Proving Bitcoin's Relation with Crime and Google Trends

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***Abstract*— Google Trends and cybercrime rate are investigated against Bitcoin price to see if they follow a correlation between each other. Different from other findings, trying to find if crime rate has a relationship of when Bitcoin goes up in price. With the evolution of the internet into Web 3.0 cryptocurrency are being used more and more making money more digital then ever. So, with the increase prices of Bitcoin and increase rate of cybercrime do these cause each other. Google Trends shows how popular something ~~through~~ society during time periods. This leads to more people using and taking advantage of the trend. The more Bitcoin became popular and higher in price does cybercrime increase at the same rate.**

Keywords—Google Trends, Cybercrime, Web 3.0, cryptocurrency, and Bitcoin.

I. Introduction

As stated by Nakamoto [11] the creation of Bitcoin in 2009, the market of cryptocurrencies was open to the public. When it started to become more popular throughout society, the usage of it became more and more vast. Bitcoin started where you could buy a pizza with it, and now has turned into buying cars, black market items, and even buying a house with Bitcoin. The popularity of Bitcoin created new things that can be done on the internet and what could be bought.

With the dynamic invention of this new currency, it changed the internet permanently. This influenced how our economy is conducted today. Also due to how close knit the internet is with society it also has changed some societal norms like how most money is digital now a days. Bitcoin being held in a digital wallet; it has also created more theft through the online space. These changes have led to more theft than in previous years. Also, with the creation of social media there is more trackable information available throughout society.

With Google Trends [8] being available to the public there is a relation that can be compared in the increase of price of Bitcoin and other cryptocurrencies. Also, it can be related to databases of the increase of cyber-crimes. With the ever-changing scope of currencies and online transactions, there must be a link between popularity of the currency, price, and the number of crimes that is committed due to those relations. Many researchers have found that the correlation between social media and cryptocurrency is apparent but is there a relation that can be tested with a neural network between popularity of search history, cybercrime rate and price. Some questions that have not been asked are what relation cybercrime has with Bitcoins popularity, how has does popularity of the coin effect its price, and does the popularity effect the amount of cybercrime that has occurred. Dimov [20] studies about cyber-attack called crypto jacking he found that the systems are getting hacked used for mining because they need high GPU for mining.

fix

This paper will have the following format, in related work it will go other the groundwork for the following experiment that will follow, in Section 3 we describe the methodology of the experiment and the results, in Section 4 we describe the threats of validity that our experiment would have , in Section 5 we describe the future works that can expand this experiment if time was plausible, in Section 6 we describe the conclusion of the study of our experiment. The questions that we will strive to answer during our experiment:

RQ1: To find the correlation between Google Search Trends and Bitcoin Price?

RQ2: To find the correlation between Crime and Bitcoin Price.

II. Related Work

In this section we will discuss the current works on Bitcoin, its security, its relations it has throughout society, and the relation of popularity through Google Trends.

A. Outside Influences on Volility of Bitcoin

~~In~~ Colianni et al. ~~study~~ [12] they test how the correlation between Twitter and the price fluctuations of Bitcoin and Ethereum. The experiment found that price fluctuations are correlated to social media like Twitter. There is more of a relation between the tweets with Ethereum rather than Bitcoin.

Though in other studies this idea of showing a relation is expanded into more social media sites. 9

In [1] Smut's investigates the relation between Bitcoin and Telegram popularity, and Google Trend fluctuations. They used a sediment study to find the correlation. The method focused more on the type of messages that was posted and what frequency it produced. Unlike in Colianni et al. [12] there was a focus on the training the algorithm to produce the results. The conclusions differ because Smuts [1] found an almost perfect correlation between the price and the number of messages graphed by time. Google Trends was added after to the algorithm, but it produces little to no improvement in errors. Through this conclusion it is shown that there is a correlation between the two but was not able to completely prove that one affects the other, rather that they are related to each other. Smut used Native Bayes, logistic regression, and support vector machine to find these correlations. Though Google Trends is not a social media source it does provide good datasets that can be used in deep learning like in the previous researchers.

B. *Website Influences on Bitcoin*

10 Websites that provide information are more blog type play an important role in this as well. Some studies focus more on websites Stack Overflow and GitHub and Gitlab. This is because they can see the number of projects that are made for Bitcoin or with Bitcoin to find if there is an increase of projects due to price or popularity. Such in Ortu et al. [6], the study that was performed was more focused on the commits and projects of Bitcoin and Ethereum rather than the social media messages. The authors took a similar approach of using deep learning and showing the amount of training, and testing done with the algorithm, but they used four different neural network algorithms. In conclusion, when using the neural networks without social media indicators the percentage of accuracy was much less than when the algorithms used with social media indicators. features? Learn

Expanded more onto with an experiment focusing on Wikipedia and Google Trends, Stolarski et al. [10]. The experiment focuses on the number of articles that were created based on time and what the articles referred to. This is different than Ortu et al. [6] because the focus was mostly on crypto as a whole and started by ranking the articles on of how many Wikipedia articles there were in each language for each cryptocurrency. The focus turned to the ranking of the popularity of the coins throughout different countries through Google Trends search history, and Wikipedia visits. With the conclusion of this section of their research came to that Bitcoin, Litecoin, and Ripple were the most popular throughout the entire world based on the input datasets. The implications that the authors came to was how the crypto economy is affected by articles and authors of Wikipedia, and the popularity of the coin throughout the world. Also, Stolarski et al. [10] went more in depth of the world as a whole and different countries, not just America.

C. *The Crimes and Crime rate related to Crytpocurriences*

In Christin& Bingham [18] study they came across the crimes that takes place by using cryptocurrency and the usage of cryptocurrency in the online marketplace like silk road. Bearman [16] study found that $1.2 billion dollar transactions are made on this silk road and found that most of the items listed for buying are illegal products.

Russo[19] research found that 90% of bitcoins were utilized for illegal activities five years earlier from 2013 to 2018. 12

Cipher trace [17] is a company which is used by crypto exchanges safely process cryptocurrency has a report that transactions done in the biggest crypto exchanges most of bitcoin transactions can be recognized that are from criminal sources. 13

Crosman [14] study came up with many ways how the money launder takes place by using cryptocurrencies one of the ways that is mostly used is by using the services like shapeshift. 12

From this services Scheck & Shifflett [15], study found that almost $9 million dollars are laundered in a period of just 2 years. 12

Foley, Karlsen, & Putnins [13] has done a study on level of illicit use of cryptocurrencies their study found that one fourth of Bitcoin users and half of bitcoin transactions are for illicit purposes. Foley [13] came up with an experiment he used user information found on the dark web and found that 24 million Bitcoin users were found to be using it for illegal purposes, and 36 million illegal transactions ~~adding~~ per year.

Fanusie & Robinson [19], has done a study on the cryptocurrency conversion services like tumblers found that from 2013 to 2016 the money laundering has increased to $1 Billion dollars. 14

III. APPROACH TO EXPERIMENT

The goal is to find the correlation between Google Trends and crimes with bitcoin price by using the Pearson correlation ~~method~~.

We first started by finding at least three datasets that would meet the requirement of the inputs. We found Google Trends [8] search history of Bitcoin, then we found the dataset of monetary damage caused by cybercrimes which is in yearly manner [9]. We found a historical dataset of Bitcoin prices throughout the years and its fluctuation [14]. Finally, we also found the dataset related to number of terrorist attacks happened in the period of 1970 to 2017 [20] which is country wise showing the number of successful attacks happened in a specific country on the specific date. The date in dataset is divided into three columns which are year, month, and day. They are concatenated and a new column is created to specify the whole date. Every country's successful attack number is combined by using grouping function on the date column, so that all the attacks happened worldwide on that specific date could be presented in one column. 15

The Google search trends dataset has the data from the year 2014 to 2020 on a day-to-day basis. So, the bitcoin price dataset is also reduced and taken from 2014 onwards. The google search trends will have the value ranging from 0 to 100, where 0 specifies low or no search has been done and 100 specifies the highest search trend on that time.

15 The monetary caused because of cybercrimes dataset has values in yearly manner which is from 2011 to 2021. So, the bitcoin price is also reduced yearly by using mean function. These datasets are the key to the experiment of finding the relation that is held between Google search trends, crimes, and Bitcoin.

After we locate these datasets, first we import the datasets and find the null values in the data. If there exist any null values those values would be updated using forward fill method. We used the Pearson method to find the correlation between them. To find the correlation using the Pearson method which uses the below formula:

$$r = \sum (X - X')(Y - Y') / \sqrt{\sum (X - X')^2 (Y - Y')^2}$$

Here,

- r is the correlation coefficient
- X' is mean of variable X
- Y' is mean of variable Y

Normally the correlation coefficient value would be between -1 to +1, where -1 indicates negative correlation, it shows that when one variable change other variable change in opposite direction, 0 indicates that there is no relationship between them and +1 indicates the positive correlation which shows that when one variable changes the other variable change in the same direction.

16 The feature selection would also be done using the same correlation method. Then we compare all three datasets together to find out the relation between all the datasets if any. This paper addresses the following research questions

- **RQ1:** To find the correlation between Google Search Trends and Bitcoin Price?
- **RQ2:** To find the correlation between Crime and Bitcoin Price?

IV. EXPERIMENT RESULTS

fix This section discusses the results of the experiment, separated by each RQ. Each section contains a confusion matrix along with a graph that shows the given experiment on the data.

22 **RQ1:** To find the correlation between Google Search Trends and Bitcoin Price?

19 To address RQ1 we correlate the bitcoin search trends with the bitcoin price data which is extracted in day-to-day manner. First, we tried to find the null values that are existing in the data and those null values are updated using the forward fill method which will fill the null value with last valid observation. To find the correlation the data type should be integer, the dtypes function is used to find the data type. From that the data which is numeric is taken out and made a list of them and another data frame is created using the numeric datasets. The newly created data frame is used to find the correlation matrix.

After applying the Pearson correlation coefficient method to the data frame, we ~~go~~ get the below correlation as output: 20

	BTC Price	BTC search trends
BTC Price	1.000000	0.731624
BTC search trends	0.731624	1.000000

Table 1 17

In Fig 1 if we observe the correlation value is 0.73 which is nearer to one. As per the correlation values the higher the correlation the more it affects the other variable. As bitcoin google search trends increases, bitcoin price also increases relative to that.

Below is the graph between Bitcoin value vs Google search trends showing correlation (graph axis are scaled):

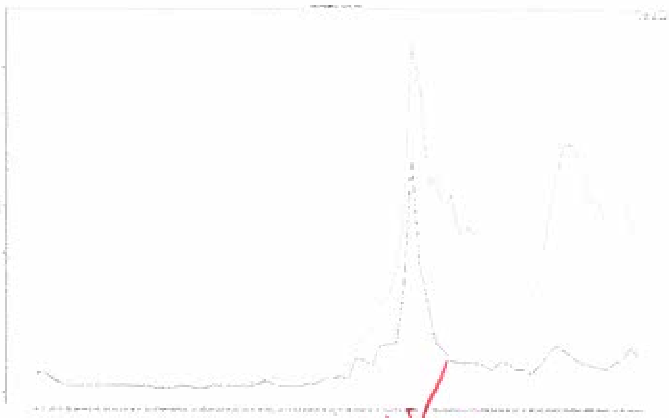


Fig 1 18

In Fig 2 we can observe from the above graph that the yellow line indicates the bitcoin price and purple line indicates the google search trends, when the google search trend increases significantly on dec 2017 the bitcoin price also increased.

RQ1 Summary: From the experimental results we can observe that the bitcoin price can vary with increase in google search trends.

21 **RQ2:** To find the correlation between Crime and Bitcoin Price?

25 Here we are going to find the correlation of bitcoin price with two different crimes which are terror crimes and cybercrimes. 23

~~A.~~ To address RQ2 we correlate the terror crimes with the bitcoin price data which in extracted in day-to-day manner. The data is processed in the same way as we did for the google search trends dataset like cleaning the data by forward filling the null values and feature selection by using correlation.

After applying the Pearson correlation coefficient method to the data frame, we ~~go~~ get the below correlation as output:

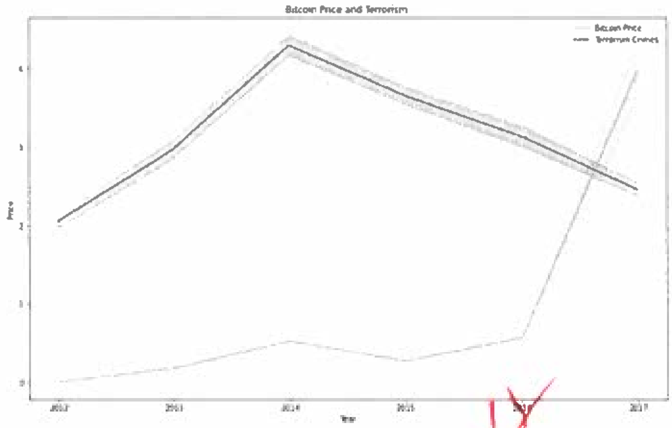
24

	Price	High	Low	Terror Attacks
Price	1.000000	0.999113	0.998523	-0.170109
High	0.999113	1.000000	0.997460	-0.169855
Low	0.998523	0.997460	1.000000	-0.170311
Terror Attacks	-0.170109	-0.169855	-0.170311	1.000000

Table 2 17

In Fig 3 if we observe the correlation value is -0.170109 which is in negatives which is closer to 0 from that we can conclude that terror attacks have little to no significant relation with bitcoin price.

Below are the graph bitcoin value vs terror attacks showing correlation (graph axis are scaled):



18

Fig 2

In Fig 4 we can observe from the above graph that the yellow line indicates the bitcoin price and purple line indicates the terror attacks. The graph shows there is no relation between these two.

B. Here we used the yearly data of the monetary damage done due to cybercrimes (ransomware attack, WannaCry etc.) and correlate these data with yearly bitcoin price data. As the data is taken in the yearly manner there were only 11 columns available. Below is the correlation coefficient output:

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	Monetary Damage	BTC Price
Monetary Damage	1.000000	0.914618
BTC Price	0.914618	1.000000

17

Table 3

If we observe the correlation matrix the relation is about 0.91, the bitcoin price is highly affected by the monetary damage caused by cybercrimes as some of them demand the ransom amount in crypto.

Below are the graph bitcoin value vs cybercrimes showing correlation (graph axis are scaled):

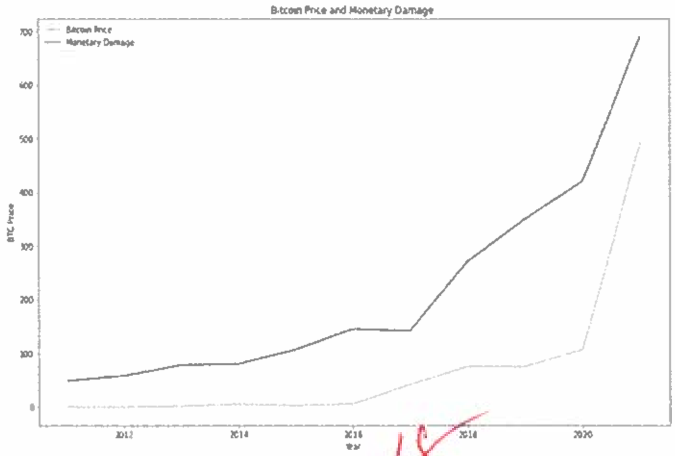

Fig 3 18

In Fig 5 we can observe from the above graph that the yellow line indicates the bitcoin price and purple line indicates the cybercrime and the graph shows there is relation between these two.

V. Threats of Validity

A. *Internal Threats* 27

The threats to our experiment would be internal. If we were able to have more time, we could compile more data that we could test that could make our algorithm more accurate error rate. Also, if the time would permit, we could try different formulas and algorithms that would give a different confusion matrix that could be observed.

B. *External Threats* 27

The threats to our experiment would be external if we could not find a dataset that directly correlated to Bitcoin based crimes. This could have made the data more accurate because it would not be just all monetarily damage, but it would just Bitcoin that was stolen or used. Also finding a dataset that would show the increase of usage of Bitcoin on the Dark Web.

VI. Future Works

Future works that we could expand our experiment would be using different crypto currencies besides Bitcoin. Due to the increasing market and more valid coins, there could be a case that some of these coins are used more in cybercrimes. This could only be possible if there was a dataset that would show the breakdown of usage of each coin. Though the majority of the population knows about Bitcoin rather than some other Altcoins.

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VII. Conclusion

This experiment is aimed to find the relation between the price of Bitcoin with google search trends, cybercrimes, and terror crimes. The data is cleaned by removing null values and made feature selection based on correlation values. The newly obtained data is used to form another dataset with the columns which have better correlation values.

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The RQ1 analysis has been done between bitcoin price and google search trends. The datasets obtained for both are on day-to-day basis for better outcome, both the datasets are merged by the common column which is date. The correlation we found is between the bitcoin price and the number of searches for the term bitcoin. We got the correlation value of about 0.73, this specifies that the significant growth in google search trends then their price of bitcoin if there is growth. If we observe Fig2 the growth can be seen in both google search trends and bitcoin price is relative, then in the next year there is a drop in search trends as well as bitcoin price also. This specifies the effect of one on another.

The RQ2 analysis has been done on two types of crim. The first one is in relation to terror crimes and bitcoin price. The terror crime dataset is from the years 1970 to 2017 but because of the availability of Bitcoin from 2011 the data of terrorism attacks has been reduced to meet the requirements. For terrorism data the attacks are analyzed on day-to-day basis like the Google search trends data. The correlation value that we got for these datasets is -0.17 which shows negative or almost no relation between them. Normally the negative correlation specifies if there is growth in one variable then the other variable is dropped. From Fig4 we can observe that both the values are acting on their own. After the year 2016 the growth in bitcoin price increased significantly and on the other hand the terrorism crimes have gone down as specified in the correlation matrix.

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The second analysis in RQ2 is to find the relation between monetary damage caused due to cybercrimes and bitcoin price. This monetary damage dataset is in yearly manner, so the bitcoin price is also reduced to yearly by using means of monthly price, then both the datasets are correlated by using the common column year. We got the correlation value of 0.91 which specifies that both the variables bitcoin price and monetary damage by cybercrimes highly affect each other as for some cyber-attacks the ransom should be sent out in the form of cryptocurrency because of its anonymity. If we observe in Fig5 both the values are growing continuously relative to the time, as the usage of web increased significantly in past few years the relative cybercrimes also increased and with the intrusion of cryptocurrencies in the market, they became the priority mode of payment for illicit activities.

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