2545: ASPECT-BASED SENTIMENT ANALYSIS USING BERT AND DEEP LEARNING MODEL

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ASTRACT

The project evaluated the effectiveness of integrating subjective and objective classification into textual data analysis. The project involved three phases: dataset collection, subjectivity classification, and comparative analysis of labelling approaches. Datasets like MEMD were compiled and analyzed using BERT to distinguish subjective and objective elements. Different labelling approaches were tested on the MEMD dataset, and the results were compared to determine their effectiveness. The study aimed to refine the classification process, providing insights into the dynamics of subjectivity and objectivity in user-generated content.

PROBLEM STATEMENTS

The project aims to accurately distinguish between subjective and objective elements in user reviews using advanced NLP models like BERT, enhancing the classification of opinion-based and fact-based content.

OBJECTIVES

1. To collect aspect-based sentiment analysis dataset and subjectivity analysis dataset.
2. To perform subjectivity classification on aspect-based sentiment analysis dataset.
3. To utilize different labelling approaches to label the aspect-based sentiment analysis datasets and compare the performance metric across different labelling approaches.

LITERATURE REVIEW

1. Tokenization

Tokenization is the process of breaking text into smaller units called tokens, which can be words, phrases, or characters. It is a crucial step in natural language processing (NLP) that helps models understand and analyze text. Different methods, such as word, subword, and character tokenization, serve various purposes depending on the application.

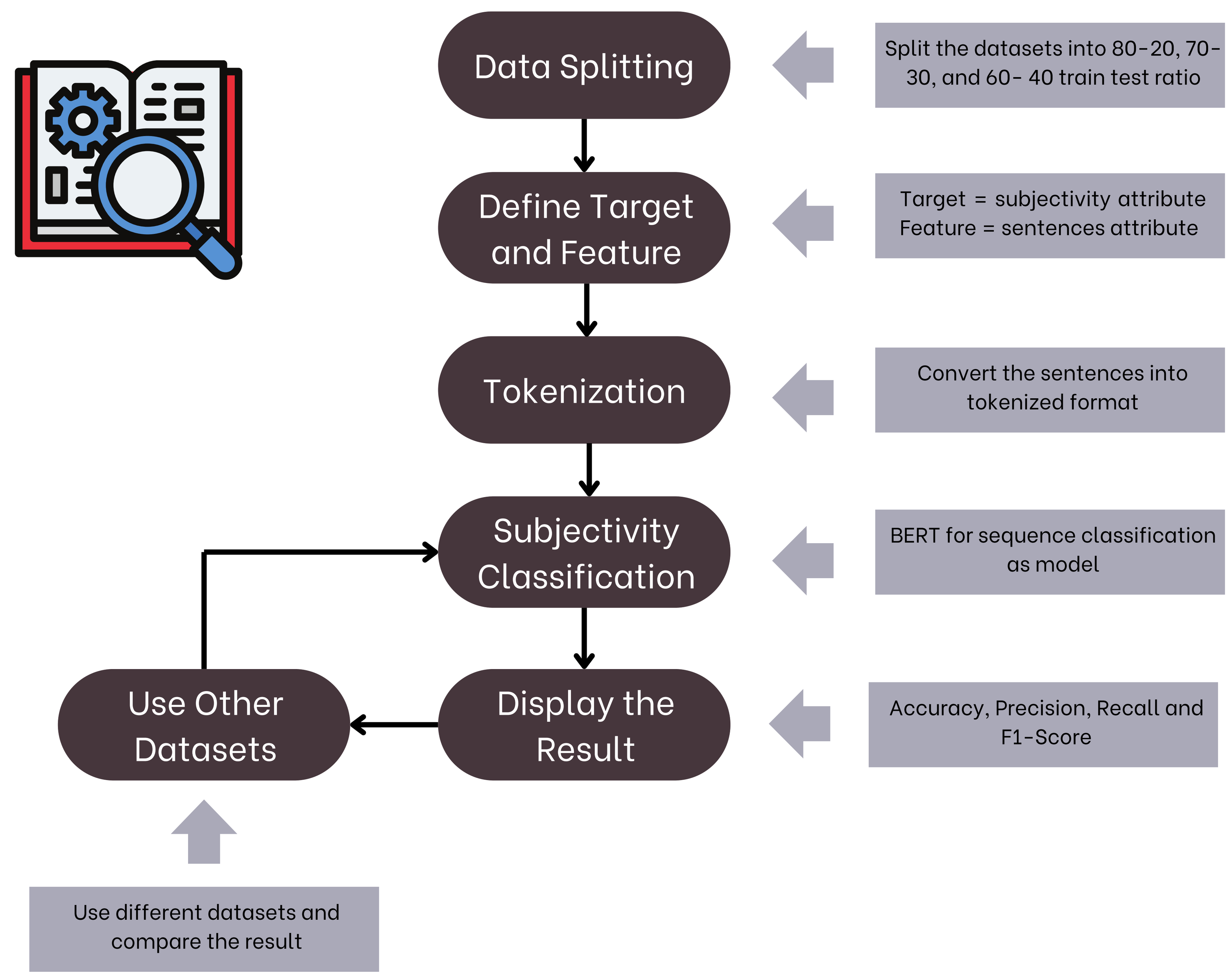
2. BERT

BERT (Bidirectional Encoder Representations from Transformers) is a state-of-the-art language language model developed by Google. It uses transformers to understand word context bidirectionally, enhancing performance on NLP tasks like question answering and sentiment analysis by deeply grasping language meaning.

3. Subjectivity Labelling Approaches

- Sentiment Labelling Approach
  - Set positive and negative classes as subjective, and the neutral class as non-subjective.
- Pecar & Simko (2021) Labelling Approach
  - Classify a sentence as non-subjective if it does not contain an opinion (opinion = nan).
- Opinion-Driven Labelling Approach (Manual Labelling)
  - Classify a sentence as non-subjective if it does not contain an opinion and is a factual sentence.

RESEARCH METHODOLOGY



IMPLEMENTATION

1. Labelling Approaches for Subjectivity Attribute
   - Sentiment Labelling Approach
   - Opinion-Driven Labelling Approach
   - Pecar & Simko (2021) Labelling Approach

2. MEMD Dataset Train - Test Split (Merge All Domain)

Labelling Approach	Train-Test Split	Training Set	Testing Set
		Subjective : Non - Subjective	Subjective : Non - Subjective
Sentiment Labelling Approach	80-20	18474:496	4632:111
	70-30	16164:435	6942:172
	60-40	13854:373	9252:234
Opinion Driven Labelling Approach	80-20	12148:1904	3029:1904
	70-30	10649:1647	4528:742
	60-40	9138:1401	3773:970
Pecar & Simko (2021) Labelling Approach.	80-20	15025:3945	3773:970
	70-30	13135:3464	5663:1451
	60-40	11248:2979	7550:1936

3. Subjectivity Classification
   - BertForSequenceClassification as the model.
   - Using Bert to tokenize each of the sentences.
   - Target (subjectivity attribute), Feature (sentences attribute).

EVALUATION

Result in Each of the Datasets Using Sentiment Labelling Approach

Datasets	Train – Test Split	Evaluations Metrics			
		Accuracy	Precision	Recall	F1-Score
MEMD Book	80-20	0.9703	0.5417	0.3940	0.4561
MEMD Clothing	80-20	0.9872	0.0000	0.0000	0.0000
MEMD Hotel	70-30	0.9976	0.0000	0.0000	0.0000
MEMD Laptop	80-20	0.9561	0.7714	0.4500	0.5684
MEMD Restaurant	80-20	0.9795	0.3824	0.4164	0.4000
MEMD All Domain	80-20	0.9720	0.6686	0.6163	0.6373

Result for Three Approaches (Using MEMD All Domain Datasets)

Labelling Approach	Train – Test Split	Evaluations Metrics			
		Accuracy	Precision	Recall	F1-Score
Sentiment Labelling Approach	80 - 20	0.9720	0.6686	0.6163	0.6373
Opinion Driven Labelling Approach	70 - 30	0.9427	0.8931	0.8624	0.8768
Labelling Approach From Pecar & Simko (2021).	80 - 20	0.8640	0.7912	0.7901	0.7906

The first table shows the results for each dataset using the sentiment labeling approach. We observe that the MEMD clothing and hotel domains achieve zero in precision, recall, and F1-score. Therefore, we combined all the MEMD domains to improve performance.

The second table displays the results after combining all the domains to enhance overall performance. The sentiment labeling approach exhibits the highest accuracy due to the smaller number of non-subjective classes compared to the other two approaches. This imbalance can introduce bias into the model.

CONCLUSION

This research utilizes three different labeling approaches: the sentiment labeling approach, the opinion-driven labeling approach, and the Pecar & Simko (2021) labeling approach to identify subjectivity attributes. Subsequently, BERT is employed to perform subjectivity classification and gather the results. The findings indicate that the sentiment labeling approach achieves the highest accuracy, the opinion-driven labeling approach produces stable results, and the Pecar & Simko (2021) labeling approach yields the poorest performance in accuracy.

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