Bitcoin Investment Strategies Based on Google Trends and AI Models

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The evolution of the price of bitcoin has captured the attention of analysts in recent years. But how can a cryptocurrency be valued? Given that the price is linked to expectations, we propose, in this paper, to predict the trend of bitcoin using Google Trends as an explanatory variable. To do so, we develop two alternative algorithmic trading systems that buy or sell bitcoin depending on whether the searches for this term in Google increase or decrease. The approach is powered using artificial intelligence. The results of these trading systems are positive and show that trading strategies can be implemented based on investors’ mood about an asset, in this case measured through Google Trends. The use of artificial intelligence in trading is new and this is an example of its potential.

Keywords: bitcoin, investors’ mood, Google Trends, artificial intelligence, algorithmic trading systems.

Currently stock-exchange studies are improving due to the incorporation of new technological tools. Those tools are used to predict the evolutions of quotes in different stock markets. This development appears because of internet which is creating new habits in the users. For instance, one of the Google services “Google Trends” has a significant advantage over traditional surveys. The efficiency of Google trends is based on several reasons such as geographical location, the classification in different categories, timeline, etc. (Gómez, 2013). This analytical tool complements the information provided until now in
the stock-exchange speculation, for example, by surveys of consumer confidence (Lemmon and Portniaguina, 2006).

The aim of this investigation is to analyse the use of Google Trends to predict the variations on the price of the bitcoin (BTC). To obtain that prediction, we test the correlation between the bitcoin price and the volume of researches made in Google of the term ‘bitcoin’. If this correlation is positive and significant, it is believed that is a valid predictor about the evolution of the bitcoin. Form this point, different trading systems can be designed.

CONCEPTUAL FRAMEWORK

Harding and He (2011) analysed and proved that investors who are in a good mood are more likely to take risks while investors who are in a bad mood are less risks tolerant. If we accept that investors’ mood influences on the financial investment decisions then a new challenge is created, which is how to measure the investors’ mood and how to relate that with the matter of the study (Kahneman and Tversky, 1979).

Many reports relate the mood variations with several causes. One of them are known as “Halloween effect” or “sell in May and go away” studied by Bouman and Jacobsen (2002) which analysed the profitability of several countries during May to October and compared that with the rest of the year. Bouman and Jacobsen justified that there is a significant and positive relationship between the period of the year and the investment activity (Andrade et al., 2013) due to summer holidays. On their own, years later, Dichtl and Drobetz (2015) made the same research and they proved that the effect “sell in May and go away” has no longer the same effect as years before.

Another pattern highly recognised and studied is the “January effect”. Depending on the behaviour of that month there are more likely to perform during the year to come (Kim, 2016). In case that the month of January has “negative returns” it proves weakness which means that the year might have low return. On the other hand, in case of January having “positive returns” the year is more likely to have high remuneration (Sharman and Deo, 2014). This relationship is based on a number of premises studied by Seyhun and Nehat (1998): psychological factors (e.g. investing in January gives us the chance to rectify errors in case of lost) legal factors (e.g. during the month of January usually the pensions mutual funds shown an increase), the end of the year (which caused the shortening of the sessions and the decisions plan are more likely to be delay until the month of January) or other factors related with the budget (e.g. liquid assets give money to their traders in order to invest and start once again.)

In addition, it is proven that there are several different ways to predict the evolution in the stock-markets rather than look in the calendar. Hirshleifer and Shumway (2003) claimed that mornings with clear sky conditions have a positive effect on the stock indexes. The profitability of the sessions when the sky is clear, and the sun is shining in New York is 24,8%, whereas if the sky is cloudy
the average is 8.7%. Yuan et al. (2006) are studying how the phases of the moon affects the trading performances in around 48 countries.

Even more, various investigations relate sports results with trading evolution due to the investors mood. Sports such as basketball, football, American football, rugby and cricket (Verstoep et al., 2015) are being studied in order to predict the evolution on the stock market. That is caused because sports results have a significant influence on our state of mind. Consequently, mood is also affected, and the evolution of the markets depends on the investor’s feelings. (Edmans et al., 2007). Berument and Ceylan (2012) analysed how matches of the national teams of United Kigdomn, Tukey, Spain and Chile affect in the performance of the financial market by means of the social mood of their populations. Another studies (Gómez and Prado, 2014b) carried out a similar research in which they studied 8 stock indexes the day after the national teams matches between the years 1992-2012. The conclusion of the report was that if the result of football national team is positive (a victory) the stock index raises the day after the match, on the other hand if the result is negative (a defeat) the index drops.

Currently the technological evolution is provided new tools (internet, social network, mobility, etc) and new lines of action which might be applied to investors’ mood investigation and the relationship between mood and stock prices. Other studies analysed the relationship between the messages published on Twitter and the evolution in Spanish stock market (Gómez et al., 2017). Using Stockbuzz (an initiative of BBVA innovation centre) tweets are analysed using natural language algorithms to show investors’ mood. One of their conclusions is that Twitter is a valid tool to generate investment alerts. Gerow and Keane (2011) studied the relationship between several words named in press and their correlation to the market. Another approach uses Google Trends as an indicator of the investors mood and their relationship with their risk tolerance (Gómez, 2013). As a result, a risk aversion index is obtained, an index generated by the volume of searches made in Google of some economical and financial terms which are correlated with the market evolution. This paper supports the idea that the statistics of searches provide relevant information about the evolution of the main stock indexes. Therefore, if the risk index increases it is expected that the profitability drops and vice versa.

Numerous researches are focusing their efforts on the predictive analysis with Google Trends because it is proved to have predictive capabilities, for example to measure the evolution of entrepreneurship (Gómez et al., 2015). Rose and Spiegel (2012) studied the liquids assets of the dollar. Vlastakis and Markellos (2012) analysed NYSE and NASDAQ. McLaren and Shanbhogue (2011) considered the evolution of the labour and the property market in Great Britain and other works that also confirmed the utility of Google Trends (Gómez and Prado, 2014a; Graefe and Armstrong, 2010; Moussa et al., 2017, etc.).

Therefore, if Google Trends can be applied to predict the evolution of stock prices, then this relationship could be also applied to the bitcoin price. The bitcoin (BTC) is a “virtual currency” which was born using a system described in Nakamoto (2008). In which it is explained as an “effective system step by step” thanks to a various number of algorithms. The bitcoins are given and generated for
the computer users which can resolve pre-established cryptographical problems. Yermack (2015) specifies that problems turn more difficult and less frequent with time. Nakatomo (2008) analysed as well possible problems and weaknesses of the actual electronical payment system and identified their expensive costs as well as a defence against this new system. The bitcoin is closer to a speculative active rather than to a traditional currency. In fact, this is created because of the unknowledge around the bitcoin. Blau (2018) claims that speculation could damage the bitcoin as a common currency.

**METHODOLOGY**

The purpose of this study is to analyse if the volume of searches of the term ‘bitcoin’ in Google is a valid predictor for bitcoin’s price, assuming that Google Trends are a thermometer of the investors interest on bitcoin. We assume that investors go to Google to answer questions about investing in this asset. As a result, the volume of searchers increases which means that this certain term is raising the awareness of the investors just like Blackwell, Miniard and Egel exposed in 2005. Must be kept in mind that Google is the principal searcher on the internet with around 85% of the internet search traffic. Google Trends record the searches made by the users, it monotonize them and provide statistics for free.

Therefore, in this study we assume that the process of finding information about bitcoin investment follows this flow:

1. The investor is thinking about investing in Bitcoin (probably because the very high returns observed in the past) and wants to learn more about how to invest in this asset.
2. The investor collects information about this investment on the Internet.
3. From the information collected, the investor evaluates the different investment alternatives, for example, direct investment through an “exchange”, investment through derivatives such as futures or ETFs.
4. If the information collected meets the needs of the investor, then he decides to invest.
5. Once the investment has been made, the investor continues to search for information by monitoring it.

Therefore, if this workflow is correct, the more information sought, the more bitcoin purchases will be made and therefore the higher its price will be.

As we notice in Figures 1 and 2, we can verify that searches around the term ‘bitcoin’ are deeply related to the bitcoin price. It is shown that the increase of Google searches corresponds to a price increment.

Figure 1 shows a scatter graph that relates the price of bitcoin in US dollar (downloaded from www.investing.com) versus the volume of Google searches for the term ‘bitcoin’. We see in the regression line of the graph that there is a clear positive and statistically significant relationship.
According to this positive relation, Figure 2 shows both time series graph, on primary and secondary axis, and its similar evolution.

As this relationship is positive and statistically significant, we might assume that Google Trends is an accurate predictor for the evolution of bitcoin’s price. From this point we will simulate alternative trading systems based on Google Trends between February 2018 and July 2018 in a prospective way. The trading systems created follow the following definition:

**Figure 2. Evolution of the BTC price related to the Google searches of the term ‘bitcoin’**

Source: Own research from Google Trends and <www.investing.com>.
**Simple Trading Systems**

This system uses exclusively the Google Trends of the ‘bitcoin’. Consequently, the common trading systems based on technical analysis are not use at all. If the searches of the word ‘bitcoin” increases, we will simulate a long position in the bitcoin for the next week, whereas if the searches decreases, we will open a short position. From this point, we propose two alternative trading systems:

1. **Long/short system:** If the Google searches increases it opens a long position and if Google searches fall it opens a short position. On the other hand, if the searches stay in the same level the system will stay out of the market.
2. **Swing system:** It persistently stay in the market long (if the searches increased) or short (if the searches drop) as long as an opposite signal does not appear.

**Artificial Intelligence Systems**

An artificial intelligence model might be created using not only Google Trends of the term ‘bitcoin’. We will add predictors of another economic terms that had been search on Google. Since the historical available (Google Trends provides weekly statistics for 5 years and monthly since 2004) we might train two artificial intelligence (AI) models based on Bayesian networks. These models will predict the evolution of bitcoin (up or down) for the next period and we will simulate a long or short position in the future of bitcoin.

The process followed by this trading system is:

1. Download the historical series form Google Trends.
2. Train the AI models (with weekly and monthly frequency)
3. Prediction of the next week/month evolution (up or down)
4. Simulation of the strategy taken (long/short)
5. Result validation
6. Starting over the first point.

Just like in simple system we propose two systems of trading:

1. **Google Trends Weekly System:** It is simulated in the future bitcoin market the prediction of the weekly model.
2. **Google Trends Combined System:** It is simulated in the future market using the weekly prediction only if it is the same as the prediction generated by the monthly model. In case of discrepancy it will stay out of the market.
HYPOTHESIS

The hypothesis we try to prove is:

$H_0$: Google Trends is a valid predictor for the evolution of the bitcoin price.

The hypothesis will be validated thanks to the trading systems already described. If these systems are profitable in a long short context, we will accept the hypothesis of this research. In addition, we might be able to compare the performance of the different systems designed to choose the better one.

DATA

The data obtained from Google Trends statistics to train the models are available in a weekly base for the last 5 years. All the historical data of Google Trends, data from 2004, are presented in a monthly base.

The prospective analysis starts in February of 2018, date when the first AI model was trained, and ended on June 2020.

The statistics of this research had been downloaded from the Google Trends webpage <https://trends.google.com>, and the bitcoin prices have been downloaded directly from Investing webpage <www.investing.com/>. The decision to use this financial portal for bitcoin prices is based on the fact that it is one of the most used globally, which has been the first to develop a specific section for cryptocurrencies as an emerging asset and, undoubtedly, because it is gratuitous.

RESULTS

Figure 3 shows the evolution of the prospective validation of the Simple Trading System. On the graphic we can observe the long/short method as well as the swing method. Those systems only use as a predictor, the level of Google searches made of the term ‘bitcoin’.

We noticed that during the prospected period analysed the bitcoin has experienced a gross profit of $905 for each bitcoin, a 11% return. On the other hand, the strategy long/short has record a positive result of $1.196,60 a 14% return. The swing strategy is the most profitable of the three strategies which has obtained $4.630,70, that is a return of 54%.

Regarding to success ratio of the predictions of the systems, we noticed that the strategy Long/Short has opened position the 70% of the prospecting weeks, achieving a 51% success rate, while Swing strategy has open position 100% of the prospected week (as it was defined) achieving a 52% success rate. The profit factor of the Long/Short System is 1,05 dollars for every missed dollar while the Swing System has obtained 1,14 profit ratio. These Simple Trading Systems are profitable as they present over a 50% success rate and over a 1 profit factor.
Figure 3. Profit and loss evolution of the simple sand AI trading systems on BTC

Source: Own research.

The algorithms used for the creation of the IA models of this paper belong to the IT company Apara\textsuperscript{1}. Those are implemented in their data-mining platform dVelox, which is the first data-mining platform developed in Spain.

The workflow that has been developed in dVElox for the training of artificial intelligence models follows the following steps, as shown in Figure 4:

1. Home
2. Read the data of a flat file that has been prepared from the sources described above.
3. Columns with irrelevant data (such as date in dd / mm / yyyy format) are removed
4. The series is discretized
5. The IA model is trained. In Figure 5 we appreciate one of the Bayesians networks trained for the artificial intelligence systems.

The second branch of the workflow of Figure 4 follows the same steps but in step 4, instead of training, the already trained model is validated to check its predictive capacity retrospectively. In this case, this validation has not been used, since a prospective analysis that is considered more adjusted to reality has been preferred.

\textsuperscript{1} For more information visit <www.apara.es>.
Using that model and following the strategy already explained, we observe in Figure 3 the evolution of the artificial intelligence trading algorithmic system. It is noticed that the Google Trends IA Week System which follows the predictions of the AI model has had a positive result of $17,100.70, which means a profitability of 199% not annualised. On the other hand, the combined model has performed a better result of $14,133.10, and a return on investment of 165%, because this strategy stays out of the market the weeks that there was no match between weekly and monthly AI prediction. The success ratio of the AI weekly system is 56% whereas the combined model has reached the 58% with a profit factor of 1.71 and 2.37 respectively.

**Figure 4. dVelox Workflow for training IA models**

![dVelox Workflow for training IA models](source)

**Figure 5. Bayesian network trained with dVelox to predict the bitcoin evolution**

![Bayesian network trained with dVelox](source)
Table 1 sums ups the performance of the different trading systems proposed compared with bitcoin’s return.

<table>
<thead>
<tr>
<th>Trading System</th>
<th>Return</th>
<th>ROI</th>
<th>Success rate</th>
<th>Profit Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bitcoin</td>
<td>$904,90</td>
<td>11%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Long/Short</td>
<td>$1,196,60</td>
<td>14%</td>
<td>51%</td>
<td>1,05</td>
</tr>
<tr>
<td>Swing</td>
<td>$4,630,70</td>
<td>54%</td>
<td>52%</td>
<td>1,14</td>
</tr>
<tr>
<td>IA Weekly + Monthly</td>
<td>$14,133,10</td>
<td>165%</td>
<td>58%</td>
<td>2,37</td>
</tr>
<tr>
<td>IA Weekly</td>
<td>$17,100,70</td>
<td>199%</td>
<td>56%</td>
<td>1,71</td>
</tr>
</tbody>
</table>

Source: Own elaboration.

**CONCLUSIONS**

An enterprise could be valued by the cash flows or by the estimation of how many dividends this company might generate in the future, as a result we can consider if the enterprise is overrated or underrated. From this point, we can plan and define our investment strategy. However, currencies and raw materials do not generate cash flow so the theoretical price estimation is much more complex. Nevertheless, there are certain variables that might determine the evolution of its price, for example the interest rates, the variation of production, political decisions, etc. Nonetheless, what do we have in cryptocurrencies that might help us to predict and estimate its price? Do we only have the investors’ mood as a tool?

Following that reasoning, in this research we propose to take investment decisions about the bitcoin evolution by using exclusively investor’s mood metrics, in this case statistics provided by Google Trends in the financial category. The hypothesis we have explored in this paper is if Google Trends is a valid predictor for the evolution of the bitcoin price.

Following this approach, four long/short trading systems, two of them simple and another two using Artificial intelligence has been created. All of them obtained positive returns in a prospective simulation. With those results the hypothesis of this study have been proved and the objective of the paper fulfilled.

Above all the systems proved, the ones that had obtained more profitability had been the algorithmic trading systems based on AI models which used as predictor the Google Trends of certain economical and financial terms plus ‘bitcoin’ and ‘cryptocurrency’.

In this study it is proven that Google Trends is a solid predictor to anticipate the evolution of financial active prices, in this case the bitcoin. Also, it is confirmed that artificial intelligence can manage different investment strategies using the investors’ mood, with no other component. The results prove as well
that those AI systems generated positive outcomes in bullish contexts as well as in bear moments.

Therefore, a new research field is open. On the one hand, it must cover the own limitation of the studied asset that is new and has a reduced history. On the other hand, research should be done on the algorithmic trading systems developed, to make them more efficient and to generate better returns with better risk control and therefore higher Sharpe ratios. Furthermore, this research could be extended to other cryptocurrencies, comparing the different expected returns.

To continue with this research, InvestMood Fintech\(^2\) has been created, the first Quant Advisor in Spain that proposes as a differential value the use of big data, artificial intelligence and investor sentiment as analysis tools, as an alternative to traditional technical analysis and fundamental. On its website the reader can find information and data on this and other developed models.

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\(^2\) For more information visit <http://www.investmood.com/>.

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