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Exploring Transfer Learning for News Sentiment Classification: An In-depth Analysis

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Abstract

In this paper, two approaches of transfer learning i.e. feature and fine-tuning from pre-trained models are analyzed for the downstream task of banking financial news sentiment classification. In the feature-based approach, the study assesses how well two distinct strategies perform in determining whether news events are neutral, positive, or negative sentiments. The first method, DistilBERT, uses a language representation that understands context fully, whereas the conventional technique, TF-IDF, does not. Both techniques are evaluated with a Random Forest classifier to see whether feature-based transfer learning from pre-trained contextualized embeddings DistilBERT performs better at sentiment classification. The results showed that DistilBERT was better at understanding the semantics of news events and achieved higher accuracy compared to TF-IDF. Moreover, the fine-tuning of the pre-trained BERT-base-uncased model using the same dataset, the accuracy of classification is further improved by 12% compared to the feature-based approach. The study found that fine-tuning BERT on the downstream task of banking news sentiment classification leads to an accuracy of 90%. Whereas the BERT-base-cased variant produces 88% accuracy which means that casing (capitalization) does not play a crucial role in classifying sentiments of banking financial news events.

Keywords: Sentiment classification, Transfer Learning, Transformers, and Machine Learning classifiers.

1 Introduction

1.1 News Sentiment Classification

In the field of natural language processing (NLP), the task of sentiment classification in textual data is a rapidly expanding area. Presently, it finds widespread applications in various business domains, including customer experience assessment, algorithmic trading, human resources management, and social media analysis. Transfer learning is a potent method for enhancing the performance of a given task, such as sentiment classification, by utilizing knowledge obtained from previously trained models. Our study assesses the performance of two transfer learning methods for sentiment classification: feature-based transfer learning and fine-tuning.

Based on a review of the literature, it is evident that financial markets can demonstrate peculiar actions in response to acts of terrorism, socio-political events, natural disasters, and other factors [1]. With the increasing abundance of newsgroups and opinions, there is a growing interest in analyzing perspectives and sentiments within the news domain. Prior studies in this field have concentrated on sentiment classification techniques applicable to political news, technological advancements, and global events. Specifically, these studies have examined columns from diverse news websites which could potentially influence financial markets [2]. The researchers propose incorporating emotional terms as features to describe the sentiment of news articles related to the stock market. They believe that the sentiment expressed in financial news can impact the behavior of stock or financial markets [3]. However, there has been no well-organized or structured approach to address the task of automating sentiment prediction in the context of banking news events. It indicates a possible absence of comprehensive methodologies, frameworks, or established practices for handling sentiment analysis in this domain.

According to what we now know, no systematic effort has been made to examine the tone of communication of financial events reported in various web newswires. This may be due to the difficulty of compiling all conceivable banking-related events that could have an impact on stock markets. In a recent study, we focused on classifying articles or occurrences from the financial news for the years 2017 to 2020 [3]. We took several articles about global events, governmental moves, merger or acquisition announcements, RBI policies, results (annually or quarterly), fraud, and ratings agencies' or experts' views from this dataset.

In this paper, our objective is to automate the process of sentiment classification for these mentioned news events. We will explore multiple approaches to transfer learning, including feature-based transfer learning and fine-tuning, to assess the performance of sentiment classification on our dataset.

1.2 Transfer Learning

The study mainly concentrates on categorizing different types of news related to banking, finance, and other related topics into sentiment classes. The primary goal is to classify each news article as having a neutral, positive, or negative sentiment. Transfer learning is a technique used to improve sentiment analysis of news items on banking by applying knowledge learned from pre-trained language models to massive amounts of text data. Even in situations where there may be little labeled data specifically for sentiment analysis in the banking domain, transfer learning enables the sentiment classification model to benefit from the language understanding abilities collected during pre-training. Transfer learning is a practical and efficient method for sentiment analysis because it starts with learned models, saving substantial computational resources and training time.

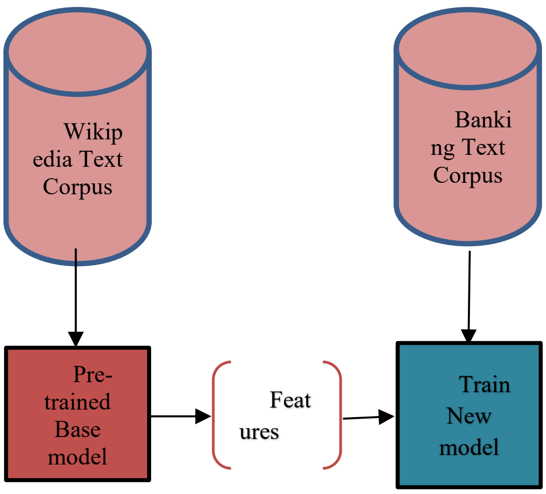

Fig 1: Feature-based Transfer Learning

In recent years, a new way of using pre-trained language models called Transfer Learning has become important for many language-related tasks. This method has made a big impact in the field of NLP [4]. Utilizing pre-trained language models like BERT [5], DistilBERT [6], or RoBERTa [7] is the initial step. These models gain sophisticated semantic representations and contextual language understanding through training on enormous volumes of text data from many sources. In some situations, feature extraction is performed, where banking articles are converted into contextualized word embeddings or features using a pre-trained language model as shown in Fig 1. The underlying meaning of the words and sentences in the banking context is captured by these embeddings. The more typical method is fine-tuning, which involves adapting or fine-tuning the large language model using specific labeled sentiment samples from banking articles as shown in Fig 2. The factors of the model are modified while fine-tuning based on the sentiment classification task particular to banking news.

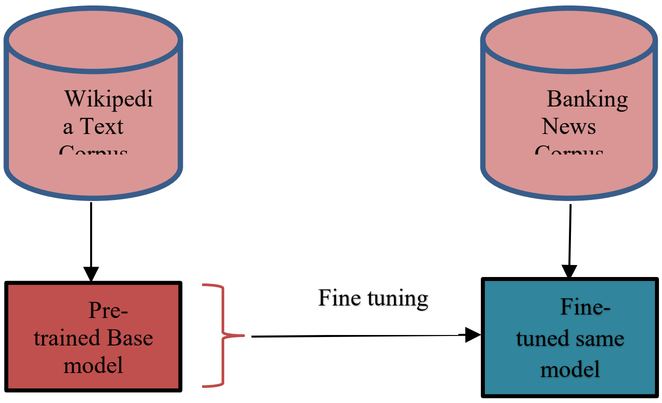

Fig 2: Fine Tuning-based Transfer Learning

BERT's influence on NLP has been transformational, as shown by its ability to give the best outcomes on a diverse range of tasks with very minimum fine-tuning and pre-training on unlabeled data. The research community has also looked into techniques like distillation to develop models like DistilBERT that are faster and more compact without sacrificing task performance. These developments open up the possibilities for NLP models that are more effective and efficient and have a wider range of real-world applications.

In this study, we investigate the benefits of sentiment classification using transfer learning from both BERT and its more concise counterpart DistilBERT. Concerning Indian banking and financial news as well as associated articles covering seven important events, we employ these two approaches: feature-based and fine-tuning. To our knowledge, this is the first attempt to look into these methods for sentiment classification on a variety of events, including global events, governmental actions, merger or acquisition announcements, RBI policies, financial results (annually or quarterly), fraud incidents, and ratings agencies' or experts' views. This study's main goal is to better understand the sentiments expressed in publications by utilizing the contextual and semantic linkages between words in those articles. The majority of previous studies in this field use context-free techniques that just take individual words and their polarity into account when classifying them. We seek to enhance the accuracy and efficiency of sentiment classification by utilizing transfer learning and contextual data. Section 2 of the paper presents an overview of prior research, including studies on news sentiment classification, exploring the developments in this field up to the recent state-of-the-art.

2 Related Work

Text classification is a learning process in which features are taken from a corpus of text documents and used by a classifier to discriminate between specified classes. Researchers are exploring a wide range of applications, such as accessing the tone of communication of news on the stock market and its implications, domain transformation for sentiment analysis, as well as several other fields of study, as a result of the technique's major interest in practical situations. Comprehending texts framed in any natural language stands as a formidable area in machine learning, and text classification is no exception. The difficulty comes from the fact that most algorithms require numerical feature vectors with fixed dimensions as input, making it impossible to directly feed these models textual data with different lengths. To close this gap and enable efficient text classification, the following subsection explores several text classification methods, starting with traditional approaches and moving forward to the most state-of-art NLP models. Moreover, the selection of a text classification method is influenced by the difficulty of the task, the accessibility of labeled data, the available computing power, and the level of accuracy that is sought. The best approach for a given text classification challenge may be determined through testing and evaluation.

2.1 Features-based Supervised Machine Learning

There is an extensive amount of research on various ML approaches and algorithms used for the classification of text. The Naive Bayes algorithm has been the subject of substantial research by several researchers because it is simple, efficient, and capable of handling large amounts of data [8]. However, it is very susceptible to feature selection because of its underlying assumption of feature independence [9]. In multiclass (negative, positive, neutral) classification, the datasets may be imbalanced among the labels while training the classifier. For such cases, SVM is a potent supervised learning technique [10]. It is also preferred especially in scenarios where the data is not linearly separable. However, when features are appropriately constructed, the simple and understandable method of logistic regression can be effective for classifying text documents [11]. For classification purposes logistic regression closely resembles neural networks, deep learning models, which have revolutionized text classification in recent years. For the News Sentiment classification, the Decision Tree algorithms are sometimes preferred over other algorithms. Decision Trees can provide feature importance rankings similar to the attention technique in the neural networks, indicating which features are more influential in making decisions. Moreover, Random Forests aggregate multiple decision trees to improve generalization [12]. The Bag-of-Words technique is frequently applied in transforming the text before the classification stage. Every term in the text sample is handled as a feature in this method, regardless of word order or context. After that, the documents are transformed into feature vectors, each of which is composed of a frequency count to represent each feature. Additionally, the TF-IDF (Term Frequency-Inverse Document Frequency) word weighting system has been identified. Very high word frequencies may not yield a meaningful information gain, according to TF-IDF, whereas rare words are more beneficial to the model. By using this technique, the researcher illustrates an upgraded feature subset that includes features of both word frequency and document frequency [13].

The process of converting words into vectors in a vector known as vector space is referred to as word embedding. The CBOW method captures the words surrounding a target word to predict that particular word. For word embedding, the authors recommended utilizing CBOW [14]. Additionally, they suggested the GLOVE concept for distributed word representation [15]. We also employ text embeddings, such as word2vec, that convert words into n-dimensional vectors. For the classification of texts, RNN-based designs are utilized to identify word relationships and structures. RNN problems like gradient vanishing or exploding are resolved with LSTM. To gather text features, a Bidirectional-LSTM (Bi-LSTM) model is employed with maximum pooling [16].

On current NLP challenges, researchers have demonstrated the value of pre-training neural network models. A bidirectional language model is used to teach the deep context-dependent representation known as ERINE [17]. It is supplied into the classifier and utilized to produce text embeddings. The Transformer attention approach is used in a new representation known as BERT to comprehend the contextual relationships between words in a document. Information distillation was used to produce DistilBERT, a scaled-down version of BERT that omitted several elements. In this work, text classification tasks are carried out using embeddings from DistilBERT [6].

2.2 Fine-Tuning-based Transfer Learning from LLMs

Utilizing fine-tuning-based transfer learning is a method working to enhance the usefulness and competence of a machine learning model by expanding on the knowledge obtained from pre-trained LLMs (large language models). The pre-trained models such as BERT (Bidirectional Encoder Representations from Transformers), DistilBERT, and GPT (Generative Pre-trained Transformer) have delivered state-of-the-art classification results and have learned a lot about language from large datasets [18], [19]. We then give them a smaller dataset that is customized to the task at present, for instance, news sentiment classification in this study (determining if a text is neutral, positive, or negative). The fine-tuning phase occurs when the pre-trained model modifies its capabilities to get better at the downstream task at hand. The benefit of fine-tuning is that it allows the model to focus on sentiment analysis for a specific domain even when there isn't enough labeled data to do it directly.

Both BERT and GPT use transformers, which are a type of neural network architecture. When processing text sequentially, RNN designs suffer from inefficiencies. Transformers overcome this problem by calculating the relevance of each word in a phrase at the same time, making it significantly faster [20]. This approach is ideal for pre-training on massive text datasets, resulting in large gains in accuracy for tasks such as text classification. BERT and DistilBERT are transformer-based models that generate contextualized bi-directional representations derived from an unannotated text by considering the context on both the left and right sides. We can handle massive amounts of data and processing using deep learning without necessitating significant manual engineering efforts.

3 Experimental Setup

To analyze the task of text sentiment classification, we examine the transferability of the neural network through both feature-based and fine-tuning approaches. This analysis focuses on news articles within the domain of banking and financial news, intending to classify them as signifying positive, negative, and neutral sentiments.

3.1 Data

Using contextual language representations can help build better models even with limited data. These representations can reduce the amount of required training data significantly. In this study, news articles communicated between 2018-2020 on various topics like RBI communications, Governmental policies, Mergers, Fraud, Ratings Agencies' Views, Results, and Global events were labeled as neutral, negative, or positive to create a dataset for training the models. According to research, even experts in the financial sector might have difficulty appropriately defining financial news events. This issue comes mostly from the complexities of financial news, which includes aspects such as quarterly earnings reports, analyst ratings, and evaluations of central bank policy. The author who labels these news events needs to have the ability to classify them as having a positive, neutral, or negative tone. The data is divided into two sets for analysis: 75% for training the model and 25% for testing its performance. This divide ensures that the model learns from a substantial amount of the data while being tested on previously unseen cases to determine its effectiveness.

3.2 Embeddings and Fine-Tuning of Language Models

In this study, we used a language representation model called DistilBERT to transform the financial text into features-embeddings. We fed these representations into five different supervised learning classifiers Logistic Regression, Linear SVC, Decision Tree, Random Forest, and Multilayer perceptron (MLP). The Python libraries used to implement this are named; sklearn and transformers.

We found that the Random Forest classifier when applied to DistilBERT representations, performed the best in terms of accuracy [12]. We also tried using traditional word representations called TF-IDF with Random Forest. The standard word representations used in traditional models don't consider the order and context of words in the text, whereas DistilBERT captures this information to provide a better understanding[21-36].

We wanted to compare if the extra complexity of deep contextual models like DistilBERT was worth it in this task. So, we compared the performance of the traditional machine learning algorithm Random Forest (with DistilBERT embeddings, TF-IDF features) with large language models (BERT base-uncased, and BERT base-cased) fine-tuned on financial data for classification evaluation.

4 Results and Discussion

This section compares two methods for analyzing the tone of communication of banking news articles into sentiment labels: DistilBERT and TF-IDF-based transformation with Random Forest classifier to find which technique works better.

4.1 TF-IDF and DistilBERT embeddings with Random Forest classifier to classify banking news-events sentiments

Table 1 shows how well TF-IDF and DistilBERT embeddings, combined with the Random Forest classifier, classify sentiments in banking news articles. The results are presented with the evaluation metric recall (R), precision (P), and F-1 score. Table 2 presents the results of Random Forest with both techniques in terms of accuracy metric.

Table 1. Evaluation of banking news-events sentiments classification with Random Forest classifier using TF-IDF and DistilBERT embeddings

Text Transformation	TF-IDF			DistilBERT		
	P	R	F_1	P	R	F_1
Negative	0.48	0.58	0.53	0.57	0.72	0.63
Neutral	0.76	0.76	0.76	0.88	0.88	0.88
Positive	0.85	0.74	0.79	0.88	0.74	0.81

From the TF-IDF and DistilBERT text transformation techniques, the DistilBERT with Random Forest achieved the best F-1 score for each sentiment class negative, neutral, and positive as shown in Table 1. Random Forest performed well in terms of both recall and precision for the 'Positive' and 'Neutral' labels with higher F-1 scores. This performance was consistent for the 'Negative' class as well, except for the 'Negative' class where it showed good recall and precision.

Table 2. Accuracy of the Random Forest classifier with TF-IDF and DistilBERT embeddings

Classifier	Accuracy
TF-IDF + Random Forest	0.70
DistilBERT + Random Forest	**0.78**

Among the different models tested, the Random Forest combined with DistilBERT achieved the highest accuracy at 78%. Table 2 presents the comparison of the two feature-based approaches using Random Forest classifiers for analyzing sentiment in Banking News-Events is presented, where the classifiers' accuracy ranges from 70% to 78%.

4.2 Evaluation of fine-tuning of large language pre-trained model BERT for Banking News-Events sentiments classification

Table 3 shows the outcome of sentiment classification for banking news events using the fine-tuned BERT language model in terms of recall, precision, and F-1 score. The accuracy of the model is presented in Table 4.

Table 3. Evaluation of sentiments classification of banking news-events using fine-tuning of BERT

Language model	Bert-base-uncased			Bert-base-cased		
	P	R	F_1	P	R	F_1
Negative	1.00	0.71	0.83	0.80	0.86	0.83
Neutral	0.95	1.00	0.97	0.89	0.89	0.89
Positive	0.79	0.94	0.86	0.93	0.88	0.90

From the uncased BERT and cased BERT, the BERT model without case sensitivity (BERT-base-uncased) achieved the highest F-1 score, as indicated in Table 3. Although the BERT model with case sensitivity (BERT-base-cased) had higher recall and precision for the 'Positive' class, the overall F-1 score was higher for BERT-base-uncased in both the 'Neutral' and 'Negative' classes.

Table 4. Accuracy of the fine-tuning BERT on banking news-events sentiments

Classifier	Accuracy
BERT-base-uncased	**0.90**
BERT-base-cased	0.88

Also, from the uncased BERT and cased BERT, the highest performance is shown by BERT-base-uncased model, with an accuracy of 90%, as indicated in Table 4. Table 3 compares these two versions for three different sentiment labels in Banking News-Events. It shows how well they did with F1-score, recall, and precision. The accuracy of these classifiers ranged from 88% to 90%.

On concluding the classification using feature-based and fine-tuning-based transfer from LLMs, it is observed from Table 1 to Table 4 that accuracy of fine-tuning BERT-base-uncased has performed best with 90% accuracy which is 12% more as compared to DistilBERT feature-based accuracy with Random Forest.

5 Conclusion and Future direction

This study focuses on understanding how we can use transfer learning from pre-trained neural networks models to improve sentiment analysis of banking news. We want to analyze if two different methods work well: one that uses features embeddings and another that fine-tunes a pre-trained model for downstream task. We are evaluating news articles about banking events and trying to assess if they are positive, negative, or neutral sentiments. We used a large language model called DistilBERT for text representation along with Random Forest to perform sentiment classification, and we compared it with a popular traditional method called TF-IDF. Our main goal was to see if using DistilBERT can help us do this task better. It is evaluated that DistilBERT with Random Forest gave us better accuracy than TF-IDF with Random Forest. The accuracy results 78%, which is 7% more accurate than the other method. This means that using this LLM improved the ability to understand the sentiment of banking news. Using the fine-tuning-based approach, a powerful pre-trained large language model BERT was used and adapted it for classifying banking news-events sentiments with base-uncased and base-cased variants. BERT-base-uncased has produced 90% accuracy which is 2% better with BERT-base-cased and 12% better than feature-based transfer learning approach. In conclusion, even though contextual neural models take more time to train and need more memory, if the ability to transfer learning from different pre-trained is more important, it's better to go with these models rather than traditional methods. Moreover, fine-tuning all layers of pre-trained model for downstream sentiment classification of banking news events observed better in accuracy than feature-based transfer learning. In the future, we can gather more instances for training and testing to make sure the findings about sentiment analysis in banking news apply more fine-grained. We can also explore different kinds of evaluation metrices to compare models more accuractely. Additionally, we could develop sets of rules based on dictionaries for each sentiment class (positive, negative, neutral). These rules could support the classification when combined with language models or pre-trained models.

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