

# TOPICBERT: SENTIMENTAL CLASSIFICATION-OPTIMIZED TOPIC-ENHANCED NEURAL LANGUAGE MODEL

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**Abstract:** Sentiment classification is a kind of data analytics in which data is mined to extract people's sentiments and opinions regarding something. However, with the recent development of the BERT framework and its pre-trained neural language models, sentiment classification has seen newfound success. They are adequate models for certain natural language processing tasks right out of the box. Most models, however, are fine-tuned using domain-specific information to improve accuracy and usefulness. Motivated by the idea that more fine-tuning would increase performance for downstream sentiment classification tasks, we developed Topic BERT—a BERT model fine-tuned to recognize topics at the corpus level in addition to the word and sentence levels. Topic BERT comprises two variants: Topic BERT-ATP (aspect topic prediction), which captures topic information via an auxiliary training task, and Topic BERT-TA, where topic representation is directly injected into a topic augmentation layer for sentiment classification. With Topic BERT-ATP, the topics are predetermined by an LDA mechanism and collapsed Gibbs sampling. With Topic BERT-TA, the topics can change dynamically during the training. Experimental results

show that both approaches deliver the state-of-the-art performance in two different domains with SemEval 2014 Task 4. However, in a test of methods, direct augmentation outperforms further training. Comprehensive analyses in the form of ablation, parameter, and complexity studies accompany the results

**Keywords:** Sentiment classification, Neural Language Model, Machine Learning, Natural Language Processing, Textual Data, Opinion Mining, Topic Augmentation

## 1. INTRODUCTION

SENTIMENT classification is a fundamental but challenging task in the field of data mining. Sentiment classification is the automated process of identifying and classifying emotions in text as positive sentiment, negative sentiment, or neutral sentiment based on the opinions expressed within. Automatically capturing the general public's sentiments about social events, marketing campaigns, product preferences, and the like has attracted much attention in both the scientific community and the business world. Furthermore, the advent of automatic

tools capable of mining sentiments has lent momentum to the emerging fields of affective computing. These new branches of study leverage human-computer interaction and information retrieval to distill people's sentiments from the increasing amount of online social networking data. Aspect term sentiment classification (ATSC) is a fine-grained form of sentiment classification that aims to predict sentiment polarity, i.e., whether the sentiment of a phrase toward a target term (the aspect term) is positive, negative, or neutral.

Sentiment analysis, a crucial aspect of natural language processing, has garnered significant attention in recent years due to its applications in diverse domains such as marketing, business intelligence, and social media. This paper presents an overview of key contributions in sentiment analysis and opinion mining, reflecting the evolution and advancements in this field. The foundation of sentiment analysis can be traced back to seminal works such as "Sentiment Analysis and Opinion Mining" by B. Liu [1] and "Opinion Mining and Sentiment Analysis" by B. Pang and L. Lee [2]. As the field progressed, researchers addressed challenges and explored multimodal approaches, as evidenced by Poria et al.'s work on "Multimodal Sentiment Analysis" [3]. The development of ontologies, exemplified by OntoSenticNet [4], has further enriched sentiment analysis by incorporating commonsense knowledge. Beyond textual data, sentiment analysis has extended to other modalities, as illustrated by Stappen et al.'s exploration of "Sentiment Analysis and Topic Recognition in Video Transcriptions" [5].

In business contexts, sentiment analysis has proven valuable, with Saura et al. contributing methods for leveraging user-generated content (UGC) in business intelligence analysis [6]. They also delved into the application of sentiment analysis for detecting indicators of startup success [7] and integrating data sciences into digital marketing [8]. Advancements in machine learning techniques have played a pivotal role, with attention-emotion-enhanced convolutional LSTM [10], aspect-based polarity classification [11], and adaptive recursive neural networks [12] emerging as notable methodologies. The exploration of effective LSTM models for target-dependent sentiment classification [13] and end-to-end memory networks [14] has further expanded the repertoire of sentiment analysis techniques.

This introduction provides a glimpse into the rich landscape of sentiment analysis, showcasing its evolution from foundational works to contemporary approaches, spanning diverse applications and methodologies. The citations included serve as guideposts to the comprehensive exploration of sentiment analysis presented in the subsequent sections of this paper.

## 2. LITERATURE REVIEW

Sentiment analysis and opinion mining have gained significant attention in recent years due to the proliferation of user-generated content on the internet. This literature survey aims to provide an overview of key works in the field, discussing methodologies, challenges, and advancements in sentiment analysis. The cited references encompass a range of approaches, from traditional methods to cutting-edge techniques that leverage deep learning. Bing Liu's comprehensive work, "Sentiment Analysis

and Opinion Mining" [1], and Pang and Lee's "Opinion Mining and Sentiment Analysis" [2], serve as foundational texts in the domain. Liu's synthesis lectures offer a broad perspective, covering various aspects of sentiment analysis, including techniques, challenges, and applications. Pang and Lee delve into the foundational trends of information retrieval related to opinion mining. Multimodal sentiment analysis has become increasingly important with the growth of diverse data types.

Poria et al. [3] address key issues and establish baselines in this domain. Their work highlights the need for considering multiple modalities, such as text, images, and audio, to enhance sentiment analysis accuracy. OntoSentNet, proposed by Dragoni, Poria, and Cambria [4], introduces a commonsense ontology specifically designed for sentiment analysis. This ontology facilitates a deeper understanding of sentiments by incorporating common-sense knowledge, contributing to more context-aware sentiment analysis.

Stappen et al. [5] explore sentiment analysis and topic recognition in video transcriptions, extending sentiment analysis to multimedia content. Their work reflects the evolving nature of sentiment analysis applications beyond traditional text data. Saura and Bennett [6] propose a three-stage method for data text mining, emphasizing the use of user-generated content in business intelligence analysis. Their approach showcases the practical application of sentiment analysis in extracting valuable insights from unstructured data. In the realm of startup business success, Saura, Palos-Sanchez, and Grilo [7] apply sentiment analysis using text data mining to detect indicators for startup success. This work

illustrates the potential of sentiment analysis in the entrepreneurial context.

Saura's contributions extend to the intersection of data sciences and digital marketing [8]. The framework, methods, and performance metrics proposed by Saura provide insights into leveraging data sciences, including sentiment analysis, to optimize digital marketing strategies. Cambria et al.'s work [9] on affective computing and sentiment analysis offers a practical guide to understanding the emotional dimensions of sentiment. This foundational knowledge is crucial for developing more nuanced sentiment analysis models. The literature also includes advanced neural network models for sentiment analysis.

Huang et al. [10] present an attention-emotion-enhanced convolutional LSTM, showcasing the integration of emotion-aware attention mechanisms for improved sentiment classification. Target-dependent sentiment classification is addressed by Dong et al. [12] and Tang et al. [13]. Dong et al. propose an adaptive recursive neural network, while Tang et al. focus on effective LSTM architectures, demonstrating the evolution of methodologies for fine-grained sentiment analysis. End-to-end memory networks, as introduced by Sukhbaatar et al. [14], represent an innovative approach to sentiment analysis, emphasizing the importance of memory-augmented models in capturing context and dependencies.

Li et al.'s transformation networks [15] contribute to target-oriented sentiment classification, showcasing the significance of adapting neural network architectures to specific targets for more accurate sentiment analysis. In conclusion, this literature

survey highlights the evolution of sentiment analysis from traditional methods to state-of-the-art deep learning techniques. The diverse range of approaches and applications presented in the cited works reflects the growing importance of sentiment analysis across various domains. The integration of multimodal data, commonsense knowledge, and advanced neural network architectures further enriches the field, paving the way for more sophisticated sentiment analysis models.

### 3. METHODOLOGY

In previous work they developed an unsupervised sentiment classification method for Twitter data using emoticons. They propose an algorithm called USA-Emoticons for this purpose. They also analyze the classification accuracy of their proposed algorithm by varying the percentage of tweets with emoticons used for training the classifier. They observe that when the percentage of tweets with emoticons used for training is between 10% to 50%, the accuracy of classification increases substantially. Another research developed an Attention-based Long Short-Term Memory Network for aspect-level sentiment classification. They develop a model that can concentrate on different parts of a sentence when different aspects are given, making it more competitive for aspect-level classification. The key idea of their proposal is to learn aspect embeddings and let aspects participate in computing attention weights.

#### Drawbacks:

1. Emoticons may not fully capture the complexity of sentiments expressed in tweets, leading to potentially oversimplified or inaccurate sentiment classification.
2. The performance of USA-Emoticons heavily relies on the presence and frequency of emoticons in the training data. If emoticon usage patterns change or if tweets with emoticons are not representative of the entire dataset, the algorithm's accuracy may suffer.
3. Since the USA-Emoticons algorithm is unsupervised, it may lack the adaptability and flexibility required to handle varying sentiment expressions and topics in the Twitter data.
4. The LSTM-based model might be less adaptable to dynamic changes in sentiment patterns and themes within the Twitter data.
5. The attention mechanism in LSTM models can be computationally expensive, particularly for long sentences and a large number of aspects. Implementing the Attention-based LSTM model might require more computational resources.

We developed Topic BERT, a BERT model that has been modified to recognize themes at the corpus level in addition to at the word and sentence levels, motivated by the notion that a further fine-tuning step will enhance the performance for downstream sentiment classification tasks. Two variations of Topic BERT exist: Topic BERT-TA, where topic representation is immediately injected into a topic augmentation layer for sentiment classification, and Topic BERT-ATP (aspect topic prediction), which captures topic information via an auxiliary training task. By using a collapsed Gibbs sampling method and an LDA mechanism, Topic BERT-ATP

predetermines the subjects. The topics can alter dynamically throughout the training with Topic BERT-TA.

#### Benefits:

1. TopicBERT goes beyond word and sentence-level analysis and introduces corpus-level theme recognition. This means that the model can identify and understand overarching topics and themes present in a collection of tweets.
2. TopicBERT-TA allows the dynamic alteration of topics throughout the training process. This flexibility enables the model to adapt to changing patterns and trends in Twitter data, making it more robust in handling variations in sentiment expression over time
3. In TopicBERT-ATP, the incorporation of the collapsed Gibbs sampling method and LDA mechanism to predetermine subjects for aspect topic prediction can help in capturing more nuanced sentiment aspects and improve the overall sentiment analysis results.
4. Compared to LSTM our proposed model BERT is an efficient for sentiment classification. Because Single multiplication per layer improves efficiency on TPU, which means the effective batch size is the number of words and not sequences.

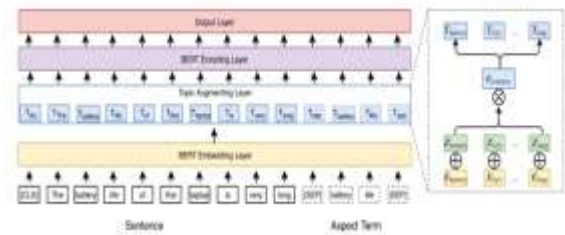


Fig 1 System Architecture

#### Modules:

The modules are:

- Data loading: using this module we are going to import the dataset.
- Data Preprocessing: using this module we will explore the data.
- Splitting data into train & test: using this module data will be divided into train & test
- Model generation: Building the model - BERT Small -BERT Large -Topic BERT (BERT with Topic Modelling) -LSTM - LSTM + GRU
- User signup & login: Using this module will get registration and login
- User input: Using this module will give input for prediction
- Prediction: final predicted displayed

#### 4. IMPLEMENTATION

BERT Small –BERT is an open source machine learning framework for natural language processing (NLP). BERT is designed to help computers

understand the meaning of ambiguous language in text by using surrounding text to establish context.

**BERT Large** –The top large language models include GPT-3, GPT-2, BERT, T5, and RoBERTa. These models are capable of generating highly realistic and coherent text and performing various natural language processing tasks, such as language translation, text summarization, and question-answering.

**Topic BERT (BERT with Topic Modelling)** –BERTopic is a topic modeling python library that combines transformer embeddings and clustering model algorithms to identify topics in NLP (Natural Language Processing). In this tutorial, we will talk about the following: How transformers, c-TF-IDF, and clustering models are used behind the BERTopic?

**LSTM** – Long short-term memory (LSTM) network is a recurrent neural network (RNN), aimed to deal with the vanishing gradient problem present in traditional RNNs. Its relative insensitivity to gap length is its advantage over other RNNs, hidden Markov models and other sequence learning methods.

**LSTM + GRU**- the LSTM ( Long -short-term memory ) and GRU ( Gated Recurrent Unit ) have gates as an internal mechanism, which control what information to keep and what information to throw out. By doing this LSTM, GRU networks solve the exploding and vanishing gradient problem.

## 5. EXPERIMENTAL RESULTS

### Dataset Description:

Two domain-specific datasets for laptops and restaurants, consisting of over 6K sentences with fine-grained aspect-level human annotations have been provided for training.

*Restaurant reviews:* This dataset consists of over 3K English sentences from the restaurant reviews of Ganu et al. (2009). The original dataset of Ganu et al. included annotations for coarse aspect categories (Subtask 3) and overall sentence polarities; we modified the dataset to include annotations for aspect terms occurring in the sentences (Subtask 1), aspect term polarities (Subtask 2), and aspect category-specific polarities (Subtask 4). We also corrected some errors (e.g., sentence splitting errors) of the original dataset. Experienced human annotators identified the aspect terms of the sentences and their polarities (Subtasks 1 and 2). Additional restaurant reviews, not in the original dataset of Ganu et al. (2009), are being annotated in the same manner, and they will be used as test data.

*Laptop reviews:* This dataset consists of over 3K English sentences extracted from customer reviews of laptops. Experienced human annotators tagged the aspect terms of the sentences (Subtask 1) and their polarities (Subtask 2). This dataset will be used only for Subtasks 1 and 2. Part of this dataset will be reserved as test data.

Dataset format:

The sentences in the datasets are annotated using XML tags.

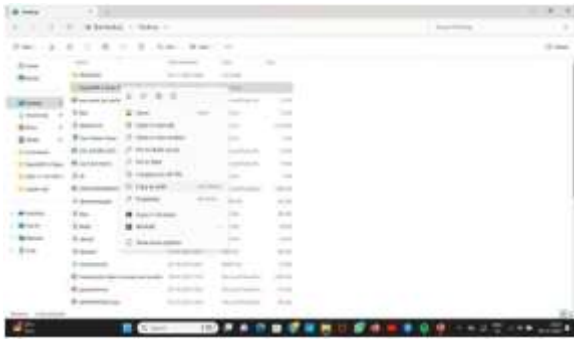


Fig 2 Display the project code folder

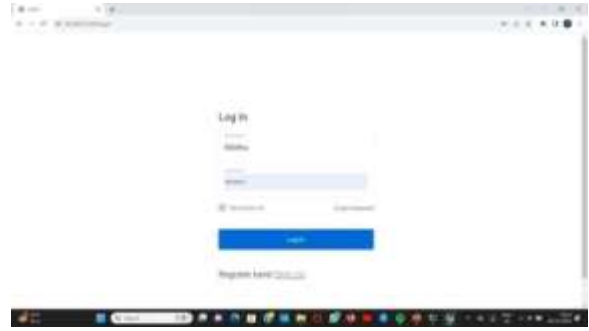


Fig 6 Signup Credentials



Fig 3 Anaconda prompt



Fig 7 Sign In Credentials



Fig 4 URL



Fig 8 Input text box



Fig 5 Dash board

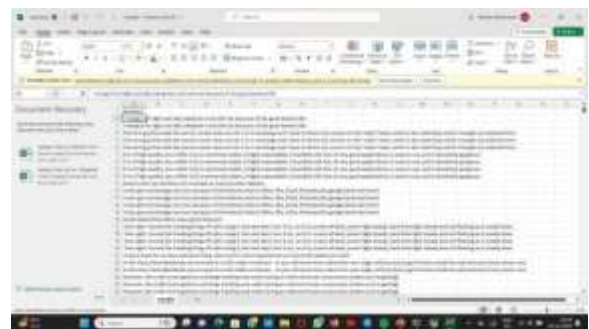


Fig 9 Sample file



Fig 10 Text box to enter input



Fig 11 Result displayed



Fig 12 analyzing each word of input text

## 6. CONCLUSION

In this work, we proposed a novel topic-augmented fine-tuning paradigm for BERT pre trained language models, called Topic BERT. Topic BERT jointly considers both the context within the sentence and the global latent topic information to benefit ATSC tasks. Topic information is introduced from an unsupervised LDA model and two different

implementations are presented, each involving a different fine-tuning method such as Topic BERT-ATP which incorporates topic information through an auxiliary task and Topic BERT-TA which aggregates topic information from individual words to enrich the discriminating semantic topics. Extensive experiments show that both implementations are effective. Further analyses and visualizations demonstrate that when BERT models are enhanced with topic information, they can better understand the fine-grained polarities of sentiment toward a target. In addition, we plan to extend our method to other pre training language models, such as RoBERTa and ALBERT, and other tasks, such as summarization and event extraction.

## FUTURE ENHANCEMENTS

Future models might explore multi-task learning, where the model is trained to perform both sentiment analysis and topic classification simultaneously. This approach can leverage shared representations and potentially improve the overall model's performance. Models could be designed to dynamically adapt their understanding of sentiment based on the context of the conversation. This might involve incorporating contextual information from previous sentences or considering the evolving nature of sentiment in a given text. There could be a focus on making models more interpretable and explainable, allowing users to understand why a model makes a specific sentiment prediction or how it incorporates topic information in its decision-making process. Future models might be enhanced to better handle linguistic phenomena like sarcasm and irony, which can significantly impact sentiment analysis accuracy. Models could be designed to continually learn and adapt to changing

linguistic patterns and sentiments over time, ensuring that they remain effective in evolving language usage.

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