



Product Recommendation - PoC

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Change history

Doc Version	Author & Created Date	Change Description & Section	Reviewed By & Review Date	Approved By & Approved Date
1.0	Vaisakh B 06 November 2019	All		

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Product Recommendation Systems

"A system to assist user discover new and relevant products, creating a delightful user experience while driving incremental revenue through cross sell and up sell."

Classification of Recommendation Systems

- Popularity Based Filtering
- Content Based Filtering
- Collaborative Filtering

Popularity Based Filtering

- We can recommend items to a user which are most popular among all the users
- **Non - Personalized Recommendation**

Content Based Filtering

- Serves recommendations based on the meta-data or characteristics of the product
- **Semi – Personalized Recommendation**
- Challenges
 - Lack of novelty and diversity
 - Scalability is a challenge

Collaborative Filtering

- Serves recommendations based on user similarity
- **Personalized Recommendation**

Advantages of Collaborative Filtering

- Benefits from large user bases
- Produces more serendipitous recommendations
- Flexible across different domains

Implementation Methods

- Memory based approach
- Model based approach

Memory Based Approach

- User - User filtering
 - Finds the similarity between users based past rating
 - Predicts the user preference for an item as the weighted sum of user similarities and rating of the given item by different users
- Item – Item filtering
 - Finds the similarity between items based on its rating
 - Predicts the user preference for an item as the weighted sum of item similarities and the given user's rating for different items
- Algorithms
 - KNN
 - Cosine similarity
 - Pearson correlation

Disadvantages of Memory Based Approach

- Scalability
 - When there is large number of users and products, computation power becomes an issue
- Data Sparsity
 - There may be large number of users and products. But user rating for products won't be available in good numbers, in which case recommendation won't be accurate.

Model Based Approach [Latent Factor Method]

- Solves scalability and sparsity problems
- In this approach, CF models are developed using parametric machine learning algorithms to predict user's rating of unrated items
- The idea behind such models is that preferences of user can be determined by a small number of hidden factors
- These factors are called embeddings/latent features

Different Latent Factor Methods

- Matrix Factorization Method
 - We decompose our original user-item rating matrix into product of 2 low rank orthogonal matrices, which represents the embeddings
 - We will be using Funk SVD method (Regularized SVD)
- Deep Learning
 - Hidden layers models embeddings / new feature space

Evaluation of Recommendation Systems

- User Studies
- Online Evaluation
- Offline Evaluation

Major Challenges

- Cold Start Problem
 - Hybrid approach
 - Product Cold Start => Content based filtering
 - Visitor Cold Start => Demographic clustering + Popularity based strategy
- Data
 - Data Collection
 - Explicit
 - Implicit
 - Rating function based on behavioral data
 - Time decay algorithm
 - Inverse frequency factor
- Anonymous Users

State of the Art

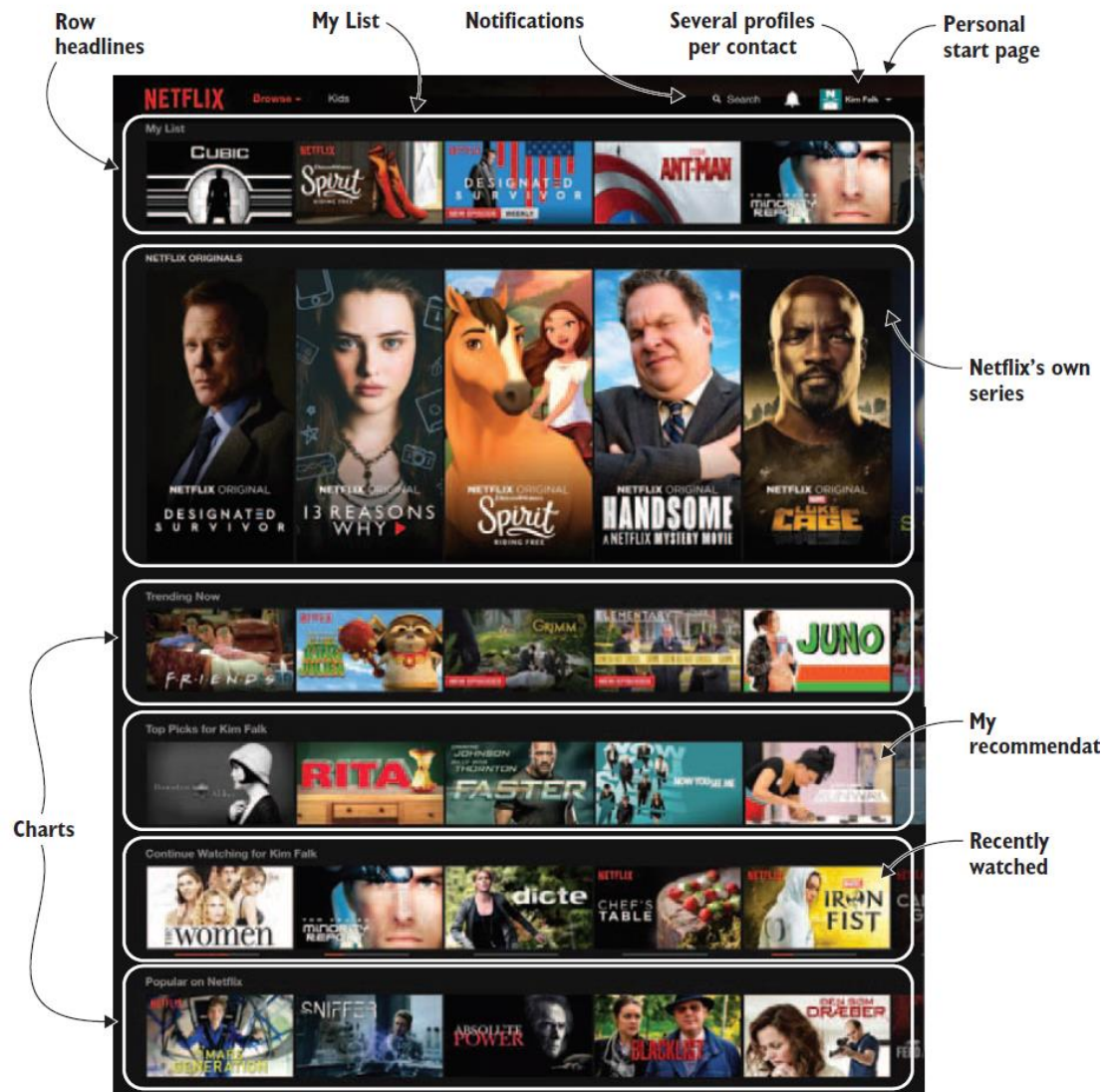


Figure 1.1 The Netflix start page (before it changed the layout)

Appendix 1 - CF Memory Based Method Prediction Equation

- User – User filtering
- Item – Item filtering

$$P_{u,i} = \frac{\sum_v (r_{v,i} * s_{u,v})}{\sum_v s_{u,v}}$$

$$P_{u,i} = \frac{\sum_N (s_{i,N} * R_{u,N})}{\sum_N (|s_{i,N}|)}$$

Appendix 2 - Algorithm : Funk SVD Method

- Define baseline prediction function
- Calculate the error function
- Optimize the error function using SGD

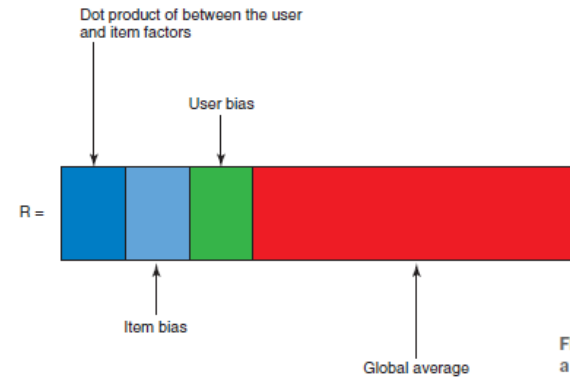


Figure 11.16 A predicted rating is a combination of these four things.

$$\min_{b,p,q} \sum_{(u,i) \in K} (r_{ui} - \mu - b_u - b_i - q_i p_u)^2$$

$$\begin{aligned} \blacksquare \quad & b_u \leftarrow b_u + \gamma * (e_{ui} - \lambda * b_u) \\ \blacksquare \quad & b_i \leftarrow b_i + \gamma * (e_{ui} - \lambda * b_i) \\ \blacksquare \quad & q_i \leftarrow q_i + \gamma * (e_{ui} * p_u - \lambda * q_i) \\ \blacksquare \quad & p_u \leftarrow p_u + \gamma * (e_{ui} * q_i - \lambda * p_u) \end{aligned}$$

References

- Practical Recommender Systems Book by Kim Falk
- <https://www.analyticsvidhya.com/blog/2018/06/comprehensive-guide-recommendation-engine-python/>



Thank You