Crypto-gurus: Analysing Credibility and Profitability

BT4222   Mining Web Data For Business Insights

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1. Introduction

1.1 Problem Description

Whether one believes in the hype or not, cryptocurrency is a hot topic being discussed widely right now due to its potentially high returns. Some argue they hold no intrinsic value and buying in would mean buying into a bubble, others argue these coins hold tremendous potential. Either way, there are high risks involved in trading cryptos as it a very volatile market. Precision on when to buy, sell or hold is extremely essential.

As a result, many new investors turn to online channels such as twitter to receive investment advice from more experienced ones, called “crypto-gurus”. However, with so many self-proclaimed “crypto-gurus” out there with so large followings, are any of them really credible?

While there are many schools of thought and technical indicators that can be derived from the market prices, the team is not attempting to predict the prices of crypto-currencies in any way. Instead, we will let these “gurus” and pundits play their own game and strategy and we will evaluate their performance based on the past advice they have given out on their twitter account.

Many of these crypto-trading accounts have gained many followers on Twitter and submit daily trades and advice. One way of assessing the performance and credibility of these accounts is to look at their past record. We intend to do this by running a simulation on the previous buy and sell advice given by each different account and track their individual performance throughout the course of 2017. Knowing the performance and profitability of the different Twitter accounts allow us to gain an insight on who, if any, has advice worth taking.

Moreover, analysis on the impactful keywords that each crypto-guru uses to suggest buy/sell/hold would be useful. After all, each tweet may be subjective to one's understanding and by drawing a more definite link on the words use to suggest buy for example, would make it easier for followers how the guru determines his buys and sells.

The team understands that it is almost impossible for an individual to predict the future and the market; however, we hope our analysis will also shed some light the possibility of timing crypto-currency trades and who is best at doing so.

2. Datasets

The data we require will be in two main sets: the Tweets dataset and the cryptocurrency price dataset.

2.1 Tweets Dataset

Our analysis will first start out by choosing the Twitter accounts for analysis. The accounts we have chosen are based on some basic criteria, including the number of investment recommendations, followers, reputation in the community mentions on other social media sites, and others. We have shortlisted 5 Twitter Accounts and detailed information in the appendix.

From each Twitter account, we have scrapped tweets dating May 2017 to February 2018 using the Selenium package in R (RSelenium). The details are as following:

Variable	Type	Variable	Type
Id	String	Date	POSIXct
Permalink	String	Retweets (Number of)	Integer
Username	String	Favorites (Number of)	Integer
Tweet	String		

After crawling all tweets, each individual tweet that has been cleaned up slightly was tagged manually by us as buy/sell/neutral for machine learning model building. In order to ensure fairness, each account's tweet was split evenly to the 5 group members so as to reduce biases when interpreting the sensitivity of the tweet.

2.2 Cryptocurrency Price Dataset

The cryptocurrency prices will be gathered via the Poloniex API in R (PoloniexR). For each of the coins in mentioned in the tweets, we will extract the following variables:

Variable	Type
Timestamp	POSIXct
Price (Close)	Numeric

The data will be extracted using a 5-minute interval over the year of 2017. We will repeat this data retrieval for the subset of relevant coins mentioned in the tweets.

After scraping the tweets from the 5 accounts, we realised that there were alot of noise and redundant text that were present in the tweets, for instance href to an image that the tweeter shared. This is then removed.

2.3 Combining the Datasets

With the "buy", "sell" and "neutral" signals for each tweet ascertained, the next step was to perform the simulation to get the daily net worth of each account from May 2017 to February 2018.

3. The Analysis

The main area of interest would be the relation of the tweets (from the Twitter dataset) to the prices (from the coin prices' dataset). These two datasets can be stringed to one another via the coin mentioned in the tweet (in ways such as "$BTC" or "$ETH") and their time-stamp.

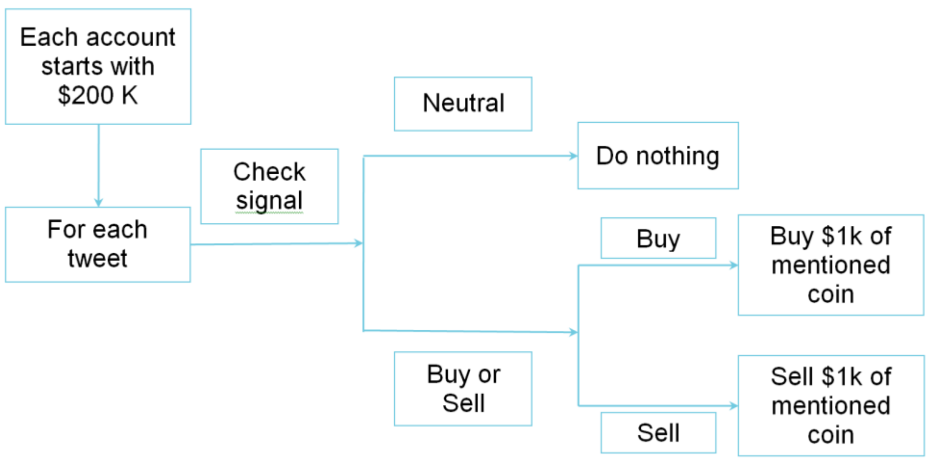
3.1 Simulation - Determining Profitability

The period of evaluation would be from May 2017 to February 2018. We chose this time frame to be as close to a year as possible since most funds are also evaluated on an annual basis. Moreover, we also believe that a year is long enough to identify any consistencies in one's trading picks. In other words, what we hope to achieve is to overlook any lucky buying and selling and focus more on long-term consistency.

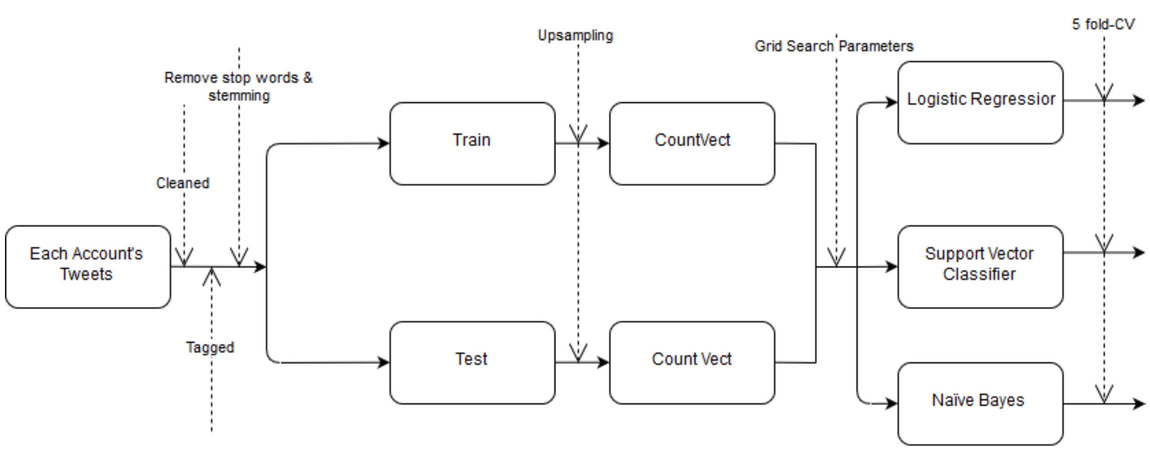
The simulation required the combining of the buy and sell signals to determine the buy and sell prices at their respective times and to determine each account's daily net worth (sum of all coin holdings + cash) at the end of the end of each day. The coin's 5-minute interval prices were used for the former while the coin's daily closing prices were used for the latter.

The following steps will be carried out for the simulation of each account's daily net worth:

1. Assume each trader (account) starts with $200,000 USD (an arbitrarily large amount)
2. With the tagged buy/sell/neutral signals of each tweet, performing each the the steps respectively:
    a. If it's a buy signal: simulate a purchase of $1,000 (USD) worth of that particular cryptocurrency at the current price (determined by looking at the time-stamp and cross-referencing it to the price dataset)
    b. If it's a sell signal: simulate a sale of $1,000 (USD) worth of that particular cryptocurrency at the current price (determined by looking at the time-stamp and cross-referencing it to the price dataset)
    c. If it is neutral: ignore
3. As the end each day of the evaluation period, tally up each account's daily net worth



3.2 Machine Learning Methods



3.2.1 Pre-Processing Methods

The tweets of crypto-gurus undergo a few cleaning and preparation processes before fitting them into models. The processes are Word Stemming, Up-Sampling, and removing Stop Words in Count Vectorizer.

3.2.1.1 Word Stemming

Using the "NLTK" package, "Snowball Stemmer" was used to stem the cleaned tweets. A stemmer was used not to distinguish words that have the same meaning but for similar verb tense. For example, words "ran", "run" and "running" would be converted in to word "run". The purpose of stemming these tweets is to convert words that are grammatically modified to be the same.

3.2.1.2 Up-sampling

Up-sampling refers to increasing the data size of the classes with lower data sizes up to the size of the class with the largest data size. To make up the difference in data size between the larger class and the lesser class, a random sampling of the lesser class' tweets is added. To perform proper up-sampling in fitting the models, in the case we use 5-Fold Cross Validation (5FCV), the following cases were considered for its use.

3.2.1.2.1 Randomization

As mentioned earlier, class imbalances are levelled using random sampling of the lower classes' tweets. Just one instance of this sampling may impose a bias on the model's learning ability of the tweets. To overcome this, we would train the model 100 times and for each time, 5FCV would be used. This is done such that each run observes a different up-sampling of the lower classes' tweets and the results obtained from the models would most probabilistically provide a comprehensive learning of the crypto-gurus' tweets.

3.2.1.2.2 Train and Test Splits

When performing 5FCV with Up-Sampling, the ordering of which there are performed is crucial. The train-test split is done before the up-sampling. This is done such that we do not pollute the train set with data that is within the test set which would contaminate the learning of the models and provide incorrect representations of the model's accuracies. Thus, to ensure independence of the train and test sets, up-sampling is performed after train and test splits.

3.2.1.3 Count Vectorizer

Count Vectorizer is a commonly used function in the Sci-Kit Learn library as a pre-processing before fitting the machine learning models. In Count Vectorizer, stop words were defined to be removed from the tweets. The stop words are defined using "Spacy" library's defined stop words. Another additional stop word, "buy", is added into the mix. As one of the classes we are predicting is "buy", the word "buy" may appear multiple times and show much significance in the machine learning models. This may not provide any new insight in our analysis and thus is removed. The words "sell" and "neutral" for their respective classes were not added as they did not provide much significance in the learning model.

3.2.2 Modelling

3.2.2.1 Linear Support Vector Machine (SVC)

SVC helps us find an optimized maximum linear split between the different classes of tweets. In this 3-class classification problem, the learner uses a “One vs All” method to perform multi-class classification. This breaks the problem into different binary classifiers which refers to the number of classes in the problem.

The parameters were optimized using “GridSearchCV” in the Sci-Kit Learn library. From a finite set of parameters used, the best ones that came out were like the default settings of the learner defined in Sci-Kit Learn.

3.2.2.2 Logistic Regression (LR)

LR allows us to probabilistically determine a class given the occurrences of the words in each tweet. Similar to SVC, LR also uses “One vs All” for multi classification problems.

3.2.2.3 Multinomial Naïve Bayes (MNB)

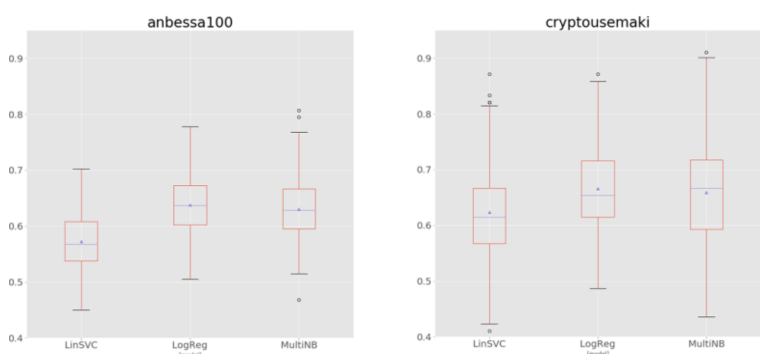
MNB applies a set of supervised learning algorithms based on applying Bayes’ theorem with the “naive” assumption of independence between every pair of features. Similar to SVC, MNB also uses “One vs All” for multi classification problems.

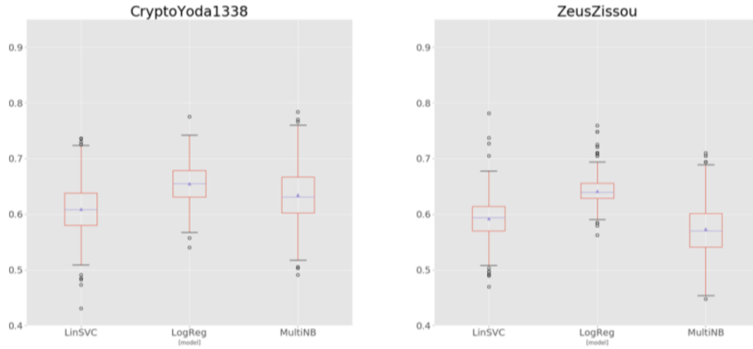
3.2.2.4 Results Capturing

For each of these models, we collated all their “coefs” parameters which provide us an idea on the importance of the occurrence of a word and its effect on the classification of the action signals.

3.2.3 Results

3.2.3.1 Basic Models





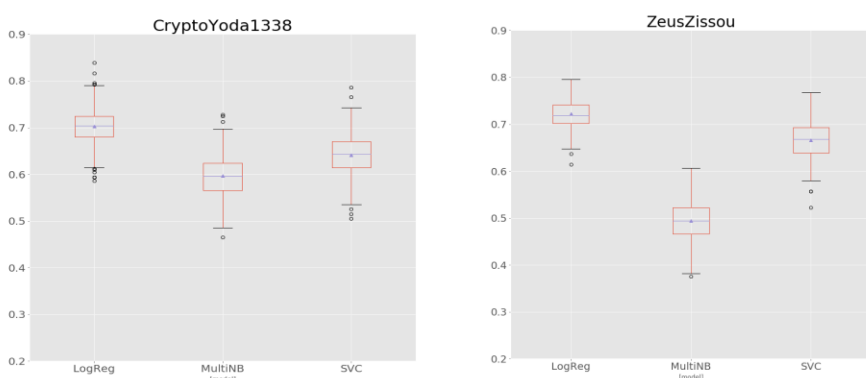
The boxplots above reflect the test scores of the 3 models used. The values considered consist of the each of the splits in 5FCV and for each of the 100 runs. As observed from these models, there is a large variance of the model's performance. In particular for the user 'Cryptousemaki', under MNB the test accuracy ranges from 0.4 to 0.9.

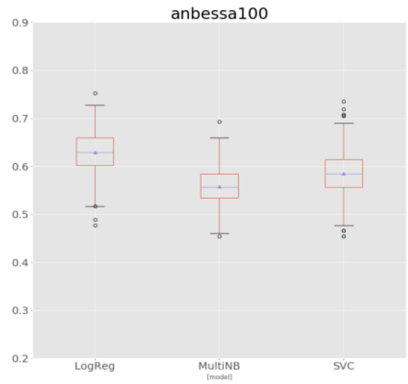
3.2.3.2 GridSearchCV

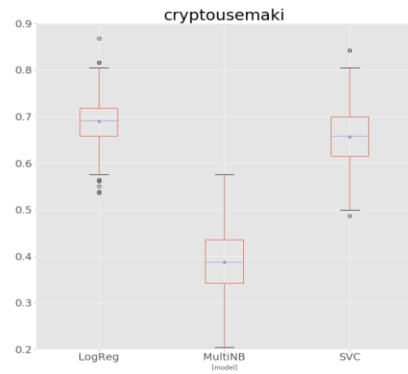
In the previous approach, the default parameters were used for the machine learning models and for Count Vectorizer with the exception of using Stop Words for Count Vectorizer. GridsearchCV is used to determine the best parameters for the machine learning models to obtain the best mean test score. The results are as shown in Appendix: Best parameters from GridSearchCV.

3.2.3.3 Best Parameters and Results

From the best Parameters (details explained in the appendix 6.2), we observe some slight differences in performance shown as the figure below. In general, the variance of the test accuracies has significantly decreased as compared to the models without tuning. Also, improvement on the mean of test accuracy can be observed from above 0.6 to around 0.7 for Logistics Regression and Linear SVC. It is important to note that although accuracies observed in this modelling have not shown much significance such as the case for the Multinomial Naïve Bayes model for user crytousemaki where test accuracy ranges from 0.2 to about 0.6. We would like to venture into the words used by these crypto-gurus to understand the words that were most frequent in predicting the corresponding signal.







4. Insights

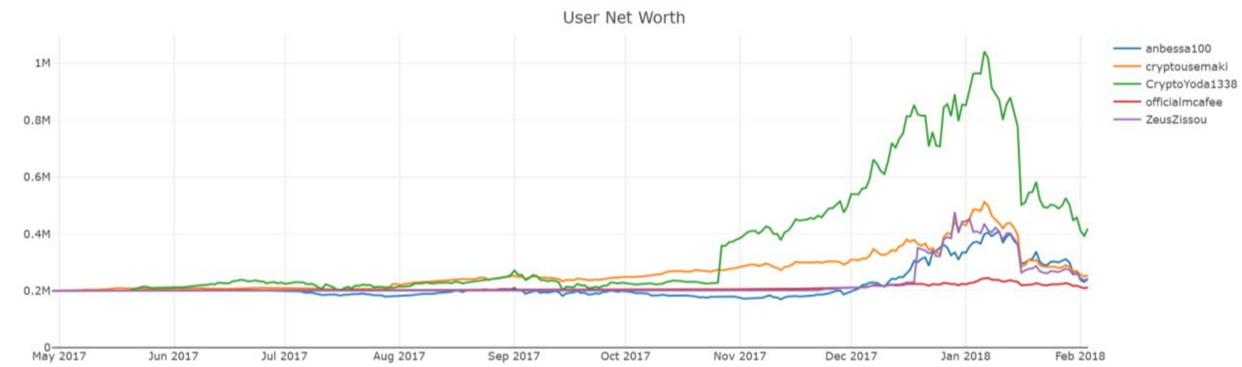
4.1 Insights from Visualisation

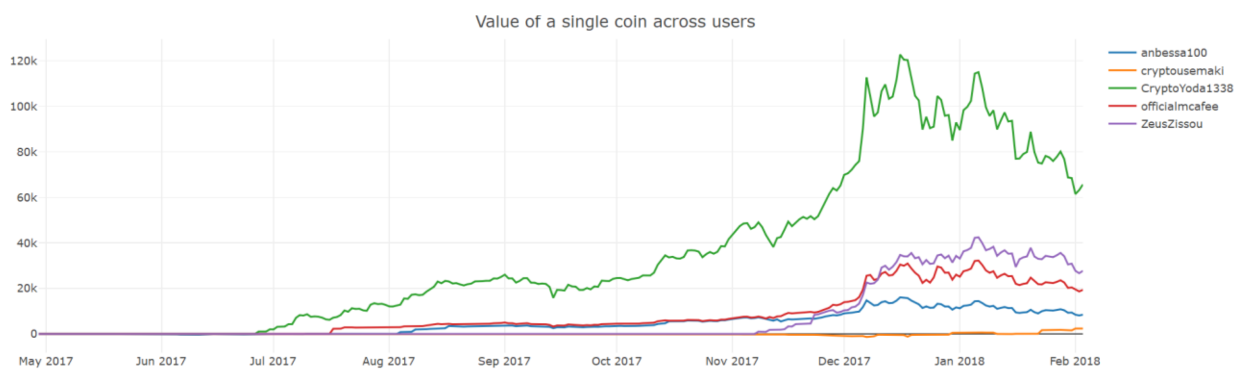
From each pundit's net worth graph (which starts off at 0.2 million), it is noticeable that following Cryptoyoda1338 would reap the most profit, even peaking at 1 million net worth at one point of time (December 2017). McAfee, on the other hand, has his net worth relatively constant at around 0.2 million. This could be attributed to Cryptoyoda1338 being a more effective trader compared to McAfee. However, the net worth is a reflection on all the coins that the user tweets about and perhaps Cryptoyoda1338 transacted with much more coins compared to the other traders. As a result, more analysis will have to be done to understand the scenario better.

Next, analysis on which coin each trader is most successful offers a different value proposition as compared to overall net worth. From our analysis, Anbessa100 is most successful with nxt, Cryptousemaki is most successful with bcc, Cryptoyoda1338 is most success with bcc, McAfee is most successful with btc, ZeusZissou is most successful with bcc too. As seen from this analysis, it seems that multiple pundits are most successful with the value of bcc. However, perhaps a side-by-side comparison of values within the coin would be helpful in determining who the best for each coin is.

After comparison across the pundits on bcc, Cryptoyoda1338 profited the most from bcc across the time period. However compared to Cryptousemaki, Cryptoyoda1338 didn't invest into bcc until quite late into the year. For btc, even though McAfee is seen to be most successful with it from the previous paragraph analysis, when compared across all 5 pundits, he loses out to Cryptoyoda1338 who earned a lot more (around 5 times). Even though the 2 examples given so far showed Cryptoyoda1338 to be effective in predicting coin prices, there are certain coins which other pundits have proved to be more effective. For example, for trx both ZeusZissou and Cryptousemaki coin valuation were a lot higher compared to Cryptoyoda1338. This shows the how each pundit has leveraged on different coins to build his net worth.

Bitcoin prices from official website: (https://blockchain.info/charts/market-price?timespan=1year)





Graphs from dashboard, they follow a similar pattern when compared to the prices from the official website. This also verify that the credibility of CryptoYoda's strategy as he buys and sells at the right time

4.2 Insights from Machine Learning

Another interesting insight would be to recognise certain keywords that these pundits use that could result in a buy/hold/sell signal. After all tweets are subjective and with a machine learning model, a more definite and concrete correlation can be made about the sensitivity of the words used. Words such as buy, sell, hold were removed in the machine learning model since these words already reveals the signals respectively. Analysis on the top 10 words used to represent each signal is tabulated.

After some analysis, the most interesting insight will be from the buy words. Since Cryptoyoda1338 has proven to be the most valued cryptoguru from our insights from visualisation, the team decided to take a look on how he fares compared to the rest.

Cryptoyoda1338:

Overall buy: look, breakout, soon, revers, level, trigger, higher, upsid, doubl, uptrend

Cryptousemaki:

Overall buy: bought, level, befor, usd, retrac, bullish, masternod, coin, rsi, fomo

Anbessa100:

Overall buy: high, undervalu, anticip, bought, imo, babi, cheap, boun, hodl, good

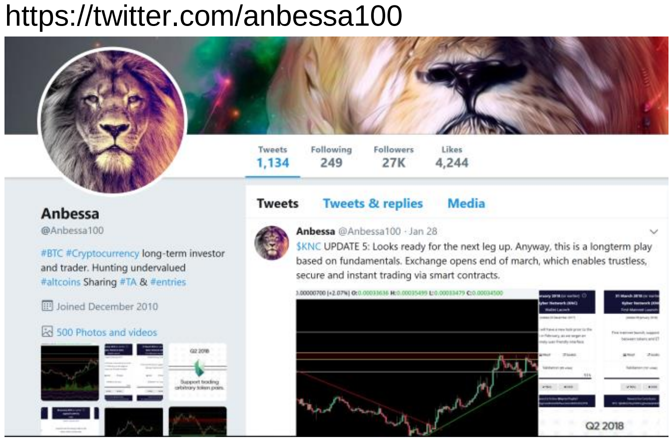
From the examples given, Cryptousemaki and Anbessa100 uses emotive words such as “fomo” (fear of missing out) and “imo” (in my opinion) compared to Cryptoyoda1338 who uses more technical terms such as revers/trigger. This is inline what we already know that a more objective trader is better in predicting cryptocurrency movement compared to “gut feel”/more subjective traders.

5. Conclusion

To sum it all up, logreg is the best model in terms of accuracy score for classifying tweets into “buy”, “neutral” or “sell”. Cryptoyoda1338 seems to be the best crypto-guru to follow for most of the cryptocurrencies and his list of words which implies each signal has been analysed by the team. Once again to re-emphasise, the team is not trying to predict the prices of cryptocurrency and through our analysis, the team has managed to gain better insights on what is going inside the minds of these crypto-gurus. Most importantly, even though John McAfee makes a big claim about his confidence on bitcoin, following him does not bring about much value in terms of crypto-trading since his tweets were largely neutral/irrelevant towards crypto-trading.

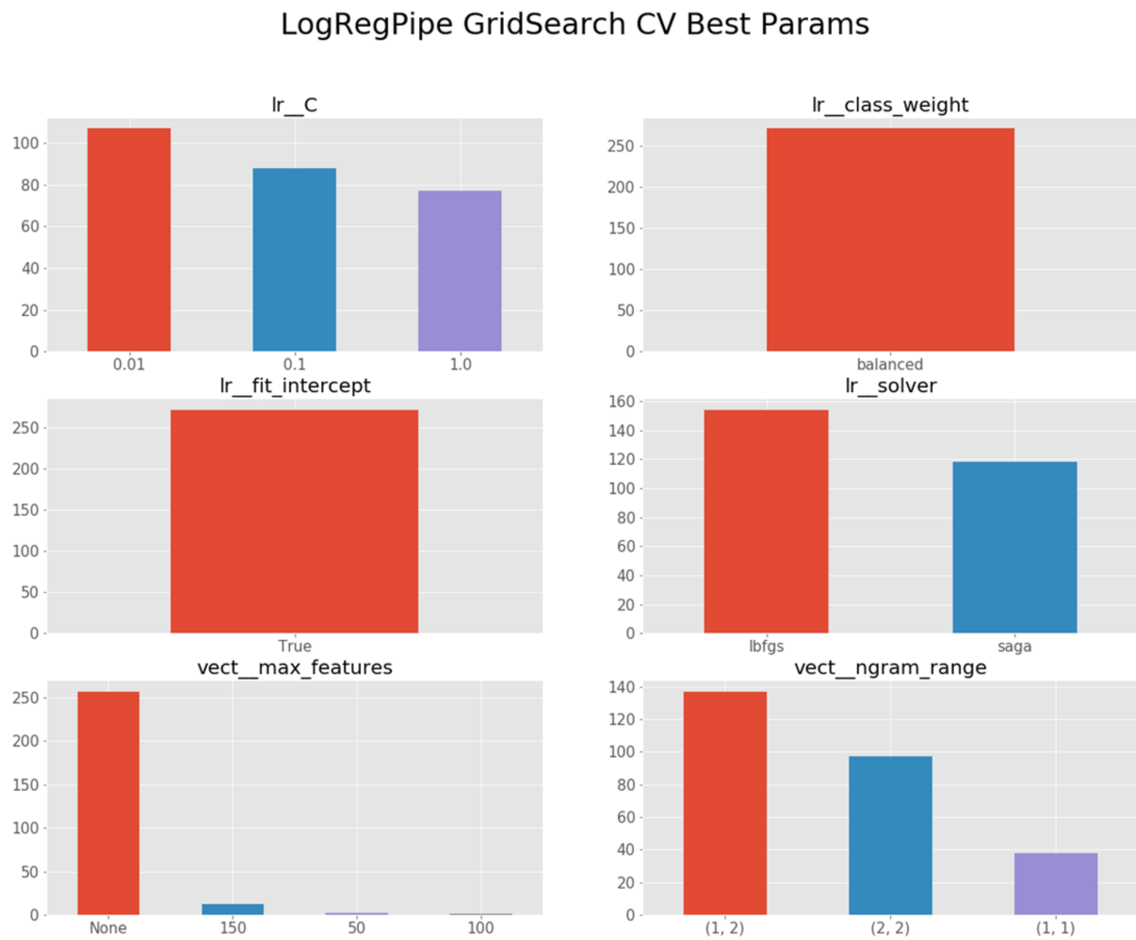
6. Appendix

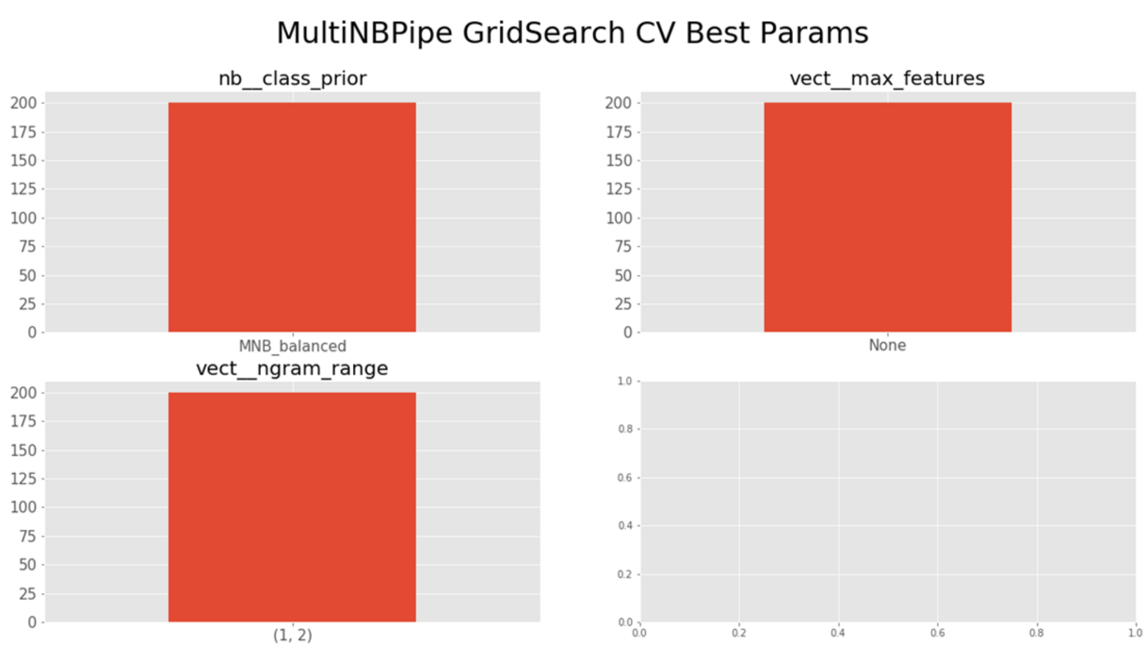
6.1 Twitter Accounts

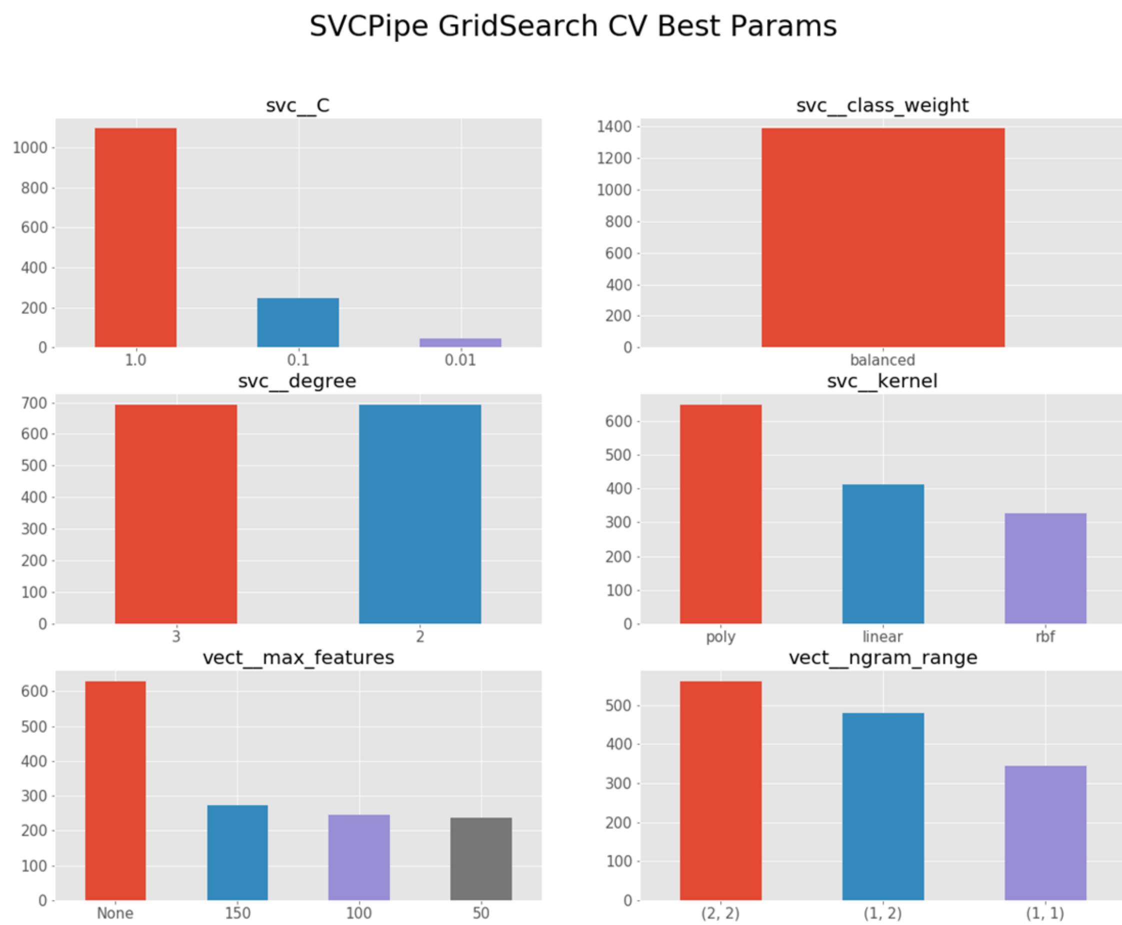
User	Details	Rationale
CryptoYoda	https://twitter.com/CryptoYoda1338 	Most reputable in the cryptocurrency recommendation community
John McAfee	https://twitter.com/officialmcafee 	Most notable, perhaps controversial
Anbessa	https://twitter.com/anbessa100 	Great recommendation performance shown by steemit post
Cryptousem aki	https://twitter.com/cryptousemaki	Bitcoin and altcoin trading analyst. Has a

		relatively smaller following compared to the rest
ZeusZissou	https://twitter.com/zeuszissou 	A trader that does not let his emotion dictate a trade, has a huge following and made many good calls previously. Analyst at USC group which provides paid trading advice.

6.2 Best Parameters from GridSearchCV







Grid Search Best Parameters

Model	Parameters	Value
Logistic Regression	C	0.01
	class_weight	balanced
	fit_intercept	True
	solver	lbfgs
Logistic Regression's CountVectorizer	max_features	None
	ngram_range	(1,2)

Multinomial Naïve Bayes	class_prior	balanced*
Multinomial Naïve Bayes' CountVectorizer	max_features	None
	ngram_range	(1,2)
Support Vector Classifier	C	1
	class_weight	balanced
	kernel	linear
Support Vector Classifier's CountVectorizer	max_features	None
	ngram_range	(1,2)

6.3 Top 10 words from Word Cloud

Comparison between results without GridSearchCV parameters with results using GridSearchCV parameters

For all pundits:

Overall buy: level, look, bought, breakout, dip, high, good, close, bull, befor

Overall sell: stop, profit, escap, got, leg, incom, crash, doe, price, far

Overall hold: bitcoin, chart, need, amp, new, btc, market, price, use, trade

Vs

Overall buy: look, high, rsi, bought, breakout, dip, level, higher, stoch, support

Overall sell: stop, escap, loss, got, price, profit, valu, doe, current, hamp

Overall hold: market, bitcoin, amp, new, chart, price, trade, use, crypto, time

Anbessa100:

Overall buy: high, undervalu, anticip, bought, imo, babi, cheap, boun, hodl, good

Overall sell: escap, far, pullback, hamp, came, exit, hope, journey, accumul, market

Overall hold: new, worth, amp, breakout, break, soon, ethereum, billion, marketcap, daili

Vs

Overall buy: imo, high, dip, nice, bought, support, good, look, iter, split

Overall sell: escap, hamp, downtrend, price, pullbak, far, moon, level, hope, mayb

Overall hold: market, amp, breakout, resist, updat, break, chart, new, start, soon

Multinb buy: good, high, imo, bought, bounc, nice, alreadi, hold, longterm

Multinb sell: moon, hamp, support, resist, expect, price, escap, volum, manag, fund

Multinb hold: amp, breakout, updat, break, soon, new, chart, look, market, like

Vs

Multinb buy: good, support, dip, imo, high, nice, look, bought, strong, expect

Multinb sell: hamp, moon, escap, price, return, fund, rsi, probabl, downtrend, far

Multinb hold: amp, resist, updat, breakout, chart, market, break, soon, volum, new

LinSVC buy: undervalu, cheap, lil, babi, dot, right, anticip, sunday, escal, gbytebtc

LinSVC sell: escap, far, came, exit, pullback, grab, journey, accumul, hope, declin

LinSVC hold: worth, ethereum, launch, investor, need, guess, job, rent, marketcap, attent

Vs

LinSVC buy: worth, far, launhc, goe, alway, prior, daili, touch, doesn, care

LinSVC sell: escap, exit, pullback, let, level, came, grab, far, mayb, journey, enjoy

LinSVC hold: market, total, downtrend, price, littl, accumul, check, declin, hope, continu

Logreg buy: high, good, undervalu, babi, cheap, anticip, mil, dot, bought, hold

Logreg sell: came, exit, far, hamp, hope, pullback, escap, market, journey, continu

Logreg hold: billion, becom, purpl, daili, new, ascend, ethereum, money, onli, marketcap

Vs

Logreg buy: good, imo, iter, split, high, bought, dip, nice, bounc, undervalu

Logreg sell: escap, downtrend, hamp, price, moon, far, level, hope, exampl, expect

Logreg hold: updat, amp, start, target, money, new, best, bag, market, like

Cryptousemaki:

Overall buy: bought, level, befor, usd, retrac, bullish, masternod, coin, rsi, fomo

Overall sell: profit, got, stop, revers, incom, die, becaus, fill, alreadi, greed

Overall hold: use, onc, price, btc, ath, pampit, pump, watch, hodl, bitcoin

VS

Overall buy: stoch, rsi, bought, coin, befor, level, daili, good, pampit, let

Overall sell: stop, loss, got, profit, cloud, fill, set, dump, short, revers

Overall hold: bitcoin, use, btc, price, market, onc, ath, amp, let, watch

Multinb buy: level, bought, stoch, rsi, befor, daili, coin, target, order, entri

Multinb sell: stop, profit, loss, got, cloud, fill, let, dump, set, short

Multinb hold: bitcoin, use, amp, market, price, btc, new, time, alt, watch

VS

Multinb buy: level,bought, daili, coin, rsi, stoch, befor, start, good, target

Multinb sell: stop, loss, got, profit, cloud, short, set, fill, dump, airdrop

Multinb hold: market, price, bitcoin, use, amp, btc, time, let, new, watch

LinSVC buy: level, retrac, usd, definit, masternod, bullish, bought, disgrac, usdbtc, upsid

LinSVC sell: stop, profit, incom, revers, die, becaus, greed, alreadi, welcom, got

LinSVC hold: pampit, onc, pump, ath, btc, price, permabul, great, near, use

VS

LinSVC buy: pampit, let, price, ath, great, onc, permabul, near, btc, strong

LinSVC sell: revers, die, alreadi, stop, runat, becaus, greed, got, incom, rektfest

LinSVC hold: bitcoin, profit, welcom, short, bull, cash, hour, enoughsold, decid, direct

Logreg buy: bought, level, befor, usd, retrac, shitcoin, fomo, bullish, line, coin

Logreg sell: stop, profit, got, incom, revers, die, becaus, alreadi, fill, greed

Logreg hold: use, onc, price, pump, ath, pampit, watch, hodl, btc, trade

VS

Logreg buy: rsi, stoch, level, bought, befor, coin, order, good, fomo, daili

Logreg sell: stop, loss, set, profit, got, cloud, dump, fill, short, incom

Logreg hold: use, bitcoin, btc, onc, price, ath, market, hodl, signal, exchang

Cryptoyoda1338:

Overall buy: look, breakout, soon, revers, level, trigger, higher, upsid, doubl, uptrend

Overall sell: leg, crash, lower, brutal, view, ain, mistak, instead, rebound, preceed

Overall hold: crypto, observ, btce, futur, interest, bitfinex, wedg, time, chart, dash

VS

Overall buy: higher, breakout, trigger, revers, high, entri, upsid, low, look, amp

Overall sell: leg, dow, drop, crash, instead, mistak, hold, lower, think, trader

Overall hold: bitcoin, crypto, year, money, time, trade, interest, market, chart, new

Multinb buy: high, higher, trigger, breakout, revers, retest, low, look, entri, break

Multinb sell: leg, trend, amp, think, lower, potenti, trader, drop, crash, price

Multinb hold: bitcoin, crypto, time, chart, trade, year, market, new, interest, money

VS

Multinb buy: breakout, high, higher, revers, trigger, amp, retest, low, entri, look

Multinb sell: crash, drop, lower, leg, think, trader, convic, mainstream, altitud, dow

Multinb hold: bitcoin, market, crypto, time, chart, trade, year, new, interest, money

LinSVC buy: chase, instabuy, probabl, perspect, ltc, look, level, doubl, soon, uptrend

LinSVC sell: ain, brutal, view, preceed, similiar, instead, mistak, lower, rebound, crash

LinSVC hold: btce, observ, bitfinex, futur, usdt, wedg, dash, buyin, moment, veri

VS

LinSVC buy: observ, btce, interest, future, wedg, usdt, ani, polo, second,nutshel

LinSVC sell: leg, mistak, stop, dow, instead, incom, hold, pattern, vix, add

LinSVC hold: ain, brutal, crash, preceed, similiar, rebound, lower, view, liquid, major

Logreg buy: trigger, look, soon, level, develop, upsid, uptrend, doubl, technic, way

Logreg sell: crash, leg, brutal, view, ain, instead, mistak, preceed, similiar, rebound

Logreg hold: crypto, interest, observ, futur, btce, case, posit, bitcoin, wedg, coin

VS

Logreg buy: higher, breakout, trigger, revers, upsid, entri, look, low, break, high

Logreg sell: crash, leg, mainstream, lower, drop, mistak, potenti, dow, rebound, instead

Logreg hold: bitcoin, crypto, money, year, futur, interest, coin, best, peopl, trade

ZeusZissou:

Overall buy: dip, close, look, time, bull, huge, cloud, breakout, div, eye

Overall sell: valu, denial, mustread, doe, calm, abc, sold, sourc, current, cure

Overall hold: need, chart, ask, amp, btc, tether, edit, bimpress, bitcoin, profit

VS

Overall buy: close, bull, look, time, dip, div, bullish, huge, volum, cloud

Overall sell: valu, doe, scale, current, lose, transfer, credit, mustread, resist, sell, denial

Overall hold: need, bitcoin, amp, profit, market, like, chart, new, holder, ask

Multinb buy: close, bull, look, dip, bullish, time, div, cloud, breakout, huge

Multinb sell: doe, scale, peopl, current, resist, valu, bitcoin, credit, short, crisi

Multinb hold: trade, amp, need, chart, market, best, stop, exchang, bitcoin, profit

VS

Multinb buy: bull, look, close, time, support, volum, dip, bullish, hge, cloud

Multinb sell: doe, scale, valu, current, financi, sell, credit, hors, bankrupt, resist

Multinb hold: bitcoin, trade, amp, market, like, new, need, chart, best, exchang

LinSVC buy: bulljuic, dipbuy, bitstamp, shkreli, brb, dip, korea, rise, list, hypothesi

LinSVC sell: abc, calm, denial, mustread, hepat, credibl, sourc, sold, cure, lose
LinSVC hold: need, bimpress, edit, tether, myspac, baller, mega, proceed, margin, ask

VS

LinSVC buy: need, edit, bimpress, myspac, baller, mega, tether, adjust, proceed, analyst

LinSVC sell: denial, mustread, reach, sourc, credibl, hepat, cure, abc, calm, lose

LinSVC hold: holder, current, doe, human, onli, import, credit, massiv, price, dos

Logreg buy: close, dip, bull, look, huge, cloud, moar, soon, div, time

Logreg sell: denial, mustread, holder, calm, abc, doe, value, sold, cure, sourc
Logreg hold: need, ask, chart, trader, ema, btc, profit, discount, cryptocurr, bitcoin

VS

Logreg buy: bull, look, close, div, dip, huge, time, cloud, rsi, bullish

Logreg sell: doe, current, valu, scale, credit, sell, transfer, resist, price, lose

Logreg hold: need, profit, ask, trader, cryptocurr, bitcoin, chart, order, btc, twitter