An Integrated System for Occupational Category Classification based on Resume and Job Matching

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Abstract: Resume plays an important role in the recruitment process; it decides the candidate's first impression on the recruiter. However, according to recent studies, resume analysis is still a time-consuming task. The primary focus of the model proposed – Smart Resume Selector (SRS) in this paper is to automatically choose the right candidate for a job profile which reduces the efforts, time, and extra cost spent. The SRS model proposed in this paper first segments a resume to extract vital information. The resume is then converted into tokens which are compared with the defined array of information and skill set as per the company's requirement. An overall score is calculated for each resume and its area of expertise out of the basic 5 occupational categories. After performing the tests on over 200 resumes collected from datasets from Indeed, LinkedIn, AngelList and other datasets available online and comparing the desired output with the experimental output, an accuracy of 83.5% was achieved in the general category resumes and 89% in a specific category type. These findings will help to shortlist the candidate initially based on their resume for further process. It will automate the process of resume screening making it easy and time-efficient.

1. Introduction

In today's fast-paced world, the recruitment procedure remains one of the strenuous challenges that any organization faces. The number of people seeking jobs is rapidly increasing. It is a very challenging task for the recruiters to select the right candidate, but with the help of resumes half of the process is done. But manually shortlisting the resumes is a cumbersome task.

Job is an important phase of a person's life as it brings out the true personality and tests you in pressure handling situations. So, finding a correct job that suits your fields of interest can sometimes become difficult. It is often seen that the correct person is not placed for the position and later organizations find that the selected employee does not have the required skills and qualifications which results in dissatisfaction with employees.

Screening resumes are the most time consuming and challenging part of recruiting. Also, most of the Talent Acquisition leaders say it is the hardest part of recruitment. To solve these kinds of issues some companies provide their own format for candidates' details thinking it will make the process a bit easier. But the process is still boring and less efficient. Since resumes are a form of unstructured data, it is really hard to programmatically read a resume and extract useful information from it. A significant amount of time is spent by recruiters to manually screen the resumes and select the candidates best suited for the job. For this reason, there has been an increase in the use of text recognition and extraction from documents such as PDF files and images.

The radical growth of the job market has proven that traditional methods of recruitment are becoming less useful and inefficient (Yahiaoui et al., 2006). Internet technology has rapidly changed the process of human resources management and has become an important and effective means of communication means (Kessler et al., 2009).

In 2017 (Zaroor et al., 2018) the classification of the resume was done based on an integrated knowledge base where resumes are already categorized and skill set is extracted from those resumes.

The main aim of the model proposed in this paper is to extract information and analyse it from the semi-structured text format. This will help make this time-consuming process very fast and convenient for the recruiters and help to recruit fresh talent well suited for the desired job.

1.1. Evolution of Recruitment Procedure

The recruitment process has evolved and matured over time. In earlier days a lot of human effort was required. HR teams would advertise their openings in print media, television, etc. Interested candidates would send their resumes followed by manual screening by the recruiters. In recent times hiring agencies have come into the picture, they act as a middleman between job-seeking candidates and recruiting organizations. Candidates submit their resumes along with their job preferences to the hiring agency. These hiring agencies would then forward the suitable resumes to companies based on their requirement. But in today's age of Artificial intelligence, such a cumbersome task is not required. 'Smart resume screening for intelligent hiring' will help organizations to drastically cut down the time and efforts spent on hiring procedures. The candidate's resume is used to check whether a candidate has the required skills for the job. If the person passes the criteria then he or she can be called for the next round. We have implemented a system that will segment the resume and extract the information from it and finally evaluate the extracted data to detect whether the candidate is fit for the job or not. This model will eliminate the expenditure that an organization has to bear for hiring a recruitment agency and will result in an efficient way of selecting potential candidates.

1.2. Problem Statement

The field of resume screening is becoming vast day by day. It's still a cumbersome task for the recruiters to filter out the prime resumes from a batch and it's time-consuming. There is a high demand for e-recruitment systems and even though a lot of work is done, there is still a need for betterment. In reference to the International Association of Employment Web Sites (IAEWS), there are more than 60,000 e-recruitment systems until 2017. In these systems, the main focus is on using different approaches and methods so as to solve issues related to matching, screening and classification of candidate resumes. For instance, in one of the system candidate's resumes and their job offer is automatically matched (Hong et al., 2013; Kmail et al., 2016; Kumaran and Sankar, 2013). In Other approaches, there has been an effort that will automate the process of extraction of segmented information from both resumes and job posts which can be later used for the matching and classification processes (Kessler et al., 2009; Yu et al., 2005). Even though these approaches results in high precision ratios in selecting the perfect candidates to select for a job post (Kmail et al., 2016), they are less focused on the run time complexity of the matching process i.e. every resume in the corpus will be matched with the job offer instead of selecting and matching the resumes that are only sufficient to their occupational need. The main focus should be reducing the efforts on organizing and managing resumes, and also to screen out the unnecessary candidates.

Therefore, to overcome these problems we have proposed Smart Resume Selector (SRS) in this paper that focuses on matching occupational category and job post requirements with the candidates resume which results in easy management and reducing time, efforts and extra cost spent for this process.

1.3. Motivation

Job searching is a vast process and there has been a lot of work done in this field. Whereas the process of selecting a suitable candidate for the required post is still not completely automated. This sometimes results in rejection of talented and selection of wrong candidates which leads to disappointment among colleagues. To solve this issue, the SRS model proposed in this paper overcomes these types of problems so that the process of resume selection can become more cost-saving, easy, and fast for others.

To overcome these limitations mentioned in section 1.2, we present a hybrid approach to classify candidate's resumes and the corresponding job post by introducing an integrated occupational categories knowledge base which includes default skills needed for any occupational category and further scoring the resume based on various parameters which are discussed in section 3.

We summarize our work contributions as follows:

- Automatic occupational category classification of resumes
- Section-based scoring
- NLP independent therefore can adapt to new domains
- Sorting resumes based on category and score

The remainder of this paper is organized as follows. In section 2, we introduce the previous work in the extraction and ranking of resumes. Section 3 describes an overview of the model proposed architecture and provides the details of the modules in the SRS system. Experimental validation of the effectiveness and accuracy of our proposed system is presented in section 4 and 5. In section 6, we discuss the conclusions and outline future work.

2. Related Work

There has been some great work in the field of resume analysis and job processing but still, this whole process hasn't been automated yet. There are so many techniques and approaches that have been proposed for resolving the issues of e-recruitment. Considering this, in some methods, there is an attempt to address problems related with the matching process between the job offer and available candidate resumes, while in some other cases they try to classify job posts and resumes before the start of the matching process (Fazel-Zarandi and Fox, 2009; Kessler et al., 2007; Martinez-Gil et al., 2016)

A conceptual model of Artificial Intelligent (AI) (Mahmoud et al., 2019), showcases the hiring process using the performance and social screening to predict the candidate expected performance by considering historical performances and current conditions of the employee. But it requires a lot of information about historical data including the tracking of performance, personal information collected from several sources like surveys and social media and the data can be incorrect.

Most of the previous models mainly focused on using NLP (Natural Language Processing) as the primary technology for extracting the segmented information and then analyzing it. But the problem with NLP is its domain is fixed, it can work on a range of data only. In the case of adaptive nature, it fails to show prominent results. One of the other drawbacks is that precision is low in most results.

Upon reading all these, it can be said that as there is more data available which can be used for better efficiency. The chances of better accuracy are high in comparison to traditional systems. But considering everything in all the cases, there has been a dependency on the training data to predict the classification for a given text.

Table 1 – Comparison of SRS model with other models

Features	Traditional Methods	Other Models	SRS Model
Machine learned resume-job matching.	No	Yes	Yes
Per section based scoring.	No	Yes	Yes
Reducing time, cost, and effort.	No	Yes	Yes
Exact matching between keywords extracted from job posts and candidate resumes.	Yes	No	No
Analyzing unstructured job format.	No	Yes	Yes
Section based segmentation.	Yes	Yes	Yes
Sorting resumes based on category and score.	No	No	Yes

Occupational Category based matching.	No	No	Yes
Skill set based matching.	Yes	Yes	Yes
Finding the best occupational category for a candidate.	No	No	Yes
Compatibility with large scale real-world database.	No	No	Yes

3. Smart Resume Selector (SRS) Model

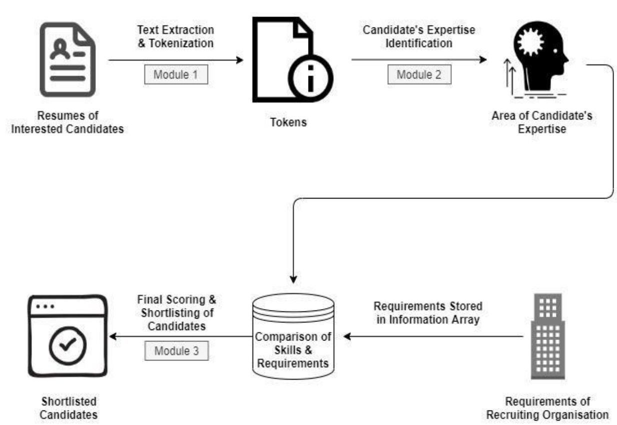

Fig. 1 - Architecture of SRS

In this section, we present an overview of the model - Smart Resume Selector (SRS) architecture and discuss its three main modules. As shown in the above Figure 1, the proposed system in this paper comprises several modules that are organized as follows. First, a text extraction based and tokenization module is used to extract a list of candidate skills, in addition to information such as email, professional experience, college name, extra co-curriculum activities, and more. After the segmentation and tokenization that has been performed in the first module, we move on to our next module which is finding out the candidate's area of expertise. This module of our proposed system takes the set of skills extracted from candidates' resumes as input and matches the same with the default arrays of basic five corresponding occupational categories which are Software, Core Engineering, Business Management, Finance, and Arts. If the recruiter wants some specific skills required from the candidate then s/he will be asked to give those skills as input under those basic occupational categories to the system in order to match that specific skill set with the candidate's skill set and not with the corresponding occupational category default arrays. This will help us to find the best occupational category for which the candidate is suitable and thus if the candidates best category does not match with the required occupational category that the job post requires then s/he won't be selected thus this sets out our first criteria in selecting or not selecting the candidate for further rounds.

Now let's overview our second criteria for selection which is defined by our third module i.e. Final score. As per our model in this paper, the final score is the summation of the candidate's best category score, professional experience, extra co-curriculum activities, the word count of the resume i.e. if the resume is either too short or too long, educational qualification, and college. Each of the sub-criteria under the final score has its own formulation, arrays, and conditions which help us to reach an effective final score that helps us to know if the candidate is good enough for the job post or not. Moreover, the recruiter can set minimum final score criteria like all candidates having a final score above 60% will be selected for the next round. More details about the calculation of the final score are discussed in section 3.1.

3.1 Methodology

SRS is broadly divided into two phases- resume information recognition and analysis. The working of the system depends on various procedures. We have categorized the whole system into various modules which are independently discussed below.

Module 1: Extracting information from the resume

This is the initial step in SRS, where we tokenize each candidate resume using the header file PDFMiner and extract information like skills, professional experience, education, college, etc. This extracted information further helps us to match the candidate skills set with the default arrays of the basic five corresponding occupational categories while the other information extracted from the candidate resume is used for the calculation of the final score.

Module 2: Best Occupational Category

Now that we have got candidate resume skill set and various section information, we will be calculating scores for each occupational category i.e. software, finance, core engineering, management, and arts score out of the default arrays of basic five corresponding occupational categories defined in SRS. It should be noted that if the recruiter doesn't provide their own defined array of skill set then the system will use the default array in the SRS system for the calculation of the best occupation category for the candidate. These five occupational category scores will help us to know the best field of expertise for the candidate and help the recruiter with the selection procedure by setting it as the first criteria for selection.

Example of default arrays of basic five corresponding occupational categories:

softwareKeyWords = ["computer", "software", "engineering","computer science","programming", "developing", "server administration", "machine learning",...]

engineeringKeyWords = ["chemical", "civil", "engineering", "mechanical", "CAD", "build", "modeling", "buildings",...]

managementKeyWords = ["data analysis", "automation", "planning", "operational development", "customer", "business", "consumer", "implement",...]

financeKeyWords = ["financial reporting", "excel", "finance", "trend analysis", "liquidy", "money", "stocks"...]

artKeyWords = ["editing", "editorial", "social work", "design", "artist", "musician", "collaborative", "blog", "journalism", "creative", "innovative",...]

Scores in each occupational category are calculated based on how many of the extracted resume skill set keywords have matched with the default array keywords.

After getting scores for each of the five categories, we will be calculating the following scores to know the candidate's area of expertise:

- **Best category score:** the following score helps us know for which of the basic five occupational category candidate resume seems best suited for i.e. the category having the highest score of all the five categories.
- **Overall score:** it analyzes how well your resume is scored across different categories using the formula

$$\textit{Overall Score} = (\textit{Software} + \textit{Engineering} + \textit{Finance} + \textit{Management} + \textit{Arts} - \min(\textit{Software}, \textit{Engineering}, \textit{Finance}, \textit{Management}, \textit{Arts}))\ /\ 4 \quad (1)$$

The above formula defined in SRS does nothing but calculates the average of the best 4 categories in which the resume has scored.

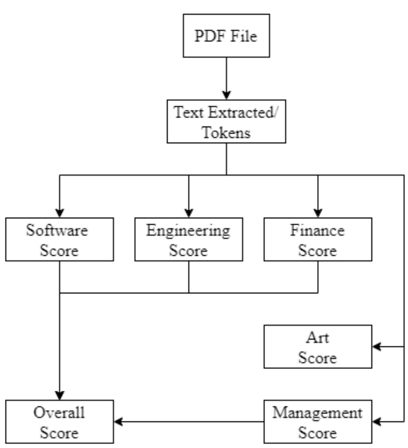

Fig. 2 – Calculation of Overall Score

Module 3: Section based segmentation

Now, we'll be calculating various section scores which will help us to calculate an efficient final score or by which any resume can stand out. All these conditions are discussed as follows:

- **Programming Score:** It is another default array that consists of all types of programming skills and the reason that it is not under occupational categories is that any kind of programming language is necessary for any type of occupational category be it finance, arts, or software.

  The default array for programming skills is defined as follows:

  programming = ["assembly", "marg", " c " "c++", "tableau", "html", "css", "excel", "latex", "unity", "python",...]

  It is also calculated on the basis of how many of the extracted resume skill set keywords have matched with the default array programming keywords.

- **College Score:** Graduating from a good tier college adds value to your resume as you study that university coursework for the duration of the degree and having updated coursework matters a lot which is further decided by the university only thus we decide to consider degree and college name as a deciding factor in SRS final score calculation too. We decide to calculate college scores on the basis of how high your school/college is ranked among the top 200 college names in SRS system default college array. Lower your global college rank, higher your college score will be.

- **Word Count Score:** One page or two pages? One of the surprisingly active sources of debate among candidates when it comes to résumé-writing. Some think having a longer resume will lead to higher chances of being called for the interview while some try to keep it short and crisp and highlighting skills that can benefit the company.

TalentWorks recently conducted a survey from 6,000+ job applications (across 66 industries) and concluded that the chances of landing an interview tend to dip once the résumé exceeds 600 words. And on analyzing these resumes from the Dice resume database lead us to a conclusion that on an average word-count was 475 words for the selected job applicants.

Keeping this in mind, we hence decided to keep word count too as a deciding factor in SRS system as this shows how efficiently a candidate can express and describe their skills, experience, achievements within the word limits, and still be suitable for the job post.

In SRS system, we have calculated word count score with the help of below formula:

$$\textit{Score} = 10(\textit{default score for all resumes})$$
$$\textit{score} = \textit{score} - \min(\textit{abs}(400 - \textit{count})\ /\ 20, 5) \quad (2)$$

In the above formula, count denoted the number of words in the resume. By using this formula, if the word count is very much below or above the average word count like 25, 200, 500 words then you will score 5 but if you have a decent word count like 350, 425 you will score above 5 or between 6 to 9 which will bring a difference in each candidate's final score.

Thus, it's worth bringing up an old point: your résumé isn't the only way to express your capabilities to a potential employer, and you should always include a cover letter that further makes your case for a job.

- **Per section score:** This scoring factor includes each candidate evaluation for professional experience, extra co-curriculum activities, publications, achievements, projects, leadership.
  It is too calculated based on the word count in each section and finally formulating it all using the below formula:

  $$Score = \min(\, sum(word\ count) / 450 \,,\, 1) * 10 \qquad (3)$$

  where word count is word count summation of all these sections.

Module 4: Final Score

Now, we have calculated scores for each sub-criteria needed for the formulation of final score thus we can formulate the final score as per SRS model as:

$$Final\ score = Average\ of\ Best\ category\ score + overall\ score + programming\ score + word\ count\ score + college\ score + per\ section\ score \qquad (4)$$

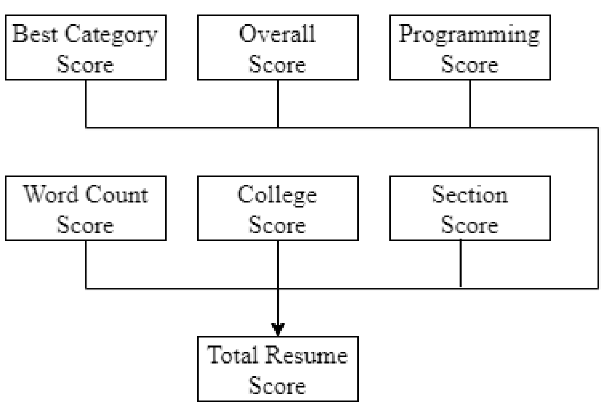

Fig. 3 – Calculation of Total Resume Score

Now that we have a final score for each resume, we can set minimum score criteria to select the best possible candidate/s for the job opening. For the results, we have set it to irrespective of any category to 50% i.e. if the final score is greater than 50% then the person is selected for the later process, otherwise, the resume is rejected.

4. Experimental Evaluation

To evaluate the efficiency and the effectiveness of SRS system, we have collected a total training data set of 3250 resumes downloaded from Linkedin, Indeed4, monster, shine6, and AngelList. The collected resumes from these employment-related search engines are unstructured documents in different document formats such as (.pdf) and (.doc) and we have considered about 200 resumes under the general category and specific category as test-data.

A short sample of a job seeker's resume:

> I am an innovative and enthusiastic MS-CS graduate from the University of Pennsylvania with a strong foundation in the entire software development lifecycle and programming principles. Astute knowledge of Agile/Scrum Methodology and object-oriented programming.
> I have the following skills: Java (2 years), SQL (2 years), Object-Oriented Principles (2 years), Android Framework (2 years), Android Studio (2 years), JSON (Less than 1 year), HTML 5 (1 year), CSS3 (1 year), Eclipse (2 years)
> Employment Details:
> 1) Software developer 2 in Frugal Innovation Hub - Santa Clara, CA - October 2016 to 2019
> 2) Software designer and tester in Cody IT Services - June 2013 to June 2014

Occupational category classification results and final score of the above resume:

```
\section{}
\textbf{Software:} 21.666666666666666 (out of 25)\\
\textbf{Engineering: } 14.0 (out of 25)\\
\textbf{Finance:} 5.928571428571429 (out of 25)\\
\textbf{Management Skills:} 8.620689655172415 (out of 25)\\
\textbf{Arts:} 11.068965517241379 (out of 25)\\
\textbf{Average Score: } 9.225\\
\textbf{Programming Languages:} \\
Java, sql, html, css, android, oops, json: 7.0\\
\textbf{University of Pennsylvania} \textbf{score:}
6.949999999999999\\
\testbf{Per section score:} 1.904 (out of 10)
\textbf{Best category: } software\\
\textbf{Final Score: }6.222390530925013 (out of 10)\end{document}
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The above candidate is suitable for the job post as his best occupational category is Computer science (Software) and his final score is 62.22%. Now, in the further sections, we will see the efficiency of SRS system and conclusion.

5. Results

After working with the algorithm and completing the analysis step. The SRS system first calculates the candidate's best score and presents it with their field of specialization out of the basic 5 occupational categories which sets out our first criteria. In this way, the SRS system predicts that the candidate is best suited for which field and whether that candidate is fit for the job occupational category requirements or not by keeping the final score as the second criterion in selecting or not selecting a candidate for further interview process.

In the output, the SRS system predicts the best field for the candidate with their final score and provides their email id so that the company can contact the selected candidate for further proceedings.

For calculating the accuracy confusion matrix (Chen et al., 2009; Jones, 1972) is used which is a summary of prediction results on a classification problem. The confusion matrix represents the ways in which your model is confused when it makes any predictions. It gives us an idea not only of the mistakes made by a classifier but above all of the types of mistakes that are made.

For calculation of accuracy score, we have considered actual values to be complete unity or selected (Chen et al., 2009; RYLAND and ROSEN, 1987) which means all the individual 200 input resumes were good enough to be called for the next round of recruitment process as per company's requirements.

As our actual value entries are all unity while our predicted value entries depend on the SRS output, therefore, it leads us to the conclusion that our True Negative [TN] and False Positive [FP] will be zero i.e. TN=FP=0 as there will be no matching entry for 0-1 and 0-0 as our actual values are all unity.

Accuracy = (TP + TN) / (TN +FP + FN + TP)

The confusion matrix for specific candidate's resumes of the engineering field is shown in table 3 which depicts the accuracy of 89%.

Table 2 – Confusion Matrix for Resumes in Engineering Field

n=200	**Predicted: No**	**Predicted: Yes**	
Actual: No	TN=0	FP=0	0
Actual: Yes	FN=22	TP=178	200
	22	178	

Table 3 – Classification Report for Resumes in Engineering Field

Features	Precision	Recall	F1-Score	Support
0	0.00	0.00	0.00	0
1	1.00	0.89	0.94	200
Accuracy			0.89	200
Macro Average	0.50	0.45	0.47	200
Weighted Average	1.00	0.89	0.94	200

The confusion matrix for the general field candidate's resumes is shown in table 5 which depicts the accuracy of 83%.

Table 4 – Confusion Matrix for Resumes in General Category

n=200	**Predicted: No**	**Predicted: Yes**	
Actual: No	TN=0	FP=0	0
Actual: Yes	FN=33	TP=167	200
	33	167	

Table 5 – Classification Report for Resumes in General Category

Features	Precision	Recall	F1-Score	Suppor t
0	0.00	0.00	0.00	0
1	1.00	0.83	0.91	200
Accuracy			0.83	200
Macro Average	0.50	0.42	0.46	200
Weighted Average	1.00	0.83	0.91	200

The following graphs represent the accuracy percentage comparison of 50 and 200 resumes from general category and specific category.

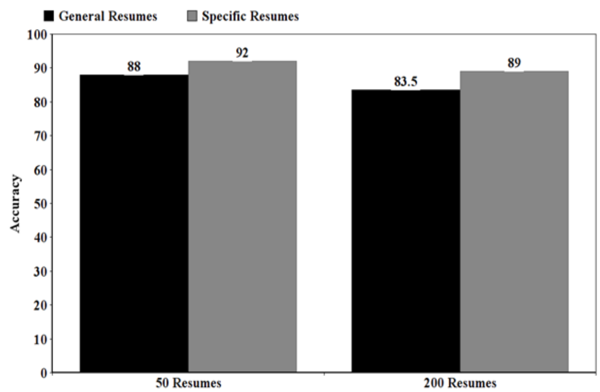

Fig. 4 – Accuracy score for different test-data sets

6. Conclusion and Future Work

In Smart Resume Selector (SRS) we have implemented a system that is extracting the vital information from the candidate's resume and analyzing it so that a final score can be given to the candidate according to their skills, experience, and education. It also predicts a best category for the candidates resume depending on the defined array of occupational category skill set defined by the job post requirement. The whole process consists of different segments that work independently and combine the result at the end to deliver the final conclusion. The SRS system is successful in automating the initial screening based on candidates' resumes.

SRS model can be further improved by adding several features that can be beneficial to both job seekers and recruiters. Following are the features which we are planning to integrate in our existing SRS model:

- Automated mailing system which sends email confirmation to shortlisted candidates.
- Candidates can view jobs which are suitable to them based on their experience.
- Job requirements will be automatically fetched from portals like Linekdin, etc
- Job seekers will be notified if a job opening with requirements matching the candidate's skill set is posted.

These features will completely digitize the recruitment procedure and will help organizations save time, effort and money spent on hiring new talents. Job seekers can analyze their score on per section basis and improve their skill set to match the company's requirements.

References

Van der Geer, J., Hanraads, J. A. J., & Lupton, R. A. (2000). The art of writing a scientific article. *Journal of Science Communication, 163*, 51–59.
Strunk, W., Jr., & White, E. B. (1979). *The elements of style* (3rd ed.). New York: MacMillan
Metam, G. R., & Adams, L. B. (1999). How to prepare an electronic version of your article. In B. S. Jon by7, es & R. Z. Smith (Eds.), *Introduction to the electronic age* (pp. 281–304). New York: E-Publishing Inc.
Fachinger, J., den Exter, M., Grambow, B., Holgerson, S., Landesmann, C., Titov, M., et al. (2004). Behavior of spent HTR fuel elements in aquatic phases of repository host rock formations, 2nd International Topical Meeting on High Temperature Reactor Technology. Beijing, China, paper #B08.
Fachinger, J. (2006). Behavior of HTR fuel elements in aquatic phases of repository host rock formations. *Nuclear Engineering & Design,236*, 54.

Chen, J., Luo, D.L., Mu, F.X., 2009. An improved ID3 decision tree algorithm. In: Proceedings of 2009 4th International Conference on Computer Science and Education, ICCSE 2009.
Fazel-Zarandi, M., Fox, M.S., 2009. Semantic matchmaking for job recruitment: An ontology-based hybrid approach. In: CEUR Workshop Proceedings.
Hong, W., Zheng, S., Wang, H., Shi, J., 2013. A job recommender system based on user clustering. J. Comput.
Jones, K.S., 1972. A statistical interpretation of term specificity and its application in retrieval. J. Doc.
Kessler, R., Béchet, N., Torres-Moreno, J.M., Roche, M., El-Bèze, M., 2009. Job offer management: How improve the ranking of candidates. In: Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics).
Kessler, R., Torres-Moreno, J.M., El-Bèze, M., 2007. E-gen: Automatic job offer processing system for human resources. In: Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics).
Kmail, A.B., Maree, M., Belkhatir, M., 2016. MatchingSem: Online recruitment system based on multiple semantic resources. In: 2015 12th International Conference on Fuzzy Systems and Knowledge Discovery, FSKD 2015.
Kumaran, V.S., Sankar, A., 2013. Towards an automated system for intelligent screening of candidates for recruitment using ontology mapping (EXPERT). Int. J. Metadata, Semant. Ontol.
Mahmoud, A.A., Al Shawabkeh, T., Salameh, W.A., Al Amro, I., 2019. Performance Predicting in Hiring Process and Performance Appraisals Using Machine Learning. In: 2019 10th International Conference on Information and Communication Systems, ICICS 2019.
Martinez-Gil, J., Paoletti, A.L., Schewe, K.D., 2016. A smart approach for matching, learning and querying information from the human resources domain. In: Communications in Computer and Information Science.
Pawar, P.Y., Gawande, S.H., 2012. A Comparative Study on Different Types of Approaches to Text Categorization. Int. J. Mach. Learn. Comput.
RYLAND, E.K., ROSEN, B., 1987. Personnel Professionals' Reactions to

Chronological and Functional Résumé Formats. Career Dev. Q.

Yahiaoui, L., Boufaida, Z., Prié, Y., 2006. Semantic annotation of documents applied to e-recruitment. In: CEUR Workshop Proceedings.

Yu, K., Guan, G., Zhou, M., 2005. Resume information extraction with cascaded hybrid model. In: ACL-05 - 43rd Annual Meeting of the Association for Computational Linguistics, Proceedings of the Conference.

Zaroor, A., Maree, M., Sabha, M., 2018. Jrc: A job post and resume classification system for online recruitment. In: Proceedings - International Conference on Tools with Artificial Intelligence, ICTAI.

Zhang, J., Niu, Y., Nie, H., 2009. Web document classification based on fuzzy k-NN algorithm. In: CIS 2009 - 2009 International Conference on Computational Intelligence and Security.