Recommendation Systems

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Introduction

Recommendation Systems are becoming more and more popular. Using a good recommendation system has become an essential part of most businesses. More and more companies are using their own version of recommendation systems. Big companies like Netflix, Youtube, Amazon, Airbnb, Facebook all have their recommendation systems. People are becoming more platform dependent, we want the application to tell us what we want. A Netflix user is satisfied because the recommendation they get for movies and shows are more personalized for their need. Amazon sells more product when they show products that a person would like to buy. Ads are more likely to generate revenue when the ads are relevant. [1]
In this study, we would learn different recommendation systems and how they function. We aim to develop our own recommendation systems using Deep Learning and Machine Learning methods.

Types of Recommendation Systems

Popularity Based Recommendation Systems

This recommendation system works on the basis of trends and popularity. The goal of this recommendation system is to recommend what is trending among the targetted group of users. This recommendation system does not need the historical data from the users. This recommendation system has its own advantages because there's no need for the historical dataset. The recommendation system doesn't suffer from a well known problem of most recommendation systems, known as "Cold Start Problem."
We can possibly use this recommendation system when we do not have any data from the user and also have this as a "Popularity Section" for every user so they can easily find what's popular in their preffered genre.[2]

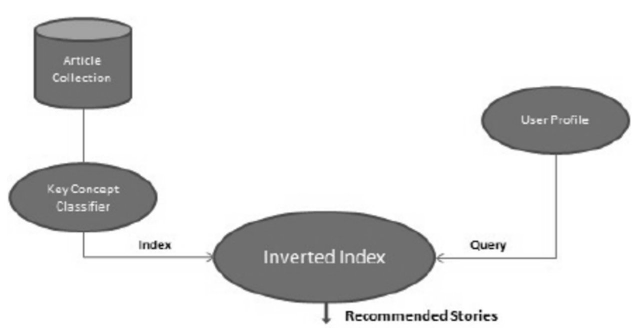

Figure 1: Architecture of the Popularity-based Recommender System [3]

Classification Model

This recommendation system uses features of both the product and the user to predict whether the recommendation will be liked/disliked by the given user. This model employees a classifer based on certain rules to perform the prediction. [2]

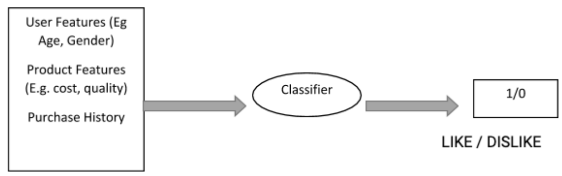

Figure 2: Classification Model Recommender System [2]

Conent-Based Recommendation Systems

This recommendation system also uses content/product features to determine the recommendations. This recommendation system does not employee the historical data of the user. There are multiple methods that are used to determine the recommendations. We usually use Euclidean distance between the contents to find the nearest recommenations that a user may like. There are also other methods that can be used such as using a pearson correlation coffecient, and recommend the content/product if they're closely correlated. We would get more in depth overview of these recommendation systems in this study. [2]

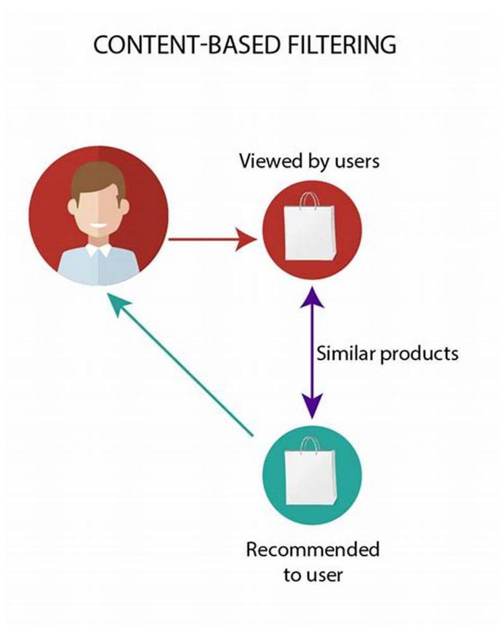

Figure 3: Content-Based Recommendations System [4]

Collaborative Filtering Recommendation Systems

This type of recommendations systems are widely used and considered to be the intelligent recommendation system. Collaborative filtering uses historical data of the users. Collaborative filtering finds similarties between users and makes prediction for better recommendations. Collaborative filtering requires data, and having more data makes the prediction better, which results in better recommendations. We have many methods for collaborative filtering that we will be doing futher study in this paper. [2]

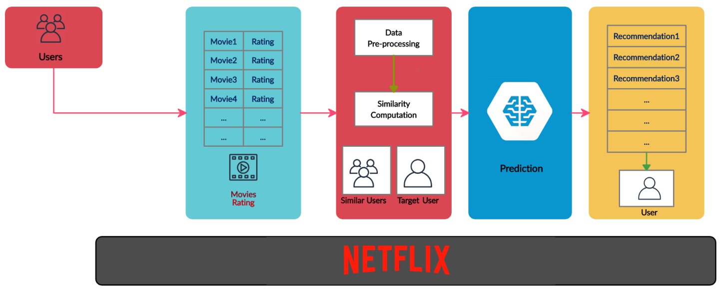

Figure 4: Collaborative Filtering Recommendation System [5]

Hybrid Recommendation Systems

This type of recommendations systems uses both Content-based filtering and Collaborative filtering algorithms. These recommendation systems can produce better recommendations as they have both historical data and also using the contents to provide users with the recommendations. We can expect more accurate recommendations even with less data and we may be able to overcome cold start problems. A hybrid recommendation systems may also use other recommendation systems algorithms to provide us with more accurate results. We will be doing more in-depth study of hybrid recommendations system in this paper. We will be also comparing performance of a conventional recommendations system with some hybrid recommendations systems. [6]

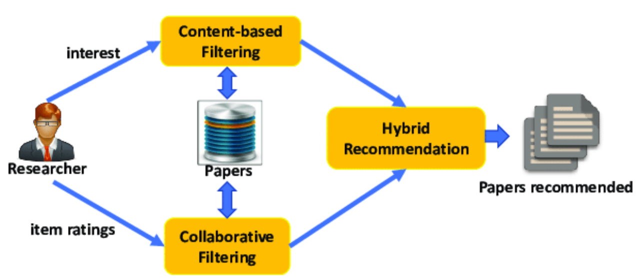

Figure 5: Hybrid Recommendation System [6]

Problems with Recommendation Systems

Cold Start Problem

One of the major problem that we encounter while working with recommendation systems are the Cold Start Problem. In this study, we have mentioned "Cold Start Problem" several times, but what is a cold start problem? Let's understand why it is a problem and how we resolve these issues.
Cold Start Problems occur when there is no/less data available realted to user or the product. As we know most recommendation systems are dependent on hisotrical data about the user or product and sometimes both. So not having data/information available, would be an issue and we can't make expect our recommendation system to produce meaningful recommendations. There are multiple mitigation techniques that can be used to resolve this issue and expect better recommendations in such cases. We will be using those techniques to resolve any cold start problems. To learn more about Cold Star Problem and it's mitigation techniques, see [7]

Models to build Recommendation Systems

Matrix Factorization Model

The matrix factorization model factorizes the rating matrix into the product of two lower-rank matrix. Matrix facotization is one of the most reiable model to build a recommendation system.
Let $\mathbb{R} \in \mathbb{R}^{p \times q}$ denote the interation matrix with 'p' number of users and 'q' number of products. Then the user-item matrix will be factorized into a user latent matrix $\mathbf{A} \in \mathbb{R}^{p \times k}$ and a product latent matrix $\mathbf{B} \in \mathbb{R}^{q \times k}$ where k < p, k < q.
Here, **k** denotes the latent factor size. Let a_u denote the u$^{\text{th}}$ row of $\mathbf{A}$ and b_i denote the i$^{\text{th}}$ row of $\mathbf{B}$.
Now, we estimate the predicted ratings by

$$\hat{\mathbb{R}} = AB^T$$

Where $\hat{\mathbb{R}} \in \mathbb{R}^{p \times q}$ is the matrix that represents predicted ratings. We can calculate the predicted ratings of a product given by user u by a product.

$$\hat{\mathbb{R}} = a_u {b_i}^T + c_u + c_i$$

Now, we train our model by minimizing the objective fucntion given below.

$$\underset{A,B,C}{\arg\max} \sum_{(u,i) \in k} \|\mathbb{R}_{ui} - \hat{\mathbb{R}}_{ui}\| + \beta({\|A\|_F}^2 + {\|B\|_F}^2 + {C_u}^2 + {C_i}^2)$$

Where β is the rate of regularization. $\beta({\|A\|_F}^2 + {\|B\|_F}^2 + {C_u}^2 + C_i^2)$ is term that avoids overfitting of data.
We use Root Mean Square Error (RMSE) to evaluate the matrix factorization model.
RMSE is calculated by

$$RMSE = \sqrt{\tfrac{1}{|T|} \textstyle\sum_{ui \in T} (\mathbb{R}_{ui} - \hat{\mathbb{R}}_{ui})^2}$$

Here, T is the set of pairs of users and products evaluated.

Bibliography

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