Title:

Bitcoin price prediction using Bayesian neural networks

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Abstract:

In this research, we aim to determine the price of a specific cryptocurrency by utilizing Bayesian neural networks and data from the Commitment of Traders Report (COT) spanning from 2018 to October 2019. The COT report, published on a weekly basis, provides valuable insights into trader activity. We also incorporate data on the weekly price of Bitcoin, as it is the most widely recognized cryptocurrency.

One challenge in predicting the price of this cryptocurrency using the traders' commitment report data lies in the temporal discrepancy between the report publication dates and the weekly Bitcoin price data. This disparity makes it challenging to effectively combine these two datasets. As a result, it is possible to predict the price for the upcoming week only five days in advance.

Our approach combines Bayesian neural networks, posterior probability estimation, and defined formulas to achieve a prediction accuracy of 71% for this cryptocurrency. While there are methods that exhibit high accuracy in short-term price prediction, they may not be as effective in the long term.

Chapter 1 : Research overview

1-1 Introduction

With the growing popularity of digital currencies, particularly Bitcoin, the need for accurate price prediction methods has become crucial. Bitcoin, being a cryptocurrency, has captured the attention of both the economic and computer science communities over the past decade due to its integration with the financial system (Jang and Lee, 2017). It operates on a completely peer-to-peer basis, allowing for transactions without the involvement of any financial institution. Several factors influence the price of Bitcoin, including supply and demand, network difficulty, Bitcoin/dollar exchange rate, Dow Jones index, Nasdaq index, and more (Jang and Lee, 2017).

In addition to these factors, other elements like Brent oil, gold, and exchange rates of the euro and yen have also been observed to impact the price of Bitcoin (Mohammed Y., 1387). As the demand and investment in this cryptocurrency continue to rise, there is an increasing need to predict its price accurately and reduce investment risks. This study aims to leverage blockchain information and other relevant data sources to predict the price of Bitcoin using Bizon Neural Networks.

1-2 Statement of the Problem:

Several approaches have been employed to predict the price of Bitcoin, encompassing network algorithms and learning algorithms (Graves et al., 2015). In this study, our objective is to explore the influence of new variables and utilize them as inputs for Bayesian neural networks in predicting the price of Bitcoin. The demand for Bitcoin is influenced by various factors, as indicated in the same source (Graves et al., 2015, p. 14): Economic volume of Bitcoin (E), price of goods and services (P), growth rate of Bitcoin (V), market demand (D), and Bitcoin itself (B).

$$(1\text{-}1) \qquad D_B = PE / V$$

According to the same source (Graves et al., 2015, p. 14), Bayesian Neural Networks (BNN) are a modified version of Multilayer Perceptron (MLP), which falls under the category of Artificial Neural Networks (ANN) in machine learning. BNNs have demonstrated strong performance in various domains, including face recognition, pattern recognition, natural language processing, and financial time series analysis.

The structure of BNNs comprises three main components: an input layer, an output layer, and one or more hidden layers. These layers collectively enable the network to process information and make predictions. Notably, neural networks with multiple hidden layers have the ability to solve complex problems such as the unique OR (XOR) problem.

1-3_ Main Research Questions:

1-3-1_ The first main question: How can Bizon Neural Networks and specific input variables be utilized to improve the accuracy of Bitcoin price prediction?

1-3-2_ The first Sub-Question : Which input variables are conducive to enhancing the accuracy of Bitcoin price prediction using Bizon Neural Networks?

1-4 Research Objectives:

1-4-1_ Scientific Goals: To integrate existing methods with novel variables to achieve a more precise forecast of Bitcoin price.

1-4-2_ Practical Goals: To develop a robust model that can be utilized as a framework for estimating Bitcoin prices in the cryptocurrency market.

1-5 The Necessity and Importance of Research:

With the highly volatile nature of the cryptocurrency market and the increasing investments in Bitcoin, there is a growing need for a decision support system to mitigate losses and risks for investors. Several recent studies have focused on Bitcoin and its price prediction using new market variables.

1-6 Related Literature:

Bitcoin, introduced by Satoshi Nakamoto in 2009, has gained significant popularity as a digital currency. Over the past decade, numerous studies have been conducted to model Bitcoin prices, employing techniques such as GARCH analysis (Katsiampa, 2017; Diehrberg, 2016). These studies have explored various statistical and economic properties of Bitcoin prices, with a particular emphasis on analyzing price dynamics and comparing them to other currencies (Barivira et al., 2017; Chu et al., 2015).

Furthermore, linear models have been used to examine the effects of different agents and market transitions on Bitcoin prices (Urquhart, 2016). Machine learning techniques, such as Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks, have been employed to forecast Bitcoin prices (McNally, 2016; Madan et al., 2015). Bayesian Neural Networks (BNN) have also been utilized for practical analysis and prediction of Bitcoin prices to the same source (McNally, 2016; Madan et al., 2015).

In addition, the utilization of BNN, a type of Bayesian Network, has shown promise in analyzing and predicting Bitcoin prices due to its ability to capture non-linear and complex relationships (Tabatabayi and Dashtizadeh, 1387). This method provides a powerful tool for modeling relationships and making future payment system assessments. The Bayesian Network approach accommodates imperfect and inaccurate information, enabling robust results even in the presence of imperfect data (Mr. Y and Dehghan, 2017).

It is important to note that the Bayesian Network approach offers the flexibility to model uncertain and non-certain situations, making it highly applicable for modeling complex systems with multiple variables and uncertain conditions (Tabatabayi and Dashtizadeh, 1387). This methodology provides valuable insights for decision-making in uncertain environments by considering the interplay between causes and effects (Mr. Y and Dehghan, 2017).

1-7 Research background:

Numerous studies have been conducted on Bitcoin and its price prediction, and we will examine some of them below. In a study by Shahu and Zhang (2014), price patterns of Bitcoin were analyzed using Bayesian regression. They aimed to identify the most accurate pattern for predicting Bitcoin price using the latent source model (LSM). The study explored patterns such as head and shoulders, reversionary patterns, and trending trends. Bayesian inference played a fundamental role, utilizing experimental data as a known sample across various fields.

In another study by Madan et al. (2015), two datasets were employed. The first dataset consisted of daily data, including price and 26 other features related to the Bitcoin network. These features encompassed concepts like investment in the Bitcoin market and the relationship between Bitcoin trading volume and USD volume. The second dataset comprised Bitcoin price data at 10-second and 10-minute intervals. The data were collected from Coinbase API and analyzed using two-dimensional logistic regression, support vector machine, and random forest methods to determine the most effective approach for predicting coin prices within specified time frames.

Graves et al. (2015) focused on studying Bitcoin price changes using transaction graphs. The article introduced input variables such as the current price of Bitcoin, the number of transactions per hour, the average transaction value, and the total number of mined bitcoins for network algorithms and learning algorithms. The study aimed to identify the most accurate method for predicting Bitcoin price.

In the study conducted by Stanqvist and Lenovo (2017), the prediction of Bitcoin price was explored by considering tweets published on Twitter. The model utilized Twitter's streaming API and Tweepy to analyze tweets containing specified keywords. The model exhibited better performance within one-hour time frames.

1-8 Conceptual criteria of the research:

Bitcoin, as a digital currency or cryptocurrency, is influenced by various factors across different dimensions. These factors can be broadly categorized into internal and external factors. Internal factors include the number of transactions, the number of generated bitcoins, and the volume of purchases and sales within the transaction graph's main nodes. Additionally, factors like the Bitcoin/dollar exchange rate, Dow Jones index, Nasdaq index, and others can impact the price of Bitcoin. In the subsequent chapters, we will delve into the internal factors affecting Bitcoin's price.

1-9 Research method:

The research method aims to explain, interpret, and determine the direction of investigation to uncover facts related to the research subject. Initially, we will conduct library studies to gather relevant articles. After gaining a comprehensive understanding of the research background and familiarizing ourselves with the utilized variables, we will analyze and assess the prediction of Bitcoin price using Bayesian neural networks.

1-10 Data analysis method:

The analysis of library data and information banks involved the use of descriptive statistics and inferential statistics methods. Descriptive statistics encompassed frequency distribution tables, distribution ratios, geometric and visual representations, and similar concepts. Additionally, the analytical method was applied to the input variables of Bayesian neural networks to explore the prediction of Bitcoin price.

1-11 Research applications:

As mentioned previously, developing a model for accurately predicting Bitcoin price can be utilized to construct an effective framework for estimating Bitcoin's price in the cryptocurrency market. This framework can assist investors in avoiding significant losses. However, it should be noted that in this volatile market, nothing can be predicted with 100% certainty, and these models should be used as decision-support systems based on probabilities.

1-12 Novelty and innovation of research:

While various methods have been employed to predict Bitcoin, such as the GARCH model, transaction graphs, and Bayesian regression, the use of Bayesian neural networks was investigated in (McNally, 2016; Madan et al., 2015). In this research, 26 different variables, including internal factors like miners' income, average block size, bitcoin price, hash rate, and external factors like exchange rates, stock market indices (e.g., Nasdaq, Dow Jones), and gold index, were utilized as inputs to the model. Furthermore, the research aims to incorporate future market data from the Commitment of Traders report in the United States as input for Bayesian neural networks to assess its impact on Bitcoin's price and improve prediction accuracy.

1-13 Research problems and limitations:

The high volume of transactions and daily fluctuations in the Bitcoin market pose significant challenges, potentially resulting in substantial losses for investors. Additionally, the multitude of variables contributing to these fluctuations makes it impractical to consider all of them for accurate prediction. Another limitation is the discrepancy between the release days of weekly Bitcoin price data and the traders' commitment report, which affects the analysis.

Chapter 2：Theoretical foundations of research

2-1 Introduction:

Digital currencies have been the subject of extensive research due to their complex price mechanisms and the influence of various external and internal factors. These currencies are impacted by external factors such as political and social events, as well as internal factors. Researchers have focused on studying these aspects over the years.

One popular method used to understand the relationship between digital currencies and macroeconomic variables is nonlinear causality testing. Researchers have employed various nonlinear models to examine this relationship and have mostly found better results compared to linear models. These studies often analyze the relationship between the exchange rate of the currency, macroeconomic variables, stock market movements, currency price, currency volume, and economic growth.

The current research is structured into five chapters. The second chapter provides an overview of the research concepts and related work. In the third chapter, the data used, data collection methods, and analysis techniques are explained. The fourth chapter presents the research findings and results. Finally, the fifth chapter concludes the research.

2-2 Factors affecting the price of Bitcoin:

The buying process in the cryptocurrency market is influenced by numerous internal and external factors. External factors include economic, political, and cultural factors, while internal factors consist of biorhythmic factors, international market indices, analysis indicators, compatibility between the buyer's perception and the company's image, risk tolerance level, number of bitcoins produced, buying and selling activities in significant transaction nodes, and self-confidence level. Studying and measuring these factors can provide valuable insights into investor behavior, contributing to the growth and development of the cryptocurrency market.

This research focuses on investigating the internal factors that impact the price of Bitcoin. Specifically, the data obtained from the traders' commitment report will be utilized as input for the Bayesian neural network. The correlation coefficient is one of the criteria used to assess the relationship between the two variables examined in this study.

2-3 Previous works:

Recent studies have focused on various models and techniques to predict the price of Bitcoin. Examples include the use of the autoregressive conditional heteroskedasticity (GARCH) model and swing analysis (Katsiampa, 2017; Diehrberg, 2016). These articles explore the financial capabilities of GARCH models in predicting Bitcoin prices. However, in this research, we employ a simple Bayesian network for Bitcoin price estimation, although hidden Markov models or dynamic Bayesian neural networks can also be used for this purpose.

Other studies have examined the statistical properties and economic characteristics of Bitcoin prices. Barivira et al. (2017) and Chu et al. (2015) have focused on the statistical properties of Bitcoin and the comparison of price dynamics across different cryptocurrencies. Notably, Gupta et al. (2005) employed hidden Markov models to predict stock prices, while Abishek et al. (2012) utilized artificial neural networks for stock prediction, specifically using Microsoft company shares from 2011 onwards. Ticknor (2013) introduced Bayesian artificial neural networks as a novel method for stock market prediction, and Wang et al. (2015) used dynamic Bayesian graphs to predict stock market trends. Elal et al. (2011) combined neural networks and fuzzy logic to predict the trend of the Egyptian stock market.

Several other studies have explored the application of Markov chain analysis in stock market forecasting. Zhang et al. (2009) proposed a Markov process model to forecast stock market trends. Landaskas et al. (2011) developed a simulation-based approach using Monte Carlo methods and Markov chains to relax the assumptions of stock price probability distribution. Osobeda et al. (2012) aimed to predict the trend of the Prague Stock Exchange index using Markov chain analysis. Lee and Shi (2009) combined discrete Markov chains and Gaussian models to enhance the predictability of stock returns. Toner et al. (1989) investigated different models where the portfolio's excess returns variance depends on a state variable generated by a first-order Markov process. Despite these efforts, forecasting stock market trends remains a challenging research area.

In the work by Shahu and Zhang (2014), Bayesian regression is used to analyze price patterns and identify the most effective patterns for accurate Bitcoin price prediction using the latent source model (LSM). These patterns include head and shoulders, reversionary patterns, and trending trends. Bayesian inference relies on empirical data as a known sample, applicable in various contexts.

In the study conducted by Madan et al. (2015), two datasets are employed. The first dataset consists of daily data, including Bitcoin price and 26 other features related to the Bitcoin network. These features encompass concepts such as Bitcoin market investments and the relationship between Bitcoin transaction volume and USD volume.

2-4 Applied concepts:

2-4-1 Artificial Neural Networks:

Artificial neural networks have their origins in the theory of artificial neurons, which gained prominence in the 1940s through the work of renowned psychologists and mathematicians like McCulloch and Pitts. In 1943, they laid the foundation for the first approximation of a neural network, known as a single-layer perceptron. Neural networks can approximate complex patterns and address issues such as pattern recognition, nonlinear relationships, memory association, self-organization, and control. The practical application of artificial neural networks began with Rosenblatt's introduction of the perceptron and the development of multilayer perceptron (MLP) networks. MLP networks consist of layers, including input, hidden, and output layers. The number of neurons in each layer is determined by the network architecture, and it can be optimized through trial and error to minimize errors (Moghadamnia et al., 2009).

2-4-2 Bayesian networks:

Bayesian neural networks (BNN) are a modified version of multilayer perceptrons (MLP), which are part of the broader field of artificial neural networks (ANN) in machine learning. Bayesian networks, also known as belief networks, causality networks, or causal networks, are graphical representations of random variables and their direct relationships. The structure of a Bayesian network visually depicts the interactions between variables and can model the domain structure. When the network structure represents causality, it offers insights into variable interactions and facilitates the prediction of external effects. Bayesian network nodes are typically depicted as circles or ellipses (BayesFusion, 2017).

In this study, Bayesian networks are used to discover relationships among variables and create a model for predicting the price of a specific digital currency. The Bayesian network is constructed by defining the variables and their connections, forming a graph where each edge represents a relationship between variables. Conditional probability tables are used to describe the probabilistic relationships. The software GeNIe 2.0 is employed to create the Bayesian network in this research.

2-4-3 Influence diagrams:

In Bayesian networks or influence diagrams, edges represent influences, indicating that the node at the beginning of an edge affects the value or probability distribution of the node at the end. These influences are depicted as straight lines. Some edges in the influence diagram convey causality, where a direct path from a decision node to a chance node signifies that the decision affects the probability distribution of that node. Edges entering decision nodes denote temporal precedence rather than influence, as decision nodes require information from preceding nodes. Informational edges are depicted as dashed lines.

2-5 Solving decision models:

In decision theory, decision models are designed to calculate the expected efficiency of each possible decision option or strategy in multiple decision-making scenarios, enabling the selection of the alternative or strategy with the highest expected efficiency. The first inference algorithm in influence diagrams was modified by Olmsted (1983) and later by Schachter (1988). This algorithm reverses edges and removes nodes in the network structure until the desired probabilistic query can be directly obtained from the graph. Cooper (1988) proposed an algorithm for inference in influence graphs, transforming the influence graph into a Bayesian network and repeatedly inferring the network to determine the expected efficiency of each decision option.

The value of information plays a crucial role in studying theoretical models of decision-making, considering the importance of observing a variable and reducing its uncertainty to zero before making a decision. Sensitivity analysis examines the impact of inaccuracies in numerical parameters on the solution of the decision model.

It is essential to recognize that gaining insight into a decision problem, including its qualitative structure, available options, expected efficiency of each option, and the significance of different sources of uncertainty, is far more important than relying solely on theoretical frameworks.

2-5-1 Decision analysis:

Decision analysis is the application of decision theory, which is an axiomatic theory that describes how decisions are made. It is based on the assumption that humans can logically define a decision problem, identify possible alternatives, determine relevant factors, assess uncertainty and preferences, but may struggle to combine this information into a logical decision (BayesFusion, 2017).

Decision analysis provides empirically tested tools for decision-making, problem formulation, reducing uncertainty and biases, identifying critical factors in the decision model, and evaluating the value of information for reducing uncertainty. Probability theory and decision theory are utilized to integrate observations and optimize decisions. GeNIe software is one tool that offers these capabilities. While decision analysis is rooted in quantitative theories, namely probability theory and decision theory, its foundations are qualitative and based on rational axioms. The objective of decision analysis is to gain insights into decision-making rather than providing a definitive recommendation (BayesFusion, 2017).

2-5-2 Discrete and continuous variables:

Variables can be classified into two fundamental categories based on their range of values: discrete and continuous. Discrete variables represent a limited set of conditions and assume specific, usually small, values (BayesFusion, 2017). Continuous variables can take on an infinite number of values. For example, body temperature is a continuous variable that can range between 30 and 45 degrees Celsius.

Most Bayesian network algorithms are designed for discrete variables. Therefore, Bayesian network models typically involve discrete variables or conceptual continuous variables that are discretized for reasoning purposes (BayesFusion, 2017).

While the distinction between discrete and continuous variables is clear, the distinction between discrete and continuous values can be ambiguous. Many values can be expressed as either discrete or continuous. Discrete variables often approximate real-world values sufficient for reasoning. For instance, investment success can be represented by a continuous variable such as financial profit or stock price, or it can be expressed as categories like [good, average, bad] or price per share [$5, $20, $50]. Body temperature can be viewed as a continuous variable, but it can also be categorized as low, normal, fever, or high fever. Practical experience in decision-analytical modeling has shown that expressing continuous variables using three to five-point discrete approximations works well in most cases (BayesFusion, 2017)

2-5-3 Different interpretations of possibilities:

• Probability interpretations:

In decision theory and decision analysis, uncertainty is addressed using probabilities. There are three fundamental interpretations of probability:

- Frequentist interpretation: Probability is defined as the limiting frequency of an event occurring in an infinite number of trials.
- Objective interpretation: Probability is determined by the physical, objective, or production process characteristics of the object under consideration.
- Subjective interpretation: Also known as Bayesian interpretation, probability depends on an individual's subjective belief in the occurrence of an event (BayesFusion, 2017) .

2-5-4 Productivity and effectiveness:

Priority is an integral element of all decision problems, essential for making decisions. Objective quantities such as material usage, factory output, or financial profit often serve as the basis for priority. However, decision problems frequently involve values that lack obvious numerical

measurements, such as health status, customer satisfaction, or pain. Conflicting possibilities, such as price and quality, present another case (BayesFusion, 2017).
Decision theory introduces efficiency as a measure of priorities. Productivity is a function that represents the attributes of potential decision outcomes using real numbers. Productivity is assumed to exhibit linear change, meaning the decision maker's preference for different options can be expressed by multiplying productivity by non-negative numbers and adding a constant. This implies that productivity has no zero interpretation or scale. It is subjectively assumed that different decision makers, even with shared ideas, may choose differently due to their preference structure and distinct productivity functions. Obtaining a productivity function for a decision problem is known as productivity selection (BayesFusion, 2017) .

2-6 Blockchain definition:

Decentralization is a fundamental characteristic of all cryptocurrencies, distinguishing them from public currencies controlled by central banks. Decentralization can be defined by the following objectives: (i) Who maintains and manages transaction direction? (ii) Who has the right to validate transactions? (iii) Who creates new bitcoins? Blockchain is the only technology capable of achieving all three goals simultaneously. In the context of Bitcoin, block production directly impacts the supply and demand of bitcoins (Jang and Lee, 2017).

The combination of blockchain technology and the Bitcoin market exemplifies the fusion of advanced cryptocurrencies and market economics. In the following explanation, we detail how blockchain accomplishes the aforementioned goals within the Bitcoin environment. Participants on the Bitcoin network contribute their computer hardware resources to form a distributed system. All releases and transactions occur through peer-to-peer (P2P) networks (Jang and Lee, 2017).

All transaction history is recorded on the blockchain, shared among network participants, and verified by all. Each "block" contains recent transactions and the hash value of the previous block. These blocks are created using an irreversible data hash function and form the chain by linking to the next block. Figure 1 illustrates the general structure of the blockchain. The time required to generate a block ensures the security of the blockchain against tampering. This algorithm, called Proof of Work (PoW), automatically adjusts the network's difficulty to solve any problem within less than 10 minutes. The proof-of-work algorithm also incentivizes participants to maintain the value of Bitcoin by rewarding them with Bitcoin for creating blocks. However, the proof of work algorithm is associated with several inherent challenges and errors (Jang and Lee, 2017).

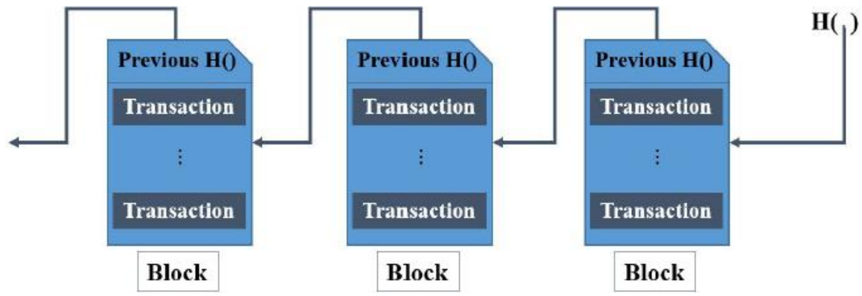

Figure (2-1) how blockchain is formed (Jang and Lee, 2017)

Figure (2-1) illustrates the formation of a blockchain. There are several key aspects to consider. First, the block's validity can be determined by a majority of 51% of the participants. Second, in the event of a blockchain split, it takes a considerable amount of time to establish a consensus and merge the chains into the longest one. This delay in consensus building affects transaction processing, rendering transactions impossible during this period. Lastly, there may exist limitations on the blockchain's capacity or on the performance of individual nodes. The security of the current blockchain can be assessed by examining measurable variables on the blockchain.info website (Jang and Lee, 2017).

chapter 3: Research methodology

3-1 Introduction:

As previously mentioned, the price of Bitcoin can be influenced by various internal and external factors. External factors include economic, political, and cultural influences, while internal factors encompass factors such as trading volume, global trade indicators, and inherent power analysis. In this research, we aim to examine the impact of periodic factors on Bitcoin's price.

In this study, we utilize future market data obtained from the United States to analyze the effects of this data on the price of Bitcoin cryptocurrency. The future market data is provided on a weekly basis, and our analysis focuses on the weekly time frame. We employ the correlation coefficient as one of the criteria to assess the correlation between the variables under investigation.

3-2 Dataset

For this research, we utilized the dataset from the website related to the Commitment of Traders (COT) report. The dataset spans from the beginning of 2018 to the end of October 2019. The COT report provides weekly data on futures market exchanges across different sectors and currencies.

3-2-1 Futures Market :

The futures market is where traders engage in buying and selling futures contracts and commodities. Futures contracts involve the delivery of assets on a specified future date. Participants in the futures market trade contracts and goods to be delivered in the future (Cornell, 1999).

A futures contract is an agreement to buy or sell an asset at an agreed-upon price on a future date. These contracts are standardized and typically trade on stock exchanges. Parties agree to buy a specific quantity of securities or commodities and deliver them on a predetermined date (Cornell, 1999).

Futures trading provides a fast and cost-effective means to trade financial and commodity markets. These standardized contracts enable traders worldwide to manage risk and seek profit in dynamic markets (Cornell, 1999).

3-2-2 Commitment of Traders (COT) Report:

The Commodity Futures Trading Commission (CFTC) publishes COT reports to help traders understand market dynamics. These reports are of interest to traders in futures and options futures markets who initiate trades at or above the reporting level set by the CFTC (COMMISSION, U.S. CFTC, 2014).

3-2-3 Traders Futures (TFF) Report:

The Traders Futures (TFF) Report, introduced by the Commodity Exchange Commission (CFTC) on July 22, 2010, improved transparency by incorporating data from the CFTC's Weekly Traders Obligations Report (COT). This new report categorizes large traders in the financial markets into four groups: dealer/intermediary, asset/institutional manager, leveraged funds, and other reports. The COT report only separates reported traders into "commercial" and "non-commercial" groups (COMMISSION, U.S. CFTC, 2012).

3-2-3-1 Seller/Intermediary:

These participants are referred to as the "sell side" of the market. While they may not sell futures wholesale, they do sell various financial assets to clients. They tend to take less risk and use futures contracts as part of pricing and risk balancing activities. This category includes major banks (US and non-US) and sellers of securities and derivatives (ibid.: 6). The rest of the market constitutes the "buy side" and is divided into the following three categories:

3-2-3-2 Asset/Institutional Manager:

This category includes institutional investors such as pension funds, endowments, insurance companies, mutual funds, and portfolio/investment managers whose clients are mainly institutional (COMMISSION, U.S. CFTC, 2012).

3-2-3-3 Leveraged Funds:

This category typically consists of hedge funds and various money managers, including registered commodity trading advisors (CTAs). Their strategies may involve exiting trades completely or changing direction within the market. Some traders in this category may manage and execute proprietary futures transactions on behalf of clients (COMMISSION, U.S. CFTC, 2012).

3-2-3-4 Other Reports:

Traders who do not fall into the first three categories are grouped under "Other Reports." Traders in this category primarily use the markets to hedge business risks related to foreign exchange, stocks, or interest rates. It includes corporate treasuries, central banks, smaller banks, mortgage loan originators, credit unions, and other reportable traders not covered by the previous categories (COMMISSION, U.S. CFTC, 2012).

4-2-3 COT Data:

The COT report data is separately announced for each of the four categories mentioned above. The report includes transactions made in each category for various currencies, such as Canadian Dollar, Euro, British Pound, Swiss Franc, Japanese Yen, and exchanges involving Euro/Dollar, Pound/Dollar, Dow Jones Index, S&P500 Index, and other exchanges specified in the report.

3-3 Software Introduction:

Since this research focuses on predicting the price of Bitcoin using Bayesian neural networks, we will use software specifically designed for modeling Bayesian networks. Based on reviews, the GENIE 2.0 software has proven to be effective in creating Bayesian neural networks, and we will utilize it in our research.

3-3-1 GeNIe software (GENIE 2.0):

GeNIe is a development environment for constructing graphical decision models. This software was created and developed between 1995 and 2015 at the Laboratory of Decision Systems, University of Pittsburgh (COMMISSION, U.S. CFTC, 2012).

In 2015, a company called BayesFusion, LLC was established and licensed GeNIe from the University of Pittsburgh. To enhance the theoretical methods of decision-making in decision support systems, it was made available free of charge to the academic community for research and teaching purposes. GeNIe has undergone extensive testing in educational, research, and commercial environments and is continuously being improved. GeNIe is designed for Windows operating systems. While full compatibility is not guaranteed, it can be run on Mac OSX using Wine software. With GeNIe, users can create models of any size and complexity, with the only limitation being the computer's operating memory capacity. GeNIe serves as a modeling environment, and the models developed using GeNIe can be utilized by SMILE in any application and computed on any operating system (BayesFusion, 2017) .

3-4 Algorithms for Bayesian networks:

Since Bayesian neural networks operate based on Bayes' rule, various algorithms are employed to calculate the probabilities associated with each node's evidence. Figure (3-1) presents a list of these algorithms.

The information in this chart was compiled from the same source (BayesFusion, 2017), and it is important to note that all these algorithms can be implemented in the GeNIe software.
In general, Bayesian neural networks aim to minimize the sum of the following errors (Jang and Lee, 2017).

$$E_B = \frac{\alpha}{2}\sum_{n=1}^{N}\sum_{k=1}^{K}(t_{nk} - o_{nk})^2 + \frac{\beta}{2}\lessapprox_B^T\lessapprox_B \tag{1-3}$$

Where E_B is the sum of errors, N is the number of training instances, the size of the output layer, t_{nk} represents the k variable of the n_{th} target vector, O_{nk} is the k_{th} output variable of the n_{th} training vector, α and β are hyperparameters, and B⪷ is the weight vector of the Bayesian neural network.

3-4 Bayesian learning structure:

There are various methods and algorithms for training Bayesian neural networks, and we will describe some of them here. Each of these algorithms utilizes data in different ways to establish relationships using Bayesian neural networks.

3-5-1 Bayesian search algorithm:

The Bayesian search learning algorithm structure is one of the earliest and most popular algorithms used. It was introduced by Cooper and Herskovits in 1992 and later improved by Hackerman in 1995. The Bayesian search algorithm is effective in identifying theoretical constraints based on data, as it produces a straightforward graphical representation (ibid.: 3).

3-5-2 PC algorithm:

The PC learning algorithm, introduced by Spirtes in 1993, is another well-known and widely used algorithm. Unlike other structured learning algorithms, the PC algorithm allows for continuous data and assumes multivariate normal distribution. Empirical studies by Wortman and Droudzel in 2008 have confirmed the robustness of the PC algorithm to the assumption of multivariate normality (BayesFusion, 2017) .

3-5-3 Basic graph search algorithm:

The basic graph search learning algorithm combines constraint-based search (primarily the PC algorithm) and the Bayesian search approach. Proposed by Dash and Droudzel in 1999, this algorithm utilizes the PC algorithm to search for fundamental diagrams and scores them using the Bayesian search method. The algorithm generates a graphical representation with the highest score, which is proportional to the probability assigned to the data given the structure and vice versa (BayesFusion, 2017) .

3-5-4 Simple Bayes Augmented Tree Algorithm (TAN):

The simple Bayes augmented tree learning algorithm is a graphical structure learning method based on the Bayesian search approach, explained in detail by Friedman et al. in 1997. The TAN algorithm starts with a simple Bayes structure where only one variable is the parent of all remaining variables. It then adds links between attribute variables to create potential dependencies, conditional on the parent variable of the class. However, this algorithm has the limitation of allowing only one parent. It is worth noting that the simple Bayes structure assumes independence between the features and the class variable, which may lead to inaccuracies when they are dependent. The TAN algorithm is simple yet has demonstrated higher reliability compared to the simple Bayes algorithm (BayesFusion, 2017) .

3-5-5 Simple Bayes algorithm:

The simple Bayesian learning algorithm falls under this category as it directly creates a Bayesian network from the data using the predefined structure and its parameters. The structure of a simple Bayesian network is assumed to be fixed, with the class variable serving as the parent of all other attribute variables, and no connections between network nodes. However, this algorithm assumes independence among the features with respect to the class variable, leading to inaccuracies when they are not independent.

3-6 Validation:

Validation is a crucial step in neural network learning to assess the accuracy of the model and compare it with other models. It helps ensure the reliability and performance of the created model in practical applications (BayesFusion, 2017) .

3-6-1 Mutual validation method:

Cross-validation is a commonly used validation method in which the data is divided into training and test sets. GeNIe incorporates a powerful form of cross-validation known as K-fold validation. This approach divides the dataset into K equal-sized chunks, trains the network on K-1 chunks, and evaluates its performance on the remaining chunk. This process is repeated K times, with a different chunk used for testing each time (BayesFusion, 2017) . The accuracy of the network is calculated using the mutual validation method, which is described as follows (Jang and Lee, 2017).

$$accuracy_K = \sum_{k=1}^{K} \frac{n_k}{N} \frac{1}{n_k} \sum_{i=1}^{n_k} (1 - Loss(\hat{y}_i^k, y_i)) \quad (2\text{-}3)$$

In the equation, N represents the total number of original datasets. y_i represents the correct output data for the i-th training instance, while $\hat{y}_i^k$ denotes the estimated output for the i-th instance. The estimated output is denoted as k_i. Loss represents the loss function used in the model.

3-7 Dynamic Bayesian Networks (DBN) :

A Bayesian network represents a system at a specific moment and is suitable for modeling systems in equilibrium states. However, many real-world systems undergo changes over time, and understanding their evolution is often more important than their static state. To address this, we require a modeling tool capable of capturing dynamic systems (BayesFusion, 2017) .

A Dynamic Bayesian Network (DBN) is an extension of a Bayesian network that incorporates additional mechanisms to model temporal effects (Jang, as cited in Murphy and Rachel, 2002). The temporal extension in a DBN does not imply dynamic changes in the network structure or parameters. Rather, it enables the representation of a dynamic system. DBN serves as a model for stochastic processes.

Chapter 4: Research Analysis and Findings

4-1 Introduction:

In this section, we will collect and preprocess data, build a model, and calculate probabilities to determine the posterior probability of Bitcoin price based on the input and selected data. The algorithms of Bayesian neural networks in the criminal software were briefly explained in the previous chapter. The main database for Bitcoin price prediction is derived from the information published by the United States Traders Commitment Web, specifically related to the futures market. Before using the data correlation coefficient, we preprocess the data based on the numerical ratio between the price of Bitcoin and the desired data. It is important to note that the traders' commitment report is published on a weekly basis, so all the data used in this research is in the weekly time frame, and the neural network is created to predict the weekly price of Bitcoin.

4-2 Proposed System Framework:

The proposed model, based on Bayesian networks, is presented in Figure (1-4). This framework consists of three main phases. Phase one involves data preparation, phase two focuses on extracting relevant features, and phase three covers predicting the future price trend. In the first phase, we preprocess the data by considering the numerical fit between Bitcoin price and the desired data before applying the correlation coefficient. We calculate Bitcoin price data for prediction and perform further preprocessing. In the second phase, the preprocessed data from the previous phase are used to construct and model the Bayesian network. The connections between features are determined using Bayesian network probabilities. In the third phase, after establishing the connections between nodes and employing the desired algorithm, we calculate input probabilities for each node. This calculation involves considering the ratio of the node's price difference to the price of Bitcoin and the node's price difference over the past two weeks, ultimately predicting the future price of Bitcoin. The research steps are depicted in Figure 1-4. It is important to conduct an initial preprocessing step to select variables that are suitable for Bitcoin price changes. In this stage, we selected 25 variables that showed the highest numerical compatibility with the price of Bitcoin.

4-3 Data Extraction and Organization:

4-3-1 Preprocessing of Data:

The data is in Excel file format. Weekly Bitcoin price data is obtained from the investing.com website, and trader commitment data is obtained from the cftc.gov website. Considering the traders' commitment report published weekly, our goal in this research is to predict the weekly price of Bitcoin.

To manage the large amount of data in the traders' commitment report, we applied a preprocessing step based on past experiences and the numerical fit between the index or desired currency and the price of Bitcoin. Next, using the correlation coefficient, we selected the data with the highest correlation to the Bitcoin price, resulting in 12 selected variables. These variables include three main indicators and two exchange currencies, with their values varying based on the number of traders in different market categories discussed in the third chapter. The correlation coefficients of these variables with the Bitcoin price were calculated separately. Table (1-4) shows the list of selected variables most related to the price of Bitcoin.

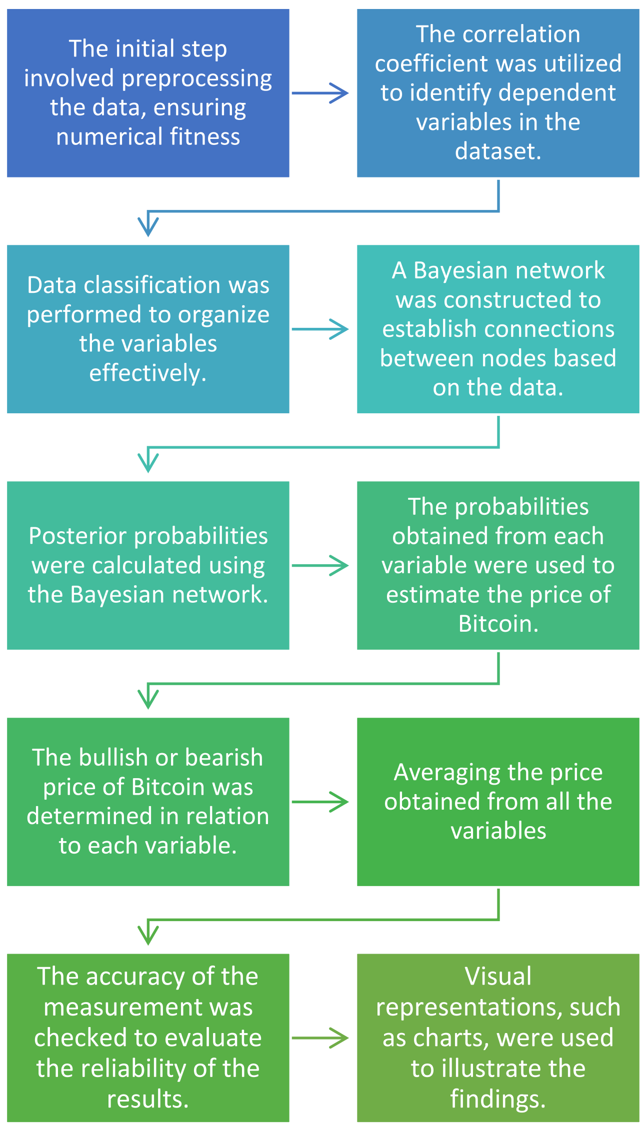

Figure (4-1): Research Phases

The main variable	Variable name	Row	The main variable	Variable name	Row
USD Currency	US DOLLAR Asset Manager Long	**7**	VIX INDEX	VIX Future Asset Manager Long	**1**
USD Currency	US DOLLAR Asset Manager Short Positions	**8**	VIX INDEX	VIX Future Asset Manager Short Positions	**2**
USD Currency	US DOLLAR Dealer Long Positions	**9**	VIX INDEX	VIX Future Dealer Long Positions	**3**
NAZDAQ INDEX	NASDAQ-100 Asset Manager Long Positions	**10**	GBP Currency	British Pound Asset Manager Long Positions	**4**
S&P 500 INDEX	S&P 500 Asset Manager Long Positions	**11**	GBP Currency	British Pound Asset Manager Short Positions	**5**
S&P 500 INDEX	S&P 500 Asset Manager Short	**12**	GBP Currency	British Pound Dealer Long Positions	**6**

Table (4-1): Variables Influencing the Price of Bitcoin

4-3-2 Classification:

After preprocessing the data, we proceed with their classification. The price status of each variable, compared to the price of the previous week, is categorized into three states: Increase, Decrease, or Stable. An example of the original data and the classified data is shown in Table (2-4).

4-4 Creation of a Bayesian Network:

As mentioned in the previous chapter, a Bayesian network represents a sequence of variable states, which form the nodes of the network. Once the data preprocessing and classification are completed, it is time to create the Bayesian network. We input the classified data into the software used for criminal analysis, which employs the learning methods described in the third chapter to establish the relationships between the variables.

raw data							Preprocessed data	
Date	BTC Price	VIX Asset Long	VIX Asset Short		Date	BTC Price	VIX Asset Long	VIX Asset Short
1-Sep-19	10,488.00	127007	67154		1-Sep-19	increase	decrease	Increase
25-Aug-19	9,623.90	131924	62324		25-Aug-19	decrease	increase	Decrease
18-Aug-19	10,152.00	128666	67845		18-Aug-19	decrease	decrease	Increase
11-Aug-19	10,228.00	138071	67096		11-Aug-19	decrease	increase	Decrease
4-Aug-19	11,314.00	132484	76521		4-Aug-19	increase	increase	Decrease
28-Jul-19	10,822.00	129463	121466		28-Jul-19	increase	decrease	Decrease
21-Jul-19	9,465.70	130085	122740		21-Jul-19	decrease	increase	Decrease

Table (4-2): An example of classified data

The simple Bayes augmented tree algorithm (TAN) is used to determine the relationships between variables. The general structure of communication and the input percentages from each node to another node are depicted in Figure (4-2). In this algorithm, it is necessary to select a main variable. Since our objective is to predict the price of Bitcoin, the weekly Bitcoin price will serve as our main variable, denoted by the BTC node and highlighted in yellow in Figure (4-2). Figure (4-2) provides information about the input of the main node to each of the other nodes and the connections between the nodes. Figure (3-4) displays the percentage of input to the nodes in each of the defined classes.

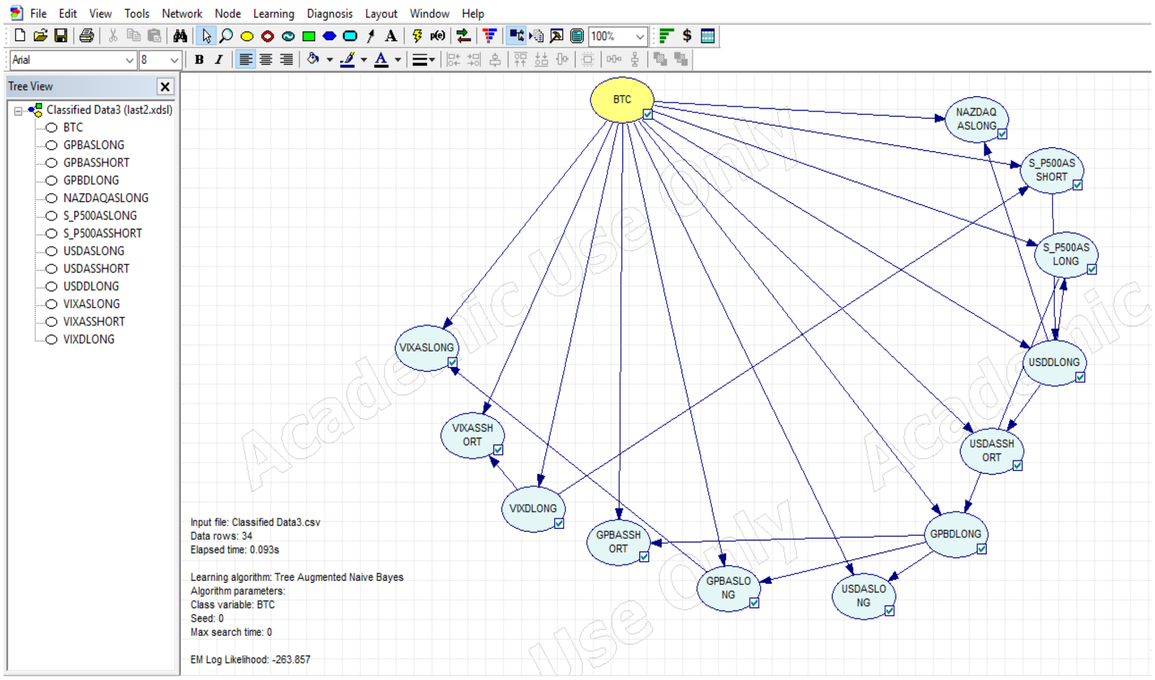

Figure (4-2): showing the connection between nodes

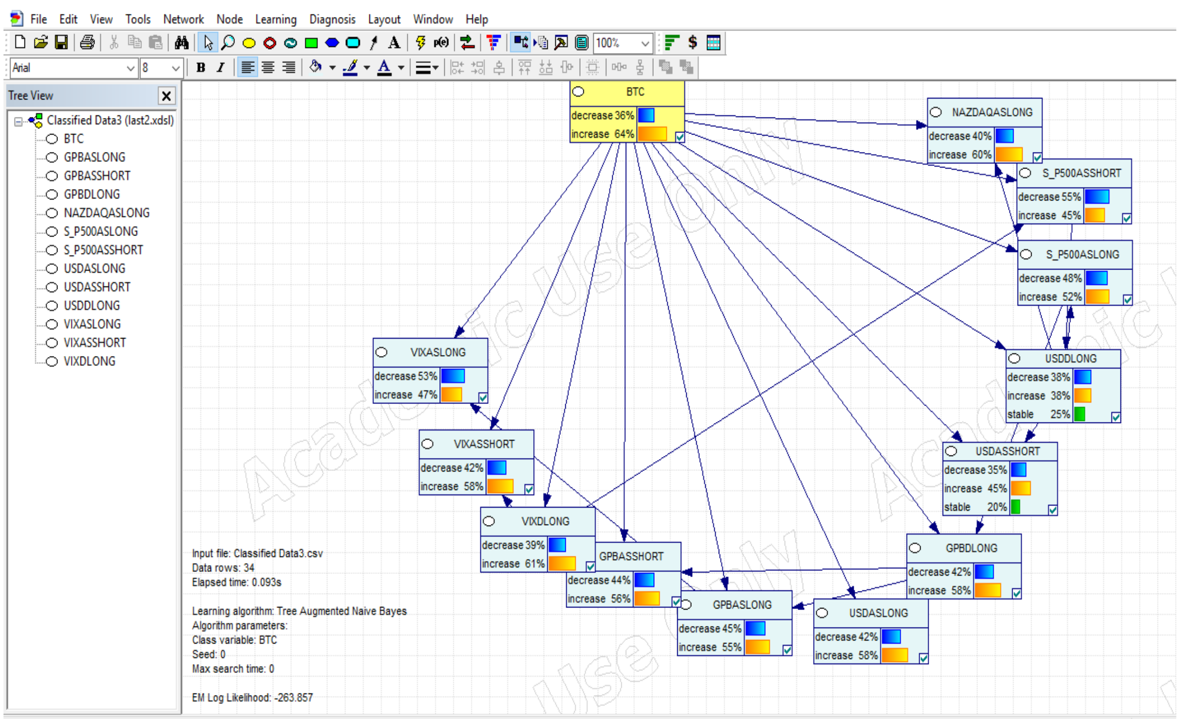

Figure (4-3): showing the percentage of input to each node

4-5 Bayesian network training and initial validation :

In this step, we select our desired algorithm from the ones introduced in the third chapter, which operate based on Bayes' rule and examine the posterior probability of the node. After that, we re-enter the classified data into the software and train the network to determine the overall probability of the defined classes for each variable. The algorithm used in this research is the clustering algorithm, which is a subset of exact algorithms.

After specifying the algorithm and running the network again, we can obtain the percentage of the posterior probabilities for each node, including the input probabilities related to the price of Bitcoin. An example of the obtained probabilities is shown in Figure (4-4).

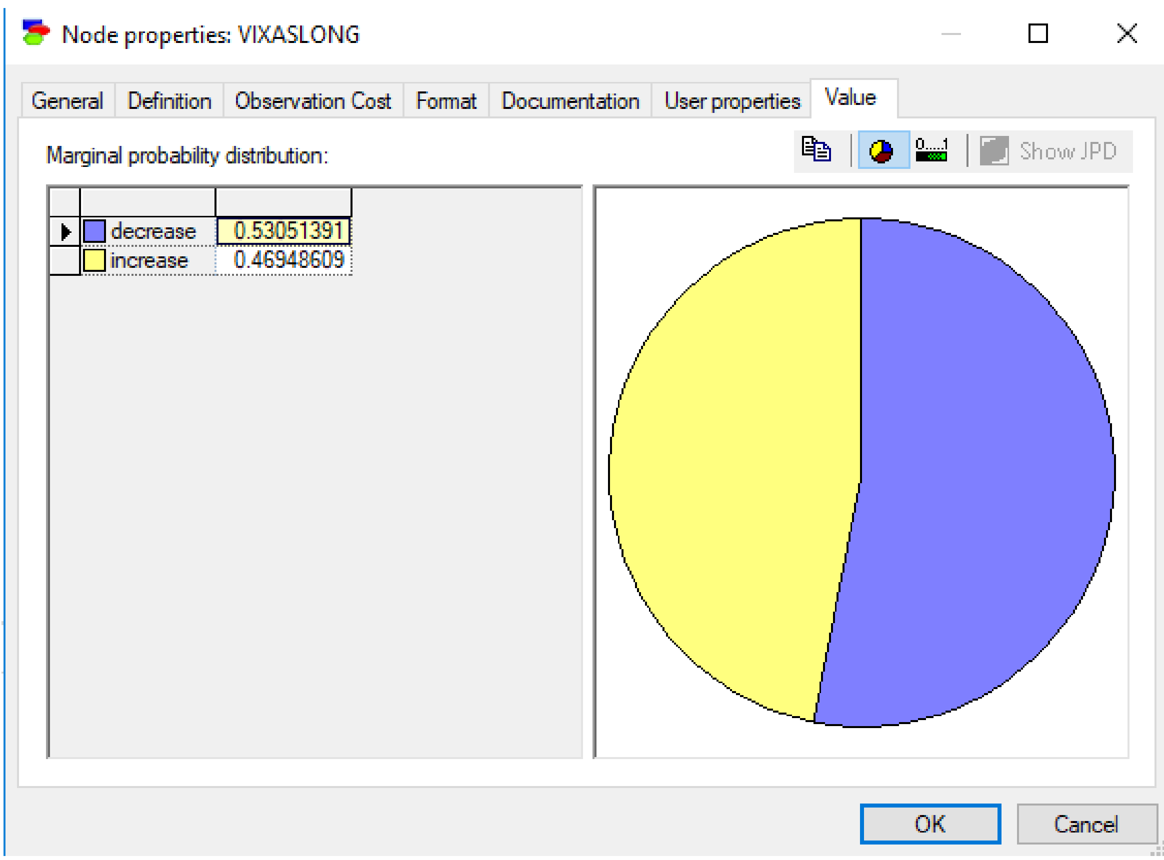

Figure (4-4): Posterior probabilities of VIX index node

After obtaining the posterior probabilities of each node, it becomes possible to predict whether each node will increase or decrease compared to the price of Bitcoin. The process of predicting the Bitcoin price will be fully explained in the following sections.

In the continuation of this step, an initial validation can be performed using the Validation part. In this particular case, the created network achieves an accuracy of 61%, as shown in Figure (4-5). To conduct this validation, we utilize the previous data and employ the cross-validation method discussed in the third chapter. We choose to have 3 layers, with 2 layers dedicated to training and 1 layer for testing. Additionally, we select the BTC node, representing the price of Bitcoin, as the variable of interest for examination.

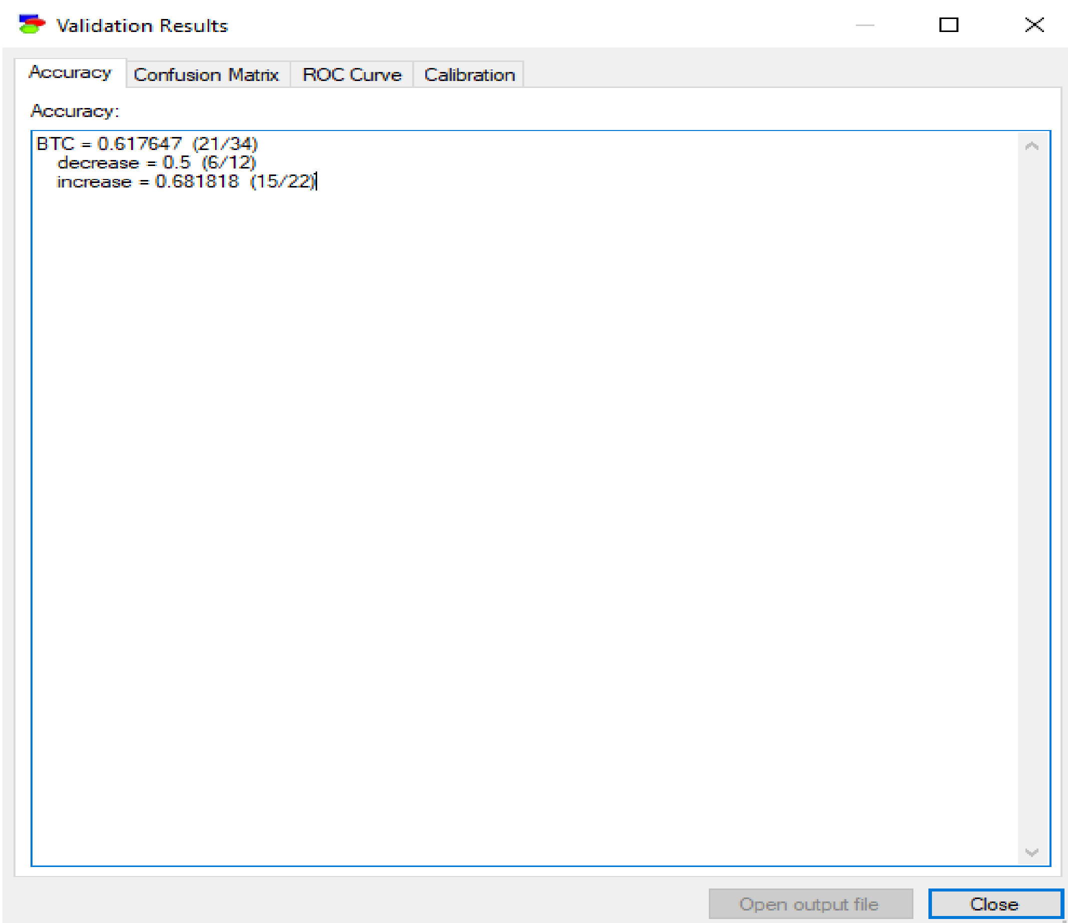

Figure (5-4): calculated accuracy for the current network

4-6 Calculation of Bitcoin Price for Variables:

After obtaining the probabilities for each node, it is time to calculate the price for each variable. However, since the probability of price stability (0.500) in the variables is low, we have not calculated the price for those cases. Instead, we have used formula (1-4) to determine the increase or decrease in price for each variable.

$$P_{FBTC} = (PD_{vI} \quad (P_{BTC} / P_{V}) \quad P_{BTC}) + P_{BTC} \qquad (4\text{-}1)$$

This formula calculates the value of the next week's price of Bitcoin P_{FBTC} based on the variable upside probability PD_{vI}, where P_{BTC} represents the current price of Bitcoin and P_{V} is the variable price.

$$P_{FBTC} = (PD_{vD} \quad (P_{BTC} / P_{V}) \quad P_{BTC}) - P_{BTC} \qquad (4\text{-}2)$$

In the second formula, the price of Bitcoin next week P_{BTC} is calculated based on the probability distribution PD_{vD}.

Table (4-3) provides an example of the obtained values for each variable, and Table (4-4) shows an example of the obtained probabilities for each variable.

4-7 Calculating the average forecast price:

After calculating the price for each variable, we obtain the forecast price by taking the average of all the individual prices. Finally, with the total price calculated, we can proceed to validate and evaluate the proposed method.

4-8 Evaluation of the proposed method:

To evaluate the accuracy of Bitcoin price predictions, we have utilized the traders' commitment data from 2019. Initially, we assess the performance of the proposed system using a confusion matrix. In this matrix, positive values indicate an increasing class, negative values represent a decreasing class, and it's important to note that the price stability class is not considered due to the small number of instances in that category.

Date	Bitcoin price	Trading volume in the VIX index	The possibility of an increase in the price of Bitcoin.	The possibility of a decrease in the price of Bitcoin.
1-Sep-19	10,488.00	62567	10469.27145	9,086.42
25-Aug-19	9,623.90	66977	10971.18158	9,631.17
18-Aug-19	10,152.00	76912	11019.23736	9,724.94
11-Aug-19	10,228.00	80825	12122.3782	10,800.04
4-Aug-19	11,314.00	96803	11478.53286	10,404.58
28-Jul-19	10,822.00	109051	9987.732518	9,133.79
21-Jul-19	9,465.70	104925	11443.8097	10,292.52

Table (4-3): Example of the value obtained for the price of Bitcoin

Classes	VIX Total Dealer Long	VIX Total Assess Long	VIX Total Assess Short	NAZDAQ ASSET LONG	S&P500 ASSET LONG
Increase	0.568424453	0.484573057	0.536828751	0.463158402	0.442123281
Decrease	0.431575547	0.515426943	0.463171249	0.536841598	0.557876719
Stability	0	0	0	0	0

Table (4-4) : An example of the obtained probabilities for the variables

True positive (TP) refers to the number of days with increased prices that are correctly predicted by the proposed system. True negative (TN) represents the number of days with decreasing prices that are correctly predicted. False positive (FP) corresponds to the number of increasing days that are incorrectly predicted, and false negative (FN) indicates the number of days with decreased prices that are wrongly predicted. These four criteria in the confusion matrix serve as the basis for evaluating the performance of the proposed system (Alamtian and Vafai Jahan, 2014). An example of a confusion matrix, also known as a clutter table, is presented in Table (4-5).

Bitcoin price	Average expected price	TP	TN	FP	FN
10,488.00	9,744.18	1	0	0	**0**
9,623.90	10,284.40	0	0	1	**0**
10,152.00	10,360.50	0	0	1	**0**
10,228.00	11,473.52	0	0	1	**0**
11,314.00	10,969.45	1	0	0	**0**
10,822.00	9,601.85	1	0	0	**0**
9,465.70	10,907.80	0	0	1	**0**

Table (4-5): An example of a clutter table

In this table, a value of 1 is entered if the condition is true, and 0 is entered if it is false. Finally, the values are summed.

4-8-1 Evaluation criteria:

accuracy, recall, precision, mean absolute percentage error, and F1-measure:

When evaluating classifiers, accuracy and precision alone are not sufficient parameters. Therefore, another criterion called recall is used. Recall, also known as the true positive rate, measures the proportion of correct positive responses predicted by the proposed system (Alamtian and Vafai Jahan, 2014).

Recall indicates how many of the total number of increasing days in the test dataset are correctly predicted by the proposed system. F1-measure is a combined metric of precision and recall. It measures the success of the proposed system in predicting accurate and stable results. Both accuracy and recall are considered in the calculation of this metric (Alamatian and Vafai Jahan, 2014).

$$\text{precision} = Tp/(Tp+Fp) \qquad (4\text{-}3)$$

$$\text{Recall} = Tp/(Tp+Fn) \qquad (4\text{-}4)$$

$$\text{F1-measure} = (2 \quad \text{Recall} \quad \text{precision})/(\text{Recall}+\text{precision}) \qquad (5\text{-}4)$$

Another important evaluation criterion is the accuracy criterion. The previously mentioned evaluation criteria assess the performance of the system in terms of the incremental class.

$$\text{Accuracy}= (Tp+Tn)/(Tp+Tn+Fp+Fn) \quad (4\text{-}6)$$

Additionally, the average percentage of absolute error (MAPE) is considered as another criterion. It is calculated using the following formula:

$$\text{MAP} = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{yi - \tilde{y}i}{yi} \right| \qquad (4\text{-}7)$$

where y_i is the predicted value for the i-th week, $\tilde{y}_i$ is the actual value for the i-th week, and N is the number of weeks studied

In this research, we have employed various evaluation criteria to enable a comprehensive comparison with previous studies. The results of the evaluation using these criteria on the test dataset are presented in Table (4-6).

Variable	Precision	F1-measure	Accuracy	MAP	calling
BTC	75%	81%	71%	0.06	90%

Table (4-6): The results obtained for the desired criteria

4-8-2 Checking the accuracy of the prediction process chart:

In this section, the results of plotting the accuracy of the price prediction trend using the proposed system and the actual price trend are presented. Figure (4-6) shows the Bitcoin price chart in blue and the estimated price chart in orange.

From the figure, it can be observed that the forecast provides a reasonably close approximation of the Bitcoin price. However, it slightly lags in predicting sudden trend changes. This issue can be addressed by modifying the general prediction formula and incorporating internal variables of the Bitcoin network data.

To predict the price trend of Bitcoin, 92 weeks of traders' commitment report data were analyzed, and the aforementioned results were obtained. The difference in the release days between the traders' commitment report (published every Tuesday) and the weekly Bitcoin price calculation (every Sunday) is not significant. The goal is to predict the next week's Bitcoin price based on the Tuesday-published traders' commitment report, using the previous week's Bitcoin price.

4-8-3 Comparison with previous research:

This section reviews the existing research on Bitcoin price prediction, considering factors such as time period, input data, combined methods, and average percentage of absolute error. Typically, the input data consists of a combination of international stock market indices, gold prices, internal Bitcoin network data, and future market data related to the Commitment of Traders (COT) report. Table (7-4) presents a comparison between similar research and the current study.

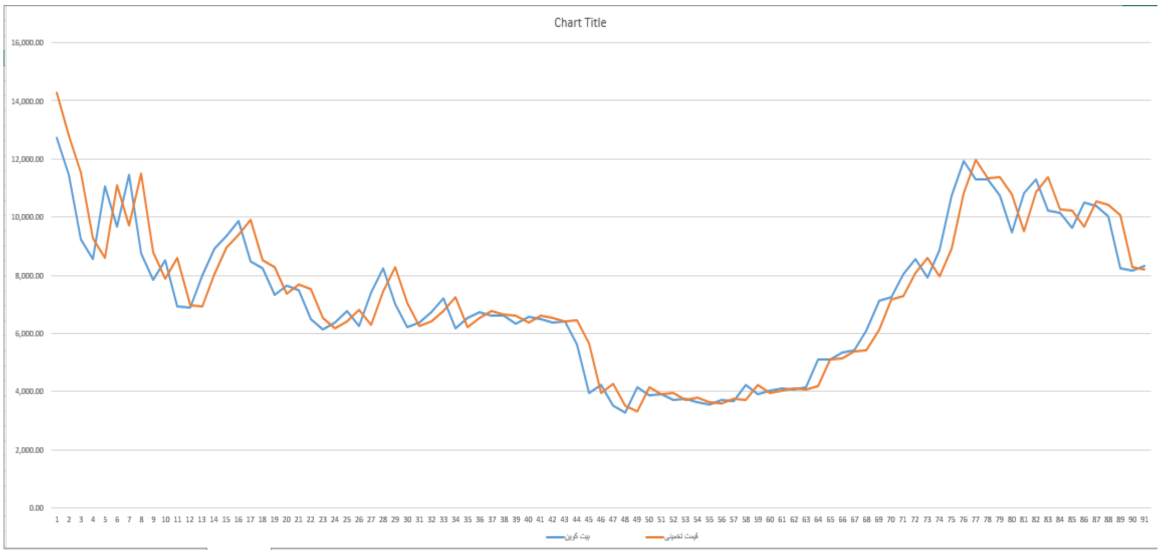

Figure (4-6): Bitcoin Price Chart with Estimated Prices from 2018 to October 2019

Author	period	Input data	Algorithm used	Accuracy	MAP
(Jang and Lee, 2017)	week 1	Domestic network and international market	BNN	0.68	**0.0856**
Current research	week 1	The futures market of the international stock exchange	BNN	0.71	**0.0642**
(Jang and Lee, 2017)	minutes 10	Domestic network and international market	BNN	0.91	**0.0200**
Current research	minutes 10	The futures market of the international stock exchange	BNN	0.82	**0.0320**
(Madan et al., 2015)	minutes 10	Bitcoin network futures market	GLM	0.539	**------**

Table (4-7): Comparison of the results of the proposed model with previous works

Chapter Five: Conclusion and Suggestions

5-1 Introduction:

This research aimed to test different methods and achieve better results compared to previous studies. Among the tested methods, the ones described in the previous chapter were used. The findings demonstrated the usefulness of using trader commitment report data for price prediction, especially in shorter and more volatile time frames.

5-2 Tests Performed:

5-2-1 One-year and two-year data testing:

The research initially examined one-year data from the traders' commitment report and then expanded to two-year data, which yielded more favorable results compared to the latter.

5-2-2 Moving data over time:

Due to the different publication days of the Traders Commitment Report (Tuesday) and the Bitcoin Weekly Price Report (Sunday), two scenarios were tested. The first scenario involved using the weekly Bitcoin price data published on Sunday and the previous week's trader commitment report data to predict the following week's Bitcoin price. The second scenario utilized the Traders Commitment Report released on Tuesday and the weekly Bitcoin price data from the previous Sunday.

5-2-3 Increasing the accuracy of Bitcoin price prediction:

Formulas (4-1) and (4-2) demonstrated the use of the previous week's Bitcoin price and the desired variable's price to calculate the next week's price. In addition to this, our method incorporates the average of 91 weeks. By incorporating the Bitcoin price and predicted prices, the first scenario provided more accurate predictions.

5-3 Suggested Methods:

In this research, we utilized Bizon neural networks and traders' commitment report data to predict the weekly price of Bitcoin with relatively good accuracy. However, for more precise predictions, it is recommended to incorporate additional data such as indicators and the internal network of Bitcoin. These factors can contribute to more accurate predictions, especially in smaller time frames. Additionally, the use of dynamic Bayesian neural networks can provide greater flexibility in analyzing time series data, while the hidden Markov model shows promise in handling such data.

5-4 Research Limitations:

As discussed in section 2-1-5, one limitation of this research is the challenge posed by the time difference between the release of data on the weekly price of Bitcoin and the traders' commitment report. However, this issue can be addressed by refining the formula used for price prediction and finding the appropriate combination of variables.

5-5 Conclusion:

Bayesian networks are proposed for the weekly prediction of Bitcoin price trends. The research initially examined the correlation between indicators and exchange currencies from the traders' commitment report and the target stocks for prediction. Twelve pre-selected variables, including general indices, exchange currencies, and buying/selling amounts from institutional managers and leveraged funds, demonstrated the highest correlation. These variables were then incorporated into the Bayesian network, which was modeled using the simple Bayes augmented tree learning algorithm (TAN). The Bayesian network algorithms were employed to determine the posterior probability of each variable, which was subsequently used to predict the price of Bitcoin. The proposed model was evaluated on the weekly price data of Bitcoin, yielding an accuracy percentage of 71-70%. The findings indicate that the incorporation of traders' commitment report data and the use of Bayesian networks for variable probabilities can be effective in predicting Bitcoin price trends.

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