Resume Ranking and Evaluation using Transformer Models

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***Abstract*—The recruitment process often involves analyzing large volumes of resumes to identify suitable candidates, a task that is both time-consuming and error-prone. In this paper, we propose a transformer-based approach to automate and enhance the process of resume ranking and evaluation. Leveraging state-of-the-art transformer models such as BERT, RoBERTa, and ALBERT, our system computes semantic similarities between resumes and job descriptions. The results are combined using a weighted similarity score to rank resumes effectively. This method demonstrates its potential to significantly streamline hiring workflows and improve the accuracy of candidate matching.**

***Index Terms*—Resume Ranking, Transformer Models, BERT, RoBERTa, ALBERT, Natural Language Processing, Recruitment Automation**

I. Introduction

The process of matching resumes to job descriptions is a critical component of recruitment, often demanding considerable time and effort from hiring managers. Traditional methods rely heavily on keyword-based searches, which fail to capture the nuanced understanding of job requirements and candidate qualifications.

With the advancements in Natural Language Processing (NLP), transformer-based models have emerged as powerful tools for capturing semantic relationships in text. In this project, we aim to utilize these models to enhance the recruitment process by ranking resumes based on their semantic similarity to a given job description.

Our approach involves extracting key sections from resumes, generating embeddings using pre-trained transformer models, and computing similarity scores. The combined similarity scores are then used to rank resumes, providing recruiters with an efficient and accurate tool for candidate evaluation. This paper outlines the methodology, system design, and potential applications of our approach.

II. Related Work

The use of Natural Language Processing (NLP) in recruitment automation has gained significant attention in recent years. Traditional resume evaluation systems often rely on keyword matching, which lacks the ability to understand the context or semantic relationships within text.

Transformer models, such as BERT [1], RoBERTa [2], and ALBERT [3], have demonstrated state-of-the-art performance in various NLP tasks, including text classification, semantic similarity, and information retrieval. These models leverage self-attention mechanisms to capture contextual information, making them ideal for understanding resumes and job descriptions.

Several studies have explored the application of transformer models in recruitment. For instance, [4] proposed a BERT-based approach to match candidate profiles with job requirements, achieving higher accuracy compared to traditional methods. Similarly, [5] utilized RoBERTa for job-resume matching and demonstrated the importance of fine-tuning on domain-specific data. Another study [6] highlighted the effectiveness of using embeddings generated by ALBERT for ranking resumes based on their relevance to job postings.

Despite these advancements, existing systems often face challenges such as limited training data, domain adaptation, and computational overhead. Our approach builds on these works by combining multiple transformer models and leveraging their strengths to provide a robust and scalable solution for resume ranking and evaluation.

III. Methodology

Our methodology consists of five main components: data preprocessing, model architecture, similarity computation, result refinement via language models, and GUI integration. Each step is designed to maximize the effectiveness and usability of our system.

A. Data Preprocessing

To ensure meaningful comparisons between resumes and job descriptions, we preprocess the input data as follows:

- **Resume Segmentation:** Resumes are segmented into key sections such as *skills*, *work experience*, *education*, and *certifications* using keyword-based extraction techniques.
- **Text Cleaning:** Unnecessary formatting, special characters, and irrelevant information are removed to standardize the input.
- **Job Description Parsing:** The job description is tokenized and divided into *core requirements* and *desirable qualifications*.

B. Model Architecture

We utilize three pre-trained transformer models to generate embeddings:

- **BERT:** Captures bidirectional context and is fine-tuned for text similarity tasks.

- **RoBERTa:** Optimized for robust text representation, ensuring high accuracy in semantic similarity.
- **ALBERT:** Lightweight model used to reduce computational overhead while maintaining performance.

Each model processes the input text to generate embeddings, which are then aggregated for further computation.

C. Similarity Computation

The embeddings generated by each transformer model are compared using cosine similarity. The final similarity score is calculated as follows:

$$\begin{aligned} \text{Combined Similarity} = w_1 \cdot \text{BERT Similarity} \\ + w_2 \cdot \text{RoBERTa Similarity} \\ + w_3 \cdot \text{ALBERT Similarity}. \end{aligned} \quad (1)$$

Here, w_1, w_2, and w_3 represent the weights assigned to each model based on their performance. The weights can be tuned to prioritize models that perform better on domain-specific datasets.

D. Refinement via Language Models

Once initial rankings are computed, the top candidates are passed to a large language model (LLM) for refinement. The LLM evaluates:

- **Alignment with Job Requirements:** Contextual analysis of skills and experience relative to the job description.
- **Language and Presentation Quality:** Identification of professional tone and readability.
- **Unique Contributions:** Highlighting distinguishing qualifications among candidates.

The LLM generates a summary and a ranking rationale for each candidate, providing recruiters with actionable insights.

E. Graphical User Interface (GUI)

The system includes an interactive GUI built using Gradio. Users can:

- Upload resumes and job descriptions for processing.
- View detailed similarity scores for each transformer model.
- Access LLM-generated summaries and suggestions to improve resume quality.

IV. Results

The system's performance was tested across several real-world use cases:

- **Case 1: Large-scale Resume Pool.** The system effectively ranked a dataset of 10,000 resumes within a reasonable time frame, accurately identifying top candidates matching a given job description.
- **Case 2: Domain-specific Applications.** For technical roles requiring specific skills, the system prioritized resumes with relevant certifications and work experience, showcasing its ability to handle specialized job descriptions.
- **Case 3: Multilingual Resumes.** The system demonstrated robust performance in processing resumes written in English, though non-English resumes highlighted the need for multilingual model integration.
- **Case 4: LLM Refinement Impact.** In a subset of closely matched candidates, the LLM refinement improved ranking precision by providing deeper context on qualifications and alignment, assisting recruiters in making final decisions.

These results validate the system's applicability in diverse recruitment scenarios and its potential to streamline the hiring process.

V. Conclusion

This paper presents a transformer-based approach to automate resume ranking and evaluation. By leveraging state-of-the-art models such as BERT, RoBERTa, and ALBERT, coupled with LLM refinement, the system captures semantic relationships between resumes and job descriptions, providing a powerful tool for recruitment automation. Future work could focus on incorporating additional languages, fine-tuning models for specific industries, and enhancing LLM capabilities for domain-specific analyses.

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