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Forecasting Transactional Amount in Bitcoin Network Using Temporal GNN Approach

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ABSTRACT: Banks and other financial institutions regularly make predictions about how much money an individual will have in his or her account in the near future. This may assist banks in classifying their clients so that they can recommend financial products that meet their clients' requirements. For the purpose of predicting the amount a customer will receive from his or her transacting partners at a specific time, we looked at historical financial transactions in this work. Particularly, we make use of the Bitcoin transactional dataset, which possesses two primary features: network and temporal, respectively. For the purpose of predicting the amount of Bitcoins a customer will receive at a specific timestamp, the Temporal-Graph Convolutional Network (T-GCN) method utilized in this paper makes a contribution. When compared to 11 standard approaches (such as Support Vector Regression (SVR), Random Forest Regression (RFR), Vector Auto-Regressive (VAR), Long Short-Term Memory (LSTM), and others), the T-GCN approach produced lower errors. Clearly demonstrate the T-GCN approach's effectiveness. Additionally, our findings demonstrate that time is a crucial aspect of these kinds of predictive tasks.

KEYWORDS: Cryptocurrency, Regression, Financial Transactional Network, Graph Convolutional Network, and Temporal Graph Neural Network

I. INTRODUCTION

From the exchange of commodities (commodities), precious metals (coins), paper money, and online transactions, financial transactions have advanced significantly. Nowadays, the majority of customers prefer to conduct day-to-day business through online platforms for a variety of reasons, including: availability of a variety of online platforms, including websites and mobile apps; ii) security: Individuals are not required to carry cash, and privacy: Only those who conduct business are aware of it. Online financial transactions have been the subject of numerous investigations in the past. Using network theory, one area of study focuses on analyzing financial transactional networks, such as how users behave in a static network, how the network changes over time, and how to make use of the network with data from third parties like social media and call records. Another area of study uses various machine learning methods to predict financial transactions, such as credit, stock market predictions, and company financial distress. Bitcoin, created by Satoshi Nakamoto, is a cryptocurrency based on block-chain technology. At the moment, financial, business, and government institutions are interested in Bitcoin.

The number of Bitcoin transactions has skyrocketed over the past few years. Coinmarketcap.com estimates that Bitcoin's market capitalization is approximately \$100 billion as of May 2019. The Bitcoin network is rapidly evolving as the number of transactions increases, but there is also a problem. For instance, Bitcoin exchange handling costs have expanded, yet exchange affirmation times have been deferred. To deal with the expansion and issues of Bitcoin networks, it is crucial to anticipate the number of transactions in each block. Using a variety of machine learning algorithms, various studies are currently underway to predict the number of transactions contained in the Bitcoin block in order to predict the number of transactions as in.

Over a hundred main cryptocurrencies have been proposed since Bitcoin's inception, but Bitcoin is still the most popular and relevant cryptocurrency in terms of market capitalization. Bitcoin is now used not only as a cryptocurrency but also as an investment tool, similar to stocks or securities, after its early days. In order for investors

to make accurate medium- and long-term price predictions for Bitcoin, these new scenarios necessitate the development of novel strategies and tools.

The prediction of online financial transactions is the subject of this work. Our particular objective is to anticipate the total amount a user will have in their account at a given time from all transactions made by other users. The issue of predicting online financial transactions is important because the amount of money a person has not only reflects their social status in terms of finances but also helps financial institutions like banks classify customers into various financial categories. Banks can use this data to make recommendations for financial products or offer specific loans to customers based on their income.

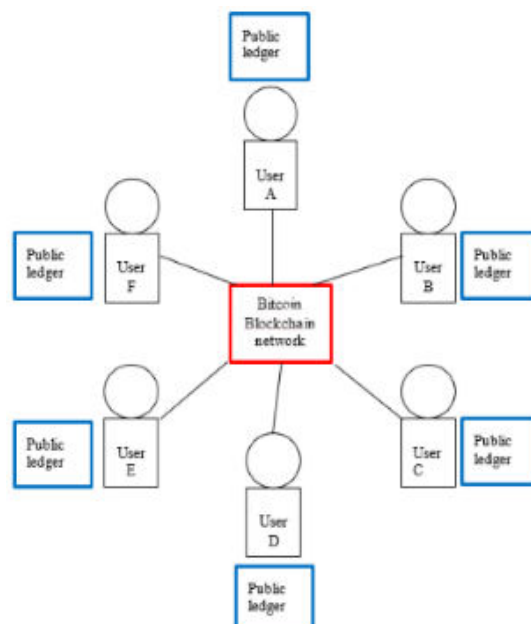
1) Aspects of the Network: These include features like the source user, the target user, and the amount of Bitcoins transferred that help form a network. In addition, the characteristics of the network features include: a) Straight edges: The receiver and initiator of the transaction are indicated by the direction. Take, for instance, the transaction depicted in Figure 1, in which A transfers 10 to B at time t . b) Multiple edges: When making financial transactions, it is highly likely that a user will be involved in more than one transaction at the same time. B transacts with C twice at timestamp t , as shown in Figure 1. Multiple edges in the graph are the name given to this property of the graph. 2) Aspects of Time: The specific timestamp at which a particular transaction occurred is referred to by this feature as the time aspect. Additionally, the network's structure evolves over time. For instance, A only transacts with B at time t , whereas at time $t+0$, Band C is handling A's business.

DATASET DESCRIPTION.

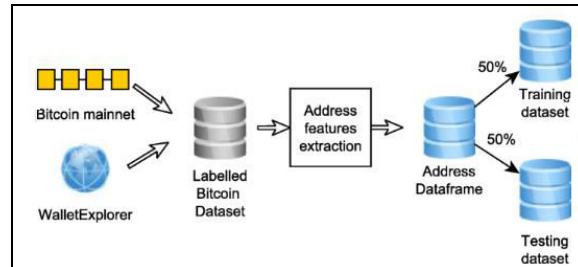
We used a 3 GB BTC Blockchain processed dataset, a publicly available Bitcoin dataset, in this paper. From 2009 to 2017, this dataset includes a processed Bitcoin blockchain transaction network with over one billion transactions and 100,000 unique users. There are four columns in the text file that contains this dataset. In particular, the four columns are the source id, which represents the user who initiated the transaction; the target id, which represents the user who will receive the transaction amount; the timestamp, which represents the Unix transaction time (seconds since 1970-01-01); and the amount, which represents the quantity of bitcoins that will be transferred from the source node id to the target node id at a specific timestamp. We use the terms "user" and "id" interchangeably throughout this paper. The Bitcoin dataset's annual descriptive statistics are presented in Table I.

Artificial neural networks of the recurrent neural network (RNN) type follow a temporal sequence of connections between nodes in a directed graph. The prediction of time series data is the focus of the RNN algorithm. used Twitter sentiment as input data for RNN to predict the price of Bitcoin, and their overall price prediction accuracy using RNN was found to be 77.62 percent. Their results demonstrated the possibility of applying RNN to time series data. predicted the BTCEUR exchange rate. They attempted to use RNN to predict the Bitcoin market trend using fourteen input variables that are associated with Bitcoin prices.

BITCOIN FRAMEWORK



TRAINING AND TEST DATASETS



II. RELATED WORK

Financial transactions generally fall into two groups: one is associated with conventional financial institutions, while the other is associated with cryptocurrencies. As a result, we include works related to both of these domains. Work on financial transactional predictive analysis is discussed first, followed by work on financial transactional predictive analysis. A. Financial transactions Cryptocurrency research has received a lot of attention lately. We focus primarily on Bitcoin, Ethereum, and Namecoin-related works. The secure blockchain technology serves as the foundation for these digital currencies. However, there are issues with management, taxation, and anti-money laundering strategies raised by the use of cryptocurrencies. A reliable method for tracking transactions was proposed in to address some issues, primarily the lack of government involvement in cryptocurrencies. However, it has been demonstrated that these alternative currencies can complement conventional currencies. The patterns of transactions on static and dynamic networks have also been looked at by researchers. Network theory has also been used to look at cryptocurrency transactions, including Bitcoin, Ethereum, and Namecoin. In order to comprehend user behavior in a static network snapshot, some studies looked at transaction patterns. While others have reported that network densification only occurred during the initial years of these currencies' conception, they have analyzed the evolution of these networks.

In contrast, we looked at a financial transactional network in a non-evolutionary way. In conventional monetary organizations, the organization hypothesis has been utilized for breaking down client to-client, organizations, banks organizations, to give some examples. In addition, very few researchers have combined financial data with third-party data like call records and social media data to analyze it. 479 Authorized use restricted to the following: East Carolina College. retrieved from IEEE Xplore on June 25, 2021 at 20:50:34 UTC Subject to restrictions. B. Analytical prediction.

Past research on various aspects of financial forecasting is discussed in this section. Predicting companies' financial difficulties has been the subject of some research. However, the majority of publications have dealt with stock market prediction in various forms, including stock market return, forecast price variation, and price rate variation. These works have used survey, Twitter, search engine data, and news, particularly breaking news, to analyze text. In terms of digital currencies, previous studies have used Deep Learning models like RNNs to study network-based features and regression models to predict the price of cryptocurrencies like Bitcoin, Litecoin, Ethereum, Digital Cash, and Ripple. In contrast, a framework for predicting price volatility has been developed in traditional financial fields.

There aren't many studies that have used machine learning to predict people's financial behavior, especially in retail banking. Some studies have also used external data sources like phone-based call features to predict a person's credit risk. In addition, customer lifetime value, customer potential value in the insurance industry, and financial credit losses have all been the subject of predicting analytics. Our work intersects with these other works. To be more specific, we will be analyzing the Bitcoin transaction network using the regression task. In this paper, we utilized T-GCN approach to conjecture the conditional sum got by a person at a particular course of events.

III. PROPOSED SYSTEM

We make use of the Bitcoin transactional dataset, which possesses two primary features: network and temporal, respectively. For the purpose of predicting the amount of Bitcoins a customer will receive at a specific timestamp, the Temporal-Graph Convolutional Network (T-GCN) method utilized in this paper makes a contribution. When compared to 11 standard approaches (such as Support Vector Regression (SVR), Random Forest Regression

(RFR), Vector Auto-Regressive (VAR), Long Short-Term Memory (LSTM), and others), the T-GCN approach produced lower errors. Clearly demonstrate the T-GCN approach's effectiveness. Additionally, our findings demonstrate that time is a crucial aspect of these kinds of predictive tasks.

ADVANTAGES

Digital currencies are called bitcoins. It makes use of cryptographic protocols and an algorithm. They are impossible to counterfeit because of this. Bitcoin transactions are anonymous in every way. Neither the sender nor the recipient are required to provide any sensitive or personal information during a Bitcoin transaction. It aids in identity theft prevention. A pull mechanism is used by credit and debit cards. This means that they ask for your credentials, start a payment, and then take money out of your account. Bitcoins operate on a push mechanism, allowing you to send any amount to any recipient at any time.

SYSTEM ARCHITECTURE

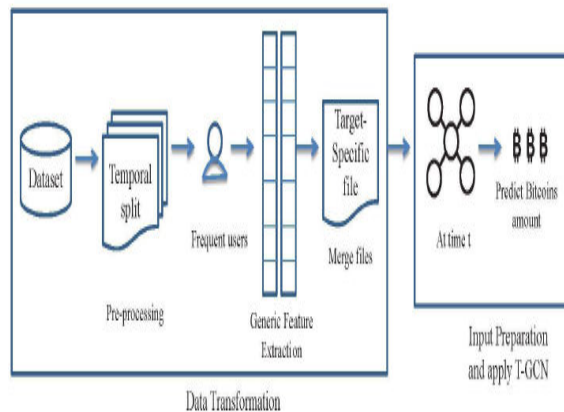


Fig.1.1 System Architecture

IMPLEMENTATION

Message Passing Neural Networks (MPNNs) are extended to temporal graphs by the project's implementation of Temporal Graph Networks (TGNs). They accomplish this by introducing a node memory that serves as a compressed representation of the node's previous interactions and represents the state of the node at a given time.

TESTING

The theoretical design becomes a working system during the project's implementation phase. This is the most common method for converting a new framework into a functional one, and it is the final and most important stage of the framework life cycle.

UNIT TESTING

Unit testing is a set of tests performed by a single programmer before a unit is integrated into a larger system. The module interface is put through tests to make sure that data enters and exits the program unit correctly. At each stage of an algorithm's execution, the local data structure is examined to guarantee that the temporarily stored data will remain the same. The module is tested under boundary conditions to guarantee that it works as intended within processing restrictions.

BLOCK BOX TESTING

Black-box testing is a method of software testing that examines an application's functionality without examining its internal workings or design. This approach makes it possible to test virtually every level of software testing.

IV. CONCLUSION

The prediction of the online financial transactional network is the subject of this paper. More specifically, the

goal is to use a user's past transaction data to predict how much money they will spend on transactions in a given year. T-GCN outperforms the other standard machine learning algorithms because it can capture the network and temporal aspects of the dataset, as demonstrated by our extensive experiments. This paper's subsequent work includes: 1) Methods based on dynamic GNN: To further reduce errors, we would like to apply this data to dynamic GNN approaches like Evolve GCN. 2) GNN methods based on attention: We want to improve the model by expanding this work and applying attention-based models to only focus on relevant features. 3) Brand-new data: Additionally, we would like to conduct experiments on additional datasets by incorporating cryptocurrency datasets like Ethereum and Litecoin.

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