_2 \succ A_1 \succ A_4$. Therefore, option A_3 , i.e., the investment to improve healthcare, is the one chosen by the group of experts.

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5. Discussion and Conclusions

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The theorem proposed in this study shows that GDM systems can be verified in a simple and fast way. This verification allows programmers to know if the system is well implemented or if there is a logical error. In addition, experts can also verify that the solution provided by the system is reliable and that the decision is well-founded based on their evaluations. Concretely, this theorem has the following advantages:

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- Verification of errors. With this demonstration, it is possible to verify that the Decision-Making process has been carried out correctly and that there are no errors when applied to a concrete Decision-Making problem. This is helpful when performing a programming process [41].
- It can be applied without assigning weights to the experts by using the arithmetic mean, a particular case of the OWA operator.
- Applicable to several areas of study related to the Decision-Making process. This demonstration can be applied to different areas of Decision-Making systems, from GDM processes to Large Scale Group Decision Making processes [40], including processes conducted in Multi-granular [22] and Multi-criteria environments [27].
- Mathematical proof. Being a proved theorem and not having any counterexample invalidating it, it allows the researchers to use the theorem to base their results obtained on a proven mathematical theory. It implies a greater solidity to the conducted study.

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These advantages are restricted to the fulfilment of the hypothesis of the developed theorem. For this reason, the main limitation of the application of the theorem is its own hypothesis. Nonetheless, if the hypothesis is fulfilled by the system, then it can be applied to the system,

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regardless of the area which it belongs to. This shows a practical advantage because it is not subject to a specific area.

Regarding the practical relevance of the proposed solution, it can be mentioned that all works using a Decision-Making system with additive matrices and using the QGDD for the ordering of the alternatives should use this theorem to reinforce that the order established in the QGDD is reliable and that there are no variations that favour one alternative over another. Furthermore, it can be seen how the application of a mathematical theorem to a Decision-Making method improves the reliability of that method. This improved reliability means that the users who have participated in the Decision-Making process can feel more confident with the decision made by the system.

In addition, the generality of application of this theorem is also its major limitation because the theorem is restricted to the fulfilment of the hypothesis, which means that it cannot be applied if any of the matrices used is not an additive matrix. As future work, two strands can be analysed. The first is to investigate new theorems for other score/choice functions such as the Quantifier-Guided Non-Dominance Degrees (QGNDD) and the second is to investigate a Decision-Making method that transforms non-additive matrices into additive matrices.

Finally, as a conclusion, this paper can show how mathematical theorems are useful to reinforce the results shown by Decision-Making systems making them more robust and reliable.

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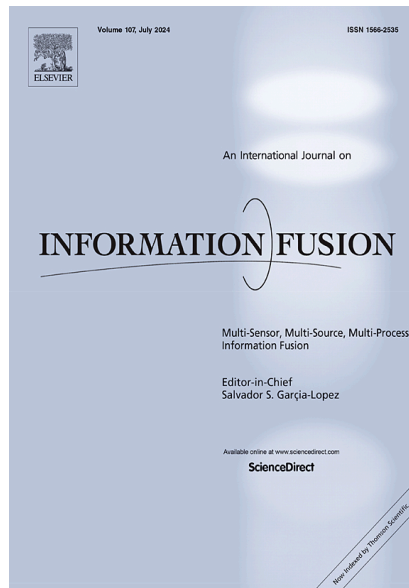
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*“Wir reiten in die Kreuz und Quer
Nach Freuden und Geschäften;
Doch immer kläfft es hinterher
Und bellt aus allen Kräften.
So will der Spitz aus unserm Stall
Uns immerfort begleiten,
Und seines Bellens lauter Schall
Beweist nur, daß wir reiten.”*
- J. W. Goethe

*“En busca de fortuna y de placeres
Más siempre atrás nos ladran,
Ladran con fuerza. . .
Quisieran los perros del potrero
Por siempre acompañarnos
Pero sus estridentes ladridos
Sólo son señal de que cabalgamos”*
- J. W. Goethe

2.2. A large scale group decision making system based on sentiment analysis cluster



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A Large Scale Group Decision Making System Based on Sentiment Analysis Cluster

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Abstract

Nowadays, group decision making is an everyday occurrence in different scenarios, such as marketing or social networks. These social networks have facilitated communication between experts because they do not need to meet in person. However, communication between experts through the internet generates three problems: the management of large amounts of information, the fact that experts often provide their information using natural language, and the lack of analysis of experts' intentions. In this paper, we propose a novel large scale group decision making method to manage the information generated by a large number of experts, using the natural language processing approach, specifically sentiment analysis. This approach makes it possible to detect the degree of positivity and aggressiveness of each expert and thus proceed to a classification. Once the behaviors are detected, the experts are grouped according to them and, for each group, a weight and a unique preference relation is obtained. In addition, we propose an optimized consensus analysis process, in which it is not necessary to compare all experts with each other, but only groups of experts.

Keywords: Large Scale Group Decision Making, Sentiment Analysis, Natural Language Processing, Classification

1. Introduction

Nowadays, group decision making (GDM) is part of our daily lives. With social networks and globalization, the paradigm in which decisions are made has completely changed [1]. Since almost everyone has access to the internet, it has become easier for people to participate in GDM processes [2]. Furthermore, the amount of information generated is becoming increasingly larger and difficult to

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administer. To deal with such a load, a new area has arisen within GDM, called large scale group decision making (LSGDM) [3, 4, 5, 6]. This phenomenon has been gaining importance in recent years [7].

10 Social networks have become an environment for carrying out LSGDM methods because people from different parts of the world can express their opinions on a topic without having to travel [8, 9]. When people communicate using social networks, they use natural language in order to express their ideas [10]. Natural language processing (NLP) is a line of research that has become relevant
15 in this area, since it allows experts to provide inputs using natural language. Thanks to this, experts can express themselves in a way that they are used to in real life [11].

Nevertheless, using natural language and social networks to create an LSGDM method can be problematic because this language needs a sentiment analysis process to obtain information from the comments made by experts. In addition, the amount of information used by LSGDM processes is larger than that used by GDM processes. This creates some challenges that need to be solved, as managing the amount of information to perform an efficient method is necessary and adding the information generated during the discussion to obtain a process
25 with more complete information.

For this reason, this paper proposes an LSGDM method that solves the problems mentioned above. This LSGDM method uses sentiment analysis to obtain information from the comments made by the experts during the discussion. Along with that, we will use a variable selection process to remove
30 irrelevant data. By deleting irrelevant data, less information is handled and the process is optimised [12]. Moreover, in this method, we will apply clustering to group similar information [13] because the realisation of clustering in LSGDM processes allows us to manage the amount of information efficiently [14, 15, 7].

There are different approaches for grouping experts [16, 17]. Using natural language, experts convey their ideas and opinions in a comfortable way. It is possible to carry out a behavioural detection process by analysing natural language and detecting keywords associated with a sentiment. This process is interesting because it uses the comments made by experts and detects which words are related to which sentiment [18, 19]. Furthermore, our novel process
40 classifies each comment according to two sentiments, positivity and aggressiveness. Consequently, a process based on the developed LSGDM is proposed that analyses the experts' behaviour during the debate and using the results of the analysis, the parameters of the experts, such as the weight of their decisions during the process, are adjusted.

45 To solve the behaviour problem, this paper is going to propose a bag-of-words approach. The bag-of-words approach has a feature that differs from other perspectives, since it searches for words independently of the context, which is useful because the comments that are used to create the bag-of-words approach are isolated comments about a specific topic. The analysis of the emotion of positivity makes it possible to detect people who are for and against
50 the different positions in a debate, while the analysis of aggressiveness can help us to detect experts with inflexible views and who probably do not listen to

others. For these reasons we create a degree for each emotion. These degrees adjust the weightings of the groups, taking into account different aspects, such as the number of experts in the group and the average degree of aggressiveness and positivity of the experts in a group. Finally, a consensus optimisation process is applied over the groups in order to determine the convergence into the final decision choice. Using the aforementioned strategies, this paper proposes an novel LSGDM method that employs sentiment analysis to thoroughly analyse the debate.

Thanks to the method proposed in this paper, it is possible to solve an LSGDM problem by calculating the consensus using the aggressiveness and positivity of the experts. By using sentiment analysis, it is feasible to detect experts' behaviour through the comments they provide in discussions. The method can deal with scenarios with a high number of experts and alternatives. Finally, the method proposes a consensus process focusing on comparison in terms of aggressiveness and positivity.

This document is organized as follows. In Section 2, basic concepts of LSGDM and sentiment analysis are exposed. In Section 3, the stages of the proposed method are described in detail. It explains the system based on sentiment analysis integrated with an LSGDM method. In Section 4, an example that shows how the method proposed in this paper works is illustrated. In Section 5, the advantages and disadvantages are discussed by comparing the proposed system with other similar systems from the current literature. Finally, in Section 6, conclusions are drawn.

2. Preliminaries

This section shows the concepts necessary to understand the method presented in this document. In Section 2.1, we proceed with a review of the documents related to sentiment analysis and explain its basic concepts, namely, the steps necessary to construct a bag of words. In Section 2.2, the fundamental concepts related to LSGDM problems are introduced.

2.1. Sentiment analysis

Natural language is the main way human beings communicate and express their desires and emotions. This language is made up of ambiguous and imprecise concepts. In contrast, computers perform their computations and present their outputs using numerical expressions. Therefore, there is a communication gap between natural language and numerical language. One way of solving this communication problem is to use NLP. Specifically, our method focuses on detecting experts' sentiment in their contribution to the debate [20].

Experts are more comfortable with natural language when discussing topics. Therefore, it is necessary to use methods that can allow computers to work using natural language. Most of the methods that are available in the literature extract concepts and information that can be useful for the computer to handle the data. Sentiment analysis allows the LSGDM method to know what sentiments experts show when they communicate with each other [21, 22].

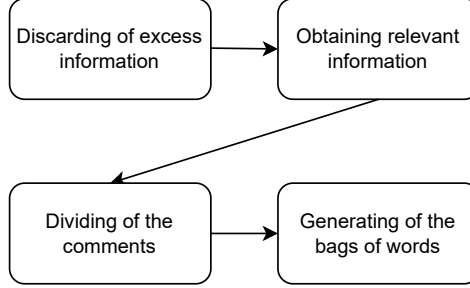


Figure 1: Graphical schematic of sentiment analysis.

Sentiment analysis can be applied using different methods [23]. One of the most popular is the bag-of-words approach. Before creating the bags, it is necessary to discard irrelevant information, for instance, articles and prepositions. Furthermore, the unigrams must be simplified to avoid the same words, written with different suffixes or prefixes, being in the same bag (see figure 1). The procedure for creating the bags of words is as follows:

- **Discarding of excess information:** this first step consists of removing words, symbols and numbers, which are not relevant for extracting knowledge from the text. The removal of non-relevant information, such as articles or prepositions, generates easily actionable comments. This suppression optimises the generation of a bag of words. Moreover, it improves the detection process.
- **Obtaining relevant information:** this second step consists in obtaining the relevant information from the comments. For performing this step, it is necessary to use the comments obtained in the previous process, and to analyse the roots of the words to find unigrams. This step, like the previous one, allows the bag of words to be simplified.
- **Dividing of the comments:** the fraction of a comment is called n-gram, where $n \in \mathbb{N}$. If $n = 1$, the comments are divided by words and these words are called unigrams. By dividing the comments in unigrams, it is possible to obtain which linguistic terms belong to which emotion. In our proposal, aggressiveness and positivity are employed.
- **Generating of the bags of words:** for generating the bags of words, it is necessary to define classes according to the sentiments that we want to

120 track. In this document, we employ four different classes, each unigram
appears only once in the bag of words corresponding to each class.

There is a wide variety of papers on the recent literature that uses natural lan-
guage processing and sentiment analysis. In [24], a new e-commerce sentiment
analysis model is based on the sentiment lexicon and combines a convolutional
125 neural network and a bidirectional recurrent unit which has been developed.
In [25], a method based on sentiment analysis that removes noise from tweets
has been generated. The method takes into account word sentiment, semantics,
syntax and polysemy, and encodes the representation of tweets as explained. In
[26], a GDM method for dynamic contexts using sentiment analysis to obtain
130 extra information from experts has been created. Finally, in [27], a sentiment
analysis model using a neural network with a blockchain layer with an LSTM
architecture is presented. This model is responsible for classifying comments
and uses emotions to improve classification accuracy.

2.2. Large scale group decision making problems

135 An LSGDM problem is characterised by a scenario where a large number of
experts have to make a choice [28, 29]. Therefore, a set of m experts, denoted as
 E , is defined. This set of experts will have to choose from a set of n alternatives,
denoted as X , using a set of preferences $P_s; s = 1, \dots, m$.

In the current literature, different ways of representing expert ratings can
140 be found [30], such as the representation by using preference relations [31, 32].
The preference relations are used for this LSGDM problem because they allow a
comparison and subsequent consistency analysis of the preferences given by the
expert. This preference indicates the comparison between alternatives by means
of a function $\mu_s : X \times X \rightarrow [0, 1]$. The matrix $P_s = (p_s^{ij}; i \neq j = 1, \dots, n)$, where
145 $p_s^{ij} = \mu_s(x_i, x_j); x_i, x_j \in X$ and has dimension $n \times n$, is used to represent the
preference.

Each stage on the new method proposed in this document is detailed below.
For coming up with a solution to an LSGDM problem, a process has to be
carried out that consists of different stages. Each of them are explained below:

- 150 • **Providing opinions:** initially, experts carry out a debate whose main
purpose is the exchange of views on the alternatives. When the debate is
over, they provide their opinions on the alternatives [32]. Experts provide
their preferences to the system using a preference relation matrix.
- 155 • **Analysing consensus:** for checking the agreement on the decision re-
sults, we verify the consensus that exists among experts or groups of ex-
perts [33, 34]. This stage consists in analysis the differences of opinions
that exist between the groups of experts. The higher the consensus value,
the more supported and beneficial the option chosen is [35]. Nonethe-
less, to decide that the consensus value is high enough, a threshold value,
160 $\alpha \in [0, 1]$ is stipulated. This threshold indicates the minimum value that
the average consensus value must reach to determine that it is sufficient
for acceptable agreement [36]. Nevertheless, if the process does not reach

the limit α , the process must be repeated and experts must consider their ratings. To avoid creating an infinite process, a certain number of rounds is determined [28]. When the limit is reached, the ranking of alternatives is created independently of the consensus reached by the experts [37].

- **Aggregation information:** the third stage aims to aggregate the information in order to create a single piece of information containing all the experts' opinions. The way to achieve this objective is to create a matrix called collective preference relation and denoted by C_G . This matrix uses aggregation operators [31].
- **Ranking of alternatives:** this last stage uses the matrix C_G to obtain a ranking of options ordered according to the experts' preferences. This ranking can be done using different approaches such as the quantifier guided dominance degree (QGDD) [38] and quantifier guided non-dominance degree (QGNDD) [39]. In order to take into account both criteria, an arithmetic average of the approaches is performed, thus obtaining a ranking taking into account both measures.

Currently, there is a large number of papers in the literature proposing a solution to LSGDM problems. In [40], a social network is analysed to detect conflicts in an LSGDM process based on a trust relationship model. This trust model includes a trust propagation process, a conflict detection and elimination process and a selection model. In [5], a method that identifies opinion leaders is presented. For this purpose, a cluster-based consensus model for LSGDM problems and a k-core decomposition are used. In [6], a two-stage composite method is shown to support the consensus elicitation process for large-scale multi-attribute group decision making problems. In [41], a model is presented that solves a hesitant LSGDM problem where expert decision makers express their opinions by using hesitant fuzzy preference relations. In [42], a consensus-based LSGDM model is presented to analyse non-cooperative behaviour among experts. For this purpose, the model suggests a collective setting and determines a degree of rationality. Finally, in [43], an LSGDM model is presented that uses imprecise information generated by users to perform a decision making process. This imprecise information is applied using probabilistic terms.

3. Large scale group decision making system based on sentiment analysis cluster

In this section, the novel method created to solve LSGDM problems is described in detail. Our method detects the aggressiveness and positivity manifested by the experts through the comments they make during the debate. Sentiment analysis will be used in order to achieve this goal. This way, it is possible to detect the degree of positivity and aggressiveness of the experts [44, 45]. Firstly, our method use the bag-of-words approach to rank expert comments according to their aggressiveness and positivity. Next, experts are grouped based

on the sentences they provide to the system. The LSGDM method (see figure
2) carries the following steps:

- **Detecting behaviour in comments:** first, our method identifies the comments made by experts and assigns them a degree of aggressiveness and a degree of positivity. This stage is divided into two steps:
 - **Removing and simplifying words:** words that do not provide information are removed from the comments. Afterwards, all words are simplified to their root word. In this way, a set of words per comment is obtained that is less than or equal to the set of words extracted from the original comment. Thanks to this step, the method becomes more efficient.
 - **Creating the bags of words and calculating the membership degree:** the obtained texts are divided into words and, using the classes associated with each comment, a bag of words is created. Consequently, we create two categories with two bags of words for each category. A total of four bags of words are obtained: positive, negative, non-aggressive, and aggressive. Once the bags have been created, the words found in the two bags belonging to the same sentiment category are removed. Finally, the degree of aggressiveness and positivity of the comment is calculated.
 - **Providing opinions:** after the experts have completed their comments and have discussed their opinions with everyone, they provide their preferences. The way to represent the experts' opinions is by using preference relations.
 - **Creating the groups of experts:** experts are grouped according to the degrees of aggressiveness and positivity obtained through their comments. Consequently, the following four groups are obtained:
 - Aggressive - Positive
 - Aggressive - Negative
 - Non-Aggressive - Positive
 - Non-Aggressive - Negative
- Once that the experts are grouped, four preference relations are calculated, one per each group. For this purpose, experts' preference relation matrices are aggregated in each group. In this phase, the same weight is given to all of them.
- **Computing the weights of the groups:** once that a single preference relation matrix has been calculated for each group, different weights are assigned to each of them based on the following criteria:
 - The consensus between the experts of the same group.

- The number of experts belonging to the same group.
- The degree of aggressiveness.
- The degree of positivity.

• **Analysing consensus:** this stage is in charge of analysing the consensus that exists between the different groups and inside the same group to study the group cohesion. In this way, it is possible to observe whether there is a significant difference of opinion between the different groups and whether there is an opinion associated with a particular group. Thanks to this step, it is possible to comprehend how each of the created groups behave.

• **Calculating the collective preference relation:** this stage uses the preference relations of each group and the associated weight to obtain the collective preference relation. To this effect, it is necessary to use aggregation operators.

• **Creating the ranking of alternatives:** this last stage creates a ranking of alternatives, taking into account the QGDD and QGNDD operators [38, 39], to choose the alternative that experts prefer.

Each stage about the new method proposed in this document is detailed below.

3.1. Detecting behaviour in comments

When experts provide their comments using a social network or a forum, it is possible to apply sentiment analysis in order to detect their behaviour. To perform this analysis, this paper is going to use a bag-of-words approach to detect the sentiments that the experts are experiencing. Consequently, if an expert provides a comment, the algorithm counts how many unigrams belong to each bag of words of each sentiment and once it decides which sentiments the expert has. Next, it calculates the degree of membership using the bags of words. These bags of words are constructed by using two datasets that already exist. Each dataset contains words to detect different emotions [46, 47]:

- A training dataset with aggressive and non-aggressive comments.
- A training dataset with positive and negative comments.

In this document, the two datasets mentioned above will be used to detect the behaviour of the experts. However, each dataset needs to create two bags of words that will allow us to calculate the degree of the two sentiments. For this purpose, we perform two steps:

1. It is necessary to remove the words that do not provide information to the comment. These words are articles, symbols, and all kinds of words that do not add information to the text. This process is called **stopped technique** [48]. Then, the words are simplified, this process is called **stemmer technique** [49]. This technique converts all words into their root form. These two processes aim to obtain a reduced bag of words that will optimise the behaviour detecting process.

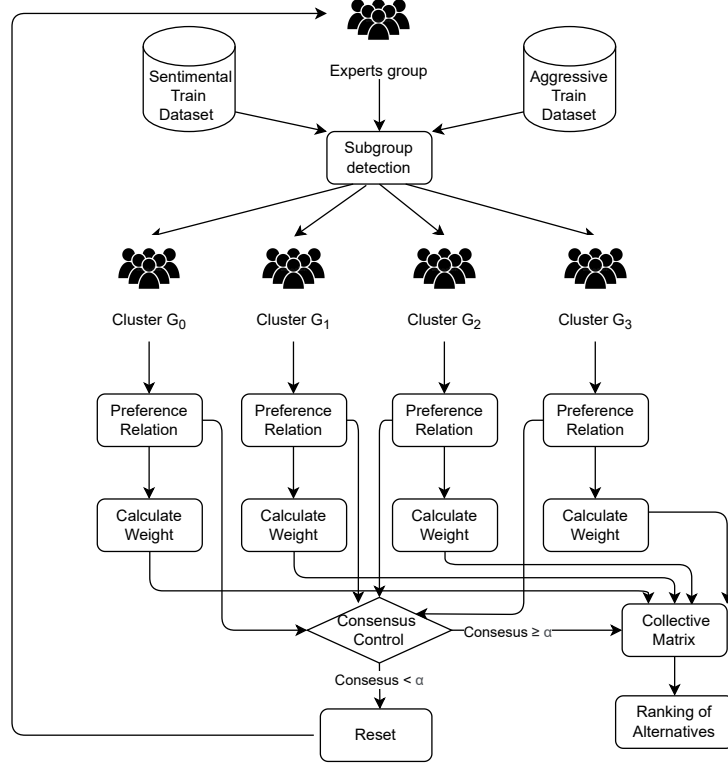


Figure 2: Graphical scheme of the method proposed.

2. Once that the comments have been optimised, we proceed to divide the texts in different fractions. Each fraction of a text is called n-gram, where $n \in \mathbb{N}$. For this paper, we propose that $n = 1$ and thus, the texts are divided into unigrams. Each part generated from the division of a text is called unigram, and we introduce into the bag the words belonging to the class of each text. Finally, the degree of aggressiveness and positivity of the text is computed and the arithmetic mean of the degrees is calculated to obtain the final degree of positivity and aggressiveness.

All these steps are exposed in more detail on the following subsections.

3.1.1. Eliminating and simplifying words

In this stage, the stopped and stemmer techniques are applied in order to improve the performance of the behaviour detection algorithm. There are different techniques for optimising the bag-of-words comparison. In this paper, two

techniques have been selected to optimise bags of words for each of the aspects to be analysed. The techniques are:

- **The stopped technique:** this process is responsible for removing all the words that are not relevant to the analysis. Non-relevant information includes: symbols, numbers, articles, and all words that do not contribute information to the comment. Finally, once all irrelevant words have been removed, a text is obtained that is equal to or shorter in length than the original comment.
- **The stemmer technique:** this second process is responsible for transforming the words into their root. This results in a reduction of the word pool, as all words with a similar root are transformed into the same word. Consequently, by reducing the number of words, the word bag is optimised.

Once these two processes have been carried out, texts are optimised and ready for the bag of words creation process.

3.1.2. Creating the bags of words and calculating the membership degree

Once that experts' comments have been optimised, word sets must be generated. We took the texts and divide them into unigrams (see figure 3).

After the unigrams have been calculated, a vector of unigrams is obtained for each text. Next, the class associated with each text is used and a vector is created for each different class in the training dataset, this vector is the bag of words. For this document, each training dataset has two different classes. Therefore, four bags of words are obtained.

To each of the bags of words, we start adding the unigrams of the texts that have the corresponding class label associated with them. In this way, if a text has the label "aggressive" associated with it, then all the unigrams that make up the text will be added to the bag of aggressive words.

When this aggregation process is finished, it can occur that there are unigrams that are in one bag of words and in the opposite one. To solve this problem, we remove these words since they do not help to classify the texts.

Once the bags of words have been created, the degree of aggressiveness, denoted as *dagr*, and the degree of positivity, denoted as *dpos*, of the experts' texts are calculated. For that purpose, the texts made by experts are initially simplified using the stopped and stemmer techniques described above. Subsequently, the texts are divided by unigrams, obtaining the vector of unigrams associated with the expert's text.

To verify membership, the unigrams of each word are counted with the bags of words. For this propose, we create four counters: *cnagr*, *cneg*, *cagr*, and *cpos*. Next, they are initialised to 0. Each counter is determined by the following formulas:

- If the unigram belongs to the aggressive bag of words, this formula is checked:

$$cagr = cagr - 1 \quad (1)$$

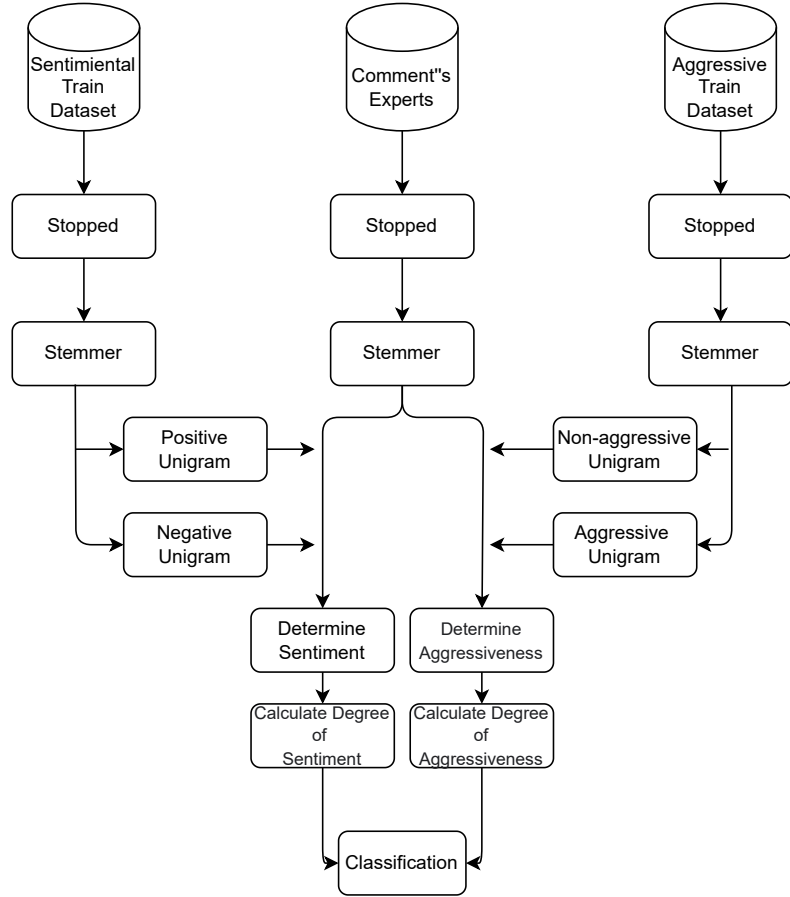


Figure 3: Sentiment training dataset, experts' comments y aggressively detection training dataset.

- If the unigram belongs to the non-aggressive bag of words, this formula is checked:

$$cnagr = cnagr + 1 \quad (2)$$

340

- If the unigram belongs to the negative bag of words, this formula is checked:

$$cneg = cneg - 1 \quad (3)$$

- If the unigram belongs to the bag of positive words, this formula is checked:

$$cpos = cpos + 1 \quad (4)$$

Finally, we denote as *ctotal* the number of unigrams composing expert, texts
 345 and *nagr* the maximum number of unigrams belonging to a single bag of words:

$$nagr = \begin{cases} cnagr; & \text{if } |cnagr| \geq |cagr| \\ cagr; & \text{if } |cnagr| < |cagr| \end{cases} \quad (5)$$

The degree of aggressiveness of a text *k*, *dagr(k)*, is then calculated as:

$$dagr(k) = \frac{2 \cdot nagr}{ctotal} \quad (6)$$

Likewise, *npos* is defined as the maximum number of unigrams belonging to a single bag of words (positive/negative):

$$npos = \begin{cases} cpos; & \text{if } |cpos| \geq |cneg| \\ cneg; & \text{if } |cpos| < |cneg| \end{cases} \quad (7)$$

350 Finally, the degree of positivity of the text *k*, *dpos(k)*, is calculated:

$$dpos(k) = \frac{2 \cdot npos}{ctotal} \quad (8)$$

These two degrees will be used in later sections to determine which of the four possible groups the experts belong to. Therefore, we create four groups because we combine the two sentiments.

3.2. Providing opinions

355 When experts have finished providing their texts and have argued their opinions and ideas with everyone, they provide their preferences to the system. In this section, we expose how the method deals with this information. Preference relations are used to allow experts to give their ratings. Let $E = \{e_1, \dots, e_m\}$ be the set of experts and $X = \{x_1, \dots, x_n\}$ the set of alternatives. A preference
 360 relation $P_s = (p_s^{ij}; i \neq j = 1, \dots, n)$ denotes how much expert e_s prefers alternative x_i over x_j . For this study, we use the representation values between $[0, 1]$ [39, 50]. Consequently, where p_s^{ij} is less than 0.5 it is indicated that option x_j is preferred over option x_i . In the case of equality $p_s^{ij} = 0.5$, both are considered equal by the expert e_s . If the option $p_s^{ij} > 0.5$ then the expert prefers x_i over
 365 x_j .

3.3. Creating the groups of experts

In this stage, we are going to create the group of experts. In order to create these groups, we classify the experts according to the degree they possess in each feeling. For that purpose, two main behaviours are analysed, aggressive
 370 behaviours and positive behaviours [51]. On the one hand, aggressive behaviour is the behaviours shown by people to incite or provoke them, for example by

insults. On the other hand, there is positive behaviour that indicates the behaviour when evaluating an alternative. By combining these two behaviours, we can have four, being the combination of the two mentioned. The first is the aggressive-negative, this behaviour may indicate an insult in a comparison. The second is the aggressive-positive, this behaviour implies when some alternative is overly liked, and the expert is not able to soften his behaviour. The third is non-aggressive-negative, this behaviour is simply when one alternative may not be liked by an expert compared to another. Finally, the non-aggressive-positive behaviour is the opposite of the previous behaviour, and one alternative is liked more when compared to another. These four behaviours are calculated using sentiment analysis.

To create the cluster, we need to define two variables, $lagr, lpos \in [-2, 2]$, (see figure 4). These variables will delimit the boundary separating the two groups in each bag. For this paper, we have chosen $lagr = 0$ and $lpos = 0$.

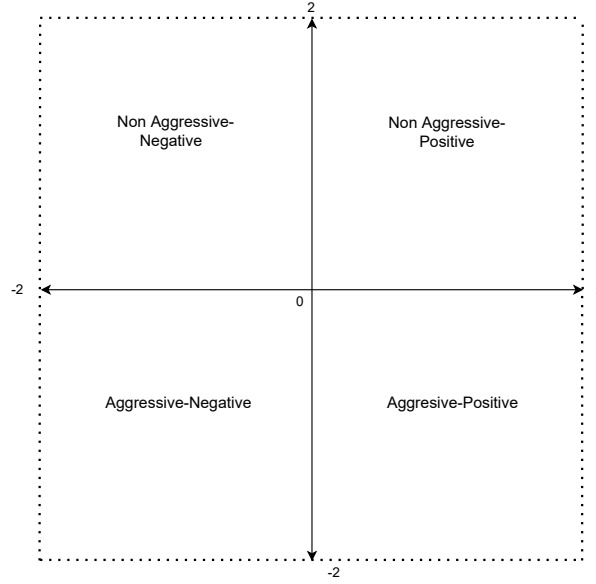


Figure 4: Graphical diagram of the two-dimensional distribution of the groups according to positivity and aggressiveness.

Subsequently, we apply the analysis over the comments made by each expert. Each comment is denoted as k_i^j ; $i = 1, \dots, c_j$; $j = 1, \dots, m$, where c_j is the number of texts provided by expert j . Two vectors are created for each expert. On the one hand, a vector for the degrees of aggressiveness. This vector is

390 defined as:

$$vdagr_j = \{dagr(k_i^j); i = 1, \dots, c_j\} j = 1, \dots, m \quad (9)$$

$$vdagr_j^z = dagr(k_z^j) \quad (10)$$

On the other hand, the vector for the degrees of positivity is defined as follows:

$$vpos_j = \{dpos(k_i^j); i = 1, \dots, c_j\} j = 1, \dots, m \quad (11)$$

$$vdpos_j^z = dops(k_z^j) \quad (12)$$

395 Once these two vectors have been defined, we proceed to calculate the average to obtain the degree of the two aspects. On the one part, the degree of aggressiveness of expert e_j is defined as:

$$mdagr(k_j) = \frac{\sum_{z=1}^{c_j} vdagr_j^z}{c_j} \quad (13)$$

On the other part, we define the degree of positivity of expert e_j , as:

$$mdpos(k_j) = \frac{\sum_{z=1}^{c_j} vdpos_j^z}{c_j} \quad (14)$$

400 Using $lagr$ and $lpos$, it is verified that if $mdagr(k_j) > lagr$ the text has aggressive connotations and, if $mdpos(k_j) \geq lpos$, it is considered a positive text (see figure 4). Thus, using the degree of aggressiveness, $mdagr(k_j)$, and the degree of positivity, $mdpos(k_j)$, experts can be categorised into the following groups:

- Aggressive - Negative (G_0)
- Aggressive - Positive (G_1)
- 405 • Non-Aggressive - Negative (G_2)
- Non-Aggressive - Positive (G_3)

Upon categorising the experts, the weights of each group are calculated.

3.4. Computing the weights of the groups

410 When experts have been classified into their groups, by employing the texts they have made, we proceed to calculate the weight of the groups. The purpose of calculating the weights of the groups is to obtain a preference relation that groups all the information generated by the experts. Next, we will obtain the collective preference relation. The collective preference relation is a single matrix that integrates the preference relations of the groups.

415 Creating the collective preference relation, it is necessary to add all the information generated by the experts. This can be done through an aggregation

function [52]. For this paper, the WA operator is used [53, 54]. As a parameter of the operator, we employ the groups created in the previous subsection.

For this method, a novel approach has been developed to obtain the weight of the groups. It contains the following elements:

- The number of experts belonging to the group.
- The arithmetic mean of the degree of aggressiveness of the experts belonging to the same group.
- The arithmetic mean of the degree of positivity of the experts belonging to the same group.
- The consensus that exists among the members of the same group.

To calculate the first element, we proceed to define the experts belonging to the same group as U_h ; $h \in \{G_0, G_1, G_2, G_3\}$. Consequently, we can define an expert belonging to the vector U_h , as o ; $o \in U_h$ and the texts made by an expert belonging to a group as $k_o^{U_h}$. Thereafter, the number of members belonging to the same group is counted, this variable will be denoted as cu_h ; $h \in \{G_0, G_1, G_2, G_3\}$. With this variable, we proceed to calculate the membership rate of a group. The membership rate, denoted as t_h , is defined as follows:

$$t_h = \frac{cu_h}{m} \quad (15)$$

For the second element, the expert membership is calculated using the arithmetic mean of the degree of aggressiveness of experts belonging to the same group. This element, denoted as, $Magr_h$; $h \in \{G_0, G_1, G_2, G_3\}$, is defined as:

$$Magr_h = \frac{2 + \frac{\sum_{o=1}^{cu_h} mdagr(k_o^{U_h})}{cu_h}}{4} \quad (16)$$

Similarly, we define the third element, the arithmetic mean of the degree of aggressiveness of experts belonging to the same degree, $Mpos_h$; $h \in \{G_0, G_1, G_2, G_3\}$. Nevertheless, instead of using $mdagr$, $mdpos$ is used in order to calculate the average positivity of each group. Therefore, $Mpos_h$ is defined as:

$$Mpos_h = \frac{2 + \frac{\sum_{o=1}^{cu_h} mdpos(k_o^{U_h})}{cu_h}}{4} \quad (17)$$

Afterwards, the consensus between members of the same group is used to verify whether there is a relationship between their texts and their preferences. This element, defined as $Cons_h$, measures the average consensus among group members. To calculate it, it is necessary to calculate the distance between two experts. For that purpose, we will use the average Euclidean distance, denoted by the variable $dist(P_i, P_j)$, where P_i and P_j are two relations. Therefore, a valuation of P_i , is defined as $p_i^{\delta z}$. This distance is defined as:

$$dis(P_i, P_j) = 1 - \frac{\sqrt{\sum_{\delta=1}^n \sum_{z=1}^n \sum_{\delta \neq z} (p_i^{\delta z} - p_j^{\delta z})^2}}{n \cdot n - n} \quad (18)$$

With this definition, we proceed to calculate the consensus among the members of the same group as follows:

$$Cons_h = 2 \cdot \frac{\sum_{i=1}^{cu_h-1} \sum_{j=i+1}^{cu_h} dis(P_i, P_j)}{cu_h^2 + cu_h} \quad (19)$$

450 We then proceed to calculate the weight of each group using the geometric mean. The weight of each group, denoted by the variable w_h ; $h \in \{G_0, G_1, G_2, G_3\}$ is defined as follows:

$$w_h = \sqrt[4]{t_h \cdot Magr_h \cdot Mpos_h \cdot Cons_h} \quad (20)$$

Finally, since the sum of the weights may not equal unity, the weights are normalised. The normalised weight for each group is denoted as W_h ; $h \in \{G_0, G_1, G_2, G_3\}$ and is defined as:

$$W_h = \frac{w_h}{w_{G_0} + w_{G_1} + w_{G_2} + w_{G_3}} \quad (21)$$

The values obtained in W_h indicate the weights associated with each group.

3.5. Analysing consensus

The possibility of achieving consensus among the groups is the motivation for the consensus process. This process seeks to achieve a high level of agree-
460 ment between the groups, before starting the process of selecting alternatives. When high consensus is achieved, the final decision is ratified by all the experts participating in the decision process. To achieve consensus, experts can modify their opinions and experts who are considered aggressive are recommended to change their behaviour to gain an understanding between them. This process is
465 divided into different stages: The first stage is to measure the consensus among the groups and the second stage determines whether the level reached is sufficient or not [55]. In the case that the level is sufficiently high since it exceeds the threshold α , we proceed to calculate the collective preference relation and consequently, the ranking of alternatives. In case the level does not exceed α ,
470 then a feedback mechanism has to be applied to allow the groups to carry out more debate and make their opinions closer.

To compute consensus, we employ an approach that works over the collective fuzz preference relation of each group, denoted as C_h ; $h \in \{G_0, G_1, G_2, G_3\}$. Each of the preference relations is used by calculating the average preference
475 values of each group. We apply the same weight to each of the experts of the group. To calculate the consensus, it is necessary to use expression (18) (see section Section 3.4). The consensus can be determined as follows:

$$Consensus = 2 \cdot \frac{\sum_{i=0}^2 \sum_{j=i+1}^3 dis(C_{G_i}, C_{G_j})}{3^2 + 3} \quad (22)$$

Once that the consensus between the groups has been obtained, it is necessary to check whether it is high enough to calculate the final ranking results.

480 For that purpose, we check whether the obtained consensus value is greater than
or equal to the variable α . The value that can be assigned to α depends on the
problem [55]. In the case that the value obtained is greater than or equal to α ,
it is affirmed that there is a high consensus between the groups. Nevertheless,
485 in the case that the limit α is not exceeded, experts should carry out another
debate round. To avoid an infinite cycle without enough agreement, a finite
number of decision rounds is established, denoted by the variable $R \in \mathbb{N}$ [56]. If
 R is reached, the final ranking of alternatives is calculated.

3.6. Calculating the collective preference relation

Once the preference relations of the groups, C_h , have been calculated, it is
490 possible to calculate the global collective preference relation, C_G .

For this paper, we have chosen to use the associated weights of the groups and
use an arithmetic mean to calculate the preferences belonging to the collective
preference relation [57, 58]. We define the collective preference relation as $C_G =$
 $(p_{C_G}^{ij})$, where p_G^{ij} is expressed as:

$$p_{C_G}^{ij} = \sum_{k=0}^3 W_{G_k} \cdot p_{G_k}^{ij} \quad (23)$$

495 Where $p_{G_k}^{ij}$ is a value belonging to the preference relation G_k . When the col-
lective preference relation has been obtained, the ranking of alternatives can
be calculated. Its purpose is to determine which are the options that are most
supported by the experts.

3.7. Creating the ranking of alternatives

500 This stage is in charge of sorting the alternatives according to the experts'
preferences. For this purpose, different functions can be used, [39, 38]. QGDD
and QGNDD operators are used to calculate the ranking. The arithmetic mean
between the results will be the value used to sort the alternatives. This way,
the criteria taken into account by both measures are used. These operators are
505 described below:

- The quantifier-guided dominance degree ($QGDD_j$): This operator is used
to calculate the dominance of an option x_j over the other alternatives.
To this effect, it is necessary to use the collective preference relation, C_G .
Formally, it can be applied as follows:

$$QGDD_j = \frac{1}{n-1} \sum_{s=1; s \neq j}^n p_{C_G}^{js} \quad (24)$$

- 510 • The quantifier-guided non-dominance degrees ($QGNDD_j$): The function
is used to calculate the non-dominance of an option x_j by the others. To
obtain the values of each option, the collective preference relation, C_G , is
used. Previously, we define the degree of the option x_j dominated by the

option x_s as $d_{sj} = \max\{p_G^{sj} - p_G^{js}, 0\}$. Accordingly, the function $QGNDD_j$ can formally be defined as follows:

$$QGNDD_j = \frac{1}{n-1} \sum_{s=1; s \neq j}^n 1 - d_{sj} \quad (25)$$

Once the QGDD (24) and QGNDD (25) operators have been developed, we proceed to obtain the value that the experts have predicted. The process is carried out as follows:

- The enforcement of $QGDD_j$ on the set of alternatives X is performed as follows:

$$X^{QGDD} = \{x_j \in X \mid QGDD_j = \sup_{x_s \in X} QGDD_s\} \quad (26)$$

- The enforcement of $QGNDD_j$ on the set X^{QGDD} is performed as follows:

$$X^{QGNDD} = \{x_j \in X \mid QGNDD_j = \sup_{x_s \in X} QGNDD_s\} \quad (27)$$

Finally, the arithmetic mean of the two functions' values is calculated. This way, the set of selection options is obtained.

4. Illustrative Example

In this section, we show an illustrative example for the understanding of the method we have proposed in this article. In the example, we are going to decide what measures a government has to take by a group of 1000 experts. This group of experts is defined as $E = \{e_1, \dots, e_{1000}\}$. Furthermore, four alternatives are proposed, denoted as $X = \{x_1, x_2, x_3, x_4\}$ where x_1 is to improve investment in security, x_2 is to improve investment in industry, x_3 is to improve investment in health, x_4 is to improve investment in roads. Each expert provides a set of fourteen texts. When referring to texts, these can be of different lengths, from one sentence to a monologue. The use of the word text is since this word groups together the whole range of lengths. Moreover, it is considered if an expert makes less than 14 sentences because an "empty" text implies that the expert has neutrality in his commentary and would remain in the centre of the axis shown in figure 4. Consequently, 14 sentences are written to have a number to be able to average a considerable number of texts to position the experts according to their aggressiveness/positivity. If there are fewer, the rest are considered empty texts. They will be gradually classified into:

- Aggressive and Non-Aggressive.
- Positive and Negative.

Some examples are:

- That's a stupid opinion. (Aggressive - Negative)
- That idea is the best, the rest are foolish ideas. (Aggressive - Positive)
- I like your opinion. (Non-Aggressive - Positive)
- I think your idea is not sustainable. (Non-Aggressive - Negative)

After providing comments, each expert makes a comparison between the investments. Some preference relations are as follows:

$$P_1 = \begin{pmatrix} - & 0.1 & 0.0 & 0.5 \\ 0.7 & - & 0.3 & 0.8 \\ 0.9 & 0.6 & - & 0.6 \\ 0.4 & 0.2 & 0.4 & - \end{pmatrix} \quad P_6 = \begin{pmatrix} - & 0.9 & 0.2 & 0.9 \\ 0.2 & - & 0.1 & 0.8 \\ 0.9 & 0.7 & - & 0.8 \\ 0.0 & 0.2 & 0.3 & - \end{pmatrix}$$

$$P_{1000} = \begin{pmatrix} - & 0.0 & 0.4 & 0.2 \\ 0.8 & - & 0.3 & 0.0 \\ 0.6 & 0.8 & - & 1.0 \\ 0.9 & 1.0 & 0.0 & - \end{pmatrix}$$

Once that we have the degree of aggressiveness and the positivity degree of each text, we obtain the average of the degrees and proceed to classify the expert in the group that corresponds to them. In this way we obtain Table 1.

Table 1: Mean degrees obtained from the group classification

	Nº Experts	Mean degree of aggressiveness	Mean degree of positivity	Consensus of the Group
Aggressive and Negative (G_0)	65	-1.8287	-0.9520	0.6865
Aggressive and Positive (G_1)	46	-1.8309	0.5183	0.6895
Non-Aggressive and Negative (G_2)	504	1.8204	-0.9335	0.6878
Non-Aggressive and Positive (G_3)	385	1.7337	0.7052	0.6886

Table 1 shows the number of people belonging to each group, the average degree of aggressiveness and positivity and the consensus among the experts. In this part, we can calculate the preference relations between the components of the same group. We obtain the following relations:

$$C_{G_0} = \begin{pmatrix} - & 0.418 & 0.449 & 0.408 \\ 0.460 & - & 0.552 & 0.435 \\ 0.671 & 0.668 & - & 0.632 \\ 0.478 & 0.429 & 0.489 & - \end{pmatrix} \quad C_{G_1} = \begin{pmatrix} - & 0.407 & 0.324 & 0.454 \\ 0.415 & - & 0.480 & 0.487 \\ 0.620 & 0.635 & - & 0.670 \\ 0.576 & 0.485 & 0.428 & - \end{pmatrix}$$

$$C_{G_2} = \begin{pmatrix} - & 0.457 & 0.452 & 0.460 \\ 0.442 & - & 0.440 & 0.448 \\ 0.665 & 0.654 & - & 0.625 \\ 0.664 & 0.606 & 0.636 & - \end{pmatrix} \quad C_{G_3} = \begin{pmatrix} - & 0.439 & 0.473 & 0.484 \\ 0.444 & - & 0.450 & 0.448 \\ 0.651 & 0.658 & - & 0.646 \\ 0.477 & 0.442 & 0.436 & - \end{pmatrix}$$

With the values provided in Table 1, we can calculate the weights assigned to the groups. The acquisition of weights is calculated according to formulas (20) and (21). In the first formula, the weight is calculated as the geometric mean of four parameters: the number of experts belonging to the group, the consensus among the experts belonging to the same group, the average degree of aggressiveness and the average degree of positivity. This calculation of the weights, unlike the traditional ones, has the advantage that it uses sentiment analysis and, by using the geometric mean and not the Euclidean mean, all the factors that make up the calculation of the weight of the experts are important since if any of them is equal to 0, the whole weight of the cluster will be equal to 0. Finally, as the sum of the weights of the clusters may be different from 0, then normalization of the weights is performed, thus obtaining that the sum of the weights of the clusters is equal to 1. Finally, the following weights (see Table 2) are obtained:

Table 2: Weights obtained for each group

Group	Weights
G_0	0.0994
G_1	0.1133
G_2	0.3622
G_3	0.4251

Next, we will verify the differences between the groups. The consensus among the groups is estimated. Table 3 contains information about the consensus of the groups.

Table 3: Consensus among the groups

Groups	Consensus
G_0, G_1	0.9427
G_0, G_2	0.9704
G_0, G_3	0.9698
G_1, G_2	0.9502
G_1, G_3	0.9551
G_2, G_3	0.9864
Consensus Average	0.9624

As the global consensus value is higher than α (set as 0.75 in this example) it can be affirmed that the groups have enough agreement with the ranking that

has been established. If the average value of the consensus had been lower than the established value of α , it is recommended that experts carry out a more profound debate. Therefore, another decision round is made.

After we have calculated the weights and the preference relations for each group, we use the WA operator to calculate the collective preference relation matrix using the expression (23). It is given as follows:

$$C_G = \begin{pmatrix} - & 0.440 & 0.446 & 0.465 \\ 0.442 & - & 0.460 & 0.451 \\ 0.654 & 0.655 & - & 0.640 \\ 0.484 & 0.433 & 0.440 & - \end{pmatrix}$$

With the C_G matrix estimated, we proceed to apply the QGDD and QGNDD operators shown in (24) and (25) respectively. Table 4 shows the QGDD, QGNDD and the final ranking results.

Table 4: QGDD and QGNDD values using the collective preference relation C_G .

Values\Investment	x_1	x_2	x_3	x_4
QGDD	0.4503	0.4509	0.6495	0.4522
QGNDD	0.9237	0.9350	1.0000	0.9275
Average	0.6870	0.6930	0.8248	0.6898

By sorting alternatives using the average value from Table 4, the following ranking is obtained: $\{x_3, x_2, x_4, x_1\}$. Therefore, the chosen investment is x_3 , to improve investment in health.

5. Discussion

The method described in this paper is innovative because it studies the aggressiveness and positivity of the experts and creates a ranking system according to their comments using Natural Language Processing. Natural language processing is central to the process and the model presented in this article cannot be conceived without natural language processing. There are several reasons for this: the first reason is that natural language is responsible for the clustering between the experts creating the four groups presented. The second reason is that the average degree of aggressiveness and positivity of the experts subsequently influences the weight of the clusters. Finally, the last reason is that if natural language processing were eliminated, it would not be possible to create all the clusters or to adjust their weights. This would mean that this model would not be conceivable, not even comparable with a classical consensus model because the weight adjustment of each cluster would not be correct, as half of the components of the weight adjustment formula (20) depend on the comments made by the experts during the discussion.

The approach presented in this paper on natural language processing is novel because although it uses bag-of-words, a technique widely used within natural

600 language processing, it uses bags of words that have class-specific terms. Consequently, bags of words with unique terms are obtained, making the process of class membership a faster process than if all the words that make up the sentences of each class were used. On the other hand, applying natural language processing implies a special contribution to group decision making because the
605 comments made by the experts during the debate through the comments are added to the group decision making system. Consequently, the debate gains importance in the process, since also to the fact that the experts can provide their opinions after the debate is over, the way they express those opinions consequently influences the rest of the process.

610 The advantages of our method are the following:

- **Scalability on the number of experts:** our method does not depend on the number of experts involved in the process. The method can be applied to an indeterminate number of experts, which means that the usefulness of the method is increased in different domains.
- 615 • **classification of the experts according to aggressiveness and positivity with optimised word bags:** our method studies the inner behaviour of the experts in order to determine their involvement in the debate. Experts are classified according to this in order to detect groups of experts that have similar behaviours. Furthermore, the type of natural
620 language used is sentiment analysis of written comments made by experts. Sentiment analysis allows us to obtain whether the comment made by an expert implies aggressiveness or not. Moreover, this article is also used to detect whether a comment is positive or not. By applying the classification to each expert's comment, a degree of positivity and a degree
625 of aggressiveness is obtained for each of them, which allows them to be grouped into different clusters. On the other hand, the consensus model is faster for two reasons: the first reason is that the bags of words have unique words in each bag, which means that there are no two bags of contradictory words with the same word, for example, the same term does not
630 exist in the bag of aggressive words and the bag of non-aggressive words. This results in the creation of optimised bags of words, as terms found in both bags are eliminated. Furthermore, this process only performs consensus among experts in the same group, thus avoiding comparing all experts with each other. Finally, the innovation of this study is noticeable in that it classifies the experts based on sentiment analysis and uses
635 the comments made to adjust other elements within the large-scale group decision-making process, such as adjusting the weight of each cluster.
- **Adjustment of weights based on group texts:** the method creates a fair weighting system that gives more importance to those experts that are
640 more likely to listen to other experts' points of view and that communicate in a non-aggressive way. This means that the weight allocation takes into account all the factors associated with the group, thus making the

allocation of weights to each group fairer than assigning the same weight to all groups.

645 This method shows advantages that make it an innovative and suitable GDM system. However, one aspect to take into account is that the words used to classify the texts are contained in a number of comments. This means that there may be words used by experts that are not in the bags of words. As future work, more comments will be investigated and added to the list of comments
650 used to classify experts.

The presented method shows a novel LSGDM method that classifies experts into groups based on the texts they produce. Nonetheless, there are works in the literature that use LSGDM methods or systems that use sentiment analysis for the decision making process. In [59], authors analyse each word and give
655 it a positivity value based on how many times it was in a positive or negative comment. Once the scores have been obtained, they look at whether a comment is positive, negative or neutral and perform a GDM process. In contrast, our method analyses not only the positivity or negativity of a comment, but also the aggressiveness and uses these sentiments to cluster the experts into
660 different groups. In [60], a consensus model of heterogeneous LSGDMs with non-cooperative behaviour is created and applied in financial inclusion while in [61], a new framework for efficient consensus building in large-scale social groups and its application to an urban resettlement problem is created. The main difference between this method and the other two is that the proposed method
665 detects two expert sentiments and uses a degree of positivity and aggressiveness to cluster them. Moreover, the two degrees are also used to adjust the weight of the clusters. Consequently, sentiment analysis has a dual function within the process. Finally, this method clusters according to sentiment, thus avoiding grouping experts according to their preferences or their ability to cooperate. In
670 [26], a sentiment analysis is used to create a GDM method. In comparison, our model uses sentiment analysis utilizing an LSGDM, which implies an increase in the number of experts involved in the process. Furthermore, our model uses sentiment analysis based on two emotions unlike the paper mentioned above, which is based on a single sentiment. In [62], an LSGDM model based on limited
675 trust is presented, while our paper shows an LSGDM model based on sentiment analysis, which implies that experts' behaviour is analysed based on their feedback and not on cues. Moreover, the model performs clustering of the experts and adjusts the groups according to the feedback of the experts.

6. Conclusions

680 In this article, we present a novel LSGDM system that employs the aggressiveness and attitude of experts' behaviours in order to improve the GDM process. The recent GDM methods do not take into account experts' behaviour on the debate in order to model the decision process.

The proposed method employs sentiment analysis over experts' comments in
685 order to analyse their behaviour. The main advantage is the evaluation of the

degree of aggressiveness and positivity of the comments made by the experts. By analysing these degrees, experts can be grouped and from these clusters, a new measure of consensus is created that is used to modify the weights of the groups. A high consensus level in a group makes it possible to show how close
690 experts' opinions are on that group.

The presented algorithm uses different texts to detect words considered as positive and negative. For this reason, as future work, it is possible to investigate different sets of words, analyse the comments in which they are contained and thus create a generic global dataset.

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*“Decirle al señor Duque de Enguin que agradecemos sus palabras, pero este
es un tercio español.”*
- Diego Alatríste.
Alatríste (2006)

2.3. A group decision-making method based on the experts' behavior during the debate

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A Group Decision-Making Method Based on the Experts' Behaviour During the Debate

José Ramón Trillo, Enrique Herrera-Viedma, *Fellow, IEEE*, Juan Antonio Morente-Molinera, and Francisco Javier Cabrerizo

Abstract—Debate is a process consisting in arriving at a reasoned opinion on a proportion in which individuals must be truly capable of defending their own judgments. It has been used within group decision-making (GDM) problems to help experts make better decisions. However, whether experts engage in a vigorous debate, it can result in the use of aggressive language that may diminish consensus, which is the major objective of GDM. To avoid it, we present a novel method for GDM problems that can identify aggressive comments during the debate by incorporating a classifier based on sentiment analysis techniques. According to the information extracted during the debate, two procedures are developed to assign weights to the experts, which are used to introduce two new consensus measures and to make the final decision. Unlike the existing GDM methods, this new one can take advantage of the information extracted during the debate (i.e., experts' behaviour) throughout the decision process, making it in rapport with real-world GDM processes.

Index Terms—Group decision-making, consensus, sentiment analysis.

I. INTRODUCTION

MAKING decisions is a common task, from the professional to the personal level, that involves emotions [1]. Due to it, individuals sometimes make wrong decisions because of their mood or the mood of others [2], [3]. This leads to not choosing the best possible course of action when individuals' feelings cloud their judgments or they suffer regret or discomfort [4], which is a common issue when individuals face group decision-making (GDM) processes [5].

In GDM processes, a group of individuals, usually experts in the problem under discussion, are generally involved in a debate in which they give their assessments on a set of possible alternatives or courses of action and provide arguments supporting them [6]. The objective is to attain a consensual solution that takes advantage of all individuals' ideas [7]. It is due to individuals are more likely to implement decisions they accept, and consensus makes acceptance more likely [8].

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The existing approaches supporting GDM processes assist experts in choosing the best solution within a set of possible alternatives or courses of action. Most of these approaches focus on helping experts reach the highest consensus possible before making the final decision [9]–[11]. To do it, they are usually based on the assessments provided by the experts, but not considering the arguments conveyed by them to express such assessments. However, when an expert expresses an assessment, for instance, “this wine brand is much better than that other,” it is not only important the given assessment but also the arguments provided to support such assessment [12].

Experts provide arguments to justify their assessments, and it can make known information that is relevant to the GDM process. Firstly, the style of the speaker may be the tiebreaker if experts are equally matched in refutation and argumentation [8]. Second, aggressive language has been shown to negatively affect the reliability of the speaker using it and the credibility of his or her information [13], and consensus demands a high level of trust among the members of the group. Third, aggressive language can also lead to the deterioration of the debate, making experts get defensive and emotional. As a result, they could provide unsuitable assessments [14]. In summary, if the experts' behaviour, in the sense of the language used by the experts to argue their assessments, during the debate is not analysed, information, which may be relevant to the decision-making process, will be lost.

On the one hand, several approaches have been proposed to analyse the debate carried out between the experts before providing their assessments [15]–[19]. However, these approaches do not consider the experts' behaviour during the debate. On the other hand, several approaches have been proposed to take into account the experts' behaviour during the decision-making process [20]–[23], but from a different point of view. Concretely, these approaches deal with non-cooperative behaviours in the sense that experts with such behaviour try to obstruct the improvement of consensus by providing assessments very different from the ones expressed by the rest of the group members. To handle such behaviours, these approaches generally penalize experts with non-cooperative behaviours during the decision-making process. Therefore, the approaches analyzing the debate carried out between the experts in GDM processes should consider both the assessments provided by the experts during the debate and the language used to express their arguments because this information could be of interest to the rest of the decision-making process.

The objective of this study is to develop a new method for GDM processes considering the experts' behaviour in the debate throughout the decision-making process. Firstly, it in-

corporate a classifier based on sentiment analysis techniques [24] that can categorize the language used by the experts during the debate as aggressive or non-aggressive. Several data preprocessing techniques are applied to extract many parameters (number of insults, number of words in capital letters, and so on) allowing to obtain a better classification. Secondly, based on the information generated by the classifier, two new procedures are designed to assign weights to the experts, which are used both to define two new consensus measures and to make the final decision. In consequence, this new method improves the existing ones by taking advantage of the information extracted in the debate (i.e., the experts' behaviour) during the whole decision-making process.

The content of this study is divided into five sections. In Section II, we recall the basic concepts and techniques associated with the proposed method. In Section III, we elaborate on the new method for GDM. Strong attention is given to how the experts' behaviour is extracted during the debate and how this information is used in the rest of the decision-making process. Section IV provides a real-world case study that helps understand the performance of the proposed method. Finally, Section V provides some concluding remarks about the advantages and disadvantages of the proposed method along with some further research directions.

II. BACKGROUND

In this section, we recall the necessary background to understand the GDM method developed in this study. Section II-A is dedicated to sentiment analysis, in particular, the steps needed to build a classifier are described. Section II-B is devoted to introducing the basic concepts concerning GDM problems.

A. Sentiment Analysis

Natural language, which is used by humans for communication, is extraordinarily diverse and complex. It is composed of vague and imprecise concepts that are far from the binary language used by computers, in which communication occurs through millions of ones and zeros, instead of words, to produce logical actions. Therefore, to help computers understand humans in their own language, natural language processing is required [25], [26].

When individuals hold a debate on a topic, they tend to use natural language. Consequently, the use of tools translating this language into one that can be understood by a computer is necessary. These tools can also help extract useful information from the data. For instance, in GDM processes, it is interesting to know how experts feel. This can be done by analyzing the language employed by the experts during the debate to gain insights into their sentiments and emotions, which can reveal the experts' behaviour during the debate. To do this, sentiment analysis, one of the most important fields of natural language processing, can be used [24], [27].

Two distinct approaches using machine learning can be implemented to perform sentiment analysis [28]: a supervised learning approach, which depends on the existence of labelled training data, and an unsupervised learning approach, which uses libraries or tools to classify opinions without an already

labelled output. In this study, we assume a supervised learning approach as it is the most basic approach and offers good performance.

Classifiers based on supervised learning for sentiment analysis make use of two data sets. The first one, called training data set, helps the classifier know which concepts are associated with a feeling and which ones are not. The second one, called test data set, allows us to know whether the classifier detects those feelings appropriately. Based on both data sets, the steps for building a classifier for sentiment analysis are [24]:

- **Preprocessing.** The first step to be done is the preprocessing step, which is very important in sentiment analysis as it cleans the data sets from any noisy data, thus reducing their complexity to prepare the data for the next steps.
- **Training.** The second step consists in taking content that is known to belong to a specific class (training data set) and creating a classifier based on that known content employing machine learning algorithms. It is an iterative process whereby the best classifier possible is built.
- **Classification.** The third step consists in taking the classifier built with such training data set and running it on unknown content to determine class membership for the unknown content (test data set). It is a one-time process designed to run on unknown content.

In recent literature, there exist plenty of articles that use sentiment analysis. For instance, in [29], a method for analysing investor behaviour is presented. For this purpose, it analyses the sentiments through the phrases that investors make during their buying and selling process. In [30], it is presented a hardware framework for optimising text sentiment analysis using a memristor-based long short-term memory system. And, in [31], bidirectional recurring units are used by the process to capture contextual information when learning word representations in sentiment analysis.

B. GDM Processes

A GDM process, otherwise called a collective decision-making problem, characterizes a process in which several individuals (experts) collectively arrive at a choice from some alternatives. It is formally characterized by a finite collection of alternatives, $X = \{x_1, x_2, \dots, x_n\}$, and a finite group of experts, $E = \{e_1, e_2, \dots, e_m\}$, where every expert, based on her or his knowledge of the problem under study, provides her or his assessments of the alternatives. The objective is to build a collective ranking of the alternatives from best to worst as a possible solution to the problem [5], [32].

The experts' assessments of the alternatives can represent either the preference degree of one alternative over other one or the degree up to which an alternative is chosen as possible solution to the problem. In any case, a particular representation domain must be selected to model the assessments. Notably, fuzzy set theory has been successfully used in the resolution of decision-making processes because they are cognitive processes in which humans (experts) take part [33]. In fact, the fuzzy set theory and its extensions have been demonstrated to be useful in characterizing decision information pervaded with human uncertainty [34].

To solve a GDM problem, different stages are carried out, which start with the experts holding a debate and providing their assessments of the alternatives and end by deriving a ranking of the alternatives [10]:

- Holding a debate. The experts discuss the different alternatives related to the problem. During this debate, the experts give reasons for their assessments and share their knowledge about the alternatives and the problem to make easier the procedure of afterwards providing their assessments [6].
- Providing assessments. The experts express their assessments of the alternatives employing a certain representation format and a particular representation domain [35].
- Analyzing consensus. The experts must reach enough agreement before making the final decision. It means that we need to compute some consensus measures allowing us to identify the consensus achieved [36]–[38]. The greater the consensus, the more reliable the decision made. On the contrary, if the consensus achieved is not enough, the experts should reconsider their assessments and, then, the above stages must be carried out again [39], [40]. To avoid a cyclical and never-ending process, a limited number of consensus rounds is generally established. When the limit is reached, the ranking of the alternatives must be obtained independently of the consensus achieved.
- Computing a collective assessment. The individual assessments provided by the experts are aggregated to compute a collective assessment summarizing them. To do so, different aggregation functions can be used [41].
- Ranking the alternatives. The information contained in the collective assessment is exploited to rank the alternatives. Different functions can be applied to do it [42], [43]. According to this rank, the best alternative is selected as a solution to the decision problem. This stage is also known as the exploitation stage.

III. A GDM METHOD BASED ON EXPERTS' BEHAVIOUR IN THE DEBATE

In this section, we describe a new method for GDM problems that considers the experts' behaviour during the debate stage throughout the GDM process. This new method makes use of sentiment analysis techniques to identify the experts' feelings through the comments provided by them to support their assessments during the debate, i.e., it can detect the experts' conduct, allowing us to understand how experts feel. It implies that we can know some important information, such as how the decision to be made affects the experts [44], [45].

This new GDM method incorporates a sentiment analysis classifier capable of detecting aggressive language in the experts' debate. It is composed of the following stages (see Fig. 1): (i) detecting aggressive language during the debate, (ii) providing assessments, (iii) computing experts' weights, (iv) analyzing consensus, (v) computing a collective assessment, and (vi) ranking the alternatives. In the following subsections, we elaborate on in detail each of the stages.

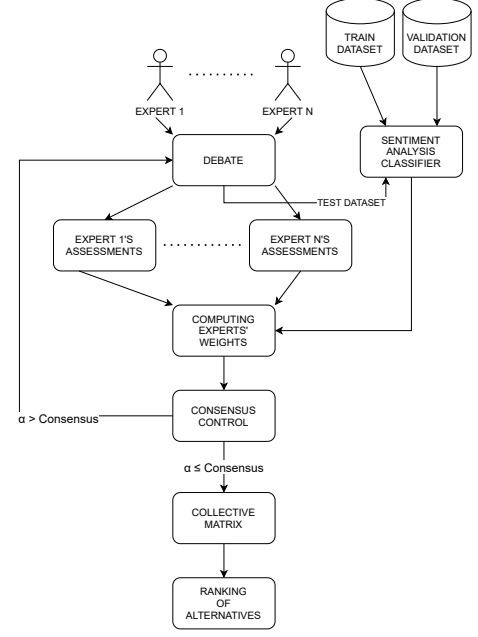


Figure 1. General outline of the proposed GDM method.

A. Detecting Aggressive Language During the Debate

The first stage is devoted to identifying aggressive language in the comments provided by the experts while they debate. This is done by means of a classifier based on supervised learning for sentiment analysis. As described in Section II-A, to build the classifier, different machine learning algorithms, namely, support vector machine (SVM), Naïve Bayes, k-nearest neighbours (KNN), and so on, can be used [46]. In addition, a training data set is needed to adjust the parameters of the classifier and, once this has been done, a test data set must be used to verify the quality of the classifier.

Once the classifier has been constructed, this stage is carried out as follows. Several debate rounds, $\zeta \in \mathbb{N}$, are performed. In every debate round, first, the comments provided by the experts are preprocessed to clean and prepare them for classification and, second, they are classified as aggressive or non-aggressive via the classifier. At the end, the number of aggressive comments provided by each expert in every debate round is computed. The value of ζ depends on problem under discussion, i.e., if the effects of the decision adopted are transcendent, the number of debate rounds should be logically high. On the contrary, if the consequences of the decision are still important, but not so transcendental, or it is urgent to adopt the decision, a low number of debate rounds is required.

In the following, we elaborate on in detail both the preprocessing and the classifier constructed.

1) *Preprocessing*: The preprocessing of the comments provided by the experts is required to transform them into a useful and efficient format for the classifier. It is also necessary for transforming the raw data of both the training data set and the test data set, which are used to build the classifier. Here, as training data set and test data set, we use the data set offered by [47].

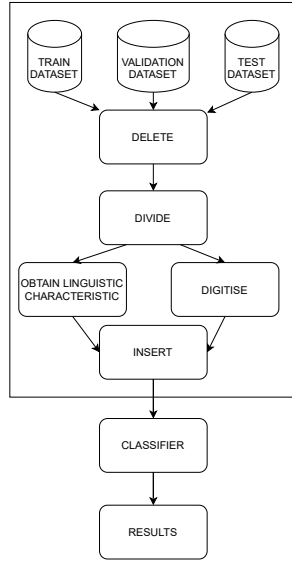


Figure 2. Outline of the proposed sentiment analysis algorithm.

There exist different techniques for preprocessing [48]. Among them, we have selected the following ones that allow us to divide the comments, detect what type of words we have, and optimally reduce the bag of words generated: (i) tokenization, which segments the comments into words, or sets of words (it also separates out words and removes punctuation), (ii) stemming and lemmatization, which reduce words to a root by removing inflexion via dropping unneeded characters (usually suffixes), (iii) removal of stop words, which removes commonly used words unlike to be useful for learning, and (iv) part-of-speech tagging (POS-tagging), which consists in assigning parts of speech to every word, such as an adjective, verb, noun, and so on. Using these techniques, the preprocessing is composed of five steps (see Fig. 2):

- 1) Delete. It consists in simplifying words to their root word and removing the elements that do not give useful information, that is, removing non-relevant words, numbers and double blanks. This is done by using stemming, lemmatization and removal of stop words.
- 2) Divide. It consists in breaking down the comments into n-grams, that is, the comments are divided into words or sets of words. This is done by using tokenization.
- 3) Obtain linguistic characteristics. It consists in associating more information with the comments by applying linguistic features. Concretely, the following ones have been used because, after an intensive experimentation, they have shown a good performance to classify comments:
 - Length of the comments. This characteristic represents the number of words composing a comment. It is extracted because an aggressive comment is usually either very long or short and direct.
 - Number of characters. This characteristic determines the total number of characters in the comment. It complements the above characteristic because a comment with a few words but a great number of characters may indicate that the comment is aggressive.

- Number of negative, neutral and positive emojis. They represent the number of emojis whose predominant value is negative, neutral and positive, respectively. They are extracted because a significant number of negative emojis can determine that the comment is aggressive while a significant number of neutral or positive emojis can determine that the comment is non-aggressive [49].
- Number of emojis. This characteristic represents the total number of emojis composing a comment. There exists a direct relationship between the total number of emojis and the type of comment because the absence of emojis can determine the type of comment.
- Number of negative, neutral and positive words. These characteristics determine the number of words whose values in a database are lower, equal and greater than 0, respectively. They are extracted because a large number of negative words can represent an aggressive comment while a great number of neutral or positive words can represent a non-aggressive comment. Refer to [50] to determine the value of a word.
- Number of words with repeated characters. This characteristic indicates the number of words having consecutive repeated characters. It is used because the increase of repeated characters in a word can determine that the expert is relaxed while writing the comment and, therefore, it can indicate that he or she does not write a comment with aggressive content.
- Number of consecutive words repeated. It represents the number of consecutive repeated words. Similar to the previous one, a more formal tone is usually used when trying to offend someone and, therefore, fewer word repetitions or misspellings are generated.
- Number of repeated exclamations. It represents the number of consecutive repeated exclamations. It is chosen because the use of repeated exclamations increases the intensity of the comment and, therefore, it can offer information about the expert's intention.
- Number of negative and positive classic emoticons. These characteristics represent the number of classic emoticons whose value in a database is negative and positive, respectively. These characteristics complement the emojis as the use of these types of emoticons can determine that a comment is non-aggressive and aggressive, respectively [51].
- Number of complete words in capital letters. This characteristic represents the total number of words written completely in capital letters. It is extracted because it can determine the intensity to which a comment or a word is expressed. For example, an uppercase comment indicates a very high intensity, which determines that the comment is aggressive.
- Number of insults. It determines the number of insults composing the comment. A great number of insults indicates that the comment is aggressive.
- POS-tagging. It allows us to determine the type of each word composing the comment. Using it, we can obtain relevant information about the comment.

4) Digitise. It consists in taking the set of n-grams and digitising them to obtain a numeric matrix. This can be done in three different ways:

- Binary frequency of terms. It generates a binary numeric matrix as follows: if the word or set of words is found in the comment, a value of 1 is placed; otherwise, a value of 0 is set.
- Frequency of terms. It works similarly to the previous one. However, instead of placing 1 if the word or set of words is found in the comment, it places the number of times that the word or the set of words are found in the comment. Therefore, it generates a numeric matrix containing the frequency of terms.
- Term frequency-inverse document frequency (TF-IDF). It intends to reflect how important a word is to a document in a corpus or collection. Therefore, here, it aims to weigh the importance of a word to comment on in the debate. It generates a numeric matrix containing the TF-IDF.

5) Insert. Once the linguistic characteristics have been obtained, they are added to the numeric matrix. Finally, another column is added to the matrix, which represents whether the comment is aggressive (a value of 1 is then added) or non-aggressive (a value of 0 is placed).

2) *Classifier*: Several machine learning algorithms can be used to construct the classifier based on supervised learning for sentiment analysis [46]. Among them, we have chosen the following ones, which are not based on deep learning and, as a result, allow us a faster training:

- SVM [52]. It tries to discover the best hyperplane in more than two dimensions, or the best line in two dimensions, to separate the space into classes. The line (hyperplane) is obtained by means of the maximum margin, i.e., the maximum distance between data points of both classes.
- Naïve Bayes [53]. The crux of this algorithm is based on the Bayes theorem and in the assumption that the predictor variables are independent, i.e., the presence of a particular predictor variable does not affect the others.
- KNN [54]. It is based on the principle that instances within a data set usually exist close to others having similar properties. If the instances are tagged with a label, then the label of an unclassified instance can be obtained by observing the class of its k nearest neighbours and assigning to it the most frequent class label.

A classifier can be built based on each algorithm. First, we must adjust its parameters via a training data set (as mentioned, the data set offered by [47] is used as a training data set). To do so, the training data set must be preprocessed as described in Section III-A1 to obtain a numeric matrix that is used as input for the algorithm [55]. Second, once the classifier has been built, we must evaluate its quality by means of a test data set (the data set offered by [47] is also used as test data set), which must be preprocessed too.

The best accuracy, i.e., the percentage of words classified correctly as aggressive and non-aggressive, reached by each algorithm is shown in Fig. 3. This best accuracy is achieved by using these combinations:

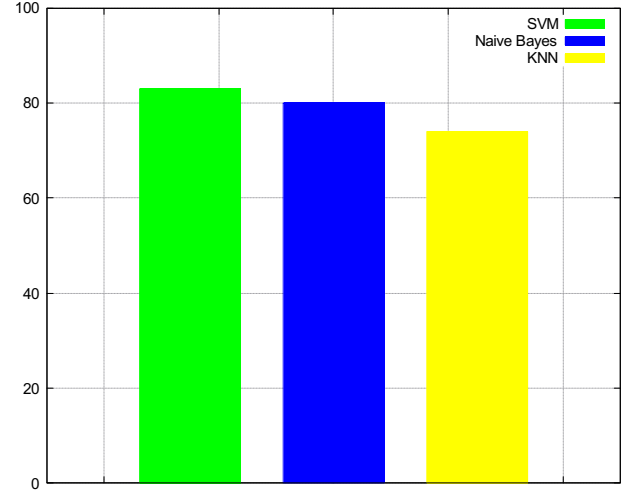


Figure 3. Best accuracy achieved by SVM, Naïve Bayes, and KNN.

- SVM. The best combination is based on the use of stemming and removal of stop words, all the linguistic characteristics, unigrams, and the TF-IDF matrix. Using this combination, the SVM reaches an accuracy of 83%.
- Naïve Bayes. The best combination is based on the use of stemming and removal of stop words, all the linguistic characteristics, unigrams, and the binary matrix. Using this combination, the Naïve Bayes algorithm reaches an accuracy of 80%.
- KNN. The best combination is based on the use of stemming and removal of stop words, unigrams, the frequency matrix, a value of 4 for k , and without linguistic characteristics. Using this combination, the KNN algorithm reaches an accuracy of 74%.

According to these results, the classifier based on the SVM algorithm will be used to identify aggressive comments during the debate as it has achieved the best accuracy. In addition, in order to not be only based on the data set offered by [47], this classifier is reinforced with other dictionaries, such as the insult dictionary, and other data sets measuring emotions. In this way, the classifier does not rely solely on the comments contained in the training data set.

B. Providing assessments

Once the debate is closed, the experts must provide their assessments. As mentioned in Section II-B, we can find both different representation formats and distinct representation domains to model these assessments [35]. Among them, in this study, we assume preference relations as representation format and $[0,1]$ -values as representation domain, i.e., we assume fuzzy preference relations due to they have been widely and successfully used in GDM [56].

The fuzzy preference relation P^z provided by the expert e_z on a collection of alternatives X is modelled by a function $\mu_{P^z} : X \times X \rightarrow [0, 1]$. To represent the fuzzy preference relation P^z given by the expert e_z , a matrix $P^z = (p_{jk}^z)$ of size $n \times n$ is generally utilized, being $p_{jk}^z = \mu_{P^z}(x_j, x_k)$ the

preference degree of x_j over x_k ($j \neq k$) according to e_z . Concretely, whether $p_{jk}^z > 0.5$, then x_j is preferred over x_k by e_z ; whether $p_{jk}^z < 0.5$, then x_k is preferred over x_j by e_z ; and whether $p_{jk}^z = 0.5$, then both x_j and x_k are equally preferred or deemed as indifferent by e_z . Therefore, assuming a group of experts, $E = \{e_1, e_2, \dots, e_m\}$, and a collection of alternatives, $X = \{x_1, x_2, \dots, x_n\}$, in this stage, we obtain a set of m fuzzy preference relations, P^z , $z = 1, \dots, m$.

C. Calculating experts' weights

The experts' behaviour during the debate is considered to assign weights to them. That is, we know that an aggressive behaviour leads to the deterioration of the debate and hinders the achievement of consensus [13], [14]. Therefore, lower weights should be assigned to experts using an aggressive language during the debate.

Two different methods are developed, which use the results returned by the classifier: (i) a global method, and (ii) an iterative method.

- Global method. First, we calculate the total number of aggressive comments, $ac_z \in \mathbb{N} \cup \{0\}$; $ac_z \leq tc_z$; $z = 1, \dots, m$, and the total number of comments provided, $tc_z \in \mathbb{N}$; $z = 1, \dots, m$, i.e., both aggressive and non-aggressive comments, expressed by the expert e_z during all the debate rounds. They are computed as follows:

$$ac_z = \sum_{j=1}^{\zeta} ac_z^j \quad (1)$$

$$tc_z = \sum_{j=1}^{\zeta} tc_z^j \quad (2)$$

being $ac_z^j \in \mathbb{N} \cup \{0\}$; $ac_z^j \leq tc_z^j$ the number of aggressive comments given by the expert e_z in the round j and $tc_z^j \in \mathbb{N}$ the number of comments, both aggressive and non-aggressive comments, provided by the expert e_z in the round j .

Second, a peaceful coefficient, pc_z , assuming values in-between $[0, 1]$ is computed for each expert e_z as follows:

$$pc_z = 1 - \frac{ac_z}{tc_z} \quad (3)$$

The lower the value of pc_z , the greater the aggressiveness of e_z .

Third, the weight, w_z^g , associated with each expert e_z , being $\sum_{z=1}^m w_z^g = 1$, is determined by dividing her or his peaceful coefficient, pc_z , by the total sum of all the peaceful coefficients of the experts:

$$w_z^g = \frac{pc_z}{\sum_{z=1}^m pc_z} \quad (4)$$

- Iterative method. Unlike the global method, it uses the weights obtained in previous debate rounds to compute the weight of the current round. This method starts initializing the weight associated with each expert, w_z^0 , with a value equal to $\frac{1}{m}$, being m the number of experts. Then, a peaceful coefficient, pc_z^j , assuming values in-between $[0, 1]$ is computed for each expert e_z . Unlike

the peaceful coefficient calculated by the global method, it is calculated according to the number of aggressive comments and the number of comments, both aggressive and non-aggressive comments, provided in the round j :

$$pc_z^j = 1 - \frac{ac_z^j}{tc_z^j} \quad (5)$$

Using the peaceful coefficient computed in each round, the weight associated with each expert, e_z , in the debate around j is calculated as follows:

$$w_z^j = \frac{pc_z^j \cdot w_z^{j-1}}{\sum_{z=1}^m pc_z^j \cdot w_z^{j-1}} \quad (6)$$

In the case that all experts have a weight equal to 0 since all of them have provided only aggressive comments in a given round, the weights are reset to $\frac{1}{m}$. Finally, the weight, w_z^i , associated with each expert e_z is determined by the weight reached in the last round, i.e.:

$$w_z^i = w_z^\zeta \quad (7)$$

D. Analyzing consensus

Motivated by the possibility that some experts might exhibit disagreements with each other's assessments or they may sometimes not accept the decision made, consensus reaching processes were introduced as a very important requirement in GDM processes to reach a high level of collective agreement before making the decision [10]. Reaching consensus needs experts to change their first assessments, bringing them closer to each other, towards a collective assessment deemed as good enough by the group. Its principal steps are: (i) consensus measurement, i.e., determining the current closeness level between assessments via a consensus measure [57], (ii) consensus control, i.e., determining whether the required consensus level has been reached, and (iii) reconsideration of judgments, i.e., debating again and modifying assessments to bring the furthest assessments closer to the remainder of the group members' assessments to increase the consensus.

To determine the consensus achieved, we introduce two novel approaches considering the experts' behaviour during the debate:

- An approach based on the standardised Euclidean distance, called *SED*, which makes use of the Euclidean distance between the experts' assessments and the experts' weights to compute the agreement between two experts. Because there exist two methods to compute the weights, by applying this approach we obtain two consensus measures, $CGSED_y^z$ and $CISED_y^z$, measuring the agreement between the experts, e_z and e_y , when using the global method and the iterative method, respectively, to compute the experts' weights:

$$CGSED_y^z = 1 - \frac{\sum_{j=1}^n \sum_{k=1; k \neq j}^n \sqrt{(p_{jk}^z - p_{jk}^y)^2 + (w_z^g - w_y^g)^2}}{(n^2 - n) \cdot \sqrt{2}} \quad (8)$$

$$CISED_y^z = 1 - \frac{\sum_{j=1}^n \sum_{k=1; j \neq k}^n \sqrt{(p_{jk}^z - p_{jk}^y)^2 + (w_z^i - w_y^i)^2}}{(n^2 - n) \cdot \sqrt{2}} \quad (9)$$

Once the consensus measures between every pair of experts have been computed, two global consensus measures, $CGSED$ and $CISED$ are computed:

$$CGSED = 2 \cdot \frac{\sum_{z=1}^{m-1} \sum_{y=z+1}^m CGSED_y^z}{m^2 - m} \quad (10)$$

$$CISED = 2 \cdot \frac{\sum_{z=1}^{m-1} \sum_{y=z+1}^m CISED_y^z}{m^2 - m} \quad (11)$$

- An approach based on the product of the consensus between the experts' assessments and the consensus between the experts' weights. It assumes that experts should have both similar assessments and a similar degree of aggressiveness, which is determined by the weights. As before, by applying this approach, we obtain two consensus measures, CGP_y^z and CIP_y^z , measuring the agreement between the experts, e_z and e_y , when using the global method and the iterative method, respectively, to compute the experts' weights:

$$CGP_y^z = \left(1 - \frac{\sum_{j=1}^n \sum_{k=1; k \neq j}^n |p_{jk}^z - p_{jk}^y|}{(n^2 - n)} \right) \cdot (1 - |w_z^g - w_y^g|) \quad (12)$$

$$CIP_y^z = \left(1 - \frac{\sum_{j=1}^n \sum_{k=1; k \neq j}^n |p_{jk}^z - p_{jk}^y|}{(n^2 - n)} \right) \cdot (1 - |w_z^i - w_y^i|) \quad (13)$$

Once the consensus measures between every pair of experts have been computed, two global consensus measures, CGP and CIP are computed as follows:

$$CGP = 2 \cdot \frac{\sum_{z=1}^{m-1} \sum_{y=z+1}^m CGP_y^z}{m^2 - m} \quad (14)$$

$$CIP = 2 \cdot \frac{\sum_{z=1}^{m-1} \sum_{y=z+1}^m CIP_y^z}{m^2 - m} \quad (15)$$

Once the consensus among the experts has been measured, we must check whether it is enough. To do so, a consensus threshold $\alpha \in [0, 1]$ is established, which depends on the problem [10]. Whether the consensus achieved is equal to or greater than the consensus threshold, we can obtain the ranking of the alternatives derived from the collective assessment. Otherwise, the experts must reconsider their assessments by starting a new discussion round, i.e., the first stage is carried

out again. A limited number of discussion rounds, $\beta \in \mathbb{N}$, is established to avoid a never-ending decision-making process. When this limit is achieved, we proceed to obtain the ranking of the alternatives independently of the agreement achieved.

E. Obtaining the collective assessment

To compute the collective assessment, all the individual assessments must be aggregated. Here, as we are modelling the assessments via fuzzy preference relations, we must fuse all of them to obtain a collective fuzzy preference relation by means of an aggregation function [41].

To consider the experts' behaviour during the debate stage in the calculation of the collective assessment, the weights associated with the experts are used to obtain the fuzzy collective preference relation. Concretely, the weighted mean is used as an aggregation function. However, other aggregation functions such as the power average operator or the Bonferroni mean-type aggregation functions could be considered [58], [59]. As two methods can be applied to compute the weights, two collective fuzzy preference relations can be obtained:

- A collective fuzzy preference relation, $C^g = (c_{jk}^g)$, using the global method is obtained as follows:

$$c_{jk}^g = \sum_{z=1}^m w_z^g \cdot p_{jk}^z \quad (16)$$

- A collective fuzzy preference relation, $C^i = (c_{jk}^i)$, using the iterative method is obtained as follows:

$$c_{jk}^i = \sum_{z=1}^m w_z^i \cdot p_{jk}^z \quad (17)$$

Once the collective fuzzy preference relations have been computed, the ranking of alternatives can be derived from them. This is done in the next stage.

F. Ranking the alternatives

In this stage, the information contained in the collective fuzzy preference relation is exploited to rank the alternatives from best to worst as solutions to the decision-making process. Among the different functions that can be applied to do it [42], [60], we use both the quantifier-guided dominance degree and the quantifier-guided non-dominance degree:

- The quantifier-guided dominance degrees, $QGDD_j^g$ and $QGDD_j^i$, determine the dominance that x_j has over the other alternatives when using the collective fuzzy preference relations, C^g and C^i , respectively. They are computed as:

$$QGDD_j^g = \frac{1}{n-1} \sum_{k=1; k \neq j}^n c_{jk}^g \quad (18)$$

$$QGDD_j^i = \frac{1}{n-1} \sum_{k=1; k \neq j}^n c_{jk}^i \quad (19)$$

- The quantifier-guided non-dominance degrees, $QGNDD_j^g$ and $QGNDD_j^i$, determine the degree in which x_j is not dominated by the other alternatives

when using the collective fuzzy preference relations, C^g and C^i , respectively. They are computed as:

$$QGNDD_j^g = \frac{1}{n-1} \sum_{k=1; k \neq j}^n 1 - d_{kj}^g \quad (20)$$

$$QGNDD_j^i = \frac{1}{n-1} \sum_{k=1; k \neq j}^n 1 - d_{kj}^i \quad (21)$$

being $d_{kj}^g = \max\{c_{kj}^g - c_{jk}^g, 0\}$ and $d_{kj}^i = \max\{c_{kj}^i - c_{jk}^i, 0\}$, respectively, which determine the degree in which the alternative x_j is dominated by the alternative x_k .

The application of these choice degrees over the set of alternatives X is performed according to the following approach:

- The application of $QGDD_j^g$ and $QGDD_j^i$ over X to get the following sets of alternatives:

$$X^{QGDD^g} = \{x_j \in X \mid QGDD_j^g = \sup_{x_k \in X} QGDD_k^g\} \quad (22)$$

$$X^{QGDD^i} = \{x_j \in X \mid QGDD_j^i = \sup_{x_k \in X} QGDD_k^i\} \quad (23)$$

- The application of the intersection to the above sets to get the following set of alternatives:

$$X^{QGDD} = X^{QGDD^g} \cap X^{QGDD^i} \quad (24)$$

If $\#X^{QGDD} = 1$, then this is an alternative chosen as a solution to the problem. Otherwise, continue.

- The application of $QGNDD_j^g$ and $QGNDD_j^i$ over X^{QGDD} to get the following set of alternatives:

$$X^{QGNDD} = \{x_j \in X \mid QGNDD_j = \sup_{x_k \in X} QGNDD_k\} \quad (25)$$

where

$$QGNDD_k = \frac{QGNDD_k^g + QGNDD_k^i}{2} \quad (26)$$

This is the selection set of alternatives.

IV. CASE STUDY: PROFITABLE PRODUCT SELECTION

This section conducts a real-world problem in which an enterprise is looking at changing its solar panel product line for the next year. It wants to carry only one brand of solar panels. It has received four offers, $X = \{x_1, x_2, x_3, x_4\}$, from different solar panel manufacturers. The enterprise consults four experts, $E = \{e_1, e_2, e_3, e_4\}$, about the brand that could offer the highest total profit. Specific enterprise, brands, and experts, are omitted for privacy reasons.

First, the experts' behaviour during the debate is determined. For this proposal, in every debate round, the experts discuss the alternatives and the classifier described in Section III-A is applied to detect the aggressive language. Here, the number of debate rounds, ζ , is equal to 5 (4 rounds to compare options and 1 round to draw conclusions). In Table I, the results returned by the classifier are shown. Due to space limitations, we do not list the comments provided during the debate rounds

Table I
NUMBER OF AGGRESSIVE COMMENTS (ac) AND TOTAL COMMENTS (tc)
PROVIDED BY THE EXPERTS IN EVERY DEBATE ROUND

Round	ac_1	tc_1	ac_2	tc_2	ac_3	tc_3	ac_4	tc_4
1	2	10	1	14	3	11	1	15
2	3	11	2	11	5	12	2	14
3	0	10	1	13	3	13	1	10
4	3	15	1	10	4	10	0	10
5	1	13	4	13	1	11	1	11

in this paper, but we upload it as supplementary material and available at <http://iee-dataport.org/10589>.

Second, and once the debate stage has finished and the aggressive comments have been detected, the experts provide their assessments:

$$P^1 = \begin{pmatrix} - & 0.8 & 0.8 & 0.9 \\ 0.2 & - & 0.5 & 0.6 \\ 0.1 & 0.5 & - & 0.6 \\ 0.2 & 0.3 & 0.4 & - \end{pmatrix} \quad P^2 = \begin{pmatrix} - & 0.2 & 0.5 & 0.4 \\ 0.8 & - & 0.9 & 0.8 \\ 0.4 & 0.2 & - & 0.5 \\ 0.5 & 0.1 & 0.5 & - \end{pmatrix}$$

$$P^3 = \begin{pmatrix} - & 0.5 & 0.0 & 0.3 \\ 0.6 & - & 0.1 & 0.4 \\ 1.0 & 0.8 & - & 0.9 \\ 0.6 & 0.5 & 0.2 & - \end{pmatrix} \quad P^4 = \begin{pmatrix} - & 0.5 & 0.3 & 0.1 \\ 0.5 & - & 0.5 & 0.2 \\ 0.6 & 0.4 & - & 0.0 \\ 0.8 & 0.9 & 1.0 & - \end{pmatrix}$$

Third, based on the aggressive language used during the debate, the weights associated with the experts are obtained to take them into account in the rest of the decision-making process. Using (4) and (7), the weights are calculated according to the global method and the iterative method, respectively:

$$\begin{aligned} w_1^g &= 0.2540 & w_2^g &= 0.2555 & w_3^g &= 0.2156 & w_4^g &= 0.2748 \\ w_1^i &= 0.2529 & w_2^i &= 0.2572 & w_3^i &= 0.1048 & w_4^i &= 0.3852 \end{aligned}$$

As it can be seen, the iterative and the global methods assign similar weights to the experts e_1 and e_2 . However, the weights assigned to the experts e_3 and e_4 are very different. This is because the iterative method uses the weight obtained in the previous debate round whereas the global method makes a global calculation. In such a way, it could be the case that all comments provided by an expert in a debate round are aggressive. Then, the global method would decrease the weight assigned to the expert whereas the iterative method would cancel his or her weight out during the whole debate.

Fourth, the consensus achieved is measured and compared with the consensus threshold, α , established, which is 0.7 in this problem. Using (8), (9), (12) and (13), the consensus measures $CGSED_y^z$, $CISED_y^z$, CGP_y^z and CIP_y^z , measuring the agreement between the experts e_z and e_y , are calculated:

$$\begin{aligned} CGSED_2^1 &= 0.77 & CISED_2^1 &= 0.77 \\ CGP_2^1 &= 0.67 & CIP_2^1 &= 0.67 \end{aligned}$$

$$\begin{aligned} CGSED_3^1 &= 0.71 & CISED_3^1 &= 0.69 \\ CGP_3^1 &= 0.57 & CIP_3^1 &= 0.50 \end{aligned}$$

$$\begin{aligned} CGSED_4^1 &= 0.69 & CISED_4^1 &= 0.67 \\ CGP_4^1 &= 0.55 & CIP_4^1 &= 0.48 \end{aligned}$$

$$\begin{aligned} CGSED_3^2 &= 0.72 & CISED_3^2 &= 0.69 \\ CGP_3^2 &= 0.58 & CIP_3^2 &= 0.51 \end{aligned}$$

$$\begin{aligned} CGSED_4^2 &= 0.73 & CISED_4^2 &= 0.71 \\ CGP_4^2 &= 0.60 & CIP_4^2 &= 0.54 \end{aligned}$$

$$\begin{aligned} CGSED_4^3 &= 0.74 & CISED_4^3 &= 0.66 \\ CGP_4^3 &= 0.60 & CIP_4^3 &= 0.46 \end{aligned}$$

Then, the global consensus measures, $CGSED$, $CISED$, GCP and CIP , are computed by means of (10), (11), (14) and (15), respectively:

$$\begin{aligned} CGSED &= 0.72 & CISED &= 0.70 \\ GCP &= 0.59 & CIP &= 0.53 \end{aligned}$$

Due to two of the global consensus measures are lower than α , the experts must discuss again and reconsider their assessments to increase the consensus. Therefore, a new discussion round (the second one) is carried out (we suppose the maximum number of discussion round, β , is equal to 5 in this problem). In Table II, the results returned by the classifier in the second debate round are shown (check <http://iee-dataport.org/10589> to see the comments provided by the experts during this debate round).

Once the debate has finished and the aggressive comments have been detected, the experts provide their new assessments, which are:

$$\begin{aligned} P^1 &= \begin{pmatrix} - & 0.5 & 0.4 & 0.9 \\ 0.8 & - & 0.0 & 0.6 \\ 1.0 & 0.9 & - & 1.0 \\ 0.0 & 0.2 & 0.1 & - \end{pmatrix} & P^2 &= \begin{pmatrix} - & 0.2 & 0.1 & 0.6 \\ 1.0 & - & 0.3 & 0.7 \\ 0.9 & 0.9 & - & 0.8 \\ 0.2 & 0.2 & 0.5 & - \end{pmatrix} \\ P^3 &= \begin{pmatrix} - & 0.5 & 0.0 & 0.3 \\ 0.6 & - & 0.1 & 0.4 \\ 1.0 & 0.8 & - & 0.9 \\ 0.6 & 0.5 & 0.2 & - \end{pmatrix} & P^4 &= \begin{pmatrix} - & 0.4 & 0.4 & 0.9 \\ 0.9 & - & 0.4 & 0.8 \\ 0.8 & 0.8 & - & 0.9 \\ 0.3 & 0.2 & 0.2 & - \end{pmatrix} \end{aligned}$$

It can be observed that expert e_3 has decided to keep their initial assessments and, therefore, e_3 provides the same fuzzy preference relation.

Using the results provided by the classifier in this second discussion round, the weights associated with the expert are recalculated:

$$\begin{aligned} w_1^g &= 0.2613 & w_2^g &= 0.2302 & w_3^g &= 0.2575 & w_4^g &= 0.2510 \\ w_1^i &= 0.3058 & w_2^i &= 0.1468 & w_3^i &= 0.2892 & w_4^i &= 0.2583 \end{aligned}$$

Table II
NUMBER OF AGGRESSIVE COMMENTS (ac) AND TOTAL COMMENTS (tc)
PROVIDED BY THE EXPERTS IN EVERY DEBATE ROUND

Round	ac_1	tc_1	ac_2	tc_2	ac_3	tc_3	ac_4	tc_4
1	0	14	2	12	2	14	3	15
2	3	12	3	11	4	14	0	12
3	0	14	1	13	1	12	0	12
4	2	14	5	11	1	14	3	15
5	2	14	2	15	0	15	3	11

Using these new weights, the consensus measures $CGSED_y^z$, $CISED_y^z$, CGP_y^z and CIP_y^z , are computed again:

$$\begin{aligned} CGSED_2^1 &= 0.85 & CISED_2^1 &= 0.81 \\ CGP_2^1 &= 0.78 & CIP_2^1 &= 0.67 \end{aligned}$$

$$\begin{aligned} CGSED_3^1 &= 0.83 & CISED_3^1 &= 0.83 \\ CGP_3^1 &= 0.76 & CIP_3^1 &= 0.75 \end{aligned}$$

$$\begin{aligned} CGSED_4^1 &= 0.89 & CISED_4^1 &= 0.90 \\ CGP_4^1 &= 0.86 & CIP_4^1 &= 0.83 \end{aligned}$$

$$\begin{aligned} CGSED_3^2 &= 0.79 & CISED_3^2 &= 0.82 \\ CGP_3^2 &= 0.73 & CIP_3^2 &= 0.64 \end{aligned}$$

$$\begin{aligned} CGSED_4^2 &= 0.86 & CISED_4^2 &= 0.89 \\ CGP_4^2 &= 0.83 & CIP_4^2 &= 0.76 \end{aligned}$$

$$\begin{aligned} CGSED_4^3 &= 0.82 & CISED_4^3 &= 0.82 \\ CGP_4^3 &= 0.75 & CIP_4^3 &= 0.73 \end{aligned}$$

Then, the global consensus measures, $CGSED$, $CISED$, GCP and CIP , are:

$$\begin{aligned} CGSED &= 0.85 & CISED &= 0.83 \\ GCP &= 0.78 & CIP &= 0.73 \end{aligned}$$

As all the global consensus measures are equal or higher than $\alpha = 0.7$, we can proceed to obtain the ranking of the alternatives. It means the collective fuzzy preference relations, C^g and C^i , are calculated according to (16) and (17), respectively:

$$\begin{aligned} C^g &= \begin{pmatrix} - & 0.4316 & 0.2279 & 0.6764 \\ 0.8196 & - & 0.1952 & 0.6217 \\ 0.9268 & 0.8492 & - & 0.9031 \\ 0.2758 & 0.2773 & 0.2429 & - \end{pmatrix} \\ C^i &= \begin{pmatrix} - & 0.4591 & 0.2403 & 0.6825 \\ 0.7973 & - & 0.1763 & 0.6085 \\ 0.9337 & 0.8453 & - & 0.9159 \\ 0.2803 & 0.2868 & 0.2134 & - \end{pmatrix} \end{aligned}$$

Using both collective fuzzy preference relations, the ranking of alternatives is generated. To do so, the quantifier-guided dominance degrees and the quantifier-guided non-dominance degrees are computed using (18), (19), (20) and (21):

$$\begin{aligned} QGDD_1^g &= 0.4606 & QGNDD_1^g &= 0.6561 \\ QGDD_1^i &= 0.4453 & QGNDD_1^i &= 0.6377 \\ QGDD_2^g &= 0.5274 & QGNDD_2^g &= 0.7770 \\ QGDD_2^i &= 0.5455 & QGNDD_2^i &= 0.7820 \\ QGDD_3^g &= 0.8983 & QGNDD_3^g &= 1.0000 \\ QGDD_3^i &= 0.8930 & QGNDD_3^i &= 1.0000 \\ QGDD_4^g &= 0.2602 & QGNDD_4^g &= 0.5246 \\ QGDD_4^i &= 0.2653 & QGNDD_4^i &= 0.5316 \end{aligned}$$

Using these choice degrees, the following sets of alternatives are obtained:

$$\begin{aligned} X^{QGDD^g} &= \{x_3\} \\ X^{QGDD^i} &= \{x_3\} \end{aligned}$$

Hence, $X^{QGDD} = \{x_3\}$ and x_3 is chosen as the solution to the decision-making problem according to the experts' assessments, i.e., x_3 must be selected as panel solar brand.

V. CONCLUDING REMARKS

In this study, we have presented a new GDM method based on the experts' behaviour during the debate stage carried out before providing the assessments. The existing GDM methods do not take into account the experts' behaviour during the debate stage in the remainder of the decision-making process and, by not considering it, information that could be of interest is lost. However, this new GDM method incorporates a classifier based on sentiment analysis techniques that can extract additional data generated during the debate stage (i.e., the experts' behaviour) and take advantage of it. Concretely, based on the experts' behaviour, two procedures have been developed to assign weights to the experts and two new consensus measures have been proposed.

Whether the models for GDM deal with different aspects of the decision-making process, a comparison of the results returned by a model with others is not a straightforward task. The features considered by the models are different and, as a consequence, a quantitative comparison would not be meaningful. In any case, in the following, we analyse some advantages and shortcomings of the proposed approach:

- By incorporating a classifier, which is based on sentiment analysis techniques and makes use of different linguistic features, the proposed model can categorize the experts' behaviour during the debate stage. In comparison with the existing methods based on sentiment analysis techniques that analyse the debate conducted between the experts [15]–[19], it is a notable advantage because it has been demonstrated that, first, an aggressive language negatively affects the trustworthiness of the speaker and her or his credibility [13] and, second, it also leads to the deterioration of the debate [14]. Both scenarios must be avoided because they make difficult the achievement of consensus, which is the most important point in GDM processes [10]. Therefore, the model proposed in this study, by exploiting the information returned by the sentiment analysis classifier, can better model the consensus reaching process carried out in a GDM process.
- Related to the above advantage, it introduces two new procedures assigning weights to the experts according to their behaviours during the debate stage. This allows considering the experts' behaviour in the remainder of the GDM process, specifically, in the analysis of the consensus (when calculating the consensus achieved between the experts' assessments) and in the computation of the collective assessment (when the individual experts' assessments are aggregated). On the one hand, the procedure calculating the overall weight obtains an average weighting of the aggressive comments provided by an expert. Its advantage is that even if all the comments provided in a round are aggressive, the weight of the expert can be compensated in other rounds where any aggressive comment is provided. Nevertheless, it has

the disadvantage that it is more general, which implies that the expert's behaviour can only be seen during the debate as a whole and not in each round. On the other hand, the procedure calculating the iterative weight uses the weight of the previous round to calculate the new one. It has the advantage that it can be analyzed in each round in a more detailed way because the weight related to the expert is altered according to the previous round. However, it is stricter because in the case that all the comments provided by an expert are aggressive, the weight of this expert will be equal to zero, although, in the other rounds, the expert does not provide any aggressive comments. Then, by using these new two procedures, two novel consensus measures and two novel methods to compute the collective assessment that consider the experts' behaviour during the debate stage are proposed.

- The classifier based on sentiment analysis techniques uses different linguistic characteristics that provide relevant information when classifying the comments. It presents the following advantages. First, it detects aggressive comments by using different linguistic characteristics that complete the preprocessing. Some of them have already been used, such as the use of POS-tagging, but others are new, such as the number of complete words written in capital letters or the consecutive number of repeated exclamations, to cite some examples. Second, it uses an optimised preprocessing matrix built via different methods to remove words that do not provide useful information and to reduce words to their word stems (it reduces the number of elements in the bag of words). However, its shortcoming is that it could not find out all the linguistic characteristics that are present. As a result, the numeric matrix would be less complete and this could generate some false negatives, i.e., an aggressive comment could be classified as a non-aggressive comment.
- Consensus measures. Usually, the consensus is determined by looking at the difference between the experts' assessments. However, this is incomplete as the experts' behaviour can be as relevant as the assessments. For instance, two experts can agree that a given alternative is better than other one, but the reasons given by each expert can be different. Consequently, both experts have the same opinion, but the arguments considered to give that opinion are different. For this reason, the consensus measures proposed in this study do only consider the assessments but also the behaviour shown to provide them. It makes the consensus measures more complete than if only the experts' assessments are considered.

The number of GDM models using sentiment analysis has grown in the last years. In [18], the authors present a method based on sentiment analysis and apply it to decision-making. The method creates two bags of words from its dictionaries. Nevertheless, it creates a bag of words from pre-classified comments and uses a ranking algorithm to classify the comments made by experts. Moreover, it applies that ranking, influencing the weights of the experts. In [19], the authors introduce a method applicable to a large number of

alternatives that uses sentiment analysis to find out which alternative is better in each round. However, our method uses two procedures that allow us to check who expert is more aggressive, in general, and in each round, during the debate and that could be applied to each alternative in future works. Thus, obtaining a classifier that analyses the likes/dislikes of each expert on an alternative. Furthermore, the method presented in this paper uses a previously defined bag of words and does not use a classifier while ours uses a classifier, such as a SVM and uses a known data set containing comments. Finally, in [16], the authors develop a method that can analyse the debate in social networks by using sentiment analysis. Nonetheless, the method presented in this paper does not only analyses the debate by using sentiment analysis but also applies it to the GDM model by adjusting the weights in two different ways. This aims to have a double analysis of the debate, one in a general way and the other in an iterative way.

This research may be continued as follows. First, as we have mentioned, the sentiment analysis classifier could ignore some linguistic characteristics, classifying a comment in a wrong way. Therefore, new linguistic characteristics should be investigated and verified if they are useful or not to classify comments as aggressive or non-aggressive. Second, social networks have changed the scenario in which GDM processes are carried out. They have facilitated that people participate in the decision-making processes, which has increased the number of individuals trying to solve a GDM problem. It has given rise to a new research area within GDM, called large-scale GDM [61], that has gained great attention in recent years. For instance, sustainable building material selection and bid evaluation are two examples of real-life scenarios in which large-scale GDM methods have been applied [62], [63]. The existing methods dealing with large-scale GDM usually divide the experts into groups according to their assessments, i.e., experts providing similar assessments are in the same group. However, other criteria could be also used to group the experts. For example, the behaviour during the debate stage could be considered to classify experts with similar behaviour in the same group. In such a case, an optimization process could be required in the process of aggressiveness detection due to the high amount of information generated. And third, to help experts improve the consensus in successive debate rounds, a feedback mechanism could be incorporated to advise experts on how they should modify their assessments if they want to make their positions converge, and, consequently, to improve the consensus [64].

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Capítulo 3

Actividades realizadas

Artículos de Revista

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En proceso de revisión

- Large-Scale Group Decision-Making using Intuitionistic Fuzzy Sets and Sentiment Analysis.
- Z-Number Generation Model and its Application in a Rule-Based Classification System.
- Explainable Artificial Intelligence System for Medical Data based on Fuzzy Exception and Base Rules via Genetic Algorithm with 2-tuples.
- Multi-criteria, multi-granular Consensus-based Large-scale Group Decision-Making Using Sentiment Analysis to account for experts' aggressiveness.
- An Alternative Consensus Measure Based on the Gini Index for Group Decision Making Problems.
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Artículos de Congreso

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- Trillo, J. R., & Trillo, F. (2021) Ajedrez Un Deporte Profesional, Igualitario y Feminista.
- Vílchez, J. R. T., Vílchez, F. T., Guevara, O. C. M., & Chirinos, J. R. M. (2021). Genetic algorithm with fitness function based on the gender of the students and their grade point averages for the formation of equitable school groups. In Investigación e innovación educativa frente a los retos para el desarrollo sostenible (pp. 591-602). Dykinson.
- Vílchez, J. R. T., & Vílchez, F. T. (2021). The strategy of resource management explained through gamification of the Total War Saga. In Investigación e innovación educativa frente a los retos para el desarrollo sostenible (pp. 286-294). Dykinson.
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- Trillo, J. & Trillo, F. (2022). Explicación del Arte utilizando el Sesgo del Superviviente para la Comprensión de las Obras Clásicas.
- Trillo, J. R (2023). SCHACH-EIN PROFESSIONELLER, GLEICHBERECHTIGTER UND FEMINISTISCHER SPORT. Federación Alemana de Ajedrez.

Informes de Biblioteca

- Viedma, E. H., Gijón, J. L., Burgos, S. A., & Vílchez, J. R. T. ESTUDIO DE CALIDAD DE LOS SERVICIOS DE LA BIBLIOTECA DE LA UNIVERSIDAD DE GRANADA (2020-2021).
- Viedma, E. H., Gijón, J. L., Burgos, S. A., & Vílchez, J. R. T. ESTUDIO DE CALIDAD DE LOS SERVICIOS DE LA BIBLIOTECA DE LA UNIVERSIDAD DE GRANADA (2021-2022).
- Viedma, E. H., Gijón, J. L., Burgos, S. A., & Vílchez, J. R. T. ESTUDIO DE CALIDAD DE LOS SERVICIOS DE LA BIBLIOTECA DE LA UNIVERSIDAD DE GRANADA (2022-2023).

Másteres

Másteres realizados

- Master Universitario en Matemáticas en la Universidad de Granada (2022-2023)

Másteres en proceso

- Máster Propio en Ciberseguridad en la Universidad de Granada (2023-2024)

Idiomas

Inglés

- Obtención del título de B2 en inglés en el año 2020.
- Obtención del título de C1 en inglés en el año 2021.
- Obtención del título de C2 en inglés en el año 2021.

Italiano

- Obtención del título de B2 en italiano en el año 2022.

Portugués

- Obtención del título de B1 en portugués en el año 2022.

Proyectos

Proyectos Europeos

- TechTransfer - Technology Transfer Together.
- MICROBE - Minimizing the influence of coronavirus and negative emotions in a built environment by behavioral change.
- DX.SEA (Digital Transformation for Higher Education Institutions in Southeast Asia)
- Integrante de la Alianza ARQUS con la Universidad de Granada.

Proyectos Nacionales y autonómicos

- Participante en el Proyecto de la Junta de Andalucía titulado: Nuevos sistemas difusos para la toma de decisiones: Aplicaciones en entornos digitales con referencia P20_00673.
- PID2019-103880RB-I00. Sistemas de toma de decisiones en grupo disruptivos en ambiente difuso: aplicaciones en gestión inteligente de energía y empleados. Ministerio de Ciencia e Innovación.
- PID2022-139297OB-I00. Nuevos sistemas difusos explicables de toma de decisiones en grupo: aplicaciones en el mundo digital. Ministerio de Ciencia e Innovación.

Cursos Realizados

- Academic Writting in English (Universidad de Granada dic 2019 - dic 2019)
- Workshop de inteligencia Artificial (MICROSOFT y Universidad de Granada dic 2019 - dic 2019)
- Herramientas para el Desarrollo de la Investigación (Universidad de Granada, mar 2020)
- Comercio electrónico (GOOGLE may 2020)
- Competencias digitales para profesionales (GOOGLE may 2020)
- Cloud Computing (GOOGLE may 2020)
- Fundamentos de Marketing Digital (GOOGLE may 2020)

- Desarrollo de Apps Móviles (GOOGLE may 2020)
- Introducción al Desarrollo Web (GOOGLE may 2020)
- Introducción al Desarrollo Web II (GOOGLE may 2020)
- Productividad Personal (GOOGLE may 2020)
- Transformación digital para el empleo (GOOGLE may 2020)
- Digitaliza paso a paso tu negocio con Google My Business y YouTube (Google ago 2020)
- Protege tu Negocio: Ciberseguridad en el Trabajo (GOOGLE sep 2020)
- Comercio electrónico y e-administración (Junta de Andalucía, dic 2020 – dic 2020)
- Community manager: Conviértete en un profesional de las redes sociales (Junta de Andalucía, dic 2020 – ene 2021)
- Conoce tu dispositivo móvil en profundidad: sistema operativo y aplicaciones principales (Junta de Andalucía, nov 2020 – dic 2020)
- Esfuerzo de integración para personas inmigrantes (Junta de Andalucía, nov 2020)
- Edición de audio digital y podcast (Junta de Andalucía, dic 2020 – dic 2020)
- Gestión de la asociación (Junta de Andalucía, dic 2020 – dic 2020)
- Curso sobre explotación de infraestructuras públicas para el despliegue de redes (Junta de Andalucía, nov 2020 – dic 2020)
- Posicionamiento online en portales de turismo y hostelería (Junta de Andalucía, ago 2020)
- Retoque digital con GIMP (Junta de Andalucía, dic 2020 – ene 2021)
- Sensibilización de género (Junta de Andalucía, dic 2020 – ene 2021)
- Tu opinión cuenta: e-democracia y participación ciudadana (Junta de Andalucía, dic 2020 – dic 2020)
- Uso sano y responsable por parte de los menores de edad (Junta de Andalucía, dic 2020 – dic 2020)
- Aplicaciones en la nube para la mejora de la productividad (Junta de Andalucía, ene 2021 – feb 2021)

- Iniciación a la programación web: php (Junta de Andalucía, ene 2021 – feb 2021)
- Iniciación al diseño y la programación web (Junta de Andalucía, feb 2021 – mar 2021)
- Promociona tu negocio a través de internet: marketing digital (Junta de Andalucía, ene 2021 – feb 2021)
- Seguridad Informática (Junta de Andalucía, feb 2021 – mar 2021)
- Curso relativo a los controles sobre el despliegue de redes de telecomunicaciones por las entidades locales andaluzas (Junta de Andalucía may 2021 – jun 2021)

Actividades Formativas

- Rankings de revistas en Scopus: SJR y Journal Metrics (Universidad de Granada, jul 2020)
- Diez reglas de oro para publicar en revistas científicas de impacto (Universidad de Granada, jul 2020)
- Preguntas fundamentales sobre el acceso abierto a la ciencia - Open Access (Universidad de Granada, nov 2020)
- Cómo optimizar el registro de ORCID (Universidad de Granada, jul 2020)
- DST a través de Twitter: cómo investigar el proceso de circulación de una narrativa digital (Universidad de Granada, dic 2020)
- Estilos bibliográficos. Revisión de estilos. Áreas donde se usan. Diferencias entre ellos. Relación con gestores bibliográficos. Particularidades de las citas y referencias (Universidad de Granada, dic 2020)
- Atajos bibliográficos (Universidad de Granada, dic 2020)
- Trabaja con seguridad en la nube cifrando documento (Universidad de Granada, ene 2021)
- Revisión por pares - Peer Review II: Elaborando la respuesta a revisores (Universidad de Granada, ene 2021)
- Análisis sistemáticos de la literatura científica con Bibliometrix -BiblioShiny App (Universidad de Granada, ene 2021)
- Cómo construir el marco teórico (Universidad de Granada, ene 2021)

- Formación de un documento de Word para la tesis (Universidad de Granada, feb 2021)
- Organización del evento Tu tesis sobre fuzzy en 5 minutos en (XXI Congreso Español sobre Tecnologías y Lógica Fuzzy, (Toledo 4 al 7 de septiembre de 2022).

Cargos Unipersonales

- Consejero del Programa de Doctorado de Tecnología de la Información y Comunicación en el Consejo de Representantes de la Universidad de Granada. (jul 2021- jul 2024)
- Presidente del Consejo de Representantes de la Universidad de Granada. (jul 2021- jul 2024).
- Integrante de la Comisión de la garantía interna del Programa de Doctorado de Tecnología de la Información y Comunicación. (2022-2024)

Premios académicos

- 9th International Conference on Computers Communications and Control, Mayo 2022: Premio Ioan Dziţac por el trabajo científico más apreciado presentado en el ICCCC 2022 por un joven investigador promotor. Título del artículo: Some Trends in Fuzzy Decision Making.
- The 35th International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems, Julio 2022 (IEA/AIE 2022): Premio a Mejor Artículo presentado en el IEA/AIE 2022. Título: Multi-Granular Large Scale Group Decision-Making Method with a new Consensus Measure Based on Clustering of Alternatives in Modifiable Scenarios.
- The Tenth International Conference on Information Technology and Quantitative Management, Agosto 2023 (ITQM 2023): Premio a Mejor Artículo presentado en el ITQM 2023. Título: Reviving stagnated debates in Group decision-making environments with high number of alternatives.
- Ganador del HackForGood de Telefónica de Granada (2024) con el grupo BienStart.
- Mención de honor en la Sesión de pósteres de ETSIIT JTIC 2024 (Abril 2024).

Charlas Impartidas

- Charla en el XXI Encuentro Nacional de Estudiantes de Matemáticas el 30 Julio 2020, Valladolid (España), titulada: ¿Puede la Inteligencia Artificial detectar el cyberbullying?
- Charla en el Instituto de Matemáticas de la Universidad de Granada el 19 de mayo de 2021, Granada (España), titulada: HFER: promoting explainability in fuzzy systems via hierarchical fuzzy exception rules.
- Charla en la Universidad Tecnológica Centroamericana el 25 de octubre del 2021, Tegucigalpa (Honduras), titulada: Innovación Digital y Emprendimiento.
- Charla en la Primera Semana Internacional de la Investigación (SIDI 2021) organizada por la Universidad Politécnica de Querétaro, el 26 de octubre del 2021, Santiago de Querétaro (México), titulada: Investigación: etapas, consulta y difusión.
- Charla en la Universidad Tecnológica Centroamericana el 26 de septiembre del 2022, Tegucigalpa (Honduras), titulada: Investigación Orientado a la Tecnología.
- Charla en la Universidad Tecnológica Centroamericana el 25 de marzo del 2023, Tegucigalpa (Honduras), en la clase de Metodología de la Investigación, impartiendo la charla a los maestrandos del Programa de Maestría en Gestión de Tecnología de la Información.
- Charla en la Universidad Tecnológica Centroamericana el 14 de agosto del 2023, Tegucigalpa (Honduras), en la clase de Metodología de la Investigación, impartiendo la charla a los maestrandos del Programa de Maestría en Gestión de Tecnología de la Información.
- Charla en la Universidad Tecnológica Centroamericana el 16 de septiembre del 2023, Tegucigalpa (Honduras), en la clase de Metodología de la Investigación, impartiendo la charla a los maestrandos del Programa de Maestría en Gestión de Tecnología de la Información.
- Charla en el seminario Seminario sobre “Nuevas tecnologías en Salud Visual: intervención multidisciplinar”. Madrid (España) 16 de Marzo del 2024.
- Impartición de 10 horas en el “Título Propio de Diploma de Especialización en Capacidades Visuales de Deportistas con Discapacidad y Convencionales” ofertado en el curso académico 2023-2024 por la Universidad Complutense de Madrid (Centro de Formación Permanente).

Premios deportivos

Dentro del ámbito universitario

- Medalla de Bronce en el Campeonato de España Universitario de Lucha Libre Olímpica. Categoría -62 Kg. (Año 2022).

Fuera del ámbito universitario

- Medalla de Bronce en el Campeonato Autonómico de Andalucía de Lucha Libre Olímpica. Categoría -65 Kg. (Año 2022).
- 3º Clasificado en Categoría Veterano-Masculino del Campeonato de Natación Ciudad de Jódar Verano 2022 (Año 2022).
- 3º Clasificado en Sub-1600 del XXIII Open de Ajedrez Activo. y XI Memorial Paco Garrido (Año 2022).
- 3º Clasificado en Local del VIII Torneo de Garrucha de Ajedrez 2023 (Año 2023).

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