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CryptoComparator: A Visual Analytics Environment for Cryptocurrencies Analysis

Pietro Manganelli Conforti, Matteo Emanuele, Pietro Nardelli, Giuseppe Santucci and Marco Angelini

Sapienza University of Rome

Abstract

Cryptocurrencies are a novel phenomenon in the finance world that is gaining more attention from the general public, banks, investors, and lately also academic research. A characteristic of cryptocurrencies is to be the target of investments that, due to the volatility of most of the cryptocurrencies, tends to be at high risk and behave very differently from classic currencies. A way of reducing this risk is to look at the history of existing cryptocurrencies and compare them in order to spot promising trends for increased gain. This paper introduces CryptoComparator, a Visual Analytics tool designed for allowing analysis of correlations and trends of cryptocurrencies. The system exploits an initial proposal for a double elliptic graph layout, reconfigurable with three different ordering functions, in order to support fast visual search of cryptocurrencies by correlation strength. One use-case developed with a domain expert in cryptocurrency financial activities demonstrates qualitatively the usage of the system.

CCS Concepts

• ***Human-centered computing*** $\rightarrow$ ***Visualization systems and tools; Visual analytics;***

1. Introduction

Since the birth in 2009 of the first cryptocurrency, Bitcoin [Nak08], numerous private cryptocurrencies have been introduced. Bitcoin is by far the most successful one, but many others gained their space in the market, drawing a lot of media attention as a whole new financial phenomenon, which in 2020 reached a total market value higher than 950 billion dollars [noaa]. Cryptocurrencies such as Bitcoin, Ethereum or Litecoin have been attracting the attention of information technology professionals, economists, investors, banks, governments, and lately also academic research. Investing and predicting the trends of cryptocurrencies may be complex due to their high volatility and difference in behavior with respect to classic currencies or stocks. The macroeconomist Peter Tchir in 2018 declared on Forbes [Tch] that the forecasting on cryptocurrencies are "overhyped", stating that many of the speculations on the single financial asset are led by reasons that are not "fundamentals" (e.g., quantitative analysis, financial evaluation). The usage of a tool for analysis of small groups of cryptocurrencies to compare them efficiently can help analysts look for more rigorous reasons to lead decision-making in the field. For this reason, in this paper we propose: (1) CryptoComparator, a visual analytics solution for cryptocurrencies analysis. Its goal is to allow the user to analyze trends of different features of a cryptocurrency and cross-analysis of groups of cryptocurrencies, helping the identification of patterns to inform decision making; (2) an initial customized proposal for a double elliptic graph layout, used in CryptoComparator for fast visual search and visual arrangement of cryptocurrencies, inspired by the circle concentric layout (Cytoscape); (3) A use-case developed with a domain expert in cryptocurrencies financial activities that demonstrate the usage of Cryptocomparator.

2. Related work

Analysis of cryptocurrencies is becoming a subject of study for several academic research fields. Omane-Adjepong et al. [OAA19] examine inter-linkages among seven leading crypto markets. They used correlation with linear and nonlinear causality methods, to report levels of connectedness and volatility spillovers. Liew et al. [LLBS19] consider the top 100 cryptocurrencies ranging from 2015 to early 2018 with the aim of increasing the understanding of cryptocurrencies' behavior. Their comparison is done using the correlation of daily prices. Guo et al. [GTH18] use the daily return of the currency, or other fundamental characteristics as the hashing function used, to build a similarity network where each node represents a cryptocurrency and each link a similarity between them. Another work from Lucchini et al. [LAL*20] shows the connections between developers and the return of cryptocurrencies with a nested network. However, all these works focus on automated analysis and occasionally on static visualizations, and do not provide explorable environments.

On the other hand, several Visual Analytics solutions exist for the analysis of cryptocurrencies transactions, blockchain records, exchanges of cryptocurrencies, as well summarized in Tovanich et al. work [THFI21]. Zhong et al. [ZWX*20] propose SilkViser, a cryptocurrency transaction data viewing tool that helps new users to understand cryptocurrency transaction mechanisms and expert users to recognize more advanced transaction information. Kinkeldey et

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al. [KFBI21] present BitConduite, a tool to explore financial activities within the Bitcoin network. It focuses on identifying groups of subjects using Bitcoin(e.g., commercial services) in similar ways. Bistarelli et al. [BS17] build a tool dedicated to visual analysis of bitcoin transactions called BlockChainVis. They provide a new graph visualization (archipelago) that displays all the islands (i.e. isolated sub-graphs) of the Bitcoin transactions. However, those studies do not focus explicitly on relations among cryptocurrencies and their comparison, which is the target of this work. Additionally, while most of those solutions target intermediate and expert users [THFI21] our work targets also the general public (e.g., small private investors) who might not have a strong financial background. To the best of the authors' knowledge, no work exists that explicitly targets cryptocurrencies comparison and analysis of their relations. Focusing on similar proposals, all of them use a node-link representation. Yue et al. [YSZ*19] propose BitExtract, a visual tool that points out transaction and connection patterns of Bitcoin exchanges. A circular node-link diagram allows one to visualize inter-exchange behavior and find transaction patterns. The same is valid for The Bitcoin Big Bang [noac], a tool that represents large transactions of cryptocurrencies across multiple years. They visualize them through a concentric structure to expose the time differences (distance between the center and all the other elements). Different from our work, they explore only relations among transactions. CryptoComparator exploits a double concentric elliptic layout, a variation of a circular-shaped graph that is among the most prominent conventions used to draw graphs [GK07]. One of the few examples we found is used in netTerrain [noab]. They built a network diagram that can be rearranged using an ellipse layout where objects are placed in different "layers" based on type. However, their tool does not target cryptocurrencies. Another software to mention is Cytoscape [SMO*03] It provides the "concentric" layout that organizes the nodes into concentric circles, locating nodes with high values in the innermost circle, and then proceeding to the outward one. However, this layout cannot be customized to implement an elliptic geometry.

3. Data

We collected data about the top 100 cryptocurrencies, actually representing around 88% of the market coverage. Each data sample is representing financial information related to a single day on the market. We collected six different attributes: *Date* shows the date related to each sample; *Open Value/Close value* records the value of a single unit of the cryptocurrency at which opened/closed the market; *Low value/High value* records the minimum/maximum value reached by the cryptocurrency; *Market Cap* shows the amount of money spent into that cryptocurrency until a specific day, and *Volume* is the amount of coins exchanged.

For each attribute of a cryptocurrency we compute two different types of correlation based on how the two time-series x, y are managed (e.g. $x^{BTC}_{marketCap}$, $y^{ETH}_{marketCap}$):

Time zero: we first horizontally shifted one of the two such that they both start from the same time t_0. Then, to use Pearson correlation, the longest one is truncated so that they have the same length.

Year: we compute the Pearson correlation coefficient only on two time-series that present samples for the whole selected year. In this way, the truncation is made from the start of the selected year to the end of it (e.g. $x^{BTC}_{marketCap,2017}$, $y^{ETH}_{marketCap,2017}$) so that we can formulate a correlation that focuses on a specific span of time.

4. CryptoComparator

CryptoComparator is a multi-coordinated environment composed of five interactive visualizations: the double elliptic network graph, the correlation heatmap, the line charts, the dimensionality reduction scatterplot, and the Twitter window. CryptoComparator is available at the following link: `https://github.com/pietro-nardelli/CryptoComparator`.

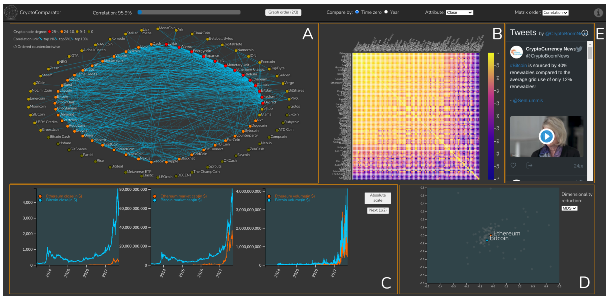
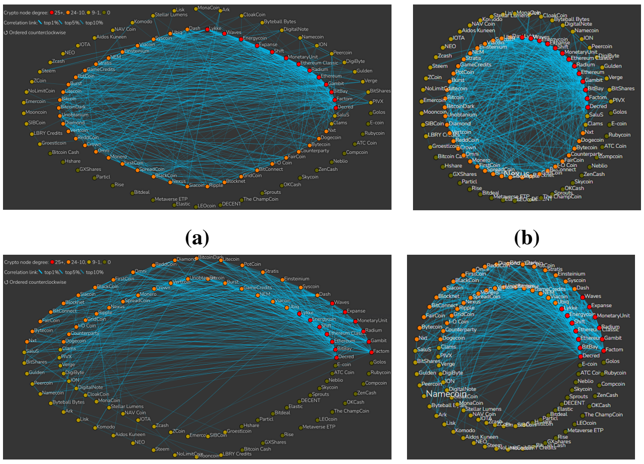


Figure 1: *An overview of CryptoComparator: The double elliptic graph (A); the Correlation Heatmap (B); the Line Charts (C); the Dimensionality reduction scatterplot (D); the Twitter window (E).*

Double Elliptic Network Graph The main visualization of CryptoComparator is the double elliptic network graph (see Figure 1.A). Each node in the graph represents a cryptocurrency and a link between two nodes outlines their correlation. The rationale behind the decision to use this graph-based visual encoding lies in the fact that we need a detailed analysis of the network while scaling up to reach a maximum of 200 elements, as suggested in [YAD*18]. The requirements that this visualization must support are: being visually useful during a single cryptocurrency search (R1) and distinctly exposing the whole correlations graph and sub-graphs generated by a user selection (R2). In order to exploit the structure of the graph, we decided to focus on an elliptic layout. This layout has the advantage of being better space-filling with respect to the screen aspect ratio in contrast with a circular one. We initially tested a double circular layout, but we experienced problems in visual space required and worse overlap of cryptocurrencies labels between inner and outer circles. As we can see in Figures 2b, 2d the concentric circular layout proposed by Cytoscape [SMO*03] could introduce visual cluttering. To solve this problem would have been necessary to rotate node names (e.g., [YSZ*19]) and/or use abbreviations (e.g., [GTH18]). The first solution affects the readability while the latter one is feasible only for expert users that are accustomed to such abbreviations. For these reasons, we opted for a double ellipses based layout. The choice of a double ellipse (inner and outer) helps in accommodating in the same space more visual elements (nodes), without affecting the readability. Supporting the decision to use an elliptic-based graph, the curvature is an important predictor of beauty in node-link diagrams. Moreover, interest can be triggered from the very early beginning by complexity, given that interest is a crucial variable that induces long-term attention to a stimulus [CMRW18]. With the aim of increasing the complexity without affecting unacceptably the curvature, we decided to increase linearly the cosine contribute and non-linearly the sine one, respectively for the x,y coordinates value of each node. The result is an ellipse with a spike approaching the vertical axis. Even if find-



(a) (b)

(c) (d)

Figure 2: *Two of the three available graph orderings, one per row, displayed using on the left the proposed double elliptical layout and on the right the double concentric layout Ellipse degree ordering (2a, 2b) and Sector degree ordering (2c, 2d).*

ing a path between two nodes is proved to work well, as soon as the size and density of a node-link diagram increase, it can become a very difficult task [GFC05]. Thus, to support the exploration of different correlation strength intervals without incurring in visual clutter, this chart provides interactive control (a slider) over the amount of important correlations to show. Using the slider it is possible to reduce the number of links shown on the graph, which is set by default to the top 10% correlated links. Finally, the main problem of graph visualizations is readability, which is affected by edge crossing [Pur97]. To mitigate this problem, some techniques such as edge bundling [KSB*09] and edge splatting [BVB*11] may be used. While these techniques would orthogonally add some benefits to the readability, it could not be enough. In particular, even though circular layouts often lead to long edges and an overall dense drawing, caused by the rigid restriction on node placement [GK07], they will also provide the possibility to reduce the visual clutter by choosing the direction that produces the shorter links [BW14]. To better mitigate the visual clutter it may introduce, CryptoComparator implements three different types of graph ordering (counterclockwise sorted): alphabetical, by the degree of nodes with respect to correlation strength from the inner to the outer ellipse and by the degree of nodes radially.

Alphabetical order. In the first case the nodes are placed in alphabetical order. Together with the double ellipses layout, it helps to solve the user's difficulty in searching for a specific node, since the readability of a node-link diagram can worsen quickly as its size increases [GFC05]. They are ordered radially, which means that nodes are grouped such that they are on the same angle with respect to the center of both the ellipses. In this way, similar names are close together, instead of putting them on a unique sequence spanning both ellipses. Grouping nodes together can speed up the retrieval for a specific cryptocurrency thanks to *skimming*. This technique is applied by a reader when the goal is to quickly move one's eyes through the text to find a specific word or piece of information and may suffice if complete and detailed comprehension of the text is not a priority [RSM*16]. The user, skimming through both the ellipses simultaneously, can focus on two nodes at a time leading to a faster search process.

Ellipse degree ordering. The second ordering is based on the degree of nodes starting from the inner to the outer ellipse. This means that the nodes inside the inner ellipse have more connections among them with respect to the nodes placed on the outer ellipse, exploiting the capability of this layout to split nodes into two groups. Thanks to this setting, the majority of the most important correlations are represented in the inner ellipse, significantly reducing the number of links that cross both ellipses and that could create visual cluttering problems. As we can see from Figure 2a the graph readability is improved compared to an alphabetic graph ordering (see supplemental material), while new information such as the most and least connected cryptocurrencies are more easily found.

Sector degree ordering. The third ordering function is still based on the degree of nodes, but placed on both inner and outer ellipses. The nodes that are on the right side of the graph are the ones that have more connections (greater degree) while continuing counterclockwise there would be nodes progressively less connected. This choice allows the analyst to understand at a glance the nodes that are more and less connected. As we can see from Figure 2c the analyst has the capability to immediately identify clusters of cryptocurrencies strongly related. At the same time, a small drawback is represented by more visual clutter introduced with respect to the ellipse degree ordering. The presented trade-offs among the different implemented orderings justified the implementation of real-time layout change triggered by the analyst on demand.

Regardless of which ordering function is chosen, each node is colored differently to represent the percentage of links: red (at least 25 %), orange (between 25 % and 10 %), yellow (between 10 % and 1 %), dark yellow (0 %). These colors suggest how much a cryptocurrency is correlated to others. In addition, the thickness of the links is used to show the correlation strength, encoding on three levels the ranking of correlations according to the following rules: large thickness (top 10%), medium thickness (between 10% and 50%), and small thickness (between 50% and 100%). When a node is clicked the sub-graph containing all the nodes and links that target the clicked node is highlighted. As a final means for slight adjustments of the layout, the user can alter a node position using a drag and drop feature. If the user deemed necessary, the nodes can be displaced from their original position in order to obtain a customized layout that best reflects her own perspective.

Correlation Heatmap To ease the interpretation and perception of correlation values exploiting node-link and matrix representation [GFC04], CryptoComparator implements also a color-coded correlation heatmap (see Figure 1.B.). The heatmap gives the possibility for the user to understand at a glance the distribution of the correlations (one value per cell) between cryptocurrencies. It visualizes cell values by the use of a color gradient, giving a good overview of the largest and smallest values, revealing patterns, and displaying similarity among cryptocurrencies [MV15]. We chose to map the values on a power scale, and then use a sequential multi-hue color scheme called "plasma" [CSH20]. In this way, the differences between high correlation values can be easily spotted. The user has also the possibility to change the starting correlation threshold for the node-link diagram directly from the heatmap thanks to a brush activated on its legend with the visual support of a color gradient. When no correlation can be computed (e.g., at least one cryptocurrency is inactive in the selected year) the cells are colored in black (background color). By default the heatmap presents all the cryptocurrencies sorted by similarity values in descending order. The user can choose to apply an alphabetical order to make the search of a cryptocurrency easier. The size of the heatmap changes according to the selected subset of currencies from the graph or by using the interactive legend on the right by brushing the chosen correlation interval, The heatmap is interactive (cells selection) and coordinated with the other views.

Dimensionality reduction We designed CryptoComparator to provide, along with correlation information, even similarity information among cryptocurrencies. We implemented four different 2D dimensionality reduction techniques: MDS [Kru64], PCA [MR93], t-SNE [vdMH08] and UMAP [MHM18] selectable by the user.

Line Charts When a cryptocurrency or a pair of cryptocurrencies is selected in CryptoComparator, the time series of the different attributes are drawn using separate line charts (see Figure 1.C.). Through a brush operation it is possible to zoom into the time series to study their behaviors. It is possible to change from absolute to relative scale for better clarity. Three out of six attributes are selected by default, given their informativeness in finance: *Close value*, *Market Capitalization*, and *Volume*.

Twitter window A considerable amount of cryptocurrency activities are communicated through social media, and Twitter can be considered one of their main communication channel [PL19]. To allow the analyst to monitor the social activities and link them to cryptocurrencies behavior (from which they are strongly affected), CryptoComparator implements a Twitter window (see Figure 1.E.), tuned on the last news about the set of selected cryptocurrencies.

5. Use case: supporting volatility reduction of a crypto wallet

The use case described below has been developed with a domain expert in the cryptocurrency field assisted by members of our team. The objective is to find a cryptocurrency to add as the first element of a crypto wallet, investing in a promising asset. One of the most traded currencies in the past year has been *Dogecoin*. Since such currency showed an increment in price of 14 180%, it seems a promising asset to invest in; sadly, high volatility has to be taken into account because of the anomalous increment in price, which is not recommended to make safe investments. Instead, a good strategy may be to invest in a correlated cryptocurrency, having more probability to increase in price with less volatility than Dogecoin. Using CryptoComparator it is possible to accomplish this task with a few steps. The user first selects the attribute “*Close value*” for the correlation measure. Since the user wants to find a specific coin, the alphabetical ordering of the graph is used. Clicking the Dogecoin node on the graph triggers the visualization of the sub-graph of nine correlated currencies. The user explores a correlation threshold of 98% using the slider in the upper part of the window, reducing the analysis to two currencies: GameCredits (98.4%) and Bytecoin (98.5%). Now the user checks if any of these cryptocurrencies are correlated to Dogecoin also for other financial attributes, i.e., the Market Cap, looking for a stronger correlation. Highlighting the Dogecoin sub-graph for such attribute, the user identifies

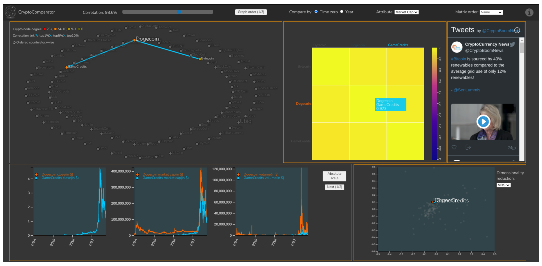


Figure 3: *The user analyzes the Dogecoin sub-graph for the attribute “Market capitalization”. She sorts the graph in alphabetical order to find Dogecoin. Then, increasing the correlation strength threshold, she discovers that Bytecoin could be a good choice.*

the same couple of currencies: GameCredits (97.3%) and Bytecoin (97.4%) are strongly correlated also for the Market Cap. The user will now conduct further analysis for both the candidates, starting from Bytecoin. Clicking on the Dogecoin-Bytecoin cell in the correlation heatmap, the user sees from the line charts how the trends for the most important financial attributes share similar behavior, confirmed by their similarity in the MDS scatterplot. Similar results are obtained for GameCredits, confirming a comparable strong correlation(97.3%). The user should now check what level of correlation they share; in case of positive correlation, she will only select one. Clicking on Bytecoin she discovers Gamecredits belongs to its sub-graph. From the line charts it is possible to notice how Bytecoin presents a much bigger Market Cap and Volume, which means that it is a more actively traded and capitalized coin. This biases the user toward choosing it. Finally, the user wants to check how the analyzed behavior is stable during the years. Selecting "Compare by year", and checking the year 2016, the user notices that the sub-graphs associated with Dogecoin are empty, and a lower threshold was automatically set to a correlation value of 84.6%. To inspect further the situation, the user proceeds with the use of the correlation heatmap. Led by the color-coded interactive legend, she brushes to select the range that represents positive correlation. Selecting Dogecoin the user notices that Gamecredits is not anymore in the subgraph (the currencies were not correlated in the year 2016 despite their whole life high correlation); Bytecoin is still included. Through the slider the user explores the minimum value of correlation above which Bytecoin gets filtered out from the graph (50.0%). At the end of such analysis the user adds Bytecoin to the crypto wallet since it shows a high correlation (97%) with Dogecoin and less volatility in behavior with respect to Gamecredits.

6. Conclusions

This paper presented CryptoComparator, a Visual Analytics solution supporting the analysis of correlations, similarity, and market trends for cryptocurrencies. It introduced a graph layout, double ellipse layout, as a variation of a double circular layout, customized for fast identification of a cryptocurrency and correlation-based grouping of cryptocurrencies. One use case demonstrated the interesting fit of this solution for a domain expert. As future works we envision conducting more evaluation on the properties of the introduced graph layout, and to conduct a user study to understand better the efficacy of the proposed solution.

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