Resume Classification

Using Machine Learning

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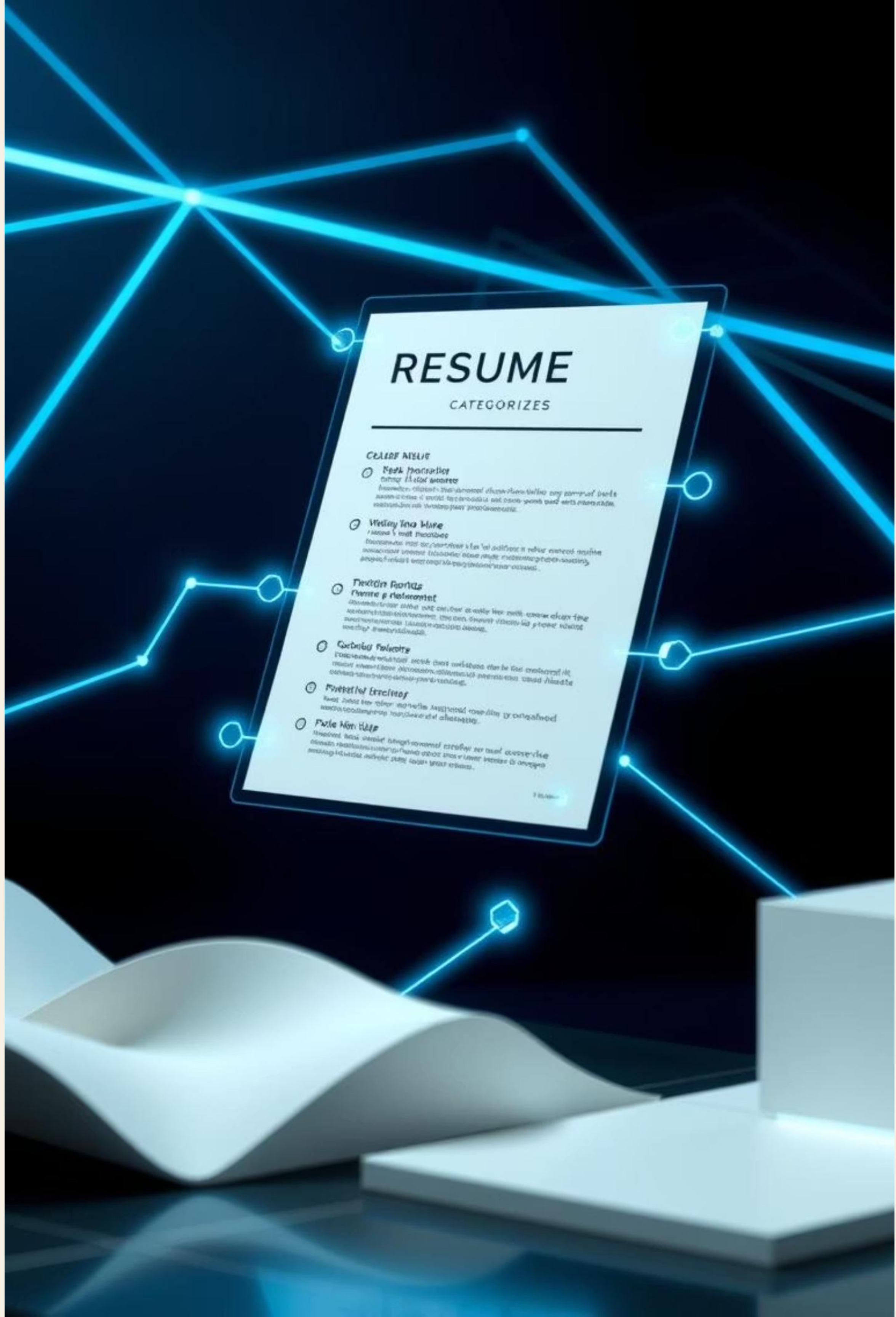

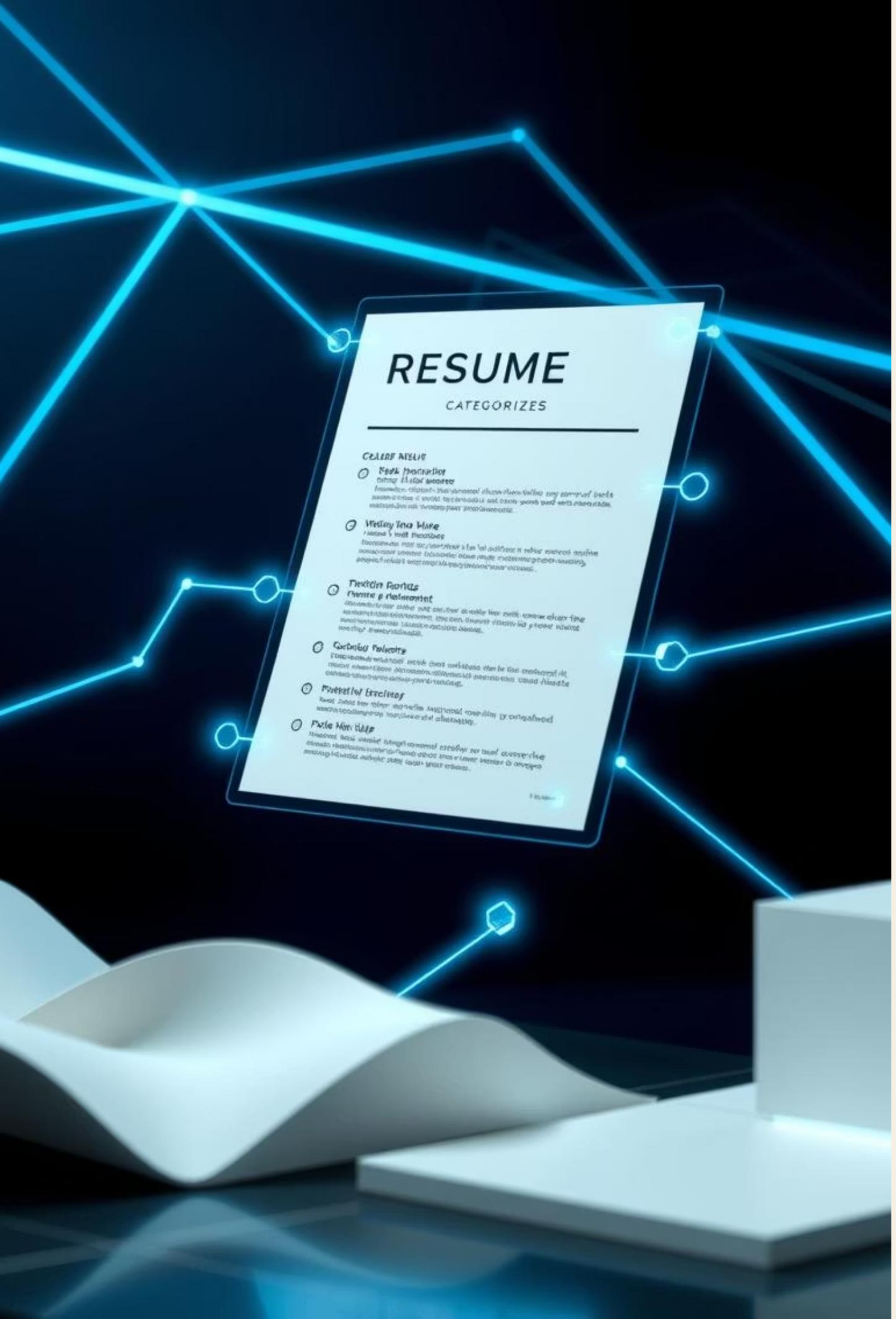

Resume Classification

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Mentors:

Karthik Muskula

Prajwal A N

Introduction to Resume Classification

The Challenge:

ⓘ *Recruiters spend an average of **23 hours** screening resumes for a single hire.*

Manual resume screening is time-consuming and prone to human bias, impacting hiring efficiency and candidate experience.

Our Solution:

Automated Categorization

Leveraging machine learning to instantly classify resumes into predefined job roles, saving valuable time.

Enhanced Efficiency

Enabling recruiters to focus on qualified candidates, reducing time-to-hire and improving overall productivity.

Leveraging Machine Learning

Utilizes advanced ML models for accurate and scalable resume screening , minimizing human error.

Dataset Overview

*Our prototype was developed using a carefully curated dataset comprising **79 resumes** to train and validate our classification models.*

*These resumes are distributed across **four distinct job categories**, reflecting common roles in the tech industry:*

- *React Developer*
- *SQL Developer*
- *PeopleSoft Consultant*
- *Workday Consultant*

Exploratory Data Analysis (EDA)

Class Distribution

We analyzed the distribution of resumes across the four categories to understand dataset balance.

Keyword Frequency

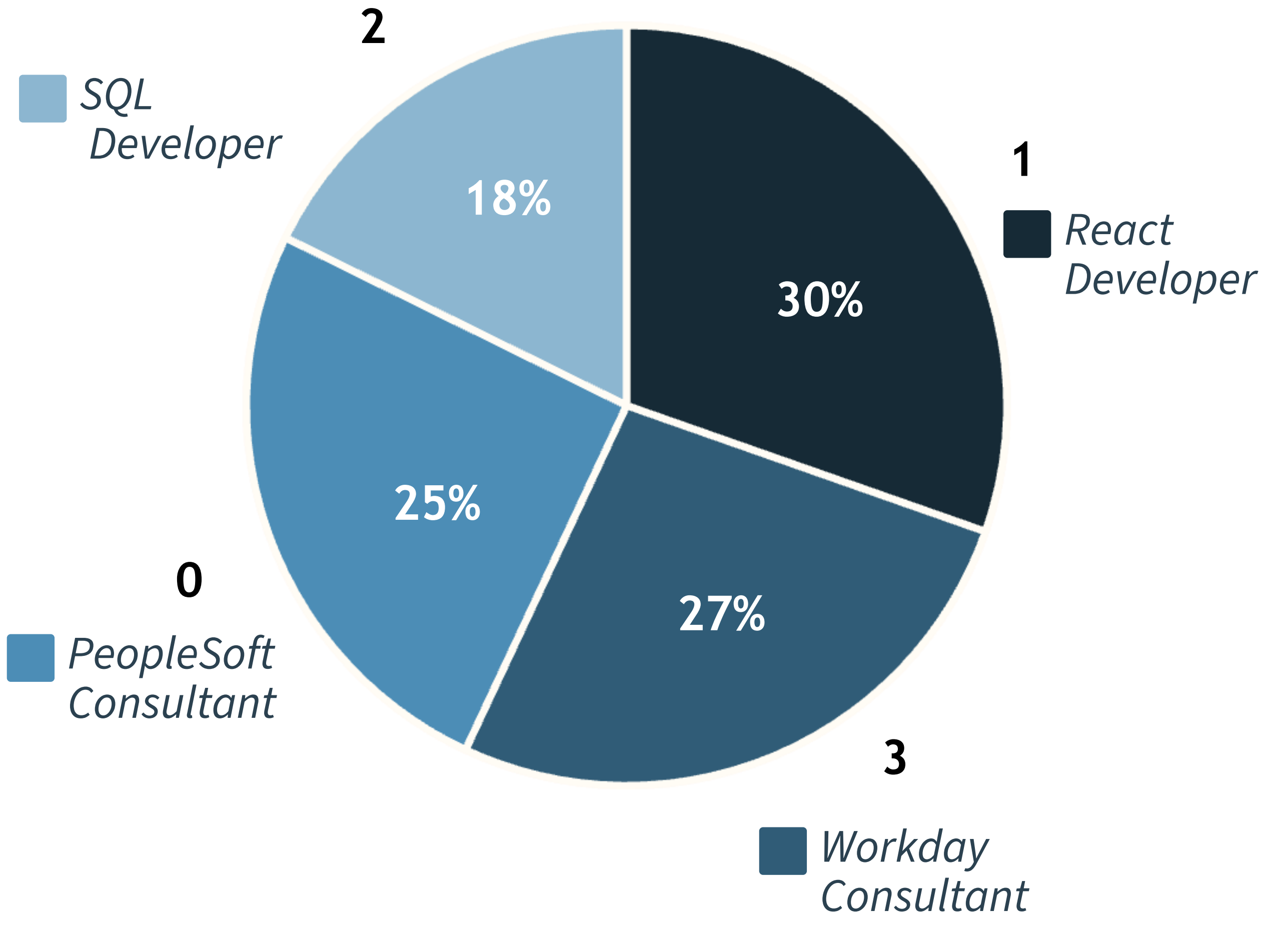
Examined the most frequent keywords associated with each job role, revealing distinctive patterns.

Clear Distinctions

Our analysis observed clear distinctions between classes based on these keywords, indicating strong signal for classification.

The EDA phase was crucial for understanding the inherent structure and characteristics of our resume dataset, guiding subsequent feature engineering and model selection.

Class Distribution: A Balanced View



The target variable 'role' is a multiclass feature comprising four distinct classes. The distribution is not significantly imbalanced; the largest class contains 24 samples, which is only 1.7 times the smallest class with 14 samples.

In most NLP classification tasks, such a minor imbalance is considered acceptable and typically does not require oversampling or class balancing techniques, ensuring our model learns effectively from all categories.

Feature Engineering: Crafting Custom Resume Metrics

To enhance our model's predictive power, we engineered custom features directly from the raw resume content. This involved extracting quantitative metrics that reflect the structural characteristics of each resume:

Character Count

The total number of characters in a resume, providing a measure of its overall length and verbosity.

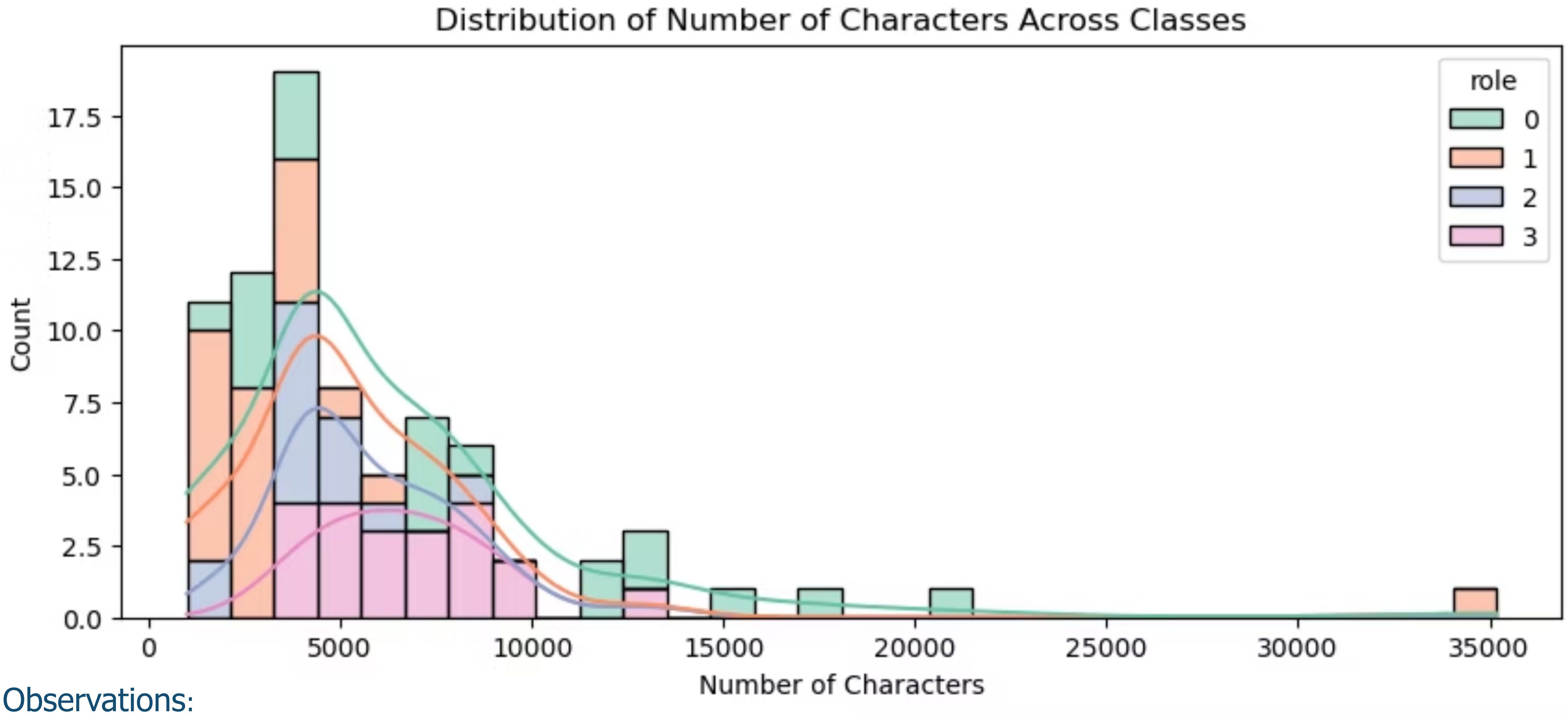
Word Count

The total number of words, offering insights into content density and detail.

Sentence Count

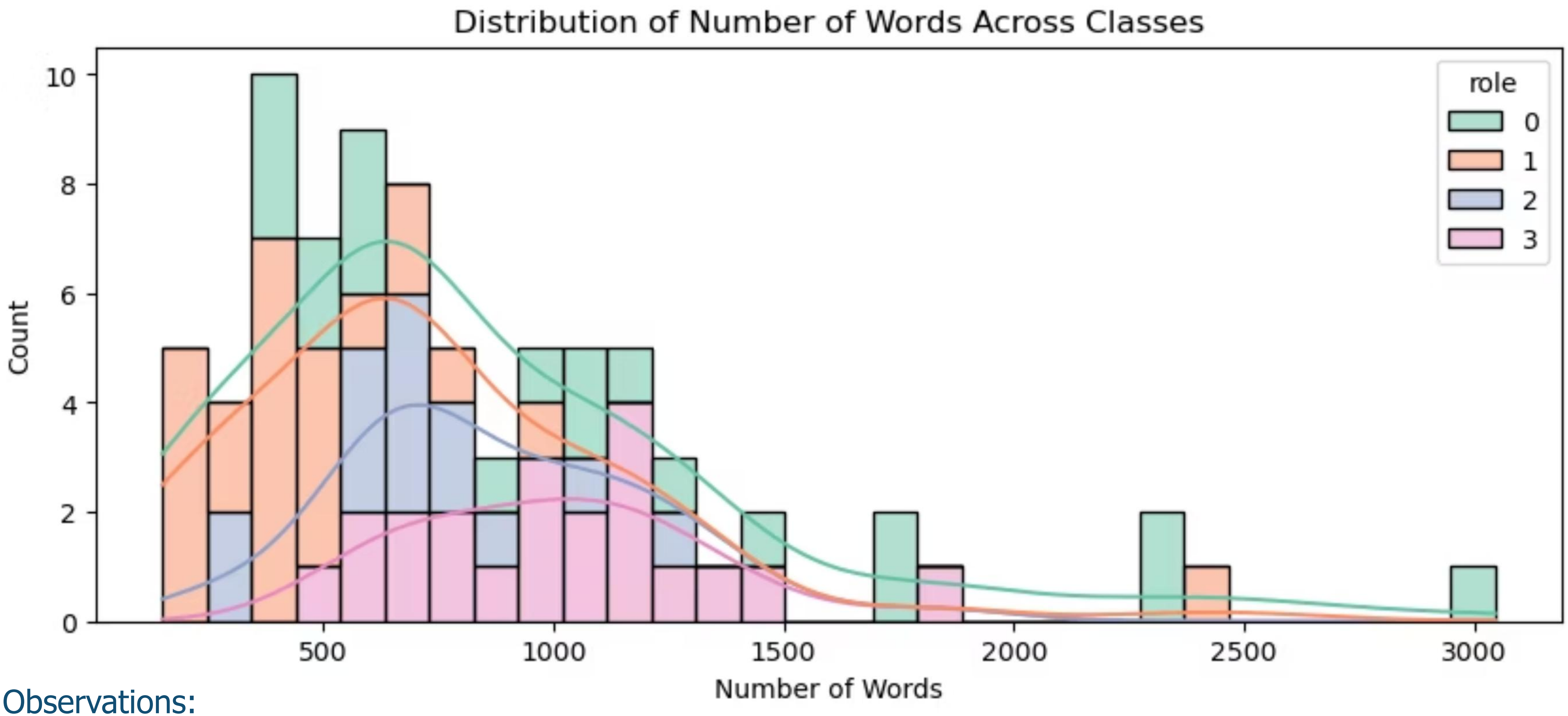
The number of sentences, indicating narrative structure and flow.

These engineered features allow our machine learning models to leverage beyond keyword-based information, capturing nuanced differences between resume types.



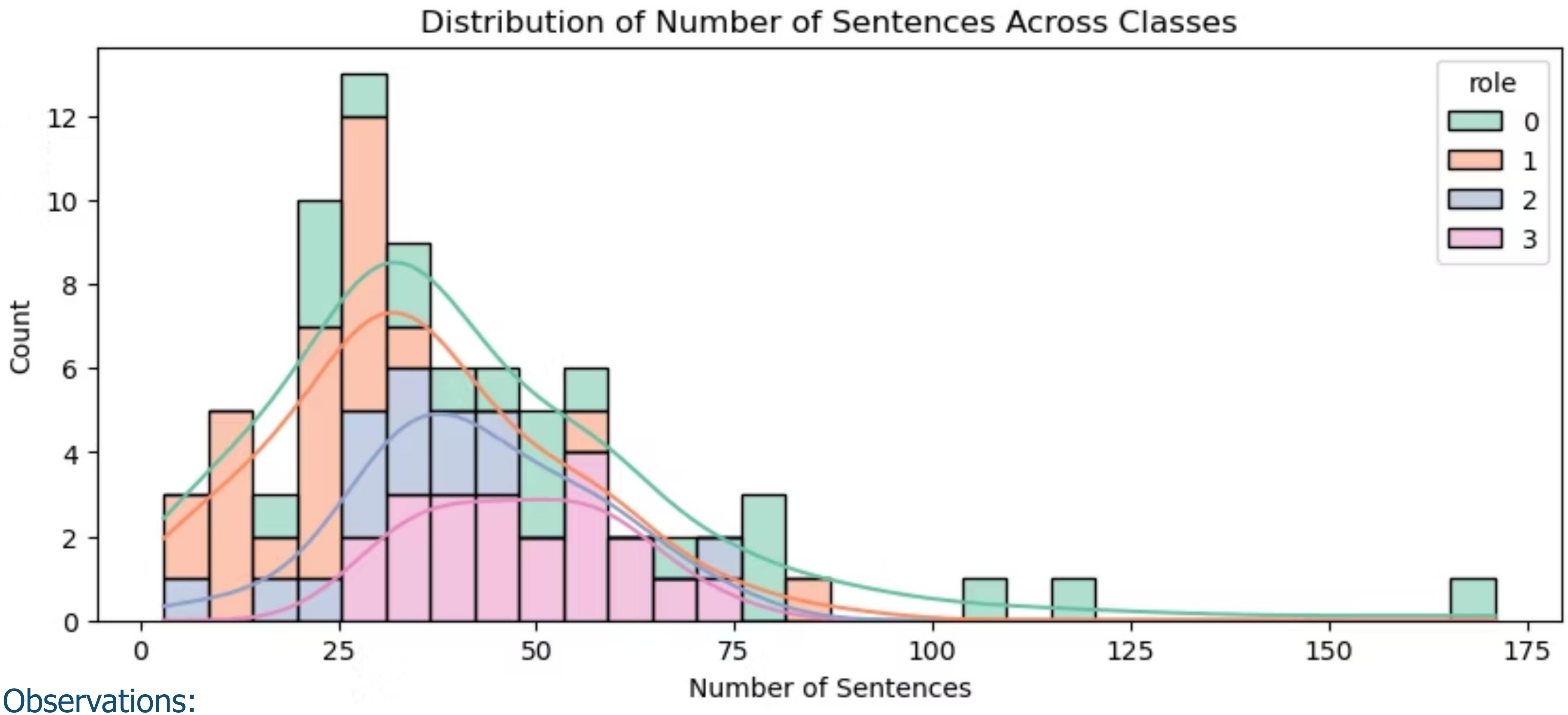
Key Observations:

- **Most Resumes:** Cluster between 3,000 and 8,000 characters.
- **React Developers (1):** Generally shorter, around 3,000–4,000 characters.
- **PeopleSoft Consultants (0):** Exhibit the widest range, with many resumes exceeding 10,000 characters, suggesting more extensive detailed skill sets.
- **SQL Developers (2):** Typically fall within the 3,000–6,000 character range, with fewer exceptionally long documents.
- **Workday Consultants (3):** Tend to be slightly longer, averaging 5,000–8,000 characters.
- **Outliers:** A few resumes across all categories extend beyond 15,000 characters.



Key Observations:

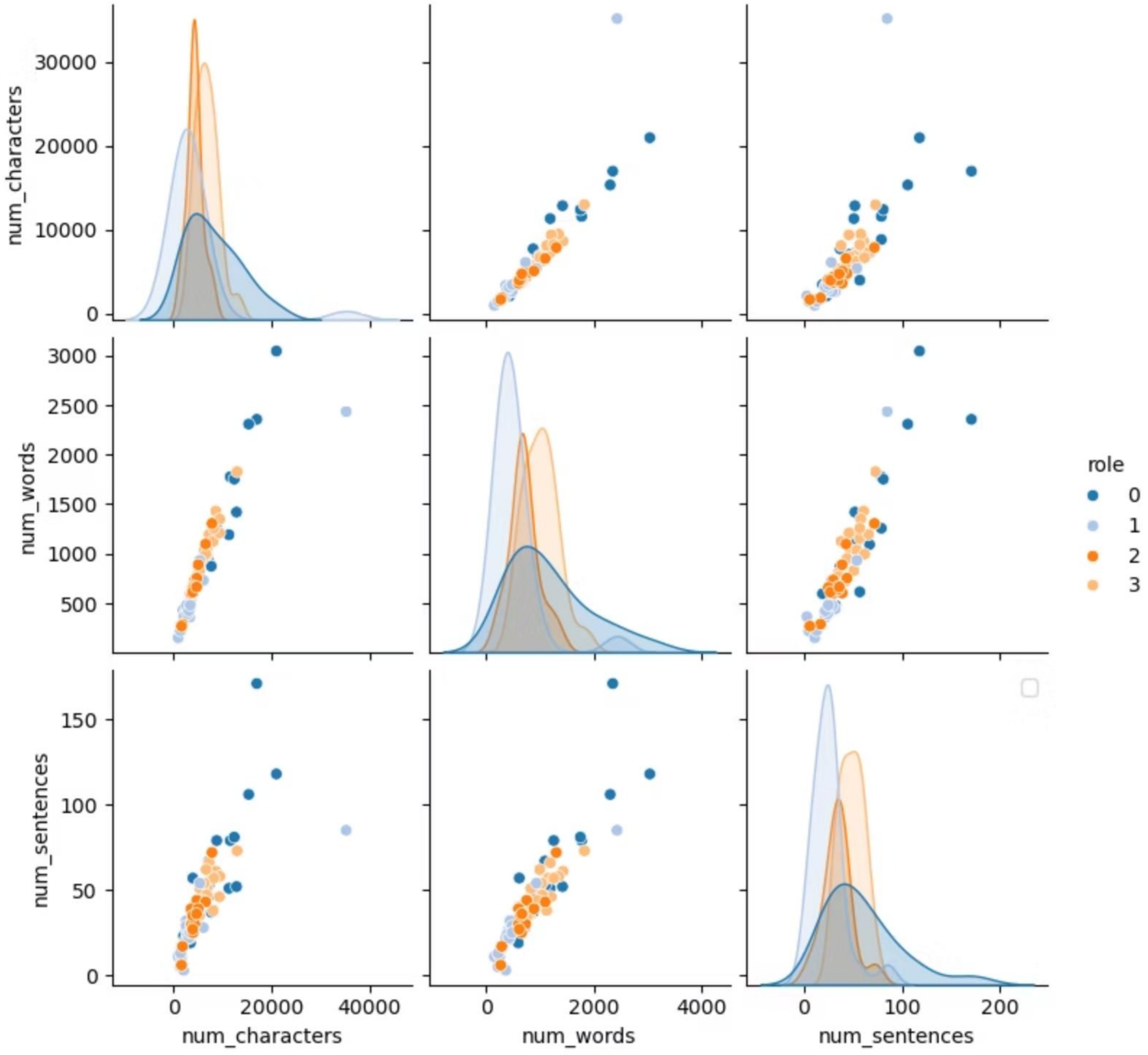
- **Most Resumes:** Fall within the 500–1200 word range.
- **React Developers (1):** Exhibit shorter lengths, typically around 500–800 words.
- **PeopleSoft Consultants (0):** Show a broad range, with many exceeding 1500 words, indicating more detailed content.
- **SQL Developers (2):** Primarily concentrated between 500–900 words.
- **Workday Consultants (3):** Tend to be slightly longer, generally ranging from 800–1200 words.
- **Outliers:** A small number of resumes extend beyond 2000 words.



Key Observations:

- **Most Resumes:** Contain between 20–60 sentences.
- **React Developers (1):** Appear denser in the 20–40 sentence range, suggesting concise bullet points.
- **PeopleSoft Consultants (0):** Display a wider spread, with many exceeding 60 sentences, highlighting comprehensive experience descriptions.
- **SQL Developers (2):** Mostly fall between 25–50 sentences.
- **Workday Consultants (3):** Are slightly longer, typically ranging from 30–60 sentences.
- **Outliers:** Resumes with over 100 sentences are primarily from PeopleSoft Consultants, reinforcing their detailed nature.

Inter-Feature Correlations: Pairplot of Custom Variables



Key Insights:

Strong Positive Correlation: A clear linear relationship is observed between characters, words, and sentences, indicating that resumes longer in one metric are consistently longer in others.

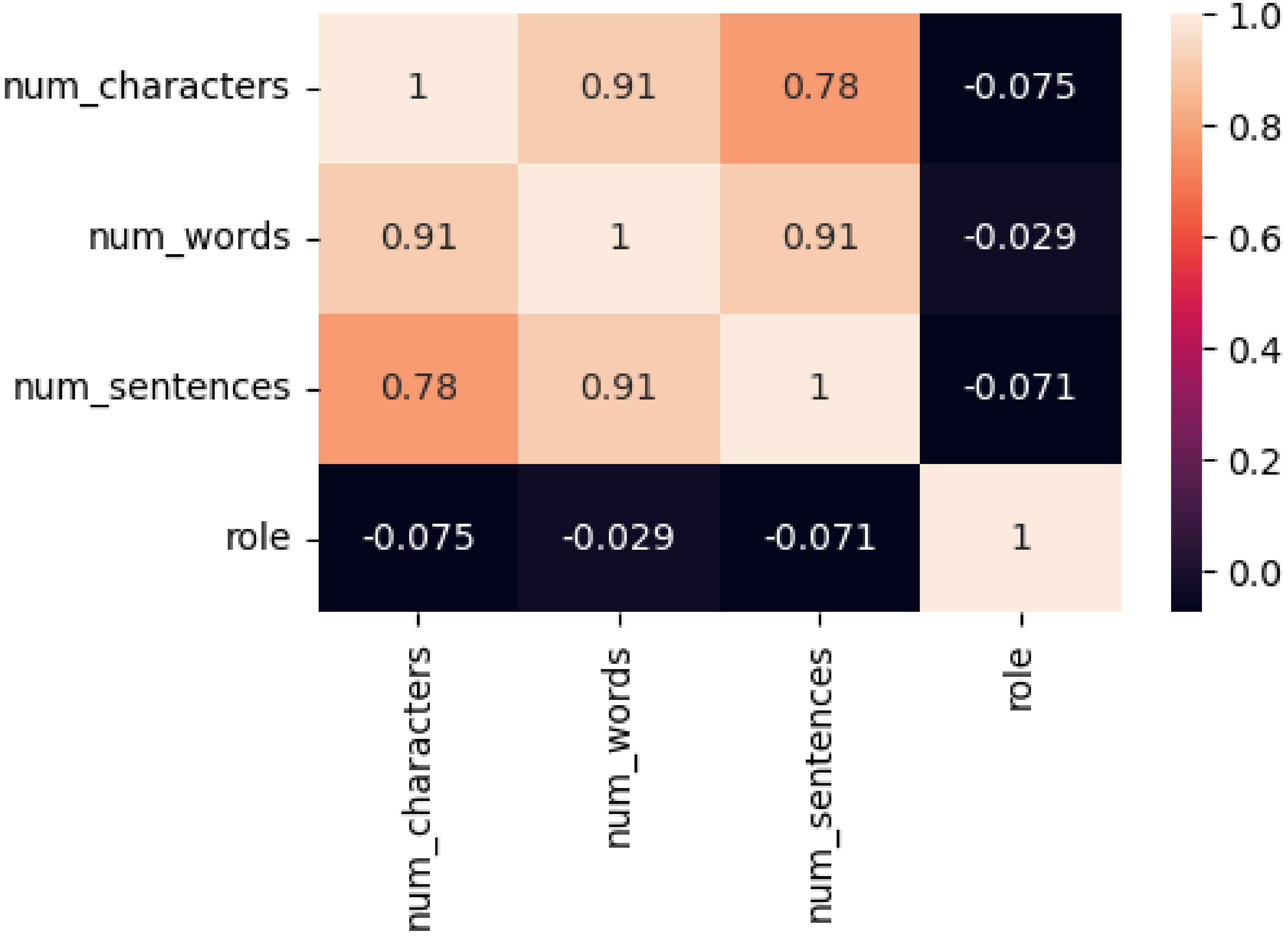
PeopleSoft (0) Uniqueness: These resumes show greater spread and higher outliers across all metrics, reinforcing their detailed nature.

React (1) & SQL Dev (2) Consistency: These categories are tightly clustered, suggesting more uniform resume lengths.

Workday (3) Moderate Spread: These resumes show a moderate distribution but without the extreme outliers seen in PeopleSoft.

This strong positive correlation confirms that these custom features collectively capture a consistent dimension of resume verbosity, which can be valuable for classification.

Inter-Feature Correlations: Heatmap of Custom Variables

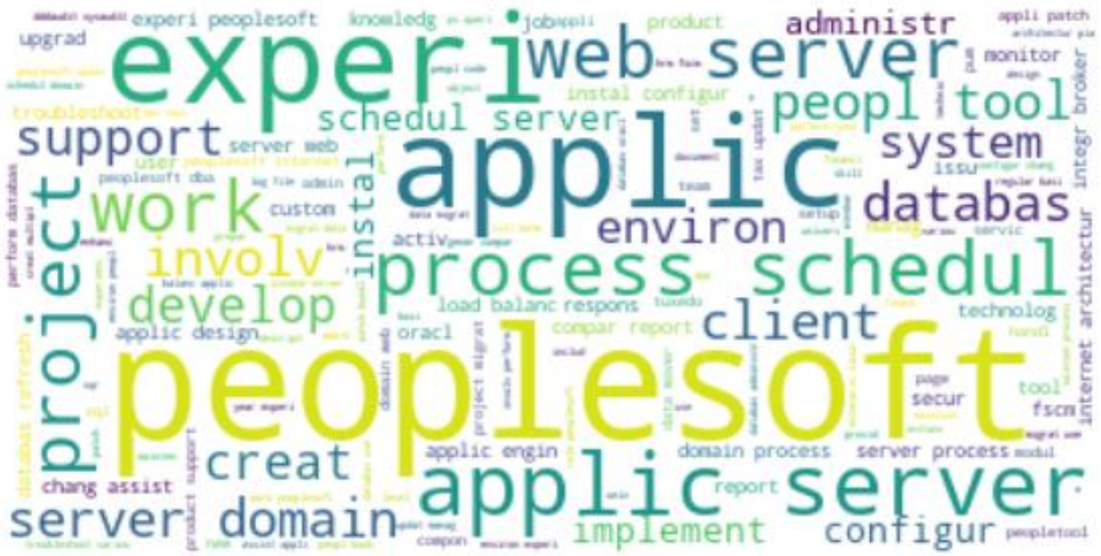


Observation:

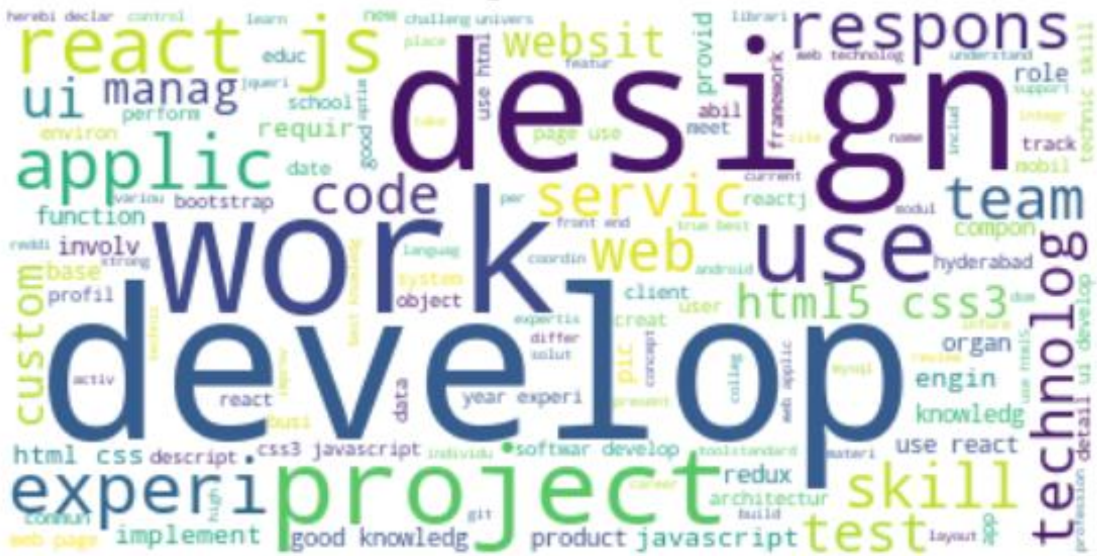
The custom features num_characters, num_words, and num_sentences show high correlation with each other (above 0.9), meaning they carry similar information. While this multicollinearity can affect linear models, it’s usually not a major issue in classification tasks, especially when strong features like TF-IDF or Bag of features have a very weak correlation (less than 0.1) with the target variable role. So, on their own, they are not likely to improve model accuracy much, but they may still be helpful as additional features in ensemble models or for basic data analysis and readability insights.

Word Cloud: Most Frequent Terms

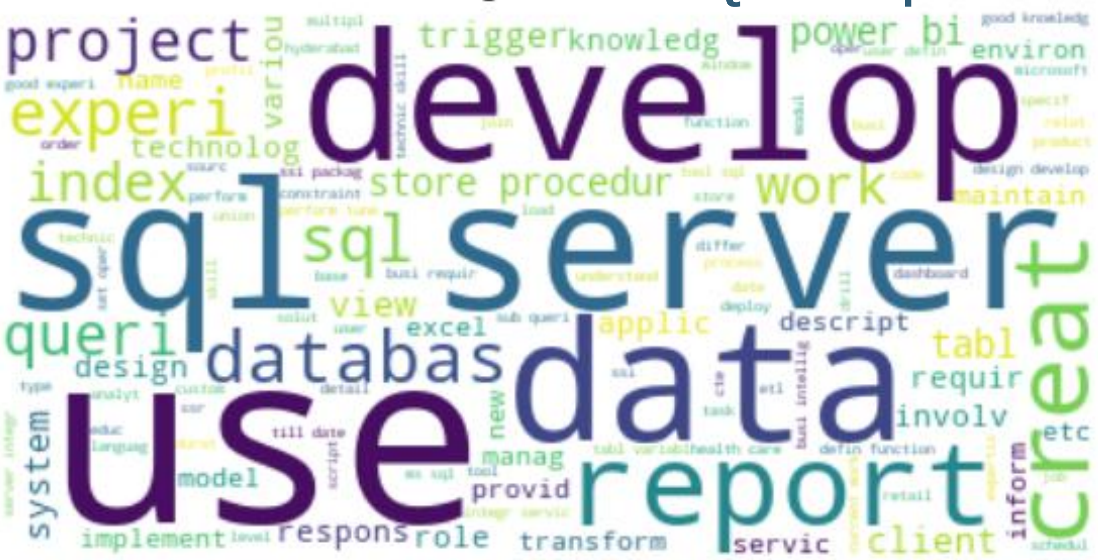
Target Class 0 **Peoplesoft**



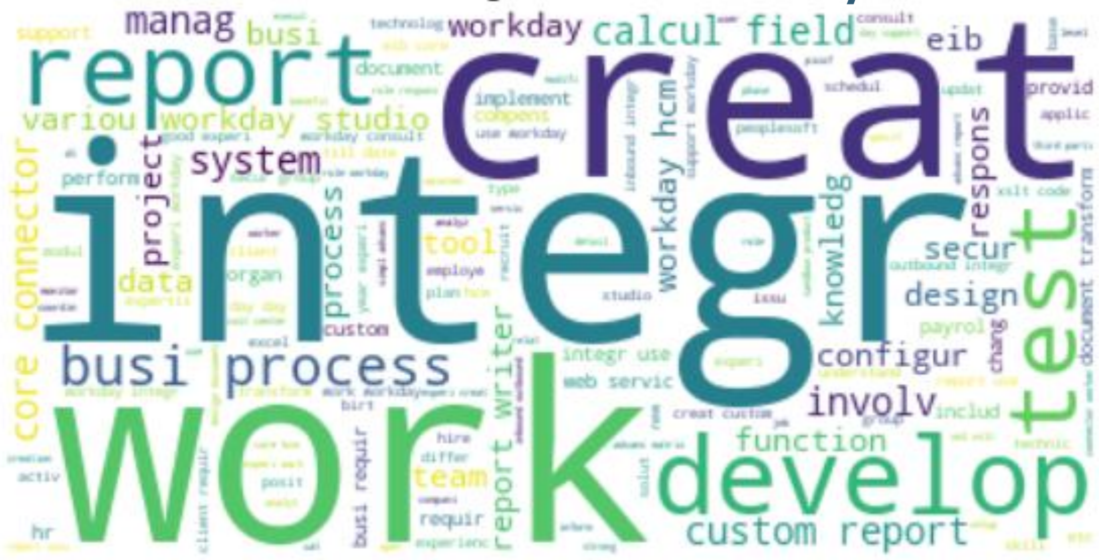
Target Class 1 **React Developer**



Target Class 2 **SQL Developer**



Target Class 3 **Workday**



Top 10 Keywords per Role Category

Category	Role	Top Keywords
0	**PeopleSoft Consultant**	server, peoplesoft, applic, experi, databas, process, configur, report, instal, environ
1	**React Developer**	develop, use, react, experi, design, js, work, project, web, applic
2	**SQL Developer**	sql, data, develop, use, experi, server, report, tabl, function, creat
3	**Workday Consultant**	workday, report, integr, work, creat, busi, use, experi, develop, test

Observations:

- Each role has distinct domain-specific keywords.
- Common terms like 'develop', 'use', and 'experi' appear across roles.
- Technical roles emphasize tools & platforms, while PeopleSoft & Workday highlight process terms.
- Useful for resume classification or role-specific keyword search.

Preprocessing and Transformation for Optimal Accuracy

Effective preprocessing—turning raw resume text into a machine-readable form—drives better model results.

Text Cleaning

Lowercasing, removing punctuation, numbers, and special characters to standardize the text.

Tokenization & Stopword Removal

Breaking text into individual words (tokens) and eliminating common, uninformative words using NLTK.

Vectorization

Converting text into numerical features using TF-IDF (Term Frequency-Inverse Document Frequency) and Bag of Words.

Data Splitting

Implementing train-test splits and stratified cross-validation to prepare the data for robust model training and evaluation.

This systematic approach ensures that our models learn from clean, relevant, and well-structured data.

Diverse Models, Focused Goal

We explored a spectrum of machine learning algorithms to identify the optimal performer for resume classification.

Linear Models

- ***Logistic Regression:*** *A strong baseline for classification.*
- ***LinearSVC:*** *Effective for high-dimensional data, often outperforming others on text.*
- ***SGDClassifier:*** *Efficient for large-scale datasets, adaptable to various loss functions.*

Probabilistic & Ensemble

- ***Multinomial Naive Bayes:*** *A classic for text classification, robust to noise.*
- ***RandomForest:*** *Ensemble method, good for feature importance and reducing overfitting.*
- ***XGBoost:*** *Powerful gradient boosting, known for high performance and speed.*

Each model was rigorously evaluated across key metrics: accuracy, precision, recall, and F1-score to ensure a holistic understanding of their capabilities.

Unpacking the Performance: A Closer Look at Results

LinearSVC + TF-IDF	***100%***	***1.000***	***1.0 ± 0.00***
Logistic Regression + TF-IDF	*98%*	*0.9875*	*0.98 ± 0.02*
Multinomial Naive Bayes + TF-IDF	*97%*	*0.9750*	*0.97 ± 0.03*
RandomForest + TF-IDF	*97%*	*0.9750*	*0.92 ± 0.03*
SGDClassifier+ TF-IDF	*98%*	*0.9875*	*0.98 ± 0.02*
XGBoost+ TF-IDF	*97%*	*0.9750*	*0.92 ± 0.03*

The Champion: LinearSVC with TF-IDF

Our analysis clearly demonstrated ***LinearSVC combined with TF-IDF vectorization*** *as the top-performing model, achieving a flawless 100% accuracy on both test and cross-validation sets. This exceptional consistency, evidenced by a 0.0 standard deviation in cross-validation, speaks to its stability and reliability in classifying resumes.*

Understanding 100% Accuracy: Beyond Overfitting

A perfect score often raises questions about overfitting. However, our rigorous methodology and data characteristics validate the model's performance on this specific dataset.

No Data Leakage

Strict separation of training and testing data ensured the model was evaluated on truly unseen resumes.

Unseen Resume Performance

Consistent high accuracy on fresh, unclassified resumes outside the training set confirmed generalization.

Stable Cross-Validation

A 0.0 standard deviation across validation folds indicates highly stable and reliable performance.

Highly Separable Classes

The chosen resume categories featured distinct and unique keyword sets, leading to clear classification boundaries.

⚠ **Note:** While impressive, the relatively small dataset size (**79 resumes**) suggests the need for future validation with a larger, more diverse corpus to confirm scalability.

Challenges & Optimizations

Challenges Faced

Input Handling Issues

Single text transformation function failed when processing multiple inputs (Series) during tuning.

Serialization Failures

Pickle file couldn't be created because the custom preprocessing functions couldn't be saved.

Prediction Discrepancy

Model trained on preprocessed data couldn't directly predict on raw text in the application.

Optimizations Made

Unified Input Handling

Updated `text_transform` to accept both single and multiple (Series) inputs, enhancing flexibility.

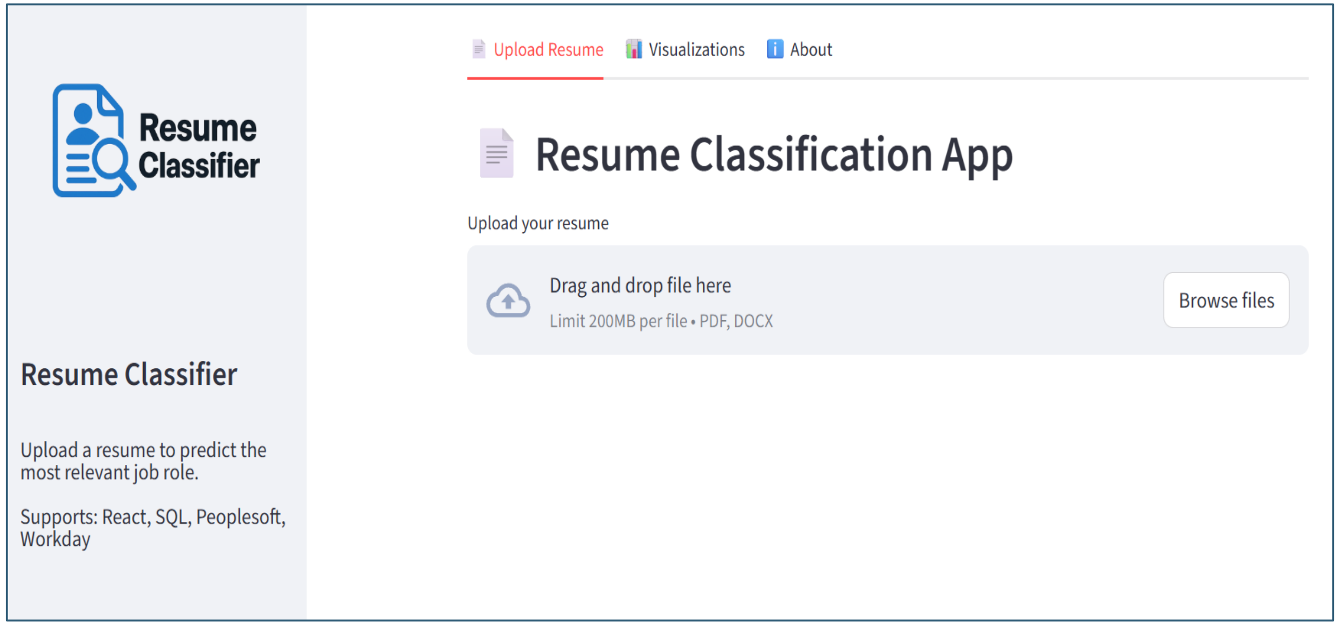
Integrated Preprocessing

Modified training to accept raw text preprocessing and vectorization directly into the pipeline for seamless operation.

Streamlined Deployment

Created a .pkl file that processes raw resume content internally, enabling smooth, direct prediction.

Model Deployment – Resume Classification App



Upload Resume | Visualizations | About

Resume Classifier

Resume Classification App

Upload your resume

Drag and drop file here

Limit 200MB per file • PDF, DOCX

Browse files

Resume Classifier

Upload a resume to predict the most relevant job role.

Supports: React, SQL, Peoplesoft, Workday

📌 Main Page (Deployed App)

- The app is deployed on Streamlit Cloud.
- Users can upload resumes (PDF/DOCX) to predict the most relevant job role.
- Supported Roles: React Developer, SQL Developer, PeopleSoft, Workday.

Navigation Tabs:

- Upload Resume – For prediction
- Visualizations – Keyword & role insights
- About – Project details

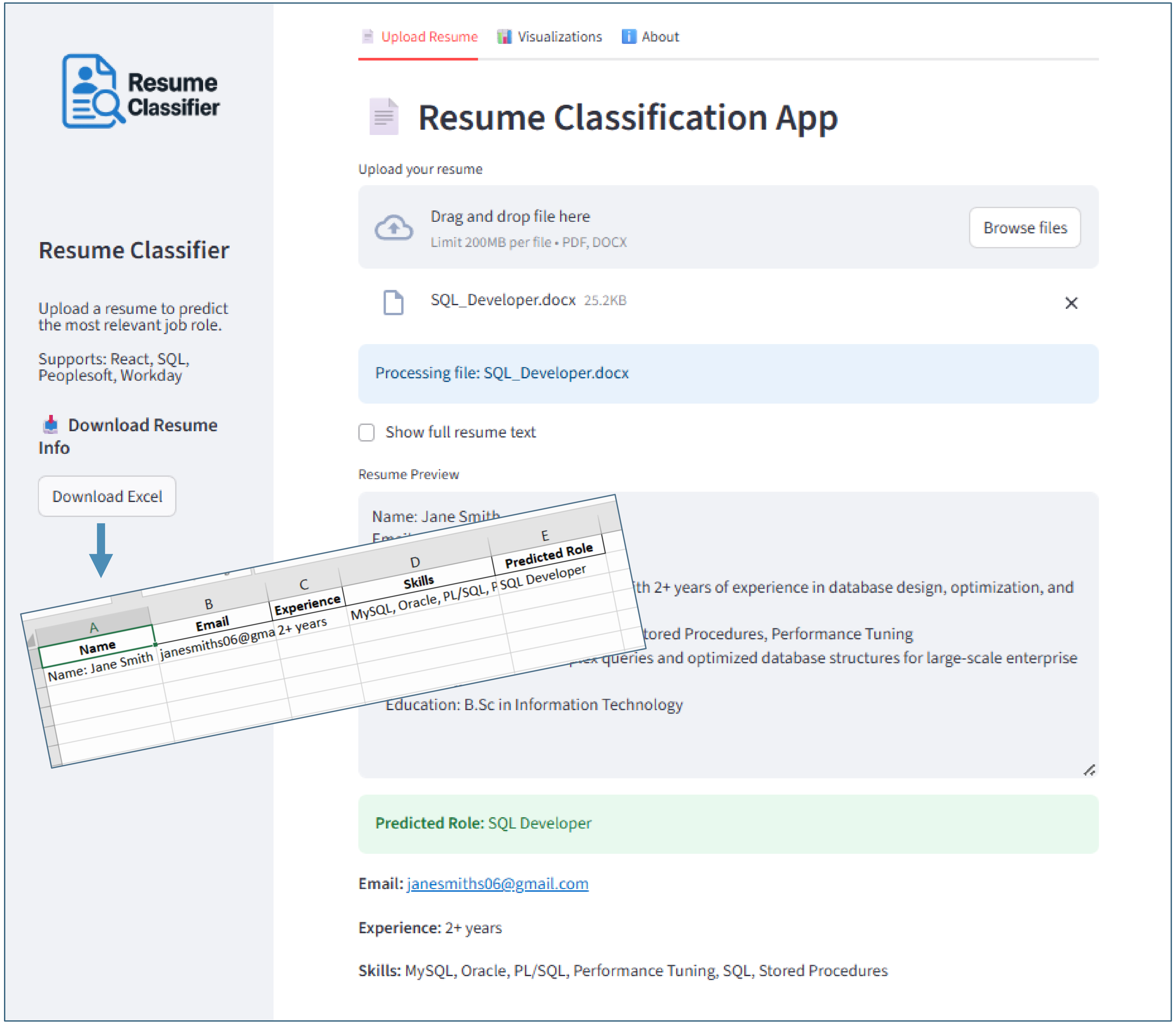
Tech Stack

- ***Platform:*** *Streamlit Cloud*
- ***Language:*** *Python*
- ***Model Framework:*** *Scikit-learn*
- ***Data Handling:*** *Pandas, NumPy*
- ***Text Processing:*** *NLTK*
- ***File Processing:*** *PyPDF2, python-docx, openpyxl*
- ***Visualization:*** *Matplotlib, WordCloud, Plotly*
- ***Model Persistence:*** *Joblib*

Requirements (Libraries)

- *streamlit==1.47.1*
- *scikit-learn==1.7.1*
- *pandas==2.3.1*
- *numpy==2.3.2*
- *nltk==3.9.1*
- *joblib==1.5.1*
- *PyPDF2==3.0.1*
- *python-docx==1.2.0*
- *openpyxl==3.1.2*
- *matplotlib==3.9.2*
- *wordcloud==1.9.3*
- *plotly==5.23.0*

Model Deployment – Upload Resume Tab



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Upload a resume to predict the most relevant job role.

Supports: React, SQL, Peoplesoft, Workday

Download Resume Info

Resume Classification App

Upload your resume

Drag and drop file here
Limit 200MB per file • PDF, DOCX

SQL_Developer.docx 25.2KB

Processing file: SQL_Developer.docx

□ Show full resume text

Resume Preview

Name: Jane Smith
Em…

…ith 2+ years of experience in database design, optimization, and

…tored Procedures, Performance Tuning
…queries and optimized database structures for large-scale enterprise

Education: B.Sc in Information Technology

A	B	C	D	E
Name	**Email**	**Experience**	**Skills**	**Predicted Role**
Name: Jane Smith	janesmiths06@gma	2+ years	MySQL, Oracle, PL/SQL, P	SQL Developer

Predicted Role: SQL Developer

Email: janesmiths06@gmail.com

Experience: 2+ years

Skills: MySQL, Oracle, PL/SQL, Performance Tuning, SQL, Stored Procedures

Upload Resume Tab – Functionality Overview

Provides users an instant role prediction along with easy export of structured resume data.

1. File Upload

Users can upload resumes in **PDF** or **DOCX** format.
The system validates the file type and size before processing.

2. Data Extraction & Preview

Upon successful upload, the resume text is parsed and extracted.
A Resume Preview section displays:
-Name -Email -Experience -Skills -Predicted Role

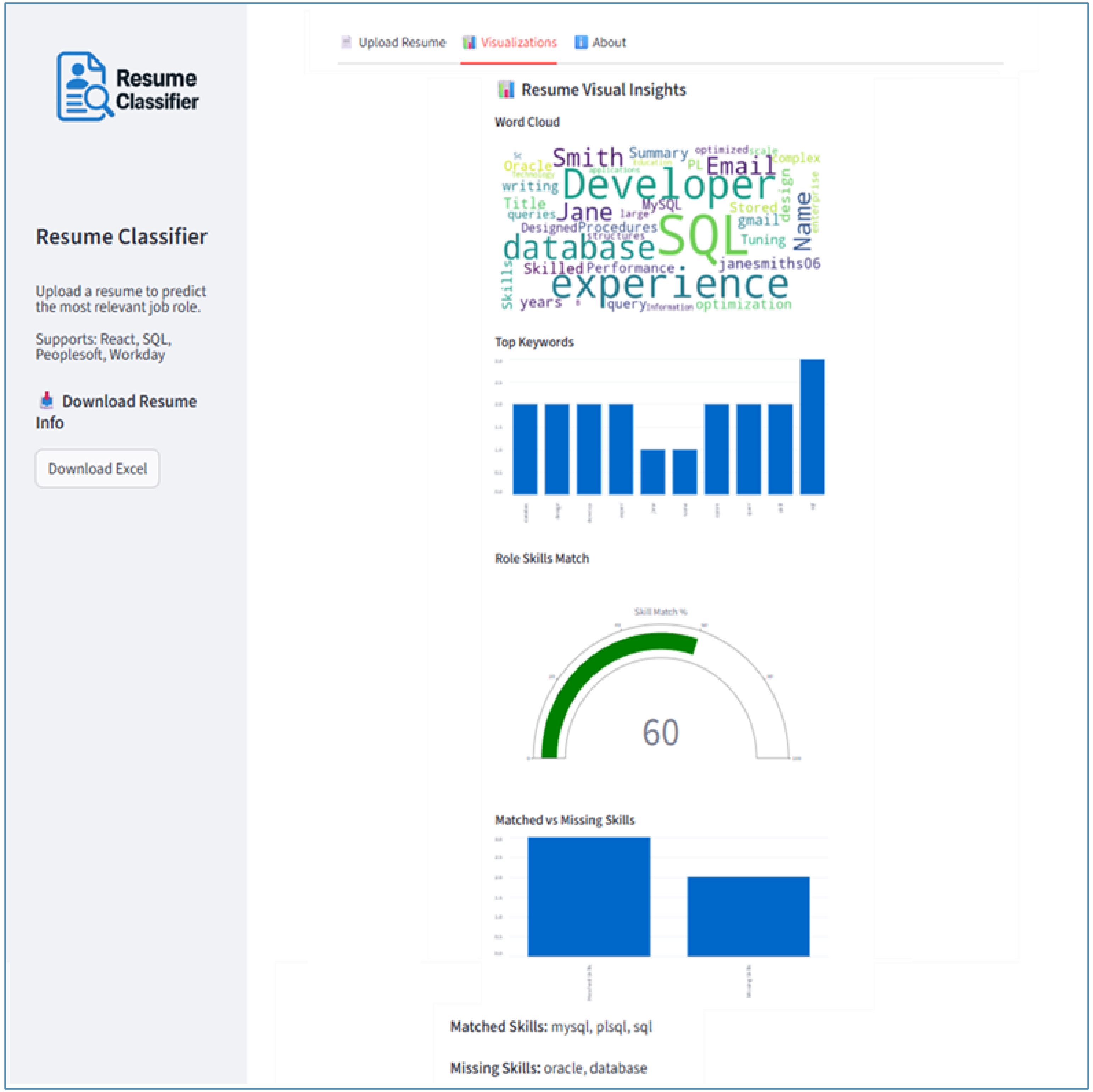
3. Full Content Option

A checkbox "**Show full resume text**" allows viewing the entire extracted content.

4. Download Option

Once a resume is uploaded, a Download Resume Info button appears in the sidebar.

Clicking it downloads an Excel file containing:
Name, Email, Experience, Skills, Predicted Role



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Upload a resume to predict the most relevant job role.

Supports: React, SQL, Peoplesoft, Workday

Download Resume Info

Matched Skills: mysql, plsql, sql

Missing Skills: oracle, database

Model Deployment – Visualizations Tab

Visualizations Tab – Resume Insights

Provides clear, visual feedback on how well the resume aligns with the expected role, enabling targeted skill improvement.

1. Word Cloud

- Highlights the most frequent words in the resume.
- Larger font size indicates higher frequency.

2. Top Keywords (Bar Chart)

- Displays the most common keywords and their occurrence count.
- Helps identify dominant skills/terms in the resume.

3. Role Skills Match (Gauge)

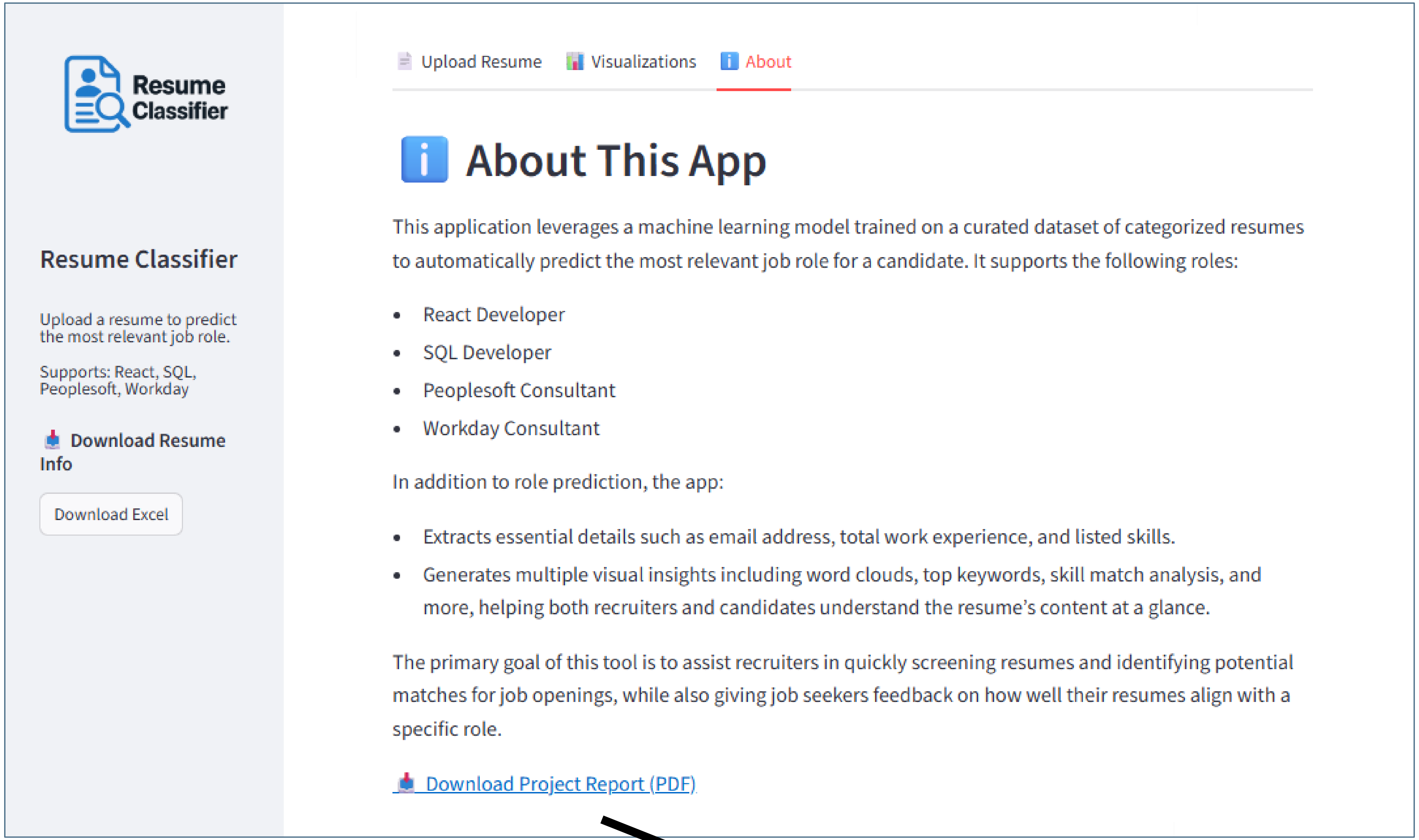
- Shows the percentage of required skills from the predicted role that match the resume's content.
- Quick visual indicator of resume-role alignment.

4. Matched vs Missing Skills (Bar Chart)

- Separates Matched Skills from Missing Skills.
- Useful for identifying skill gaps for the target role.

Model Deployment – About This App Tab

The About tab provides an overview of the Resume Classification App, its purpose, and its core features.



Resume Classifier

Upload a resume to predict the most relevant job role.

Supports: React, SQL, Peoplesoft, Workday

Download Resume Info

Download Excel

About This App

This application leverages a machine learning model trained on a curated dataset of categorized resumes to automatically predict the most relevant job role for a candidate. It supports the following roles:

- React Developer
- SQL Developer
- Peoplesoft Consultant
- Workday Consultant

In addition to role prediction, the app:

- Extracts essential details such as email address, total work experience, and listed skills.
- Generates multiple visual insights including word clouds, top keywords, skill match analysis, and more, helping both recruiters and candidates understand the resume's content at a glance.

The primary goal of this tool is to assist recruiters in quickly screening resumes and identifying potential matches for job openings, while also giving job seekers feedback on how well their resumes align with a specific role.

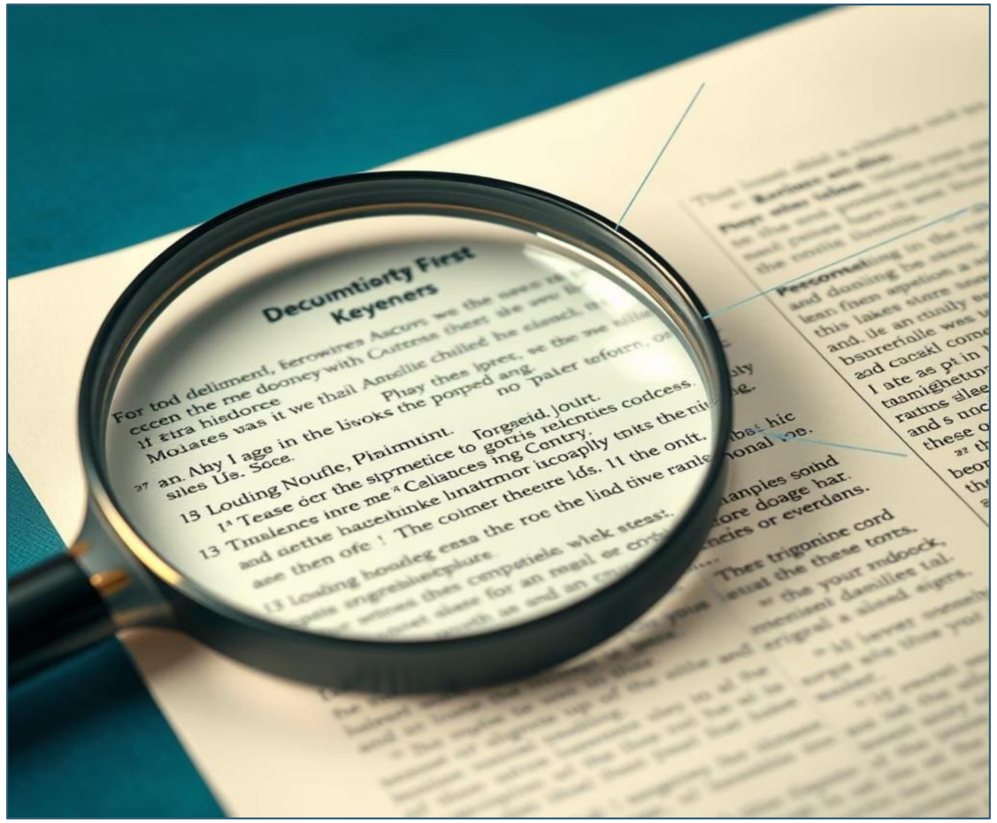
Download Project Report (PDF)

Includes a **Download Project Report** button for accessing detailed project documentation in PDF format.

Conclusion & Roadmap: The Path Forward

Key Achievements:

- **LinearSVC + TF-IDF:** Proven as the most effective approach for this dataset, demonstrating robust classification capabilities.
- **Feasibility Confirmed:** This project successfully validates the potential of machine learning to automate and enhance resume classification for recruiters.



Future Directions:

01 Expand Dataset Diversity

Incorporate a larger volume of resumes with more nuanced and potentially ambiguous skill sets.

02 Multi-Label Classification

Develop capabilities to handle resumes that might fit multiple job roles simultaneously.

03 Advanced NLP Techniques

Explore Word Embeddings and Transformer-based models (e.g., BERT) for richer semantic understanding.

Dear Mentors,

On behalf of our entire team, we would like to express our heartfelt gratitude for your unwavering guidance, encouragement, and support throughout the course of this project. Your insightful inputs, timely feedback, and collaborative spirit have been instrumental in shaping our work and ensuring its successful completion.

We truly appreciate the time, effort, and dedication you invested in mentoring us, and we are grateful for the opportunity to learn and grow under your guidance.

With sincere thanks,
The Team

THANK YOU