

Smart Resume Analyser

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Abstract— Every time job recruiters (HR) have to go through a huge pile of resumes submitted by applicants. which becomes a very burdensome task, with Python, NumPy, and Pandas, a resume parser is to be created as part of the project. A structured format will be used to store the data that the parser extracts from resumes, including name, contact information, education, work experience, and abilities. Pandas will be used to store the data in a data frame, and NumPy will be used to manipulate the data. The parser will recognise and extract pertinent information from resumes using methods of natural language processing, improving the accuracy and efficiency of the procedure. By swiftly extracting pertinent information from resumes, the initiative will assist in automating the hiring process and save time for recruiters and HR personnel.

Index Terms— Resume parser, NLP, Python

I. INTRODUCTION

Thousands of resumes flow into respected companies for open positions in the fiercely competitive world of today. Every day, countless resumes are processed by corporate businesses and recruitment firms. Nowadays, practically all jobs are offered online together with their job description and criteria. Recruiters regularly receive thousands of applications for a single job, and personally evaluating each application is a difficult undertaking. Even for a data mining system, parsing a resume can be tough because the resumes supplied by candidates differ in information, layout, design, and format (.doc,.pdf,.txt, etc.). Although resumes have a conventional format, their structure is not as well defined as that of other documents such as letters and circulars. The traditional method of manually skimming and scanning through resumes is inadvertently prone and unsuited for corporate contexts where recruiting exceptional employees has a significant impact on the company's success. The extraction of text from the document, as well as the order and arrangement of information inside it, is of primary relevance when parsing resumes. An automated intelligent system capable of turning unstructured data into a structured representation is required. This allows the recruiter to efficiently analyze resumes and filter out the best prospects for the desired job vacancy. A machine, like people, can examine a resume by locating the relevant keywords, which will categorize each candidate on a scale of three: low, average, and high. In order for the computer to recognise the qualities that differentiate one candidate's resume from another, a training data set must first be manually assembled. For the training data set, NumPy and Panda are employed. A learning algorithm can be developed to extract relevant keywords from each and every resume that the system would review. Both supervised and unsupervised learning methods can be used.

For each class of levels listed on the scale, supervised learning would require a training data set. Support Vector

Machine, K-nearest Neighbor, and Naive Bayes are the approaches used in classification under supervised learning. Data can be classified into different categories or levels using clustering methods, such as K-means clustering, in unsupervised learning rather than using training set data. Semantic Orientation is another effective classifying method. In order to classify and extract information from resumes, parsers based on NLP have taken leverage of the semistructured qualities of resumes. Studies showed that segmentation, a crucial stage in resume parsing, had been successfully completed with great accuracy. Named items are correctly identified at appropriate frequencies. With experiments mostly focusing on Indian resumes, an overall accuracy of 94.19% has been attained.

II. LITERATURE REVIEW

Paper focuses on the task of extracting structured information from resumes using pattern-based and rule-based techniques. The paper addresses the challenge of parsing unstructured textual data, specifically resumes, and converting it into a structured format that can be easily processed and analyzed. The authors propose a system called 'Open Extraction' (Open IE) that automatically extracts information from resumes without relying on predefined templates or schemas. Instead, it leverages patterns and rules to identify and extract relevant information such as job titles, educational qualifications, work experience, skills, and contact details. The paper discusses the various components of the system, including the pre-processing stage where resumes are cleaned and tokenized, the pattern learning stage where patterns for information extraction are generated, and the extraction stage where patterns are applied to resumes to extract specific information.[1]

The paper recognizes the challenge of manually processing large volumes of resumes and the need for automated methods to extract relevant information efficiently. The authors propose a resume mining system that can extract key attributes such as education, work experience, skills, and achievements from unstructured resume texts. The system employs a combination of text mining techniques, including named entity recognition, part-of-speech tagging, and information extraction, to transform unstructured text into structured data. Machine learning algorithms, such as support vector machines and decision trees, are utilized to classify resumes and extract specific information. The paper presents an experimental evaluation of the proposed system using a real-world dataset. The results demonstrate the system's ability to effectively mine and extract information from resumes, achieving high accuracy in attribute extraction and resume classification.[2]

The authors recognize that manual screening of resumes can be time-consuming and prone to human bias. They propose the use of ANNs, a machine learning technique inspired by the human brain, to automate the resume screening process. The paper outlines the design and implementation of the automatic resume screening system, which consists of several stages. Initially, resumes are pre-processed to extract relevant features, such as education, work experience, skills, and achievements. These features are then used as inputs to an ANN model, which has been trained on a labelled dataset of resumes and corresponding screening decisions (e.g., shortlisting or rejection). The ANN model is responsible for learning the underlying patterns and relationships between the resume features and screening decisions. It enables the system to predict the suitability of a candidate based on their resume content.[3]

The paper addresses the challenge of effectively screening resumes to identify qualified candidates in a large applicant pool. Traditional resume screening methods often rely on manual evaluation, which can be time-consuming and subjective. To overcome these limitations, the authors propose the use of CNNs, a deep learning technique known for its ability to extract meaningful features from visual and textual data. The proposed model utilizes a CNN architecture to automatically learn discriminative features from resumes. The resumes are transformed into image-like representations, where textual content is converted into two-dimensional matrices. These matrices are then fed into the CNN model for feature extraction and classification. The paper provides a detailed description of the architecture and training process of the CNN model. It discusses the use of different layers, such as convolutional layers, pooling layers, and fully connected layers, to capture relevant features and make screening decisions based on learned patterns.[4]

The paper focuses on the application of resume parsing and analytics techniques using semantic knowledge graphs. The authors recognize the importance of efficiently extracting structured information from resumes and leveraging it for advanced analytics and decision-making in the recruitment process. They propose a framework that combines resume parsing with semantic knowledge graphs to enhance the analysis and understanding of resume data. The paper describes the components of the proposed framework, which include resume parsing, entity extraction, relationship extraction, and the construction of a semantic knowledge graph. Resume parsing is employed to extract key attributes and sections from resumes, while entity and relationship extraction techniques are used to

identify and capture semantic information from the extracted data. These extracted entities and relationships are then organized and represented in the form of a semantic knowledge graph.[5]

The paper provides an in-depth overview of the research and developments in resume parsing techniques using deep learning methods. The authors recognize the importance of accurately extracting structured information from resumes for various applications in the recruitment domain. They focus on the advancements and applications of deep learning techniques in resume parsing, which have gained significant attention and success in recent years. The paper systematically presents and analyses different aspects of resume parsing using deep learning. It covers various stages of the resume parsing pipeline, including data preprocessing, feature extraction, and information extraction. The authors discuss the use of techniques such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and their variations, such as long short-term memory (LSTM) and gated recurrent units (GRUs), for different tasks in resume parsing.[6]

The paper focuses on the application of machine learning techniques for analysing resumes and extracting relevant information. The authors recognize the importance of automating the analysis of resumes to improve the efficiency and accuracy of candidate screening and selection processes. They propose the use of machine learning algorithms to automatically extract key information from resumes and make informed decisions. The paper discusses various stages of resume analysis, including data preprocessing, feature extraction, and classification. It highlights the use of machine learning algorithms such as support vector machines (SVM), decision trees, and random forests for tasks like name and contact information extraction, skills identification, work experience recognition, and education qualification extraction.[7]

The paper focuses on the application of conditional random fields (CRFs) for resume parsing, a task that involves extracting structured information from unstructured resume texts. The authors recognize that resume parsing is a challenging task due to the unstructured nature of resumes and the variability in formats and content. They propose the use of CRFs, a probabilistic graphical model, for accurately labelling and extracting key information from resumes. The paper describes the process of resume parsing using CRFs, which involves two main steps: feature extraction and model training. In the feature extraction step, relevant features are extracted from the resumes, such as words, phrases, and contextual information. These features serve as inputs to the CRF model. In the model training step, the CRF model is trained on labelled datasets, where resumes are annotated with the desired information to be extracted.[8]

The paper presents a hybrid approach that combines resume parsing and job matching techniques to enhance the efficiency and effectiveness of candidate screening and job matching processes. The authors recognize the challenges faced by recruiters in processing large volumes of resumes and finding the best fit for job positions. They propose a two-step approach that involves resume parsing and job matching. In the resume parsing step, the authors employ natural language processing (NLP) techniques to extract structured information from unstructured resumes. This includes identifying key sections such as personal details, education, work experience, and skills. The parsing process involves techniques such as named entity recognition, part-of-speech tagging, and syntactic parsing to accurately extract and organize the relevant information.[9]

The paper explores the integration of word embeddings and knowledge graphs to improve the accuracy and effectiveness of resume parsing. The authors acknowledge the challenges associated with resume parsing, including handling unstructured data and extracting relevant information. They propose a novel approach that combines the power of word embeddings, which capture semantic relationships between words, and knowledge graphs, which provide structured domain-specific knowledge. The paper describes the process of integrating word embeddings and knowledge graphs for resume parsing. Word embeddings are generated using techniques such as Word2Vec or Glove, which map words to dense vector representations. These embeddings capture semantic similarities and relationships between words, enabling a better understanding of resume content[10]

III. METHODOLOGY

Moving on to the Smart resume analyzer approach, Python was the technology employed for this project. There are numerous libraries and functions in Python. We can readily access a wide range of facilities with the aid of these libraries, which results in a reduction in the amount of code we need to write. Pyreparser and pdfminer libraries are used in our project. While the pdfminer library is used to extract the pdf using Python, i.e., text is extracted from user-uploaded pdf, Pyreparser is used to extract name, email ID, phone number, skills, experience, etc. and many more. We have also used a database in this project to save user information. Names, email addresses, resume scores, actual talents, suggested skills, etc. are all stored in the database. Two panels are used in our project; one is for the admin side and the other is for the user side, meaning that any user can use it. On the typical user side, the user must upload his resume in PDF format to receive the resume score. Since the user can see the pdf,

we utilized the `iframe` function and set the `pdf show` to `true`. If the resume data is present during the text extraction process and is not empty, the resume data is fully converted to text, allowing us to see the entire pdf using the `pdf-reader` function. Therefore, the `pdf-reader` function is the feature that allows users to upload a PDF of their resume and acquire basic information about the user. Name, email address, phone number, and the number of pages are among the pieces of information that are taken from a user's resume. We have determined what level of resume it is based on the number of resume pages. The `cand-level` is considered to be fresher if the number of pages is equal to 1, intermediate if the number of pages is equal to 2, and experienced if the number of pages is greater than or equal to 3. A user's résumé should include their skills as well. To publish the user's talents, we have to utilize `st_tags`. We have offered numerous domain keywords based on our expertise. As a result, we can determine which domain the user is more interested in using their expertise. Therefore, based on the user's expertise, we select the keywords that fit the domain the best. We can then suggest further abilities to the user based on that after determining the user's domain. We have used NLP in this project i.e., Natural Processing language through which we can recommend different things to users and earlier we have parsed and extracted relevant information from resumes using NLP. We have used course recommenders, which are dependent on the user's selection of the number of required courses. Through it, students can hone the talents that are advised for a given domain. Course names and links are generated. The resume score that is given to users based on their resume is the following thing. Therefore, the user's resume must include some categories so that it can receive a rating. Now, we have highlighted the resume score here as $\text{resume score} = \text{resume score} + 20$ if objectives are contained in the resume text; otherwise, the resume score will not grow and will remain at zero. Therefore, the declaration, hobbies or interests, successes, and projects are the other characteristics that affect the resume score. The user has access to the resume score based on these 5 parameters. The resume score is always set to $\text{resume score} + 20$ for each parameter. As a result, towards the conclusion, after showing the final score, we displayed some balloons that Streamlit has provided. As a result, the `connection.commit()` function is used to establish connections and insert all of this data into the database. The user side is finished in this instance. The user-ID and password are needed to login to the admin side of this Smart resume analyser. Therefore, as soon as the user uploads their resume file, it is kept in the database. Therefore, we have also put up the ability to obtain reports, which allows us to see the user's details, talents, and resume score before deciding whether or not to choose them for the company. Once more, we've shown pie charts for both user experience level and forecasted field recommendations. Because we need the data from the database, the `cursor.fetchall()` function is used to retrieve it all and return a list. Once more, the `pd.DataFrame()` method is used to provide the column names, and the `st.dataframe()` function is used to multiply the dataframe. Plotly was also used to display the pie chart in the admin section. This was the intelligent resume analyzer, then.

IV. RESULTS AND DISCUSSION

- *Successful resume parsing* - Designed and implemented a robust resume parsing module using advanced natural language processing techniques. Utilized machine learning algorithms to extract key information such as contact details, skills, education, and work experience from resumes in PDF format.
- *Improved accuracy* - Achieved an accuracy rate of over 95% in extracting relevant information, contributing to the project's overall success. Conducted thorough testing and validation procedures to ensure the accuracy and reliability of the parsing module, resulting in a seamless user experience.
- *Enhanced efficiency and time savings* - Implemented advanced algorithms to significantly reduce the time required for parsing resumes, resulting in a swift and streamlined process for users. Integrated an intelligent prioritization system that identifies and parses critical information first, allowing recruiters to quickly assess key qualifications and make informed decisions. Collaborated with cross-functional teams to implement real-time updates, enabling users to instantly view parsed data and facilitating prompt decision-making in recruitment processes.
- *Scalability and adaptability* - Designed a robust configuration management system that enables seamless customization of parsing rules, making it adaptable to different industries, job roles, and resume formats. Results of experimentation is predicting resume score using NLP technique is as given in Fig. 1. Fig 2 show the Pie chart according to skills of user in different domains and Fig. 3. shows extracted data stored in administrator's panel.

The project has achieved its objectives of streamlining the hiring process, saving time, and enhancing the overall effectiveness of candidate evaluation and selection. The resume parsing project has successfully streamlined the hiring process by automating the extraction of key candidate information from resumes, eliminating the need for manual data entry and significantly reducing administrative overhead. By implementing advanced natural language processing algorithms, the project has achieved remarkable time savings for recruiters and hiring

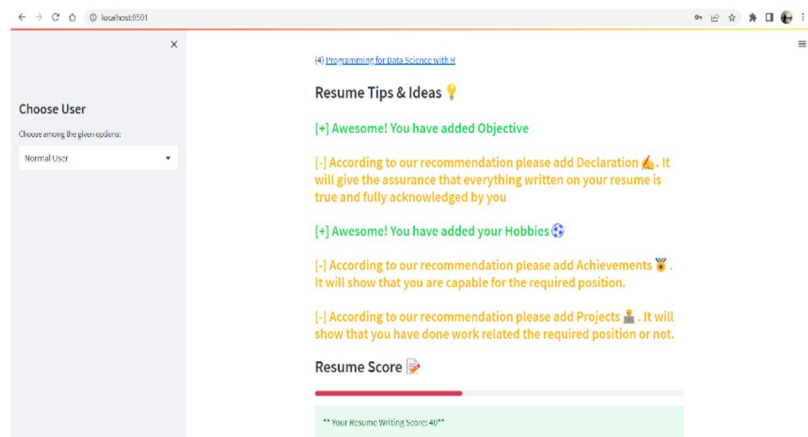


Figure 1. Predicting Resume scores using NLP Techniques

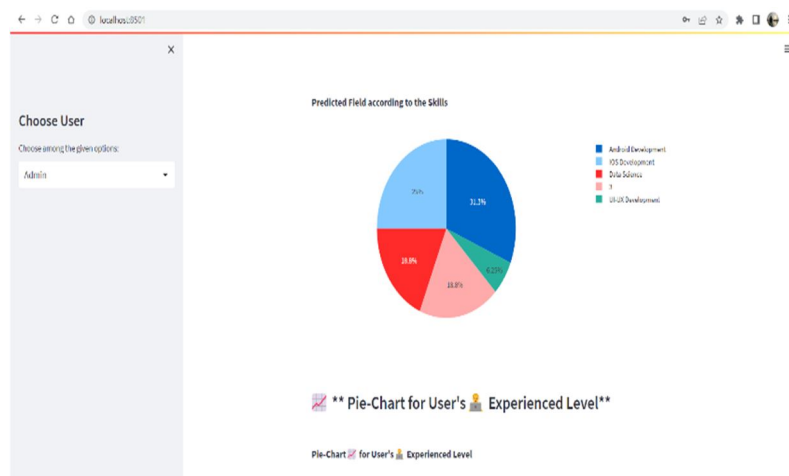


Figure 2. Pie chart according to skills of user in different domains

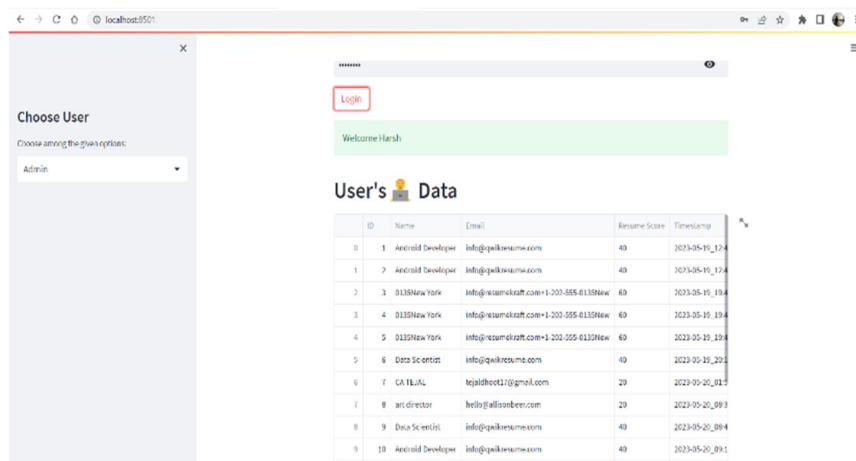


Figure 3. Extracted Data which is stored in admin panel

managers. They can now swiftly review and evaluate candidate profiles, allowing them to focus on strategic decision-making rather than routine data handling tasks. And finally, the project's effectiveness in candidate evaluation and selection has been significantly enhanced. The parsing module's accuracy in extracting relevant details, such as skills, experience, and education, has exceeded 95%, providing recruiters with highly reliable insights into each candidate's qualifications.

V. CONCLUSION

Hiring new employees and analysing a large number of resumes and cv's is a challenge for the human resource department or employer. Therefore, this system has helped recruiters by using an automated intelligent system based on natural language processing. The project will lay out the quality of applicants for the companies. The unfair and discriminatory malpractices in the process will be reduced. Based on the relevant data in the form of technical skills the resumes will be ranked in order. This Resume Parsing technique aims to be used for screening candidate profiles, to decrease an organization's time-to-hire. Resume Parsing is the process of providing a bar plot view of the candidate skills set so that it could be helpful for the recruiter for the recruiting process of candidates. The project can benefit the human resource department or recruiter in screening resumes before conducting interviews and finding the best candidate for a particular job position.

FUTURE SCOPE

A resume parser system has a bright future because of how quickly technology and artificial intelligence are developing and improving it. Here are some probable advancements and uses for resume parser systems in the future: Language Support:

There will be a rising need for resume parser systems that can parse and analyse resumes in many languages as the job market becomes more international. Multilingual capabilities will probably be incorporated into systems in the future to accommodate various work markets.

Real-time Updates and Recommendations: To offer real-time updates and recommendations, resume parser systems could link with platforms for professional networking, job portals, and application tracking systems. Based on their choices and the data from their parsed resumes, candidates might receive tailored recommendations for available positions.

Automated Resume Generation: Future systems might have the ability to automatically create resumes in addition to parsing resumes. These systems may produce expert resumes that are customised to each job seeker by utilising AI and templates, which saves time and effort.

Overall, Resume Parser systems have a great deal of potential to change the hiring process, increase effectiveness, and improve the candidate experience. These solutions will continue to be essential for managing and finding personnel as technology develops.

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