

*# This jupyter notebook was prepared by Jason Saini*

```
import warnings
warnings.filterwarnings('ignore')
```

## 1. Load and Perform Basic EDA

*##### import libraries*

```
import pandas as pd
import numpy as np
```

```
%matplotlib inline
import matplotlib.pyplot as plt
```

```
import seaborn as sns
import missingno as msno
from scipy import stats
```

```
import sklearn
```

*# II. import the data to a dataframe and show number of rows & cols*

```
df = pd.read_csv("hrdata2.csv")
print("Number of rows: " + str(df.shape[0]))
print("Number of cols: " + str(df.shape[1]))
```

Number of rows: 8955

Number of cols: 15

*# Show top 5 and last 5 rows*

```
df.head()
```

	Unnamed: 0	enrollee_id	city	city_development_index	gender	\
0	1	29725	city_40	0.776	Male	
1	4	666	city_162	0.767	Male	
2	7	402	city_46	0.762	Male	
3	8	27107	city_103	0.920	Male	
4	11	23853	city_103	0.920	Male	

	relevent_experience	enrolled_university	education_level	\
0	No relevent experience	no_enrollment	Graduate	
1	Has relevent experience	no_enrollment	Masters	
2	Has relevent experience	no_enrollment	Graduate	
3	Has relevent experience	no_enrollment	Graduate	
4	Has relevent experience	no_enrollment	Graduate	

	major_discipline	experience	company_size	company_type
last_new_job	\			
0	STEM	15	50-99	Pvt Ltd
>4				
1	STEM	21	50-99	Funded Startup
4				
2	STEM	13	<10	Pvt Ltd

```
>4
3          STEM          7          50-99          Pvt Ltd
1
4          STEM          5          5000-9999          Pvt Ltd
1
```

```
      training_hours  target
0             47         0
1              8         0
2             18         1
3             46         1
4            108         0
```

```
df.tail()
```

```
      Unnamed: 0  enrollee_id      city  city_development_index
gender \
8950      19147      21319  city_21              0.624
Male
8951      19149         251  city_103              0.920
Male
8952      19150      32313  city_160              0.920
Female
8953      19152      29754  city_103              0.920
Female
8954      19155      24576  city_103              0.920
Male
```

```
      relevent_experience  enrolled_university  education_level \
8950  No relevent experience  Full time course  Graduate
8951  Has relevent experience  no_enrollment  Masters
8952  Has relevent experience  no_enrollment  Graduate
8953  Has relevent experience  no_enrollment  Graduate
8954  Has relevent experience  no_enrollment  Graduate
```

```
      major_discipline  experience  company_size      company_type
last_new_job \
8950      STEM          1      100-500          Pvt Ltd
1
8951      STEM          9      50-99          Pvt Ltd
1
8952      STEM          10     100-500  Public Sector
3
8953      Humanities      7      Oct-49  Funded Startup
1
8954      STEM          21      50-99          Pvt Ltd
4
```

```
      training_hours  target
8950             52         1
```

```
8951          36          1
8952          23          0
8953          25          0
8954          44          0
```

*#Show how many columns have null values*

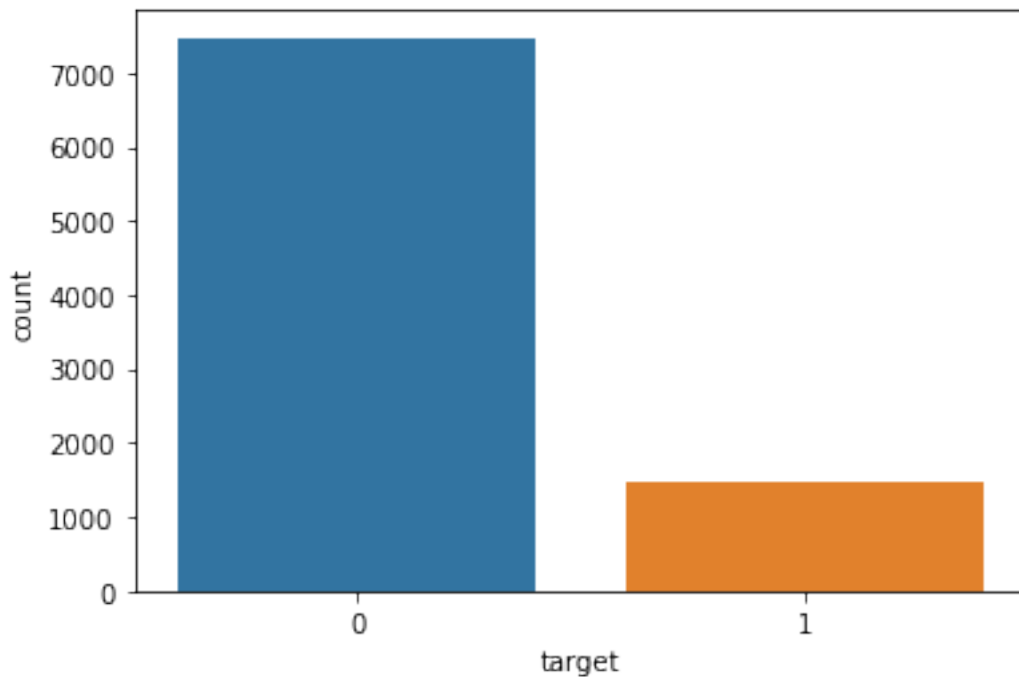
```
df.isnull().any()
```

```
Unnamed: 0          False
enrollee_id         False
city               False
city_development_index False
gender             False
relevent_experience False
enrolled_university False
education_level     False
major_discipline    False
experience          False
company_size        False
company_type        False
last_new_job        False
training_hours      False
target             False
dtype: bool
```

**dataset has no missing values.**

*# Plot the count of target*

```
ax = sns.countplot(x = "target", data = df)
```



discuss its imbalances and probably issues and solutions:

Clearly the data has a lot more 0 values for target, which will definitely cause a bias in our classification models. Our classifier will not be able to properly identify each class, and will most likely overfit to the 0.0 labels. We could solve this by oversampling targets with value 1.0 or undersampling targets with 0.0. After researching from the assignment specs, I see that we can use SMOTE (Synthetic Minority Oversampling Technique) to oversample (in this case 1.0) to generate new instances of minority cases to help balance the data.

```
df = df.drop("Unnamed: 0",axis = 1)
df
```

	enrollee_id	city	city_development_index	gender \
0	29725	city_40	0.776	Male
1	666	city_162	0.767	Male
2	402	city_46	0.762	Male
3	27107	city_103	0.920	Male
4	23853	city_103	0.920	Male
...	...	...	...	...
8950	21319	city_21	0.624	Male
8951	251	city_103	0.920	Male
8952	32313	city_160	0.920	Female
8953	29754	city_103	0.920	Female
8954	24576	city_103	0.920	Male

	relevent_experience	enrolled_university	education_level \
0	No relevent experience	no_enrollment	Graduate
1	Has relevent experience	no_enrollment	Masters
2	Has relevent experience	no_enrollment	Graduate
3	Has relevent experience	no_enrollment	Graduate
4	Has relevent experience	no_enrollment	Graduate
...	...	...	...
8950	No relevent experience	Full time course	Graduate
8951	Has relevent experience	no_enrollment	Masters
8952	Has relevent experience	no_enrollment	Graduate
8953	Has relevent experience	no_enrollment	Graduate
8954	Has relevent experience	no_enrollment	Graduate

	major_discipline	experience	company_size	company_type
last_new_job \				
0	STEM	15	50-99	Pvt Ltd
>4				
1	STEM	21	50-99	Funded Startup
4				
2	STEM	13	<10	Pvt Ltd
>4				
3	STEM	7	50-99	Pvt Ltd
1				
4	STEM	5	5000-9999	Pvt Ltd
1				

```

...
...
8950          STEM          1      100-500      Pvt Ltd
1
8951          STEM          9        50-99      Pvt Ltd
1
8952          STEM         10      100-500  Public Sector
3
8953  Humanities          7      Oct-49  Funded Startup
1
8954          STEM         21        50-99      Pvt Ltd
4

```

```

      training_hours  target
0             47         0
1              8         0
2             18         1
3             46         1
4            108         0
...
8950          52         1
8951          36         1
8952          23         0
8953          25         0
8954          44         0

```

[8955 rows x 14 columns]

## 2. Feature Selection and Pre-processing

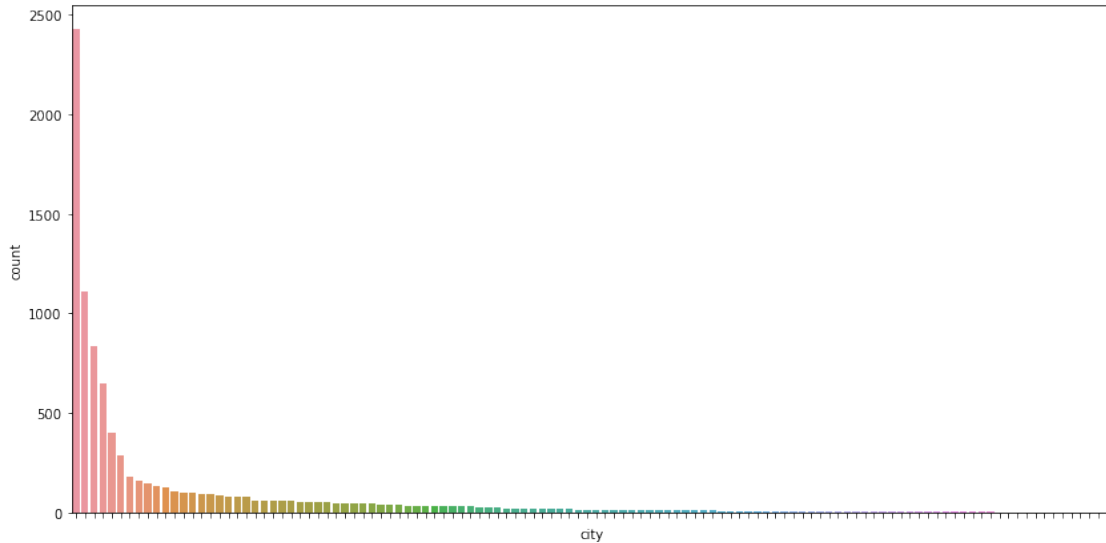
### 2.1. Preprocessing City

*# Plot #of records per city so that the highest city counts are shown in descending order*

```

plt.figure(figsize=(14,7))
ax = sns.countplot(x = "city", data = df, order =
df["city"].value_counts().index)
ax.set(xticklabels=[])
plt.show()

```



How many rows belong to the top 5 cities in total and how many for the remaining?

```
df["city"].value_counts()
```

```
city_103    2426
city_21     1111
city_16      836
city_114     648
city_160     401
...
city_127      1
city_107      1
city_62       1
city_109      1
city_25       1
Name: city, Length: 116, dtype: int64
```

**The top 5 cities:**

```
top_cities = df["city"].value_counts().head(5)
top_cities
```

```
city_103    2426
city_21     1111
city_16      836
city_114     648
city_160     401
Name: city, dtype: int64
```

**And the rest have 1 row per city**

```
# Replace the city name with city_others if the city name is not
within the top 4 city names
df = df.loc[~df["city"].isin(top_cities)].rename(columns={'city' :
'city_others'})
```

#records have changed accordingly

df

	enrollee_id	city_others	city_development_index	gender	\
0	29725	city_40	0.776	Male	
1	666	city_162	0.767	Male	
2	402	city_46	0.762	Male	
3	27107	city_103	0.920	Male	
4	23853	city_103	0.920	Male	
...	...	...	...	...	
8950	21319	city_21	0.624	Male	
8951	251	city_103	0.920	Male	
8952	32313	city_160	0.920	Female	
8953	29754	city_103	0.920	Female	
8954	24576	city_103	0.920	Male	

	relevent_experience	enrolled_university	education_level	\
0	No relevent experience	no_enrollment	Graduate	
1	Has relevent experience	no_enrollment	Masters	
2	Has relevent experience	no_enrollment	Graduate	
3	Has relevent experience	no_enrollment	Graduate	
4	Has relevent experience	no_enrollment	Graduate	
...	...	...	...	
8950	No relevent experience	Full time course	Graduate	
8951	Has relevent experience	no_enrollment	Masters	
8952	Has relevent experience	no_enrollment	Graduate	
8953	Has relevent experience	no_enrollment	Graduate	
8954	Has relevent experience	no_enrollment	Graduate	

	major_discipline	experience	company_size	company_type
last_new_job \				
0	STEM	15	50-99	Pvt Ltd
>4				
1	STEM	21	50-99	Funded Startup
4				
2	STEM	13	<10	Pvt Ltd
>4				
3	STEM	7	50-99	Pvt Ltd
1				
4	STEM	5	5000-9999	Pvt Ltd
1				
...	...	...	...	...
...				
8950	STEM	1	100-500	Pvt Ltd
1				
8951	STEM	9	50-99	Pvt Ltd
1				
8952	STEM	10	100-500	Public Sector
3				
8953	Humanities	7	Oct-49	Funded Startup

1				
8954	STEM	21	50-99	Pvt Ltd
4				

	training_hours	target
0	47	0
1	8	0
2	18	1
3	46	1
4	108	0
...	...	...
8950	52	1
8951	36	1
8952	23	0
8953	25	0
8954	44	0

[8955 rows x 14 columns]

## 2.2. Preprocessing Education Level

*# unique values of education level*

```
df["education_level"].unique()
```

```
array(['Graduate', 'Masters', 'Phd'], dtype=object)
```

*# Replace the value of Education level column like ordinal values*

*# "Graduate" -> 0, Masters->1, and Phd -> 2*

```
education_mapper = {"Graduate": 0, "Masters": 1, "Phd": 2}
```

```
df["education_level"] =
```

```
df["education_level"].replace(education_mapper)
```

```
df["education_level"]
```

0	0
---	---

1	1
---	---

2	0
---	---

3	0
---	---

4	0
---	---

...	..
-----	----

8950	0
------	---

8951	1
------	---

8952	0
------	---

8953	0
------	---

8954	0
------	---

Name: education\_level, Length: 8955, dtype: int64

*# updated values of education level*

```
df["education_level"].unique()
```

```
array([0, 1, 2], dtype=int64)
```



### 2.3. Preprocessing Company size

*# unique values of the company\_size column*

```
df["company_size"].unique()
```

```
array(['50-99', '<10', '5000-9999', '1000-4999', '0ct-49', '100-500',  
      '10000+', '500-999'], dtype=object)
```

*# Change the values of the company\_size column from*

*# 0 to 7 where 0 is <10 and 7 is 10000+*

```
df.loc[df.company_size == '<10', 'company_size'] = 0  
df.loc[np.logical_or(df.company_size == '0ct-49', df.company_size ==  
  '10-49'), "company_size"] = 1  
df.loc[df.company_size == '50-99', 'company_size'] = 2  
df.loc[df.company_size == '100-500', 'company_size'] = 3  
df.loc[df.company_size == '500-999', 'company_size'] = 4  
df.loc[df.company_size == '1000-4999', 'company_size'] = 5  
df.loc[df.company_size == '5000-9999', 'company_size'] = 6  
df.loc[df.company_size == '10000+', 'company_size'] = 7
```

```
df["company_size"].unique()
```

```
array([2, 0, 6, 5, 1, 3, 7, 4], dtype=object)
```

### 2.4 Preprocessing last new job

*# unique values of the company\_size column*

```
df["last_new_job"].unique()
```

```
array(['>4', '4', '1', '3', '2', 'never'], dtype=object)
```

*# Convert the values of this column*

```
LNJ_mapper = {"never": 0, "1": 1, "2": 2, "3": 3, "4": 4, ">4": 5}
```

```
df["last_new_job"] = df["last_new_job"].replace(LNJ_mapper)
```

*# updated values of last\_new\_job*

```
df["last_new_job"].unique()
```

```
array([5, 4, 1, 3, 2, 0], dtype=int64)
```

### 2.5 Remaining columns

*# Show the unique values of*

*# company\_type, major\_discipline, enrolled\_university,*

*# relevant\_experience, gender, and updated\_city column*

```
df["company_type"].unique()
```

```
array(['Pvt Ltd', 'Funded Startup', 'Early Stage Startup',  
      'Public Sector', 'NGO', 'Other'], dtype=object)
```

```
df["major_discipline"].unique()
```

```
array(['STEM', 'Humanities', 'Business Degree', 'Other', 'No Major',  
      'Arts'], dtype=object)
```

```

df["enrolled_university"].unique()

array(['no_enrollment', 'Part time course', 'Full time course'],
      dtype=object)

df["relevent_experience"].unique()

array(['No relevent experience', 'Has relevent experience'],
      dtype=object)

df["gender"].unique()

array(['Male', 'Female', 'Other'], dtype=object)

df["city_others"].unique()

array(['city_40', 'city_162', 'city_46', 'city_103', 'city_61',
      'city_114', 'city_159', 'city_21', 'city_160', 'city_16',
      'city_83', 'city_64', 'city_105', 'city_104', 'city_73',
      'city_75',
      'city_100', 'city_93', 'city_67', 'city_13', 'city_36',
      'city_71',
      'city_57', 'city_65', 'city_11', 'city_136', 'city_97',
      'city_50',
      'city_173', 'city_82', 'city_89', 'city_150', 'city_90',
      'city_98',
      'city_28', 'city_115', 'city_94', 'city_165', 'city_142',
      'city_12', 'city_43', 'city_74', 'city_102', 'city_116',
      'city_99',
      'city_23', 'city_138', 'city_45', 'city_41', 'city_72',
      'city_19',
      'city_101', 'city_20', 'city_106', 'city_10', 'city_157',
      'city_144', 'city_91', 'city_133', 'city_145', 'city_123',
      'city_175', 'city_128', 'city_167', 'city_84', 'city_54',
      'city_126', 'city_81', 'city_176', 'city_131', 'city_149',
      'city_24', 'city_27', 'city_118', 'city_152', 'city_141',
      'city_76', 'city_70', 'city_143', 'city_78', 'city_53',
      'city_158',
      'city_2', 'city_77', 'city_117', 'city_120', 'city_9',
      'city_39',
      'city_80', 'city_155', 'city_179', 'city_37', 'city_30',
      'city_44',
      'city_14', 'city_55', 'city_42', 'city_1', 'city_59',
      'city_69',
      'city_7', 'city_109', 'city_26', 'city_62', 'city_18',
      'city_127',
      'city_33', 'city_134', 'city_146', 'city_107', 'city_166',
      'city_121', 'city_129', 'city_48', 'city_139', 'city_25'],
      dtype=object)

# function to one-hot-encode our categorical columns
def one_hot_encode(in_df, cat_cols):

```

```

    for col in cat_cols:
        temp_df = pd.get_dummies(in_df[col], prefix = col, drop_first
= True)
        in_df = in_df.drop(columns = col)

        encoded_df = pd.merge(
            left = in_df,
            right = temp_df,
            left_index = True,
            right_index = True,
        )
    if(col in encoded_df.columns):
        encoded_df = encoded_df.drop(columns = col)
    print(encoded_df)
    return encoded_df

# show all columns for one-hot encoding
pd.set_option('display.max_columns', None)
one_hot_encoded_df = one_hot_encode(df,
["company_type","major_discipline","enrolled_university","relevent_exp
erience", "gender", "city_others"] ) #pd.get_dummies(df, columns =
["company_type","major_discipline","enrolled_university","relevent_exp
erience", "gender", "city_others"], drop_first = True)

```

	enrollee_id	city_development_index	education_level	experience
\				
0	29725	0.776	0	15
1	666	0.767	1	21
2	402	0.762	0	13
3	27107	0.920	0	7
4	23853	0.920	0	5
...	...	...	...	...
8950	21319	0.624	0	1
8951	251	0.920	1	9
8952	32313	0.920	0	10
8953	29754	0.920	0	7
8954	24576	0.920	0	21

	company_size	last_new_job	training_hours	target
city_others_city_10 \				
0	2	5	47	0
0				
1	2	4	8	0
0				
2	0	5	18	1
0				
3	2	1	46	1
0				
4	6	1	108	0
0				
...	...	...	...	...
...				
8950	3	1	52	1
0				
8951	2	1	36	1
0				
8952	3	3	23	0
0				
8953	1	1	25	0
0				
8954	2	4	44	0
0				

	city_others_city_100	city_others_city_101	city_others_city_102
\			
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_103	city_others_city_104	city_others_city_105
\			
0	0	0	0
1	0	0	0
2	0	0	0
3	1	0	0
4	1	0	0
...	...	...	...
8950	0	0	0
8951	1	0	0
8952	0	0	0
8953	1	0	0
8954	1	0	0

	city_others_city_106	city_others_city_107	city_others_city_109
\			
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0

8954	0	0	0
------	---	---	---

	city_others_city_11	city_others_city_114	city_others_city_115
\			
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...

8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_116	city_others_city_117	city_others_city_118
\			
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...

8950	0	0	0
8951	0	0	0
8952	0	0	0

8953	0	0	0
8954	0	0	0

	city_others_city_12	city_others_city_120	city_others_city_121
\			
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_123	city_others_city_126	city_others_city_127
\			
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...
8950	0	0	0
8951	0	0	0

8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_128	city_others_city_129	city_others_city_13
\			
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...

8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_131	city_others_city_133	city_others_city_134
\			
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...
8950	0	0	0



8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_136	city_others_city_138	city_others_city_139
\			
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_14	city_others_city_141	city_others_city_142
\			
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...

8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_143	city_others_city_144	city_others_city_145
\			
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_146	city_others_city_149	city_others_city_150
\			
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

...	...	...	...
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_152	city_others_city_155	city_others_city_157
\			
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

...	...	...	...
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_158	city_others_city_159	city_others_city_16
\			
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0

4	0	0	0
...	...	...	...
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_160	city_others_city_162	city_others_city_165
\			
0	0	0	0
1	0	1	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...
8950	0	0	0
8951	0	0	0
8952	1	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_166	city_others_city_167	city_others_city_173
\			
0	0	0	0
1	0	0	0
2	0	0	0

3	0	0	0
4	0	0	0
...	...	...	...
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_175	city_others_city_176	city_others_city_179
\			
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_18	city_others_city_19	city_others_city_2	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

...	...	...	...
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0
	city_others_city_20	city_others_city_21	city_others_city_23 \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...
8950	0	1	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0
	city_others_city_24	city_others_city_25	city_others_city_26 \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0
	city_others_city_27	city_others_city_28	city_others_city_30 \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0
	city_others_city_33	city_others_city_36	city_others_city_37 \
0	0	0	0
1	0	0	0
2	0	0	0

3	0	0	0
4	0	0	0
...	...	...	...
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_39	city_others_city_40	city_others_city_41	\
0	0	1	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	
...	...	...	...	
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_42	city_others_city_43	city_others_city_44	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	
...	...	...	...	
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_45	city_others_city_46	city_others_city_48	\
0	0	0	0	
1	0	0	0	
2	0	1	0	
3	0	0	0	
4	0	0	0	
...	...	...	...	
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_50	city_others_city_53	city_others_city_54	\
0	0	0	0	

1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_55	city_others_city_57	city_others_city_59	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	
...	...	...	...	
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_61	city_others_city_62	city_others_city_64	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	
...	...	...	...	
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_65	city_others_city_67	city_others_city_69	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	
...	...	...	...	
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	



	city_others_city_7	city_others_city_70	city_others_city_71	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	
...	...	...	...	
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_72	city_others_city_73	city_others_city_74	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	
...	...	...	...	
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_75	city_others_city_76	city_others_city_77	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	
...	...	...	...	
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_78	city_others_city_80	city_others_city_81	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	
...	...	...	...	
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	

8954	0	0	0
	city_others_city_82	city_others_city_83	city_others_city_84 \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_89	city_others_city_9	city_others_city_90 \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_91	city_others_city_93	city_others_city_94 \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_97	city_others_city_98	city_others_city_99
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...
8950	0	0	0
8951	0	0	0

8952	0	0	0
8953	0	0	0
8954	0	0	0

[8955 rows x 123 columns]

one\_hot\_encoded\_df.head()

	enrollee_id	city_development_index	education_level	experience	\
0	29725	0.776	0	15	
1	666	0.767	1	21	
2	402	0.762	0	13	
3	27107	0.920	0	7	
4	23853	0.920	0	5	

	company_size	last_new_job	training_hours	target
city_others_city_10	\			
0	2	5	47	0
0				
1	2	4	8	0
0				
2	0	5	18	1
0				
3	2	1	46	1
0				
4	6	1	108	0
0				

	city_others_city_100	city_others_city_101	city_others_city_102	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	city_others_city_103	city_others_city_104	city_others_city_105	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	1	0	0	
4	1	0	0	

	city_others_city_106	city_others_city_107	city_others_city_109	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	city_others_city_11	city_others_city_114	city_others_city_115	\
--	---------------------	----------------------	----------------------	---

0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	city_others_city_116	city_others_city_117	city_others_city_118	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	city_others_city_12	city_others_city_120	city_others_city_121	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	city_others_city_123	city_others_city_126	city_others_city_127	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	city_others_city_128	city_others_city_129	city_others_city_13	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	city_others_city_131	city_others_city_133	city_others_city_134	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	city_others_city_136	city_others_city_138	city_others_city_139	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	city_others_city_14	city_others_city_141	city_others_city_142	\
--	---------------------	----------------------	----------------------	---

0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	city_others_city_143	city_others_city_144	city_others_city_145	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	city_others_city_146	city_others_city_149	city_others_city_150	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	city_others_city_152	city_others_city_155	city_others_city_157	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	city_others_city_158	city_others_city_159	city_others_city_16	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	city_others_city_160	city_others_city_162	city_others_city_165	\
0	0	0	0	
1	0	1	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	city_others_city_166	city_others_city_167	city_others_city_173	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	city_others_city_175	city_others_city_176	city_others_city_179	\
--	----------------------	----------------------	----------------------	---

0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	city_others_city_18	city_others_city_19	city_others_city_20 \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	city_others_city_20	city_others_city_21	city_others_city_23 \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	city_others_city_24	city_others_city_25	city_others_city_26 \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	city_others_city_27	city_others_city_28	city_others_city_30 \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	city_others_city_33	city_others_city_36	city_others_city_37 \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	city_others_city_39	city_others_city_40	city_others_city_41 \
0	0	1	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

	city_others_city_42	city_others_city_43	city_others_city_44 \
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0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
	city_others_city_45	city_others_city_46	city_others_city_48 \
0	0	0	0
1	0	0	0
2	0	1	0
3	0	0	0
4	0	0	0
	city_others_city_50	city_others_city_53	city_others_city_54 \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
	city_others_city_55	city_others_city_57	city_others_city_59 \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
	city_others_city_61	city_others_city_62	city_others_city_64 \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
	city_others_city_65	city_others_city_67	city_others_city_69 \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
	city_others_city_7	city_others_city_70	city_others_city_71 \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
	city_others_city_72	city_others_city_73	city_others_city_74 \

0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
	city_others_city_75	city_others_city_76	city_others_city_77 \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
	city_others_city_78	city_others_city_80	city_others_city_81 \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
	city_others_city_82	city_others_city_83	city_others_city_84 \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
	city_others_city_89	city_others_city_9	city_others_city_90 \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
	city_others_city_91	city_others_city_93	city_others_city_94 \
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
	city_others_city_97	city_others_city_98	city_others_city_99
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

```
one_hot_encoded_df.tail()
```



	enrollee_id	city_development_index	education_level	experience
\				
8950	21319	0.624	0	1
8951	251	0.920	1	9
8952	32313	0.920	0	10
8953	29754	0.920	0	7
8954	24576	0.920	0	21

	company_size	last_new_job	training_hours	target
city_others_city_10				
\				
8950	3	1	52	1
0				
8951	2	1	36	1
0				
8952	3	3	23	0
0				
8953	1	1	25	0
0				
8954	2	4	44	0
0				

	city_others_city_100	city_others_city_101	city_others_city_102
\			
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_103	city_others_city_104	city_others_city_105
\			
8950	0	0	0
8951	1	0	0
8952	0	0	0
8953	1	0	0

8954	1	0	0
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	city_others_city_106	city_others_city_107	city_others_city_109
--	----------------------	----------------------	----------------------

\			
8950	0	0	0

8951	0	0	0
------	---	---	---

8952	0	0	0
------	---	---	---

8953	0	0	0
------	---	---	---

8954	0	0	0
------	---	---	---

	city_others_city_11	city_others_city_114	city_others_city_115
--	---------------------	----------------------	----------------------

\			
8950	0	0	0

8951	0	0	0
------	---	---	---

8952	0	0	0
------	---	---	---

8953	0	0	0
------	---	---	---

8954	0	0	0
------	---	---	---

	city_others_city_116	city_others_city_117	city_others_city_118
--	----------------------	----------------------	----------------------

\			
8950	0	0	0

8951	0	0	0
------	---	---	---

8952	0	0	0
------	---	---	---

8953	0	0	0
------	---	---	---

8954	0	0	0
------	---	---	---

	city_others_city_12	city_others_city_120	city_others_city_121
--	---------------------	----------------------	----------------------

\			
8950	0	0	0

8951	0	0	0
------	---	---	---

8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_123	city_others_city_126	city_others_city_127
\			
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_128	city_others_city_129	city_others_city_13
\			
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_131	city_others_city_133	city_others_city_134
\			
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_136	city_others_city_138	city_others_city_139
--	----------------------	----------------------	----------------------

\			
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_14	city_others_city_141	city_others_city_142
\			
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_143	city_others_city_144	city_others_city_145
\			
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_146	city_others_city_149	city_others_city_150
\			
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0

8954	0	0	0
------	---	---	---

	city_others_city_152	city_others_city_155	city_others_city_157
--	----------------------	----------------------	----------------------

\			
8950	0	0	0

8951	0	0	0
------	---	---	---

8952	0	0	0
------	---	---	---

8953	0	0	0
------	---	---	---

8954	0	0	0
------	---	---	---

	city_others_city_158	city_others_city_159	city_others_city_16
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\			
8950	0	0	0

8951	0	0	0
------	---	---	---

8952	0	0	0
------	---	---	---

8953	0	0	0
------	---	---	---

8954	0	0	0
------	---	---	---

	city_others_city_160	city_others_city_162	city_others_city_165
--	----------------------	----------------------	----------------------

\			
8950	0	0	0

8951	0	0	0
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8952	1	0	0
------	---	---	---

8953	0	0	0
------	---	---	---

8954	0	0	0
------	---	---	---

	city_others_city_166	city_others_city_167	city_others_city_173
--	----------------------	----------------------	----------------------

\			
8950	0	0	0

8951	0	0	0
------	---	---	---

8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_175	city_others_city_176	city_others_city_179
\			
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_18	city_others_city_19	city_others_city_2	\
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_20	city_others_city_21	city_others_city_23	\
8950	0	1	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_24	city_others_city_25	city_others_city_26	\
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_27	city_others_city_28	city_others_city_30	\
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_33	city_others_city_36	city_others_city_37	\
--	---------------------	---------------------	---------------------	---

8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_39	city_others_city_40	city_others_city_41	\
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_42	city_others_city_43	city_others_city_44	\
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_45	city_others_city_46	city_others_city_48	\
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_50	city_others_city_53	city_others_city_54	\
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_55	city_others_city_57	city_others_city_59	\
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_61	city_others_city_62	city_others_city_64	\
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_65	city_others_city_67	city_others_city_69	\
--	---------------------	---------------------	---------------------	---

8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_7	city_others_city_70	city_others_city_71	\
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_72	city_others_city_73	city_others_city_74	\
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_75	city_others_city_76	city_others_city_77	\
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_78	city_others_city_80	city_others_city_81	\
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_82	city_others_city_83	city_others_city_84	\
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_89	city_others_city_9	city_others_city_90	\
8950	0	0	0	
8951	0	0	0	
8952	0	0	0	
8953	0	0	0	
8954	0	0	0	

	city_others_city_91	city_others_city_93	city_others_city_94	\
--	---------------------	---------------------	---------------------	---



8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

	city_others_city_97	city_others_city_98	city_others_city_99
8950	0	0	0
8951	0	0	0
8952	0	0	0
8953	0	0	0
8954	0	0	0

```
one_hot_encoded_df.shape
```

```
(8955, 123)
```

### 3. X/Y and Training/Test Split with stratified sampling and SMOTE

```
# Copy all the features into X and the target to Y
```

```
X = one_hot_encoded_df.drop(columns = "target")
```

```
y = one_hot_encoded_df["target"]
```

```
# function to calculate ratio of 1 to 0 in column
```

```
def cal_ratio(x):
```

```
    n_1 = sum(x['target'].values == 1)
```

```
    n_0 = sum(x['target'].values == 0)
```

```
    return '{:}/{:}'.format(n_1, n_0)
```

```
# apply above function to get 1:0 ratio for target
```

```
y.value_counts()
```

```
0    7472
```

```
1    1483
```

```
Name: target, dtype: int64
```

```
print("1:0 ratio of y = " + str(y.value_counts()[1]/y.value_counts()[0]))
```

```
1:0 ratio of y = 0.19847430406852248
```

```
# split data into train and test sets with 30% of records in test. stratify to Y
```

```
from sklearn.model_selection import train_test_split
```

```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = .3, random_state=0, stratify = y)
```

```
y_train.value_counts()
```

```
0    5230
```

```
1    1038
```

```
Name: target, dtype: int64
```

```
# 1:0 ratios for y_train (should have 50% each class)
print("1:0 ratio of y_train = " + str(y_train.value_counts()
[1]/y_train.value_counts()[0]))
```

1:0 ratio of y\_train = 0.19847036328871892

**We need to use SMOTE to balance it!**

```
from imblearn.over_sampling import SMOTE, ADASYN
```

```
# convert text data in x to numeric before applying SMOTE
```

```
from sklearn.feature_extraction.text import CountVectorizer
vectorizer = CountVectorizer(lowercase = False)
```

```
X_train_res, y_train_res = SMOTE().fit_resample(X_train, y_train)
```

```
y_train_res.value_counts()
```

```
0    5230
```

```
1    5230
```

```
Name: target, dtype: int64
```

```
print("1:0 ratio of y_train = " + str(y_train_res.value_counts()
[1]/y_train_res.value_counts()[0]))
```

1:0 ratio of y\_train = 1.0

#### 4. PCA and Logistic Regression

```
# Principal Component Analysis and Boxplot
```

```
from numpy import mean
```

```
from sklearn.datasets import make_classification
```

```
from sklearn.linear_model import LogisticRegression
```

```
from sklearn.decomposition import PCA
```

```
from sklearn.pipeline import Pipeline
```

```
from sklearn.model_selection import RepeatedStratifiedKFold
```

```
from sklearn.model_selection import cross_val_score
```

```
X_train_res.shape
```

```
(10460, 122)
```

```
y_train_res.shape
```

```
(10460,)
```

```
def get_dataset():
```

```
    X, y = make_classification(n_samples = 10460, n_features = 15,
random_state = 7)
```

```
    return X,y
```

```
def get_models():
```

```
    models = dict()
```

```
    for i in range(1,15):
```

```

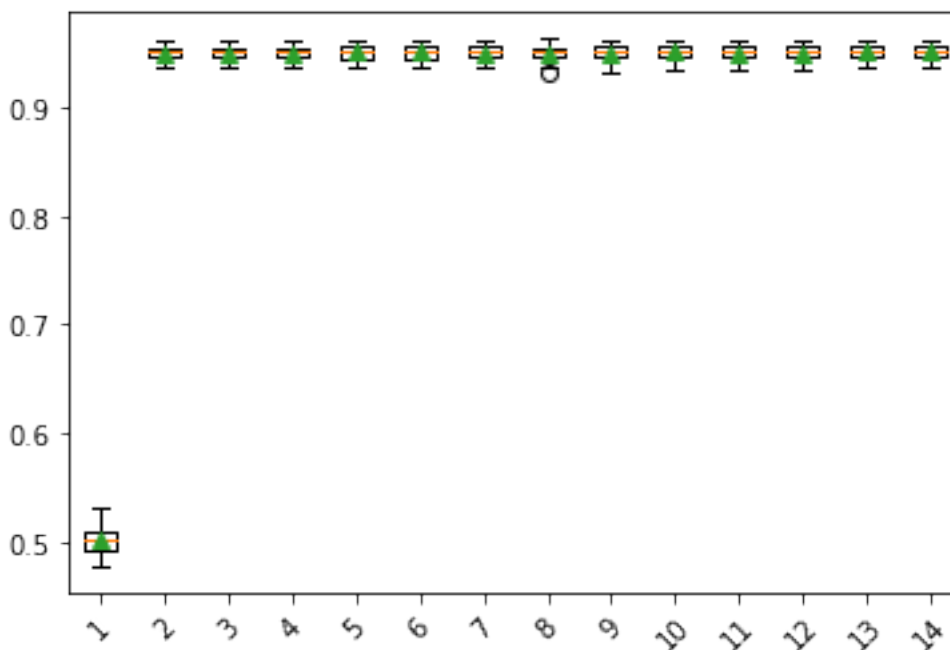
        steps = [('pca', PCA(n_components = i)), ('m',
LogisticRegression())]
        models[str(i)] = Pipeline(steps = steps)
    return models

def evaluate_model(model, X, y):
    cv = RepeatedStratifiedKFold(n_splits = 10, n_repeats = 3,
random_state = 1)
    scores = cross_val_score(model,X,y,scoring='accuracy', cv=cv,
n_jobs = -1, error_score = 'raise')
    return scores

X,y = get_dataset()
models = get_models()
results, names = list(), list()
for name, model in models.items():
    scores = evaluate_model(model,X,y)
    results.append(scores)
    names.append(name)

plt.boxplot(results, labels = names, showmeans= True)
plt.xticks(rotation = 45)
plt.show()

```



*# evaluate the model for accuracy*

```

steps = [('pca', PCA(n_components = 15)), ('m', LogisticRegression())]
model = Pipeline(steps=steps)

```

```

%%capture --no-stdout
model.fit(X_train_res,y_train_res);
y_pred = model.predict(X_test);

print("Predicted Class: %d" % y_pred[0])

Predicted Class: 1

# accuracy score of PCA model
cross_val_score(model, X_train_res, y_train_res, cv = 3, scoring =
'accuracy')

array([0.70490393, 0.64009177, 0.73580034])

# create confusion matrix
from sklearn.metrics import confusion_matrix
confusion_matrix(y_test,y_pred)

array([[1642,  600],
       [ 161,  284]], dtype=int64)

Interpretation:

# precision, recall and F1 score for test set and predicted values
from sklearn.metrics import precision_score, recall_score, f1_score
precision_score(y_test, y_pred)

0.3212669683257919

recall_score(y_test,y_pred)

0.6382022471910113

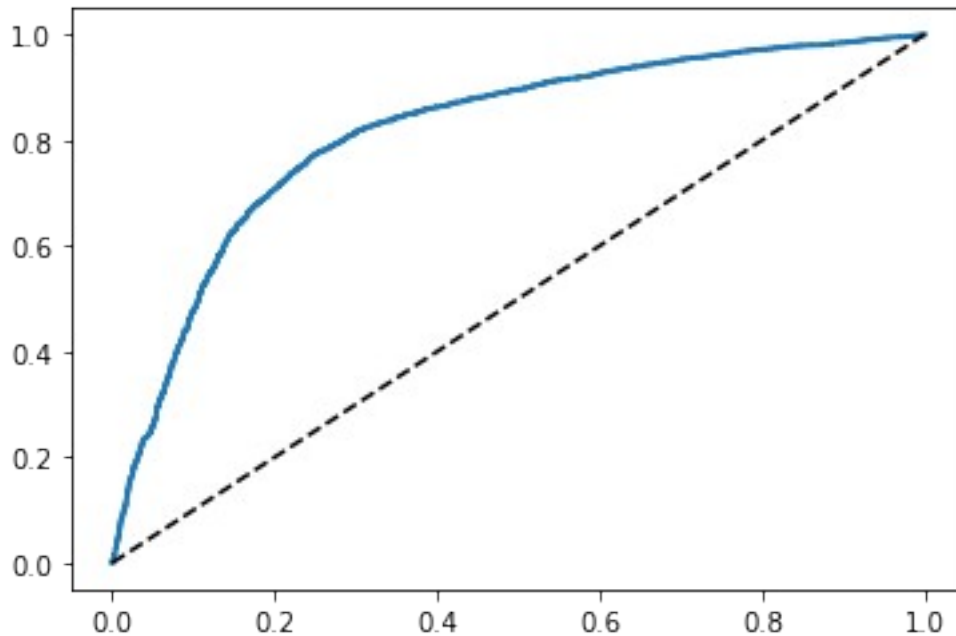
f1_score(y_test,y_pred)

0.4273890142964635

# plot ROC curve
from sklearn.metrics import roc_curve
y_scores = model.decision_function(X_train_res)
fpr, tpr, thresholds = roc_curve(y_train_res, y_scores)
def plot_roc_curve(fpr,tpr, label = None):
    plt.plot(fpr,tpr, linewidth = 2, label = label)
    plt.plot([0,1],[0,1], 'k--')

plot_roc_curve(fpr,tpr)

```



## 5. Softmax Regression

**How is softmax regression related to logistic regression? What library can you use for softmax?**

*Both are used for classification tasks. Softmax can be used for multiclass classification (assuming the classes are mutually exclusive) and logistic regression can be used on binary classes.*

*While there are specific libraries for softmax regression (keras and tensorflow), we can also use scikit learn's logistic regression class for softmax by setting the multi-class parameter to "multinomial"*

## 6. KNN

*# Use sklearn's KNN to train and predict based on unbalanced training set*

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report
knn = KNeighborsClassifier(n_neighbors = 10)
knn.fit(X_train,y_train)
y_pred = knn.predict(X_test)

from sklearn import metrics
print("Accuracy: " , metrics.accuracy_score(y_test,y_pred))
```

Accuracy: 0.8299218459248232

```
# confusion matrix
confusion_matrix(y_test,y_pred)
```

```
array([[2226, 16],
       [ 441,  4]], dtype=int64)
```

```
#classification report
```

```
print(classification_report(y_test,y_pred))
```

	precision	recall	f1-score	support
0	0.83	0.99	0.91	2242
1	0.20	0.01	0.02	445
accuracy			0.83	2687
macro avg	0.52	0.50	0.46	2687
weighted avg	0.73	0.83	0.76	2687

```
#KNN with balanced set
```

```
knn = KNeighborsClassifier(n_neighbors = 10)
```

```
knn.fit(X_train_res,y_train_res)
```

```
y_pred = knn.predict(X_test)
```

```
print("Accuracy: " , metrics.accuracy_score(y_test,y_pred))
```

```
Accuracy: 0.6270934127279494
```

```
# confusion matrix
```

```
confusion_matrix(y_test,y_pred)
```

```
array([[1501, 741],
       [ 261, 184]], dtype=int64)
```

```
#classification report
```

```
print(classification_report(y_test,y_pred))
```

	precision	recall	f1-score	support
0	0.85	0.67	0.75	2242
1	0.20	0.41	0.27	445
accuracy			0.63	2687
macro avg	0.53	0.54	0.51	2687
weighted avg	0.74	0.63	0.67	2687

## tune KNN hyperparameters using GridSearch

```
from sklearn.model_selection import GridSearchCV
knn_params = { "n_neighbors":
range(1,20,2), "weights": ["uniform","distance"], "metric": ["euclidean", "manhattan",
"minkowski"] }
```

```
cv = RepeatedStratifiedKFold(n_splits = 10, n_repeats = 3, random_state = 101) grid_search
= GridSearchCV(estimator = knn, param_grid = knn_params, n_jobs = 1, cv=cv, scoring=
"accuracy", error_score = 0) grid_results = grid_search.fit(X_train_res, y_train_res)
```

## best params

```
print(grid_results.best_params_)
```

## train and test model using new parameters

```
final_model = knn.set_params(**grid_results.best_params) final_model.fit(X_train_res,
y_train_res) y_pred = final_model.predict(X_test)

confusion_matrix(y_test, y_pred)

classification_report(y_test,y_pred)
```

## plot ROC curve

```
from sklearn.metrics import roc_curve y_scores =
grid_search.decision_function(X_train_res) fpr, tpr, thresholds = roc_curve(y_train_res,
y_scores) def plot_roc_curve(fpr,tpr, label = None): plt.plot(fpr,tpr, linewidth = 2, label =
label) plt.plot([0,1],[0,1], 'k--')

plot_roc_curve(fpr,tpr)
```

## 7. Naive Bayes

```
# train and test a model with GaussianNB
from sklearn.naive_bayes import GaussianNB
clf = GaussianNB()
clf.fit(X_train_res,y_train_res)
y_pred = clf.predict(X_test)
```

```
# confusion matrix
confusion_matrix(y_test,y_pred)
```

```
array([[ 939, 1303],
       [  79,  366]], dtype=int64)
```

```
print("Accuracy: " , metrics.accuracy_score(y_test,y_pred))
```

```
Accuracy:  0.4856717528842575
```

```
# classification report
print(classification_report(y_test,y_pred))
```

```
precision    recall  f1-score   support
```

0	0.92	0.42	0.58	2242
1	0.22	0.82	0.35	445
accuracy			0.49	2687
macro avg	0.57	0.62	0.46	2687
weighted avg	0.81	0.49	0.54	2687

```
# number of misclassifications
print("Number of misclassifications out of %d points: %d"
      % (X_test.shape[0], (y_test != y_pred).sum()))
```

Number of misclassifications out of 2687 points: 1382

### Categorical NB

```
# train and test a model with CategoricalNB
from sklearn.naive_bayes import CategoricalNB
clf = CategoricalNB()
clf.fit(X_train_res,y_train_res)
y_pred = clf.predict(X_test[2:3])
```

```
# confusion matrix
confusion_matrix(y_test[2:3],y_pred)
```

```
array([[1]], dtype=int64)
```

```
# classification report
print(classification_report(y_test[2:3],y_pred))
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	1
accuracy			1.00	1
macro avg	1.00	1.00	1.00	1
weighted avg	1.00	1.00	1.00	1

```
# number of misclassifications
print("Number of misclassifications out of %d points: %d"
      % (X_test.shape[0], (y_test[2:3] != y_pred).sum()))
```

Number of misclassifications out of 2687 points: 0

## 8. Support Vector Machines

```
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
# train using SVC
clf = make_pipeline(StandardScaler(), SVC(gamma = "auto"))
clf.fit(X_train_res,y_train_res)
```



```

# test model
y_pred = clf.predict(X_test)

confusion_matrix(y_test,y_pred)

array([[2057, 185],
       [ 210, 235]], dtype=int64)

print(classification_report(y_test,y_pred))

```

	precision	recall	f1-score	support
0	0.91	0.92	0.91	2242
1	0.56	0.53	0.54	445
accuracy			0.85	2687
macro avg	0.73	0.72	0.73	2687
weighted avg	0.85	0.85	0.85	2687

```

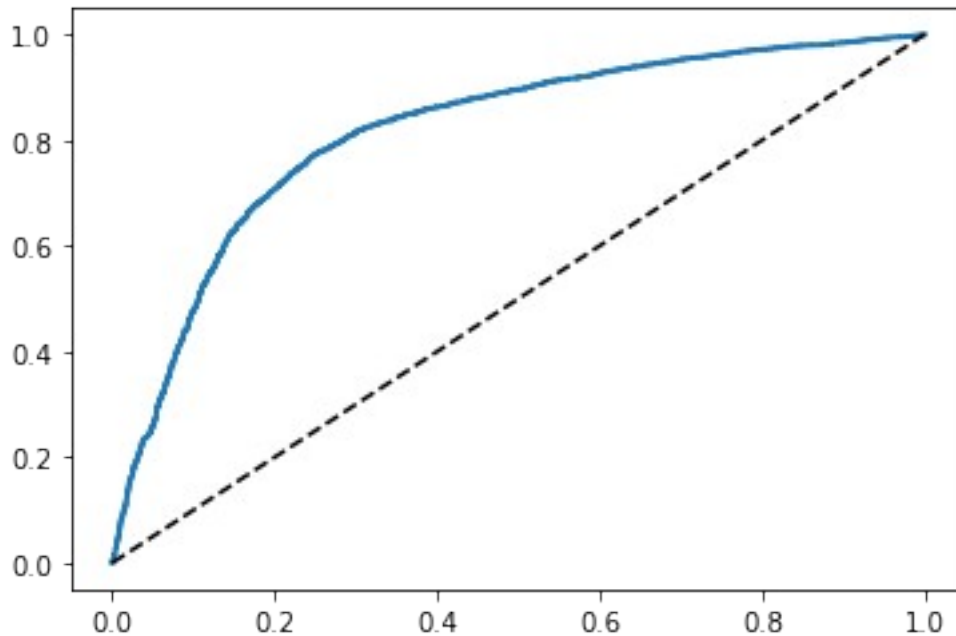
# number of misclassifications
print("Number of misclassifications out of %d points: %d"
      % (X_test.shape[0], (y_test != y_pred).sum()))

Number of misclassifications out of 2687 points: 395

# plot ROC curve
from sklearn.metrics import roc_curve
y_scores = model.decision_function(X_train_res)
fpr, tpr, thresholds = roc_curve(y_train_res, y_scores)
def plot_roc_curve(fpr,tpr, label = None):
    plt.plot(fpr,tpr, linewidth = 2, label = label)
    plt.plot([0,1],[0,1], 'k--')

plot_roc_curve(fpr,tpr)

```

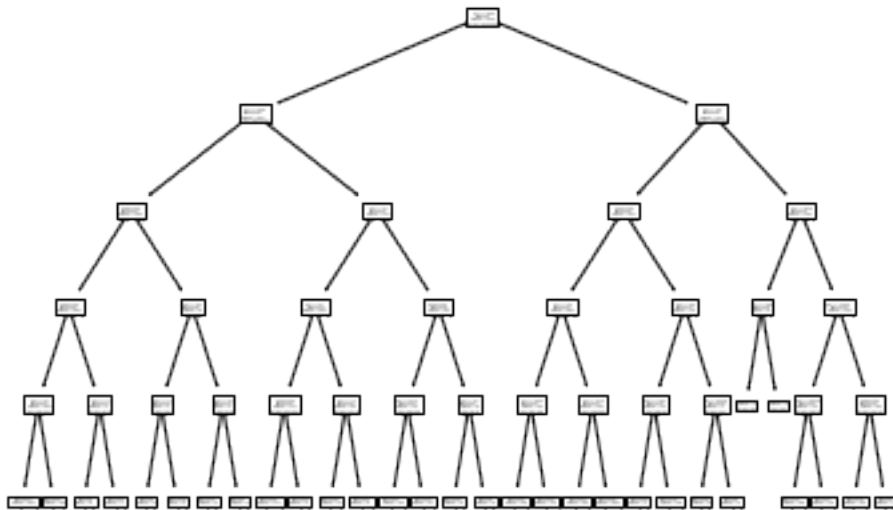


## 9. Decision Tree

```
from sklearn.tree import DecisionTreeClassifier
# train and predict w/ Decision Tree on balanced training set
clf = DecisionTreeClassifier(random_state = 0, max_depth = 5)
clf.fit(X_train_res,y_train_res)
y_pred = clf.predict(X_test)
```

```
# plot decision tree
from sklearn import tree
tree.plot_tree(clf)
%%capture
```

UsageError: Line magic function `%%capture` not found.



```
# confusion matrix
confusion_matrix(y_test,y_pred)

# classification report
print(classification_report(y_test,y_pred))

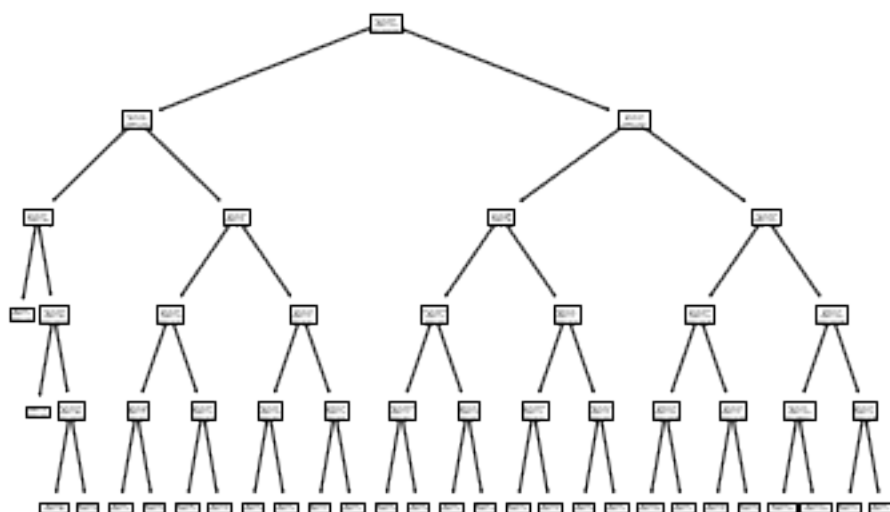
# plot ROC curve
from sklearn.metrics import roc_curve
y_scores = clf.decision_function(X_train_res)
fpr, tpr, thresholds = roc_curve(y_train_res, y_scores)

plot_roc_curve(fpr,tpr)

# repeat w/ unbalanced training set
clf = DecisionTreeClassifier(random_state = 0, max_depth = 5)
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)

# plot decision tree
tree.plot_tree(clf)
%%capture

UsageError: Line magic function `%%capture` not found.
```



```
# confusion matrix
confusion_matrix(y_test,y_pred)

array([[2078, 164],
       [ 223, 222]], dtype=int64)
```

```
# classification report
print(classification_report(y_test,y_pred))
```

	precision	recall	f1-score	support
0	0.90	0.93	0.91	2242
1	0.58	0.50	0.53	445
accuracy			0.86	2687
macro avg	0.74	0.71	0.72	2687
weighted avg	0.85	0.86	0.85	2687

```
# plot ROC curve
from sklearn.metrics import roc_curve
y_scores = clf.decision_function(X_train_res)
fpr, tpr, thresholds = roc_curve(y_train_res, y_scores)
plot_roc_curve(fpr,tpr)
```

```
-----
-----
AttributeError                                Traceback (most recent call
last)
~\AppData\Local\Temp\ipykernel_13024\300530386.py in <module>
      1 # plot ROC curve
      2 from sklearn.metrics import roc_curve
```

```

----> 3 y_scores = clf.decision_function(X_train_res)
      4 fpr, tpr, thresholds = roc_curve(y_train_res, y_scores)
      5 plot_roc_curve(fpr,tpr)

```

AttributeError: 'DecisionTreeClassifier' object has no attribute 'decision\_function'

Differences between balanced and unbalanced training sets:

- Interestingly enough, the unbalanced training set yielded more accurate predictions (8% increase) The first decision tree seems more skewed to the right

## 10. Random Forest

*# use grid search to tune max\_depth, min\_samples\_leaf, n\_estimators*

```

from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

```

```

rf_clf = RandomForestClassifier(random_state = 42, n_jobs = -1,
max_depth = 5, n_estimators = 100, oob_score = True)
rf_clf.fit(X_train_res,y_train_res)

```

```

params = {
    'max_depth' : [2,3,5,10,20],
    'min_samples_leaf': [5,10,20,50,100,200],
    'n_estimators' : [10,25,30,50,100,200]
}

```

```

grid_search = GridSearchCV(estimator = rf_clf, param_grid = params, cv
= 4, n_jobs = -1, verbose = 1, scoring = "accuracy")

```

```

%%time
grid_search.fit(X_train_res,y_train_res)

```

Fitting 4 folds for each of 180 candidates, totalling 720 fits

```

grid_search.best_score

```

```

rf_best = grid_search.best_estimator_
rf_best

```

*# plot ROC curve*

```

from sklearn.metrics import roc_curve
y_scores = rf_clf.decision_function(X_train_res)
fpr, tpr, thresholds = roc_curve(y_train_res, y_scores)
def plot_roc_curve(fpr,tpr, label = None):
    plt.plot(fpr,tpr, linewidth = 2, label = label)
    plt.plot([0,1],[0,1], 'k--')

```

```

plot_roc_curve(fpr,tpr)

```

## 11. Boosting Algorithms

### Gradient boosting

```
# use Gradient boosting classifier to train
from sklearn.ensemble import GradientBoostingClassifier

gbc = GradientBoostingClassifier(n_estimators = 500, learning_rate =
.05, random_state = 100, max_features = 15)
gbc.fit(X_train_res, y_train_res)

# predict using gradient boost
gbc.predict(X_test)

# gradient boost confusion matrix
confusion_matrix(y_test,y_pred)

# gradient boost classification report
print(classification_report(y_test,y_pred))

# gradient boost's misclassifications
print("Number of misclassifications out of %d points: %d"
      % (X_test.shape[0], (y_test != y_pred).sum()))
```

### Adaboost

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from sklearn.ensemble import AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier
# Train adaboost with Decision tree classifier
dt = DecisionTreeClassifier()
clf = AdaBoostClassifier(n_estimators = 100, base_estimator = dt,
learning_rate = 1)
clf.fit(X_train_res, y_train_res)

# predict using adaboost
y_pred = clf.predict(X_test)

# adaboost confusion matrix
confusion_matrix(y_test,y_pred)

# ada boost classification report
print(classification_report(y_test,y_pred))

# ada boost's misclassifications
print("Number of misclassifications out of %d points: %d"
      % (X_test.shape[0], (y_test != y_pred).sum()))
```

## 12. Discussion

Based on accuracy, KNN and Naive Bayes were the highest contenders for an ideal classification model. In the future, I could work on hyperparameter tuning and resampling/scaling data specifically for each of these models.

