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Forecasting Trends in Cryptocurrencies through the Application of Association Rule Mining Techniques

Mohamed EL MAHJOUBY[1], Mohamed Taj Bennani[1], Khalid El Fahssi[2], Said Elgarouani[2], Mohamed Lamrini[1], Mohamed EL FAR[1]

[1] Department of Computer Science Laboratory (LPAIS), Faculty of Science Dhar El Mahraz, USMBA, Fez, Morocco
[2] Department of Computer Science Laboratory (LISAC), Faculty of Science Dhar El Mahraz, USMBA, Fez, Morocco

mohamed.elmahjouby@usmba.ac.ma, bennani.taj@gmail.com, khalid.elfahssi@usmba.ac.ma, said.elgarouani@usmba.ac.ma, mohamed.lamrini@usmba.ac.ma, mohamed.elfar@usmba.ac.ma

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Abstract: Data mining in the stock market and cryptocurrencies is the most used. In this paper, we applied a data mining approach to implement association rules. Our significant contribution is to ascertain a robust correlation between four cryptocurrencies: Bitcoin, Litecoin, Ethereum, and Monero. Specifically, this paper used data mining techniques to predict and discover association rules between four cryptocurrencies (Bitcoin, Litecoin, Ethereum, and Monero) to identify optimal points for selling and buying. Our suggested models utilized the apriori algorithm to forecast and determine association rules in our datasets. Our significant contribution is to ascertain a robust correlation between four cryptocurrencies: Bitcoin, Litecoin, Ethereum, and Monero. Specifically, we aim to ascertain the current link between Bitcoin and other items during the next 24 hours. In addition, if there is a current buy or sell of Bitcoin, we can forecast, for instance, the movement of Litecoin over the next three hours. We have already carried out this prediction for the other items. Our objective is to propose a prediction model to generate and discover associations between the cryptocurrency, Bitcoin, Litecoin, Ethereum, and Monero. In our research, we used apriori algorithm to produce the association rules. We evaluated the quality of these rules using two metrics: Support and lift. Experiment analysis proves that our method successfully generates a strong association rule. We have already carried out this prediction for the other items.

Keywords: *Cryptocurrency, Bitcoin, Apriori, association rules, Ethereum, Litecoin*

1. Introduction

Data mining involves extracting valuable insights, patterns, and knowledge from extensive datasets. Referred to as "knowledge discovery in databases," this approach reveals meaningful patterns within databases, contributing to informed decision-making. Employing data mining confers significant competitive benefits to companies [1].

The exploration of data mining has emerged as a prominent area of research, with the ongoing challenge of extracting valuable knowledge from vast datasets. Effectively processing extensive data poses a difficulty for current computing software and hardware systems [2]. Studying association rules is essential for data mining in multiple disciplines: Bioinformatics, medical informatics, scientific data analysis, financial analysis, consumer profiling, and beyond. In recent years, there has been a notable rise in the amount of data available for analysis across all these application areas [3].

The authors of reference [4] combined LSTM and genetic algorithm (GA) approaches to provide an approach to stock market trend forecasting. According to their investigation, this method performed better than the benchmark model by the industry. Numerous machine learning techniques were employed by the authors of reference [5], including bagging, AdaBoost, logistic regression, extreme gradient boosting classifier, random forest classifier, and Gaussian naïve Bayes. Your objective is to predict the best times to buy and sell the euro about the dollar.

The authors of reference [6] used deep learning to improve the performance of the prediction models. We employed methodologies from Machine Learning and Deep Learning. Different academics generally utilized time series to forecast prices using deep learning and machine learning methodologies.

E-mail:author's email

Machine learning is used to forecast fluctuations in the price of Bitcoin and has proven to be a helpful tool in this quest, according to [7]. A reusable trading strategy that trained on historical data collected at 4-hour intervals was provided by the authors of reference [8] using candlesticks of six different currency pairings: two minor pairs, like EUR/GBP and GBP/JPY, and four pairs, like GBP/USD, EUR/USD, USD/JPY, and USD/CHF. To predict the prices of nine well-known cryptocurrencies, Chowdhury et al. [9] looked at ensemble methodologies based on machine learning, including KNN, ANN, gradient-boosted trees, and a mixed ensemble model. According to the results, the ensemble-learning model had the lowest prediction error. This work suggests using linear regression as the base estimator for machine learning in conjunction with an adaptive boosting regression technique [10]. With this combination, the closing values of the gold commodity, the EUR/USD, the GBP/USD, and the NASDAQ are all forecasted. This method uses seven technical indicators to supply data for the adaptive boosting regression.

To forecast the stock market, writers in reference [11] presented association rule mining, a type of data mining. To make predictions, they used technical trading indicators and stock closing prices. To produce such as buy, sell, or hold for shares, the authors created rules based on the signals produced by each technical trading indicator. They then applied these rules to the current date query.

This paper used data mining techniques to predict and discover association rules between four cryptocurrencies (Bitcoin, Litecoin, Ethereum, and Monero) to identify optimal points for selling and buying. Our suggested models utilized the apriori algorithm to forecast and determine association rules in our datasets. Our significant contribution is to ascertain a robust correlation between four cryptocurrencies: Bitcoin, Litecoin, Ethereum, and Monero. Specifically, we aim to ascertain the current link between Bitcoin and other items during the next 24 hours. In addition, if there is a current buy or sell of Bitcoin, we can forecast, for instance, the movement of Litecoin over the next three hours. We have already carried out this prediction for the other items. Unlike other studies [12] that focus solely on the next few hours, our analysis has the advantage of extracting strong rules across the four cryptocurrencies over the next 24 hours.

This paper is structured as follows: in the first section, we provide an introduction. In the second section, we present some literature reviews and related works. In the third, we define association rules mining and the apriori algorithm and describe and explain our methodologies. In the fourth section, we discuss the results. In the last section, we provide a conclusion and future works.

2. Literature Review

In this section, we have shown some literature review and related work. In reference [13], the authors conducted a study exploring associations within the Warsaw Stock Exchange. They applied a data mining methodology to detect co-movements among various stocks listed on the exchange. The Apriori algorithm is the method of choice for uncovering these associations.

In the paper by Nandgaonkar (2015), [11] the authors introduced a data mining method, specifically association rule mining, for predicting stock market trends. Their approach involved incorporating technical trading indicators and the closing prices of stocks into the forecasting process. According to signals produced by individual technical trading indicators, these rules were then applied to the current date query, resulting in signals such as buy, sell, or hold for shares.

Jiangtao Qiu and his colleagues [14] Devised a model known as COREL (customer purchase prediction model) designed to anticipate customer buying patterns. This model operates through two stages: firstly, it establishes a roster of potential products by analyzing associations among products to forecast customer motivations; subsequently, it selects the most frequently purchased products, taking into account customer preferences. The researchers gathered data on customer information and product reviews from the "Jingdong" e-commerce platform. Their findings underscored the substantial impact of customer preferences on purchasing decisions.

Several methods and models are available for time series AR, ARIMA, SARIMA, and LSTM. The authors of [15] studied predicting gold commodities using SVM and ARIMA. In reference [16], the authors utilize Long Short-Term Memory (LSTM) and subsequently integrate and contrast it with the ARIMA model. In reference [17], the authors utilize a basic three-layer Long Short-Term Memory (LSTM) model to forecast stock prices based on the LQ45 indices, achieving a mean absolute percentage error of 18.6135.

A recent study [18] examines Bitcoin price forecasting using empirical analysis. The research compares Bayesian neural networks with established linear and non-linear benchmark techniques, providing valuable practical insights. In reference [19], the authors utilized a stochastic neural network model to forecast the prices of Cryptocurrencies. In reference [20], authors explored novel deep learning models for predicting multi-step-ahead time series difficulties.

Using the Apriori algorithm, authors in reference [21] examined association rules between BIST100 stocks. When choosing equities, we employed two strategies. We began with all 87 stocks in the first technique, identified association rules between them, eliminated two stocks based on the best two rules, and then discovered additional association rules. In the second approach, we established association rules on sectoral base sets and divided the stocks according to these sets.

The authors of reference [12] used association rules to determine the best times to buy and sell. By examining the prediction of association rules between currency pairs, gold, and the NASDAQ, our work advances the field of research. The Apriori approach to forecast and find association rules in datasets is used.

In reference [22], the authors presented a new method for predicting trends in financial time series. They achieve this by reconstructing the time series through high-order structures known as motifs. Convolutional neural networks are then employed to learn the underlying patterns in the reconstructed sequence, offering valuable insights for predicting upward and downward trends.

The suggestion in reference [23] involves integrating LSTM networks with machine learning models for forecasting Bitcoin prices. The research outlined in [23] integrates LSTM to extract organized financial data from news and employs this information in a machine learning model. In reference [24], the authors employed a combination of RNN and LSTM techniques, achieving a classification accuracy of 52% and a RMSE of 8%. The claim made by the authors is that the utilization of RNN with LSTM yields superior performance compared to conventional RNN and ARIMA models.

The authors in reference [25] introduced a time series forecasting approach employing Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) specifically for predicting electricity load in Turkey. Yu [26] introduced hybrid models combining Principal Component Analysis (PCA) and Support Vector Machine (SVM), while Zbikowski [27] put forward an SVM model based on Fisher. In all conducted experiments, hybrid models outperformed individual models.

In [28], this research utilizes machine learning and deep learning algorithms to forecast stock market movements. The study focused on four stock market sectors: diversified financials, petroleum, non-metallic minerals, and metals, specifically from the Tehran stock exchange. The dataset encompassed ten years of historical data, incorporating ten technical features.

Chang introduced a business analytics approach for assessing stock market performance, enabling investors to monitor and evaluate the market behavior of their selected stocks. He opted for the Heston model and its corresponding API to calculate the anticipated movements in stock indices, providing a significant level of accuracy [29]. In [30], the authors performed experiments focusing on forecasting stock trends. They utilized SVM, Random Forest, KNN classifiers, coupled heat mapping, and ensemble learning methodologies, Striving to achieve enhanced precision in forecasting stock fluctuations.

In [31], the authors suggested utilizing ARIMA and ANN models to predict future gold prices. The results obtained from experiments conducted on a standard gold dataset demonstrated that the Feed Forward Neural Network (FFNK) exhibited greater accuracy, as measured by Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), compared to the ARIMA model. However, in experiments predicting sales values conducted by authors in [32], the ARIMA model effectively projected future sales values.

3. METHODOLOGY AND ASSOCIATION RULE MINING

In this section, we have presented association rules, the apriori algorithm, and our methodology.

A. ASSOCIATION RULES

Association rules represent a methodology within machine learning that relies on rules for analysis to discover relationships or associations among a set of variables in large datasets. This approach is often used in data mining and market basket analysis, where the goal is to identify patterns or correlations between different items or attributes. The primary utilization of association rules is typically in analyzing transactional data, such as customer shopping baskets. The rules are: "If A, then B" are expressed. The occurrence of item A aligns with the presence of item B. The strength of the association is measured using metrics like support and lift. Here are the key concepts related to association rules:

Support: Support measures the frequency or occurrence of a specific item set in the dataset. Equation (1) outlined here delineates the procedure for quantifying Support.

$$\mathrm{Support(A)} = \frac{\mathrm{TransactionsContainingA}}{\mathrm{TotalTransactions}} \tag{1}$$

Lift: Lift measures how much more likely item B is purchased when item A is purchased, in contrast to the scenario where item B is bought independently of item A. Equation (2) outlined here delineates the procedure for quantifying Lift [12].

$$\mathrm{lift}(\mathrm{A} \rightarrow \mathrm{B}) = \frac{\mathrm{Confidence}(\mathrm{A} \rightarrow \mathrm{B})}{\mathrm{Support}(\mathrm{B})} \tag{2}$$

Association rule mining algorithms, such as the Apriori algorithm, are commonly used to extract these rules from large datasets. The Apriori algorithm, for example, works by iteratively finding frequent itemsets and generating association rules based on those itemsets. In practical terms, association rules can be applied in various domains, including retail, e-commerce, healthcare, and more, to uncover valuable insights and improve decision-making processes.

B. APRIORI ALGORITHM

The Apriori algorithm is a popular algorithm used in data mining and machine learning for discovering association rules within large datasets. It is for conducting market basket analysis and identifying connections between various items bought in tandem. The proposed algorithm dates back to 1994 by Rakesh Agrawal and Ramakrishnan Srikant [33].

C. DATASETS

This research utilized a dataset comprising hourly prices collected without gaps from December 16, 2020, to December 16, 2023. The dataset encompasses Bitcoin, Ethereum, Litecoin, and Monero, spanning 17416 days. The dataset features columns Open, High, Low, Close, and Volume.

D. FEATURE ENGINEERING

The objective of the techniques described in this paper is to detect relationships or associations of cryptocurrencies (BTC_USD, ETC_USD, LTC_USD, and XMR_USD) of variable categories in data files. We have used the apriori algorithm. We collected the data on the four cryptocurrencies containing the following features: Open, High, Low, Close, and Volume. Then, we added 24 columns to each database with values: single buying and single selling. Tables that list the characteristics of Bitcoin, Ethereum, Litecoin, and Monero are Tables I through IV. We used these attributes to identify any relationships, such as the movement of Bitcoin today and other products over the next 24 hours. Each attribute has a description for each of the four cryptocurrencies.

TABLE I. Attributes for Bitcoin

Attribute	Description
Bitcoin_H00	Bitcoin hour action
Bitcoin_H01	The subsequent move of the Bitcoin hour
Bitcoin_H02	The forthcoming movement of Bitcoin within the next two hours
Bitcoin_H03	The forthcoming movement of Bitcoin within the next 3 hours
Bitcoin_H04	The forthcoming movement of Bitcoin within the next 4 hours
Bitcoin_H05	The forthcoming movement of Bitcoin within the next 5 hours
Bitcoin_H06	The forthcoming movement of Bitcoin within the next 6 hours
Bitcoin_H07	The forthcoming movement of Bitcoin within the next 7 hours
Bitcoin_H08	The forthcoming movement of Bitcoin within the next 8 hours
Bitcoin_H09	The forthcoming movement of Bitcoin within the next 9 hours
Bitcoin_H10	The forthcoming movement of Bitcoin within the next 10 hours
Bitcoin_H11	The forthcoming movement of Bitcoin within the next 11 hours
Bitcoin_H12	The forthcoming movement of Bitcoin within the next 12 hours
Bitcoin_H13	The forthcoming movement of Bitcoin within the next 13 hours
Bitcoin_H14	The forthcoming movement of Bitcoin within the next 14 hours
Bitcoin_H15	The forthcoming movement of Bitcoin within the next 15 hours
Bitcoin_H16	The forthcoming movement of Bitcoin within the next 16 hours
Bitcoin_H17	The forthcoming movement of Bitcoin within the next 17 hours
Bitcoin_H18	The forthcoming movement of Bitcoin within the next 18 hours
Bitcoin_H19	The forthcoming movement of Bitcoin within the next 19 hours
Bitcoin_H20	The forthcoming movement of Bitcoin within the next 20 hours
Bitcoin_H21	The forthcoming movement of Bitcoin within the next 21 hours
Bitcoin_H22	The forthcoming movement of Bitcoin within the next 22 hours
Bitcoin_H23	The forthcoming movement of Bitcoin within the next 23 hours
Bitcoin_H24	The forthcoming movement of Bitcoin within the next 24 hours

TABLE II. Attributes for Litecoin

Attribute	Description
LTC_H00	Litecoin hour action
LTC_H01	The subsequent move of the Litecoin hour
LTC_H02	The forthcoming movement of Litecoin within the next two hours
LTC_H03	The forthcoming movement of Litecoin within the next 3 hours
LTC_H04	The forthcoming movement of Litecoin within the next 4 hours
LTC_H05	The forthcoming movement of Litecoin within the next 5 hours
LTC_H06	The forthcoming movement of Litecoin within the next 6 hours
LTC_H07	The forthcoming movement of Litecoin within the next 7 hours

LTC_H08	The forthcoming movement of Litecoin within the next 8 hours
LTC_H09	The forthcoming movement of Litecoin within the next 9 hours
LTC_H10	The forthcoming movement of Litecoin within the next 10 hours
LTC_H11	The forthcoming movement of Litecoin within the next 11 hours
LTC_H12	The forthcoming movement of Litecoin within the next 12 hours
LTC_H13	The forthcoming movement of Litecoin within the next 13 hours
LTC_H14	The forthcoming movement of Litecoin within the next 14 hours
LTC_H15	The forthcoming movement of Litecoin within the next 15 hours
LTC_H16	The forthcoming movement of Litecoin within the next 16 hours
LTC_H17	The forthcoming movement of Litecoin within the next 17 hours
LTC_H18	The forthcoming movement of Litecoin within the next 18 hours
LTC_H19	The forthcoming movement of Litecoin within the next 19 hours
LTC_H20	The forthcoming movement of Litecoin within the next 20 hours
LTC_H21	The forthcoming movement of Litecoin within the next 21 hours
LTC_H22	The forthcoming movement of Litecoin within the next 22 hours
LTC_H23	The forthcoming movement of Litecoin within the next 23 hours
LTC_H24	The forthcoming movement of Litecoin within the next 24 hours

TABLE III. Attributes for Ethereum

Attribute	Description
ETC_H00	Ethereum hour action
ETC_H01	The subsequent move of the Ethereum hour
ETC_H02	The forthcoming movement of Ethereum within the next two hours
ETC_H03	The forthcoming movement of Ethereum within the next 3 hours
ETC_H04	The forthcoming movement of Ethereum within the next 4 hours
ETC_H05	The forthcoming movement of Ethereum within the next 5 hours
ETC_H06	The forthcoming movement of Ethereum within the next 6 hours
ETC_H07	The forthcoming movement of Ethereum within the next 7 hours
ETC_H08	The forthcoming movement of Ethereum within the next 8 hours
ETC_H09	The forthcoming movement of Ethereum within the next 9 hours
ETC_H10	The forthcoming movement of Ethereum within the next 10 hours
ETC_H11	The forthcoming movement of Ethereum within the next 11 hours
ETC_H12	The forthcoming movement of Ethereum within the next 12 hours
ETC_H13	The forthcoming movement of Ethereum within the next 13 hours
ETC_H14	The forthcoming movement of Ethereum within the next 14 hours
ETC_H15	The forthcoming movement of Ethereum within the next 15 hours
ETC_H16	The forthcoming movement of Ethereum within the next 16 hours
ETC_H17	The forthcoming movement of Ethereum within the next 17 hours
ETC_H18	The forthcoming movement of Ethereum within the next 18 hours
ETC_H19	The forthcoming movement of Ethereum within the next 19 hours
ETC_H20	The forthcoming movement of Ethereum within the next 20 hours
ETC_H21	The forthcoming movement of Ethereum within the next 21 hours
ETC_H22	The forthcoming movement of Ethereum within the next 22 hours
ETC_H23	The forthcoming movement of Ethereum within the next 23 hours
ETC_H24	The forthcoming movement of Ethereum within the next 24 hours

TABLE IV. Attributes for Monero

Attribute	Description
monero_H00	Monero hour action
monero_H01	The subsequent move of the Monero hour
monero_H02	The forthcoming movement of Monero within the next two hours
monero_H03	The forthcoming movement of Monero within the next 3 hours
monero_H04	The forthcoming movement of Monero within the next 4 hours
monero_H05	The forthcoming movement of Monero within the next 5 hours
monero_H06	The forthcoming movement of Monero within the next 6 hours
monero_H07	The forthcoming movement of Monero within the next 7 hours
monero_H08	The forthcoming movement of Monero within the next 8 hours

monero_H09	The forthcoming movement of Monero within the next 9 hours
monero_H10	The forthcoming movement of Monero within the next 10 hours
monero_H11	The forthcoming movement of Monero within the next 11 hours
monero_H12	The forthcoming movement of Monero within the next 12 hours
monero_H13	The forthcoming movement of Monero within the next 13 hours
monero_H14	The forthcoming movement of Monero within the next 14 hours
monero_H15	The forthcoming movement of Monero within the next 15 hours
monero_H16	The forthcoming movement of Monero within the next 16 hours
monero_H17	The forthcoming movement of Monero within the next 17 hours
monero_H18	The forthcoming movement of Monero within the next 18 hours
monero_H19	The forthcoming movement of Monero within the next 19 hours
monero_H20	The forthcoming movement of Monero within the next 20 hours
monero_H21	The forthcoming movement of Monero within the next 21 hours
monero_H22	The forthcoming movement of Monero within the next 22 hours
monero_H23	The forthcoming movement of Monero within the next 23 hours
monero_H24	The forthcoming movement of Monero within the next 24 hours

After eliminating the absent data points, we consolidated the data of the four cryptocurrencies into a unified database, aligning them based on identical dates. Subsequently, we retained only the columns that depict the subsequent hourly movements of LTC_USD, ETC_USD, and XMR_USD, along with the action of BTC_USD, referred to as the Bitcoin_H00. Each column indicates "SA" for a simple buying or "SV" for a simple sale.

Ultimately, we transformed every attribute into binary form, assigning values of 0 or 1 to each attribute within the dataset (We have utilized Bibliotheque get_dummies). 0 means single buying, and 1 means single selling. We performed identical procedures for the remaining three datasets (Litecoin, Ethereum, and Monero). Finally, we have applied the apriori algorithm to generate strong association rules.

E. PROPOSED APPROACH

The exploration of connections and associations between variables within a database has increasingly relied on association rule mining methods. These approaches leverage statistical analysis and artificial intelligence algorithms to uncover prevalent patterns. Utilizing established patterns, integrating particular criteria such as minimum support and lift. In this research, we classified association rules based on the subsequent criteria:

1) The consequences of the rules: "single buying" or "single selling" are categorized.
2) The antecedents of the rules: "single buying" or "single selling" are categorized.
3) We established the minimum support threshold at 0.25
4) We established a minimum lift threshold of 1.

We have proposed an algorithm with two main phases: initially, the extraction of association rules through the Apriori algorithm, followed by the evaluation of the obtained association rules using multicriteria analysis. We suggest a method that employs data mining to pinpoint the most advantageous moments for purchasing and selling cryptocurrency. Our objective is to define optimal rules for determining buy and sell points. Our suggested model comprises several primary stages: datasets, Feature engineering, retrieval of frequent itemsets, generating association rules, and identification of compelling association rules. Figure 1 represents our approach.

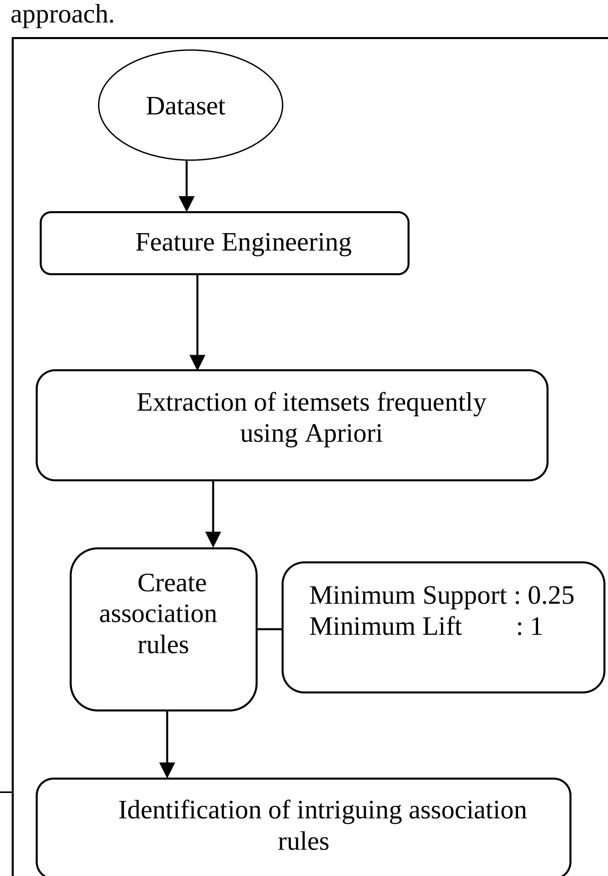

Fig. 1 . Our approach

4. RESULTS AND DISCUSSION

Following data preparation, we proactively identified a subset of significant records. Our initial approach involved employing the Apriori algorithm, with a minimum support threshold set at 0.25, to extract frequent itemsets. The frequent sets identified during this phase were crucial in the following step, which involved creating association rules.

In addressing the issue of monotonous and uninspiring regulations, we implemented our approach in the subsequent stage, the preferences of those making decisions. We assessed the previously derived rules as options using specific quality metrics. Out of the numerous metrics suggested in existing literature, we honed in on two criteria: support and lift.

This research highlighted the robust correlation patterns for Bitcoin, Litecoin, Monero, and Ethereum. We created association rules that link the behavior of BTC_USD at a given moment to the behavior of the next hour for three other cryptocurrencies (ETC_USD, LTC_USD, and XMR_USD). Table 5 displays the foremost association rules for Bitcoin. The guidelines for linking Bitcoin with other commodities within the subsequent 24 hours are displayed.

TABLE V. Top association rules for Bitcoin

N°	Antecedents	Consequents	Support	Lift
R1	Bitcoin_H00_SA	ETC_H11_SV	0.279614	1.014665
R2	Bitcoin_H00_SA	LTC_H11_SV	0.278237	1.017145
R3	Bitcoin_H00_SV	Bitcoin_H02_SA	0.287879	1.070736
R4	Bitcoin_H00_SV	Bitcoin_H05_SA	0.289256	1.037920
R5	Bitcoin_H00_SV	ETC_H01_SA	0.290634	1.058865
R6	Bitcoin_H00_SV	ETC_H02_SA	0.305785	1.070270
R7	Bitcoin_H00_SV	ETC_H04_SA	0.286501	1.033240
R8	Bitcoin_H00_SV	ETC_H05_SA	0.293388	1.079950
R9	Bitcoin_H00_SV	LTC_H01_SA	0.304408	1.070711
R10	Bitcoin_H00_SV	LTC_H02_SA	0.298898	1.091767
R11	Bitcoin_H00_SV	LTC_H04_SA	0.290634	1.029891

Rule 1 in the transaction "Bitcoin_H00_SA => ETC_H11_SV", the antecedent represents a simple buying now of Bitcoin, they demonstrate a simple selling next 11 hours of ETC_USD (Ethereum) with a lift level surpassing 1, and a support level of 0.27.

Rule 2 in the transaction "Bitcoin_H00_SA => LTC_H11_SV", the antecedent represents a simple buying now of Bitcoin, they demonstrate a simple selling next eleven hours of LTC_USD (Litecoin) with a support level of 0.27 and lift level surpassing 1.

Rule 3 in the transaction "Bitcoin_H00_SV => Bitcoin_H02_SA", the antecedent represents a simple selling now of Bitcoin, they demonstrate a simple buying next two hours of Bitcoin with a support level of 0.28, and a lift level surpassing 1.

Rule 4 in the transaction "Bitcoin_H00_SV => Bitcoin_H05_SA", the antecedent represents a simple selling now of Bitcoin, they demonstrate a simple buying next five hours of Bitcoin with a support level of 0.28, and a lift level surpassing 1.

Rule 5 in the transaction "Bitcoin_H00_SV => ETC_H01_SA", the antecedent represents a simple selling now of Bitcoin, they demonstrate a simple buying next hour of ETC_USD (Ethereum) with a support level of 0.29, and a lift level surpassing 1.

Rule 6 in the transaction "Bitcoin_H00_SV => ETC_H02_SA", the antecedent represents a simple selling now of Bitcoin, they demonstrate a simple buying next two hours of ETC_USD (Ethereum) with a support level of 0.30, and a lift level surpassing 1.

Rule 7 in the transaction "Bitcoin_H00_SV => ETC_H04_SA", the antecedent represents a simple selling now of Bitcoin, they demonstrate a simple buying next four hours of ETC_USD (Ethereum) with a support level of 0.28, and a lift level surpassing 1.

Rule 8 in the transaction "Bitcoin_H00_SV => ETC_H05_SA", the antecedent represents a simple selling now of Bitcoin, they demonstrate a simple buying next five hours of ETC_USD (Ethereum) with a support level of 0.29, and a lift level surpassing 1.

Rule 9 in the transaction "Bitcoin_H00_SV => LTC_H01_SA", the antecedent represents a simple selling now of Bitcoin, they demonstrate a simple buying next hour of LTC_USD (Litecoin) with a support level of 0.30, and a lift level surpassing 1.

Rule 10 in the transaction "Bitcoin_H00_SV => LTC_H02_SA", the antecedent represents a simple selling now of Bitcoin, they demonstrate a simple buying next two hours of LTC_USD (Litecoin) with a support level of 0.29, and a lift level surpassing 1.

Rule 11 in the transaction "Bitcoin_H00_SV => LTC_H04_SA", the antecedent represents a simple selling now of Bitcoin, they demonstrate a simple buying next four hours of LTC_USD (Litecoin) with a support level of 0.29, and a lift level surpassing 1.

After that, we created association rules that link the behavior of ETC_USD at a given moment to the behavior of the next hour for three other cryptocurrencies (BTC_USD, LTC_USD, and XMR_USD). Table 6 displays the foremost association rules for Ethereum. The guidelines for linking Ethereum with other commodities within the subsequent 24 hours are displayed.

TABLE VI. Top association rules for Ethereum

N°	Antecedents	Consequents	Support	Lift
R1	ETC_H00_SA	ETC_H11_SV	0.297521	1.085743
R2	ETC_H00_SA	Bitcoin_H11_SV	0.283747	1.080498
R3	ETC_H00_SA	LTC_H11_SV	0.296143	1.088721
R4	ETC_H00_SA	monero_H19_SA	0.278237	1.048788
R5	ETC_H00_SA	monero_H21_SA	0.290634	1.112413
R6	ETC_H00_SV	ETC_H01_SA	0.289256	1.048181
R7	ETC_H00_SV	ETC_H02_SA	0.297521	1.035745
R8	ETC_H00_SV	ETC_H04_SA	0.289256	1.037566
R9	ETC_H00_SV	ETC_H15_SV	0.289256	1.072876
R10	ETC_H00_SV	Bitcoin_H05_SA	0.290634	1.037255
R11	ETC_H00_SV	LTC_H01_SA	0.300275	1.050498
R12	ETC_H00_SV	LTC_H02_SA	0.297521	1.080893
R13	ETC_H00_SV	LTC_H04_SA	0.289256	1.019499
R14	ETC_H00_SV	monero_H20_SA	0.289256	1.019499

Rule 1 in the transaction "ETC_H00_SA => ETC_H11_SV", the antecedent represents a simple buying now of Ethereum, they demonstrate a simple selling next 11 hours of ETC_USD (Ethereum) with a lift level surpassing 1, and a support level of 0.29.

Rule 2 in the transaction "ETC_H00_SA => Bitcoin_H11_SV", the antecedent represents a simple buying now of Ethereum, they demonstrate a simple selling next eleven hours of BTC_USD (Bitcoin) with a support level of 0.28 and lift level surpassing 1.

Rule 3 in the transaction "ETC_H00_SA => LTC_H11_SV", the antecedent represents a simple buying now of Ethereum, they demonstrate a simple selling next eleven hours of LTC_USD (Litecoin) with a support level of 0.29, and a lift level surpassing 1.

In Rule 4 of the transaction "ETC_H00_SA => monero_H19_SA", the condition signifies the immediate purchase of Ethereum. It indicates a subsequent purchase of Monero against USD occurring in the next 19 hours, with a support level set at 0.27 and a lift level exceeding 1.

Rule 5 in the transaction "ETC_H00_SA => monero_H21_SA", the antecedent represents a simple buying now of Ethereum, they demonstrate a simple buying next 21 hours of XMR_USD (Monero) with a support level of 0.29, and a lift level surpassing 1.

Rule 6 in the transaction "ETC_H00_SV => ETC_H01_SA", the antecedent represents a simple selling now of Ethereum, they demonstrate a simple buying next hour of ETC_USD (Ethereum) with a support level of 0.28, and a lift level surpassing 1.

Rule 7 in the transaction "ETC_H00_SV => ETC_H02_SA", the antecedent represents a simple selling now of Ethereum, they demonstrate a simple buying next two hours of ETC_USD (Ethereum) with a support level of 0.29, and a lift level surpassing 1.

Rule 8 in the transaction "ETC_H00_SV => ETC_H04_SA", the antecedent represents a simple selling now of Ethereum, they demonstrate a simple buying next four hours of ETC_USD (Ethereum) with a support level of 0.28, and a lift level surpassing 1.

Rule 9 in the transaction "ETC_H00_SV => ETC_H15_SV", the antecedent represents a simple selling now of Ethereum, they demonstrate a simple selling next 15 hours of ETC_USD (Ethereum) with a support level of 0.28, and a lift level surpassing 1.

Rule 10 in the transaction "ETC_H00_SV => Bitcoin_H05_SA", the antecedent represents a simple selling now of Ethereum, they demonstrate a simple buying next five hours of BTC_USD (Bitcoin) with a support level of 0.29, and a lift level surpassing 1.

Rule 11 in the transaction "ETC_H00_SV => LTC_H01_SA", the antecedent represents a simple selling now of Ethereum, they demonstrate a simple buying next four hours of LTC_USD (Litecoin) with a support level of 0.30, and a lift level surpassing 1.

Rule 12 in the transaction "ETC_H00_SV => LTC_H02_SA", the antecedent represents a simple selling now of Ethereum, they demonstrate a simple buying next two hours of LTC_USD (Litecoin) with a support level of 0.29, and a lift level surpassing 1.

Rule 13 in the transaction "ETC_H00_SV => LTC_H04_SA", the antecedent represents a simple selling now of Ethereum, they demonstrate a simple buying next four hours of LTC_USD (Litecoin) with a support level of 0.28, and a lift level surpassing 1.

Rule 14 in the transaction "ETC_H00_SV => monero_H20_SA", the antecedent represents a simple selling now of Ethereum, they demonstrate a simple buying next 20 hours of XMR_USD (Monero) with a support level of 0.28, and a lift level surpassing 1.

After that, we created association rules that link the behavior of XMR_USD at a given moment to the behavior of the next hour for three other cryptocurrencies (BTC_USD, LTC_USD, and ETC_USD). Table 7 displays the foremost association rules for Monero. The guidelines for linking Monero with other commodities within the subsequent 24 hours are displayed.

TABLE VII. Top association rules for Monero

N°	Antecedents	Consequents	Support	Lift
R1	monero_H00_SA	monero_H21_SA	0.316298	1.076248
R2	monero_H00_SA	LTC_H11_SV	0.310773	1.025883
R3	monero_H00_SA	Bitcoin_H08_SV	0.306630	1.017266
R4	monero_H00_SA	Bitcoin_H11_SV	0.309392	1.058176
R5	monero_H00_SA	Bitcoin_H21_SA	0.308011	1.064425
R6	monero_H00_SV	monero_H24_SA	0.258287	1.044451
R7	monero_H00_SV	LTC_H04_SA	0.258287	1.033954
R8	monero_H00_SV	LTC_H17_SA	0.265193	1.114820
R9	monero_H00_SV	LTC_H24_SA	0.255525	1.097338
R10	monero_H00_SV	Bitcoin_H17_SA	0.255525	1.085633
R11	monero_H00_SV	ETC_H01_SA	0.255525	1.043878
R12	monero_H00_SV	ETC_H02_SA	0.261050	1.016997
R13	monero_H00_SV	ETC_H04_SA	0.259669	1.058093
R14	monero_H00_SV	ETC_H11_SV	0.255525	1.012718

Rule 1 in the transaction "monero_H00_SA => monero_H21_SA", the antecedent represents a simple buying now of Monero, they demonstrate a simple buying next 21 hours of XMR_USD (Monero) with a lift level surpassing 1, and a support level of 0.31.

Rule 2 in the transaction "monero_H00_SA => LTC_H11_SV", the antecedent represents a simple buying now of Monero, they demonstrate a simple selling next 11 hours of LTC_USD (Litecoin) with a support level of 0.31, and lift level surpassing 1.

Rule 3 in the transaction "monero_H00_SA => Bitcoin_H08_SV", the antecedent represents a simple buying now of Monero, they demonstrate a simple selling next 8 hours of Bitcoin with a support level of 0.30, and a lift level surpassing 1.

Rule 4 in the transaction "monero_H00_SA => Bitcoin_H11_SV", the antecedent represents a simple buying now of Monero, they demonstrate a simple selling next eleven hours of BTC_USD (Bitcoin) with a support level of 0.30, and a lift level surpassing 1.

Rule 5 in the transaction "monero_H00_SA => Bitcoin_H21_SA", the antecedent represents a simple buying now of Monero, they demonstrate a simple buying next 21 hours of BTC_USD (Bitcoin) with a support level of 0.30, and a lift level surpassing 1.

Rule 6 in the transaction "monero_H00_SV => monero_H24_SA", the antecedent represents a simple selling now of Monero, they demonstrate a simple buying next 24 hours of XMR_USD (Monero) with a support level of 0.25, and a lift level surpassing 1.

Rule 7 in the transaction "monero_H00_SV => LTC_H04_SA", the antecedent represents a simple selling now of Monero, they demonstrate a simple buying next four hours of LTC_USD (Litecoin) with a support level of 0.25, and a lift level surpassing 1.

Rule 8 in the transaction "monero_H00_SV => LTC_H17_SA", the antecedent represents a simple selling now of Monero, they demonstrate a simple buying next 17 hours of LTC_USD (Litecoin) with a support level of 0.26, and a lift level surpassing 1.

Rule 9 in the transaction "monero_H00_SV => LTC_H24_SA", the antecedent represents a simple selling now of Monero, they demonstrate a simple buying next 24 hours of LTC_USD (Litecoin) with a support level of 0.25, and a lift level surpassing 1.

Rule 10 in the transaction "monero_H00_SV => Bitcoin_H17_SA", the antecedent represents a simple selling now of Monero, they demonstrate a simple buying next 17 hours of BTC_USD (Bitcoin) with a support level of 0.25, and a lift level surpassing 1.

Rule 11 in the transaction "monero_H00_SV => ETC_H01_SA", the antecedent represents a simple selling now of Monero, they demonstrate a simple buying next hour of ETC_USD (Ethereum) with a support level of 0.25, and a lift level surpassing 1.

Rule 12 in the transaction "monero_H00_SV => ETC_H02_SA", the antecedent represents a simple selling now of Monero, they demonstrate a simple buying next two hours of ETC_USD (Ethereum) with a support level of 0.26, and a lift level surpassing 1.

Rule 13 in the transaction "monero_H00_SV => ETC_H04_SA", the antecedent represents a simple selling now of Monero, they demonstrate a simple buying next four hours of ETC_USD (Ethereum) with a support level of 0.25, and a lift level surpassing 1.

Rule 14 in the transaction "monero_H00_SV => ETC_H11_SV", the antecedent represents a simple selling now of Monero, they demonstrate a simple selling next 11 hours of ETC_USD (Ethereum) with a support level of 0.25, and a lift level surpassing 1.

After that, we created association rules that link the behavior of LTC_USD at a given moment to the behavior of the next hour for three other cryptocurrencies (BTC_USD, ETC_USD, and XMR_USD). Table 8 displays the foremost association rules for Litecoin. The guidelines for linking Litecoin with other commodities within the subsequent 24 hours are displayed.

TABLE VIII. Top association rules for Litecoin

N°	Antecedents	Consequents	Support	Lift
R1	LTC_H00_SA	LTC_H11_SV	0.294766	1.025708
R2	LTC_H00_SA	monero_H21_SA	0.289256	1.047936
R3	LTC_H00_SA	Bitcoin_H08_SV	0.294766	1.046377
R4	LTC_H00_SA	ETC_H11_SV	0.292011	1.008651
R5	LTC_H00_SA	ETC_H22_SV	0.290634	1.047540
R6	LTC_H00_SV	LTC_H01_SA	0.290634	1.074537
R7	LTC_H00_SV	LTC_H02_SA	0.279614	1.073558
R8	LTC_H00_SV	LTC_H04_SA	0.274105	1.020989
R9	LTC_H00_SV	monero_H20_SA	0.274105	1.020989
R10	LTC_H00_SV	Bitcoin_H02_SA	0.272727	1.066253
R11	LTC_H00_SV	ETC_H01_SA	0.280992	1.076087
R12	LTC_H00_SV	ETC_H02_SA	0.278237	1.023649

Rule 1 in the transaction "LTC_H00_SA => LTC_H11_SV", the antecedent represents a simple buying now of Litecoin, they demonstrate a simple selling next 11 hours of LTC_USD (Litecoin) with a lift level surpassing 1, and a support level of 0.29.

Rule 2 in the transaction "LTC_H00_SA => monero_H21_SA ", the antecedent represents a simple buying now of Litecoin, they demonstrate a simple buying next 21 hours of XMR_USD (Monero) with a support level of 0.28, and lift level surpassing 1.

Rule 3 in the transaction "LTC_H00_SA => Bitcoin_H08_SV", the antecedent represents a simple buying now of Litecoin, they demonstrate a simple selling next 8 hours of Bitcoin with a support level of 0.29, and a lift level surpassing 1.

Rule 4 in the transaction "LTC_H00_SA => ETC_H11_SV", the antecedent represents a simple buying now of Litecoin, they demonstrate a simple selling next eleven hours of ETC_USD (Ethereum) with a support level of 0.29, and a lift level surpassing 1.

Rule 5 in the transaction "LTC_H00_SA => ETC_H22_SV", the antecedent represents a simple buying now of Litecoin, they demonstrate a simple selling next 22 hours of ETC_USD (Ethereum) with a support level of 0.29, and a lift level surpassing 1.

Rule 6 in the transaction "LTC_H00_SV => LTC_H01_SA", the antecedent represents a simple selling now of Litecoin, they demonstrate a simple buying next hour of LTC_USD (Litecoin) with a support level of 0.29, and a lift level surpassing 1.

Rule 7 in the transaction "LTC_H00_SV => LTC_H02_SA", the antecedent represents a simple selling now of Litecoin, they demonstrate a simple buying next two hours of LTC_USD (Litecoin) with a support level of 0.27, and a lift level surpassing 1.

Rule 8 in the transaction "LTC_H00_SV => LTC_H04_SA", the antecedent represents a simple selling now of Litecoin, they demonstrate a simple buying next four hours of LTC_USD (Litecoin) with a support level of 0.27, and a lift level surpassing 1.

Rule 9 in the transaction "LTC_H00_SV => monero_H20_SA", the antecedent represents a simple selling now of Litecoin, they demonstrate a simple buying next 20 hours of XMR_USD (Monero) with a support level of 0.27, and a lift level surpassing 1.

Rule 10 in the transaction "LTC_H00_SV => Bitcoin_H02_SA", the antecedent represents a simple selling now of Litecoin, they demonstrate a simple buying next two hours of BTC_USD (Bitcoin) with a support level of 0.27, and a lift level surpassing 1.

Rule 11 in the transaction "LTC_H00_SV => ETC_H01_SA", the antecedent represents a simple selling now of Litecoin, they demonstrate a simple buying next hour of ETC_USD (Ethereum) with a support level of 0.28, and a lift level surpassing 1.

Rule 12 in the transaction "LTC_H00_SV => ETC_H02_SA", the antecedent represents a simple selling now of Litecoin, they demonstrate a simple buying next two hours of ETC_USD (Ethereum) with a support level of 0.27, and a lift level surpassing 1.

This article utilized the apriori algorithm to produce robust association rules. The association rules presented in the four tables assist investors in making informed decisions regarding optimal buying and selling times for the next 24 hours across four cryptocurrencies: Bitcoin, Monero, Litecoin, and Ethereum.

We have determined a strong link between Ethereum, Monero, Litecoin, and Bitcoin. More specifically, during the following day, we hope to determine the present connection between Bitcoin and other goods. Furthermore, if there is a buy or sell of Bitcoin, we can predict, for example, how Litecoin will move over the next three or four hours. For the other goods, we have already executed this prediction.

The association rules displayed in the four tables are robust and produced by the apriori algorithm. We discovered the associations between the various attributes in the "feature engineering" step. With a support level of 0, 29, and a lift level greater than 1, the antecedent in the transaction "LTC_H00_SA => Bitcoin_H08_SV" shows a straightforward immediate purchase of Litecoin. They also show a straightforward selling of Bitcoin during the following eight hours, as per Table VIII, Rule 3.

In line with the other regulations about strong ties, Litecoin's current purchase of Bitcoin will result in a straightforward sale within the next eight hours.

One benefit of our analysis is that it helps investors decide which of the four cryptocurrencies to buy or sell at what time during the next 24 hours. However, the study's authors [12] focused solely on the next day.

5. Conclusion and Future Work

Several researchers in this domain use the association rules to forecast and discover association rules and explore frequent item sets. In our paper, we used apriori algorithm to generate the association rules. We have made a substantial contribution by establishing a strong correlation between four cryptocurrencies: Ethereum, Monero, Litecoin, and Bitcoin. In particular, we want to find out what connection is between Bitcoin and other things during the next day. We evaluated the quality of these rules using two metrics: support and lift. We extracted the strong association rules with a support level of 0,25 and a lift level surpassing 1. In forthcoming research, we intend to utilize our suggested model across various cryptocurrencies, commodities, and other stocks.

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Mohamed EL MAHJOUBY received the master's degree in information systems engineering (MSID) from Sidi Mohamed Ben Abdellah University, Fez, Morocco, in 2020. His thesis is ''Stock Market Predictive System Analysis and Modeling.'' His research interests include artificial intelligence and machine learning.

Mohamed Taj Bennani received the master's and Ph.D. degrees in computer science and networking from the Science Faculty of Tangier, Tangier, in 2011 and 2019, respectively.

He has been a Professor with the Faculty of Science of Dhar El Mahraz Fez, since 2019. He has also been a Qualified University Professor, since June 2023.

Khalid El Fahssi received the Ph.D. degrees in mathematics and computer science from the Faculty of Sciences Ain Chock, Hassan II University, Casablanca, Morocco, in 2018. Since 2019, he has been with the Faculty of Sciences dhar el mehraz, sidi mohamed ben abdellah University, Fez, Morocco, as an Associate Professor. He is currently with the Department of Computer Science, Faculty of Sciences dhar el mehraz, sidi mohamed ben abdellah University, Fez, Morocco. His research interests are related to based image retrieval (CBIR) and artificial intelligence for medical applications.

Said ELGAROUANI is currently a professor with Sidi Mohamed Ben Abdellah University in Fez, Morocco.

Mohamed Lamrini received the PhD degree from the Claude Bernard –Lyon University in 1993. He is currently a professor of computer science at USMBA-Fez University. He is also a member of the LPAIS Laboratory. His research interests include software quality (CMMI, Six sigma, ISO 9001…), Industrial Engineering (Methods and statistical tools). and a short biography

Mohamed EL FAR is currently a Professor with Sidi Mohamed Ben Abdellah University, Fez, Morocco. He teaches computer science. He had published many researchers. His research interests include data science, big data, and artificial intelligence.