SKILL AND JOB RECOMMENDER

Abstract:

In the last years, job recommender systems have become popular since they successfully reduce information overload by generating personalized job suggestions. Although in the literature exists a variety of techniques and strategies used as part of job recommender systems, most of them fail to recommending job vacancies that fit properly to the job seekers profiles. Thus, the contributions of this work are threefold, we: i) made publicly available a new dataset formed by a set of job seekers profiles and a set of job vacancies collected from different job search engine sites; ii) put forward the proposal of a framework for job recommendation based on professional skills of job seekers; and iii) carried out an evaluation to quantify empirically the recommendation abilities of two state-of-the-art methods, considering different configurations, within the proposed framework. We thus present a general panorama of job recommendation task aiming to facilitate research and real-world application design regarding this important issue.

Literature review:

1 **Introduction**

Nowadays, job search is a task commonly done on the Internet using job search engine sites like LinkedIn1 , Indeed2 , and others. Commonly, a job seeker has two ways to search a job using these sites: 1) doing a query based on keywords related to the job vacancy that he/she is looking for, or 2) creating and/or updating a professional profile containing data related to his/her education, professional experience, professional skills and other, and receive personalized job recommendations based on this data. Sites providing support to the former case are more popular and have a simpler structure; however, their recommendations are less accurate than those of the sites using profile data. Personalized job recommendation sites implemented a variety of types of recommender systems, such as content-based filtering, collaborative filtering, knowledge-based and hybrid approaches [AlO12]. Moreover, most

1 https://www.linkedin.com

2 https://www.indeed.com

of these job recommender systems perform their suggestions based on the full profile of job seekers as well as by considering other data sources such as social networking activities, web search history, etc.

2 **Background**

In this section, we briefly describe two methods used in our experiments: Term Frequency-Inverse Document Frequency (TF-IDF) and Word2vec. Moreover, for Word2Vec we also present two models commonly used over it: Continuous Bag-of-Words (CBOW) and Skip-gram.

3 **Proposal**

In this section, we describe our framework for job recommendation. We narrow down the scope and focus on recommendation of job vacancies for Information Technology (IT) professionals acting in the Brazilian market. The proposed framework, depicted in Fig.1, is composed by three stages: data collection, data preparation and recommendation.

4 **Experimental**

Results In this section, we present extensive empirical experiments focused on evaluating the quality of job recommendations. For these experiments, we take the case of recommending a set of job offers given a specific professional profile. Our data set is composed by 50 professional profiles from LinkedIn and 3877 job offers from Catho. Both profiles and job offers correspond to Brazilian professionals and companies from the IT field. Due to the extensive of the IT field, professional profiles can also differ a little bit among them. Table 2 shows the distribution of subfields within our sample of 50 professional profiles which reflects the greater number of developers and BI consultants.First, we use our framework to generate 10 job offer recommendations for 50 different profiles. Thus, for each evaluated technique, we obtained a total of 500 recommendations. Second, a group of 5 Resource Human professionals evaluated manually these recommendations and allocate a score ranging from 1 to 10. The more accurate or suitable the recommendation, the greater the score. In order to make the results more understandable, we standardize these scores dividing them by the maximum score. Third, once these scores are obtained, we averaged them and also calculated Precision and Minimum Effectiveness (ME).

5 **Conclusion**

In this paper, we proposed a framework for job recommendation task. This framework facilitates the understanding of job recommendation process as well as it allows the use of a variety of text processing and recommendation methods according to the preferences of the job recommender system designer. Moreover, we also contribute making publicly available a new dataset containing job seekers profiles and job vacancies. Future directions of our work will focus on performing a more exhaustive evaluation considering a greater amount of methods and data as well as a comprehensive evaluation of the impact of each professional skill of a job seeker on the received job recommendation.

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