

RESUME RANKING WEB APPLICATION USING NLP

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Abstract - In today's competitive job market, efficiently screening resumes is crucial for recruiters to identify the most suitable candidates. This paper presents a novel approach to resume ranking using Flask, a micro web framework for Python, and natural language processing (NLP) techniques. The system allows recruiters to upload a job description and multiple resumes, which are then analyzed to determine their similarity to the job requirements. The system leverages various NLP tools, including spaCy for named entity recognition (NER) and PyPDF2 for PDF text extraction. Resumes are pre-processed to extract relevant information such as names and emails, which are used alongside the textual content for analysis. Text similarity between the job description and each resume is calculated using the Term Frequency-Inverse Document Frequency (TF-IDF) vectorization method and cosine similarity. Furthermore, the system provides a user-friendly web interface for interaction, allowing recruiters to seamlessly upload job descriptions and resumes, and obtain ranked results based on similarity scores. Additionally, the system offers the functionality to download the ranked resumes in CSV format for further analysis or archival purposes. Overall, this system offers a streamlined approach to resume screening, enabling recruiters to efficiently identify potential candidates that closely match the job requirements, thereby enhancing the hiring process.

Keywords: Natural language processing, PyPDF2, spaCy, Term Frequency-Inverse Document Frequency, Cosine similarity

I. INTRODUCTION

In today's rapidly evolving job market, the process of resume screening stands as a crucial challenge for recruiters and job seekers alike. Traditional methods often prove time-consuming and labor-intensive, leaving much to be desired in terms of efficiency and accuracy. To address these pain points, we present a groundbreaking Flask-based application that redefines the resume screening process. By seamlessly integrating advanced

technologies such as natural language processing (NLP) and machine learning (ML), our application offers a comprehensive solution to streamline recruitment efforts.

Our application boasts several key features designed to enhance the efficiency and effectiveness of the resume screening process. Firstly, we leverage the PyPDF2 library to extract text seamlessly from PDF resumes, ensuring that no valuable information is overlooked during parsing. This feature eliminates the need for manual data entry and enhances the overall accuracy of the screening process.

Our application utilizes sophisticated Named Entity Recognition (NER) techniques powered by spaCy to identify crucial entities such as names and emails from the extracted text. This functionality provides recruiters with valuable metadata for organizing and categorizing resumes efficiently, thereby streamlining the candidate evaluation process. Application employ TF-IDF (Term Frequency-Inverse Document Frequency) vectorization to transform raw text data into numerical vectors. This approach allows for meaningful comparisons between job descriptions and resumes, enabling recruiters to identify the most relevant candidates based on their skills and experiences.

Furthermore, our application computes similarity rankings between resumes and job descriptions using the cosine similarity metric. By prioritizing candidates whose profiles closely match the requirements of the job, recruiters can expedite the selection process and focus their attention on the most promising candidates. In addition to these core functionalities, our application features a user-friendly web interface built using Flask, providing recruiters with an intuitive platform for uploading job descriptions and resumes. Real-time feedback on candidate suitability enhances the efficiency of the hiring process, allowing recruiters to make informed decisions quickly.

Lastly, our application offers CSV export functionality, enabling recruiters to export ranked resumes for further analysis and

reporting. This feature facilitates seamless collaboration and communication within hiring teams, allowing recruiters to maintain organized records and track candidate interactions effectively. By combining these key features, our Flask-based application empowers recruiters to streamline the resume screening process, saving valuable time and resources while ensuring the identification of top talent.

II. LITERATURE REVIEW

Recruitment processes undergone significant transformations with the integration of technology, particularly in automating resume screening tasks. The utilization of machine learning (ML) and natural language processing (NLP) techniques has become increasingly prevalent in recent years, aiming to enhance the efficiency and accuracy of candidate evaluation. This literature review aims to explore the existing research and advancements in this domain, focusing on Flask-based applications, text extraction from PDFs, entity recognition, and similarity ranking methods.

Flask, a micro web framework for Python, has gained popularity in the development of recruitment applications due to its simplicity and flexibility. Researchers have explored the utilization of Flask to create user-friendly interfaces for uploading job descriptions and resumes, facilitating seamless interaction between recruiters and the screening system (Adams, 2019). By leveraging Flask's modular structure, developers can integrate various components such as text extraction and similarity ranking algorithms to build comprehensive recruitment solutions (Smith et al., 2020).

Extracting text from PDF resumes is a fundamental task in automating the screening process. PyPDF2, a Python library for interacting with PDF files, has been extensively utilized for this purpose. Researchers have investigated different approaches to efficiently extract text from PDFs, considering factors such as formatting inconsistencies and document layout variations (Jones & Brown, 2018). Strategies involving iterative parsing and text normalization have been proposed to improve the accuracy and reliability of text extraction from diverse PDF formats (Garcia et al., 2021).

Named Entity Recognition (NER) plays a crucial role in identifying key entities such as names and emails from extracted resume text. SpaCy, a popular NLP library, offers pre-trained models for entity recognition tasks. Studies have explored the integration of spaCy's NER capabilities into recruitment systems, emphasizing the importance of accurately identifying candidate information for effective profiling and categorization (Chen et al., 2019). Additionally, researchers have investigated the incorporation of custom entity recognition rules to handle specific patterns and formats commonly found in resumes (Kim & Lee, 2020).

Cosine similarity ranking algorithms have emerged as effective methods for assessing the relevance of resumes to job descriptions. By vectorizing textual data using techniques such

as TF-IDF (Term Frequency-Inverse Document Frequency), researchers have demonstrated the ability to quantify the similarity between documents and rank candidates accordingly (Wang et al., 2021). Studies have explored enhancements to traditional cosine similarity approaches, including the incorporation of semantic embeddings and domain-specific weighting schemes to improve the accuracy of candidate evaluation (Zhang & Liu, 2019).

In recent years, deep learning approaches have gained traction in the field of resume analysis. Researchers have explored the application of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) for tasks such as resume classification and information extraction (Li et al., 2020). These approaches leverage the hierarchical structure of resumes and sequential dependencies in text data to achieve superior performance compared to traditional machine learning methods. Additionally, studies have investigated the integration of attention mechanisms and transfer learning techniques to enhance the generalization and adaptability of deep learning models in resume analysis tasks (Yang et al., 2021).

The increasing reliance on algorithmic decision-making in recruitment processes has raised important ethical considerations. Researchers have examined issues related to bias, fairness, and transparency in automated resume screening systems (Muller & Brown, 2020). Studies have highlighted the potential risks of algorithmic discrimination and the need for robust mechanisms to mitigate biases in decision-making processes. Additionally, researchers have proposed frameworks for ethical design and evaluation of recruitment algorithms, emphasizing principles such as accountability, interpretability, and inclusivity (Gupta et al., 2021).

III. PROPOSED METHODOLOGY

1. **Data Collection:** Job descriptions and resumes are collected from various sources, such as job boards and applicants.
2. **Text Extraction:** Resumes are converted from PDF format to text using PyPDF2 library.
3. **Entity Extraction:** Relevant entities such as names and emails are extracted from resumes using spaCy NER model.
4. **TF-IDF Vectorization:** Both job descriptions and resumes are converted into TF-IDF vectors using sklearn's TfidfVectorizer.
5. **Similarity Calculation:** Cosine similarity is calculated between the TF-IDF vectors of job descriptions and resumes to determine their similarity.
6. **Ranking:** Resumes are ranked based on their similarity scores, with higher scores indicating a closer match to the job description.

7. **Web Application:** The system is implemented as a web application using Flask framework, allowing recruiters to easily upload job descriptions and resumes and receive ranked results.

IV. IMPLEMENTATION

A. Import Necessary Modules:

- Import Flask, render_template, request, spacy, PyPDF2, TfidfVectorizer, cosine_similarity, re, csv, and os.
- These modules are required for building the Flask web application, processing PDF files, performing text analysis, and handling file operations.

B. Initialize Flask App:

- Create an instance of the Flask application using `Flask(__name__)`.
- This initializes the Flask web application.

C. Load Model:

- Load the spaCy Named Entity Recognition (NER) model "en_core_web_sm" using `spacy.load("en_core_web_sm")`
- This model will be used to extract entities such as names and emails from text.

D. PDF Text Extraction:

- Define a function to extract text from PDF files using PyPDF2.
- This function reads the content of the PDF file and returns the extracted text.

E. Entity Extraction:

- Implement the function `extract_entities(text)` to extract entities such as emails and names using regular expressions.
- This function identifies emails and names from the given text data.

F. Flask Routes:

- Define Flask routes to handle both GET and POST requests, including the index route (`/`) and the route for downloading CSV (`/download_csv`).
- These routes specify the endpoints for accessing different functionalities of the application.
- Implement the logic for the index route (`/`) to handle POST requests for processing job descriptions and uploaded resumes.
- This logic processes the form data submitted by the user.

G. Process Uploaded Resumes:

- Create a directory named "uploads" if it doesn't exist to store uploaded resumes.

- Iterate through each uploaded resume, extract text from PDF files, and extract entities (names and emails) from the resume texts.

H. Calculate Similarity Scores:

- Use TfidfVectorizer to convert text data into numerical vectors.
- Calculate cosine similarity between the job description vector and each resume vector.
- This step measures the similarity between the job description and each resume.

I. Rank Resumes

- Rank the resumes based on their similarity scores in descending order.
- Create a list of tuples containing names, emails, and similarity scores, and sort them based on similarity scores.
- This step determines the relevance of each resume to the job description.

V. RESULTS

The screenshot shows a web browser window with the title "Resume Analyzer". The interface includes a "Job Description:" text area containing the text: "nlp specialists: develop and implement nlp algorithms, proficiency in python and nlp libraries and ml frameworks required." Below this is an "Upload Resumes (PDF):" section with a "Choose Files" button and an "Analyze Resumes" button. At the bottom, there is a "Ranked Resumes:" table with the following data:

Rank	Name	Email	Similarity in %
1	Emily Williams	emily.williams@example.com	83.39078479367939
2	Alex Johnson	alex.johnson@example.com	57.32367797886339
3	Jane Smith	jane.smith@example.com	46.35235823621443

Fig 1. Web Application

VI. CONCLUSION AND FUTURE WORK

A. Conclusion:

In this paper, we developed a Flask web application for ranking resumes based on their similarity to a given job description. We utilized natural language processing techniques, including text extraction from PDFs, named entity recognition (NER) using spaCy, and cosine similarity calculation using TF-IDF vectorization.

The application allows users to input a job description and upload multiple resumes. Resumes are processed to extract relevant information such as names and emails using NER. Then, TF-IDF vectorization is employed to represent both the job description and resumes as numerical vectors, enabling the calculation of cosine similarity scores. Resumes are ranked based on their similarity to the job description, and the results are displayed to the user.

B. Future Work:

In future iterations, several enhancements could be implemented to refine the functionality and usability of the Flask web application for ranking resumes. Firstly, improving the named entity recognition (NER) capabilities by either fine-tuning existing models or integrating more advanced NER techniques could enhance the accuracy of information extraction from resumes. Additionally, exploring more sophisticated methods for measuring semantic similarity, such as leveraging word embeddings or deep learning models, could provide a more nuanced understanding of the relationships between job descriptions and resumes. Implementing user authentication features would bolster security, ensuring that only authorized users can access and upload resumes, which becomes crucial for deployment in production environments.

Moreover, optimizing the application for scalability to efficiently handle large volumes of resumes and concurrent user requests, potentially through cloud deployment and load balancing strategies, would enhance its performance. Incorporating a feedback mechanism for users to provide input on the relevance of ranked resumes could enable iterative improvements to the ranking algorithm. Robust error handling mechanisms and user interface enhancements, including real-time updates and interactive visualizations, would further contribute to a smoother and more intuitive user experience. By addressing these areas for future work, the application could evolve into a highly effective tool for streamlining the resume screening and hiring process for organizations.

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