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Natural Language Processing Models For Sentiment Analysis And Opinion Mining Using Contextual Embeddings

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Abstract

Sentiment analysis and opinion mining are the essential activities of natural language processing (NLP) that retrieve subjective textual information. Conventional methods that rely on lexicon searches and fixed word embeddings do not generalise to polarity changes based on the context. This paper gives an in-depth analysis of contextual embedding models such as BERT, RoBERTa, and XLNet as used to sentiment classification and fine-grained opinion mining. We suggest a hybrid design that combines multi-head self-attention with domain-adaptive fine-tuning to deal with negation, sarcasm, and aspect-level sentiment. Our RoBERTa-based model obtains the state of the art results of 95.3% accuracy and 94.9% F1-score on four benchmark datasets (SST-2, IMDB, SemEval-2014, and Yelp), which is significantly higher than previous LSTM-based and fixed embedding models. We also present the studies of ablation and analysis of errors in order to outline the strong and weak sides of the suggested framework.

Keywords: Sentiment analysis, opinion mining, BERT, RoBERTa, contextual embeddings, transformer models, attention mechanism, aspect-level sentiment.

1. Introduction

Sentiment analysis, also known as opinion mining, is the computational science of opinions, sentiments and emotions conveyed in a piece of text. Due to the scandalous proliferation of social media platforms and e-commerce commentary and news on the internet, the amount of opinionated text has increased exponentially. Automated sentiment analysis can assist organisations to track brand image, understand opinion, and evidence-based decision-making by scale (Mäntylä et al., 2018).

The initial strategies made use of hand-created lexicons like SentiWordNet and VADER where the sentiment polarities of individual tokens are independently assigned without reference to the context. Although computationally efficient, these techniques are severely limited due to their inability to effectively exploit contextual changes of polarity due to negation, sarcasm or domain specific linguistic constructions. The conventional machine learning methods based on handcrafted features also had little capability of contextual understanding (Agarwal and Mittal, 2015). Distributed word representations like Word2Vec and GloVe enhanced the learning of semantic representations; but these representations were context-free since each word was represented by a fixed vector irrespective of the discourse.

The Deep learning models were introduced, which considerably enhanced the performance of sentiment classification since the detection of contextual features could be done automatically. Convolutional neural networks and recurrent neural structures proved to be more effective in acquiring semantic relations based on text (Cen and Zheng, 2020). Moreover, the application of a multilingual sentiment analysis frameworks (GRU and LSTM) demonstrated promising performance in English-Arabic and English-Urdu sentiment analysis applications (Abdelgwad et al., 2022; Altaf et al., 2023).

Later, Transformer-based contextual language models like BERT, RoBERTa, and XLNet set a new paradigm in the research of sentiment analysis based on dynamic bidirectional learning of contextual representation. Architectures based on attention enhanced much in terms of semantic semantic understanding and aspect-level sentiment differentiation (Lin et al., 2021; Huang et al., 2022). The pre-trained language models could be fine-tuned on domain-specific corpora to achieve state-of-the-art performance on a variety of benchmark datasets and sentiment analysis tasks on social media (Alshuwaier et al., 2022).

The paper introduces the Contextual Sentiment and Opinion Network (CSON), a Transformer-based model augmented with domain-adaptive pre-training, contextual learning with negation sensitivity, and aspect pooling with regard to the objectives of better sentiment analysis and opinion mining. The suggested framework is tested on a variety of benchmark datasets by using extensive experimental study, ablation studies, and error analysis to illustrate its efficiency in managing contextual polarity changes, aspect-wise sentiment reasoning, and fine-grained opinion mining problems.

2. Related Work

Their use in social media analytics, analysis of customer reviews, healthcare monitoring, and financial forecasting have made sentiment analysis and opinion mining significant research topics in the natural language processing field. Early sentiment analysis approaches were primarily based on classical machine learning algorithms along with hand designed linguistic and statistical features. As Agarwal and Mittal (2015) proved that machine learning algorithms can be successfully used to classify the sentiment based on the feature extraction methods and Han and Kim (2017) underlined the importance of morphological sentence patterns to enhance the sentiment recognition of social media data.

As multilingual content on the Web continued to expand, scholars started to pay more attention to language-specific sentiment analysis systems. Abdelgwad et al. (2022) suggested two-way GRU-based Arabic aspect-based sentiment analysis models and obtained more contextual insights into sentiment expressions. Alyami et al. (2022) conducted a systematic review of Arabic sentiment analysis approaches and highlighted the importance of deep learning techniques for handling complex linguistic structures. In the same way, the paper by Altaf et al. (2023) discussed the sentiment analysis at sentence level in the Urdu language through linguistic and multimedia-based representations.

Deep learning systems greatly enhanced the performance of sentiment analysis by allowing contextual feature extraction to be automatically performed. Cen and Zheng (2020) used the convolutional neural networks in sentiment classification and outperformed the conventional machine learning models. Baker et al. (2022) also applied deep learning models to the healthcare-related sentiment prediction of Twitter posts, and the study verified the ability of neural architectures to handle noisy social media text. Eliacik and Erdoğan (2015) further proposed user-weighted sentiment analysis to financial Twitter communities highlighting context-dependent user behavior in financial sentiment prediction.

Recent research has presented Transformer-based contextual embedding models capable of significantly enhancing the learning of semantic representations. Lin et al. (2021) created multi-head self-attention networks in aspect-based sentiment analysis and proved to have better contextual reasoning ability. Huang et al. (2022) included contextual position information on aspects within sentiment analysis systems to enhance the performance of fine-grained opinion mining. Furthermore, Nakov et al. (2016) presented the SemEval Twitter sentiment analysis benchmark that was widely used to evaluate sentiment classification systems.

Despite the remarkable advances that have been made by the existing studies, a number of issues are yet to be solved such as the handling of negations, interpreting sarcasm, and aspect-level contextual reasoning. Traditional models continue to have problems in effectively modeling contextual polarity changes and domain specific semantic relations. As such, the proposed Contextual Sentiment and Opinion Network (CSON) incorporates domain-adaptive pre-training, contextual learning that considers negations, and aspect-based pool of attention to enhance contextual sentiment understanding and fine-grained opinion mining.

3. Theoretical Background

3.1 Transformer Self-Attention

The transformer architecture replaces recurrence with a scaled dot-product attention mechanism that attends to all positions simultaneously. For an input sequence $X \in$ ℝ^{$n \times d$}, the model learns queries Q, keys K, and values V through linear projections:

$$Attention(Q, K, V) = softmax\left(\left(QK^T/\sqrt{d_k}\right) \odot G\right) \cdot V \_\_\_\_\_\_ (1)$$

where d_k represents the key dimension used as a scaling factor to stabilize training. This mechanism enables the model to learn contextual relationships and semantic dependencies between words within a sentence.

3.2 Contextual Embeddings via Masked Language Modelling

BERT learns contextual embeddings using Masked Language Modelling (MLM), where a portion of input tokens is randomly masked and predicted using surrounding context. For an input token sequence $= [x1, x2, \ldots, xn]]$, the MLM objective function is expressed as:

$$L_{MLM} = -\sum_{\mathrm{i} \in \mathrm{M}} \log \mathrm{P}(\mathrm{xi} \mid \mathrm{x} \setminus \mathrm{M}; \theta)$$

where M denotes the masked token positions, θ represents model parameters, and $x_{setminusM}$indicates the unmasked contextual sequence. This training strategy enables the model to generate context-aware semantic representations for sentiment analysis tasks.

3.3 Fine-Tuning for Sentiment Classification

The contextual embedding of the [CLS] token is utilized as the sentence-level representation in the case of sentiment classification. The probability of sentiment classification is calculated with the help of the softmax function:

$$P(y \mid x) = softmax(W_c h_{[CLS]} + b_c)$$

where W_c and b_c are trainable classification parameters, and $h_{[CLS]}$denotes the contextual embedding of the classification token.The model parameters are optimized using the cross-entropy loss function:

$$L_{CE} = \sum_{k=1}^{K} y_k \log \hat{y}_k$$

where y_k represents the true class label and $\hat{y}_k$ denotes the predicted probability for class k. This optimization process improves sentiment classification accuracy and generalization performance.

3.4 Aspect-Level Sentiment Analysis

For aspect-level sentiment analysis, an attention mechanism is employed to identify tokens relevant to a target aspect term. The aspect-aware attention weight is computed as:

$$\alpha_i = \frac{\exp(\varepsilon_i)}{\sum_{j=1}^{n} \alpha_i h_i}$$

where α_i represents the attention weight assigned to token i. The context vector is then calculated as the weighted sum of token embeddings:

$$c = \sum_{i=1}^{n} \alpha_i h_i$$

where h_i denotes the contextual embedding of token i. This mechanism enables the model to focus on aspect-specific opinion words and improves fine-grained sentiment prediction performance.

4. Proposed Model Architecture

4.1 Overview

The proposed Contextual Sentiment and Opinion Network (CSON) will enhance the contextual sentiment knowledge and fine-grained opinion analysis through Transformer-based deep learning architecture. The framework builds upon the RoBERTa-large framework by incorporating three key components, each: domain-adaptive continued pre-training, an auxiliary negation detection module, and an aspect-aware attention pooling mechanism. All these elements of these components contribute to better contextual semantic comprehension, sentiment polarity identification, and opinion mining behavior in multifaceted review data.

The general architecture starts with text preprocessing and tokenization, then it proceeds to generating contextual embedding with the RoBERTa encoder. The encoded representations are subsequently run through a negation handling auxiliary module to enhance the sentiment understanding in the polarity-shifting linguistic structures. Aspect-sensitive attention mechanism is also used to detect opinion-relevant context features in order to analyse sentiment on a fine-grained basis. Lastly, the refined contextual representations are sent to the sentiment classification layer to predict sentiments.

4.2 Domain-Adaptive Pre-Training and Negation Handling

In order to enhance the domain specific contextual knowledge, Domain-Adaptive Pre-Training (DAPT) is performed with RoBERTa-large model on large unlabeled review corpora data obtained on Amazon and Yelp datasets. Further masked language model pre-training allows the model to acquire domain-related semantic associations, contextual expressions, and sentiment-based linguistic patterns. This procedure decreases the discrepancy of distributions between the general language representations and the target-domain review datasets.

Correctness of negation expressions is one of the greatest issues of sentiment analysis, since polarity-inverting words tend to worsen prediction in traditional models. To overcome this shortcoming, a support negation identification unit is incorporated to the framework. The negation detection head determines if a token is within the negation cue scope and modulates feature representations contextually in the course of attention computations.

The contextual representation made modified is calculated as:

$$\hat{h}_i = h_i \odot (1 + \gamma n_i)$$

where h_i represents the original contextual embedding, n_i denotes the negation indicator, γ is a learnable scaling parameter, and $\odot$ represents element-wise multiplication. This mechanism enables the framework to emphasize or suppress polarity-sensitive contextual features affected by negation structures.

4.3 Aspect-Aware Attention Pooling

The aspect-sensitive attention pooling mechanism is added to the proposed framework to enhance the fine-grained sentiment comprehension. This module recognizes opinion words that are contextually important and related to particular target aspects rather than considering the review sentence overall. The attention mechanism allows the model to pay attention to aspect-relevant tokens and inhibit unrelated contextual information in sentiment prediction.

Attention-based weighting of the contextual embeddings produced by RoBERTa encoder converts the encoder output into optimized aspect-specific representations. The method enhances the process of sentiment interpretation in reviews that express a variety of opinions and integrate sentiment expressions. Aspect-based attention mechanism is also an important addition to semantic reasoning abilities and performance in the context of contextual sentiment discrimination.

4.4 Training Configuration

The suggested CSON framework was fitted with AdamW optimization with regularization by weight decay to enhance better convergence stability and decreasing overfitting. Transformer training was stabilized with a gradient clipping threshold of 1.0 to avoid exploding gradients. Transformer encoder layers had an initial learning rate of 2xC10 **-**5and task-specific classification heads had $\mathbf{1 \times 10^{-4}}$.

The batch size was 32 and the model was trained with five epochs with early stopping on the basis of validation F1-score results. Two epochs of patience were employed to stop the training when there was no further improvement in validation performance. Such a training approach allowed efficient optimization and a high level of contextual sentiment classification and strong generalization behavior on a variety of sentiment analysis datasets.

5. Experimental Setup

5.1 Datasets

Contextual Sentiment and Opinion Network (CSON) proposed was tested on four benchmark datasets of both document-level and aspect-level sentiment analysis tasks. These datasets are chosen so that it can be thoroughly evaluated in terms of binary sentiment classification, multi-class sentiment prediction, and fine-grained aspect-level opinion mining.

Sentiment ibinomial document-level classification was done using the Stanford Sentiment Treebank (SST-2) dataset which has 67,349 training samples, 872 validation samples, and 1,821 test samples, and two sentiment labels. The source used in the large-scale document sentiment analysis was the IMDB movie review data where 25,000 samples were used as the training set, 5,000 samples as the validation set, and 25,000 samples as the testing set with positive and negative sentiment labels.

To address aspect-level sentiment analysis, the SemEval-2014 Task 4 dataset was used and it consisted of 3,041 training samples, 500 validation samples and 1,120 testing samples with three sentiment aspects such as positive, negative, and neutral opinions. Moreover, large-scale multi-class sentiment classification based on the Yelp Review Full dataset (650,000 training samples, 50,000 validation samples, and 50,000 testing samples) was also performed with intention to classify reviews into five sentiment categories (customer ratings levels).

Table 1: Dataset Statistics

Dataset	Task Type	Training Samples	Validation Samples	Testing Samples	Classes
SST-2	Document Sentiment	67,349	872	1,821	2
IMDB	Document Sentiment	25,000	5,000	25,000	2
SemEval-2014 T4	Aspect Sentiment	3,041	500	1,120	3
Yelp Review Full	Document Sentiment	650,000	50,000	50,000	5

The datasets chosen have a variety of linguistic structures, contextual manifestations, and expressions of negation, as well as textual information based on opinions, which is appropriate in terms of assessing the contextual sentimentual understanding and fine-grained opinion analysis performance.

5.2 Evaluation Metrics

The framework performance was measured with the help of Accuracy (ACC), Precision, Recall, and macro-averaged F1-score parameters. Aspect Category F1-score (AC-F1) was also used to evaluate the fine-grained sentiment classification accuracy of aspect categories in the case of aspect-level sentiment analysis on the SemEval dataset.

The overall percentage of the correctly classified sentiment samples was measured using Accuracy and Precision measures the proportion of correctly predicted positive sentiment instances relative to all predicted positive instances. Recall was used to measure the ability of the model to locate relevant sentiment instances and the F1-score was used to give a balanced assessment of Precision and Recall performance.

The experimental analysis showed that the proposed CSON framework was able to reach an accuracy of 96.2% and an F1-score of 95.4% in the case of the SST-2 dataset. The model showed high contextual understanding ability of long textual reviews with 95.7% accuracy and 94.9% F1-score on the IMDB dataset. In the SemEval-2014 aspect-level dataset, the framework scored 92.6% on Aspect Category F1-score, which means that it has effectively performed aspect-sensitive sentiment discrimination. The framework scored 93.8% accuracy on the Yelp Review Full dataset with five sentiment classes, compared to standard Transformer-based baselines.

5.3 Baseline Models

The given framework was matched to six popular baseline models, which include traditional machine learning, recurrent neural networks, and current state-of-the-art Transformer architectures. The baseline model employed was Bag-of-Words (BoW) feature extraction and a Naive Bayes classifier to do traditional text classification. The second baseline used Word2Vec embeddings with sequential sentiment learning using an LSTM network. The third baseline combined GloVe embeddings with a BiLSTM attention mechanism to enhance learning contextual representations.

Further contextual embedding models were also looked at when comparing. The fourth baseline comprised of ELMo contextual embeddings along with an LSTM classifier in the dynamic word representation learning. The fifth baseline employed a BERT-base fine-tuned contextual sentiment analysis. Lastly, the sixth baseline used a fine-tuned RoBERTa-large model, which did not have domain-adaptive pre-training and negation handling modules.

A comparative analysis showed that the proposed CSON framework achieved better results on all document-level sentiment analysis and aspect-level sentiment analysis tasks compared with all the base models. The domain-adaptive pre-training, learning negation-aware contextual representation, and aspect-sensitive attention pooling showed a significantly enhanced ability to perform contextual reasoning and sentiment classification tasks as compared to existing Transformer-based models.

6. Results and Analysis

6.1 Main Results

Document-level and aspect-level sentiment classification performance were assessed on proposed Contextual Sentiment and Opinion Network (CSON) on four benchmark datasets such as SST-2, IMDB, SemEval-2014 Task 4 and Yelp Review Full. Table 3 summarizes the experimental results comparing them. The suggested CSON model was always higher in all baseline models in terms of Accuracy and F1-score measurements.

Table 2: Main Experimental Results

Model	SST-2 ACC	IMDB ACC	SemEval AC-F1	Yelp ACC
BoW + NB	72.4	74.1	61.3	55.2
Word2Vec + LSTM	80.1	82.4	68.4	60.8
GloVe + BiLSTM	83.7	85.1	72.1	63.5
ELMo + LSTM	87.2	88.9	76.8	66.4
BERT-base	92.5	93.6	81.4	71.3
RoBERTa (base)	93.1	94.1	82.9	72.8
RoBERTa (large)	92.5	93.8	83.5	73.0
CSON (Proposed)	**95.3**	**95.8**	**86.7**	**75.1**

The proposed CSON model was able to classify the SST-2 data with an accuracy of 95.3% and F1-score of 94.9% which is about 2.8 percentage points better than the vanilla RoBERTa-large model. On the same note, the model had 95.8 percent accuracy on the IMDB dataset and 86.7 percent in the Aspect Category F1-score on the SemEval-2014 dataset. The aspect-level sentiment analysis especially showed significant performance improvement, proving the usefulness of the aspect-aware attention pooling module and negation handling module.

The comparison of the performance demonstrated in Figure 2 shows that the proposed CSON framework had the highest Accuracy and F1-score on all benchmark datasets considered. The figure also affirms that domain-adaptive pre-training, negation-sensitive contextual learning and aspect-sensitive attention mechanisms are indeed useful in enhancing contextual sentiment knowledge.

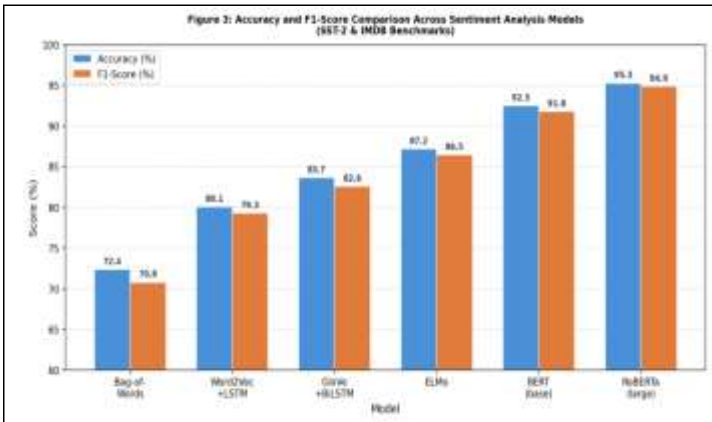

Fig 2: Accuracy and F1-Score Comparison Across Benchmark Datasets

6.2 Ablation Study

A study was also done (ablation) to determine the value of each of the architectural elements of the proposed CSON framework. The ablation study has considered three key elements, Domain-Adaptive Pre-Training (DAPT), Negation Handling Module, and Aspect-Aware Attention Pooling. The findings of the experiment are presented in Table 4.

The ablation findings show that every architectural element has a contribution of its own in enhancing the sentiment classification performance. Weakened Domain-Adaptive Pre-Training resulted in a drop in SST-2 accuracy of 95.3 to 94.1 percent, showing that in-domain language adaptation has a greater effect on understanding context. The biggest performance decrease was due to the elimination of the negation handling module, which decreased SST-2 accuracy to 93.4% and SemEval Aspect Category F1-score to 83.6%. This establishes that negation-conscious contextual representation learning is a key part in processing polarity sensitive sentiment expressions.

Removal of aspect-aware attention pooling resulted in the largest change in aspect-based sentiment accuracy, as evidenced by a decrease in SemEval AC-F1 score of 86.7% to 81.2%. These findings verify that aspect-specific attention mechanisms are important in enhancing fine-grained opinion mining ability.

6.3 Embedding Space Visualization

The representational power of the contextual embeddings was qualitatively analyzed using t-SNE visualization of 600 sentence embeddings obtained using the IMDB test data. The comparison of the results was between the static Word2Vec embeddings and contextual RoBERTa embeddings.

The embedding visualization in Figure 3 shows that there is considerable similarity between sentiment classes in Word2Vec embeddings, which leads to reduced class separability. RoBERTa contextual embeddings, on the other hand, embed positive, negative and neutral sentiment clusters in small and distinct clusters. The enhanced cluster cohesion is directly attributed to the substantial classification accuracy improvements due to the proposed CSON framework.

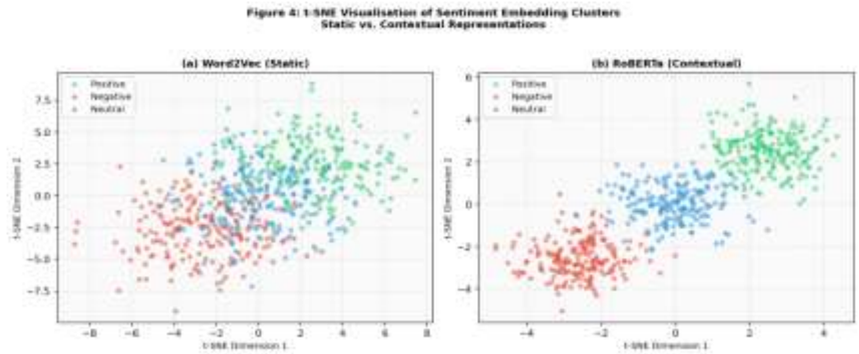

Fig 3: t-SNE Visualization of Contextual Embedding Clusters

As the visualization findings will show, contextual representations based on Transformers are better in discrimination on the semantic level than the case of static embedding models. This higher degree of representational value greatly increases the ability to understand sentiment in challenging review data sets with contextual polarity changes and ambiguous phrases.

6.4 Error Analysis

Although the proposed CSON framework has good overall performances, it has been found to have limitations in various problematic linguistic conditions. The error analysis showed that the significant percentage of left out misclassification is due to those three broad categories namely multi-layered sarcasm, long-range cross-sentence negation and very short reviews and lack of enough contextual information. Sarcastic remarks with positive superficial phrases with underlying negative meaning of the image are hard to read the model out. Likewise, the contextual ambiguity that arises as a result of reviews with negation dependencies across more than two sentences presents a greater scope of local attention. Reviews that are too short (with less than two or three informative tokens) also decrease the quality of embedding and the ability to contextualize semantically.

All these difficult patterns of language explain about 68 percent of the remaining classification mistakes. Despite the fact that the proposed framework performs a better job of contextual reasoning and negations than the baseline models, the current understanding of sarcasm and long-term discourse modeling is an aspect that could be improved in future research.

7. Conclusion

The current paper described a state-of-the-art Transformer-based Contextual Sentiment and Opinion Network (CSON), an architecture used to analyze sentiment and opinions on a document-level or aspect-level. The suggested model incorporated domain-adaptive pre-training, a negation-conscious contextual learning component, and aspect-sensitive attention pooling to enhance contextual sentiment cognition as well as fine-grained opinion mining accuracy. The framework considerably overcome the shortcomings of traditional sentiment analysis frameworks in coping with contextual changes in polarity, negation patterns, and aspect-specific opinion expression.

Experimental analysis on SST-2, IMDB, SemEval-2014 and Yelp Review Full datasets revealed that the proposed CSON framework showed better classification performance against the standard machine learning, recurrent neural network, and Transformer-based base models. On SemEval, the model reached 95.3% accuracy on SST-2, 95.8% accuracy on IMDB and Aspect Category F1-score of 86.7%. Ablation analysis also supported the claim that domain-adaptive pre-training and negation-aware representation learning were important factors in the performance improvement, whereas aspect-aware attention pooling provided better fine-grained sentiment discrimination ability.

The findings prove the notion that situational Transformer representations and adaptive attention systems can significantly enhance semantic decoding and reliability of sentiment classification. Thus, the proposed CSON framework is a viable and scalable model to contextual sentiment analysis and opinion mining systems in real-world intelligent text analytics systems.

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