University of Minnesota

coursera

Capstone Project:

Recommender System

Part I: Designing a Measurement and Evaluation Plan

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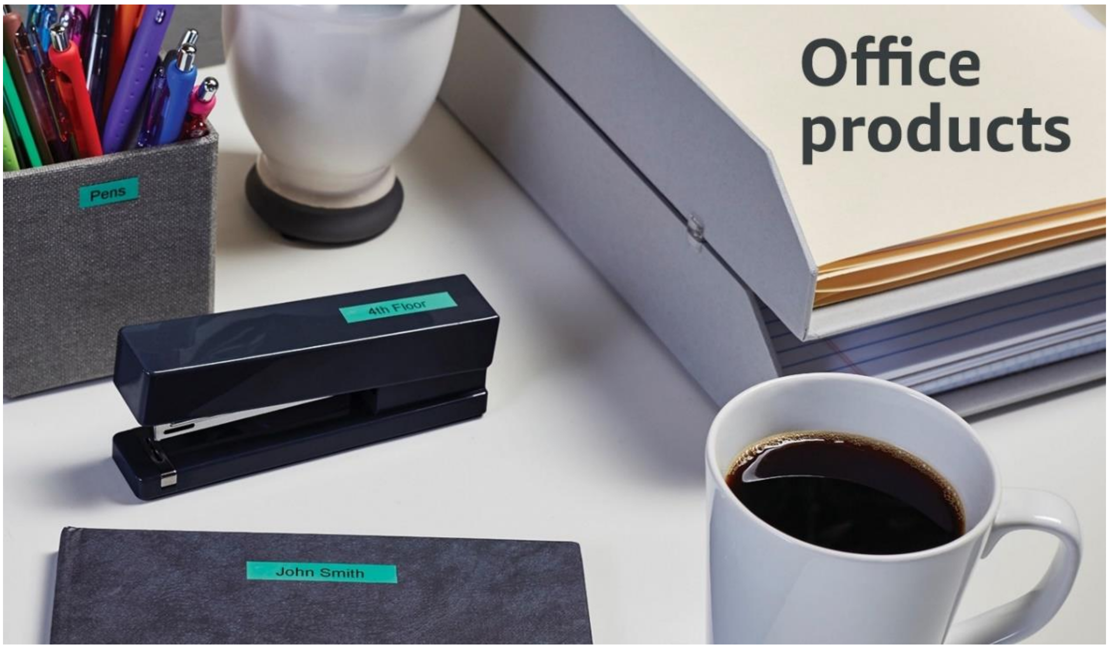

Overview

Nowadays, we need recommender systems almost everywhere in our lives. Therefore, retailers are become more interested in recommender systems to analyze patterns of user interest in products and provide personalized recommendations. The first goal of this project is to Design, Measure, Mix, and a proposal. The second goal is to develop a recommender system to increase sales of office products during this important time period 'Back-to-School'. To maximize business value.

Business Objective

Knowing that our site 'Nile-River.com' unfortunately, does not experience as large a surge in office product sales during the back-to-school period due to an experience surge which is far below our offline competitors.

Giving good product recommendations based on customer's overall profiles, not their current browsing or basket would increase sales of the office product during the "Back-to-School "period, that will maximize the business value.

Data

I will be using a data set derived from Amazon.com with product metadata and ratings data on office products. The data set is provided thanks to Julian McAuley at UCSD, and involves actual data from the period May 1996-July 2014. To make your computation more tractable, we've used a dense subset of the data (called the 5-core subset) that only includes items and users with at least five ratings.

Note that the original datasets are available at http://jmcauley.ucsd.edu/data/amazon/,

Note: There are separate data set extracts for those of you completing the programming (honors) track and the non-programming track. The non-programming track dataset is smaller to make it more feasible for use in spreadsheet computation.

For each item, your meta-data includes:

- An item number
- Amazon's ITEM number ("asin")
- The item's brand name
- The item title
- The item category (both leaf category and full path)

- A Price in dollars
- An availability score between 0 and 1 that reflects how widespread the product is in retail stores; higher scores reflect broad availability; lower scores indicate products not found in most big box store. Note that the availability score is synthetic (we created it), but for purposes of this capstone, treat it as if it were real data.

Also, I am provided with a ratings matrix with a row for each item and columns representing each user (ratings are on a 1-5-star scale). Your ratings matrix includes all the ratings data. I choose to separated manually and take only 200rows each.

Remark: I will be using the office-product.xlsx

Metrics

For the metrics I will be using these below:

- RMSE
- nDCG
- Top N
- Precision @N
- Popularity
- Price Diversity
- Availability Diversity

Algorithms

I will the whole 5 algorithms listed below:

- Content based
- Item-item
- User-user
- Matrix-fact
- Pers-bias

Hybridization Techniques

We are trying four different types of hybridization here.

1. Linear ensemble
2. Nonlinear ensemble
3. Top 1 from each recommender
4. Recommender switching

The first two options approach the recommender's performance in terms of how good it predicts the users' ratings, so its only evaluation will be in terms of RMSE.

The third approach have the intuition that, if we get the top 1 recommendation from each algorithm, the resulting 5 item list will have a better performance in terms of identifying 'good' items to users. In this case, we defined the good items if the recommender suggested an already bought item for a user. Therefore, the final measurement of this hybridization mechanism is through the precision@5, as we end up with a 5-item list.

The final mixing algorithm has the underlying theory of how collaborative filtering mechanisms perform with items that had not enough users/items in its calculations. As a well-known weakness of these recommenders, the idea was to check how many items we would affect if we established a threshold of enough data in order for us to use a collaborative filtering. Otherwise, if the item doesn't have enough support in form of users' ratings, we could have a support of a content-based recommendation, or even, in last case, a non-personalized one.