A multi-approach analysis of the Bitcoin Blockchain

Blockchain And Its Application (IFT6056)

April 2022

Louis MEECKERS (20229187) & Alexis ROGER (20175864)

***Abstract*—In order to analyze the Bitcoin blockchain, several approaches have been studied and implemented. We decided to model the blockchain as a knowledge graph in order to be able to browse and search through the graph based on the Resource Description Framework. This allowed us to discover its strengths and limitations. We also performed a statistical analysis to understand the price variations in relation to the difficulty of mining, the average number of transactions per block, the block fee and other criteria. Finally we analyzed the correlation between the price of Bitcoin and Ethereum.**

Code: github.com/louismeeckers/blockchain-analysis

I. Introduction

Blockchains are growing immensely in popularity. With Bitcoin being seen as the first wide-spread digital currency and Ethereum developing smart-contracts, they are here to stay. To this end, it is important that we start developing tools and techniques to analyze said blockchains to ensure no illegal or fraudulent activity occurs on them. This is why we have decided to try and streamline an initial analysis of the blockchains, mainly to understand how they are used currently. Are they used as a store of wealth? as a currency? or as a highly volatile investment tool? To perform this analysis, we will first look into visualisation techniques, namely knowledge graphs, before going into a more statistical analysis of the blockchain, and finishing with a comparison of Bitcoin and Ethereum to see if a correlation can be found.

II. Introduction to Knowledge Graphs

A knowledge graph is a semantic network that allows structuring data as a graph composed of nodes and edges. The nodes correspond to the entities and the edges are the relations between these entities. Each entity of our graph has an assigned type and has relations to other entities, the number of relations can vary from one entity to another.

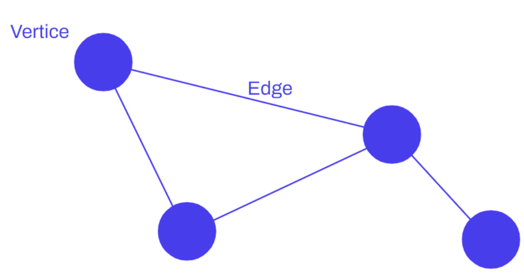

Fig. 1. Graph structure

A. What are the benefits of using knowledge graphs?

Knowledge graphs allow storing any kind of information in a new way that is more flexible than a traditional database where the data is stored in tables. Indeed, there is no structure related to the different types and therefore it is possible to feed any kind of data in an unstructured way. This model facilitates the integration of knowledge from different domains as it can be combined by using shared relations and therefore create relations between entities of different data sets.

Moreover, the graph paradigm is intuitive for humans to understand but also for machines as formal semantics can be encoded for machine interpretation.

It also enables analysis. Decades of research on graph analysis and querying algorithms can be reused to explore, mine and analyse knowledge graphs.

B. Applications

Knowing it is just a different way of storing data and exploiting it, the range of applications is very wide. However, we can see the real advantage of this structure in some applications:

- Wikipedia uses knowledge graphs to make relations between a subject and its entities which can be very specific to each subject and therefore could not fit correctly in a traditional database.
- Facebook data can be seen as a social graph by making all the relations between its users, the pages, their interests etc. Facebook even release a version to the public in 2013 to give answers to user natural language queries.
- Search engines and virtual assistants to be able to process natural language queries (example in Figure 2) and easily link a question and the corresponding data/answer.

The fact that entities of those applications have very different attributes from one to another exploits the potential of an unstructured graph which would not fit easily in a traditional database.

III. Use of Knowledge Graph for the Bitcoin Blockchain

A. Graph Model

There are several ways to model the Bitcoin blockchain data. Each one brings advantages and disadvantages. Indeed, some models make it easier to find information by simplifying the structure and therefore removing some data.

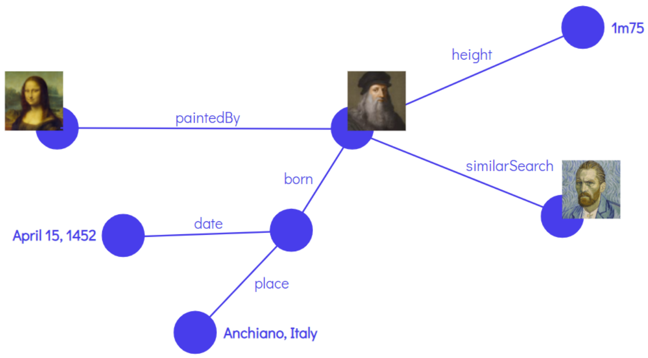

Fig. 2. Mapping of an NLP query and its data

The main types of the bitcoin blockchain that we are going to consider are the following:

- Block (parent element of transactions)
- Transaction (parent element of UTXOs)
- UTXO
- Address

1) Blocks, transactions, UTXOs and addresses: In this graph model, all types of entities cited above are included. This allows having a complete model of the bitcoin blockchain as nothing is simplified and the bitcoin's structure directly transposed. The main advantage of this model is its completeness. Indeed, every component is included and therefore is the subject of a search. Due to its completeness, the model is more complex and it may take longer and be more complicated to execute searches.

This model allows us to highlight important characteristics of the blockchain: transparency and traceability. Indeed, with this model is it possible to check how a transaction is built and which UTXOs are used to validate a transaction. But also, to check who are the addresses related to transactions. Thus, with all the links between entities, it is possible to trace any transaction and to know all the information related to it.

2) Blocks, transactions and addresses: In this case, only blocks, transactions and addresses are retained. This allows simplifying the model by not considering the UTXOs. It is thus necessary to include the information relating to these directly in the transactions and to create links from transactions to addresses. An edge from an address to a transaction would be considered as the source of a transaction. While edges from a transaction to addresses would be considered as the destination of the transaction.

The following of this paper addresses the first model in order to best represent the bitcoin blockchain and not make any compromises.

B. Conversion of the data

1) Collect the data: For this project, our objective is to recover a sample of the blockchain from a starting point that corresponds to a block to an ending block. In order to demonstrate traceability, no cut off is allowed. Knowing that the blockchain is the equivalent of a linked list, it is enough to recover continuously the following blocks.

To collect data from the bitcoin blockchain we choose to use Blockchain.com Exchange API. This tool allows us to retrieve all block data and their transactions in JSON format.

2) Data cleaning: This step allows the process of the data retrieved from the API and keep only the relevant information and perform transformations on some of them if necessary. Indeed, some information is not interesting, such as the locking and unlocking scripts. But also other information that is just deducted from the others. Such as the fees of a transaction that are not written in the blockchain but calculated from the difference between the sum of the values of the inputs and the sum of the values of the outputs of a transaction.

Moreover, to be able to exploit the search in our knowledge graph, it is convenient to convert some data to another format. For example, the date on which a block is recorded is in timestamp and will be easier to have it in UTC format.

Finally, once all the manipulations are done on the data, we format them back in JSON format by assigning all the entities of the same type to a corresponding file to facilitate the next step.

3) RML Mapping [5, 6]: To understand how the construction of the graph and thus the mapping works it is important to introduce some basics:

Resource Description Framework (RDF) [3] is a standard format developed by World Wide Web Consortium, which formally describe elements of a graph and their metadata. It provides multiple syntax notations and data serialization formats. A document structured in RDF is a set of triple statements (subject, predicate, object) and therefore result in the creation of a directed graph. The elements of triple statements use defined vocabulary to describe relationships between entities.

```
<subject> <predicate> <object> .
```

There exist multiple RDF serialization formats: Turtle, N-Triples, JSON-LD... The most used is turtle [4] which is defined as a compact and human-friendly syntax and file format for expressing data in the RDF data model. Hence, we chose this one for our project. Finally to map the JSON data created by the ”data cleaning” step into turtle file. We use RMLmapper (process in Figure 3) which is an application that on the basis of declarative rules makes the transition from a specific format to the desired format. Below is an example of an entity, its metadata and its relations to other entities (some of the same type as the entity itself and some not):

```
<https://example.org/udem/ift6056/block/000...4bb>
  a schema:Block;
  rdfs:label "721702";
  ex:height 721702;
  ex:prev_block <https://example.org/udem/ift6056/
```

```
ex:time_gmt "2022-02-03T22:14:33"^^xsd:dateTime;
ex:timestamp 1643926473 .
```

4) Load data to semantic graph database: There exist dozens of semantic graph databases, each has their advantages and disadvantages. We decided to use GraphDB [8] as it is compliant with the RDF standards and has an easy to use platform to perform search and visualization of the graph. However, we encounter a limitation to the use of GraphDB due to its file size limit which prevent us from loading too big samples of the bitcoin blockchain.

C. Visualization of graph

GraphDB allow to search any node in the sample loaded and to observe all its relations to other nodes as shown in the Figure 4. It shows how traceable and chronological is the blockchain. Indeed it shows that every input of the transaction are the outputs of transactions of previous blocks. Some patterns are easily identifiable.

D. Search in the graph

In order to search in the graph we need to use SPARQL which is the standard RDF query language. The syntax is similar to SQL. Useful queries can be found in the appendix:

- Count number of blocks
- Count number of transactions for all blocks
- Count number of utxos in outputs of all transactions of each block
- Count number of utxos in inputs of all transactions of each block
- Get top 10 UTXO based on their value
- Get total value of satoshi each address hold
- Count number of transactions for each address
- Get all transactions in a specific timeframe

IV. STATISTICAL ANALYSIS OF THE BLOCKCHAIN

In this part we will conduct a more in-depth analysis of the bitcoin blockchain. We will break this analysis down into two main time-frames of interest: the initial introduction of cryptocurrency to the general public in late 2017 and then the Chinese ban of 2020.

A. The first hype

For this section we will investigate how the Bitcoin blockchain reacted to its initial debut in the public spotlight at the end of 2017. To this end, we will analyze data gathered from the 10^{th} of August 2017 until the 5^{th} of September 2018. This corresponds to the block heights of 480'000 to 540'000. Again, all the data we use here regarding the Bitcoin Blockchain was gathered with the $blockchain.info$ API [1]. Additionally, the financial data we will use was gathered through the Yahoo Finance API [9]. The data about the internet search trends was gathered on Google Trends [2].

A media-assisted rise: Let us begin this analysis by looking at the price of a single Bitcoin against the amount of searches for the term "bitcoin" every week on Google. By looking at

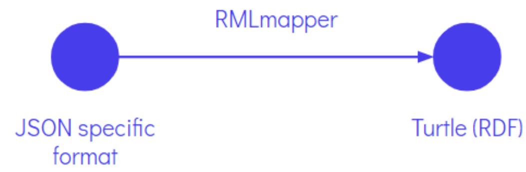

Fig. 3. Mapping to turtle (RDF) with RMLmapper

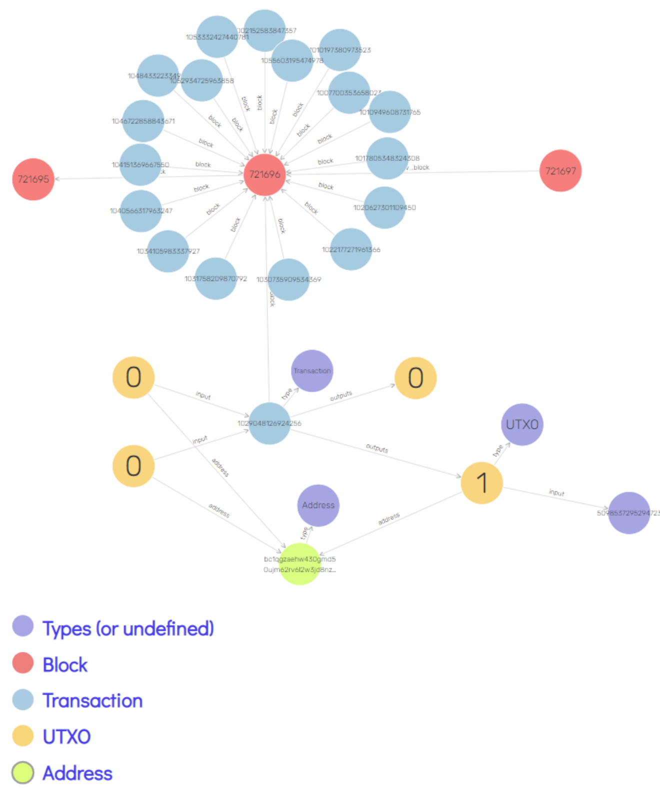

Fig. 4. Graph Visualization

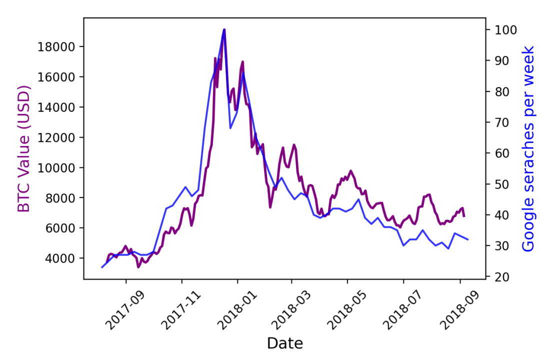

Fig. 5. Price of a Bitcoin correlated with the amount of Google searches for "blockchain"

figure 5, we can clearly identify the moment where Bitcoin's value ballooned up in December 2017, going from a mere 4 thousand US dollars to almost 20 thousand US dollars. It is then followed by another peak a couple months later before oscillating back down to about 7 thousand US dollars.

What is particularly interesting to note is how the amount of Google searches for the term "blockchain" seems to just barely precede the movements in the price of Bitcoin. Mid to late 2017 was the first time the general public was really exposed to the term "blockchain" as the media started catching on to the technology. From there it quickly spiraled out of control with a massive influx of interest. This is the main reason why buying Bitcoin at that time was called "taking the hype train". It is also the first sign that the popularity of Bitcoin is not only due to the technology but may also be due to some speculative investments.

A difficulty estimate: In order to analyze the Bitcoin network, we will also need to be able to estimate how many miners were on the network for a given block, and by extension what was to network's hash rate for each block. The hash power of the network correlates directly to the difficulty of mining a block. We will hence use the difficulty directly. We can compute the actual difficulty of each block of the network from the target, however the target is updated once every 2 weeks. We will therefore use the target to analyze macro-movements in the difficulty but to analyze rapidly changing situations we will compute a difficulty estimate from the amount of leading 0s in the block hash. As mining a block consists of finding a nonce such as the block's hash is inferior to a certain target, this seems like a reasonable estimate, as we can also see on figure 6. Furthermore, this difficulty estimate follows a linear progression which is easier to comprehend. Adding a leading 0 to the hash becomes exponentially harder, requiring exponentially more hash power to solve. However, simply counting the amount of 0s leads to the difficulty being in a sort of log-scale, which aligns it better with the other data. This effect can be clearly seen on figure 6, with the hash value slowly leveling out while the difficulty estimate rises linearly.

A correlation with the price: We will now look into a few interesting correlations that can be seen between the price of Bitcoin, and therefore its hype, and a few of the blockchain's parameters, namely: the difficulty [7], the amount of transactions per block [8] and the block fee [9].

To begin, we note that the difficulty spikes as Bitcoin first reaches the main-stream with many main-stream early-adopters joining in to the mining frenzy and it then follows a linear increase throughout the time frame, reflecting an exponential increase in the amount of hash power in the network. Looking into the evolution of the amount of transactions per blocks, we see a different story: as the interest increases, the amount of transactions naturally increases, until hitting the maximum of almost 2'500 transactions per block. However, instead of maintaining itself, this amount crashes along with the Bitcoins price early 2018 as everyone bails an interest dies down. It then hovers around half of the maximum transaction

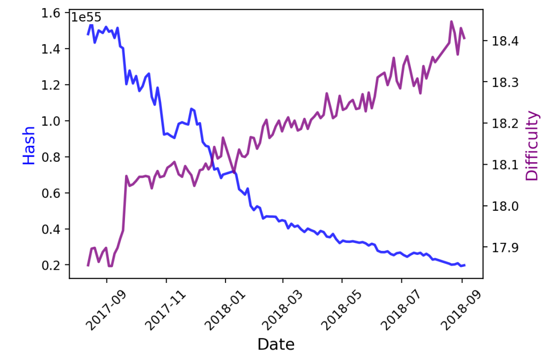

Fig. 6. Correlation graph between the hash value and the estimated difficulty

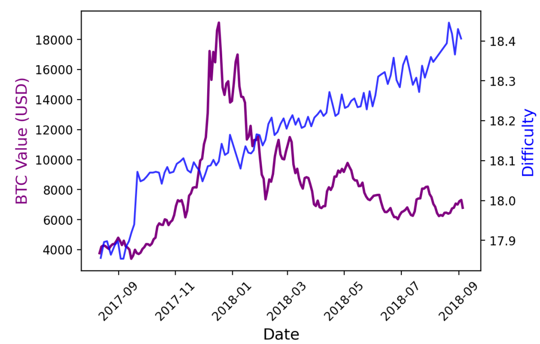

Fig. 7. Correlation graph between the price of Bitcoin and the estimated difficulty

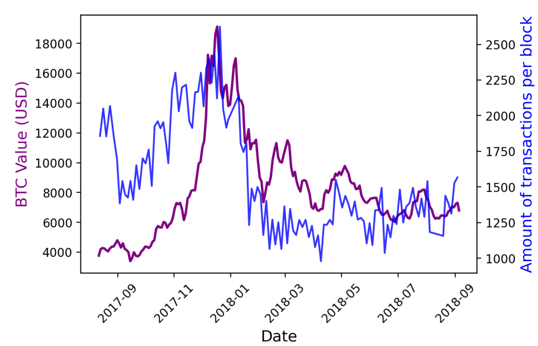

Fig. 8. Correlation graph between the price of Bitcoin and the amount of transactions per block

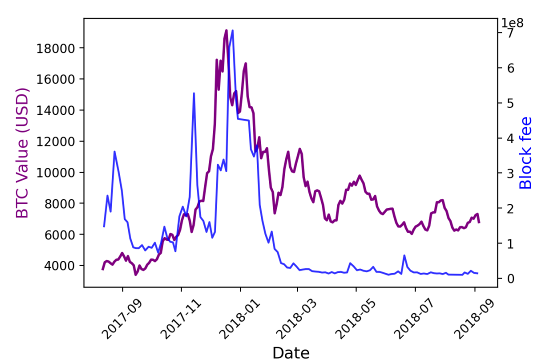

Fig. 9. Correlation graph between the price of Bitcoin and the block fee

allowance. This is particularly interesting when it is put next to the block fees. We can clearly see the big pumps and dumps in the fees as every time they occur, the network becomes congested and the fees sky-rocket. We also note that in calmer times, as in the second quarter of 2018, as the amount of transactions is stable and well under the limit, the fees slowly tend to 0 as the backlog of transactions is processed.

Finding the nonce: Finally, we will conclude this initial analysis of the 2017 Bitcoin hype by study the "nonce" and time required to find it more closely. In its design, the Bitcoin network aims to complete one block every 10 minutes, or every 600 seconds. To this end, the network adjusts its difficulty dynamically based on the time taken to solve the previous blocks. However, this adjustment occurs every 2016 blocks, approximately every 2 weeks. Furthermore, it is limited to an adjustment of a factor of 4. This means that the difficulty cannot go above 4 times its current one or below a quarter of it. This leads to the adjustments happening re-actively and slowly. Therefore, in periods such as late 2017, which saw a very rapid influx of new miners, the difficulty does not adjust fast enough and the mining time of each block will decrease. This is portrayed by figure 10, where a histogram of the time taken to solve the blocks was plot. The Gaussian curve which fits this data is in orange, and the red line is the theoretical ideal, the 10 minute mark, which should line up with the peak of the Gaussian curve. We can note that on average the blocks are mined almost a minute to fast, this is mainly due to the new miners in September 2017, which we saw in figure 7.

Additionally, we also plot the spread of the nonce over their possible space in figure 11. As an unsigned integer, they can range from 0 to 2^{32}. As hash functions are near random, as in a small change in the input drastically effects the output, we would expect the nonce values to be uniformly distributed over these possible values. This seems to hold over most values except every 2^{30} where there is a small slice of under-used nonce values. As much as we tried we were unable to find a proper explanation for this phenomenon.

B. The Chinese ban

In May of 2021, China announced it was considering a ban of cryptocurrency mining. Before this announcement, China was one of the main mining spots thanks to the combination of lax rules, cheap electricity, labor and land, along with a proximity to the main ASIC R&D and production centers. This meant that close to half of Bitcoin's hash power was going to need to be relocated and had a profound impact on the blockchain, as well as destroy China's commanding lead in the cryptocurrency space. A few months after announcing it, the Chinese ban came into effect. To this end, we will study the blocks mined from the 11th of May 2020 to the 14th of October 2021, which equates to the blocks of height 630'000 through 705'000.

The fluctuation in mining power: To begin we can start by looking at the evolution of the value of a Bitcoin over this period. Interest around blochchains started rising again late

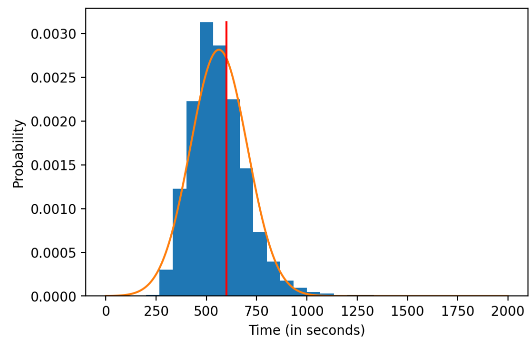

Fig. 10. Histogram of the time taken to solve each block

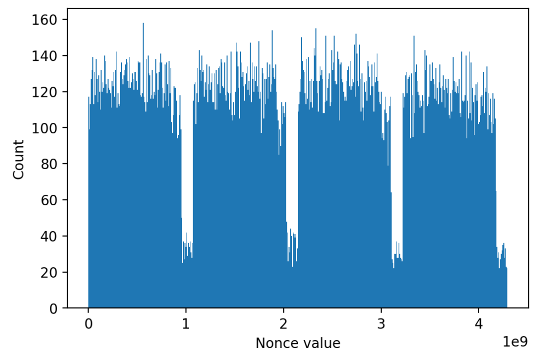

Fig. 11. Histogram of the different nonce values

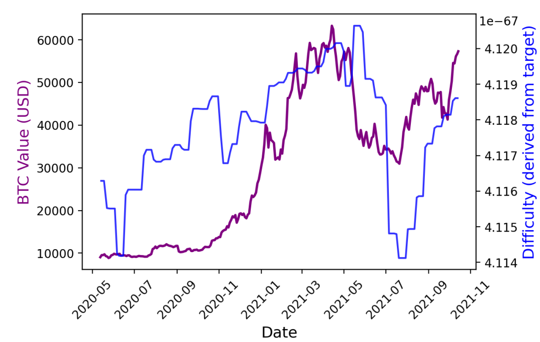

Fig. 12. Correlation graph between the price of Bitcoin and the block difficulty

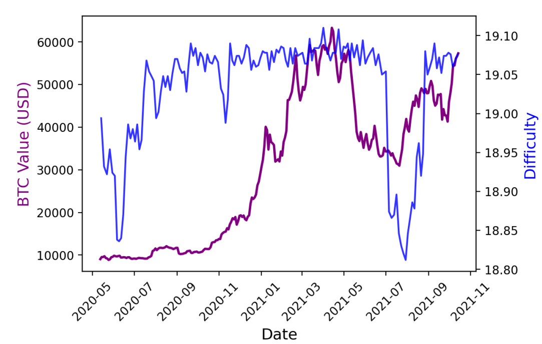

Fig. 13. Correlation graph between the price of Bitcoin and the block approximate difficulty

2020 and this is clearly reflected with the bitcoin value starting to hike up again, as can be seen in figure 12. However, it started a lot higher at 10 thousand US dollars and broke a new record by going above 60 thousand US dollars. It is just after this milestone that China announced its ban, leading to a 50% valuation crash. If we plot this valuation against the target, as in figure 12, we can have a few interesting observations. Before this, we will start by using a difficulty calculated from the target, which is stored in each block. As mentioned above, the target is reviewed every two weeks, giving the graph a step-function appearance. The difficulty taken was calculated as the inverse of the target multiplied by 2^{192}. The 192 bit shift aligns the target to be the maximum accepted hash and taking the inverse of this allows the difficulty to directly correlate with the hash-power of the network. As in figure 7, we note that as interest grows, so does the difficulty. Additionally, we note a crash a few weeks after the Chinese announced their ban, and, more importantly, well after the market crashed. This goes to show that the market crashed on the possibility of regulations, and well before the underlying machines were shutdown. This is our first of many clues that Bitcoin remains a asset used for speculative investment and is still not at the same level as a fiat currency.

If we change our difficulty estimate to use the amount of leading 0s, as computed in the previous part, we get an even more obvious representation of the Chinese ban. As seen on figure 13, we can see the clear drop in mining power a month after the Chinese announcement as the difficulty crashes. However, this clearly shows that barely two months later it was back where it was before. This leads us to the conclusion that the Chinese operations were shutdown but the equipment was immediately moved abroad and turned back on, as the overall difficulty, and hence mining power before and after the crash are relatively close.

It is also interesting to plot on the same time-scale the difficulty of a block and the time required to mine said block. This was done in graph 14 and shows how the target is re-actively adjusted to maintain the reference block time of 600 seconds. When the Chinese miners turned their machines off in June 2021, the block time skyrocket, before the difficulty was adjusted to a more reasonable level. However, as the mining power came back online, the opposite phenomena occurred with blocks being a little faster before the difficulty had time to rise again.

The ever-present fees: In the same way as before, figure 15 shows how the transaction fees peak with the interest. When a sharp gain or loss in value starts, everyone tries to buy or sell, respectively. This leads to a massive amount of transactions and a fee spike. This behavior strengthens the point we made previously that Bitcoin is still being used as a highly volatile and purely speculative asset. It is sadly still being used by investors trying to get rich quick on the hype-train rather than as a digital currency as it was initially intended.

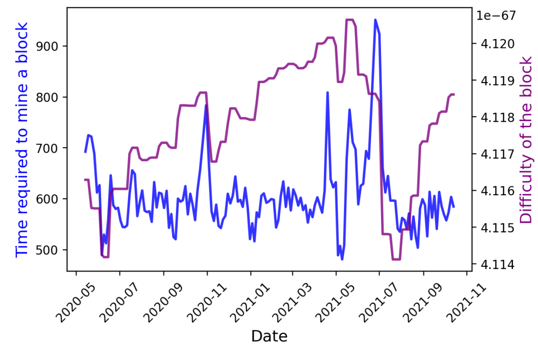

Fig. 14. Correlation graph between the time to mine and difficulty of a block

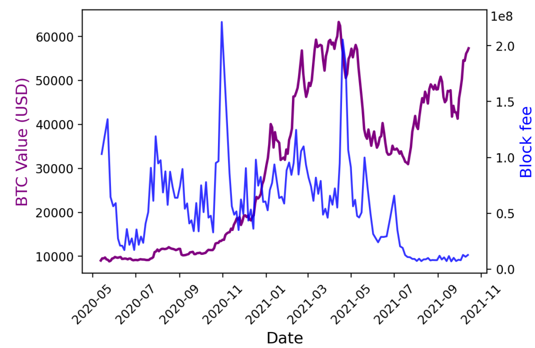

Fig. 15. Correlation graph between the price of Bitcoin and the block fee

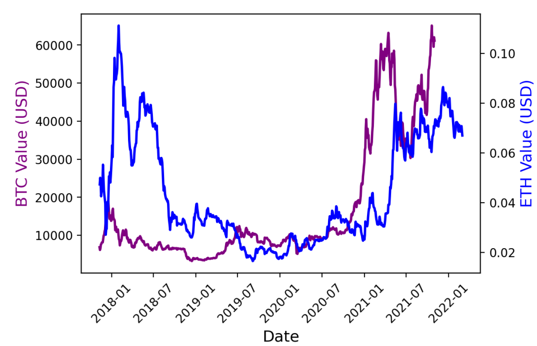

Fig. 16. Graph showing the value of Bitcoin and Ethereum with regards to the US dollar

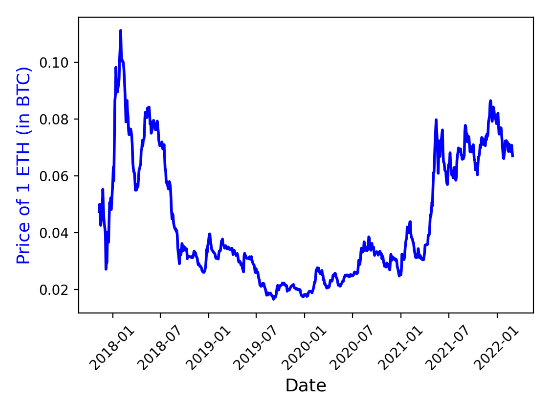

Fig. 17. Graph showing the value of an Ethereum in Bitcoin

V. Correlation between Bitcoin and Ethereum

A final interesting study which we can conduct is to compare the values of Bitcoin and Ethereum tokens. This can provide valuable insights in the uses of these to coins, and whether or not the Bitcoin hegemony of the cryptocurrency market may come to an end any time soon. To begin, these two cryptocurrencies are the two most prominent one to date, with Bitcoin having a market cap of 772 billion US dollars at the time of writing while Ethereum has about half as much and no other cryptocurrency even comes close to their market cap.

If we begin with plotting the value of Ethereum and Bitcoin on the same graph [16], we realize that both have very similar fluctuations. As we have shown previously, the rise and fall of Bitcoin's valuation is mainly due to outside factors, mainly interest and speculations. This coordinated movement shows how Ethereum follows Bitcoin, with the general idea that when one cryptocurrency goes up, they all do. This is further compounded by piloting the value of Ethereum as a function of Bitcoin, in figure 17. The graph is relatively stable with a few corrections, but even these remain around a relative times two or half value. For cryptocurrencies, this is actually surprisingly small. Again, this shows how these two are pillars of the cryptocurrencies. Although Ethereum has been catching up to Bitcoin in volume traded and total market cap, it still is hard to believe that it may surpass it.

We decided to experiment with an automated market maker to see if it would prefer one cryptocurrency over the other. Following the paper *Deep Reinforcement Learning for Automated Stock Trading: An Ensemble Strategy* (2020) by Hongyang Yang et al. [10], we implemented three actor-critic algorithms: a Proximal Policy Optimization (PPO), an Advantage Actor Critic (A2C) and a Deep Deterministic Policy Gradient (DDPG) as well as the ensemble strategy. The implementation provided by the authors had its issues so we made our own [7]. The naive method we chose was to start with a 50/50 split between Ethereum and Bitcoin at the start and just hold it to see the evolution. The agents were given an initial capital to invest and every day they would get a series of indicators, such as the market open and close price, volume and the relative strength index. They could then choose to buy, sell or hold their positions. The results are shown in figure 18, where we can clearly see that the advantage actor critic method dominates this highly volatile market. An interesting observation of the behavior of the algorithms is that they did not really day-trade, which is risky. With the huge returns in Bitcoin they just waited it out using a "buy and hold" strategy. For instance, the advantage actor critic simply went all-in in Bitcoin and as it had a better growth, it outperformed the others which allocated part of their portfolio to Ethereum. Hence, according to this, it is preferable to invest primarily in Bitcoin, however this may change for any number of reasons in the near future.

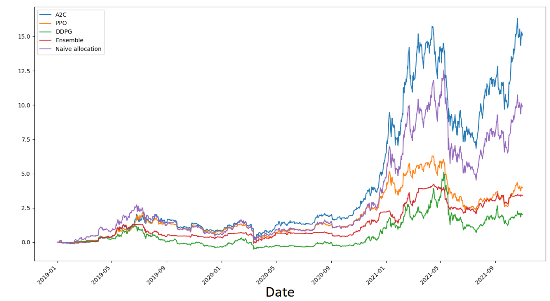

Fig. 18. Graph showing the return of different trading strategies

VI. Conclusion

To conclude, knowledge graphs provide a unique insight into blockchains. They allow to have a representation which is both convenient and very visual all the while remaining fully searchable by a machine with simple queries. On top of this, our statistical analysis allows for the spotting of trends in a blockchain and of potential correlations between seemingly unrelated values. And as much as there seems to be a dependence on Bitcoin by the other blockchains, Ethereum is quickly catching up and trying to close the gap. It will be very interesting to keep surveying Ethereum and see how it behaves if it reaches the size of Bitcoin. Finally, it remains rather obvious that blockchains are used primarily for their speculative investments, thanks to their unusually large variance. There is still a long way to go before we abandon our fiat currency for a public blockchain.

References

[1] *Blockchain information*. URL: https://blockchain.info. (accessed: 20.04.2022).

[2] *Google Trends*. URL: https://trends.google.com/trends/. (accessed: 20.04.2022).

[3] *RDF - Semantic Web Standards*. https://www.w3.org/RDF/.

[4] *RDF 1.1 Turtle*. https://www.w3.org/TR/turtle/.

[5] *RDF Mapping Language (RML)*. https://rml.io/specs/rml/.

[6] *RMLio/rmlmapper-java: The RMLMapper executes RML rules to generate high quality Linked Data from multiple originally (semi-)structured data sources*. https://github.com/RMLio/rmlmapper-java.

[7] *Trading environment implementation*. URL: https://github.com/Alexis-BX/automated_trading. (accessed: 01.03.2022).

[8] *What is SPARQL? — Ontotext Fundamentals Series*. https://www.ontotext.com/knowledgehub/fundamentals/what-is-sparql/.

[9] *Yahoo Finance*. URL: https://www.yahoofinanceapi.com/. (accessed: 20.04.2022).

[10] Zhong Shan Yang Hongyang Liu Xiao-Yang and Walid Anwar. "Deep Reinforcement Learning for Automated Stock Trading: An Ensemble Strategy". In: *SSRN Electronic Journal* (Sept. 2020). DOI: 10.2139/ssrn.3690996.

Appendix

A. SPARQL queries

Prefixes of requests:

```
PREFIX ex: <https://example.org/ift6056/>
PREFIX schema: <https://schema.org/>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
```

Count number of blocks:

```
SELECT (COUNT(?block) AS ?count)
WHERE {
?block a schema:Block .
}
```

Count number of transactions for all blocks:

```
SELECT ?block
(COUNT(?transaction) AS ?nb_transactions)
WHERE {
?transaction a schema:Transaction ;
ex:block ?block .
}
GROUP BY ?block
ORDER BY DESC(?nb_transactions)
```

Count number of utxos in outputs of all transactions of each block:

```
SELECT ?block (COUNT(?utxo) AS ?nb_utxos)
WHERE {
?utxo a schema:UTXO .
    ?transaction a schema:Transaction ;
ex:block ?block ;
     ex:outputs ?utxo .
}
GROUP BY ?block
ORDER BY DESC(?nb_utxos)
```

Count number of utxos in inputs of all transactions of each block:

```
SELECT ?block (COUNT(?utxo) AS ?nb_utxos)
WHERE {
?utxo a schema:UTXO ;
ex:input ?transaction .
    ?transaction a schema:Transaction ;
ex:block ?block .
}
GROUP BY ?block
ORDER BY DESC(?nb_utxos)
```

Get top 10 UTXO based on their value:

```
SELECT ?address ?value
WHERE {
    ?utxo a schema:UTXO ;
          ex:value ?value ;
          ex:address ?address .
}
ORDER BY DESC(?value)
LIMIT 10
```

Get total value of satoshi each address hold:

```
SELECT ?address (SUM(?value) as ?total)
WHERE {
    ?utxo a schema:UTXO ;
          ex:value ?value ;
          ex:address ?address .
}
GROUP BY ?address
ORDER BY DESC(?total)
```

Count number of transactions for each address:

```
SELECT ?address
(COUNT(?transaction) as ?nb_transactions)
WHERE {
    SELECT DISTINCT ?address ?transaction
    WHERE {
        ?transaction a schema:Transaction ;
            ex:block ?block ;
            ex:outputs ?utxo .
        ?utxo a schema:UTXO ;
            ex:value ?value ;
            ex:address ?address .
    }
}
GROUP BY ?address
ORDER BY DESC(?nb_transactions)
```

Get all transactions after a specific time:

```
SELECT ?block ?transaction ?time_gmt
WHERE {
    ?transaction a schema:Transaction ;
ex:block ?block ;
        ex:outputs ?utxo .
    ?block a schema:Block ;
        ex:time_gmt ?time_gmt .

    FILTER(?time_gmt >
    "2022-02-03T06:06:06"^^xsd:dateTime)
}
```