Risk Prediction of Peer-to-Peer Lending Market by a LSTM Model with Macroeconomic Factor

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ABSTRACT

In the peer to peer (P2P) lending platform, investors hope to maximize their return while minimizing the risk through a comprehensive understanding of the P2P market. A low and stable average default rate across all the borrowers denotes a healthy P2P market and provides investors more confidence in a promising investment. Therefore, having a powerful model to describe the trend of the default rate in the P2P market is crucial. Different from previous studies that focus on modeling the default rate at the individual level, in this paper, we are the first to comprehensively explore the monthly trend of the default rate at the aggregative level for the P2P data from October 2007 to January 2016 in the US. We use the long short term memory (LSTM) approach to sequentially predict the default risk of the borrowers in Lending Club, which is the largest P2P lending platform in the US. Although being first applied in modeling the P2P sequential data, the LSTM approach shows its great potential by outperforming traditionally utilized time series models in our experiments. Furthermore, incorporating the macroeconomic feature *unemp_rate* (i.e., unemployment rate) can improve the LSTM performance by decreasing RMSE on both the training and the testing datasets. Our study can broaden the applications of the LSTM algorithm by using it on the sequential P2P data and guide the investors in making investment strategies.

CCS CONCEPTS

 \bullet Computer systems organization \rightarrow Machine learning; Modeling.

KEYWORDS

LSTM, Long short-term memory, Macroeconomic factor, Risk prediction, P2P lending

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1 INTRODUCTION

Peer to peer (P2P) lending, which means lending money from investors directly to borrowers through a virtual platform, is one of the fastest-growing segments in the financial lending market. Through the P2P lending platform, approved borrowers could take control of their finance while investors benefit via earning potentially competitive returns [1]. To help the investors make the investment decision, the lending institutions continuously focus on exploring methods to understand the behavior of loan applicants during the economic cycles. They attempt to model the default risk of the borrowers (i.e., repayment of the loans) and then provide credit assessment to the lenders [15]. Meanwhile, it is equally important for the investors to have a whole understanding of the entire P2P market by evaluating the borrowers' risk at the aggregate level as time going on. Lending platform with a continuously low and stable default risk may denote a healthy P2P lending environment, thus could provide more confidence to the investors to have a successful investment [3][22][2]. Therefore, how to model the trend of the default risk at the aggregative level becomes a critical question that needs to be addressed.

The long short term memory (LSTM) model, which is one of the state-of-the-art methods to model the sequential data (i.e., the order of the data matters), has been widely used in language modeling, disease forecasting, and speech recognition [29][19][11][5]. In the financial domain, LSTM has shown its superiority over traditional time series models in individual credit risk classification, overdue of bank loan prediction, and credit card fraud detection [14][17][31]. Although the LSTM model has been applied to the above-mentioned fields, no research has been found to analyze the time series data in the aggregative level generated in the P2P lending market. It is worth noting that different from modeling on the individual repayment that focuses on individual characteristics, modeling on the aggregative data will also need to consider the macroeconomic factors that are relevant to the P2P market. For example, one macroeconomic factor, the unemployment rate, is shown to be closely correlated to the interest rate in the P2P lending market [4]. Moreover, the unemployment rate is empirically correlated with gross domestic product (GDP) [28]. All these findings show strong evidence that we need to incorporate the macroeconomic factors when modeling the default rate in the P2P market.

Motivated by the aforementioned research, in this paper, we demonstrate a comprehensive case study with the goal to model the trend of the default rate of the P2P market at the aggregative level in the US. In our empirical study, we use the Lending Club data to test the robustness of LSTM. We first combine the P2P data from the individual level to the aggregative level. Next, we incorporate

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the employment rate (i.e., *unemp_rate*) across different time points into the aggregated data by matching the date. Then, the LSTM model is employed to fit the aggregated default rate. The superiority of the LSTM method is confirmed by comparing its performance to traditional time series models. Furthermore, the importance of the macroeconomic factor is proved by comparing the performance of the LSTM models with or without *unemp_rate*. The authors believe that our findings could provide a reference from the aggregative level for the investors for making their decisions. In summary, our study makes contributions from the following aspects:

- It is the first attempt that utilizes LSTM on the aggregated sequence data in P2P lending. The LSTM model is shown to be superior than the traditionally used time series models;
- It is the first attempt that incorporates the macroeconomic factor named unemployment rate into LSTM modeling for the repayment prediction at the aggregative level. We found that adding the macroeconomic factor is beneficial to the model performance.

The rest of the paper is structured as follows. Section 2 summarizes the related work in the P2P lending market. Section 3 provides a description of the LSTM algorithm along with its origin algorithm – recurrent neural network (RNN). Section 4 introduces the details of our analysis and Section 5 presents the results. Section 6 is the conclusion of our study.

2 RELATED WORK

Many previous studies focus on exploring different machine learning algorithms to model the repayment of individual borrowers in P2P lending. They employ different models such as random forest, decision tree, and neural network, to improve the classification accuracy for loan status or to extract efficient features that are predictive of default [20][25][34]. These studies could guide the investment strategies for the investors by providing evaluations of individual borrowers. However, there is seldom research that describes the sequential development of the default risk in the P2P market as time going on. In other words, there is no research that could provide a reference to the investors on the overall evaluation of the default risk at the aggregative level in the P2P market. A deep learning approach has been explored in many other areas for modeling the sequential data. For example, RNN has been introduced into the Internet recommendation system for building a recommendation system in [8]. LSTM has shown to be effective in the prediction of the future behavior of customers in the e-commerce based data in [23]. In addition, LSTM has shown its superior over the traditionally utilized time series models when being applied to model the transaction fraud and credit scoring in [32][31]. Although not been applied in modeling the sequential P2P data at the aggregative level, LSTM is expected by us to have its potential. Thus, we did an empirical study to confirm our conjecture and details of our study will be discussed in Section 4.

3 ALGORITHMS

Since the LSTM model is used in this study, in this section, we will first briefly discuss RNN, which is the origin of LSTM, and then illustrate the principle of LSTM.

3.1 Recurrent Neural Network

In traditional feed-forward neural networks (NNs), the information of the data moves towards one direction: from the input layer, through the hidden layer(s), and finally reaches the output layer. Thus, NNs only store the current information they received and have no memory of the past. As a result, they have limited power when being used on sequential data such as transaction data or speech data [12]. On the other hand, RNN, a special class of NNs, has shown its potential in modeling data with temporal dynamic behavior by many studies [6] [9]. Different from NNs, data information cycles in RNN and the current information along with the previous step information can both be stored. In other words, RNN has the internal while short-term memory of the information that NNs do not [16]. Figure 1 displays an illustrative example of an RNN structure. Each rectangle denotes a fully-connected NN structure (note: the structure in Figure 1 is shown as an illustrative example and the exact NN structure needs to be self-defined in different studies) and the RNN is composed of a chain of repeating the same NN structure. At each timestamp t, besides using the values of the independent variables at time t (i.e., \mathbf{X}_t) as the input, RNN also uses the output from the previous timestamp (i.e., S_t) as the input. The output at time t of RNN (i.e., O_t) can be calculated using Equation 1, where "." denotes the Hadamard product (i.e., pointwise multiplication), activation denotes a certain activation function (such as sigmoid function), W and U denote the weight matrix for \mathbf{X}_t and \mathbf{S}_t , and \mathbf{b} denotes the bias. By doing this, 'memory' could be added on RNN and the sequential information of the data is stored as time goes on. It is worth noting that in RNN, values of O_t and S_{t+1} are the same for each time point t, with the former denotes the current output and the latter represents the information passing to the next time point t + 1.

$$\mathbf{O}_t = activation(\mathbf{W} \cdot \mathbf{X}_t + \mathbf{U} \cdot \mathbf{S}_t + \mathbf{b}) \tag{1}$$

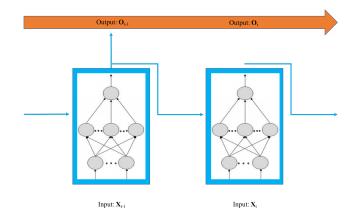
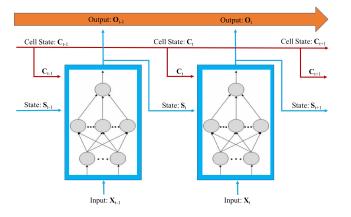


Figure 1: Illustrative Figure for an Example of RNN Structure

3.2 Long Short Term Memory

LSTM is a variant of RNN but it is capable of remembering the information over a long period of time and learning long-term dependencies of the information. In other words, it extends the 'memory' and could learn from inputs that have a very long time lags in between. Figure 2 displays an illustrative example of a LSTM structure. Comparing with the RNN structure in Figure 1, it is found that in Figure 2, LSTM contains an additional sequence of cell states C_t , which not only stores the previous information, but also the information obtained many steps ahead. Similarly, the output of LSTM at time t (i.e., O_t in Figure 2) can be calculated using Equation 2, where W_o , U_o , and V_o denote the corresponding weight matrix (for X_t , S_t , and C_t respectively), and b_o denotes the bias [7]. Similar as those in RNN of Figure 1, values of O_t and S_{t+1} are the same for each time point t, with the former denotes the current output and the latter represents the information passing to the next time point t + 1.



 $\mathbf{O}_{t} = activation(\mathbf{W}_{o} \cdot \mathbf{X}_{t} + \mathbf{U}_{o} \cdot \mathbf{S}_{t} + \mathbf{V}_{o} \cdot \mathbf{C}_{t} + \mathbf{b}_{o})$ (2)

Figure 2: Illustrative Chart for an Example of LSTM Structure

The critically innovative structure of LSTM is the cell state C_t . Its detailed structure is summarized based on the illustrations from previous studies [10][27]. As shown in Figure 2, the sequence of cell states is similar to a conveyor belt or a carry track that controls whether to input, store, or delete information. For each cell state, it contains different gates that could optionally delete, store, or output information: the forget gate f_t (particially) deletes the information from previous state if it is not important, the input gate \mathbf{i}_t determines the percentage of new input, and the output gate \mathbf{O}_t denotes the output at the current time step t. f_t can be obtained by using Equation 3, where \mathbf{W}_f and \mathbf{U}_f denotes the weight matrix for \mathbf{X}_t and \mathbf{S}_t of the forget gate, and \mathbf{b}_f denotes the bias. Similarly, i_t can be obtained by using Equation 4, where W_i and U_i denotes the weight matrix for \mathbf{X}_t and \mathbf{S}_t of the input gate, and \mathbf{b}_i denotes the bias. After obtaining the information that passing through the input gate (i.e., \mathbf{i}_t), LSTM uses another layer to generate a new candidate value \tilde{C} , which denotes the information that could be added to the current state C_t . The candidate value \tilde{C} can be obtained by using Equation 5, where \mathbf{W}_k and \mathbf{U}_k denotes the weight matrix for \mathbf{X}_t and \mathbf{S}_t , and \mathbf{b}_k denotes the bias. Finally, the current cell state \mathbf{C}_t can be updated into the new cell state C_{t+1} by using Equation 6, where

* denotes the matrix multiplication, $\mathbf{f}_t^* \mathbf{C}_t$ denotes the information LSTM wants to delete at time *t*, and $\mathbf{i}_t^* \tilde{C}$ denotes the information LSTM wants to remain. Then, C_{t+1} would be used to calculate the output in the next time step t + 1 (i.e., \mathbf{O}_{t+1}) [18].

$$\mathbf{f}_t = activation(\mathbf{W}_f \cdot \mathbf{X}_t + \mathbf{U}_f \cdot \mathbf{S}_t + \mathbf{b}_f)$$
(3)

$$\mathbf{i}_{t} = activation(\mathbf{W}_{i} \cdot \mathbf{X}_{t} + \mathbf{U}_{i} \cdot \mathbf{S}_{t} + \mathbf{b}_{i})$$
(4)

$$\tilde{C} = activation(\mathbf{W}_k \cdot \mathbf{X}_t + \mathbf{U}_k \cdot \mathbf{S}_t + \mathbf{b}_k)$$
(5)

$$\mathbf{C}_{t+1} = \mathbf{f}_t * \mathbf{C}_t + \mathbf{i}_t * \tilde{C}$$
(6)

During the training of LSTM, the sequential cell states (examples including C_{t-1} , C_t , and C_{t+1}) are trained at a series of time points (including t - 1, t, and t + 1) by identifying the optimal weights and bias with the goal of minimizing the pre-defined loss function. As mentioned above, since each square in Figure 1 and 2 denotes a fully-connected NN structure, LSTM contains similar hyper-parameters as traditional NNs, such as 'number of nodes', 'batch_size' (i.e., number of samples used for propagation in each iteration), and 'number of epochs' (i.e., number of times that the learning algorithm sees the entire dataset). The optimal values of the hyper-parameters need to be identified for different datasets before starting the model training.

4 EMPIRICAL STUDY

4.1 Dataset

The empirical study in this paper uses the Lending Club data downloaded via the website ¹. The dataset records the P2P lending transactions from Lending Club (which is the largest US P2P lending platform) ranging from 2007 to 2017. Since Lending Club is the largest lending platform in the US, the data is a good representative of the entire P2P market in the US. There are millions of loan transactions and each transaction is identified by the unique ID. For each transaction, there are over thirty features that describe the financial information of the money borrowers as well as the information related to the loan such as the starting date, the amount of the loan, and the term of the loan. The variable *loan_status* describes the different status of the loan transactions: ongoing, fully paid off, or default. In our study, we remove the loan cases that are still ongoing. As a result, the target variable *loan_status* retains two categories: fully paid off or default.

The features in the dataset mainly fall into three categories: personal property (PP), credit information (CI), or loan information (LI). Table 1 provides the descriptions, types, as well as the categories of the retained variables after we removing those with ambiguous meanings. Except for the target variable *loan_status*, most features are numerical and there are only three categorical features. It is worth noting that since our analysis will be based on the aggregative level, it is critical to explore some macroeconomic factors in addition to the individual factors. This concern has been proved by many previous research, which showed the potential effect of the macroeconomic behavior on *loan_status* such as unemployment rate and S&P500 index [13]. In our analysis, we collect one

 $^{^{1}} https://www.lendingclub.com/info/download-data.action$

macroeconomic feature using the website ². The feature is named as *unemp_rate* and it is recorded monthly. It will be served as an additional numerical feature in the following analysis.

4.2 Data Pre-processing

Before applying the LSTM algorithm, several data pre-processing procedures are performed as follows:

(a) Remove redundant information: With respect to the target variable *loan_status*, as mentioned in Section 4.1, observations with *loan_status* valued 'ongoing' are removed. With respect to the features (both numerical and categorical), those having missing/invalid percentage larger than 80% were removed. We then transform the target variable *loan_status* to numerical by giving the observations with *loan_status* valued 'fully paid off' a value '0' while those valued 'default' a value '1'. As a result, there remain around one million observations and the transaction time ranges from October 2007 until January 2016.

(b) EDA on categorical features: Exploratory data analysis (EDA) is implemented with the goal to first understand the distribution of each categorical feature and then to determine whether we should pool different categories of a variable together. As described in Table 1, except for the target variable, there are only three categorical features in the dataset: home_ownership, verification_status, and application_type. Take home_ownership as an example to show our data pre-processing step on the categorical features. Figure 3 displays the percentage of delinquency (i.e., the percentage of *loan_status* = 1) in each level of *home_ownership*. The Wilcoxon rank-sum test shows that at a significant level of 0.05, there is a statistically significant difference in the percentage of default among the six different levels of *home_ownership*. Therefore, we keep all these six levels and use the one-hot-encoding method to convert each category into numerical values [26]. Similar strategies are applied to verification_status (including three levels: 'not verified', 'verified', and 'source verified') and application_type (including two levels: 'individual' and 'joint application').

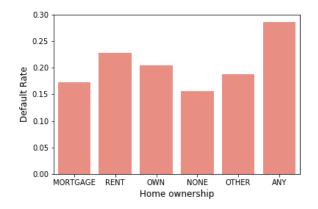


Figure 3: Default Rate in the Borrowers with Different Categories of Home Ownership

(c) Missing value imputation: For the three categorical features shown in Table 1, they have all been coded into numerical values after the one-hot-encoding transformation. Their missing values are imputed using the mode values. For the numerical features shown in Table 1, median-based imputation is applied.

(d) Transfer data into the aggregative level: We aggregate the data by month to get the sequentially monthly information of the P2P market. The details of our aggregation are described as follows. (1): For the target variable *loan_status*, we calculate the percentage of *loan_status* = 1 within each month and use this as the aggregated value. As a result, we obtain the monthly default rate of the P2P lending market and we name it as *default_rate* in the further analysis; (2): For the independent variables, they all have been transformed into numerical values as mentioned in steps (b) and (c). Therefore, the monthly aggregated values are obtained by taking the monthly average for each feature.

(d) Append the macroeconomic factor: The monthly values of *unemp_rate* is finally merged with the aggregated Lending Club data by matching the date.

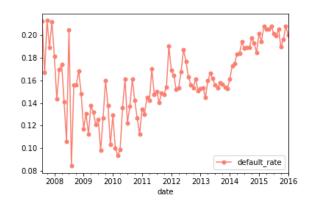


Figure 4: Monthly Change of the Default Risk at the Aggregative Level

4.3 Prediction of Default Risk

4.3.1 LSTM. After the aforementioned data pre-processing, we obtain 102 observations on the aggregative level along with 20 variables (18 independent variables from the original data, 1 macroeconomic factor, and 1 dependent variable). We plot the trend of the *default_rate* at the aggregative level using the line plot and the result is displayed in Figure 4. It is observed that default_rate gradually decreases from October 2007 to early 2010 with big variations but it begins to increase afterward and the variation becomes smaller. The LSTM approach is applied to model the aggregated sequential default rate. The dataset obtained from Section 4.2 was split into a 80% training and 20% testing. To be specific, we use the data from October 2007 to May 2014 as the training set while using that from June 2014 to January 2016 as the testing set. The implementation of the LSTM model is based on the Keras library in Python 3 on a personal laptop with a 3.3 GHz Intel Core i7 processor, 16GB RAM, and Mac OS system. The loss function used in

² https://datahub.io/core/employment-us#data.

Feature name	Description	Category	Туре
application_type	Indicates whether the loan is an individual application or a joint application with two co-borrowers	LI	Categorical
home_ownership	Home ownership status of the borrowers		Categorical
varification_status	Indicates if income was verified by LC, not verified, or if the income source was verified		Categorical
loan_status (target)	The loan is fully paid off or default	LI	Binary
annual_inc	Annual income reported by the borrowers	PP	Numerical
collection_recovery_fee	Post charge off collection fee	LI	Numerical
delinq_amnt	The past-due amount owed for the accounts on which the borrower is now delinquent	CI	Numerical
delinq_2yr	Number of over 30 days past-due incidences of delinquency in the borrow- ers' credit files for the past 2 years	CI	Numerical
int_rate	Interest rate on the loan	LI	Numerical
installment	The monthly payment owed by the borrower if the loan originates	LI	Numerical
last_pymnt_amnt	Last total payment amount received	LI	Numerical
loan_amnt	The amount of the loan	LI	Numerical
open_acc	Number of accounts opened in past 24 months	CI	Numerical
pub_rec	Number of derogatory public records	CI	Numerical
recoveries	Post charge off gross recovery	LI	Numerical
revol_bal	Total credit revolving balanced	CI	Numerical
total_acc	The total number of credit lines in the borrower's credit file	CI	Numerical
total_pymnt	Payments received to date for total amount funded	LI	Numerical
total_rec_late_fee	Late fees received to date	LI	Numerical

Table 1: Variables Kept in the P2P Lending Transaction Dataset

LSTM is the square root of mean squared error (RMSE) between the predicted and the true default rate [21]. During the training process, we tuned several hyper-parameters of LSTM including 'number of nodes', 'batch_size', and 'number of epochs' via a trial and error approach with the goal of minimizing the cross-validated RMSE. We keep the default settings in the Keras library for the rest of the hyper-parameters in LSTM.

To identify whether the incorporated macroeconomic feature, *unemp_rate*, is beneficial to the mode performance, two LSTM models are implemented as follows: (I) the LSTM model without using *unemp_rate*, denoted as LSTM(1); (II) the LSTM model by using *unemp_rate* as an additional feature, denoted as LSTM(2). It is worth noting that LSTM is relatively robustness to the multicollinearity problem [36], making us confident to use all the features simultaneously in the modeling stage.

4.3.2 Further Comparison. To further explore the robustness and superiority of the LSTM technique in modeling the sequential default rate of the P2P lending data, traditional time series analysis is applied and evaluated on the same dataset described in Section 4.3. In our initial analysis, we considered both the univariate time series model (UTS, i.e., *default_rate* depends only on time) and multivariate time series model (MTS, i.e., *default_rate* depends on

several time-dependent variables) [35] [33]. In UTS, the plots of the auto-correlation function (ACF) and the partial autocorrelation function (PACF) of the data are investigated with the goal of looking for the most appropriate time series model. In MTS, we applied the most commonly used method – vector auto regression (VAR) on the datasets with and without the additional feature *unemp_rate* [30], respectively. The implementation of the UTS and MTS models are based on R and the Statsmodels library in Python 3, respectively.

5 RESULTS

As discussed in Sections 4.3 and 4.3.2, we first implement LSTM methodology and further compare its performance with traditional time series models. The critical step before the implementation of LSTM is the hyper-parameter tuning. By applying the trial and error approach via minimizing the loss on the test set, we finalized the values of the hyper-parameters as follows. The value of 'number of nodes' is set to 70. 'batch_size' is set to 50 via trying different values ranging from 10 to 100 with a step of 10. 'number of epochs' is selected as 1000 to ensure the convergence of the algorithm. Figures 5 and 6 show the changing of the loss value of training set and test set during each epoch for LSTM(1) and LSTM(2), respectively. LSTM(2) shows a smaller loss than LSTM(1) during the initial training stage but finally, the training process converges on both models.

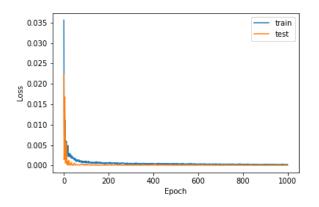


Figure 5: Loss on the Training and Test Sets for LSTM(1)

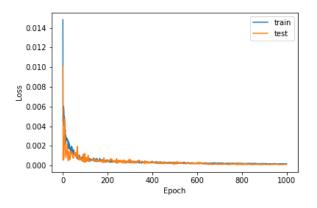


Figure 6: Loss on the Training and Test sets for LSTM(2)

On the other hand, the critical step before the implementation of traditional time series models is to ensure the stationary of the data. The dataset is taken the first difference by making it stationary. From the ACF and PACF plot, we see that autocorrelation decaying towards zero while PACF plot cuts off quickly towards zero. Therefore, for UTS, we only keep autoregressive component and have fitted traditional autoregressive models with order p (i.e., AR(p)) while the value of p ranges from 1 to 3 in our study. The optimal value of p in the AR model is identified as the one that generates the lowest Bayesian information criterion (BIC) value [24]. Results show that AR(2) produces the lowest BIC values among the three AR models we compared (including AR(1), AR(2), and AR(3)). For MTS, it is interesting to find that VAR models perform much worse than AR(2) with respect to BIC, no matter whether the macroeconomic feature *unemp_rate* is used or not. Therefore, AR(2) is selected as the appropriate traditional time series model based on the P2P data in this study.

Figure 7 shows the predicted trend of *default_rate* from October 2007 to January 2016 along with the true trend using LSTM(1), LSTM(2), and AR(2) respectively. The trend on the left of the vertical line is generated using the training data (i.e., data from October

2007 to May 2014) while the trend on the right is based on the test set (i.e., data from June 2014 to January 2016). We see that the predicted trend generated by LSTM(1) and LSTM(2) is very similar. Moreover, both LSTM models can capture the default trend very well. However, there is an obvious delay in AR(2) in the ability of detecting the change. We further compare the RMSE values of the three models and the result is shown in Table 2. AR(2) gives a much higher RMSE value on the testing set than that from either of the two LSTM models. Therefore, we conclude that LSTM shows its robustness in modeling the default rate of P2P market, no matter whether the macroeconomic feature unemp rate is used or not. Furthermore, since LSTM(2) gives lower RMSE values on both training and testing set, indicating that incorporating the macroeconomic feature unemp_rate could further improve the model performance. All the above findings could further confirm the robustness of the LSTM method in modeling the sequential P2P data.

Table 2: RMSE Comparison of the Three Models

Model	Training Set	Testing Set
LSTM(1)	0.013	0.010
LSTM(2)	0.011	0.007
AR(2)	0.019	0.021

6 CONCLUSION

In this study, we aim to explore the monthly trend of the default rate on the aggregative level in the P2P lending market in the US. LSTM algorithm is first employed as a technique to model the sequential P2P transaction data. Considering the effect of the macroeconomic factor on the P2P market, we incorporate the unemployment rate (i.e. unemp_rate) as an additional predictor. The result shows that although seldomly used in the P2P market, LSTM is a good alternative and even a more powerful tool to model the P2P transaction data compared to traditional time series models. It is also demonstrated that adding unemp_rate could improve the LSTM performance by decreasing RMSE on both the training and the testing datasets. Different from previous studies that focus on modeling default risk at the individual level, our study provides a more comprehensive analysis of the P2P market by sequentially modeling the risk at the aggregative level. Therefore, our study successfully broadens the application of the LSTM algorithm in the P2P market. Furthermore, our findings provide a good reference for investors to understand the entire status of the P2P market, especially the monthly trend of the default rate on an aggregative level. This is very critical in making their future investment strategies.

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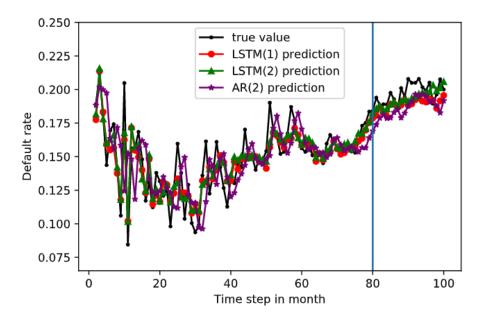


Figure 7: Predicted Trend of the Default Rate along with the True Trend from LSTM(1), LSTM(2), and AR(2)

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