A Deep Learning Approach to Credit Rating

Stanford University

Raphael Abbou

Introduction

Modeling Credit Risk has been a major field of study in quantitative finance since the 2008 crisis. Highly non-linear dependencies between credit events and loan features make Deep Learning a particularly adapted approach for that purpose. We train Neural Networks on family loans originated between 2014 and 2015 (i.e. 500k loans) by Freddie Mac and test it on loans originated between 2016 and 2017 (300k loans), in order to predict defaulting loans on a 2-year time-window.

About the Data

For each loan we use 26 features: financial data like FICO score, Debt-to-Income.. and others like Postal Code, Loan purpose.. The Dataset provides different the type of default that occurs (REO, Short Sale..), but too few instances of some categories to create a classifier.

We then pre-process the data:

- Equivalence [Str0, Str1, Str2…] → [0, 1, 2..]
- Managing missing values
- Normalizing Inputs

Data is unbalanced with defaulting loans occurring way less

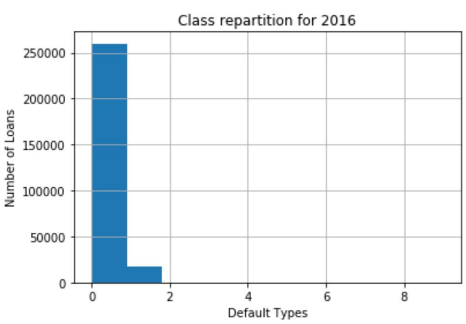

Figure 1. Data Distribution : nb defaults/non-defaults

Model and Results

We use a Deep Neural Network to forecast the default of our loan.

Metric: A high accuracy is not a good measure, since we have a vast majority of non-defaulting loans. We switch to ROC and AUC metric.

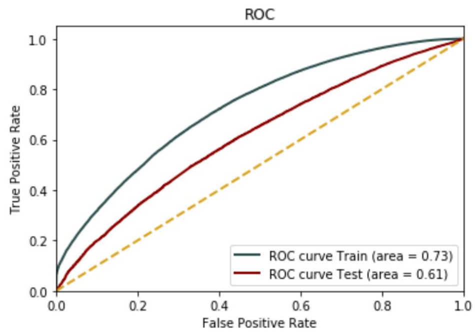

Figure 2. Baseline Model

We first reduce the bias of our model (#Layers + weights), then the variance (Dropout, Normalization..):

$$Cost = \sum_{i=0}^{m} \omega_i \hat{y}^i + (1-y^i)log(1-\hat{y}^i) + \lambda \sum_{l=1}^{L} ||W_l||_2^2$$

Optimizing:	AUC Train Set	AUC Dev Set	Running Time
Data	++		
Nb Epochs			+
Learn. Rate			
Batch Size			+
#Layers	++	+	
Weights	+		
Dropout		+	
L2 Norm.		+	

Figure 3. Optimized parameters and Impacts

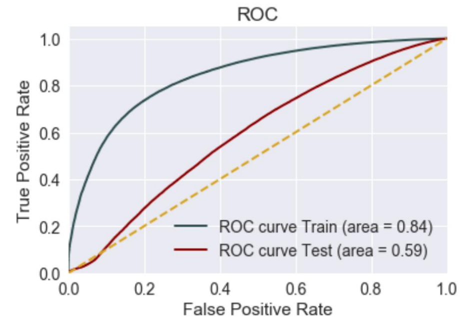

Figure 4. After Bias Reduction

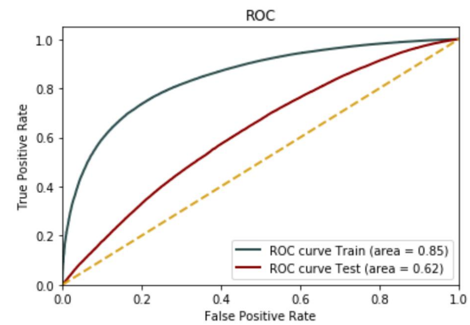

Figure 5. After Variance Reduction

Conclusion

We manage to have correct predictive results on loan default for train and test set, hence DNN seems to be a good approach to understand relationships between features and defaults. However, even regularization techniques did not help us that much for improving results on test set.

Future Work

In order to make the prediction usable in the industry, we should rather predict the probability of transiting from a delinquency status to an other. Our approach is a first step to select features and show that they are relevant to predict a default.