# Forecasting Interaction of Exchange Rates Between Fiat Currencies and Cryptocurrencies Based on Deep Relation Networks

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***Abstract*—Forecasting exchange rates is difficult because financial time-series data is too complicated to analyze. In traditional financial studies, economic models and statistic approaches were widely used for predicting exchange rates. Recently, machine learning and deep learning techniques have played increasingly important roles in financial technology studies. This study adopts a deep learning technique called relation networks (RNs) to predict the exchange rates of fiat currencies and cryptocurrencies. To discover the relationship among different currencies, the concept of visual question answering (VQA) is applied in RNs. We also propose a specially designed architecture for the feature extraction stage to consider both spatial and temporal relationships simultaneously. The experimental results show that the proposed approach can achieve higher prediction performance for cryptocurrencies with approximately 65% accuracy rate. We aim to improve traditional approaches and construct a model using the concept of VQA based on RNs to optimize the prediction performance between fiat currencies and cryptocurrencies.**

***Keywords—visual question answering, exchange rates, relation networks, deep learning***

## I. INTRODUCTION

Nowadays, predicting exchange rates has become an important issue in the financial industry because of the increasing popularity of international trading with developments in transportation and technology. Thus, many studies are attempting to discover the relationships among different currencies to gain profits and decrease losses in investment decisions. Forecasting exchange rates has been a challenging problem because it is hard to model the fluctuations in the financial market. Further, financial time-series data contain considerable noise, making it even harder to predict exchange rates accurately. With rapid advances in technologies, deep learning techniques have been applied in several fields such as computer vision and natural language processing to solve numerous difficult tasks. In this study, we apply the concept of visual question answering based on relation networks (RNs) to discover the relationships among different fiat currencies and cryptocurrencies. Through a series of empirical analysis, we attempt to model the exchange rates with state-of-the-art technology.

Cryptocurrency, which is built upon blockchain technology, is a digital asset that is designed to assure trading security and control the creation of trading units. Bitcoin, the first decentralized cryptocurrency created by Satoshi Nakamoto in 2009 [8], has attracted considerable attention worldwide in the financial field. Based on cryptographic, a Bitcoin transaction allows two parties to trade without a trusted third party such as financial institutions or banks to monitor the transactions. Recently, an increasing number of cryptocurrencies are emerging on the market, resulting in an increase in cryptocurrency transactions. The price of all cryptocurrencies increased greatly in 2017 and then decreased greatly in 2018. Relative to fiat currencies, cryptocurrencies have higher volatility, thereby increasing the potential risk when making an investment. As a result, modeling their exchange rates remains a challenging and unsolved problem.

Previous studies have used statistical approaches to evaluate exchange rates among different currencies. However, these methods usually set many hypotheses, in contrast to the real world. Although several machine learning algorithms have been proposed to efficiently and economically forecast exchange rates, few studies have focused on modeling the relationship with cryptocurrencies instead of fiat currencies. This study applies a deep learning technique called RNs to examine the dynamics of exchange rates. RNs can be used to discover the relationships among different cryptocurrencies and fiat currencies.

The major contribution of this study is to forecast exchange rates between fiat currencies and cryptocurrencies using RNs. Knowing the future trend of currencies will help investors to obtain higher profits and reduce losses while making trading decisions. Moreover, modeling volatility will give professional traders an insight into the financial market. This will enable them to trade different financial derivatives such as forwards, futures, swap, and options to hedge simultaneously. In addition, unlike traditional studies on exchange rates that always forecast absolute values in the future, we predict exchange rates by discovering the relationships among different currencies in terms of volatility and price trend.

The remainder of this paper is organized as follows. Section II reviews several previous studies that have focused on exchange rates, visual question answering, and relational reasoning. Section III introduces the proposed method and presents the implementation details of RNs. Section IV presents empirical experiment results. Section V discusses the major contributions of this study and suggests potential future improvements to the proposed system as well as future research issues.

## II. RELATED WORKS

This section briefly discusses existing studies on visual question answering (VQA), RNs, and exchange rates.

Exchange rate forecasting is an important and extensively studied problem in financial research. Traditional techniques for forecasting exchange rates are mostly based on economic models. [1] discovered that proper understanding of fundamentals is highly correlated with forecasting exchange rates. According to [2], new methodologies and approaches have been proposed to model the fluctuation of exchange rates. Recently, some advanced machine learning techniques such as neural networks have been proposed and widely applied for predicting exchange rates. [3] improved a deep belief network with restricted Boltzmann machines to forecast exchange rates. The proposed model worked better than typical forecasting models such as a feed forward neural network. The exchange rate of both fiat currencies and cryptocurrencies such as Bitcoin has attracted increasing public attention nowadays. Traditional approaches for predicting the trends of cryptocurrencies are based on statistical methods. [4] forecasted Bitcoin exchange rates using the autoregressive integrated moving average. The results indicated that the proposed method could predict the Bitcoin exchange rate under a high-volatility environment. [5] analyzed exchange rates of several cryptocurrencies by fitting the optimal parametric distributions to them.

VQA [6] is a multidisciplinary problem that combines studies in computer vision, natural language processing, and knowledge representation and reasoning. The general concept of a VQA framework can be briefly described as follows. Given an image and a question about the image, a VQA system can generate an appropriate answer. Most research frameworks concerning VQA can be divided into three parts. First, a convolutional neural network (CNN) is used to extract features from original images into several feature maps. Second, questions are embedded into feature vectors by using Bag-of-Words models, recurrent neural network models, or long short-term memory network models to obtain better representations. Finally, answers are produced based on the visual features and question embedding. Recently, VQA studies have increasingly focused on the design of the attention mechanism [9][10]. In other words, in addition to modeling the basic relationship between images and questions, "where to look" and "what words to focus" have become essential issues nowadays.

Relational reasoning is an inferential process that uses logic to discover relationships among objects. Traditional methods such as symbolic approaches and statistical learning have few progresses on relational reasoning. In recent years, DeepMind, an artificial intelligence company, has published several significant studies on this issue. RNs [7], a neural network model designed for relational reasoning, are one of the well-known approaches for solving VQA problems. The core concept of RNs is to consider features extracted by a CNN as an object in an image. Then, two different features and a corresponding question are combined as a pair to output a relation feature. Finally, all relations are added using a neural network to obtain a consequence. The major idea behind RNs is to constrain the framework of neural networks by forcing them to learn potential relationships between different objects. [7] popularized the concept of relational reasoning. [11] presented a new architecture called graph network, which provided a straightforward method to analyze structured knowledge and information. [12] designed a new memory module to perform complicated relational.

In this study, we apply the concept of VQA based on RNs to forecast the exchange rate of different currencies. We aim to model the relationship with fiat currencies and cryptocurrencies in the financial market.

## III. RN ARCHITECTURE

Our RN comprises three components: (1) a deep CNN for extracting the price information, (2) fixed-length binary strings to construct question representations, and (3) a binary component that generates answers based on the information from the first two parts. In the feature extraction part, a deep CNN is used to extract the price feature map as the price representation. The question understanding part adopts several one-hot encodings of a price-related question. The answer generation part answers a question using a binary classifier based on the combination of the price feature map and the question representation. The rest of this section provides details about each component of our RN and the data we use.

### *A. Data description*

This study uses data for seven fiat currencies and five cryptocurrencies. The cryptocurrency exchange rates were retrieved using an application programming interface from Poloniex, one of the most active cryptocurrency exchanges in the world, and Bitcoin historical data were obtained from a dataset on Kaggle. The fiat currency exchange rates were downloaded from Dukascopy Bank's website. For our analysis, we used per 5 min data from 1 January 2016 to the end of 2017. We addressed the missing data problem by using a linear interpolation approach. Because the Bitcoin price is higher than that of other cryptocurrencies, we performed some preprocessing to restrict the values to the range of 0 to 1. We calculated the return of each data by subtracting the forward and backward values and dividing by the forward value. By doing so, we can obtain the price trend of cryptocurrencies and normalize the data. Equation 1 shows the formula for calculating the return.

$$\frac{p_t - p_{t-1}}{p_{t-1}} \tag{1}$$

### *B. Price feature extraction*

The information in each price sequence is represented by an N×D feature, where N is the sequence length and D is the number of currencies. Feature maps are generated by dividing inputs into D×D grids and convoluting all sequences. In the first experiment, a one-dimensional CNN extracts a feature vector for each rolling window. The final K×D price feature maps are generated, where K is the number of kernels in the final convolution layer. Moreover, to indicate their relative temporal positions, an additional feature map is appended with an x-coordinate in the range of 1 and −1. When we use a one-dimensional CNN to extract the price representation, it means that we consider all types of currencies and neglect their respective influences. In other words, we consider all currencies together and try to discover relationships among them.

### C. Question understanding

To discover exchange rate relationships among different currencies, we set two questions in the experiment: the price trend question and the volatility question. In the former, we aim to determine whether the exchange rate of one cryptocurrency will be higher than that of another cryptocurrency in the future. In the latter, we aim to determine the relationship between two currencies. Questions are encoded as fixed-length binary strings to decrease the difficulty during the training process. Thus, we model questions into several one-hot vectors and concatenate them to form a final question.

### D. Answer generation

We consider VQA problems as a classification task. The answer generation part is a binary classifier according to the price feature map and one-hot encoded question. In addition, binary cross entropy is used as a loss function to evaluate the performance of the forecasting model.

$$-\frac{1}{N}\sum_{i=0}^{N} y_i * \log(\hat{y}_i) + (1-y_i) * \log(1-\hat{y}_i) \qquad (2)$$

### E. RNs

An RN [7] is a deep neural network model designed for complicated rational reasoning. Equation (3) is the simplest form of an RN, which is a composite function.

$$\mathrm{RN}(O) = f_{\emptyset}\left(\sum_{i,j} g_{\theta}(o_i, o_j)\right) \qquad (3)$$

where $(o_i, o_j)$ is a set of objects and $f_{\emptyset}$ and $g_{\theta}$ are fully connected neural networks with different parameters. The input of an RN is a pair of objects; in our case, we use a CNN to transform the original price sequences into feature maps. After convolving the price sequences of different cryptocurrencies with D×D kernels, each of $D^2$ cells was treated as an object of an RN. The object could somehow explain a particular relationship among different currencies, including timeframe, price changes, and volatility. Then, because object pairs and questions should be highly dependent, we concatenate one-hot embedded questions to objects. The modified RN architecture is given by equation (4).

$$\text{Modified RN}(O) = f_{\emptyset}\left(\sum_{i,j} g_{\theta}(o_i, o_j, q)\right) \qquad (4)$$

### F. RNs with two-dimensional CNN

We often use a one-dimensional CNN to transform time-series data into a feature representation. However, when we use a one-dimensional CNN, we consider the information of all currencies and do not premeditate the effect of each currency separately. As a result, to make our model better consider each currency instead of the mixture information of all currencies, we adopt a two-dimensional CNN to obtain price information during the feature extraction stage. For the additional feature map that is applied to indicate temporal positions in a one-dimensional CNN, in the two-dimensional CNN, we use a novel idea to illustrate both relative temporal positions and spatial positions. In our case, each currency is an independent individual; therefore, we cannot use the concept of a coordinate for modeling. Instead, we use the concept of one-hot encoding to indicate the relationship among different currencies. Therefore, we append several feature maps after original feature maps. One is for the temporal position and the other, for spatial positions, because we have several types of currencies.

## IV. Experimental Results

### A. Experimental setup and benchmark

We used Keras to develop our model and used the Adam optimizer with a base learning rate of 0.00003. We set the batch size to 4096 and train for 30 epochs. We adopted a sliding window mechanism to train and test our model's performance. In our experiment, we considered three months as the training period and one month as the testing period. We compared our results to two rule-based approaches: a random selection rule method and a trend rule method. In the former, we made the machine choose the answer that has appeared more times than other answers to realize accuracy. In the latter, the rule is that if the price increases, the machine predicts that the price will increase in the next moment as well, and vice versa.

### B. Spatial relationship design

In this experiment, we explored the effect of a one-dimensional CNN during the price feature extraction stage for fiat currencies and cryptocurrencies. The rows indicate the testing period we used and the columns indicate different benchmarks and training and testing results. The values indicate the accuracy rates of the prediction results. Tables 1 and 2 respectively illustrate the performance of fiat currencies and cryptocurrencies. As seen in Table 1, the performance of the trend rule was substantially higher than that of the random selection rule. The consequence indicates that there probably exists some momentum phenomenon in the fiat currency market. Further, the average performance of the testing data was higher than that of the random selection approach but lower than that of the trend rule approach. Thus, we can conclude that a one-dimensional CNN can catch some time series patterns but still cannot outperform the trend rule. As shown in Table 2, the average performance of testing data outperformed both the random selection approach and trend rule approach. This may be because the price of cryptocurrencies is primarily affected by price information than fiat currencies.

TABLE I. Performance of one-dimensional CNN for fiat currencies

| | Training | Ran_ rule | Trend_ rule | Testing |
|---|---|---|---|---|
| 2017/4 | 0.6028 | 0.5331 | 0.6569 | 0.6050 |
| 2017/5 | 0.6023 | 0.5270 | 0.6486 | 0.6043 |
| 2017/6 | 0.5937 | 0.5306 | 0.6472 | 0.5982 |
| 2017/7 | 0.5979 | 0.5292 | 0.6497 | 0.5952 |
| 2017/8 | 0.5964 | 0.5305 | 0.6460 | 0.5890 |
| **average** | **0.5986** | **0.5301** | **0.6497** | **0.5983** |

TABLE II. PERFORMANCE OF ONE-DIMENSIONAL CNN FOR CRYPTOCURRENCIES

| | Training | Ran_ rule | Trend_ rule | Testing |
|---|---|---|---|---|
| 2017/4 | 0.6716 | 0.6165 | 0.6039 | 0.6254 |
| 2017/5 | 0.6688 | 0.6179 | 0.6040 | 0.6336 |
| 2017/6 | 0.6676 | 0.6228 | 0.6017 | 0.6528 |
| 2017/7 | 0.6698 | 0.6182 | 0.6033 | 0.6337 |
| 2017/8 | 0.6650 | 0.6215 | 0.6019 | 0.6552 |
| **average** | **0.6686** | **0.6194** | **0.6030** | **0.6401** |

### C. Spatial and temporal relationship design

In the first experiment, we only considered the spatial relationships of cryptocurrencies. However, in the second experiment, we considered the temporal effect. From Table 3, we see that the performance of testing data was not higher than that in the first experiment. By contrast, the prediction performance for cryptocurrencies, seen in Table 4, was higher than that in the first experiment. As a result, we conclude that if the effect of each cryptocurrency is premeditated, we can obtain more favorable results. Moreover, from Table 4, the performance of the trend rule was higher than that of the random selection rule. We infer that because cryptocurrencies mostly increased during 2017, the random selection rule achieved a higher accuracy rate.

TABLE III. PERFORMANCE OF TWO-DIMENSIONAL CNN FOR FIAT CURRENCIES

| | Train | Ran_ rule | Trend_ rule | Test |
|---|---|---|---|---|
| 2017/4 | 0.6065 | 0.5331 | 0.6569 | 0.6024 |
| 2017/5 | 0.6127 | 0.5270 | 0.6486 | 0.5992 |
| 2017/6 | 0.6088 | 0.5306 | 0.6472 | 0.5883 |
| 2017/7 | 0.6058 | 0.5292 | 0.6497 | 0.5990 |
| 2017/8 | 0.6117 | 0.5305 | 0.6460 | 0.5920 |
| **average** | **0.6091** | **0.5301** | **0.6497** | **0.5962** |

TABLE IV. PERFORMANCE OF TWO-DIMENSIONAL CNN FOR CRYPTOCURRENCIES

| | Train | Ran_ rule | Trend_ rule | Test |
|---|---|---|---|---|
| 2017/4 | 0.6736 | 0.6165 | 0.6039 | 0.6541 |
| 2017/5 | 0.6782 | 0.6179 | 0.6040 | 0.6362 |
| 2017/6 | 0.6723 | 0.6228 | 0.6017 | 0.6578 |
| 2017/7 | 0.6733 | 0.6182 | 0.6033 | 0.6448 |
| 2017/8 | 0.6707 | 0.6215 | 0.6019 | 0.6215 |
| **average** | **0.6736** | **0.6194** | **0.6030** | **0.6429** |

## V. CONCLUSION AND FUTURE WORKS

In this study, we apply relation networks based on the concept of VQA to forecast exchange rates between fiat currencies and cryptocurrencies. The experimental results show that the prediction performance of cryptocurrencies is higher than that of fiat currencies with nearly 65% accuracy rate. In future works, we will apply a graph neural network to discover a more accurate relationship between fiat currencies and cryptocurrencies. Then, we will collect more data, including longer testing periods and a larger number of different currencies, to verify our results. Finally, we will develop some trading strategies based on the prediction results to achieve the goal of gaining profits and reducing losses in the real world.

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