Purchase Prediction

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Definition

Project Overview

Recommender Systems are to help people discover new content, find the content we were already looking for, discover which things go together, personalize user experiences in response to user feedback, recommend incredible products that are relevant to our interests and identify things that we like, which are basically to model people's preferences, opinions and behavior. Our recommender system model in this project can be used for evaluating users' purchase habits, predicting whether or not users may buy some items. Then we can recommend book items to users. If you have used services like Amazon, Job Board or Netflix, it is often to find some recommendations suggesting items for you to buy, jobs you may be interested or movies to watch. We will use this idea to build a similar application like them.

In this project, we will build a recommender systems to make predictions related to reviews of Books on Amazon. The dataset is 1,000,000 Amazon Book Reviews, which provided us purchase information. Our target was to predict whether the user purchased the item based on these reviews.

Problem Statement

We got 1,000,000 reviews to be used for training, since the dataset is really large, we are not going to use all reviews for training. The fields in this file are [1]:

itemID The ID of the item. This is a hashed product identifier from Amazon.
reviewerID The ID of the reviewer.
rating Rating of the review.
helpful Helpfulness votes for the review.
reviewText The text of the review.
summary Summary of the review.
unixReviewTime Time of the review in seconds since 1970.
reviewTime Plain-text representation of the review time.

category Category labels of the product being reviewed.
pairs Purchase.txt Pairs on which you are to predict whether a user purchased an item or not.

Our task is to predict given a (user, item) pair from 'pairs_Purchase.txt' whether the user purchased the item (really, whether it was one of the items they reviewed). The test set has been constructed such that exactly 50% of the pairs correspond to purchased items and the other 50% do not.

In order to solve this problem, we considered three methods. First, the baseline prediction was to find the most popular products that accounts for 50% of purchases in the training data, return '1' whenever such a product is seen at test time, '0' otherwise; Then we applied logistic regression, here we found two ways to generate features and response in training and validation set, we will talk in detail later. Finally, we built an user-based collaborative filtering which was implemented by Jaccard similarity between users. Besides, we refined the percentage threshold that works better than a simple 50% threshold.

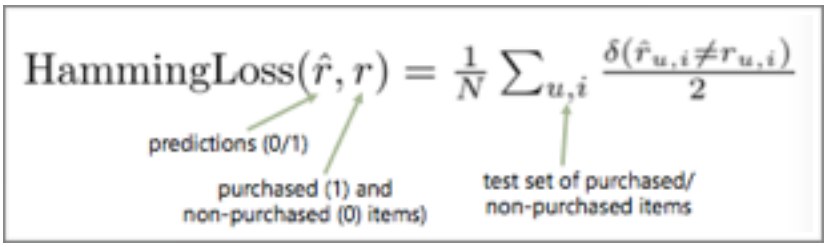
Metrics

In the test data, we are given pairs like these:

userID - itemID, prediction
U321264570-I114057426
U746082164-I893042700
U370790476-I428256969
U914546038-I075600973
U856169033-I867837160
U076653335-I149935550

We need to estimate the final column, predict '1' if the user purchased the item, otherwise predict '0'.

The evaluation for this task is the categorization accuracy (fraction of instances labeled correctly), which is defined as: 1 - Hamming loss(fraction of misclassifications)



Analysis

Data Exploration

The original reviews data is "train.json.gz", we read the data as a list dataset in python. The current reviews list has 1000000 dictionary type objects, which stores review information, here is an example of one of the reviews, each object has 9 features:


```
{'category': [['Books']],
 'helpful': {'nHelpful': 0, 'outOf': 0},
 'itemID': 'I572782694',
 'rating': 5.0,
 'reviewText': 'favorite of the series...May not have been as steamy as
 some of the others...but the characters, their depth, and believability
 were amazing.  wanted to curl up with Devlin and make it all better(wink
 wink). an amazing series...found Laura Kate when I stumbled onto Hearts
 in Darkness(one of my all time faves)...this series ranks up there with
 my Kresley Cole and Gena Showalter favorites.',
 'reviewTime': '05 3, 2014',
 'reviewerID': 'U243261361',
 'summary': 'Loved it',
 'unixReviewTime': 1399075200}
```


Here are some basic statistics about dataset:

The total number of reviews in this dataset: 1000000
Unique pairs: 1000000
The total number of users: 35736
The total number of items: 37801
Average user frequency: 27.9829863443
Average item frequency: 26.4543266051
The average rating: 4.218463
The average length of review text: 1151.411355
The average helpful rate: 0.738431763713

The dataset has 1000,000 user-item pairs int, however there are only 35736 unique users and 37801 unique items. The average user frequency(the number of reviews a user has contributed) is around 27.9 and the average item frequency (the number of reviews for a particular book) is around 26.4, which means each

users has many purchase records and each item has been reviewed by different users. So in the following algorithm section, we considered to include frequency of users and items as a feature.

The 'rating', 'reviewText' and 'summary' features seem to be useful features, because we can conclude how much each user like the item they purchased, but in the original dataset, we do not have 'rating' information of 'non-purchased' user-item pairs, there may be some issues when using validation set to test the model without 'rating' in 'non-purchased' pairs. So we decided to drop this feature.

As a result, what we only care about is the purchase information. So we generated user-item pairs from the original dataset and stored them in a list:

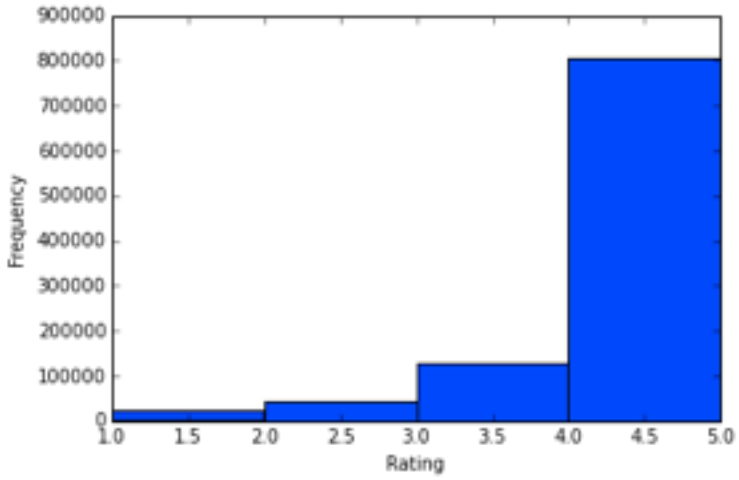
['U243261361-I572782694',
 'U947346309-I172992448',
 'U405075077-I236549536',
 'U931293227-I707281702',
 'U398632015-I127335134',
 'U282193926-I970107598',
 'U681436293-I732947093',
 'U913252976-I273175352',
 'U584647862-I040055669',
 'U887091398-I563838330']

Since we only care about user-item pairs in this project, we do not need to be worried about abnormalities problem in any other features, in the reveiwerID and itemID features, there aren't really any outliers and missing values.

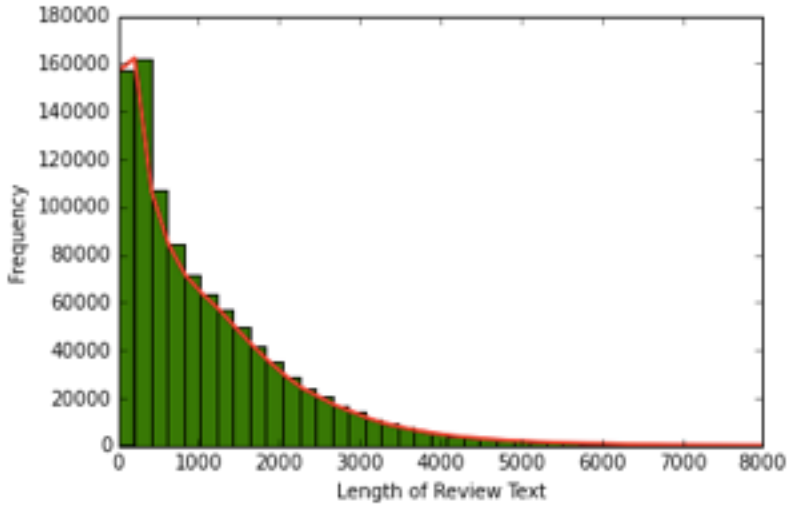
We need to do some other reconstructions of training and validation set in the later steps according to specific learning algorithms and methods, we will talk about them in details later in this report.

Exploratory Visualization

Here are some visualizations of features:

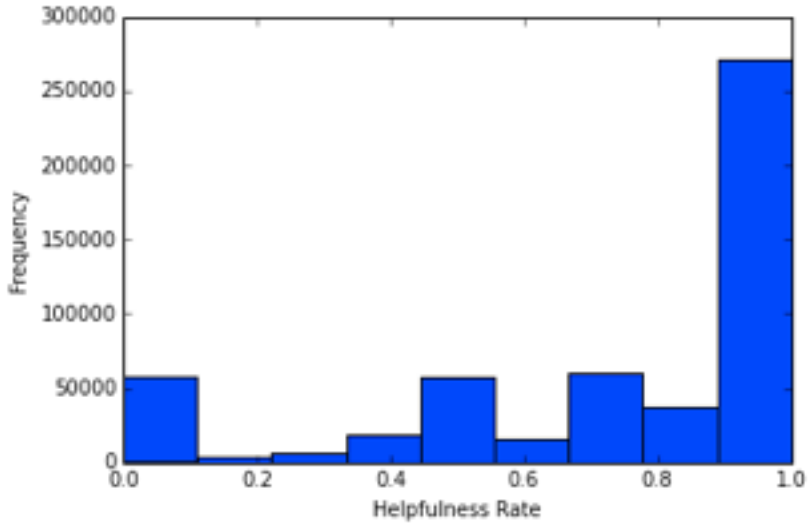


From the histogram of Rating, we found the most frequency rating value is between 4.0 to 5.0, which means most reviewers may be satisfied with their purchases, and we can consider this as an implicit reason for most popular items are easily chosen by users. Usually when we are searching online, reviewers points and ratings are important source for the items quality.



From the histogram of length of review Text, we found most review content are not very long. Usually if the review are really long, the reviewers may complain

about the items, so we can use this as another implicit evidence which shows that most users are satisfied with their purchase.



From the Helpfulness Rate histogram, this is very straightforward to show us that usually users reviews are considered to be very helpful and useful since the frequency of helpfulness rates between 0.9-1.0 are much higher than others. So users' feedback is a very useful resource to affect other people's feelings about items.

Algorithm and Techniques

We planned to use three methods for prediction:

1) Baseline popularity model: the baseline for this task simply ranks products by popularity, and returns '1' for popular products, by finding the most popular product that account for 50% of purchases.

2) Logistic Regression: a good and common choice for classification problem, here we used the popularity which got from baseline model as a feature in a logistic regressor. The specific Logistic Regression code is from sklearn library [2].

3) user-based Collaborative Filtering: this is a method performs recommendation in terms of user/user similarity. This method was implemented by Jaccard Similarity between users. Jaccard Similarity between users is defined as the intersection of two users divided by the union of them. Evaluated if items were purchased by users based on similarity measures between users. The items we

may infer to be purchased by a user are drawn from those purchased by similar users.

The collaborative filtering is a good idea for recommender system model, but we still have a few problems, since this method is actually kind of slow given a huge enough dataset.

Reason:

1) Based on the evaluation in data exploration, we found popularity is a very important feature. In reality, usually the popular items are purchased in high probability, so we chose the baseline popularity model to implement this idea.

2) There are lots of other classification machine learning algorithms, for example, SVMs. But we do not use SVMs here because they do not work well in very large data sets and the training time happens to be cubic in the size of the dataset.

3) Collaborative Filtering works best when the user space is large and more or less insensitive to user size. In this project, we have a large user space and collaborative filtering is a good idea for recommender systems.

Benchmark

Our expectation of the accuracy 0.638, this is because when we considered the baseline popularity method with the best threshold, the accuracy is 0.638, we are hoping to select some other models which perform better than the baseline.

Methodology

Data Preprocessing

- Generate non-purchases data:

We need to think harder to generate a validation set for this data. Instead of just taking the last 100k reviews for validation, we instead took 50,000, but also randomly select 50,000 'non-purchases' by randomly selecting a user and an

item, and checking that they do not already show up together in the training set. Now we got non-purchases dataset:

['U397588427-I813144071',
 'U454189910-I330894170',
 'U693620828-I808282678',
 'U859618515-I402834954',
 'U068129025-I236309750',
 'U373069520-I897843947',
 'U291061728-I184108297',
 'U589861647-I028854182',
 'U577955868-I085427379',
 'U703013088-I946727291']

- Split Training and Validation set:

Since we don't have access to the test labels. We will need to simulate validation/test sets of our own. Now we split the training data as follows:
Reviews 1-900,000 for training
Reviews 950001 - 1,000,000 + 50,000 non-purchases for validation

In the Collaborative Filtering model, since it takes really a long time for prediction when testing set is large, so we used a smaller size validation set (500 Reviews + 500 non-purchases). This may cause the accuracy of Collaborative Filtering model to be lower than using the same size of original validation set. We should considered this situation when comparing three models.

- Build feature matrix for logistic regression:

In order to get the model feature matrix X for logistic regression, we will convert features represented as lists of dict object to matrix, each row of the matrix represents for each user-item pair. For example, if there are three pairs in dataset [item3 - user1, item1 - user2, item2 - user3]:

```
[{'item': 'item3', 'user': 'user1'},
 {'item': 'item1', 'user': 'user2'},
 {'item': 'item2', 'user': 'user3'}]
```

We want to build a matrix to represent all pairs in the above list as the feature matrix in logistic regression:

```
array([[ 0.,  0.,  1.,  1.,  0.,  0.],
       [ 1.,  0.,  0.,  0.,  1.,  0.],
       [ 0.,  1.,  0.,  0.,  0.,  1.]])
```

Each vector in a row of the matrix represents each pair, each row can be visualized as two small vectors, for example, the first row [0,0,1, 1,0,0] stands for the pair item3 - user1, here the first half of this vector [0,0,1] represents item3, and the second half [1,0,0] represents user 1, the combination of these two vectors is the row for pair item3 - user1.

If you just look at the first half of the whole matrix:

```
array([[ 0.,  0.,  1.,
       [ 1.,  0.,  0.,
       [ 0.,  1.,  0.,
```

There are three vectors (rows), they represent three items, the first row [0,0,1] is item3, the second row [1, 0, 0] is item1 and the third row [0, 1, 0] is item2. The other half of the whole matrix is similar for representing all users id.

To implement this transformation, we used DictVectorizer() function from sklearn library, this can be used for transforming lists of feature-value mappings to vectors. This transformer turns lists of mappings (dict-like objects) of feature names to feature values into Numpy arrays or scipy.sparse matrices for use with scikit-learn estimators[4].

Implementation

1) Baseline Popularity Model:

First we generated a popularity list to record how many times each item was purchased and sorted items by decreasing popularity:

```
popularity[0:10]
```

```
[(82, 'I528315047'),
 (82, 'I410621777'),
 (68, 'I674661294'),
 (64, 'I844628367'),
 (57, 'I409321766'),
 (56, 'I937737186'),
 (55, 'I699768130'),
 (53, 'I051931455'),
 (50, 'I650532728'),
 (47, 'I845728367')]
```

Then we picked out the most popularity items that accounts for 50% of purchases.(The sum of purchases of these items is 50% of the total purchases). To predict the pairs 'user-item' in test set, if the item showed up in the most popularity list, we predict this pair as '1'(purchase), otherwise, considered the pair as '0' (non-purchase).

The above is item popularity model, we also applied an user popularity model, which is similar to the item popularity model. In the user popularity model, we generated list to record purchase numbers of each user. And predict the pairs by checking if users showed up in the most popular users list.
Result: the accuracy of the baseline item popularity model on the validation set is 0.6366 (threshold = 0.5), the accuracy of the baseline user popularity model on the validation set is 0.65174 (threshold = 0.5).

2) Logistic regression:

In python, logistic regression package is available in scikit-learn library, linear_model class. In my model, I set all parameters as default [2] [3]:

```
from sklearn.linear_model import LogisticRegression
clf = LogisticRegression()
clf.fit(X_train, y_train)
pred = clf.predict(X_val)
```

In order to implement logistic regression, our first step is to construct the response in training set. This is because the training set are all "purchase" , which means y_train = [1,1,…,1], so we only have label 1 without any label 0. The idea to construct response is to use the popularity of items, if the pair in training is considered to be popular, then we label the pair as '1', otherwise as '0'. In other words, we generate the response by using baseline popularity model to predict on the training set, we got response:

```
y_train = pred_user_popu_model(train_set, train_set, 0.5)
y_train[0:10]
```

```
[0, 0, 1, 1, 0, 0, 1, 0, 1, 0]
```

In the data preprocessing step, we have already got the model matrix X by using DictVectorizer to convert features list, now we got a one-zero matrix to represent the purchase information, each row in the matrix represents for each user-item pair.

The logistic Regression aims to model p(labelldata) by training a classifier of the form:

$$y_i = \begin{cases} 1 & \text{if } X_i \cdot \theta > 0 \\ 0 & \text{otherwise} \end{cases}$$

In the fitting process, the classifier are trying to find the theta such that meets the conditions above, then in the prediction process, we input the test matrix, find the product of the matrix and the theta, the product will determine the result.

Result: The accuracy of logistic regression with threshold = 0.5 is 0.65174.

3) Collaborative Filtering:

Collaborative filtering is to build a matrix which shows the relationship between users or items, then we can infer the preference of an user by checking the matrix and matching the user's information.

- Similarity Measure:

In this project, we measured the similarity by Jaccard Similarity, the Jaccard similarity between A and B is calculated by the following formula:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}.$$

Here, to simplify the problem, we considered if two users purchased at least one common item, then recorded the similarity between two users as 1, otherwise is 0.

- Utility Matrix:

First we built a matrix, the row label represents each user and column label represents each item. The value in this matrix is either 1 or NaN, 1 represents the user purchased the item and the value is given for each user-trim pair. The matrix is sparse, meaning that most of the entries are unknown. Here is an example of a matrix, describing three users: user1, user2, user3. The available items: item1, item2, item3:

item	item1	item2	item3
user			
user1	1	NaN	1
user2	1	NaN	NaN
user3	NaN	1	1

- Prediction Process:

The goal of the recommender engine is to predict the 'NaN' in a matrix. For example, we want to predict user1-item2, we checked other users who purchased item2, here we found user3 purchased item2. The second step is to measure the Jaccard similarity between user1 and user3, since user1 and user3

have common purchase item-item3, so according to the definition of Jaccard similarity above, the similarity between user1 and user3 is 1. So we predict the value of user1-item2 as 1.

As another example of prediction, suppose we want to predict user2-item2, we checked other users who purchased item2 and we found user3. Then we measure the similarity between user2 and user3, they have no items in common, so the similarity of user2 and user3 is 0. As a result, we predict the value of user2-item as 0.

Here, because this model is time-consuming when test set is large, so we reduced the validation set to 5000.

Result: the accuracy of user-based collaborative filtering is 0.771

4) Metric:
The accuracy is calculated by (true positive + true negative) / all predictions.

5) Complications:
- In this project, we need to think harder to generate validation set for this data. Instead of just split the original dataset. We took the last 50,000, but also randomly select 50,000 'non-purchases' by randomly selecting a user and an item, and checking that they don't already show up together in the training set.

- The computation time is large when implementing Collaborative Filtering, so we reduced the validation set size for this model to only 5000, this may cause the result not accurate.

Refinement

Instead of using a simple 50% threshold, we compared the performance of many different thresholds and select the best threshold, we checked the performance of the following thresholds:

```
threshold
```

```
array([ 0.1 ,  0.11,  0.12,  0.13,  0.14,  0.15,  0.16,  0.17,  0.18,
        0.19,  0.2 ,  0.21,  0.22,  0.23,  0.24,  0.25,  0.26,  0.27,
        0.28,  0.29,  0.3 ,  0.31,  0.32,  0.33,  0.34,  0.35,  0.36,
        0.37,  0.38,  0.39,  0.4 ,  0.41,  0.42,  0.43,  0.44,  0.45,
        0.46,  0.47,  0.48,  0.49,  0.5 ,  0.51,  0.52,  0.53,  0.54,
        0.55,  0.56,  0.57,  0.58,  0.59,  0.6 ,  0.61,  0.62,  0.63,
        0.64,  0.65,  0.66,  0.67,  0.68,  0.69,  0.7 ,  0.71,  0.72,
        0.73,  0.74,  0.75,  0.76,  0.77,  0.78,  0.79,  0.8 ,  0.81,
        0.82,  0.83,  0.84,  0.85,  0.86,  0.87,  0.88,  0.89,  0.9 ,
        0.91,  0.92,  0.93,  0.94,  0.95,  0.96,  0.97,  0.98,  0.99])
```

The best accuracy of baseline item popularity model is 0.63865 with threshold = 0.56.
The best accuracy of baseline user popularity model is 0.65683 with threshold = 0.6.
The best accuracy of logistic regression model is 0.65683 with threshold = 0.6.

Results

Model Evaluation and Validation

- Compared the performance of three methods:

1) Baseline Popularity Model: the most efficiency model, very fast, but the performance is not good as my expectation. The user popularity model performs better than the item popularity model, the best performance of the user popularity model is 0.63357.

2) Logistic Regression: slower than the baseline popularity model, the performance is similar to the baseline popularity model.

3) User-Based Collaborative Filtering: Performs best with really high accuracy, but when test set is large, this method is slower than the above two. The accuracy is 0.771 on the validation set.

Although the collaborative filtering is the slowest one, we still considered this model as our final model, since it's performance is really good compare to the baseline and logistic regression.

- Compared to Benchmark:

To demonstrate the result of our final model is significantly better than the benchmark, we considered running the code 20 times with different pools of randomly selected data and applied t-test to justify the hypothesis, we got accuracies:

0.774, 0.788, 0.775, 0.761, 0.795, 0.8, 0.793, 0.769, 0.766, 0.779, 0.794, 0.788, 0.795, 0.784, 0.8, 0.8, 0.769, 0.776, 0.782, 0.798

we got t statistic = 47.8 and p value = 2.856e-21, p value is smaller than 0.05, so we can reject the hypothesis: mean of accuracy is equal to 0.65, which demonstrate that the result of collaborative filtering model is significantly better than the benchmark.

Justification

Finally we decided to use user-based collaborative filtering to do prediction, the result of the validation set is 0.771 which is higher than the accuracy we expected.

But the accuracy was got by just testing on 5000 validation set, which is not large enough, so the reliability of the accuracy should be doubted. But we still have reason to justify that the collaborative filtering works better than the baseline and logistic regression, this is because when generated the validation set in the first two methods, we got non-purchase data set by generation instead of from real world, so the validation set is not as reliable as what we used in the last model.

Conclusion

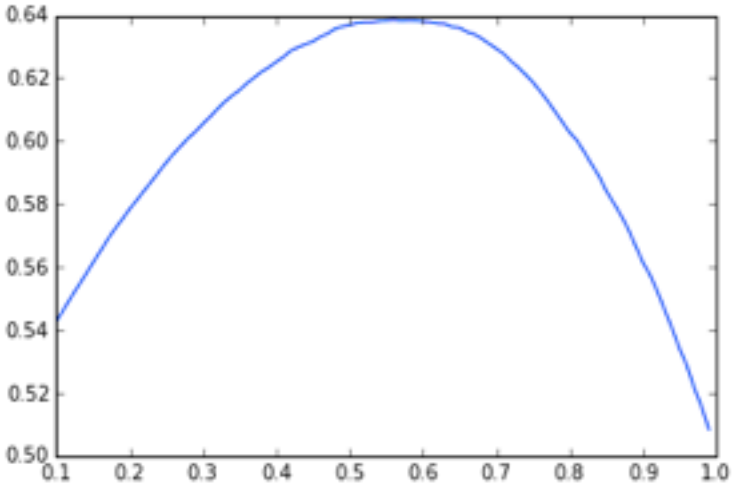
Reflection

This project is a recommender system problem, the main idea is to evaluate people's preference and purchase habits and make some recommendations. In this specific problem, we are given 1 million Amazon book reviews, which provided us purchase information, our target is to predict when user purchased the item given some user-item pairs.

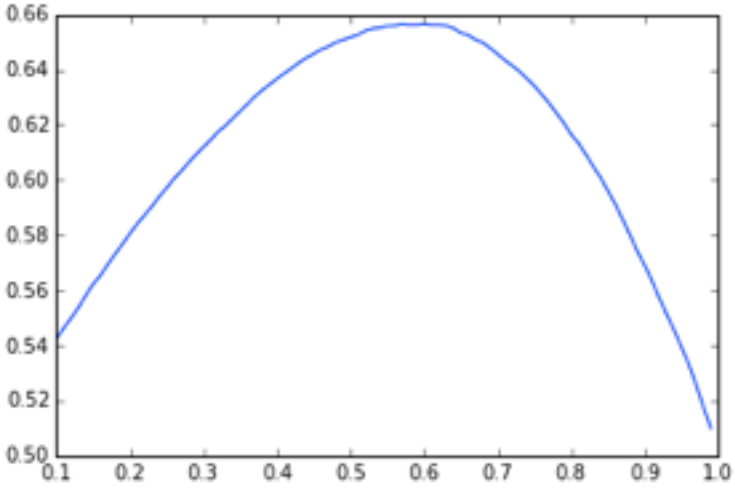
To solve the problem, first we generate a user-item list from the original list of review information. Then we reconstruct the training and validation data by randomly selecting user-item pairs which do not show up in the training set as non-purchase pairs. As for models, we considered three models: popularity model, logistic regression and collaborative filtering. Here is a table displaying average accuracy of different methods over 20 times:

	Average Accuracy
item popularity	0.63851
user popularity	0.65647
logistic regression	0.65647
collaborative filtering	0.78430

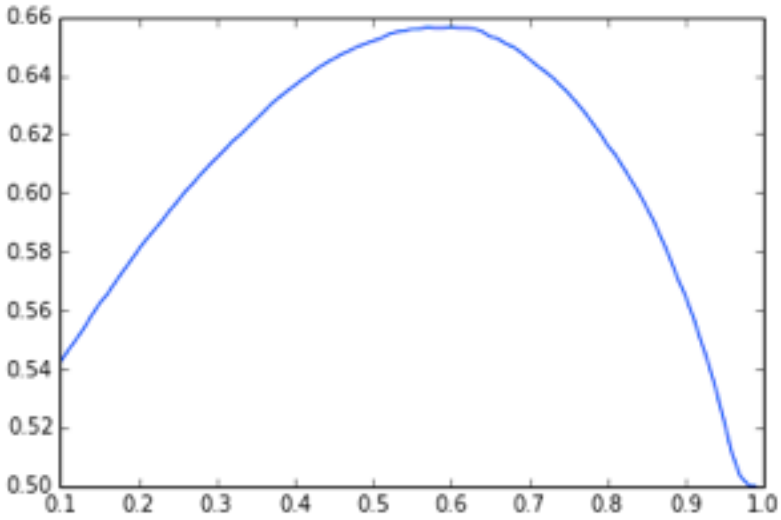
For popularity model, we considered the most popular items that accounts for 50% of purchases as label 1, and to refine the result, we compare the accuracy of different thresholds and found the best threshold is 0.56:



Similarly, we considered the most 'popular' users that accounts for 50% of purchases as label 0, and compare the accuracy of different thresholds to refine the result, the best threshold is 0.6:



For logistic regression, we combined the popularity in popularity model as a feature in logistic regression model, in other words, we use the prediction of popularity model on training set as the model response, and then transform the feature list to one-zeroes matrix to fit the model, also we select the best threshold by comparing the results of different thresholds, the best threshold is 0.6.



For collaborative filtering, we implemented this model by using Jaccard similarity to measure the similarity between users and evaluated users' preference.

We met some difficulties when we worked with the entire dataset for collaborative filtering model, working on the whole dataset is time-consuming, so we changed the validation set size to be smaller. This may resulted in a lower accuracy and undermine the comparison of three models.

As for interesting aspect of this project, recommender systems are increasingly popular application of Machine Learning in many industries. By evaluating the users and items popularities and users similarities, we can infer the users preference and purchase habits, which is a very practical and useful application in a variety of areas, we can use this idea in many other places such as music , movies and news recommendation, social tags or online dating.

Improvement

We still have a few problems left to address:

1. Collaborative filtering in practice is kind of slow given a huge enough dataset. In this project, we reduced the validation set size short the prediction time, but this solution may undermine the comparison of models because of the differences of validation set size. Considering some other models which also have good performance but faster than collaborative filtering may be a good idea.

2. In reality, the non-purchase pairs will be comparatively larger than purchased pairs, so the metrics of using accuracy may not be a good idea in practice, we should consider assign additional weight to negative instances, for example, F_1 score.

Reference

[1] http://cseweb.ucsd.edu/classes/fa15/cse190-a/files/assignment1.pdf
[2] http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html
[3] https://github.com/scikit-learn/scikit-learn/blob/51a765a/sklearn/linear_model/logistic.py#L925
[4] http://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.DictVectorizer.html