# Final Exam - Recommendation System

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## I. Introduction

A Recommendation System is an information filtering system that suggests certain paths that a user can take depending on what path previous users have taken. These systems have been incredibly popular in the recent years. They are widely used by e-commerce sites, by sites like LinkedIn that give recommendation to users for possible connections that they can add to their circles. The things that one needs to keep in mind while designing a recommendation system are as follows:

- Quality of Predictions: The predictions should not be random, and should consider criteria that will help it make more relevant predictions.
- Speed: Most recommender systems work in a commercial and/or online setting, and so it is important that they can start making recommendations for a user almost instantly.
- Scalability: Systems in a commercial and/or online setting can have a huge dataset. The algorithm must maintain its speed even if there is a huge amount of data.
- Easily Updated: The datasets behind recommender systems are constantly being updated. So, the Algorithm should be able to handle this.
- **Sparse Data Handling:** Sometimes when the datasets are very sparse, we still want to be able to make good predictions.

Discussed in the next section are some common algorithms used in recommender systems.

# II. SOME COMMON ALGORITHMS

# A. Collaborative Filtering

Collaborative filtering methods are based on collecting and analyzing a large amount of information on users behaviors, activities or preferences and predicting what users will like based on their similarity to other users. A key advantage of the collaborative filtering approach is that it does not rely on machine analyzable content and therefore it is capable of accurately recommending complex items such as movies without requiring an "understanding" of the item itself. Many algorithms have been used in measuring user similarity or item similarity in recommender systems, like the k-nearest neighbor (kNN) approach. This approach may suffer from scalability

and sparsity problems.

## B. Content Based Filtering

Another common approach when designing recommender systems is content-based filtering. Content-based filtering methods are based on a description of the item and a profile of the users preference. In a content-based recommender system, keywords are used to describe the items and a user profile is built to indicate the type of item this user likes. In other words, these algorithms try to recommend items that are similar to those that a user liked in the past (or is examining in the present). In particular, various candidate items are compared with items previously rated by the user and the best-matching items are recommended. A key issue with content-based filtering is whether the system is able to learn user preferences from users' actions regarding one content source and use them across other content types.

## C. Hybrid Recommender Systems

Recent research has demonstrated that a hybrid approach, combining collaborative filtering and content-based filtering could be more effective in some cases. Hybrid approaches can be implemented in several ways:

- By making content-based and collaborative-based predictions separately and then combining them
- By adding content-based capabilities to a collaborativebased approach (and vice versa)
- By unifying the approaches into one model

# III. MY APPROACH

All the codes, along with the README and this report have been uploaded to the GitHub directory - "

# A. Data Cleaning

The following pre processing was done on the data before actually using it for recommendation:

 The data contained many non-ASCII characters like bullet points, right arrow and other garbage value. This was removed. This was done before the data was used in the recommender modules. Recommendation System Aashima Yuthika

- The separation of skills in the data were based on different delimiters. Some were separated by '&&' while some had ',' separating them. This was made uniform and all these were separated using commas. This was done while processing the data for the recommender system.
- There were duration for which a user has had that skill.
   This was removed as there was no uniformity in it.

#### B. Recommendation

For the recommendation system I have used some ideas from Collaborative Filtering. There are basically two approaches that I have tried for the same.

# 1) Approach 1

- This first sees what career goal is right for the user or what the user wants
- It then makes an exhaustive list of all the skills that users have in that profession
- We then make a matrix S of each user and their skills for that profession
- ullet The matrix S is then summed along the column to find how many users have a particular skill
- Then the top 3 frequencies are taken
- All skills having the above frequency are shown to the user

# 2) Approach 2

- This first sees what career goal is right for the user or what the user wants
- It then makes an exhaustive list of all the skills that users have in that profession
- We then make a matrix S of each user and their skills for that profession
- We then make a matrix T of pairs of skills and how many time they occur together
- After this the Jaccard Index of all pairs of skills is calculated and stored in a matrix J where J(i,j) is the Jaccard Index of Skills i and j. The Jaccard Index of two values are calculated as follows:

$$J = \frac{AB}{A + B - AB}$$

where,

- A: Number of times that A occurs B: Number of times that B occurs AB: Number of times that AB occur together
- Then the Skills having the top 3 Jaccard Indices are suggested to the user

# IV. RESULTS

## A. Module 1

The Career is selected randomly and the user to whom career path is to be suggested is too. Below is the result using the Frequency of Skills Approach (Approach 1) and the Jaccard Index Approach (Approach 2).



Fig. 1: Suggesting Career Path using Frequency Approach

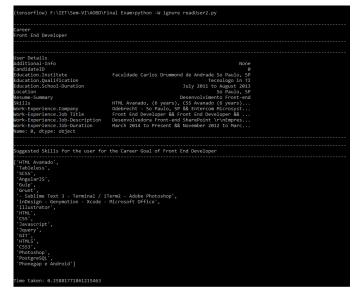


Fig. 2: Suggesting Career Path using Jaccard Indices Approach

# B. Module 2

The User is asked to select a Career from the list of options and then the suggested skill set is shown to the user. Below is the result using the Frequency of Skills Approach (Approach 1) and the Jaccard Index Approach (Approach 2).

Recommendation System Aashima Yuthika

```
ensorflow) F:\IET\Sem-VI\AOBD\Final Exam>python -W ignore userGoal.py
Automation Test Engineer
 Computer Systems Manager
Customer Support Administrator
Customer Support Specialist
 Data Center Support Specialist
Data Quality Manager
Database Administrator
 Desktop Support Manager
Desktop Support Specialist
   Front End Developer
   Java Developer
Junior Software Engineer
  Junior Software Engineer
Lead Information Developer
Senior IT Architect
Senior Network Engineer
Senior Network System Administrator
Senior Programmer Analyst
Senior Security Specialist
Senior Software Engineer
   Senior System Architect
Senior System Designer
Senior Systems Analyst
   Senior Web Administrator
Senior Web Developer
    Software Architect
   Software Developer - Backend
Software Developer
   Software Enginee
   Software Quality Assurance Analyst
Sr. Software Engineer
   support engineer
System Architect
    Systems Analyst
   Systems Designer
Technical Operations Officer
Technical Specialist
Technical Support Specialist
   UI Developer
  cose your Career Goal from the options above >> 10
```

Fig. 3: Giving options to the user for Career Path

```
You chose
Front End Developer

Suggested Skills for the user for the Career Goal of Front End Developer

HTML
CSS
Photoshop
Dagery
GIT

Time taken: 9.026953381413717236
```

Fig. 4: Suggesting Career Path using Frequency Approach

Fig. 5: Suggesting Career Path using Jaccard Indices Approach

The Frequency Approach, although has a time complexity  $O(n^2)$  it's suggestions may not be as beneficial as that of the Jaccard Indices Method, which has a time complexity of  $O(mn^2)$  where m is the number of users and n is the number of skills. This is true because the second method takes into account as to which skills are most frequently seen together and hence, giving a better and more connected career path to the user.

#### REFERENCES

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