TERM PAPER

On

SMART TALENT RESUME RANKER

Submitted in fulfilment of the requirements for the Degree of

B.Tech in Information Technology

By

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Introduction

The project aims to rank the resumes for a particular job description to predict the best suited candidate on the basis of their resumes. The set of resumes will be loaded as the input data along with the job description and analysis on the resume to predict the best suited candidate.

The summary in this report is a collection of our analysis on the basis of the research paper that was read during the course of this project. The research papers are mainly based on the concepts of how to read data of unstructured format and from different kinds of files such as pdf and document to find the relevant details from it. We also found out how entities of unstructured data are matched from another unstructured data to get the desired outcome and further learnt about feature selection models used to get better accuracy.

The ideas and algorithms are summarized together and hence our research to get the right outcome is taken forward.

Paper - 1

Paper Title	A Job Recommendation Method Optimized by Position Descriptions and Resume Information.
Author	Peng Yi, Cheng Yang, Chen Li, Yingya Zhang
Publisher	IEEE
Year	2016
Summary	Job recommendation algorithms which utilize recommendation methods to filter positions that do not meet the requirements and recommend the proper positions for job hunters play an important role in the recruitment websites. Based on the analysis of real recruitment data and the comparison of the existing recommendation methods, item based collaborative filtering algorithm has been used as the basic algorithm for a job recommendation. This paper produced an optimization algorithm to improve the accuracy of job recommendations. Historical delivery weight calculated by position descriptions and similar user weight calculated by resume information were added as two influencing factors in the preference prediction. The experiments tested on real recruitment data have shown that the optimization algorithm has greatly improved the final recommendation result. The F1-score of the optimized algorithm produced 9.6% better results than the basic algorithm.

TABLE IV. F1-MEASURE RESULTS

N	Basic Algorithm	Optimized Algorithm
1	41.21%	45.16%(+9.6%)
2	35.20%	38.75%(+10.%)
3	35.04%	38.25%(+9.2%)
4	34.57%	38.03%(+10.0%)
5	30.51%	32.18%(+5.5%)
6	28.57%	30.17%(+5.6%)

Paper - 2

Paper Title	A Job Post and Resume Classification System (JRC) for Online Recruitment
Author	Abeer Zaroor, Mohammed Maree, Muath Sabha
Publisher	International Conference on Tools with Artificial Intelligence, IEEE
Year	2017
Summary	The system exploits an integrated knowledge base for carrying out the classification task. Unlike conventional systems that attempt to search globally in the entire space of resumes and job posts, JRC matches resumes that only fall under their relevant occupational categories. The exploited knowledge base assists in (i) classifying resumes and job offers under their corresponding occupational categories and (ii) automatically ranking applicants that best match the announced offers. 1) Skill-Based Resume Classification Module: In this module, each skill in the skills set is submitted to the exploited knowledge base sequentially in order to obtain a list of candidate occupational categories. As a result, a list of weighted occupational categories is obtained and sorted by the highest weight (as one skill may return zero, one, or more than one occupational category) 2) Job Post Classification Module: In the Job Post Classification module, we use both the job title and the required skills from the structured job post for classification purposes.

TABLE VII. COMPARATIVE EVALUATION – JRC VS. OTHER APPROACHES

Job title	Resume index	Manual score	Tf-idf Auto score	MatchingSem Auto score	JRC Auto score
Back-end web developer	CV1	**0.38**	0.16	0.30	**0.45**
	CV2	**0.26**	0.19	0.19	**0.19**
	CV3	**1.0**	0.56	0.70	**1.0**
Java developer	CV4	**0.61**	0.35	0.50	**0.65**
	CV5	**0.46**	0.35	0.40	**0.46**
	CV6	**0.53**	0.21	0.35	**0.54**
Animator or Designer	CV7	**0.35**	0.20	0.20	**0.35**
	CV8	**0.70**	0.61	0.70	**0.75**
	CV9	**0.20**	0.20	0.25	**0.25**

Paper - 3

Paper Title	Best Fit Resume Predictor
Author	Sujit Amin, Nikita Jayakar, M. Kiruthika, Ambarish Gurjar
Publisher	International Research Journal of Engineering and Technology (IRJET)
Year	2019
Summary	This paper focuses on the solution developed in the form of a web application to predict the best fit resumes against a given job description posted by a job recruiter. In this prototype, the web application can intelligently predict which resumes are better fit against the given job listing based on key factors of any candidate. These key factors include, but not limited to, education, number of years of experience and skills. This solution was developed on the purpose of significantly reducing the workload of the recruiters of any company who otherwise experience the pain of manually going through the details of each and every candidate's resume from the given pool of prospective candidates. The output of this will be visible only to the recruiter in the form of a rank list of all the candidates based on the overall resume scores assigned to each and every applicant on the basis of their education, work experience etc. The NLP framework used for the web application for data extraction was the SpaCy English model. The datasets used for dependency parsing on every candidate's resume were in the CSV format. The database which was used to store information of the job applicants including their resumes was MySQL. The accuracy achieved for the NLP model for this web application was around 67%.

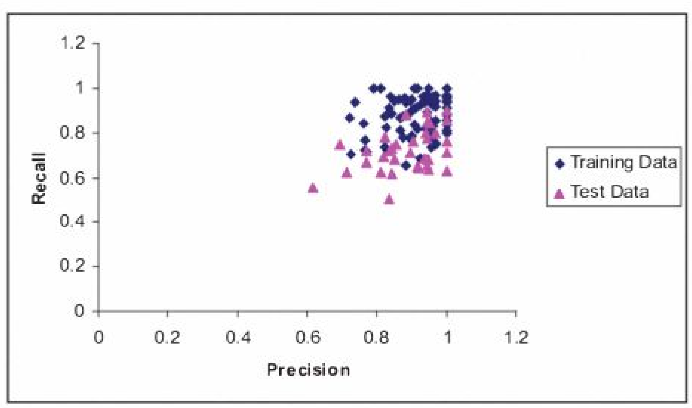
Paper - 4

Paper Title	Towards an Information Extraction System based on Ontology to Match Resumes and Jobs
Author	Duygu Çelik, Aşkın Karakaş, Gülşen Bal, Cem Gültunca, Atilla Elçi, Başak Buluz, Murat Can Alevli
Publisher	IEEE 37th Annual Computer Software and Applications Conference Workshops
Year	2013
Summary	In this mentioned project, the system enables a free structured format of resumes to transform them into an ontological structure model. The produced system based on an ontological structure model and called Ontology based Resume Parser (ORP) is tested on a number of Turkish and English resumes. The proposed system is kept in a Semantic Web approach that provides companies to find job seekers in an efficient way. The system parses information from a resume such as general information, personal information, education information, work experience, qualifications, projects, certificates, references, other information etc and analyzes its data and infers new concepts from the written ontological rules with existing data. The system makes inference with the predefined semantic rules based on the resume knowledge that makes it differ substantially from other studies.

Paper - 5

Paper Title	Web Application for Screening Resume
Author	Sujit Amin, Nikita Jayakar, Sonia Sunny, Pheba Babu, M.Kiruthika, Ambarish Gurjar
Publisher	IEEE, International Conference on Nascent Technologies in Engineering
Year	2019
Summary	This paper focuses on a web application for screening Resumes of various candidates. The recruiters from various companies can post the details of the job openings available in their respective companies. The interactive web application allows the job applicants to submit their resume and apply for the job postings they may still be interested in. The resumes submitted by the candidates are then compared with the job profile requirement posted by the company recruiter by using techniques like machine learning and Natural Language Processing (NLP). Scores can then be given to the resumes and they can be ranked from highest match to lowest match. This ranking is made visible only to the company recruiter who is interested to select the best candidates from a large pool of candidates. The scores as well as the rank list will only be visible to the recruiter and not to the candidates. The recruiter can then make an informed decision on when to select for the next round of the hiring process. The job description text file is retrieved from the database. After that, the relevant entities of the candidate resume text file as well as the job description text file are then compared and a score is assigned to the candidate.

Paper - 6

Paper Title	Automatic Extraction of Usable Information from Unstructured Resumes to Aid Search
Author	Sunil Kumar Kopparapu
Publisher	IEEE
Year	2010
Summary	This paper describes a system for automated resume information extraction to support rapid resume search and management. The system is capable of extracting several important informative fields from a free format resume using a set of natural language processing (NLP) techniques. A working system is described, for automatic resume management. The system is capable of extracting six major fields of information. Experimental results carried out on a large number of resumes show that the proposed system can handle a large variety of resumes in different document formats with a precision of 91% and a recall of 88%.  *Figure 5 Precision and recall plot for train dataset (♦) and test datasets (▲).*

Paper - 7

<table>
<tr><td>Paper Title</td><td>A Machine Learning approach for automation of Resume Recommendation System</td></tr>
<tr><td>Author</td><td>Pradeep Kumar Roy, Sarabjeet Singh Chowdhary, Rocky Bhatia</td></tr>
<tr><td>Publisher</td><td>International Conference on Computational Intelligence and Data Science, Elsevier</td></tr>
<tr><td>Year</td><td>2019</td></tr>
<tr><td>Summary</td><td>The System produced in this paper, works with a large number of resumes first for classifying the right categories, then as per the job description top candidates would be ranked using Content-based recommendation using cosine similarity and KNN to identify the CV’s that are nearest to the provided job description. The classification was done using four different models and their accuracy score was recorded. 1) Random Forest 2) Multinomial Naive Bayes 3) Logistic Regression 4) Linear SVC

Results using the different classifiers
<table>
<tr><th>Classifier</th><th>Accuracy</th></tr>
<tr><td>Random Forest</td><td>0.3899</td></tr>
<tr><td>Multinomial Naive Bayes</td><td>0.4439</td></tr>
<tr><td>Logistic Regression</td><td>0.6240</td></tr>
<tr><td>Linear Support Vector Machine Classifier</td><td>0.7853</td></tr>
</table>

The confusion matrix for the prediction done through Linear SVC is given below :</td></tr>
</table>

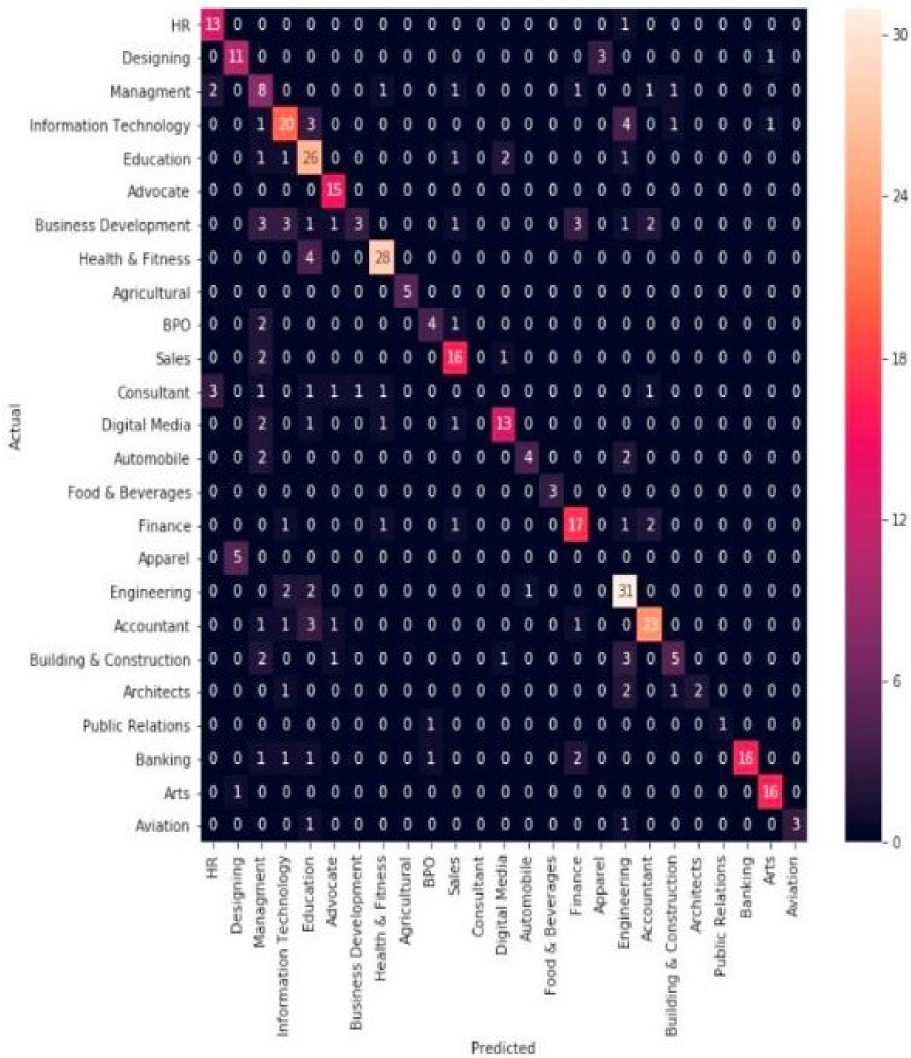


Fig. 4. Confusion matrix using Linear SVC classifier

Paper - 8

<table>
<tr><td>Paper Title</td><td>An Automatic Online Recruitment System based on Exploiting Multiple Semantic Resources and Concept-relatedness Measures</td></tr>
<tr><td>Author</td><td>Aseel B. Kmail, Mohammed Maree, Mohammed Belkhatir, Saadat M. Alhashmi</td></tr>
<tr><td>Publisher</td><td>IEEE 27th International Conference on Tools with Artificial Intelligence</td></tr>
<tr><td>Year</td><td>2015</td></tr>
<tr><td>Summary</td><td>This paper focuses on an automatic online recruitment system that employs multiple semantic resources to highlight the semantic contents of resumes and job posts. Additionally, it utilizes statistical concept-relatedness measures to further enrich the highlighted contents with relevant concepts that were not initially recognized by the used semantic resources. The system has been instantiated and validated in a precision-recall based empirical framework. The semantics-based system used is EXPERT which constructs ontology documents that describe both job posts and resumes based on the concept linking approach, and then ontology documents of job posts are mapped to ontology documents of resumes. The comparison of the system is given below :

TABLE VI. PRECISION/ RECALL RESULTS

<table>
<tr><th>System / Indicator</th><th>Our system</th><th>EXPERT</th></tr>
<tr><td>P</td><td>0.91</td><td>0.89</td></tr>
<tr><td>R</td><td>0.88</td><td>0.93</td></tr>
<tr><td>F-measure</td><td>0.89</td><td>0.87</td></tr>
</table>

They have assigned different weights for optional and obligatory requirements, and then used these weights in computing the relevance scores between job posts and resumes.</td></tr>
</table>

Paper - 9

Paper Title	Smart Talents Recruiter – Resume Ranking and Recommendation System
Author	Ashif Mohamed, Wickram Bagawathinathan, Usama Iqbal
Publisher	IEEE
Year	2018
Summary	Smart Applicant Ranker is a candidate recommendation tool designed to supervise recruiters while they input their job requirements into the system. This system is designed using Ontology where they compare the resume models with the given job requirements to match the best comparable candidates. Two ranking algorithms are underlined in this system which will be invoked to assign a ranking point to the recommended candidates against the other candidates on the recommendation pool. This system will be kept in a Semantic Web approach that provides IT recruitment firms to seek experts in an efficient way. The ontology based web application is implemented using J2EE technologies running with Apache Tomcat server. In order to handle the business logics and the client calls to the server, Model View Controller pattern is used while MySQL database with JDBC interface is used to process simple user manipulations. For creating and manipulating Ontologies, OWL API is used via Apache Jena. The mode works has 3 main modules: A) Information Extraction B) Candidate search C) Candidate Ranking Algorithms. The similarity of skills is matched by the given formula : $\text{SimSkill}(J_i, R) = \begin{cases} 1, & J_i \in R \\ \max(\text{Skill}(J_i, R)), & J_i \notin R \end{cases}$ The performance of the candidate ranking module of the

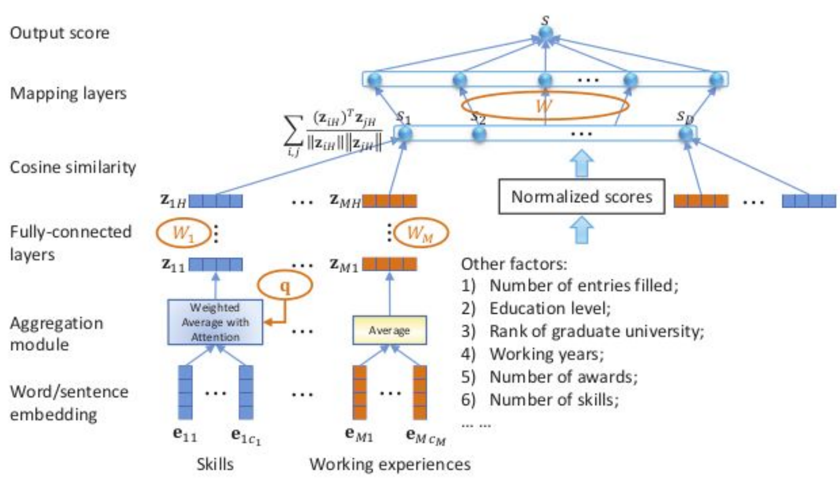
system is evaluated by the number of correctly ranked resumes with regard to the total number of resumes used for testing. In order to find out whether a resume is ranked correctly or not, the ranking assigned by the system is compared with the manual ranking given for that particular resume. If the ranking difference is not more than five, either positive or negative, the ranking given by the system is considered as correct

Table 2: Resume matching compatibility results

Resume No	Algorithm I	Algorithm II			Relative Score (RS)	SAR Ranking	Manual Ranking
		SWE	*SK*	*(SWE+SK)÷2*			
Resume 1	0.245	0.375	0.33	0.3525	0.29875	6	6
Resume 2	0.319	0.25	0.20	0.225	0.272	7	7
Resume 3	0.690	0.875	1.00	0.9375	0.81375	1	1
Resume 4	0.750	0.375	0.50	0.4375	0.59375	5	4
Resume 5	0.293	0.125	0.00	0.0625	0.17775	8	8
Resume 6	0.634	0.625	0.50	0.5625	0.59825	4	5
Resume 7	0.746	0.75	0.90	0.825	0.7855	2	2
Resume 8	0.789	0.75	0.66	0.705	0.747	3	3
Resume 9	0.165	0.125	0.14	0.1325	0.14875	9	9
Resume 10	0.075	0.25	0.00	0.125	0.1	10	10

The results show that the system is useful in real-world online recruitment and ranking of candidate resumes, and has a better recommendation precision and efficiency than current existing systems.

Paper - 10

Paper Title	A Learning-based Framework for Automatic Resume Quality Assessment (RQA)
Author	Yong Luo, Huaizheng Zhang, Yongjie Wang, Yonggang Wen, Xinwen Zhang
Publisher	IEEE, International Conference on Data Mining
Year	2018
Summary	This paper throws light on the fact that from the talent perspective, many recruiters may want to know whether a resume is good enough or not. Therefore, the tool was developed to assess the quality of each resume automatically. Although there exist some resume quality assessment (RQA) websites (e.g., http://rezscore.com/), their underlying assessment schemes or algorithms are unknown and there is no public dataset for model training and evaluation. To tackle these issues, the authors had built a dataset and developed a general model for the same. The diagram of the system is given below :  From the system designed, following conclusions can be drawn that : 1) Learning adaptive weights using the attention scheme to

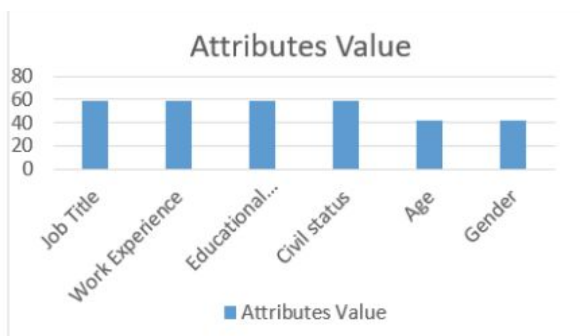
aggregate multiple embeddings is superior to the simple average in general.

2) Either using the designed pair/triplet-based loss or adding a regularization term to utilize unlabeled data can improve the performance, it seems that the model based on triplet loss achieves the best performance overall.

TABLE I
A COMPARISON OF OUR MODELS WITH THE OTHER APPROACH IN TERMS OF F1-MEASURE.

Methods	F1-measure
L2	0.459±0.022
Contrastive	0.500±0.054
Triplet	0.541±0.051
MR	0.492±0.109
Rezscore	0.341

Paper - 11

Paper Title	Feature Selection for Job Matching Application using Profile Matching Model
Author	Leah G. Rodriguez, Enrico P. Chavez
Publisher	IEEE, 4th International Conference on Computer and Communication Systems
Year	2019
Summary	This paper aims to extract the relevant information from resumes and analyze it based on the different attributes. With the identification of the attributes, the proposed system is directed to adopt a clustering algorithm to match the profile of the job seekers against the requirements of the job posted by the prospect employers. Computing similarity scores between two profiles was the important task. For the similarity score, the values of common attributes in both profiles are extracted and their similarity scores are then computed and compared. Then, the obtained similarity scores are tuned in order to have more realistic scores that take into consideration the importance assigned to each attribute. By doing so, the new similarity value will tend to increase or decrease depending on the importance of each attribute. This tuning is an attribute based operation that outputs a new similarity score to each attribute by applying a weight to the computed similarity scores. The below graph shows the ranking of the attributes :  Figure 2. Ranking of identified attributes for profile matching.

Paper - 12

Paper Title	A Research of Job Recommendation System Based on Collaborative Filtering
Author	Yingya Zhang, Cheng Yang, Zhixiang Niu
Publisher	IEEE, 7th International Symposium on Computational Intelligence and Design
Year	2014
Summary	This paper contrasts between user-based and item-based collaborative filtering algorithms to choose a better performed one. They take background information including students' resumes and details of recruiting information into consideration, bring weights of co-apply users (the users who had applied the candidate jobs) and weights of student used-liked jobs into the recommendation algorithm. It also takes into consideration four Methods of Similarity Calculation (i) Cosine Similarity (ii) Tanimoto Coefficient (iii) Log Likelihood (iv) The City Block Distance. The accuracy for both the filtering methods is given as follows:

TABLE I. PRECISION AND RECALL OF DIFFERENT RECOMMEDERS

Recommender(r_num=3)	Similarity	Precision	Recall
User-Based CF (n=10)	Log likelihood	62.82%	53.85%
	City Block	83.33%	56.41%
	Tanimoto	65.38%	53.85%
Item-Based CF	Log likelihood	58.33%	58.33%
	City Block	0.00%	0.00%
	Tanimoto	41.67%	41.67%

Paper - 13

Paper Title	Dynamic User Profile-Based Job Recommender System
Author	Wenxing Hong, Siting Zheng, Huan Wang
Publisher	IEEE. 8th International Conference on Computer Science & Education
Year	2013
Summary	This paper challenges the traditional job applicant system that takes the personal information and job intention of an applicant, and uses it to generate the recommendation result by employing the recommendation algorithms. It stated the shortcomings such as, the personal information and job intention may not be true because of the job applicant's cognitive deviation. Further, the job applicant does not update his/her personal information in general after entering the information on the recruiting website for the first time. Considering these situations they employed the dynamic recommendation in a job recommender system. It uses a threefold method : • Based on the basic features of jobs applied by an applicant which indicate his/her preference, the basic features of this applicant are updated automatically and at regular intervals. • From the perspective of dimensionality, they used the extracted feature for feature selection to extend the number of features. Along with the increasing number of applied jobs, the number of extended features will become greater and they will change. • According to the characteristics of dynamic user profiles, they used a hybrid recommendation algorithm, i.e. user based collaborative filtering algorithm, for improving the accuracy and effectiveness of the recommendation results.

Paper - 14

<table>
<tr><td>Paper Title</td><td>Quantifying Skill Relevance to Job Titles</td></tr>
<tr><td>Author</td><td>Wenjun Zhou, Yun Zhu, Faizan Javed, Mahmudur Rahman, Janani Balaji, Matt McNair</td></tr>
<tr><td>Publisher</td><td>IEEE, International Conference on Big Data</td></tr>
<tr><td>Year</td><td>2016</td></tr>
<tr><td>Summary</td><td>In this study, the goal was to profile job titles by effectively quantifying the relevance of skills. It started with using a naive, frequency-based skill ranking approach, which resulted in the most generic skills ranked on the top and hence they adopted a number of alternative metrics and compared their performances on a number of job titles. They adapted information theoretic metrics and measurements of variation to assess the (un)certainty of a skill to a title, to adjust for the frequency of very commonly required skills. The basic idea was to leverage the dispersion of a skill term across different job titles. The intuition was the more titles that require a skill (i.e., the skill is “dispersed”), the less unique the skill is to any title. On the contrary, if a skill was required by just a few titles, it was quite unique to those titles.
Gathering expert ranking was also very crucial for example :
EXAMPLE SKILLS FOR TWO NURSING RELATED TITLES
<table>
<tr><th></th><th>Registered Nurse</th><th>Certified Nursing Assistant (CNA)</th></tr>
<tr><td>Essential</td><td>• Health Care
• Nursing
• Registered Nurse</td><td>• Health Care
• Nursing
• Nursing Assistance
• Certified Nursing Assistant</td></tr>
<tr><td>Important</td><td>• Hospitalization
• Basic Life Support
• Advanced Cardiovascular Life Support (ACLS)
• Intensive Care Unit</td><td>• Hospitalization
• Basic Life Support
• Blood Pressure
• Bed-Making
• Assisted Living</td></tr>
</table>
The compared results are as follows :</td></tr>
</table>

METHODS IMPLEMENTED AND OVERALL PERFORMANCE (ACROSS ALL TITLES)

ID	Method	Importance	Uniq.(global)	Uniq. (local)	P@K	MAP	NDCG	Norm. Avg.	Ranking
M1	TF_ONLY	TF_{raw}	(None)	(None)	0.7000	0.6153	0.8111	0.7896	20
M2	TF_RAW_IDF_RAW	TF_{raw}	IDF_{raw}	(None)	0.8063	0.7608	0.8371	0.9523	5
M3	TF_RAW_IDF_MAX	TF_{raw}	IDF_{max}	(None)	0.8094	0.7514	0.8611	0.9658	3
M4	TF_LOG_IDF_RAW	TF_{log}	IDF_{raw}	(None)	0.6656	0.5899	0.6908	0.6713	22
M5	TF_LOG_IDF_MAX	TF_{log}	IDF_{max}	(None)	0.6781	0.6033	0.7003	0.6928	21
M6	TF_RAW_ENTROPY_global	TF_{raw}	Entropy	(None)	0.7500	0.6705	0.8342	0.8664	12
M7	TF_RAW_ENTROPY_ENTROPY	TF_{raw}	Entropy	Entropy	0.7500	0.6675	0.8370	0.8668	11
M8	TF_RAW_ENTROPY_G	TF_{raw}	Entropy	G	0.7313	0.6495	0.8290	0.8399	14
M9	TF_LOG_ENTROPY_global	TF_{log}	Entropy	(None)	0.8063	0.7129	0.7873	0.8918	8
M10	TF_LOG_ENTROPY_ENTROPY	TF_{log}	Entropy	Entropy	0.8063	0.7454	0.8577	0.9582	4
M11	TF_LOG_ENTROPY_G	TF_{log}	Entropy	G	0.7375	0.6581	0.8247	0.8454	13
M12	TF_RAW_DP_global	TF_{raw}	DP	(None)	0.7375	0.6557	0.7819	0.8145	18
M13	TF_RAW_DP_DP	TF_{raw}	DP	DP	0.7688	0.6893	0.8283	0.8842	9
M14	TF_RAW_DP_G	TF_{raw}	DP	G	0.7688	0.6891	0.8173	0.8765	10
M15	TF_LOG_DP_global	TF_{log}	DP	(None)	0.2969	0.1690	0.3807	0.0000	23
M16	TF_LOG_DP_DP	TF_{log}	DP	DP	0.8375	0.7810	0.8622	1.0000	1
M17	TF_LOG_DP_G	TF_{log}	DP	G	0.8188	0.7577	0.8136	0.9421	7
M18	TF_RAW_VAR_global	TF_{raw}	VAR	(None)	0.7219	0.6431	0.8190	0.8237	16
M19	TF_RAW_VAR_VAR	TF_{raw}	VAR	VAR	0.7219	0.6418	0.8189	0.8229	17
M20	TF_RAW_VAR_G	TF_{raw}	VAR	G	0.7156	0.6322	0.8145	0.8108	19
M21	TF_LOG_VAR_global	TF_{log}	VAR	(None)	0.8219	0.7743	0.8612	0.9860	2
M22	TF_LOG_VAR_VAR	TF_{log}	VAR	VAR	0.8000	0.7383	0.8552	0.9488	6
M23	TF_LOG_VAR_G	TF_{log}	VAR	G	0.7313	0.6507	0.8187	0.8334	15

While the TF-IDF measure only considers the skill-title relationship like document-term relations, they have further considered the variation within a given job title, where the variation among job ads were considered. By collecting and comparing with expert ranked skills for a random set of job titles, our experiments showed that the (un)certainty measures did help improve skill rankings, especially when they used the DP for both global and local uniqueness measures. They also found that the performance of all such measure vary greatly among different titles, and deduplicating similar ads before computing relevance scores has consistently helped improve the performance.

Paper - 15

Paper Title	Skills and the graduate recruitment process: Evidence from two discrete choice experiments
Author	Martin Humburg, Rolf van der Velden
Publisher	Elsevier
Year	2015
Summary	In this study the authors elicit employers' preferences for a variety of CV attributes and types of skills when recruiting university graduates. Using two discrete choice experiments, they simulate the two common steps of the graduate recruitment process: (1) the selection of suitable candidates for job interviews based on CVs, and (2) the hiring of graduates based on observed skills. In line with the preferences in the first step, employers' actual hiring decision is mostly influenced by graduates' level of professional expertise and interpersonal skills. Other types of skills also play a role in the hiring decision but are less important, and can therefore not easily compensate for a lack of occupation specific human capital and interpersonal skills. From the results they concluded that there was a large impact of interpersonal skills on graduates' chances to get hired is in line with earlier studies emphasizing the increasing importance of communication in today's work-life in general, and especially for team productivity. Other types of skills and attributes also play a role in the recruitment process but are less important and can therefore not easily compensate for a lack of more specific human capital and interpersonal skills. The large standard deviations of the estimated mean coefficients imply that there is not one graduate profile which all employers prefer. Rather, employers' demand for skills varies substantially. Some employers may not want to recruit

the graduates with the highest skill levels because the job does not require them and they fear that graduates will get bored too quickly. Other employers, and the in-depth interviews confirm this, may not have a strong preference for graduates with high professional expertise because they have the internal training facilities to teach them the occupation specific knowledge they need. The same employers may therefore put more emphasis on other, more transversal types of skills such as general academic skills because they are an important ingredient for further professional growth.

Employers' willingness to pay for skills.

	MeanWTP	SD
Professional expertise		
High	14.9%	28.5%
Average	Ref.	
Low	−35.9%	38.2%
General academic skills		
High	9.0%	19.3%
Average	Ref.	
Low	−26.5%	33.5%
Innovative/creative skills		
High	11.5%	19.4%
Average	Ref.	
Low	−30.7%	34.6%
Strategic/organizational skills		
High	11.1%	20.4%
Average	Ref.	
Low	−25.8%	25.3%
Interpersonal skills		
High	12.4%	24.8%
Average	Ref.	
Low	−39.1%	39.7%
Commercial/entrepreneurial skills		
High	7.3%	33.4%
Average	Ref.	
Low	−32.8%	32.5%

Summarization

From the above research papers, here’s an excerpt :

SNo.	Paper	Algorithm/Model	Challenges	Drawbacks
1	Paper - 1	Item-based, user-based recommendation system User-similarity, major similarity	Due to the limited data, it is difficult to calculate the similarity of major just by the name of major	It is a static based algorithm.
2.	Paper - 2	NLP after parsing the resumes to read the skills and experience (N-gram and Tokenization). Tf-Idf for skill set matching.	Finding and hiring the right talent from a wide and heterogeneous range of candidates remains one of the most important and challenging tasks.	The main drawback of this approach is the huge run time complexity of the matching process. Also a large fraction of the produced results suffer from low precision since the information extraction process passes through two loosely coupled stages,
3	Paper - 3	Cosine Similarity for matching the profile with resumes. NLP for data extraction. Regex matching to extract name, email and contact information.	This resume is raw and unstructured data and it is a challenge to extract relevant important data.	There were issues while calculating the number of years of relevant experience for any prospective job candidate.
4	Paper - 4	N-Gram Algorithm which creates different	Using different classes to store the information of the	Wrong/incomplete information might be

		combinations of words Jaro-Winkler Algorithm to eliminate misspelling errors Regex to check mail addresses or mobile, dates etc. Knowledge Based Expert System	candidates.	provided to the system.
5	Paper - 5	NLP for data extraction. Spacy Pipeline for scoring the candidate resume.	To reduce the time complexity of comparing and matching the candidate's profile and job posted.	It converts the input data first into JSON format to be passed to the NLP pipeline for matching.
6	Paper - 6	A mix of NLP techniques and heuristics were used to build information extraction modules to aid extraction of useful information from resumes. The knowledge base was created using reference resumes and the system was tested on a large number of resumes which was not part of the reference resumes.	Automatic extraction of information from resumes with high precision and recall is not an easy task essentially because of the non-standardization of resume structure. In spite of constituting a restricted domain, resumes can be written in multitude of formats (e.g. structured tables or plain texts) and in different file types (e.g txt, .pdf, .doc(x) etc.)	Extracting some information using only HR-XML
7	Paper - 7	It uses Content-based collaborative recommendation using cosine similarity and KNN for identifying the CV's closest to the job profile.	Different structure and format of every CV. Mapping the CV to the right job description	i) Model takes CVs in CSV format. ii) Generation of a summary using genism library might cause loss of important information due to compression of

				the text.
8	Paper - 8	Tf-idf weighting, Semantic resources, Semantic Networks, Semantic Network Enrichment	Approaches based on keyword matching ignore the semantics of the job post and resume contents; and consequently a large portion of the matching results is irrelevant. The more recent semantics-based models are influenced by the limitations of the used semantic resources, namely the incompleteness of the knowledge captured by such resources and their limited domain coverage.	Drawbacks associated with the limited domain coverage and semantic knowledge incompleteness problems
9	Paper - 9	Ontology models, Ontology Language (OWL), Natural Language Processing, Ranking Algorithm, Cosine similarity	Currently, various job portals utilize a combination of distinct algorithms so as to rank applicant profiles. The ranking policies are still inefficient, considering the way that highly impactful and conceivable factors that would describe an individual are not considered.	The incomplete analysis of the resume analysis.
10	Paper - 10	Multi-layer neural network, Cosine Similarity	Since there is no public algorithm for RQA, we submit our labeled resumes to a website (http://rezscore.com/), which can assign a grade for each resume.	Lacking a larger corpus that includes job-post information and identify more useful features for RQA
11	Paper - 11	Feature selection, Cosine Similarity,	One of the most challenging tasks of this type of job	Lack of training data set from job seekers

		Weighted Similarity for ranking.	matching was that there was a bulk of information to coordinate against and it was in free form.	and company, need to conduct tests of the clustering model to verify reliability and performance of the job matching system
12	Paper - 12	Collaborative Filtering, Cosine Similarity, Tanimoto Coefficient, Log Likelihood, The city block distance.	Collaborative Filtering approaches often suffer from three problems: cold start, scalability and sparsity.	It's a comparison between the two kinds of recommendation systems so it doesn't rank the candidates, it just compares based on the accuracy.
13	Paper - 13	User based collaborative filtering, TF-IDF, Feature selection using Information Gain	Given a job applicant, his/her user profile is updated and extended dynamically, and then a hybrid recommendation algorithm is employed to generate the results and achieve the dynamic recommendation.	The context formed in the peak season and the off season has an influence on the job desire of a job applicant.
14	Paper - 14	TF-IDF, NLP, min-max normalization	Frequency-based skill weighting resulted in the most generic skills ranked on the top, yet they were not the most relevant, we first considered TF-IDF adjustments	Weighted versions of the metrics needs to be considered
15	Paper - 15	Econometric model, Experimental Survey	Problems of unob-served heterogeneity that often hampers conclusions based on cross-sectional data	Hypothetical bias – the divergence of stated and revealed preferences – cannot be entirely excluded.

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