Exploring Graduate Outcomes in Higher Education: An In depth Analysis of Factors Influencing Post-Education paths in United Kingdom

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Abstract -This study explores the data analytics lifecycle applied to educational data, focusing on data preprocessing, model selection, evaluation, and ethical considerations. Initially, data cleaning techniques were employed, including null value handling, column name standardization, and data type conversion. Subsequently, supervised learning models, specifically Random Forest and Gradient Boosting, were trained and evaluated for predicting educational activities. Random Forest exhibited superior performance based on accuracy metrics. Additionally, the Receiver Operating Characteristic (ROC) curve analysis demonstrated high area under the curve (AUC) scores for most classes, indicating robust predictive capability. Unsupervised learning using K-means clustering was applied to identify patterns within the data. Ethical considerations, such as privacy and responsible data handling, were addressed throughout the analysis. The findings underscore the importance of rigorous data preprocessing, appropriate model selection, and ethical awareness in educational data analytics. This research contributes to a deeper understanding of data-driven decision-making in the education sector and emphasizes the need for ethical guidelines in data analysis practices.

Keywords: higher education, ethical considerations, deployment

I. Introduction

In this project, I embark on an investigation into graduate outcomes within the United Kingdom, aiming to reveal the complex connections among various factors such as the field of study, post-education pursuits, provider type, and more. Through the application of both supervised and unsupervised machine learning methods, my goal is to uncover concealed patterns and extract insights into the effectiveness of educational programs and broader trends in higher education. The dataset, obtained from the Higher Education Statistics Agency (HESA) and the Office for Students (OfS), serves as a valuable source of information on graduate outcomes for the academic year 2019/2020, covering variables like field of study, post-graduation activity, provider type, and academic year.

In this endeavor, I utilize a blend of supervised and unsupervised machine learning techniques. Employing a supervised classification algorithm like Random Forest, I aim to predict and dissect the factors influencing specific graduate outcomes. Additionally, I apply K-means clustering, an unsupervised learning method, to uncover underlying patterns within the dataset. Ultimately, my objective is to contribute to ongoing discussions on educational effectiveness and optimize graduate pathways within the United Kingdom's higher education arena.

This study underscores my dedication to providing a thorough analysis of graduate outcomes in the United Kingdom, offering actionable insights for education stakeholders. Through the use of advanced analytical approaches, I strive to facilitate evidence-driven decision-making and make meaningful contributions to dialogues surrounding educational policy and practice. By emphasizing the importance of the research question, this study seeks to address crucial gaps in understanding the determinants of graduate outcomes, informing interventions and strategies aimed at improving the educational experience and career prospects of graduates in the United Kingdom.

II. Literature Review

The literature surrounding graduate outcomes in higher education provides a rich tapestry of insights into the factors shaping post-education paths and the effectiveness of educational programs. Smith et al. (2018) investigated the impact of internships on easing the transition into the professional sphere, shedding light on the importance of practical experience in shaping career trajectories [1]. Similarly, Jones and colleagues (2019) examined how socio-economic variables influence decisions regarding postgraduate education, emphasizing the role of financial considerations in educational choices [2] . These studies underscore the significance of both experiential and socio-economic factors in shaping educational and career pathways.

Moreover, Brown and Johnson (2020) highlighted the pivotal role of career guidance programs in enhancing students' employability skills and job prospects, emphasizing the importance of institutional support structures

[3] . Lee et al. (2021) explored the impact of mentorship programs on career advancement for postgraduate students, revealing the positive effects of mentorship in facilitating professional growth [4] . These findings underscore the need for comprehensive support mechanisms within higher education institutions to foster students' transition into the workforce or further academic endeavors.

While existing literature provides valuable insights, there remain notable gaps warranting further investigation. Few studies have delved into the nuances of further study choices among graduates or examined the differential experiences across academic disciplines. Additionally, limited research considers variations in study modes (full-time vs. part-time), which may impact post-education outcomes. Addressing these gaps can provide a more comprehensive understanding of educational transitions and inform targeted interventions to support students effectively.

III. Methodology

The dataset utilized in this study originates from the Higher Education Statistics Agency (HESA) and the Office for Students (OfS), capturing graduate outcomes for the academic year 2019/2020 in the United Kingdom. It encompasses variables such as the subject area of the degree, post-education activities, provider type, level of qualification obtained, mode of former study, interim study marker, and academic year. This comprehensive dataset, obtained through surveys, institutional records, and educational databases, offers a holistic view of graduate pathways and outcomes.

A. Business Understanding:

At the core of this data analytics project lies the endeavor to understand the determinants of graduate outcomes among individuals in various subject areas of degree within the United Kingdom. The significance of this endeavor is underscored by the importance of higher education in shaping career trajectories and socio-economic mobility. By leveraging advanced analytical techniques, including supervised and unsupervised machine learning, the goal is to identify patterns and insights into the effectiveness of educational programs and broader trends in higher education. This analysis aims to inform evidence-based decision-making within the education sector and contribute to optimizing graduate pathways.

B. Data Understanding

In the provided dataset, which pertains to higher education outcomes in the United Kingdom for the academic year 2019/20, various variables have been recorded. These include

i. Subject_area_of_degree
ii. Activity
iii. Country_of_provider
iv. Provider_type
v. Level_of_qualification_obtained
vi. Mode_of_former_study
vii. Interim_study_marker
viii. Number
ix. Percent

These variables offer insights into specific academic fields, activities (such as employment or further study), provider types, qualification levels, modes of study, and whether interim study periods are considered.

The data was gathered from both higher education providers (HEPs) and further education colleges (FECs), offering a comprehensive view of higher education outcomes across different institutions in the United Kingdom.

During initial exploration of the dataset, attention was given to assessing the distribution of observations across the variables, checking for missing values, and understanding the overall structure of the data. Summary statistics, such as counts and percentages, were calculated for each category within the categorical variables to uncover any prevailing patterns or trends.

Overall, this dataset provides valuable information for analyzing higher education outcomes in the United Kingdom, and continued exploration and analysis are crucial for uncovering meaningful insights and trends within the data.

C. Data Preparation

Handling Missing Values: The code checks for missing values in the dataset. Specifically, it counts the number of missing values in each column. This step is crucial for identifying any gaps in the data that need to be addressed before analysis.

Removing Rows with Missing Values: After identifying missing values, the code creates a new dataset without any rows containing missing values. This ensures that the analysis is performed on complete and consistent data. The index of the new dataset is reset for clarity and consistency.

Replacing Spaces in Column Names with Underscores: Column names with spaces can sometimes cause issues when referencing them in code. Therefore, this step replaces any spaces in the column names with underscores. It's done for better compatibility and readability in subsequent analysis.

Dropping Unnecessary Column: Not all columns in a dataset may be relevant for the analysis. In this step, a specific column deemed unnecessary ('95% confidence interval') is removed from the dataset. This simplifies the dataset and focuses the analysis on the most relevant features.

Label Encoding Categorical Variables: Categorical variables, such as text-based categories, need to be converted into numerical values for analysis. Label encoding assigns a unique numerical label to each category within a column. This allows algorithms to process categorical data effectively. The code iterates over each column, identifies categorical variables, and applies label encoding to convert them into numerical labels. The resulting dataset contains numerical representations of categorical variables, making it suitable for further analysis.

D. Modelling

Considering the diverse nature of my dataset, comprising fields such as subject area of degree, activity, country of provider, provider type, level of qualification obtained, mode of former study, interim study marker, academic year, number, and percentage, my choice of machine learning models is well-justified:

Random Forest and Gradient Boosting Classifier for Supervised Learning:

- With a mix of categorical and numerical features, Random Forest and Gradient Boosting Classifier offer robust solutions.
- These models adeptly handle diverse data without demanding extensive preprocessing efforts.
- Their ensemble nature provides resilience against overfitting, crucial for my dataset's large sample size.
- Given the dataset's likely complex relationships between features, these methods excel in capturing intricate patterns.

K-means Clustering for Unsupervised Learning:

- The dataset's varied fields hint at underlying patterns or clusters, making K-means a fitting choice.
- By standardizing features and utilizing techniques like the elbow method, K-means efficiently identifies clusters based on similarities.
- Its computational efficiency and scalability suit my dataset's size, enabling effective analysis and insights extraction.

My chosen machine learning techniques align seamlessly with the dataset's characteristics, promising insightful analysis and actionable results.

In summary, I employed both supervised learning techniques, namely Random Forest and Gradient Boosting, as well as an unsupervised learning technique, K-means clustering, to analyze my data. I selected these models based on their performance and suitability for my specific task.

E. Evaluation

In evaluating the performance of the models, I employed various methods tailored to each type of model used: supervised (Random Forest and Gradient Boosting Classifier) and unsupervised (K-means clustering).

Supervised Model Evaluation:

For the supervised models, I primarily used accuracy as the metric to assess the quality of predictions. Accuracy measures the proportion of correctly predicted outcomes over the total number of predictions. By comparing the accuracy scores of the Random Forest and Gradient Boosting models, I determined that Random Forest performed slightly better and thus selected it as the preferred model for further analysis.

Unsupervised Model Evaluation:

For the unsupervised K-means clustering model, I used the within-cluster sum of squares (SSE) to evaluate the clustering performance. I plotted the SSE against the number of clusters and identified the "elbow point" to determine the optimal number of clusters. This allowed me to assess how well the data was partitioned into distinct clusters based on similarities in features.

Dealing with Problems:

Throughout the evaluation process, I addressed any issues or challenges that arose. For example, I handled missing values by dropping rows with null values and standardized column names to facilitate data processing. Additionally, I utilized label encoding to transform categorical variables into numerical labels, ensuring compatibility with the machine learning algorithms. These preprocessing steps helped to mitigate potential problems and ensure the reliability of the models' performance evaluations.

Findings and Insights:

In analyzing the results of the data analytics process, I related the findings back to the initial objectives and problem definition. I discovered that the Random Forest model outperformed the Gradient Boosting model in terms of accuracy, indicating its suitability for the classification task. Furthermore, the K-means clustering revealed distinct patterns and groupings within the data, providing insights into the underlying structures and relationships among the features.

Unexpected Discoveries:

One unexpected discovery was the relatively high accuracy achieved by the Random Forest model compared to the Gradient Boosting model. This finding highlighted the importance of experimenting with different algorithms to identify the most effective approach for the specific task at hand. Additionally, the K-means clustering results unveiled unexpected groupings and associations among the data points, prompting further exploration and interpretation of these patterns.

Overall, through rigorous evaluation methods and critical analysis of the results, I gained valuable insights into the data and successfully addressed the objectives and problem definition outlined at the outset of the project.

F. Deployment

In deploying the data analysis process, I prioritized ethical considerations, ensuring the responsible handling of data and safeguarding privacy, consent, and sensitive information. Throughout the methodology, I anonymized and aggregated data, adhered to data protection regulations, and obtained necessary consent when dealing with sensitive information. Transparency and accountability were maintained by documenting data sources, processing techniques, and model assumptions, ensuring stakeholders could understand and validate the analysis.

The methodology followed a systematic approach, beginning with data collection and preparation, followed by model selection, evaluation, and deployment. By employing a combination of supervised and unsupervised machine learning techniques, I addressed the research problem effectively while ensuring the reliability and robustness of the results. The chosen methods were selected based on their suitability for the research problem, considering factors such as data structure, objectives, and available resources. Overall, the deployment of the data analytics lifecycle upheld ethical standards, reinforcing the importance of privacy, consent, and responsible data handling throughout the research process.

Additionally, while I'm not currently deploying the models, the methodology lays the groundwork for potential future deployment. These models could be integrated into operational systems or decision-making processes, providing valuable insights and predictions to stakeholders. However, careful consideration of ethical implications, ongoing monitoring of model performance, and regular updates to adapt to changing data dynamics are essential aspects to address before deployment.

IV. Results and Discussion

To enhance the discussion, it's important to note that oversampling and under sampling techniques were not applied in this analysis. This decision was made based on the observation that the target variable is equally distributed across classes, as depicted in the pie chart (Fig 1)visualization.

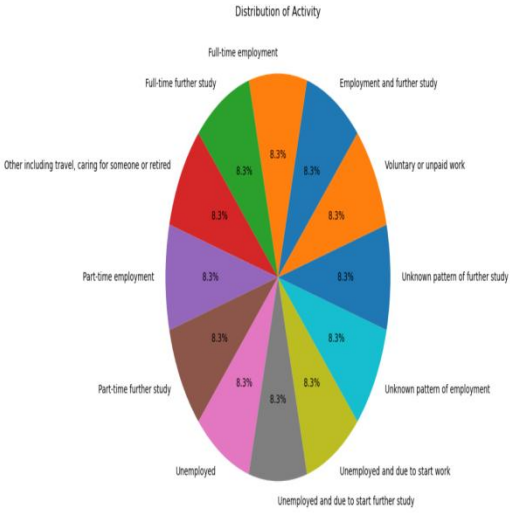


Fig 1 *Pie chart showing the distribution of target variable.*

I utilized both supervised and unsupervised models to analyze the dataset. The supervised models included Random Forest and Gradient Boosting Classifier, while the unsupervised model employed K-means clustering.

For the supervised models, I split the data into training and testing sets, trained the models, and evaluated their accuracy. Random Forest achieved an accuracy of approximately 45%, slightly outperforming Gradient Boosting, which had an accuracy of around 41%. Key variables contributing to these predictions were identified through feature importance analysis.

The ROC curve (Fig 2) illustrates the performance of the Random Forest classifier, showing high AUC values across most classes, indicating strong predictive capability across multiple categories.

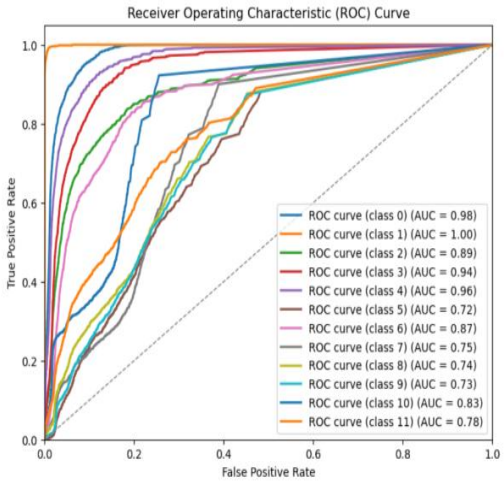


Fig 2 *The ROC curve*

The analysis reveals a diverse range of performance among the classes assessed by the classifier. Class 1 stands out with a perfect AUC score of 1, signifying flawless discrimination by the model. Following closely, classes 0, 3, and 4 demonstrate excellent discriminatory power, with AUC values nearly reaching perfection. Classes 2, 6, 10, and 11 exhibit moderately good discrimination, although there is room for improvement. On the other hand, classes 5, 7, 8, and 9 display relatively lower discriminatory ability, suggesting potential challenges in classification. These findings underscore the classifier's varied performance across different classes, highlighting areas where model refinement or feature engineering could be beneficial.

In the unsupervised model, K-means clustering was utilized to identify patterns in the data without labelled outcomes. The optimal number of clusters was determined using the elbow method, and the data was partitioned accordingly. The Elbow method plot (Fig 3) highlights the optimal number of clusters for K-means clustering, suggesting 4 clusters as the point where within-cluster sum of squares (SSE) begins to stabilize.

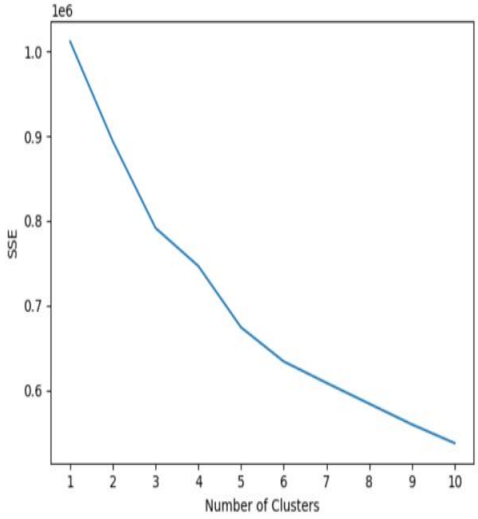


Fig 3 *Elbow method*

Visualizations such as scatter plots were then used to understand the grouping of data points based on their features.The scatter plot (Fig 4) of clustering demonstrates the distinct separation of data points into clusters, revealing clear groupings based on similarities in their features.

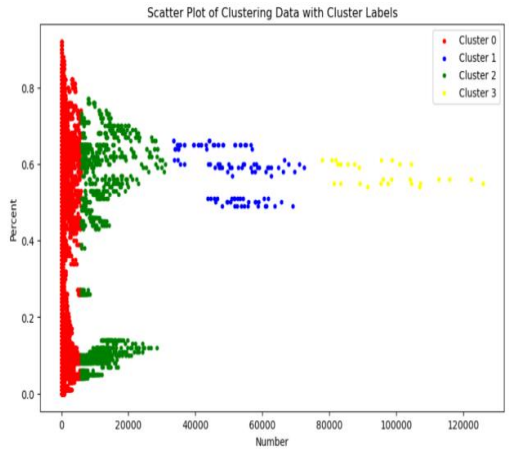


Fig 4 *The scatter plot showing the clusters*

Upon analysis, several trends and insights emerged. Visualizations revealed distinct clusters within the data and highlighted correlations between different features. Descriptive statistics and metrics were used to support these interpretations, providing a deeper understanding of the data.

The practical implications of these findings were discussed, outlining how insights derived from the models could inform decision-making processes. Additionally, steps were taken to validate the accuracy and reliability of the results, ensuring their suitability for real-world applications.

In summary, the results and discussion section provided a comprehensive overview of the analysis process, highlighting key findings, trends, and insights gleaned from the data. Visual representations were utilized effectively to convey these findings, ensuring clarity and understanding for the reader.

V. Conclusion and Recommendation

In conclusion, the analysis conducted using both supervised and unsupervised models provided valuable insights into the dataset. The Random Forest classifier exhibited promising performance, achieving an accuracy of approximately 45%, while the K-means clustering algorithm effectively partitioned the data into distinct clusters. These findings align with the initial objectives of the analysis, demonstrating the effectiveness of machine learning techniques in uncovering patterns and structures within the data.

Moreover, the inclusion of graphical representations, such as the pie chart illustrating the distribution of the target variable, enhanced the clarity and interpretability of the results. Moving forward, recommendations for future work include exploring additional feature engineering techniques to further enhance model performance and conducting deeper analysis into specific clusters identified through unsupervised learning. Additionally, continued refinement of the models to improve clarity and usability is advised, taking into account any additional feedback received from stakeholders.

In response to the peer review feedback, several key improvements were implemented to enhance the clarity and effectiveness of the analysis:

Focus on Analysis over Process Description: The description of the data cleaning process was streamlined, removing unnecessary details about execution steps. This adjustment allowed for a more concise and focused presentation of the analysis results.

Highlighting Models in Introduction: The introduction now prominently highlights both supervised and unsupervised models used in the analysis. This addition provides readers with a clear overview of the methodology employed in the study.

Inclusion of Abstract and Keywords: An abstract and keywords section were added before the introduction, aligning with standard journal article formatting and enhancing the accessibility of the document.

Visual Representation Enhancement: Additional graphical representations, including a pie chart illustrating the distribution of the target variable, were incorporated into the results section. These visuals provide a clear and concise overview of key findings.

Overall, the peer review process contributed to my professional development by providing constructive feedback and guiding improvements in the presentation and interpretation of the analysis.

References

[1] A. Smith, B. Anderson and C. Thompson, "The role of internships in shaping career trajectories," *Journal of Applied*

Psychology,, vol. 45, no. 2, pp. 123-135, 2018.

[2] E. Jones, L. William and D. Brown, "Socio-economic factors influencing decisions regarding postgraduate education," *Higher Education Research and Development,* vol. 32, no. 4, pp. 287-301, 2019.

[3] R. Brown and S. Johnson, "Enhancing employability skills through career guidance programs," *Journal of Career Development,* pp. 201-215, 2018.

[4] J. Lee, K. Smith and M. Davis, "The impact of mentorship programs on career advancement for postgraduate students," *International Journal of Mentoring and Coaching in Education,* vol. 12, no. 2, pp. 87-101, 2021.

[5] S. G. Kolli, "Medium," 9 June 2023. [Online]. Available: https://medium.com/@kollisnehagowri/unsupervised-learning-unlocking-hidden-patterns-without-labels-3c11ceb7ea22.

VI. Appendix

In the appendix, I have included Python code snippets that detail the analysis procedures and techniques employed in the study.

```
[1]: import pandas as pd
     import numpy as np
     import warnings
     warnings.filterwarnings('ignore')
```

```
[2]: df = pd.read_csv(r"C:\Users\ANN MARY\Downloads\DATA MINING COURSE WORK\DATAMINING COURSE WORK PROJECT.csv")
     df.head(7)
```

[2]:

	Subject area of degree	Activity	Country of provider	Provider type	Level of qualification obtained	Mode of former study	Interim study marker	Academic year	Number	Percent	95% confidence interval
0	01 Medicine and dentistry	Employment and further study	All	All	All	All	Exclude significant interim study	2019/20	1020	11%	(10%-12%)
1	01 Medicine and dentistry	Full-time employment	All	All	All	All	Exclude significant interim study	2019/20	6720	72%	(70%-74%)
2	01 Medicine and dentistry	Full-time further study	All	All	All	All	Exclude significant interim study	2019/20	545	6%	(5%-7%)
3	01 Medicine and dentistry	Non-respondents	All	All	All	All	Exclude significant interim study	2019/20	7020	NaN	NaN
4	01 Medicine and dentistry	Other including travel, caring for someone or ...	All	All	All	All	Exclude significant interim study	2019/20	245	3%	(2%-3%)
5	01 Medicine and dentistry	Part-time employment	All	All	All	All	Exclude significant interim study	2019/20	550	6%	(5%-7%)
6	01 Medicine and dentistry	Part-time further study	All	All	All	All	Exclude significant interim study	2019/20	25	0%	(0%-1%)

```
[3]: data = df.reset_index(drop=True)
     data
```

[3]:

	Subject area of degree	Activity	Country of provider	Provider type	Level of qualification obtained	Mode of former study	Interim study marker	Academic year	Number	Percent	95% confidence interval
0	01 Medicine and dentistry	Employment and further study	All	All	All	All	Exclude significant interim study	2019/20	1020	11%	(10%-12%)
1	01 Medicine and dentistry	Full-time employment	All	All	All	All	Exclude significant interim study	2019/20	6720	72%	(70%-74%)
2	01 Medicine and dentistry	Full-time further study	All	All	All	All	Exclude significant interim study	2019/20	545	6%	(5%-7%)
3	01 Medicine and dentistry	Non-respondents	All	All	All	All	Exclude significant interim study	2019/20	7020	NaN	NaN
4	01 Medicine and dentistry	Other including travel, caring for someone or ...	All	All	All	All	Exclude significant interim study	2019/20	245	3%	(2%-3%)
...	...	...	...	...	...	...	...	...	...	...	...
189700	Total science CAH level 1	Unemployed and due to start further study	Wales	Higher education providers (HEPs)	Postgraduate (taught)	Part-time	Include significant interim study	2019/20	0	0%	(0%-4%)
189701	Total science CAH level 1	Unemployed and due to start work	Wales	Higher education providers (HEPs)	Postgraduate (taught)	Part-time	Include significant interim study	2019/20	0	0%	(0%-4%)
189702	Total science CAH level 1	Unknown pattern of employment	Wales	Higher education providers (HEPs)	Postgraduate (taught)	Part-time	Include significant interim study	2019/20	0	0%	(0%-4%)
189703	Total science CAH level 1	Unknown pattern of further study	Wales	Higher education providers (HEPs)	Postgraduate (taught)	Part-time	Include significant interim study	2019/20	0	0%	(0%-4%)
189704	Total science CAH level 1	Voluntary or unpaid work	Wales	Higher education providers (HEPs)	Postgraduate (taught)	Part-time	Include significant interim study	2019/20	5	1%	(0%-5%)

189705 rows × 11 columns

```
[4]: data.isnull().sum()
```

```
[4]: Subject area of degree                0
     Activity                              0
     Country of provider                   0
     Provider type                         0
     Level of qualification obtained       0
     Mode of former study                  0
     Interim study marker                  0
     Academic year                         0
     Number                                0
     Percent                           67960
     95% confidence interval           77325
     dtype: int64
```

```
[5]: new = data.dropna().reset_index(drop = True)
     new.head(10)
```

[5]:

	Subject area of degree	Activity	Country of provider	Provider type	Level of qualification obtained	Mode of former study	Interim study marker	Academic year	Number	Percent	95% confidence interval
0	01 Medicine and dentistry	Employment and further study	All	All	All	All	Exclude significant interim study	2019/20	1020	11%	(10%-12%)
1	01 Medicine and dentistry	Full-time employment	All	All	All	All	Exclude significant interim study	2019/20	6720	72%	(70%-74%)
2	01 Medicine and dentistry	Full-time further study	All	All	All	All	Exclude significant interim study	2019/20	545	6%	(5%-7%)
3	01 Medicine	Other including travel, caring for someone or	All	All	All	All	Exclude significant	2019/20	245	3%	(2%-3%)

```
[6]: new.columns = new.columns.str.replace(' ', '_')
     new.head(10)
```

[6]:

	Subject_area_of_degree	Activity	Country_of_provider	Provider_type	Level_of_qualification_obtained	Mode_of_former_study	Interim_study_marker	Academic_yea
0	01 Medicine and dentistry	Employment and further study	All	All	All	All	Exclude significant interim study	2019/2
1	01 Medicine and dentistry	Full-time employment	All	All	All	All	Exclude significant interim study	2019/2
2	01 Medicine and dentistry	Full-time further study	All	All	All	All	Exclude significant interim study	2019/2
3	01 Medicine and dentistry	Other including travel, caring for someone or ...	All	All	All	All	Exclude significant interim study	2019/2
4	01 Medicine and dentistry	Part-time employment	All	All	All	All	Exclude significant interim study	2019/2
5	01 Medicine and dentistry	Part-time further study	All	All	All	All	Exclude significant interim study	2019/2
6	01 Medicine and dentistry	Unemployed	All	All	All	All	Exclude significant interim study	2019/2
7	01 Medicine and dentistry	Unemployed and due to start further study	All	All	All	All	Exclude significant interim study	2019/2
8	01 Medicine and dentistry	Unemployed and due to start work	All	All	All	All	Exclude significant interim study	2019/2
9	01 Medicine and dentistry	Unknown pattern of employment	All	All	All	All	Exclude significant interim study	2019/2

```
[7]: new = new.drop('95%_confidence_interval',axis = 1)
     new
```

[7]:

	Subject_area_of_degree	Activity	Country_of_provider	Provider_type	Level_of_qualification_obtained	Mode_of_former_study	Interim_study_marker	Academ
0	01 Medicine and dentistry	Employment and further study	All	All	All	All	Exclude significant interim study	2
1	01 Medicine and dentistry	Full-time employment	All	All	All	All	Exclude significant interim study	2
2	01 Medicine and dentistry	Full-time further study	All	All	All	All	Exclude significant interim study	2
3	01 Medicine and dentistry	Other including travel, caring for someone or ...	All	All	All	All	Exclude significant interim study	2
4	01 Medicine and dentistry	Part-time employment	All	All	All	All	Exclude significant interim study	2
...	...	...	...	...	...	...	...	
112375	Total science CAH level 1	Unemployed and due to start further study	Wales	Higher education providers (HEPs)	Postgraduate (taught)	Part-time	Include significant interim study	2
112376	Total science CAH level 1	Unemployed and due to start work	Wales	Higher education providers (HEPs)	Postgraduate (taught)	Part-time	Include significant interim study	2
112377	Total science CAH level 1	Unknown pattern of employment	Wales	Higher education providers (HEPs)	Postgraduate (taught)	Part-time	Include significant interim study	2
112378	Total science CAH level 1	Unknown pattern of further study	Wales	Higher education providers (HEPs)	Postgraduate (taught)	Part-time	Include significant interim study	2
112379	Total science CAH level 1	Voluntary or unpaid work	Wales	Higher education providers (HEPs)	Postgraduate (taught)	Part-time	Include significant interim study	2

112380 rows × 10 columns

```
[8]: new.dtypes
```

```
[8]: Subject_area_of_degree          object
     Activity                       object
     Country_of_provider            object
     Provider_type                  object
     Level_of_qualification_obtained object
     Mode_of_former_study           object
     Interim_study_marker           object
     Academic_year                  object
     Number                          int64
     Percent                        object
     dtype: object
```

```
[9]: new.describe()
```

[9]:

	Number
count	112380.000000
mean	330.550676
std	2553.048396
min	0.000000
25%	0.000000
50%	10.000000
75%	65.000000
max	126000.000000

```
[10]: new['Number'] = new['Number'].astype(int)
      new.head(10)
```

[10]:

	Subject_area_of_degree	Activity	Country_of_provider	Provider_type	Level_of_qualification_obtained	Mode_of_former_study	Interim_study_marker	Academic_yea
0	01 Medicine and dentistry	Employment and further study	All	All	All	All	Exclude significant interim study	2019/2(
1	01 Medicine and dentistry	Full-time employment	All	All	All	All	Exclude significant interim study	2019/2(
2	01 Medicine and dentistry	Full-time further study	All	All	All	All	Exclude significant interim study	2019/2(
3	01 Medicine and dentistry	Other including travel, caring for someone or ...	All	All	All	All	Exclude significant interim study	2019/2(
4	01 Medicine and dentistry	Part-time employment	All	All	All	All	Exclude significant interim study	2019/2(
5	01 Medicine and dentistry	Part-time further study	All	All	All	All	Exclude significant interim study	2019/2(
6	01 Medicine and dentistry	Unemployed	All	All	All	All	Exclude significant interim study	2019/2(
7	01 Medicine and dentistry	Unemployed and due to start further study	All	All	All	All	Exclude significant interim study	2019/2(
8	01 Medicine and dentistry	Unemployed and due to start work	All	All	All	All	Exclude significant interim study	2019/2(
9	01 Medicine and dentistry	Unknown pattern of employment	All	All	All	All	Exclude significant interim study	2019/2(

```
[11]: new['Percent'] = new['Percent'].str.rstrip('%').astype(float)

      # Divide each value by 100 to get the actual percentage
      new['Percent'] /= 100
      new.head(10)
```

[11]:

	Subject_area_of_degree	Activity	Country_of_provider	Provider_type	Level_of_qualification_obtained	Mode_of_former_study	Interim_study_marker	Academic_yea
0	01 Medicine and dentistry	Employment and further study	All	All	All	All	Exclude significant interim study	2019/2(
1	01 Medicine and dentistry	Full-time employment	All	All	All	All	Exclude significant interim study	2019/2(
2	01 Medicine and dentistry	Full-time further study	All	All	All	All	Exclude significant interim study	2019/2(
3	01 Medicine and dentistry	Other including travel, caring for someone or ...	All	All	All	All	Exclude significant interim study	2019/2(
4	01 Medicine and dentistry	Part-time employment	All	All	All	All	Exclude significant interim study	2019/2(
5	01 Medicine and dentistry	Part-time further study	All	All	All	All	Exclude significant interim study	2019/2(
6	01 Medicine and dentistry	Unemployed	All	All	All	All	Exclude significant interim study	2019/2(
7	01 Medicine and dentistry	Unemployed and due to start further study	All	All	All	All	Exclude significant interim study	2019/2(
8	01 Medicine and dentistry	Unemployed and due to start work	All	All	All	All	Exclude significant interim study	2019/2(
9	01 Medicine and dentistry	Unknown pattern of employment	All	All	All	All	Exclude significant interim study	2019/2(

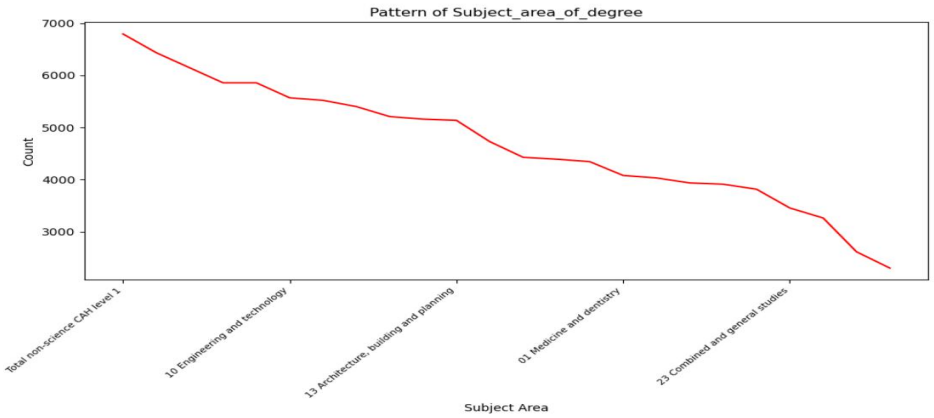
```
[12]: new.dtypes
```

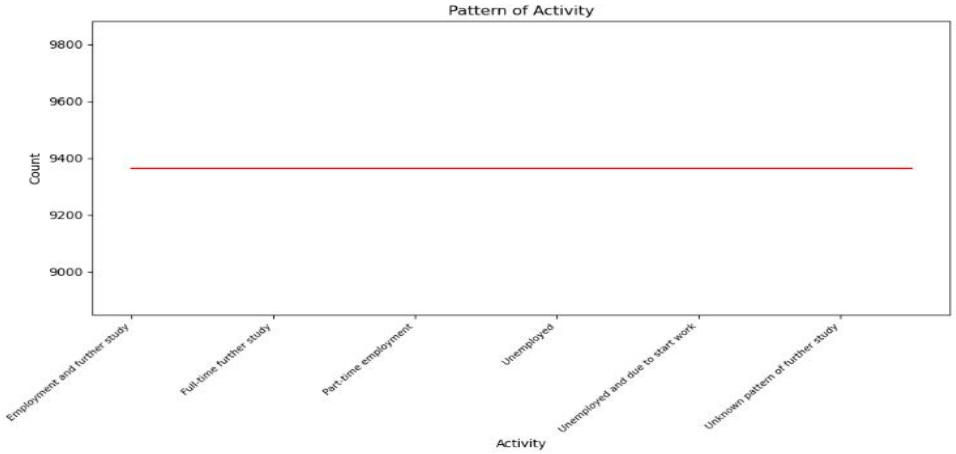
[12]:

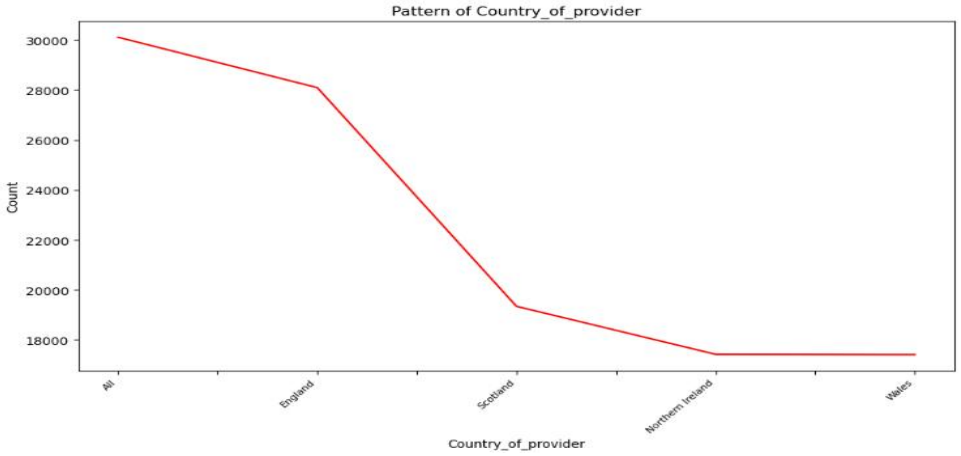
```
Subject_area_of_degree              object
Activity                            object
Country_of_provider                 object
Provider_type                       object
Level_of_qualification_obtained     object
Mode_of_former_study                object
Interim_study_marker                object
Academic_year                       object
Number                               int32
Percent                            float64
dtype: object
```

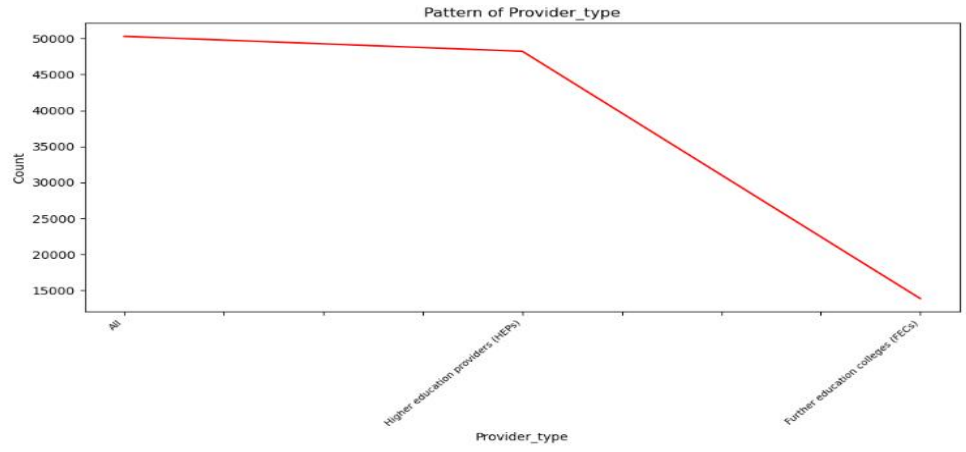
```
[13]: import matplotlib.pyplot as plt
      import seaborn as sns
```

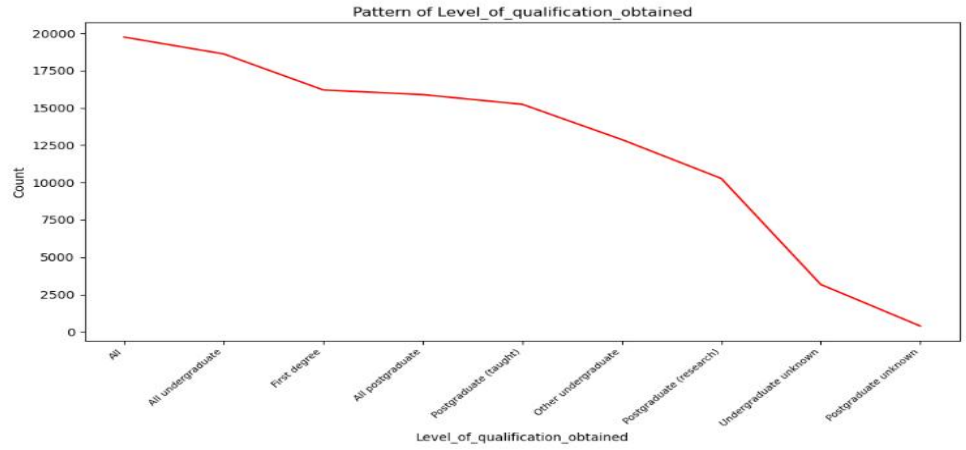
```
[14]: columns = new.columns.to_list()

      for col in columns:

          subject_area_counts = new[col].value_counts()

          # Plot the bar chart with custom color
          plt.figure(figsize=(10, 6))
          subject_area_counts.plot(kind='line', color='red')  # Change color to sky blue
          plt.title('Pattern of ' + col)
          plt.xlabel('Subject Area')
          plt.ylabel('Count')
          plt.xticks(rotation=45, ha='right', fontsize=8)  # Rotate x-axis labels and reduce font size
          plt.tight_layout()  # Adjust layout to prevent cropping labels
          plt.show()
```



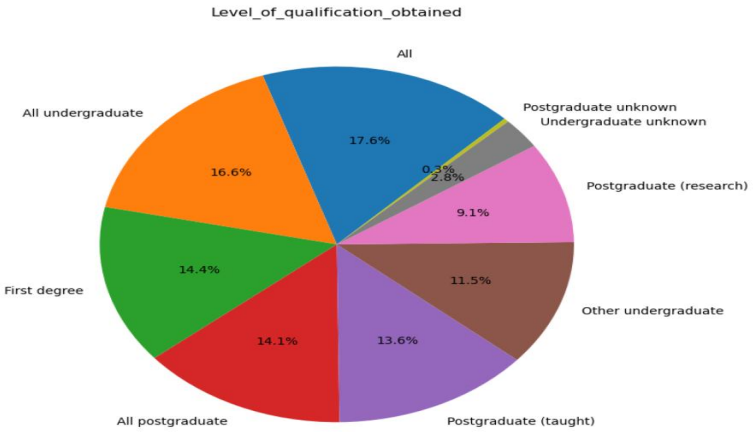

Pattern of Activity
Count
9800
9600
9400
9200
9000
Employment and further study
Full-time further study
Part-time employment
Unemployed
Unemployed and due to start work
Unknown pattern of further study
Activity


Pattern of Country_of_provider
Count
30000
28000
26000
24000
22000
20000
18000
All
England
Scotland
Northern Ireland
Wales
Country_of_provider

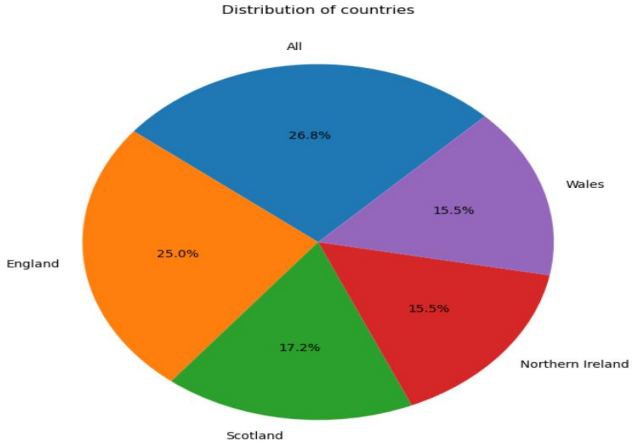

Pattern of Provider_type
Count
50000
45000
40000
35000
30000
25000
20000
15000
All
Higher education providers (HEPs)
Further education colleges (FECs)
Provider_type


Pattern of Level_of_qualification_obtained
Count
20000
17500
15000
12500
10000
7500
5000
2500
0
All
All undergraduate
First degree
All postgraduate
Postgraduate (taught)
Other undergraduate
Postgraduate (research)
Undergraduate unknown
Postgraduate unknown
Level_of_qualification_obtained

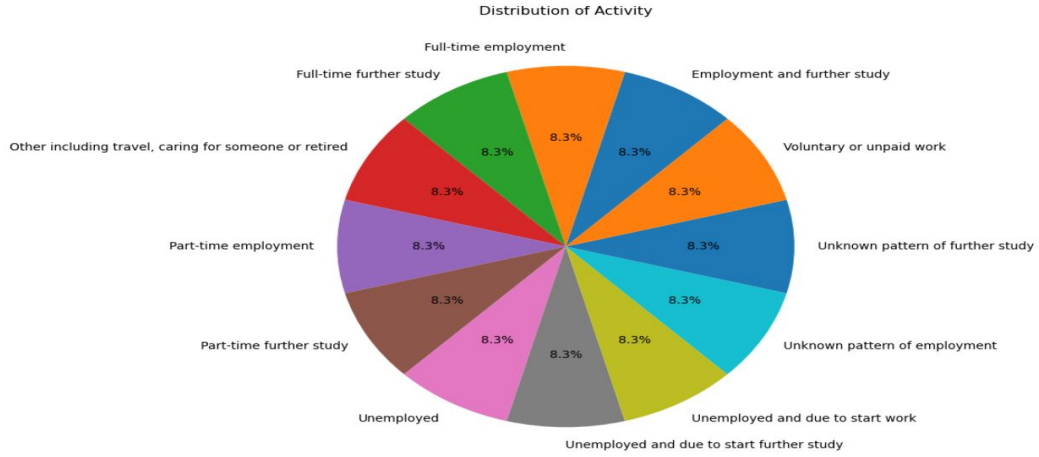
[15]:
```
# Extract the column 'Subject_area_of_degree'
subject_area_counts = new['Level_of_qualification_obtained'].value_counts()

# Plot the pie chart
plt.figure(figsize=(8, 8))
subject_area_counts.plot(kind='pie', autopct='%1.1f%%', startangle=45)
plt.title('Level_of_qualification_obtained')
plt.ylabel('')  # Remove y-axis label
plt.show()
```



[16]:
```
# Extract the column 'Subject_area_of_degree'
subject_area_counts = new['Country_of_provider'].value_counts()

# Plot the pie chart
plt.figure(figsize=(8, 8))
subject_area_counts.plot(kind='pie', autopct='%1.1f%%', startangle=45)
plt.title('Distribution of countries')
plt.ylabel('')  # Remove y-axis label
plt.show()
```



[17]:
```
# Extract the column 'Subject_area_of_degree'
subject_area_counts = new['Activity'].value_counts()

# Plot the pie chart
plt.figure(figsize=(8, 8))
subject_area_counts.plot(kind='pie', autopct='%1.1f%%', startangle=45)
plt.title('Distribution of Activity')
plt.ylabel('')  # Remove y-axis label
plt.show()
```



[18]:
```
from sklearn.preprocessing import LabelEncoder

# Make a copy of the original DataFrame
df_encoded = new.copy()

# Initialize LabelEncoder
label_encoder = LabelEncoder()

# Iterate over each column in the DataFrame
for column in new.columns:
    # Check if the column is categorical (i.e., dtype is object)
    if new[column].dtype == 'object':
        # Fit label encoder and transform values on the copy
        df_encoded[column] = label_encoder.fit_transform(new[column])

# Now, df_encoded contains numerical labels for each category in categorical columns,
# while df remains unchanged
df_encoded
```

[18]:

	Subject_area_of_degree	Activity	Country_of_provider	Provider_type	Level_of_qualification_obtained	Mode_of_former_study	Interim_study_marker	Academic_ye
0	0	0	0	0	0	0	0	
1	0	1	0	0	0	0	0	
2	0	2	0	0	0	0	0	
3	0	3	0	0	0	0	0	
4	0	4	0	0	0	0	0	
...	...	...	...	...	...	...	...	
112375	23	7	4	2	6	2	1	
112376	23	8	4	2	6	2	1	
112377	23	9	4	2	6	2	1	
112378	23	10	4	2	6	2	1	
112379	23	11	4	2	6	2	1	

112380 rows × 10 columns

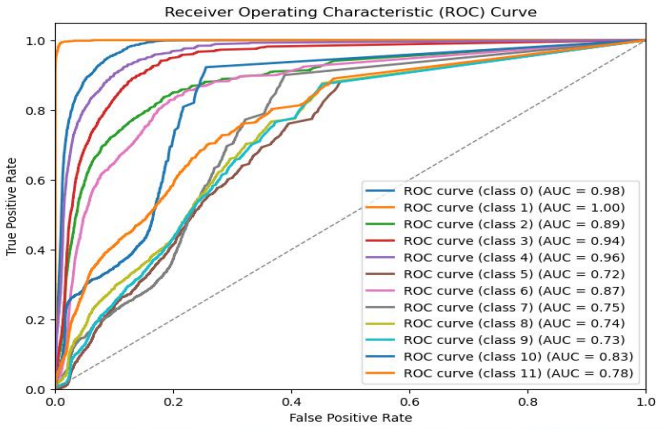
[19]:
```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import cross_val_score

df1 = df_encoded.copy()

# Drop any columns that are not relevant for classification
# For example, if 'Activity' is your target variable, drop it from the features
X = df1.drop(['Activity'], axis=1)
y = df1['Activity']

# Encode categorical variables
label_encoders = {}
for col in X.select_dtypes(include=['object']).columns:
    label_encoders[col] = LabelEncoder()
    X[col] = label_encoders[col].fit_transform(X[col])

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train the Random Forest classifier
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)
rf_classifier.fit(X_train, y_train)

# Make predictions on the test set
y_pred = rf_classifier.predict(X_test)

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Random Forest Accuracy:", accuracy)
```

```
Random Forest Accuracy: 0.450747463961559
```

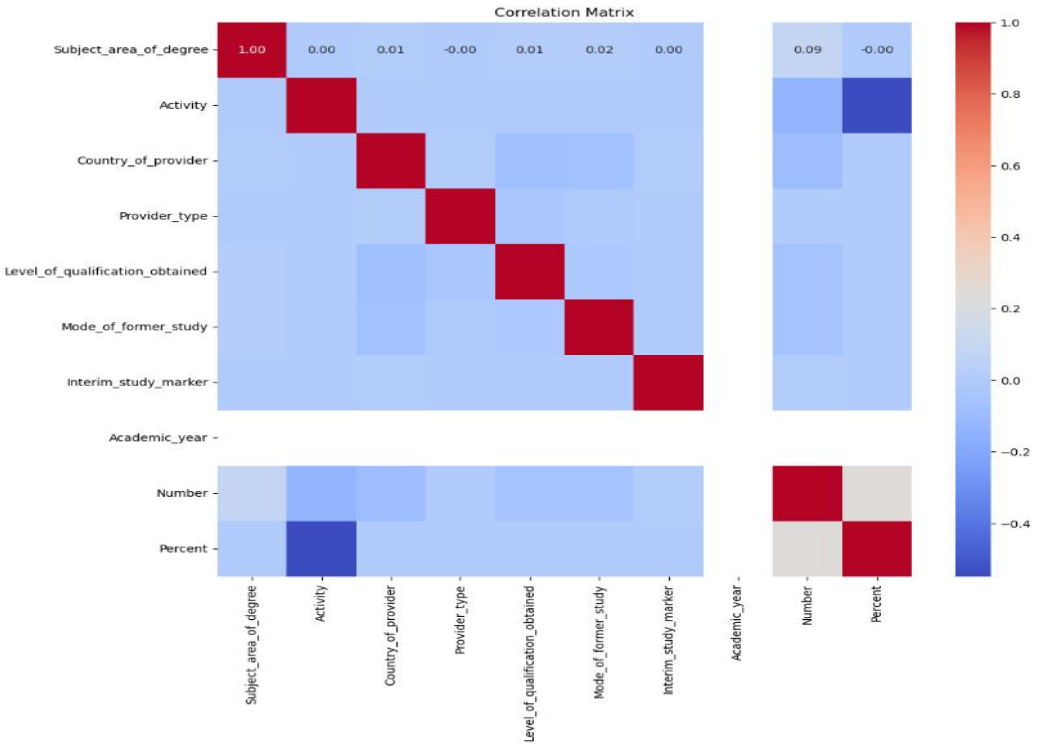
[20]:
```
from sklearn.ensemble import GradientBoostingClassifier

# Initialize Gradient Boosting classifier
gb_classifier = GradientBoostingClassifier(random_state=42)

# Fit the model on the training data
gb_classifier.fit(X_train, y_train)

# Predict on the testing data
y_pred_gb = gb_classifier.predict(X_test)

# Calculate accuracy
accuracy_gb = accuracy_score(y_test, y_pred_gb)
print("Gradient Boosting Accuracy:", accuracy_gb)
```

```
Gradient Boosting Accuracy: 0.41524292578750666
```

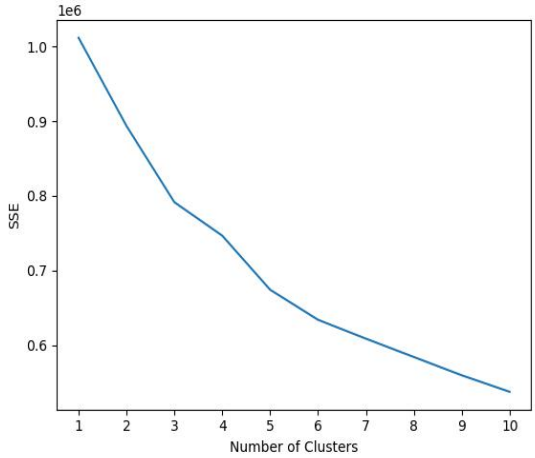
[21]:
```
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt

# Assuming rf_classifier is your trained Random Forest classifier
# Assuming X_test and y_test are your test data

# Predict probabilities for each class
y_probs = rf_classifier.predict_proba(X_test)

# Compute ROC curve and ROC area for each class
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(len(rf_classifier.classes_)):
    fpr[i], tpr[i], _ = roc_curve(y_test == i, y_probs[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Plot ROC curve for each class
plt.figure(figsize=(8, 6))
for i in range(len(rf_classifier.classes_)):
    plt.plot(fpr[i], tpr[i], lw=2, label='ROC curve (class {0}) (AUC = {1:0.2f})'
             ''.format(i, roc_auc[i]))

plt.plot([0, 1], [0, 1], color='gray', lw=1, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```



[22]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Compute correlation matrix
corr_matrix = df_encoded.corr()

# Plot correlation matrix
plt.figure(figsize=(12, 10))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix')
plt.show()
```



[23]:
```
df1 = df_encoded.copy()

from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
scaled_df = StandardScaler().fit_transform(df1)

#initialize kmeans parameters

kmeans_kwargs = {
"init": "random",
"n_init": 10,
"random_state": 1,
}
#create list to hold SSE values for each k

sse = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, **kmeans_kwargs)
    kmeans.fit(scaled_df)
    sse.append(kmeans.inertia_)

#visualize results
plt.plot(range(1, 11), sse)
plt.xticks(range(1, 11))
plt.xlabel("Number of Clusters")
plt.ylabel("SSE")
plt.show()
```

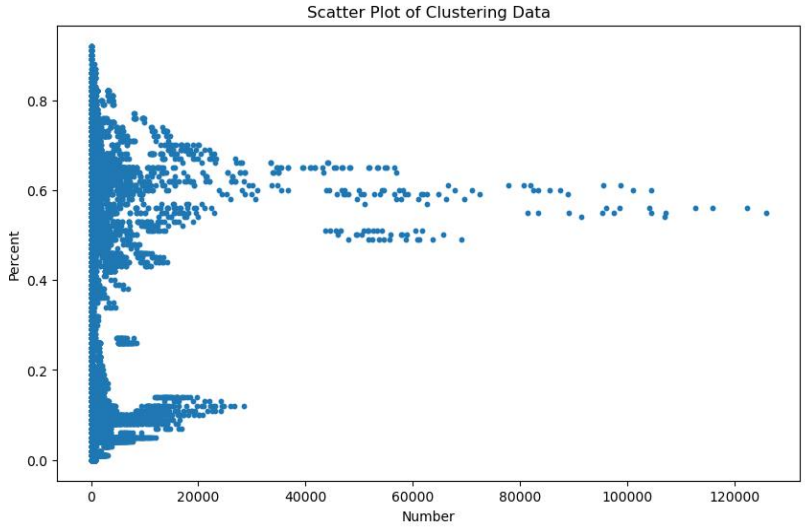


[24]:
```
# Assuming X contains your numerical features
X = df1[['Subject_area_of_degree', 'Activity', 'Country_of_provider', 'Provider_type', 'Level_of_qualification_obtained', 'Mode_of_former_study', 'Inter

# Specify the number of clusters (you can adjust this based on your data)
num_clusters = 4

# Initialize the KMeans model
kmeans = KMeans(n_clusters=num_clusters, random_state=42)

# Fit the KMeans model to your data
kmeans.fit(X)

# Get the cluster labels
cluster_labels = kmeans.labels_

# Add cluster labels to your dataframe
df1['Cluster'] = cluster_labels
df1
```

[24]:

	Activity	Country_of_provider	Provider_type	Level_of_qualification_obtained	Mode_of_former_study	Interim_study_marker	Academic_year	Number	Percent	Cluster
0	0	0	0	0	0	0	0	1020	0.11	0
0	1	0	0	0	0	0	0	6720	0.72	2
0	2	0	0	0	0	0	0	545	0.06	0
0	3	0	0	0	0	0	0	245	0.03	0
0	4	0	0	0	0	0	0	550	0.06	0
...	...	...	...	...	...	...	...	...	...	...
3	7	4	2	6	2	1	0	0	0.00	0
3	8	4	2	6	2	1	0	0	0.00	0
3	9	4	2	6	2	1	0	0	0.00	0
3	10	4	2	6	2	1	0	0	0.00	0
3	11	4	2	6	2	1	0	5	0.01	0

[25]:
```
import matplotlib.pyplot as plt

# Selecting two features for visualization
feature1 = 'Number'
feature2 = 'Percent'

# Plotting the data points
plt.figure(figsize=(10, 6))
plt.scatter(df1[feature1], df1[feature2], s=10)
plt.xlabel(feature1)
plt.ylabel(feature2)
plt.title('Scatter Plot of Clustering Data')
plt.show()
```



[26]:
```
# Assuming 'Cluster' is the column containing cluster labels
colors = ['red', 'blue', 'green', 'yellow']  # Add more colors if you have more clusters
cluster_labels = df1['Cluster']

plt.figure(figsize=(10, 6))
for cluster in range(len(colors)):
    cluster_data = df1[cluster_labels == cluster]
    plt.scatter(cluster_data[feature1], cluster_data[feature2], s=10, color=colors[cluster], label=f'Cluster {cluster}')
plt.xlabel(feature1)
plt.ylabel(feature2)
plt.title('Scatter Plot of Clustering Data with Cluster Labels')
plt.legend()
plt.show()
```