INNOV8 2.0

FINALS SOLUTION

Team ModuleNotFound

IIT KHARAGPUR

1 Introduction

Resume screening has traditionally been a labor-intensive process, requiring recruiters to manually review each application. This is changing as companies increasingly adopt **automated hiring systems**. AI-driven tools now streamline the screening process, quickly filtering candidates based on qualifications, reducing manual effort, and promoting more efficient and objective hiring.

In a world where careers are shaped by networks, connections, and credibility, we are presenting **Satya**, which aims to revolutionise the HR landscape. Powered by AI, Satya is designed to uncover hidden patterns in candidate data, verify credentials with accuracy, and **transform traditional hiring practices**. Its goal is to create a more efficient, reliable, and objective approach to **resume screening** and **talent acquisition**.

In the following sections, we will:

- Generate Resume Scores using **quantifiable features** like grammatical errors, total skills, resume length etc.
- Build a recommendation network with directed edges to quantify **Recommendation Credibility**
- Present Algorithms used to compute the Recommendation Credibility score
- Analyze Relationships between resume features and credibility scores to uncover patterns and insights
- Develop and evaluate a System to predict **overall candidate quality** based on the generated scores and analysis

With our detailed approach, we aim to address the critical issue of candidate evaluation and its impact on hiring efficiency. By developing a predictive model, we hope to optimize the hiring process, improve candidate selection, and ensure the credibility of recommendations within the recruitment pipeline.

2 Challenges

In developing our system for candidate evaluation and credibility scoring, we faced several significant challenges:

1. **Limited Dataset:** Due to the availability of a limited dataset of around 1000 rows, we encountered difficulties in:
   - Fine-tuning lightweight transformers like BERT or RoBERTa, which are typically effective for quick inference.
   - Ensuring that the model generalizes well despite the small size of the dataset.
2. **Large and Incoherent Textual Data:** Each ID is associated with a large corpus of recommendations and resumes, leading to:
   - Reliance on Large Language Models (LLMs) to process the incoherent and unstructured data.
   - Significant costs when using high-performing LLMs for large-scale text understanding.
3. **Use of Open-Source LLMs:** Open-source models introduced challenges such as:

- High inference times, particularly when compared to proprietary models like GPT-4.
- Frequent rate limit errors, which slowed down the project timeline.

4. **System Scalability:** Our system needed to:
   - Scale efficiently despite the small dataset, ensuring that performance remains consistent as new data is added.
   - Handle both resumes and recommendation letters in parallel while maintaining accuracy and speed.

Addressing these challenges is crucial for developing a reliable system that can predict candidate quality and recommendation credibility. Our solutions will be detailed in the following sections.

3 Approach

3.1 Pipeline

The recruitment pipeline described is divided into three main stages, utilizing advanced NLP techniques and graph-based analysis to streamline and enhance the hiring process.

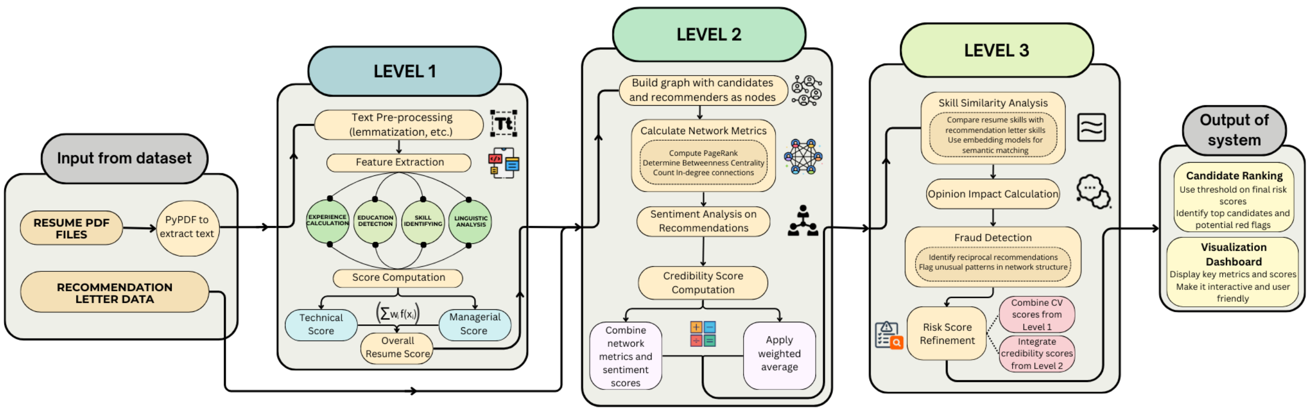

Figure 1: Flowchart of the multi-level pipeline

3.1.1 Level 1: Resume Screening and Initial Scoring

The first level of the recruitment pipeline employs efficient analysis and retrieval of relevant information in textual form from resumes using **PyPDF** library. Advanced natural language processing (NLP) techniques are used to extract and analyze various measures from resumes, providing objective metrics for candidate comparison. These metrics offer deep insights into candidates' qualifications, skills, and overall suitability for the role, significantly enhancing the effectiveness and efficiency of the recruitment process.

Here are some key attributes and scores that are calculated from the resume data:

- **Years of Experience:** Extracted using **regular expressions** to identify date patterns, this metric quantifies a candidate's professional tenure. It's crucial for assessing career progression and domain expertise.

- **Education Level:** Utilizing **pattern matching algorithms**, we categorize candidates' highest educational attainment (e.g., PhD, Master's, Bachelor's). This helps in evaluating academic qualifications and potential for advanced roles.
- **Spell Check Ratio:** Implemented using the **LanguageTool** library, this measure assesses the linguistic accuracy of the resume. It reflects attention to detail and communication skills, both vital in professional settings.
- **Resume Section Score:** Through semantic analysis, we identify the presence and quality of key resume sections (e.g., education, experience, skills). This score indicates how well-structured and comprehensive the resume is.
- **Brevity Score:** Calculated based on word count and content density, this metric evaluates the resume's conciseness. It helps identify candidates who can present information efficiently.
- **Skill Count and Relevance:** Using a combination of **keyword extraction and semantic similarity analysis**, we identify and count relevant skills. This provides insights into the candidate's technical and soft skill set.
- **Technical Score:** A composite score derived from education level, years of experience, and identified technical skills. It quantifies the candidate's technical proficiency relative to the job requirements.
- **Managerial Score:** Leveraging sentiment analysis and achievement quantification algorithms, this score assesses leadership potential and impact in previous roles.
- **Overall Score:** A weighted combination of all previous scores, providing a holistic evaluation of the candidate. The weights are adjustable based on specific job requirements.
- **Job Match Score:** Using **TF-IDF vectorization** and cosine similarity, we compare the resume content with the job description, quantifying how well the candidate's profile aligns with the specific role.

The combination of technical skills assessment, experience quantification, education level classification, sentiment analysis, and overall resume quality ensures a holistic evaluation of each candidate. This approach not only identifies candidates with the right technical skills but also those who demonstrate strong communication abilities, leadership potential, and attention to detail. Moreover, the flexibility of the system allows for customization of scoring weights and job-specific criteria, ensuring that the evaluation process can be tailored to the unique requirements of different roles and organizations.

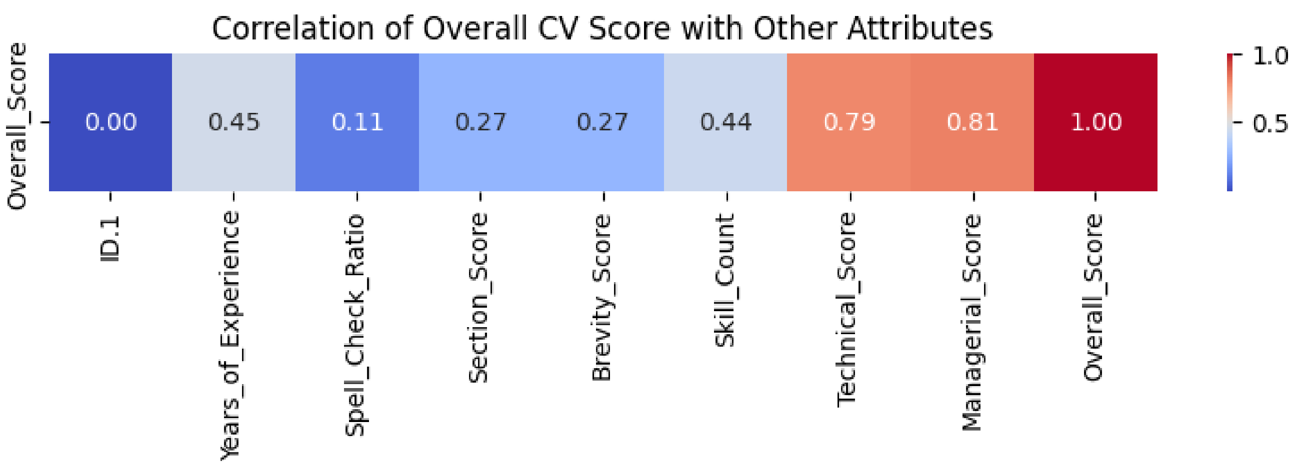

Figure 2: Resume Score Correlation

3.1.2 Level 2: Network Analysis - A Graph-Based Analysis of Recommendations

Network analysis is crucial for understanding the structure and relationships between different entities within a system. This section outlines the process for generating and analyzing a network, specifically focusing on extracting various network properties such as node connections, centrality, clustering, and communities. We also address the **issue of circular endorsements** and **identifying influential actors**, providing a deeper insight into the social dynamics within the candidate pool.

A directed graph $G(V, E)$ is constructed by defining a set of vertices V and a set of directed edges E, where each edge $(u, v) \in E(u, v)$ represents a recommendation relationship, i.e., directed from the recommender u to the candidate v, capturing the flow of recommendations within the network. By mapping these connections, we aim to identify **potentially fake or fraudulent recommendation patterns** and score each candidate based on their recommendation credibility.

An edge is weighted based on the **authenticity of the recommendation**, which is estimated using the recommender's years of experience, Managerial CV Score, and the number of recommendations they have provided.

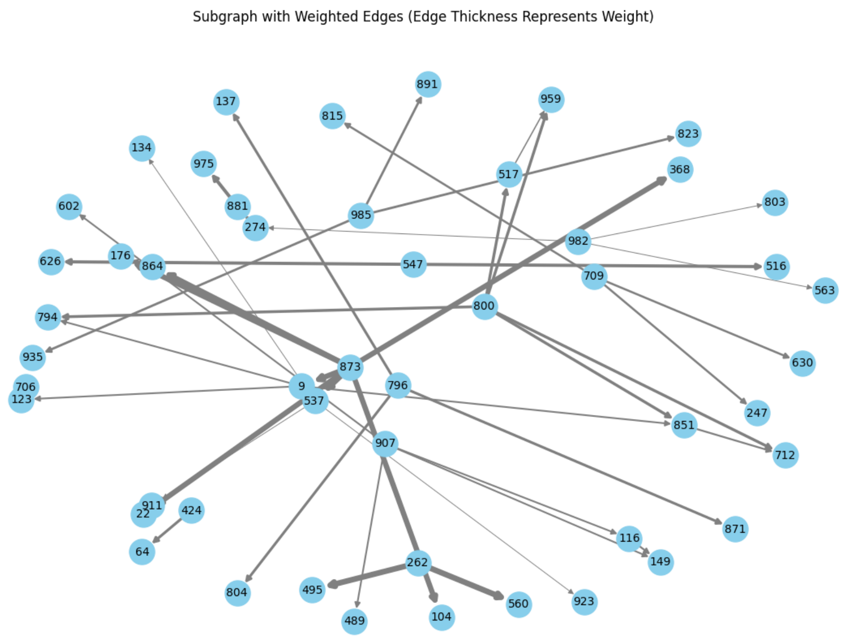

Figure 3: Network Graph (n=50) depicting recommendation connections

A composite score, termed the Credit Score (C), is calculated for each candidate by considering the following metrics:

PageRank (P): PageRank helps identify candidates and recommenders who are influential within the network, allowing for a more informed assessment of their credibility. A higher PageRank (P) indicates a candidate or recommender with more significant connections, suggesting that they are likely more credible or trusted within the network.

Inverse Betweenness (B): Inverse Betweenness (B) is particularly useful for flagging candidates who may possess genuine potential and credibility but are not heavily entrenched in the network. By including inverse betweenness in the final composite score, we promote a more balanced evaluation of candidates.

In-Degree (D): In a recommendation graph, the in-degree (D) of a node represents the number of incoming edges, which translates to how many people have recommended that candidate.

Reciprocity (R): Reciprocity is represented as a binary flag added to nodes involved in reciprocal edges, i.e., instances where a candidate has recommended their recommender in return. This is later used to penalize reciprocal relationships while calculating the Credit Score (C).

$$C = W \times \left(\frac{0.4 \times P + 0.3 \times B}{D + 1} \right) - 0.3 \times R$$

$$C = 100 \times \frac{C - \min(C)}{\max(C) - \min(C)}$$

Legend:

- C: Credit Score
- W: Incoming Edge Weight Sum
- P: PageRank
- B: Inverse Betweenness
- D: In-Degree
- R: Reciprocity

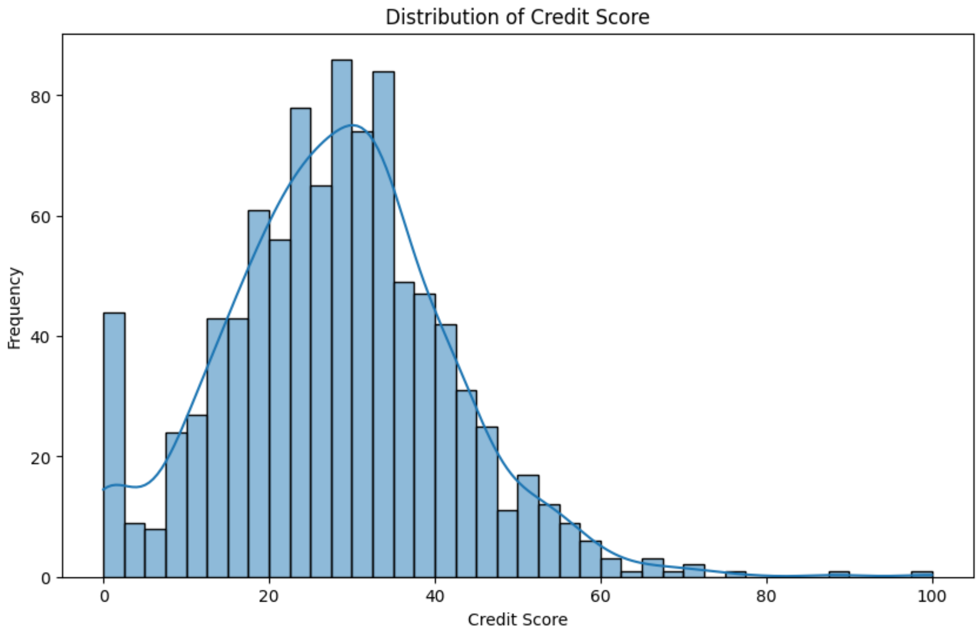

Figure 4: Distribution of Credit Score (depicting credibility of recommender)

3.1.3 Level 3: Recommendation Validation

In the third part of the pipeline, we implement a **skill matching mechanism** to assess the authenticity of recommendations provided for candidates. This process involves comparing the **skills claimed by candidates** in their resumes with the **skills mentioned in their Letters of Recommendation (LORs)**.

To extract skills from the candidates' resumes, we utilize **regular expressions (regex)**. This method allows us to identify specific keywords and phrases that correspond to the skills relevant to the job description. Utilizing regex not only streamlines the extraction process but also conserves both time and computational resources compared to using large language models (LLMs) for this task.

For skill extraction from the LORs, we employ **Skilner**, a specialized tool designed for identifying and extracting skills from text. Skilner effectively captures relevant skills mentioned in the LORs, providing a comprehensive representation of the recommenders' insights regarding the candidate's capabilities.

Once we have extracted skills from both the resumes and the LORs, we perform **pairwise comparison** using the **Roberta** model, a transformer-based natural language processing model that excels in understanding context and semantic meaning. This model helps quantify the **degree of alignment** between the skills extracted from the resume and those highlighted in the LORs by calculating a **similarity score**.

Finally, we take the average of these similarity scores to provide a comprehensive measure of the alignment between the skills claimed by the candidate and those emphasized in the recommendations. This average score serves as a key indicator of the authenticity and credibility of the recommendations, ensuring a more reliable evaluation of the candidate's qualifications.

Using the three metrics - Overall CV Score from Level 1, Credit Score from Level 2 and Skill Similarity from Level 3, we compute a Final Score using the formula:

$$\text{Final Score} = 0.60 \times \text{Overall CV Score} + 0.25 \times \text{Credit Score} + 0.15 \times \text{Skill Similarity Score}$$

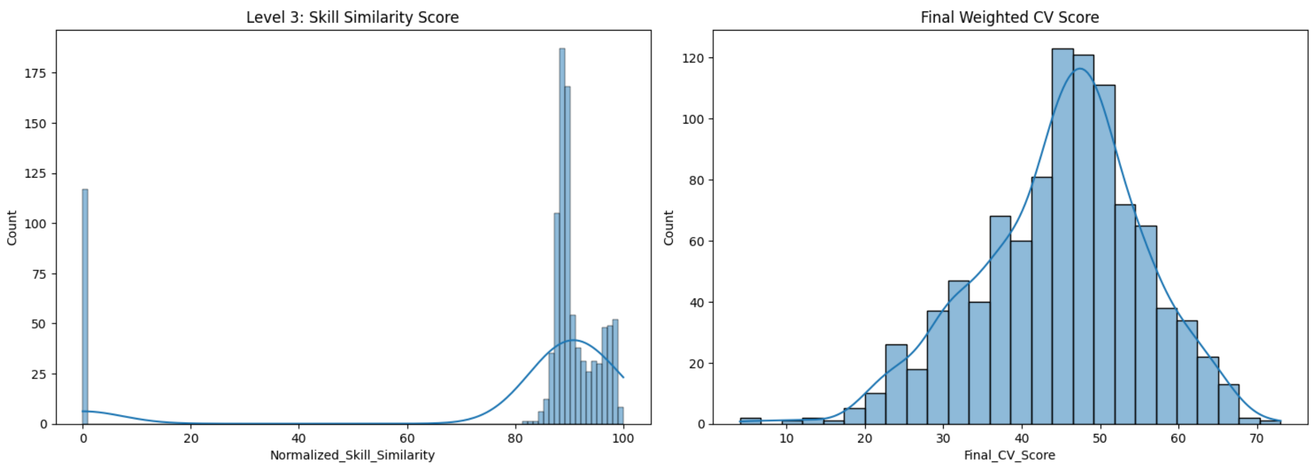

Figure 5: Similarity Score and Final Score

3.2 Additional Points

In addition to our comprehensive pipeline, which addresses various challenges, we have incorporated several additional features in our system to further enhance its capabilities.

3.2.1 Dealing with Exaggerated Claims

We also design **sentiment_calculator**, a tool designed to analyze recommendation letters by examining the claims made within the text and **distinguishing between typical and exag-**

gerated assertions. It works by reading the input recommendation letter and utilizes advanced language processing techniques to evaluate the sentiments expressed. The tool employs a **LLaMA** model to identify various claims, assigns sentiment scores to them, and highlights any claims that may be overly exaggerated. The output includes an **overall sentiment score**, which reflects the balance between the normal and exaggerated claims, along with a list of the flagged exaggerated assertions.

3.2.2 Interactive Resume Engagement via ChatBot

Our solution includes the functionality of a ChatBot which provides valuable services to HR professionals by serving as a **virtual assistant**, guiding them through their resume content, answering questions, and **providing personalized feedback**. Hiring Managers can also inquire about specific sections of candidates' resumes, such as skills, work experience, or education, and receive immediate responses.

3.2.3 Filter by Skills

We have streamlined the recruitment process for HR professionals by incorporating a robust functionality that allows users to **filter candidates based on specific skills** that are essential for the positions they aim to fill. This feature enables hiring managers to define a tailored skill set that **aligns with the requirements of the job**, thereby narrowing down the candidate pool to those who best match their needs.

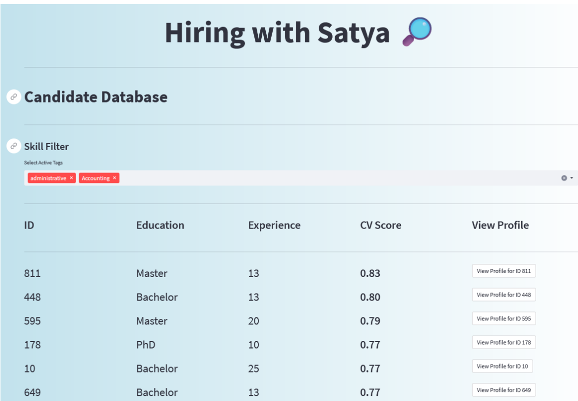

Figure 6: User Interface showing Filter by Skill functionality

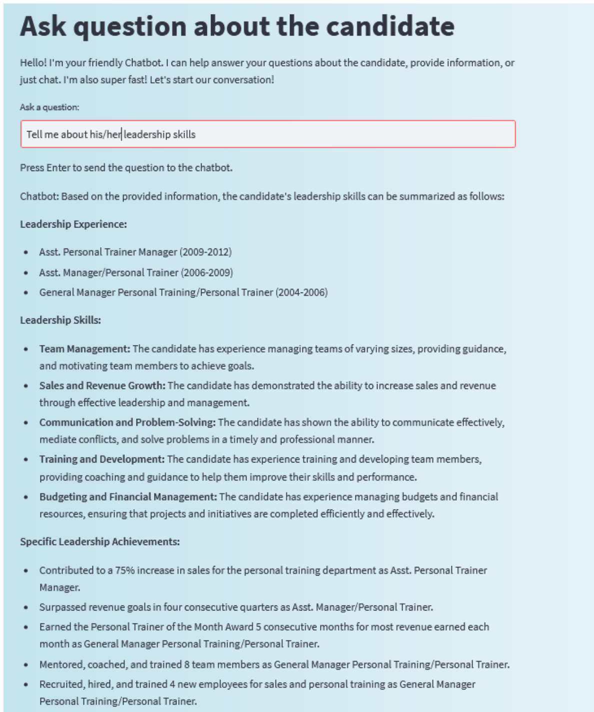

Figure 7: Interactive Resume Engagement

4 Scalability and Future Scope

4.1 LLM-Based SLM Fine-Tuning

We can **overcome the compute and inference latency issues** faced by our current solution at several points in our proposed pipeline by incorporating LLM-Based SLM Fine-Tuning.By integrating insights from LLMs into our Statistical Language Models (SLMs) through fine-tuning, we can enhance the accuracy of the SLMs without compromising speed. This process allows the SLMs to leverage the rich contextual understanding provided by the LLMs, resulting in improved coherence and relevance in their outputs.

4.2 Improving Recommendation Credibility

We utilize time-based information to ensure that there is a meaningful overlap between the candidate's and the recommender's work experience, verifying the legitimacy and relevance of the recommendation. By analyzing the timelines of both individuals, we check for an intersection in their professional history, such as shared tenures at the same organization or overlapping projects. This ensures that the recommender has had firsthand experience working with the candidate, making them eligible and credible to provide a recommendation. If no significant overlap is found, it may raise questions about the recommender's ability to accurately assess the candidate's qualifications, reducing the credibility of the recommendation.

4.3 Enhancing Fact-Checking in Resumes

One effective approach is to implement **automated verification tools** that **cross-reference resume claims** against verified databases, such as educational institutions and professional organizations. These tools can efficiently check the **authenticity of degrees, certifications, and employment histories** by directly accessing institutional records or utilizing APIs that provide real-time data validation. By automating this process, organizations can significantly reduce the time and resources spent on manual checks while increasing the accuracy of verification.

5 Conclusion

To conclude, our approach offers a **data-driven, customizable, and comprehensive approach** to recruitment, combining **resume analysis, network evaluation, and recommendation validation**. The pipeline ensures a holistic candidate evaluation while identifying fraud or exaggerated claims, enhancing the recruitment process's effectiveness and reliability. Additionally, features like a **sentiment calculator, interactive chatbot, and skill-based filtering** further streamline the hiring process, offering greater precision and convenience for HR professionals.