Cryptocurrency Return Prediction
Using Investor Sentiment Extracted by
BERT-Based Classifiers
From News Articles, Reddit Posts and Tweets

*Master’s Thesis*

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1. Introduction

Cryptocurrency markets are considered to be volatile, risky and prone to overreaction (Stavroyiannis, 2018). The rise in the popularity of cryptocurrency trading has been heavily accompanied by a constant flow of commentary on expected price developments. These opinions are expressed not only via traditional news outlets, but also increasingly on social media platforms.

Numerous studies have examined the level of influence of news and social media commentary when predicting the particular direction of future stock market movements (Bollen, et al., 2011; Antweiler & Frank, 2004; Kearney & Liu, 2014). Building on the research focusing on stock market predictions, it is of scientific interest to find reliable evidence on the explanatory value of news and social media posts on the predictability of price changes in the ever more relevant cryptocurrency market.

The objective of this paper is to analyze whether and to what extent the sentiment from news and social media contributes to the predictability of future cryptocurrency prices using machine learning models. We aim to capture the text sentiment similar to the way a human would process it in the context of trading cryptocurrencies.

The scope of this study puts focus on the analysis of textual data from scraped news articles, Reddit posts and Tweets related to the two largest cryptocurrencies by market capitalization. At the time of writing this paper, the two cryptocurrencies with the largest market capitalization are Bitcoin and Ethereum.

In order to draw conclusions from the explanatory value of the text data described above, a sentiment score is assigned to each text data sample. A BERT-based (Devlin, et al., 2018) modeling approach is chosen for the purpose of performing sentiment classification. Due to the truly bidirectional structure of BERT, the sentiment score can be derived by capturing the full and contextual meaning of the text. The sentiment analysis outcomes are used as input features in the daily return prediction models to investigate whether they provide additional predictive power and lead to better investment gains. The gains are calculated based on a trading strategy that is simulated over multiple test periods that demonstrate both bullish and bearish market patterns.

This research contributes to the literature in the following ways:

- Fine-tuning a BERT-based sentiment classifier to the specific task of extracting the beliefs, emotions and motivations of cryptocurrency traders based on combined data from news articles, Tweets and Reddit posts
- Testing the applicability of a weak supervision approach to train BERT on an unlabeled cryptocurrency-related news and social media dataset by introducing pseudo-labels from a
zero-shot classifier, such that BERT’s task-specific and contextual learning ability is not significantly impacted by the weakness of the labels.

- Collectively evaluating the predictive performance of various financial machine learning models with and without the extracted sentiment features. Based on those models, the performance is translated and analyzed by potential trading profit gains from using these predictions for buy/sell decision-making in the scope of a specific trading strategy.

This work handles the implementation as well as the evaluation of sentiment analysis and price prediction as two separate but highly interconnected parts. We first refer to related literature and research in Section 2 before explaining our textual and financial datasets in Section 3. We then allocate Section 4 to describing the implementation and analysis of the BERT-based sentiment classifiers. The extracted sentiment information is used as input data to financial predictors, which are described and evaluated elaborately in Section 5. This section also includes the selected trading strategy for the investment simulation. Section 6 concludes the paper by summarizing the key findings, outlining the limitations of this paper and suggesting promising areas for future research in this domain.

2. Literature Review

We refer to related literature regarding (1) BERT-based news and social media sentiment classification, (2) the weak labeling approach to tackle the unlabeled dataset problem, (3) predicting future returns using extracted sentiment features in machine learning models, and (4) trading strategies for investment simulation.

2.1. BERT-Based News and Social Media Sentiment Classification

BERT (Devlin, et al., 2018), Bidirectional Encoder Representations from Transformers, is a natural language processing model pre-trained on very large corpus data and is publicly available for possible tailoring to downstream tasks. Since the pre-trained BERT is already able to capture bidirectional context from text, fine-tuning the model to a specific NLP task requires only a small dataset. BERT is therefore an effective and efficient model choice for textual implementations such as the tasks at hand in the context of this piece of work. In this paper, we apply BERT to perform sentiment classification on text from various online sources, and therefore, focus on literature with similar applications.

Human concordance, meaning the correct classification of text sentiment, is only between 70-79% (Gwet, 2014). This would indicate that the approximately 70% accuracy achieved by various
papers for sentiment classification of stock-related Tweets can be considered as a successful rate (Pagolu, et al., 2016; Chen & Lazer, 2013). Nasekin and Chen (2020) study public sentiment about 425 cryptocurrencies using a BERT-based classifier with text data consisting of posts on StockTwits, a social media platform where traders share ideas. This study concludes that the addition of a domain-specific lexicon to the token list of BERT contributes to higher classification performance. Ortu et al. (2022) use a BERT-based approach to perform emotion and sentiment classification on GitHub and Reddit comments related to Bitcoin and Ethereum. Each social media comment is classified based on certain emotions, including joy, anger and sadness, as well as overall sentiment. Pota et al. (2020) fine-tune various BERT models for Tweets sentiment classification, by first further pre-training the model on plain text created from abundant Twitter data to make the model learn Twitter jargon, and then fine-tuning on relevant Tweets for classification. The proposed approach outperforms other traditional models. Shapiro et al. (2020) study economic sentiment from various news sources from 1980 until 2015 using a BERT-based model with added domain-specific lexicon and find a strong relationship between the extracted sentiment scores and consumer sentiment measures as well as economic shocks.

2.2. Unlabeled Dataset Issue and Weak Labeling Approach

A text dataset with reliable labels makes it possible to successfully fine-tune BERT to a classification task and evaluate its performance with metrics such as accuracy. There are various studies that have access to manually labeled news data related to the stock market (Malo, et al., 2014; Lutz, et al., 2020; Van de Kauter, et al., 2015). It would be feasible to fine-tune BERT for sentiment classification using an expert-labeled dataset. Araci (2019), for instance, fine-tunes a BERT-based classifier, called *FinBERT*, using the stock news data from Malo et al. (2014). However, finding a good quality expert-labeled news and social media dataset is more challenging in the context of cryptocurrencies. Therefore, researchers need to find alternative ways to work with unlabeled datasets. For example, Vo et al. (2019) label news as positive or negative based on the immediate price change of the cryptocurrency after their release. They therefore imply a certain degree of causality between news and price changes. Köse (2020) manually labels a subset of news data and labels the rest using a random forest classifier. Another method would be to use a “dataless classification” model, which categorizes text into defined categories without domain knowledge or labeled data (Chang, et al., 2008).

We handle the issue of unlabeled text datasets by using a weakly supervised approach, as it is applied in a similar fashion by the work of various researchers mentioned in the subsequent section (Lison, et al., 2020; Xiong, et al., 2019; Mekala & Shang, 2020). Yu et al. (2020) use semantic
rule-based approaches to assign labels to text data through positive and negative sentiments of certain words and word groups. Their research proposes a RoBERTa (Liu, et al., 2019) model that is fine-tuned on the weakly-labeled dataset with regularization specifications. It concludes that a fine-tuned RoBERTa on a weakly-labeled dataset performs similarly compared to a fully supervised model, across most of the tested text classification tasks.

Mylonas et al. (2020) acknowledge the issue of lacking labeled data and propose a zero-shot classifier to label a contextual dataset about biomedical articles. A zero-shot classifier is an unsupervised model that can classify text from any domain into previously unseen classes. Zero-shot learning and its usage in our paper is explained in Section 4.2 in depth. Mylonas et al. (2020), with the goal of further improving classification performance, train a linear kernel support vector machine using the zero-shot predictions as pseudo-labels to the unlabeled dataset. This approach is referred to as weakly supervised learning. It is built on the assumption that the zero-shot classifier predictions are at least somewhat trustworthy. The usefulness of zero-shot classifiers for assigning weak labels is proven, by showing that classification ability is boosted by the additional training step using support vector machines. This approach indicates that the lack of labeled data is no longer a critical problem for the case researched by Mylonas et al. (2020).

Arachie and Huang (2021) test weak supervision approaches on various datasets, an example being the IMDB movie review dataset for sentiment classification. Weak labels are generated using rule-based sentiment classification for each review. A few other keyword- or proximity-based approaches to assign weak labels are conducted. A supervised model, which is a simple two-layer neural network with a sigmoid final layer, is then trained using the weak labels. For all the four text classification tasks, the supervised model built by training on the weak labels outperforms its weak labels in terms of test accuracy. This indicates that in a case of unavailable labeled data, fitting a supervised model using weak labels can outperform the sole use of unsupervised models.

Popa and Rebedea (2021) use simple unsupervised labelers, including n-grams, for a topic classification task. A pre-trained BART model is then fine-tuned using the output from the unsupervised labelers, defining this as a weakly-supervised approach. This work also concludes that meaningful labels are obtained by fine-tuning pre-trained models on a weakly-labeled dataset, supporting the outcomes from previously described research. We conclude that a similar approach can be applied in this piece of work to tackle the challenge of unlabeled text data.

2.3. Price Movement Prediction Using Investor Sentiment

Predicting future stock or cryptocurrency price movements has long been a field of interest for researchers. Cryptocurrency price- or return- prediction models, as observed in the recent
academic literature, commonly include the so-called price, technical, blockchain, macroeconomic and other currency-related features (Jang & Lee, 2017; Huang, et al., 2019; Mallqui & Fernandes, 2019). Price features consist of Open-High-Low-Close (OHLC) data, and technical features express volume, volatility, trend and momentum. Blockchain features include trading volume, block size, hash rate and such blockchain-related information. Macroeconomic features consist of various indices including S&P500 and external economic factors including inflation, and other currency features consist of price data of various cryptocurrencies, precious metals such as gold, or fiat currencies.

A growing number of papers are investigating the potential value of adding features derived from investor sentiment, in addition to the above described commonly used price, technical, blockchain and macroeconomic-related features (Jin, et al., 2020; Antweiler & Frank, 2004; Nasekin & Chen, 2020). Sentiment from investment-related social media and other online platforms is shown to reflect the subjective perception and characteristic approach of investors (Kearney & Liu, 2014). Pagolu et al. (2016), for example, implement sentiment classification on a large dataset of stock-related Tweets and find strong correlation between prices and public sentiment. The works of Jin et al. (2020) and Antweiler and Frank (2004), similarly, perform sentiment analysis on online stock-related comments to classify them as bullish or bearish, in order to introduce them as additional features to financial models. Sonkiya et al. (2021) use a BERT-based classification model to extract sentiment from news articles about selected stocks. They then predict future stock prices using a generative adversarial network with price, technical and sentiment features, significantly reducing the test error. Heston and Sinha (2017) conclude that positive sentiment from news elevates stock returns quickly, whereas negative sentiment causes a longer-term reaction. Li and Wu (2022) build a support vector classifier for stock return direction prediction, with input features consisting of various technical indicators and sentiment features. The technical features are created using the Python library TA-Lib (mrjbq7, et al., 2021), an open-source library for technical indicator computations.

Similar research has been conducted about the additional predictive power of public sentiment regarding cryptocurrency prices or returns. Nasekin and Chen (2020) show that sentiment from StockTwits extracted by BERT with added domain-specific tokens contributes to return predictability of numerous cryptocurrencies. Chen et al. (2019) use public sentiment from Reddit and StockTwits to conclude the value of sentiment as features in a return prediction model, with the condition that the text classifier uses a domain-specific lexicon. This study is applied to 25 cryptocurrencies by the greatest message volume in StockTwits. Polasik et al. (2015) indicate that Bitcoin prices are highly driven by news volume and news sentiment. Vo et al. (2019) show that
sentiment scores from news articles from seven days in retrospective increases the predictive performance of an LSTM model in predicting cryptocurrency price directions. Lamon et al. (2017) apply an approach to directly predict future prices using news and social media posts without having to first compute sentiment scores as inputs to an additional financial model. Kim et al. (2016) conclude posts in online communities to be significant for Bitcoin price forecasting at daily granularity. Ortu et al. (2022) conclude that adding sentiment from GitHub and Reddit comments as input features significantly improves hourly and daily return direction predictability of Bitcoin and Ethereum using deep learning models.

Price movement prediction using investor sentiment poses a challenge to the researcher, namely the varying granularity and frequency of the sentiment features and the target. News and social media posts are distributed irregularly throughout time, whereas price or returns data needs to have a constant period. Researchers therefore have to take price or returns at a certain frequency and aggregate news or social media data to the same granularity. In this piece of work, we define the target as daily returns. We therefore need to aggregate those sentiments in a suitable form to a daily measure, in order to input sentiment as a feature in the predictive models. Previous research has found a number of promising methods to do so. Some examples from the literature include computing the logarithmic ratio of bullish to bearish posts per day (Antweiler & Frank, 2004), ratio of the exponential moving averages of bullish to bearish cases to reduce noise (Leow, et al., 2021), or simply taking the ratio of the number of positive to negative posts (Bollen, et al., 2011). In this paper, we accept an aggregation approach that involves taking the difference of positive to negative samples and scaling it by the total number of posts that day, including neutral samples (Hiew, et al., 2019). Bollen et al. (2011) additionally include daily text sample count as a feature to the financial model.

2.4. Trading Strategies for Investment Simulation

Price direction prediction models can be difficult to interpret solely in terms of metrics such as accuracy. It is more appropriate to simulate the potential monetary gain that a predictive model would provide. Therefore, researchers often select a trading strategy and simulate a test investment period, by making buying and selling decisions based on the model predictions. A strategy example is shown in the work of Chen and Lazer (2013), which involves buying stocks if future return prediction is positive, at an amount proportional to the certainty of the prediction, and selling stocks at an amount based on the certainty that prices will decrease. Sebastião and Godinho (2021) use a different daily trading approach of buying or selling cryptocurrency one day before price direction changes and staying passive at other times. Li and Wu (2022) implement a trading
strategy to buy one stock share at the opening price and sell at the closing price of the same day, if prices are predicted to increase. If conversely, the price prediction is negative, one would sell a share at the opening price and buy back at the closing price.

The potential gain attained from investment simulations is easily interpretable when compared to the so-called benchmark scenarios. The benchmark ideal trading scenario, which simulates a case of perfect knowledge, is used to evaluate the maximum attainable profit. It simulates the case that the trader has complete foresight and always buys at peaks and sells at troughs (Lin, et al., 2011; Jasic & Wood, 2004; Fernandez-Rodriguez, et al., 2000). Another benchmark is when the trader has no information or opinion about future market developments, which would be equivalent to random decision-making (Chen & Lazer, 2013). The passive buy-and-hold (B&H) strategy, where the trader buys at the beginning of a period and holds the asset until a predefined closing time, is also commonly used as a benchmark for price movement prediction models (Leow, et al., 2021; Sebastião & Godinho, 2021). The use of these common benchmarks for this work is explained in Section 5.5.2.

3. Data

3.1. Text Data

This study focuses on sentiment analysis and financial prediction for Bitcoin and Ethereum, which are currently the two largest cryptocurrencies in terms of market capitalization in USD value of all circulated coins. Both of these cryptocurrencies are also commonly known and more frequently the subject of discussions, compared to those that are less popular or created more recently. Their popularity and relatively long period of existence establish them as preferable choices for this study, due to easier access to more data for a longer time period.

Bitcoin and Ethereum have their own text datasets and are handled separately. Both datasets consist of news articles, Tweets and Reddit posts in the time period from 01/08/2019 until 15/02/2022 and scraped using different Python libraries, as shown in Table A1 in the Appendix.

The raw text dataset is filtered and prepared for the analysis. The approach differs for the different data sources, due to their unique format and varying ways of accessing them. News articles in the GoogleNews RSS feed are filtered to include only those published by CoinDesk and CoinTelegraph, and contain the name or code of the relative currency, i.e., “Bitcoin” or “BTC” and “Ethereum” or “ETH”, adding up to on average 20 news articles per day per currency. There is no further filtration for the news samples, since there are no spam samples.
Twitter data is filtered by selecting and searching for the name and code of each currency from all Tweets that day. They are then eliminated based on several criteria, which are a minimum threshold number of retweets, number of likes, number of followers of the corresponding account and whether the account ID is verified. It is aimed to eliminate scams, advertisements or irrelevant samples, and rather include more publicly viewed posts published by relevantly important accounts. The underlying implicit assumption is that a post with a larger reach has a more significant reflection of the community sentiment in relation to cryptocurrency price changes.

The r/Bitcoin and r/ethereum subreddits are scraped for each respective currency, and further eliminated based on the number of likes and comments. Here, the assumption is that the priority lies in the commonly commented and discussed posts that likely have a more critical content. Also, posts that are very short or just contain a URL are eliminated, as they would be meaningless to train or predict with the sentiment classification models.

There are common text samples between the Bitcoin and Ethereum datasets, especially in news and Tweets. The samples that contain both Bitcoin’s and Ethereum’s name or code are included in both datasets. However, this is a very rare case in the Reddit samples, since the posts are scraped directly from each currency’s own specific subreddit, without such a filtering approach by name.

3.2. Financial Data

The target variable in the financial models is the daily rate of return. For each currency, daily return at time $t$ is computed as the percentage change from the closing price at time $t$ to the closing price at time $t+1$. There is exactly one day between successive time periods, since data granularity is defined as daily for all features and the target. The beginning time of each day is taken as 00:00 Greenwich Mean Time, acting as the separation between the daily time periods. Each time period covers the entire day, until the time the next day starts.

The input features we use are categorized into types of price, blockchain, macroeconomic, technical, sentiment and dummy features and listed in Table 1. These feature types are introduced in Section 2.3. We additionally input week day dummies to account for any weekly seasonality effects. All features in Table 1, except for the blockchain features, are included for both Bitcoin and Ethereum return prediction models, based on their own characteristics. The blockchain features were available for free only for Bitcoin and it was not possible to find similar network data for Ethereum online without having to pay high costs. We use the Python wrapper for TA-lib (mrjbq7, et al., 2021) to compute the technical features shown in Table 1.
| Feature type         | Number of features (without lags) | Feature list                                                                                                                                                                                                 | Lags |
|---------------------|-----------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------|
| Price features      | 5                                 | Open, high, low, close and adjusted close prices                                                                                                                                                           | 0    |
| Blokchain features* | 9                                 | Average block size 7-day MA, estimated transaction volume, hash rate 7-day MA, market capitalization, miners’ total revenue, number of total transactions, number of total transactions 7-day MA, network difficulty, number of transactions per block | 0, 1, 2 |
| Macroeconomic features | 5                          | 5-year breakeven inflation, 7-month treasury bill, S&P 500 close price, return of S&P 500 close price, volatility index of S&P 500                                                                                  | 0, 1, 2 |
| Technical features (lagged) | 10                                  | Daily return between closing and opening prices, log of daily return, cumulative return, trading volume, price volatility by 30-day moving standard deviation of price, Parkinson volatility, relative intraday price change, closing price of the other cryptocurrency, daily return on the other cryptocurrency, volume of the other cryptocurrency** | 0, 1, 2 |
| Technical features*** (non-lagged) | 78                                  | **Volume**: money flow index, accumulation/distribution index, on-balance volume, Chaikin money flow, force index, ease of movement, volume-price trend, negative volume index, volume weighted average price  
**Volatility**: average true range, Bollinger bands, Keltner channel, Donchian channel, Ulcer index  
**Trend**: simple moving average, exponential moving average, weighted moving average, moving average convergence divergence (signal line, histogram), average directional movement index, vortex indicator (positive, negative, difference), Trix, mass index, commodity channel index, detrended price oscillator, KST oscillator, Ichimoku Kinko Hyo (span A, span B), parabolic stop and reverse (up, down), Schaff trend cycle  
**Momentum**: relative strength index, stochastic relative strength index, true strength index, ultimate oscillator, stochastic oscillator, Williams %R, awesome oscillator, Kaufman’s adaptive moving average, rate of change, percentage price oscillator (signal, histogram), percentage volume oscillator (signal, histogram) | 0 |
| Sentiment features | 6                                 | Daily count of news articles, count of Tweets, count of Reddit posts, daily overall sentiment score of news, score of Tweets, score of Reddit posts                                                                | 0    |
| Dummy features      | 7                                 | Day dummies                                                                                                                                                                                                | 0    |

* Blockchain features are only included in the Bitcoin models  
** Other cryptocurrency refers to Bitcoin for the Ethereum models and vice versa  
*** Computed using the open-source library TA-Lib (mrjbr7, et al., 2021)  

Table 1: List of all features in the financial prediction models

The sentiment features are computed using the predictions of the best-performing sentiment classifier selected in Section 4. How daily sentiment scores are then aggregated is explained in depth in Section 5.2 of this paper.

The one- and two-day lags of some features are also added to the models, as shown in Table 1. The financial models in this paper aim to predict only the return of the following day and not a
more further horizon. Therefore, up to two lags are sufficient, considering the trade-off of high complexity and overfitting that would come with the inclusion of more lags. In total, including the lagged versions, there are 178 and 151 features for BTC and ETH models, respectively.

We do not use additional lags of the sentiment-related features. The sentiment features are already inherently lagged, since we aggregate the sentiment from the posts in the last 24-hours to form a daily score, as explained further in Section 5.2. Efficient market hypothesis indicates that whereas forecasters seek predictable patterns in price, these patterns are unlikely to be valid for a long time, due to the immediate adaptation of prices when new information is revealed (Jordan, 1983). The patterns will disappear once a large enough number of people realize them and make trading decisions accordingly (Timmermann & Granger, 2004). It is likely that news and social media posts would already spread to a significant follower body on these online platforms in the duration of one day. We therefore assume that one day is already a long time period for cryptocurrency prices to incorporate external effects, making it irrelevant to further lag sentiment-related features.

Figure 1: Training and test data split for Bitcoin and Ethereum price data

The data is split into training and test datasets, such that the training data is from 01/08/2019 until 31/07/2021, and the test data is from 01/08/2021 until 15/02/2022. The test period covers both a bullish and bearish pattern, in order to prevent the prediction and investment gain outcomes.
from being biased due to a single-direction price movement during the test period. The daily closing prices of Bitcoin and Ethereum during the training and test periods are plotted in Figure 1.

The training and test datasets are standardized using the mean and standard deviation characteristics of the training data. Standardization is applied to all features with continuous values. Binary features, which are only the weekday dummy variables in this case, do not need to be standardized, since “one standard deviation change” has no meaningful explanation for a feature that can only have the values of 0 or 1.

Standardization is important for models that perform regularization based on the magnitude of coefficients, such as ridge regression. It is also critical for models that exploit distances, including k-nearest neighbors and support vector machines. Standardizing the data has no real contribution to the performance of tree-based models. Tree partitioning algorithms are not affected by monotonic transformations of the data. Therefore, since some models chosen in this paper benefit from standardization and others are not affected, we standardize the data and apply it to all models. The whole list of selected models is introduced in Section 5.4.

4. Sentiment Classification Models

4.1. BERT-Based Models

We have built BERT-based models to classify the sentiment of text data samples. The BERT-based classifiers implemented in this work consist of a pre-trained uncased BERT base model with an additional classification layer. This final classification layer provides output for the predicted sentiment class as positive, neutral or negative. Its input is the [CLS] output of BERT, which represents the meaning of the entire text input and therefore is suitable for classification tasks (Devlin, et al., 2018).

The BERT-based classifiers are fine-tuned using the cryptocurrency-related text dataset to tailor the models to the specific context. We have built three variations of the aforementioned sentiment classifiers:

- BERT-Frozen: Fine-tuned by freezing all pre-trained BERT layers and only updating the classification layer weights
- BERT-Unfrozen: Fine-tuning involves changing the weights in all of pre-trained BERT and classification layers
- BERT-Context: Same as BERT-Unfrozen, but with additional cryptocurrency-related contextual tokens added to the tokenizer. Therefore, fine-tuning involves improving the randomly initialized weights for these previously unknown tokens as well.
BERT-Frozen is the least elaborate model for sentiment classification. It would possibly underperform compared to the other two models, due to its limited learning of the specific task. Keeping the pre-trained BERT layers unchanged makes it more difficult for the classifier to capture contextual sentiment. The original output of BERT is not necessarily optimal for predicting sentiment classes. BERT-Unfrozen tackles this issue by updating BERT layers as well as the classification layer during training. This enables the BERT layers to adjust to delivering a more relevant output to the classification layer. Also, the tokens and their positions in the text samples are taken into account in a tailored manner, for the purpose of performing sentiment classification on our dataset.

The tokens list of the pre-trained BERT model does not include cryptocurrency-related vocabulary, such as Bitcoin, Blockchain, or even the word cryptocurrency itself. Therefore, the first two BERT-based classifiers cannot make sense of such contextual vocabulary as a whole. They simply consider such words as unknown vocabulary and break them up into subword units to input them as separate tokens. Thereby, by adding contextual tokens to the BERT tokens list, BERT-Context builds further relevancy to the task of cryptocurrency-related sentiment prediction. It would be expected that BERT-Context is able to capture the contextual sentiment of text data more accurately than the other classifiers.

Ensemble models can deliver elevated performance metric scores by synthesizing several models (Polikar, 2012; Lin, et al., 2022). In this paper, we combine the output of multiple selected text models to classify sentiment more accurately. The final prediction of an ensemble is computed by taking the majority vote of the single models. The selected ensembles are defined in upcoming subsections, where the model outputs are described.

There are some specifications when computing the majority vote of the models involved in an ensemble model. In the case that there is a draw between the number of negative and positive prediction votes, the ensemble predicts a neutral label. However, in the case of a draw between neutral and either positive or negative votes, an ensemble can have two possible tendencies. This paper refers to “neutrality-biased” (NB) ensembles, which predict a neutral label in that case, or “polarity-biased” (PB) ensembles, which predict positive or negative, respectively.

4.2. Unlabeled Dataset Problem

The lack of expert-labeled text data related to cryptocurrencies poses a significant challenge. This paper involves working with an unlabeled news and social media text dataset. Even though labels are crucial for tailoring BERT to a specific task, we do not have enough time, resources or
availability to manually label numerous text samples to form a reliably labeled dataset. Various approaches that tackle the issue of unlabeled text data are already introduced in Section 2.2.

This paper suggests solving the problem of an unlabeled text dataset by assigning a zero-shot classifier’s predictions as its true labels, without demanding any human supervision. We refer to these labels as “weak labels”, since they are simply outputted from an unsupervised model. This approach would be applicable to our purpose, if the predictive performance of a BERT-based classifier fine-tuned on such weakly-labeled data would be similar to that of a model trained on real labels.

Zero-shot text classification (0Shot-TC) involves a model that performs single- or multi-class text labeling in an unseen domain with no prior training or pre-defined classes. The model works by predicting a probability for the correctness of a hypothesis defined for a piece of text, in an unsupervised manner. In our case, there are three hypotheses for all samples, which are “This text is positive/ neutral/ negative.” The hypothesis with the highest likelihood is the predicted class for the corresponding text sample. We are using a pre-trained BART multi-genre natural language inference (MNLI) model (Lewis, et al., 2019) that performs zero-shot text classification as our model of choice. The predictions from the BART model are assigned as the pseudo-labels of the data, with which our BERT-based classifiers are then fine-tuned.

If BERT-based classifiers can be fine-tuned to a specific task using a weakly-labeled dataset, then the problem of the lack of unlabeled text data would no longer be a major cause for concern in the scope of our research. In order to validate the strength of this weak labeling approach, a trial experiment needs to be conducted to justify its use in the following work. Only then can we prove the generalizability of this approach and apply it to our research case.

4.3. Weak Labeling Approach Experiment

FinBERT (Araci, 2019) is a BERT-based sentiment classification model, fine-tuned on the Financial Phrasebank data (Malo, et al., 2014), which is a 4840-sample financial news dataset labeled by the majority vote from 16 individuals with adequate financial knowhow. The sentiment labels are either positive, neutral or negative. This paper makes use of this expert-labeled dataset by using it as reference data to compare the reliability of a weak labeling approach using pseudo-labels from BART, against expert-labeled sentiment scores. In order to make experiment results directly comparable, the dataset is divided into train, validation and test datasets exactly as defined in the FinBERT fine-tuning algorithm.

Firstly, the entire dataset is classified using the BART 0Shot-TC model (Lewis, et al., 2019), generating labels with 79.0% accuracy based on the expert labels. Then, as if the data is unlabeled,
these predicted labels are taken as the pseudo-labels to fine-tune the BERT-Frozen and BERT-Unfrozen models on this dataset. For each of the two models, hyperparameter tuning is performed using grid search based on accuracy, precision and recall performances on the validation dataset. The best set of hyperparameters are used to then train on the combination of the train and validation datasets to build the final classifier. The following ensemble models are introduced to increase performance and compare how the models complement each other:

- Ensemble 0B-NB: Neutrality-biased majority vote from BART 0Shot-TC and Unfrozen BERT

- Ensemble 0BB: Majority vote from BART 0Shot-TC, Unfrozen BERT and Frozen BERT

Table 2 shows the performance metrics of all models based on the 970 test samples. The chosen metrics are accuracy and unweighted macro-averaged precision, recall and F1 scores. Unweighted macro-averaging approach is chosen to treat all three classes with equal importance. Neutral samples make up 59.3% of the test dataset, whereas negative and positive classes are only 13.2% and 27.5%, respectively, and therefore, weighing by class would otherwise significantly prioritize the neutral class.

| Model            | Accuracy | Precision | Recall | F1 Score |
|------------------|----------|-----------|--------|----------|
| BART 0Shot-TC    | 0.790    | 0.775     | 0.771  | 0.773    |
| FinBERT          | 0.822    | 0.787     | 0.823  | 0.805    |
| BERT-Frozen      | 0.688    | 0.622     | 0.583  | 0.602    |
| BERT-Unfrozen    | 0.789    | 0.769     | 0.754  | 0.761    |
| Ensemble 0B-NB   | 0.795    | 0.816     | 0.717  | 0.763    |
| Ensemble 0BB     | 0.787    | 0.784     | 0.737  | 0.760    |

Table 2: Sentiment classification performance metrics with respect to the actual labels

BERT-Unfrozen, trained on the 0Shot-TC predictions as pseudo-labels, has a prediction accuracy of 78.9%, which is not significantly lower than the 82.2% accuracy of FinBERT, trained directly on the actual labels. In terms of accuracy, Ensemble 0B-NB is the best model that performs closest to FinBERT, with accuracy of 79.5%.

| Real Labels | FinBERT Predictions | BERT-Unfrozen Pred. |
|-------------|---------------------|---------------------|
|             | Pos.    | Neg.    | Neu.    | Pos.    | Neg.    | Neu.    |
| Pos.        | 22      | 0.72    | 4.5     | 20      | 0.93    | 6.5     |
| Neg.        | 0.1     | 11      | 2.1     | 0.41    | 9.2     | 3.6     |
| Neu.        | 6.8     | 3.6     | 49      | 7.8     | 1.9     | 50      |

Table 3: Confusion matrices (a) for FinBERT and (b) for BERT-Unfrozen predictions, in percentages
Table 3 shows the confusion matrices for the predictions of FinBERT and BERT-Unfrozen, compared to the actual labels. It is observed that BERT-Unfrozen successfully distinguishes between positive and negative samples, as does FinBERT, and most of the inaccuracy comes from incorrect labeling of negative or positive samples as neutral and vice versa. Neutral class is by definition between the positive and negative classes. It would have been a larger problem to misclassify positives as negatives or negatives as positives.

Even people who are knowledgeable about the specific context can disagree on the sentiment labels of a piece of text. So far, we have measured accuracy based on the test samples for which at least eight of the 16 labelers agreed on a single label. Table 4 presents the performance metrics on the 433 test samples that all of the 16 individuals agreed on. It is observed that the prediction accuracy scores of FinBERT and BERT-Unfrozen increase significantly to 92.6% and 91.7%, respectively. Ensemble 0BB even outperforms FinBERT based on the F1 score, indicating a better combined precision-recall performance, and achieves a very similar accuracy score of 92.4%.

| Model              | Accuracy | Precision | Recall | F1 Score |
|--------------------|----------|-----------|--------|----------|
| BART 0Shot-TC      | 0.919    | 0.896     | 0.925  | 0.910    |
| FinBERT            | 0.926    | 0.900     | 0.902  | 0.901    |
| BERT-Frozen        | 0.783    | 0.695     | 0.701  | 0.698    |
| BERT-Unfrozen      | 0.917    | 0.889     | 0.890  | 0.889    |
| Ensemble 0B-NB     | 0.917    | 0.930     | 0.871  | 0.900    |
| Ensemble 0BB       | 0.924    | 0.916     | 0.896  | 0.906    |

Table 4: Performance metrics of the sentiment classifiers on the samples that all labelers agree

|                   | FinBERT Predictions | Ensemble 0BB Pred. |
|-------------------|----------------------|--------------------|
|                   | Pos. | Neg. | Neu. | Pos. | Neg. | Neu. |
| **Real Labels**   |      |      |      |      |      |      |
| Pos.              | 21   | 1.6  | 2.1  | 20   | 1.4  | 3.5  |
| Neg.              | 0    | 12   | 1.4  | 0    | 12   | 1.2  |
| Neu.              | 1.2  | 1.2  | 60   | 1.6  | 0    | 61   |

(a) (b)

Table 5: Confusion matrices (a) for FinBERT and (b) for Ensemble 0BB predictions, in percentages

Table 5 portrays confusion matrices for the predictions of FinBERT and Ensemble 0BB on the selected samples. Regarding the significant performance increase of the models after filtering of the text samples that all labelers agree, the cases that the models predict incorrectly are also those that humans cannot all agree on a single label. This disagreement happens mostly between negative-neutral and positive-neutral labels, which is expected, since it is difficult to very clearly define the boundaries between these label pairs.
This experiment justifies that BERT-based sentiment classification models fine-tuned on weak labels of 0Shot-TC predictions can perform just as well or even outperform a similar model trained on the same data with the actual labels. Therefore, we justify the validity of accepting the zero-shot classified weak labels as the actual labels of the text samples in our main task that involves fine-tuning of the BERT models to extract the sentiment from cryptocurrency news and social media posts.

4.4. BERT-Based Models for Cryptocurrency Data

Having proven the applicability of the weak labeling approach of unlabeled datasets in the context of stock market news data, we now generalize this outcome to the scope of our similar data related to cryptocurrencies. In this section, we use that approach to generate weak labels for our cryptocurrency-related news and social media data. These labels are then used to fine-tune BERT-classifiers for sentiment prediction.

News articles, Reddit posts and Tweets for Bitcoin and Ethereum between 01/08/2019 and 31/07/2021, corresponding to the training period for the financial prediction models, are classified using BART MNLI 0Shot-TC (Lewis, et al., 2019) and FinBERT (Araci, 2019). In order to reduce the number of training samples and only keep those that are more likely to be correctly labeled, only the samples that both models classified with the same label are filtered. Then, more data samples are eliminated to obtain a 6,022-sample subset that is balanced in terms of sentiment class, source type and related cryptocurrency. The BERT models in this paper are fine-tuned for the task of classifying the sentiment from all text sources related to both cryptocurrencies, and therefore, it is important to balance the training dataset to give equal priority to each text type.

The words that are not included in the default BERT tokens list are detected and ordered by count of occurrence. More relevant tokens are then manually selected from the most common words. The added new tokens are btc, bitcoin, eth, ethereum, crypto, cryptocurrency, blockchain, defi, nft, binance, bullish and bearish, all being in lower case, since we use uncased BERT. These tokens appear 50 to 1000 times in the BERT training dataset, making it possible for the model to successfully update these token weights during fine-tuning. It is important to keep the number of new tokens to a minimum of only the most essential words, since too many randomly initialized tokens can require a large number of samples to train on, and if not, reduce the classification performance of the model.

BERT-Frozen, BERT-Unfrozen and BERT-Context are fine-tuned on the weakly-labeled cryptocurrency text dataset. Each sample is defined as either positive, neutral or negative. Firstly, hyperparameter tuning is performed using grid search and the best set of hyperparameters is
selected according to a combined score of accuracy, precision and recall metrics on the validation dataset. Then, a final model is trained on the entire training and validation dataset using the optimized hyperparameters. This process is repeated for each of the three BERT-based classifiers to obtain their final and optimized versions. The classifiers are then evaluated based on their performance on unseen data in the following subsection.

4.5. Model Performance Metrics by Manual Labeling

The optimized BERT-based sentiment classifiers should be compared in terms of their classification performances. However, the lack of real-labeled data again poses a significant challenge. Obtaining realistic performance scores requires the availability of true labels. In order to achieve this, a small but representative subset of the data is manually labeled by three individuals. These people consist of an economics PhD candidate, an economics master’s graduate and me.

From the period of 01/08/2019 to 31/07/2021, text samples that have not been included in the BERT training dataset are selected. Therefore, the selected subset is unseen data for the BERT classifiers. Then, these samples are eliminated to 540 text samples that are balanced in terms of sentiment class, text source and related cryptocurrency. We use the labels from BART predictions to balance the data subset in terms of class, since the real labels are not yet defined at the time of preparing this selected set. In addition, we adjust it such that a third of the selected subset consists of text pieces that all models agree on, another third consists of samples that BERT-Context differs from the weak labels it trained on, and the rest are cases that the three BERT models predict different classes. Such selection is pursued to make the small sample set as representative as possible of the whole dataset by including a variety of cases.

The three individuals agree on the labeling of 78.0% of the samples. The real label of each sample is defined by the majority vote of the three individuals. The performance metrics of the sentiment classification models are displayed in Table 6.

Additionally, after comparing several ensembles that combine different models, the best-performing ensemble is included in the comparison:

- Ensemble 0BBF-PB: Polarity-biased majority vote from BART 0Shot-TC, BERT-Unfrozen, BERT-Context and FinBERT

The previous claim that a weakly-labeled dataset can still be valuable to fine-tune a task-specific BERT model is verified once again. BART 0Shot-TC and FinBERT perform sentiment classification with 58.7% and 58.0% accuracy, respectively, whereas the BERT-Context model,
which is trained on a dataset with their predictions as pseudo-labels, outperforms them with an accuracy of 61.1%.

| Model             | Accuracy | Precision | Recall | F1 Score |
|-------------------|----------|-----------|--------|----------|
| BART 0Shot-TC     | 0.587    | 0.647     | 0.621  | 0.634    |
| FinBERT           | 0.580    | 0.579     | 0.575  | 0.577    |
| BERT-Frozen       | 0.517    | 0.542     | 0.563  | 0.552    |
| BERT-Unfrozen     | 0.580    | 0.580     | 0.622  | 0.600    |
| BERT-Context      | 0.611    | 0.605     | 0.636  | 0.620    |
| Ensemble 0BBF-PB  | 0.700    | 0.685     | 0.708  | 0.696    |

Table 6: Performance metrics of the models based on the manually classified labels

BERT-Context is the best-performing one out of the three fine-tuned models in this paper, in terms of accuracy and F1 score. It is the only model that can process some cryptocurrency vocabulary as they are, without splitting them into multiple subword tokens, as the other BERT models do. Therefore, it is expected that BERT-Context outperforms the other models.

BERT-Context achieves a higher accuracy score than both FinBERT and BART, which have not been trained on our specific dataset. This shows that in our case of unlabeled data, instead of simply using an unsupervised model or a model that is trained on a different kind of data, it brings additional value to fine-tune a supervised BERT classifier using weak labels. This outcome is deduced based on the specific sampling of the manually labeled subset, and we assume that the metrics in Table 6 reflect the general performance of the models.

Ensemble 0BBF-PB, which combines the models BART, BERT-Unfrozen, BERT-Context and FinBERT by polarity-biased majority vote, outperforms all single models and other considered ensembles, in terms of both accuracy and F1 score. The confusion matrix in Table 7 shows that this ensemble is able to distinguish between positive and negative classes relatively successfully, and most of the inaccuracy comes from the neutrality class. Since Ensemble 0BBF-PB is the superior sentiment classifier in this section, we use its predictions as the sentiment labels in the implementation of financial prediction models, in the upcoming Section 5.

| Manual Labels | Pos. | Neg. | Neu. |
|---------------|------|------|------|
| Pos.          | 35   | 3.5  | 11   |
| Neg.          | 1.3  | 15   | 3    |
| Neu.          | 7.2  | 4.3  | 20   |

Table 7: Confusion matrix for Ensemble 0BBF-PB based on the manually classified labels, in percentages
Table 7 also shows that the data subset selected for performance evaluation is not balanced, with positive class being over-represented. This is because the subset was selected in a balanced way based on the classes predicted by BART 0Shot-TC, which vary significantly from the manually labeled classes. Performance metrics could have been more representative if the subset would be balanced by manual labels, but this would require more labeling time and be quite labor intensive.

4.6. Interpretation of Model Predictions

We look at some special cases from the manually labeled dataset in Section 4.5. Table 8 presents various special cases that are used for interpreting the model predictions. The Data Type column in Table 8 indicates the dataset that the text sample belongs to. For example, text Ex. 3 is used for the sentiment score of both Bitcoin and Ethereum.

Some observations from the special cases, along with their corresponding examples from Table 8, include:

- The models tend to misclassify the text samples that have a positive sentiment about one cryptocurrency but a negative one for the other. Since we fine-tune the BERT models using a combined dataset for Bitcoin and Ethereum, the models do not learn to make a distinction. (Ex. 4, 7)

- When the text has sarcastic, vague or indirect language, the models tend to misclassify. (Ex. 1, 2, 5, 6)

- In cases that there are too many domain-specific words, BERT-Context and Ensemble 0BBF-PB can classify correctly whereas the others misclassify. This is because the other models can only consider such words as subword tokens and cannot interpret them in a meaningful way. (Ex. 3)
| Example Index | Data Type | Text Sample | Manual Labels | Comparison and Evaluation |
|---------------|-----------|-------------|---------------|---------------------------|
| Ex. 1         | BTC, Twitter | “America has gone from one of the toughest Presidents, Trump, to the most incompetent President, Biden. Our problems to grow bigger, sadly like human tragedy at Southern border. Dollar, economy will be destroyed. Buy gold, silver, Bitcoin.” | All pos. | All models label as negative. The main message has a negative sentiment, but it is indeed a positive message about cryptocurrencies. |
| Ex. 2         | BTC, Twitter | “Breaking: The US dollar has fallen to a 1/39,700th of a Bitcoin.” | All pos. | All models label as negative. The sentence is structured in a misleading way to express the price of Bitcoin. |
| Ex. 3         | BTC and ETH, Twitter | “With the abundance of bad news happening in the world currently, here is some good! Daily active addresses for both #Bitcoin and #Ethereum are showing clear bullish divergences compared to their respective prices, according to our @santimentfeed data. SETH in particular” | All pos. | Only BERT-Context and Ensemble 0BBF-PB classify correctly. The reason might be that these are the only models that incorporate domain-specific vocabulary. The other models cannot process “Bitcoin”, “Ethereum” or “bullish” as words. |
| Ex. 4         | ETH and BTC, Twitter | “SETH is literally trying to drag the entire market down When $BTC gets free of this we rocket imo” | One pos., one neg., one neu. | All models classify as negative. The same news article appears for both Bitcoin and Ethereum datasets, and it is positive for Bitcoin and negative for Ethereum, but the sentiment classifiers cannot distinguish this. |
| Ex. 5         | BTC, news | “Morgan Stanley exec says Bitcoin is the ‘Kenny from South Park’ of money” | All neu. | Models mostly predict neutral. This post is not interpretable without background knowledge regarding South Park or Morgan Stanley. Even the human annotators said they do not know how to label this sample. |
| Ex. 6         | BTC and ETH, news | “Whenever Bitcoin Prices Go Up or Down, Google Searches Soar” | Two pos., one neu. | BERT-Context and Ensemble 0BBF-PB classify as positive, all others as negative or neutral. This is tricky, because it indicates that people are enthusiastic when prices increase. However, it could also mean that they have panic when prices decrease. |
| Ex. 7         | ETH, Reddit | “This got censored from /r/CryptoCurrency but is an important read: As a Venezuelan, cryptocurrencies are a blessing.” | All pos. | A case that only BERT-Context and Ensemble 0BBF-PB classify correctly. |

Table 8: Cases for analysis and comparison of the model predictions
5. Financial Prediction Models

In this section, different regression and classification models are built to predict daily cryptocurrency returns. The purpose is to analyze the contribution of public sentiment, described in the previous section, to the predictive performance of the financial models and the potential gains from simulated trading periods.

5.1. Target and Features

The financial predictors are implemented separately for Bitcoin and Ethereum. The target and the features are explained in Section 3.2. Regression models predict the value of daily returns, whereas classification models classify returns as positive or negative.

5.2. Daily Sentiment Aggregation

The sentiment classes of text samples are labeled by the best-performing BERT-based Ensemble 0BBF-PB model in Section 4. Daily sentiment scores for each text source are then computed by aggregating the sentiment of all samples within the same day, as shown in Equation (1). Each positive, neutral or negative sample is considered to add 1, 0 or -1 points, respectively, to the daily score, which is then scaled by the number of text samples that day. Even though there are common text samples found in the datasets of Bitcoin and Ethereum, the daily sentiment scores for the cryptocurrencies are different, since different sets of text data are included in each day.

Equation (1) shows how daily sentiment scores for source $s$, namely news, Tweets or Reddit posts, at day $t$ are calculated (Hiew, et al., 2019).

$$Sentiment\ Score_{t,s} = \frac{\text{pos}_{t,s} - \text{neg}_{t,s}}{\text{pos}_{t,s} + \text{neu}_{t,s} + \text{neg}_{t,s}}$$  \hspace{1cm} (1)$$

The count of text samples from each source during the course of a day are also included as sentiment-related features, separately for each cryptocurrency.

5.3. Evaluation of Sentiment Features Using VIF

Variance inflation factor (VIF) measures the extent to which a feature can be explained as a linear combination of the other features in a dataset. It indicates the level of multicollinearity of a certain feature with respect to all the other features. In this paper, we use VIF to analyze whether sentiment-related features add unique information that other features do not already contain, in the scope of linear relationships.
VIF values range from one, equivalent to no multicollinearity, to infinity, indicating perfect multicollinearity. It is commonly accepted that moderate collinearity exists when VIF is between 5 and 10, and there is severe multicollinearity when VIF is above 10 (Shrestha, 2020; Belsley, 1991). In this paper, we firstly evaluate our feature set using a cutoff value of 5. Then, we consider a more conservative approach and evaluate the features at a maximum VIF value of 2.5.

Elimination is performed iteratively, by computing VIF for each feature, removing the one with the highest value, and repeating until no feature has VIF above the cutoff. Table 9 shows the sentiment-related features that remain after iteratively removing all features with VIF values above 5. From the 178 and 151 features for Bitcoin and Ethereum, respectively, 46 and 42 features remain after the elimination. Table 9 also marks the features that still remain when the maximum VIF threshold is lowered to 2.5, leading to 34 and 32 features for Bitcoin and Ethereum, respectively.

| Count Features | News | BTC Reddit | Tweets | News | ETH Reddit | Tweets |
|----------------|------|------------|--------|------|------------|--------|
| Sentiment Features | Yes* | Yes* | Yes* | Yes* | Yes* | Yes* |

* Indicates features that are still not eliminated at a VIF cutoff of 2.5

Table 9: Remaining features after elimination by VIF with a cutoff value of 5

It is observed that for both cryptocurrencies, all sentiment features are retained after elimination, even at a VIF threshold of 2.5. This means that the news, Reddit and Tweets sentiment features cannot be explained as linear combinations of each other or all of the other features. Although this analysis is restricted to linear relationships only, it is still insightful to observe that the sentiment features add unique value to the feature set.

Out of all sentiment-related count features, Reddit post count is the only one that does not get eliminated at a VIF level of 2.5. It is shown that the Reddit count feature contributes to the feature set with unique linear value. The news and Tweets counts are, on the other hand, shown to have high collinearity with other features, and therefore, do not bring additional linear value to the feature set at a great extent.

5.4. Return Prediction Models

The regression and classification models shown in Table 10 are implemented separately for each cryptocurrency. The purpose is to evaluate the contribution of sentiment features to the predictability of future returns. A variety of models are built, in order to minimize the dependency of evaluation outcomes on specific model choices and characteristics. By testing with many
models, the results are more generalizable, so that the outcome of this work provides a more solid foundation.

Each model is built two times, such that one is trained on the entire feature set and the other with all features except for the sentiment features. Fitting the 23 models in Table 10 for each of the two feature sets, which are then repeated for both cryptocurrencies, adds up to 92 models in total. Using all of these models, we then compare models with and without sentiment features, as well as performances of regressors and classifiers.

All of the selected models inherently prioritize the most relevant features. This is why a feature selection or elimination process is not necessary prior to the model fitting. Tree-based models split based on information gain, by selecting the feature that provides the most valuable separation at each split. Similarly, the other models in Table 10 can designate smaller coefficients or different margins to insignificant features.

| Regression Models                      | Classification Models                       |
|----------------------------------------|---------------------------------------------|
| Ridge Regression                       | Logistic Regression                           |
| Support Vector Regressor               | Support Vector Classifier                    |
| Multi-Layer Perceptron Regressor       | Linear Perceptron Classifier                 |
| Stochastic Gradient Descent Regressor  | Multi-Layer Perceptron Classifier            |
| Decision Tree Regressor                | K-Nearest Neighbors Classifier               |
| Random Forest Regressor                | Decision Tree Classifier                     |
| AdaBoost Regressor                     | Random Forest Classifier                     |
| Extreme Gradient Boosting (XGBoost) Regressor | AdaBoost Classifier                              |
| Light GBM Regressor                   | Extreme Gradient Boosting (XGBoost) Classifier |
| Voting Ensemble Regressor              | Light GBM Classifier                          |
| Linear Regression Ensemble Stacking Regressor | Voting Ensemble Classifier                  |
|                                      | Decision Tree Ensemble Stacking Classifier   |

Table 10: List of classification and regression models for daily return prediction

The models used in this work also use regularization to avoid overfitting. This is also a form of feature elimination that the models inherently perform. Tree-based models achieve this by pruning, coefficient-based models penalize large coefficients, and distance-based models adjust margins. These regularization approaches cause more important features to be prioritized while diminishing the contribution of irrelevant ones. It is a direct and effective approach to allow the models to perform inherent feature elimination, since each model can select those features that contribute the most to its predictive performance. Letting the models inherently perform feature
elimination is also beneficial to have more insights about the impact of sentiment on various models.

Ensemble models synthesize different machine learning models and are commonly built for the purpose of achieving higher accuracy scores. We implement voting and stacking ensembles, which are included in Table 10. Although some models, including XGBoost and random forest, are also ensemble models, consisting of many decision trees, we refer only to the voting and stacking ensembles as ensembles in the rest of the paper, for simplicity.

The ensemble regressors combine all regressors, and likewise, the ensemble classifiers combine all classifiers in Table 10. A voting classifier predicts a class based on majority vote, whereas a voting regressor takes an unweighted average of the single model predictions. A stacking ensemble combines single models by fitting linear regression or a decision tree to their outputs, based on whether it is a regressor or classifier, respectively.

Hyperparameter tuning is performed separately for each Bitcoin and Ethereum model using stratified five-fold cross validation with three repeats on the training dataset. Balanced accuracy score is the metric for selecting the optimal. For regressor models, this metric is computed by converting the predicted return values to binary classes. For both Bitcoin and Ethereum, the training dataset is slightly unbalanced, with the positive return class representing 52.3% and 54.4% of the samples, respectively. We chose to keep the training dataset as it is, and instead, used balanced accuracy to treat the two classes equally during model fitting. Then, the selected hyperparameters that provide the best cross-validated performance scores are used to fit final models on the entire training dataset. The models are tested on multiple test periods using an investment simulation.

5.5. Investment Simulation

5.5.1. Multiple Test Periods

The test period, throughout which the investment strategy is tested, ranges from 01/08/2021 until 15/02/2022. During this timeframe, Bitcoin and Ethereum prices, in USD, change by 11.9% and 23.8%, respectively. This time period contains a bullish pattern in approximately the first half and a bearish one in the other half, for both cryptocurrencies. The closing prices in the test period are shown in Figure 1.

Measuring the potential gains using a single test period would make the outcome susceptible to bias based on the specific price movements in the chosen test period. This bias would make it less reliable to compare models in terms of profit in a single period. Thereby, we propose selecting multiple shorter test periods within the entire test period to create a distribution of potential gains.
The entire test period consists of 199 days. We take 60-day test periods with starting dates shifted ten days forward each time, which leads to 14 different test periods. A distribution of 14 values for potential gains is formed.

The purpose of using multiple test periods covering various price movements is to have a more generalizable profit metric. It has been mentioned that using a single test period would make the results heavily reliant on the specific price changes during that time. For example, if the test period only covers a bullish period, then we would only be able to evaluate the model based on its trading performance during a bullish pattern, which would not be a reliable judgement for comparing different models. We aim to consider the trading output during various price patterns and develop a more generalizable outcome about the predictive power of the models based on trading gain.

In order to tackle this, we consider the trading output during the 14 test periods as a distribution. We compute the mean and standard deviation of the potential gains and compare models based on their mean generated value. Each of the test periods covers a particular price pattern, making the mean value a reliable output expectation. This allows us to ensure a greater generalizability of the measured investment performance. Future prices can move in any direction, and therefore, it is important to have a measurement metric that considers a variety of possible price movements.

It is important to note that we do not build a new model for each test period. All test periods are evaluated using the same model built using the defined training period. This multiple test period approach should not be confused with the typical sliding window training approach used in time series forecasting (Selvin, et al., 2017; Yang, et al., 2005). We select the test periods as multiple intersecting time frames, in order to have more values in the distribution using the test dataset.

5.5.2. Trading Strategy and Benchmark Scenarios

Trading simulations are conducted separately for Bitcoin and Ethereum. It is only possible to buy and sell one cryptocurrency using USD as fiat money, in our investment simulation. The trader’s wallet contains 1000 USD and no cryptocurrency assets at the start of each test period. Return, which is the target variable, is calculated as the percentage change in the closing price of the following day compared to that of the current day, at a 1-day horizon. Therefore, the trading strategy allows trading decisions to be made only at closing time every day, depending on which direction the closing price of the following day is expected to change.

Various possible trading strategies have been introduced in Section 2.4. The trading strategy applied in this paper involves buying the corresponding cryptocurrency with all fiat money at the first time step that predicts a positive return for the next day. Then, the trader holds the assets as
long as the price is still predicted to rise each following day. On the first day that the closing price is predicted to fall the next day, the trader sells all of the cryptocurrency in the wallet and keeps it as USD until an upcoming day that a positive return is forecasted again. We therefore use the trading strategy also used by Sebastião and Godinho (2021), as explained in Section 2.4, which they apply to Bitcoin, Ethereum and Litecoin.

At the end of the test period, the trader’s wallet value is recorded in terms of USD. If the wallet contains cryptocurrencies, then its equivalent USD is considered, for easier comparability to the input amount. This trading strategy aims to buy and sell at the points that price movement direction changes, which would be equivalent to the local minima and maxima of closing prices.

In most cryptocurrency trading platforms, there is a percentage cost applied to each transaction. It is therefore important to apply transaction costs to our trading simulation to make it closer to a real-life scenario. These costs typically vary between 0.1% to 0.5% in the literature (Kim, 2017; Alessandretti, et al., 2018; Żbikowski, 2016). We apply a transaction cost of 0.2% of the transaction amount.

We define three benchmark cases for the purpose of comparing our investment output for different models: the ideal, random and holding scenarios. Examples of their applications in the literature are explained in Section 2.4 of this paper.

Figure 2: Plot of the ideal scenario implemented to our trading strategy, where the trader buys Bitcoin at the local minima and sells at the local maxima

The ideal case based on our trading strategy would be to always accurately predict the next-day price change direction. This would be equivalent to perfect foresight. Therefore, one could capture all local minima and maxima as the price fluctuates, and consistently increase gains during the trading period. The transactions during the ideal scenario for investing in Bitcoin are displayed
in Figure 2. This benchmark is used to evaluate the highest attainable profit from investing using the trading strategy selected in this paper.

The random scenario involves assigning a random positive or negative return label to each day in the test periods and applying our trading strategy using these labels as predictions. This baseline is used to evaluate whether trading using the predictive models in this paper deliver higher gains than random decision-making. It simulates a trader who is investing in cryptocurrencies without any substantial opinion about future price changes, but still actively trades these assets. Such a person would have a random view about how the next day’s price would change. This hypothetical trader’s investment output is used as a baseline to compare whether the predictive models we build add value to investment returns, compared to having no grounded opinion.

The holding scenario involves following the buy-and-hold (B&H) strategy, which is a common baseline for return prediction models, as mentioned in Section 2.4. B&H is a passive and long-term approach that works by buying the cryptocurrency in the first day and keeping it until selling again on the last day of each test period. The percentage gain from this strategy is equivalent to the percentage price change of the corresponding cryptocurrency in terms of USD. This simulates a person who decides to invest in cryptocurrencies, but does not make trading decisions based on opinions about short-term future price changes. The trader rather buys assets and waits, with the belief that this would bring positive returns in a longer horizon. We therefore compare the trading gains from models to this passive approach, to analyze the feasibility of trying to obtain profits from short-term fluctuations in price.

|                         | For Bitcoin* | For Ethereum* |
|-------------------------|--------------|---------------|
| **Input Amount**        | 1000.00 (0)  | 1000.00 (0)   |
| **Ideal Output Amount** | 2011.80 (404.82) | 2494.01 (473.74) |
| **Random Output Amount**| 805.18 (216.63) | 900.23 (271.94) |
| **Holding Output Amount**| 1017.42 (291.39) | 1056.41 (292.37) |

*All refer to a distribution, indicated by the mean and standard deviation values, the latter in brackets.

Table 11: Ideal and baseline scenarios for Bitcoin and Ethereum, all values indicated in USD

The input amount is 1000 USD for each of the 14 test periods of 60-day duration. Output amount refers to the USD amount in the trader’s wallet at the last day of each test period. The benchmark output amounts in USD are shown in Table 11. The ideal scenario shows the maximum possible obtainable profit using the predefined trading strategy. Random scenario leads to a loss from the input budget, on average. The mean output of the holding scenario indicates positive gains compared to the input amount, and therefore outperforms the random scenario with the current trading approach. Each output amount in Table 11 refers to a distribution of 14 test outputs,
and therefore, each value is expressed as mean and standard deviation, the latter expressed in brackets.

5.6. Model Performances and Comparison

5.6.1. Comparison of Best-Performing Models

Tables 12 and 13 display the model performances and trading output for the best-performing ten models for Bitcoin and Ethereum, respectively. These ten models provide the highest gain compared to the random scenario as the baseline. We describe later in this subsection, how the relative gain values are computed. The results from all of the models built in this paper are included in Tables A2-A5 in the Appendix.

The cross-validated training accuracy refers to the same metric used during hyperparameter optimization. This performance metric is five-fold stratified and three-times repeated cross-validated balanced accuracy score, which is chosen due to slightly unbalanced classes in the training datasets.

Unbalanced accuracy score is used as the metric for test period predictions. The entire test period consists of 50.8% positive return samples for each cryptocurrency, which constitutes a very small imbalance. We keep the unbalanced accuracy metric as it is, in order to capture the performance on the test period as it occurs.

The models are evaluated in terms of test period accuracy and potential gain from using the predictions for investment decisions. Accuracy as a performance metric is directly calculated for classification output. For the regression models, the predictions are transformed into the resulting positive or negative return. The accuracy measure is then calculated based on whether the regressor correctly predicts the direction of return. It is important to evaluate the models in terms of both accuracy and potential profit. A high accuracy score does not inherently imply high gains from trading. This paper focuses on the effect of sentiment on the predictability of returns as well as the trading performance resulting from the use of sentiment features given the selected strategy. Therefore, both measures are analyzed in order to derive conclusions on the added value from the sentiment derived features.

The output amount of trading based on model predictions are shown in Tables 12 and 13. It is observed that the mean number of transactions across the 60-day periods for the listed models differ from 4 to 18, equating to making a transaction every 3 to 18 days. Total trading costs, computed as 0.2% of each transaction as decided in Section 5.5.2, are also included in the output tables.
### Table 3: THEBREW - Performance metrics and trading output of the ten best-performing models, in descending order

**Scenario**

| Num | Model | Amount (USD) | Gain Scaled | Test Acc. % | Feature Selection | Feature Selection Type |
|-----|-------|--------------|-------------|-------------|-------------------|------------------------|
| 18  | * SVM  | 1165.86 (105.87) | 0.573 | 0.558 | no sent. | SVM |
| 15  | * Ridge | 1165.31 (120.65) | 0.573 | 0.558 | no sent. | Ridge |
| 14  | MLP  | 1181.38 (119.45) | 0.568 | 0.636 | no sent. | MLP |
| 13  | * Ridge | 1181.46 (273.32) | 0.568 | 0.636 | no sent. | Ridge |
| 12  | * Linear Classification | 1243.33 (253.93) | 0.528 | 0.553 | no sent. | Linear Classification |
| 11  | * Mlp Reg | 1253.49 (225.42) | 0.528 | 0.553 | no sent. | Mlp Reg |
| 10  | * Lasso | 1253.32 (273.32) | 0.528 | 0.553 | no sent. | Lasso |
| 9   | * Gbr | 1285.68 (273.32) | 0.528 | 0.553 | no sent. | Gbr |
| 8   | * Lasso | 1293.48 (205.42) | 0.528 | 0.553 | no sent. | Lasso |
| 7   | * Lasso | 1303.48 (205.42) | 0.528 | 0.553 | no sent. | Lasso |
| 6   | * Gbr | 1303.48 (205.42) | 0.528 | 0.553 | no sent. | Gbr |

**Table 12: BITCOR - Performance metrics and trading output of the ten best-performing models, in descending order**

| Num | Model | Amount (USD) | Gain Scaled | Test Acc. % | Feature Selection | Feature Selection Type |
|-----|-------|--------------|-------------|-------------|-------------------|------------------------|
| 18  | * SVM  | 1165.86 (105.87) | 0.573 | 0.558 | no sent. | SVM |
| 15  | * Ridge | 1165.31 (120.65) | 0.573 | 0.558 | no sent. | Ridge |
| 14  | MLP  | 1181.38 (119.45) | 0.568 | 0.636 | no sent. | MLP |
| 13  | * Ridge | 1181.46 (273.32) | 0.568 | 0.636 | no sent. | Ridge |
| 12  | * Linear Classification | 1243.33 (253.93) | 0.528 | 0.553 | no sent. | Linear Classification |
| 11  | * Mlp Reg | 1253.49 (225.42) | 0.528 | 0.553 | no sent. | Mlp Reg |
| 10  | * Lasso | 1253.32 (273.32) | 0.528 | 0.553 | no sent. | Lasso |
| 9   | * Gbr | 1285.68 (273.32) | 0.528 | 0.553 | no sent. | Gbr |
| 8   | * Lasso | 1293.48 (205.42) | 0.528 | 0.553 | no sent. | Lasso |
| 7   | * Lasso | 1303.48 (205.42) | 0.528 | 0.553 | no sent. | Lasso |
| 6   | * Gbr | 1303.48 (205.42) | 0.528 | 0.553 | no sent. | Gbr |
We compare the investment output amounts to the benchmark scenarios to interpret the model performances in a more tangible way. The output amount of trading based on the ideal, random and holding scenarios have been previously mentioned in Table 11. In Tables 12 and 13, the column *Gains Scaled by Random Scenario* indicates the ratio of the gain from trading based on the model output compared to the gain from the random scenario. This gain ratio is calculated for each of the 14 test periods separately. This computation leads to a distribution of the relative investment gain, consisting of these 14 observations. *Gains Scaled by Random Scenario* shows the mean and standard deviation, the latter being in brackets, from this distribution. It is important to calculate the gain ratio separately for each test period, since a different price trend occurs in each test period and therefore, the distribution shows the overall performance as tested on a variety of possible future price changes. The motivation behind the multiple test period approach has been described in Section 5.5.1. Similarly, *Gains Scaled by Hold Scenario* refers to the distribution of the gain from trading using model predictions as a ratio to the gain from the passive holding scenario.

We analyze the degree of differentiation of our investment gains from the baseline scenarios. The t-values of the gain ratio distributions are computed to check for significance, with the null hypothesis being that gain ratio is zero and the model does not add significant value compared to the baseline scenarios. The columns *t-value Random Scenario* and *t-value Hold Scenario* indicate the t-values of the distributions from *Gains Scaled by Random Scenario* and *Gains Scaled by Hold Scenario*, respectively. T-distribution is selected due to the small number of observations. Additionally, t-distribution does not assume that the population standard deviation is known, making it applicable to our case. We use two-tailed t-test to evaluate both directions of change from the baseline.

The highest test data accuracy scores attained by the models are 61.3% and 58.8% for Bitcoin and Ethereum models, respectively. Fama (1970) defines efficient capital markets as those in which the prices fully reflect the information that is available. With the assumption that financial markets should immediately respond to external factors under efficient conditions, predicting future prices of assets should not be possible (Timmermann & Granger, 2004). This assumption, if true for the Bitcoin and Ethereum markets, would not allow for forecasts to be significantly better than a random guess, represented by the so-called random baseline scenario. The best models for Bitcoin and Ethereum lead to gains of 0.572 and 0.501 in comparison to the random case, respectively. As displayed by the *t-value Random Scenario* values, all of the best ten models lead to significant improvements at the 90% confidence level, and most even at 99% confidence level. This result indicates that cryptocurrency markets are not fully efficient and there is room for
successful predictions of future prices, which our predictive models achieve at a significant rate. It has been mentioned before that the random scenario baseline represents a trader who does not have an opinion about future cryptocurrency prices regarding market information, social media or macroeconomic data. It is thus shown that investing in cryptocurrencies using our model predictions significantly adds value to a trader who randomly makes trading decisions.

All models listed in Tables 12 and 13 deliver a mean output value greater than 1000 USD, which is the input amount at the beginning of each test period. This implies that basing trading decisions on the model predictions leads to a higher output amount in USD, compared to not entering the cryptocurrency market at all. It is also observed that even the best-performing models for Bitcoin and Ethereum do not even nearly lead to gains as high as in the ideal scenarios shown in Table 11.

Trading based on the applied ten best-performing predictive models during the test periods all lead to higher returns than entering the market at the first day and selling at the end of the trading period. The B&H strategy would be applied by a rational trader only if a bullish market trend is expected in the long-term. Although all of the models listed in Tables 12 and 13 outperform the holding scenario, only the best one model for Bitcoin and best two for Ethereum achieve this at a confidence level of 90%. Therefore, most of the best ten models do not significantly perform better than the holding scenario, but still surpass it.

It is observed that models with the highest test accuracy do not necessarily yield the highest profit. While support vector regressor has a higher test accuracy than ridge regression for Bitcoin, for example, the latter outperforms the former in terms of relative gains compared to the random scenario. This difference is caused by the specific trading strategy selected in this paper. A different trading strategy could have created a different ranking. The strategy we use values correct predictions at points of price direction change. It aims to capture the local minima and maxima in the price plot. Therefore, a model with a lower test accuracy can outperform another model with more accurate predictions, simply by correctly capturing time periods that indicate a price direction change. This would lead to successfully buying at lower prices and selling at higher prices.

Out of the ten best-performing models for Bitcoin and Ethereum, four and six models, respectively, use the sentiment features. Also, the highest test accuracy is achieved by models that include sentiment features, for both cryptocurrencies. These results indicate that the sentiment features are contributing positively to the predictive performance of the models, and more importantly to trading returns above the random scenario baseline. Given that the features are generated from aggregated sentiment extracted from information with a relative long-term lag to the actual closing price used, these results are promising.
For the cases that the model without sentiment outperforms the same model with sentiment, for example, multi-class perceptron regressor for Bitcoin, it is expected that the two models are performing quite similarly. The models inherently select the most relevant features, as described in Section 5.4, and therefore, the addition of sentiment features should not lower the performance significantly, even if they would be irrelevant for the model. We observe consistent results in our output tables in this regard. The slight performance difference in the cases that the model without sentiment outperforms the model with sentiment could be described by the possible selection of different optimal hyperparameters. This would not produce identical results, but also not lead to drastically differing outcomes, regarding which our results appear to be reasonable.

The ensemble models that combine all other models by voting or stacking approaches, do not necessarily perform better than the single models in this case. There are two voting or stacking ensembles for each of Bitcoin and Ethereum in the best ten models. Voting and stacking ensembles aim to synthesize models, but if the single models are not very strong, then they can be combining their deficiencies as well. In our case, some single models perform quite poorly, and thus, having added them to the ensembles could have exacerbated performance levels.

5.6.2. Collective Evaluation of the Models

Table 14 summarizes the output from all models for the purpose of directly comparing models with and without sentiment features. The percentage of models in each category that outperform the random and holding baseline scenarios are shown in the columns Outperf. Random Scenario and Outperf. Hold Scenario, respectively. For example, 100% of all model types outperform the random scenario, meaning that all model predictions lead to a higher mean profit compared to the random case. The percentage of models that significantly, at a confidence level of 90%, outperform the baselines are also shown in the columns Signif. Random Scenario and Signif. Hold Scenario.

It is shown that regressors tend to outperform classifiers for both cryptocurrencies. They tend to have higher mean test accuracy scores and a higher outperformance rate of the hold scenario. Both regressors and classifiers outperform the random scenario at a rate of 100%, but more of the regression models achieve this significantly, at the 90% confidence level. This difference can be explained by the differences in the target variables. Regressors train on the magnitude and direction of next-day returns. Even though we then utilize the regression predictions in terms of their directions as positive or negative, regressors still learn to predict the magnitude of returns. This allows them to differentiate between cases with small and large magnitudes of positive or negative returns. Classifiers, on the other hand, train on a binary target. This can lead to information loss that causes the classifiers to have a poorer performance in labeling the test data accurately.
The regressors have a higher test accuracy when they include sentiment features, whereas classifiers have a lower test accuracy in the same case, on average, for both cryptocurrencies. However, the differences are not drastic enough to generalize.

All models outperform the random scenario. For both cryptocurrencies and model types, more of the models that include the sentiment features outperform this baseline significantly, at a confidence level of 90%, compared to models that do not include these features. On average, this means that sentiment features can be adding a unique value to the feature set that further separates the potential profit distribution from the random case profit distribution. This relation does not hold true for each of the models, but it is valid when analyzing all models collectively.

Bitcoin models with sentiment features are more likely to outperform the holding scenario compared to those without. This does not hold true for Ethereum models. Ethereum regressors without sentiment outperform at a higher rate, and Ethereum classifiers have the same outperformance rate for models with and without the sentiment features. Only a very small percentage of all models outperform the hold scenario significantly at a 90% confidence level. Therefore, even though the mean output amount using model predictions are greater than the output amount from holding, for most cases, this difference is not large enough to accept it as a different output distribution. Using model predictions in decision-making supports the trader to get less affected by the rapidly fluctuating prices of cryptocurrencies, and still adds some additional value compared to simply holding assets for a long term. For traders planning to invest in large volumes, every slight reduction in risk by having more accurate price predictions poses a significant opportunity in terms of profit.

By testing the value of sentiment on various models, it is shown that sentiment features contribute to higher investment gains, on average. It is important to conclude that this does not
equate to a definite outcome that including news and social media sentiment-related features consistently leads to higher profits. Tables A2-A5 in the Appendix show that this does not hold true for all models and cryptocurrencies. However, Table 14 summarizes that the models with sentiment features improve decision-making in cryptocurrency trading in a generalized manner. It is therefore shown that public sentiment extracted from various online sources improves the predictive power of machine learning models to estimate future price direction changes of Bitcoin and Ethereum.

6. Conclusion and Future Work

6.1. Key Outcomes

This paper studies the contribution of investor sentiment from news articles, Reddit posts and Tweets to the predictability of daily cryptocurrency returns. For this purpose, we compared twenty-three models, eleven of which are regressors and twelve are classifiers, for each of the selected cryptocurrencies Bitcoin and Ethereum. Our comparison metrics were test accuracy as well as additional investment gain compared to baseline scenarios. The overall outcome is that sentiment features contribute to improved accuracy and additional returns for a number of different models among a large set of tested machine learning models.

Our results indicate that sentiment adds value to the return prediction models in various cases. When analyzed collectively, we observe that test accuracy is higher for regressors with sentiment, whereas it is lower for classifiers with sentiment. However, the test accuracy scores are only slightly different, with differences of 0.6-1.7%.

The investment simulation results suggest that the mean output amount from the trading periods is higher for models with sentiment features, in most cases. All models implemented in this paper outperform the baseline random scenario, whereas the models with sentiment features more often achieve this significantly, at the 90% confidence level. Bitcoin and Ethereum markets cannot be considered efficient as defined by the Efficient Market Theorem by Fama (1970), given that we are able to predict future price changes at a better rate, even significantly, than random guesses (Timmermann & Granger, 2004).

The generalized positive impact of sentiment, however, does not hold true for each of the twenty-three individual models. When we listed the best ten models for each of Bitcoin and Ethereum, we observed that four and six models, respectively, include the sentiment feature. This indicates that investor sentiment leads to higher gains compared to the random scenario for approximately half of the cases, but not all.
With respect to working with unlabeled data, we can conclude that the weak labels approach generated using a zero-shot classifier delivers promising results and proves its value for future use in this context. We have shown with an initial experiment that fine-tuning BERT-based classifiers using BART predictions as pseudo-labels only slightly lowers sentiment classification accuracy. Using this approach, we obtain a BERT-based sentiment classifier ensemble that achieves 70% accuracy on unseen news and social media text.

6.2. Limitations and Future Work

There are various ways that future research can build on our work. The limitations exhibited by our research are explained in this subsection. The limitations stem from imperfect data quality, common sentiment classifier for both cryptocurrencies, unweighted daily sentiment aggregation, and possible non-ideal data granularity.

The data scraping process can be improved to obtain a higher quality dataset. Firstly, Reddit posts and Tweets have some advertisement and promotional samples that are not completely filtered out using the approach in this paper. An effective solution could be to fit a simple spam detection classification to the raw data. We tried to eliminate spam posts using the BART zero-shot classifier by defining the hypotheses as “This text is spam/ not spam.”, but the results did not deliver much value. Secondly, the scope of filtering the sources can be expanded. News are only from two websites, Reddit data is only from two subreddits and Tweets are selected only by a few key words. It is possible that these selections do not necessarily represent the actual overall investor sentiment, and therefore, expanding the search could be beneficial. Thirdly, the approach of searching posts by key words can perform poorly in some cases. For example, one Tweet related to “ETH Zurich” has been selected due to searching for the term “ETH” in all Tweets. Searching for posts can be improved by identifying key Twitter accounts, scraping other crypto-related subreddits, and collecting news from more news websites.

The sentiment classification models trained in this paper are not able to distinguish the sentiment based on the target cryptocurrency. For example, if a text sample has a positive sentiment for one currency and a negative one for the other, the classifier would predict the same label for both currencies. This is because we have trained a single model for both Bitcoin and Ethereum text data. With the presence of a labeled dataset that has sentiment labels for the targeted cryptocurrency, researchers can fine-tune separate models for each currency and capture the sentiment more accurately.

A promising improvement could be obtained by implementing a better sentiment aggregation approach. In this paper, we treat each text sample with equal importance when aggregating them.
to form a daily sentiment score. In reality, some posts are much more influential than others. Ante (2021), for example, shows that Elon Musk’s Tweets lead to significant price changes for Dogecoin. Aggregating text samples with weights based on potential impact on price could improve the quality of the sentiment features.

Our financial models are trained on data with daily granularity. It would be valuable to experiment with different levels of granularity to find the optimal level for return forecasting using sentiment. Our approach involves aggregating text samples from the last 24-hours to obtain a daily sentiment score, which already makes the sentiment feature inherently lagged. However, it is possible that the price change triggered by a news article or social media post loses its effect during this time span. If all investors quickly react to the new information, then the trader using our predictions would already be too late and not be able to gain profit as the early-Reactors do. Therefore, it is critical to define a granularity that effectively captures the effects of sentiment on price changes.

The notebooks and scripts used for our empirical study can be found in this repository: https://github.com/duingstuff/MSc-Thesis-Cryptocurrency-Return-Forecasting-Using-BERT-Based-Sentiment
Declaration of Academic Honesty

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Duygu Ider
Berlin, 07.04.2022
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## Appendix

| Cryptocurrency | Data Type | Python Library | Source | Filtering |
|----------------|-----------|----------------|--------|-----------|
| Bitcoin        | News articles | ReadRSS from BeautifulSoup | Coin Telegraph, Coin Desk | Searching “bitcoin” or “btc” in GoogleNews |
|                | Reddit post titles | PMAW wrapper for the Pushshift API | r/Btcin subreddit | All post titles in the subreddit |
|                | Tweets from Twitter | Sntwitter from the Snscrape library | From all Tweets in Twitter | Searching “bitcoin” or “btc” from all posts |
| Ethereum       | News articles | BeautifulSoup ReadRSS | Coin Telegraph, Coin Desk | Searching “ethereum” or “eth” in GoogleNews |
|                | Reddit post titles | PMAW wrapper for the Pushshift API | r/Ethereum subreddit | All post titles in the subreddit |
|                | Tweets from Twitter | Sntwitter from the Snscrape library | From all Tweets in Twitter | Searching “ethereum” or “eth” from all posts |

Table A1: Text data scraping sources and proces
| Model   | Feature Set | Train CV Acc. | Test Acc. | Output Amount* (USD) | Gain Scaled by Hold Scenario* | t-test Gain Scaled by Hold | Gain Scaled by Random Scenario* | t-test Gain Scaled by Random | Total Trading Cost* | Num Tran.* |
|---------|-------------|---------------|-----------|----------------------|-------------------------------|---------------------------|--------------------------------|-------------------------------|-------------------|------------|
| ada     | all no sent. | 0.722         | 0.497     | 943.61 (101.6)       | -0.016 (0.204)                | 0.4                       | 0.232 (0.233)                   | 0.051                        | 38.84 (9.47)      | 20 (4)     |
|         |             | 0.683         | 0.518     | 973.88 (170.38)      | -0.007 (0.14)                 | 0.65                      | 0.248 (0.177)                   | 0.037                        | 45.73 (14.58)     | 22 (5)     |
| ens. stack | all no sent. | 0.445         | 0.508     | 1017.42 (291.39)     | 0.0 (0.0)                     | 1                         | 0.264 (0.139)                   | 0.046                        | 4.04 (0.58)       | 1 (0)      |
|         |             | 0.408         | 0.508     | 1017.42 (291.39)     | 0.0 (0.0)                     | 1                         | 0.264 (0.139)                   | 0.046                        | 4.04 (0.58)       | 1 (0)      |
| ens. vote | all no sent. | 0.911         | 0.508     | 984.53 (178.43)      | 0.003 (0.14)                  | 0.73                      | 0.255 (0.13)                    | 0.03                         | 55.44 (9.47)      | 27 (3)     |
|         |             | 0.967         | 0.533     | 942.68 (79.65)       | -0.005 (0.248)                | 0.39                      | 0.243 (0.277)                   | 0.047                        | 39.89 (15.72)     | 20 (7)     |
| knn     | all no sent. | 0.553         | 0.472     | 1011.86 (210.77)     | 0.024 (0.14)                  | 0.96                      | 0.283 (0.141)                   | 0.021                        | 44.3 (10.46)      | 22 (4)     |
|         |             | 0.717         | 0.482     | 925.77 (116.21)      | -0.035 (0.206)                | 0.31                      | 0.204 (0.221)                   | 0.092                        | 33.06 (3.95)      | 17 (2)     |
| lgbm    | all no sent. | 0.685         | 0.497     | 938.35 (59.65)       | 0.0 (0.282)                   | 0.35                      | 0.25 (0.323)                    | 0.05                         | 50.89 (9.46)      | 26 (5)     |
|         |             | 0.695         | 0.503     | 831.97 (58.95)       | -0.11 (0.259)                 | 0.041                     | 0.106 (0.281)                   | 0.67                         | 37.3 (7.03)       | 20 (3)     |
| lr      | all no sent. | 0.697         | 0.513     | 1029.16 (302.58)     | 0.009 (0.049)                 | 0.92                      | 0.272 (0.117)                   | 0.04                         | 16.21 (8.06)      | 6 (3)      |
|         |             | 0.703         | 0.553     | 1163.76 (293.58)     | 0.158 (0.07)                  | 0.21                      | 0.459 (0.127)                   | 0.0017                        | 25.56 (8.54)      | 10 (3)     |
| mlp     | all no sent. | 0.554         | 0.533     | 967.69 (47.24)       | 0.03 (0.279)                  | 0.55                      | 0.284 (0.308)                   | 0.019                        | 31.16 (11.8)      | 16 (5)     |
|         |             | 0.542         | 0.477     | 924.46 (124.81)      | -0.043 (0.182)                | 0.3                       | 0.194 (0.177)                   | 0.1                          | 24.84 (8.5)       | 13 (5)     |
| per     | all no sent. | 0.561         | 0.503     | 1015.11 (293.57)     | -0.003 (0.004)                | 0.98                      | 0.26 (0.139)                    | 0.049                        | 5.42 (1.16)       | 2 (1)      |
|         |             | 0.632         | 0.568     | 1053.4 (69.88)       | 0.121 (0.312)                 | 0.67                      | 0.396 (0.338)                   | 0.0012                        | 27.61 (9.3)       | 13 (4)     |
| rf      | all no sent. | 0.871         | 0.513     | 974.32 (123.65)      | 0.009 (0.189)                 | 0.63                      | 0.266 (0.22)                    | 0.024                        | 36.96 (14.62)     | 19 (7)     |
|         |             | 0.967         | 0.518     | 931.98 (89.81)       | -0.0 (0.31)                   | 0.33                      | 0.253 (0.368)                   | 0.068                        | 27.73 (3.41)      | 14 (2)     |
| svm     | all no sent. | 0.717         | 0.523     | 1061.77 (217.92)     | 0.074 (0.126)                 | 0.66                      | 0.357 (0.2)                     | 0.0057                        | 22.87 (6.23)      | 10 (3)     |
|         |             | 0.95          | 0.518     | 927.38 (120.15)      | -0.037 (0.194)                | 0.32                      | 0.202 (0.202)                   | 0.09                          | 46.72 (17.84)     | 24 (10)    |
| tree    | all no sent. | 0.878         | 0.497     | 1007.05 (203.29)     | 0.023 (0.154)                 | 0.92                      | 0.292 (0.223)                   | 0.021                        | 31.91 (14.28)     | 16 (8)     |
|         |             | 0.76          | 0.518     | 1014.6 (100.39)      | 0.07 (0.276)                  | 0.97                      | 0.343 (0.324)                   | 0.0053                        | 26.99 (12.05)     | 14 (7)     |
| xgb     | all no sent. | 0.772         | 0.523     | 921.41 (128.88)      | -0.039 (0.213)                | 0.29                      | 0.196 (0.211)                   | 0.11                         | 45.55 (8.93)      | 23 (3)     |
|         |             | 0.701         | 0.513     | 921.64 (84.39)       | -0.033 (0.219)                | 0.27                      | 0.205 (0.231)                   | 0.089                        | 45.68 (4.94)      | 23 (2)     |

*Mean and standard deviation, the latter inside brackets, are used to represent columns that refer to a distribution.

Table A2: Performance metrics and trading output of the classifiers for Bitcoin return prediction.
| Model | Feature Set | Train CV Acc. | Test Acc. | Output Amount* (USD) | Gain Scaled by Hold Scenario* | t-test Gain Scaled by Hold | Gain Scaled by Random Scenario* | t-test Gain Scaled by Random | Total Trading Cost* | Num Tran. * |
|-------|-------------|---------------|-----------|----------------------|-------------------------------|---------------------------|-------------------------------|-------------------------------|-------------------|-------------|
| ada   | all         | 0.605         | 0.548     | 1028.94 (127.0)      | 0.076 (0.248)                | 0.9                        | 0.353 (0.303)                | 0.0042                        | 37.02 (4.72)      | 18 (2)      |
|       | no sent.    | 0.608         | 0.543     | 987.71 (126.54)      | 0.023 (0.194)                | 0.74                       | 0.282 (0.219)                | 0.016                         | 37.09 (6.06)      | 18 (3)      |
| ens.  | stack       | 0.444         | 0.528     | 1085.1 (89.97)       | 0.142 (0.274)                | 0.44                       | 0.424 (0.292)                | 0.00046                       | 8.39 (8.25)       | 4 (4)       |
|       | no sent.    | 0.855         | 0.467     | 987.93 (190.0)       | 0.005 (0.138)                | 0.76                       | 0.267 (0.196)                | 0.031                         | 28.81 (8.21)      | 14 (5)      |
| ens.  | vote        | 0.788         | 0.538     | 1049.9 (46.08)       | 0.117 (0.303)                | 0.7                        | 0.394 (0.34)                 | 0.0013                        | 21.37 (11.04)     | 10 (5)      |
|       | no sent.    | 0.728         | 0.568     | 1124.43 (109.37)     | 0.192 (0.326)                | 0.23                       | 0.497 (0.39)                 | 0.00014                       | 33.84 (14.63)     | 16 (6)      |
| lgbm  | all         | 0.882         | 0.508     | 997.71 (37.37)       | 0.063 (0.297)                | 0.81                       | 0.327 (0.332)                | 0.0071                        | 36.77 (9.18)      | 18 (4)      |
|       | no sent.    | 0.858         | 0.548     | 1030.81 (126.74)     | 0.070 (0.209)                | 0.88                       | 0.34 (0.237)                 | 0.0039                        | 51.47 (9.24)      | 24 (3)      |
| mlp   | all         | 0.648         | 0.573     | 1165.31 (120.65)     | 0.226 (0.306)                | 0.11                       | 0.54 (0.361)                 | 0.000038                      | 33.35 (8.13)      | 15 (3)      |
|       | no sent.    | 0.639         | 0.583     | 1181.38 (119.45)     | 0.235 (0.27)                 | 0.078                      | 0.544 (0.296)                | 0.000022                      | 32.36 (6.06)      | 14 (2)      |
| rf    | all         | 0.666         | 0.487     | 1015.74 (26.91)      | 0.085 (0.31)                 | 0.98                       | 0.355 (0.351)                | 0.0039                        | 12.4 (13.12)      | 6 (7)       |
|       | no sent.    | 0.701         | 0.482     | 959.31 (38.22)       | 0.018 (0.267)                | 0.49                       | 0.272 (0.301)                | 0.024                         | 8.72 (5.27)       | 4 (3)       |
| ridge | all         | 0.661         | 0.583     | 1204.9 (133.8)       | 0.254 (0.255)                | 0.049                      | 0.572 (0.291)                | 0.000011                      | 29.47 (13.43)     | 13 (5)      |
|       | no sent.    | 0.641         | 0.558     | 1183.63 (202.02)     | 0.211 (0.186)                | 0.1                        | 0.518 (0.202)                | 0.000096                      | 29.78 (11.07)     | 13 (4)      |
| sgd   | all         | 0.613         | 0.482     | 983.33 (48.85)       | 0.059 (0.333)                | 0.68                       | 0.325 (0.388)                | 0.012                         | 6.6 (6.84)        | 3 (4)       |
|       | no sent.    | 0.601         | 0.497     | 1037.48 (55.75)      | 0.099 (0.286)                | 0.81                       | 0.375 (0.325)                | 0.002                         | 16.79 (11.68)     | 8 (6)       |
| svm   | all         | 0.678         | 0.613     | 1174.86 (155.87)     | 0.213 (0.215)                | 0.1                        | 0.518 (0.227)                | 0.000044                      | 40.23 (7.29)      | 18 (2)      |
|       | no sent.    | 0.636         | 0.553     | 1050.86 (93.05)      | 0.122 (0.327)                | 0.7                        | 0.395 (0.353)                | 0.0015                        | 25.32 (8.92)      | 12 (3)      |
| tree  | all         | 0.748         | 0.503     | 1021.77 (93.73)      | 0.104 (0.372)                | 0.96                       | 0.385 (0.438)                | 0.004                         | 7.61 (2.06)       | 4 (1)       |
|       | no sent.    | 0.719         | 0.523     | 1000.72 (107.07)     | 0.049 (0.252)                | 0.85                       | 0.311 (0.279)                | 0.0088                        | 28.43 (10.26)     | 14 (5)      |
| xgb   | all         | 0.832         | 0.492     | 962.66 (266.72)      | -0.047 (0.074)               | 0.62                       | 0.206 (0.174)                | 0.11                          | 25.29 (10.72)     | 13 (6)      |
|       | no sent.    | 0.722         | 0.457     | 855.39 (123.5)       | -0.119 (0.149)               | 0.082                      | 0.108 (0.187)                | 0.48                          | 29.43 (9.84)      | 16 (5)      |

* Mean and standard deviation, the latter inside brackets, are used to represent columns that refer to a distribution.

Table A3: Performance metrics and trading output of the regressors for Bitcoin return prediction.
| Model  | Feature Set | Train CV Acc. | Test Acc. | Output Amount* (USD) | Gain Scaled by Hold Scenario* | t-test Gain Scaled by Hold | Gain Scaled by Random Scenario* | t-test Gain Scaled by Random | Total Trading Cost* | Num Tran.* |
|--------|-------------|---------------|-----------|----------------------|-------------------------------|--------------------------|-------------------------------|-------------------------------|------------------|-----------|
| ada    | all         | 0.842         | 0.538     | 912.67 (155.28)      | -0.078 (0.238)                | 0.13                      | 0.11 (0.346)                  | 0.89                          | 35.0 (11.38)     | 18 (6)    |
| ens.   | stack       | 0.539         | 0.508     | 1056.41 (292.37)     | 0.0 (0.0)                     | 0.0          | 0.189 (0.112)                 | 0.17                          | 4.12 (0.59)      | 1 (0)     |
| ens.   | vote        | 0.945         | 0.503     | 1035.51 (89.46)      | 0.053 (0.273)                 | 0.81                      | 0.259 (0.365)                 | 0.11                          | 53.98 (6.65)     | 26 (3)    |
| knn    | all         | 0.580         | 0.487     | 1040.86 (326.82)     | -0.024 (0.064)                | 0.9                       | 0.157 (0.102)                 | 0.24                          | 18.14 (4.46)     | 8 (3)     |
| lgbm   | all         | 0.732         | 0.518     | 1126.77 (251.03)     | 0.09 (0.119)                  | 0.52                      | 0.289 (0.133)                 | 0.036                         | 48.11 (4.79)     | 22 (4)    |
| lr     | all         | 0.686         | 0.533     | 1080.84 (105.68)     | 0.099 (0.287)                 | 0.78                      | 0.307 (0.366)                 | 0.039                         | 13.09 (11.17)    | 6 (5)     |
| mlp    | all         | 0.689         | 0.588     | 1293.98 (263.42)     | 0.267 (0.202)                 | 0.039                    | 0.501 (0.244)                 | 0.009                         | 27.52 (13.93)    | 11 (5)    |
| per    | all         | 0.575         | 0.492     | 1051.39 (298.11)     | -0.006 (0.046)                | 0.97                      | 0.18 (0.093)                  | 0.19                          | 5.99 (3.5)       | 2 (3)     |
| rf     | all         | 0.929         | 0.497     | 1049.95 (242.88)     | 0.022 (0.161)                 | 0.95                      | 0.21 (0.19)                   | 0.15                          | 45.11 (7.67)     | 21 (4)    |
| svm    | all         | 0.712         | 0.543     | 1073.71 (55.74)      | 0.097 (0.305)                 | 0.84                      | 0.309 (0.395)                 | 0.041                         | 15.39 (12.34)    | 7 (6)     |
| tree   | all         | 0.925         | 0.513     | 1054.63 (76.31)      | 0.089 (0.352)                 | 0.98                      | 0.307 (0.468)                 | 0.067                         | 48.69 (8.27)     | 23 (4)    |
| xgb    | all         | 0.657         | 0.467     | 910.34 (95.31)       | -0.076 (0.245)                | 0.11                      | 0.102 (0.322)                 | 0.9                           | 54.04 (9.38)     | 28 (3)    |

*Mean and standard deviation, the latter inside brackets, are used to represent columns that refer to a distribution.

Table A4: Performance metrics and trading output of the classifiers for Ethereum return prediction.
| Model | Feature Set | Train CV Acc. | Test Acc. | Output Amount* (USD) | Gain Scaled by Hold Scenario* | t-test Gain Scaled by Hold | Gain Scaled by Random Scenario* | t-test Gain Scaled by Random | Total Trading Cost* | Num Tran. |
|-------|-------------|--------------|-----------|----------------------|-------------------------------|-------------------------|-------------------------------|-------------------------------|----------------|-----------|
| ada   | all         | 0.577        | 0.497     | 963.18 (66.78)       | -0.003 (0.327)                | 0.28                     | 0.194 (0.425)                 | 0.43                          | 15.6 (11.19) | 8         |
|       | no sent.    | 0.555        | 0.513     | 999.85 (36.93)       | 0.041 (0.353)                 | 0.5                      | 0.248 (0.468)                 | 0.21                          | 6.81 (5.06)  | 3         |
| ens. stack | all    | 0.245        | 0.573     | 1243.33 (253.93)     | 0.211 (0.147)                 | 0.094                    | 0.447 (0.259)                 | 0.0026                        | 39.76 (9.77) | 16        |
|       | no sent.    | 0.546        | 0.568     | 1137.06 (143.07)     | 0.15 (0.289)                  | 0.38                     | 0.367 (0.371)                 | 0.012                         | 19.63 (18.05) | 8         |
| ens. vote | all    | 0.722        | 0.533     | 1114.25 (119.4)      | 0.129 (0.29)                  | 0.52                     | 0.343 (0.368)                 | 0.018                         | 9.69 (10.58) | 4         |
|       | no sent.    | 0.748        | 0.533     | 1048.1 (100.78)      | 0.078 (0.33)                  | 0.92                     | 0.286 (0.418)                 | 0.084                         | 3.47 (4.99)  | 2         |
| lgbm  | all         | 0.723        | 0.548     | 985.63 (179.26)      | -0.027 (0.178)                | 0.46                     | 0.167 (0.283)                 | 0.35                          | 41.29 (6.34) | 20        |
|       | no sent.    | 0.770        | 0.528     | 993.55 (74.59)       | 0.04 (0.373)                  | 0.46                     | 0.248 (0.495)                 | 0.25                          | 15.45 (6.44) | 8         |
| mlp   | all         | 0.606        | 0.588     | 1181.46 (155.42)     | 0.191 (0.285)                 | 0.19                     | 0.416 (0.367)                 | 0.004                         | 24.91 (14.25) | 11        |
|       | no sent.    | 0.611        | 0.538     | 1033.33 (81.04)      | 0.061 (0.309)                 | 0.79                     | 0.266 (0.401)                 | 0.11                          | 4.77 (4.35)  | 2         |
| rf    | all         | 0.661        | 0.523     | 1028.35 (64.87)      | 0.067 (0.352)                 | 0.74                     | 0.277 (0.465)                 | 0.12                          | 2.21 (5.82)  | 1         |
|       | no sent.    | 0.675        | 0.528     | 1034.79 (84.47)      | 0.073 (0.353)                 | 0.8                      | 0.284 (0.466)                 | 0.11                          | 1.95 (4.24)  | 1         |
| ridge | all         | 0.630        | 0.573     | 1165.61 (188.26)     | 0.169 (0.28)                  | 0.27                     | 0.386 (0.342)                 | 0.0082                        | 13.17 (6.94) | 6         |
|       | no sent.    | 0.627        | 0.568     | 1188.31 (196.79)     | 0.192 (0.284)                 | 0.19                     | 0.412 (0.341)                 | 0.005                         | 10.31 (10.0) | 4         |
| sgd   | all         | 0.563        | 0.508     | 953.85 (61.15)       | -0.008 (0.336)                | 0.24                     | 0.19 (0.438)                  | 0.5                           | 6.97 (7.16)  | 4         |
|       | no sent.    | 0.575        | 0.518     | 966.9 (45.72)        | 0.004 (0.33)                  | 0.29                     | 0.201 (0.427)                 | 0.4                           | 14.11 (11.89) | 7         |
| svm   | all         | 0.649        | 0.548     | 1155.45 (166.78)     | 0.163 (0.284)                 | 0.3                      | 0.38 (0.35)                   | 0.0087                        | 8.26 (10.49) | 4         |
|       | no sent.    | 0.629        | 0.533     | 1076.91 (101.69)     | 0.102 (0.314)                 | 0.81                     | 0.312 (0.402)                 | 0.043                         | 5.87 (6.98)  | 3         |
| tree  | all         | 0.736        | 0.518     | 1095.41 (73.55)      | 0.134 (0.377)                 | 0.65                     | 0.359 (0.489)                 | 0.025                         | 13.0 (6.69)  | 6         |
|       | no sent.    | 0.764        | 0.503     | 1018.08 (42.24)      | 0.056 (0.346)                 | 0.65                     | 0.264 (0.455)                 | 0.15                          | 2.46 (5.13)  | 1         |
| xgb   | all         | 0.874        | 0.467     | 953.3 (204.31)       | -0.067 (0.152)                | 0.31                     | 0.121 (0.262)                 | 0.58                          | 24.22 (13.59) | 12        |
|       | no sent.    | 0.892        | 0.457     | 948.72 (122.03)      | -0.034 (0.27)                 | 0.24                     | 0.161 (0.371)                 | 0.56                          | 35.35 (15.58) | 18        |

* Mean and standard deviation, the latter inside brackets, are used to represent columns that refer to a distribution.

Table A5: Performance metrics and trading output of the regressors for Ethereum return prediction