Stock Movement Prediction with Financial News using Contextualized Embedding from BERT

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新闻事件(标题)影响股价波动;

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News events can greatly influence equity markets. In this paper, we are interested in predicting the short-term movement of stock prices after financial news events using only the headlines of the news. To achieve this goal, we introduce a new text mining method called Fine-Tuned Contextualized-Embedding Recurrent Neural Network (FT-CE-RNN). Compared with previous approaches which use static vector representations of the news (static embedding), our model uses contextualized vector representations of the headlines (contextualized embeddings) generated from Bidirectional Encoder Representations from Transformers (BERT). Our model obtains the state-of-the-art result on this stock movement prediction task. It shows significant improvement compared with other baseline models, in both accuracy and trading simulations. Through various trading simulations based on millions of headlines from Bloomberg News, we demonstrate the ability of this model in real scenarios.

Keywords: Stock Movement Prediction; Natural Language Processing; Neural Network; Data Mining

JEL Classification: C67, G11, G14

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1. Introduction

Stock movement prediction has attracted a considerable amount of attention since the beginning of the financial market, although the stock prices are highly volatile and non-stationary. Fama (1965) showed that the movement of stock prices can be explained jointly by all known information.

With the development of Internet, there is a rapid increase in the amount of financial news data (Figure 1), and more studies have been done to use computational methods to predict stock price changes based on financial news (Oliveira *et al.* 2013, Si *et al.* 2013, Xie *et al.* 2013, Nguyen and Shirai 2015, Luss and d'Aspremont 2015, Rekabsaz *et al.* 2017, Ke *et al.* 2019, Li *et al.* 2020, Coqueret 2020). Following previous works, we explore an accurate method to transform textual information into stock movement prediction signal.

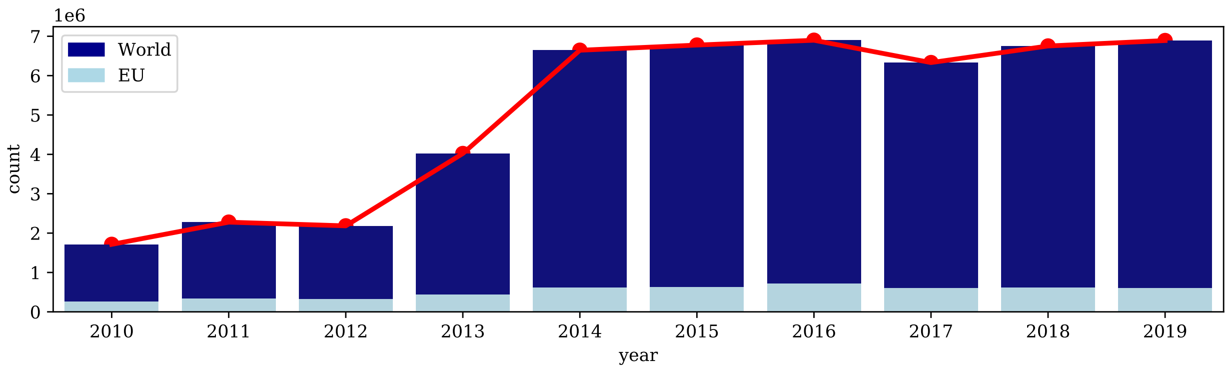


Figure 1. The number of news recorded by Bloomberg each year. For both world and European countries, there is a significant increase in the number of news from 2014.

参考综述

Schumaker and Chen (2009) use a classical feature engineering method to predict the market behavior. More recently, deep learning methods are more frequently applied on this task. Ding *et al.* (2014, 2015) employ structured representations to normalize a news then apply a Convolutional Neural Network (CNN) on this formulation. Hu *et al.* (2018) apply an improved Transformer model (Vaswani *et al.* 2017) to handle all the words in the raw text simultaneously to predict the forward return. Luss and d'Aspremont (2015) propose a statistical learning method to combine text data and the historical returns. Xu and Cohen (2018) improve the idea from Luss and d'Aspremont (2015) by designing a deep neural network. Ke *et al.* (2019) adopts a simple but effective classification method combining both regression and Term-Frequency Inversed Document Frequency (TF-IDF) model (Jones 1972). Del Corro and Hoffart (2020) further introduce an unsupervised method to extract market moving events from text data, which overcomes the problem of lacking reliable labels in financial data.

Before applying computational models mentioned above, the first step usually involves converting words into fixed-length vectors (these fixed-length vectors are called embeddings in natural language processing, details are presented in Section 2.2). Mikolov *et al.* (2013) propose Word2Vec model to embed words based on words co-occurrence prediction and Pennington *et al.* (2014) propose a similar GloVe model based on words co-occurrence frequencies. However, both methods can only generate static non-contextualized embeddings. It means that a word is converted to the same vector no matter its meaning or its context. This approach ignores the fact that the meaning of a word can change significantly in different contexts, which impacts the performance of the model. As most of the previous researches rely heavily on static non-contextualized embedding such as Word2Vec or GloVe, there can be accuracy loss.

Cer *et al.* (2018) and Peters *et al.* (2018) propose methods to generate contextualized embeddings by jointly considering all the words together. They published their models trained on large English corpus. Although effective, the model is fixed and does not contain domain-specific knowledge in finance.

Devlin *et al.* (2018) introduce a general-use language model called Bidirectional Encoder Representations from Transformers (BERT). It is one of the most promising models in natural language processing and it showed significant improvement on multiple benchmarks (Wang *et al.* 2018). The BERT model is pre-trained on a very large scale of textual data to leverage all the features in natural languages, and it also provides the ability to fine-tune this pre-trained model with domain-specific data without needing to start from the scratch. As we have a large amount of financial texts, we can use them to add financial knowledge to the BERT model and generate contextualized embeddings with domain-specific knowledge in finance from BERT.

In addition, previous researches evaluate the performance of the models based on the accuracy calculated on all the news (Ding *et al.* 2015, Xu and Cohen 2018, Hu *et al.* 2018). However, this evaluation metric does not reflect the real capability of the model since investors only care about the news which can move the market significantly. The news identified as neutral have little impact on investors' decisions, as investors will simply ignore the news if they are classified as neutral.

In this paper, aiming to solve the problems mentioned above, we want our research to have the following characteristics:

-内容嵌入取代统计嵌入;
-模型通过了领域微调;
-预测更准确;

- It adopts the contextualized embeddings instead of the static embeddings.
- The contextualized embeddings contain financial domain-specific knowledge.
- Our model has a better prediction on the news which can move the market significantly.

Hence, based on previous work (Sec. 2), we propose Fine-Tuned Contextualized-Embedding Recurrent Neural Network (FT-CE-RNN) to predict the stock price movement based on the headlines (Sec. 3). Using Bloomberg News dataset (Sec. 4), this model generates contextualized embeddings with domain-specific knowledge using all the hidden vectors from the BERT model fine-tuned on financial news. Then FT-CE-RNN uses a recurrent neural network (RNN) to make use of the generated embeddings. (Sec. 5) We also introduce a new evaluation metric which calculates the accuracy on various percentiles of the prediction scores on the test set instead of the whole test set to better incorporate investors' interests. Our experiments show that our FT-CE-RNN achieves a state-of-the-art performance compared with other baseline models. We also evaluate our model by running trading simulations with different trading strategies. (Sec. 6)

2. Related Work

2.1. *Stock Movement Prediction*

Stock movement prediction is a widely discussed topic in both finance and computer science communities. Researchers predict the stock market using all available information, including historical stock price, company fundamentals, third-party news sentiment score, financial news, social media texts and even satellite images.

The most classical method is to use the historical stock prices to predict the future prices. Kraft and Kraft (1977), Sonsino and Shavit (2014), Ariyo *et al.* (2014), Kroujiline *et al.* (2016), Jiang *et al.* (2018) use time series analysis techniques to extract the patterns of historical returns, and predict the future stock movement based on these patterns. More recently, researchers start to use neural networks to analyze this pattern (Kohara *et al.* 1997, Adebiyi *et al.* 2012, Tashiro *et al.* 2019, Chen and Ge 2019, Mäkinen *et al.* 2019, Bai and Pukthuanthong 2020).

Financial analysts usually use companies' fundamental indicators from their financial reports to predict the stocks' prices in the future (Zhang and Yan 2018). This includes the use of earnings per share (EPS) (Patell 1976), debt-to-equity (D/E) ratio (Bhandari 1988), cash flow (Liu *et al.* 2007), etc. Nonejad (2021) builds a conditional model to jointly consider historical prices and financial indicators.

With the rapid development of the natural language processing and deep learning, researchers start to focus on predicting stock movement based on textual data, such as financial news and social media texts, which were viewed as difficult to process systematically. Financial news data vendors such as Bloomberg, ThomsonReuters and RavenPack all include their proprietary sentiment analysis on the news. Coqueret (2020) thoroughly analyzes the sentiment classification given by Bloomberg and finds disappointing results on its predicting power. Ke *et al.* (2019) include the RavenPack's proprietary score as a benchmark and find it less performing than other models.

Hence, more researchers propose their own natural language processing models to improve the predictability based on financial news. Luss and d'Aspremont (2015) propose an improved Kernel learning method to extract the features in the texts. Ke *et al.* (2019) use statistical learning methods to determine the sentiment of the words in the news. More recently, computer scientists begin using state-of-the-art deep learning techniques to solve this problem. Ding *et al.* (2015), Hu *et al.* (2018), Xu and Cohen (2018), Li *et al.* (2020) propose different deep learning models to extract information from both financial news and social media texts.

There are also other researches which use uncommon data to predict future stock prices. The data includes key people compensation (Cooper *et al.* 2016), satellite images (Donaldson and Storeygard 2016) and the pictures included in the news (Obaid and Pukthuanthong 2021).

2.2. *Contextualized Embedding*

In the natural language processing, the first step usually involves transforming words or sentences into fixed-length vectors to allow numerical computations. These fixed-length vectors are known as the embeddings of the words or the sentences.

Historically, researchers use one-hot embeddings (Stevens *et al.* 1946) to encode words. However, the dimension of the one-hot embedding is large since each unique word takes one dimension. Hence, researchers start to develop methods to make the word embeddings denser.

The most widely used methods for word embedding are Word2Vec (Mikolov *et al.* 2013) and GloVe (Pennington *et al.* 2014), both of which are based on word co-occurrences. Such models take in a large number of texts and output a fixed vector for each word in the texts. The more frequently the two words co-occur, the more correlated two embeddings are. Once the model is trained, the embeddings of the words no long change, therefore we call these embeddings static embeddings. Such model generates the same embedding for one word no matter its context, although the meanings of the words can depend on the context in which this word occurs.

Researchers propose contextualized embeddings to solve this issue. Instead of taking only one words as input, the contextualized embedding model accepts the whole sentence as its input. The model then generates the embeddings for each word in the sentence by jointly considering the word and all the other words in the sentence. Cer *et al.* (2018) proposes Universal Sentence Encoder (USE) to encode the whole sentence contextually. However, USE only gives the embedding of the sentence as a vector without specifying the embedding of each word. Peters *et al.* (2018) proposed Embeddings from Language Models (ELMo) to embed words based on their linguistic contexts, but ELMo is trained on general English language, making the generated embeddings lack of financial domain-specific knowledge. However, Yang *et al.* (2020) showed domain-specific model outperforms general models in most of the tasks.

Recent researches on general-use language model such as BERT (Devlin *et al.* 2018) and XLNet (Yang *et al.* 2019) reported impressive result on all natural language processing tasks. More interestingly, these models propose a way to fine-tune its pre-trained model on general English with domain-specific data.

Hence, we propose FT-CE-RNN to complement existing researches. FT-CE-RNN generates contextualized embeddings with domain-specific knowledge from the BERT model, it then makes the stock movement prediction based on this more advanced embedding.

3. Problem Formulation

Suppose that we have a stock s with a headline $h_{s,t}$ recorded at time t, and the headline has N words, we denote them by $w_1, ..., w_N$. We first need to transform them into fixed-length embeddings. Suppose that the length of the embedding is l_e, this process can be written as:

$$Emb_i = f_s(w_i) \tag{1}$$

where $Emb_i \in \mathbb{R}^{l_e}$ is the embedding of the word w_i and f_s denotes the static embedding encoder. In this case, each word has a fixed embedding independent of its context.

A contextualized embedding encoder has the same function of converting a word into a vector, unless it considers all the words in a sentence together. We use f_c to denote this contextualized embedding encoder, it can be written as:

$$Emb_i = f_c(w_i | w_1, ..., w_N) \tag{2}$$

We concatenate the embeddings of all words to get the embedding of the headline $h_{s,t}$. We define the embedding of this headline as:

$$Emb_{h_{s,t}} = [Emb_1, ..., Emb_N] \tag{3}$$

where $Emb_{h_{s,t}} \in \mathbb{R}^{l_e \times N}$.

Following the work of Luss and d'Aspremont (2015), Ding *et al.* (2015), Xu and Cohen (2018), Ke *et al.* (2019), we formulate the stock movement prediction as a binary classification task[1]. It means that we predict if a news has a **positive** impact or a **negative** impact on the related stock.

We define its market-adjusted return $r_{s,t}$ as

预测股票涨跌任务：二分类

$$r_{s,t} = \frac{P_{s,t+\Delta t}}{P_{s,t}} - \frac{P_{m,t+\Delta t}}{P_{m,t}} \tag{4}$$

where $P_{s,t}$ denotes the price of stock s at time t and $P_{m,t}$ denotes the value of the equity index at time t.

We notice that it is necessary to use market-adjusted return instead of the simple return, as the information contained in the price change is partially due to the information related to this stock (such as news), and also partially due to the information related to other macroeconomic information (such as interest rate, fiscal policies, etc.). As the macroeconomic effect impacts all stocks, it can be explained by a weighted sum of all stocks, such as market index. We can simply remove this impact by subtracting the index return from the stock return, and this adjusted return can better explain the impact of the news.

Most researches in the stock movement prediction based on news simply suppose that all the news induce the market change in the same way (Luss and d'Aspremont 2015, Xu and Cohen 2018, Hu *et al.* 2018, Ke *et al.* 2019), and therefore use the same Δt to calculate the forward returns of all news. However, Fedyk (2018) suggests that the news during the trading hours and the news outside the trading hours have different market impact.

交易日的新闻 和 非交易日的新闻影响程度不一样;

Hence, for different news, we choose different Δt. For example, for the news published during the trading hours, the price can change in several minutes after the arrival of the news. In this case, we can choose a smaller Δt of several minutes or several hours. However, for the news published out of

[1] We can also formulate this problem as a multi-class classification task (Pagolu *et al.* 2016). It means that, instead of classifying a news into positive news and negative news, we can classify them into positive news, negative news or neutral news, making it a three-class classification task. Moreover, we can classify a news into different return intervals, making it a multi-class classification task. However, we find that the performance with multi-class classification setup is less impressive. We provide the details of this study in Section 6.7.

the trading hours, as the market is already closed, we cannot observe the effect of the news until the next market open. Therefore, we need to choose a Δt of several days.

We define the stock price movement as:

训练目标 Y

$$Y_{s,t} = \begin{cases} 1, & r_{s,t} > 0 \\ 0, & r_{s,t} \leq 0 \end{cases} \tag{5}$$

The goal is to predict $Y_{s,t}$ from the embeddings of the headlines $Emb_{h_{s,t}}$. It can be written as:

$$\hat{Y}_{s,t} = g(Emb_{h_{s,t}}) \tag{6}$$

where g represents the prediction model.

4. Data

4.1. *Data Description*

The dataset that we use is Bloomberg News[1]. In this dataset, each entry contains a *timestamp* showing when this news is published, a *ticker* which tells the stock related to this news and the *headline* of this news. In addition to the necessary information above, there are two fields given by Bloomberg's proprietary classification algorithm. The *score* is among -1, 0 and +1, which indicates if the news is either negative, neutral or positive. *Confidence* is a value between 0 and 100 related to *score*. A higher *confidence* value means that Bloomberg's model is more sure about its *score*. Bloomberg's classification will serve as one of the benchmarks for our prediction model. We present a sample dataset in Table 1.

Table 1. A small sample from the Bloomberg News dataset

Headline	TimeStamp	Ticker	Score	Confidence
1st Source Corp: 06/20/2015 - 1st Source announces the promotion of Kim Richardson in St. Joseph	2015-06-20T05:02:04.063	SRCE	-1	39
Siasat Daily: Microsoft continues rebranding of Nokia Priority stores in India opens one in Chennai	2015-06-20T05:14:01.096	MSFT	1	98
Rosneft, Eurochem to cooperate on monetization at east urengoy	2015-06-20T08:01:53.625	ROSN RM	0	98

We need to address that in our dataset, we only have the headlines of the news instead of the whole article.

In our experiment, we use the news data on all the stocks from the STOXX Europe 600 index[2] which represents the 600 largest stocks of the European market. In order not to overfit, we select a short period (from 01/01/2016 to 30/06/2018) as our training set and another short period (from 01/07/2018 to 31/12/2018) as our development set. We tune the parameters of the models only based on this subset of the data, we then test on the whole period (from 01/01/2011 to 31/12/2019) on a 3-year rolling basis. It means that we generate the classification result of the year y using model trained between $y-3$ and $y-1$, without varying the parameters initially obtained. Detailed statistics of the dataset are in Table 2. We can also find the number of news in each year from Figure 1.

[1] https://www.bloomberg.com/professional/product/event-driven-feeds/
[2] https://www.stoxx.com/index-details?symbol=SXXP

Table 2. Statistics of the Bloomberg News dataset

	Train	Dev	Test[a]
Total news	1,616,922	316,944	5,253,345
Word counts	17,650,629	3,554,324	55,410,309
From date	01/01/2016	01/07/2018	01/01/2011
End date	30/06/2018	31/12/2018	31/12/2019

[a] Note that we do not simply apply our model trained on the training set on the test set. The training set and the development set are only used to find the hyper-parameters for our models. We generate the scores on test set using different models trained on a 3-year rolling basis, as described in section 4.1

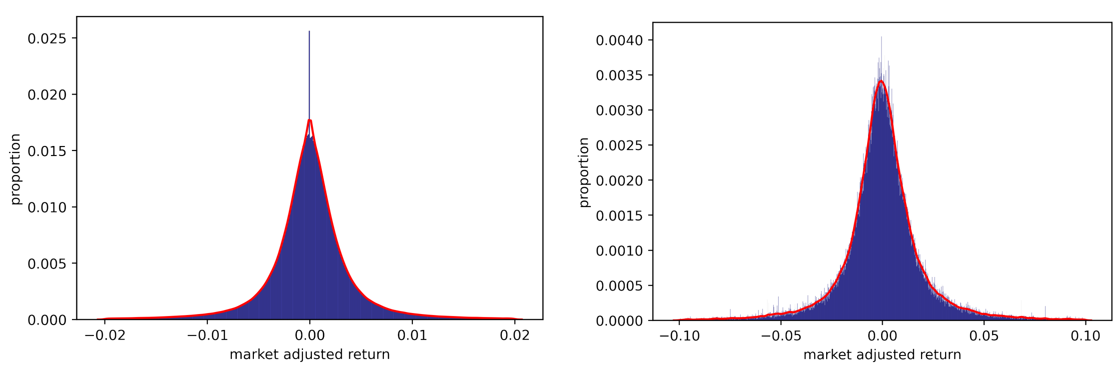
In addition to the Bloomberg news dataset, we also use the cooperate action adjusted share prices at market close and intraday minute bar share prices for all the stocks. The share prices are used to label our data and simulate our trading strategies.

4.2. *Data Labelling*

For this supervised learning task, we need to provide our model with the ground-truth as its target. However, our data is simply the headlines of the financial news, it does not tell us if a news is positive or negative. Hence, we need to give each news in the training set a label (positive or negative) before training our model.

The intuition behind our labelling method is simply that if a news is positive, the investors will start to overbuy the related stocks, the stock should therefore outperform the market and vice versa. We use Equation 4 to calculate the market adjusted return for each news. As discussed in Section 3, we consider the different effects of the news which occur during the trading hour[1] and those outside the trading hour. We use different Δt (Eq. 4) for the news during the trading hours and outside the trading hours. For the news inside trading hours, we choose Δt_i and for the news outside the trading hours, we use Δt_e.[2] We show an example of the distribution of the returns for all the news in Figure 2.

研究思路：新闻积极，投资者就开始买股票



(a) In trading hours

(b) Outside trading hours

Figure 2. The distribution of the $r_{s,t}$ for both the news in the trading hour and those outside the trading hour. The returns are calculated on all the news in the training set. For the news in the trading hour (Figure (a)), we use the forward return of 30 minutes ($\Delta t_i = 30minutes$), and for those outside the trading hour (Figure (b)), we use the forward return of 1 day($\Delta t_e = 1day$). We can see that the market adjusted returns are symmetrically distributed.

We label the data based on the market-adjusted return mentioned above. As our task is to identify

[1]9:00 to 17:30 CET for most European markets

[2]For Δt_i, we test 5,30,60,120 minutes; for Δt_e, we test 1,2,3,5 days.

训练过程：x—条新闻--> 嵌入--> delta T时间的股票价格反应
预测过程：一条新闻输入--> 判断积极or消极--> 针对该股票判断多条新闻计分，最后的得分是正or负

研究任务：鉴别投资者关注的标志性新闻

market-moving news which investors focus on, we need to remove news which do not have significant impact on the price. As we found that the return distribution is quite balanced for the training set (Figure 2), we simply label the 15% news with most positive return as 1 and the 15% news with most negative return as 0. This can be written as:

过滤掉那些中性、没影响的新闻

$$Y_{s,t,train} = \begin{cases} 1, & r_{s,t} \textit{ in top } 15\% \\ 0, & r_{s,t} \textit{ in bottom } 15\% \\ removed, & otherwise \end{cases} \tag{7}$$

where $Y_{s,t,train}$ is the label for the news $e_{s,t}$ for stock s recorded at time t in the training set.

However, for development and test sets, we label **all** news with positive return as 1 and all news with negative return as 0. This can be written as:

$$Y_{s,t,dev/test} = \begin{cases} 1, & r_{s,t} > 0 \\ 0, & r_{s,t} \leq 0 \end{cases} \tag{8}$$

This difference in labelling is simply to avoid the information leakage. In real-life scenario we cannot know the forward return of a news when it is published. Therefore, we cannot know if the news is in the top 15-percentile or the bottom 15-percentile. We are supposed to give each news a score when it is published regardless its forward return.

However, we can choose to exclude a news according to its score when calculating the metrics, as this information is available immediately after we receive the news. We use this idea to construct different test sets to evaluate of model. We present the details in Section 6.2.

5. Prediction Model

bert 模型上的 神经网络结构

There are two main components in our model: a contextualized embedding encoder from BERT model and a Recurrent Neural Network (RNN) which takes the contextualized embedding as input and outputs the classification probability for both classes.

5.1. *Contextualized Embedding Encoder from BERT*

The Bidirectional Encoder Representations from Transformers (BERT) proposed by Devlin *et al.* (2018) is a widely used language model in the natural language processing applications. It is first pre-trained on very large scale data (WikiBooks[1] and Wikipedia[2]) to learn the basic characteristics of a language. After this pre-training phase, we can obtain a pre-trained base BERT model for all other downstream tasks (such as text classification). This pre-training process is computationally intensive, we simply use the pre-trained BERT model published by Google[3].

Figure 3 shows the structure of BERT model. It has L layers and each layer has N nodes, each node is a Transformer (Vaswani *et al.* 2017). The first layer takes a tokenized headline as input and the BERT model generates $N \times L$ hidden vectors, denoted by $T_{i,j}$. The first token at the first layer is a special [CLS] token reserved for fine-tuning.

For a specific downstream task, we can fine-tune the base BERT model suitable for this specific task. It means that we do not initialize the parameters of BERT model randomly, we use the pre-trained BERT model as our initial state instead. We update the parameters in the base model with our domain-specific data. This approach adds domain knowledge to the large scale language model

领域知识微调bert

[1]https://en.wikibooks.org/
[2]https://en.wikipedia.org/
[3]https://storage.googleapis.com/bert_models/2020_02_20/uncased_L-12_H-768_A-12.zip

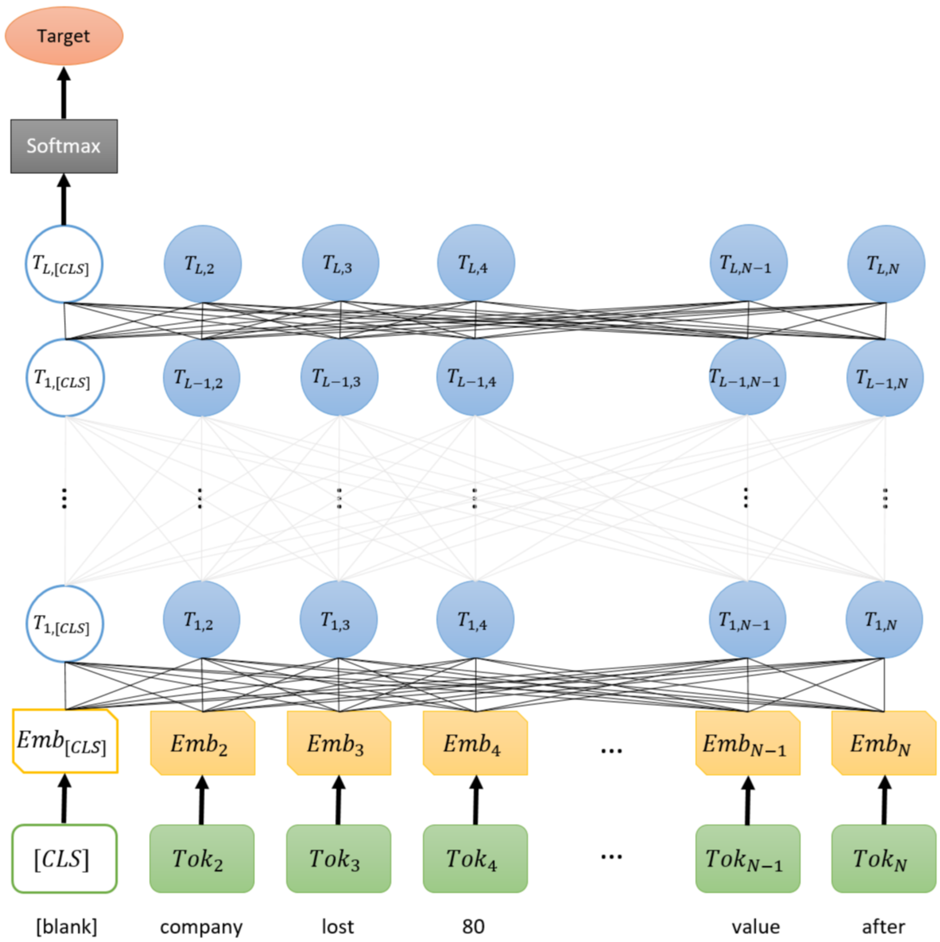


Figure 3. BERT model with input headline "*company lost about 80 percent of its market value after interim data*" and the maximum length of model is set to 10 ($N = 10$). The last two words *interim* and *data* are therefore trimmed. There are L layers in this BERT model. Tok_i denotes the *i-th* token of the tokenized news and N denotes the maximum length of a headline. $T_{i,j}$ represents the hidden vector for the j-th transformer at layer i. The first [CLS] label is simply a special string we choose to signify the class of this headline. This label is only used when fine-tuning the model, we leave it blank when we generate the embeddings. The original method to use BERT as classification model is to use directly [CLS] vector to represent the whole sentence, while we choose to use all hidden vectors at one layer to represent the sentence. The embedding generated with the model is shown in Equation 11.

(Yang *et al.* 2020), it can help the BERT model better understand the texts in specific situations. In our case, we can fine-tune the base BERT model with our labelled financial news data mentioned in Section 4.2 to make it specialize in financial texts.

The fine-tuning process is straightforward. We input the class label (0 or 1) together with the tokenized headline into the first layer of a pre-trained BERT model. We set the target to the class label and loss function to cross-entropy, defined as:

1.居然用正负分类任务微调bert

$$loss = \sum Y_i ln(P_i^+) + (1 - Y_i) ln(1 - P_i^+) \quad (9)$$

where Y_i is the label for the news i and P_i^+ denotes the probability that the news i is positive given by the model. We use back-propagation (Hecht-Nielsen 1992) to update the parameters in the model. We repeat such operation for several epochs until the loss converges.

In order to generate the contextualized embedding, we can either directly use the base BERT model or use the fine-tuned model. We first tokenize our headlines using SentencePiece tokenizer (Kudo and Richardson 2018). If the number of tokens is smaller than N, we simply pad it to N

tokens by adding null tokens at the end. If there are more than N tokens, we remove the last tokens to make this sentence have exactly N tokens. We input these tokens into pre-trained BERT model as shown in Figure 3 with the first token which stands for [CLS] label left blank. Suppose that our BERT model has L layers, we can then generate L different embeddings, denoted by $Emb_{base,l}$. We have,

$$Emb_{base,l} = [T_{l,2}, T_{l,3}, ..., T_{l,N}] \tag{10}$$

where $Emb_{base,l}$ is a $size(T_{l,i}) \times (N-1)$ matrix representing this headline and l denotes the layer from which we generate the embedding. We have $1 \leq l \leq L$.

Similarly, we can generate another L embeddings from the fine-tuned BERT model, denoted by $Emb_{tuned,l}$. We have,

$$Emb_{tuned,l} = [T'_{l,2}, T'_{l,3}, ..., T'_{l,N}] \tag{11}$$

where $T'_{l,i}$ denotes the hidden vector for the *i-th* token at the *l-th* layer for the fine-tuned model.

5.2. *RNN Prediction Model*

The structure of our prediction model is simple and straightforward, it is shown in Figure 4.

2.用股价波动预测训练RNN

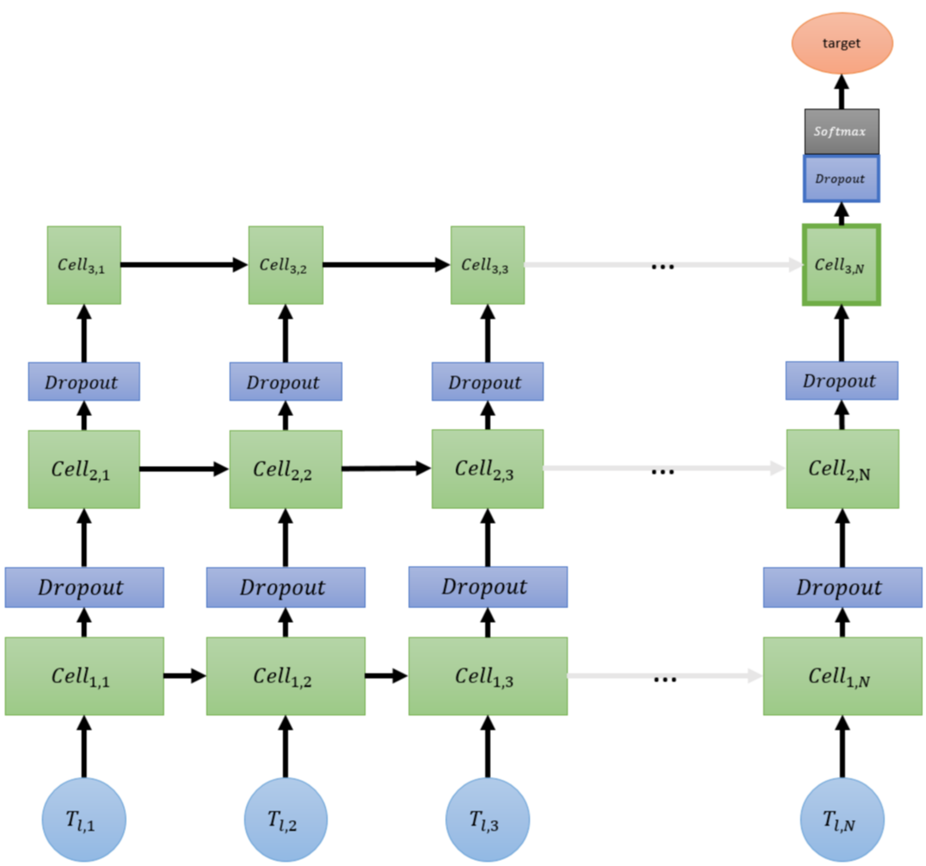


Figure 4. Structure of our RNN network. $Cell_{i,j}$ denotes the *j-th* cell on the *i-th* layer. The cell can be either Vanilla RNN, LSTM or GRU. In addition, the output size reduces when it approaches the last layer of the model.

There are several layers of cells which can either be Vanilla RNN (Cleeremans *et al.* 1989), Long-Short Term Memory (LSTM) (Hochreiter and Schmidhuber 1997) or Gated Recurrent Unit (GRU) (Cho *et al.* 2014). The size of output at each layer shrinks in order to reduce the dimension of our features gradually and to make the remaining features more meaningful. Two neighbor layers are connected by a dropout to overcome the overfitting problem in the network. At the end of the last layer, a softmax is added to calculate the probability for each class based on the last vector on the last layer.

Suppose that we choose to use $Emb_{base,l}$ to represent a sentence. We first initialize the parameters in the RNN model randomly and input the embeddings of tokens ($T_{l,i}$) sequentially into the cells ($Cell_{1,i}$) in the first layer of the recurrent neural network. At the same time, we set the target to the corresponding label of the headline. We use the same cross-entropy loss mentioned in Equation 10 as our loss function. We use the same back propagation procedure in Section 5.1 to update the parameters in the model until we have a stable loss.

6. Experiments

In this section, we introduce our experiment setup and results in detail. We also include the results of some baseline models to prove the effectiveness of our model. In addition to the final result, we add some ablation experiment results to show the effect of some factors in our model.

6.1. *Training Setup*

We use the pre-trained 12-layer, 768-dimension, 12-heads BERT model[1] to generate $E_{base,l}$, then we fine-tune this base model using our labelled dataset with the method mentioned in section 4.2.[2] We choose the best-performing fine-tuned model to generate $E_{tuned,l}$. Empirically, the layer of BERT used as embedding should not be too close to the first layer, otherwise the contextualized embedding will be too similar to the static embedding. Hence, we only test embeddings with $l = L, L-1\ or\ L-2$. This choice will be discussed in detail in Section 6.6.

The maximum length of a sentence is set to 32 tokens, as there are at most 29 tokens for all headlines in our dataset. If there are fewer tokens, we pad it to 32 with null tokens.

For our RNN model, the cells are set to be LSTM. We use a four-layer single-directional RNN[3] with a dropout rate of 50%.

6.2. *Evaluation Metrics*

Because of the huge volume of news that we receive daily, it is not realistic for either human investors or systematic trading algorithms to react on all news. Otherwise, we lose a considerable amount of transaction fees on the news which do not significantly move the market. It is more logical that an investor first reads the news, then buys or sells the stock if he thinks that the news can have substantial impact on the stock price. If he thinks that the news is neutral, he will simply ignore the news. In this type of neutral-insensitive scenario, evaluating our model on all news is less meaningful. Instead, we evaluate our model only on certain ”extreme” news chosen based on their sentiment classification results.

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We define the score of a news, denoted by S_{news}:

$$S_{news} = (P_+(news) - 0.5) \times 2 \tag{12}$$

[1]This is the base pre-trained model published by Google, it is available at https://storage.googleapis.com/bert_models/2020_02_20/uncased_L-12_H-768_A-12.zip

[2]We choose batch size: 32, 64, 128 and learning rate: 2e-6, 5e-6, 1e-5

[3]The hidden size for each layer is set to 256, 128, 64, 32 respectively.

where $P_+(news)$ denotes the probability that this news belongs to the positive class given by the prediction model. S_{news} is therefore a value between -1 and 1.

We use P_n to denote the n^{th} percentile of all scores on the **training** set. We can then choose the set on which we want to evaluate our model. We define this set E_{2n} by:

$$\begin{aligned} E_n^- &= \{news | S_{news} < P_n\} \\ E_n^+ &= \{news | S_{news} > P_{100-n}\} \\ E_{2n} &= E_n^- \cup E_n^+ \end{aligned} \tag{13}$$

We assume that the distributions of scores on the training set and the test set are the same. It should contain about $n\%$ highest-score news and $n\%$ lowest-score news from the test set. We evaluate our model on these subsets of news instead of all news in the test set.

Standard Metrics

Given a confusion matrix $\left(\begin{smallmatrix} tp & fn \\ fp & tn \end{smallmatrix}\right)$ which contains the number of samples classified as true positive (tp), false positive (fp), true negative (tn) and false negative (fn). We use both the accuracy and the Matthews Correlation Coefficient (MCC) (Matthews 1975) to evaluate our models. These two values are defined by:

Accuracy:

$$\frac{tp + tn}{tp + tn + fp + fn} \tag{14}$$

Matthews Correlation Coefficient (MCC):

$$\frac{tp \times tn - fp \times fn}{\sqrt{(tp + fp)(tp + fn)(tn + fp)(tn + fn)}} \tag{15}$$

Trading Strategies

However, those two metrics introduced above do not perfectly reflect the reality, as the profits are quite different when the price goes up significantly or mildly, although they are both counted as true positive. Hence, it is necessary to simulate these trades on real markets. We use two simple trading strategies for simulations.

Strategy 1 (S1).

We simply follow the strategy used by Ke *et al.* (2019).

Before each market close, we search for all the news belonging to E_n with a maximum age of A days. We group the selected news by stock and we calculate the average score for each stock. We choose the 20 stocks with the highest scores, our target position for these stocks is \$T. We also choose the 20 stocks with the lowest scores, our target position for these stocks is -\$T.

Strategy 2 (S2).

The advantage of S1 is that it perfectly balances the long leg and the short leg.[1] As such, we have no exposure to the market, and it reduces the risk of the market movement. However, the fallback of S1 is that it only focuses on the highest scores instead of considering all the stocks. In this case, we will not be able to fully use our predictions. Hence, we design the following strategy to solve this problem:

1. We first calculate the average score for each stock using the same method as described in S1.

[1] The long leg means the total amount invested positively, the short leg means the total amount invested negatively

2. We choose all the stocks with positive scores, s_i^+ denotes the score for the stock i.
3. The target position for the stock i is $\$20T \times s_i^+ / \sum_j s_j^+$.[2]
4. We invest in the stocks with negative scores in the same way. For a negatively scored stock i, we invest $-\$20T \times s_i^- / \sum_j s_j^-$.

This strategy not only uses all the available classification results, but also has no exposure to the market as S1, since the long position and the short position are both $20T$.

To evaluate the performance of these strategies, we use the following two commonly used indicators in finance.

Annualized return: defined by

$$\frac{1}{N} \sum_{t=1}^{N} r_t \times D \tag{16}$$

where D is the number of trading days in one year[1], and r_t denotes the daily return of the portfolio for the day t, defined by the ratio of the profit on day t to the total position on day t.

Annualized Sharpe Ratio: defined by

$$\frac{\bar{\mathbf{r}}}{\sigma(\mathbf{r})} \times \sqrt{D} \tag{17}$$

$\bar{\mathbf{r}}$ denotes the mean of all the r_i and $\sigma(\mathbf{r})$ represents the standard deviation all the r_i.

6.3. *Baselines and Proposed Models*

We use the following models as baselines.

- **NBC** (Maron 1961): *Naive Bayes Classifier*
  One of the most traditional language classification models based on word frequency.
- **SSESTM** (Ke *et al.* 2019): *Supervised Sentiment Extraction via Screening and Topic Modeling.*
  A regression model based on word frequency and stock returns.
- **Bloomberg** (Proprietary): *Bloomberg Sentiment Score*
  The sentiment score from Bloomberg's proprietary model, which comes along with the Bloomberg News dataset. An example of this sentiment score is shown in Table 1.
- **BERT** (Devlin *et al.* 2018): *Bidirectional Encoder Representations from Transformers*
  A general and powerful language model for a wide range of NLP tasks. We directly use the [CLS] label as the final prediction, as proposed by the author.
- **FinBERT** (Yang *et al.* 2020): *Financial Sentiment Analysis with BERT*
  The same structure as the BERT model but pre-trained with financial domain-specific data.

To make a detailed analysis of the improvement brought by our proposed models, in addition to the final version of our model (FT-CE-RNN), we add two other intermediate variants of our RNN model.

- **RNN**: *Recurrent Neural Network*
  The recurrent neural network introduced in Section 5.2. Instead of using contextualized embeddings, we use the static Word2Vec embedding as its first layer.

[2]The multiplier 20 is to guarantee the homogeneity with S1. We invest \$20T for each leg in both strategies.
[1]For the sake of simplicity, we choose 250 as the number of trading days for one year.

- **CE-RNN**: *Contextualized Embedding - Recurrent Neural Network.*
  The network structure is the same as RNN, but we use contextualized embedding generated from base BERT model instead of Word2Vec.
- **FT-CE-RNN**: *Fine-Tuned - Contextualized Embedding - Recurrent Neural Network*
  The same RNN using contextualized embedding generated from fine-tuned BERT.

6.4. *Results*

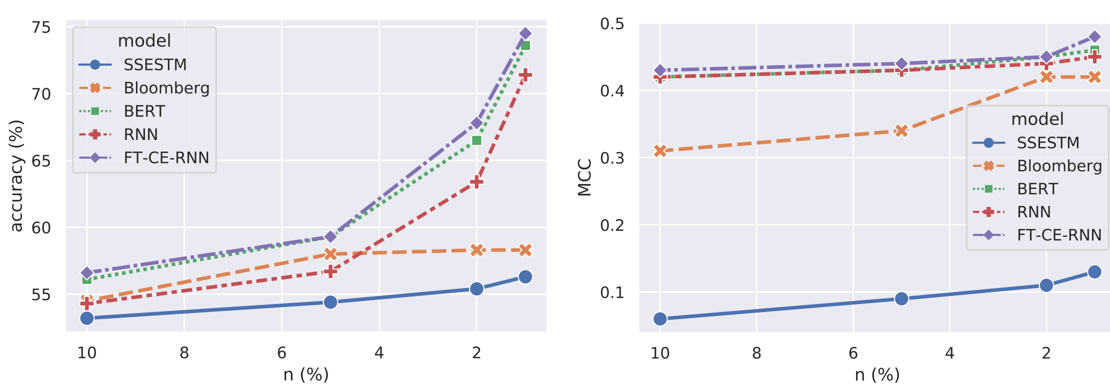
The detailed results for standard metrics are shown in Table 3 and Figure 5. We also list the results from trading simulations in Table 4.

Table 3. Performance of baseline models and our proposed RNN variants evaluated in accuracy and MCC

	1%[a]		2%		5%		10%	
	Acc	MCC	Acc	MCC	Acc	MCC	Acc	MCC
NBC	59.8	0.2	56.1	0.12	54.3	0.09	53.4	0.07
SSESTM	56.3	0.13	55.4	0.11	54.4	0.09	53.2	0.06
Bloomberg [b]	58.3	0.42	58.3	0.42	58.0	0.34	54.5	0.31
BERT	73.6	0.46	66.5	**0.45**	**59.3**	0.43	56.1	0.42
FinBERT	73.9	0.46	66.5	**0.45**	59.2	0.43	55.6	0.42
RNN	71.4	0.45	63.4	0.44	56.7	0.43	54.3	0.42
CE-RNN	70.9	0.42	63.8	0.28	57.9	0.16	54.7	0.09
FT-CE-RNN	**74.5**	**0.48**	**67.8**	**0.45**	**59.3**	**0.44**	**56.6**	**0.43**

[a] 1% signifies that we test our result on E_1, which includes about 1% of all news on the test set.

[b] In Bloomberg dataset, we have about 4% of the news with a maximum level score, therefore we have the same result for E_1 and E_2.



(a) Accuracy (b) MCC

Figure 5. Accuracy and MCC results of different models varied with E_n, the horizontal axis represents the value of n

We find that in terms of accuracy, our FT-CE-RNN outperforms all the other baselines models. Especially, comparing the accuracy of RNN and FT-CE-RNN, there is an improvement of 4.1% when we test on the 1% most extreme news (E_1). This result shows the power of contextualized embedding against static embedding. We also notice that there is an improvement of 0.9% compared with BERT result. This result explains that using all hidden vectors instead of only one [CLS] vector helps improve the result. However, if we directly use the embedding from the base BERT (CE-RNN) instead of the fined-tuned BERT (FT-CE-RNN), there is a clear disadvantage. This result shows the necessity of including the domain knowledge in the embeddings.

In addition, we observe that all our models have a significant margin compared with the Bloomberg and SSESTM sentiment score, which is completely independent of our data labelling and modelling

Table 4. Performance of baselines and proposed models in trading simulations[a]

		1%		2%		5%	
Strategy	Model	Ret.[b]	Sharpe	Ret.	Sharpe	Ret.	Sharpe
S1	NBC	9.61	1.09	2.35	0.26	2.44	0.27
	SSESTM	2.39	0.41	1.57	0.24	2.74	0.35
	Bloomberg	8.83	1.19	8.83	1.19	8.03	1.10
	BERT	9.33	1.42	8.08	1.11	8.21	1.09
	FinBERT	8.83	1.22	8.29	1.10	7.86	1.13
	RNN	9.86	1.43	8.06	1.13	6.43	0.89
	CE-RNN	8.39	1.07	7.31	0.99	7.62	1.01
	FT-CE-RNN	10.75	1.50	12.31	1.70	11.32	1.50
S2	NBC	7.93	0.62	0.57	0.06	0.80	0.15
	SSESTM	4.75	0.47	3.02	0.35	2.76	0.38
	Bloomberg	10.76	1.61	10.76	1.61	9.82	1.56
	BERT	13.10	1.42	11.42	1.56	9.87	1.53
	FinBERT	11.35	1.24	9.85	1.21	12.85	1.97
	RNN	17.53	1.75	15.47	1.72	12.70	1.79
	CE-RNN	12.58	1.33	10.37	1.25	8.29	1.05
	FT-CE-RNN	**19.72**	**2.11**	**18.39**	**2.49**	**15.01**	**2.31**

[a]The simulation does not consider transaction costs.

[b]The annualized return, presented in percent.

process, this result can prove the efficiency of our models compared with other widely used models in the industry.

In our trading simulations, we use a look-back window of 5 days ($A = 5$ *days*). We find that the result of our FT-CE-RNN outperforms all other models in most of the cases. The most significant improvement is on Sharpe Ratio. When trading on the 1% most extreme news using strategy S2, there is an improvement of 0.69 (49%) in Sharpe ratio and an improvement of 6.62 (51%) in return if we compare BERT and FT-CE-RNN. It means that our model using contextualized embedding is not only more profitable but also more stable.

We can also find that S2 performs better than S1, since S2 uses all the signals while S1 only uses the signals on the top/bottom stocks. This proves that our classification is valid for most of the stocks, making it a robust method.

An example of trading simulation is shown in Figure 6. It shows how our profit evolves with time. We observe that FT-CE-RNN is not only better on profitability and stability but also on the absolute profit in dollars.

6.5. *Transaction costs*

Table 5. Trading simulation results with transaction costs[a]

	No cost		With cost	
Model	Ret.	Sharpe	Ret.	Sharpe
NBC	7.93	0.62	2.09	0.16
SSESTM	4.75	0.47	-1.80	-0.18
Bloomberg	10.76	1.61	4.49	0.67
BERT	13.10	1.42	5.98	0.65
FinBERT	11.35	1.24	3.88	0.42
RNN	17.53	1.75	11.57	1.15
CE-RNN	12.58	1.33	6.15	0.65
FT-CE-RNN	**19.72**	**2.11**	**12.60**	**1.35**

[a]The result is obtained based on E_1 test set using the trading strategy S2.

Our trading simulations ignore transaction costs thus far, since the primary goal of this research

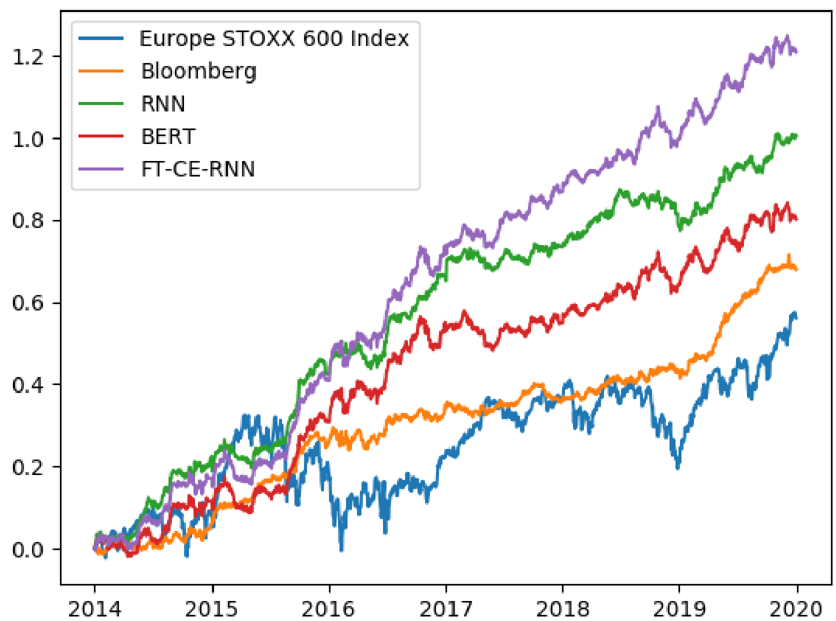


Figure 6. Trading simulation result in absolute profit. This trading simulation is run on 1% most extreme news (E_1) using strategy S2. We also include the market return, represented by Europe STOXX 600 Index. We can see our models largely exceed the market return and the Bloomberg sentiment score.

is to prove the effectiveness of our sentiment model with contextualized embedding. The transaction costs have no impact on the result because all the models are in the same no-cost environment.

That said, applying this model in real-life trading is another separate but interesting question. To understand the real gain of our FT-CE-RNN model for the asset management, we rerun our trading simulations with transaction costs.

In our simulations, we assume a transaction cost of 4bps[1] proportional to the daily turnover[2]. The simulation results with transaction costs are shown in Table 5.

Although the transaction costs cut our profits significantly, we can still have a profitable margin when using our FT-CE-RNN model.

6.6. *Effect of Embedding Layer*

In this section, we discuss our choice of BERT hidden layer to be used as embedding.

Empirically, the final layer of BERT model should be used to generate our contextualized embedding as the final layer is more "mature" and contains more information compared with other layers which are closer to the first layer. However, our result listed in Table 6 shows the opposite.

We find that the best result for CE-RNN is acquired when we use layer L while the best result for FT-CE-RNN is obtained when using layer $L-1$. The reason for this phenomenon is that the ~~last layer of the fine-tuned BERT is biased towards~~ the classification result, since the goal for the fine-tuning process is to make the first token of the last layer close to the classification target. If we use the last layer of the fine-tuned BERT as the input for RNN, we are simply replicating the classification process of the BERT, instead of improving the result. Using one deeper layer ($L-1$) helps reduce this bias (Xiao 2018). However, the base BERT does not have this bias on the last layer

[1] basis points, 10^{-4}
[2] defined as $|pos_i - pos_{i-1}|$ for day i

Table 6. Accuracy result using different layers of BERT model as contextualized embedding[a]

Embedding layer	L^{b}	$L-1$	$L-2$
CE-RNN	**70.9**	68.1	63.3
FT-CE-RNN	73.0	**74.5**	66.7

[a]The result is acquired on the E_1 test set.

[b]L denotes the last layer of the BERT model, $L-n$ represents the n-th last layer of the BERT model.

since it has no previous knowledge on the training set. This explains why CE-RNN has a better performance when using the embedding from the last layer (L).

If we use an even lower layer to generate contextualized embedding, such as $L-2$, the performance declines as it is too close to the embedding layer and lacks contextualized characteristics.

6.7. *Effect of Classification Classes*

During our initial researches, we also explored the possibility of using a 3-class classification instead of a 2-class classification. It means that we do not classify a news into a positive or a negative news, we classify if a news is either positive, negative or neutral. This is the method adopted in the Bloomberg's proprietary model.

Table 7. The accuracy result for a 2-class classification model and a 3-class classification model[a b]

Acc	1%	2%	5%	10%
2-class	74.5	67.8	59.3	56.6
3-class	61.0	58.4	55.5	53.6

[a]The result is based on the test set E_1.

[b]For 3-class classification, we choose the $n/2\%$ largest scores for the positive class and the $n/2\%$ largest scores for the negative class as our E_n. The guarantees the same number of the news considered in both cases.

The result of using a 3-class classification model is shown in Table 7. We find a significant worse performance if we add another possibility to our model. This is because a 3-class model supposes a clear difference between the market-moving news and the neutral news, however, this is not always the case. It is not obvious to find a threshold, above which the news is positive and below which the news is neutral. In this scenario, we are not able to construct a clear training set for our model to learn the difference between a neutral news and a market-moving news.

Hence, in our final model, we decide to classify the news into two classes instead of three.

6.8. *Qualitative Analysis of the Classification Result*

We analyze the news in E_1 to see if there is any pattern, for example, some frequent words in them. We include the 50 most frequent words appeared in $E_{0.5}^{+}$ and 50 most frequent words in $E_{0.5}^{-}$ in Appendix A, along with their frequencies. We exclude all the stopwords in English, such as *to*, *for*, *a*, etc.

We can find that for the news identified as the most positive, some common words include *buy*, *upgrade*, *raise*, etc. For the news identified as the most negative, *downgrade*, *cut* and *miss* are among common words. These are also logical keywords for the humans, making the result from the neural network intuitive.

We can also find in this collection that there are also some less natural words, such as *fly*, *say neutral*, etc. However, as these words appear in both categories, the effect of such words is neutralized if we empirically assume the effect of a word is its positive impact minus its negative impact.

This result is similar to the result we get from the word frequency-based method, such as NBC and SSESTM. However, we demonstrate that our FT-CE-RNN model is significantly more powerful than these two baseline models (Section 6.4). This phenomenon implies that our model is capable of capturing complex information in the news on top of the word frequency.

7. Conclusion

We build the whole pipeline for the stock movement prediction task with headlines from financial news, including labeling the news, generating contextualized embedding, training a neural network model, validating the model with various metrics and building trading strategies based on the model output.

We design a FT-CE-RNN model which uses fine-tuned contextualized embeddings from BERT instead of the traditional static embeddings. We also introduce our new evaluation metrics focusing on market-moving news, which are more suitable for asset manager's needs.

Through various experiments on the Bloomberg News dataset, we demonstrate the effectiveness of our FT-CE-RNN model. We find a better performance, in both accuracy and trading simulations, than other widely used baseline models. We also include other ablation studies to discuss the choice of some important parameters and to demonstrate the intuitiveness of the result.

In the future, we will continue our research on the stock movement prediction using natural language processing methods based on longer texts (such as earning call transcripts, financial reports, etc.) instead of the headlines. By using more information, we aim to build a model which helps achieve better stock movement prediction result.

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Appendix A: Frequent Words in Market Moving News

Table A1. The most frequent words in the most positvely scored news and the most negatively scored news

positive		**negative**	
word	*frequency*	*word*	*frequency*
buy	0.0344	downgraded	0.0252
upgraded	0.0187	cut	0.0240
deal	0.0172	fly	0.0173
said	0.0172	bank	0.0142
raised	0.0158	misses	0.0110
fly	0.0131	falls	0.0106
order	0.0107	neutral	0.0092
talks	0.0094	hold	0.0092
gets	0.0075	cuts	0.0088
neutral	0.0071	sell	0.0086
raises	0.0065	buy	0.0078
wins	0.0054	miss	0.0078
hold	0.0054	estimates	0.0073
billion	0.0053	outlook	0.0061
street	0.0052	sales	0.0058
stake	0.0048	profit	0.0054
unit	0.0047	earnings	0.0054
insider	0.0046	tradegate	0.0050
buyback	0.0041	says	0.0049
outlook	0.0038	sees	0.0043
offer	0.0037	downgrades	0.0036
agrees	0.0036	shares	0.0036
buys	0.0035	revenue	0.0035
says	0.0034	underperform	0.0029
group	0.0032	underweight	0.0029
berenberg	0.0030	credit	0.0028
near	0.0029	close	0.0028
sell	0.0029	lower	0.0027
bid	0.0026	results	0.0027
tradegate	0.0026	loss	0.0025
approval	0.0025	leave	0.0025
new	0.0025	forecast	0.0023
buyout	0.0025	guidance	0.0022
bank	0.0025	growth	0.0022
acquire	0.0025	overweight	0.0021
outperform	0.0024	negative	0.0020
rises	0.0023	downgrade	0.0020
worth	0.0023	outperform	0.0020
eu	0.0022	loses	0.0019
contract	0.0022	weight	0.0019
close	0.0021	seeking	0.0019
overweight	0.0020	drops	0.0018
credit	0.0020	equal	0.0018
set	0.0019	close	0.0017
fiat	0.0018	new	0.0017
gains	0.0018	perform	0.0017
sees	0.0017	indicated	0.0016
merger	0.0017	price	0.0016
takeover	0.0016	target	0.0016