Association rules forecasting for the foreign exchange market

Mohamed El Mahjouby, Mohamed Taj Bennani, Mohamed Lamrini, Mohamed El Far
Department of Computer Science, Faculty of Science, University Sidi Mohamed Ben Abdellah, Fez, Morocco

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ABSTRACT

Several association rule mining algorithms exist, and among them, Apriori is one of the most commonly used methods for extracting frequent item sets from vast databases and generating association rules to gain insights. In this research, we have applied a data mining technique to implement association rules and explore frequent item sets. Our study introduced a model that employs association rules to uncover associations between the foreign exchange market, the gold commodity, and the National Association of Securities Dealers automated quotations (NASDAQ). We suggested a method that used data mining to identify the good points of buying and selling in the foreign exchange market by utilizing technical indicators such as moving average convergence divergence (MACD) and the stochastic indicator to create association rules. The experimental findings indicate that the proposed model successfully generates strong association rules.

Corresponding Author:

Mohamed El Mahjouby
Department of Computer Science, Faculty of Science, University Sidi Mohamed Ben Abdellah
Fez, 30000, Morocco
Email: mohamed.elmahjouby@usmba.ac.ma

1. INTRODUCTION

People commonly engage in trading, which involves the selling and buying of financial mechanisms like stocks, commodities, or currencies to profit from short-term price movements. Traders can participate in various markets, including stock markets, foreign exchange markets, futures markets, and cryptocurrency markets. Trading encompasses a range of strategies and approaches.

In this study, we utilized data mining techniques, specifically association rules, to identify optimal points for buying and selling. Our work contributes to the research by studying the prediction of association rules between currency pairs, gold, and NASDAQ. Our proposed model utilizes the Apriori algorithm to forecast and discover association rules in our datasets.

Many fields apply data mining and analytical tools to turn unprocessed data into knowledge [1]. The process of obtaining understanding and obtaining knowledge from data is data mining. Activities related to data mining may center on forecasting, prediction, or knowledge discovery [2]. Data mining involves extracting valuable information, patterns, and knowledge from extensive datasets. It is known as "knowledge discovery in databases" and helps uncover meaningful and valuable patterns within databases, aiding in decision-making. Data mining provides significant competitive advantages to organizations [3]. It can be categorized into three primary groups: prediction, clustering, and associations. Prediction involves forecasting future events, while classification, also known as supervised induction, analyzes historical data to create a model for predicting future behavior. Association, extensively studied in data mining, refers to the technique used to discover interesting relationships between variables in large datasets [4].

Association rule mining is a machine-learning technique to uncover relationships between items in data. It falls under unsupervised learning and is crucial for extracting insights from extensive databases. An association rule described $X => Y$, where X is the antecedent, and Y is the consequent. This rule indicates that customers who sell X are more expected to sell Y [5]. The relevance of rules is evaluated based on support and confidence, which indicate the usefulness and reliability of the discovered rules. Association rules wish to satisfy both minimum support and minimum confidence criteria to meet user-defined requirements. Apriori is one of the most widely used algorithms in this domain. It finds applications in various fields, including scientific data analysis. Some researchers employ technical methodologies such as technical statistics, principal component analysis, principal component analysis (PCA), and association rules to forecast the foreign exchange market. Traditional forecasting techniques aim to forecast future sequences by extrapolating statistical information borrowed from historical data arranged in chronological order [6].

We have shown some classical statistical forecasting methods, which build: The autoregression (AR) technique treats the next step in a sequence as a linear combination of past observations. It is a suitable strategy for analyzing single-variable data that does not exhibit trends or seasonal patterns [7]. The autoregressive moving average (ARMA) approach predicts the next step in a sequence by considering it as a linear combination of past observations and residual errors. It combines elements of AR and moving average (MA) models to achieve this prediction [8].

The autoregressive integrated moving average (ARIMA) technique represents the subsequent step in a sequence by utilizing a linear relationship between differenced observations and residual errors from previous time steps. Furthermore, an ARIMA model can be employed to create AR, MA, and ARMA models [9]. The seasonal autoregressive integrated moving average (SARIMA) approach predicts the next step in a sequence by considering it a linear combination of differenced observations, differenced seasonal observations, and seasonal errors from previous time steps. SARIMA combines the capabilities of an ARIMA model with the ability to perform similar autoregression, differencing, and moving average modeling at the seasonal level [10]. SARIMAX extends the SARIMA model by incorporating exogenous variables that can provide additional information for forecasting [11]. Long short-term memory (LSTM) is an extensively employed architecture in natural language processing and statistical forecasting. It belongs to the category of recurrent neural networks (RNNs) [12]. Chung and Shin [13] introduced a novel strategy for forecasting stock market trends, employing a combination of LSTM and genetic algorithm (GA) methodologies. According to their research, this approach demonstrated superior performance compared to the standard benchmark model.

We have presented some principal component analysis forecasting methods. The study [14] introduces a time-efficient neural network model called the stochastic time effective function neural network, STNN for time series prediction. The STNN model incorporates PCA. PCA is first used to extract the principal components from the input data. Then, the STNN model is applied to predict financial price series.

We have explained association rules, and the Apriori algorithm is one of the most commonly used algorithms for discovering association rule mining. Agrawal *et al.* [15] initially introduced the concept of association rules and the challenge of discovering them. In this context, we now explain this problem based on references [15], [16].

Consider $\{I = i1, i2, i3, \ldots\ldots\ldots\ldots\ldots\ldots, im\}$ as a collection of distinct literals referred to as items. Generally, any grouping of items is termed an item. Let *D* represent a collection of transactions, where each transaction *T* is a set of items such that *T* is a subset of *I*. An association rule described $X => Y$, where *X* and *Y* are disjoint subsets of *I*, and their intersection ($X\ n\ Y$) is an empty set. *X* is the antecedent, and *Y* is the consequent of the rule.

The support of an item *X*, which signifies its statistical significance, is referred to as the support count. It is represented as $sup(X)$ and determined by counting the number of transactions in *D* that contain *X*. The support or statistical significance of an association rule $X => Y$ is indicated by $sup(X => Y)$ and is defined as $sup(X\ U\ Y)$. Moreover, an association rule is well-known by confidence, which reflects its strength. The confidence of an association rule $X => Y$ is represented as $conf(X => Y)$ and calculated as the ratio by (1):

$$Conf(X => Y) = sup(X\ U\ Y)/sup(X) \quad (1)$$

Relying solely on confidence may not provide a complete assessment of a rule's descriptive power. Rules that have a high confidence level could be mere coincidences. It is necessary to examine the statistical independence between the antecedent and the consequent items [17]. This observation has sparked the development of several measures to gauge the interest in association rules. Lift is one of these metrics, and (2) defines it:

$$Lift(A => B) = conf(A => B)/sup(B) \quad (2)$$

The Apriori algorithm, introduced by Agrawal and Srikant [18], is the pioneering and fundamental method for identifying frequent item sets. Utilizes a technique known as level-wise exploration, which involves examining k itemsets to discover k+1 itemsets. Frequent one-item sets are identified by scanning the database and determining which meets the minimum support criteria. Then, frequent two itemsets by utilizing the frequent one itemsets. The iterative process continues until frequent sets of k items are recognized.

The Apriori algorithm property is known as anti-monotonicity, which means that any subset of a frequent itemset must also be frequent. It utilizes a breadth-first search approach to count the occurrence of candidate items. The algorithm consists of two primary steps:

a) The joining step: Lk, which represents a set of candidate k itemsets, is obtained by combining ($Lk-1$) with itself [19].
b) The pruning step: Any ($k-1$ items that do not meet the frequency threshold are removed from the set, as they cannot be a subset of a frequent k itemset [19].

For several years, database researchers have actively engaged in the exploration of association rule discovery. The long-association relationship, demonstrated by the long-distance historical data, was proposed by Li and Yu [20] and applied to the synthetic time series data. Vianita *et al.* [21] initially presented the issue of association rule mining and recognized the identification of frequent itemsets as a crucial step in the process of association rule. Most researchers employed a data mining approach to investigate frequent itemsets and uncover association rules.

Karpio *et al.* [22] researched mining associations in the Warsaw stock exchange. They employed a data mining approach to identify co-movements between stocks recorded on the exchange. They utilized the Apriori algorithm to explore associations.

Abdulsalam, Abdulsalam *et al.* [23] used the Apriori algorithm to bear market basket analysis. Their objective was to depict the purchasing trends of a supermarket using a dataset consisting of 30 individual transactions involving six distinct products. They set a minimum support threshold of 50% and implemented the Apriori algorithm using the Java Language to identify frequently occurring itemsets.

Qiu *et al.* [24] developed a model called customer purchase prediction model (COREL) to predict customer purchase behavior in e-commerce. This model consists of two stages: they created a list of potential products based on associations among products to predict customer motivations and then select the most frequently purchased products based on customer preferences. The authors collected data on customers' information and product reviews from the e-commerce platform 'Jingdong' Their research showed that customer preferences significantly influence purchase decisions.

Wu and Huang [25] focus on creating a data structure that can efficiently mine association rules. They utilized this data structure to identify generalized association rules from frequent itemsets and a taxonomy tree. They employed a frequently closed enumeration table as the structure, which stored only necessary data and extracted the maximum amount of information from itemsets through a hash function. To generate new generalized association rules, they implemented pruning techniques.

Umbarkar and Nandgaonkar [26] introduced a data mining technique, specifically association rule mining, to forecast the stock market. They utilized technical trading indicators and the closing prices of stocks in the prediction process. The authors established rules based on signals generated by each technical trading indicator and applied these rules to the current date query to produce signals such as buy, sell, or hold for shares.

2. METHOD

2.1. Proposed approach

Determination of connections and associations between variables in a database has increasingly relied on association rule mining methods. These methods utilize statistical analysis and artificial intelligence algorithms to discover frequent patterns. Based on these patterns, association rules under specific criteria are produced, such as minimum support and minimum confidence. In this study, we categorized association rules using the following criteria: i) The consequences of the rules are "single buying", "single selling", "strong buying", or "strong selling" categorized; ii) The antecedents of the rules consist of the maximum values of the dataset's attributes; iii) We set the minimum support to 0.25; and iv) We set the minimum confidence to 0.70. We have suggested an algorithm that includes two primary stages: firstly, extracting association rules using the Apriori algorithm, and secondly, assessing the extracted association rules using multicriteria analysis.

We propose an approach that utilizes data mining to identify optimal buying and selling in the foreign exchange market. This approach utilizes specific technical indicators such as moving average convergence divergence, moving average convergence divergence (MACD), and the stochastic indicator to generate association rules. The objective is to specify the best rules for the buy and sell points. Our suggested framework comprises several primary stages: dataset extraction, feature engineering, dataset categorization, extraction of frequent itemsets, generation of association rules, and analysis. Figure 1 provides an elaboration of the proposed methodology.

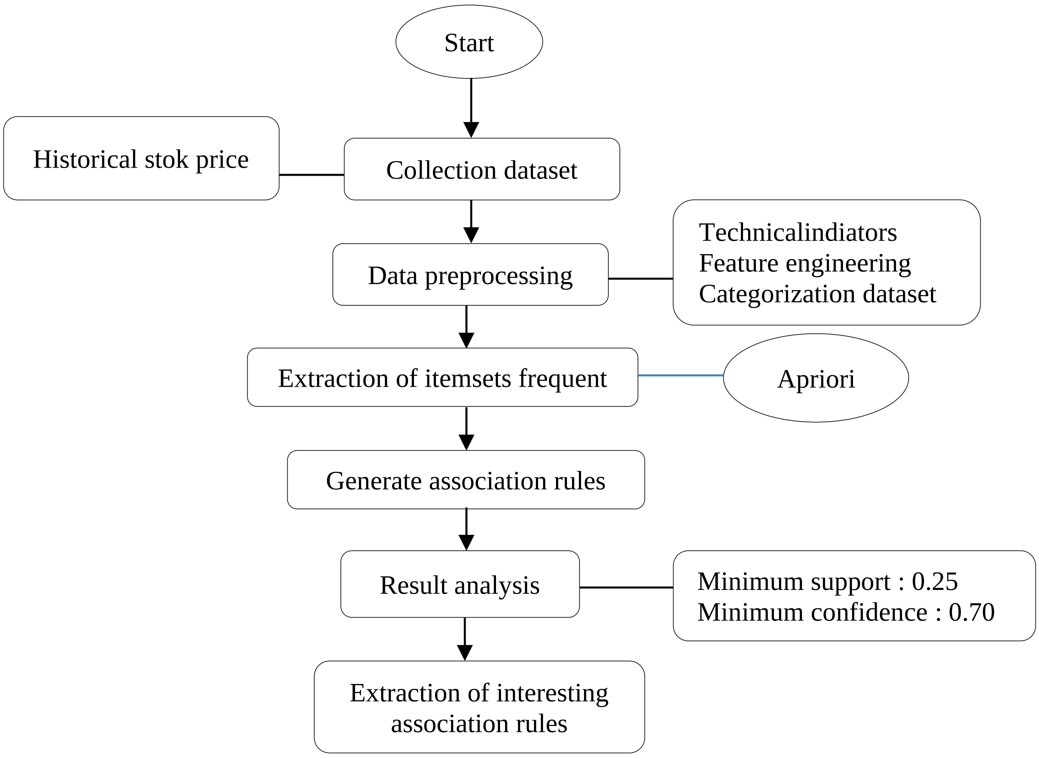

Figure 1. Proposed approach

2.2. Extract dataset

This paper used a stock dataset covering twenty years from April 2003 to April 2023. The dataset included currency pairs EUR_USD: euro against the United States dollar, GBP_USD: British pound against the United States dollar, USD_CHF: United States dollar against the Swiss franc, and USD_JPY: United States dollar against the Japanese yen, gold, and NASDAQ, with a total of 5036 days. These datasets contained columns with information such as Date, High, Open, Close, Low, and Volume. We then eliminated the volume column from each database.

2.3. Feature engineering

The following features in our datasets contained: Date, Open, High, Low, and Close. We calculate the MACD indicator for each day and determine the stochastic indicator for one-day, six-day, and one-month periods. Afterward, we added a categorical column called *ClosePrime* to our dataset, which includes four values: single buying, single selling, strong buying, and strong selling.

2.4. Categorization dataset

Categorizing a dataset involves organizing or grouping the data based on specific criteria or characteristics. This process includes assigning labels or categories to the data points, enabling more effective analysis or interpretation. After calculating relevant indicators, we sorted our datasets, with Table 1 detailing our attributes. Ultimately, we converted each attribute into a binary format by assigning values of either 0 or 1 to them within the dataset.

2.5. Extracting frequent itemsets

Association rule mining is a crucial technique in data mining and has predominantly concentrated on extracting frequent patterns. However, in precise domains, there is a compelling interest in uncovering patterns that are not frequent but exhibit strong relationships. Frequent itemsets are sets of items that occur together in a dataset or transactional database. Apriori, a widely utilized algorithm, is known for identifying frequent item sets through candidate generation. Researchers in computer science and algorithmic studies have extensively studied the extraction of association rules, which is seen as the approach for deriving such association rules but can be time-consuming due to the need for multiple database scans.

2.6. Generating association rules and analysis

Data mining extensively uses association rule mining as a widely adopted and researched technique. The objective is to reveal meaningful relationships between variables stored in databases. The process typically involves two crucial steps: identifying frequent itemsets and extracting association rules from the obtained frequent patterns. Executing this task can be costly in terms of both execution time and the volume of generated rules. In our module, we employed the Apriori algorithm to extract association rules.

Table 1. Description of the attribute

Attribute	Description
Open_Oa	The minimum value of the Open price
Open_Ob	The average value of the Open price
Open_Oc	The maximum value of the Open price
High_Ha	The minimum value of the High price
High_Hb	The average value of the High price
Low_La	The minimum value of the Low price
Low_Lb	The average value of the Low price
Low_Lc	The maximum value of the Low price
Close_Ca	The minimum value of the Close price
Close_Cb	The average value of the Close price
Close_Cc	The maximum value of the Close price
Stoch_k_1_Sk1a	The minimum of the stochastic indicator for one-day %k
Stoch_k_1_Sk1b	The average of the stochastic indicator for one-days %k
Stoch_k_1_Sk1c	The maximum of the stochastic indicator for one-day %k
Stoch_k_6_Sk6a	The Minimum of the stochastic indicator for six-day %k
Stoch_k_6_Sk6b	The average of the stochastic indicator for six-day %k
Stoch_k_6_Sk6c	The maximum of the stochastic indicator for six-day %k
Stock_k_24_Sk24a	The minimum of the stochastic indicator for one-month %k
Stock_k_24_Sk24b	The average of the stochastic indicator for one-month %k
Stock_k_24_Sk24c	The maximum of the stochastic indicator for one-month %k
Stock_d_1_Sd1a	The minimum of the stochastic indicator for one-day %D
Stock_d_1_Sd1b	The average of the stochastic indicator for one-day %D
Stock_d_1_Sd1c	The maximum of the stochastic indicator for one-day %D
Stock_d_6_Sd6a	The minimum of the stochastic indicator for six-day %D
Stock_d_6_Sd6b	The average of the stochastic indicator for six-day %D
Stock_d_6_Sd6c	The maximum of the stochastic indicator for six-day %D
Stock_d_24_Sd24a	The minimum of the stochastic indicator for one-month %D
Stock_d_24_Sd24b	The average of the stochastic indicator for one-month %D
Stock_d_24_Sd24c	The maximum of the stochastic indicator for one-month %D
MACD_Ma	The minimum value of the MACD
MACD_Mb	The average value of the MACD
MACD_Mc	The maximum value of the MACD

3. RESULTS AND DISCUSSION

After data preparation, we actively selected a group of crucial records. We began by applying the Apriori algorithm in the initial step to extract frequent item sets, setting a minimum support threshold of 0.25. The frequent item sets identified at this stage are essential for generating association rules in the following phase. To address the issue of redundant and uninteresting rules, we utilized our approach in the subsequent step, taking into account the preferences of the decision. We evaluated the previously extracted rules as alternatives based on selected quality measures. Among the several measures proposed in the literature, we focused on three criteria: support, confidence, and lift. We have showcased the robust association rules for NASDAQ, gold, and four currency pairs: EUR_USD, GBP_USD, USD_CHF, and USD_JPY. As shown in Table 2, explain the top association rules for NASDAQ.

Table 2. Top association rules for NASDAQ

N°	Confidence	Support	Lift	Rules
R1	0.92	0.25	1.71	$frozenset(\{'High\_Ha','MACD\_Mb',stoch\_k\_1\_Sk1c'\}) => ClosePrime\_SA$
R2	0.75	0.25	1.39	$frozenset(\{'Low\_La','Open\_Oa','stoch\_k\_6\_Sk6c'\}) => ClosePrime\_SA$
R3	0.73	0.26	1.34	$frozenset(\{'stoch\_d\_24\_Sd24c','stoch\_k\_24\_Sk24c','stoch\_k\_6\_Sk6c'\})$ $=> ClosePrime\_SA$

Rule 1 transactions that include $'High\_Ha'$, $'MACD\_Mb'$, and $'stoch\_k\_1\_Sk1c'$ as antecedents exhibit a predictive capability for the "single buying" outcome with a confidence level exceeding 80%. Rule 2: Transactions that include $'Low\_La'$, $'Open\_Oa'$, and $'stoch\_k\_6\_Sk6c'$ as antecedents exhibit a predictive capability for the "single buying" outcome with a confidence level exceeding 70%. Rule 3: Transactions that include $'stoch\_d\_24\_Sd24c'$, $'stoch\_k\_24\_Sk24c'$, and $'stoch\_k\_6\_Sk6\,c'$ as antecedents exhibit a predictive capability for the "single buying" outcome with a confidence level exceeding 70%. Following that, we created association rules, shown in Table 3, and explained the most crucial association rules for gold.

Table 3. Top association rules for gold

N°	Confidence	Support	Lift	Rules
R1	0.71	0.26	1.44	$frozenset(\{'stoch\_d\_1\_Sd1b','stoch\_k\_1\_Sk1a','stoch\_k\_6\_Sk6c'\})$ $=> ClosePrime\_SA$
R2	0.70	0.25	1.05	$frozenset(\{'High\_Hb','Low\_Lb','Open\_Ob'\}) => ClosePrime\_SV$
R3	0.70	0.32	1.28	$frozenset(\{'MACD\_Mb','stoch\_d\_1\_Sd1a','stoch\_k\_1\_Sk1a'\}) => ClosePrime\_SV$

Rule 1 transactions that include $'stoch\_d\_1\_Sd1b'$, $'stoch\_k\_1\_Sk1a'$, and $'stoch\_k\_6\_Sk6c'$ as antecedents exhibit a predictive capability for the "single buying" outcome with a confidence level exceeding 70%. Rule 2: Transactions that include $'High\_Hb'$, $'Low\_Lb'$, and $'Open\_Ob'$ as antecedents exhibit a predictive capability for the "single selling" outcome with a confidence level exceeding 70%. Rule 3: Transactions that include $'MACD\_Mb'$, $'stoch\_d\_1\_Sd1a'$, and $'stoch\_k\_1\_Sk1a'$ as antecedents exhibit a predictive capability for the "single selling" outcome with a confidence level exceeding 70%. Following that, we created association rules, shown in Table 4, and explained the most crucial association rules for EUR_USD.

Table 4. Top association rules for EUR_USD

N°	Confidence	Support	Lift	Rules
R1	0.70	0.28	1.13	$frozenset(\{'stoch\_d\_1\_Sd1a','stoch\_k\_1\_Sk1a','stoch\_k\_6\_Sk6a'\})$ $=> ClosePrime\_SV$
R2	0.70	0.25	1.03	$frozenset(\{'High\_Hb','Low\_Lc','Open\_Ob'\}) => ClosePrime\_SA$
R3	0.70	0.25	1.02	$frozenset(\{'Low\_Lc','Open\_Ob','stoch\_k\_1\_Sk1a'\}) => ClosePrime\_SA$

Rule 1 transactions that include $'stoch\_d\_1\_Sd1a'$, $'stoch\_k\_1\_Sk1a'$, and $'stoch\_k\_6\_Sk6a'$ $Sk1a'$ as antecedents exhibit a predictive capability for the "single selling" outcome with a confidence level exceeding 70%. Rule 2: Transactions that include $'High\_Hb'$, $'Low\_Lc'$, and $'Open\_Ob'\,Sk1a'$ as antecedents exhibit a predictive capability for the "single buying" outcome with a confidence level exceeding 70%. Rule 3: Transactions that include $'Low\_Lc'$, $'Open\_Ob'$, and $'stoch\_k\_1\_Sk1a'$ as antecedents exhibit a predictive capability for the "single buying" outcome with a confidence level exceeding 70%. Following that, we created association rules, shown in Table 5, and explained the most crucial association rules for GBP_USD.

Table 5. Top association rules for GBP_USD

N°	Confidence	Support	Lift	Rules
R1	0.72	0.26	1	$MACD\_Mb, Low\_Lb\ => \ ClosePrime\_SV$
R2	0.70	0.26	1.24	$stoch\_d\_1\_Sk1a, stoch\_k\_1\_Sd1a\ => \ ClosePrime\_SA$
R3	0.70	0.26	1.03	$stoch\_d\_1\_Sd1a, MACD\_Mb\ => \ ClosePrime\_SA$

Rule 1 transactions that include $'MACD\_Mb'$ and $'Low\_Lb\ Sk1a'$ as antecedents exhibit a predictive capability for the "single selling" outcome with a confidence level exceeding 70%. Rule 2: Transactions that include $'stoch\_d\_1\_Sk1a'$ and $'stoch\_k\_1\_Sd1a\ Sk1a'$ as antecedents exhibit a predictive capability for the "single buying" outcome with a confidence level exceeding 70%. Rule 3: Transactions that include $'stoch\_d\_1\_Sd1a'$ and $'MACD\_Mb'$ as antecedents exhibit a predictive capability for the "single buying" outcome with a confidence level exceeding 70%. Following that, we created association rules, shown in Table 6, and explained the most crucial association rules for USD_CHF.

Table 6. Top association rules for USD_CHF

N°	Confidence	Support	Lift	Rules
R1	0.73	0.30	1.03	$Open\_Ob, High\_Hb\ => \ ClosePrime\_SV$
R2	0.72	0.31	1.03	$Low\_Lb, Open\_Ob\ => \ ClosePrime\_SV$
R3	0.74	0.30	1.01	$frozenset(\{'MACD\_Mb','stoch\_d\_1\_Sd1b'\}\ => \ ClosePrime\_SV$

Rule 1 transactions that include $'Open\_Ob'$ and $'High\_Hb'$ as antecedents exhibit a predictive capability for the "single sell" outcome with a confidence level exceeding 70%. Rule 2: Transactions that include $'Low\_Lb'$ and $'Open\_Ob'$ as antecedents exhibit a predictive capability for the "single sell" outcome with a confidence level exceeding 70%. Rule 3: Transactions that include $'MACD\_Mb'$ and $'stoch\_d\_1\_Sd1b'$ as antecedents exhibit a predictive capability for the "single sell" outcome with a confidence level exceeding 70%. Following that, we created association rules, shown in Table 7, and explained the most crucial association rules for USD_JPY.

Table 7. Top association rules for USD_JPY

N°	Confidence	Support	Lift	Rules
R1	0.71	0.25	1.12	$Open\_Ob\ , High\_Hb => ClosePrime\_SA$
R2	0.74	0.26	1.05	$MACD\_Mb, Low\_Lb => ClosePrime\_SA$
R3	0.71	0.29	1.13	$stoch\_k\_1\_Sk1b, MACD\_Mb =>\ ClosePrime\_SV$

Rule 1 transactions that include $'Open\_Ob'$ and $'High\_Hb'$ as antecedents exhibit a predictive capability for the "single buying" outcome with a confidence level exceeding 70%. Rule 2: Transactions that include $'MACD\_Mb'$ and $'Low\_Lb'$ as antecedents exhibit a predictive capability for the "single buying" outcome with a confidence level exceeding 70%. Rule 3: Transactions that include $'stoch\_k\_1\_Sk1b'$ and $'MACD\_Mb'$ as antecedents exhibit a predictive capability for the "single selling" outcome with a confidence level exceeding 70%.

First, we combined the currencies and selected a single *ClosePrime* value for each currency pair. Then, we analyzed the relationship between the merged attribute values and the target *ClosePrime* value for each currency pair, extracting association rules. Following that, we created association rules, shown in Table 8, and explained the most crucial association rules for *Devise_UCH*.

Table 8. Top association rule for *Devise_UCH*

N°	Confidence	Support	Lift	Rules
R1	0.76	0.25	1.25	$frozenset(\{'Low\_EU\_Lc','stoch\_k\_1\_EU\_Sk1a','stoch\_k\_1\_UCH\_Sk1a'\}$ $=> ClosePrime\_UCH\_SV$
R2	0.77	0.27	1.26	$frozenset(\{'MACD\_EU\_Mb','stoch\_d\_1\_EU\_Sd1a','stoch\_k\_1\_UCH\_Sk1a'\})$ $=> ClosePrime\_UCH\_SV$

Rule 1 transactions that include $'Low\_EU\_Lc'$, $'stoch\_k\_1\_EU\_Sk1a'$, and $'stoch\_k\_1\_UCH\_Sk1a'$ Hb' as antecedents exhibit a predictive capability for the "sell the *USD_CHF*" outcome with a confidence level exceeding 70%. Rule 2: Transactions that include the $'MACD\_EU\_Mb'$, $'stoch\_d\_1\_EU\_Sd1a'$, and $'stoch\_k\_1\_UCH\_Sk1a'$ as antecedents exhibit a predictive capability for the "sell the USD_CHF" outcome with a confidence level exceeding 70%. Following that, we created association rules, shown in Table 9, and explained the most crucial association rules for *Devise_GU*.

Table 9. Top association rule for *Devise_GU*

N°	Confidence	Support	Lift	Rules
R1	0.70	0.26	1.24	$frozenset(\{'stoch\_d\_1\_EU\_Sd1a'\ ,'stoch\_d\_1\_GU\_Sd1b','stoch\_k\_1\_GU\_Sk1b'\}$ $=> ClosePrime\_GU\_SA$
R2	0.7	0.28	1.26	$frozenset(\{'Low\_EU\_Lc','stoch\_k\_1\_EU\_Sk1a','stoc\_k\_1\_G\ U\_Sk1a'\})$ $=> ClosePrime\_GU\_SV$

Rule 1 transactions that include *'stoch_d_1_EU_Sd1a'*, *'stoch_d_1_GU_Sd1b'*, *'stoch_k_1_GU_Sk1b'* as antecedents exhibit a predictive capability for the "sell the GBP_USD" outcome with a confidence level exceeding 70%. Rule 2: Transactions that include $'Low\_EU\_Lc'$, $'stoch\_k\_1\_EU\_Sk1a'$ and

$'stoch\_k\_1\_GU\_Sk1a'$ as antecedents exhibit a predictive capability for the "sell the GBP_USD" outcome with a confidence level exceeding 70%. Following that, we created association rules, shown in Table 10, and explained the most crucial association rules for *Devise_EU*.

Table 10. Top association rule for *Devise_EU*

N°	Confidence	Support	Lift	Rules
R1	0.74	0.26	1.01	frozenset({'Low_GU_Lb','MACD_EU_Mb','MACD_GU_Mb'}) => ClosePrime_EU_SV
R2	0.73	0.26	1.15	frozenset({'Low_UJ_Lb','MACD_UCH_Mb','MACD_UJ_Mb'}) => ClosePrime_EU_SA
R3	0.73	0.26	1.16	frozenset({'Open_UJ_Ob','stoch_d_1_EU_Sd1a','stoch_d_1_GU_Sd1b'}) => ClosePrime_EU_SA

Rule 1 transactions that include $'Low\_GU\_Lb'$, $'MACD\_EU\_Mb'$, and $'MACD\_GU\_Mb'$ as antecedents exhibit a predictive capability for the "sell the EUR_USD" outcome with a confidence level exceeding 70%. Rule 2: Transactions that include $'Low\_UJ\_Lb'$, $'MACD\_UCH\_Mb'$ and $'MACD\_UJ\_Mb'$ as antecedents exhibit a predictive capability for the "buy the EUR_USD" outcome with a confidence level exceeding 70%. Rule 3: Transactions that include $'Open\_UJ\_Ob'$, $'stoch\_d\_1\_EU\_Sd1a'$, and $'stoch\_d\_1\_GU\_Sd1b'$ as antecedents exhibit a predictive capability for the "buy the *EUR_USD*" outcome with a confidence level exceeding 70. Following that, we created association rules, shown in Table 11, and explained the most crucial association rules for *Devise_UJ*.

Table 11. Top association rule for *Devise_UJ*

N°	Confidence	Support	Lift	Rules
R1	0.72	0.32	1.13	frozenset({'Low_EU_Lc','stoch_k_1_EU_Sk1a','stoch_k_1_UJ_Sk1b'}) => ClosePrime_UJ_SV
R2	0.71	0.27	1.15	frozenset({ 'MACD_EU_Mb', 'MACD_UCH_Mb','stoch_k_1_UJ_Sk1b'} => ClosePrime_UJ_SV
R3	0.72	0.27	1.16	frozenset({'stoch_d_1_EU_Sd1a','stoch_d_1_GU_Sd1b','stoch_k_1_UJ_Sk1b'}) => ClosePrime_UJ_SV

Rule 1 transactions that include $'Low\_EU\_Lc'$, $'stoch\_k\_1\_EU\_Sk1a'$, and $'stoch\_k\_1\_UJ\_Sk1b'$ as antecedents exhibit a predictive capability for the "sell the USD_JPY" outcome with a confidence level exceeding 70%. Rule 2: Transactions that include $'MACD\_EU\_Mb'$, $'MACD\_UCH\_Mb'$, $'stoch\_k\_1\_UJ\_Sk1b'$ as antecedents exhibit a predictive capability for the "sell the USD_JPY" outcome with a confidence level exceeding 70%. Rule 3: Transactions that include $'stoch\_d\_1\_EU\_Sd1a'$, and $'stoch\_d\_1\_GU\_Sd1b'$, $'stoch\_k\_1\_UJ\_Sk1b'$ as antecedents exhibit a predictive capability for the "sell the USD_JPY" outcome with a confidence level exceeding 70%. We merged the currencies with gold and obtained association rules between the $ClosePrime$ values and gold. Following that, we created association rules, shown in Table 12, and explained the most crucial association rules for $Devise\_gold$.

Table 12. Top association rule for *Devise_gold*

N°	Confidence	Support	Lift	Rules
R1	0.71	0.51	1	frozenset({'MACD_gold_Mb','stoch_d_1_EU_Sd1a','stoch_k_1_gold_Sk1a'}) => ClosePrime_gold_SV
R2	0.70	0.40	1.24	frozenset({'stoch_d_1_EU_Sd1a','stoch_k_1_gold_Sk1a','stoch_k_6_gold_Sk6c' => ClosePrime_gold_SA
R3	0.75	0.43	1.01	({'MACD_EU_Mb','MACD_UCH_Mb','stoch_d_1_EU_Sd1a'}) => ClosePrime_gold_SV

Rule 1 transactions that include *'MACD_gold_Mb'*, *'stoch_d_1_EU_Sd1a'*, *'stoch_k_1_gold_Sk1a'* are present as antecedents they demonstrate a predictive capability for the "sell the gold" outcome with a confidence level surpassing 70%. Rule 2: Transactions that include $'stoch\_d\_1\_EU\_Sd1a'$, $'stoch\_k\_1\_gold\_Sk1a'$, and $'stoch\_k\_6\_gold\_Sk6c'$ predict the "buy the gold" with a confidence rate that exceeds 70%. Rule 3: Transactions that include the $'MACD\_EU\_Mb'$, $'MACD\_UCH\_Mb'$, $'stoch\_d\_1\_EU\_Sd1a'$ predict the "sell the gold" with a confidence rate that exceeds 70%. We have completed the merging process, and for each iteration, we extracted association rules using a *ClosePrime* value. Following that, we created association rules, shown in Table 13, and explained the most crucial association rules for *Devise_gold_nasdaq_ClosePrime_nasdaq*.

Table 13. Association rules for *Devise_gold_nasdaq_ClosePrime_nasdaq*

N°	Confidence	Support	Lift	Rules
R1	0.92	0.40	1.70	$frozenset('MACD\_EU\_Mb', 'stoch\_k\_1\_gold\_Sk1a','stoch\_k\_1\_nasdaq\_Sk1c'\})$ => $ClosePrime\_nasdaq\_SA$
R2	0.92	0.40	1.70	frozenset({'stoch_d_1_EU_Sd1a', 'stoch_k_1_EU_Sk1a', 'stoch_k_1_nasdaq_Sk1c'}) => $ClosePrime\_nasdaq\_SA$

Rule 1 transactions that include *'MACD_EU_Mb'*, *'stoch_k_1_gold_Sk1a'*, *'stoch_k_1_nasdaq_Sk1c'* as antecedents exhibit a predictive capability for the "buy the Nasdaq" outcome with a confidence level exceeding 70%. Rule 2: transactions that include $'stoch\_d\_1\_EU\_Sd1a'$, $'stoch\_k\_1\_EU\_Sk1a'$, and $'stoch\_k\_1\_nasdaq\_Sk1c'$ as antecedents exhibit a predictive capability for the "buy the Nasdaq" outcome with a confidence level exceeding 70%. Following that, we created association rules, shown in Table 14, and explained the most crucial association rules for *Devise_gold_nasdaq_ClosePrime_gold*.

Table 14. Top association rules for *Devise_gold_nasdaq_ClosePrime_gold*

N°	Confidence	Support	Lift	Rules
R1	0.71	0.45	1	$frozenset(\{'MACD\_gold\_Mb','stoch\_d\_1\_EU\_Sd1a','stoch\_k\_1\_gold\_Sk1a'\})$ => $ClosePrime\_gold\_SV$
R2	0.70	0.40	1.24	$frozenset(\{'stoch\_d\_1\_EU\_Sd1a','stoch\_k\_1\_gold\_Sk1a','stoch\_k\_6\_gold\_Sk6c'\}$ => $ClosePrime\_gold\_SV$
R3	0.71	0.45	1.01	$frozenset(\{'Low\_EU\_Lc','MACD\_gold\_Mb','stoch\_k\_1\_EU\_Sk1a'\})$ => $ClosePrime\_gold\_SV$

Rule 1 transactions that include *'MACD_gold_Mb'*, *'stoch_d_1_EU_Sd1a'*, and *'stoch_k_1_gold_Sk1a'* as antecedents exhibit a predictive capability for the "sell the gold" outcome with a confidence level exceeding 70%. Rule 2: Transactions that include $'stoch\_d\_1\_EU\_Sd1a'$, $'stoch\_k\_1\_gold\_Sk1a'$, and $'stoch\_k\_6\_gold\_Sk6c'$ as antecedents exhibit a predictive capability for the "sell the gold" outcome with a confidence level exceeding 70%. Rule 3: Transactions that include $'Low\_EU\_Lc'$, $'MACD\_gold\_Mb'$, and $'stoch\_k\_1\_EU\_Sk1a'$ as antecedents exhibit a predictive capability for the "sell the gold" outcome with a confidence level exceeding 70%. Following that, we created association rules, shown in Table 15, and explained the most crucial association rules for *Devise_gold_nasdaq_ClosePrime_EU*.

Table 15. Top association rules for *Devise_gold_nasdaq_ClosePrime_EU*

N°	Confidence	Support	Lift	Rules
R1	0.75	0.40	1.01	$MACD\_nasdaq\_Mb, stoch\_d\_1\_EU\_Sd1a, stoch\_k\_1\_EU\_Sk1a$ => $ClosePrime\_EU\_SV$
R2	0.74	0.40	1	$MACD\_GU\_Mb, stoch\_k\_1\_EU\_Sk1a, stoch\_k\_1\_gold\_Sk1a$ => $ClosePrime\_EU\_SV$
R3	0.75	0.40	1.01	$MACD\_nasdaq\_Mb, stoch\_k\_1\_EU\_Sk1a, stoch\_k\_1\_gold\_Sk1a$ => $ClosePrime\_EU\_SV$

Rule 1 transactions that include $'stoch\_d\_1\_Sd1a'$, $'stoch\_k\_1\_Sk1a'$, and $'stoch\_k\_6\_Sk6a'$ as antecedents exhibit a predictive capability for the "sell pair EUR_USD" outcome with a confidence level exceeding 70%. Rule 2: Transactions that include $'High\_Hb'$, $'Low\_Lc'$, and $'Open\_Ob'$ as antecedents exhibit a predictive capability for the "sell pair *EUR_USD*" outcome with a confidence level exceeding 70%. Rule 3: Transactions that include $'Low\_Lc'$, $'Open\_Ob'$, and $'stoch\_k\_1\_Sk1a'$ as antecedents exhibit a predictive capability for the "sell pair EUR_USD" outcome with a confidence level exceeding 70%. Following that, we created association rules, shown in Table 16, and explained the most crucial association rules for *Devise_gold_nasdaq_ClosePrime_GU*.

Table 16. Top association rules for *Devise_gold_nasdaq_ClosePrime_GU*

N°	Confidence	Support	Lift	Rules
R1	0.71	0.46	1	$frozenset(\{'Low\_EU\_Lc','stoch\_k\_1\_EU\_Sk1a'\})$ => $ClosePrime\_GU\_SV$
R2	0.72	0.41	1.05	$frozenset(\{'MACD\_UJ\_Mb','stoch\_d\_1\_EU\_Sd1a'\})$ => $ClosePrime\_GU\_SV$
R3	0.72	0.41	1	$frozenset(\{'MACD\_EU\_Mb','MACD\_UCH\_Mb'\})$ => $ClosePrime\_GU\_SV$

Rule 1 transactions that include $'Low\_EU\_Lc'$ and $'stoch\_k\_1\_EU\_Sk1a'$ as antecedents exhibit a predictive capability for the "sell pair GBP_USD" outcome with a confidence level exceeding 70%. Rule 2: Transactions that include $'MACD\_UJ\_Mb'$ and $stoch\_d\_1\_EU\_Sd1a'$ as antecedents exhibit a predictive capability for the "sell pair GBP_USD" outcome with a confidence level exceeding 70%. Rule 3: Transactions that include $'MACD\_EU\_Mb'$ and $'MACD\_UCH\_Mb'$ as antecedents exhibit a predictive capability for the "sell pair GBP_USD" outcome with a confidence level exceeding 70%. Following that, we created association rules, shown in Table 17, and explained the most crucial association rules for *Devise_gold_nasdaq_ClosePrime_UCH*.

Table 17. Top association rules for *Devise_gold_nasdaq_ClosePrime_UCH*

N°	Confidence	Support	Lift	Rules
R1	0.72	0.58	1	$frozenset\ (\{\ 'MACD\_GU\_Mb','MACD\_gold\_Mb','stoch\_k\_1\_gold\_Sk1a'\})$ => $ClosePrime\_UCH\_SV$
R2	0.76	0.26	1.05	$frozenset(\{'MACD\_EU\_Mb','stoch\_d\_1\_EU\_Sd1a','stoch\_k\_1\_EU\_Sk1a'\})$ => $ClosePrime\_UCH\_SV$

Rule 1 transactions that include $'MACD\_GU\_Mb'$, $'MACD\_gold\_Mb'$, and $'stoch\_k\_1\_gold\_Sk1a'$ as antecedents exhibit a predictive capability for the "sell pair USD_CHF" outcome with a confidence level exceeding 70%. Rule 2: Transactions that include $'MACD\_EU\_Mb'$, $'stoch\_d\_1\_EU\_Sd1a'$, and $'stoch\_k\_1\_EU\_Sk1a'$ as antecedents exhibit a predictive capability for the "sell pair USD_CHF" outcome with a confidence level exceeding 70%. Following that, we created association rules, shown in Table 18, and explained the most crucial association rules for *Devise_gold_nasdaq_ClosePrime_UJ*.

Table 18. Top association rules for *Devise_gold_nasdaq_ClosePrime_UJ*

N°	Confidence	Support	Lift	Rules
R1	0.75	0.44	1	$frozenset\ (\{'MACD\_UCH\_Mb','stoch\_k\_1\_EU\_Sk1a','stoch\_k\_1\_gold\_Sk1a'\})$ => $ClosePrime\_UJ\_SV$
R2	0.76	0.40	1.03	$frozenset(\{'Low\_GU\_Lb','stoch\_d\_1\_EU\_Sd1a','stoch\_k\_1\_gold\_Sk1a'\})$ => $ClosePrime\_UJ\_SV$

Rule 1 transactions that include *'MACD_UCH_Mb'*, *'stoch_k_1_EU_Sk1a'*, and *'stoch_k_1_gold_Sk1a'* as antecedents exhibit a predictive capability for the "sell pair USD_JPY'" outcome with a confidence level exceeding 70%. Rule 2: Transactions that include $'Low\_GU\_Lb'$, $'stoch\_d\_1\_EU\_Sd1a'$, and $'stoch\_k\_1\_gold\_Sk1a'$ as antecedents exhibit a predictive capability for the "sell pair *USD_JPY*" outcome with a confidence level exceeding 70%. In this paper, we have analyzed association rules for the signal "selling out" in "*ClosePrime_SV*", and the signal "buying in" in "*ClosePrime_SA"*. We focused on uncovering only the significant rules. The validation procedure included confirming that the lift value surpassed 1, the confidence value surpassed 70%, and the support value was higher than 0.25.

We present the obtained rules in the tables. We could identify the most significant connections present in the data. This finding has implications for investors or individuals interested in understanding the stock market and identifying optimal points for buying and selling.

4. CONCLUSION

Researchers have suggested numerous algorithms to extract association rules, leading to the generation of an overwhelming number of rules. This large volume of regulations can pose a difficulty for decision-makers in identifying the most crucial ones. In our study, we utilized the Apriori algorithm to generate the rules. We then evaluated the quality of these rules using three metrics: support, confidence, and lift. Based on these metrics, we ranked the rules, enabling a more informed decision-making process and identifying optimal points for buying and selling between currency pairs, gold, and NASDAQ. In our future research, we intend to apply the other technical indicators with other approaches to enrich the accuracy of buying and selling.

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BIOGRAPHIES OF AUTHORS

Mohamed El Mahjouby received his master's degree in information systems engineering (MSID) from the Sidi Mohamed Ben Abdellah University in Fez, Morocco in 2020. His research focus on artificial intelligence and machine learning. His thesis is "Stock market predictive system analysis and modeling". He can be contacted at email: mohamed.elmahjouby@usmba.ac.ma.

Mohamed Taj Bennani received his Master's degree in computer science and networking from Science Faculty of Tangier, Tangier in 2011. He received his Ph.D. in 2019 (Computing science and networking) from Science Faculty of Tangier. At present, he is working as professor in Faculty of Science of Dhar el Mahraz Fez since 2019. He is qualified university professor since June 2023. He can be contacted at email: taj.bennani@usmba.ac.ma.

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). He can be contacted at email: mohamed.lamrini@usmba.ac.ma.

Mohamed El Far is a professor of the Sidi Mohamed Ben Abdellah University in Fez, Morocco. He teaches computer science. His research focus on data science, big data and artificial intelligence. He had published many researchers. He can be contacted at email: mohamed.elfar@usmba.ac.ma.