Irony Sentence Detection Techniques Using Fuzzy Historical Classifier

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Abstract. The purpose of this study is to presents a new approach to the extraction of the meaning of sentences that are irony, that is by way of classifying someone based on their utterances in the past. The history of one's utterances influences the assessment of a sentence having an irony tendency or not, for example when someone often speaks negatively, suddenly gives positive opinion on a topic while other people give negative opinions on the topic. The fuzzy logic method needs to be used to assess the historical tendency of one's utterance when the values of positive and negative sentiments are almost balanced so that the value of the majority of sentiments is unclear. The results show that the greater the level of difference in sentiment between a topic and the higher the level of the historical tendency of a person's utterance, the higher the value of the potential irony of the utterance.

1. Introduction

Sentiment analysis methods are considered effective for getting information about whether other people have a positive or negative view of a topic. Sentiment analysis is the process of understanding, extracting, and processing textual data automatically to get information, Bo Pang and Lillian[1]. However, many people do not directly convey what they feel like using irony utterances in order to mock or criticize. An irony is a smart form of utterance where the speaker or writer says or writes the opposite of what they mean, Bing Liu[2]. With irony, sentiment analysis methods are difficult to understand.

Research on identification of irony utterance in the context of sentiment analysis has been carried out. Among them, Riloff et.al[3] detect irony if it shows clear differences between positive sentiments towards negative situations. Lunando and Purwarianti[4] propose unigram+negativity+interjection method where the sentence is an irony usually begins with words that contain interjection words such as “aha”, “bah”, “nah”, “wew”, etc. Anupam et.al[5] propose Historical Tweet-based Predictor which identifies the irony if the sentiment expressed towards the entity in the target tweet agrees with the sentiments expressed by the author towards that entity in the past[6]. This research presents a new approach to the extraction of the meaning of sentences that are irony that aims to classify a person based on his utterance history.

The history of one's utterances influences the assessment of a sentence having irony tendencies or not[7]. For example, when someone often speaks negatively, it suddenly gives a positive opinion of a topic while other people give negative opinions on the topic[8]. However, the problem will arise when the value of positive and negative sentiments is almost balanced so that the majority of sentiment values are not clear, therefore it is necessary to use the fuzzy logic method to assess the historical tendency of one's utterance.
2. Method
The use of fuzzy was very necessary because the number of one's utterance continues to increase so as to make data sources that would be classified to be dynamic.

The stages of the Fuzzy Historical Classifier process begin by identifying utterances that have positive sentiments among the majority of utterances that have negative sentiments towards a topic while collecting historical utterance data of the person using sentiment analysis techniques to get the number of utterances, the number of positive utterances, and the number of negative utterances. After that, the calculation of the average calculation is done to classify the positive and negative sentiment values by means of the number of positive or negative sentiments divided by the total utterance and multiplied by 100 to form the measurement parameters. When the calculation results are obtained, that value will be included in the fuzzy classification tool to determine whether the utterance is really positive or even irony that improves the calculation of sentiment analysis on the topic because the utterance will be classified into negative sentiment utterance. The testing stages carried out in this study consist of four stages of testing which include:

1. Calculation of the composition of positive and negative sentiments on a topic using sentiment analysis.
2. Calculation of the composition of positive, negative, and neutral sentiments from one's utterance history using sentiment analysis also calculate the percentage composition of the negative and positive sentiment values.
3. The calculation of the utterance is irony or not using fuzzy Mamdani.

2.1. Calculation of the Sentiment Composition of a Topic
The calculation of sentiment composition as shown by figure 1 below, is a calculation done to calculate the number of positive and negative sentiments on the topic. The provision is to set a topic that is responded to by others with the majority of negative sentiment values and a minority of positive sentiment values. The data model chosen is data with a greater number of negative sentiments compared to the number of positive sentiments with the difference being made in multiples of 200 between sentiments. Like the picture below (see Figure 1).

![Figure 1](image_url)

Figure 1. The Process of Calculating the Composition of Sentiments Against a Topic

2.2. Calculation of Sentiment Composition from the History of Someone's Utterance
The calculation of the composition of sentiments from the history of one's utterances is a process to calculate the number of positive, negative, and neutral sentiments of the person's utterance history. The provision is to determine the utterance of someone who has a positive sentiment among the majority of
negative sentiments and has more negative sentiment value than the positive sentiment from the collection of his utterances.

The next step is calculating the number of positive and negative sentiments. The provision is to calculate each percentage of positive and negative sentiments by means of the number of positive or negative sentiments divided by the total utterance and multiplied by 100 to form the measurement parameters.

2.3. Calculation of The Target Utterance Using Fuzzy

The calculation of the target’s utterance using fuzzy as shown by figure 2 below is a calculation to determine whether the target’s utterance has a positive sentiment value or is actually worth irony. Like the picture below (see Figure 2)

![Fuzzy Historical Classifier Diagram](image)

**Figure 2.** Detail Process of Fuzzy Historical Classifier

The provision is that the target utterance is a positive utterance from the majority of negative utterances on a topic, and the utterance of the target held by someone with utterance history is worth more negative sentiment compared to the value of the positive sentiment.

The series of fuzzy historical classifier processes start from determining the value of the tendency of the utterance history of a person based on the input generated from the calculation. After that 3 input variables were made, namely Ineg (negative input), Inet (neutral input), Ipos (positive input). Then three membership functions are made, namely low, medium, high.

The next step is the formation of fuzzy rules that will determine the results of the series of fuzzy steps. These rules are formed to express the relation between input and output variables from the results of the set formation process. Where each rule is an implication. The rules made are a series of possibilities or probabilities of combining the three input variable conditions based on the three membership functions, resulting in 27 rules for this step. And here are the rules made to calculate the value of the historical tendency of this utterance.
3. Results and Discussion
Tests in this study use data sourced from Twitter's social media called Tweets using the crawling method to make it easier to find utterances on the same topic and also collect the history of one's utterance[8-9]. The amount of data used is 1000 Tweets for utterance on a topic and someone's utterance history[10]. The testing process in this study is no longer through the sentiment analysis stage where each sentiment is analyzed by sentiment, but this study is assumed to have passed the sentiment analysis phase with the best method and obtained the results of the sentiment analysis process which is labeled as a number[11].

3.1 Results of the Data Model Testing of Sentiment Analysis on a Topic.
At this stage, simple mathematical calculations are carried out by means of the number of negative sentiments minus the number of positive sentiments[12]. The data model used for this stage is a topic where have a negative comment is higher than a positive comment[13]. Table 1 shows the results obtained from testing the data model in the sentiment analysis of a topic. Like the table below (Table 1)

Table 1. Test Result Data Model for Calculation of Sentiment Composition on a Topic

| Topic Name | Negative Sentiment (Pcs) | Positive Sentiment (Pcs) | Sentiment Difference |
|------------|--------------------------|--------------------------|---------------------|
| Topic A    | 900                      | 100                      | 800                 |
| Topic B    | 800                      | 200                      | 600                 |
| Topic C    | 700                      | 300                      | 400                 |
| Topic D    | 600                      | 400                      | 200                 |

3.2 Results of Analysis Sentiment Utterance Historical Data
Table 2 shows the results obtained from testing the data model in the analysis of one's utterance history sentiment using fuzzy [14]. Like the table below (Table 2):

Table 2. Test Results Data Model Calculation of Sentiment Percentage of Utterance History

| Negative Sentiment (Percent) | Neutral Sentiment (Percent) | Positive Sentiment (Percent) | Value of Tendency |
|------------------------------|-----------------------------|------------------------------|------------------|
| 90                           | 0                           | 10                           | -65.6            |
| 80                           | 10                          | 10                           | -61.6            |
| 70                           | 20                          | 10                           | -61.6            |
| 60                           | 30                          | 10                           | -61.6            |
| 50                           | 40                          | 10                           | -65.6            |
| 40                           | 50                          | 10                           | -65.6            |
| 50                           | 20                          | 30                           | -42.8            |
| 40                           | 40                          | 20                           | -55.8            |
| 40                           | 30                          | 30                           | -42.8            |
| 30                           | 50                          | 20                           | -17.2            |

The results obtained in this step have a varied value, but the polarity tends to be similar because the unit used as a comparison between sentiments is a multiple of 10 [15]. If the results obtained from the testing process of this data are negative numbers, the level of historical tendency of the person's utterance is negative [16]. And vice versa if the results obtained from the testing process of this data are positive numbers, then the value of the level of historical tendency of the utterance of the person is positive.
3.3 Results of Data Model for Targeting Utterance

Table 3 shows the results obtained from the test of utterance calculations, which are thought to mean irony using fuzzy. Like the table below (Table 3):

| Utterance | Sentiment Difference of a Topic | Value of Tendency | Potential Value of Irony |
|-----------|--------------------------------|------------------|--------------------------|
| Utterance 1 | 800                             | -72.6            | 59.8                     |
| Utterance 2 | 600                             | -72.6            | 56.8                     |
| Utterance 3 | 400                             | -72.6            | 53.2                     |
| Utterance 4 | 200                             | -72.6            | 47.3                     |
| Utterance 5 | 800                             | -69.4            | 58.4                     |
| Utterance 6 | 600                             | -69.4            | 57.4                     |
| Utterance 7 | 400                             | -69.4            | 54.5                     |
| Utterance 8 | 200                             | -69.4            | 44.5                     |
| Utterance 9 | 800                             | -29.1            | 54.4                     |
| Utterance 10| 600                             | -29.1            | 44.5                     |
| Utterance 11| 400                             | -29.1            | 44.5                     |
| Utterance 12| 200                             | -29.1            | 40.3                     |
| Utterance 13| 800                             | -14.9            | 42.3                     |
| Utterance 14| 600                             | -14.9            | 26.9                     |
| Utterance 15| 400                             | -14.9            | 26.9                     |

Based on Table 3, it shows that the greater the value of the difference between negative and positive sentiments in a topic and the greater the level of the negative tendency of one's utterance history, the greater the positive utterance has the potential to be irony[7]. Both of these variables are formed to meet each other the criteria determined by fuzzy rules. Where the form of the criteria is the number of sentiment differences on a topic that has more negative comments than positive comments and the value of the historical tendency of someone whose utterance is negative is more than the number of utterances is positive.

4. Conclusion

Based on the testing of the research that has been conducted, some conclusions can be drawn from the technique of detecting irony sentences using this Fuzzy Historical Classifier. This research provides a new approach to the scientific field of sentiment analysis especially in the detection of irony sentences. With the use of fuzzy in this study, it is able to determine the value of the historical tendency of the utterance of someone who has a positive and negative meaning; the value is similar.
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