

Student Dropout and Academic Success

Objective of the Analysis

The main objective of this project is to develop a machine learning model capable of clustering into one of three categories. Original dataset has three different target class: Dropout, Enrolled, or Graduate. The goal is to explore various clustering techniques and analyze their effectiveness in identifying patterns within the student data. While the original dataset includes a predefined target variable, it is only used for evaluation rather than training the clustering models.

Dataset Overview

The dataset was acquired from the UCI Machine Learning Repository, created from a higher education institution's student records. The data was gathered from several disjoint databases related to students enrolled in different undergraduate degrees. This dataset aims to help predict student dropout and academic success. It help identify at-risk students, ultimately contributing to efforts aimed at reducing academic dropout and failure in higher education. This dataset consist :

- Number of Instances: 4424 student records
- Number of Features: 36, covering a wide range of attributes such as academic path, demographics, and socio-economic factors.
- Target/Predictor: Three category classification (dropout, enrolled, and graduate) representing student risk at the end of the normal duration of the course. This column will not be used in clustering model. However will used as reference to compared with model result

Data Exploration and Preprocessing

Exploratory Data Analysis (EDA)

- No missing values were found in the dataset.
- Feature correlations were examined, revealing some highly correlated columns.
- All features were numeric, which streamlined the clustering process.

Feature Engineering and Transformation

- Most columns were integers, so they were converted to float data types for consistency.
- Some features exhibited high skewness, which was corrected using logarithmic transformation.
- Standard Scaling was applied to normalize the data, ensuring all features were on a comparable scale.
- Stratified Shuffle Split was implemented to maintain the class distribution when splitting data for evaluation.

Model Training

Three different unsupervised machine learning models used. :

- 1. KMeans
- 2. Gaussian Mixture
- 3. Agglomerative Clustering

The same dataset was used for all three models, and the predicted cluster labels were appended to the dataset. To compare model performance, value counts for each model’s predicted clusters and the original target labels were stored in a separate DataFrame for evaluation.

Model Evaluation

All three clustering models produced similar results, indicating that the dataset contains clear structure and patterns. K-Means and GMM showed particularly close results, suggesting that both approaches capture similar underlying distributions in the data. When comparing model predictions to the target column, discrepancies were observed, but a notable pattern emerged where one cluster consistently had a much higher representation compared to the other two.

result_df

	Target(Reference)	kmeans_cluster	gmm_cluster	agglomerative_cluster
0	2209	3503	3496	3390
1	1421	741	748	719
2	794	180	180	315

Final Model Recommendation

While the initial clustering models provided valuable insights, there are several ways to enhance model performance:

- 1. Dimensionality Reduction: Applying Principal Component Analysis (PCA)
- 2. Hyperparameter Tuning: Adjusting the number of clusters, covariance type (for GMM), and linkage criteria (for Agglomerative Clustering) may improve results.
- 3. Feature Selection: Removing redundant or highly correlated features could improve model interpretability and efficiency.

This project demonstrates the potential of clustering models to uncover patterns in student success and dropout trends. Further refinements and additional data sources could enhance predictive capabilities, supporting educational institutions in proactive decision-making.

Unsupervised Machine Learning: Final Project

Import Libraries

```
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import OneHotEncoder, LabelEncoder, OrdinalEncoder, StandardScaler, MinMaxScaler
from sklearn.model_selection import StratifiedShuffleSplit, train_test_split, GridSearchCV
from sklearn.cluster import KMeans
from sklearn.cluster import AgglomerativeClustering
from sklearn.mixture import GaussianMixture
```

Load Data and Explore

```
# Load dataset

# from google.colab import drive

# drive.mount('/content/drive', force_remount=True)

students_data = pd.read_csv('/content/drive/My Drive/Machine_Learning/Coursera/IBM_Machine_Learning/Unsupervised_Machine_Learning/Final_P
students_data.head()
```

↻

	Marital Status	Application mode	Application order	Course	Daytime/evening attendance	Previous qualification	Previous qualification (grade)	Nacionality	Mother's qualification	Father's qualification
0	1	17	5	171	1	1	122.0	1	19	
1	1	15	1	9254	1	1	160.0	1	1	
2	1	1	5	9070	1	1	122.0	1	37	:
3	1	17	2	9773	1	1	122.0	1	38	:
4	2	39	1	8014	0	1	100.0	1	37	:

5 rows × 37 columns

```
# Display basic dataset information
students_data.info()
```


↻

<class 'pandas.core.frame.DataFrame'>			
RangeIndex: 4424 entries, 0 to 4423			
Data columns (total 37 columns):			
#	Column	Non-Null Count	Dtype
0	Marital Status	4424 non-null	int64
1	Application mode	4424 non-null	int64
2	Application order	4424 non-null	int64
3	Course	4424 non-null	int64
4	Daytime/evening attendance	4424 non-null	int64
5	Previous qualification	4424 non-null	int64
6	Previous qualification (grade)	4424 non-null	float64
7	Nacionality	4424 non-null	int64
8	Mother's qualification	4424 non-null	int64
9	Father's qualification	4424 non-null	int64
10	Mother's occupation	4424 non-null	int64
11	Father's occupation	4424 non-null	int64
12	Admission grade	4424 non-null	float64
13	Displaced	4424 non-null	int64
14	Educational special needs	4424 non-null	int64
15	Debtor	4424 non-null	int64
16	Tuition fees up to date	4424 non-null	int64
17	Gender	4424 non-null	int64
18	Scholarship holder	4424 non-null	int64
19	Age at enrollment	4424 non-null	int64
20	International	4424 non-null	int64
21	Curricular units 1st sem (credited)	4424 non-null	int64
22	Curricular units 1st sem (enrolled)	4424 non-null	int64
23	Curricular units 1st sem (evaluations)	4424 non-null	int64
24	Curricular units 1st sem (approved)	4424 non-null	int64
25	Curricular units 1st sem (grade)	4424 non-null	float64

```
26 Curricular units 1st sem (without evaluations) 4424 non-null int64
27 Curricular units 2nd sem (credited) 4424 non-null int64
28 Curricular units 2nd sem (enrolled) 4424 non-null int64
29 Curricular units 2nd sem (evaluations) 4424 non-null int64
30 Curricular units 2nd sem (approved) 4424 non-null int64
31 Curricular units 2nd sem (grade) 4424 non-null float64
32 Curricular units 2nd sem (without evaluations) 4424 non-null int64
33 Unemployment rate 4424 non-null float64
34 Inflation rate 4424 non-null float64
35 GDP 4424 non-null float64
36 Target 4424 non-null object
```

dtypes: float64(7), int64(29), object(1)
memory usage: 1.2+ MB

```
# Generate descriptive statistics for the dataset and transpose the result for better readability
students_data.describe().T # Transpose the summary statistics to display features as rows
```



Marital Status	4424.0	1.178571	0.605747	1.00	1.00	1.000000	1.000000	6.000000
Application mode	4424.0	18.669078	17.484682	1.00	1.00	17.000000	39.000000	57.000000
Application order	4424.0	1.727848	1.313793	0.00	1.00	1.000000	2.000000	9.000000
Course	4424.0	8856.642631	2063.566416	33.00	9085.00	9238.000000	9556.000000	9991.000000
Daytime/evening attendance	4424.0	0.890823	0.311897	0.00	1.00	1.000000	1.000000	1.000000
Previous qualification	4424.0	4.577758	10.216592	1.00	1.00	1.000000	1.000000	43.000000
Previous qualification (grade)	4424.0	132.613314	13.188332	95.00	125.00	133.100000	140.000000	190.000000
Nacionality	4424.0	1.873192	6.914514	1.00	1.00	1.000000	1.000000	109.000000
Mother's qualification	4424.0	19.561935	15.603186	1.00	2.00	19.000000	37.000000	44.000000
Father's qualification	4424.0	22.275316	15.343108	1.00	3.00	19.000000	37.000000	44.000000
Mother's occupation	4424.0	10.960895	26.418253	0.00	4.00	5.000000	9.000000	194.000000
Father's occupation	4424.0	11.032324	25.263040	0.00	4.00	7.000000	9.000000	195.000000
Admission grade	4424.0	126.978119	14.482001	95.00	117.90	126.100000	134.800000	190.000000
Displaced	4424.0	0.548373	0.497711	0.00	0.00	1.000000	1.000000	1.000000
Educational special needs	4424.0	0.011528	0.106760	0.00	0.00	0.000000	0.000000	1.000000
Debtor	4424.0	0.113698	0.317480	0.00	0.00	0.000000	0.000000	1.000000
Tuition fees up to date	4424.0	0.880651	0.324235	0.00	1.00	1.000000	1.000000	1.000000
Gender	4424.0	0.351718	0.477560	0.00	0.00	0.000000	1.000000	1.000000
Scholarship holder	4424.0	0.248418	0.432144	0.00	0.00	0.000000	0.000000	1.000000
Age at enrollment	4424.0	23.265145	7.587816	17.00	19.00	20.000000	25.000000	70.000000
International	4424.0	0.024864	0.155729	0.00	0.00	0.000000	0.000000	1.000000
Curricular units 1st sem (credited)	4424.0	0.709991	2.360507	0.00	0.00	0.000000	0.000000	20.000000
Curricular units 1st sem (enrolled)	4424.0	6.270570	2.480178	0.00	5.00	6.000000	7.000000	26.000000
Curricular units 1st sem (evaluations)	4424.0	8.299051	4.179106	0.00	6.00	8.000000	10.000000	45.000000
Curricular units 1st sem (approved)	4424.0	4.706600	3.094238	0.00	3.00	5.000000	6.000000	26.000000
Curricular units 1st sem (grade)	4424.0	10.640822	4.843663	0.00	11.00	12.285714	13.400000	18.875000
Curricular units 1st sem (without evaluations)	4424.0	0.137658	0.690880	0.00	0.00	0.000000	0.000000	12.000000
Curricular units 2nd sem (credited)	4424.0	0.541817	1.918546	0.00	0.00	0.000000	0.000000	19.000000
Curricular units 2nd sem (enrolled)	4424.0	6.232143	2.195951	0.00	5.00	6.000000	7.000000	23.000000
Curricular units 2nd sem (evaluations)	4424.0	8.063291	3.947951	0.00	6.00	8.000000	10.000000	33.000000
Curricular units 2nd sem (approved)	4424.0	4.435805	3.014764	0.00	2.00	5.000000	6.000000	20.000000
Curricular units 2nd sem (grade)	4424.0	10.230206	5.210808	0.00	10.75	12.200000	13.333333	18.571429
Curricular units 2nd sem (without evaluations)	4424.0	0.150316	0.753774	0.00	0.00	0.000000	0.000000	12.000000
Unemployment rate	4424.0	11.566139	2.663850	7.60	9.40	11.100000	13.900000	16.200000
Inflation rate	4424.0	1.228029	1.382711	-0.80	0.30	1.400000	2.600000	3.700000
GDP	4424.0	0.001969	0.269935	-4.06	-1.70	0.320000	1.790000	3.510000

✎ Exploratory Data Analysis and Feature Engineering

Start coding or [generate](#) with AI.

```
# Check Target Column. We will drop this column later. We will try to see whether we can get similar propotion with 3 cluster.
students_data.Target.value_counts(normalize=True)
```



proportion

Target

Graduate	0.499322
Dropout	0.321203
Enrolled	0.179476

dtype: float64

```
feature_columns = students_data.select_dtypes(exclude=['object']).columns.tolist()
students_data[feature_columns].info()
```



<class 'pandas.core.frame.DataFrame'>

RangeIndex: 4424 entries, 0 to 4423

Data columns (total 36 columns):

#	Column	Non-Null Count	Dtype
0	Marital Status	4424 non-null	int64
1	Application mode	4424 non-null	int64
2	Application order	4424 non-null	int64
3	Course	4424 non-null	int64
4	Daytime/evening attendance	4424 non-null	int64
5	Previous qualification	4424 non-null	int64
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25	Curricular units 1st sem (grade)	4424 non-null	float64
26	Curricular units 1st sem (without evaluations)	4424 non-null	int64
27	Curricular units 2nd sem (credited)	4424 non-null	int64
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31	Curricular units 2nd sem (grade)	4424 non-null	float64
32	Curricular units 2nd sem (without evaluations)	4424 non-null	int64
33	Unemployment rate	4424 non-null	float64
34	Inflation rate	4424 non-null	float64
35	GDP	4424 non-null	float64

dtypes: float64(7), int64(29)

memory usage: 1.2 MB

```
# The correlation matrix
corr_mat = students_data[feature_columns].corr()

# Strip out the diagonal values for the next step
for x in range(len(students_data[feature_columns].columns)):
    corr_mat.iloc[x,x] = 0.0

corr_mat
```



	Marital Status	Application mode	Application order	Course	Daytime/evening attendance	Previous qualification	Previous qualification (grade)	Nacionality	Mother's qualification
Marital Status	0.000000	0.264006	-0.125854	0.046365	-0.274939	0.062529	-0.022406	-0.008843	0.193163
Application mode	0.264006	0.000000	-0.286357	0.065385	-0.304092	0.422411	-0.039020	-0.000661	0.118974
Application order	-0.125854	-0.286357	0.000000	0.059507	0.158657	-0.184315	-0.064484	-0.022416	-0.064956
Course	0.046365	0.065385	0.059507	0.000000	-0.043151	0.006654	-0.081013	-0.033923	0.054543
Daytime/evening attendance	-0.274939	-0.304092	0.158657	-0.043151	0.000000	-0.071871	0.052597	0.018530	-0.204767
Previous qualification	0.062529	0.422411	-0.184315	0.006654	-0.071871	0.000000	0.104072	-0.029214	-0.013190
Previous qualification (grade)	-0.022406	-0.039020	-0.064484	-0.081013	0.052597	0.104072	0.000000	0.054088	-0.060670
Nacionality	-0.008843	-0.000661	-0.022416	-0.033923	0.018530	-0.029214	0.054088	0.000000	-0.049946
Mother's qualification	0.193163	0.118974	-0.064956	0.054543	-0.204767	-0.013190	-0.060670	-0.049946	0.000000
Father's qualification	0.130353	0.083276	-0.050288	0.050724	-0.139894	-0.006614	-0.035234	-0.085282	0.530724
Mother's occupation	0.034994	0.051600	-0.039039	0.031265	-0.019067	0.014822	-0.011415	0.043187	0.071871
Father's occupation	0.031609	0.036707	-0.030014	0.028881	-0.015477	0.016263	-0.019284	0.020626	0.050724
Admission grade	-0.004771	-0.013271	-0.096930	-0.125058	0.007970	0.184183	0.580444	0.028176	-0.050724
Displaced	-0.234886	-0.301197	0.332362	-0.087399	0.251767	-0.115188	-0.011001	-0.007448	-0.080670
Educational special needs	-0.028343	-0.030779	0.025597	-0.018795	0.031017	-0.010461	-0.001458	-0.005982	-0.020476
Debtor	0.034304	0.122818	-0.072151	-0.032673	0.006658	0.095104	-0.037507	0.051989	0.013190
Tuition fees up to date	-0.087158	-0.136262	0.055891	0.018381	0.038799	-0.068453	0.060578	-0.026115	-0.020476
Gender	-0.014738	0.160130	-0.089559	-0.099571	-0.012326	0.078684	-0.047874	-0.023258	-0.050724
Scholarship holder	-0.053765	-0.163117	0.073709	0.017138	0.093912	-0.070513	0.055965	-0.010490	0.043187
Age at enrollment	0.522717	0.516243	-0.271154	0.042994	-0.462280	0.156234	-0.111377	-0.003647	0.290724
International	-0.027905	0.003438	-0.028801	-0.026737	0.027973	-0.026226	0.048529	0.790935	-0.030724
Curricular units 1st sem (credited)	0.061209	0.247426	-0.133354	-0.096335	-0.127466	0.166025	-0.008872	-0.000370	0.043187
Curricular units 1st sem (enrolled)	0.052107	0.164299	-0.016808	0.328461	-0.043056	0.078702	-0.029169	-0.013292	0.050724
Curricular units 1st sem (evaluations)	0.058030	0.225938	-0.092156	0.272845	-0.045889	0.130597	-0.070702	-0.007763	0.043187
Curricular units 1st sem (approved)	-0.031027	-0.029055	0.035580	0.180500	0.016935	0.022020	0.048410	-0.002268	-0.010476
Curricular units 1st sem (grade)	-0.059811	-0.117741	0.058308	0.389349	0.063974	-0.000497	0.059438	0.000869	-0.030724
Curricular units 1st sem (without evaluations)	0.034711	0.045828	-0.031699	0.034514	0.045630	0.002887	-0.003926	0.009145	0.000000
Curricular units 2nd sem (credited)	0.062831	0.238445	-0.125815	-0.089817	-0.111953	0.143031	-0.018489	-0.007278	0.043187
Curricular units 2nd sem (enrolled)	0.039026	0.130046	0.028878	0.401539	0.000371	0.056179	-0.031649	-0.020113	0.030724
Curricular units 2nd sem (evaluations)	0.022784	0.167872	-0.055089	0.278797	0.014610	0.114850	-0.061355	-0.025721	0.020476

(evaluations)									
Curricular units 2nd sem (approved)	-0.043739	-0.071526	0.071793	0.198032	0.034022	-0.008632	0.050263	-0.017880	-0.014
Curricular units 2nd sem (grade)	-0.071506	-0.115424	0.055517	0.348728	0.050493	0.000942	0.053239	-0.008497	-0.03
Curricular units 2nd sem (without evaluations)	0.020426	0.047983	-0.015757	0.030816	-0.004229	0.005102	-0.019015	-0.014041	0.02
Unemployment rate	-0.020338	0.089080	-0.098419	0.007153	0.061974	0.111958	0.045222	-0.000651	-0.11
Inflation rate	0.008761	-0.016375	-0.011133	0.017710	-0.024043	-0.063736	0.018710	-0.008922	0.05
GDP	-0.027003	-0.022743	0.030201	-0.020265	0.022929	0.064069	-0.052620	0.034478	-0.08

36 rows × 36 columns

```
# Pairwise maximal correlations
corr_mat.abs().max().sort_values()
```



0

Educational special needs	0.046131
Inflation rate	0.112295
Scholarship holder	0.202704
Gender	0.224266
Application order	0.332362
Unemployment rate	0.335178
GDP	0.335178
Displaced	0.362032
Course	0.401539
Debtor	0.408454
Tuition fees up to date	0.408454
Previous qualification	0.422411
Daytime/evening attendance	0.462280
Application mode	0.516243
Age at enrollment	0.522717
Marital Status	0.522717
Father's qualification	0.535140
Mother's qualification	0.535140
Admission grade	0.580444
Previous qualification (grade)	0.580444
Curricular units 2nd sem (without evaluations)	0.583261
Curricular units 1st sem (without evaluations)	0.583261
Curricular units 2nd sem (evaluations)	0.778863
Curricular units 1st sem (evaluations)	0.778863
Nacionality	0.790935
International	0.790935
Curricular units 1st sem (grade)	0.837170
Curricular units 2nd sem (grade)	0.837170
Curricular units 2nd sem (approved)	0.904002
Curricular units 1st sem (approved)	0.904002
Father's occupation	0.910472
Mother's occupation	0.910472
Curricular units 1st sem (enrolled)	0.942627
Curricular units 2nd sem (enrolled)	0.942627
Curricular units 2nd sem (credited)	0.944811
Curricular units 1st sem (credited)	0.944811

dtype: float64

Check skew values in anticipation of transformations.

```
skew_columns = (students_data[feature_columns].skew().sort_values(ascending=False))

skew_columns = skew_columns.loc[skew_columns > 0.75]
skew_columns
```




0

Nacionality	10.703998
Educational special needs	9.154976
Curricular units 1st sem (without evaluations)	8.207403
Curricular units 2nd sem (without evaluations)	7.267701
International	6.104830
Father's occupation	5.395173
Mother's occupation	5.339227
Curricular units 2nd sem (credited)	4.634820
Marital Status	4.399764
Curricular units 1st sem (credited)	4.169049
Previous qualification	2.871207
Debtor	2.434652
Age at enrollment	2.054988
Application order	1.881050
Curricular units 1st sem (enrolled)	1.619041
Scholarship holder	1.164871
Curricular units 1st sem (evaluations)	0.976637
Curricular units 2nd sem (enrolled)	0.788114
Curricular units 1st sem (approved)	0.766262

dtype: float64

```
# Perform log transform on skewed columns
for col in skew_columns.index.tolist():
    students_data[col] = np.log1p(students_data[col])
```

```
# Perform standard scaler
scaler = StandardScaler()
students_data[feature_columns]= scaler.fit_transform(students_data[feature_columns])

students_data[feature_columns]
```



	Marital Status	Application mode	Application order	Course	Daytime/evening attendance	Previous qualification	Previous qualification (grade)	Nacionality	Mother's qualification	quali
0	-0.323463	-0.095470	2.322256	-4.209520	0.350082	-0.395901	-0.804841	-0.153037	-0.036018	
1	-0.323463	-0.209869	-0.606025	0.192580	0.350082	-0.395901	2.076819	-0.153037	-1.189759	
2	-0.323463	-1.010660	2.322256	0.103404	0.350082	-0.395901	-0.804841	-0.153037	1.117723	
3	-0.323463	-0.095470	0.474716	0.444115	0.350082	-0.395901	-0.804841	-0.153037	1.181819	
4	1.787906	1.162916	-0.606025	-0.408389	-2.856470	-0.395901	-2.473171	-0.153037	1.117723	
...	
4419	-0.323463	-1.010660	2.733134	0.444115	0.350082	-0.395901	-0.577342	-0.153037	-1.189759	
4420	-0.323463	-1.010660	0.474716	0.444115	0.350082	-0.395901	-0.956508	9.046312	-1.189759	
4421	-0.323463	-1.010660	-0.606025	0.311805	0.350082	-0.395901	1.621820	-0.153037	1.117723	
4422	-0.323463	-1.010660	-0.606025	0.140722	0.350082	-0.395901	3.593483	-0.153037	1.117723	
4423	-0.323463	-0.495866	-0.606025	0.444115	0.350082	-0.395901	1.470154	5.505993	1.181819	

4424 rows × 36 columns

```
students_data[feature_columns].describe().T
```

	count	mean	std	min	25%	50%	75%	max
Marital Status	4424.0	-3.244341e-16	1.000113	-0.323463	-0.323463	-0.323463	-0.323463	6.200020
Application mode	4424.0	-1.477621e-16	1.000113	-1.010660	-1.010660	-0.095470	1.162916	2.192505
Application order	4424.0	-1.991575e-16	1.000113	-2.453564	-0.606025	-0.606025	0.474716	3.683829
Course	4424.0	2.288706e-16	1.000113	-4.276402	0.110674	0.184826	0.338945	0.549769
Daytime/evening attendance	4424.0	7.066881e-17	1.000113	-2.856470	0.350082	0.350082	0.350082	0.350082
Previous qualification	4424.0	-8.753295e-17	1.000113	-0.395901	-0.395901	-0.395901	-0.395901	3.120153
Previous qualification (grade)	4424.0	-3.589654e-16	1.000113	-2.852337	-0.577342	0.036907	0.560156	4.351815
Nacionality	4424.0	-2.778569e-16	1.000113	-0.153037	-0.153037	-0.153037	-0.153037	9.132138
Mother's qualification	4424.0	-5.781993e-17	1.000113	-1.189759	-1.125662	-0.036018	1.117723	1.566400
Father's qualification	4424.0	0.000000e+00	1.000113	-1.386793	-1.256427	-0.213496	0.959802	1.416085
Mother's occupation	4424.0	6.986575e-17	1.000113	-2.381500	-0.389656	-0.164014	0.468185	4.144378
Father's occupation	4424.0	3.180096e-16	1.000113	-2.537909	-0.474360	0.128257	0.414362	4.229452
Admission grade	4424.0	-9.708930e-16	1.000113	-2.208378	-0.626926	-0.060642	0.540172	4.352230
Displaced	4424.0	-7.388103e-17	1.000113	-1.101914	-1.101914	0.907512	0.907512	0.907512
Educational special needs	4424.0	3.212219e-17	1.000113	-0.107993	-0.107993	-0.107993	-0.107993	9.259865
Debtor	4424.0	-2.650080e-17	1.000113	-0.358167	-0.358167	-0.358167	-0.358167	2.791994
Tuition fees up to date	4424.0	-1.317010e-16	1.000113	-2.716392	0.368135	0.368135	0.368135	0.368135
Gender	4424.0	1.027910e-16	1.000113	-0.736572	-0.736572	-0.736572	1.357640	1.357640
Scholarship holder	4424.0	-2.328858e-17	1.000113	-0.574914	-0.574914	-0.574914	-0.574914	1.739390
Age at enrollment	4424.0	1.856662e-15	1.000113	-1.019819	-0.608706	-0.418328	0.415030	4.334881
International	4424.0	-4.818328e-17	1.000113	-0.159682	-0.159682	-0.159682	-0.159682	6.262442
Curricular units 1st sem (credited)	4424.0	-1.284887e-17	1.000113	-0.358314	-0.358314	-0.358314	-0.358314	4.666063
Curricular units 1st sem (enrolled)	4424.0	5.203794e-16	1.000113	-4.222784	-0.260006	0.080924	0.376251	3.066514
Curricular units 1st sem (evaluations)	4424.0	-7.388103e-17	1.000113	-3.069388	-0.190988	0.180758	0.477591	2.593958
Curricular units 1st sem (approved)	4424.0	-6.424437e-18	1.000113	-2.019551	-0.185334	0.351140	0.555098	2.341197
Curricular units 1st sem (grade)	4424.0	-1.702476e-16	1.000113	-2.197102	0.074163	0.339635	0.569711	1.700182
Curricular units 1st sem (without evaluations)	4424.0	-8.030546e-18	1.000113	-0.245125	-0.245125	-0.245125	-0.245125	9.079579
Curricular units 2nd sem (credited)	4424.0	7.709324e-17	1.000113	-0.339689	-0.339689	-0.339689	-0.339689	5.240482
Curricular units 2nd sem (enrolled)	4424.0	5.219855e-16	1.000113	-4.325593	-0.268547	0.080493	0.382846	2.870413
Curricular units 2nd sem (evaluations)	4424.0	-8.994212e-17	1.000113	-2.042630	-0.522682	-0.016033	0.490616	6.317081
Curricular units 2nd sem (approved)	4424.0	-1.509743e-16	1.000113	-1.471527	-0.808050	0.187165	0.518904	5.163242
Curricular units 2nd sem (grade)	4424.0	3.212219e-17	1.000113	-1.963489	0.099764	0.378064	0.595585	1.600935
Curricular units 2nd sem (without evaluations)	4424.0	-2.890997e-17	1.000113	-0.238476	-0.238476	-0.238476	-0.238476	8.580943
Unemployment rate	4424.0	-5.460771e-17	1.000113	-1.489043	-0.813253	-0.175007	0.876222	1.739731
Inflation rate	4424.0	1.445498e-16	1.000113	-1.466871	-0.671242	0.124386	0.992345	1.787974
GDP	4424.0	2.569775e-17	1.000113	-1.789667	-0.749872	0.140122	0.787790	1.545607

So far what we have done are:

- We have removed Target columns
- Converted all the feature columns to float columns
- Columns with higher skew(>0.75) have been log tranform
- And all the columns have been rescaled to standard scaller

Now we are ready to perform cluster. Intention to do 3 cluster from this dataset.

Model Clustering

1. KMeans

```
km = KMeans(n_clusters=3, random_state=42)
km = km.fit(students_data[feature_columns])
```