Term Project Final

201631513 Hwang ByungHoon
201635825 Oh SeongWon
201635841 Lee ChaeHyeon
201835437 Kim JinKyung

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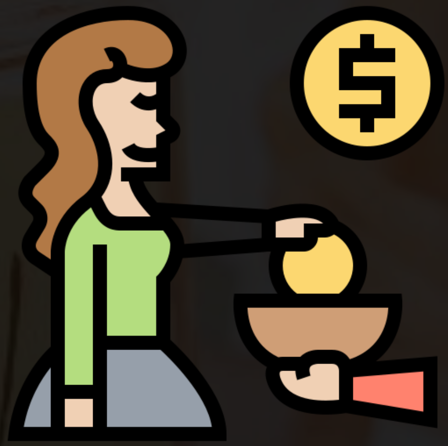
– Concept of project

In Classification



OR

The classification goal is
to predict if the client
will subscribe a term deposit

- Dataset description

In Classification

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	campaign	pdays	previous	poutcome	emp.var.rate	cons.price.i	cons.conf.id	euribor3m	nr.employed	y
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon	261	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
1	57	services	married	high.school	unknown	no	no	telephone	may	mon	149	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
2	37	services	married	high.school	no	yes	no	telephone	may	mon	226	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
3	40	admin.	married	basic.6y	no	no	no	telephone	may	mon	151	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
4	56	services	married	high.school	no	no	yes	telephone	may	mon	307	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
5	45	services	married	basic.9y	unknown	no	no	telephone	may	mon	198	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
6	59	admin.	married	professional	no	no	no	telephone	may	mon	139	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
7	41	blue-collar	married	unknown	unknown	no	no	telephone	may	mon	217	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
8	24	technician	single	professional	no	yes	no	telephone	may	mon	380	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
9	25	services	single	high.school	no	yes	no	telephone	may	mon	50	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
10	41	blue-collar	married	unknown	unknown	no	no	telephone	may	mon	55	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
11	25	services	single	high.school	no	yes	no	telephone	may	mon	222	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
12	29	blue-collar	single	high.school	no	no	yes	telephone	may	mon	137	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
13	57	housemaid	divorced	basic.4y	no	yes	no	telephone	may	mon	293	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
14	35	blue-collar	married	basic.6y	no	yes	no	telephone	may	mon	146	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
15	54	retired	married	basic.9y	unknown	yes	yes	telephone	may	mon	174	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
16	35	blue-collar	married	basic.6y	no	yes	no	telephone	may	mon	312	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
17	46	blue-collar	married	basic.6y	unknown	yes	yes	telephone	may	mon	440	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
18	50	blue-collar	married	basic.9y	no	yes	yes	telephone	may	mon	353	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
19	39	management	single	basic.9y	unknown	no	no	telephone	may	mon	195	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
20	30	unemployed	married	high.school	no	no	no	telephone	may	mon	38	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
21	55	blue-collar	married	basic.4y	unknown	yes	no	telephone	may	mon	262	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
22	55	retired	single	high.school	no	yes	no	telephone	may	mon	342	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
23	41	technician	single	high.school	no	yes	no	telephone	may	mon	181	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
24	37	admin.	married	high.school	no	yes	no	telephone	may	mon	172	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
25	35	technician	married	university.de	no	no	yes	telephone	may	mon	99	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
26	59	technician	married	unknown	no	yes	no	telephone	may	mon	93	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
27	39	self-employe	married	basic.9y	unknown	no	no	telephone	may	mon	233	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
28	54	technician	single	university.de	unknown	no	no	telephone	may	mon	255	2	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
29	55	unknown	married	university.de	unknown	unknown	unknown	telephone	may	mon	362	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
30	46	admin.	married	unknown	no	no	no	telephone	may	mon	348	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
31	59	technician	married	unknown	no	yes	no	telephone	may	mon	386	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
32	49	blue-collar	married	unknown	no	no	no	telephone	may	mon	73	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
33	54	management	married	basic.4y	unknown	yes	no	telephone	may	mon	230	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
34	54	blue-collar	divorced	basic.4y	no	no	no	telephone	may	mon	208	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
35	55	unknown	married	basic.4y	unknown	yes	no	telephone	may	mon	336	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
36	34	services	married	high.school	no	no	no	telephone	may	mon	365	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
37	52	technician	married	basic.9y	no	yes	no	telephone	may	mon	1666	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
38	41	admin.	married	university.de	no	yes	no	telephone	may	mon	577	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
39	56	technician	married	basic.4y	no	yes	no	telephone	may	mon	137	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
40	58	management	unknown	university.de	no	yes	no	telephone	may	mon	366	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
41	32	entrepreneur	married	high.school	no	yes	no	telephone	may	mon	314	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
42	38	admin.	single	professional	no	no	no	telephone	may	mon	160	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
43	57	admin.	married	university.de	no	no	yes	telephone	may	mon	212	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
44	44	admin.	married	university.de	unknown	yes	no	telephone	may	mon	188	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
45	42	technician	single	professional	unknown	no	no	telephone	may	mon	22	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
46	57	admin.	married	university.de	no	yes	yes	telephone	may	mon	616	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
47	40	blue-collar	married	basic.9y	no	no	yes	telephone	may	mon	178	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no
48	35	admin.	married	university.de	no	yes	no	telephone	may	mon	355	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191	no

File
bank-additional-full.csv

Size
21 Columns,
41188 Rows

Dataset Link
https://www.kaggle.com/henriqueyamahata/bank-marketing?select=bank-additional-full.csv

- Dataset

In Classification

Numeric

- Age
- Duration
- Campaign
- Pdays
- Previous
- emp.var.rate
- cons.price.idx
- cons.conf.idx
- euribor3m
- nr.employed

Categorical

- Job
- Marital
- Education
- Default
- Housing
- Loan
- Contact
- month
- day_of_week:
- Poutcome
- **Y (target)**

"There is no null value in the data"

```
print("In Initial data, total dirty data count = ", sum(df.isna().sum()))
```

```
In Initial data, total dirty data count =  0
```

- Dataset

In Classification: Data selection

Numeric

- **Age**
- Duration
- Campaign
- Pdays
- Previous
- **emp.var.rate**
- **cons.price.idx**
- **cons.conf.idx**
- **euribor3m**
- **nr.employed**

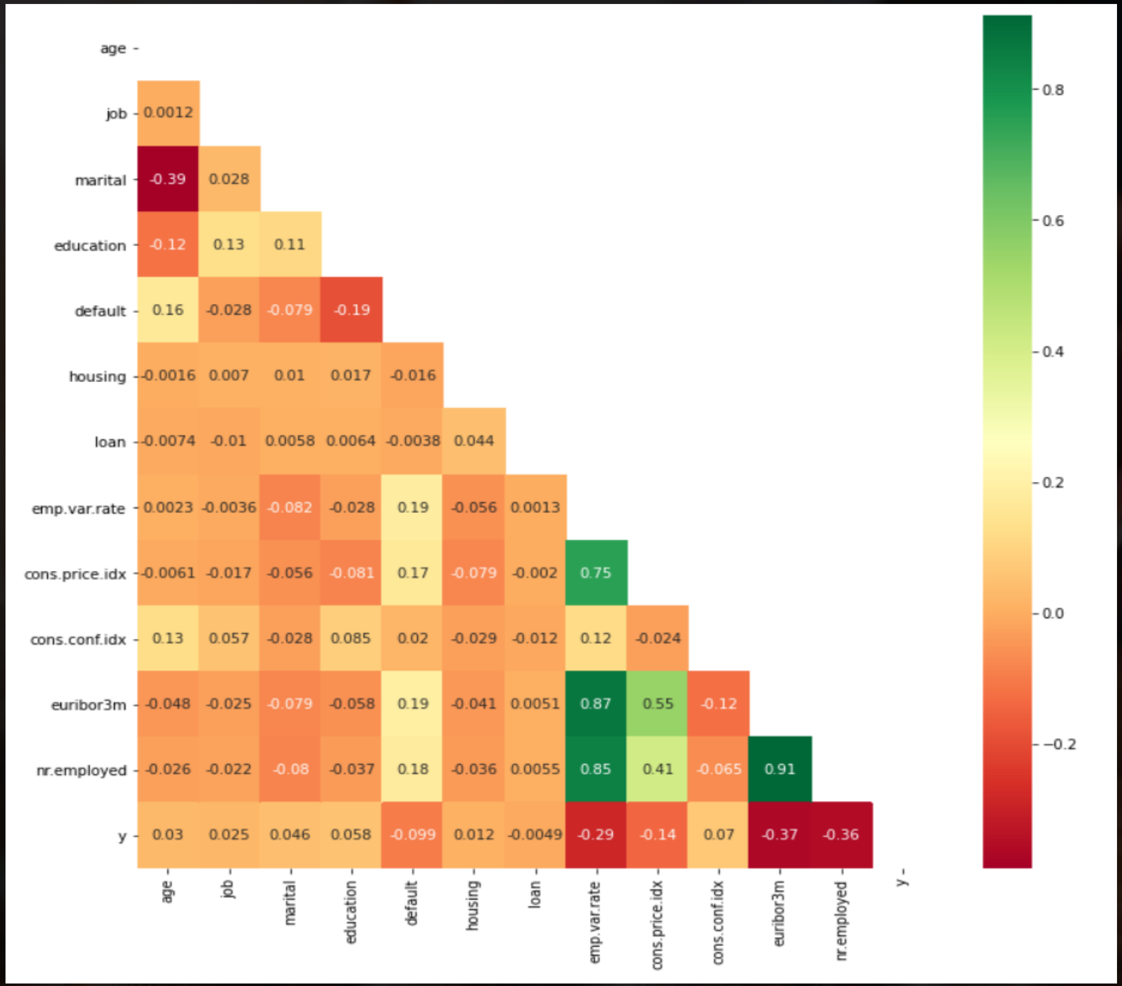
Categorical

- **Job**
- **Marital**
- **Education**
- **Default**
- **Housing**
- **Loan**
- Contact
- month
- day_of_week:
- Poutcome
- **Y (target)**

We chose "12 features"

– Dataset

In Classification : Correlation heatmap



- Data Preprocessing

In Classification

Apply One Hot Encoding to Categorical data

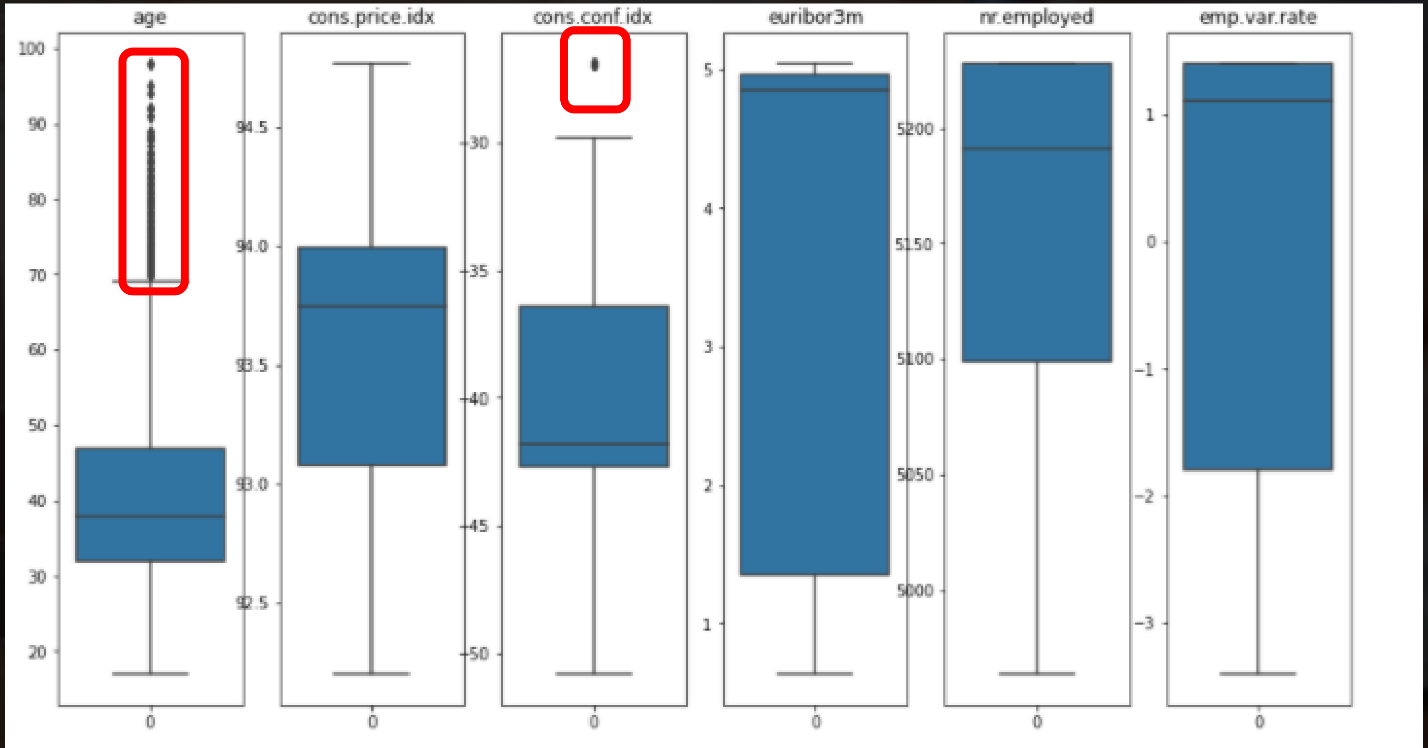
```
# ------------------------------------------------------------------
#            One Hot encoding
# ------------------------------------------------------------------
job_one_hot = pd.get_dummies(df2['job'], prefix='job')
marital_one_hot = pd.get_dummies(df2['marital'], prefix='marital')
education_one_hot = pd.get_dummies(df2['education'], prefix='education')
default_one_hot = pd.get_dummies(df2['default'], prefix='default')
housing_one_hot = pd.get_dummies(df2['housing'], prefix='housing')
loan_one_hot = pd.get_dummies(df2['loan'], prefix='loan')
```

Rows: 41188, Columns: 13 (12 (features) + 1 (target))

→ Rows: 41188, **Columns: 40**

– Data Preprocessing

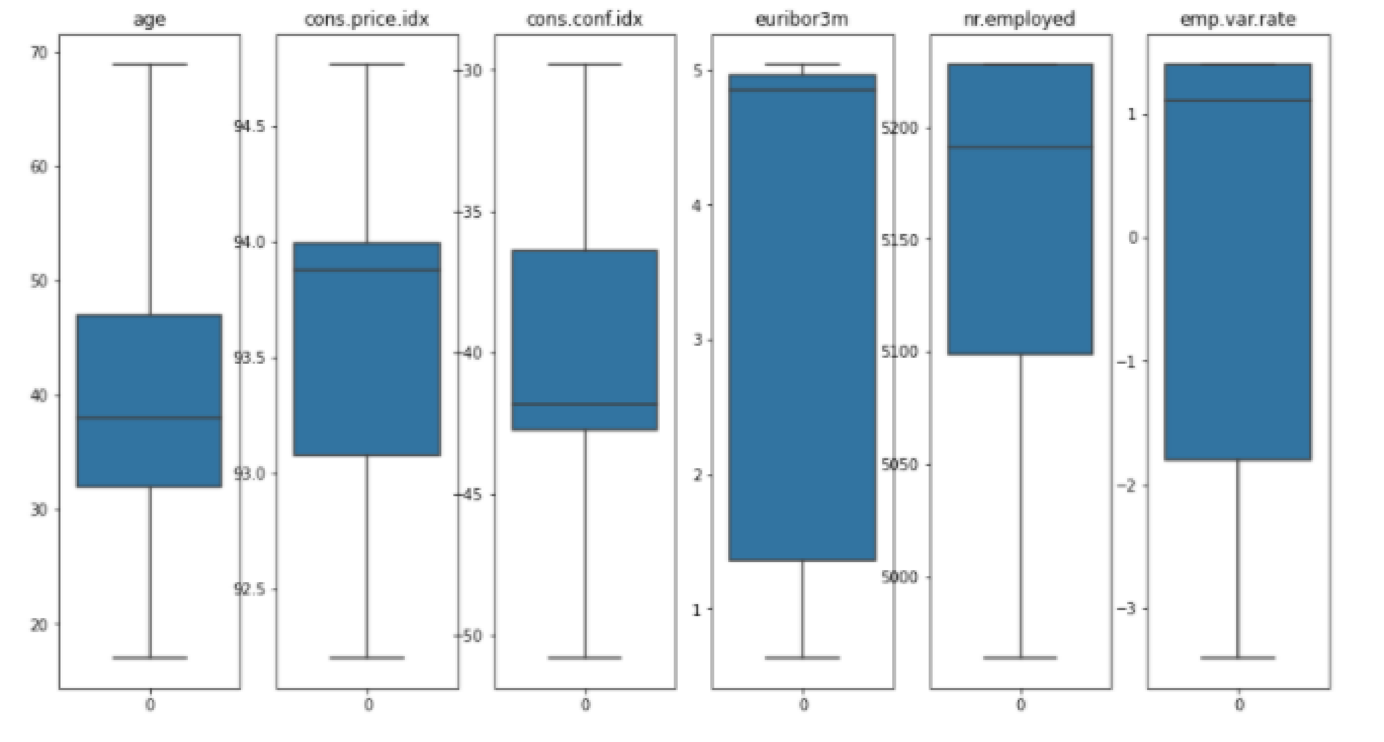
In Classification : Data Inspection & Outlier detection




```python
# ---------------------------------------------------------------
#          Function of getting of outlier index
# ---------------------------------------------------------------
def get_outlier(df=None, column=None, weight=1.5):

  quantile_25 = np.percentile(df[column].values, 25)
  quantile_75 = np.percentile(df[column].values, 75)

  IQR = quantile_75 - quantile_25
  IQR_weight = IQR*weight

  lowest = quantile_25 - IQR_weight
  highest = quantile_75 + IQR_weight

  outlier_idx = df[column][ (df[column] < lowest) | (df[column] > highest) ].index
  return outlier_idx
```

- Data Preprocessing

In Classification : Data Inspection & Outlier detection



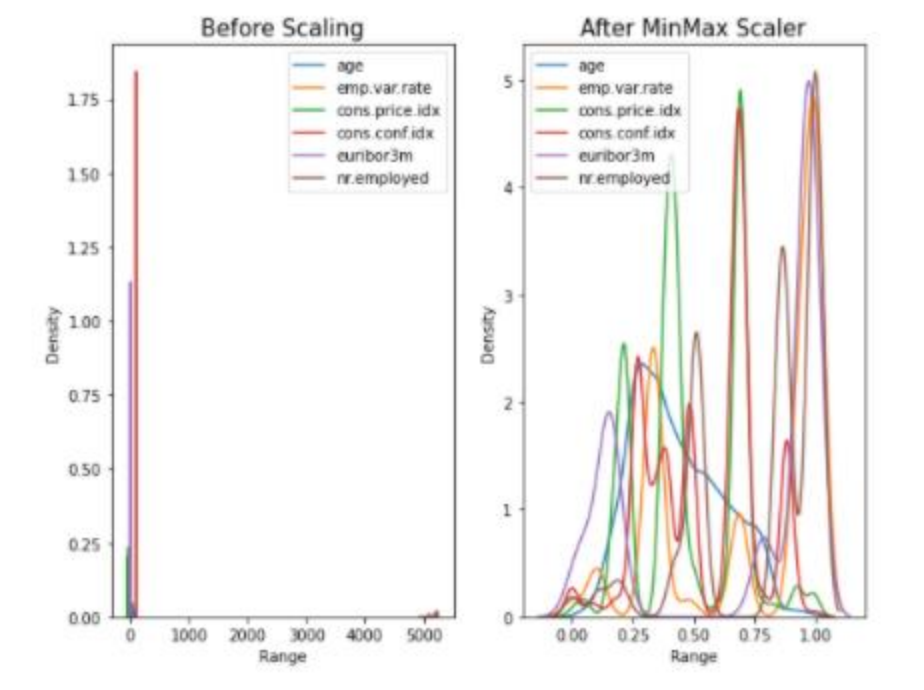
- Data Preprocessing

In Classification : Data Preparation

- Feature Scaling

min-max Scaler

```
# ---------------------------------------------------------
#                Normalization
# ---------------------------------------------------------
scaler = MinMaxScaler()
scaled_x = MinMaxScaler().fit_transform(X)
scaled_x = pd.DataFrame(scaled_x, columns=X.columns, index=list(X.index.values))
scaled_x.head()
```



- Training & Evaluation

In Classification

Model

- Decision Tree
- Logistic Regression
- KNN
- Gradient Boosting

Evaluation Method

- Accuracy
- Mean Square Error
- F1 Score
- Precision
- Recall

- Training & Evaluation

In Classification

Training Setting

```
# ─────────────────────────────────
#            Split data
# ─────────────────────────────────
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(scaled_x, y, test_size=0.2, shuffle=True, random_state=0)

kf = KFold(n_splits=5)
```

```
# ─────────────────────────────────────────────────
#            Logistic Regression
# ─────────────────────────────────────────────────
logisticRegr = LogisticRegression()
parameters = {'C': [0.1, 1.0, 10.0],
              'solver': ['liblinear', 'lbfgs', 'sag'],
              'max_iter': [50, 100, 200]}

reg_clf = GridSearchCV(logisticRegr, parameters, cv=kf)
```

Training data and test data were divided into 20% ratios

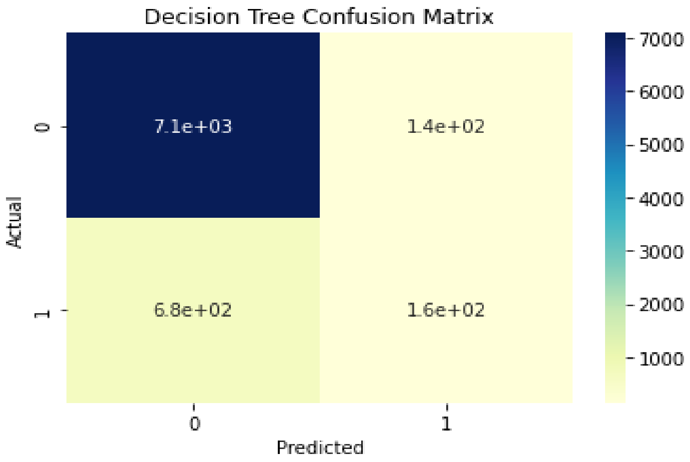
The optimal parameters were found using GridSearchCV

- Training & Evaluation

In Classification

Decision Tree

```
----------------- < Decision Tree > -----------------
Accuracy: 0.897
MSE(Mean Square Error):  0.103
F1 Score:  0.875
```

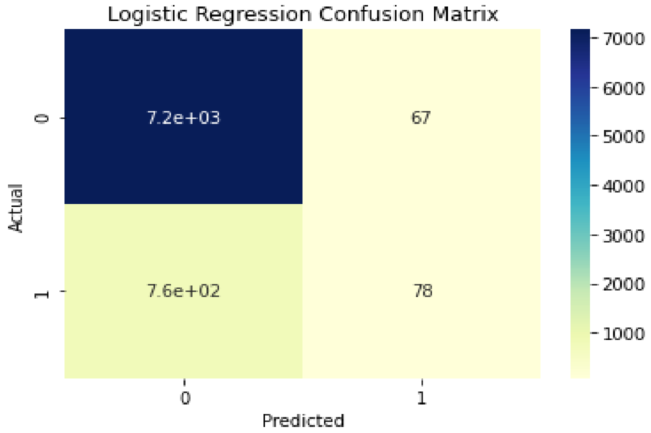


Decision Tree Classification Report

	precision	recall	f1-score	support
No	0.912	0.980	0.945	7223
Yes	0.526	0.190	0.279	843
accuracy			0.897	8066
macro avg	0.719	0.585	0.612	8066
weighted avg	0.872	0.897	0.875	8066

Logistic Regression Classification

```
----------------- < Logistic Regression > -----------------
Best parameters: {'C': 1.0, 'max_iter': 50, 'solver': 'lbfgs'}
Best score: 0.894
Accuracy: 0.897
MSE(Mean Square Error):  0.103
F1 Score:  0.863
```



Logistic Regression Classification Report

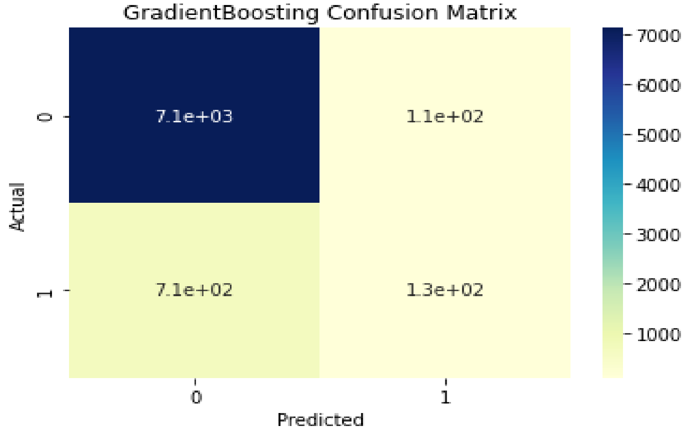
	precision	recall	f1-score	support
No	0.903	0.991	0.945	7223
Yes	0.538	0.093	0.158	843
accuracy			0.897	8066
macro avg	0.721	0.542	0.551	8066
weighted avg	0.865	0.897	0.863	8066

- Training & Evaluation

In Classification

Gradient Boosting

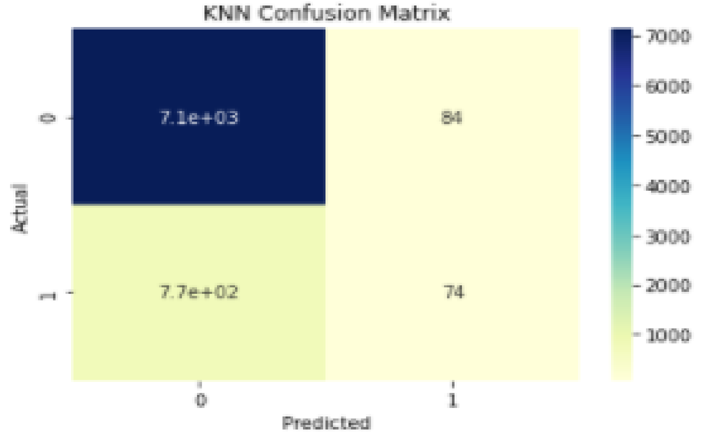
```
----------------- < GradientBoosting > -----------------
Accuracy: 0.898
MSE(Mean Square Error):  0.102
F1 Score:  0.872
```




```
GradientBoosting Classification Report
              precision    recall  f1-score   support

          No      0.909     0.985     0.945      7223
         Yes      0.547     0.159     0.246       843

    accuracy                          0.898      8066
   macro avg      0.728     0.572     0.596      8066
weighted avg      0.871     0.898     0.872      8066
```

KNN

```
---------------- < KNN > ----------------
Best parameters: {'algorithm': 'ball_tree', 'weights': 'uniform'}
Best score: 0.890052964403106
Accuracy: 0.894
MSE(Mean Square Error):  0.106
F1 Score:  0.86
```




```
KNN Classification Report
              precision    recall  f1-score   support

          No      0.903     0.988     0.944      7223
         Yes      0.468     0.088     0.148       843

    accuracy                          0.894      8066
   macro avg      0.686     0.538     0.546      8066
weighted avg      0.857     0.894     0.860      8066
```

- Training & Evaluation

In Classification

Final result

----------------- < Result > -----------------

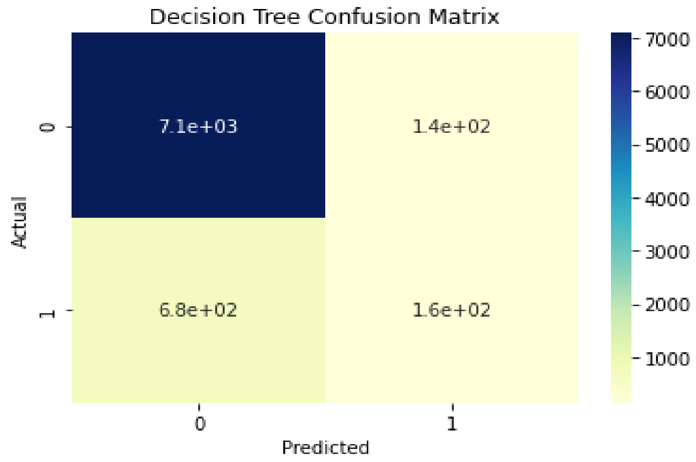
	Algorithm	Accuracy	MSE	F1-score
0	Decision Tree	0.897	0.103	0.875
1	Logistic Regression	0.897	0.103	0.863
2	KNN	0.894	0.106	0.860
3	GradientBoosting	0.898	0.102	0.872

- Training & Evaluation

In Classification

Decision Tree

```
----------------- < Decision Tree > -----------------
Accuracy: 0.897
MSE(Mean Square Error):  0.103
F1 Score:  0.875
```

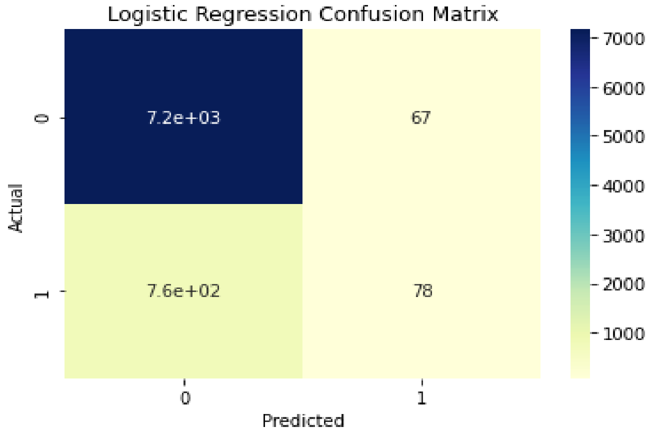


Decision Tree Classification Report

	precision	recall	f1-score	support
No	0.912	0.980	0.945	7223
Yes	0.526	0.190	0.279	843
accuracy			0.897	8066
macro avg	0.719	0.585	0.612	8066
weighted avg	0.872	0.897	0.875	8066

Logistic Regression Classification

```
----------------- < Logistic Regression > -----------------
Best parameters: {'C': 1.0, 'max_iter': 50, 'solver': 'lbfgs'}
Best score: 0.894
Accuracy: 0.897
MSE(Mean Square Error):  0.103
F1 Score:  0.863
```



Logistic Regression Classification Report

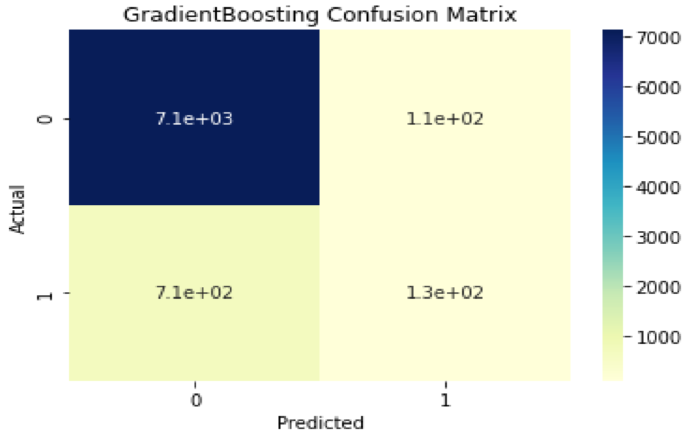
	precision	recall	f1-score	support
No	0.903	0.991	0.945	7223
Yes	0.538	0.093	0.158	843
accuracy			0.897	8066
macro avg	0.721	0.542	0.551	8066
weighted avg	0.865	0.897	0.863	8066

- Training & Evaluation

In Classification

Gradient Boosting

```
----------------- < GradientBoosting > -----------------
Accuracy: 0.898
MSE(Mean Square Error):  0.102
F1 Score:  0.872
```

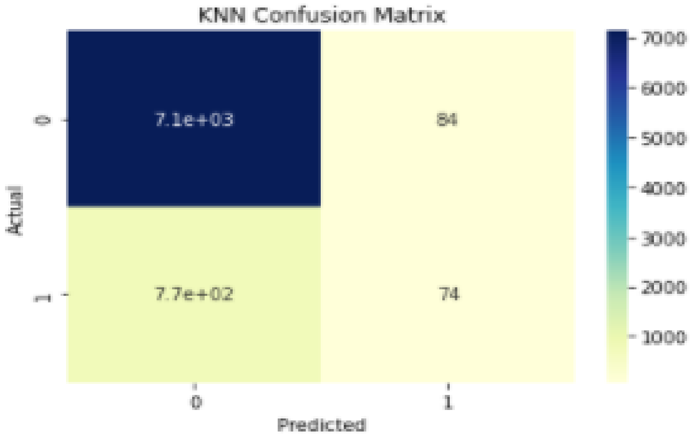


GradientBoosting Classification Report

	precision	recall	f1-score	support
No	0.909	0.985	0.945	7223
Yes	0.547	0.159	0.246	843
accuracy			0.898	8066
macro avg	0.728	0.572	0.596	8066
weighted avg	0.871	0.898	0.872	8066

KNN

```
----------------- < KNN > -----------------
Best parameters: {'algorithm': 'ball_tree', 'weights': 'uniform'}
Best score: 0.890052964403106
Accuracy: 0.894
MSE(Mean Square Error):  0.106
F1 Score:  0.86
```



KNN Classification Report

	precision	recall	f1-score	support
No	0.903	0.988	0.944	7223
Yes	0.468	0.088	0.148	843
accuracy			0.894	8066
macro avg	0.686	0.538	0.546	8066
weighted avg	0.857	0.894	0.860	8066

- Training & Evaluation

In Classification

Evaluation analysis

There is a <u>difference in the ratio of target data</u>

```
y_idx = df2['y'].unique()

y_count = df2['y'].value_counts()

sum = y_count[0] + y_count[1]
print("yes's ratio = {:.2f}%".format(y_count[1] / sum * 100))
print("no's ratio = {:.2f}%".format(y_count[0] / sum * 100))
```

```
yes's ratio = 10.56%
no's ratio = 89.44%
```

```
# ---------------------------------------------
#                Undersampling
# ---------------------------------------------

from collections import Counter
from imblearn.under_sampling import RandomUnderSampler
# summarize class distribution
print(Counter(y))

# define undersample strategy
undersample = RandomUnderSampler(sampling_strategy='majority')
# fit and apply the transform
X_under, y_under = undersample.fit_resample(X, y)

# summarize class distribution
print(Counter(y_under))
```

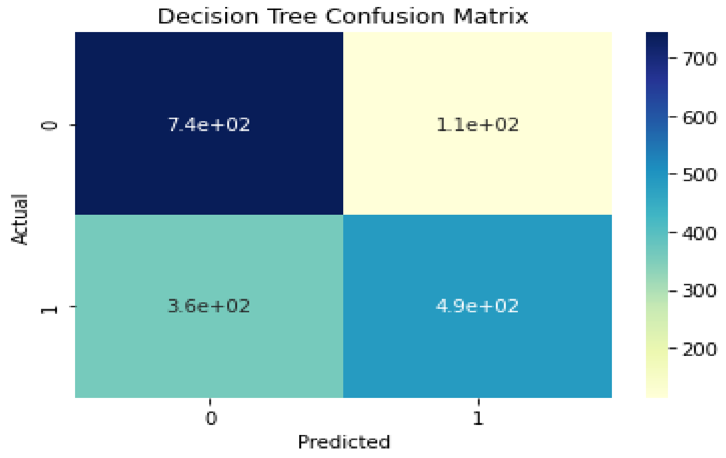
```
Counter({0: 36068, 1: 4259})
Counter({0: 4259, 1: 4259})
```

– Training & Evaluation

In Classification

Decision Tree

```
------------------ < Decision Tree > ------------------
Accuracy: 0.721
MSE(Mean Square Error):  0.279
F1 Score:  0.715
```

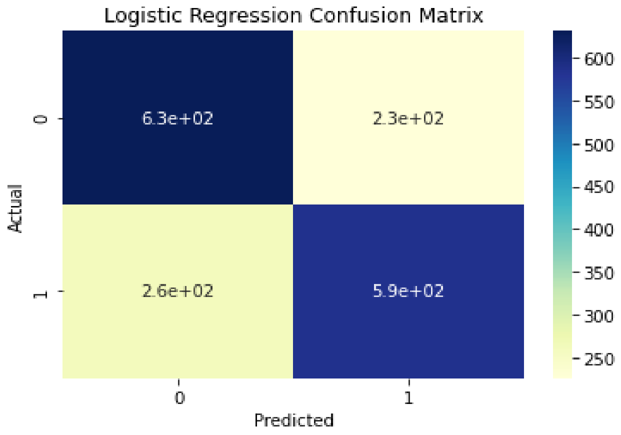


Decision Tree Classification Report

	precision	recall	f1-score	support
No	0.673	0.867	0.758	857
Yes	0.810	0.574	0.672	847
accuracy			0.721	1704
macro avg	0.742	0.720	0.715	1704
weighted avg	0.741	0.721	0.715	1704

Logistic Regression Classification

```
------------------ < Logistic Regression > ------------------
Best parameters: {'C': 0.1, 'max_iter': 50, 'solver': 'liblinear'}
Best score: 0.713
Accuracy: 0.714
MSE(Mean Square Error):  0.286
F1 Score:  0.714
```



Logistic Regression Classification Report

	precision	recall	f1-score	support
No	0.707	0.736	0.722	857
Yes	0.722	0.692	0.706	847
accuracy			0.714	1704
macro avg	0.715	0.714	0.714	1704
weighted avg	0.714	0.714	0.714	1704

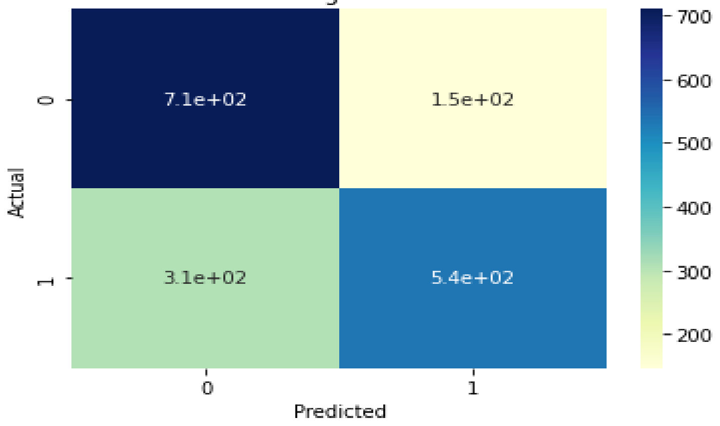
- Training & Evaluation

In Classification

Gradient Boosting

```
----------------- < GradientBoosting > -----------------
Accuracy: 0.732
MSE(Mean Square Error):  0.268
F1 Score:  0.73
```

GradientBoosting Confusion Matrix



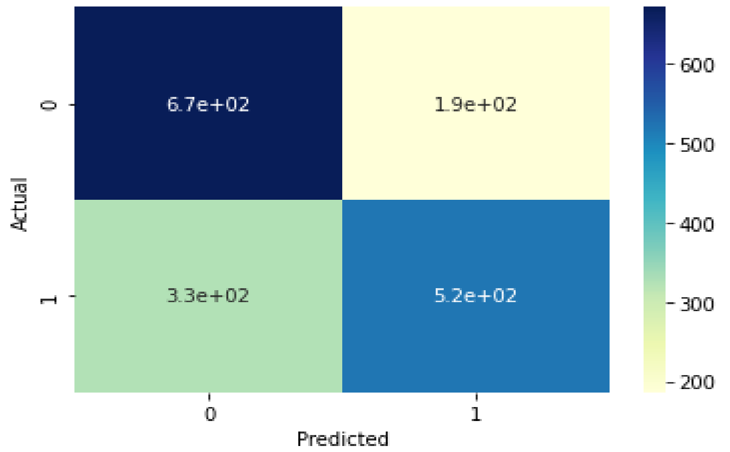
GradientBoosting Classification Report

	precision	recall	f1-score	support
No	0.697	0.828	0.757	857
Yes	0.785	0.635	0.702	847
accuracy			0.732	1704
macro avg	0.741	0.732	0.730	1704
weighted avg	0.741	0.732	0.730	1704

KNN

```
Accuracy: 0.7
MSE(Mean Square Error):  0.3
F1 Score:  0.697
```

KNN Confusion Matrix



KNN Classification Report

	precision	recall	f1-score	support
No	0.673	0.783	0.724	857
Yes	0.737	0.615	0.671	847
accuracy			0.700	1704
macro avg	0.705	0.699	0.697	1704
weighted avg	0.705	0.700	0.697	1704

Clustering

– Concept of project

In Clustering

The clustering goal is
to cluster the relationship between income groups
and population growth

- Dataset

In Clustering

Indicators.csv → Country Name& 2014 Population growth

Country.csv → Country Name & InComeGroup

	CountryName	IncomeGroup	Value
0	Afghanistan	Low income	3.033473
1	Albania	Upper middle income	-0.099830
2	Algeria	Upper middle income	1.940399
3	American Samoa	Upper middle income	0.238405
4	Andorra	High income: nonOECD	-4.191941

Shape

214 (Number of country) * 3

– Data Preprocessing

In Clustering

Apply Label Encoding to Categorical data

```python
# ENCODING
def ENCODING(df, column):
  encoder = LabelEncoder()
  encoder.fit(df[column])
  df[column] = encoder.transform(df[column])
  return df


df_mergeData = ENCODING(df_mergeData, 'IncomeGroup') # Label encoding

df_mergeData.head()
```

	IncomeGroup	Value
0	2	3.033473
1	4	-0.099830
2	4	1.940399
3	4	0.238405
4	1	-4.191941

```
Label encoding index = 0, label = High income: OECD
Label encoding index = 1, label = High income: nonOECD
Label encoding index = 2, label = Low income
Label encoding index = 3, label = Lower middle income
Label encoding index = 4, label = Upper middle income
```

– Training

In Clustering

Use 3 Machine Learning Algorithms

K Means, DBSCAN, EM

```python
def KMEANS_CLUSTERING(dataset1, dataset2):
  n_clusters = [2, 3, 4, 5, 6]
  max_iter = [50, 100, 200, 300]
  for i in n_clusters:
      for j in max_iter:
          print("n_cluster = {}, max_iter = {}".format(i,j))
          kmeans = KMeans(n_clusters=i, max_iter=j)
          pd_kmeans = kmeans.fit_predict(dataset1)
          dataset2['KMeans']=pd_kmeans
          # ------------------------------------------
          #  VISUALIZE BEST RESULT AS SCATTER PLOT
          # ------------------------------------------
          scatter_plot(pd_kmeans, dataset1, 'K-Means')
          make_Map(dataset2, 'KMeans')
```

```python
# Compute DBSCAN
def DBSCAN_CLUSTERING(dataset1, dataset2):

  # DBSCAN PARAMETER
  eps = [0.001, 0.002, 0.005, 0.01, 0.02, 0.05, 0.1, 0.2, 0.5]
  min_samples = [3, 5, 10, 15, 20, 30, 50, 100]
  for i in eps:
      for j in min_samples:
          print("eps = {}, min_samples = {}".format(i,j))
          dbscan = DBSCAN(eps=i, min_samples=j)
          pd_dbscan = dbscan.fit_predict(dataset1)
          dataset2['DBSCAN'] = pd_dbscan
          # ------------------------------------------
          #  VISUALIZE BEST RESULT AS SCATTER PLOT
          # ------------------------------------------
          scatter_plot(pd_dbscan, dataset1, 'DBSCAN')
          make_Map(dataset2, 'DBSCAN')
```

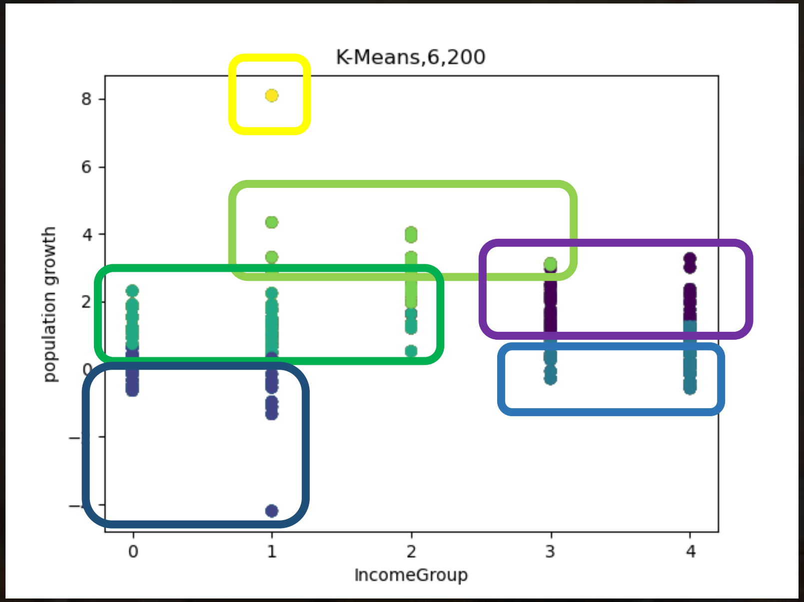
```python
def EM_CLUSTERING(dataset1, dataset2):
  # EM PARAMETER
  n_components = [2, 3, 4, 5, 6]
  max_iter = [50, 100, 200, 300]
  for i in n_components:
      for j in max_iter:
          print("n_components = {}, max_iter = {}".format(i,j))
          em = GaussianMixture(n_components=i, max_iter=j)
          pd_em = em.fit_predict(dataset1)
          dataset2['EM']=pd_em
          # ------------------------------------------
          #  VISUALIZE BEST RESULT AS SCATTER PLOT
          # ------------------------------------------
          scatter_plot(pd_em, dataset1, 'EM')
          make_Map(dataset2, 'EM')
```

Term Project Final

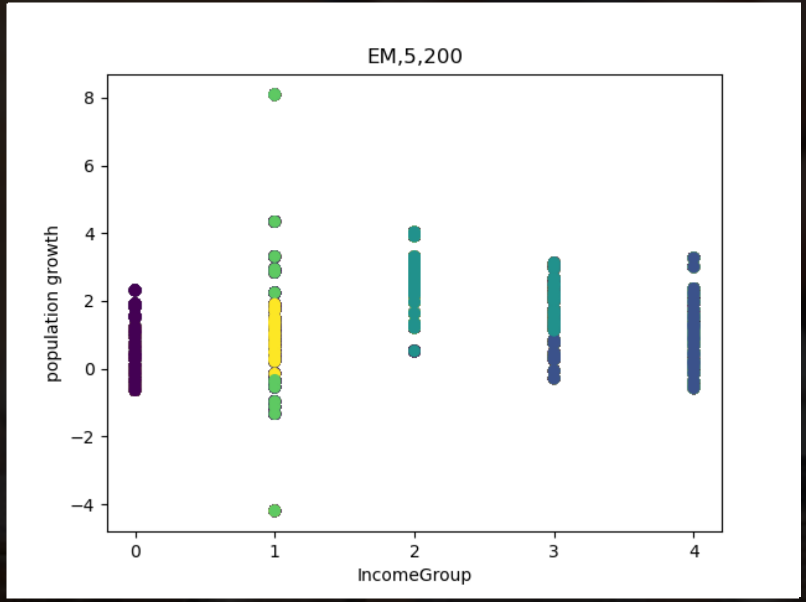
– Result

In Clustering

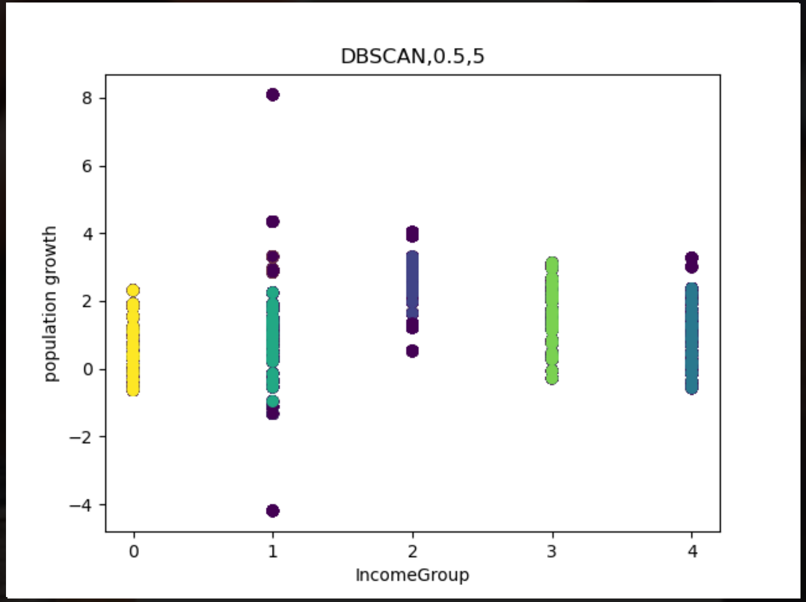
K-Means



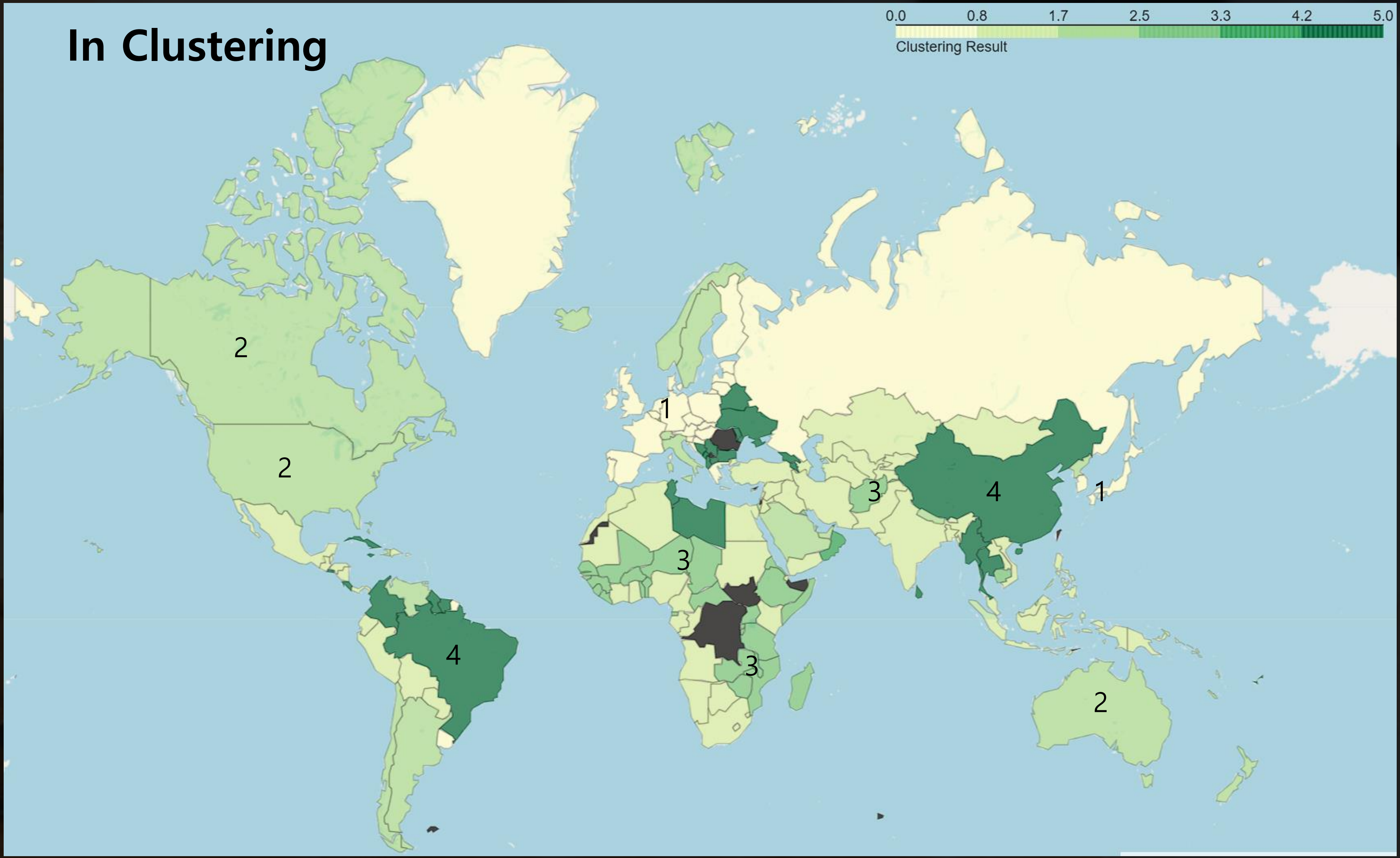
EM



DBSCAN



– Conclusion


In Clustering
0.0
0.8
1.7
2.5
3.3
4.2
5.0
Clustering Result
2
2
1
3
4
1
3
4
3
2

- Conclusion

In Classification

DON'T BE FOOLED

by the evaluation method of accuracy

Various evaluation methods should be analyzed.

The proportion of the Label in the data should be considered.

Q & A

Thank You