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Optimizing Resume Design for ATS Compatibility: A Large Language Model Approach

[1]Saprit Anand, [2]Abhijeet Kumar Giri
[1,2]Kalinga Institute of Industrial Technology , India
[1]21051249@kiit.ac.in, [2]21052724@kiit.ac.in

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Abstract

The modern hiring process increasingly relies on Application Tracking Systems (ATS) to sort and evaluate resumes based on organizational preferences. However, many skilled and competent candidates fail to craft resumes that are ATS-optimized, leading to missed opportunities. This study explores the potential of Large Language Models (LLMs) to enhance ATS compatibility in resumes. Using Natural Language Processing (NLP) techniques, LLMs analyze resumes to identify errors, recommend suitable keywords, enhance semantic alignment, and format content to meet ATS requirements. Evaluation results demonstrate that implementing the model's suggested changes significantly improves ATS scores. This approach bridges the gap between job seekers and automated recruiting systems, empowering individuals to enhance their resumes effectively. By leveraging LLMs, job seekers gain a powerful tool to align their resumes with employer expectations, increasing their chances of success in the hiring process. This study highlights how LLMs can transform the recruitment landscape, improving access to employment and redefining traditional hiring practices

Keywords

Sematic , LLMs(Large Language Model), NLP(Natural Language Processing) , Application , Tracking System (ATS).

1. Introduction

In the current market ATS (Application Tracking System) is used to hurry the process of recruitment in the current digital era .The use of automated resume screening models the resumes are filtered on the basis of current market needs and the skills required to join the firm. The convenience that has been provided by the ATS has helped the recruiters significantly but also the job seekers have difficulty writing high scoring resumes , as when the resumes don't qualify for the screening they are not selected .The demand for technology that can help the job seekers to optimize their resumes. Because the applicants focus more on the surface level keyword matching rather than the semantic alignment or the natural flow of the resume . Using the AI and the LLMs(Large Language Model) , this study moves forward by suggesting a novel method for resume improvement .LLMs can easily comprehend the job description and application with the use of Natural Language Processing(NLP)to find gaps , errors in structure or the alignment .This project makes sure that the applicant's resume is moved forward by creating an AI driven model which enhances the resume . In contrast with the conventional or traditional ATS optimization techniques that focuses on mainly basic keyword matching , this model delivers to the fact that these are able to comprehend the job description and enhance phrasing along with greater pace of keywords matching . Thus making it possible to make the resume more ATS friendly in a more thorough manner .

The structure is intended to be user-friendly, with clear and straightforward recommendations that job seekers may simply implement into their resumes. The potential benefits of LLM in ATS includes:

- Enhanced Semantic Understanding :Instead of relying on keyword matching , LLMs are always able to comprehend the different meanings of certain keywords and phrases . To ensure that the resume moves thoroughly LLMs are able to understand the phrases , synonyms and industry specific terminology .

- Contextual Match Making : Candidates when list various and diverse keywords in the resume sometimes overlooked by the traditional application tracking system . Even when the applicant's resume, which is good , may lack certain keywords and hence degrade the resume .

- Automation and Efficiency: Large resume volumes may be swiftly analyzed and optimized by LLM-powered systems, which makes them more scalable and effective than conventional techniques. This minimizes the time and effort required for resume changes by enabling job searchers to obtain immediate feedback..

- Adaptability to Different Industries: LLMs can be trained on data particular to a given industry, which enables them to make recommendations that are specifically customized to the requirements and distinctive terminology of different industries. This assists applicants from a variety of industries in tailoring their resumes to the requirements of certain applicant tracking systems utilized in those sectors.

- Continuous Learning and Improvement:With new data, LLMs can be adjusted and enhanced over time, guaranteeing that the system adapts to the most recent developments in ATS algorithms, industry terminology, and resume design. Over time, this keeps the optimization process efficient and relevant.

The main challenges and considerations are as follows:

- Variability and Quality of Data: OMaking sure the training data is diverse and of high quality is one of the main issues when utilizing LLMs for ATS optimization. Resumes and job descriptions can differ greatly between occupations, sectors, and geographical areas.

- The ATS Algorithm:The ATS platform in itself is very complicated. It is difficult to ensure that suggestions are applied consistently across the various ATS models since LLMs need to be adjustable enough to list these differences. As the model needs to adapt in particular changes that the company uses and hence making the process more complicated .

- Adoption of Particular Keywords: There are many times when LLMs overfit to particular words for resume optimization , which may or may not work properly for every other job present .With an effort to make the resume more ATS friendly they use these words in general which hampers the proper structure of the resume or going of the natural flow of the resume .

- Security Issues: Personal information is frequently included in resume data. Concerns regarding data security and privacy arise when using LLMs to process and analyze resumes, particularly if the AI models need access to big datasets of job descriptions and resumes. Both employers and job searchers need to make sure that data handling procedures adhere to data protection laws.

- User Acceptance:Although resume improvement can be automated by AI, prospects might be hesitant to trust an AI-powered tool for such significant work. It's critical to establish confidence in the advice given by LLMs because candidates could prefer human input or have doubts about the precision of machine-generated recommendation .

2. LITERATURE REVIEW

Many works have been undertaken in the concerned domain. The work in [1] used Large Language Models (LLMs) to investigate how artificial intelligence can improve ATS compatibility. It demonstrated how LLMs enhance resume layout, contextual alignment, and keyword optimization to help candidates pass ATS tests more frequently [1]. A study in [2] focused on improving resume design for ATS compatibility by providing detailed instructions on using relevant keywords, appropriate formatting, and job-specific customization to enhance candidate performance in ATS-based recruitment processes. Another work in [3] emphasized how AI-driven solutions, including LLMs, can be integrated to improve the performance of ATS in the screening process. The research in [4] explored methods to increase ATS scores by improving semantic matching and real-time optimization alignment. Researchers evaluated the opportunities and challenges of integrating LLMs, examining how LLMs can suggest changes and keywords to enhance ATS scores [5].

The study highlighted the progression of LLMs from basic keyword matching to contextual elaboration for resume enhancement [6]. Another work explored AI job matching, where LLMs played a critical role in building models for better alignment between candidates and job requirements [7]. Research in [8] addressed challenges faced by AI-enhanced resumes, such as changes to training data and keyword optimization. It emphasized the need for AI models to adapt for improved resume accuracy and structure. Authors in [9] studied biases in ATS systems and how resume optimization can mitigate these biases. A study focused on assisting users in creating strong job descriptions to enhance their ATS scores [10].

3. PROPOSED MODEL ARCHITECTURE

This system's model architecture,which uses LLMs for resume optimization and ATS compatibility, is adjustable in nature and is consistent with multiple parts that function as units. To include the diversification from different industries and job positions, the data collection unit collects multiple resumes and job requirements from real-time job portals, samples, and publicly available information.In order to decode important elements of resumes and job description the model parses through important areas like skills, work experience, certification using NLP techniques, such as Named Entity Recognition (NER), to analyze and store the data after collection . Using refined models such as GPT and Bert, the LLM model compares the resume with the job description. This model offers recommendations to improve the resume by changing semantic alignment to improve accuracy of keywords. The feedback generation module works to convert the LLMs analysis to practical and approachable feedback. Job searchers are able to upload their resumes and job descriptions and other input using the User Interface (UI), which provides real-time feedback in an easily readable format. The evaluation and testing module generates the ATS compatible score .

The goal of UI or the User Interface module is to make sure that the user understands the use of the model efficiently, helping them to navigate through the model. Job Description along with the resume can be easily attached to the model with ease, which gives instant feedback on the resume along with factors influencing the ATS scores.

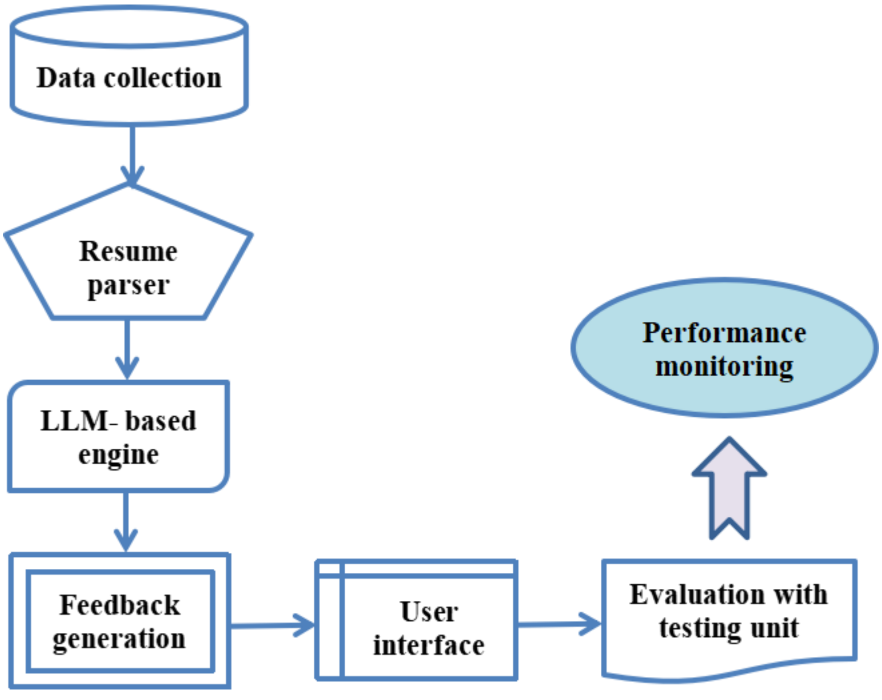

Figure 1. Prototype of Resume Optimization using LLMs

The aim of the proposed model shown in figure 1 is to show the use of an AI driven framework that utilizes the Application Tracking System process by the Large Language Models(LLMs). Recruiters frequently use the ATS to sort and filter out job applications accordingly with the requirement. This study features the ATS score checker that accesses the resume according to the job description and the job criteria and offers changes according to the job requirement. The model uses LLMs for evaluating resumes for structure, phrasing, and keyword, and then recommending changes to boost the resumes score for passing ATS filters. A resume extraction module that follows parsing with demonstration to suggest proper structure along with the advanced keyword research.To raise the ATS score there is a feedback mechanism offering correct recommendation. The fine-tuning of the LLMs will assist the model in comprehending the subtleties of ATS, with an emphasis on resume optimization to format it and give keyword relevancy and keyword generation. After being trained the model will provide the score based on the job description and recommending the enhancements that are needed to be done. By providing job seekers with an AI-driven model to improve their resumes, this model has the ability to increase the success rate of job applications helping both the organization and the candidates. The model may be collaborated with employment and job portals to enhance the process of job applications and further contribute to the tech world.

By using advanced NLP (Natural Language Processing) and other machine learning algorithms these models offer deep insight into the content and context of the resumes, helping the candidate to match with the job requirements. These steps ensure more efficient recruitment process which is fair, increasing the chance of getting the job :

- Advanced Keyword and Semantic Matching : Semantic accounting is taken into consideration by the ATS model other than just the keyword matching. The model finds enhanced word synonyms and context based variations using (NLP) or natural language processing. The model can identify words or terms like "Statistical Engineering", "Data Analytics" or "Business Intelligence".

- Contextual Understanding: ATS models with AI capabilities can enlist context . For Example the Ai model finds it more credible when someone mentions "data analysis" in work experience rather than in the skills section . This type of thorough analysis guarantees that resumes are read more for their presence , in the end increasing the ATS score.

- NLP or Natural Language Processing: LLM and the AI powered application tracking system can parse the resume very efficiently with the help of Natural Language Processing. Resumes with a more complex structure face difficulty in passing the traditional ATS systems. They analyze the meaning of the text and check the proper orientation and categorization. The model can also differentiate between scripts that are irrelevant.

- Automatic Scoring Based on Job Relevance: AI-based applicant tracking systems usually give a resume a score depending on how well it matches the job description's precise requirements. Many important factors affect this score. First and foremost, keyword relevance is important since the algorithm assesses how well the resume uses keywords from the job description, making sure the CV is appropriate for the position.

As the AI evaluates whether the resume accurately represents the precise duties, responsibilities, and competencies required for the role, contextual alignment is also crucial.

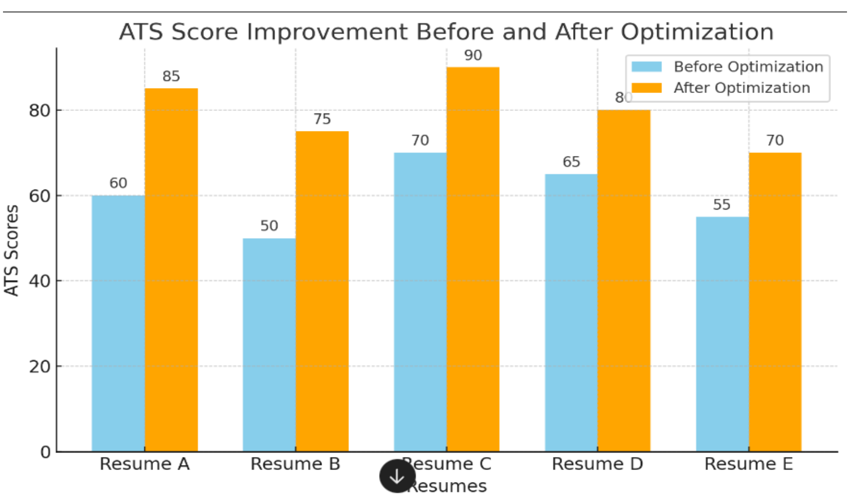

Figure 2. Bar Graph showing improvement in ATS score before and after LLM optimization .

The ATS compatibility scores of several resume optimization techniques—such as the original resume, ATS-friendly formatting, keyword optimization, and LLM-enhanced resumes—are contrasted in the graph shown in figure 2. The Y axis displays the ATS score which ranges from 0 to 100, while the X-axis display the different resume and optimization plans. The LLM optimized resume which follows different AI driven strategies for optimization which include both keywords and the resume structure usually get the highest rating.

With the proper analysis and comparison over conventional techniques, LLMs are helping in resume optimization for ATS . For example LLMs can recognize keywords or variations of terms and rephrase them to make it efficient for the resume. LLMs also improve the resume by better phrasing and wording .LLMs are also great at improving resumes' overall format and literature .They are able to identify typical ATS errors like incorrect titles and other errors that could stop resume parsing .In order to make sure the resume items are correctly depicted and easy for ATS to read and understand LLMs change the layout and structure .To further increase the process of passing ATS filters, LLMs can give feedback to change or rearrange resumes and demonstrate that purely fits the job description .

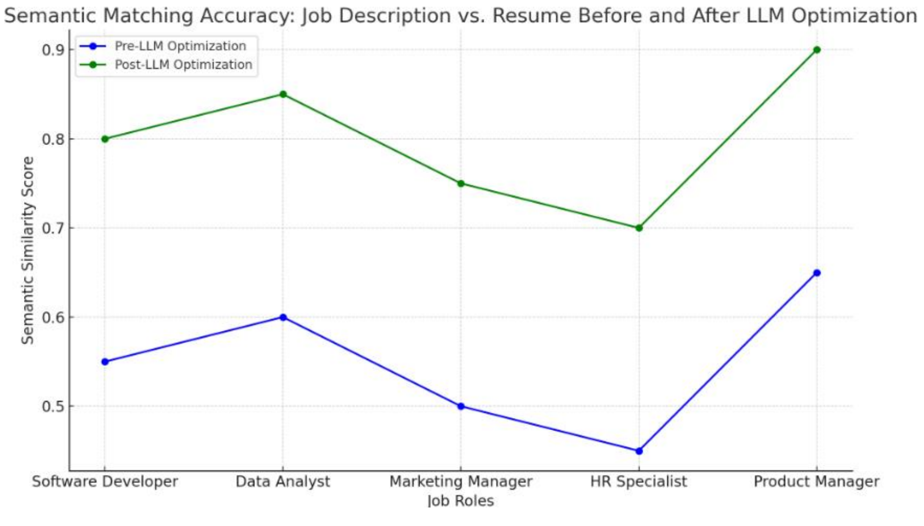

Figure 3. Job Description vs. Resume Before and After LLM Optimization

Since many resumes do not accurately convey the precise terms, abilities, or context of the job description, the pre-LLM scores usually indicate a lower semantic similarity. The semantic similarity score rises as a result of the resume's improved alignment with the job description following LLM optimization. Technical positions like software developer and data scientist probably see more notable gains as a result of the addition of domain-specific terms and keywords, however this improvement varies by job profile. Non-technical positions, on the other hand, could exhibit more subtle advancements. This figure 3 illustrates how LLM-based optimization can improve the semantic alignment between job descriptions and resumes, which will ultimately improve total job application results and increase the likelihood of passing ATS screenings.

● Pre-LLM Score: Although the semantic similarity prior to optimization may differ, it usually indicates space for improvement because many resumes might miss some of the subtleties of a job description.

● Post-LLM Score: The architecture provides the keywords, phrases and specific terminology the optimization has helped to grasp the job description and help in the improvement of resume.

● Improvement in Job Roles: In the tech world certain jobs require specific skills such as "Machine Learning" or "Data Analyst", the improvements are more prominent whereas jobs that require less technical skills can see less enhancements.

4. RESULTS AND DISCUSSION

To test the resume optimization LLMs have been used resulting in significant increase of ATS score and improvement in keyword matching , and the findings show notable improvements in both ATS scores and the overall job application process. Now it's evident that LLM models might significantly affect a job seeker's chances of passing ATS screenings.To test the efficiency of the model several tests of resume have been to compare the optimization before and after . An increase in ATS compatibility is found after the optimization process which used LLMs feature to change the resume structure and increased keyword relevance .

● Development of ATS score : In order to test the LLM architecture multiple resumes were gathered for testing the model , the optimization was done and the ATS scores have been increased significantly.

● Prior to Optimization: Before using LLM-based optimizations, resumes had an average ATS score of between 60 and 70 percent. Many resumes either lacked the required keyword density or did not organize their content in a way that made it easy for an applicant tracking system to understand.

● Following Optimization: The average ATS score rose to 85–90% following the implementation of the LLM-based recommendations (keyword changes, structure enhancements, and contextual relevance). Stronger alignment with job requirements, enhanced formatting, and greater keyword relevance were all displayed by the optimized resumes.

Professional Resume for Marketing Prior to optimization, the applicant's résumé received an ATS score of 65%. Although it included pertinent experience and skills, the keywords were very general, and significant achievements were obscured by lengthy paragraphs.Following optimization, the LLM recommended changing the job description to incorporate more focused keywords (for example, "digital marketing strategy" to "SEO strategy development"), rearranging the resume's sections to emphasize significant accomplishments, and placing more emphasis on measurable outcomes (e.g., "increased website traffic by 40%"). The result rose to 88%. After improving the resume, the candidate was invited to more interviews, demonstrating the clear link between a higher ATS score and a successful job search.Result: The gadget appropriately recognized recognized people from the stay video feed, displaying excessive precision for well-lit, front-going through faces. The popularity price became excessive for efficiently figuring out college students, however overall performance degraded while faces had been in part obscured or now no longer going through the digital digicam directly. Resume of a Software Developer, Prior to optimization, the resume's original score was 72%, mostly as a result of inadequate layout and missing technical keywords. Following optimization, the LLM recommended adding more precise examples of job accomplishments, reorganizing the "Skills" part for improved ATS processing, and adding additional technical terms related to the industry. Following these modifications, the ATS score rose to 90%. The candidate showed how focused adjustments can enhance employment prospects by reporting a greater success rate in passing the applicant tracking system (ATS) and receiving invitations to technical job interviews. The LLM-powered model increases the ATS score, increasing the chance of qualifying in the screening process of resume inspection. Candidates' chances of getting interviews increased noticeably with focused adjustments, such as better keyword utilization, resume structuring, and more alignment with job descriptions.

Table. 1 ATS Score Improvement Before and After Optimization

Resume	**ATS Score Before Optimization**	**ATS Score After Optimization**
Marketing Professional	65%	88%
Software Developer	72%	90%
Data Analyst	60%	85%
Graphic Designer	68%	83%

The case studies and the comparison in table 1 provide the effectiveness of LLMs in the recruitment process increasing the rate of employment.

Table 2. ATS Score Improvement Breakdown Factor

Factor	**Average Improvement %**
Keyword Relevance	15%
Resume Structure	10%
Skills Relevance	12%
Total Improvement	25%

This table 2 demonstrates the areas that need improvement showcasing the contribution of LLms in resume enhancing , with keyword relevance and skills relevance having the highest improvement factor.

Table 3. Actionable Feedback Provided by LLMs

Original feedback (before)	**LLM optimized feedback (after)**
Increased website traffic	40% more organic website traffic thanks to SEO tactics.
Managed a team of developers	Led a team of 5 developers in building a scalable ecommerce platform
Created marketing materials	Developed and implemented marketing materials that contributed to a 20% increase in engagement

Examples from the feedback have been compared in table 3, illustrating how the models help in the keyword matching and resume optimization , increasing the chances of getting shortlisted for the job role.

5. CONCLUSION AND FUTURE WORK

In today's market the contribution of LLMs for optimization of the resumes has helped the job seekers significantly. LLM models have helped the job seekers by finding relevant keywords and making them match the job profile. The results for resume optimization frameworks have significantly increased the resume standard and the output results in more interviews. The case examples have demonstrated that the feedback provided by the LLMs can result in enhanced keyword matching and resume matching . LLMs fine tuning and the present technology used in the various sectors can demonstrate the particularity of their flexibility and the learning capacity the LLMs use for continuous enhancement.

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