Unsupervised Extraction of Market Moving Events with Neural Attention

Luciano Del Corro∗ and Johannes Hoffart∗
Max Planck Institute for Informatics, Saarbrücken, Germany
{corrogg, jhoffart}@mpi-inf.mpg.de

Abstract
We present a method to identify relevant events associated with stock price movements without manually labeled data. We train an attention-based neural network, which given a set of news headlines for a given time frame, predicts the price movement of a given stock index (i.e., DOWN, STAY, UP). An attention layer acts as an input selector; it computes a normalized weight for each headline embedding. The weighted average of the embeddings is used to predict the price movement. We present an analysis to understand if, after the network has been trained, the attention layer is capable of generating a global ranking of news events through its un-normalized weights. The ranking should be able to rank relevant financial events higher. In this initial study we use news categories as a proxy for relevance: news belonging to more relevant categories should be ranked higher. Our experiments on four indices suggest that there is an indication that the weights indeed skew the global set of events towards those categories that are more relevant to explain the price change; this effect reflects the performance of the network on stock prediction.

1 Introduction
Anticipating stock price movements is one of the critical challenges in financial analysis. A specific event (or combination of events) might have a significant and even disruptive impact in the markets. Understanding which events may generate stock price movements is crucial for the financial industry.

In this paper, we present a method to identify relevant financial events without manually labeled data. We understand relevant events as those that contribute to stock price movements. We do not directly predict the importance of the events but use a method that automatically selects the more relevant ones to predict the price movement of a stock index.

The input of the method is a set of events in the form of news headlines, and the output is the price movement of a specific stock (i.e., DOWN, STAY, UP). The price movement is defined as the daily relative movement percentage that generates the most balanced distribution between the majority and minority output classes (e.g., for S&P500 this is +/- 0.03%). The headlines are embedded using BERT [Devlin et al., 2019] contextualized embeddings. An attention layer [Bahdanau et al., 2015] acts as input selector by computing for each headline in a time frame, a normalized weight. The weighted sum of the embeddings is used to predict the price movement.

We expect that this weight measures the contribution of a specific headline to the prediction. Here, we analyze to which extent those weights can be interpreted as the relative importance of each article to the price movement; we investigate if the attention layer allows us to generate a global ranking of events using its un-normalized weights so that it ranks higher the most relevant events when the dataset is analyzed in its entirety. In this exploratory work we use news categories as a proxy for event relevance: news belonging to more relevant categories should be ranked higher.

There is extensive literature in stock price prediction from news [Gidőfalvi, 2001; Xie et al., 2013; Ding et al., 2014]. It has mostly focused on methods to exploit profitable trading opportunities by trying to predict the stock price based on incoming news (i.e., the prediction should be solely based in recent past information). This approach presents a problem from an event extraction perspective as the event may have been already incorporated into the price before the news became public. This fact makes it difficult to develop a method that generalizes well; the association between the past input news and price movement becomes weak [Merello et al., 2018]. Our focus here differs from these approaches in that our ultimate goal is to identify which events are more informative to explain stock-prices movements. This allows us a more flexible approach as we are not conceptually bound to short time windows (in this paper we use 24 hours) or the publication time; for us, the stock prediction task is a proxy to identify relevant events.

We experiment on the most important US stock indices (i.e., S&P500, Nasdaq, Dow Jones, and Russell 1000) with the AP English news-wire subset of the Gigaword [Graff et al., 2003] dataset, a large corpus with more than 1.5 million articles spanning over 15 years (1994-2010). We first show that, as intuitively expected, the network tends to make better predictions if fed with news categories such as ‘business’ rather than ‘sports’ or ‘entertainment.’ Then we show that

∗equal contribution
when fed with all categories at the same time, the network can skew the distribution via the attention weights towards meaningful categories, allowing us to infer that the network is able to extract stronger signals from more relevant events. Interestingly, we found that these two tasks are coupled as the performance (or lack of) in the first one seems to be correlated with the strength of the effect on the second one.

2 Related Work

Stock price prediction from the news. Predicting stock prices from news has been a long-standing goal. Most literature in the field is focused on the prediction of a stock price based on recent past information. There has been a debate around the feasibility of predicting stock prices from past news [Merello et al., 2018]. We do not necessarily need to enter this debate. From the event extraction perspective, it is irrelevant whether the news headline mentioning the event was published before or after the price movement; it is enough that the headline that generated the price movement is part of the input, no matter the length of the window: we do not maximize profit but event recognition performance.

Early work by [Gidofalvi, 2001] already showed a strong correlation between news articles and stock price movement. Multiple approaches were explored to extract signals from news such as sentiment analysis, named entities, semantic parsing, or neural encodings [Schumaker and Chen, 2009; Xie et al., 2013; Li et al., 2014; Peng and Jiang, 2016]. Strategies that maximize profit also leverage other sources of information, such as past prices. The predictions usually run in chronological order.

Event extraction of financial events. One of the keys to predicting stock price movement is to understand which event may move the price in one or another direction. More recently, stock prediction literature has indeed focused on the explicit representation of events [Ding et al., 2014; Ding et al., 2015; Bach et al., 2015; Ding et al., 2016; Jacobs et al., 2018; Ein-Dor et al., 2019; Shi et al., 2019].

One line of work centered on the extraction of structured, canonical or semi-canonical events (linked to a knowledge base) [Ding et al., 2014; Ding et al., 2015; Ding et al., 2016; Peng and Jiang, 2016; Jacobs et al., 2018], while another line has focused on non-canonicalized events (e.g., headlines or sentences referring to a relevant event) [Ein-Dor et al., 2019; Shi et al., 2019]. Here we follow the second approach, focusing on the event identification task.

Jacobs et al., 2018] classify sentences into ten canonical events using manually annotated data from news articles mentioning seven companies. [Ein-Dor et al., 2019] overcome the limitation of relying purely on manually annotated data by using weak supervision to collect training data. The idea is to leverage Wikipedia to extract sentences containing events. A sentence is considered to contain a relevant event if, in a selected company Wikipedia article, the sentence is part of a specific section (e.g., history) and starts with a date. The model predicts, given an input sentence, if it is a financial event (as defined in the weakly supervised step before) or not. The text is encoded using BERT. In our approach, we adopt a fully unsupervised approach (i.e., we do not require semi-supervised annotations or other data sources), using only the price signal to detect the most relevant headlines.

[Ding et al., 2014], generate structured events from news headlines by using an open information extraction (Open IE) system [Fader et al., 2011]. The Open IE extractions are interpreted as events and linked to VerbNet and WordNet to generate canonicalized representations. [Ding et al., 2015] proposes to overcome the sparsity by using embeddings to represent the events, and [Ding et al., 2016] uses a knowledge base to improve those embeddings. Extracting event representations using Open IE is challenging. Open IE tends to generate a significant number of irrelevant and noisy facts, which eventually imposes the need for intense and informed data preprocessing as a way to improve the extractions. Here we postpone the canonicalization and concentrate on the recognition. Our end-to-end alternative approach allows us to automatically select in one-shot the relevant events avoiding any involved preprocessing, compromise on the representation of the fact, or the use of any underlying relation extraction system.

Conceptually, the closest work to ours is probably [Shi et al., 2019]. They use an unsupervised method with a setting tailored for a visualization tool meant to be used by traders. Their focus is not event extraction but interpretability. The headlines presented to the network are already pre-selected for specific companies (i.e., the company has to be mentioned in the news). This pre-selection imposes a limitation as relevant news might not necessarily mention the most affected companies (e.g., an article about an oil price spike will not mention every oil or car company or an article about a rate cut by the Fed will most surely not mention every financial institution). Our model allows us to present the network with all the news at once as the goal is to allow the network to pre-select the relevant headlines. Also, their model does not explicitly look at the full headline but only at keywords which might be shared among multiple headlines; documents are encoded into bigrams, and relevant keywords are selected using LRP [Bach et al., 2015].

Attention as input selection. A recent debate has erupted around the idea of using the attention mechanism [Bahdanau et al., 2015] as a way of explaining model output [Serrano and Smith, 2019; Jain and Wallace, 2019; Wiegreffe and Pinter, 2019]. The relation between attention weights and output has been unclear. In this regard, [Jain and Wallace, 2019] found that different weight distributions can yield equivalent predictions. [Serrano and Smith, 2019] and [Jain and Wallace, 2019] concluded that attention weights are noisy and inconsistent and should not be used to explain a decision. [Wiegreffe and Pinter, 2019] developed a set of tests to determine if attention weights are consistent enough to be taken as an explanation. In this paper, we are more interested in understanding the global effect of the attention layer and not its explainability in terms of single data point decisions. In our experiments, even though there is some variability, the global rankings generated by the unnormalized attention weights are consistent with expected results (i.e., which categories are more important to explain stock price movements) and generate consistent results across different runs and target stocks.
A question that remains for future work is if we can indeed have more fine-grained consistency apart from the news categories.

3 Unsupervised event detection

We use the stock prediction task to identify events relevant to predict the stock price movements. This approach has the advantage that it does not require manually labeled data.

We use daily news headlines representing non-canonicalized events and their categories as input to predict the daily stock movement price. Note that no other data is used. Three classes represent the output: DOWN, STAY, UP with respect to the previous trading session. We include all headlines corresponding to a given date, and as target, we use the open price of the next trading session, including after-hour price movements. The full network is described in Figure 1.

More formally, each headline $hl_1, hl_2, \ldots, hl_k$ consisting of a (padded) sequence of $N$ tokens $\{w_i\}_{i=1, \ldots, N}$ is encoded to vectors $\{\text{hl}_i\}_{i=1, \ldots, N}$ of length 768, using the pooled output of the BERT-base-uncased model:

$$\text{hl}_i = \text{BERT}(hl_i)$$

Each headline comes with a corresponding single category label $hc_1, hc_2, \ldots$ (automatically labelled, details see “News Classification” in Section 4) which is embedded to a vector of length 30

$$hc_i = \text{embed}(hc_i),$$

Both vectors are concatenated

$$h_i = \text{hl}_i \oplus hc_i$$

and projected to a vector $h_{pi}$ of length 100 by a fully connected feed forward layer with ELU activation

$$h_{pi} = \text{FF}_{\text{ELU}}(h_i)$$

Following [Yang et al., 2016], an attention layer computes normalized weights for each headline of the input day, $H_{pd} := \{h_{pi}\}_{i=1, \ldots, k}$, and aggregates them according to those weights

$$h_{ai} = \text{SelfAttention}(H_{pd})$$

The final label $l_i$ (DOWN, STAY, UP) and probabilities for each label are computed using a feed forward layer with softmax activation

$$l_i = \text{FF}_{\text{softmax}}(h_{ai})$$

Every input layer is normalized, and the weights are initialized using $He$. The dropout rate is 0.25. We use the out-of-the-box optimizer that is provided by the official TensorFlow BERT repository. All BERT weights are fine-tuned during training.

4 Evaluation

In this section, we address two challenges: First, we need to understand if the network is indeed able to extract correct signals from the headlines and second if the attention layer is able to rank the events in terms of relevance.

The first set of experiments (Sec. 4.1) address the first challenge. It shows that, as intuitively expected, the price movement prediction for a single day is generally better if the model is trained on more relevant news categories. The idea is that the network should do better if it is fed with only business news than if it is fed, for instance, with entertainment headlines.

The second round of experiments (Sec. 4.2) analyzes if the attention layer via its unnormalized weights is capable of generating a global ranking of relevant headlines coherent with the previous results, when all headlines from all categories are provided as input. We expect that in the top-k positions, the distribution is skewed towards the relevant news category according to the results of the previous experiment.

| Trading sessions | 3777 |
|------------------|------|
| Time-frame       | 11 Nov 1994 – 31 Dec 2010 |
| Headlines        | 1,532,260 |
| Mean             | 405.68 |
| Std.             | 134.49 |
| Min.             | 1 |
| Max.             | 1213 |

Table 1: Dataset

Dataset We used the AP headlines of the English Gigaword dataset [Graff et al., 2003], a collection of English newswire data with 1.5M articles published between 1994 and 2010. Regarding the stocks to be tested, we selected the most relevant US indices: S&P500, Dow Jones, Nasdaq, and Russell 1000, which we downloaded from Yahoo! Finance. Statistics of the dataset are displayed in Table 1.

1https://github.com/tensorflow/models/tree/master/official/nlp/bert
News Classification. We trained a news classifier on the TagMyNews [Vitale et al., 2012] dataset. It consists of 32,567 headlines classified into 6 categories: ‘business’, ‘entertainment’, ‘health’, ‘sci-tech’, ‘sport’, ‘us’ and ‘world’.

The input of the model is a single headline. The headline is embedded using the BERT-base-uncased pooled output, and the embedded headline serves as input to a fully connected layer that generates a binary classification score for each category. We use a dropout of 0.25 and the out-of-the-box optimizer provided by the official BERT TensorFlow distribution. The batch size was set to 120, and the max length of the headlines was limited to 15 WordPiece tokens [Wu et al., 2016]. We used early stopping with respect to accuracy to select the best model.

The size of the validation set was 0.2, and the model performance on this set was F1 0.85, which is in line with the state-of-the-art [Zeng et al., 2018] for this dataset.

The news classifier was used to categorize the headlines from the Gigaword dataset. To assign a class to a headline, we considered the class with the highest score with a threshold of 0.5. Headlines for which every category was below the threshold were left unclassified and not used in the experiments. Table 2 shows the distribution of headlines per category. In total, 66,891 headlines were discarded, 4.37% of the total.

| Category   | Number of articles | %   |
|------------|--------------------|-----|
| world      | 596,899            | 38.96 |
| sport      | 275,585            | 17.99 |
| business   | 231,083            | 15.08 |
| us         | 211,570            | 13.81 |
| unclassified | 66,891          | 4.37  |
| entertainment | 54,607         | 3.56  |
| sci-tech   | 54,057             | 3.53  |
| health     | 41,568             | 2.70  |

Table 2: Distribution of news per category

Preprocessing. Given resource constraints, we are limited to 115 headlines per day with a maximum length of 15 WordPiece tokens each. To account for more than 115 news headlines, we created stratified subsets to generate several data points for one single day. The stratified samples were generated with respect to the headline categories. We discarded dates with less than 25 headlines for each of the four most prominent categories (i.e., ‘world’, ‘sports’, ‘business’, and ‘us’), dropping 511 data points, a 13.53% of the total. We also remove headlines with less than 20 characters, which tend to be incomplete or noisy.

To generate the labels for each stock (i.e., DOWN, STAY, UP), we need to set a threshold to determine the classification of the price movement. This threshold will depend on the practitioners’ strategy. Here we pick the threshold to generate a balanced distribution among the classes in order to avoid the network learning trivial decisions. We set for each stock a symmetric threshold between [1%, 0.1%] (in steps of 0.1) such that the distribution of classes between the majority and the minority class is the most balanced.

The final class distribution for each stock in the relevant dates and the corresponding thresholds are displayed on table 3.

| Stock Index | Threshold | DOWN | STAY | UP   |
|-------------|-----------|------|------|------|
| S&P500      | +/- 0.3%  | 30.91% | 33.61% | 35.48% |
| Nasdaq      | +/- 0.3%  | 30.48% | 29.83% | 39.69% |
| Dow Jones   | +/- 0.3%  | 30.53% | 33.23% | 36.23% |
| Russell 1000 | +/- 0.3% | 29.47% | 34.38% | 36.15% |

Table 3: Thresholds and class distributions

Training setup. We ran our network on 3 Tesla V100 GPUs with a total batch size of 15. The test size was set to 0.2.

4.1 Stock price prediction

We ran the network on each news category separately to understand if the network was capable of extracting the right signals from the headlines. In this experiment we selected the model with the maximum accuracy, a maximum of 20 epochs, and a patience of 5 epochs.

As expected, ‘business’ headlines are more informative and consistent across the different indices for predicting the stock price movement. In fact, it is the only news category from which the network seems to extract a meaningful signal. For the rest of the news categories, the network does not perform much better than a random uniform choice. Except for business, the network is quite unstable, with most epochs not able to generate a precision or recall score above 0.

Regarding the individual indices, results are consistent across indices, except Nasdaq. This might be due to the generality of the dataset, most likely not suitable for Nasdaq but more appropriate for the more diversified S&P500, Dow Jones, and Russell 1000, which cover a more comprehensive range of sectors. Interestingly, the best result for Nasdaq was achieved with the sci-tech category.

Results when all news are included, with the exception of Nasdaq, are lower than the ‘only business’ setting. However it is still clear that informative signals are extracted.

Table 4 shows the results for all categories.

| News Category | S&P500 | Nasdaq | Dow Jones | Russell 1000 |
|---------------|--------|--------|-----------|--------------|
| business      | 34.43  | 43.64  | 61.97     | 55.92        |
| us            | 40.13  | 38.45  | 42.02     | 39.59        |
| world         | 41.83  | 44.89  | 39.66     | 38.73        |
| sports        | 38.94  | 44.09  | 36.36     | 38.94        |
| sci-tech      | 36.74  | 44.96  | 37.05     | 36.90        |
| entertainment | 34.57  | 42.33  | 37.98     | 38.14        |
| health        | 34.57  | 40.78  | 34.26     | 35.81        |

Table 4: Max accuracy of each news category on the stock prediction task
Figure 2: Event Detection Results
4.2 Event detection

In this experiment we analyze if the attention layer weights can be used to generate a meaningful global ranking of the news headlines. We understand meaningful as ranking that favours news categories with stronger signals in the top positions; business news according to experiments in Section 4.1.

In this case we provided the entire set of news at once, regardless of the news category. After the network was trained, we used the unnormalized weight of the attention layer to rank all the headlines across all days. There are a total of 271,520 headlines in the test set. Results are the average over five runs.

Figure 2 shows the results of the experiment, showing the 20,000 headlines with the highest unnormalized weight during prediction. They show for a given rank (e.g., top 2500) the fraction of headlines with given categories up to that rank. Figures 2b, 2c, 2d and 2e display the distribution of categories for the top-k headlines for S&P500, Nasdaq, Dow Jones and Russell 1000 respectively. Additionally, Figure 2a shows the overall distribution of the test set. For S&P500, Nasdaq, Dow Jones, and Russell 1000, the top-k distribution is strongly skewed toward business news (compared to the global distribution), with only a minimal effect for Nasdaq.

This is consistent with the results of the experiments in Sec. 4.1. The three indices for which the network extracts signals from the news tend to generate changes in the distribution of categories, and the one that does not seem to extract any signal, Nasdaq, does not.

Regarding model training: For each stock index we selected the model with the minimum loss, a maximum of 20 epochs and a patience of two epochs. Note that the model selection strategy is different than in Section 4.1 where we maximized over accuracy. Minimizing loss reduces the variance of the results across different runs.

4.3 Anecdotal data

Table 5 shows the top 26 headlines over the whole timespan, ranked using the unnormalized attention layer weights of the model trained for S&P500. The examples clearly show that the model can discriminate market-relevant headlines from ones that are not: headlines highlighting general market trends such as stock movements, significant efforts by major companies, or commentary by public institutions make up the top ranks.

Results for a random single date (2003-3-20) show the same trend (Table 6). It is interesting to note that as for a single day specific news about stock movements are not many, the top ranking has also space for other relevant economic or political events.

5 Conclusion and future work

We presented an exploratory analysis, understanding the possibility to generate a ranking of relevant events in an unsupervised way. We showed that a simple neural network is able to extract informative signals from news, and that the attention layer was able to rank higher the most relevant news category.

Future work needs to focus on a more fine-grained analysis of the data. It should try to generate stable rankings beyond news categories and understand the limits of a purely unsupervised approach. It would be important also to understand when we can trust specific rankings, probably focusing the analysis on the attention layer [Wiegreffe and Pinter, 2019].
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