Do we benefit from the categorization of the news flow in the stock price prediction problem?

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Abstract

The power of machine learning is widely leveraged in the task of company stock price prediction. It is essential to incorporate historical stock prices and relevant external world information for constructing a more accurate predictive model. The sentiments of the financial news connected with the company can become such valuable knowledge. However, financial news has different topics, such as *Macro*, *Markets*, or *Product news*. The adoption of such categorization is usually out of scope in a market research. In this work, we aim to close this gap and explore the effect of capturing the news topic differentiation in the stock price prediction problem. Initially, we classify the financial news stream into 20 pre-defined topics with the pre-trained model. Then, we get sentiments and explore the topic of news group sentiment labeling. Moreover, we conduct the experiments with the several well-proved models for time series forecasting, including the Temporal Convolutional Network (TCN), the D-Linear, the Transformer, and the Temporal Fusion Transformer (TFT). In the results of our research, utilizing the information from separate topic groups contributes to a better performance of deep learning models compared to the approach when we consider all news sentiments without any division.

Keywords: Financial news, Stock market, BERT, Topic classification, Sentiment analysis, Time-series forecasting, Deep learning, External data

1 Introduction

The connection between a company's stock market and its news and events has always been one of the hot-button issues for discussion. This area of scientific investigation, represented in our paper, is applied in a wide range of social and economic spheres. For example, the condition of big pharmaceutical companies' markets depends on the recent announcements of clinical trials, as they are intently monitored by the public [1].

More than that, in recent years, the growth of the online trading popularity has accelerated the process of accessing the informational background. Many traders started to utilize such sources of information as news sentiments, which are produced by computer algorithms that can quickly show whether a news article or a post on Twitter is positive or negative.

The main question is what kind of news should be considered to understand companies' future market trends better. The current study will investigate whether dividing news into topic groups makes sense when passing it to a deep learning model for stock price prediction as external data. We evaluate whether some topic groups give the possibility to obtain better model performance or if it is still better to pass to the model all the information without any division. For performing experiments we chose five big technological public companies: Apple, Amazon, Google, Netflix, and Tesla. The pipeline of our research is presented in the Figure 1.

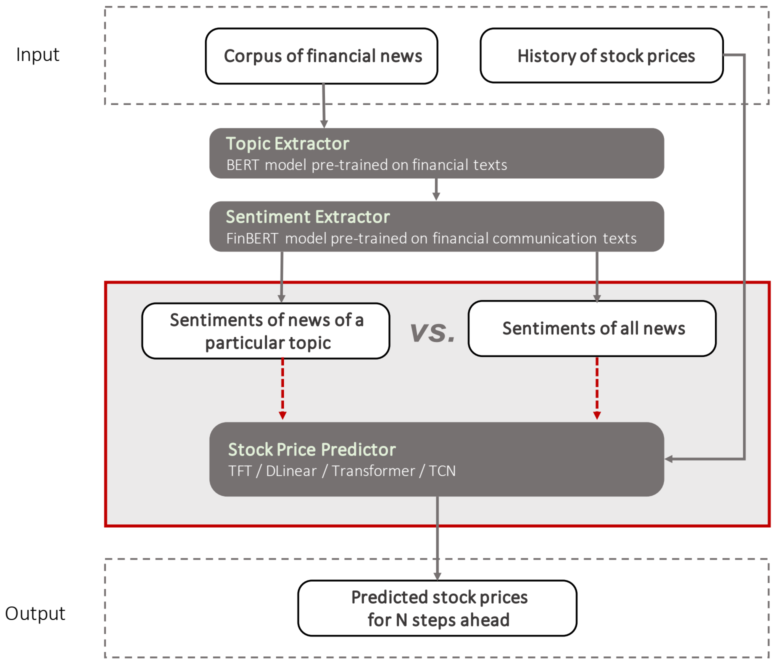

Fig. 1: The pipeline for comparison of using either sentiments of all news or sentiments of news from a particular topic group in the stock price prediction problem.

2 Related work

2.1 Stock price prediction

The main direction of the research described in our paper is improving the quality of big companies' stock price predictions. This area of the time series forecasting is reviewed in a large amount of works. In particular, in the paper [2], the qualities of stock price predictions made by different algorithms are compared. For the experiment, four Machine learning and Deep learning algorithms are chosen. The Artificial Neural Network, the Support Vector Regression, the Random Forest, and the Long Short-Term Memory are among them. The results obtained show that the best benchmarks are presented by the LSTM model, which means that we can suppose Deep learning algorithms work better than classical Machine learning algorithms.

The main idea of the another research [3] is comparing 12 machine learning algorithms for classification utilizing different types of external data: only social media news, only financial news, and both types of news concurrently. The results show that the Random Forest performs best with a social media feature on the independent testing dataset. With only financial news features the Random forest is also the best. Moreover, it is necessary to mark that with both types of news the performance appears to be the worst, and it is true for the all considered algorithms.

2.2 Financial News topic modeling

The news stream categorization is a naturally arising problem when dealing with news flows. The work [4] presents the way of clustering news according to their topics. The central idea is using a hierarchical agglomeration clustering algorithm. The constructed hierarchical tree of clusters allows cutting the tree at a particular height to obtain a more preferable amount of clusters, which is useful when we do not know the number of clusters beforehand. Many researchers pay special attention to the impact of domain-specific news sentiments on financial assets. In the survey [5], the authors investigate how different financial benchmarks depend on the domain-specific news sentiments. They consider two significant markets, the equity and the oil, and evaluate the Dow Jones Industrial Average (DJIA) and the West Texas Intermediate (WTI) crude oil. The related news was collected from websites, blogs, and online databases. The sentiment time series vector was added to the Vector Autoregression model as a feature.

2.3 Sentiment analysis for stock price prediction problem

Researchers constantly study ways of improving stock price predictions utilizing sentiments of different kinds of background information. Specifically, in [6], the authors gather the EastMoney forum post information to develop the unique sentiment dictionary and calculate the posts sentiment index. In the article [7], the scholars consider the problem of the stock trend prediction, taking into account the technical indicators and the sentiments of the social media texts. The study [8] investigates the use of an investor sentiment from social media, collecting the information from StockTwits, a social media platform for investors. For a sentiment analysis, this survey uses FinBERT, a pre-trained language model designed to analyze the sentiment of a financial text.

They consider predicting the future movement of the SPDR S&P 500 Index Exchange Traded Funds, and their results show that using the FinBERT model for a sentiment analysis provides the best results. The paper's [9] authors build the stock price prediction model based on the attention-based Long Short-Term Memory network utilizing price data, technical indicators, and sentiment information from social media. Also, they propose the fine-tuned BERT sentiment classification model and the sentiment lexicon to extract the sentiment tendency of the social media texts. According to their outcomes, the fine-tuned BERT model performs better in the sentiment classification task, and the sentiment features computed with the BERT model contribute to the higher predicting accuracy than the sentiments calculated utilizing the sentiment lexicon.

3 Methodology

3.1 Problem Setup

Our work aims to define whether we should categorize the news stream about the big public companies and what strategy of the news flow processing mainly contributes to the higher quality of companies' stock price predictions. The research results could improve our understanding of the market and its trends' dependency on different kinds of information. More than that, acquired knowledge could be applied to defining which information should be considered when analyzing and predicting future trends in public companies' markets.

The pipeline of our research, which is represented in the Figure 1, consists of the following steps:

- **Data extraction.** For our study we utilize the corpus of the financial news related to the 5 big public companies: Apple, Amazon, Google, Netflix, and Tesla, more precisely, the news headlines and historical data about the mentioned companies' stock prices.
- **Data topic labeling.** We use the pre-trained model to define each news topic according to its current headline. As an outcome, we get several topic groups.
- **Data sentiment extraction.** For the news headlines sentiment extraction, we apply the FinBERT model, which was trained on the financial communication texts and fine-tuned for the sentiment label prediction. The labels are positive, neutral, or negative.
- **Passing the external information to the model.** For each day we calculate the relation of the positive news amount and the positive + negative news amount and call it sentiments; the time series of these values we define as news sentiments time series.
- **Stock price prediction model.** Historical stock prices with sentiments time series, constructed utilizing different approaches as external data, are then passed to 4 different models: the Temporal Convolutional Network, the D-Linear, the Transformer, and the Temporal Fusion Transformer. Then, the predictions for N steps ahead are obtained.

3.2 Data labeling

In this subsection, we discuss the significant parts of the pipeline for splitting financial news into topic groups and making sentiment extraction of news.

3.2.1 Topic classification

For the division of the extensive collection of news into topic groups, we followed a topic classification approach. Firstly, we found the dataset with labeled financial texts. It is the twitter-financial-news-topic [10] dataset. It is an English-language dataset comprising tweets related to financial aspects and news. The documents in the dataset are labeled with 20 topics:

- Analyst Update
- Fed | Central Bank
- Company | Product News",
- Treasuries | Corporate Debt
- Dividend
- Earnings
- Energy | Oil
- Financials
- Currencies
- General News | Opinion
- Gold | Metals | Materials
- IPO
- Legal | Regulation
- M&A | Investments
- Macro
- Markets
- Politics
- Personnel Change
- Stock Commentary
- Stock Movement

Secondly, we selected a model [11] fine-tuned on the described labeled dataset. It is the BERT-based model. Initially, this model was trained on corporate reports, earnings call transcripts, and analyst reports or, in other words, on financial communication texts. After that, it was fine-tuned on 10,000 sentences from analyst reports, which were preliminary annotated with positive, negative, and neutral sentiment labels. The final stage was to train the model on the previously described dataset. The model's accuracy is 0.911, which made us conclude that this model is appropriate for topic classification tasks. Finally, we applied the described model to our data.

3.2.2 Sentiment labeling

In the previous stage, we got the 20 topic groups of the financial news. This subsection will describe how the derived topic groups were annotated with sentiment labels. For financial news labeling, we utilized the finbert-tone model [12]. We applied this model to each newsgroup, and as the output, we obtained the 20 topic groups of financial news with the sentiment labels (positive, negative, neutral) assigned to each news.

3.3 Time series predictions

This research stage involved studying the prediction quality change after adding the external data to the deep learning models. The models, which we utilized for our experiments, were the Temporal Convolutional Network (TCN) [13], the D-Linear [14], the Transformer [15] and the Temporal Fusion Transformer (TFT) [16]. Among them, there are two models with a transformer-based architecture. One of them is the Temporal fusion transformer model. According to the paper [16], the TFT model outperforms most existing Deep Learning models for the time series forecasting. It has an attention-based architecture, which provides a high-performance multi-horizon forecasting while studying temporal relationships. The main feature, by which the TFT model stands out among other solutions, is its ability to efficiently build the feature representation of each input type and provide a qualitative forecasting performance on a wide variety of problems. However, the authors of the [14] research argue about the success of the transformer-based architecture and surprisingly prove that the D-Linear model even outperforms existing Transformer-based models. The TCN model, which we also consider in our study, shows the highest training speed, competing with other models, according to the paper [13] and our own experience.

The advantage of the all described models is the ability to produce multi-horizon predictions, allowing users to make decisions thinking multiple steps ahead. To implement the mentioned models' architecture, we utilized the realization from the Darts library [17]. We passed 15 past-time steps to the forecasting models. This parameter is called *input chunk length*. We selected about two weeks for input data to analyze sufficient events. The forecast horizon was set to 3 for the all the models. Other model parameters took the default values. The models were trained 30 epochs with the MSE loss on the predicted stock prices.

3.3.1 Data processing

The overall algorithm of data preparation before passing it to the model:

- Making a time series from a dataset with historical prices. The frequency of the time series is business days.
- Filling missing values in stock prices time series.
- Scaling the values in the stock prices time series to the range [0, 1].
- Making a time series from a dataset with sentiments, pointing to the time series frequency as all days.
- Filling missing values of the time series with the sentiments.
- Scaling the sentiments time series.
- Transforming the sentiment dataset into time series with business days frequency.
- Cutting the stock prices and sentiments time series so that they covered the same periods.

3.3.2 Methods of constructing news sentiments time series

As mentioned in the section 3.2.1, we got the 20 topic groups after the topic labeling stage. However, for our experiments, we selected 5 out of 20 topic groups, according to the overall amount of news criteria and the degree of the topic importance for our task of the stock price prediction. We consider the three different methods of constructing the time series with the external data:

1. **Using only one news topic group.** Here, we filter the news stream of the company according to the particular topic label (For example, *Stock Commentary*). The time series consists of the daily relation between the amount of positive news

about a selected topic and the amount of positive and negative news about this particular topic.

2. **Constructing topic vectors.** The algorithm for forming a time series here is the following: for each day we take news from the 5 selected topic groups. For each group we evaluate the relation between the amount of positive news from this topic group and the amount of positive + negative news, which relate to this group. Hence, each day is described with the vector of 5 elements, which are the calculated relations.
3. **Using all news.** In this method, we take all the news about the company, without splitting it into groups, and calculate the daily positive news rate, as in the previous methods.

All the sentiment and stock price time series are cut to cover the same periods for the one company.

3.3.3 Covariates

There is an essential parameter in the Darts library called covariates. The covariates are the external data passed to the model to improve the predictions. The covariates may be future, past, and static. The past covariates are known only in the past, the future covariates are known in the future, and the static covariates are constant over time. As news sentiments (positive news ratios) in real life are known only in the past, the sentiments, as external data, we pass to the *past covariates* parameter.

3.3.4 Historical forecasts

We applied the historical forecasts method to compute the forecasts at multiple time steps. In the first step, this method takes the window from the beginning of the time series to the time point, which is passed in the *start* parameter. As the *start* parameter, we pass the start of the test part of the time series. To the forecast horizon, we give the value three steps. The stride parameter is equal to the forecast horizon, so the method predicts 3 points, then the training set end moves forward by three timesteps, and the method predicts the following 3 points. This process repeats until the end of the series.

4 Results

4.1 Dataset description

The data for our final dataset was taken from the financial news archive [18]. This dataset was collected from investing.com, bloomber.com, seekingalpha.com, 247wallst.com, zacks.com, and cnbc.com websites. The data was preprocessed by removing images, graphics, ad boxes, and punctuation. It comprises financial news of more than 800 publicly traded companies. The number of samples is 221513. After data collection, we deleted unnecessary fields so that only information about tickers, news headlines, and release dates remained. Also, we utilized the Ticker field for filtering the news headlines related only to Apple, Amazon, Google, Netflix, and Tesla for the further data labeling.

4.2 Topic classification

From the results of the topic classification, we can conclude that the most numerous groups are *Company | Product News*, *Markets*, *Stock Commentary*, *Stock Movement*, and *Financials*. To ensure that the news flow was split reasonably, we extracted the defined groups from the financial news dataset, read the news, and tried to analyze whether they connected with the particular topic and had something in common. We noticed that the groups were defined sensibly. For example, the headline, *Top Ranked Growth Stock To Buy For June 15th* was related to the *Stock Commentary* group. The news about different countries' economic updates, such as *China's Economy Slows Down* was defined as the *Macro* category. The *General news* group consists of news that is not directly connected with economics but can indirectly impact the economy and people's daily lives and consciousness. For example, *Out of control California wildfire grows forces schools to close*. Such headlines as *Apple reportedly purchases OLED production equipment*, which reflect the updates connected with popular product manufacturing, are related to the *Product news* category. The *Markets* group represents the news, which describes the general state of the markets of different countries, for example, *Belgium stocks higher at the close of trade*.

4.3 Sentiment labeling

To evaluate the quality of the model performance on different topic groups, we counted the percentage of the sum of positive and negative labels in the overall amount of labels, as there is a little interest in a significant amount of neutral news. The results can be seen in the Table 1.

Topic name	Positive amount	Negative amount	Neutral amount	Positive & Negative
Analyst Update	1872	774	4377	38%
Fed / Central Banks	384	688	2077	34%
Currencies	742	1133	1672	53%
Dividend	409	55	744	38%
Earnings	4909	2108	9578	42%
Energy / Oil	1605	2158	2671	58%
Financials	11363	5662	832	95%
General News	1061	2506	8901	29%
Gold / Metals	691	615	1036	56%
M&A / Investments	1076	318	7330	16%
IPO	103	87	643	23%
Legal / Regulation	225	1740	5391	27%
Macro	2582	3565	5063	55%
Markets	7984	7472	9540	62%
Personnel Change	109	153	2428	10%
Politics	303	641	3675	20%
Company News	8893	4275	31233	30%
Stock Commentary	9650	1634	13080	46%
Stock Movement	8862	5493	5560	72%
Treasuries / Debt	335	521	1658	34%

Table 1: Amounts of sentiment labels in each topic group. The last column indicates the percentage of emotionally charged news to the size of a topic group.

4.4 Time series predictions

We start with the construction of a simple baseline. The baseline stock price predictions repeat the values from the preceding steps. Thus, we calculate the MAPE metric for the fundamental values and the values with a shift of 3 days back. The TCN and the Transformer models' performance could be more satisfactory, as the metrics obtained according to their predictions did not outperform the baseline results. Finally, we decided to consider only the metrics for the DLinear and the TFT models because their results were superior to the baseline in most cases.

The calculated metrics for all five companies with different strategies of accounting for news sentiments are given in Tables 2, 3, 4, 5, and 6. The visualization of prediction differences induced by distinct ways of accounting for news sentiments is presented in Figure 2.

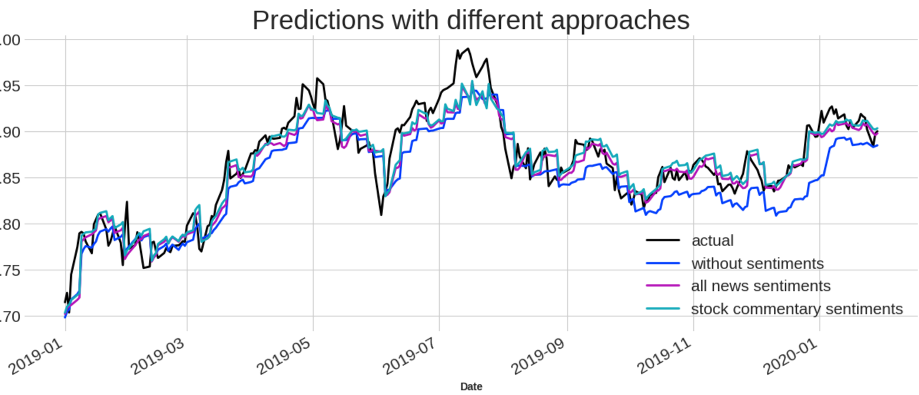

Fig. 2: The Amazon's actual stock prices and the stock prices predicted by the TFT model with different approaches to leverage sentiment information. Best runs.

Model	Eval	Used sentiments	MAPE, %	MAE	R2
DLinear	Average	General news	2.798	0.022	0.934
		All sentiments	2.837	0.022	0.931
		Without sentiments	**2.577**	**0.020**	**0.943**
	Best run	**Product news**	**2.327**	**0.018**	**0.949**
TFT	Average	**Markets**	**2.478**	**0.019**	**0.944**
		All sentiments	2.678	0.021	0.937
		Without sentiments	4.253	0.033	0.835
	Best run	**Stock Commentary**	**2.333**	**0.018**	**0.947**
Baseline			2.967		

Table 2: The values of the evaluated test metrics for Apple. The considered period is 23.11.2012 - 30.09.2019. For the TFT, the winner is the *one topic group* approach; for the DLinear, on average, predicting without news sentiments is better, but the best run shows that the *one topic* approach can provide a better performance.

Model	Eval	Used sentiments	MAPE, %	MAE	R2
Dlinear	Average	**Markets**	**2.256**	**0.019**	**0.791**
		All sentiments	2.295	0.020	0.783
		Without sentiments	2.747	0.024	0.733
	Best run	**Markets**	**1.786**	**0.015**	**0.869**
TFT	Average	**Markets**	**2.719**	**0.023**	**0.705**
		All sentiments	3.117	0.027	0.630
		Without sentiments	4.336	0.038	0.381
	Best run	**Stock Commentary**	**1.730**	**0.015**	**0.870**
Baseline			2.019		

Table 3: The values of the evaluated test metrics for Amazon. The considered period is 12.10.2012 - 31.01.2020. For the TFT and the DLinear, passing one topic group sentiments is the best option.

Model	**Eval**	**Used sentiments**	**MAPE, %**	**MAE**	**R2**
Dlinear	Average	**Macro**	**2.477**	**0.021**	**0.746**
		All sentiments	2.503	0.022	0.740
		Without sentiments	2.591	0.022	0.720
	Best run	**Macro**	**2.337**	**0.020**	**0.768**
TFT	Average	**General news**	**3.004**	**0.026**	**0.663**
		All sentiments	3.050	0.026	0.653
		Without sentiments	3.238	0.028	0.612
	Best run	**Without sentiments**	**2.286**	**0.020**	**0.788**
Baseline			2.838		

Table 4: The values of the evaluated test metrics for Google. The considered period is 14.08.2012 - 12.09.2019. For both the TFT and DLinear, the one topic group approach, on average, is also the best variant. However, sometimes, the TFT without news sentiments provides better results.

Model	**eval**	**Used sentiments**	**MAPE, %**	**MAE**	**R2**
Dlinear	Average	General news	2.946	0.023	0.886
		All sentiments	3.065	0.023	0.879
		Without sentiments	**2.882**	**0.022**	**0.891**
	Best run	**Without sentiments**	**2.619**	**0.020**	**0.908**
TFT	Average	**Product news**	**3.066**	**0.023**	**0.884**
		All sentiments	3.684	0.028	0.835
		Without sentiments	3.509	0.027	0.850
	Best run	**Stock Commentary**	**2.512**	**0.019**	**0.919**
Baseline			3.152		

Table 5: The values of the evaluated test metrics for Netflix. The considered period is 24.04.2013 - 18.12.2019. For the TFT, the winner is the *one topic group* approach. For the Dlinear, predicting without news sentiments is better in all cases.

Model	Eval	**Used sentiments**	**MAPE, %**	**MAE**	**R2**
Dlinear	Average	**Macro**	**8.039**	**0.036**	**0.926**
		All sentiments	8.088	0.037	0.921
		Without sentiments	8.130	0.037	0.920
	Best run	**Macro**	**7.423**	**0.034**	**0.930**
TFT	Average	**General news**	**8.597**	**0.039**	**0.917**
		All sentiments	9.595	0.042	0.903
		Without sentiments	11.774	0.049	0.880
	Best run	**Topic vectors**	**7.421**	**0.035**	**0.928**
Baseline			9.565		

Table 6: The values of the evaluated test metrics for Tesla. The considered period is 04.04.2014 - 09.12.2019. For both the TFT and DLinear, the one topic group approach is still the best. Besides, the best launch of the TFT was performed with the topic vectors approach.

According to the Tables 2 - 6, the best approach for Apple is utilizing one topic sentiments. The same is true for Amazon, Google, and Tesla. Regarding Netflix, the metrics indicate that running the DLinear without sentiments is better, while for the TFT, the one-topic approach still works best. From the models' point of view, the one-topic approach is also the best in most cases. Overall, the outcomes confirm that, predominantly, it is better to show our Deep learning model only one news topic group sentiments than consider all news flow or train the model without any news.

In addition, we determine which topic groups are more likely to improve predictions. We notice that the *Macro* and *Markets* groups are the best, with the *Stock Commentary* in second place and then the *General News* and the *Product News*. Here, we can draw parallels with the Table 1 and conclude that the greater the percentage of positive and negative news in a given thematic group, the more likely this group will help improve the model's performance. The higher the emotional saturation, the greater the impact on the model.

5 Conclusion

In this research, we demonstrate that it is beneficial to categorize a news stream in the stock price prediction problem. In the majority of cases, the best strategy is to split a news flow into topic groups and pass to the model only sentiments from a one particular topic group rather than accounting sentiments from the full news stream. Moreover, we find out that the prediction improvement due to sentiments from a certain thematic newsgroup is interconnected with the emotional saturation of this group. Generally, our study contributes to obtaining insights into the market, its processes, and behavior. This study can be useful for market researchers, data scientists, and people interested in better understanding of market trends.

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