Three-way Decision in Sentimental Analysis

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ABSTRACT

The binary sentiment classification method faces challenges in handling uncertainty, prompting the introduction of a three-way decision approach to enhance classification accuracy in sentiment analysis. This proposed method targets critical sentiment classification scenarios i.e. interactive social media messages. In the era of social media, particularly concerning hate speech, initial conversations may exhibit uncertainty, which intensifies as comments increase in polarity. To counter this, a sequential three-way decision-making process continually refines uncertain regions within interactive information, scrutinizing uncertain samples at varying granular levels through a three-way decision framework. Utilizing BERT, raw text documents are transformed into vectors, subsequently undergoing feature selection to simplify sentiment analysis by reducing data complexity while preserving effectiveness. This multi-step process aims to improve sentiment classification accuracy by addressing uncertainty in interactive social media content.

INTRODUCTION

In today's social media era, interactive information can be a platform for the spread of hate. Analyzing the interactive information of social media holds a significant influence on people's opinions. Previous studies on sentiment analysis have focused on two key aspects: sentiment classification and opinion summarization. Sentiment classification categorizes documents as either positive or negative based on their subjective content. For instance, a positive comment might praise a candidate's credibility while a negative one might criticize his character. Binary sentiment analysis, a subset of sentiment classification, categorizes comments into positive or negative regions. This method effectively captures the person's perspective on the candidate or the comment. However, in the evolving realm of elections and public comments, understanding people's sentiments requires moving beyond simple binary divisions, requiring more complex approaches to extract insights from comments [1].

The classification of text involves in several components: pre-processing, text feature selection, text representation, and calcifying. Preprocessing involves, "term frequency-inverse document frequency" for feature vector construction, stemming for removing the suffix of the word, stop-words for removal of frequent usage words, and Tokenization for splitting the documents into words/terms, constructing a word vector [3]. The fundamental task in binary sentiment analysis revolves around feature representation. Machine learning methods have been extensively utilized in this domain [1]. Google's Word2vec, developed towards the end of 2013, stands as an industry application of word embedding for training. Additionally, in [4], a "code only" model such as BERT could generate a 768-dimensional feature representation. This showcases the potential of utilizing context-based models like BERT to attain feature representations in sentiment analysis [4]. To reduce the Curse of dimensionality feature selection can be applied [5-8]. Feature selection is broadly categorized into three groups: filter methods, wrapper methods, and embedded methods. Filter methods assess feature subsets based on fundamental data attributes, such as feature correlation scores and Wrapper methods evaluate feature subsets by considering interactions between features and learning models.

The Naive Bayes classifier has made significant contributions to classifying the text, but struggles with intricate term relationships, impeding accurate probability calculations [9], [10]. Neural networks offer efficiency in learning but necessitate substantial computational resources [11]. The Rocchio Classifier approximates boundaries using an experimental parameter, compromising precision [12]. SVM-based classifiers excel in optimizing decision boundaries but face difficulties with non-separable samples, resulting in uncertain boundaries that affect classification accuracy [13], [14].

The challenge in binary sentiment classification lies in accurately classifying comments with unclear emotional polarity. Utilizing three-way decision theory, samples are categorized into positive, negative, and uncertain regions, with the uncertain area deemed for decision-making when information is limited. This project aims to develop a theory by applying a BERT encoder on each layer of the sequential three-way decision in interactive comments in social media which aid in reducing the uncertainty of each layer and leads to a strict division of polarity.

RELATED WORK

Sentiment Analysis

Sentiment analysis looks at understanding people's opinions in text—whether they're positive, negative, or neutral [20]. There are two main ways researchers do this. One way uses machine learning methods that learn from examples to figure out sentiments, while the other way relies on lexicon-based methods that give scores to words to understand the overall feeling in a text. These methods have their strengths: the machine learning method is flexible and can handle complicated patterns, while the dictionary method is straightforward and clear. The researchers, including Tripathy et al. [21], employed machine techniques like Naive Bayes, Maximum Entropy, Support Vector Machines, and others to understand sentiments in movie reviews. They experimented with various ways of analyzing words in these reviews, like looking at single words (unigrams), pairs of words (bigrams), and groups of three words (trigrams), combining these methods with different machine learning algorithms to classify the comments' sentiments.

Neural network models have successfully learned distributed representations of words, paragraphs, and documents. While Convolutional Neural Networks (CNNs) [22] excel in extracting textual features, they neglect essential information such as feature direction and spatial location, limiting their effectiveness in capturing long-distance dependencies in sentiment analysis. Recurrent Neural Networks (RNNs) [23] Variants like Long Short-Term Memory (LSTM) [24], Bidirectional LSTM (BiLSTM), and Gated Recurrent Units (GRUs) aim to overcome RNN limitations. Tang et al. combined LSTM with target-related information, enhancing accuracy in sentiment analysis [25]. In terms of capturing the context with less training time is with BERT transfer learning.

Three-Way Decision

Three-way decision theory, originating from probabilistic rough sets [39], has evolved beyond rough sets, becoming a pivotal approach applicable in diverse fields [40–47]. Its effectiveness spans text classification [48], credit card analysis [49], image data analysis [50], dealing with inconsistent or incomplete information [51–53], and applications in cloud computing [53]. Granular computing, simulating human thinking in addressing complex problems through granular structures, intersects with three-way decision models [54]. Yao's description of granular computing as interacting granules establishing multiple universe descriptions has influenced the introduction of sequential three-way decision models for uncertainty region divisions [55]. Yang et al. proposed a unified sequential three-way decision model with granularity for multilevel incremental processing [56]. Additionally, Chen, Zhang, and Zhao introduced a multi-granular mining method for uncertainty regions [57].

Three-Way Granular Computing

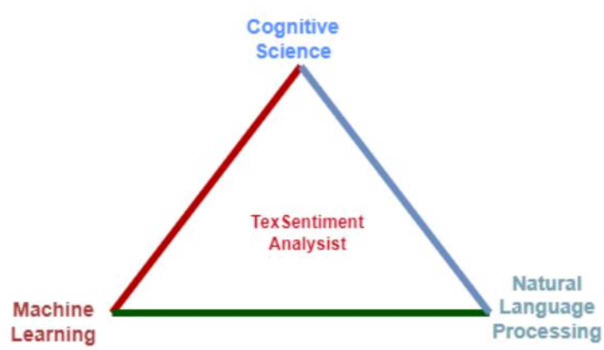
Multigranularity, formed by layers and views, constitutes a structural framework, allowing abstract description and decomposition of complex systems via granular computing [26]. Yao's cognitive three-way decision model (TAO model) categorizes objects into three segments—trisecting, acting, and outcome evaluation—enhancing interpretability in uncertain problem classification [27]. Dynamic decision-making's rise necessitates multistep approaches, leading to extensive exploration. Notable advancements include the S3WD model, utilizing penalty functions to modify cost parameters for enhanced classification accuracy [28]. Incorporating a training method into S3WD to label new samples with increased confidence has also been investigated [29]. Recent studies have extensively detailed dynamic three-way granular concepts, granular computing, S3WD, and multilevel and Multiview-based three-way granular computing [30–43].

Yao's concept of three-way decisions [34, 35], offers a method to handle uncertain problems through the decision-theoretic rough set (DTRS) and Bayesian risk decision-making [36], categorizing objects into positive, negative, and uncertain. The Sequential Three-Way Decision (S3WD) model, proposed by Yao [37], is a multilayer framework enhancing decision-making efficiency at reduced costs. Various iterations of S3WD models based on DTRS architecture have emerged. For instance, Li et al. [38] devised a cost-sensitive sequential 3WD model for image classification. This model, utilizing the DTRS model, enables superior and cost-effective decisions in facial image processing compared to conventional static strategies.

METHODOLOGY

The Tripod in Sentimental Analysis

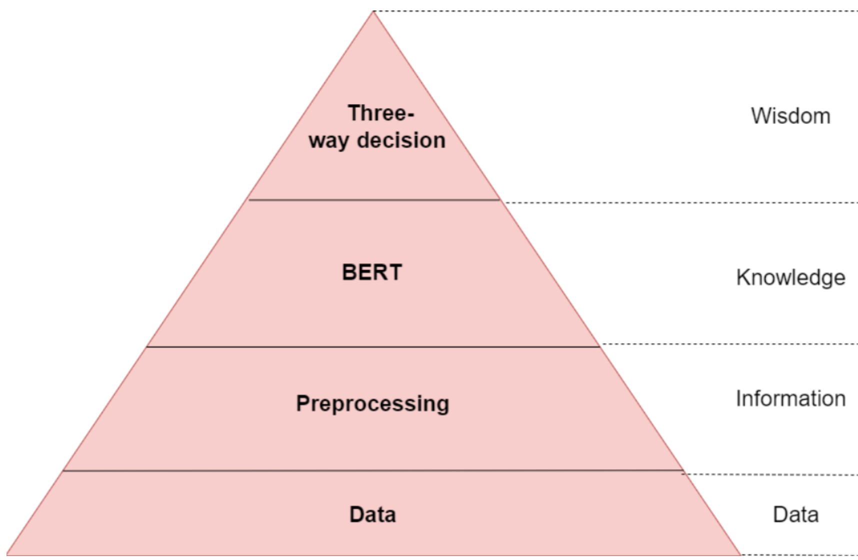
Sentimental analysis is a process of analyzing text to get emotions hidden in it. The emotions embedded in the text are extracted using three main domains they are Natural language processing for text processing, Machine learning (ML) algorithm for getting optimal features, normalization etc., cognitive sciences for calcifying the emotions which has a huge impact on dealing with uncertain emotions. By using NLP's text processing capabilities, ML's models, and understanding from cognitive sciences, sentiment analysis systems effectively discern sentiments expressed in various textual data, aiding social media interactive comments.



Tripod in sentimental analysis

DIKW in Sentimental Analysis

The DIKW (Data-Information-Knowledge-Wisdom) model illustrates the steps of how the complexity of the text is reduced to opinions. The raw text undergoes preprocessing to transform clean organized data as a pure form of information, advances through use the of model like BERT for deep understanding and extraction of knowledge from the text, and subsequently involves in three way decision-making process for emotion classification. This process combines the extracted knowledge and discernment from models with contextual understanding to derive meaningful insights. The wisdom emerges from applying this enriched knowledge in three-way decisions. This journey signifies the progression from raw data to informed actions, passing through various stages of refinement, understanding, and application of insights.



DIKW in sentimental analysis

Datasets

A possible data set for doing sentimental analysis is tweets and comments centered around discussions related to prominent leaders, particularly Narendra Modi, and opinions regarding the next Prime Minister of India during the 2019 General Elections which can be collected form Tweepy and PRAW APIs. Sentiment labels ranging from -1 to 1 have been assigned to denote the emotional tone of each entry: a score of 0 designates a neutral sentiment, 1 indicates a positive sentiment, and -1 denotes a negative sentiment [59].

Preprocessing

Tokenization: Tokenization splits text into tokens, such as words or phrases, which are then analyzed for sentiment. It enables the identification of individual words or phrases that convey sentiment. Different tokenization methods (e.g., unigrams, bigrams) may affect sentiment analysis by altering the granularity at which sentiment-bearing units are identified [3].

Natural Language Processing - > [‘Natural, ‘Language, Processing]

Stop-words Removal: Removing stop-words is crucial in sentiment analysis as it filters out commonly occurring but less informative words, reducing noise. It helps focus on the sentiment-carrying words, potentially improving the accuracy of sentiment classification [3].

['This','is','a', test'] - > ['This','test']

Stemming: Stemming reduces words to their root forms, which may assist in capturing the essence of sentiment-carrying words despite variations due to grammatical inflections. It simplifies words to their base form, potentially aiding in matching sentiments expressed through different forms of the same word [3].

Leafs - > Leaf

Leaves - > leave

Lemmatization: Like stemming, lemmatization reduces words to their base forms (lemmas), but with a focus on ensuring that the resulting lemma is a valid word. This technique helps maintain meaningful words, potentially leading to more accurate sentiment analysis by preserving the context and semantics of words [3].

Leafs - > Leaf

Leaves -> Leaf

Part-of-speech (POS) tagging: Part-of-speech (POS) tagging holds significance in sentiment analysis by aiding in the understanding of sentence structure and context. In sentiment analysis, POS tagging helps identify the grammatical categories of words within sentences, enabling a deeper comprehension of how different parts of speech contribute to expressing sentiments. By tagging words as nouns, verbs, adjectives, and adverbs, among others, it assists in analyzing the linguistic complexity and sentiment elements present in textual data, thus enhancing the accuracy and granularity of sentiment classification models [62].

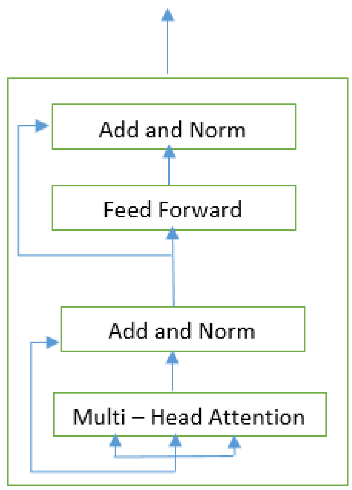
["I", "like"," to ","read", "books"] - > ["I" - > "PRP", "Like"->"VBP", "to"-> "TO", "read" - > "VB", "book" -> "NNS"]

Generating Feature Vector

BERT

BERT converts words to vectors through a multi-step process. It starts by tokenizing text into subword units using WordPiece tokenization. Each token receives a pre-trained word embedding from BERT's vocabulary table. Positional embeddings denote the token's position in the sequence, while segment embeddings differentiate between sentences in tasks involving multiple sentences. These embeddings (word, positional, segment) are combined, forming comprehensive token representations that retain both the token's meaning and its context. These representations then enter BERT's Transformer layers, where they undergo contextual refinement, producing final contextualized token vectors that encode complex contextual information, crucial for interactive sentimental analysis task [4].

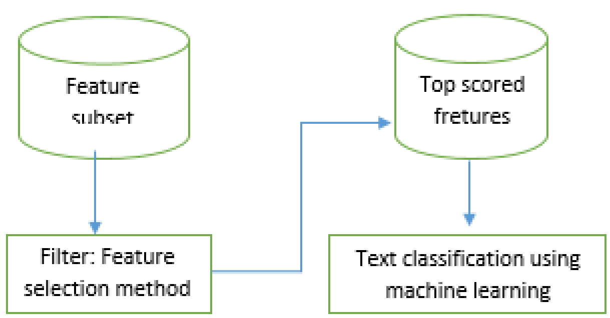
The BERT encoder, based on the Transformer architecture, uses multiple layers stacked on top of each other. Each layer has two main components: self-attention and feedforward neural networks. With self-attention, tokens analyze and weigh their connections to other tokens in the input, capturing the context between them. By computing attention scores for all token pairs, the model focuses on crucial parts of the input. Meanwhile, feedforward neural networks in each layer process and alter the outcomes of self-attention, adding complexity to capture intricate data patterns. BERT's layered design enables it to progressively enhance token representations, learning detailed contextual information for different language tasks [4].



Encoder Architecture

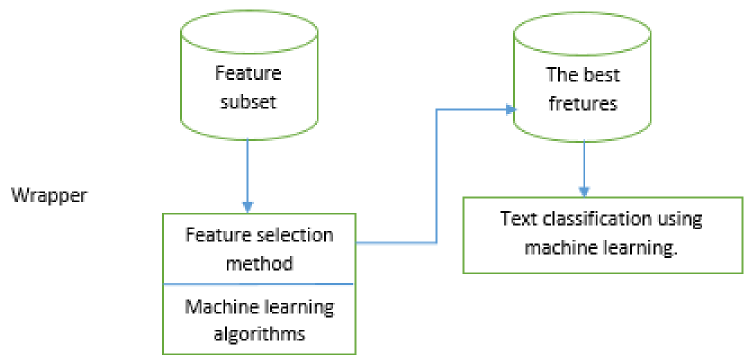
Obtaining Optimal Features

Filter Methods: Assigns scores to individual features within a dataset, determining their relevance to a specific task. These scores are calculated based on various criteria, such as information gain or statistical significance, enabling the ranking of features by their importance. Once the scoring is complete, the filter method ranks the features accordingly, and often sets a predetermined threshold to select the top-ranked features, either based on a certain percentage or a specific number. This threshold allows the retention of the most influential features while discarding less significant ones. The selected features, meeting or exceeding the threshold, are then utilized to train machine learning models. This approach, working independently of the classifier, significantly reduces the feature space before the training phase, leading to improved model efficiency, reduced computational load, and enhanced performance on learning tasks [61].



Optimal feature selection using Filter method

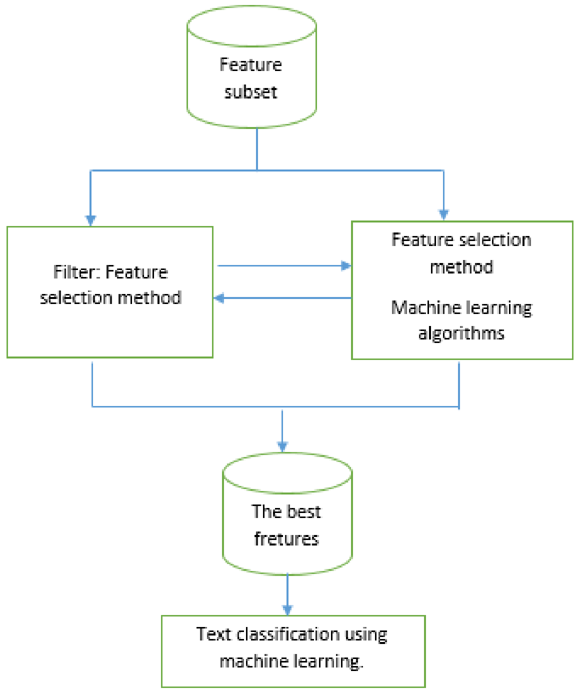
Wrapper methods: Advanced technique that engages optimization or search algorithms with machine learning models to identify essential features for a specific task. Like ensemble feature method in sentiment analysis integrates various types of features, enhancing classification accuracy by considering multiple rules. In this, five distinct feature types were utilized: domine features, textual features, Part of Speech (PoS) features, lexicon-based features, and Bag of Words (BoW) features. These diverse features contribute to a more comprehensive analysis by capturing different aspects of the sentiment expressed. Unlike filter methods, wrapper methods embed feature selection within the machine learning algorithm itself, enabling them to thoroughly assess the features' significance in enhancing the overall model performance. Wrapper methods iterate through feature selection using a machine learning algorithm, calculating values based on the accuracy achieved. This iterative process continues until it identifies the best subset of features or until specific stopping criteria are met. The selected optimal features are then utilized for text classification, contributing to improved classifier accuracy and reduced feature space [61].



Optimal feature selection using the Wrapper method

Hybrid method

In feature selection is a fusion of both filter and wrapper methods. It combines the advantages of both techniques to improve the selection process. Initially, the filter method is utilized to reduce the feature space dimensionality by selecting and ranking top-scored features. After this reduction, the wrapper method comes into play, sifting through the selected features to identify the most optimal ones. Conversely, the hybrid approach may employ the wrapper method first to identify good features and then apply the filter method to refine the selection further. This hybrid method offers a balance, leveraging the performance optimization characteristic of wrapper methods and the high efficiency typical of filter methods. The schematic representation of the hybrid method illustrates the seamless integration of both approaches, leading to improved feature selection outcomes [61].



Optimal feature selection using Hybrid method

Multigranularity Sentiment Classification

The optimal feature vectors will under go classification process using sequential three-way decision. The sequential three-way decision (S3WD) framework, when combined with multi-granularity sentiment classification for interactive information analysis, becomes highly useful, especially when data coming form the interactive comments has limited information and quick, accurate decisions seem difficult. In situations where making a wrong decision can be costly, it's better to delay conclusions when data is insufficient. As more information becomes available, the details of the analysis improve, making delayed decisions initially more favorable [47].

Integrating a step-by-step decision process with hierarchical structures, known for being time-consuming, aligns well with the concept of hierarchical granularity. When the S3WD approach is merged with Granular Computing (GrC), an efficient method emerges for classifying uncertain objects economically. This combined framework defines three distinct areas within dynamic scenarios, accommodating various conditions. These defined areas help classify uncertain elements, enhancing decision-making by offering a comprehensive method to handle uncertainties in different situations.

Let each set of messages be a granular structure let it GS = {GS1, GS_2.....GS_i} with a set of objects U_i, Condition C_i, and Evaluation function e_i. The three regions of the decision-making process at each level POS, NEV, and BND can be defined as

- POSi($e(x)_i$) represents the set of elements 'x' in the universe Ui where the absolute value of the function $e(x)_i$ is greater than or equal to the threshold value ' α_i'.
- BND($e(x)_i$) signifies the set of elements 'x' in the universe Ui where the absolute value of the function $e(x)_i$ lies within the range of ' α_i' (exclusive) and ' β_i ' (inclusive).

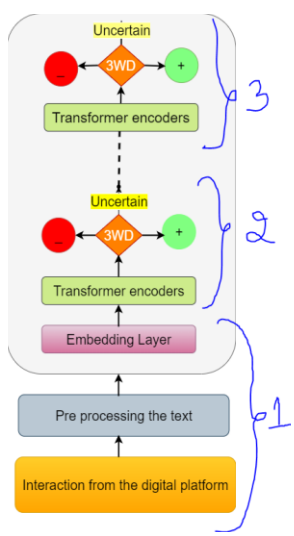
- NEGi(e(x)$_i$) denotes the set of elements 'x' in the universe Ui where the absolute value of the function e(x)$_i$ is less than or equal to the threshold value 'β_i'.

In each step of granularity, the pair of thresholds αi and βi are defined such that they satisfy the conditions: 0 is less than or equal to βi, which is strictly less than αi, and both thresholds range between 0 and 1. This setup ensures that βi represents a lower threshold value while αi represents a higher threshold value, facilitating the categorization or classification of elements based on their function e(x)i within the specified range and conditions.

Sequential Three-Way Decision (S3WD) models that aim to make decisions while considering both decision and test costs. These models involve steps in decision-making processes where different decisions lead to various losses, described using a decision loss matrix. The approach involves calculating expected losses for different decisions and minimizing decision costs. S3WD selects decisions by minimizing costs based on granular feature information. The overall cost in each step combines decision costs and test costs, where the latter is related to the training time model. Optimal decisions result from balancing misclassification costs and test costs. Minimizing cost becomes crucial in terminating the sequential decision process [46,47].

FLOW OF INTERACTIVE SENTIMENTAL ANALYSIS

1. **Preprocessing and Input:** Data obtained from digital interactive media undergoes preprocessing before being fed into the model. This step involves cleaning, tokenization, and formatting the data to make it suitable for BERT-based analysis.
2. **Model Specification:** BERT-S3WD employs a specific model architecture, based on the BERT model. It's indicated that with an increase in the number of layers in the model, the number of uncertain samples decreases. This suggests that the model's deeper layers help in reducing uncertainty in predictions.
3. **Handling Uncertain Samples:** At the final layer of the model, there's a divergence between certain and uncertain samples. This divergence implies that the model can distinguish between samples it's confident about (certain samples) and those it finds ambiguous or uncertain in terms of predictions.



The flow of Interactive Sentimental analysis

CONCLUSION

In conclusion, the usage of sequential three-way decisions in sentimental analysis gives advancement in analyzing interactive information in the social media platform when compared with traditional binary sentimental classification struggles to capture the complexity of evolving opinions. The preprocessing techniques aided in increasing the accuracy, while the BERT model will capture the context in interactive comments from social media. This model will work well against other machine learning models, especially in scenarios with class-imbalanced datasets, short texts, and quick decision-making contexts, underscoring its significance in enhancing the accuracy of sentiment classification.

FUTURE SCOPE

The advancing model of the three-way decision in sentimental analysis involves several key developments. Firstly, reducing training time without compromising performance remains crucial, achieved through improved training methodologies. Secondly, expanding the model's applicability by incorporating more domains beyond its current scope can enhance its versatility and effectiveness across various industries or fields. Lastly, enabling the system to become multi-lingual would significantly broaden its usability by allowing it to comprehend and process multiple languages, contributing to its adaptability and relevance on a global scale. Integrating these advancements would propel the model of the three-way decision towards greater efficiency, wider applicability, and enhanced linguistic capabilities, further solidifying their significance in the field of sentimental analysis.

REFERENCES

[1] Sanchez, H. and Kumar, S., 2011. Twitter bullying detection. ser. NSDI, 12(2011), p.15.

[2] Ahmad SR, Bakar AA, Yaakub MR (2019) A review of feature selection techniques in sentiment analysis. n: Intelligent data analysis, vol 1, pp 159–189

[3] Krouska, A., Troussas, C. and Virvou, M., 2016, July. The effect of preprocessing techniques on Twitter sentiment analysis. In 2016 7th International Conference on information, intelligence, systems & applications (IISA) (pp. 1-5). IEEE.

[4] Devlin, J., Chang, M.W., Lee, K. and Toutanova, K., 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

[5] Tommasel A, Godoy D (2018) A Social-aware online short-text feature selection technique for social media. Information Fusion

[6]. Wang Z, Lin Z (2020) Optimal feature selection for Learning- Based algorithms for sentiment classification. Cogn Comput 12(1):238–248

[7]. Madasu A, Sivasankar E (2020) Efficient Feature Selection techniques for Sentiment Analysis. Multimed Tools Appl 79(9):6313–6335

[8]. Kumar HMK, Harish BS (2019) A new feature selection method for sentiment analysis in short text. J

Intell Syst 29(1):1122–1134

[9] Schütze, H., Manning, C.D. and Raghavan, P., 2008. Introduction to information retrieval (Vol. 39, pp. 234-265). Cambridge: Cambridge University Press.

[10]Joachims, T., 1997, July. A probabilistic analysis of the Rocchio algorithm with TFIDF for text categorization. In ICML (Vol. 97, pp. 143-151).

[11] Nam, J., Kim, J., Loza Mencía, E., Gurevych, I. and Fürnkranz, J., 2014. Large-scale multi-label text classification—revisiting neural networks. In Machine Learning and Knowledge Discovery in Databases: European Conference, ECML PKDD 2014, Nancy, France, September 15-19, 2014. Proceedings, Part II 14 (pp. 437-452). Springer Berlin Heidelberg.

[12] Manning, C.D., 2009. An introduction to information retrieval. Cambridge university press.

[13] Joachims, T., 1998, April. Text categorization with support vector machines: Learning with many relevant features. In European conference on machine learning (pp. 137-142). Berlin, Heidelberg: Springer Berlin Heidelberg.

[14] Burges, C.J., 1998. A tutorial on support vector machines for pattern recognition. Data mining and knowledge discovery, 2(2), pp.121-167.

[15] Li, Y., Zhang, L., Xu, Y., Yao, Y., Lau, R.Y.K. and Wu, Y., 2017. Enhancing binary classification by modeling uncertain boundary in three-way decisions. IEEE transactions on knowledge and data engineering, 29(7), pp.1438-1451.

[16] Yao Y (2009) Three-Way Decision: An Interpretation of Rules in Rough Set Theory. Rough Sets and Knowledge Technology, 4 th International Conference, RSKT 2009, Gold Coast. Proceedings. Springer, Berlin

[17] Yao, Y., 2008. Probabilistic rough set approximations. International journal of approximate reasoning, 49(2), pp.255-271.

[18] Ma, M., 2016. Advances in three-way decisions and granular computing. Knowl.-Based Syst, 91(1), p.3.

[19] Y. Yao, "Decision-theoretic rough set models" in Rough Sets and Knowledge Technology, Berlin, Germany:Springer, pp. 1-12, 2007.

[20] Messaoudi, C., Guessoum, Z. and Ben Romdhane, L., 2022. Opinion mining in online social media: a survey. Social Network Analysis and Mining, 12(1), p.25.

[21] Tripathy, A., Agrawal, A. and Rath, S.K., 2016. Classification of sentiment reviews using n-gram machine learning approach. *Expert Systems with Applications*, *57*, pp.117-126.

[22] Huiping, C., Lidan, W. and Shukai, D., 2016. Sentiment classification model based on word embedding and CNN. *Application Research of Computers*, *33*(10), pp.2902-2905.

[23] Wang, X., Jiang, W. and Luo, Z., 2016, December. Combination of convolutional and recurrent neural network for sentiment analysis of short texts. In Proceedings of COLING 2016, the 26th international conference on computational linguistics: Technical papers (pp. 2428-2437).

[24] Wang, J., Yu, L.C., Lai, K.R. and Zhang, X., 2016, August. Dimensional sentiment analysis using a regional CNN-LSTM model. In Proceedings of the 54th annual meeting of the association for computational linguistics (volume 2: Short papers) (pp. 225-230).

[25] Tang, D., Qin, B., Feng, X. and Liu, T., 2015. Effective LSTMs for target-dependent sentiment classification. *arXiv preprint arXiv:1512.01100*.

[26] Yao, Y., 2016. A triarchic theory of granular computing. Granular Computing, 1, pp.145-157.

[27] Yao, Y., 2020. Three-way granular computing, rough sets, and formal concept analysis. International Journal of Approximate Reasoning, 116, pp.106-125.

[28] Zhang, Q., Pang, G. and Wang, G., 2020. A novel sequential three-way decisions model based on penalty function. *Knowledge-Based Systems*, *192*, p.105350.

[29] Dai, D., Li, H., Jia, X., Zhou, X., Huang, B. and Liang, S., 2020. A co-training approach for sequential three-way decisions. *International Journal of Machine Learning and Cybernetics*, *11*, pp.1129-1139.

[30] Yang, J., Wang, G., Zhang, Q., Chen, Y. and Xu, T., 2019. Optimal granularity selection based on cost-sensitive sequential three-way decisions with rough fuzzy sets. Knowledge-Based Systems, 163, pp.131-144.

[31] Yang, X., Zhang, Y., Fujita, H., Liu, D. and Li, T., 2020. Local temporal-spatial multi-granularity learning for sequential three-way granular computing. Information Sciences, 541, pp.75-97.

[32] Liu, D., Yang, X. and Li, T., 2020. Three-way decisions: beyond rough sets and granular computing. International Journal of Machine Learning and Cybernetics, 11, pp.989-1002.

[33] Ju, H., Pedrycz, W., Li, H., Ding, W., Yang, X. and Zhou, X., 2019. Sequential three-way classifier with justifiable granularity. Knowledge-Based Systems, 163, pp.103-119.

[34] Yao, Y., 2011. The superiority of three-way decisions in probabilistic rough set models. Information sciences, 181(6), pp.1080-1096.

[35] Yao, Y., 2010. Three-way decisions with probabilistic rough sets. Information sciences, 180(3), pp.341-353.

[36] Yao, Y., 2009. Three-way decision: an interpretation of rules in rough set theory. In Rough Sets and Knowledge Technology: 4th International Conference, RSKT 2009, Gold Coast, Australia, July 14-16, 2009. Proceedings 4 (pp. 642-649). Springer Berlin Heidelberg.

[37] Yao, Y., 2013, October. Granular computing and sequential three-way decisions. In International conference on rough sets and knowledge technology (pp. 16-27). Berlin, Heidelberg: Springer Berlin Heidelberg.

[38] Li, H., Zhang, L., Huang, B. and Zhou, X., 2016. Sequential three-way decision and granulation for cost-sensitive face recognition. *Knowledge-Based Systems*, *91*, pp.241-251.View at: Publisher Site | Google Scholar

[39] Fujita, H., Gaeta, A., Loia, V. and Orciuoli, F., 2019. Hypotheses analysis and assessment in counterterrorism activities: a method based on OWA and fuzzy probabilistic rough sets. *IEEE Transactions on Fuzzy Systems*, *28*(5), pp.831-845.

[40] Yao, Y., 2018. Three-way decision and granular computing. International Journal of Approximate Reasoning, 103, pp.107-123.

[41] Yao, Y., 2020. Tri-level thinking: models of three-way decision. International Journal of Machine Learning and Cybernetics, 11(5), pp.947-959.

[42] Yao, Y., Wang, S. and Deng, X., 2017. Constructing shadowed sets and three-way approximations of fuzzy sets. Information Sciences, 412, pp.132-153.

[43] Zhao, X., Miao, D. and Fujita, H., 2021. Variable-precision three-way concepts in L-contexts. International Journal of Approximate Reasoning, 130, pp.107-125.

[44] Yang, X., Zhang, Y., Fujita, H., Liu, D. and Li, T., 2020. Local temporal-spatial multi-granularity learning for sequential three-way granular computing. Information Sciences, 541, pp.75-97.

[45] Luo, J., Fujita, H., Yao, Y. and Qin, K., 2020. On modeling similarity and three-way decision under incomplete information in rough set theory. Knowledge-Based Systems, 191, p.105251.

[46] Yang, D., Deng, T. and Fujita, H., 2020. Partial-overall dominance three-way decision models in interval-valued decision systems. International Journal of Approximate Reasoning, 126, pp.308-325.

[47] Yue, X.D., Chen, Y.F., Miao, D.Q. and Fujita, H., 2020. Fuzzy neighborhood covering for three-way classification. Information Sciences, 507, pp.795-808.

[48] Li, Y., Zhang, L., Xu, Y., Yao, Y., Lau, R.Y.K. and Wu, Y., 2017. Enhancing binary classification by modeling uncertain boundary in three-way decisions. IEEE transactions on knowledge and data engineering, 29(7), pp.1438-1451.

[49] Qiao, J. and Hu, B.Q., 2018. On transformations from semi-three-way decision spaces to three-way decision spaces based on triangular norms and triangular conorms. Information sciences, 432, pp.22-51.

[50] Li, H., Zhang, L., Zhou, X. and Huang, B., 2017. Cost-sensitive sequential three-way decision modeling using a deep neural network. International Journal of Approximate Reasoning, 85, pp.68-78.

[51] Abdel-Basset, M., Manogaran, G., Mohamed, M. and Chilamkurti, N., 2018. Three-way decisions based on neutrosophic sets and AHP-QFD framework for supplier selection problem. Future Generation Computer Systems, 89(6), pp.19-30.

[52] HU, F., WANG, L. and ZHOU, Y., 2018. An oversampling method for imbalance data based on three-way decision model. ACTA ELECTONICA SINICA, 46(1), p.135.

[53] Afridi, M.K., Azam, N., Yao, J. and Alanazi, E., 2018. A three-way clustering approach for handling missing data using GTRS. International Journal of Approximate Reasoning, 98, pp.11-24.

[54] Jiang, C., Wu, J. and Li, Z., 2019. Adaptive thresholds determination for saving cloud energy using three-way decisions. Cluster Computing, 22, pp.8475-8482.

[55] Fujita, H., Gaeta, A., Loia, V. and Orciuoli, F., 2018. Resilience analysis of critical infrastructures: a cognitive approach based on granular computing. IEEE transactions on cybernetics, 49(5), pp.1835-1848.

[56] Yao, Y.Y., Pedrycz, W., Skowron, A. and Kreinovich, A.V., 2008. A unified framework of granular computing. Handbook of granular computing, W. Pedrycz, A. Skowron, and AV Kreinovich, eds., Wiley, Chichester, UK, pp.401-410.

[57] Yang, X., Li, T., Fujita, H., Liu, D. and Yao, Y., 2017. A unified model of sequential three-way decisions and multilevel incremental processing. Knowledge-Based Systems, 134, pp.172-188.

[58] Wang, T., Li, H., Zhang, L., Zhou, X. and Huang, B., 2020. A three-way decision model based on cumulative prospect theory. Information Sciences, 519, pp.74-92.

[60] Twitter and Reddit Sentimental analysis Dataset. (n.d.). Kaggle. https://www.kaggle.com/datasets/cosmos98/twitter-and-reddit-sentimental-analysis-dataset

[61] Min, H. and Fangfang, W., 2010, December. Filter-wrapper hybrid method on feature selection. In 2010 Second WRI Global Congress on Intelligent Systems (Vol. 3, pp. 98-101). IEEE.

[62] Balan, R.S., Walia, K. and Gupta, K., 2022, April. A Systematic Review on POS Tagging. In 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE) (pp. 1531-1536). IEEE.