Suggest Vocation Progression Path

Amee Bhuva(1401009), *Student, SEAS, Ahmedabad University*

***Abstract*—This report explores the distinctive characteristics and possibilities of various prediction techniques in job recommendation systems keeping in mind the end goal to fill in as a compass for research and practice in the field of recommendation systems. The three methodologies that quantify the suitability of a vocation searcher in a more flexible way are 1.) Collaborative and Content Based Filtering (searching and extricating required data) 2.) Matrix Completion (to recommend next arrangement of aptitudes to be obtained) and 3.) Matching profiles and occupations (to recommend a profession way); which utilize an organized form of job and the candidate's profile, created from a content analysis of the unstructured type of the expected skill set or job description.**

Catchphrases: Content-Based Filtering, Matrix Completion, Job proposal framework, Matching Profiles and Jobs

I. Introduction

In the course of the most recent couple of years, we are everyday overpowered by vast amount of data from different sources. This storm of data makes the task of discovering valuable or appropriate things/objects - for example, newspapers, websites, music, motion pictures, books or even jobs - a big challenge. Therefore, an ever-increasing number of applications have been comprehensively created and new methods have been developed to support human decisions proposing services, items and different sorts of data to clients. One field of research toward this path is that of Recommender Systems (RSs). RSs are tools that utilize different methods and algorithms to segregate superfluous data from an enormous measure of information and generate customized recommendations of a small subset of them, which a client can look at in a sensible amount of time. Typical examples like these can be found on online business administration, for example, Amazon, and on social organizations, for example, Facebook and Linkedin.

RSs normally utilize one of the following four fundamental procedures:

- **Collaborative Filtering Recommenders (CFRs)** Recommendations are generated by utilizing social knowledge (typical ratings of items by a community of users). More specifically, a CFR finds users with similar interests as the target user and suggests recommendations to him/her based on their liked items. The key function in CFRs is the computation of similarities among users.
- **Content Based Recommenders (CBRs)** Items are recommended having similar content information to those a user has liked in the past. A CBR analyzes a set of characteristics of items which are rated by the target user and build the profile of the interests of this user based on the features of the items which are rated by him. The recommendation process matches up the user profile attributes against the set of properties of item content.
- **Knowledge-Based Recommenders (KBRs)** Recommendations are generated by utilizing domain knowledge. These systems have the advantage of enhanced reliability since they usually contain less noise. However, a KBR requires considerable knowledge acquisition for setup and maintenance during their lifetime.
- **Hybrid Recommenders (HRs)** The approaches mentioned above have their limitations, such as the cold start and the sparsity problem. So, HRSs combine two or more techniques to overcome these limitations.

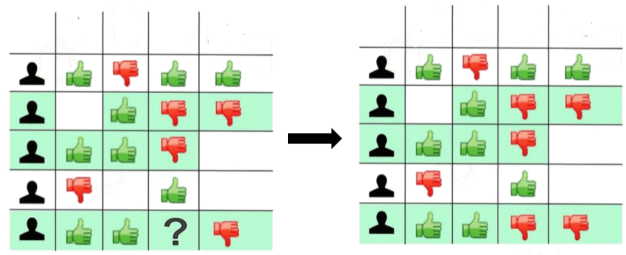

Fig. 1. Sample Data

A. Sample Data

The sample data in Fig. 1 has career goals in its rows and skill set in its columns. The **green likes** suggest that a user possess a particular skill and the **red likes** suggest the he/she does not possess a skill. The missing entry is filled using collaborative filtering approach.

II. Block Diagrams

Fig. 2 shows the block diagram of the proposed recommender system, wherein the user first logs in he/she has already registered and if not, then he signs up and creates his/her profile. Then the program reads the candidate profile which is stored in **JSON** format and is unstructured. The converted data is structured and will be used by the modules for suggesting jobs and recommending skillset.

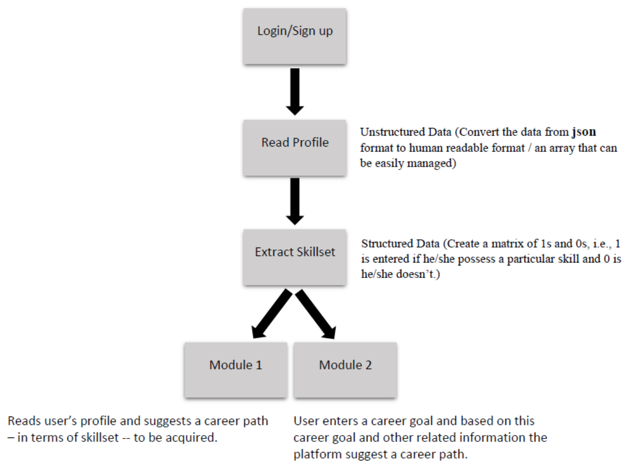

Fig. 2. Block Diagram 1

A. *Description of MODULE 1*

Module 1 shown in fig. 3 uses Collaborative filtering to fill in the missing data in the skillset matrix as shown in fig. 1. The missing data in the skillset matrix is the final output or the skills that should be recommended to the user.

- METHODOLOGY

  1 Look for the career goals that require the same skillset patterns with the career goal that the active user demands.(the user whom the prediction is for).
  2 Use the skillset from those matching patters of career goals in step 1 to calculate a prediction for the active user.

The correlation between the career goals(C_k) and skillset(S_k) is given by:

$$r(S,C) = \frac{\Sigma_k (S_k - \bar{S})(C_k - \bar{C})}{\sqrt{\Sigma_k (S_k - \bar{S})^2 (C_k - \bar{C})^2}}$$

The prediction is computed as follows:

$$p(S_i) = \frac{\Sigma C_i * x(S,C)}{n}$$

B. *Description of MODULE 2*

Module 2 shown in fig. 4 uses hybrid recommendation approach, i.e., Content based filtering as well as Collaborative filtering wherein the user provides a particular career goal, based on that and the skills he possesses, the recommender system will recommend next set of skills to be acquired. This approach is used to make predictions/recommendations based on a weighted average of the content-based recommendation and the collaborative recommendation for which the Pearson correlation co-efficient is calculated as below:

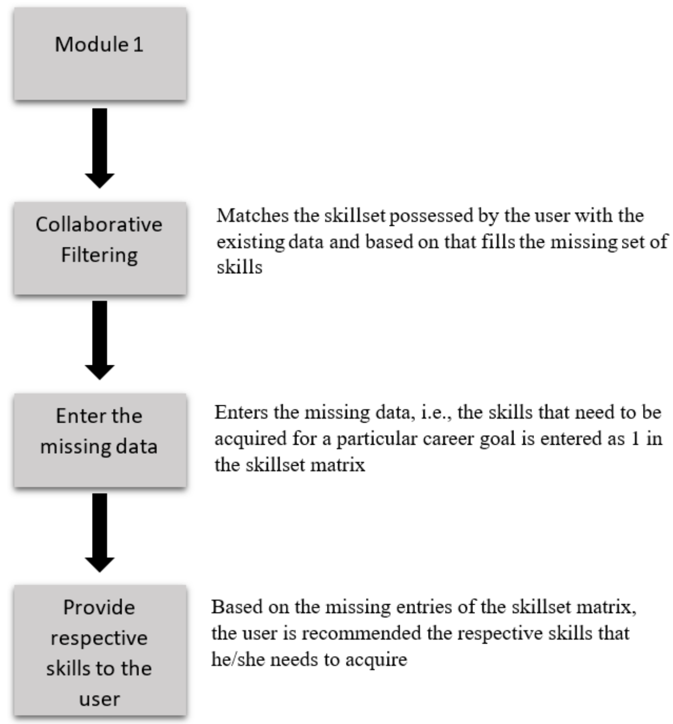

Fig. 3. Block Diagram of Module 1

$$P(i,j) = \frac{\Sigma_{c \in C}(S_{c,i} - \bar{S}_i)(S_{c,j} - \bar{C}_j)}{\sqrt{\Sigma_{c \in C}(S_{c,i} - \bar{S}_i)^2} \sqrt{\Sigma_{c \in C}(S_{c,j} - \bar{C}_j)}}$$

- METHODOLOGY

  1 Based on the users having matching skillsets, one can be recommended those skills which he/she doesn't posses but the matching user has.
  2 To do so, the nearest user is founded in terms of matching patterns. The one who has the maximum matching pattern with the active user, should be recommended the missing skills(entries in terms of matrix).
  3 The nearest user has the maximum skills in common, therefore, it is likely to achiee enhancement in the role by achieving those missing skills.

III. Conclusion

The report basically focusus on collaborative and content based filtering approach for recommendation of jobs to a registered user as well as to recommend skillset for a particular career goal provided by the user. The whole document actually focuses on matrix completion so as to retrieve the missing entries of the matrix and based on that, provide suggestions to the user by finding nearest user in terms of skillset. Also, through hybrid recommendation, one can enter a career goal of his/her choice and get recommendations about the skills he/she needs to acquire in order to achiever his/her career goal.

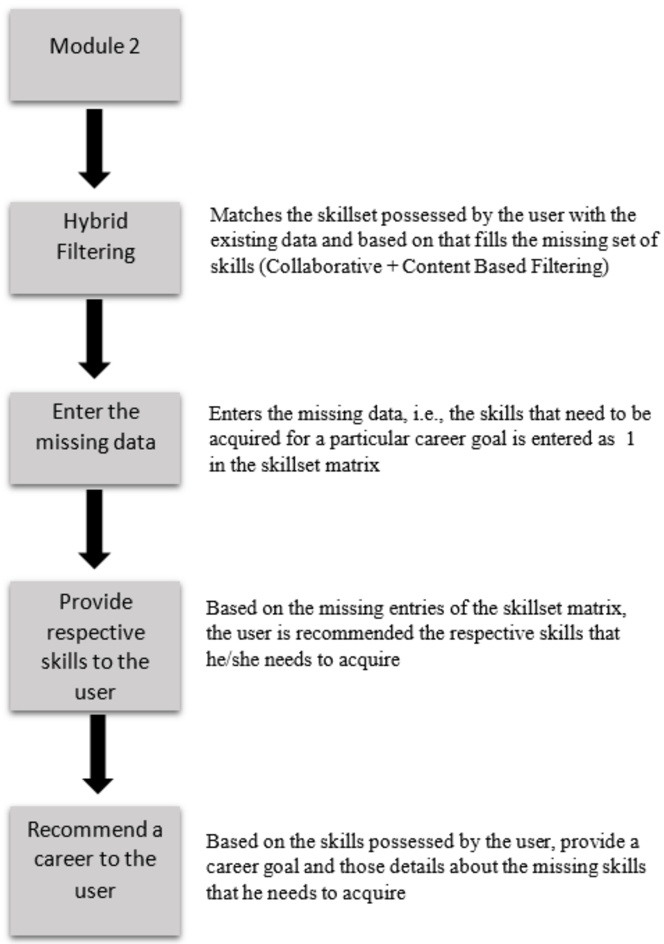

Fig. 4. Block Diagram of Module 2

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