Modeling default rate in P2P lending via LSTM

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Abstract. With the fast development of peer to peer (P2P) lending, financial institutions have a substantial challenge from benefit loss due to the delinquent behaviors of the money borrowers. Therefore, having a comprehensive understanding of the changing trend of default rate in the P2P domain is crucial. In this paper, we comprehensively study the changing trend of default rate of P2P USA market at the aggregative level from August 2007 to January 2016. From the data visualization perspective, we found that three features, including \textit{delinq.2yrs}, \textit{recoveries} and \textit{collection recovery fee}, could potentially increase the default rate. The long short-term memory (LSTM) approach shows its great potential in modeling the P2P transaction data. Furthermore, incorporating the macroeconomic feature \textit{unemp. rate} can improve the LSTM performance by decreasing RMSE on both training and testing datasets. Our study can broaden the applications of LSTM approach in the P2P market.

Keywords: peer to peer lending; default rate; long short-term memory.

1 Introduction

Peer to peer (P2P) lending, which means lending money virtually, is one of the fastest growing segment in the financial lending market. Having a thorough assessment of the loan applicants’ risk is essential for the investors to make a successful investment, since the investors aim to minimize risk while expect high return. As a result, lending institutions continuously focus on exploring methods to understand the behavior of loan applicants during the economic cycles. The long short-term memory (LSTM) model, which is one of the state-of-the-art methods to model the sequential data, has been widely used in language modeling, disease forecasting, and speech recognition (\textsuperscript{[1]}, \textsuperscript{[2]}, \textsuperscript{[3]}, \textsuperscript{[4]}). With respect to the financial domain, LSTM has shown its superiority in credit risk modeling, overdue of bank loan predictions, and credit card fraud detections (\textsuperscript{[5]}, \textsuperscript{[6]}). However, there are limited research that uses LSTM to analyze the sequential data generated in the P2P lending market.

Motivated by the aforementioned research, in this paper, we demonstrate a comprehensive case study with the goal to understand the changing trend of
the default rate on an aggregative level of the P2P transactions in USA. We first analyzed the changing trend of the features as well as their relationship with the default rate from a data visualization perspective. Then, LSTM model is employed to fit the default rate by incorporating a macroeconomic feature $unemp\_rate$ into the dataset. The findings in our study could provide a reference for the inventors of the P2P market.

The rest of the paper is structured as follows. Section 2 provides a description of the LSTM algorithm. Section 3 introduces our methodology and Section 4 presents the results. Section 5 is the conclusion of our study.

2 Algorithms
Since LSTM model is used in this study, its principle will be briefly discussed in this section. LSTM model is a variant of recurrent neural network (RNN) and it becomes popular recently in modeling sequential data ([7], [8]). Compared to RNN, the key concept of LSTM is that it contains a sequential cell states. Figure 1 is a classic explanation about the cell state inside LSTM that is illustrated in many studies ([9], [10], [11]). The cell state contains three different gates: forget gate, input gate, and output gate. The forget gate determines the information that should be removed/kept from prior steps (i.e., $f_t$) by using Equation 1, where $h_{t-1}$, $C_{t-1}$, and $x_t$ denote the previous hidden output, the previous cell state, and the current input respectively. $b_f$ and $W_f$ denotes the bias and weights in the forget gate, respectively. $\otimes$ denotes the Hadamard product (i.e., pointwise multiplication). With respective to the input gate, it decides the information that is stored from the current step (i.e., $i_t$) and then a tanh layer generates the information that should be added to the state (i.e., $\tilde{C}$). Similar to $f_t$, $i_t$ and $\tilde{C}$ can be expressed by Equations 2 and 3, respectively, where $b_i$ and $W_i$ denote the bias in the input gate, while $W_i$ and $W_c$ denote the corresponding weight. Then the previous cell state $C_{t-1}$ can be updated into the new cell state $C_t$ by using Equation 4. Finally, the output gate provides the information (i.e., $o_t$) for the next hidden state $h_t$ using Equations 5 and 6 where $b_o$ and $W_o$ denotes the bias and weights in the output gate, respectively.

\[
f_t = \sigma(W_f \otimes [h_{t-1}, x_t] + b_f)
\]
\[
i_t = \sigma(W_i \otimes [h_{t-1}, x_t] + b_i)
\]
\[
\tilde{C} = \tanh(W_c \otimes [h_{t-1}, x_t] + b_c)
\]
\[
C_t = f_t * C_{t-1} + i_t * \tilde{C}_t
\]
\[
o_t = \sigma(W_o \otimes [h_{t-1}, x_t] + b_o)
\]
\[ h_t = o_t \ast \text{tanh}(C_t) \] (6)

3 Methodology

3.1 Dataset

The case study in this paper uses a public available dataset downloaded via the following URL: https://www.lendingclub.com/info/download-data.action. The dataset records the P2P lending transactions ranging from 2007 to 2017 in USA. 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 target variable is loan status, which describes different status of the loan transactions: ongoing, fully paid off, and default.

With respective to the features in the dataset, they mainly fall into three categories: personal property (PP), credit information (CI), and loan information (LI). We remove the features that have ambiguous meanings and only keep those with clear descriptions in this study. Table 1 provides the descriptions, types,
as well as the categories of the selected features in the dataset. Except the target variable loan_status, most features are considered as numerical and there are only three categorical features. In order to obtain more information that has potential effect on loan_status, we collect one macroeconomic feature, the unemployment rate, using the following URL: https://datahub.io/core/employment-us#data. The unemployment rate is named as unemp_rate and then served as an additional numeric feature in the following analysis.

3.2 Problem statement

Based on the information provided by the dataset, we define our two main goals in this study as follows:

1. Explore the status of the loans in the P2P market as time goes on from the aggregative level (rather than the applicant level). Furthermore, explore the relationships between the features and the loan status. This could provide insights to the investors on their investments when facing with different money borrowers.

2. Since LSTM algorithm is not widely used in the P2P lending market by previous studies, we implement a LSTM model to summarize and forecast the changing trend of the loan status to explore its potential in modeling P2P transaction data.

3.3 Data pre-processing

To address the research goals described in Section 3.2, several data pre-processing procedures are performed sequentially as follows:

(a) We focus on the P2P lending that have determined status. Since most P2P lending transactions last for 36 months (some last for 60 months), most loan transactions that begin after February 2016 are still ongoing. Therefore, observations with the loan_status valued ‘ongoing’ are removed. Then, we transform the categorical feature loan_status to numerical by giving observations with loan_status valued ‘fully paid off’ a value 0 while those valued ‘default’ a value 1. As a result, there remains around one million observations and the transaction ranges from August 2007 until January 2016.

(b) The original P2P transaction dataset is aggregated by month in order to get the monthly default rate. In other words, by calculating the percentage of loan_status = 1 within each month, we obtain the default rate of the lending on the aggregative level. In this case, the original categorical target loan_status is transformed to the numerical target named default_rate. As a result, we obtain a sequence of default_rate for each month within each year ranging from August...
Table 1. Descriptions and types of the features in the dataset. PP, CI, and LI denotes personal property, credit information, and loan information, respectively.

| Feature name          | Description                                                                 | Category | Type       |
|-----------------------|------------------------------------------------------------------------------|----------|------------|
| 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                                        | PP       | Categorical|
| verification_status   | Indicates if income was verified by LC, not verified, or if the income source was verified | PP       | Categorical|
| loan_status           | The loan is fully paid off or default                                          | LI       | Categorical|
| 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 borrowers' 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 currently 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  |

2007 until January 2016.

(c) Features (both numerical and categorical) having missing/invalid percentage larger than 80% were removed. Then median-based imputation is applied on
(d) Exploratory data analysis (EDA) is implemented with the goal to transform categorical features into numerical values. As described in Table 1 besides the target variable, there are only three categorical features in the dataset: home_ownership, verification_status, and application_type. The effects of the different levels of these three categorical variables on default_rate are first visualized using the barplots and then compared using Wilcoxon rank-sum test. Figure 2 displays the average default rate in each level of home_ownership, verification_status, and application_type, respectively. From the first subplot in Figure 2, it is surprising to find that borrowers who rent or own home have higher default rate than those who have mortgage. People without home have the lowest default rate while loan applicants who select ‘ANY’ for their home_ownership have the highest default rate. Wilcoxon rank-sum test shows that at the significant level of 0.05, there are statistically significant difference in the default rate among the six different levels of home_ownership. Therefore, we keep all these six levels and use one-hot-encoding method to convert them into numerical values. In the third subplot of Figure 2, the feature application_type has two levels: ‘individual’ and ‘joint app’ (refer to Table 1 for details). Wilcoxon rank-sum test shows that loan applicants belonging to ‘joint app’ have significantly higher default rate than those belonging to ‘individual’. Thus, similar as for home_ownership, the two levels of application_type are kept and are transferred into numerical values using one-hot-encoding method. The second subplot in Figure 2 shows the effects of the three levels of verification_status on default rate. Wilcoxon rank-sum test demonstrates that verified applicants (including both verified and source verified) show significantly higher default rate than un-verified ones. However, there is no significant difference in the default rate between the level ‘verified’ and ‘source verified’. As a result, we pool the levels ‘verified’ and ‘source verified’ together as ‘verified’ and only two different levels of verification_status are kept: ‘not verified’ and ‘verified’. These two levels are further transformed into numerical values using one-hot-encoding method.

(e) After one-hot-encoding transformation, the missing values in the categorical features are imputed using the corresponding mode values.

3.4 Data trends

After data pre-processing discussed in Section 3.3, we obtained 102 observations on the aggregative level along with 19 features. We visualize the changing of all the numerical features that are described in Table 1 from August 2007 to January 2016 using line plots. Figure 3 shows the illustrative examples of the changing trend from six numerical features: default_rate, unemp_rate, annual_inc, int_rate, loan_amnt and open_acc. It is observed that default_rate gradually decrease from August 2007 to early 2010 but it begins to increase afterwards. It is surprising to note that unemp_rate changes in the opposite direction of
Fig. 2. Default rate in the borrowers with different levels of home ownership, verification status, and application type.

Fig. 3. Monthly change of some numerical features.

*default_rate, annual_inc, loan_amnt,* and *open_acc* have very similar changing trend: there is a deep decrease in these three features around the middle of 2008 and then they gradually increase until 2016 with some fluctuations. On the other hand, the changing trend of *int_rate* is different. It has a deep decrease near the end of 2011 and reaches the top value around 2013 and gradually decrease afterwards. It is worth noting that the trend of *unemp_rate* and *int_rate* has some similarities, indicating the potential correlations between these two features.
After visualizing the data trend, a heat map is then used to display the correlations between these numerical time series features. In the heat map, features that are positively correlated are ‘hot’ while negatively correlated variables are ‘cold’ ([12]). Figure 4 shows the heat map generated by the continuous features in this study. It is demonstrated that most features have positive relationship with each other except total_rec_late_fee and unemp_rate, which have a negative relationship with most of the rest features. The target variable default_rate has a very strong positive relationship with the features delinq_2yrs, recoveries and collection_recovery_fee. Therefore, these three features are considered as the critical features that can potential increase the default rate in the P2P market.

3.5 LSTM for the prediction of default rate

LSTM approach is applied to model the sequence data of P2P lending. After the data pre-processing described in Section 3.3, the dataset was split into 80% training and 20% testing sets. To be specific, we use the data from August 2007 to May 2014 as the training set while the testing set uses the data from June 2014 to January 2016. The loss function used in LSTM is to minimize the squared
root of mean squared error (RMSE) between the predicted and the true default rate via the ADAM algorithm. To identify whether the incorporated macroeconomic feature, \textit{unemp\_rate}, is beneficial to the mode performance, two LSTM models are implemented as follows: (1) LSTM model without using \textit{unemp\_rate}, denoting as LSTM(1); (2) LSTM model by using \textit{unemp\_rate} as an additional feature, denoting as LSTM(2). The implementation of the LSTM model is based on the Keras library in Python 3 on the personal laptop with 3.3 GHz Intel Core i7 processor, 16GB RAM, and Mac OS system.

4 Results

Figures 5 and 6 show the predicted monthly \textit{default\_rate} along with the true values from August 2007 to January 2016 on the two LSTM models. The predicted \textit{default\_rate} are displayed in red while the true values are shown by the black line. The subfigure on the left of the vertical line is generated using the training data (i.e., data from August 2007 to May 2014) while the subfigure on the right is based on the testing set (i.e., data from June 2014 to January 2016). We can see that both LSTM models produce a good fit on the default trend on both training and testing sets, no matter whether the macroeconomic feature \textit{unemp\_rate} is used or not. Therefore, LSTM shows its great potential in predicting the default rate in the P2P lending domain. For LSTM(1), it results in the RMSE valued 0.014 and 0.015 on training and testing set, respectively. For LSTM(2), the RMSE values are 0.011 and 0.012 on training and testing set, respectively. This indicates that incorporating the macroeconomic feature \textit{unemp\_rate} could further improve the model performance.

5 Conclusion

In this study, we aim to explore the changing trend of the default rate on the aggregative level in the P2P lending market in USA from August 2007 to January 2016. From the data visualization perspective, we found that three features, including \textit{delinq\_2yrs}, \textit{recoveries} and \textit{collection\_recovery\_fee}, could potentially increase the default rate. LSTM model is employed as a technique to fit the sequential P2P transaction data. To further improve the performance of LSTM model, we incorporate a macroeconomic feature \textit{unemp\_rate} as an additional feature. The result shows that although not widely used in the P2P market, LSTM is a good alternative to model the P2P transaction data. It is also demonstrated that the macroeconomic feature \textit{unemp\_rate} can improve the LSTM performance by decreasing RMSE on both training and testing dataset. Therefore, the case study in this paper provides a good reference for investors in their future investments. Furthermore, our study can broaden the applications of the modern data-driven approaches in the P2P market. In the future, more macroeconomic features as well as more transaction data should be incorporated with the goal
Fig. 5. Predicted values of default rate along with the true values from LSTM(1).

Fig. 6. Predicted values of default rate along with the true values from LSTM(2).
to improve the predictive power of LSTM models.

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