Sentiment Analysis Using Fuzzy Systems

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Abstract - This paper investigates the ability of fuzzy systems to perform text sentiment analysis aided by the use of SentiWordNet. In text sentiment analysis, text is generally labelled either as positive or negative. Due to the ambiguity of language, making meaningful analysis of sentiments can prove arduous. This paper uses a Mamdani fuzzy system with a novel case study to investigate accurate text sentiment analysis with evaluation of performance and different methods with the objective to make text sentiment analysis a more simplified and computationally efficient process.

I. INTRODUCTION

The prolific use of social media in the modern age means that there is an abundance of information and opinions shared online, mostly in an unorganised and chaotic manner. Obtaining the means to make sense of the large amounts of sentiments left online is important for many reasons, ranging from commercial and political, to enhancing user experience and even the detection of cyberbullying [1]. Other examples of the importance of text sentiment analysis take us back to the 2011 London riots, where social media platforms like Twitter had a huge impact on the course of events [2]. This ranged from citizen to government collaboration, such as encouraging street cleaning post riots with an engagement of 7 million users, to suspect identification of riot ring-leaders encouraging other rioters on encrypted media, such as Blackberry Messenger [2]. It has also been shown that these instantaneous messaging applications have been used in public sectors to reach new audiences and can be deemed a very powerful tool [3].

Taking this all into account, autonomous sentiment analysis can be a powerful method for understanding what is going on within societal groups and the general public's views, on the vast realm of social media for commercial and even public safety purposes. One of the many methods of sentiment analysis is the use of fuzzy systems, which is what this paper will investigate.

A. Overview of Sentiment Analysis

Sentiment analysis, which is commonly referred to as 'opinion mining', is a field of *Natural Language Processing* (NLP). The objective of sentiment analysis is to extract the overall sentiment of a message, including the emotions, opinions and attitudes expressed by individuals on a variety of topics. This can include, but is not limited to, products, services or events.

This is not easy to achieve, as machines are unable to pick up on the non-linearity and adaptability of human behaviour, working as they do on the basis of logic and linearity [4]. However it is important to make sentiment analysis autonomous, due to the exponential growth of data. It has been stated by IBM that over 80% of the world's data was made within the last two years, and the volume of data is predicted to increase by 800% in the next five years [5]. Because of this, it is unfeasible to allocate human resources to manually assess thousands to millions of written data.

B. Machine Learning Approach to Sentiment Analysis

Due to the linear nature of machines, the most modern approach to analysing the chaos of human behaviour is through machine learning [4]. Machine learning is a broad set of mathematical models that attempt to emulate human intelligence by learning from the surrounding environment [6]. Some notable machine learning algorithms well suited for text sentiment analysis include Naive Bayes (NB), Standard Vector Machine (SVM) and Multilayer Perceptrons (MLP).

i. Naive Bayes

The NB model is easy to implement with greater computational efficiency than most machine learning models [7]. Operating through supervised learning, this classifier, developed by Thomas Bayes, operates from his theorem that if given two events denoted as $e1$ and $e2$, the probability of occurrence of event $e1$ when $e2$ has already occurred is given by the following formula:

$$P(e1|e2) = \frac{P(e2|e1)\cdot P(e1)}{e2} \quad (1)$$

In the context of text sentiment analysis, it can be adapted for the sentiment of a sentence as follows [7]:

$$P(Stmnt|Sntnc) = \frac{P(Sntnc|Stmnt)\cdot P(Stmnt)}{P(Sntnc)} \quad (2)$$

Where "Stmnt" = Sentiment and "Sntnc" = Sentence.

It can also be adapted for the conditional probability of the sentiment of a word using the same principle [7]:

$$P(Wrd|Stmnt) = \frac{Occ + 1}{Wbc + Tw} \quad (3)$$

Where "Stmnt" = Sentiment, "Wrd" = Word, "Occ" = Number of word occurrences in class, "Wbc" = Number of words belonging to class and "Tw" = Total number of words.

A small scale experiment conducted using this model on 10,000 airline review tweets managed to yield 76.56% accuracy in sentiment analysis [8]. Considering the simplicity of the NB model and the scope of the experiment in a modern setting, this result is impressive for such a complicated task.

ii. Standard Vector Machine

SVM has been shown to be highly effective at text classification, whilst also generally outperforming the NB model [9]. This model works by finding a separation vector between the different classes of data, aiming to create the largest possible separation. While this model generally performs well, it has issues with high computational complexity, as quadratic programming problems need to be solved [10]. What makes SVM effective for text classification is its ability to separate high dimensionality non-linear input data with the usage of the right kernel [11].

The same experiment conducted in [8] also tested the SVM model to compare results to NB and managed to achieve a better performance, correctly identifying sentiments with 82.48% accuracy.

iii. Multilayer-Perceptrons

These neural network models are renowned for their versatility, because of their ability to learn almost all types of functions or relationships within a given input and output variable set. This is because of the backpropagation algorithm that underlies it [11].

They consist of an input layer, a specified number of hidden layers, and an output layer. For binary classification tasks, such as positive or negative, there is one output layer follow by n output layers for more complicated classifications. The backpropagation algorithm works by calculating the error in each randomly initialised weight in the network, combined with a fixed learning rate hyperparameter, to then update the weights accordingly.

The versatility of this algorithm is exemplified by the case study where the Word2Vec model had failed to identify sentiments in Arabic text, despite successfully identifying English text [12]. Another study attempted to solve this problem using an MLP, working on two datasets consisting of 500,000 entries each, one in Arabic and the other in English, with the model obtaining accuracies of 87% and 96% respectively [13].

C. Challenges of Sentiment Analysis

Raw input string data is not inherently computable by any of these algorithms, which is why text needs to go through a thorough preprocessing stage. While the use of emoticons can be one of the most concrete indicators of polarity in text [14] and text can be observed for it automatically, their meaning is not always consistent with the associated words. So in the same way that images need to be converted into matrix form for classification tasks, the same needs to be done for text, while also taking steps to remove redundancy in the data.

The general steps in text preprocessing are as follows [15]:

- Tokenization
- Lemmatising
- Stopword Removal
- POS Tagging

The way each step is performed may differ, depending on the application of these text mining techniques. For example, word tokenisation is effective for the English language and its clear word barriers. However, it gets more complicated when analysing other languages such as Japanese and its Kanji system [15].

Another notable challenge in sentiment analysis is the ambiguity of language. The meaning of a sentiment can change depending on the context of the words, culture and words have many different meanings for example. A classic example is the case of irony, where a phrase such as "Yeah, right!" can have the polar opposite of its literal meaning [30]. One approach to solve this issue was with a contextual based lexicon which has been used to help distinguish between words, which is especially useful where languages share words [16].

D. Fuzzy Systems in Sentiment Analysis

The machine learning approaches mentioned previously all work based on a crisp dataset, using binary values to denote true or false, meaning that it works in absolutes. Fuzzy logic attempts to make a more meaningful analysis of data by determining the degree to which a member belongs to a class, using a non-crisp dataset, making a black and white problem, "grey" [17].

Fuzzy logic is an often overlooked contribution: what makes it so useful is its high power of precision in a field which is inherently imprecise [18]. For the particular application this paper discusses, fuzzy logic can aid machine learning to achieve fuzzy classification with reduction of bias [19]. Given the issues mentioned in [16], fuzzy logic can provide a more human way of thinking to make better sense of ambiguity problems. This was discussed by Grobelny et al [20] where their investigation of fuzzy logic was used to model human behaviour, and outlined its potential to group ambiguous data, such as countries and colours, based on similarity which is subjective.

A fuzzy inference system has been shown to be effective for sentiment analysis in an experiment where IMDB user reviews were used as data, with over 90% accuracy achieved in matching the performance of other models such as Naive Bayes and Decision Tree [21]. Another paper detailing intensifier and diminisher words can be used to create rules for accurate sentiment analysis, where words such as 'really' and 'very' can help distinguish very positive and very negative sentiments with words like 'hardly' and 'slightly' for weaker positive and negative sentiments [22].

II. METHODOLOGY

Fuzzy logic works on fuzzy sets and fuzzy systems following these steps from input to output [23]:

- Fuzzification
    - Crisp input values are converted to fuzzy sets.
- Inference Engine
    - The matching degree of a fuzzy input is determined based on a predetermined rule base.
- Defuzzification
    - Fuzzy sets are converted back into crisp output for interpretation.

Membership functions play a salient role in the process, which displays the universe of discourse (input values) to membership values [24]. Finally, the fuzzified inputs or antecedents will be mapped to a consequent, based on set rules and what inference techniques we wish to use, and then undergo the defuzzification process to obtain an interpretable crisp output.

i. Mamdani Fuzzy Inference Systems

The three most widely used fuzzy inference systems include Mamdami, Sugeno and Tsukamoto: this paper will use a Mamdami, typically known as the Max-min method [25]. The intention of using a Mamdani inference system is to fulfil the objective of making machine-based text sentiment analysis understandable, computationally efficient and easy to use to ideally make analysis of large data sets of text more efficient and less complicated.

A typical Mamdani system consists of an *IF-THEN* rule base where if one antecedent is a and one antecedent is b then our consequent is c. These will consist of linguistic terms which increase readability, where an example of a rule could be "IF PRESSURE is HIGH THEN VOLUME is LOW" [26]. In the case of this system, we check for the membership of a value from each membership function in the boolean check to then find what consequent membership it belongs to.

ii. Text Data

The textual data that was used is a set of 1000 Yelp reviews with a crisp binary label 1 or 0 for positive or negative sentiments respectively. The data was divided into two sets where a sample of 850 reviews underwent data analysis to help define some rules, and 150 reviews were used to validate the model's performance. Afterwards, the model was tested for adaptability and robustness, with an Amazon review sentiments dataset. While the Yelp reviews were about food establishments, the Amazon reviews were about products, which introduces different contexts and acts as a more thorough test of adaptability. All textual data underwent the same preprocessing processes in order to remove redundancy and noise in the data, with the aim of keeping all parts of data with the most information gain. Both datasets were provided by the University of Portsmouth.

iii. SentiWordNet

As previously discussed, machine learning models do not have the inherent ability to understand text. After the thorough preprocessing process shown in [15], in which feature extraction methods are used. For example, Bag of Words (BOW) or Term Frequency-Inverse Document Frequency (TF-IDF) models are frequently used. Feature extraction methods can obtain information such as term frequency, opinion words, negations into numerical format for machine learning [27]. The proposed model used SentiWordNet to obtain positive and negative scores from each entry in a textual dataset to then be fuzzified and interpreted once textual data undergoes the aforementioned preprocessing process.

SentiWordNet is a database provided by WordNet that allocates a score of positivity and negativity for nearly any given word [28]. Using this to analyse each word in a sentence can already give an idea of whether a piece of text is positive or negative depending on which score is higher. Due to the subjectivity of language and human thinking [20], it is possible that a word could score equally positive or negative, or could be scored incorrectly. The application of a fuzzy system could hypothetically increase the accuracy of sentiment analysis without requiring a training process.

iv. Defining Membership Functions and Rules

The membership functions were determined and adjusted based on a statistical analysis of positive and negative scores of the preprocessed text, using SentiWordNet. The statistical investigation also aided in creating a rule base for the inference system. Statistical analysis of the data entailed obtaining metrics such as quartiles, highest and lowest values and averages. For both the positive and negative scores, which are the antecedents, there were be three categories ("LOW", "MEDIUM" and "HIGH"): by contrast, our consequent was "Overall Sentiment" which can be either ("POSITIVE" or "NEGATIVE") in conjunction with the labelled dataset.

v. Testing and Comparisons

Utilising the split datasets, the testing dataset was used with the proposed fuzzy inference system against two other machine learning models to make comparisons of performance including the NB and MLP models discussed earlier.

III. IMPLEMENTATION

The following experiment was performed using Jupyter Notebook using, most prominently, the Pandas, Numpy, MatPlotLib, Scikit Learn and SciKit Fuzzy libraries.

i. Using SentiWordNet

After the data underwent preprocessing mentioned in [15], functions were made to obtain positive and negative scores for each word in a sentence and an overall score for the whole sentence. Overall sentence scores were multiplied/stretched out by a factor of five to ensure differences between scores were more recognisable (which will be explained further on in this document). An example of the functionality is shown below in Figure 1 in console outputs for test case sentences:

```
Sentiment for word terrible: pos:0.625
neg:13.125
Sentiment for word good: pos:76.875
neg:0.625
Sentiment for sentence: food is extremely
bad but place is beautiful: pos:19.375
neg:58.75
Sentiment for sentence: food is very good
and place is beautiful: pos:98.125
neg:7.5
```

Figure 1: Sentiword Scores on Test Cases

As expected, positive sentiments score higher on the positive scale and negative sentiments score higher on the negative scale, even with some subjective language in the data. Regardless, even negative sentiments and negative words have a positive score and the same for positive sentiments having a negative score that exists.

An example of testing sentiword scores against the first element of the dataset is shown below in Figure 2 which reads as ("wow love place"):

```
Sentiment for sentence 1 with rating of
positive: pos:25.625 neg:4.375
```

Figure 2: Sentiword on first element of dataset

ii. Data Analysis

The Yelp reviews were split into two subsets of 150 and 850, being the validation set and training set respectively. The justification behind making rules based on the training dataset was to capture relationships in the data using a large sample, ideally developing an inference system that can generalise beyond the training set and in alternative domains.

Commencement of analysis entailed creating boxplots of positive and negative scores for each of the labelled positive and negative sentiment data whilst also obtaining highest and lowest scores for each of the metrics. Presented below in Figure 3 and 4 are boxplots for Negative sentiment data with Figure 5 and 6 depicting the boxplots for Positive sentiment data:

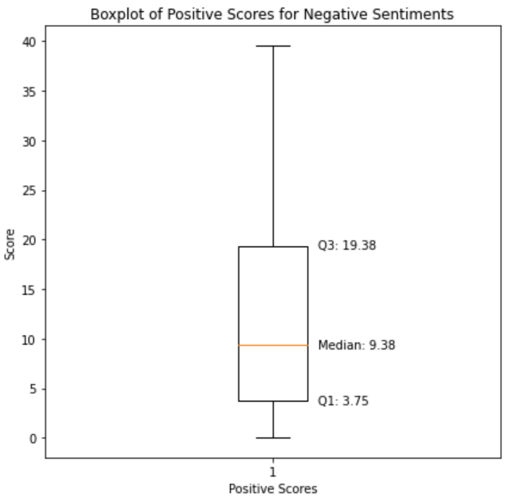


Figure 3: Positive scores of negative sentiments boxplot.

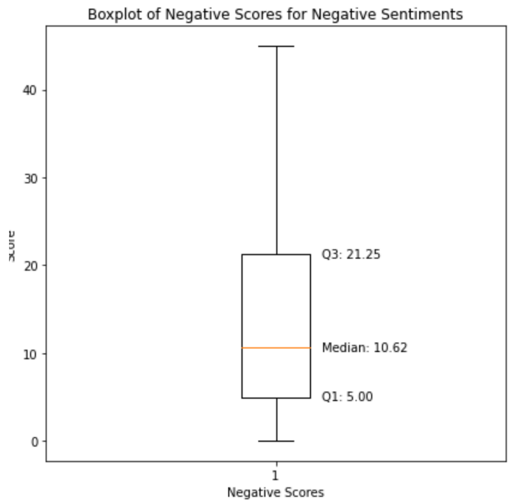


Figure 4: Negative scores of negative sentiments boxplot.

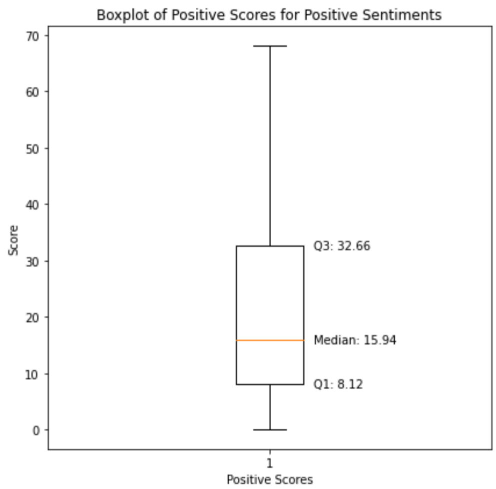


Figure 5: Positive scores of positive sentiments boxplot.

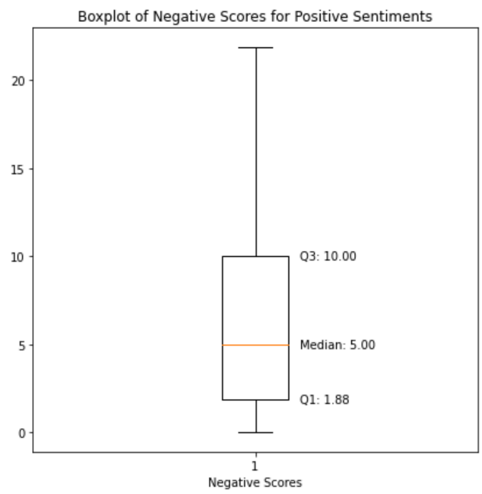


Figure 6: Negative scores of positive sentiments boxplot.

We can infer from the plots that Positive sentiments have higher positive scores and Negative sentiments have higher negative scores. However, the data distribution for negative sentiment data conveys similar patterns in positive and negative scores which could imply ambiguity in negative sentiments from the dataset. This is further emphasised when the other metrics such as averages and highest values were taken. Below in Figure 7 shows the console outputs for these metrics where a score of 0 is a negative sentiment and a score of 1 is positive:

```
Average for Sentiment Score 0: (pos:
17.137453703703706, neg:
16.466423611111107)
Average for Sentiment Score 1: (pos:
29.984162679425836, neg:
8.236531100478468)
```

Figure 7: Average SentiWordNet scores for each class.

Positive sentiments in the data set had a much greater separation of positive to negative scores than the negative sentiment class. Whilst the average positivity score using this method on negative sentiments was slightly higher than the negative score, the negative score was still on average twice that of a positive sentiment. The main conclusions that can be drawn from this data is that positive sentiments have much higher positivity and lower negativity than negative sentiments where negative sentiments have higher negativity scores.

iii. Membership Functions

There are two antecedents and one consequent in this system. The two antecedents being the 'Positive' and 'Negative' scores of a sentiment and the consequent being an 'Overall' sentiment. During the process of creating membership functions for the antecedents, configuring with the exact values of the metrics obtained in the previous section did not yield good results. On the contrary, it provided adequate guidelines for boundary separation of the different memberships. Membership functions diagrams portraying the values and membership degrees of positive and negative sentiment scores are shown below in Figure 8 and 9:

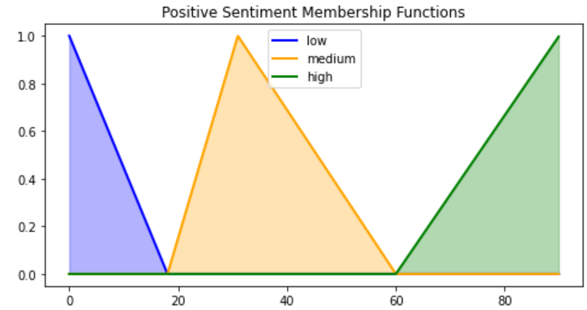


Figure 8: Positive Sentiment Membership Functions.

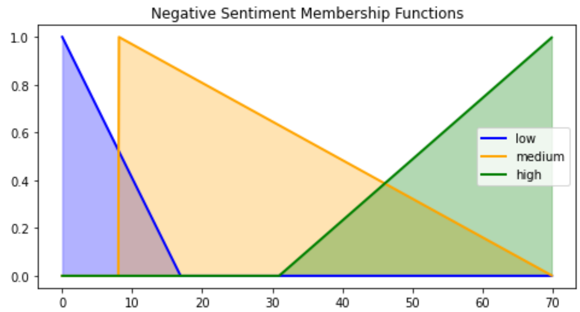


Figure 9: Negative Sentiment Membership Functions.

Where positive scores of sentiments had a much clearer separation than negative data, the allocation of boundaries was more straightforward however an overlapping approach was taken in the negative sentiment membership function in an attempt to better handle ambiguity in data in reference to the data exploratory where negative sentiments had more ambiguity between positive and negative scores than positive data. The choice in overlapping triangle membership functions was shown to be effective in handling more ambiguous data when a genetic algorithm approach to membership function adjustment was taken resulting in overlapping membership functions [29].

In this paper, the focus is binary sentiment analysis, primarily because polarity was noted to be one of the most important factors in sentiment analysis [14]. As a result, the consequent membership function is only positive and negative which is illustrated below in Figure 10:

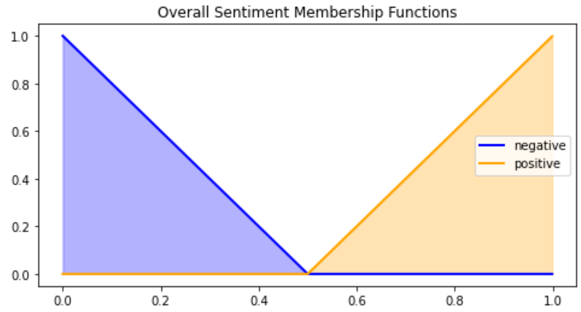


Figure 10: Overall Sentiment Membership Functions.

iv. Rule Base

Taking the results of data investigation into account, the rules are as follows:

- If POS_SCORE is LOW and NEG_SCORE is LOW, then OVERALL SENTIMENT is POSITIVE.
- If POS_SCORE is MEDIUM and NEG_SCORE is LOW, then OVERALL SENTIMENT is POSITIVE.
- If POS_SCORE is HIGH and NEG_SCORE is LOW then OVERALL SENTIMENT is POSITIVE.
- If POS_SCORE is LOW and NEG_SCORE is MEDIUM then OVERALL SENTIMENT is NEGATIVE.
- If POS_SCORE is MEDIUM and NEG_SCORE is MEDIUM then OVERALL SENTIMENT is NEGATIVE.
- If POS_SCORE is HIGH and NEG_SCORE is MEDIUM then OVERALL SENTIMENT is POSITIVE.
- If POS_SCORE is LOW and NEG_SCORE is HIGH then OVERALL SENTIMENT is NEGATIVE.
- If POS_SCORE is MEDIUM and NEG_SCORE is HIGH then OVERALL SENTIMENT is NEGATIVE.
- If POS_SCORE IS HIGH and NEG_SCORE is HIGH then OVERALL SENTIMENT is NEGATIVE.

The key takeaways from rule allocation is that higher negative scores will make a sentiment negative and lower negative scores will make a sentiment more positive. In order to combat the ambiguity of the task, rules were allocated a bit more dynamically when negative scores were at a medium value. In this case, as long as the positive score was high, the overall sentiment score was positive and negative in every other instance as negative sentiments proved to have higher positive sentiment scores frequently during the statistical investigations.

v. Application of the Fuzzy System

Using test inputs of pos_score = 18.05 and neg_score = 16.88, the activation of membership functions are visualised below with defuzzification of output:

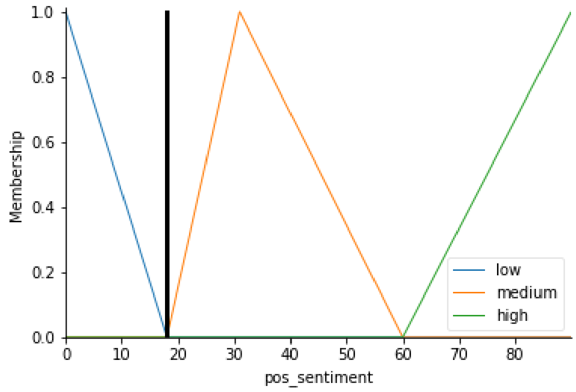


Figure 11: Test case on pos_score.

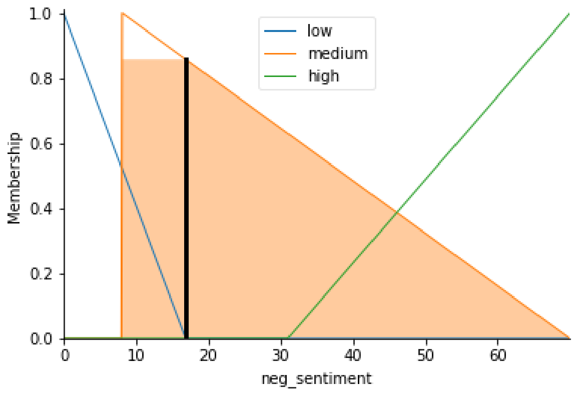


Figure 12: Test case on neg_score.

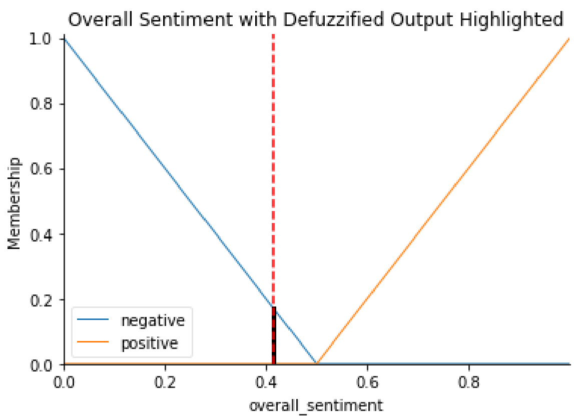


Figure 13: Test case on overall sentiment.

The test case on a successfully identified negative sentiment shows the application of membership functions and the rules to derive to the conclusion that it was a negative sentiment.

A 3D Surface was generated to convey how the mixture of positive and negative scores can lead to an overall sentiment:

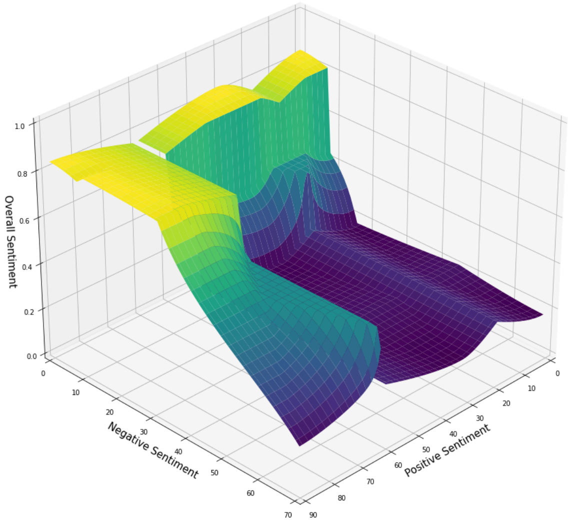


Figure 14: 3D Surface Plot of Fuzzy System.

IV. RESULTS

The system was tested on the training data initially, then on the test sample to see how it performed. Furthermore, it was also tested on a completely different dataset and then compared to the other models discussed on the test data set.

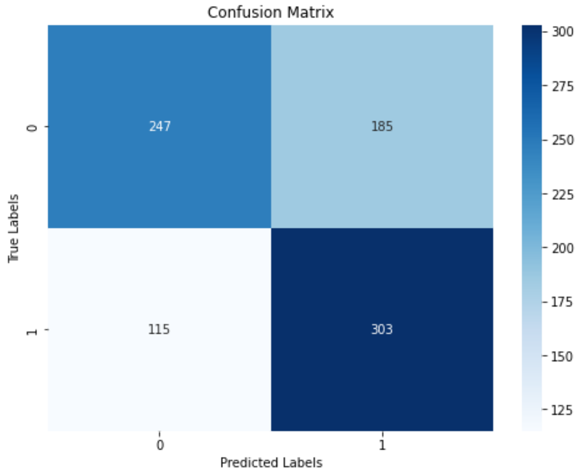
i. Training Dataset

Shown in Figure 15 is the classification report on the training dataset:

Class	**Precision**	**Recall**	**F1-Score**
0	0.68	0.57	0.62
1	0.62	0.72	0.67
Accuracy:	0.647	**MSE:**	0.353

Figure 15: Results on training dataset.

Overall, the system predicted the training dataset at 65% accuracy with a root mean squared error of 0.35. There was a precision score of 68% on negative sentiments and 62% on positive sentiments. With a higher recall and f1-score on class 1 (positive), it can be said that the positive sentiments were better at being predicted. Show in Figure 16 is the confusion



matrix:

Figure 16: Confusion Matrix for Training Set using the proposed Fuzzy System.

This accuracy is promising considering the simplicity of the model on a more complicated task. The difference between positive and negative identifications suggests room for improvement and a bias to predicting data as positive.

ii. Test Dataset

Shown in Figure 17 is the classification report on the testing dataset:

Class	**Precision**	**Recall**	**F1-Score**
0	0.67	0.60	0.64
1	0.70	0.76	0.73
Accuracy:	0.690	**MSE:**	0.313

Figure 17: Results on training dataset.

The model performed even better on the testing data achieving 69% accuracy with higher recall scores and f1-scores than the training set. The difference between these scores compared to the training set are relatively low, meaning that the model overall performed similarly and has captured most relationships in the data also identifying positive instances better. Shown in Figure 18 is the confusion matrix:

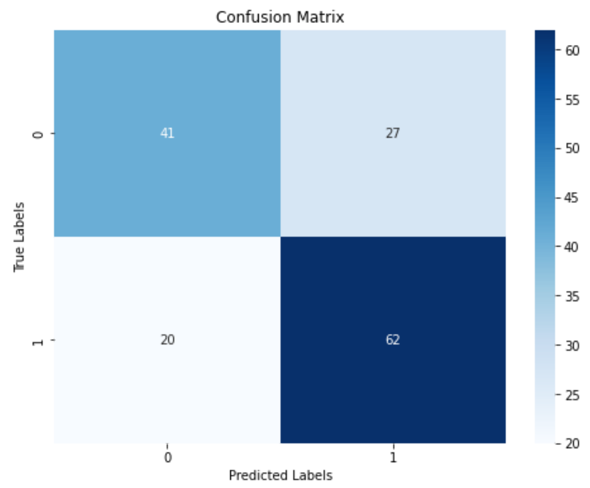


Figure 18: Confusion Matrix for Testing Set using the proposed Fuzzy System.

We can see yet again the model has a slight bias to predicting positive instances but less so in this dataset. The accuracy overall is good showing the model to be viable at predicting sentiments in similar data.

iii. Alternative Dataset

This dataset was preprocessed the same way as the Yelp Review data that was tested was and tested against the model with results shown in Figure 19:

Class	**Precision**	**Recall**	**F1-Score**
0	0.48	0.41	0.44
1	0.49	0.56	0.52
Accuracy:	0.490	**MSE:**	0.515

Figure 18: Results on Amazon Dataset.

The model performed poorly on this dataset achieving 49% accuracy but with relatively even misclassifications on each class. This could be down to a number of reasons: for example, the Yelp Review dataset was of food establishments whereas the Amazon review is of products. The significance of this lies in the input method using SentiWordNet allocating every word a sentiment score. A product review dataset will have different vocabulary to food establishment reviews meaning the vocabulary used must be weighted differently to one another. Shown in Figure 19 is the confusion matrix:

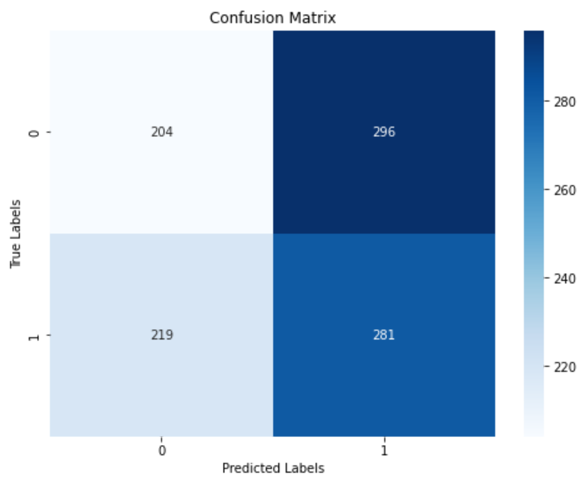


Figure 19: Confusion Matrix for Testing Set using the proposed Fuzzy System on a different dataset.

iv. Comparisons to Other Models

Using the original testing and training dataset used to design the fuzzy inference system, the datasets were transformed using TF-IDF to feed into the models and train of with results displayed in Figure 20:

Model	**Accuracy**	**MSE**
Fuzzy	0.69	0.31
MLP	0.74	0.26
NB	0.71	0.29

Figure 20: Comparing results to other models.

Both other models tested had performed at a higher accuracy however when taking precision per class into account, the fuzzy system performed better than both models. The other models failed to capture the relationship in positive data, with precision scores of 0.42 and 0.33 respectively for positive sentiments, with much higher scores on negative sentiments being 0.93 and 0.85. From this we can assume the fuzzy system was much better at predicting data with ambiguous features in this instance, with balanced accuracies across both classes and recall scores.

v. Evaluation of Results

The methodology presented here is novel in its unique combination of two sentiment analysis techniques (SentiWordNet and fuzzy systems) and unique input features to capture and understand relationships in ambiguous data.

Overall, the fuzzy system created outperformed the other models tested in capturing important relationships showcasing the power of fuzzy inference on data that is imprecise and vague. However, whilst the model created worked well for the data presented and unseen data when creating the model, it failed to generalise on different data which highlights the limitations of this system.

V. CONCLUSION

This paper discussed the relevance of sentiment analysis along with the challenges with a proposed fuzzy logic inference system to execute the task. A model that takes unlabelled text that then ranks the text with SentiWordNet and categorises them into positive or negative sentiments was created, which performed at a comparable level to other models, with superior precision, further emphasising the ability of fuzzy logic to capture human thinking and ambiguous data.

i. Future Work

Where fuzzy systems have been shown to perform well in vague data, shortcomings in the models performance was likely down to how SentiWordNet scores words. This was evident in the data exploratory phase, where negative sentiments had on average, even positive and negative scores. The performance could be improved by investigating other alternative approaches such as Word2Vec and so forth. Furthermore, similar to the study conducted by Zhang et al [29], the system could allow membership functions to change dynamically based on prediction error, using a genetic algorithm or a training algorithm like MLP and NB. This adaptive fuzzy system could then be used in conjunction with other models, using ensemble learning techniques. This paper focused on a binary text classification task, but this system could be adapted to predict text into more unique categories such as 'very negative', 'neutral' and 'positive', to further exploit the abilities of fuzzy logic.

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