Job Recommendation through Progression of Job Selection

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Abstract

Job recommendation has traditionally been treated as a filter-based match or as a recommendation based on the features of jobs and candidates as discrete entities. In this paper, we introduce a methodology where we leverage the progression of job selection by candidates using machine learning. Additionally, our recommendation is composed of several other sub-recommendations that contribute to at least one of a) making recommendations serendipitous for the end user b) overcoming cold-start for both candidates and jobs. One of the unique selling propositions of our methodology is the way we have used skills as embedded features and derived latent competencies from them, thereby attempting to expand the skills of candidates and jobs to achieve more coverage in the skill domain. We have deployed our model in a real-world job recommender system and have achieved the best click-through rate through a blended approach of machine-learned recommendations and other sub-recommendations. For recommending jobs through machine learning that forms a significant part of our recommendation, we achieve the best results through Bi-LSTM with attention.

1 Introduction

Job recommendation is nothing like a typical movie recommendation in principle even though it might seem to be because of their alignment to the user profile and preferences. On the contrary, job recommendation is a much higher stake recommendation. Imagine taking a lousy job and stay stuck in it for a couple of years as opposed to watching a bad movie for a couple of hours! Job recommendation is also dynamic and must adapt to the changing requirements of the end user. For instance, a person looking for a job at X location might not be interested in the location a few years down the line. Similarly, a job that is relevant for an individual now might not be exciting enough in the future because of a possible upskilling. Consequently, this puts the onus of accounting for such variables on the recommender system to always be context-aware and relevant. Jobs usually come with the criteria of suitability mentioned in job description that a candidate is supposed to satisfy. Some jobs are particular about the criteria while others are not, which might depend on attributes like company and designation. Certain features like skills and designations that have high dimensionality must be meticulously represented for algorithms to use them efficiently. Bastian et al. mentioned the importance of skills as an identifier of talent in [1]. Like jobs, candidates also have a few attributes associated which hints us to the kind of jobs they might prefer. For instance, a candidate having proficiency in HTML, JavaScript, Node.js and AWS may prefer a Full Stack Developer job but may be lacking the explicit mention of the latter in the candidate's profile. Candidates also have a professional summary that includes features like companies, job roles, and duration of work. Candidate preferences are not static, and they may change as they progress in their career. Data describing the progression of candidates through their academic and professional careers might provide hints of their next steps, and thus it can be a good indicator of their motivations and preferences.

The match between candidates and jobs involves a complex amalgamation of the attributes of candidates and jobs. The intent is to identify the patterns in the data for recommending relevant jobs to candidates. The prediction of jobs for a candidate is based on information derived from the data about candidates applying for jobs on a web portal. A rule-based recommender system might not be an ideal solution as it is bound to miss cases, especially the nuances that humans cannot comprehend.

2 Related Work

Recommender systems have been extensively applied to suggest concise items of interest to the users and drive higher click-through rates (CTR) [2]–[4]. Video sharing website YouTube and media-services provider Netflix extensively use recommender systems to suggest videos and movies to their users respectively. 60% of videos watched on YouTube, and 80% of movies watched on Netflix are due to recommendations [2], [3]. In some approaches improvements in CTR using recommender systems are also favored [5]. Since early literature, recommender systems have been broadly categorized into content-based, collaborative filtering and hybrid, based on the features utilized in model input [6]. Recommender systems are often required to solve the cold-start problem where there may be insufficient information about the user, item or their interactions [7]–[9]. Recommender systems have also been applied in the field of recommending jobs to prospective employees [8], [10]–[12]. Elsafty et al. used a document-based recommender system with dense representations and showed 8% relative increase in CTR [5]. They used Word2Vec [13] and
Doc2Vec [14] to extract semantic relationships between jobs using job title and job descriptions.

Kenthapadi et al. in their paper discussed the personalized job recommendation strategy at LinkedIn [11]. They observed that the job recommendation problem has fundamental differences with other recommender systems involving books, movies, etc. The difference is that a job posting results in a very controlled number of applications, unlike movies where thousands of users can be provided a recommendation.

RecSys have held competitions to garner the attention of researchers in this domain and work closely with partners from the industry for solving real-world recommendation challenges. Challenges around the process of job recommendation were hosted during the years 2016 and 2017 [7], [12]. In 2016, Zibriczky used a composition of 11 predictor instances as a solution to the challenge [15]. He showed that based on forward predictor selection, item-neighbor methods and interaction data have great potential in improving offline accuracy. In 2017, Volkovs et al. used a combination of content and neighbor-based models in their approach. They used user, item and user-item interaction features in Deep Neural Networks (DNN) and Gradient Boosting Machines (GBM), predicting in the output whether a user will positively interact with a job [16]. They observed that due to input sparsity and feature ranges training DNNs were slow. DNNs were also sensitive to the choice of normalization when dealing with sparsity. GBMs worked well without any input pre-processing or normalization. Volkovs et al. also solved the cold-start problem of missing user and item data through their approach [16]. Liu et al. in 2016 showed the use of temporal learning and sequence modeling which captured complexities of user-item interactions to improve job recommendations [17].

In our approach, we use sequence modeling with attention to capture nuances in the progression of job selection by the candidates. We also compose our approach using blended sub-recommendations that makes the final recommendation serendipitous and overcomes problems of cold-start in recommendations.

3 Experiments

Our approach uses a blend of machine learning models and other sub-recommendations to suggest jobs to candidates. Using machine learning models, we attempt to capture candidates’ progression of job selection. Consequently, using machine learning models might also help to capture any latent motivations of the candidates while they have interacted with jobs. Recommendations from a machine learning model produce jobs that the candidate is most likely to click or interact with. The dataset to train the model was constructed using implicit and explicit feedback present in candidate-job interactions from our database. Explicit feedback is when the candidate clicks on a job to further expand its contents or clicks on the apply button to apply to a job. Implicit feedback is when a recruiter tags a candidate to a job. We can use features from candidate and job data as the input to any machine learning model and train it to predict 1 if the candidate will interact or 0 if the candidate won’t interact with the job. We used several machine learning approaches as shown in Section 3.3 Models.

While machine learning methods attempt to capture the overall trends in data and the progression of job selection by the candidates, we found that job recommendations made only using machine learning methods are somewhat monotonous. For example, while it is common to recommend jobs requiring Programming skills to a Software Developer, this results in showing too many similar jobs. We experimented with several strategies to break the monotonicity. To capture the sentiment behind what makes a job exciting to a candidate, we needed to draw inspiration from real life scenarios. First, a candidate might ask for job recommendations from their peer group. Second, when a candidate applies for a job, it probably captures the specific interest of the candidate toward the job and similar jobs as opposed to the recruiter selecting the candidate for the job. We performed several experiments to capture the essence of these real life scenarios in our methodology and found that adding a small percentage jobs from a) jobs applied to by similar candidates and b) similar jobs applied to by the candidate in question could potentially make the recommendations serendipitous and might motivate candidates towards choosing jobs that excite them.

The techniques used in our blended approach also naturally solve the job and candidate cold-start problem. Due to the absence of progression, a new candidate may not aptly leverage the machine learning model for job recommendations, and neither can a new job be recommended by the model to any candidate. However, a new candidate when compared with other candidates on some similarity criteria can be shown jobs applied by the other candidates. Similarly, when comparing two jobs, a new job can get suggested when creating a recommendation based on similar jobs applied to by the candidate. Finally, we observed that using our blended approach increased the click-through rate (CTR) as a consequence of candidates interacting more frequently with the recommended jobs on our job web portal.

3.1 Methodology

The recommender system we developed is demonstrated in Figure 1. A candidate logs in to the Job Web Portal and their meta-data is forwarded to the Recommendation Composer Module. The Recommendation Composer Module then uses the features of the candidate to build a job filter using relaxed parameter values to extract a subset of relevant jobs. Consider a hypothetical example, if the
professional experience of the candidate is 4 years, then the filter specifies minimum experience as 3 years and maximum experience as 5 years. The Recommendation Composer Module sends the job filter to the Querying Module. The Querying Module then presents the Recommendation Composer Module with the results obtained from the databases using the job filter. The role of the Querying Module is to construct queries according to the filters provided to it, fetch the relevant records from the databases and present the output in both raw and vectorized formats. The vectorized format can be directly used as input to machine learning models or for other vectorized computations. The raw format can be used to compose human readable recommendations. The Recommendation Composer Module generates sub-recommendations that are generated by different methods. Finally, the Recommendation Composer Module composes the final recommendation of jobs for the candidate’s viewing. In order to learn the progression of job selection by candidates, we train a Bi-LSTM with attention model.

**Step 1 Creating a job filter:** Create a job filter using relaxed values in candidate features. This filter is submitted by the Recommendation Composer Module to the Querying Module that responds with a set of jobs, $J_{filtered}$. All sub-recommendation methods described in the next steps will use this reduced set of jobs, $J_{filtered}$, for computational efficiency.

**Step 2 Checking interaction data:** Check if the candidate has an interaction history. If interaction history is present, then go to Step 3. Else go to Step 5.

**Step 3 Applying machine learning model:** Fetch the job interaction history of the candidate. Using $J_{filtered}$ and the interaction history, the vectorized candidate and job features are used to predict the recommended jobs using a Bi-LSTM with attention model. An initial ranked recommendation is created using the decreasing order of created-on attribute of the job, $R_{machine learning}$.

**Step 4 Creating recommendations using non-machine learning methods - Similar Jobs:** Using $J_{reduced}$, find the set of jobs previously applied to by the candidate and select similar jobs where the cosine similarity score with other jobs is $\geq 0.70$. Sort these jobs on the decreasing order of their created-on attribute and prepare a job recommendation list $R_{non-machine learning I}$. We can see here that this step assists in solving the job cold-start problem since a new job will be picked up if it is similar to the job being compared to.

**Step 5 Creating recommendations using non-machine learning methods - Similar Candidates:** Using the candidate vector, select similar candidates where the cosine similarity score with other candidates is $\geq 0.80$. From $J_{reduced}$, fetch the jobs applied by the similar candidates, sort them on the decreasing order of their created-on attribute and prepare a job recommendation list $R_{non-machine learning II}$. We can see here that this step aids in solving the candidate cold-start problem since interaction history of the candidate is not required.

**Step 6 Blending Recommendations:** There are two ways to
compose the final recommendation in this step. a) If $R_{\text{machine learning}}$ is non-empty, add all the jobs in $R_{\text{machine learning}}$ to the final recommendation, $R_{\text{final}}$. Next, choose 2 jobs from $R_{\text{non-machine learning I}}$ and $R_{\text{non-machine learning II}}$ respectively and insert them at random positions in $R_{\text{machine learning}}$ for every 10 jobs. b) If $R_{\text{machine learning}}$ is empty, alternately add jobs from $R_{\text{non-machine learning I}}$ and $R_{\text{non-machine learning II}}$ to $R_{\text{final}}$. It is obvious that jobs that the candidate has already applied to will not be included in $R_{\text{final}}$. We have jumbled the recommendations, thereby attempting to break the monotonicity of machine learning recommendations.

**Step 7 Accounting for edge cases:** This step accounts for the edge case where the final recommendation, $R_{\text{final}}$, is empty. The probable causes could be an independent or combined effect of a) new candidates or jobs added to the system that are completely new and are distant from the threshold values we have assumed in the respective cases b) the candidate has already applied to all the recommended jobs. In this case, we compose the recommendation using overlap between the candidate and jobs using $J_{\text{reduced}}$. We use cosine similarities between the skills of the candidate and those stated by the jobs and perform some fuzzy matching of other candidate-job features like overlap of experience, industry and job-title. Also, a scheduled task periodically keeps a count if a job appeared in $J_{\text{reduced}}$ and was still not shown to the candidate. When this count exceeds the threshold (50) it inserts the respective jobs into random positions in the final recommendation thereby preventing some cases when a job could never get recommended.

### 3.2 Dataset and Feature Selection

We construct the dataset for our experiments using data from our organization’s database. The dataset contains 4208 distinct candidates and 2334 distinct jobs. The latest date of job that any candidate has applied for is from March 2019 and the earliest date of the job that any candidate has applied for is from April 2014. We select only those candidates who have interacted within this time span. The total interactions between the candidates and the jobs are 1125776. Interactions represent a) recruiter tagging a candidate for a job, b) candidate clicking on a job to further expand its contents and c) candidate clicking the apply button to start their job application process. These are all favorable or positive outcomes and we assume that collectively, the candidate has clicked on these jobs. While searching for a job a candidate may be shown jobs which the candidate may choose to ignore. These form the negative outcomes. For our machine learning models this translates into a classification problem where we try to predict a positive (1) outcome or a negative (0) outcome generated by a user for any given job. The dataset and interaction data have been summarized in Table 1 and Table 2 respectively.

| Feature type | Features |
|--------------|----------|
| Categorical  | Experience, Non-experience, Industry, Organization |
| Numerical    | Experience, Age, Seniority, Freshness, Latent Competency |
| Descriptor   | Function Name, Industry Name, Education, Skills |

Table 3: Feature Types

After spending a considerable amount of time and effort going through the features of candidates and jobs that are available in our system, we chose 10 features from each candidate and 11 features from each job and one common feature. Combining these, a total of 22 features are used that are described by a set of categorical, numerical or descriptor features shown in Table 3. The dimensionality of each feature is given in Table 4. Descriptor features have a vocabulary size of 4000 - 5000 and categorical features take up to 128 values. We have categorized the importance of each feature into high, medium and low in Table 5.1, Table 5.2 and Table 5.3, grouped by candidate, job and candidate-job features (derived feature from the computation of a feature in candidate and job each) respectively. We observe that skills and Organization ID are most predictive candidate features whereas industry name and skills are most predictive job features. Besides, the common feature, Latent Competency Group Similarity, is also quite predictive. The coverage of each feature in the dataset is shown in Table 6. We have used $c$ to denote candidate features, $j$ to denote job features and $c\cdot j$ to denote the Latent Competency Group Similarity feature respectively in Table 6. We split the data into 70%, 20% and 10% for training, testing and validating sets respectively. To represent candidate and job skills in our dataset, the word embeddings learned by the Word2Vec model is used. The dimensionality of the word vectors is 20, training algorithm is continuous Bag-of-Words,
window size is 5 and min_count is 5. A T-SNE plot of the final Word2Vec model with some sample skills is shown in Figure 3.

We observe that while skills are an important denominator for matchmaking, sometimes semantic information from skills alone might not suffice for ideal matchmaking. This is because there are several ways in which candidates and recruiters define skills and competencies. Sometimes one skill may portray a collective meaning for several constituent skills. For instance, a candidate who mentions Full Stack Developer as a skill might have latent competencies in Microservices, Web Development, Javascript, Angular, etc. Similarly, a recruiter posting a job having the skill requirements of a Web Developer may also be interested in candidates having competencies in HTML, Microservices, Javascript and so on. We assumed that using Latent Competency Group Similarity (defined in the subsequent paragraph) between a job and a candidate along with skills would assist our machine learning models to make better inferences.

| Features                  | Dimensions |
|---------------------------|------------|
| Tech/ Non-Tech (c)        | 1          |
| City ID: (c)              | 8          |
| Organization ID (c)       | 4          |
| Function Name (c)         | 4          |
| Industry Name (c)         | 4          |
| Education (c)             | 8          |
| Skills (c)                | 20         |
| Experience (c)            | 1          |
| Age (c)                   | 1          |
| Seniority (c)             | 1          |
| Tech/ Non-Tech (j)        | 1          |
| City ID: (j)              | 8          |
| Organization ID (j)       | 6          |
| Function Name (j)         | 6          |
| Industry Name (j)         | 5          |
| Education (j)             | 8          |
| Skills (j)                | 20         |
| Freshness level (j)       | 1          |
| Seniority (j)             | 1          |
| Minimum Experience (j)    | 1          |
| Maximum Experience (j)    | 1          |
| Latent Competency Group Similarity (c-j) | 1 |
| Total                     | 111        |

Table 4: Features Dimensionality

| City ID         | Low  |
|-----------------|------|
| Skills          | High |
| Experience      | Medium |
| Function Name   | Medium |
| Industry Name   | Medium |
| Seniority       | Low  |
| Organization ID | High |
| Tech/ Non-Tech  | Low  |

Table 5.1: Feature Importance – Candidates

| Job Features                          | Importance |
|---------------------------------------|------------|
| Freshness level                       | Medium     |
| Education                             | Low        |
| City ID                               | Medium     |
| Skills                                | High       |
| Function Name                         | Medium     |
| Industry Name                         | High       |
| Seniority                             | Low        |
| Maximum Experience                    | Medium     |
| Minimum Experience                    | Medium     |
| Organization ID                       | Medium     |
| Tech/ Non-Tech                        | Low        |

Table 5.2: Feature Importance – Jobs

| Candidate - Job Features              | Importance |
|---------------------------------------|------------|
| Latent Competency Group Similarity    | High       |

Table 5.3: Feature Importance – Latent Competency Group Similarity

| Feature                              | Coverage (%) |
|--------------------------------------|--------------|
| Experience (c)                       | 73           |
| Functional name (c)                  | 53           |
| Industry name (c)                    | 89           |
| OrganizationID (c)                   | 100          |
| Age (c)                              | 100          |
| Education (c)                        | 73           |
| City ID (c)                          | 18           |
| Skills (c)                           | 100          |
| Seniority (c)                        | 15           |
| Latent Competency Groups (c)         | 100          |

Table 5.4: Feature Coverage (%)
| Tech/Non-Tech (j)         | 100 |
|--------------------------|-----|
| Freshness level (j)      | 84  |
| CityID (j)               | 92  |
| Functional Name (j)      | 88  |
| Industry Name (j)        | 32  |
| Max. Experience (j)      | 97  |
| Min. Experience (j)      | 64  |
| OrganizationID (j)       | 100 |
| Education (j)            | 2   |
| Skills Required (j)      | 100 |
| Seniority level (j)      | 12  |
| Tech/Non-Tech (j)        | 100 |
| Latent Competency Group Similarity (c-j) | 100 |

Table 6: Feature Coverage

Competency groups are domain specific aggregation of skills. For example, skills such as linear regression, natural language processing, deep learning, data visualization and so on belong to the machine learning competency group. Data visualization can also belong to the competency group data science, hence a skill can appear in multiple competency groups. A recruiter can just state machine learning as a required skill for a job and a deserving candidate could express their skills using one or more keywords. We attempt to “reveal” the overlap of domains between jobs and candidates using competency groups and hence named this as latent competency groups. We gathered a team of data analysts and subject matter experts to create the latent competency groups. Everyone involved was compensated for the task. The final reviewed latent competencies included 100 groups.

We represent the skills of a candidate or a job by a vector where each dimension represents a latent competency group. For each candidate or job, first a vector $V$ of size 100 is created and initialized with 0’s. Each index in this vector represents a group. For each skill, the associated groups are identified, and 1 is added to the corresponding indices in $V$. Second, the values in $V$ are normalized between 0 and 1. Next, Latent Competency Group Similarity is computed which is the cosine similarity value of $V_c$ and $V_j$ where $V_c$ represents the candidate latent competency group vector and $V_j$ represents the job latent competency group vector.

The expansion of skills into latent competency groups using the above methodology attempts to capture latent skills that humans can infer but may remain hidden for machine learning models due to the brevity used by recruiters and candidates while mentioning skills. Figures 4.1 and 4.2 attempts to visually demonstrate using heatmaps how latent competencies get highlighted from skills, for candidates and jobs. In Figure 4.3, we superimpose Figures 4.1 and 4.2 such that common latent competency groups get highlighted. Note that unnormalized values have been used in Figures 4.1, 4.2 and 4.3 for easy viewing.
We experimented with several machine learning algorithms that included both tree-based approaches and deep neural networks. We chose Random Forests and XGBoost that are tree-based approaches and these methods performed well. However, deep neural networks, for example, ANN and Bi-LSTM with attention gave us more accurate results. We used these algorithms from the scikit-learn Python module. We used grid search with cross-validation for choosing the best hyperparameters. The hyperparameters we used for the different models are shown in Table 7.

### 4 Results

We used several machine learning algorithms to learn the progression of job selection by candidates, and the results have been summarized in Table 8. The Bi-LSTM with attention model gave us the best results. The diagram showing the components of the Bi-LSTM model is shown in Figure 5. Bi-LSTM provided superior results due to its ability to learn progression in the form of sequences and use interaction information from the past to predict future outcomes. The attention mechanism helps to mimic the visual attention mechanism of humans loosely. We deployed this model in our job web portal and manually checked some random recommendations. We found that when there were too many jobs to recommend, all of which had similar criteria, the recommendations became monotonous. It motivated us to dive deeper into the job application process of the candidates and take inspiration from real-life scenarios and attempt to make our job recommendations serendipitous for the candidate. We also needed to address the job and candidate cold-start problems. Hence, we introduced a blended approach where we used non-machine learning based techniques. We added a) jobs applied to by similar candidates and b) similar jobs applied to by the candidate, in small proportions to the recommendations from the Bi-LSTM with attention model. The complete process of constructing the blended recommendation along with the choice of similarity comparison method and threshold values have been described in Section 3.1 Methodology.

We found significant improvement in our job web portal with the blended approach and saw a relative increase of 63% in click-through rates (CTR). The results are statistically significant by chi-square test at p < .01.

| Model                        | Accuracy | Precision | Recall | F1-Score |
|------------------------------|----------|-----------|--------|----------|
|                              |          | Class 0   | Class 1| Class 0  | Class 1  | Class 0 | Class 1 |
| Random Forest                | 91.49    | 93.96     | 80.90  | 95.95    | 72.58    | 94.80   | 76.51   |
| XGBoost                      | 91.43    | 94.17     | 79.04  | 95.30    | 75.03    | 94.73   | 76.99   |
| ANN                          | 91.53    | 93.75     | 81.09  | 96.13    | 72.56    | 94.93   | 76.58   |
| Bi-LSTM with Attention       | 92.02    | 95.93     | 82.42  | 97.52    | 75.13    | 95.72   | 78.61   |
| Encoder Decoder              | 71.63    | 87.88     | 34.88  | 75.32    | 55.99    | 42.98   | 42.98   |

Table 8: Results
5 Conclusion and Future Work

This paper demonstrates a novel blended approach that leverages progression of job selection by candidates and attempts to make job recommendations serendipitous. Using blended methods, recommendations suggested to candidates are based on their interaction history with jobs, along with jobs that are a) similar to the other jobs applied by the candidate and b) applied by similar candidates. Our approach naturally solves the candidate and job cold-start problem in the absence of interaction data. We also demonstrated the use of latent competency groups which expand the job skill requirements and the candidate skills thereby attempting to reveal latent competencies and achieve more coverage in the skill domain. Using our methodology, we see a relative increase in click-through rates of candidates visiting our portal and applying for jobs.

As part of the future work, we plan to use features of similar candidates and jobs in sequence information. As of now, recommendation using similar candidates and jobs forms part of non-machine learning based recommendations and the initial results seem promising. Finally, it would be interesting to extend our methodology to other recommender systems.

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