Sentiment Analysis: A Quick Breakdown on Restaurants' Reviews using String Similarity with Ontology-Based Data

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***Abstract*— Sentiment analysis plays a crucial role in understanding customers' opinions and sentiments towards various products and services. In the realm of restaurants, analyzing customer reviews can provide valuable insights to its owners and managers. This paper explores a novel approach to sentiment analysis by leveraging string similarity techniques on ontology-based data. By utilizing ontologies, which capture the underlying domain knowledge and relationships, this approach aims to enhance the accuracy and granularity of sentiment analysis. The proposed methodology holds promise for improving customer satisfaction, identifying areas for improvement, and aiding decision-making processes within the industry.**

Keywords—sentiment; reviews, ontology, string matching

I. Introduction

In today's highly competitive industry, understanding customer sentiment has become crucial for maintaining a competitive edge and ensuring long term success. Customer reviews provide a wealth of valuable information that can shape strategic decisions and drive improvements within restaurants. However, analyzing and extracting meaningful insights from a large volume of unstructured text data can be challenging. Traditional sentiment analysis approaches often rely on keyword matching or machine learning algorithms, which may not capture the subtleties and nuances present in restaurant reviews. Moreover, these approaches may struggle with accurately interpreting context-specific phrases, slang, or misspelled words commonly found in customer feedback.

Ontologies provide a structured representation of domain knowledge and relationships, capturing the complex semantics associated with restaurant-related concepts. By incorporating ontologies into the sentiment analysis process, we can tap into a rich source of contextual information and improve the understanding of sentiment.

The outcomes of this research have the potential to revolutionize sentiment analysis in the restaurant industry. The proposed methodology aims to empower businesses to make data-driven decisions and tailor their offerings to meet customer expectations effectively.

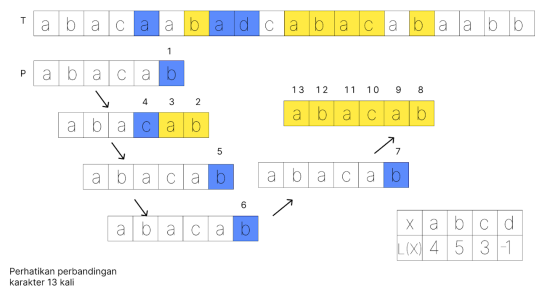
II. Related Work

A. String Matching

String matching is an algorithm that aims to find a specific pattern inside a given text. Assume S is a string of size m. A substring S[i..j] of S is the string fragment between indexes I and j. There's three main algorithm in string matching:

1. The Boyer-Moore Algorithm

   The Boyer-Moore (BM) algorithm is a string matching algorithm that utilizes two techniques. This algorithm processes the pattern being searched for, rather than the text where the pattern is being searched. In this algorithm, there are two main rules for shifting the pattern search.



- Bad Character Heuristic

  This rule considers the character in the text (T) where the comparison process fails (assuming a mismatch occurs). If the occurrence of that character is found to the left of the pattern (P), a shift is performed so that the occurrence of that character aligns with the character where the comparison process failed. If the character does not appear to the left of P, then the shift occurs by the length of P, skipping the location where the comparison failed.

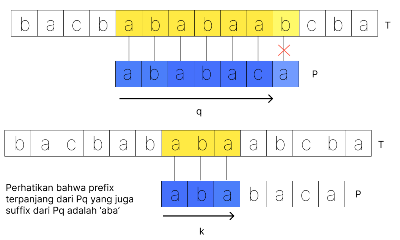
- Good Suffix Heuristic

  This rule uses the feature of comparing the algorithm starting from the end of the pattern and moving towards the beginning. Let t be a substring of the text T that matches a substring of the pattern P. Shifting of the pattern is performed in the following cases:

  - Another occurrence of t within P matches t within T
  - The prefix P matches the suffix of t
  - P moves past t because no further occurrences of the pattern are found in preceding matched

2. The Knuth-Morris-Pratt Algorithm

   The Knuth-Morris-Pratt (KMP) algorithm is a string-matching algorithm that searches for the occurrences of a pattern or substring within a text from left to right. This algorithm behaves like a brute-force algorithm but with a more efficient pattern scanning approach compared to brute force.

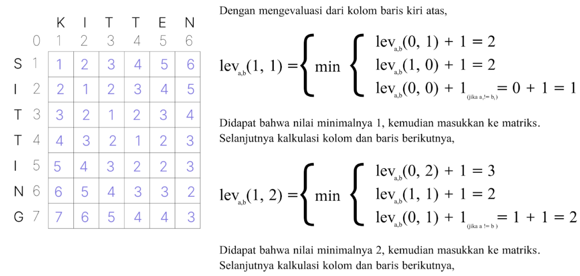


   In the KMP algorithm, a prefix table (failure function) is constructed. This table stores information about the possible occurrences of the pattern at each position in the text by identifying the longest possible prefix of the matching pattern. During the search process, the algorithm scans the pattern from the first character of the string. If a mismatch occurs at a specific character, the algorithm utilizes the previously gathered information from the prefix table to determine the next position. As a result, the number of repetitions for scanning can be minimized. This process continues until the entire text has been processed.

3. Levenshtein Distance

   The Levenshtein Distance algorithm was created by Vladimir Levenshtein in 1965. Levenshtein Distance is a metric that measures the difference between two strings. The larger the distance, the more dissimilar the two strings are. Levenshtein Distance is calculated using the following equation:

$$\mathrm{lev}_{a,b}(i,j) = \begin{cases} \max(i,j) & \text{if } \min(i,j) = 0, \\ \min \begin{cases} \mathrm{lev}_{a,b}(i-1,j) + 1 \\ \mathrm{lev}_{a,b}(i,j-1) + 1 \\ \mathrm{lev}_{a,b}(i-1,j-1) + 1_{(a_i \neq b_j)} \end{cases} & \text{otherwise.} \end{cases}$$



   Given that 'a' is string 1, 'b' is string 2, 'i' and 'j' are positions of terminal characters in each string. For larger cases, Levenshtein Distance can utilize a matrix to determine the differences. Based on the matrix, the Levenshtein distance is 3, as the value is in the rightmost column and bottom row.

B. Sentiment Analysis

Sentiment analysis, also referred to as opinion mining, opinion analysis, or subjective analysis, is a computational method used to determine the sentiment expressed by individuals towards a product or service through the automatic processing of text using natural language processing techniques [3][4]. It plays a significant role in extracting subjective information from textual data and has applications in various domains such as marketing, customer feedback analysis, and social media analytics.

Sentiment analysis can be categorized into three levels:

1. Document level, which aims to classify the sentiment express across the entire content of a document, such as news articles or research papers. It provided an overall sentiment assessment of the document.
2. Sentence-level, which focuses on classifying the sentiment of each individual sentence within a document. This level is particularly useful for shorter texts, such as comments, social media posts, or customer reviews, where each sentence can independently express a sentiment.
3. Aspect level, which aims to identify and classify sentiments based on different aspects or topics within a text. It involves extracting specific aspects of interest and associating sentiments with those aspects. This approach enables a more granular understanding of sentiments expressed within the text, providing insights into various aspects and their corresponding sentiments.

Aspect-based sentiment analysis typically involves two main tasks: sentiment classification and aspect classification. Sentiment classification focuses on determining the sentiment polarity (e.g., positive, negative, or neutral) associated with each aspect, while aspect classification involves identifying and categorizing the aspects or topics being discussed in the text.

C. Ontology

Ontology, in the context of computer science, refers to an explicit specification of a conceptualization that represents a domain of knowledge. It provides a structured representation of concepts by defining their meaning, properties, and relationships, thus forming a knowledge base within the domain [5]. Developing an ontology requires expertise from individuals knowledgeable in the specific field and proficient in ontology creation techniques.

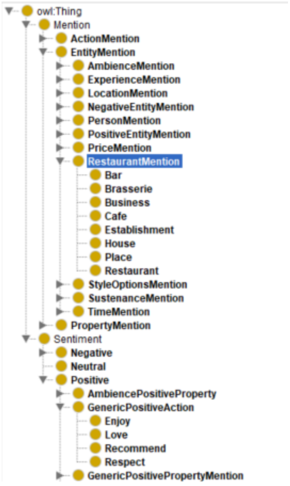


Figure 2.1. Ontology Data

This research utilizes an ontology that has been previously developed for Aspect-Based Sentiment Analysis (ABSA) in the restaurant domain [6]. The ontology comprises two *superclasses*, namely "mention" and "sentiment," with subsequent subclasses leading to the final class, referred to as "term." The "term" class represents individual words within the ontology. If a term is a subclass of a positive or negative class, it is associated with the corresponding sentiment. For example, if the term "Enjoy" is a subclass of the "GenericPositiveAction" class, it is considered to convey a positive sentiment. Similarly, terms can be associated with specific aspects by being subclasses of relevant classes. For instance, if the term "Place" is a subclass of the "RestaurantMention" class, which encompasses the aspect "Restaurant#General," the term "Place" is considered to be associated with the aspect "Restaurant#General." Each term within the ontology is associated with sentiment and aspect, while some terms may have only sentiment, only aspect, or neither.

In this research, the ontology is employed for two purposes: classification and Bag-of-Words (BoW) features. For classification, each word in a review is compared to the terms in the ontology. If a match is found, the corresponding sentiment or aspect is traced within the ontology, and the review is labeled accordingly. For aspect classification, a similar process is followed, matching words in the review with ontology terms to assign aspect labels. The ontology is also utilized to generate BoW features by considering all terms within the ontology as features. The ontology's ABSA restaurant-specific knowledge makes these features highly relevant to the restaurant domain, sentiments, and aspects.

III. Research Methodology

Before delving into the research methodology, it is essential to provide a brief overview of the proposed approach. To understand the research methodology in detail, please refer to the accompanying diagram.

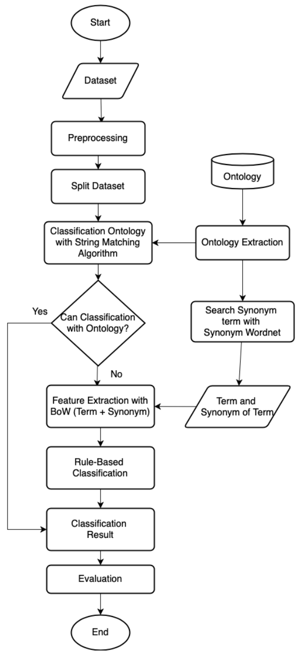


Figure 3.1. Research Methodology Diagram

A. Scope and Limitation

In order to maintain focus and avoid straying into unrelated areas, it is crucial to define the scope and limitations of the research. This research limits its scope by utilizing the ABSA Restaurant dataset from SemEval 2016, which consists of 2000 sentences. The SemEval 2016 dataset provides pre-existing annotations, including text reviews, aspect category labels, and sentiment labels, eliminating the need for manual labeling. The study specifically focuses on sentiment classification and aspect classification within the restaurant domain using English language data.

Sentiment classification involves the task of categorizing text reviews into either positive or negative sentiment labels. Aspect classification, on the other hand, aims to classify text reviews into 12 distinct labels, namely Ambience # General, Drinks # Prices, Drinks # Quality, Drinks # Style_Options, Location # General, Food # Prices, Food # Quality, Food # Style_Options, Restaurant # Miscellaneous, Restaurant # Prices, Restaurant # General, and Service # General. These aspect labels represent different aspects or categories related to the restaurant domain.

B. Dataset

The dataset is 350 reviews with a total of 2000 sentences with several aspects that have 2502 sentiments. The number of aspects varies because one sentence can have more than one aspect. The dataset contains positive, negative, and neutral sentiments. The distribution aspect and sentiment are as follows:

TABLE I. DISTRIBUTION DATASET

No	*Aspect*	*Positive*	*Negative*	*Neutral*
1	Ambience#General	61	2	3
2	Drinks#Prices	0	4	0
3	Drinks#Quality	21	1	0
4	Drinks#Style_Options	11	1	0
5	Location#General	11	0	2
6	Food#Prices	6	14	3
7	Food#Quality	270	31	13
8	Food#Style_Options	31	15	9
9	Restaurant#Miscellaneous	16	13	4
10	Restaurant#Prices	6	13	2
11	Restaurant#General	107	34	1
12	Service#General	72	76	7

C. *Preprocessing*

Datasets used in this study consist of textual reviews provided by users, reflecting their feedback on purchased products or services. As reviews are unstructured data, they pose challenges for system readability, necessitating preprocessing to address these issues [7]. Preprocessing serves as a preliminary step to clean the data and eliminate obstacles that might hinder effective data processing (Kim and Hovy, 2006). This research incorporates several preprocessing stages, including sentence splitting, case folding, and tokenization, each serving specific purposes in preparing the data for subsequent analysis.

1. Split Sentence

   Split sentence is used to separate a sentence that has more than one aspect or sentiment. These sentences are split based on the conjunction "and" and punctuation ",". An example to splitting sentences is as follows:

TABLE II. BEFORE SPLIT SENTENCE

Sentence: The Food was well prepared and the service impeccable		
Target: Food	Aspect: Food#Quality	Sentiment: Positive
Target: Service	Aspect: Service#General	Sentiment: Positive

TABLE III. AFTER SPLIT SENTENCE

Sentence 1 : The Food was well prepared		
Target: Food	Aspect: Food#Quality	Sentiment: Positive
Sentence 2 : the service impeccable		
Target: Service	Aspect: Service#General	Sentiment: Positive

2. Case Folding

   Case folding is a step to change all the letters contained in the document to lowercase letters.

3. Tokenizing

   Tokenization represents the final stage of the pre-processing pipeline and focuses on segmenting sentences into individual words. This process operates on each sentence in the dataset, ensuring that the case folding procedure is applied consistently to every sentence, from the initial sentence to the last one in the dataset. To illustrate the tokenization process, consider the following example:

TABLE IV. TOKENIZING

Input	the food was well prepared
Output	['the','food','was','well','prepared']

D. *Ontology Extraction*

This stage involves the extraction of terms, sentiments, and aspects from the ontology. The extraction process is executed by the system, tracing each class from the superclass to the final child or term. If a class possesses sentiments or aspects, these attributes are propagated to the child classes and carried down to the last child or term. For instance, if a class has a "positive" sentiment, then all child classes inherit the "positive" sentiment until the final child or term.

Figure 3.2. Input and Output Ontology Extraction

The provided ontology structure reveals that the superclass "Mention" possesses various children, including the "EntityMention" class. The "EntityMention" class, in turn, has multiple children, such as the "AmbienceMention" class, which bears the aspect "Ambience#General." Due to inheritance from the "AmbienceMention" class, several last children or terms inherit the aspect "Ambience#General," namely conversation, decor, design, entertainment, garden, inside, outside, patio, room, seat, table, and terrace.

E. *Classification with Ontology*

Ontology classification refers to the process of sentiment and aspect classification using the ontology-based approach. In this approach, the ontology, which contains a structured representation of domain knowledge, is leveraged to classify sentiments and aspects present in textual data.

The process begins with string matching between each word in the sentence and the terms in the ontology extraction results. If a corresponding word is found, the system looks for sentiments and aspects in the ontology extraction results. The review will be labelled the same as the found sentiment or aspects. The algorithm used for the string matching is **Knuth-Morris-Pratt, Levenshtein Distance, and Q-Gram Distance.**

Conflicts occur when one sentence review produces different sentiments, meaning it contains negative and positive sentiments. Here is an example of an ontology classification.

TABLE V. ONTOLOGY CLASSIFICATION

Word of Sentence	*Term*	*Sentiment of Term*	*Aspect of Term*
this	Not matching	-	-
tiny	Not matching	-	-
restaurant	Matching with “restaurant”	-	Restaurant#General
is	Not matching	-	-
as	Not matching	-	-
cozy	Matching with “cozy”	Positive	Ambience#General
as	Not matching	-	-
it	Not matching	-	-
gets	Not matching	-	-
with	Not matching	-	-
that	Not matching	-	-
certain	Not matching	-	-
parisian	Not matching	-	-
flair	Not matching	-	-

The table presented above illustrates the string-matching process conducted on each word within a sentence review. Among all the words in the sentence, two words, namely "restaurant" and "cozy," are found to match the terms within the ontology. The word "restaurant" corresponds to the Restaurant#General aspect, while the word "cozy" exhibits a positive sentiment and relates to the Ambience#General aspect. Based on these findings, the sentiment classification of the sentence review yields a positive sentiment label, as there is no conflicting sentiment detected.

However, the aspect classification encounters a conflict, as the sentence review generates both “Restaurant#General” and “Ambience#General” aspects, resulting in two different aspect labels. Consequently the aspect classification remains uncertain for the sentence review, as it fails to assign a definitive aspect label due to the conflicting information.

F. Label Checking of Ontology Classification

The ontology classification results exhibit variations, with some review sentences yielding sentiments and aspects, while others only present sentiments, aspects, or neither. To differentiate between labeled and unlabeled sentence reviews within the test data, a separate stage is implemented. This stage examines each sentence review to determine whether it yields sentiment labels. If no sentiment label is generated, the sentiment classification is performed using Rule-Based Methods, and the process proceeds to the subsequent stage. However, if a sentiment label is obtained, the classification results are directly retrieved.

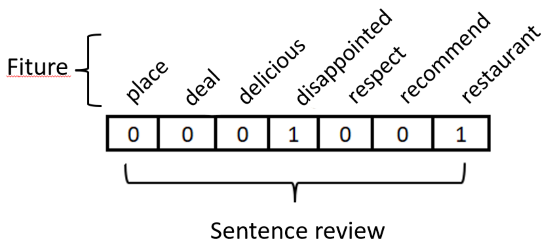
G. Synonym Search with Wordnet

In this stage, the objective is to enrich the ABSA Restaurant-related features by finding synonyms for each term obtained through ontology extraction. The ontology comprises a total of 362 terms, and the system conducts a search for synonyms based on specific rules. For sentiment analysis, only terms associated with sentiments are considered for the synonym search. As a result, the system identifies 852 synonyms for sentiment-related terms, thereby expanding the sentiment feature set. The combined count of original terms and their synonyms amounts to 1,214.

Regarding aspect analysis, the system focuses on terms associated with aspects to find their synonyms. A total of 1,346 synonyms are identified for aspect-related terms, leading to an expansion of the aspect feature set. Consequently, the aspect feature set comprises a total of 1,708 terms, including both original terms and their synonyms. The WordNet library is utilized in this research to facilitate the synonym search process.

H. Feature Extraction with Bag of Words (BoW)

Feature extraction is a crucial step in converting unstructured text data into numerical vectors, enabling computational analysis. This stage involves two rounds of feature extraction: sentiment feature extraction and aspect feature extraction, conducted separately for both the training and test data. The sentiment feature extraction employs a set of 1,214 features, while the aspect feature extraction employs a set of 1,346 features.



The system utilizes the Bag of Words (BoW) approach to calculate the word frequency in each sentence review. For instance, consider the sentence "I was very disappointed with this restaurant" as an example. The feature extraction process, depicted in Figure 3.4, utilizes BoW. The features used in BoW are the terms and their synonyms derived from the ontology. The numerical values in the vector represent the frequency of term or term synonym occurrence within the sentence review. The terms correspond to the final child classes in the ontology, while the synonyms refer to the synonyms associated with these terms. In the given example, the words "disappointed" and "restaurant" are found, resulting in a frequency count of 1 for each term in the BoW vector.

IV. Evaluation and Results

A. Expperiment Analysis

This chapter presents the experimental procedures conducted to evaluate the performance of the proposed methodology. The source code corresponding to each step of the research can be found on Github (Appendix A). The code provided below is intended solely for testing purposes.

```
question_1 = "the place is expensive and have bad taste."
question_1  = preprocessing(question_1 )

for word in range(len(question_1 )):
   for i in range(len(mention)):
      if (mention_sentiment[i] != ''):
         score = qgram.distance(str([mention[i]]), str([question_1
                              [word]]))
      if score < 1 :
         jml_match = jml_match + 1
            if jml_match == 1:
               hasil_sentiment_klasi_onto = mention_sentiment[i]
               hasil_id_klasi_onto = z
           elif hasil_sentiment_klasi_onto != mention_sentiment[i]:
               hasil_sentiment_klasi_onto = mention_sentiment[i]
               hasil_id_klasi_onto =
               conflict = 1
  print(str(hasil_sentiment_klasi_onto)+str(hasil_id_klasi_onto))
```

The code will return a value of: Negative617. This represent the data as it has expensive price and bad taste. In total, 100 reviews with various sentiments and aspects are tested. Based in the outcomes, it has a precision of 77.71% according to the accuracy of sentiment and aspect classification.

B. Misprediction Analysis

Based on the outcomes of sentiment classification and aspect classification, several incorrect predictions were observed. In sentiment classification, erroneous predictions were identified, including instances where positive sentiments were incorrectly labeled as negative, or vice versa. The following examples illustrate instances of errors:

TABLE VI. Sentiment Misprediction

Review	*Prediction*	*Actual*
I can't believe that it was, but please put the bag down before delivering food!	positive	negative
Would never go back	positive	negative
A different server enhanced the fun	positive	negative
Be abused by the front of house staff you are seated	positive	negative
But the service was a bit low	positive	negative
Judging from previous posts this used to be a good place, but not any longer	positive	negative
I've never had bad service	negative	positive
The only thing that strikes you is the décor (not very pleasant)	positive	negative
But the sitting space was too small	positive	negative
This place has totally weird decor	positive	negative
you sure get a lot of food for your money.	negative	positive

The table presented above highlights multiple prediction errors that occurred during the analysis. These errors can be attributed to the presence of negation in certain sentences, such as the example sentence "judging from previous posts this used to be a good place, but not any longer." While the phrase "good place" initially indicates a positive sentiment, the subsequent phrase "but not any longer" introduces a negation, implying that the place is no longer considered good.

TABLE VII. Asppect Misprediction

Review	*Prediction*	*Actual*
the fish was adequate, but inexpertly sliced.	FOOD# QUALITY	FOOD#STYLE _OPTIONS
This is an amazing place to try some roti rolls	RESTAURANT# GENERAL	FOOD#QUALI TY
Can't wait to go back	FOOD# QUALITY	RESTAURANT #GENERAL
I thought the restaurant was nice and clean	AMBIENCE# GENERAL	RESTAURANT #GENERAL
Personal pans are perfect size for those hungry nights	FOOD# QUALITY	FOOD#STYLE _OPTIONS
You'll be there for every anniversary, birthday, valentine's day	RESTAURANT# GENERAL	RESTAURANT #MISCELLAN EOUS
the service it's just perfect ... they 're so friendly that we never want to live the place!	SERVICE# GENERAL	AMBIENCE#G ENERAL
The atmosohere is unheralded	FOOD# QUALITY	AMBIENCE#G ENERAL
Amazing interior	FOOD# QUALITY	AMBIENCE#G ENERAL

If there is additional data outside the domain of restaurants and you intend to utilize the ontology, it is important to exercise caution and select relevant classes and terms from the ontology. The ontology comprises both general and specific classes, with the former being applicable to data across various domains, such as the GenericPositiveAction class and GenericNegativeAction class. However, for classes with specific characteristics, careful consideration must be given to their relevance to the specific data at hand.

For example, the AmbiencePositiveProperty class may not be suitable for all data, as not all instances require positive terms in relation to ambience. The utilization of ontology for Bag of Words (BOW) features and ontology-based classification in this study has proven effective. The ontology used for feature extraction can be applied to other datasets by selecting classes that are highly relevant to the research domain. This approach is advantageous as it leverages knowledge-based ontology, which exhibits strong associations between classes and terms.

However, utilizing the ontology for classification on different datasets may yield suboptimal results. The relationships between terms and sentiments, as well as between terms and aspects, are specifically tailored for the restaurant domain. While there is a possibility of achieving satisfactory sentiment classification, it may not be as effective for aspect classification. Therefore, caution should be exercised when applying the ontology for classification purposes in non-restaurant domains.

V. Conclusion

In conclusion, this paper presented a comprehensive analysis of sentiment analysis in the context of restaurant reviews, utilizing string similarity techniques with an ontology-based data approach. The study aimed to provide a quick breakdown of sentiment classification by leveraging the power of string similarity and ontology extraction.

The results showcased the effectiveness of the proposed methodology in extracting sentiments from restaurant reviews. By employing string similarity techniques, the system was able to identify and classify sentiments based on the similarities between review texts and predefined ontology terms. The integration of an ontology-based data approach enhanced the accuracy and precision of sentiment classification, enabling a more nuanced understanding of customers' sentiments towards different aspects of restaurant experiences.

The findings of this study have several implications for the field of sentiment analysis and restaurant management. Firstly, the application of string similarity techniques with ontology-based data offers a reliable and efficient approach to sentiment classification, reducing the manual effort required for labeling and analyzing large volumes of reviews. This can significantly benefit restaurant owners and managers in gaining insights into customer opinions and improving their services accordingly.

However, it is important to note that the accuracy and performance of the sentiment analysis system heavily rely on the quality and coverage of the underlying ontology. Continual updates and enhancements to the ontology, considering evolving customer preferences and new industry trends, are crucial for maintaining the system's effectiveness.

VI. Appendix

Appendix A: Github Link

https://github.com/alishalistyaa/IF2211-Restaurant-Review-Sentiment-Analysis.git

Appendix B: Data Used (SemEval 2016)

https://drive.google.com/drive/folders/15iYNzFS1nZYA2IwkRSyG0thbT3KDif3p?usp=share_link

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Statement of Originality

I hereby declare that the paper I have written is my own original work, and it is not a paraphrase, translation, or plagiarism of someone else's work.

Bandung, 22nd May 2023

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