

ECML/PKDD 2016 Discovery Challenge

Bank Branch Visits and Customer Acquisition

Prediction using Gradient Boosted Trees

Andy H.M. Chung

Data Scientist, Asia Miles Limited
andy_hm_chung@asiamiles.com

Abstract. We apply gradient boosted trees algorithm for branch visits prediction and credit card acquisition, based on customer information and card payment records for the past 2 years along with geolocation information, provided by OTP Bank Hungary. In this paper, we describe the algorithms and techniques used.

Keywords: Machine Learning, Customer Acquisition, Recommender System

1 Introduction

Our dataset contains 3 types of information:

1. Customer transaction time series
2. Customer information (Age, gender, address, income group, etc.)
3. All bank branches geolocation

The training data is a random sample of customers, with transaction records in 2014. The testing data is another random sample of customers, with transaction records in the first half of 2015. The bank branch visits record and the date at which they registered for a credit card have been removed from the testing data.

We considered two supervised learning tasks:

1. Predict the bank branches visited by the customer
2. Predict the likelihood to apply for a credit card for each customer

For task 1, we predicted top 5 out of 323 branches most likely to be visited ($p_{1i}, p_{2i}, \dots, p_{5i}$) by customer i in the second half of 2015. The evaluation metric is based on *cosine@5* for all N customers, defined by

$$\text{cosine@5} = \frac{1}{N} \sum_{i=1}^N \frac{\sum_{k=1}^5 v(p_{ki}) \hat{v}(p_{ki})}{\sqrt{\sum_{k=1}^5 v(p_{ki})^2} \sqrt{\sum_{k=1}^5 \hat{v}(p_{ki})^2}} \quad (1)$$

where the actual and predicted number of visits of the top k -th branch by customer i is denoted by $v(p_{ki})$ and $\hat{v}(p_{ki})$ respectively.

For task 2, we predicted the probability to apply for a credit card in the second half of 2015 for each customer. The evaluation metric is based on Area Under the Curve (*AUC*).

2 Algorithm

Among many machine learning algorithms, gradient boosted trees proved to have state-of-the-art performance. Based on the existing open source packages, we chose XGboost [1] as our algorithm implementation since it is computationally fast.

We will briefly review the algorithm of decision tree and gradient boosted trees.

2.1 Decision tree

For a decision tree $y = f(x)$ with J number of leaves, it partitions the input space into J disjoint regions R_1, R_2, \dots, R_J and modeled as

$$f_m(x) = \sum_{j=1}^J c_{jm} I(x \in R_{jm}) \quad (2)$$

where m equals to 1, I is the indicator function and the optimal choice of \hat{c}_{jm} is

$$\hat{c}_{jm} = \frac{1}{|R_{jm}|} \sum_{y_i \in R_{jm}} y_i \quad (3)$$

where $|R_{jm}|$ is the total number of observations in the region R_{jm} .

A greedy approach for an optimal partition is determined at each split by enumerating all the features and possible split points and choosing the one such that the loss function L reduction is maximized.

2.2 Gradient boosted trees

A gradient boosted trees $F_m(x)$ is updated as follow for a new tree f_m built at iteration m is

$$F_m(x) = \begin{cases} f_1(x) & \text{if } m = 1 \\ F_{m-1}(x) + s\gamma_m f_m(x) & \text{otherwise} \end{cases} \quad (4)$$

where s is the shrinkage parameter and γ_m is determined by

$$\gamma_m = \arg \min_{\gamma} \sum_i L(y_i, F_{m-1}(x_i) + s\gamma f_m(x_i)). \quad (5)$$

3 Data Munging and Feature Engineering

For task 1, we used 2014 1st half as training data and 2014 2nd half branch visits as target. For each customer there are 323 rows, each row represents whether the customer visited particular branch based on extracted Customer Features, Transaction Features and Branch Features.

For task 2, we merged two different time frames into one dataset:

1. 2014 1st half features, 2014 2nd half credit card registration as target
2. 2014 2nd half features, 2015 1st half credit card registration as target

For each time frame, the customer id is unique. We predicted the target using extracted Customer Features and Transaction Features.

3.1 Customer Features

All categorical data such as age group, gender, income group are handled as dummy variables. Address latitude and longitude are treated as continuous variables.

3.2 Transaction Features

The transaction time series is broken down monthly. For each month we calculated frequency of different events (high spending, morning transaction, etc.). For in-person events with geolocation information, we first calculated the distance using Euclidean distance between the customer address and the events, then we calculated the aggregate sum, standard deviation, median, maximum value of the distance grouped by customer and month.

3.3 Branch Features

Branch location latitude and longitude are treated as continuous variables. Derived features include popularity of the branch, distance between the branch and the customer. Branch index is not used for training.

4 Stacked Generalization

The idea of Stacked Generalization [2] is to use a group of first stage models to do prediction, followed by a second stage model using all the predictions from first stage models as input features. For task 2, we applied 2-folds stacking split by two different time frame and two 10-folds stacking on each time frame separately.

For a N-folds stacking:

1. Split the training set in N parts: $training_1, training_2, \dots, training_N$
2. Predict $testing$ and $training_1$ using $N - 1$ folds ($training_2, training_3, \dots, training_N$) with first stage models
3. Similarly for $training_2, training_3, \dots, training_N$, the prediction for testing is the average of N prediction of $testing$
4. Train the second stage model based on the first stage predictions

Algorithm 1 Stacking

```
1: procedure MYPROCEDURE
2:    $stringlen \leftarrow \text{length of } string$ 
3:    $i \leftarrow patlen$ 
4: top:
5:   if  $i > stringlen$  then return false
6:    $j \leftarrow patlen$ 
7: loop:
8:   if  $string(i) = path(j)$  then
9:      $j \leftarrow j - 1$ .
10:     $i \leftarrow i - 1$ .
11:    goto loop.
12:   close;
13:    $i \leftarrow i + \max(\delta_1(string(i)), \delta_2(j))$ .
14:   goto top.
```

5 Hyperparameters Optimization

We applied grid search on a subset of parameters. In general, max_depth , min_child_weight , $gamma$, $lambda$ and $alpha$ are tuned for model complexity, $subsample$, $colsample_bytree$ are tuned to avoid overfitting, $scale_pos_weight$ is used to re-balance dataset. In order to speed things up we used a high eta (shrinkage) in the first stage and ranked parameter combinations based on cross validation score. For the parameter combinations with top 5% ranking, we re-trained the model using a lower eta and selected the one with best cross validation score.

For stacking we used random parameters without optimization because in practice stacking perform better when the underlying models are diversified.

6 Performance and Conclusion

For task 1, we predicted the probability of visiting a particular branch for each customer using $logloss$ as the local evaluation metric. We selected top 5 branches with highest probability score. The $cosine@5$ on 30% of the testing data is ~ 0.65 .

The most important features are:

1. Distance between the customer and the branch
2. Popularity of the branch
3. Location category of the customer

There is still a margin of improvement for task 1, since we transformed the task as a classification problem. We discarded too much information in training as we treated customer visiting a branch multiple times same as a single time.

For task 2, we predicted the probability of acquisition for each customer using AUC as the evaluation metric. The AUC on 30% of the testing data is ~ 0.719 .

The most important features are:

1. How frequent the customer used debit card in the past 6 months
2. Whether the customer has a credit card in the last month
3. The total number of POI visited by the customer in the past 6 months
4. The income group of the customer belongs to mid range

7 Acknowledgments

We thank European Conference on Machine Learning and Principles and Practice of Knowledge Discovery (ECML/PKDD) and OTP Bank Hungary for hosting the discovery challenge.

References

1. Chen, T., Guestrin, C.: XGBoost: A Scalable Tree Boosting System (2016)
2. Wolpert, D.H.: Stacked Generalization (1992)