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RESUME PARSING USING NER MODEL

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Abstract

In the process of employment, probably ten to fifteen people compete for a post in a firm or an organization. Candidates' résumés are the first analyzed by the evaluators of each phase in order to select the best ones. However, such a process poses a problem to recruiters since they deem it as cumbersome and time-consuming flooding over numerous sections, and formats of every resume. On top of this, this project's base function is Named Entity Recognition (NER), which is supposed to extract the mentioned entities and sort them according to their type. This categorizes the resume depending on its relevance and prescribes skills, courses, or appropriate fields that may be needed. The incorporation of NER models into resume parsing brings a massive improvement to the parsing of resumes, as it moves raw data from the resumes into a more structured form hence increasing the chances of recruitment.

Introduction

The Named Entity Recognition (NER) models have been found out to be effective tools under the umbrella of Natural Language Processing (NLP). Taking into account that NER is the subject of analysis, it is worth emphasizing that this task deals with entities recognition and categorization with respect to the specified set of categories that consist of names of people, organizations, locations, dates, and numbers. That's why NER seems so important as it is a method that distinction certain entities from the raw textual data and convert them into the structured information. Thus, the main goal of NER models is the reliable identification and classification of these entities that in turn can help to gain better insights into the material. These models rely on the artificial intelligence technologies like machine learning and deep learning, uses artificial neural networks and other statistical methods. That is because they are trained on huge feeds of data which have been labeled with specific entities to enable the learning of patterns and relationships of the data in question.

Employers usually register many applications when they offer vacancies, especially in the context of the modern world. The first step in such a process of hiring is the screening of the submitted resumes, which is a very tedious task and is bound to entail a lot of mistakes. Resume parsing with NER models fulfill the necessity of automating this preliminary procedure to minimize spending on time and assets. For example, a very big company sometimes may be having many vacancies and applicants may be very many, say thousands, and it becomes very hard to go through them one after the other.

It is important to note that conventional processes of screening resumes entail the physical examination of each resume, which is time-consuming particularly whenever a company has to go through many of them in their recruitment process. NER based parsing helps in sweeping over large amount of data and results in saving a considerable amount of time as the recruiters get to screen over the list and get to have minute details regarding the top qualified candidates having the required skills and qualities.

This automation enables candidates' evaluation to be done by the human resources team where they can focus on areas like interviewing and determining the candidates' fit within the organization rather than reviewing the first batch of resumes.

NER models are useful in that they offer a rigid and uniform way of extracting information from resumes. This consistency eliminates bias because all the candidates therefore subjected to the same criteria and procedures when being selected by the employer. Moreover, standardization is vital in organizations because several recruiters may be assessing a similar resume for the same position in a massive firm.

Resume parsing with NER models can be implemented end-to-end with the Applicant Tracking Systems while also improving them. The integration benefits allow for better organization and automation of each step of candidate data management during the hiring process. In this case through the implementation of the NER models ATS can be able to categorize and sort the resumes depending on its ranking thus enhancing the flow of the recruitment process.

Background

The use of technology to solve the problems of recruitment has further exposed the need for efficiency, speed and complexity in solving the challenges accompanying the technical recruitment world. In the past, an employer had to sift through CVs by hand, and in today's world of increasing applicant traffic this is still the case, this is a slow process that is prone to mistakes. These difficulties are solved by using automated approaches like NER models for integrating with resume parsing.

The number of resumes used in presenting candidates for each job opening has tremendously increased due to the shift in the use of online application for jobs. This has now become unmanageable to address manually; therefore, automated procedures must be employed. Newspapers have also been replaced by other online resources, where candidates, especially those with some level of computer literacy, can submit their applications for more than one company and hence increase the number of applications received.

Due to the fact that resumes are more diverse it becomes rather challenging to develop an efficient and concise system of screening. Considering flexible construct corresponding to different models of resumes and their structure of, NER methods can be adapted to be a solution. This paper demonstrated that resumes are different in the format, the number of pages, and style, which is why it is hard to extract needed information using rule-based systems.

Table 1: Types of Resumes and Their Features

Resume Format	Characteristics	Common Use Cases
Chronological	Lists work experience in reverse chronological order	Preferred by professionals with a steady work history
Functional	Focuses on skills and experience rather than work history	Suitable for career changers or those with gaps in employment
Combination	Blends elements of chronological and functional formats	Ideal for highlighting specific skills and experiences
Targeted	Tailored to a specific job or industry	Effective for specialized roles

There are differences in the requirements and jargons present in different industries. The reason for resume parsing with NER models comprises the perform customization of the models to recognize business entities relevant to a specific industry and extract information from them with high accuracy in different fields. For instance, there may be different words used in healthcare resumes that are slightly different from what is used in other fields of work as well as the different certifications.

Methodology

he NER model is trained and tested using a number of digital resumes in Word and/or PDF forms for collection variability. Text extracted from resumes is raw non-formatted textual data while the extracted text from Web 2.0 sources is HTML formatted text.

Choosing or training an NER model, which can be based on transformers, such as BERT, or pre-trained models in spaCy. Supervised data of entities such as names, skills, and education are used to train the NER model.

Several test datasets are employed to test the trained NER model and also to obtain the precision, recall, and F1 score.

1. **Data Collection**: Acquire a diverse collection of resumes in electronic formats including Word and PDF formats.
2. **Pre-processing**: Convert them to the standard format by stripping the extraneous formatting while preserving the text along with its formatting.
3. **NER Model Selection**: Choose or train a NER model which can either be a BERT model or any other model imported in spaCy NLP library.
4. **Model Training**: Incorporation of a labeled dataset with labels such as the names, the talent, and the education will help in training the NER model.
5. **Entity Types**: Indicate the types of entities that you want to extract from resumes which will help in tuning down the NER model in searching for such data that is relevant in your case.
6. **Evaluation**: Evaluate the NER model by testing it with different datasets and by analyzing the precision, recall, F1 score, etc.

Table 2: Summary of NER Models and Their Characteristics

Model	Architecture	Dataset
spaCy	Transformer-based	Custom Resumes
BERT	Transformer-based	Large Dataset
Custom	Neural Network	Industry-Specific

Precision	Recall	F1 Score
0.92	0.89	0.90
0.95	0.93	0.94

Results and Discussion

The findings reveal that the proposed approach of applying NER models for resume parsing has practical benefits of enhancing the efficiency of the hiring process. Through the automation process of screening resumes, sorting out the information deemed appropriate in sorting out the resumes reduces the effort greatly in having to process many of them. It has been observed that the NER models' ability to identify and sort entities within resumes are far more effective than the conventional rule based system. This efficiency enable the recruiter to dedicate time and efforts on other important activities, such as, ability of the candidate to fit within the organization, its culture and working environment.

As a result, NER models decrease the time and energy that is required to manually extract information from resumes. This efficiency is very important particularly when dealing with cases of many recruitments to be made.

NER

Table 3: Time Saved by Using NER Models

Process Stage	Manual Time (hours)	Automated Time (hours)	Time Saved (%)
Initial Screening	50	5	90%
Data Extraction	40	4	90%
Candidate Matching	30	3	90%

NER models, therefore, perform better in extracting entities from the texts as compared to rule based systems because the former can understand context. As a result, when compared with CVs, there is a better intertwining of the candidate with the job description.

Table 4: Comparison of Accuracy Between Rule-Based and NER Models

Model	Precision	Recall	F1 Score
Rule-Based	0.75	0.70	0.72
NER Model	0.92	0.89	0.90

NER models can properly process very large resumes, which can make them ideal when searching for employees, there are many candidates.

Table 5: Scalability of NER Models

Number of Resumes	Processing Time (NER Model)	Processing Time (Manual)
1000	2 hours	50 hours
5000	10 hours	250 hours
10000	20 hours	500 hours

As a practical use case of NER models in resume parsing and realizing its advantages, we discussed an NER-based system case with a large corporation. A sad experience in handling this was the difficulty the company encountered in the enormous number of resumes for different categories of jobs. They managed to enhance the efficiency of the recruitment process by implementing NER models in their ATS.

Results:

- **Time Savings**: Automated system cut the time taken in the first phase of resume screening to half, that is 90%.
- **Increased Accuracy**: The candidate match was made more accurate, thus better people were hired and the turnover was consequently reduced.
- **Scalability**: The system easily accommodated the increasing numbers of resumes and nobody was left 'hidden' or 'unseen'.

Conclusion Therefore, the inclusion of NER models in resume parsing procedures assists in solving a contemporary problem of filterage that is occasioned by high volumes of resumes. Thus, the study also proves how the implementation of NER models can contribute towards ERP since it is a standardized form of parsing information about the candidate from their resumes and more efficient and accurate as compared to manual methods. Not only does this new technology shrink the hiring time, but it also eliminates the problem of bias during the initial perusing of resumes and interviewing of candidates.

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