Bitcoin Trading Strategies Using News and Tweets with Sentiment Analysis

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Abstract

This paper describes Bitcoin trading strategies by using related news and Tweets. We conduct sentiment analysis on each news and Tweets using Valence Aware Dictionary for sEntiment Reasoning(VADER), and then fit some models to forecast the Bitcoin market. Then, we devise some trading strategies and evaluate the performance by different measures. It seems that our trading strategies can beat the benchmark strategy significantly in the testing period. We propose explanations for the observation and study the possibilities for the further extension by the inspiration from some Artificial Intelligence(AI) articles.

1 Introduction

Bitcoin has become a very popular asset class among the public since 2016, with a drastic climb of price from less than USD 1,000 to USD 20,000 in 2017 providing a lot of investment opportunities. An extensive literature has been carried out on the Bitcoin market showing that Bitcoin returns are predictable, which indicates the Bitcoin market is contrary to Efficient Market Hypothesis(EMH), such as Urquhart(2016), Nadarajah and Chu(2017), Tiwari et al.(2018), Kjuntia and Pattanayak(2018) and Caporale et al.(2018), Kjærland et al(2018) and Blau(2018). All these papers imply that there are some factors or patterns correlating the returns that may be exploited by the investors.

Traditional methods to predict security price movements such as technical analysis and fundamental analysis have been widely studied and it is pretty hard to identify new and useful indicators to beat the market. With recent developments on Artificial Intelligence(AI), analyzing unstructured data including texts become possible by leveraging the techniques of Natural Language Processing(NLP). In this paper, we try to make use of two types of data, Twitter and news. As a major representative of Internet public mood, Twitter has shown an impact on financial market by different literature, such as Botten et al.(2018), Piñeiro Chousa et al.(2016), Sun et al.(2016), Piñeiro Chousa et al.(2018) and Urquhart et al.(2018). Meanwhile, we use Bitcoin news to get objective facts. We pass the two types of sources into sentiment analysis by Valence Aware Dictionary for sEntiment Reasoning(VADER) model, to convert the qualitative data into quantitative data for modeling and trading strategy building.

The paper is organized as follows. First, we describe the models and trading strategies building and evaluate their performance. Then, we introduce a finance article and AI article for inspiration to further studies. After that, we propose the improvement of our trading strategies from the result and inspiration to the articles.

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2 The model and trading strategies

2.1 Overview

In our trading strategies building, we first obtain the qualitative data from news and Tweets, which represents objective facts and subjective opinions respectively, and convert the data to a quantitative one. Based on the empirical data, we use different predictors and responses to fit different models for the Bitcoin market. From different models, we devise different trading strategies and evaluate the performance by different measures. During the whole building and testing, we use Python for the implementation.

2.2 Sentiment analysis: VADER

For all the news and tweets, we apply the text sentiment analysis by VADER(Valence Aware Dictionary for sEntiment Reasoning) to convert qualitative data into a quantitative one. It is sensitive to the polarity and intensity of emotion.

Initially, VADER sentiment analysis quantifies the emotion of a word from a dictionary ranging from -4 to +4, representing from the most negative emotion to the most positive emotion. Then, the sentiment score of a sentence is calculated by summing up all the scores of each word and is normalized to return a value from -1 to 1, by the following Huto's formula:

$$\frac{x}{\sqrt{x^2+\alpha}}$$

where x is the sum of the sentiment scores, α is the normalization parameter set arbitrarily.

We use Python package **vaderSentiment** for the data processing.

2.3 Data

We obtain the following data from 1 April 2018 to 31 March 2019, splitting the data from 1 April 2018 to 31 December 2018 as the training set and the data from 1 January 2019 to 31 March 2019 as the testing set.

2.3.1 News

We extract the Bitcoin-related news using CoinDesk, which is one of the leading digital media on crypto assets and blockchain technology. To get the news, we first use a Python package **request** to access the site, and use another Python package **BeautifulSoup** for getting the HTML information. Overall, there is 861 news for sentiment analysis.

2.3.2 Tweets

We extract the Bitcoin-related tweets by searching hashtags with **#Bitcoin** and **#BTC** by a Python package **twitterscraper**, allowing us to retrieve the past tweets for more than 1 year. To cleanse the data, we remove the tweets with URL and user tagging while we keep the tweets with hashtags. Also, due to the constraint on sentiment analysis package, we only keep the English tweets by using package **langdetect**. Overall, we obtain 4,018,500 tweets for sentiment analysis.

2.3.3 Bitcoin historical market data

We extract the historical Bitcoin market data from CoinMarketCap, such as Close Price, Open Price, Market Capitalization, and Volume. To calculate the return, we use the log return of Open Price.

2.4 Model and trading strategy

We fit the models from the observation of the empirical data, with extensive testing of different combination on the predictors. In the end, we select the below 3 models.

For the trading strategies, we use the following setting:

- Unlimited short selling and longing is allowed.

- Transaction cost is ignored.
- The rebalancing frequency is 1 day.
- Given the information on day t, we execute the trade based on the Open price on day $t+1$. The realized log return is conditioned on the Open price on day $t+2$

2.4.1 Model 1: Logit model on news sentiment

We define y_{t+1} as the response with +1 and 0, representing positive and negative daily log return on day $t+1$ respectively, and the predictor x_t is the average VADER score from news on day t. We perform a logistic regression for the below model:

$$logit(y_{t+1}) = \beta_0 + \beta_1 x_t$$

2.4.1.1 Regression result

```
                           Logit Regression Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  274
Model:                          Logit   Df Residuals:                      272
Method:                           MLE   Df Model:                            1
Date:                Sat, 25 May 2019   Pseudo R-squ.:                0.003778
Time:                        18:50:19   Log-Likelihood:                -189.18
converged:                       True   LL-Null:                       -189.89
                                        LLR p-value:                    0.2310
======================================================================================
                         coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------------
const                 -0.0681      0.146     -0.466      0.641      -0.355       0.218
News_Avg_Sentiment     0.2629      0.220      1.194      0.233      -0.169       0.695
======================================================================================
```

Figure 1: Model 1 result

2.4.1.2 Trading strategy

If the predicted probability is greater 0.5, the trading execution is long. Otherwise, the trading execution is short.

2.4.2 Model 2: Logit model on tweets sentiment

We define y_{t+1} as the response with +1 and 0, representing positive and negative daily log return on day $t+1$ respectively, and the predictor x_t is the average VADER score from tweets on day t. We perform a logistic regression for the below model:

$$logit(y_{t+1}) = \beta_0 + \beta_1 x_t$$

2.4.2.1 Regression result

Logit Regression Results

Dep. Variable:	y	No. Observations:	274
Model:	Logit	Df Residuals:	272
Method:	MLE	Df Model:	1
Date:	Sat, 25 May 2019	Pseudo R-squ.:	0.001853
Time:	18:53:29	Log-Likelihood:	−189.54
converged:	True	LL-Null:	−189.89
		LLR p-value:	0.4015

	coef	std err	z	P>|z|	[0.025	0.975]
const	0.7839	0.910	0.862	0.389	−1.000	2.56
Tweets_Avg_Sentiment	−4.0139	4.796	−0.837	0.403	−13.414	5.38

Figure 2: Model 2 result

2.4.2.2 Trading strategy

If the predicted probability is greater 0.5, the trading execution is long. Otherwise, the trading execution is short.

2.4.3 Model 3: Times series model on price against tweets volume

We define y_{t+1} as the response of the open price on day $t+1$, and x_t is the number of tweets on day t. We perform a time series linear regression up to $t-3$ for the below model:

$$y_{t+1} = \beta_0 + \beta_1 x_t + \beta_2 x_{t-1} + \beta_3 x_{t-2} + \beta_4 x_{t-3}$$

2.4.3.1 Regression result

OLS Regression Results

Dep. Variable:	y	R-squared:	0.387
Model:	OLS	Adj. R-squared:	0.378
Method:	Least Squares	F-statistic:	41.85
Date:	Sat, 25 May 2019	Prob (F-statistic):	3.50e−27
Time:	18:58:26	Log-Likelihood:	−2286.7
No. Observations:	270	AIC:	4583.
Df Residuals:	265	BIC:	4601.
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	2663.6554	312.293	8.529	0.000	2048.764	3278.546
Tweets_Count	0.0793	0.023	3.387	0.001	0.033	0.125
Tweets_Count_Lag1	0.0725	0.027	2.722	0.007	0.020	0.125
Tweets_Count_Lag2	0.0517	0.026	1.989	0.048	0.001	0.103
Tweets_Count_Lag3	0.1072	0.024	4.453	0.000	0.060	0.155

Omnibus:	8.475	Durbin-Watson:	0.133
Prob(Omnibus):	0.014	Jarque-Bera (JB):	8.550
Skew:	−0.370	Prob(JB):	0.0139
Kurtosis:	3.461	Cond. No.	1.15e+05

Figure 3: Model 3 result

2.4.3.2 Trading strategy

On day $t+1$, we calculate predicted $\hat{y}_{t+2}$ and $\hat{y}_{t+1}$. If $\hat{y}_{t+2}$ is greater than $\hat{y}_{t+1}$, then the trading execution is long. Otherwise, the trading execution is short.

2.5 Backtesting result in the trading strategies

The following Table 1 is the backtest result on the trading strategies for the testing period from 1 January 2019 to 31 March 2019. The Benchmark model we choose is to either long or short during the testing period without any adjustment. We also indicate different cumulative return by comparing different trading strategies in Figure 4.

Table 1: Backtest result

Trading strategy	Return	Accuracy[6]	Annualized volatility	Sharpe ratio[7]
Model 1	39.49%	62.22%	42.54%	376.45%
Model 2	25.67%	52.22%	42.86%	242.96%
Model 3	41.70%	61.11%	42.49%	397.96%
Benchmark: Long only	9.57%	N/A	42.85%	90.59%
Benchmark: Short only	-9.57%	N/A	42.85%	-90.59%

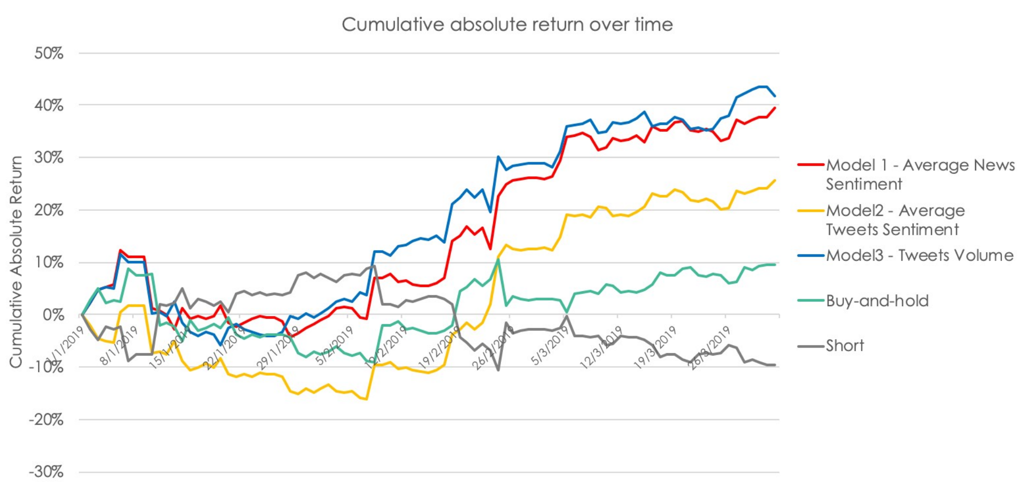

Figure 4: Cumulative return across different strategies

2.6 Discussion on the backtest result

2.6.1 Positive bias on the sentiment

From the empirical data, we observe that there is a positive bias on the news and tweets sentiment. Potentially, due to the prevalence of cryptocurrency these years, most of the related news exerts an optimistic view. Moreover, there should be fewer negative emotion found in social media because people tend to report the good news over their community, and hide their setback from their investment in Model 3. Given this human nature, in bullish market, there is more information available for modelling.

[6] Accuracy on predicting price movement
[7] Assuming risk-free rate is 0%

2.6.2 Good performance on trading strategies from Model 1 and Model 3

As from the backtesting result, both trading strategies from Model 1 and Model 3 provide a good result in return and accuracy in pricing movement, as well as the Sharpe ratio. From the result, the news sentiment is a good predictor on the log return from Model 1. It is very interesting to see that our strategy from Model 3 gives the best result, but we are using the predicted price rather than the actual price on the previous day for our decision making. Although the volume of tweets can track the price from the empirical study, the good result can also come from luck and market condition. Also, it seems that all our trading strategies are in favour of bull market. Extending the test period is needed to verify whether the good performance depends on the market condition and luck.

2.6.3 Missing transaction cost

Despite of the excellent result, the transaction cost is actually not taken into account. In Bitcoin trading, the trading spread is usually quite high, and therefore the Bid/Ask price may far away from the Open price, and in our case, if we conduct a daily rebalancing frequency, the transaction cost may be huge and greatly reduce the profit. Further studies needed to be conducted in order to verify the validity of the performance.

3 Reflection on an AI article

This section is a reflection of an article on the topic of AI. The article was chosen is titled **Who Is Going To Make Money In AI?**[8]. The article was written by Simon Greenman. Simon describes the current state of AI development as 'another gold rush in AI'. This makes a lot of sense to our group.

Consider the big amount of investment in AI in recent years. The big tech giants - Google, Amazon, Microsoft, IBM, etc., are in a fight in AI investing over $20 billion in AI in 2016. Globally, corporate venture capital groups participated in $53 billion of funding across 2,740 deals in 2018. Investments in AI surges over the globe. To many corporations, this is a race to realize the productivity benefits of AI ahead of their competitors.

We are already in an era in which AI can be seen everywhere. From Google search to the facial recognition in Apple iPhone to Amazon Alexa chatbot which enables the intelligent living. AI is embedded in our daily lives. These are the daily life example of AI which is accessible by normal people. In business fields, we can also see the power of AI to be unleashed. Corporations analyze and predict customer behaviors, manufacturers improve quality control, doctors diagnose diseases. This is really a blooming era of AI.

Analog to a gold rush, some people doing successfully can make a big fortune. Many others failed and lose. Also, not only the gold miner or mine owner would have a chance to make a profit, some other people, such as the merchants, transportation facilities and the manufacturer of picks and shovels may also make a lot of money.

This article analyses who is going to make money in AI among 7 categories of participants:

1. Chip makers
2. Platform and infrastructure providers
3. Enabling models and algorithm providers
4. Enterprise solution providers
5. Industry vertical solution providers
6. Corporate users of AI
7. Nations

In this way, the question of who is going to make money is put into a lens of the value chain of the AI landscape.

[8]The article can be accessed at https://towardsdatascience.com/who-is-going-to-make-money-in-ai-part-i-77a2f30b8cef+

3.1 Chip makers

Demands of computational power will grow endlessly. Therefore corporations who possess chip technology is advantageous. NVIDIA's stock is up 1500% in two years time, as their graphical processing unit (GPU) is excellent for machine learning. However, the cost for the chip manufacturer to sustain the top position is also very high. Chips in AI world is just like the picks and shovels for gold miners - only those who can provide the cheapest and most widely used tools survive.

3.2 Platform and infrastructure providers

Cloud is an important infrastructure for AI. Example like Amazon Web Services (AWS), Microsoft Azure and GoogleCloud fight in this battleground. Again, the one who can get the biggest user base will win.

3.3 Enabling models and algorithm providers

Google has been spending a lot of money on Research and Development, just to keep themselves at the cutting edge of the algorithms. If algorithms get a big user base, it also helps build up the popularity of the infrastructure that is built to be optimized for these algorithms. The article gives an example of Google provides its TensorFlow for free and becomes popular software for machine learning, users will more incline to choose Google Cloud as its optimized for TensorFlow.

3.4 Enterprise solution providers

This refers to the software which is designed for the need of enterprises. If an AI solution can create values to an enterprise, the enterprise will be willing to pay a good amount for the solutions. However, in order to be successful in this field, the startup solution providers need a good demonstration skill to show their values to the enterprise.

3.5 Industry vertical solution providers

This refers to AI startup that provides solutions to corporate use cases in specific fields, such as healthcare, financial services, agriculture, automotive... etc. Startups are more likely to succeed if they have the followings: (1) large and proprietary data training sets, (2) domain knowledge, (3) a deep pool of talent around applied AI and (4) sufficient capital to fund rapid growth. They'll also need to be commercial-minded who can develop market plans.

3.6 Corporate users of AI

This refers to the corporate users of AI which are able to leverage the technology to improve their profitability. Usually, large corporates are in a better position compared to smaller companies, because larger companies have bigger data assets, which is essential for AI and machine learning.

3.7 Nations

Countries can also benefit from AI, to achieve efficiency socially, and increase productivity and wealth in countries.

The article summarises the key themes where the value of this golden era for AI will migrate. Those global technology giants are the providers of the tools for the 'gold rush'. They offer chips, cloud computing power as well as algorithms to power the AI development. Startups that can identify the need of enterprise and are able to demonstrate the value will also be the winner of the race. Corporations and countries which can make good use of AI will also benefit. So how much do you think you can gain from AI?

4 Reflection on an Finance article

This section is a reflection of an article on the topic of US-China Trade War. The article chosen is titled **U.S. Weighs Letting Companies Seek New Penalties Over Currency Manipulation**[9].

Generally, countries quite like trade, or selling and buying stuff from other countries. And Americans really like buying Chinese stuff - they spend about $500 billion a year on it, more than they spend on stuff from any other country. China likes buying American stuff too, but not quite as much (they only spend $130 billion a year).

Trump called his Chinese counterpart, Xi Jinping, and now the two countries keep announcing bigger and bigger tariffs on each other's exports. Trump started it, and his tariffs are bigger - he's already taxing about half of everything China sends to America and has just announced plans to tax absolutely everything.

The latest development of the US-China Trade War is that the Commerce Department of the US is proposing to treat an undervalued currency as a subsidy that allows foreign businesses to export their goods more cheaply. **The rule would allow U.S. companies to file a complaint with the U.S. International Trade Commission**, the first stop in arguing for countervailing duties that could lead to additional tariffs on certain imports.

4.1 Is China really a currency manipulator?

According to the article, one sign of currency manipulation is when a country has a large current-account surplus, meaning that its exports far exceed its imports. **However**, for China case, the surplus is very small now compared to a decade ago. Nations with bigger current-account surpluses include Japan, South Korea, Switzerland, and Taiwan.

4.2 How could tariffs affect me?

As China has retaliated taxing US agricultural and industrial products, from soybeans, pork and cotton to airplanes, cars and steel pipes, economists are worried about this vicious cycle would continue. This also risks a chain reaction as countries start clamping down on partners, which then retaliate. Data from the US Census Bureau show how the US economy has been heavily dependent on imports. A global trade war could hurt consumers around the world by making it harder for all companies to operate, forcing them to push higher prices onto their customers.

4.3 The End Game

We literally have no idea how it all going to end. If history is any guide, then past trade wars have led to deep economic recession. In particular, the US Smoot-Hawley tariffs enacted in 1930 are thought to have inspired a trade war and led to a massive decline in global trade. The world trade fell by 66% from 1929 to 1934, while US exports and imports to and from Europe each also fell by about two-thirds. Let's keep our fingers crossed.

5 Summary of Sentiment Analysis

The following will be a brief summary of the sentiment analysis we used in this project and some further study on Artificial Intelligence on Bitcoin trading. Bitcoin, as the largest coin in the market, decides most of the trend for the crypto markets is necessary to understand that sentiment which would in turn affects its price and trading volume, etc. A lot of news flow and sell off has dampened the short term sentiment but yes there are some long-term positives which make Bitcoin an interesting study.

Bitcoin has stuck over USD 7000 and that is what is keeping the sentiment from neutral to positive. While the rally may continue, caution too would slowly creep in as the coin moves toward the upside of range, and more sentiment analysis has to be performed continuously in avoidance of sudden change of the trend.

[9]The article can be accessed at https://www.wsj.com/articles/u-s-weighs-letting-companies-seek-new-penalties-over-currency-manipulation-11558727041+.

For future study more altcoins can be analyzed, e.g. ETH, XPR, BCH, etc. All altcoins seem to be falling the Bitcoin sentiment and moving on the positive side.

6 Further Study on Artificial Intelligence

The Bitcoin price has experienced tremendous up and down throughout over the last few years. This provides a valuable opportunity for algorithm traders to be profitable from it. In the following, introduced would be the other artificial intelligence methods for prediction of Bitcoin price.

6.1 Recurrent Neural Networks

A recurrent neural network (RNN) is a class of artificial neural network where connections between nodes form a directed graph along a sequence.

An RNN shows temporal dynamic behavior for a time sequence and it can use its internal state to process sequences. In practice, this can be achieved with LSTMs and GRUs layers.

The RNN includes the following 4 steps:

1. Obtaining the BTC Data
2. Cleaning the Data with Custom Functions
3. Building an RNN with LSTM
4. Training the RNN and Predicting tomorrow's BTC Price

Literally, the network is effectively able to learn. However, we have to be aware of a risk that we may end up using a strategy in which predicting a value close to the previous one turns out to be successful in terms of minimizing the mean absolute error.

6.2 SVM

Because of the Bitcoin's volatility, there's a need for a prediction tool for investors to help them consider investment decisions for Bitcoin trade. Market technical analysis basically identifies the trend of the market in a certain period by using historical market price. Sometimes it requires an expert to analyze the technical indicators. In the following introduced would be the AI model of SVM on Bitcoin trading.

A primitive idea on SVM includes the following 3 steps:

1. Obtain daily BTC data including open, high, low and close price
2. Create unsupervised Machine Learning to differentiate low, high, breakout and null zone
3. Train in Support Vector Classifier to generates a separating hyper-plane

SVM can be use to predict current day's trend of Bitcoin on the market, but we need more knowledge to read the data, by expert on reader signal market and strategy return on the trading market. Also, market technical analysis can be used to further improve the SVM method together.

Contribution

Table 2: Contribution

Task	Paul M.Y. Fung	Alex C.Y. Leung	Alan W.M. Ng	Billy C.H. Wan	Ivan T.H. Yim
Group project coding	X	X	X	X	X
YouTube presentation					X
Report on trading strategies			X		
Reflection of a finance article				X	
Reflection of an AI article	X				
Synthesis and suggestion for further studies		X			
Contribution	20%	20%	20%	20%	20%

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