A Comprehensive Study of Resume Ranking Techniques and Their Applications

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***Abstract*—Automated resume ranking systems have become a game changer in recruitment by assisting employers in dealing with large flows of applications and increasing the relevance of the filter results. Typically, manual culling, sorting, or resume scanning that searches for relevant keywords can screen for qualifications and skills but fails to do so in the context of the position. In this review, an attempt has been made to discuss and identify advanced resume ranking algorithms, such as machine learning techniques, and NLP algorithms, such as TF- IDF, cosine similarity and NER. Such methodologies offer more effective and accurate results, avoiding simple keyword searches and understanding the context of a candidate's experience. These techniques include source-based filtering, content-based filtering, and collaborative filtering, and using hybrid solutions has proven to rank candidates more precisely as the biases are lowered while fairness shot up. This paper also discusses some of the significant controversies: the quality of input data, the issues with the algorithms, and the scalability of the ranking in different sectors. Besides, it outlines possible future work, including extending technical AI methods like BERT (Bidirectional Encoder Representations from Transformers) and the inclusion of the essential ethical standards that must inform the development of a fair and transparent hiring platform. Lastly, this paper provides a comprehensive look into today's resume ranking processes and their uses in talent procurement.**

Keywords— Resume Ranking, Natural Language Processing (NLP), Term Frequency-Inverse Document Frequency (TF-IDF), Cosine Similarity, Named Entity Recognition (NER), Machine Learning, Applicant Tracking Systems (ATS)

I. Introduction

One key piece of workforce planning is recruitment, which is how organizations attract and select the right talent . In a crowded landscape where humans are applying for more jobs than ever and there are more applications than hiring teams can handle, hiring managers deserve the best tools to help them separate the wheat from the chaff early and often [1]. A brief overview of the background and problem is provided next.

A. Background

Recruitment is essential to workforce planning, where organizations find the best talent to fill existing vacancies. Earlier, this would require sifting through presumably large numbers of applicants through their resumes, which can become tedious as the number of candidates increases. In general, companies with hundreds of employees get hundreds of applications for a single position, making manual assessment massive and error-prone. Professional resumes offer an overview of a candidate's professional profile, including achievements, competencies, and experience, and they are the first screening tools employers use. However, due to the enhancement of technology, automation of ranking resumes has become essential to enhance the efficiency of this crucial process [2].Resume screening and ranking technologies use numerous algorithms to screen and sort through resumes and make the best-match candidate selections. It is crucial for such systems to use tools such as NLP and Machine learning to parse resume content better. The traditional manual methods, which can be somewhat efficient if the scale of applications is comparatively tiny, prove to be less efficient because of their inability to be scaled and entail much randomness due to the decisions made by the recruiters [3]. As a result, very few recruitment processes are efficient without incorporating automated systems that contain data-driven methods.

B. Problem Statement

Despite the merits of automation, traditional systems of resume evaluation often imply the use of keyword search as the only means of analysis, thus missing the point and not being able to process any context of the candidate's experience or education. Such systems care about whether the resume mentions specific keywords regarding a job description that does not factor in synonyms or other more general relevant skills, thus excluding potentially suitable candidates. Also, since the systems rely on keywords, it is rather challenging to recognize different forms of presenting resumes and modified language use, which is unsuitable for different environments and recruiters' templates [4].

One of the main concerns is bias in algorithms and their decisions. Machine learning algorithms programmed and trained on past employment data will replicate those biases, resulting in prejudiced assessments of candidates from minority groups[5] . For the same reason, there are ethical issues with how these systems compare resumes, as organizations cannot explain why one resume was ranked higher than another [6].

C. Objectives and Scope of the Study

In this review, we provide an integrated view of the history, success, and shortcomings of the methods used in the ranking of the resumes with an emphasis on theories and practical's. It is intended to assess the current methods and discuss the future trends of automation of the recruitment process.

Key Focus Areas:

- Assess how resumes are ranked, be it simple keyword matching, more analytical NLP and machine learning techniques, or something in between.
- Explore the constraints: for example, data quality, algorithmic bias, and the ability to adapt to various sectors.
- Investigate the potential of new technology like deep learning and transformer models to enhance contextual understanding.
- Explore lifelong learning frameworks to keep systems in touch with the shifting job landscape.
- Suggest future research avenues that could help improve fairness, scalability, and efficiency in automated recruitment.

II. Overview of Resume Ranking Techniques

Various techniques used in automated resume ranking have, therefore, progressed, which has brought about increased precision, speed and equity in the face of the recruitment undertaking. This section explores the significant paradigms, starting with the conventional Boolean approach to state-of-the-art machine learning and mixed strategies that lead to improved resume scanning. Knowledge of such methodologies is essential, especially when designing recruitment systems that can be processed manually and are sustainable in different circumstances. Also, a summary of this is also provided in Table I providing information regarding work in these paradigms by different authors.

A. Keyword-Based Approaches

Keyword-based approaches, one of the earliest models of resume ranking, rely on keyword detection. They identify specific keywords in resumes that match those used to describe jobs. While these methods are straightforward, they struggle with handling different word forms or stems of the same root or different forms of the same word for different parts of speech, highlighting their limitations.

Term weight–There are several term weighting techniques, one of the most often used being TF-IDF (Term Frequency–Inverse Document Frequency). Among all the keyword-based techniques, TF-IDF is more complex and widespread. TF-IDF calculates the ratios of the occurrence of each word in a resume to the overall occurrence of the same word in the general resume and job description pool. This approach provides a better view of resume content than the matching algorithm since this method understates the usually frequent words and overstates the words strongly related to the job description. Nevertheless, the problem of navigating the deeper, contextual meaning of the terms remains with TF-IDF [7].

1) Keyword Matching Techniques:

Keyword matching, a process of identifying keywords in resumes that match those in the job listing, has its limitations. While it enables the use of logical operators like AND, OR, NOT to refine or broaden the search, it struggles to comprehend the context of terms and the differences in the ways skills and experiences are stated.

This approach often leads to the elimination of potentially worthy candidates who may not use the right keywords, a drawback that the audience should be aware of [8].

B. Machine Learning Techniques

While simple keyword-based methods are used in resume ranking systems, the emergence of machine learning techniques has opened new possibilities. Big data approaches, coupled with machine learning, can significantly enhance resume evaluation by learning resume patterns and improving evaluation models. This advancement makes it possible to consider more candidates, offering a promising future for resume evaluation.

1) Supervised Learning Models

Supervised learning models work on tagged data; resumes are associated with relevance scores, implicitly showing that the keywords match the job descriptions. The major algorithms used in these systems are Support Vector Machines (SVMs), Decision Trees, and Random Forests. For instance, SVMs sort resumes according to predefined attributes, and they are very accurate if trained on quality data . On the other hand, supervised models are susceptible to mimicking the bias of the training data and consume large amounts of clearly labelled data in the best-case scenario [9-10].

2) Unsupervised Learning Models

On the other hand, there are the models which belong to unsupervised learning and do not use labelled data. However, rather than analysing the text, they identify features and categorize resumes by means of comparison. By numerous measures, the K-Means and Hierarchical Clustering approaches include grouping candidates with related qualifications and skill characteristics. These models are useful for large, disparate data sets, however they may not solve the problem in the same way as the supervised methods when specific candidate-job matches exist [11].

C. Natural Language Processing (NLP) Approaches

Another interesting direction of the development of resume ranking systems is based on Natural Language Processing (NLP), which helped approach the key problem from a new perspective and interpret the semantic sense of the resumes. NLP does this by first moving systems past the simple text-based matching of keywords and instead analysing the content of resumes in a more natural manner.

Named Entity Recognition (NER) is an NLP approach that excels at identifying important data in the resume, such as job position titles, credentials, qualifications, and skills. This enhances the recognition of the features of the candidate's experience and skills. NER is perfect for identifying key entities such as job titles, qualifications, and certifications in CVs. For example, it extracts domain-specific credentials ('Nurse' or 'Public accountant' in healthcare industries) but also helps to extract unique skills like, 'Kubernetes' for cloud engineering. By finding equivalent or related named entities, candidates can be matched accurately using NER. However, it is essential to note that NER can be computationally complex and may not perform well with non-conventional or irregular resume formats [12]. A basic workflow for NER is depicted in fig 1.

D. Semantic Similarity Measures

Cosine and Word Embedding similarity (Word2Vec or BERT) to measure the relevance of words or phrases in resumes to the targeted job descriptors regarding the meanings of the two terms rather than recognizing the appearance of a similar term. These techniques determine the closeness of terms into a vector space and provide a much better context for computing resume contents. Consequently, and for its ability to capture the essence of language, systems enhanced by BERT can better gauge the relevance of a candidate's skill set concerning a set job description [13].

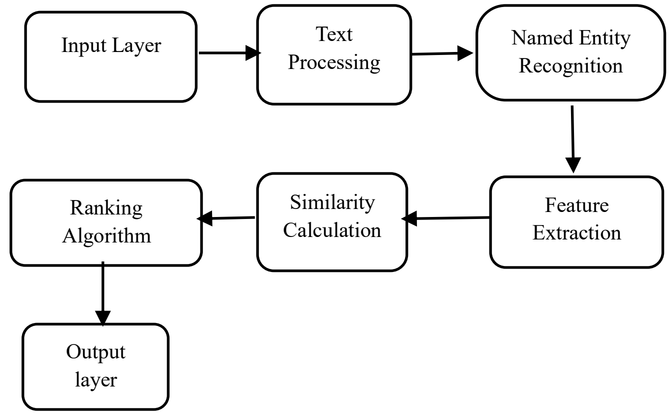

Fig. 1. Framework of the resume screening and ranking system using NE

TABLE I. SUMMARY OF LITERATURE REVIEW

References	Description	Advantages	Disadvantages	Applications	Method/Technique
[1], [5]	Measures word relevance by frequency in document.	Simple and easy to implement.	Does not capture the full context of words ignores same words	Used in basic ATS system to find specific keywords like "python"	TF-IDF
[2], [3]	Matches exact keywords from job descriptions to resumes using AND, OR etc.	Fast and efficient for small datasets.	Misses synonyms and variations of terms.	Used in early ATS to quickly filter resumes for low volume roles	Keyword Matching
[3], [5]	Measures similarity between resume and job description based on vector space models.	Captures relationships between terms.	Still limited to syntactic, not semantic, similarity.	Applied in advanced ATS for text intensive role like research.	Cosine Similarity
[4], [8]	Identifies key entities such as skills, job titles, and qualifications.	Provides a deeper understanding of resume content.	Computationally expensive; requires large datasets.	Used in domain specific jobs and checking certificates.	Named Entity Recognition (NER)
[7], [9]	Uses labelled data to predict resume relevance.	High accuracy when trained on quality data.	Prone to overfitting and biased by training data.	Used in hiring candidates based on previous data for roles	Supervised Learning
[9], [10]	Combines multiple techniques (e.g., TF-IDF, NER, ML).	Increased accuracy and fairness in rankings.	More computationally expensive than simpler models.	Used in system for high volume hiring across various industries	Hybrid Models

III. METRICS FOR RESUME RANKING

Given that resume ranking systems are intended to help improve recruitment, yet they reduce the quality of final results, it is crucial to assess their performance so that the systems can deliver results that are as good as they are efficient. The next part of the paper outlines unanswered questions and future work: 1) Performance metrics: Details of measures used to assess the efficacy of the proposed systems include precision, recall, F1 score, perceived user satisfaction, and results of real-world trials in sections 4 and 5.

A. Precision and Recall

It is well known that precision and recall are two basic measures employed to assess a system's resume ranking accuracy.

Accuracy is the number of resumes correctly matched to the number recommended by the system. It quantifies noise control, indicating how many resumes the system recommended as suitable for the particular job are precious for this position.

Precision in recruitment is of utmost importance as it allows recruiters to effectively manage the applications received, discarding those that are irrelevant to the job opening.

$$Precision = \frac{True\ Positive}{True\ positive + False\ Positive} \quad (1)$$

Recall, on the other hand, is the ratio of resumes flagged by the system and the number of relevant resumes. There, one can calculate the ratio of the number of true positives—, or actual resumes that matched the system criteria—relative to the total number of resumes resumed and so minimize the group of false negative resumes, that is, for some

$$Recall = \frac{True\ positive}{True\ positive + False\ negative} \quad (2)$$

In recruitment, high recall entails the system retrieving as many qualified candidates as possible to minimize the loss of good candidates. Precision and recall scores are both important while evaluating the resume ranking since they define the system's success/failure and find the optimal points between precision and recall .

B. F1 Score

F1 is the harmony mean of precision and recall, giving the measurement of both in a single figure. It is more helpful, especially when the distribution between the relevant and irrelevant resumes is imbalanced since it prevents focusing on either precision or recall.

$$F_1\ Score = 2 * \frac{Precison*Recall}{Precison+Recall} \quad (3)$$

A detailed comparison graph is provided showing the above-mentioned models compared on the metrics of accuracy, efficiency and context understanding is provided in fig. 2 depicting the models performance.

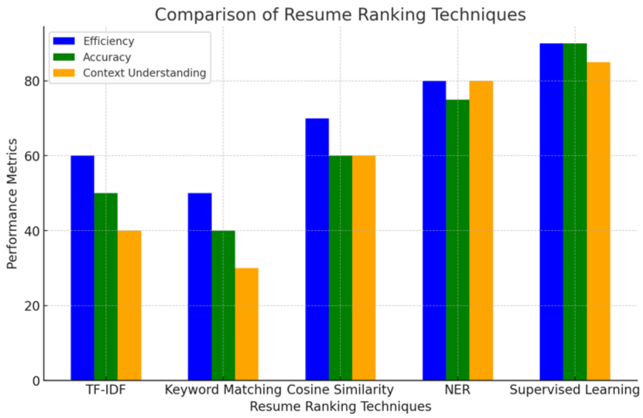

Fig. 2. Comparison of Resume Ranking Techniques

C. *Real-World Applications*

Resume ranking accuracy can also be assessed in live HR technology programs. Resume filtering is more widely incorporated into ATS, which employers use to process large numbers of applications. Several real-world applications of resume ranking systems highlight their benefits:

- ATS Integration: Resume ranking has been automated using NLP and machine learning on various ATS platforms today. For example, systems that use TF-IDF and NER can quickly analyse and sort thousands of resumes, enabling large organizations with many applications for each vacancy to adopt the process.
- Bias Mitigation: Some real-world systems, such as tech giants, explicitly utilize a bias-detection algorithm and fairness constraints to guarantee minority candidates are averted by historical data bias [14].

IV. Challenges in Resume Ranking

Several challenges affect the performance, bias, and generalizability of automated resume ranking across industries, even with advanced AI. These difficulties stem from issues of data quality, algorithmic bias, and the need for system flexibility. One crucial aspect that often gets overlooked is the regularity of updating the model to reflect the current trends in various fields of employment. This adaptability is key to ensuring the system remains relevant and effective.

A. *Data Quality and Representation*

Despite its relatively simple formulation, resume ranking poses several critical questions with susceptibility to low data quality and misrepresentation. Work resumes are available in many formats, including semi-structured documents and unstructured plain text, which hampers system-based extraction of consistent data. The current formats of writing resumes are incoherent due to differences in format between or within the sections that include work experience, qualifications, and hampers the accuracy of the results as mention in Table II . Moreover, data sparseness is a major hurdle faced by automated systems as resumes typically contain only partial or inconsistent information, which is a core input for many of the desired analyses.

TABLE II. Data Quality and Representation Issues

Challenge	Description	Impact
Diverse Resume Formats	There are many resume formats, i.e: PDF, DOCX or scanned images that make extraction inconsistent	Parsing and Data Extraction issue affecting rankings
Unstructured Data	Since there is no standard template to write a resume, it is written in free form.	It is hard to extract features such as education or work experience which affect accuracy.
Inconsistent Terminology	Resumes are often widely different in quoting job titles, skills, and experiences so each might all be credited differently towards the same expertise domain	It causes mismatches in keyword extraction or feature based summarization which results in low precision

For example, important information might be missing or presented in atypical formats or language that automated systems are likely to misread. These problems reduce the general accuracy of the ranking algorithms and may result in poor evaluations of candidates.[15]. Also, the imbalanced dataset can be handled using Bi-SMOTE a framework to handle such uncertainties. [16].

B. *Bias in Algorithms*

One of the significant impediments to resume ranking is that of algorithmic bias. Many automated systems are trained on past data on hiring, which was possibly riddled with bias as well. For instance, if an organisation has always preferred specific demographics, for example, gender, age, race, or specific education level, the algorithm will replicate these preferences and disadvantage members of those groups. This issue has raised the question of whether fairness and equity can be deconstructed and implemented in automated recruitment. Reducing algorithmic bias involves developing a well-designed system with the incorporation of fairness constraints, periodically auditing the system, and applying mitigation measures such as re-sampling or discarding over-sensitive features in the model. Failure to manage bias makes it possible for automated systems such as resume filters to increase pre-existing discrimination of minority candidates, especially women [17].

C. *Adaptability to Different Industries*

Flexibility is another difficulty because resume ranking systems must be adjusted to conform to various job-search scenarios. Most industries provide their terminologies, qualifications, and even skills requirements that separate industries. For instance, a candidate applying for a software developer position may have much different qualifications than one applying to work in the health care field. However, the two resumes may be run through a similar software. This means that it may be dangerous to follow the same classical approach and rankings of candidates without considering the specifics of different industries. Hence, systems need to be adaptable to cater to differences in the description of jobs and employ sector requirements while being efficient and precise.

D. Continuous Learning and Updating

As the job market continues to open up and expand, so does the specification that employers demand from prospective candidates for the jobs they offer them. In other words, if the resume ranking systems are to remain effective, the resume ranking paradigms must learn, adapt and evolve as well. Since the AL algorithms depend on the data and models used, there is a high chance that the system will become irrelevant. Therefore, the candidates will not get suitable jobs considering the existing demand. The second procedural aspect is related to the retraining of the machine learning models and the necessity to apply new data reflecting the orientation to the market flow. Also, feedback received from the recruiters and hiring managers can be incorporated into the system to improve its flexibility and incorporate the new changes in the job market. Even the most sophisticated ranking infrastructures may become progressively less effective if they are not supported by ongoing learning and updating [18].

V. FUTURE DIRECTIONS

That is why several developments are being made that may enhance the resume ranking system upon its continued usage. The following section outlines some major future research areas to address possibilities of new technologies, resume parsing in an ATS environment, and the need to incorporate privacy-sensitive and 'fair' techniques.

A. Emerging Technologies

The potential for the state-of-art to sort resumes is immense, based on the meanings of Artificial Intelligence (AI) and deep learning. Earlier machine learning paradigms, including supervised and unsupervised learning, are still practical for use but are restrained by the requirement for training data labelling and the absence of the ability to analyze natural languages deeply. Models like BERT (Bidirectional Encoder Representations from Transformers) enhance resume ranking by analysing the semantic relationships between terms. For instance, BERT can discern that 'data scientist' and 'machine learning engineer' have overlapping skill sets, even if the specific terms do not appear verbatim in a resume along with some challenges like computation needs and privacy. In the future, deep learning models that succeed in natural language understanding tasks could transform the resume ranking system by making the system review the resume as naturally as human beings do [19].

Furthermore, the system's adaptability is a key advantage. It can benefit from reinforcement learning, allowing it to adapt online for resume ranking. Imagine a system that learns from recruiters' feedback and evolves over time, becoming wiser as it responds to a larger number of resumes and adapts to changing hiring demands. This adaptability ensures that the system can create ranks according to the current trends in the employment market and the preferences of the recruiters, providing more accurate and suitable selections of candidates. This adaptability should reassure the audience about the system's ability to keep up with changing trends.

B. Integration with Applicant Tracking Systems (ATS)

Applicant Tracking Systems (ATS) refer to systems utilized in modern workplace recruitment to handle applications and employ some techniques for evaluating candidates. However, with many conventional ATSs, companies depend on simple keyword matching or Boolean search, which is a problem. Moreover, the build-in of the advanced concepts of resume ranking, including Natural Language Processing and machine learning, into the ATS platform will improve the device's efficiency.

The future integration will include other features of ATS systems to expand from keyword matching to using TF-IDF, cosine similarity, and NER as a rankings filter and also to have certain course recommendation depending upon domain with privacy using deep learning[20]. Further, incorporating deep learning models into ATS will allow for improvements in semantic analysis so that the recruiters can pick out candidates who may not necessarily use the right keywords but whom they need for the position. This innovation will result in a better shortlisting process, less time spent in the hiring process and a more effective recruitment process [21-22].We can also have a multi-criteria recommendation system that can take into consideration a number of parameters like skills, certification, experience etc.[23]

As companies increasingly migrate to cloud-based ATS systems, the potential for future improvements is vast. These systems will become more flexible and capable of handling large quantities of resumes and data sources. The integration with platforms like LinkedIn and other social sites will make it easier to access a candidate's work history and skill set, marking a significant step forward in the industry's progress.

C. Ethical Considerations

With resume ranking systems getting brighter in the future, there are some ethical issues, hence the need to consider privacy and fairness[24]. This means that some sensitive issues such as gender, race or age may be unfairly tilted against women, blacks, or the elderly. This problem needs to be solved by articulating fairness constraints on the algorithms so that they do not put off biased data of candidates to arrive at the ranking. In addition, audits and bias detection should be conducted periodically to keep track of the system's decisions.

D. SDN and Load Balancing for Efficient Model

The advanced and sophisticated AI and ML models need fast and better storage and networks to work efficiently. Using software defined networking-based data server computing and improved load management can help solve this for optimization [25].

VI. CONCLUSION AND FUTURE SCOPE

This study reveals how resume ranking has evolved, simplifying the selection process. Being data-driven, keyword-based techniques along with their modern machine learning methods such as NLP can analyse huge amounts of resumes. Methods like ADV/WebT, TF-IDF, cosine similarity, and NER enhance capacity to evaluate resumes at a contextual level, while hybrid models enhance overall performance.

Despite these advancements, deployment and accuracy challenges remain, including those of data uniformity, algorithmic fairness, and influencing changes in requirements as the job market continues to evolve.

Further studies need to utilize state-of-the-art AI algorithms with advanced natural language processing approaches including deep learning BERT, and various transformer-based architecture for superior analysis, contextual exploration, and evaluation. There are also some difficulties such as computational cost, fairness, or scalability. Phased rollout and reallocation of cloud resources are the solutions for these challenges. These next-gen resume ranking systems would be built to integrate with too many available platforms including social media to keep having better data exchanges on real-time to score user-based insights for smarter candidate profile evaluations and scalability.

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