INTRODUCTION TO DATA SCIENCE
Final Report

Title

Student Job and Course Recommendation System

Introduction

Students often struggle to find the right career path, job opportunities, or skill-enhancing courses that align with their aspirations. This project aims to bridge that gap using data-driven insights. By analyzing student profiles, we provide personalized recommendations to help students make informed career decisions by suggesting to them an online course and available job roles.

Our approach involves Exploratory Data Analysis (EDA) to understand key patterns in student academic backgrounds, career goals, and skillsets. We then implement Machine Learning models to recommend the most relevant job postings and courses tailored to each student's profile. This system empowers students by guiding them toward the right opportunities, ultimately improving their career prospects.

Objective

Choosing the right career path can be overwhelming for students. This project aims to simplify that journey by providing personalized job and course recommendations based on their academic background, skills, and career goals.

- Helps students find the right job opportunities by matching their skills and interests with relevant job roles.
- Suggests online courses that can help them develop in-demand skills and improve their chances of landing a great job.

Tool and Technology Stack

Programming Languages: Python

Frameworks & Tools:

- Streamlit Dashboard – For front-end development and user interaction.
- Visual Studio Code – The development environment.

Libraries & Data Analysis:

- Pandas – For data manipulation and preprocessing.
- Matplotlib, Seaborn – For data visualization and insights.
- Scikit-learn – For implementing machine learning models.

Machine Learning Models:

- Support Vector Classifier (SVC)
- Decision Tree Classifier
- Random Forest Classifier

Data Used

This project utilizes three key datasets to provide job and course recommendations.

Datasets:

[1] **Online_Courses.csv:** Lists various online courses with relevant details.
[2] **Job_Postings.csv:** Includes job opportunities along with required skills and company details.
[3] **Studentdata.csv:** Contains student academic and career-related information.

Key Features:

1. Student Data

- **Branch** – The student's field of study.
- **Percentage_10th** – Academic performance till 10th grade.
- **Percentage_12th** – Academic performance in high school.
- **Career_Goal** – The student's desired career path.
- **Skills** – Skills that the student has.

2. Courses Data

- **Title** – Name of the course.
- **Category** – The field or domain of the course.
- **Course Type** – The mode of delivery (Course, Specialization, etc.).

3. Job Data

- **Job Title** – The role title.
- **Job Skills** – The skills required for the position.

Data Source & Structure:

- **Source:** Kaggle (public datasets).
- **Format:** CSV files.

Project Timeline

Task	Date
Milestone 1: Exploratory Data Analysis	04/06/2025 - 04/11/2025
Milestone 2: Feature Engineering & Model training	04/12/2025 - 04/17/2025
Milestone 3: Streamlit dashboard Integration	04/18/2025 - 04/21/2025

Team-Work Distribution (Why is it a two-person project?)

This project was a two-person project because of the wide range of tasks involved, from data analysis and machine learning to building a fully functional user-facing application. It wasn't just about writing code, we had to carefully design a system that could clean and process data, train models, make accurate predictions, and present all of that in an intuitive way through a Streamlit dashboard.

The dashboard itself had quite a few features: it predicted course categories using a trained model, matched jobs using cosine similarity, and included several visualizations to help users explore trends in education and the job market. Balancing all of that while keeping the application responsive and user-friendly took time.

Working as a team helped us test and validate each part of the system more thoroughly, catch bugs earlier, and keep everything on track with our deadlines. Overall, this project really benefited from having two minds that one focused on the logic and the other on the experience working together to build something practical and impactful.

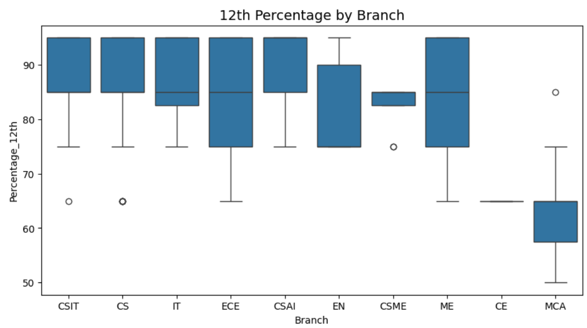
Individual Contributions

- **Sashank Boppana:** Focused more on the data side which includes cleaning, merging, creating features, training models, evaluating performance, and post training analysis.
- **Tejesh Boppana:** Concentrated on the frontend experience like setting up the Streamlit interface, making it interactive, integrating model predictions, and ensuring that users could get job and course recommendations with just a few clicks.

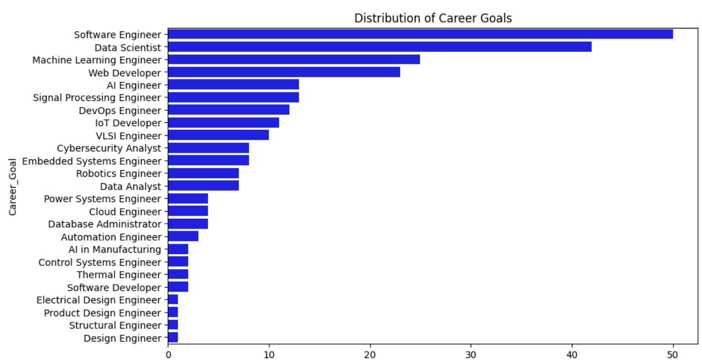
Exploratory Data Analysis

Student Data Insights

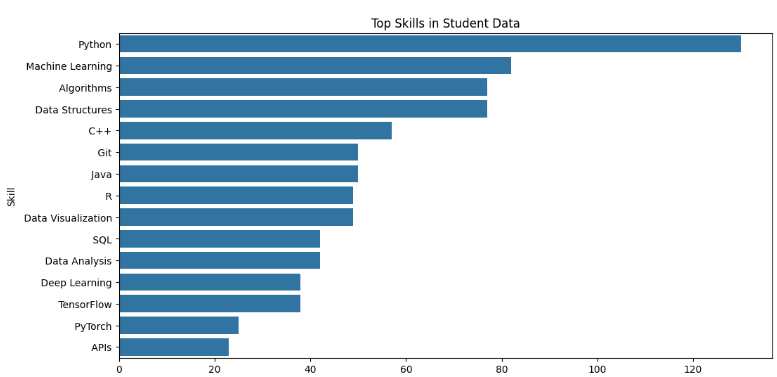
- High School Percentage Distribution: Most students have scores between 75-95%, showing a strong academic background.



- Career Goal Trends: The most common aspirations include Software Engineer, Data Scientist, Machine Learning Engineer, Web Developer roles.

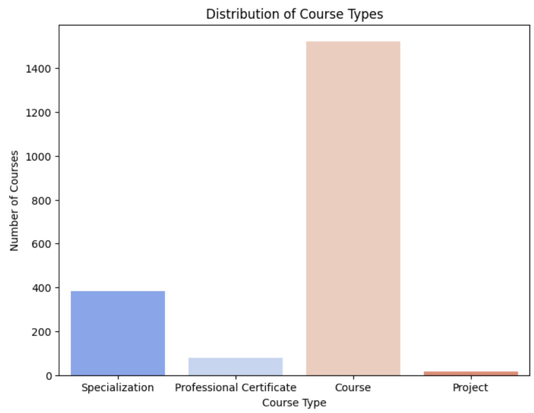


- Top Student Skills: Popular skills include Python, Machine Learning, Algorithms, Data Structures, C++.

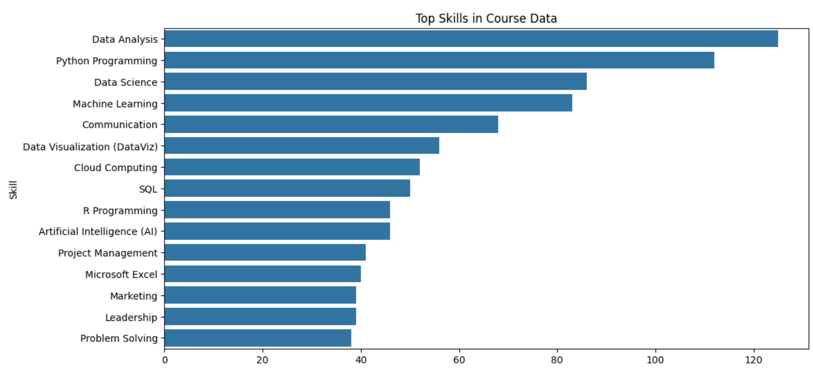


Course Data Insights

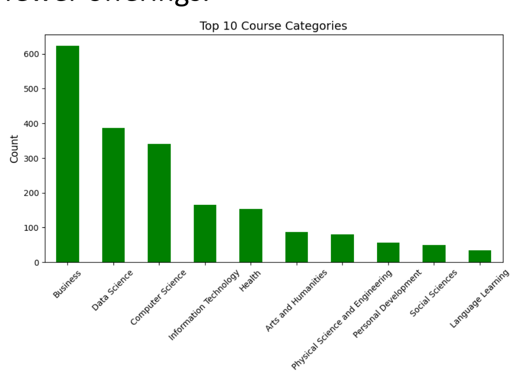
- Type of Courses Offered: Standard courses are the most preferred, surpassing specializations, professional certificates, and project-based courses.

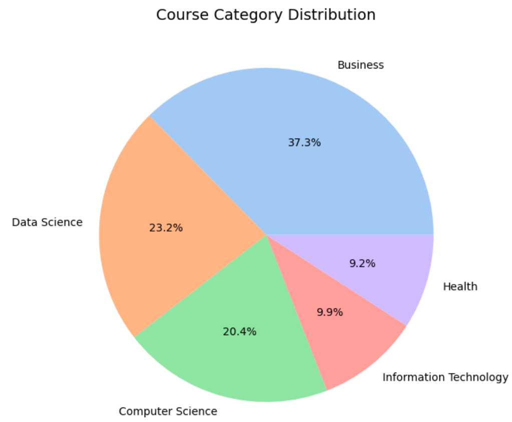


- Top Skills in Courses: Courses frequently focus on Data Analysis, Python Programming, Data Science, and Machine Learning.



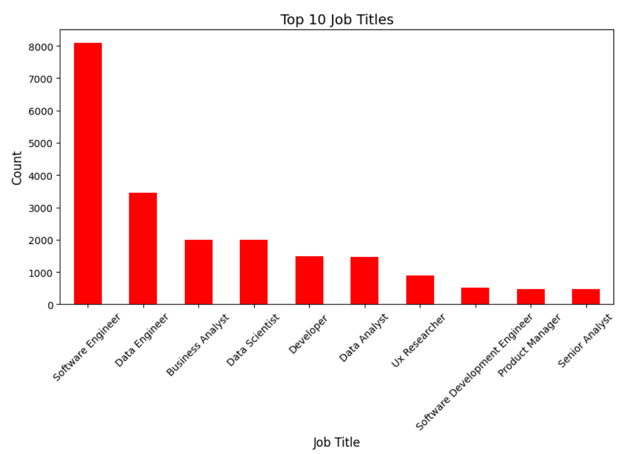
- Top Course Categories: Business and Data Science dominate, while Social Science and Language Learning have fewer offerings.



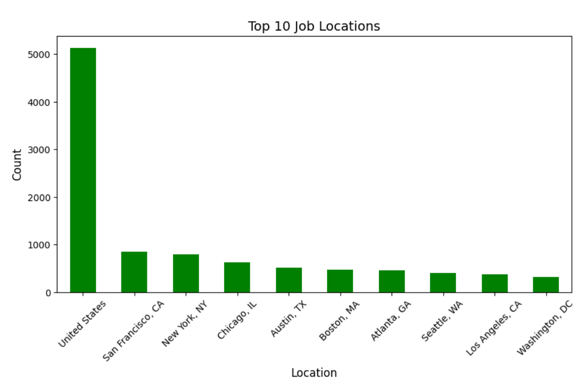


Job Market Landscape

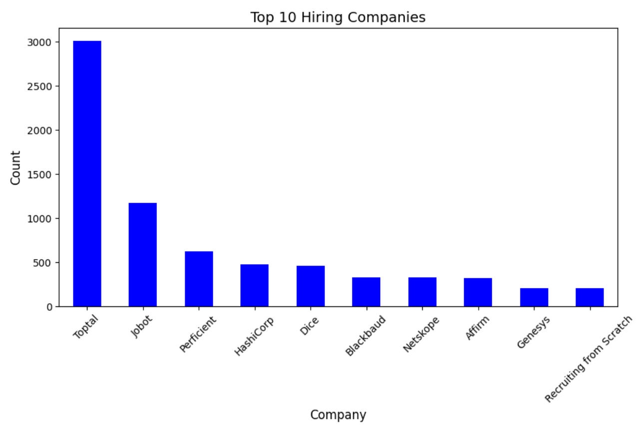
- Job Titles with Highest Demand: The most frequently posted job roles include Software Engineer, Data Engineer, Business Analyst, and Data Scientist.



- Job Locations: The United States leads in job postings, with California, New York, Chicago, and Texas as major hubs.



- Top Hiring Companies: Companies like Toptal, Jobot, and Perficient are among the top recruiters.



- Skill Requirements: A clear skill gap exists between student profiles and market demands, emphasizing the need for targeted upskilling.

Conclusion of the EDA

The EDA phase has provided crucial insights into student skills, learning preferences, and job market trends. These findings will shape our recommendation system, ensuring accurate, personalized career and course suggestions that bridge the gap between education and industry. These insights will give us an idea about the data distribution which will help our model selection, feature engineering, and training approaches in the next project phase.

Feature Engineering - Feature Creation

Four key features were engineered to enhance the dataset: Skills Vector, Skills Count, Performance Gap, and Academic Performance Score.

Skills Vector (TF-IDF Vectorization)

- **Purpose**: Converts the unstructured "Skills" text into a numerical representation for better matching with jobs and courses.
- **Impact**: Helps in finding similarities between students' skills and job/course requirements.

```
from sklearn.feature_extraction.text import TfidfVectorizer

tfidf = TfidfVectorizer(stop_words='english', max_features=1000)

Skills_tfidf = tfidf.fit_transform(df_encoded['Skills']).toarray()

tfidf_df = pd.DataFrame(Skills_tfidf, columns=tfidf.get_feature_names_out())

df_encoded = pd.concat([df.reset_index(drop=True), tfidf_df], axis=1)
df_encoded.drop(columns=['Skills'], inplace=True)
df_encoded.columns
```

0.5s

```
Index(['Percentage_10th', 'Percentage_12th', 'Skills_Count', 'Performance_Gap',
       'Course_Type_Encoded', 'Branch_Encoded', 'Course Type_Encoded',
       'Category_Encoded', 'ab', 'abatement',
       ...
       'wireless', 'work', 'workflow', 'workload', 'workloads', 'world',
       'write', 'writing', 'writingcommunicationwriting', 'xml'],
      dtype='object', length=1008)
```

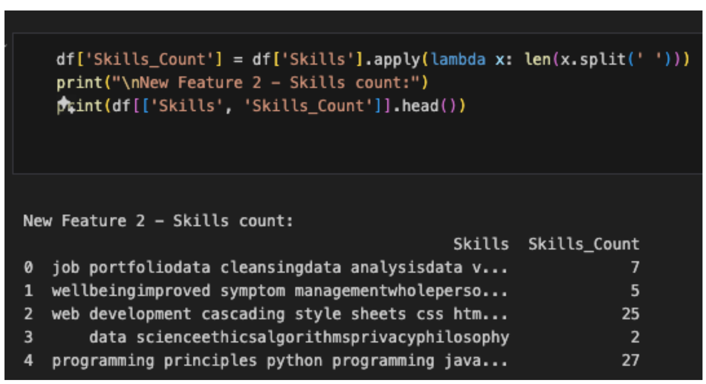
Fig. 1. Feature extraction using TF-IDF

Output Explanation

Skills column is extracted and vectorized using TD-IDF in such a way that multiple new columns are created like wireless, work, workflow, etc. These are fed to the model to improve the chance of a better model performance.

Skills Count

- **Purpose**: Provides a numerical representation of how many distinct skills a course or job requires.
- **Impact**: Helps filter recommendations based on skill intensity (e.g., beginner-friendly courses may have fewer skills listed).



```
df['Skills_Count'] = df['Skills'].apply(lambda x: len(x.split(' ')))
print("\nNew Feature 2 - Skills count:")
print(df[['Skills', 'Skills_Count']].head())
```

```
New Feature 2 - Skills count:
                                              Skills  Skills_Count
0  job portfoliodata cleansingdata analysisdata v...             7
1  wellbeingimproved symptom managementwholeperso...             5
2  web development cascading style sheets css htm...            25
3      data scienceethicsalgorithmsprivacyphilosophy             2
4  programming principles python programming java...            27
```

Fig. 2. Skills count declaration

Output Explanation

The number of specific keywords in the skills are extracted and their count is stored to be fed to the machine learning model.

Performance Gap

- **Purpose**: Measures academic improvement or decline from 10th to 12th grade.
- **Impact**: Could indicate learning ability and discipline, which might be relevant for job or course recommendations.

```
df['Performance_Gap'] = df['Percentage_12th'] - df['Percentage_10th']
print("\nNew Feature 5 - Performance Gap:")
print(df[['Percentage_10th', 'Percentage_12th', 'Performance_Gap']].head())
```

```
New Feature 5 - Performance Gap:
   Percentage_10th  Percentage_12th  Performance_Gap
0               75               65              -10
1               85               75              -10
2               75               65              -10
3               85               95               10
4               85               75              -10
```

Fig. 3. Performance gap declaration

Output Explanation

The output explains that if there is a negative integer in Performance Gap, then it means that there is a drop in the performance in 12^{th} compared to 10^{th}.

Academic Performance Score

- **Purpose**: A weighted combination of 10th and 12th-grade scores to create a holistic academic metric.
- **Impact**: Helps rank students in terms of academic strength, allowing better job/course filtering.

```
df['Academic_Score'] = 0.6*df['Percentage_12th'] + 0.4*df['Percentage_10th']
print("\nNew Feature 2 - Academic Score:")
print(df[['Percentage_10th', 'Percentage_12th', 'Academic_Score']].head())
✓ 0.0s
```

```
New Feature 2 - Academic Score:
   Percentage_10th  Percentage_12th  Academic_Score
0               75               65            69.0
1               85               75            79.0
2               75               65            69.0
3               85               95            91.0
4               85               75            79.0
```

Fig. 4. Academic score declaration

Output Explanation

The Academic score is derived by multiplying 0.6 with the 12^{th} percentage and 0.4 with the 10^{th} percentage. This gives a better idea of the students' academic performance.

Feature Inclusion Explanation

To make course and job recommendations more accurate, four important features were added to the dataset: Skills Vector, Skills Count, Performance Gap, and Academic Performance Score. The Skills Vector, created using TF-IDF, turns skill descriptions into numbers, making it easier to match students with relevant courses and jobs. Skills Count simply measures how many skills a course or job requires, helping to differentiate between beginner-friendly and advanced opportunities. The Performance Gap looks at how a student's grades changed from 10th to 12th grade, which can indicate improvement, consistency, or a drop in performance which is useful for tailoring recommendations. Finally, the Academic Performance Score combines these grades into a single metric, giving a clearer picture of a student's overall academic ability. Together, these features make the recommendation system more personalized and effective, ensuring students get suggestions that truly fit their skills and career goals

Feature Engineering - Categorical Variable Encoding

Overview of Categorical Encoding

The dataset contains several categorical variables that need to be transformed into numerical format for machine learning algorithms. In this phase, Label Encoding was applied to convert categorical variables into numerical representations.

Encoding Process

The following categorical variables were encoded:

- Branch (student's academic branch/major)
- Course Type (Course or Specialization)
- Category (subject category of the course)

```
label_encoder = LabelEncoder()
df['Course_Type_Encoded'] = label_encoder.fit_transform(df['Course Type'])

categorical_cols = ['Branch', 'Course Type', 'Category']
label_encoders = {}
for col in categorical_cols:
    le = LabelEncoder()
    df[col + '_Encoded'] = le.fit_transform(df[col])
    label_encoders[col] = le

# Drop original categorical columns
df.drop(columns=categorical_cols, inplace=True)
```

Fig. 5. Encoding using Label Encoder

Reason for choosing Label Encoder

Categorical variables are encoded using Label Encoding for efficiency and model compatibility. This method is ideal as it keeps the dataset compact, works well with tree-based models, and preserves ordinal relationships if present. It avoids the dimensionality explosion of one-hot encoding, making it a practical choice for handling Branch, Course Type, and Category.

Encoding Results

- **Transformation Examples**

Original Category	Encoded Value
Course	0
Specialization	3

- **Branch Encoding**

  The Branch variable (e.g., MCA, CSIT, CSME) was encoded with values: MCA → 7, CSIT → 2, CSME → 3.

- **Category Encoding**

  The Category variable was encoded with values: Data Science → 5, Health → 6, Computer Science → 4.

Feature Selection - Feature Importance Evaluation

Dataset Information (Dependent and Independent variables)

- Features matrix (X): (2417, 1008)

- Target variable (y): (2417,)

1. **Random Forest Feature Importance:** The Random Forest Classifier identified the following top 10 features based on their importance scores.

```
rf_selector = RandomForestClassifier(n_estimators=100, random_state=42)
rf_selector.fit(X, y)
top_rf = pd.DataFrame({
'Feature': X.columns,
'Importance': rf_selector.feature_importances_
})

top_rf = top_rf.sort_values(by='Importance', ascending=False).head(10)
```

Fig. 6. Feature importance evaluation using RF

RF Feature Importance Table

	Feature	Importance
217	data	0.081589
2	Skills_Count	0.042263
6	Branch_Encoded	0.031663
996	web	0.027003
501	learning	0.024602
986	visualization	0.018554
537	management	0.017010
266	development	0.014966
33	analysis	0.014158
698	programming	0.014143

Table. 1. Feature importance evaluation using RF

2. **Mutual Information Feature Importance:** The Mutual Information Classifier identified the following top 10 features based on their MI scores.

```
mi_scores = mutual_info_classif(X, y, random_state=42)
feature_importance_mi = pd.DataFrame({
    'Feature': X.columns,
    'MI_Score': mi_scores
})

feature_importance_mi = feature_importance_mi.sort_values(by='MI_Score', ascending=False).head(10)
```

Fig. 7. Feature importance evaluation using MI

MI Score Table

	Feature	MI_Score
217	data	0.478978
2	Skills_Count	0.206083
698	programming	0.204501
33	analysis	0.183878
501	learning	0.143011
147	cloud	0.140642
986	visualization	0.140379
535	machine	0.130174
6	Branch_Encoded	0.126582
731	python	0.115195

Table. 2. Feature importance evaluation using MI

Feature Importance Plot

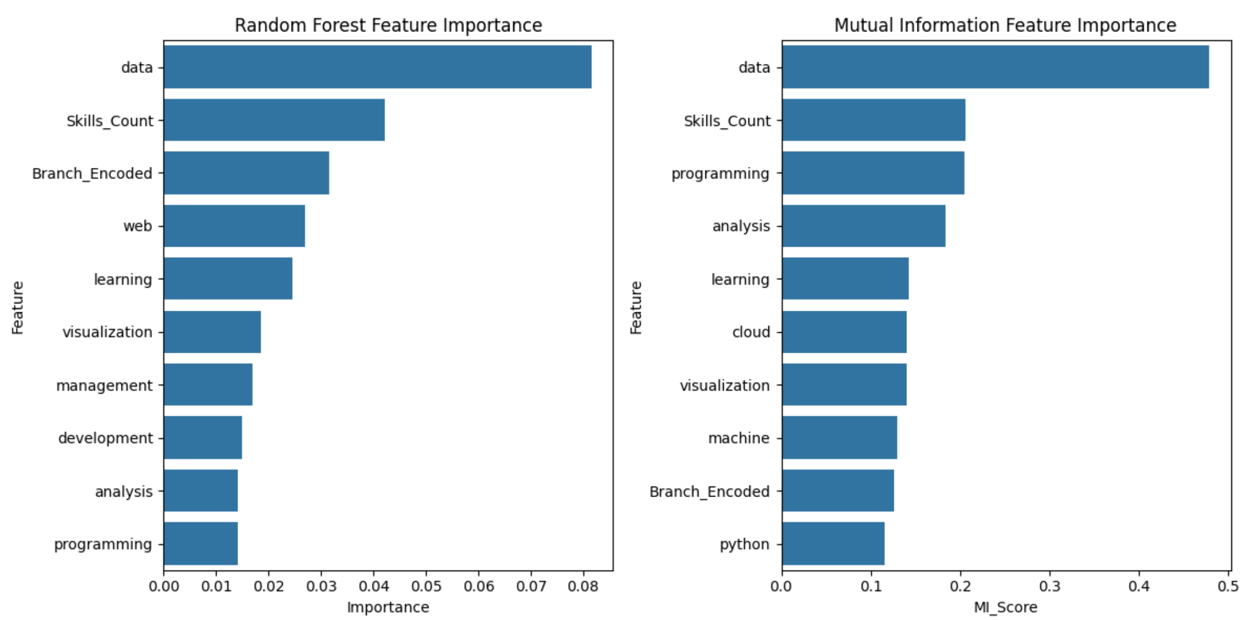


Fig. 8. Comparison between RF and MI

Combining feature importance methodologies

We used MinMaxScaler() to scale the values and then we combined both the methodologies by using the average of both the values for every specific feature.

```python
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()

top_rf['Importance_Norm'] = scaler.fit_transform(top_rf[['Importance']])
feature_importance_mi['MI_Score_Norm'] = scaler.fit_transform(feature_importance_mi[['MI_Score']])

combined_features = pd.merge(top_rf, feature_importance_mi, on='Feature', how='inner')

combined_features['Combined_Score'] = (combined_features['Importance_Norm'] + combined_features['MI_Score_Norm']) / 2

combined_features = combined_features.sort_values(by='Combined_Score', ascending=False)
```

Fig. 9. Merging RF and MI

Combined Feature Importance Plot

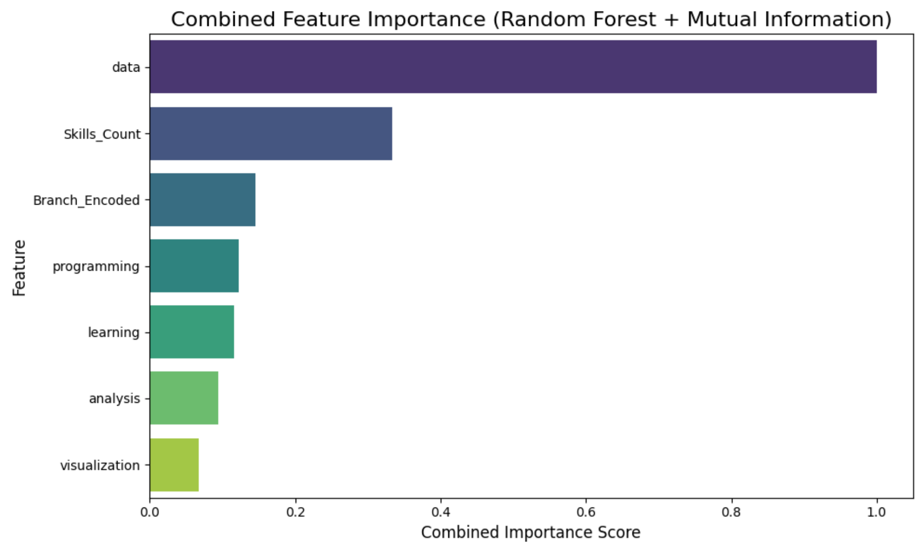


Fig. 10. Merged feature importance

Key Observations

- **Technical Keywords Are Influential:** Features like data, machine, programming, sql, analysis, data, and science appear in both rankings, indicating that courses with these keywords are more relevant for recommendations.
- **Skills Matter:** Skills_Count ranks second in both methods, reinforcing the idea that the number of skills associated with a course or job significantly impacts matching.
- **Mutual Information Highlights Domain-Specific Features:** MI scores give higher weight to domain-specific terms like visualization and dataviz. This does not appear in RF rankings; this suggests that they might provide more nuanced insights into skill relevance.

- **Balanced Feature Selection:** The combined feature importance methodology (averaging RF and MI scores) ensures a comprehensive ranking, balancing statistical dependencies (MI) with model-driven relevance (RF). This approach refines recommendations by capturing both predictive power and feature relationships.

Feature Selection - Feature Selection/Dimensionality Reduction

PCA Analysis

```python
from sklearn.decomposition import PCA
from sklearn.feature_selection import SelectKBest, f_classif

pca = PCA(n_components=0.95)  # Retain 95% variance
X_pca = pca.fit_transform(X)

print("PCA Applied: Number of Components =", pca.n_components_)
```

```
✓ 1.9s
PCA Applied: Number of Components = 3
```

Fig. 11. PCA dimensionality reduction

- **Method**: Principal Component Analysis with variance retention of 95%
- **Result**: The dimensionality was reduced from 1,007 features to just **3 principal components**
- **Significance**: This represents a 99.7% reduction in dimensionality while preserving 95% of the original variance

Feature Selection on PCA Components

```python
selector = SelectKBest(score_func=f_classif, k=10)
X_selected = selector.fit_transform(X_pca, y)

selected_component_indices = selector.get_support(indices=True)
print("Selected PCA Components:", selected_component_indices)
```

```
✓ 0.0s
Selected PCA Components: [0 1 2]
```

Fig. 12. Feature selection using PCA

- **Method**: SelectKBest with ANOVA F-value scoring (f_classif)
- **Parameter**: k=10 (maximum of 10 components requested)
- **Result**: All 3 PCA components were selected as significant
- **Selected Components**: [0, 1, 2]

Data Preparation for Modeling

1. **Train-Test Split**:
    a. Test size: 15% of the dataset
    b. Random state: 42
    c. Stratification: Applied to maintain class distribution in both sets
2. **Class Balancing**:
    a. Method: SMOTE (Synthetic Minority Over-sampling Technique)
    b. Applied only to the training set to eliminate class imbalance problem.
    c. Random state: 42

Key Insights

- **Extreme Dimensionality Reduction**: The reduction from 1,007 features to 3 features indicates that most of the original features contained redundant or non-essential information.
- **All Components Selected**: The fact that SelectKBest retained all 3 PCA components suggests that each component contributes significantly to predicting the target variable.
- **Efficient Information Preservation**: The workflow successfully distilled the essential predictive information into just 3 features, which should lead to:
    a. Faster model training
    b. Reduced risk of overfitting

This dimensionality reduction approach has successfully reduced the complexity of the data while maintaining most of its informational content, creating an excellent foundation for efficient model building.

Data Modeling - Model Training, Selection, and Evaluation

Models Used

```
models = {
    'Logistic Regression': LogisticRegression(max_iter=2000, random_state=42),
    'Decision Tree': DecisionTreeClassifier(random_state=42),
    'Random Forest': RandomForestClassifier(n_estimators=100, random_state=42),
    'Support Vector Machine': SVC(probability=True, kernel='rbf', random_state=42)
    }
```

Fig. 13. Model declaration

1. **Logistic Regression** – A simple, fast model that works well when data is linearly separable. It provides probability scores, making it easy to interpret.

2. **Decision Tree** – Splits data into decision paths, making it easy to understand. However, it can overfit if not pruned properly.
3. **Random Forest** – An ensemble of multiple decision trees that improves accuracy and reduces overfitting. Works well with both small and large datasets.
4. **Support Vector Machine (SVM)** – Finds the best boundary to separate classes, even for complex data. The RBF kernel helps capture non-linear patterns effectively.

Performance Metrics Considered

```
# Perform cross-validation (5-fold, or reduce if needed for small datasets)
cv_scores = cross_val_score(model, X_train, y_train, cv=5)

# Compute classification metrics
metrics = {
    'accuracy': accuracy_score(y_test, y_pred),
    'precision': precision_score(y_test, y_pred, average='weighted', zero_division=0),
    'recall': recall_score(y_test, y_pred, average='weighted', zero_division=0),
    'f1_score': f1_score(y_test, y_pred, average='weighted', zero_division=0),
    'cv_accuracy': np.mean(cv_scores),
}
```

```
# Compute ROC-AUC for each class
roc_auc_scores = [roc_auc_score(y_test[:, i], y_pred_proba[:, i]) for i in range(y_test.shape[1])]
metrics['roc_auc'] = np.mean(roc_auc_scores)  # Average ROC-AUC over all classes

return metrics
```

Fig. 14. Performance metrics declaration

- **Accuracy**: Measures the overall proportion of correct predictions but can be misleading in imbalanced datasets.
- **Precision**: Focuses on the correctness of positive predictions, minimizing false positives.
- **Recall**: Measures the model's ability to identify actual positive cases, minimizing false negatives.
- **F1-Score**: Balances precision and recall, useful when there is an uneven class distribution.
- **Cross-Validation Accuracy**: Assesses model consistency across different data subsets to prevent overfitting.
- **ROC-AUC**: Evaluates the model's ability to distinguish between classes, with higher AUC indicating better class separation.

Here, we considered **F1 score** as the main evaluation criteria as it maintains the balance between both precision and recall for a model as it is the harmonic mean of precision and recall

Performance

Model	Accuracy	Precision	Recall	F1 Score	CV Accuracy	ROC AUC
Decision Tree	0.942478	0.943671	0.942478	0.94305	0.901247	0.849831
Random Forest	0.929204	0.931160	0.929204	0.93003	0.916388	0.90496
Support Vector Machine	0.564159	0.859689	0.564159	0.66533	0.652927	0.816173
Logistic Regression	0.407080	0.824193	0.407080	0.526678	0.534322	0.807080

Table. 3. Performance metrics

Data Modeling - Model Evaluation and Comparison

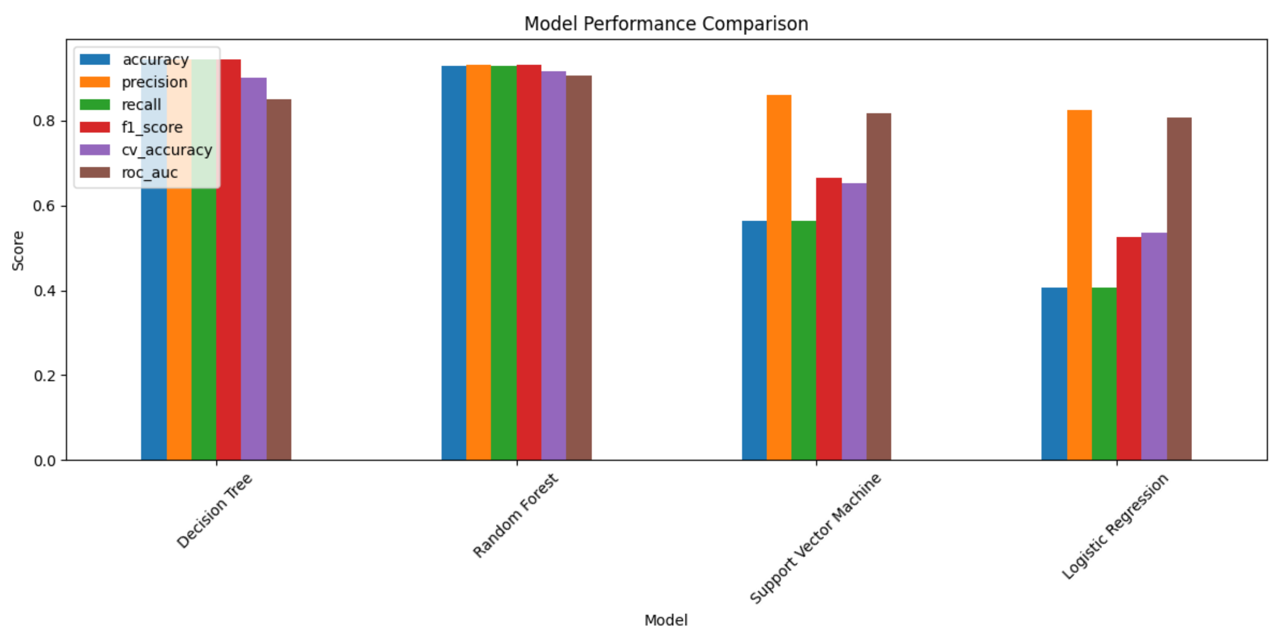


Fig. 15. Model comparison plot

Looking at the bar plot, it is evident that Tree-based models Decision Tree and Random Forest performed well since all the six classification evaluation metrics are high.

Confusion Matrix Analysis (Best Model: Decision Tree)

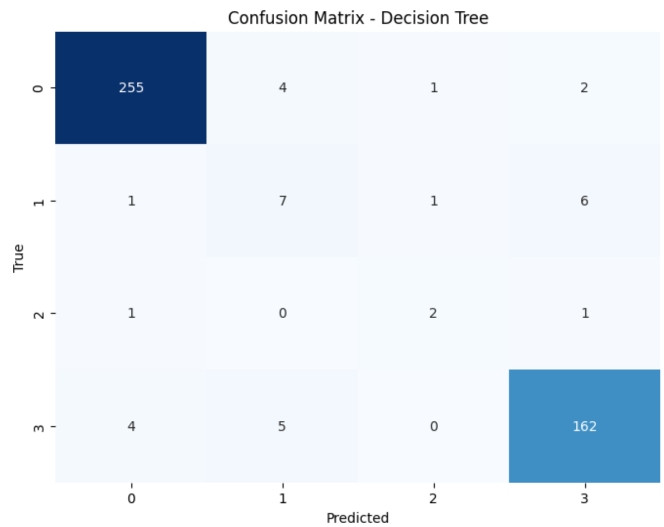


Fig. 16. Confusion matrix for Decision Tree

ROC Curve Analysis

Class 0 - AUC: 0.97, Class 1 - AUC: 0.72, Class 2 - AUC: 0.75, Class 3 - AUC: 0.96

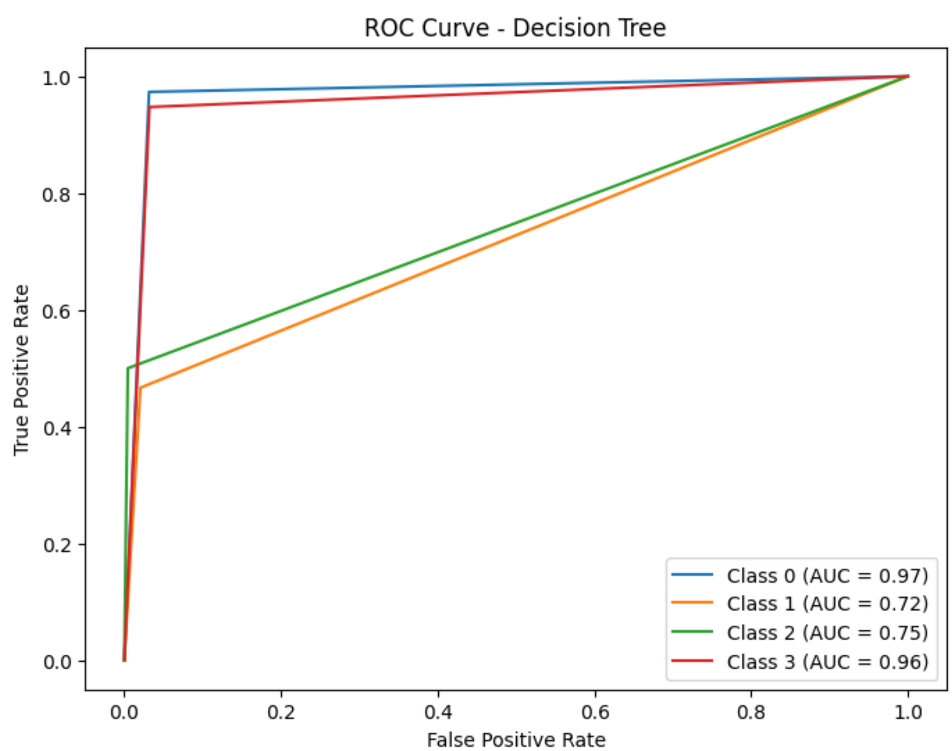


Fig. 17. ROC curve for Decision Tree

Decision Tree Model Selection

The Decision Tree model is chosen by considering all these factors:

- **F1-Score**: 94.3% – Balanced performance between precision and recall.
- **Accuracy**: 94.2% – Highest among the models.
- **Precision & Recall**: 94.4% & 94.2% – Very good at identifying the correct class without many false positives or misses.
- **Cross-Validation Accuracy**: 90.1% – Shows consistency across different data subsets, though slightly lower than training accuracy, hinting at some overfitting.
- **ROC AUC**: 85.0% – Strong ability to differentiate between classes, though Random Forest performs slightly better here.

Job Matching Results

The model implementation includes a job recommendation component using cosine similarity between course categories and job titles.

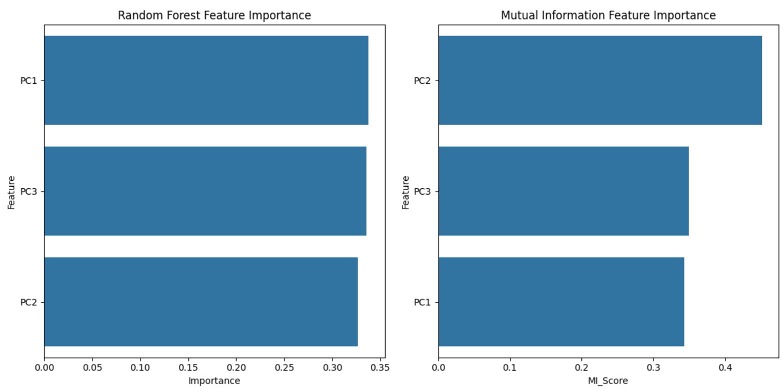
1. Job Recommendation based on the Course Title:
    - Data Science → Data Science Engineer, Data Science Manager, Data Analyst, Data Engineer
    - Business → Business Analyst, Business Consultant, Business Intelligence Analyst, Business System Analyst
    - Computer Science → Data Science Engineer, Data Science Manager, Software Engineer, Data Engineer
    - Information Technology → Software Engineer, Data Engineer, Business Analyst, Developer
2. Patterns:
    - "Software Engineer" and "Data Engineer" appear frequently as matches across diverse categories
    - Technical job titles dominate the recommendations across most categories

Post Model training evaluation

Random Forest Feature and Mutual Information (MI) Scores:

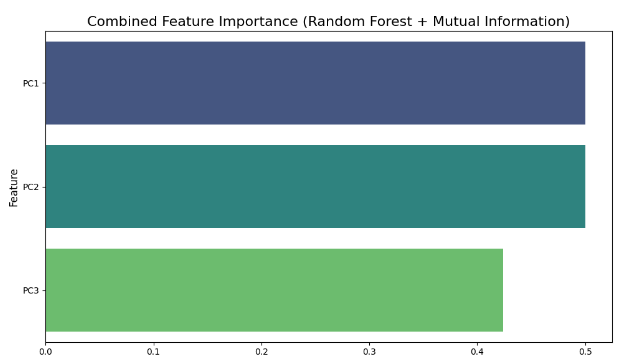
Insight 1: The importance chart clearly showed that just the top 3–5 components carried most of the predictive power, allowing us to confidently drop the rest.

Insight 2: Many of the top components from the MI scores matched those highlighted by Random Forest, strengthening our confidence in the selection.



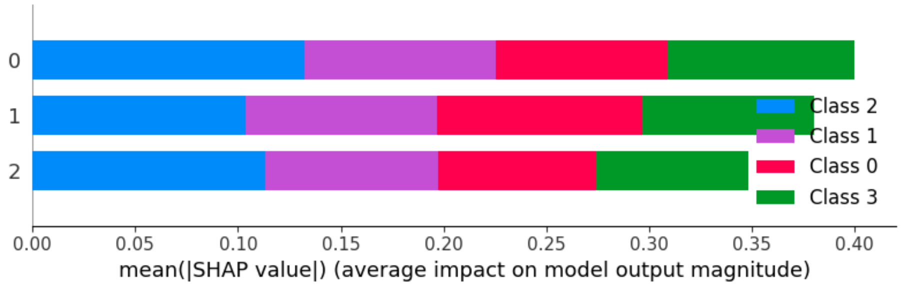
Combining Results for Better Selection

Rather than relying on a single technique, we normalized and averaged the importance scores from both Random Forest and MI scoring to get a combined feature importance score. Insight: The combined chart gave us a clearer picture of which components consistently mattered, helping us finalize a compact and meaningful feature set.



Making the Model Explainable with SHAP

To improve transparency and interpretability, we used SHAP on the PCA-reduced features. Insight: The SHAP summary plot confirmed that PC1 and PC2 had the most influence on the model's predictions, while PC3 contributed moderately. Despite the data compression, SHAP helped us retain interpretability, which is crucial for real-world use cases.



Streamlit Description and Integration [Demo Video]

Model and Data Loading:
At the start of the application, we load all trained models and preprocessed data using Joblib. This ensures that users can interact with the app without retraining models each time.

Interactive User Input:
The "Predictions" section allows users to enter their academic details and skills or load a sample student profile. This input is then preprocessed (e.g., skills are TF-IDF vectorized, and categorical features are label-encoded) to match the model's expected format.

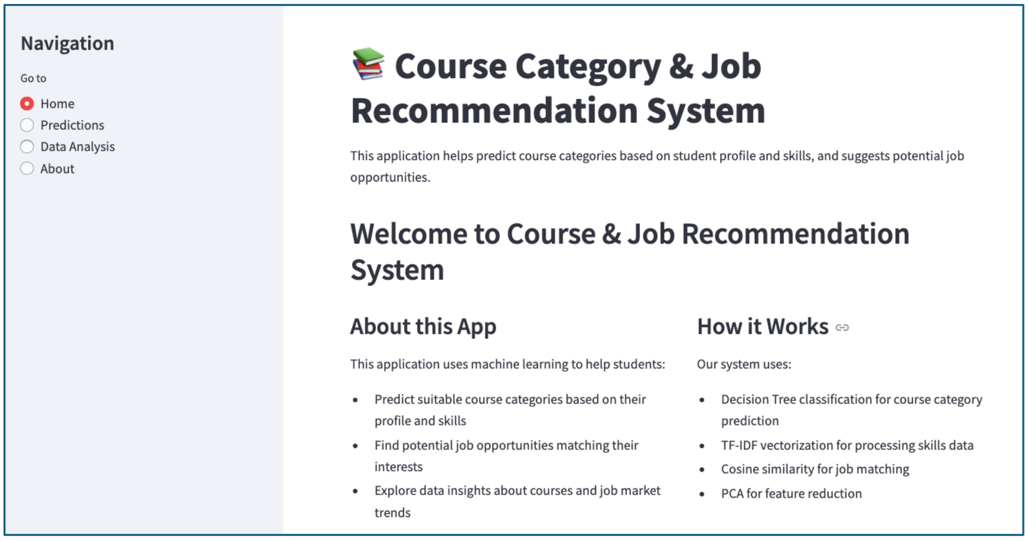
Backend Communication:
Once the input is processed, the system applies PCA, runs the trained model to predict the course category, and then uses cosine similarity to recommend relevant jobs. This happens in real-time based on what the user provides.

Visual Feedback:
The predicted course category and top job matches are displayed immediately. We also include confidence scores and use bar charts to show how well each job aligns with the predicted category.

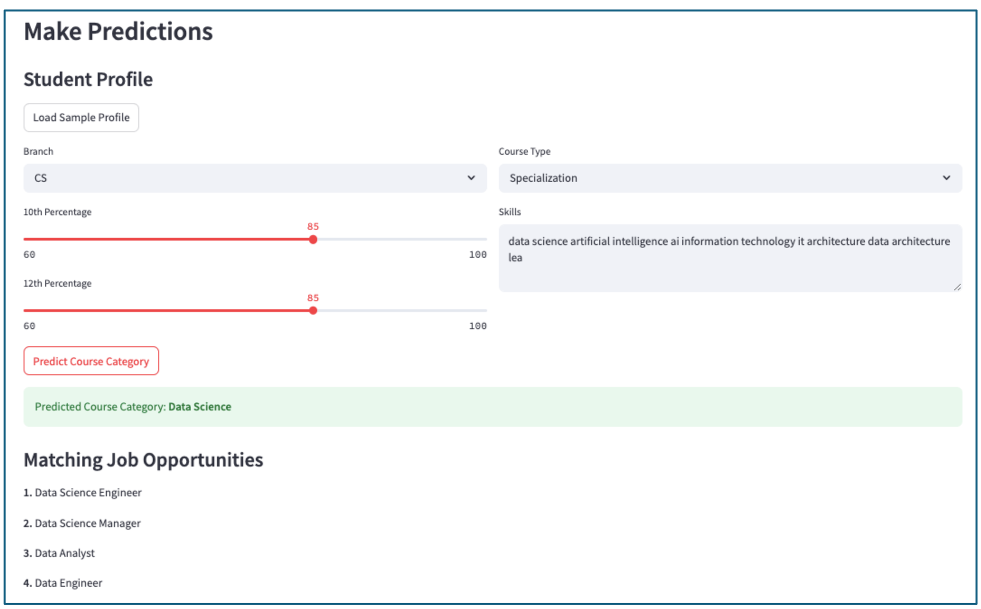
Data Analysis Tab:
This tab offers visual insights into the datasets used such as popular course categories, top job titles, and student performance distributions using plots powered by Matplotlib and Seaborn.

About Section:
For clarity and context, the "About" page walks users through the project, its purpose, and the technologies used.

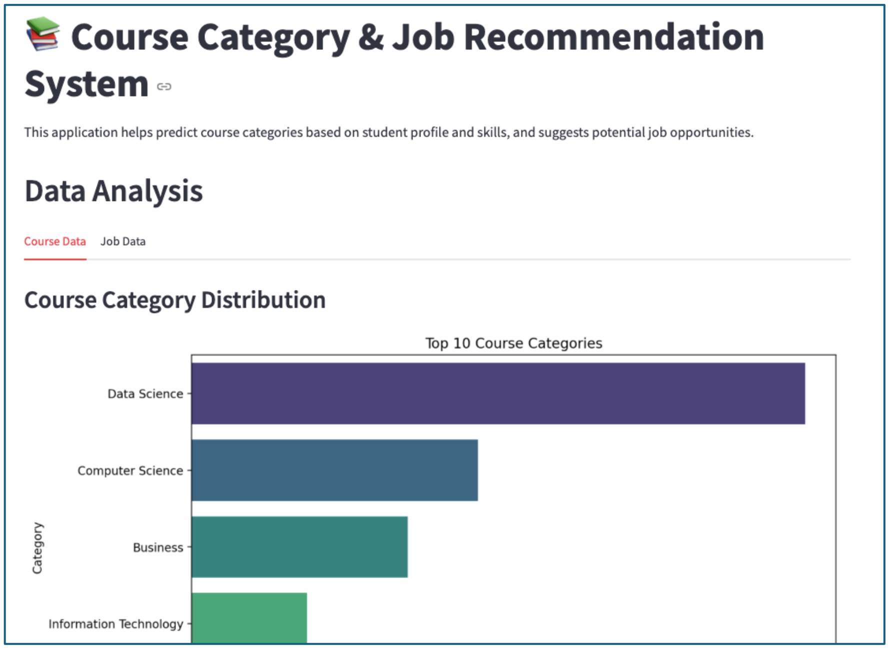
Home Interface



Prediction Interface



Data Analysis Interface



About the Tool Interface

Bias and Limitations

1. **Dataset Bias:** The datasets used were sourced from Kaggle and may not represent the full diversity of global student profiles, job markets, or course offerings. This could limit the generalizability of the recommendations.
2. **Model Overfitting Risk:** Decision Trees are inherently prone to overfitting, especially when trained on limited samples. This may impact performance on completely unseen student profiles.
3. **Dynamic Job Market:** Job postings and skill demands evolve rapidly. Since we have considered a limited set of job postings, job recommendations may not be generalized as most of the job posting would be outdated as time progresses.
4. **Dimensionality Compression Bias:** Applying PCA reduced the feature space from over 1000 dimensions to just 3 components. While this improves computational efficiency, it can discard valuable patterns in the original data. Important but the features that have low-variance features may have been lost in the compression process.
5. **Interpretability Challenges from PCA:** While we used SHAP to explain the model's decisions, applying it after PCA makes it harder to understand which exact student input features led to a particular recommendation. Since PCA compresses the data into abstract components, it becomes less clear for students to see how their input directly influenced the output.
6. **Limited Real-World Validation:** While evaluation metrics like F1-Score and ROC-AUC were high, it would be better to consider testing the model with unseen and dynamic real-world data.

Conclusion

This project successfully demonstrates how data-driven methods can simplify and enhance the career planning process for students. By leveraging machine learning, natural language processing, and interactive visual tools, we were able to build a comprehensive recommendation system that suggests both relevant courses and job opportunities based on a student's academic background and skills.

Through careful data preprocessing, feature engineering, and model selection, we ensured that the predictions were explainable and fair. The use of TF-IDF and PCA allowed us to manage high-dimensional resume data effectively, while SHAP visualizations provided transparency into how model decisions were made.

Our final deployment through a Streamlit dashboard transformed this into a real-time, user-friendly application, one that students can interact with directly to explore personalized learning paths and job roles. The seamless integration of backend with frontend simplicity ensures that the system is accessible and dynamic.

Overall, this project reflects the collaborative effort of our team in combining machine learning, data visualization, and software design to solve a meaningful problem. It serves as a helpful tool for students navigating their academic and professional journeys, and an example of how data science projects can have real-world impact.

References

[1] Khaled Atef. Online Courses Dataset, Kaggle. Link

[2] Filiberto Zurita. Job Postings Dataset, Kaggle. Link

[3] Kushagra Agarwal. Student Skillset Analysis, Kaggle. Link