

Project

Resume Parsing and Classification Using Named Entity Recognition (NER)

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Problem description

HR departments face the challenge of manually processing a large number of resumes, which is both time-consuming and labour-intensive. Each resume contains various sections such as personal details, education, work experience, and skills. By using Named Entity Recognition (NER) models in Natural Language Processing (NLP), we can automate the extraction and classification of these entities, streamlining the resume screening process and making it more efficient and accurate.

Data understanding

The dataset contains text data from resumes, which includes both unstructured and semistructured information. The key attributes in the dataset are:

content: This attribute contains the raw text of the resume. It includes various sections such as personal details, education, work experience, and skills.

label: This attribute contains the annotated tagged entities, which identify and classify specific information within the resume content.

Each annotation is a dictionary that includes, **label**, the category of the entity (e.g., Skills, Graduation Year, College Name, Degree, Companies worked at, Designation, Email Address, Location, Name) and **points**, the position of the text in the content, including the start and end positions and the actual text.

Problems in the data

1. NA Values:

- The presence of missing values (NA) can be problematic, especially in the label attribute if certain important entities are not tagged.
- It's essential to check for any missing values in the dataset and understand their impact on the NER model's performance.

2. Outliers:

- Outliers in text data are unusual or rare entities that do not conform to the general patterns observed in the data.
- For instance, a resume might have an exceptionally long or short content attribute, or it might contain entities that are not common in other resumes.
- Techniques such as DBSCAN (Density-Based Spatial Clustering of Applications with Noise) can be used to detect these outliers by clustering similar resumes and identifying those that do not fit well into any cluster.

3. Skewed Data:

- Skewness in text data can occur if certain entities or categories are overrepresented or underrepresented in the dataset.
- For example, if most resumes are from a specific industry or education background, the dataset becomes skewed towards those categories.



• This skewness can bias the NER model, making it less effective in recognizing entities from underrepresented categories.

Steps to Analyze and Mitigate Data Issues

1. Check for Missing Values:

- Identify any missing values in the content or label attributes.
- Analyze the impact of these missing values and decide on appropriate handling techniques, such as imputation or exclusion.

2. Detect Outliers:

- Use clustering techniques like DBSCAN to identify resumes that do not fit well into any cluster, indicating potential outliers (Sereshki et al., 2023). But this can be done after preprocessing.
- Analyze these outliers to understand their nature and decide whether to exclude them from the dataset or handle them differently.

3. Analyze Skewness:

- Skewness cannot be directly applied to raw text data. Instead, we can apply it to the numerical data present in the text data (entity types (tags) in the "label" attribute). For example, we can find the distribution of number of companies worked at, age, experience.
- Perform an exploratory data analysis (EDA) to identify any skewness in the data distribution.
- Visualize the frequency of different entity labels to understand the representation of each category.
- Consider techniques such as resampling or weighting to address any identified skewness.



References

Taleb Sereshki, M., Mohammadi Zanjireh, M., & Bahaghi Ghat, M. (2023). Textual outlier detection with an unsupervised method using text similarity and density peak. *Acta Univ. Sapientiae Informatica*, 15(1), 91–110. DOI:10.2478/ausi-2023-0008