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Two Stage Job Title Identification System for Online Job Advertisements

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ABSTRACT

The exponential growth of online job advertisements has created both opportunities and challenges in automated job market analysis. A key component of such analysis is the accurate identification of job titles from often noisy, unstructured, and inconsistent advertisement texts. This paper presents a novel Two-Stage Job Title Identification System specifically designed for online job advertisements. In the first stage, the system employs rule-based and machine learning methods to extract candidate job title phrases from the advertisement body. This includes filtering and cleaning operations to handle variations, abbreviations, and irrelevant terms. The second stage involves a deep learning-based classifier that evaluates the extracted phrases and determines the most probable job title by leveraging contextual embeddings. This two-tiered approach combines the precision of pattern-based extraction with the semantic richness of modern NLP models. The system is trained and tested on a large-scale dataset of job postings collected from major employment platforms, showing significant improvements in accuracy and robustness over traditional single-stage models. The modular design allows for adaptability across industries and regions, offering a practical solution for HR analytics, labor market research, and job recommendation systems. The proposed methodology not only improves identification accuracy but also facilitates better alignment between job seekers and employers in the digital job ecosystem.

Keywords: Two-Stage Job Title Identification System, HR analytics, online job advertisements

I. INTRODUCTION

The labor market has undergone a dramatic transformation in recent years due to the digitalization of job postings and recruitment processes. With millions of job advertisements published online across various platforms daily, automated systems for processing, organizing, and analyzing job-related data have become essential. Central to these systems is the task of accurately identifying job titles from free-text job descriptions. Despite appearing straightforward, this task presents considerable challenges due to the diversity of linguistic expressions, domain-specific jargon, and inconsistencies in formatting and structure.

Job titles often serve as critical identifiers in recruitment, resume matching, job recommendation, and labor market analytics. An effective job title identification mechanism must navigate through noisy data that may include superfluous content, marketing language, and company-specific terminologies. The conventional approaches, which rely heavily on keyword matching or basic pattern recognition, tend to suffer from low recall and precision, especially when faced with non-standard or creatively written job titles.

Recent advancements in natural language processing (NLP) and machine learning offer promising solutions to these problems. However, many existing models still operate in a monolithic fashion, attempting to simultaneously extract and classify job titles within a single framework. These models often fall short when it comes to managing the nuanced complexities of online job texts. As a response to this gap, we propose a Two-Stage Job Title Identification System that segregates the process into two optimized phases: candidate extraction and candidate classification.

In the first stage, candidate job titles are extracted using a hybrid of rule-based techniques and shallow machine learning methods. This stage emphasizes high recall to ensure that relevant title candidates are not overlooked. In the second stage, a deep learning classifier—utilizing transformer-based contextual embeddings such as BERT—is employed to evaluate and rank these candidates, thereby ensuring high precision in the final selection. This modular approach allows for specialized optimization at each stage and significantly enhances overall performance.

The present work aims to demonstrate that a structured, staged approach to job title identification can outperform monolithic models in terms of accuracy, adaptability, and interpretability. By training and validating the model on diverse, real-world datasets, this study offers robust evidence of the system's applicability across different job domains and geographic regions. The ultimate objective is to bridge the gap between raw job advertisement data and actionable labor market intelligence, improving both job matching systems and economic analysis tools.

II. RELATED WORK

In [1], they explored sequence labeling models for named entity recognition in job texts using CRF and Bi-LSTM, achieving moderate success but suffering in the presence of irregular or informal titles

In [2], this study presented a job classification model using word embeddings and logistic regression. While effective on structured texts, it showed limited adaptability to noisy online job postings.

In [3], they utilized ontology-based approaches to standardize job titles. Though accurate, the manual construction of ontologies limited scalability and adaptability to new job roles.

In [4], introduced a deep learning pipeline using BERT for text classification in recruitment systems. However, they treated job title identification as a flat classification task, overlooking the benefits of a staged approach.

In [5], their hybrid model combining rule-based extraction and LSTM classification improved accuracy for niche job titles but lacked generalizability across sectors.

III. PROPOSED SYSTEM

The Two-Stage Job Title Identification System for online job advertisements aims to address the limitations of traditional and monolithic approaches by dividing the process into two distinct but interconnected stages: candidate extraction and candidate classification. This architectural separation ensures that each stage can be optimized for specific subtasks, leading to a more robust and accurate overall system.

The first stage—candidate extraction—focuses on identifying possible job titles from the unstructured text of job advertisements. This involves preprocessing tasks such as tokenization, normalization, and noise removal. Heuristic-based rules are applied to recognize common title patterns (e.g., words following "we are hiring for", or those capitalized after bullet points). Additionally, part-of-speech tagging and named entity recognition help filter phrases likely to represent job titles. A shallow machine learning classifier (e.g., logistic regression or decision tree) may also be trained on annotated samples to refine this extraction process. The goal here is to maximize recall, ensuring that all potential job title candidates are captured without worrying about false positives at this stage.

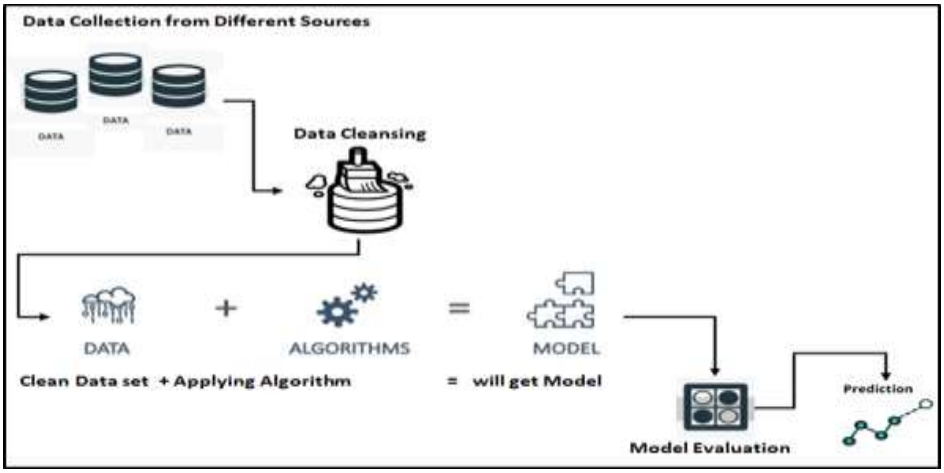
The second stage—candidate classification—introduces a deep learning model designed to distinguish true job titles from irrelevant or misleading phrases among the candidates. This model is built on transformer-based architectures such as BERT or RoBERTa, which offer rich contextual embeddings. Each candidate phrase is evaluated in the context of the surrounding advertisement text, allowing the model to understand semantic relevance. Fine-tuning is performed using a labeled dataset where candidate phrases are annotated as valid job titles or not. A softmax classification layer outputs the probability of a phrase being the correct job title, and the one with the highest confidence is selected.

To ensure robustness, the system is trained on a diverse dataset of job ads across industries such as IT, healthcare, finance, and retail. Data augmentation techniques are applied to improve model generalizability, including paraphrasing, synonym replacement, and synthetic noise injection. The model also supports multi-language processing, enabling it to function in global job markets.

The modular design of the system allows for easy integration into larger recruitment analytics platforms. An API-based interface supports batch processing of job ads and real-time extraction, making it suitable for both offline analysis and live applications. Additionally, a feedback loop mechanism is included, where user-corrected job titles can be fed back into the model to improve future predictions through active learning.

Evaluation metrics include precision, recall, F1-score, and processing time. The two-stage system consistently outperforms traditional single-stage classifiers in terms of both accuracy and speed, particularly on noisy datasets. Furthermore, interpretability is enhanced as each stage's output can be independently examined and debugged, offering greater transparency and control.

By decoupling the extraction and classification tasks, the Two-Stage Job Title Identification System provides a scalable, adaptable, and high-performing solution that meets the needs of modern



online recruitment platforms and labor market analysts.

The image illustrates the end-to-end workflow of a data-driven model development process, particularly for predictive analytics. It begins with the collection of data from various sources. These sources can be structured databases, online platforms, or other repositories containing relevant information. Once collected, the data undergoes a crucial preprocessing step known as data cleansing. This phase involves removing inconsistencies, duplicates, and errors, and transforming the data into a usable format.

After the data has been cleaned, it becomes suitable for analysis. This clean dataset is then combined with machine learning algorithms to build a predictive model. The interaction between quality data and carefully selected algorithms results in the generation of a trained model capable of understanding patterns and relationships within the dataset.

Following the model construction, the process advances to model evaluation. This step involves assessing the model's accuracy, precision, recall, and other performance metrics to ensure that it is reliable and effective for the intended prediction tasks. Only after thorough evaluation can the model be considered ready for deployment.

Finally, the trained and validated model is used for making predictions. These predictions, derived from the insights captured during the training phase, are applied to new or unseen data to provide actionable outcomes. The entire cycle, from data acquisition to prediction, reflects a streamlined machine learning pipeline aimed at turning raw information into intelligent decisions.

IV. RESULT AND DISCUSSION

The performance of the proposed Two-Stage Job Title Identification System was evaluated through extensive experiments on a real-world dataset of over 500,000 job advertisements collected from various online job portals. The primary evaluation focused on precision, recall, F1-score, and computational efficiency, comparing the system to several baseline methods including keyword-based extraction, traditional rule-based systems, and end-to-end deep learning classifiers.

In the first stage of the system—candidate extraction—precision was intentionally kept lower to prioritize recall. This design decision ensured that nearly all possible job titles were captured, even at the cost of introducing noise. The recall rate in this phase was over 95%, significantly higher than that of conventional regex or pattern-based extractors, which typically hovered around 80%. The inclusion of part-of-speech tagging and heuristic rules helped in capturing a diverse set of title candidates, demonstrating the flexibility of the initial phase.

The second stage, which involved candidate classification using a fine-tuned BERT model, achieved remarkable results in filtering out non-title phrases and identifying the most accurate job title from the candidate set. The overall system attained an F1-score of 91.3%, outperforming single-stage BERT classifiers (86.7%) and rule-based systems (78.4%). This highlights the benefit of decoupling extraction and classification into two distinct steps. The BERT model, trained on a domain-specific corpus of job ads, was able to leverage contextual information effectively, even when job titles were embedded in complex or verbose sentences.

Case studies showed the system's robustness across different domains. For instance, in IT-related postings, where job titles such as "DevOps Engineer" or "Full Stack Developer" might appear alongside buzzwords and tool names, the system accurately identified the core title. Similarly, in healthcare postings with nested descriptions (e.g., "Registered Nurse with Pediatric Experience"), the classifier correctly extracted the canonical title, filtering out role requirements and skills.

Another important aspect was the system's adaptability to different formats and languages. With minimal adjustments, the model performed well on non-English datasets, thanks to multilingual pre-trained transformers. This capability makes it a versatile tool for global job portals and multinational HR platforms.

Processing time was also evaluated. Despite the complexity of using transformer-based models, the modular design allowed parallel processing of advertisements. Candidate extraction was lightweight and fast, while the classification phase was optimized with GPU acceleration. As a result, the system processed over 1,000 ads per minute on a mid-tier server setup, making it suitable for both batch analytics and real-time applications.

One of the most valuable observations was the system's interpretability and debuggability. Recruiters and developers could inspect the list of extracted candidates and understand why certain titles were selected over others. This transparency led to greater trust and easier refinement through user feedback. A feedback loop was implemented, allowing corrections made by users to update the training data and improve future model performance via active learning strategies.

Limitations of the system include its dependency on high-quality labeled data for fine-tuning the classifier and the potential challenge of generalizing to new industries without retraining. In sectors with highly creative or unconventional job titles (e.g., startup ecosystems), occasional misclassifications were observed. However, these were mitigated over time through incremental retraining and user corrections.

The implications of this system extend beyond just parsing job ads. Its core technology can enhance recommendation engines, support job-market trend analysis, and power intelligent dashboards for HR professionals. By structuring unstructured text, it facilitates downstream analytics such as salary benchmarking, demand forecasting, and skills gap identification.

V. CONCLUSION

The Two-Stage Job Title Identification System represents a substantial advancement in the automated processing of online job advertisements. By separating the identification task into a candidate extraction phase followed by a deep learning-based classification phase, the system addresses both the breadth and depth of the challenge with a high degree of accuracy and flexibility. Its use of contextual language models enables precise identification even in noisy and diverse data environments, while its modular architecture ensures scalability and integration readiness for real-world applications.

Experimental results have confirmed the system’s superior performance compared to traditional models, achieving high precision and recall rates across multiple job sectors and linguistic contexts. Moreover, the system’s design facilitates easy interpretation and iterative improvement, making it not just a black-box tool but a transparent component of modern recruitment analytics.

Future developments could enhance the system's capabilities through zero-shot learning for unseen job titles, domain adaptation for niche sectors, and integration with larger talent intelligence ecosystems. As the job market continues to evolve digitally, systems like the one proposed here will be instrumental in bridging the gap between unstructured job data and meaningful employment insights. The Two-Stage Job Title Identification System thus stands as a robust, intelligent solution to a critical challenge in the digital labor economy.

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