

Outperforming Morningstar Analysts: Applying Enhanced LLMs to Financial Reports

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Abstract—This study examines financial analyst reports from Morningstar, revealing two key findings: firstly, analysts appear to select stocks arbitrarily, and secondly, they provide comprehensive textual justifications that enable informed decisions surpassing mere chance. We employ enhanced large language models to efficiently analyze the textual data, facilitating a broad exploration of various pre-trained models to identify the subtle underlying sentiment and extract more value from the reports than the experts themselves. The code is available at github.com/trashpanda-ai.

Index Terms—LLMs, PEFT, Adapters, Hugging Face, Finance

I. INTRODUCTION

Many search for guidance in financial analyst reports for investment purpose. Especially during the COVID-19 pandemic, the number of retail traders has increased significantly. And Morningstar is one of the most popular platforms for financial reports that are widely used by both retail traders and professionals.

However, the question arises whether these reports are actually valuable or just an illusion of expertise. In this paper, we investigate the value of analyst reports and whether they can outperform the market. We hypothesize that the reports contain valuable information that can be extracted using enhanced large language models (LLMs) to outperform the market.

II. DATA

Financial analysts provide detailed reports on single companies (equities), detailing their current situation and future prospects. These reports are based on a variety of factors, including their financial strength, economic moat and cost allocation. The reports also contain a rating and a fair price estimate.

A. Data description

The data is retrieved from Morningstar and contains the following columns:

- **ParseDate**: The date the information was retrieved.
- **Title**: The title of the analyst report.
- **CompanyName**: The name of the company.
- **TickerSymbol**: The ticker symbol (without exchange information) of the underlying stock.
- **Rating**: The analyst rating of the stock.
- **ReportDate**: The date of the release of the report.

- **AuthorName**: The name of the author of the report.
- **Price**: The price of the stock declared in the report.
- **Currency**: The given currency of the price.
- **PriceDate**: The date the price was retrieved from market data (Morningstar).
- **FairPrice**: The estimated fair price from the analyst.
- **Uncertainty**: The company's uncertainty quantified in 'Low', 'Medium', 'High' and 'Very High'.
- **EconomicMoat**: The ability to maintain competitive advantages quantified in 'Narrow' and 'Wide'.
- **CostAllocation**: Decisions on investments categorized as 'Poor', 'Standard', and 'Exemplary'.
- **FinancialStrength**: Rating of the ability to make timely payments and fulfill obligations – quantified in 'A', 'B', ... 'F'.
- **AnalystNoteDate**: The date of the analyst note.
- **AnalystNoteList**: The analyst note.
- **BullsList**: Arguments in favor of the company.
- **BearsList**: Arguments against the company.
- **ResearchThesisDate**: The date of the thesis.
- **ResearchThesisList**: Objective research thesis.
- **MoatAnalysis**: Added research on EconomicMoat.
- **RiskAnalysis**: Company's risk profile.
- **CapitalAllocation**: Text on the CostAllocation.
- **Profile**: Short text on the company profile.
- **FinancialStrengthText**: Short text on the financial strength of the company (conclusion).

The most important information for the application of LLMs is the textual data – starting with **AnalystNoteList**, which we expect to have the most effective content due to its subjective tone. We also analyze more objective texts like **BullsList** and **BearsList** as well as **ResearchThesisList**, **MoatAnalysis**, **RiskAnalysis**, **CapitalAllocation**, **Profile** and **FinancialStrengthText**. Since the target group of financial analyst reports is investors, we focus on the long term perspective and not on short-term speculation. Therefore, we look at the stock price development over a longer period. The data is retrieved from Yahoo Finance and contains the following columns: *Date*, *Open*, *High*, *Low*, *Close*, *Adj Close* and *Volume*. We base our target variable for the sentiment analysis on the *Adjusted Close* price.

B. Data Preprocessing

Since we care about investment and not speculation, we pre-process the data to remove spurious spikes and other noise. We focus on the archetype of a good investment as shown in Figure 1a and ignore spurious spikes as shown in Figure 1b and Figure 1c. This means we consider the average performance within a certain time period – here the maximum amount since the last report was released: 120 days. Inspired by the commonly used moving averages in mathematical finance [1], the preprocessing is done by calculating the average stock price over 120 days since publication and comparing it to the stock price at the time of the report. If the average stock price is higher¹ than the price at time of release, we label it as a good investment, otherwise as a bad investment. This is our binary target variable for the following analysis.

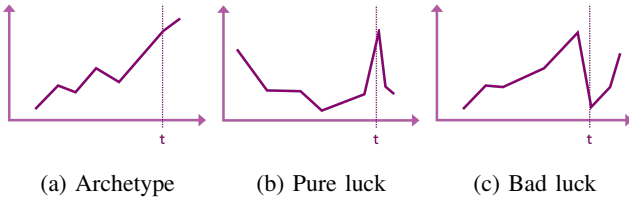


Fig. 1: Different stock developments as charts: Comparing the archetype of a good investment to spurious spikes (positive and negative).

III. FOUNDATIONS

What are the foundations of our approach? What is the goal? Sentiment Classification.

A. Transformer models

What are transformer models? Build an intuition on self-attention and multi-head attention. Use the presentation pictures (youtube video) and reproduce the images quickly in a sketch style on iPad.

B. Parameter efficient fine tuning (PEFT)

We want to explore many models and fine-tune them on our data. So we need a more efficient approach: PEFT. What are adapters? Why do we use them? How do we use them? What is so efficient about it? How does it work? [2]

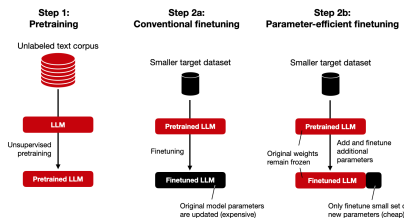


Fig. 2: process of PEFT [3]

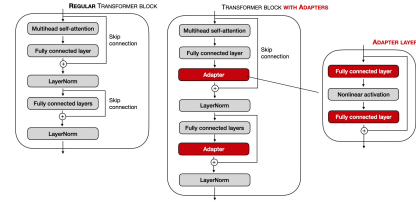


Fig. 3: process of PEFT (detailed) [3]

C. Hugging Face

What is Hugging Face? Why do we use it? What are the benefits?

IV. LITERATURE

As described in [4], there are many different applications of LLMs, and specifically for analyst reports they can provide insights into subtle tone and sentiment to add value. However, at the moment there is only research on publicly available data such as Reddit [5]. Furthermore, it has been shown that reports may have a small positive performance in the right market conditions [6], but it is unclear whether only recommendations themselves can influence markets [7] and reports have no value at all [8]. Thus, the herding factor may have an impact on stock performance [9]. In [10] they use LLMs to better interpret and analyze Korean financial analysts' reports. In this paper, however, we use data from widely spread reports (from retail traders to professionals) on globally traded firms. We show that while analysts can barely outperform the current market, they provide comprehensive textual justifications that enable informed decisions. We use enhanced large language models to efficiently analyze the textual data, allowing a broad exploration of different pre-trained models to identify the subtle underlying sentiment and extract more value from the reports than the experts themselves.

V. APPROACH

This is a classification problem based on sentiment scores Model building and training and Evaluation pipeline. Quickly describe own experiment and results as table for SST2.

A. Model selection

How did we select the models? What are the models? (all relevant to sentiment and finance)

Sentiment

- kwang123/bert-sentiment-analysis
- siebert/sentiment-roberta-large-english
- distilbert/distilbert-base-uncased-finetuned-sst-2-english

Finance

- ProsusAI/finbert
- yiyanghkust/finbert-tone

¹A sideways movement within a 2% margin is not classified as "higher".

- bardsai/finance-sentiment-pl-fast
- RashidNLP/Finance-Sentiment-Classification
- ahmedrachid/FinancialBERT-Sentiment-Analysis
- soleimanian/financial-roberta-large-sentiment
- nickmuchi/sec-bert-finetuned-finance-classification
- nickmuchi/deberta-v3-base-finetuned-finance-text-classification

B. Adapter configuration

How can adapters be configured? What are the options? What is the industry standard for our problem and what did we use?

C. Exploration to Exploitation

How do we explore the models? Just run them all on the same configuration and compare them. First model against model, then with best models we compare adapter configurations, then we compare text inputs from the report and finally we compare it to directly fine-tuning the model itself. How do we exploit the best model? We try to optimize it further and let it run for all the different text columns.

D. Evaluation

How do we evaluate the models? What are the metrics? What is the baseline? What is ROC (build intuition). Why ROC AUC and not F1 score?

In order to validate learned models we compare predictions made from the model with previously separated test data. In this way, we can objectively evaluate them according to their predictive qualities. For this comparison, we utilize these fundamental principles:

Sensitivity or true positive rate (TPR) is derived from the true positives TP, i.e., the correctly identified positives P from the test set: $TPR = \frac{TP}{P}$

Specificity or true negative rate (TNR) is derived from the true negatives TN, i.e., the correctly identified negatives N from the test set: $TNR = \frac{TN}{N}$

By plotting both the sensitivity and specificity in relation for various threshold values, we obtain the so called Receiver Operating Characteristic (ROC) curve. For the results of both measures 1.0 is the optimum, and if the curve is the diagonal, we observed a random process. In Figure 4, we can see some common examples of curves. In order to further summarize these evaluations, we can calculate the Area Under the Curve (AUC) to rank the models. Again, a value of 0.5 indicates a random process. [11] [12] [13]

We furthermore compare the models with classical approaches based on the analysts forecasts themselves and other metrics from the report to create a baseline.

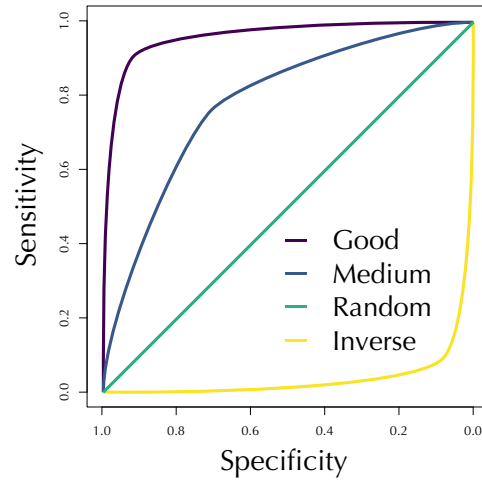


Fig. 4: Exemplary receiver operating curves for a *good*, *medium*, *random* and *inverse* model fit. The perfect score would be 1.0 on each dimension – specificity and sensitivity.

VI. RESULTS

TBD

A. Benchmarking

What are our benchmarks? What are the results? We use the analysts own predictions as input for a logistic regression model as benchmark. And we use all the categorical information from the results and yahoo finance as input for a XGBoost random forest model as benchmark. Results: show `build_roc` for `n=0` and `baseline=True`

B. Models in comparison

Discuss results and weather the performance is enough to outperform the analysts.

Show the results of the models. Show top 5 models and their ROC AUC after initial runs. First we compare the different models for the same adapter configuration and text input.

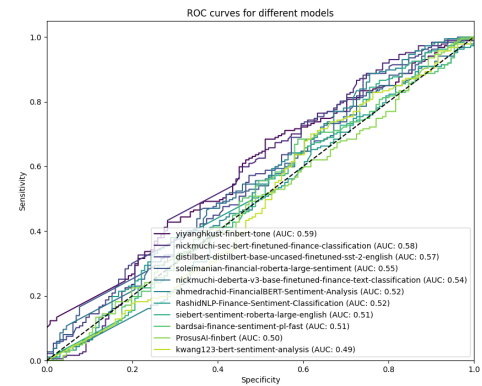


Fig. 5: First Experiment

For the best models we then compare the best adapter configurations found in literature:

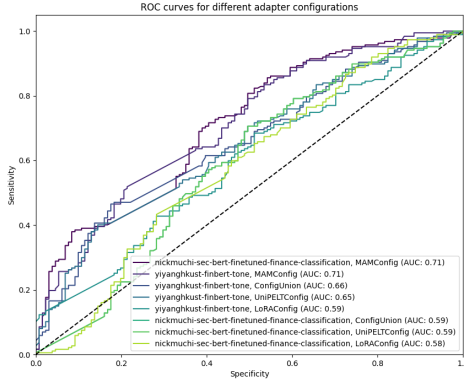


Fig. 6: Second Experiment

Next to AnalystNoteList we also explore BullsList, BearsList, ResearchThesisList, MoatAnalysis, RiskAnalysis, CapitalAllocation, Profile, and FinancialStrengthText.

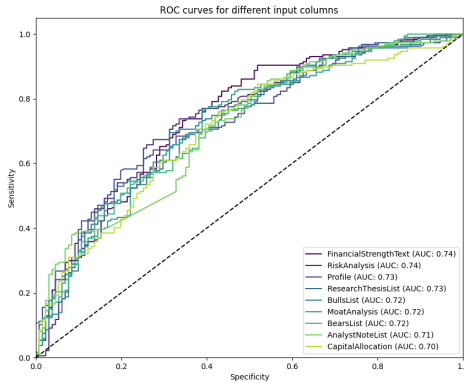


Fig. 7: Third Experiment

Finally we use the best found combination to fine-tune the underlying model directly. This only leads to a small improvement of 0.x AUC but the training time climbed from XX to YY.

While there is no overall cutoff value and it highly depends on the specific application, with values above 0.7 [14], we reached a robust predictive quality.

C. Insights via CAPTUM

What are the models using as input? Use CAPTUM and quickly describe the gradient approach to obtain feature attribution. [15]

D. Training analysis

Show some plots about runtime and training time. Compare with Loss, Accuracy etc

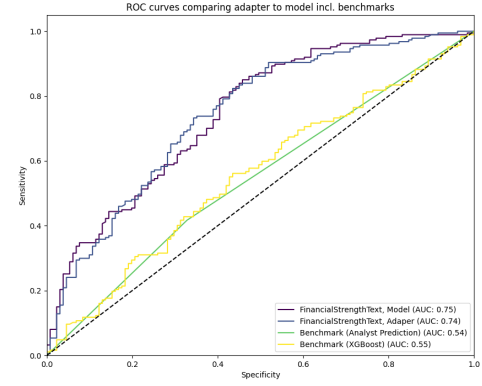


Fig. 8: Fourth Experiment

VII. CONCLUSION

Wrap it up and discuss the results. What are the implications? What are the limitations?

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