Go Beyond Sentiment! Stock Prediction Enhanced with Financial News

RAM AI Systematic Equity

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Introduction

Extensive research has been focused on extracting quantitative features from financial text (e.g., news, transcripts, etc.) to seek alpha signals such as sentiments, polarity and language complexity, among others.[5, 6, 11] Though this type of feature, which is usually in the form of scalar values, reflects specific text data characteristics, it neglects the semantic and contextual information needed to evaluate text meanings' relevance or similarity.[1, 3, 7]

Nowadays, large language models (e.g., BERT, GPT-3, etc.) are among the most impactful natural language processing techniques[1, 3, 8, 10] and have gained popularity in various applications, such as machine translation, language understanding, etc. These models use specialised neural network architectures (e.g., Transformers, Mixture of Experts, etc.)[1, 2, 10] and training paradigms to learn the transformation of text to high-dimensional numerical vectors (such as text representations or embeddings). They are trained on a large text corpus (e.g., Wikipedia, Common Crawl, etc.) to capture texts' semantic similarity in the numerical space. Moreover, the language models, which are pre-trained on a large generic corpus, can be further fine-tuned on domain-specific (small) datasets to fit into the corresponding applications.[4, 8, 9]

Our Methodology

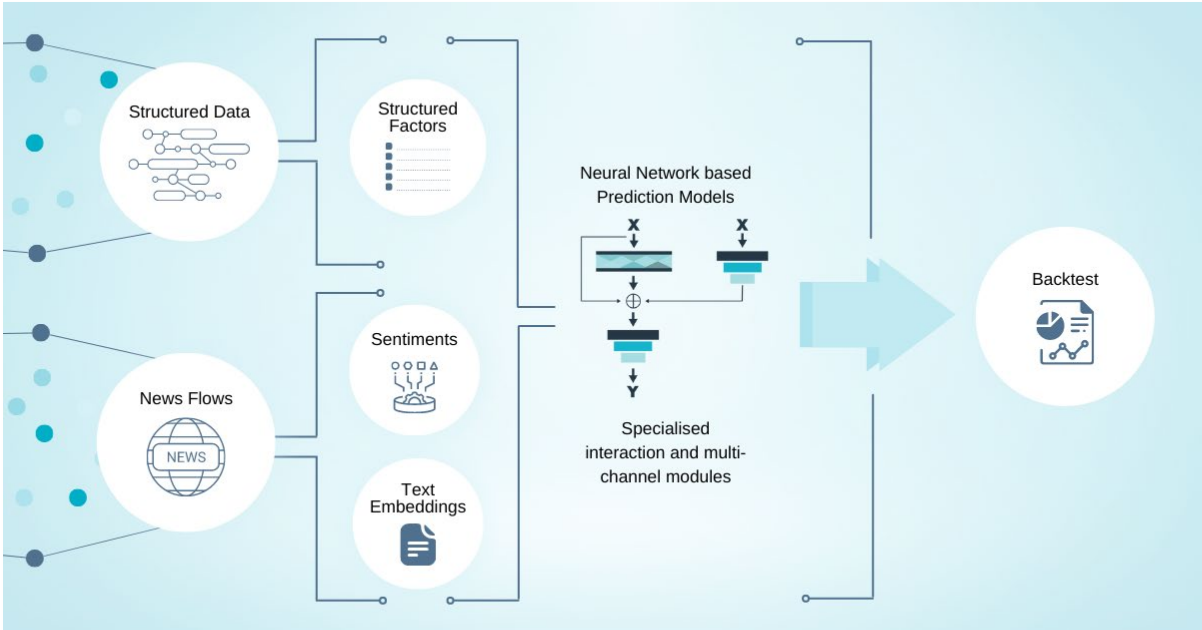


Figure 1: Illustration of the evaluation workflow.

In this paper, we will study the effect of financial news articles' sentiments and text embeddings on predicting stock returns, as shown in Figure 1. Our in-house developed deep learning framework is able to model interactions between different input features and facilitates the comparison of feature combinations.

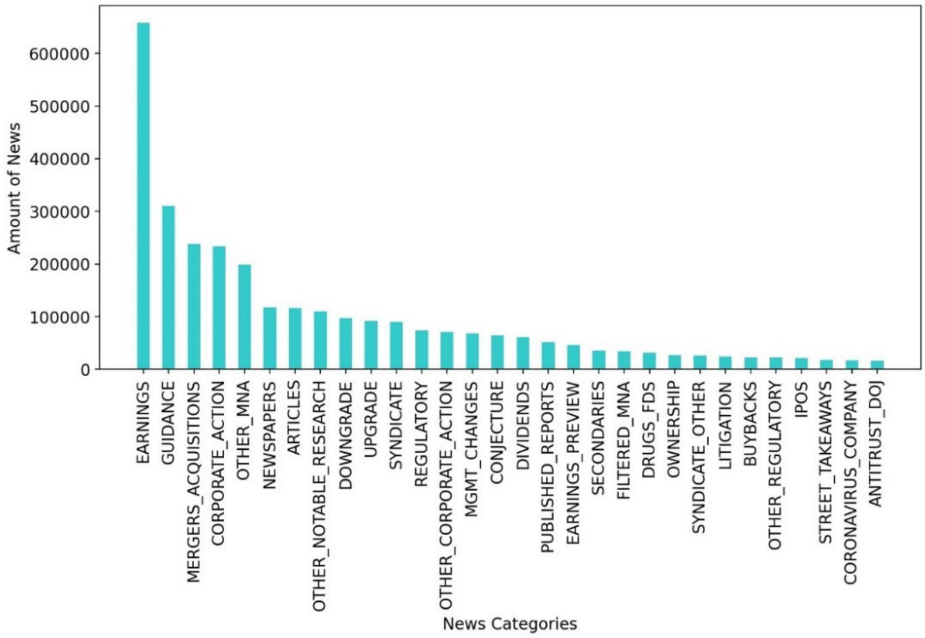


Figure 2: News categories and the respective amounts. Source: RAM AI, Factset.

The Predictive Power of Stand-Alone News

As shown in Figure 2, our newsflow dataset contains more than 2 million financial news articles from different categories. Therefore, we applied FinBERT, the BERT model[3] trained on a financial corpus, and a labelled financial sentiment dataset[4] to our news data to extract sentiments in multiple lookback time horizons and news' text embeddings. As compared to BERT, FinBERT's output sentiment values and text embeddings have shown to be more accurate and effective at capturing the semantic similarity of financial text.[4]

What is BERT?

BERT (Bidirectional Encoder Representations from Transformers) is a deep learning model that reads entire sequences at once, unlike directional models, which read inputs from left to right or vice-versa. FinBERT was developed by training BERT with financial corpora and has become a cutting-edge tool to analyse financial text sentiment.

In the first group of backtests, we trained two predictive models using sentiments only and sentiments combined with news embeddings, respectively, which allowed us to analyse the predictive power of extracted news features on future stock returns.

Combining Structured Data and Unstructured Financial News Data

Apart from unstructured data (i.e., financial news in this paper), many factors built from structured data ("structured factors") such as analyst sentiments, fundamental analysis, price, liquidity and position-based factors have shown predictive power on returns and were widely used in building the predictive models. Figure 3 shows different factor styles and the corresponding number of factors in our structured dataset.

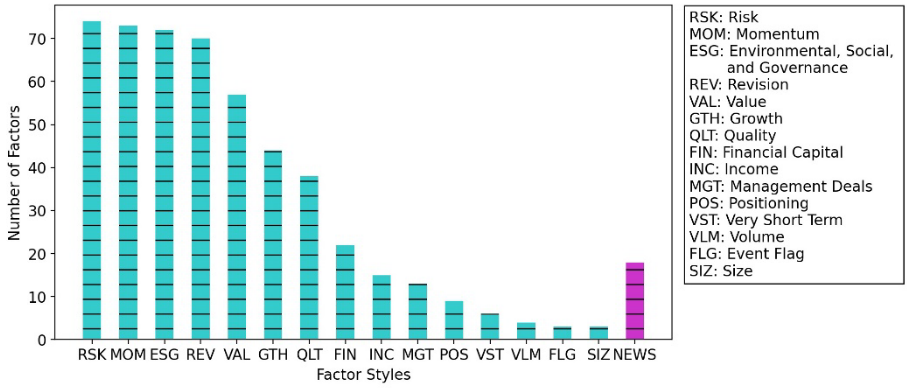


Figure 3: Structured factor styles and the corresponding number of factors. Source: RAM AI, Factset.

We then evaluated the benefit of adding financial news sentiment and embedding features to predictive models on top of the structured factors that already cover most market inefficiencies. For this, in the second group of backtests, we first trained the predictive model solely using our structured factors. Then, we trained two more models on two groups of features; structured factors and sentiments; and structured factors, sentiments, and embeddings. This allowed us to undertake a comparative analysis and determine the advantages of combining unstructured financial news data and large structured datasets in predicting stock returns.

Backtest Results

In this section, we report backtest results on an investment universe that included around 1000 names from the European market. The results include two parts; the decile returns and the performance of three investing strategies based on return predictions (i.e., equal-weighed long, short, and long/short). The decile returns were derived by collecting the stocks with the predictions falling in a certain decile and aggregating their ex-post monthly returns. The investing strategy was designed to select the stocks based on return predictions. All the results presented below are from the out-of-sample testing period.

Stock Prediction with News

Figures 4 and 5 show the results of the predictive models trained separately on news sentiments and the combination of sentiments and text embeddings.

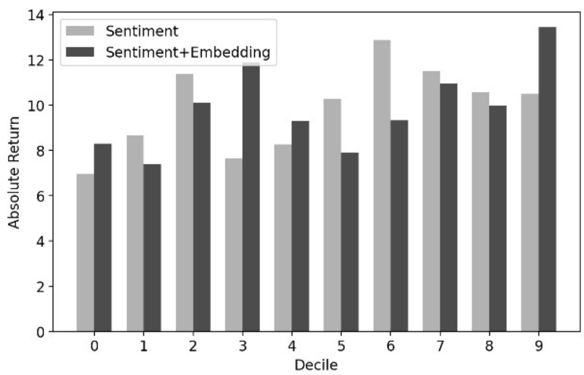


Figure 4: Decile returns of purely news-based predictions. On the x-axis, No. 0 or the bottom decile represents the set of the names with the lowest return predictions. Source: RAM AI, Factset.

Figure 4 shows that adding embeddings noticeably improves the top decile return which consists of the names with the highest return predictions at each rebalancing date. The decile returns present a slightly better monotonic pattern than for the model without embedding.

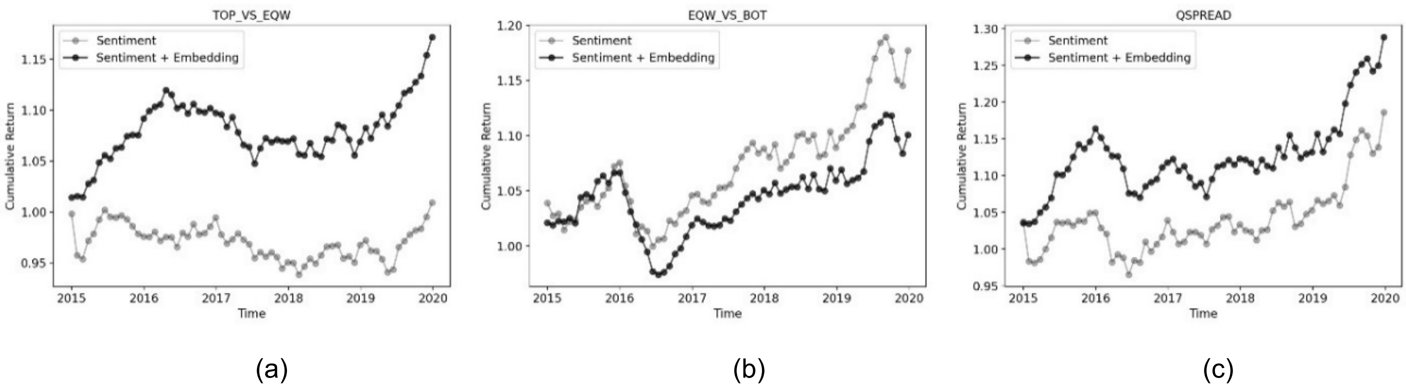


Figure 5: Performance charts. (a) the long strategy consists of the equal-weighted names in the top decile vs. the equal-weighted universe (b) the short strategy consists of the names in the equal-weighed universe benchmark vs. the bottom decile (c) long/short strategy based on the names in the top and bottom deciles. Source: RAM AI, Factset.

In Figure 5, the long strategy notably benefits from the use of both sentiments and embeddings, while the short strategy underperforms. A potential explanation of this under-performance is that negative news sentiment is predictive enough and that the relation to negative future returns is quite explicit, so adding embeddings might overly complexify the predictive relation. However, the long/short strategy using both feature sets outperforms.

Structured Factors plus News Features

Figures 6 and 7 show the results of the predictive models trained on different combinations of structured factors and news features.

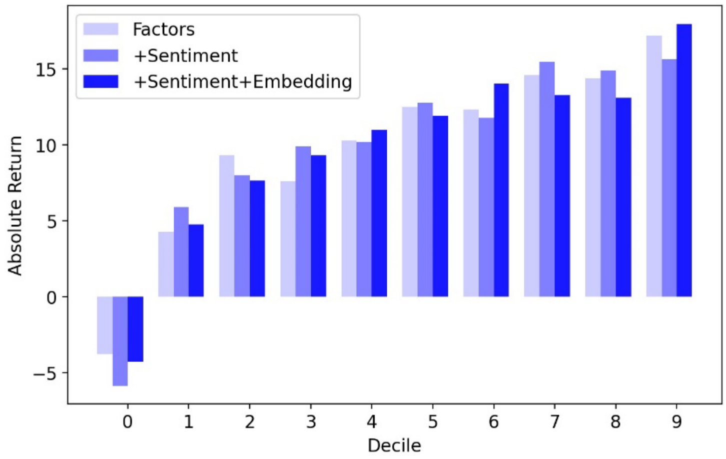
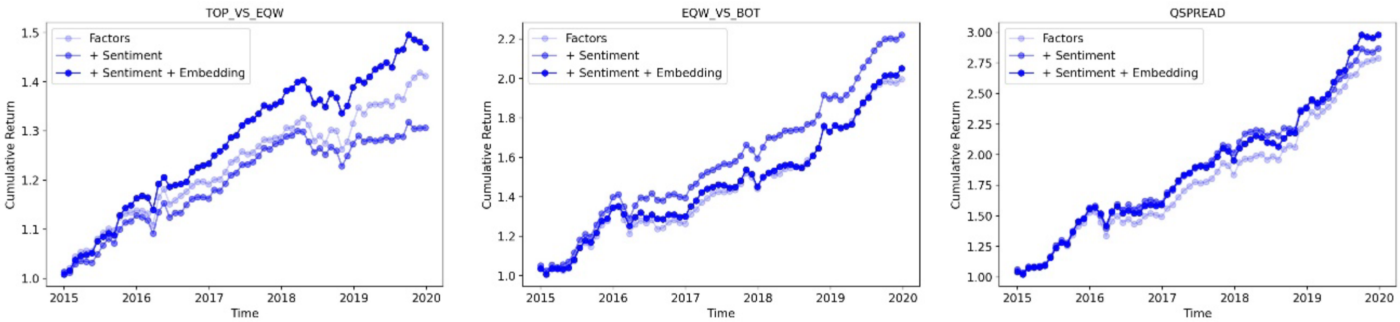


Figure 6: Decile return of news- and factor-based predictions. Source: RAM AI, Factset.

Figure 6 shows that adding sentiments and embeddings enhances the top decile return compared to using only structured factors, though it leads to a slightly lagged performance on the bottom decile. This is in line with the pattern observed in Figure 4.



(a) (b) (c)

Figure 7: Performance charts. (a) the long strategy consisted of the equal-weighted names in the top decile vs. the equal-weighed universe benchmark. (b) the short strategy consisted of the names in the bottom decile vs. equal-weighed universe benchmark. (c) the long/short strategy based on the names in the top and bottom deciles. Source: RAM AI, Factset.

Figure 7 (a) demonstrates that adding sentiments and embeddings helps enhance the long strategy's performance. Figure 7 (b) shows that news sentiments provide more complementary predictive power to structured factors and lead to better performance

than only using factors. As per Figure 7 (c), the long/short strategy is also improved by the use of both sentiments and embeddings.

Interpreting the Model

To give an idea of the news that contribute to high and low return predictions, in Figure 8 we extracted some news examples associated with return predictions falling in the top and bottom decile.

- "...warms up to idea of potential acquisitions in new markets..."
- "...reports preliminary Q1 adjusted EBITDA €535M; raises FY outlook..."
- "Fundamentals in Residential Systems segment continue to be strong, driven by the new housebuild sector..."

- "A third of dealer network is closed and a third operating with limited capacity..."
- "...have cooled down merger negotiation talks due to the uncertainties surrounding coronavirus..."
- "...comments on a significant decrease of its share price over the last few days..."

Figure 8: News snippets associated with the stocks falling in the top (green) and bottom (red) decile of the return prediction. Source: RAM AI, Factset.

Figure 9 illustrates the strength of the interaction between factors and news features. The values in this heatmap are aggregated from the model parameters learned during the training of the predictive model. Thus, it is different from conventional correlation metrics calculated on features. Meanwhile, due to the non-linear nature of neural networks, these interaction values reflect the non-linear contribution of feature pairs to the prediction.

For instance, at the bottom line of the heatmap and highlighted in blue, the negative value between NEWS and MOM implies that positive news would lower the contribution of MOM-related factors to the prediction. In contrast, the positive interaction value between NEWS and ESG suggests a reinforced positive effect of news and ESG-related factors on the return prediction.

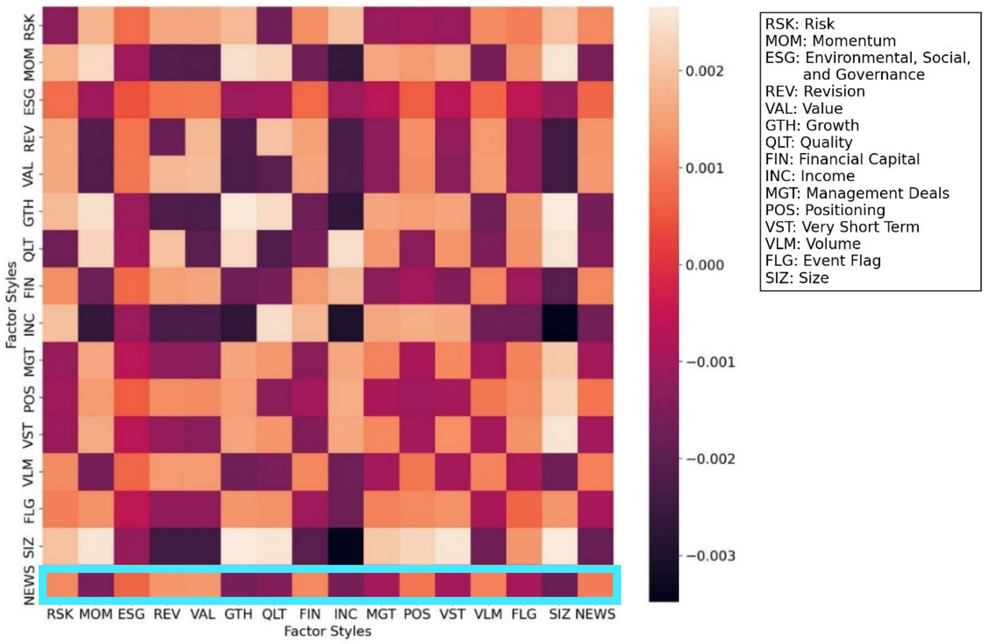


Figure 9: Visualisation of the factor styles interaction learned during the training of the predictive model using both factors and news. Source: RAM AI, Factset.

Conclusion

This case study illustrates that text information obtained from financial newsflow has predictive power on stock returns. Sentiment and embedding features extracted from newsflow also seem to be complementary to structured factors that capture price, fundamental, analyst sentiment, liquidity, or positioning-driven inefficiencies in predicting future stock returns.

Our results show that augmenting a large structured input set with news-based sentiment and embedding features can improve the accuracy of a return-prediction model and significantly enhance the returns of a deep-learning-based L/S strategy.

Figure 10: AI generated with the Stable Diffusion Model on https://beta.dreamstudio.ai/dream

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