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Bitcoin Price Prediction using Transfer Learning on Financial Micro-blogs

Jovan Davchev*, Kostadin Mishev†, Irena Vodenska‡, Ljubomir Chitkushev§, Dimitar Trajanov¶
FCSE, Ss. Cyril and Methodius University Skopje, Macedonia
Email: *jovan.davchev@finki.ukim.mk, †kostadin.mishev@finki.ukim.mk, ¶dimitar.trajanov@finki.ukim.mk
Interdisciplinary Finance and Economics Lab Metropolitan College, Boston University Boston, Massachusetts, USA
Email: ‡vodenska@bu.edu, §ltc@bu.edu

***Abstract*—We present a methodology for predicting the price of Bitcoin using Twitter data and historical Bitcoin prices. Bitcoin is the largest cryptocurrency that, in terms of market capitalization, represents over 110 billion dollars. The news volume is rapidly growing, and Twitter is increasingly used as a news source influencing purchase decisions by informing users of the currency and its popularity. Using modern Natural Language Processing models for transfer learning, we analyze tweets' meaning and calculate sentiment using the NLP transformers. We combine the daily historical Bitcoin price data with the daily sentiment and predict the next day's price using auto-regressive models for time-series forecasting.**

The results show that modern approaches for sentiment analysis, time-series forecasting, and transfer-learning are applicable for predicting Bitcoin price when we include sentiment extracted from financial micro-blogs as input. The results show improvement when compared to the old approaches using only historical price data. Additionally, we show that the NLP models based on transfer-learning methodologies improve the efficiency in sentiment extraction in financial micro-blogs compared to standard sentiment extraction methods.

***Index Terms*—NLP, transfer learning, transformers, time series prediction**

I. Introduction

Cryptocurrency is a digital asset designed to work as a medium of exchange that uses strong cryptography to secure financial transactions, control the creation of additional units, and verify the transfer of assets. Cryptocurrencies use decentralized control as opposed to centralized digital currency and central banking systems. The decentralized control of each cryptocurrency works through distributed ledger technology, typically a blockchain, containing all transactions across a peer-to-peer network. Using this technology, participants can confirm transactions without a need for a central clearing authority. Potential applications can include fund transfers, settling trades, voting, and many other operations and tasks. Cryptocurrencies have become an essential aspect of the global financial system, and their use as a payment method is expanding.

Bitcoin, first released as open-source software in 2009, is generally considered the first decentralized cryptocurrency. Since bitcoin release, over 6,000 altcoins (alternative variants of bitcoin or other cryptocurrencies) have been created. Bitcoin has become a prevalent asset class among the public since 2016, with a drastic price increase from less than 1,000 USD to 20,000 USD in 2017, as shown in Fig.1, providing attractive (and risky) investment opportunities.

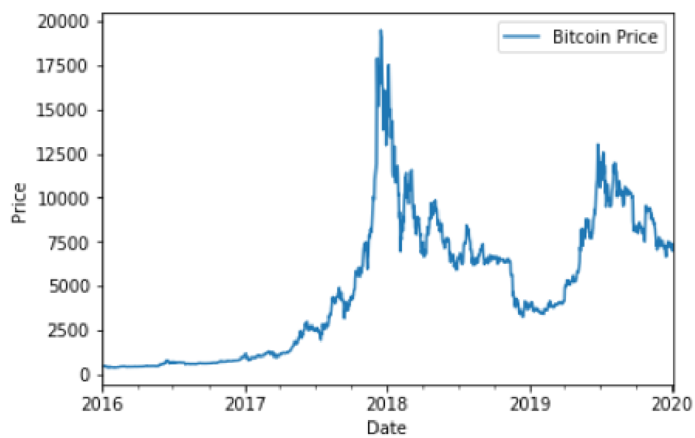

Fig. 1. Bitcoin price from 2016 to 2019

Nowadays, the amount of data posted on social networks (Twitter, Facebook, Reddit, and others) daily is enormous. People post more than two hundred thousand micro-blogs about Bitcoin every day, including 75.000 published tweets.

We also witness tremendous daily progress in many aspects of Machine Learning. Natural Language Processing or NLP is a field of Artificial Intelligence that gives machines the ability to read, understand, and derive meaning from human languages, and it is the field with probably the most improvements in recent years. With the emergence of Transformers (Transfer Learning), using pre-trained state of the art models, solving complex NLP tasks became more efficient than ever. The Transformer is the first transduction model relying entirely on self-attention to compute its input and output representations without using sequence-aligned recurrent or convolution units.

Prediction of cryptocurrency prices is a challenging task mainly because they represent a relatively new phenomenon (currency or asset) with high volatility. While researchers use standard time series forecasting methods to predict cryptocurrency prices, this method has limited applicability, especially when the time-series exhibit high volatility. Additional parameters, like the sentiment of related news or micro-blogs, can improve the prediction models. There are various models for obtaining sentiments [1] with different precision and applicability. One of the simplest and most frequently used sentiment calculation models is VADER [2], applied in [3] for forecasting Bitcoin prices based on the news and Tweets related to Bitcoin. A similar approach used in [4] employs Tweets and Google Trends to predict Bitcoin and Ethereum prices. The micro-blogs from Reddit and Tweets related to Bitcoin are applied in [5] to predict the bitcoin price, and the VADER sentiment model of bitcoin-related tweets is used in [6]. Additionally, sentiment based on the Wall Street Journal and Financial Times Bitcoin-related news, using the bag-of-words model and a dictionary-based approach, is used in [7]. The methodology in [8] is based on the Naive Bayes based model for calculating sentiments of tweets. The Vector error correction models (VECM) model and data from tweets is proposed in [9] to predict bitcoin price. In [10], data from Facebook posts, Google Trends, and Dow Jones News is proposed to predict Bitcoin price using different regression/classification models and different techniques supported by IBM Watson.

The recent advances in deep-learning, transfer-learning, and NLP have significantly improved sentiment extraction from financial news and texts [11]–[15]. In [13], Yang et al. present an inductive transfer-learning method using ULMFiT [16] for sentiment classification in financial texts. Their results show the effectiveness of inductive transfer-learning methodologies compared to traditional transfer-learning approaches.

In [15], Zhao et al. present the superior performance of recent NLP transformers, BERT, and RoBERTA in sentiment analysis compared to dictionary-based models. In [17], Mishev et al. make a thorough performance evaluation of the known algorithms for sentiment analysis applied to financial headlines. They start the evaluation with specific lexicons for sentiment analysis in finance and gradually build the study to include word and sentence encoders, up to the latest available NLP transformers. Their results show that contextual embeddings produced by NLP transformers show superior results compared to the other methodologies and algorithms.

The sentiment inferred from the sentiment analysis models applied to financial texts can be used to forecast stock prices [18]–[20], foreign exchange, and global financial market trends [21], [22], corporate earnings [23], as well as to predict the cryptocurrencies prices.

This paper proposes a transfer learning-based methodology for Bitcoin price prediction based on sentiment analysis of finance micro-blogs. We use deep learning-based NLP transformers like RoBERTa [24], to create a model for calculating finance-related sentiment of micro-blogs. We then build a model for Bitcoin price prediction based on sentiments from the news and Bitcoin historical price data using modern approaches for time series forecasting (FbProphet [25] and XGBoost [26]).

II. Datasets

A. Bitcoin tweets

We create a crawler for collecting the newest bitcoin-related tweets and analyze the tweets containing #bitcoin and #btc hashtag from Kaggle [1] between January 2016 and July 2019, accruing approximately 18 million tweets. Each tweet contains a timestamp, replies, number of likes, number of retweets, and the tweet text (Fig.2). Using this dataset, we obtain the daily volume of bitcoin-related tweets.

	timestamp	replies	likes	retweets	text
0	2019-05-21 16:49:45+00:00	47.0	51.0	54.0	BTC IS STILL GOING STRONG!!\n\nThus, we are gi...
1	2019-05-27 11:27:22+00:00	1.0	19.0	6.0	You have roughly 6 days left to get your #Laun...
2	2019-05-27 05:32:05+00:00	14.0	40.0	39.0	BTC IS GOING CRAZYYY!\n\nThus, we are giving a...
3	2009-01-11 03:33:52+00:00	790.0	14470.0	5542.0	Running bitcoin
4	2019-05-02 17:36:29+00:00	6.0	252.0	55.0	https://t.co/lp0ph5uZYn\n\n#cryptocurrency #dr...
5	2019-05-27 01:37:37+00:00	31.0	141.0	5.0	bitcoin may pump to 100k but I bet my ass 1DOG...
6	2019-05-25 10:14:41+00:00	5.0	94.0	76.0	ohh and just incase anyone is interested in so...
7	2019-05-27 11:45:45+00:00	3.0	42.0	5.0	It's beginning! https://t.co/V0MyRYS91q
8	2019-05-27 11:40:26+00:00	4.0	25.0	16.0	$BTX @BitcoregTX$ 1.11 +25.29%\ncreate your o...
9	2019-05-23 14:14:21+00:00	4.0	46.0	30.0	Cresio and Airdrop Alert in MALTA AI & BLO...

Fig. 2. Subset from Bitcoin tweets dataset

B. Bitcoin historical prices

We collect historical Bitcoin prices from Coinmarketcap [2] for the period between 2013 and December 2019 with minute resolution containing a timestamp, open price, high and low prices, close price, volume, and market capitalization (Fig.3).

	Date	Open*	High	Low	Close**	Volume	Market Cap
0	2020-01-03	6984.43	7413.72	6915.00	7344.88	25111481032	133233444755
1	2020-01-02	7202.55	7212.16	6935.27	6985.47	20802083465	126699395235
2	2020-01-01	7194.89	7254.33	7174.94	7200.17	18565664997	130580829150
3	2019-12-31	7294.44	7335.29	7169.78	7193.60	21167946112	130446112586
4	2019-12-30	7420.27	7454.82	7276.31	7293.00	22874131672	132235125152
5	2019-12-29	7317.65	7513.95	7279.87	7422.65	22445257702	134570835775
6	2019-12-28	7289.03	7399.04	7286.91	7317.99	21365673026	132659059740
7	2019-12-27	7238.14	7363.53	7189.93	7290.09	22777360996	132139502950
8	2019-12-26	7274.80	7388.30	7200.39	7238.97	22787010034	131200030100
9	2019-12-25	7325.76	7357.02	7220.99	7275.16	21559505149	131540641292

Fig. 3. Subset from Bitcoin historical prices dataset

III. Methodology

We use a methodology based on transfer learning models [27], including state-of-the-art pre-trained NLP transformers for text classification.

The proposed sentiment analysis model leverages the power of RoBERTa, which currently outperforms most of the methods used in NLP related tasks. The Facebook team introduced RoBERTa transformer to offer an alternative and optimized version of BERT [28], retrained on a ten times larger dataset with improved training methodology and different hyperparameters. RoBERTa removes the Next Sentence Prediction (NSP) objective and adds dynamics masking of words so that the masked tokens change during the training epochs. The development team uses a larger batch size as in [29], which shows that BERT is amenable to considerable batch training. The RoBERTa architecture is shown in Fig.4.

[1] https://www.kaggle.com/alaix14/bitcoin-tweets-20160101-to-20190329
[2] https://coinmarketcap.com/currencies/bitcoin/historical-data/

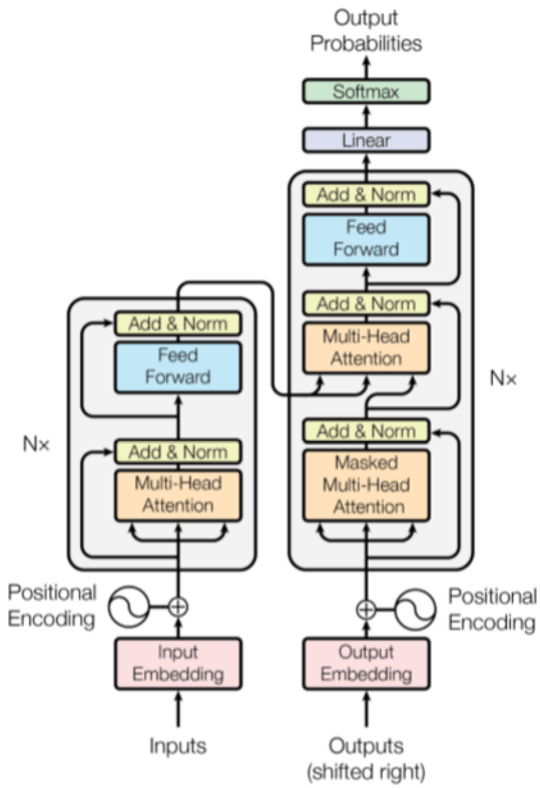

Fig. 4. RoBERTa architecture

In this paper, we fine-tune the pre-trained RoBERTa model by using a labeled dataset of general financial tweets. Next, we leverage the fine-tuned model to evaluate the sentiment of the bitcoin-related tweets, which we use as an input dataset. As output, we use the ”softmax” function to obtain probabilities for the observed sample of tweets' positive or negative sentiment. Afterward, we compose two temporal numeric streams for the news's positiveness and negativeness related to crypto-assets. We use both streams as input for recurrent and convolutional networks used for Bitcoin price prediction. We align the sentiment and price vectors temporally using the Bitcoin price's date and time and the tweets' time of publishing. We use Prophet (FbProphet) and XGBoost with different parameters for the time-series price prediction and compare the results. We evaluate different model architectures in order to identify the model that offers the best fit.

FbProphet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects. It works best with time series that have strong seasonal effects and several seasons of historical data. Prophet is robust to missing data and shifts in the trend and typically handles outliers well. FbProphet is open source software released by Facebook's Core Data Science team. It is available for download on CRAN and PyPI.

XGBoost is an optimized distributed gradient boosting library designed to be highly efficient, flexible, and portable. It implements machine learning algorithms under the Gradient Boosting framework. XGBoost provides a parallel tree boosting (also known as GBDT, GBM) that solve many data science problems in a fast and accurate way. XGBoost is widely used in many short-term time-series prediction problems [30]–[34], which makes it appropriate for evaluating our methodology.

IV. Model architecture

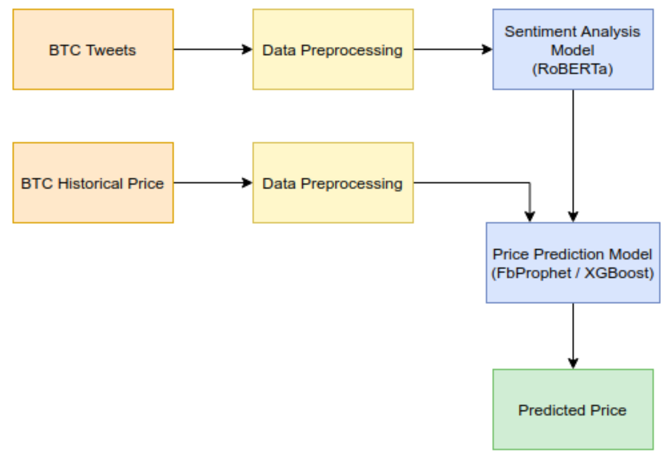

Fig. 5. Model architecture

We preprocessed the 18 million tweets that we have collected as follows:

- Removed all non-English tweets.
- Removed all tweets that do not match our pattern.
- Filtered only tweets with more than five likes, five replies, and five retweets.

After preprocessing, we train the model on our financial dataset, and we apply a state-of-the-art transformer, RoBERTa, on approximately 170k tweets left for sentiment analysis. For every tweet, there is a probability of sentiment in the interval [0, 1] where 0 means negative sentiment, and one means positive sentiment.

After calculating the daily sentiments, we merge the sentiment results with Bitcoin's historical price data indexed by date. For each day, we have open/close and high/low prices, volume, positive sentiment score, negative sentiment score, and compound score (derived attribute (coefficient) by combining positive and negative scores).

To forecast the Bitcoin price, we use a time-series' regression model with moving windows. We calculate the means and standard deviations from the most recent three, seven, and 30 days for the open price, close price, compound sentiment score, and the trading volume. Next, we apply the extracted features as inputs to FbProphet regressors and XGBoost to perform the forecasting. The extracted features used as input in the regression models are listed in Table I.

The target variable we are predicting is the Bitcoin price for the next day, as shown in Fig.5.

TABLE I
EXTRACTED FEATURES

Feature Name
date
Open price
Close price
High price
Low price
Volume
Market cap
Positive Sentiment
Negative Sentiment
Compound Sentiment
price from last day
Mean of open Price of last three days
Mean of open Price of last seven days
Mean of open Price of last 30 days
Mean of close Price of last three days
Mean of close Price of last seven days
Mean of close Price of last 30 days
Mean of the volume of last three days
Mean of the volume of last seven days
Mean of the volume of last 30 days
Mean of the compound sentiment of last three days
Mean of the compound sentiment of last seven days
Mean of the compound sentiment of last 30 days
Standard deviation for the open price of last three days
Standard deviation for the open price of last seven days
Standard deviation for the open price of last 30 days
Standard deviation for the close price of last three days
Standard deviation for the close price of last seven days
Standard deviation for the close price of last 30 days
Standard deviation of the volume of last three days
Standard deviation of the volume of last seven days
Standard deviation of the volume of last 30 days
Standard deviation of the compound sentiment of last three days
Standard deviation of the compound sentiment of last seven days
Standard deviation of the compound sentiment of last 30 days
price of the next day (Target variable)

V. Evaluation and Results

After the data preprocessing, we split the completed dataset into train and test datasets. The training dataset contains the data from 2016-2018, and the test dataset is composed of the 2019 data.

The training dataset contains 1095 instances used in cross-validation in the training phase, and the test dataset contains 21 instances used only for testing.

Using GridSearchCV, we evaluate two models for time series forecasting (FbProphet and XGBoost) with the following values for the parameters:

- Maximum depth: 2, 3, 4, 5, 6, 7, 8, 10
- Number of estimators: 50, 100, 200
- Gamma: 0, 0.001, 0.01, 0.1
- Learning rate: 0.001, 0.01, 0.1, 0.15, 0.2
- Base score: 0.3, 0.5, 0.7

We evaluate the models' accuracy by using the following metrics: Mean Absolute Error (MAE) and Root Mean Squared Error(RMSE).

Grid searching for finding the best parameters lasted for one hour and the model that best fits our methodology is the XGBoost model with the following parameters:

- Booster: gbtree
- Base score: 0.3
- Gamma: 0.01
- Learning rate: 0.15
- Maximum depth: 8
- Number of estimators: 200

The FbProphet model results show a 65 mean absolute error (MAE) and a 72.03 root mean squared error (RMSE). This result is inferior compared to the XGBoost model. The original price and predicted Bitcoin price using the FbProphet model is shown in Fig.6.

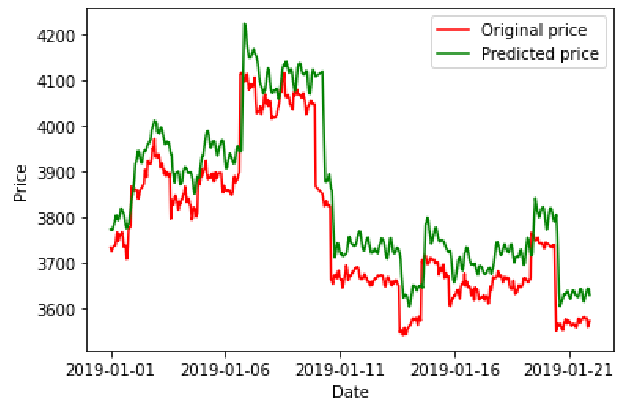

Fig. 6. FBProphet - Test dataset results

The XGBoost model shows significantly better results with 8.47 mean absolute error (MAE) and 13.08 root mean squared error (RMSE), as shown in Table II. Additionally, Fig.7 shows a much better matching of the original and predicted price by the XGBoost model compared to the FbProphet.

TABLE II
FBPROPHET AND XGBOOST MODEL EVALUATION

	FbProphet	**XGBoost**
MAE (Mean Absolute Error)	65	8.47
RMSE (Root Mean Squared Error)	72.08	13.08

We have identified and extracted the top 15 essential features that significantly affect our forecasts. In Fig.8, we can see that tweets' sentiments (compound, positive, and negative scores) and the total volume of the tweets are essential in predicting the Bitcoin price for the next day. We conclude that the price from the most recent three days is more critical (shows higher F-score) than the most recent seven and 30-day historical prices. In the context of feature importance, F-score gives the number of times we use a feature to split the data across all decision trees.

VI. Conclusion and Future Work

Our paper presents a methodology for bitcoin price prediction using modern approaches for sentiment analysis and time-series forecasting. Our model includes the RoBERTa NLP

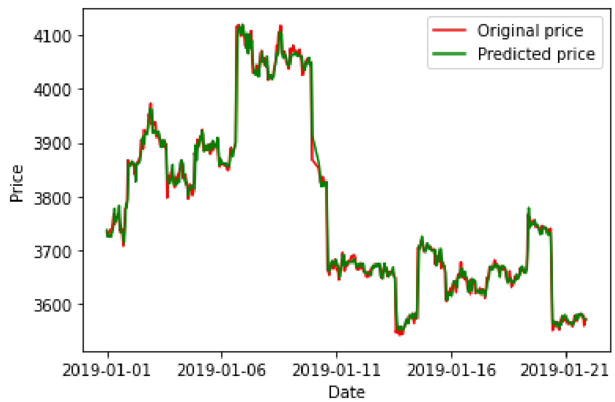

Fig. 7. XGBoost - Test dataset results

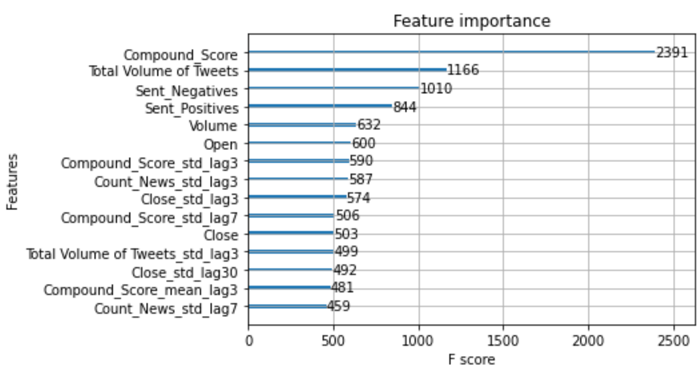

Fig. 8. XGBoost - Feature importance

transformer due to its efficiency in sentiment extraction and the XGBoost regressor for time-series forecasting.

Our results show that we can effectively use the fusion of features obtained from sentiment extraction models and historical Bitcoin prices as input into regression models to the next day's Bitcoin price. Additionally, we show that the compound score calculated from the extracted sentiment in micro-blogs plays an essential role in Bitcoin price prediction. Hence, financial micro-blogs influence Bitcoin's price and we should include them as features in Bitcoin price prediction.

In future work, we will collect news from different sources to filter and calculate sentiments more precisely. We aim to improve the model for sentiment analysis and time-series prediction. We would also consider enriching our dataset with more attributes since the Bitcoin price is very challenging to predict due to its complex nature.

Nevertheless, the sentiment analysis model proposed in this paper offers improvements compared to the base prediction models using only historical Bitcoin price data and models based on older NLP approaches.

We observe that combining the sentiment of the tweets and historical prices, using modern methodologies and approaches, can lead to much better Bitcoin price prediction.

By extracting the essential features in our model, we show that the news sentiments significantly affect Bitcoin's price and should be considered.

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