PROJECT TITLE : SKILL AND JOB RECOMMENDER

TEAM ID: PNT2022TMID07774

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LITERATURE SURVEY

1) Dynamic User Profile-Based Job Recommender System Approach/Methodology: The basic features are extracted from the job seeker's profile. The profile might get out-dated when the user does not update it in a timely manner. Based on the behaviors of the job applicant and the previous jobs which he/she applied for, the dynamic features are extracted which is an updated version of basic features. So, the system makes a statistic at regular intervals, to generate the dynamic basic features. With the increasing number of applied jobs, the number of extracted features becomes greater. Information gain is calculated for each feature. More the information gain for a feature, the more important the feature is. The dynamic recommendation system works as follows: Initially for solving the cold-start problem, the user based collaborative filtering algorithm is applied to generate the initial recommendation jobs. After having the initial recommendations, the system provides the recommendations to the job seeker and records his behavior. The interested and uninterested jobs set is generated by analyzing the job applicant's behavior. Thus, the interested job set helps in extending and updating the user profile. Thus, the new basic features are used to calculate the similarity between the job applicant and job vacancies. So, new recommendations will be made available for the job applicant.

Pros:

Job applicants do not update their profile in a timely manner. This system aims at updating and extending the user profile dynamically based on the historical applied jobs and the behavior of job applicants.

Cons:

Besides the time and the dimensionality of features, there are other factors that affect the dynamic job recommendation system. The context formed in the peak season and the off season has an influence on the job desire of a job applicant. The drawback of this system is that it does not take these other factors into consideration.

Reference:

Dynamic User Profile-Based Job Recommender System - Wenxing Hong, SitingZheng, Huan Wang School of Information Science and Technology Xiamen University Xiamen,China. The 8th International Conference on Computer Science & Education (ICCSE 2013) April 26-28, 2013. Colombo, Sri Lanka.

2) Temporal Learning and Sequence Modeling for a Job Recommender System

Approach/Methodology:

The approach combines temporal learning with sequence modeling to capture complex user-item activity patterns to improve job recommendations. It is a timebased ranking model applied to historical observations and a hybrid matrix factorization over time reweighted interactions. Second,it exploits sequence properties in user-items activities and develops a RNN-based recommendation model.

Pros:

The Model is compared to two baseline models: randomized score (Rand) and recency-based sorting (TSort) that sorts items by the latest time they appear in the history.The model clearly outperforms both the models.

Reference:

Kuan Liu, Xing Shi, Anoop Kumar, Linhong Zhu, and Prem Natarajan. 2016. Temporal learning and sequence modeling for a job recommender system. In Proceedings of the Recommender Systems Challenge (RecSys Challenge '16). Association for Computing Machinery, New York, NY, USA, Article 7, 1–4. https://doi.org/10.1145/2987538.2987540

3) Collaborative Job Prediction based on Naive Bayes Classifier using Python Platform

Approach/Methodology:

The proposed method includes implementing a recommendation system based on the collaborative filtering technique for job portals. The system is designed to suggest the jobs to the user depending upon his profile and by calculating a similarity index using Euclidean distance of two skill sets and then ranking them according to their naïve Bayes algorithm.

Pros:

It has small computational overhead compared to Machine learning models.

Cons:

Susceptible to cold-start problem.

Reference:

Choudhary, S., Koul, S., Mishra, S., Thakur, A., & Jain, R. (2016, October). Collaborative job prediction based on Naïve Bayes Classifier using python platform. In 2016 International Conference on Computation System and Information Technology for Sustainable Solutions (CSITSS) (pp. 302-306). IEEE.

4) Combining content-based and collaborative filtering for job recommendation system: A cost-sensitive Statistical Relational Learning approach

Approach/Methodology:

Developed a hybrid content-based filtering and collaborative filtering approach. The approach adapted a successful Statistical Relational Learning algorithm for learning features and weights and is capable of handling different costs for false positives and false negatives. The hybrid recommendation system is constructed by learning the Relational Dependency Network using a state-of-the-art learning approach–Relational Functional Gradient Boosting.

Pros:

Prevents the necessity for exhaustive feature engineering or pre-clustering and provides a robust way to solve the cold-start problem.

Cons:

Markov Logic Networks with Alchemy2 fail aue to large amounts of data.

Reference:

Yang, S., Korayem, M., AlJadda, K., Grainger, T., & Natarajan, S. (2017). Combining content-based and collaborative filtering for job recommendation system: A cost-sensitive Statistical Relational Learning approach. KnowledgeBased Systems, 136, 37-45.

5) **Help Me Find a Job: A Graph-based Approach for Job Recommendation at Scale**
Approach/Methodology:

The proposed approach incorporates content-based signals to the CF-based core system (hybrid recommendation). Graph-based models adopt link analysis methods from graph theory to address the shortcomings of CF-based approaches such as sparsity and improve the quality of the recommendations. A directed graph of jobs connected by multi-edges representing various behavioral and contextual similarity signals is used.

Pros:

This approach overcomes the major challenges of sparsity and scalability. It overcomes the problem of cold start by harnessing the power of deep learning in addition to user behavior to serve hybrid recommendations.

Cons:

Many of the parameters in the system were decided heuristically and with manual evaluation. For a dynamic system, such parameters are better learned in a way to maximize user's CTR (Click-Through-Rate).

Reference:

Shalaby, W., AlAila, B., Korayem, M., Pournajaf, L., AlJadda, K., Quinn, S., & Zadrozny, W. (2017, December). Help me find a job: A graph-based approach for job recommendation at scale. In 2017 IEEE international conference on big data (big data) (pp. 1544-1553). IEEE.

6) **A Combined Representation Learning Approach for Better Job and Skill Recommendation**
Approach/Methodology:

The proposed solution is representation learning based that leverages information of three graphs in order to represent each job and skill into a shared lowdimensional vector space for solving the job recommendation task from the historical job data: (i) job transition network, (ii) job-skill network, and (iii) skill co-occurrence network. The job transitional graph shows that if a person with a similar (to current job) job has changed to a specific target job, there is a higher chance that the person with the current job also gets the same target job in future. The job skill graph and skill co-occurrence graph carry crucial information to find similarity between jobs, which helps to explore similar source and target jobs.

Pros:
The proposed embedding methodology consistently outperforms three state-of-the art methods in terms of job recommendation task, which improves HR, NDCG, and pair-wise AUC by 3.4%, 6.7%, 1.2%, respectively.

Cons:
The proposed representation learning framework is transductive, i.e., it learns representation vectors of jobs and skills that are available in the input graphs and new job titles and skills are not suggested.

Reference:
Dave, V. S., Zhang, B., Al Hasan, M., AlJadda, K., & Korayem, M. (2018, October). A combined representation learning approach for better job and skill recommendation. In Proceedings of the 27th ACM International Conference on Information and Knowledge Management (pp. 1997-2005).

7) **Job Recommendation based on Job Seeker Skills: An Empirical Study**
Approach/Methodology:
The skills are extracted from the job seeker profiles using various text processing techniques. Job recommendation is performed using TF-IDF and four different configurations of Word2Vec over a dataset of job seeker profiles and job vacancies. A group of nearest job offers based on distance to the job seeker's profile is selected (job matching). In the case of TF-IDF representation, cosine distance is used, while for word embeddings, the new Word Mover's Distance (WMD) is used. Once retrieved the top ”k” job offers for the profile, they are sorted in descending order based on the inverse of this distance (ranking).

Pros:
Personalized job recommendation is done based on the job seeker's profile. Recommendations based on other data like query based on keywords related to the job vacancy that the job seeker is looking for, etc. are less accurate than personalized job recommendations.

Cons:
TF-IDF computes document similarity directly in word-count space. It makes no use of semantic similarities between words. Word2Vec model has an inability to handle unknown or out of vocabulary words.
Reference:
Jorge Valverde-Rebaza, Ricardo Puma, Paul Bustios, Nathalia C Silva - “Job Recommendation based on Job Seeker Skills: An Empirical Study”. Conference: March 2018- First Workshop on Narrative Extraction From Text (Text2Story 2018) co-located with 40th European Conference on Information Retrieval (ECIR 2018)At: Grenoble, France.

8) **Job Recommendation through Progression of Job Selection**
Approach/Methodology:
The framework consisted of the website module, brain module and worker module.The brain composes the recommendations using a blended approach of machine learning and non-machine learning strategies. The machine learning method aims to learn the sequence of job selection by the candidates, and we train a Bidirectional Long Short Term Memory Network with Attention model (BLSTM-A). For the non-machine learning strategies, we devise 3 methods: a) Using jobs

that are similar to the recent jobs applied to by the candidate, RJsimilar, where the cosine similarity between the jobs is >= 0.72 b) Using jobs applied by similar candidates, RCsimilar, where the cosine similarity score between the candidates is >= 0.86 c) A catch-all method covering the edge cases where we use fuzzy matching of candidate-job features like overlap of industry, skills, job-title and experience.

Pros:
1) BLSTM-A surpassed the other models in terms of F1 score.
2) It overcomes the cold start problem by using fuzzy matching
3)It overcomes monotonous recommendations by using a combination of RJsimilar and RCsimilar and BLSTM-A.

Reference:
A. Nigam, A. Roy, H. Singh and H. Waila, "Job Recommendation through Progression of Job Selection," 2019 IEEE 6th International Conference on Cloud Computing and Intelligence Systems (CCIS), 2019, pp. 212-216, doi: 10.1109/CCIS48116.2019.9073723.