```
#Jovian Commit Essentials

!pip install jovian --upgrade -q
import jovian
jovian.set_project('photo-quality-prediction')
jovian.set_colab_id('1jSSyHS7y541RxLob0aOb5vMfUalU3QgS')
```

Photo Quality Prediction

Image Source: https://www.oxfordonlineenglish.com/photo-editing

Dataset Link: https://www.kaggle.com/competitions/PhotoQualityPrediction

Main Objective

Given anonymized information on thousands of photo albums, predict whether a human evaluator would mark them as '**good**'.

Description

This Dataset is taken from **Kaggle** organized by **Featured Prediction Competition** which contains total **10 columns** and **40,262 rows**. It contains columns like **id, latitude, longitude, width, height, size, name, description, caption and good (target column)**. Using the relevant information given in this dataset, i will bulid two machine learning models to predict the quality of photo and let's see whether the models can give the accurate prediction using this dataset information.

1. Downloading Dataset

```
# Installing required libraries
```

```
!pip install jovian opendatasets pandas numpy scikit-learn xgboost --quiet
```

```
# Publishing notebook to Jovian profile

import jovian
jovian.commit()
```

```
[jovian] Detected Colab notebook...
[jovian] Uploading colab notebook to Jovian...
Committed successfully! https://jovian.com/kowshikchakraborty6/photo-quality-prediction
```

```
'https://jovian.com/kowshikchakraborty6/photo-quality-prediction'
```

```
import opendatasets as od
```

```
dataset_url = 'https://www.kaggle.com/competitions/PhotoQualityPrediction'
```

```
od.download(dataset_url)
```

```
Skipping, found downloaded files in "./PhotoQualityPrediction" (use force=True to force download)
```

```
data_dir = 'PhotoQualityPrediction'
```

```
!ls -lh {data_dir}
```

```
total 7.2M
-rw-r--r-- 1 root root 106K Feb 28 15:09 example_entry.csv
-rw-r--r-- 1 root root 1.6M Feb 28 15:09 test.csv
-rw-r--r-- 1 root root 5.5M Feb 28 15:09 training.csv
```

```
#Number of rows in training set

!wc -l {data_dir}/training.csv
```

```
40263 PhotoQualityPrediction/training.csv
```

```
#Number of rows in test set

!wc -l {data_dir}/test.csv
```

```
12000 PhotoQualityPrediction/test.csv
```

```
#Showing the dataset as dataframe
import pandas as pd #Importing required libraray
dataset_df = pd.read_csv('PhotoQualityPrediction/training.csv')
dataset_df
```

	id	latitude	longitude	width	height	size	name	description	caption	good
0	1	45	16	604	453	31	454 1659	NaN	NaN	1
1	2	21	-87	720	534	43	2068 483	687 1182 1309 2068 2107 78 89 453 1905 712 120...	830 2112 1914 792 814 1386 474 2146 1591 194 5...	0
2	3	38	-97	720	540	71	802	NaN	NaN	0
3	4	38	-122	604	453	24	NaN	924 1914 671 853 193 51 744 1437 1245 563 1410...	665 2040 792 1056 226 248 1612 1920 617 1365 1...	0
4	5	-29	24	720	540	13	1766 20	NaN	181 891 22 2123 2107 523 2080 683 1640 166 109...	0
...	...	...	...	...	...	...	...	...	...	...
40257	40259	39	-77	604	453	18	919 1905 2088	1490 1644 919 1905 2088 1192 796	687 830 1017 990 2123 22 1309 1903 611 1304 12...	0
40258	40260	38	-120	604	453	4	1325 1348	2018 1426	1744 2015 658 164 54	0
40259	40261	29	-82	604	453	37	51 1829 367	NaN	786 830 1347 2057 792 1826 1716 1920 2041 171 ...	0
40260	40262	24	121	604	453	25	1443 1869	NaN	368 2029 1309 1573 755 370 1905 1823 916 740 1...	1
40261	40263	31	121	604	453	10	490 1674	1976 1674 794	NaN	0

40262 rows × 10 columns

2. Finding If There Is Any Missing Values

```
# In training set

training_df = pd.read_csv('PhotoQualityPrediction/training.csv')

percent_missing_train = training_df.isnull().sum() * 100 / len(training_df)
missing_value_df_train = pd.DataFrame({'column_name': training_df.columns,
                                       'percent_missing': percent_missing_train})
missing_value_df_train
```

	column_name	percent_missing
id	id	0.000000
latitude	latitude	0.000000
longitude	longitude	0.000000
width	width	0.000000
height	height	0.000000
size	size	0.000000
name	name	11.916944

	column_name	percent_missing
description	description	68.461577
caption	caption	29.325419
good	good	0.000000

```
# In test set

test_df = pd.read_csv('PhotoQualityPrediction/test.csv')

percent_missing_test = test_df.isnull().sum() * 100 / len(test_df)
missing_value_df_test = pd.DataFrame({'column_name': test_df.columns,
                                  'percent_missing': percent_missing_test})
missing_value_df_test
```

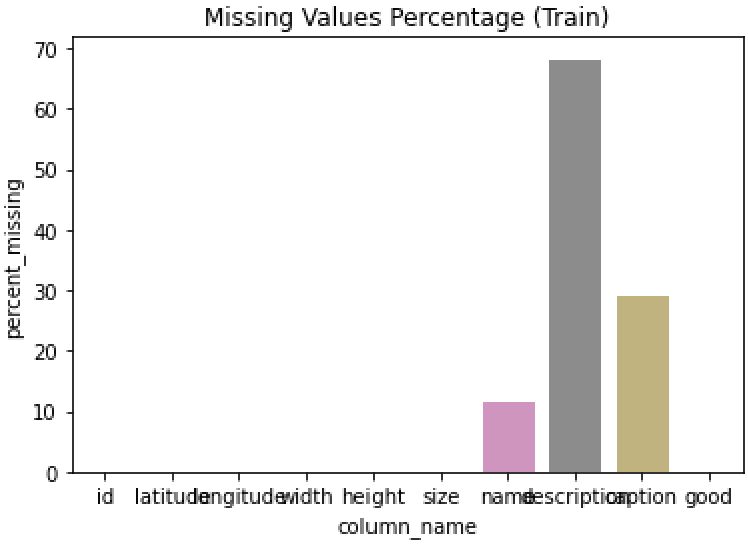
	column_name	percent_missing
id	id	0.000000
latitude	latitude	0.000000
longitude	longitude	0.000000
width	width	0.000000
height	height	0.000000
size	size	0.000000
name	name	12.283333
description	description	68.808333
caption	caption	29.650000

From the above, we found some missing values in **name, description and caption** column. The highest percentage of missing values we found in description column (aprrox 69% for both train & test set).

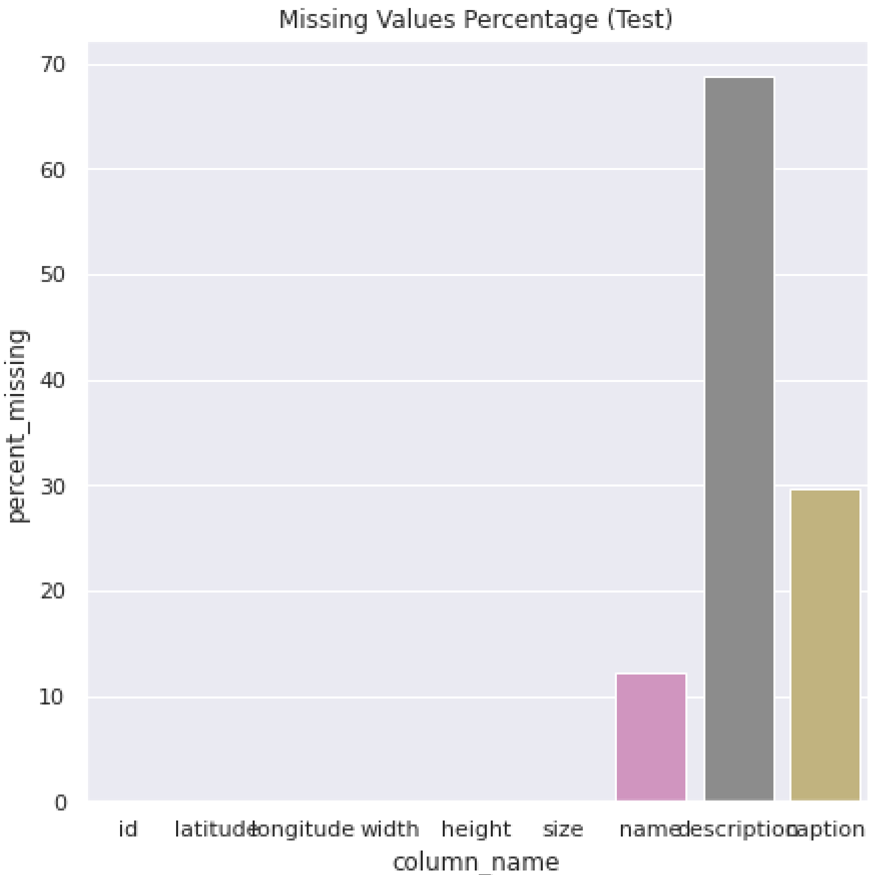
We visualized it as a barplot shown below,

```
#Installing and importing required libraries

!pip install matplotlib seaborn --quiet
!pip install plotly folium --upgrade --quiet

import matplotlib
import plotly.express as px
import seaborn as sns
import matplotlib.pyplot as plt
```

```
#In training set

plt.title('Missing Values Percentage (Train)')
sns.set(rc={'figure.figsize':(7,7)})
sns.barplot(data=missing_value_df_train, x='column_name', y='percent_missing');
```




```
#In Test set

plt.title('Missing Values Percentage (Test)')
sns.set(rc={'figure.figsize':(7,7)})
sns.barplot(data=missing_value_df_test, x='column_name', y='percent_missing');
```



3. Some Exploratory Analysis of The Dataset

```
#Importing required library

import numpy as np
```

```python
#Showing training set as dataframe

training_df
```

	id	latitude	longitude	width	height	size	name	description	caption	good
0	1	45	16	604	453	31	454 1659	NaN	NaN	1
1	2	21	-87	720	534	43	2068 483	687 1182 1309 2068 2107 78 89 453 1905 712 120...	830 2112 1914 792 814 1386 474 2146 1591 194 5...	0
2	3	38	-97	720	540	71	802	NaN	NaN	0
3	4	38	-122	604	453	24	NaN	924 1914 671 853 193 51 744 1437 1245 563 1410...	665 2040 792 1056 226 248 1612 1920 617 1365 1...	0
4	5	-29	24	720	540	13	1766 20	NaN	181 891 22 2123 2107 523 2080 683 1640 166 109...	0
...	...	...	...	...	...	...	...	...	...	...
40257	40259	39	-77	604	453	18	919 1905 2088	1490 1644 919 1905 2088 1192 796	687 830 1017 990 2123 22 1309 1903 611 1304 12...	0
40258	40260	38	-120	604	453	4	1325 1348	2018 1426	1744 2015 658 164 54	0
40259	40261	29	-82	604	453	37	51 1829 367	NaN	786 830 1347 2057 792 1826 1716 1920 2041 171 ...	0
40260	40262	24	121	604	453	25	1443 1869	NaN	368 2029 1309 1573 755 370 1905 1823 916 740 1...	1
40261	40263	31	121	604	453	10	490 1674	1976 1674 794	NaN	0

40262 rows × 10 columns

```python
#Showing test set as dataframe

test_df
```

	id	latitude	longitude	width	height	size	name	description	caption
0	40265	34	-118	640	478	1	51 125	NaN	1481 1905 2060 2071 483
1	40266	34	-83	413	604	12	744	749 1905 36 740 1433	NaN
2	40267	42	-87	720	480	44	2102 670	2040 643 594 297 1881 737 1304 2102 2136 712 1...	807 142
3	40268	54	-2	604	453	18	1744	NaN	NaN
4	40269	20	77	604	405	60	193 944	NaN	NaN
...	...	...	...	...	...	...	...	...	...
11995	52260	42	-75	720	540	71	2119	NaN	2073 880 1914 1612 1040 1304 1920 1915 1365 51...

	id	latitude	longitude	width	height	size	name	description	caption
11996	52261	26	-80	604	453	60	2068	NaN	1733 875 474 1200 469 51 1939 439 1616
11997	52262	36	-120	604	402	17	NaN	51 2070 1901 367	1048 2132
11998	52263	47	-112	604	453	33	772	NaN	2068 1123 712
11999	52264	20	77	604	453	114	1743 899 1363	NaN	NaN

12000 rows × 9 columns

```
#Showing shape (rows & columns) of training set

training_df.shape
```

```
(40262, 10)
```

```
#Showing shape (rows & columns) of test set

test_df.shape
```

```
(12000, 9)
```

```
#Showing types of features

training_df.dtypes
```

```
id              int64
latitude        int64
longitude       int64
width           int64
height          int64
size            int64
name           object
description    object
caption        object
good            int64
dtype: object
```

```
#Showing the description (total, mean etc.)

training_df.describe()
```

	id	latitude	longitude	width	height	size	good
count	40262.000000	40262.000000	40262.000000	40262.000000	40262.000000	40262.000000	40262.000000
mean	20132.204312	30.342854	-37.662213	587.654265	503.571581	39.872783	0.262133
std	11623.143325	20.503580	81.312267	108.089076	105.710218	42.195029	0.439800
min	1.000000	-55.000000	-175.000000	0.000000	0.000000	1.000000	0.000000
25%	10066.250000	24.000000	-98.000000	540.000000	453.000000	12.000000	0.000000

	id	latitude	longitude	width	height	size	good
50%	20132.500000	37.000000	-76.000000	604.000000	453.000000	27.000000	0.000000
75%	30197.750000	42.000000	19.000000	640.000000	576.000000	55.000000	1.000000
max	40263.000000	72.000000	178.000000	720.000000	720.000000	1030.000000	1.000000

```
#Showing barplot of good quality of photo accroding to size

# plt.title('Good quality of photo in terms of size')
# sns.barplot(data=training_df.head(15), x='good', y='size');
```

Let's see the relation between all the features using correlation heatmap, (A correlation heatmap is a graphical representation of a correlation matrix, which shows the pairwise correlation between different features in a dataset. The heatmap visualizes the strength and direction of the linear relationship between pairs of features.)

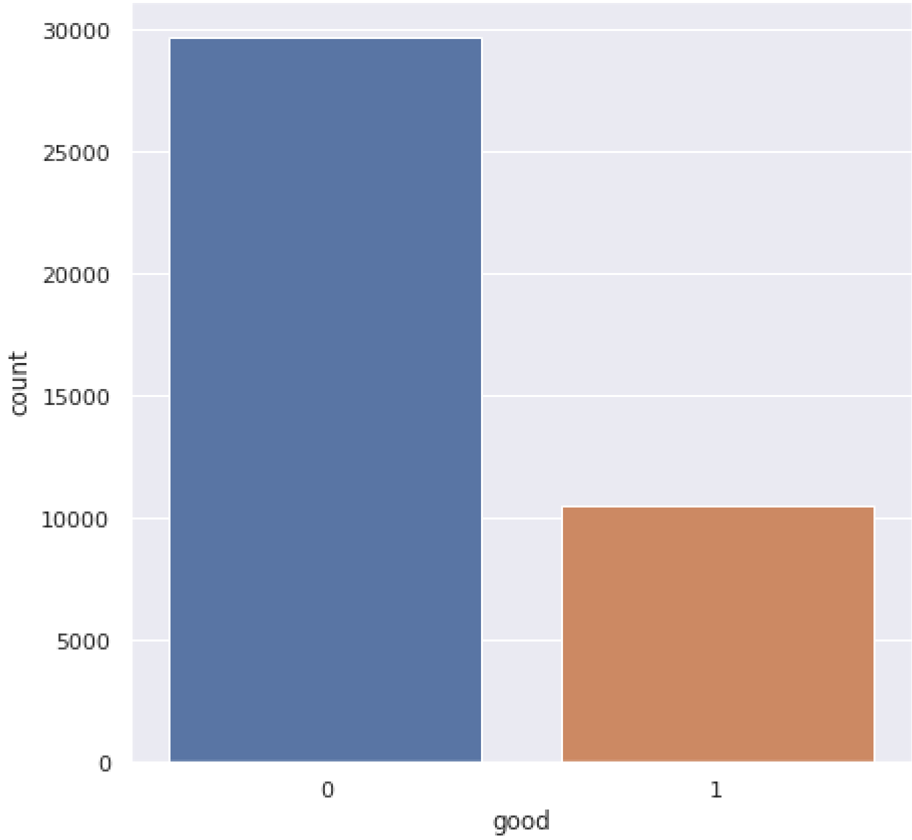
```
corr = training_df.iloc[:, :-1].corr()
correlation = corr.index
plt.figure(figsize = (16, 16))
plt.title('Correlation Heatmap')
sns.heatmap(training_df[correlation].corr(), annot = True)
```

```
<AxesSubplot:title={'center':'Correlation Heatmap'}>
```

We can see from the above correlation matrix that maxium correlation are negative correlation. There are also presence of postive correlation but overall, we can say that correlation between all the feautres are weak. (means there is not strong positive or negative relation between the features.)

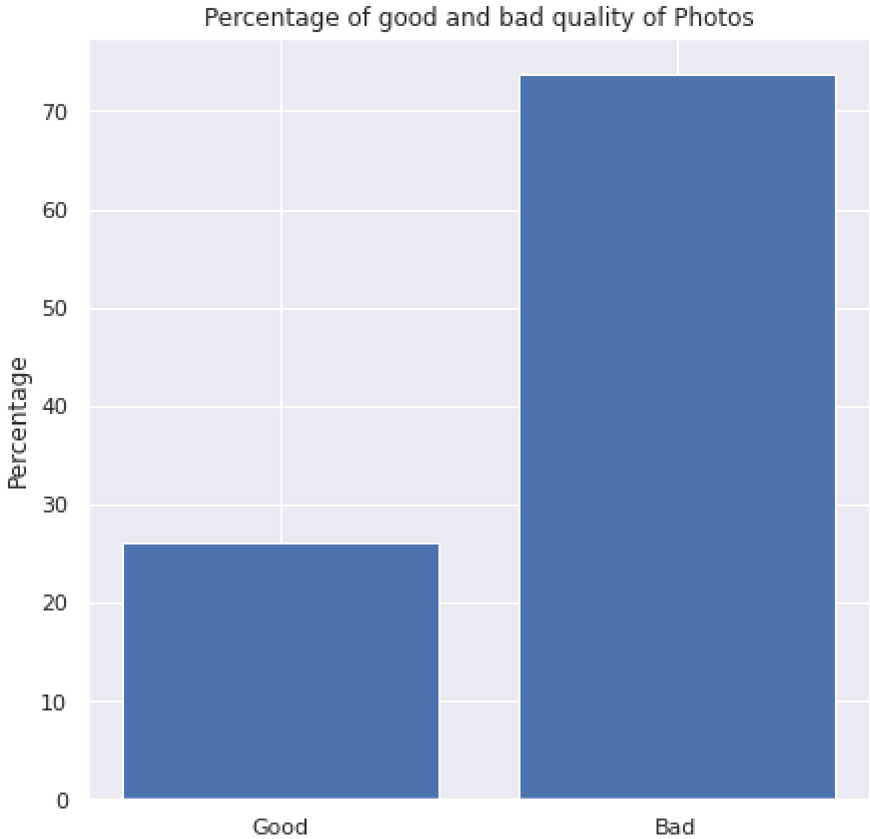
Let's check the distribution of the target variable **good**,

```
sns.countplot(x='good', data=training_df)
plt.show()
```



We also visualized it with percentage given below,

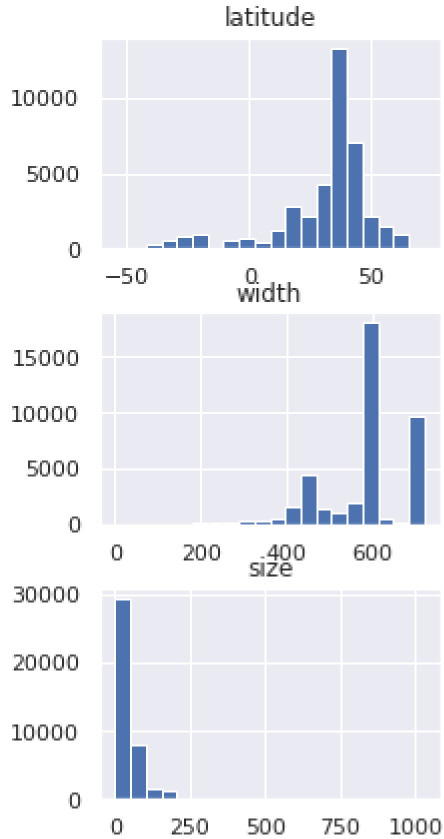
```
# Get the count of good and bad photos
good_count = (training_df['good'] == 1).sum()
bad_count = (training_df['good'] == 0).sum()

# Calculate the percentage of good and bad photos
good_percent = good_count / len(training_df) * 100
bad_percent = bad_count / len(training_df) * 100

# Create a bar plot of the percentage of good and bad photos
plt.bar(['Good', 'Bad'], [good_percent, bad_percent])
plt.title('Percentage of good and bad quality of Photos')
plt.ylabel('Percentage')
plt.show()
```



So, from the above, we can say that over 70% photos are bad quality photos and approximately 25% photos are good.

Let's visualize the distribution of some columns using histograms,

```
training_df.hist(column=['latitude', 'longitude', 'width', 'height', 'size'], bins=20)
plt.figure(figsize = (10, 10))
plt.show()
```




```
<Figure size 720x720 with 0 Axes>
```

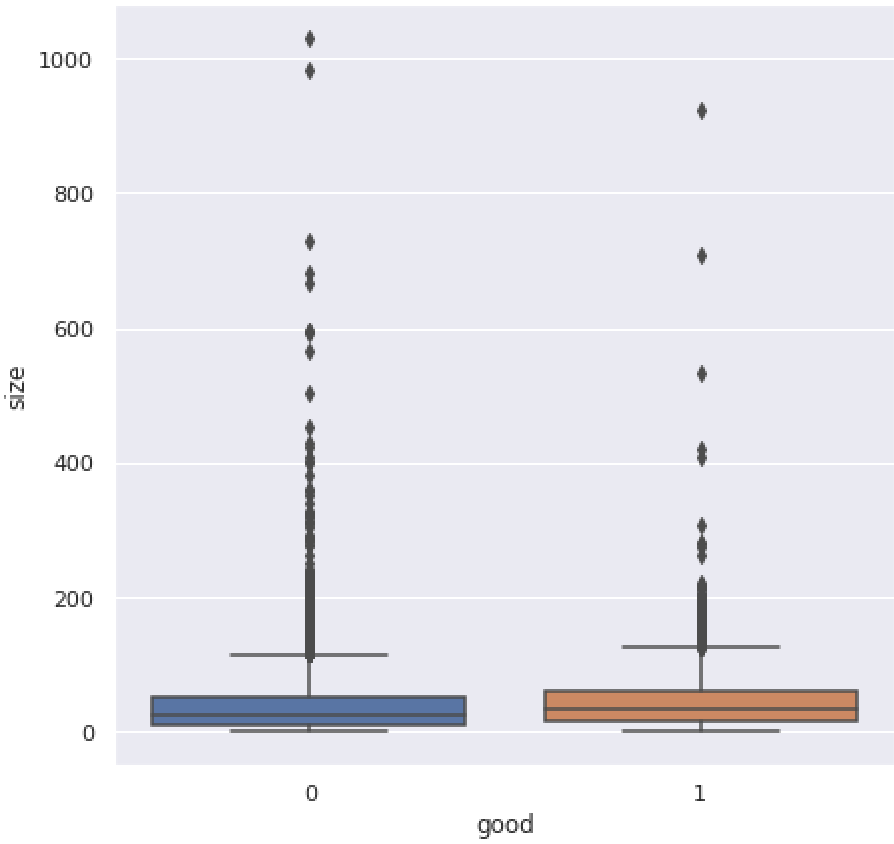
We can also explore the relationship between the target variable **good** and some of the other variables using a scatter plot,

```
sns.scatterplot(x='width', y='height', hue='good', data=training_df)
plt.show()
```

```
sns.scatterplot(x='latitude', y='longitude', hue='good', data=training_df)
plt.show()
```

Also let's Visualize the relationship between the **good** column and the **size** column,

```
sns.boxplot(x='good', y='size', data=training_df)
plt.show()
```



The above figure shows a box plot showing the distribution of the **size** column for each value of the **good** column.

4. Working With Categorical Columns

```
#identifying categorical columns
cat_training = [feature for feature in training_df if training_df[feature].dtypes == 'O
cat_test = [feature for feature in test_df if test_df[feature].dtypes == 'O']

cat_training
cat_test
```

```
['name', 'description', 'caption']
```

From the above code, we can see that there are three categorical columns ['name', 'description', 'caption']. We can make those columns numerical by extracting some numerical features from them.

At first, we should make a copy of the dataset so that we can keep the original dataset.

```
#Makaing a copy of the dataset

training_df_copy = training_df.copy(deep=True)
test_df_copy = test_df.copy(deep=True)
```

```
training_df_copy
```

	id	latitude	longitude	width	height	size	name	description	caption	good
0	1	45	16	604	453	31	454 1659	NaN	NaN	1
1	2	21	-87	720	534	43	2068 483	687 1182 1309 2068 2107 78 89 453 1905 712 120...	830 2112 1914 792 814 1386 474 2146 1591 194 5...	0
2	3	38	-97	720	540	71	802	NaN	NaN	0
3	4	38	-122	604	453	24	NaN	924 1914 671 853 193 51 744 1437 1245 563 1410...	665 2040 792 1056 226 248 1612 1920 617 1365 1...	0
4	5	-29	24	720	540	13	1766 20	NaN	181 891 22 2123 2107 523 2080 683 1640 166 109...	0
...	...	...	...	...	...	...	...	...	...	...
40257	40259	39	-77	604	453	18	919 1905 2088	1490 1644 919 1905 2088 1192 796	687 830 1017 990 2123 22 1309 1903 611 1304 12...	0
40258	40260	38	-120	604	453	4	1325 1348	2018 1426	1744 2015 658 164 54	0
40259	40261	29	-82	604	453	37	51 1829 367	NaN	786 830 1347 2057 792 1826 1716 1920 2041 171 ...	0
40260	40262	24	121	604	453	25	1443 1869	NaN	368 2029 1309 1573 755 370 1905 1823 916 740 1...	1

	id	latitude	longitude	width	height	size	name	description	caption	good
40261	40263	31	121	604	453	10	490 1674	1976 1674 794	NaN	0

40262 rows × 10 columns

```
test_df_copy
```

	id	latitude	longitude	width	height	size	name	description	caption
0	40265	34	-118	640	478	1	51 125	NaN	1481 1905 2060 2071 483
1	40266	34	-83	413	604	12	744	749 1905 36 740 1433	NaN
2	40267	42	-87	720	480	44	2102 670	2040 643 594 297 1881 737 1304 2102 2136 712 1...	807 142
3	40268	54	-2	604	453	18	1744	NaN	NaN
4	40269	20	77	604	405	60	193 944	NaN	NaN
...	...	...	...	...	...	...	...	...	...
11995	52260	42	-75	720	540	71	2119	NaN	2073 880 1914 1612 1040 1304 1920 1915 1365 51...
11996	52261	26	-80	604	453	60	2068	NaN	1733 875 474 1200 469 51 1939 439 1616
11997	52262	36	-120	604	402	17	NaN	51 2070 1901 367	1048 2132
11998	52263	47	-112	604	453	33	772	NaN	2068 1123 712
11999	52264	20	77	604	453	114	1743 899 1363	NaN	NaN

12000 rows × 9 columns

```
#Extracting train categorical columns
training_df_copy['new_name'] = training_df_copy['name'].str.extract(r'.*(\d\d).*').asty
training_df_copy['new_description'] = training_df_copy['description'].str.extract(r'.*(
training_df_copy['new_caption'] = training_df_copy['caption'].str.extract(r'.*(\d\d).*'
```

```
#Extracting test categorical columns
test_df_copy['new_name'] = test_df_copy['name'].str.extract(r'.*(\d\d).*').astype(float
test_df_copy['new_description'] = test_df_copy['description'].str.extract(r'.*(\d\d).*'
test_df_copy['new_caption'] = test_df_copy['caption'].str.extract(r'.*(\d\d).*').astype
```

```
training_df_copy
```

	id	latitude	longitude	width	height	size	name	description	caption	good	new_name	new_descriptior
0	1	45	16	604	453	31	454 1659	NaN	NaN	1	59.0	NaN

	id	latitude	longitude	width	height	size	name	description	caption	good	new_name	new_descriptior
1	2	21	-87	720	534	43	2068 483	687 1182 1309 2068 2107 78 89 453 1905 712 120...	830 2112 1914 792 814 1386 474 2146 1591 194 5...	0	83.0	13.(
2	3	38	-97	720	540	71	802	NaN	NaN	0	2.0	NaN
3	4	38	-122	604	453	24	NaN	924 1914 671 853 193 51 744 1437 1245 563 1410...	665 2040 792 1056 226 248 1612 1920 617 1365 1...	0	NaN	6.(
4	5	-29	24	720	540	13	1766 20	NaN	181 891 22 2123 2107 523 2080 683 1640 166 109...	0	20.0	NaN
...	...	...	...	...	...	...	...	...	...	...	...	..
40257	40259	39	-77	604	453	18	919 1905 2088	1490 1644 919 1905 2088 1192 796	687 830 1017 990 2123 22 1309 1903 611 1304 12...	0	88.0	96.(
40258	40260	38	-120	604	453	4	1325 1348	2018 1426	1744 2015 658 164 54	0	48.0	26.(
40259	40261	29	-82	604	453	37	51 1829 367	NaN	786 830 1347 2057 792 1826 1716 1920 2041 171 ...	0	67.0	NaN

	id	latitude	longitude	width	height	size	name	description	caption	good	new_name	new_descriptio
40260	40262	24	121	604	453	25	1443 1869	NaN	368 2029 1309 1573 755 370 1905 1823 916 740 1...	1	69.0	Na
40261	40263	31	121	604	453	10	490 1674	1976 1674 794	NaN	0	74.0	94.

40262 rows × 13 columns

So, we can now drop the three columns ['name', 'description', 'caption'] since we have created new columns for them.

```
training_df_copy.drop(columns = ['name', 'description','caption'], inplace= True)
test_df_copy.drop(columns = ['name', 'description','caption'], inplace= True)
```

```
training_df_copy
```

	id	latitude	longitude	width	height	size	good	new_name	new_description	new_caption
0	1	45	16	604	453	31	1	59.0	NaN	NaN
1	2	21	-87	720	534	43	0	83.0	13.0	41.0
2	3	38	-97	720	540	71	0	2.0	NaN	NaN
3	4	38	-122	604	453	24	0	NaN	6.0	9.0
4	5	-29	24	720	540	13	0	20.0	NaN	62.0
...	...	...	...	...	...	...	...	...	...	...
40257	40259	39	-77	604	453	18	0	88.0	96.0	97.0
40258	40260	38	-120	604	453	4	0	48.0	26.0	54.0
40259	40261	29	-82	604	453	37	0	67.0	NaN	18.0
40260	40262	24	121	604	453	25	1	69.0	NaN	62.0
40261	40263	31	121	604	453	10	0	74.0	94.0	NaN

40262 rows × 10 columns

```
#Re-odering the training dataset
training_df_copy = training_df_copy[['id','latitude','longitude','width','height','size
```

```
training_df_copy
```

	id	latitude	longitude	width	height	size	new_name	new_description	new_caption	good
0	1	45	16	604	453	31	59.0	NaN	NaN	1
1	2	21	-87	720	534	43	83.0	13.0	41.0	0
2	3	38	-97	720	540	71	2.0	NaN	NaN	0

	id	latitude	longitude	width	height	size	new_name	new_description	new_caption	good
3	4	38	-122	604	453	24	NaN	6.0	9.0	0
4	5	-29	24	720	540	13	20.0	NaN	62.0	0
...	...	...	...	...	...	...	...	...	...	...
40257	40259	39	-77	604	453	18	88.0	96.0	97.0	0
40258	40260	38	-120	604	453	4	48.0	26.0	54.0	0
40259	40261	29	-82	604	453	37	67.0	NaN	18.0	0
40260	40262	24	121	604	453	25	69.0	NaN	62.0	1
40261	40263	31	121	604	453	10	74.0	94.0	NaN	0

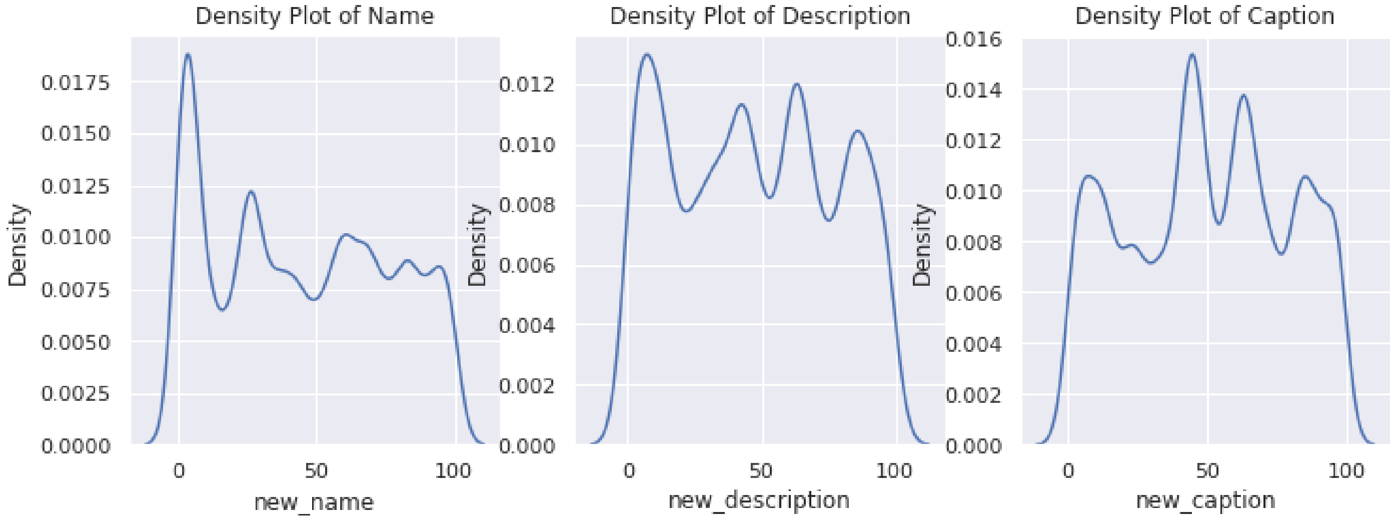
40262 rows × 10 columns

5. Working With Missing Values And Scaling

From part-2 (Finding Missing Values), we have seen that there are some missing values in **name**, **description** & **caption** columns. So, let's fill those missing values.

But at first we need to know which technique is useful (mean, median or mode) to fill the missing values in that case. To know this, we can plot density plot of **name**, **description** & **caption** columns,

```
# Create a figure with three subplots
fig, axes = plt.subplots(1, 3, figsize=(12, 4))

# Plot a histogram of the 'new_name' column
sns.kdeplot(training_df_copy['new_name'], ax=axes[0])
axes[0].set_title('Density Plot of Name')

# Plot a density plot of the 'new_description' column
sns.kdeplot(training_df_copy['new_description'], ax=axes[1])
axes[1].set_title('Density Plot of Description')

# Plot a histogram of the 'new_caption' column
sns.kdeplot(training_df_copy['new_caption'], ax=axes[2])
axes[2].set_title('Density Plot of Caption')

plt.show()
```



From the above figure, we can see that there is no normal distribution in name, description and caption columns and we know that mean technique is very useful if the data is normally distributed. So, we can not perform mean technique. We also can not perform mode here becuse mode works well in case of categorical values/data. So, there is only one option left and that is the median technique. So, we will use median technique to fill the missing values.

```
#For training set:

# Find the mean value of the non-missing values in the 'new_name' column
name_median = training_df_copy['new_name'][pd.notnull(training_df_copy['new_name'])].as

# Fill in the missing values in the 'new_name' column with the mean value
training_df_copy['new_name'].fillna(name_median, inplace=True)

# Repeat for 'new_description' and 'new_caption' columns
description_median = training_df_copy['new_description'][pd.notnull(training_df_copy['r
training_df_copy['new_description'].fillna(description_median, inplace=True)

caption_median = training_df_copy['new_caption'][pd.notnull(training_df_copy['new_capti
training_df_copy['new_caption'].fillna(caption_median, inplace=True)
```

```
/usr/local/lib/python3.8/dist-packages/pandas/core/generic.py:6392:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  return self._update_inplace(result)
/usr/local/lib/python3.8/dist-packages/pandas/core/generic.py:6392:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  return self._update_inplace(result)
```

```
/usr/local/lib/python3.8/dist-packages/pandas/core/generic.py:6392:
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See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  return self._update_inplace(result)
```

```
#For test set:

# Find the mean value of the non-missing values in the 'new_name' column
name_median = test_df_copy['new_name'][pd.notnull(test_df_copy['new_name'])].astype(flo

# Fill in the missing values in the 'new_name' column with the mean value
test_df_copy['new_name'].fillna(name_median, inplace=True)

# Repeat for 'new_description' and 'new_caption' columns
description_median = test_df_copy['new_description'][pd.notnull(test_df_copy['new_descr
test_df_copy['new_description'].fillna(description_median, inplace=True)

caption_median = test_df_copy['new_caption'][pd.notnull(test_df_copy['new_caption'])].a
test_df_copy['new_caption'].fillna(caption_median, inplace=True)
```

```
training_df_copy.isna().sum()
```

```
id                 0
latitude           0
longitude          0
width              0
height             0
size               0
new_name           0
new_description    0
new_caption        0
good               0
dtype: int64
```

```
test_df_copy.isna().sum()
```

```
id                 0
latitude           0
longitude          0
width              0
height             0
size               0
new_name           0
new_description    0
new_caption        0
dtype: int64
```

Let's identify input & target columnns,

```
input = list(training_df_copy.columns)[1:-1]
target = 'good'
```

```
train_inputs = training_df_copy[input]
train_targets = training_df_copy[target]
```

```
test_inputs = test_df_copy[input]
test_targets = training_df_copy[target]
```

Also let's see the numeric columns,

```
numeric_cols = train_inputs.select_dtypes(include=np.number).columns.tolist()
print(numeric_cols)
```

```
['latitude', 'longitude', 'width', 'height', 'size', 'new_name', 'new_description',
'new_caption']
```

Imputing Missing Numeric Values

```
from sklearn.impute import SimpleImputer #Importing required library

#Training
imputer = SimpleImputer().fit(training_df_copy[numeric_cols])
train_inputs[numeric_cols] = imputer.transform(train_inputs[numeric_cols])
```

```
/usr/local/lib/python3.8/dist-packages/pandas/core/frame.py:3678:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self[col] = igetitem(value, i)
```

```
#Test
imputer = SimpleImputer().fit(test_df_copy[numeric_cols])
test_inputs[numeric_cols] = imputer.transform(test_inputs[numeric_cols])
```

```
/usr/local/lib/python3.8/dist-packages/pandas/core/frame.py:3678:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self[col] = igetitem(value, i)
```

```
test_inputs[numeric_cols].isna().sum()
```

```
latitude           0
longitude          0
width              0
height             0
size               0
new_name           0
new_description    0
new_caption        0
dtype: int64
```

Scaling Numeric Features

```
from sklearn.preprocessing import RobustScaler #Importing required library

#Training
scaler = RobustScaler().fit(training_df_copy[numeric_cols])
train_inputs[numeric_cols] = scaler.transform(train_inputs[numeric_cols])
```

```
/usr/local/lib/python3.8/dist-packages/pandas/core/frame.py:3678:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self[col] = igetitem(value, i)
```

```
#Test
scaler = RobustScaler().fit(test_df_copy[numeric_cols])
test_inputs[numeric_cols] = scaler.transform(test_inputs[numeric_cols])
```

```
/usr/local/lib/python3.8/dist-packages/pandas/core/frame.py:3678:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self[col] = igetitem(value, i)
```

```
from sklearn.model_selection import train_test_split #Importing required library

X_train, X_val, Y_train, Y_val = train_test_split(
    train_inputs[numeric_cols], train_targets, test_size=0.30, random_state=42)
```

Training ML Models

Decision Tree Classifier

```
#Importing required library

from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
```

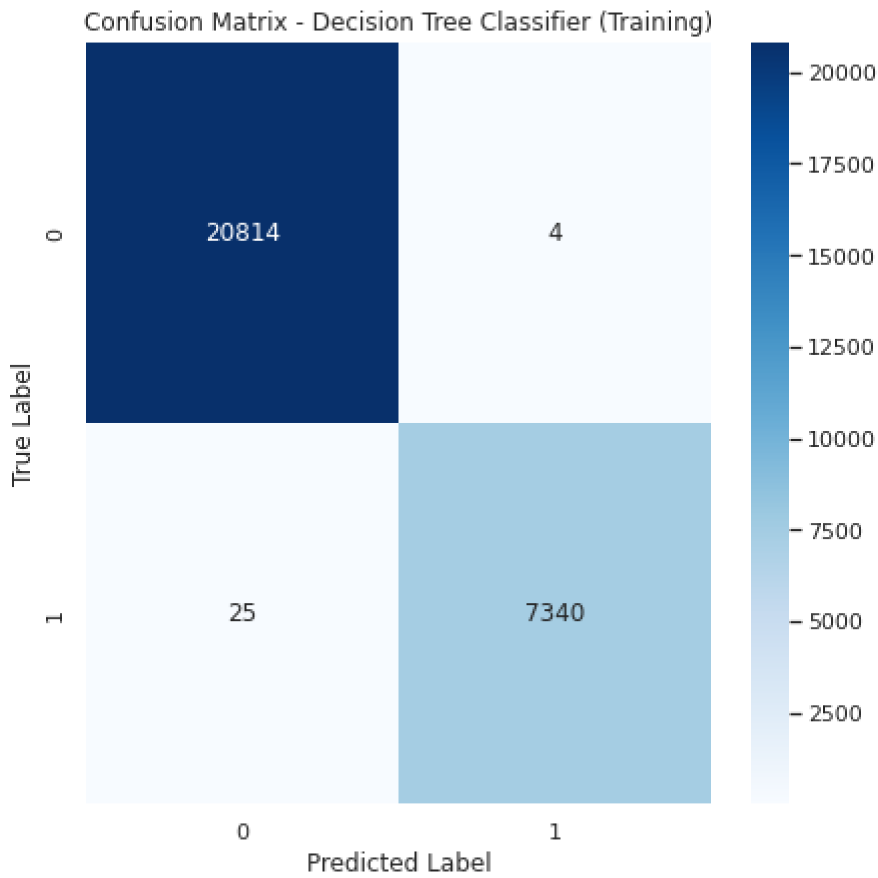
```
dtc = DecisionTreeClassifier()
dtc.fit(X_train, Y_train)
```

```
DecisionTreeClassifier()
```

```
def predict_and_plot(inputs, targets, name=''):
  # predict the target variable on the test set
  preds = dtc.predict(inputs)

  # evaluate the accuracy of the classifier
  acc = accuracy_score(targets, preds)
  print("Decision Tree classifier accuracy:", acc)

  # create a confusion matrix
  cm = confusion_matrix(targets, preds)

  # plot the confusion matrix
  sns.heatmap(cm, annot=True, cmap="Blues", fmt="d")
  plt.title("Confusion Matrix - Decision Tree Classifier {}".format(name));
  plt.xlabel("Predicted Label")
  plt.ylabel("True Label")
  plt.show()

  return preds
```

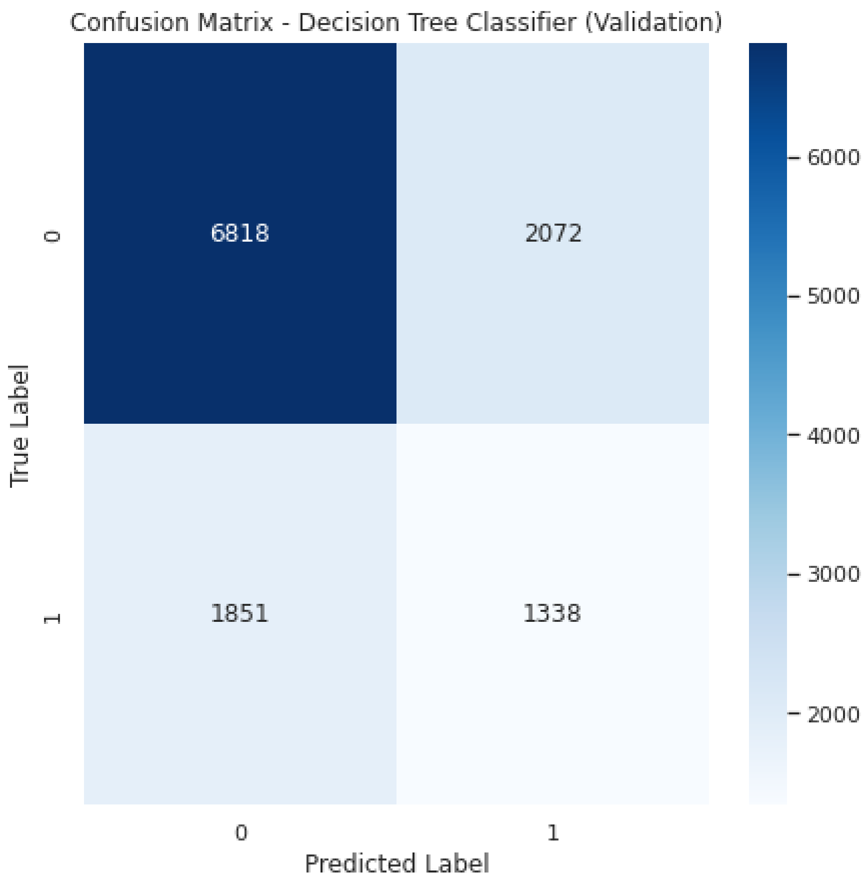
```
train_preds = predict_and_plot(X_train, Y_train, '(Training)')
```

```
Decision Tree classifier accuracy: 0.9989710108930916
```




```
test_preds = predict_and_plot(X_val, Y_val, '(Validation)')
```

Decision Tree classifier accuracy: 0.6752214587300274




```
test_pred = dtc.predict_proba(test_inputs[numeric_cols])
decision_tree_pred = pd.DataFrame(test_pred)
```

```python
decision_tree_pred.columns = ['No', 'Yes']
decision_tree_pred
```

	No	Yes
0	1.0	0.0
1	1.0	0.0
2	1.0	0.0
3	0.0	1.0
4	1.0	0.0
...	...	...
11995	1.0	0.0
11996	1.0	0.0
11997	1.0	0.0
11998	0.0	1.0
11999	1.0	0.0

12000 rows × 2 columns

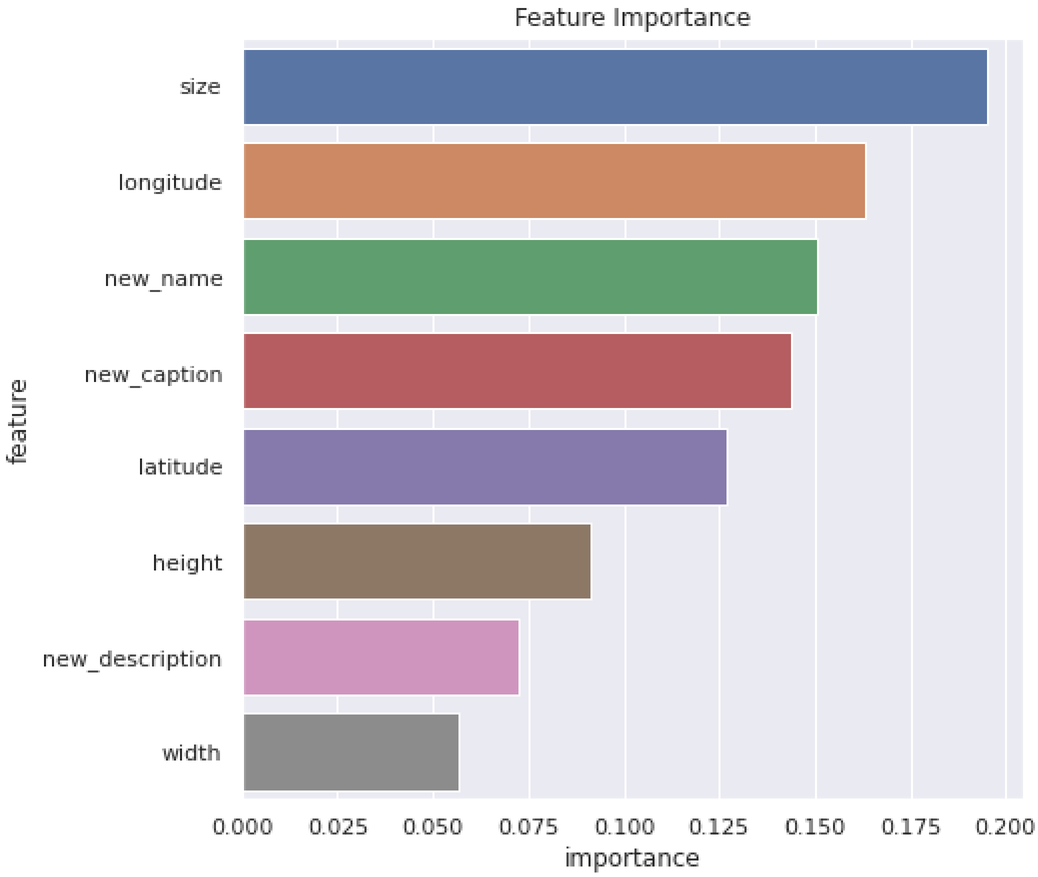
Let's see the feature importance of this model,

```python
importance_df = pd.DataFrame({
    'feature': X_train.columns,
    'importance': dtc.feature_importances_
}).sort_values('importance', ascending=False)
```

```python
importance_df.head(10)
```

	feature	importance
4	size	0.195083
1	longitude	0.163024
5	new_name	0.150483
7	new_caption	0.143698
0	latitude	0.127127
3	height	0.091270
6	new_description	0.072362
2	width	0.056953

```python
plt.title('Feature Importance')
sns.barplot(data=importance_df.head(10), x='importance', y='feature');
```



From the above, we can say that **size** & **longitude** are two important features.

XGBoost Classifier

```
from xgboost import XGBClassifier #Importing required library
```

```
xgb = XGBClassifier()
xgb.fit(X_train, Y_train)
```

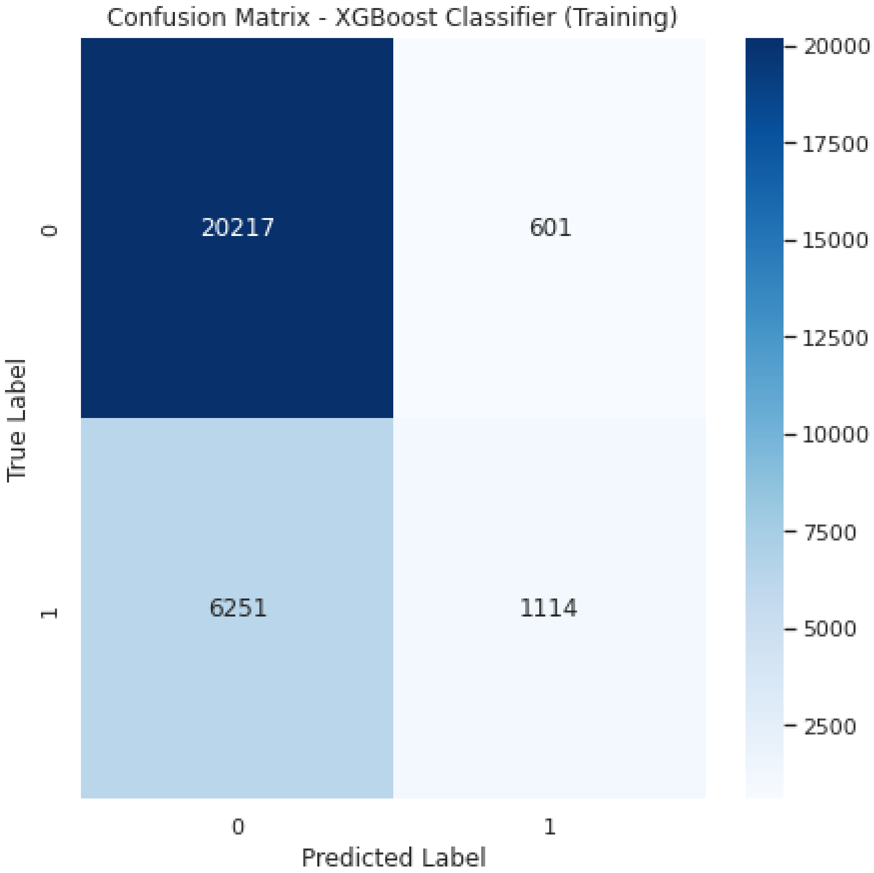
```
XGBClassifier()
```

```
def predict_and_plot(inputs, targets, name=''):
  # predict the target variable on the test set
  preds2 = xgb.predict(inputs)

  # evaluate the accuracy of the classifier
  acc2 = accuracy_score(targets, preds2)
  print("XGBoost classifier accuracy:", acc2)

  # create a confusion matrix
  cm = confusion_matrix(targets, preds2)

  # plot the confusion matrix
  sns.heatmap(cm, annot=True, cmap="Blues", fmt="d")
  plt.title("Confusion Matrix - XGBoost Classifier {}".format(name));
  plt.xlabel("Predicted Label")
  plt.ylabel("True Label")
```

```
    plt.show()

    return preds2
```

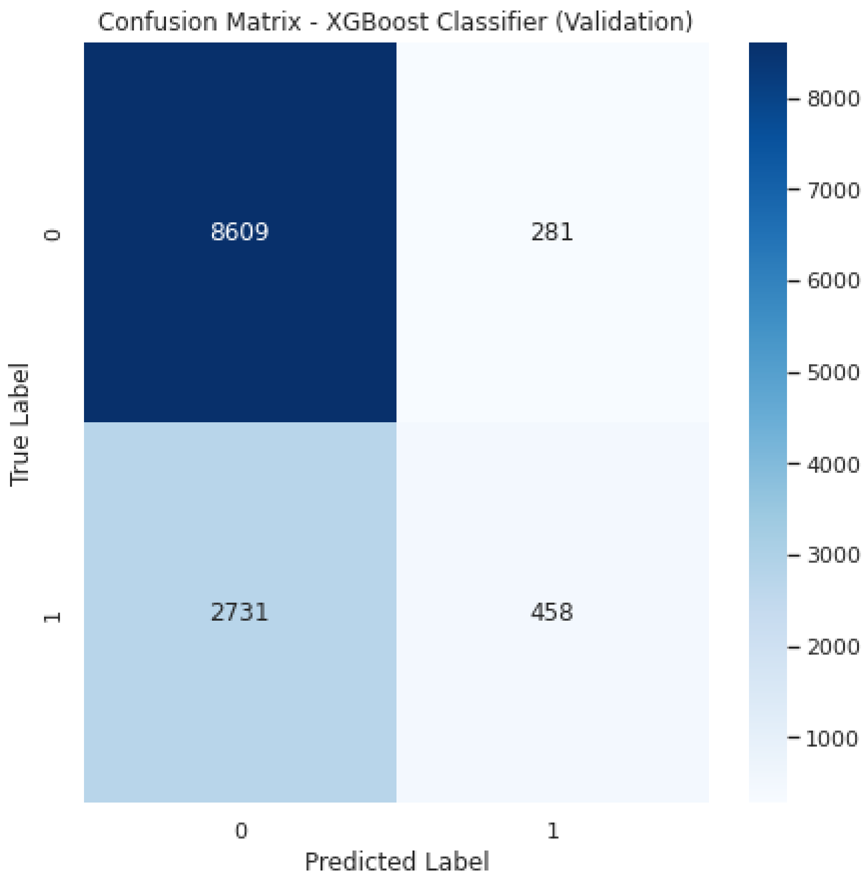
```
train_preds2 = predict_and_plot(X_train, Y_train, '(Training)')
```

```
XGBoost classifier accuracy: 0.7568747117056381
```




```
test_preds2 = predict_and_plot(X_val, Y_val, '(Validation)')
```

```
XGBoost classifier accuracy: 0.750641609404752
```

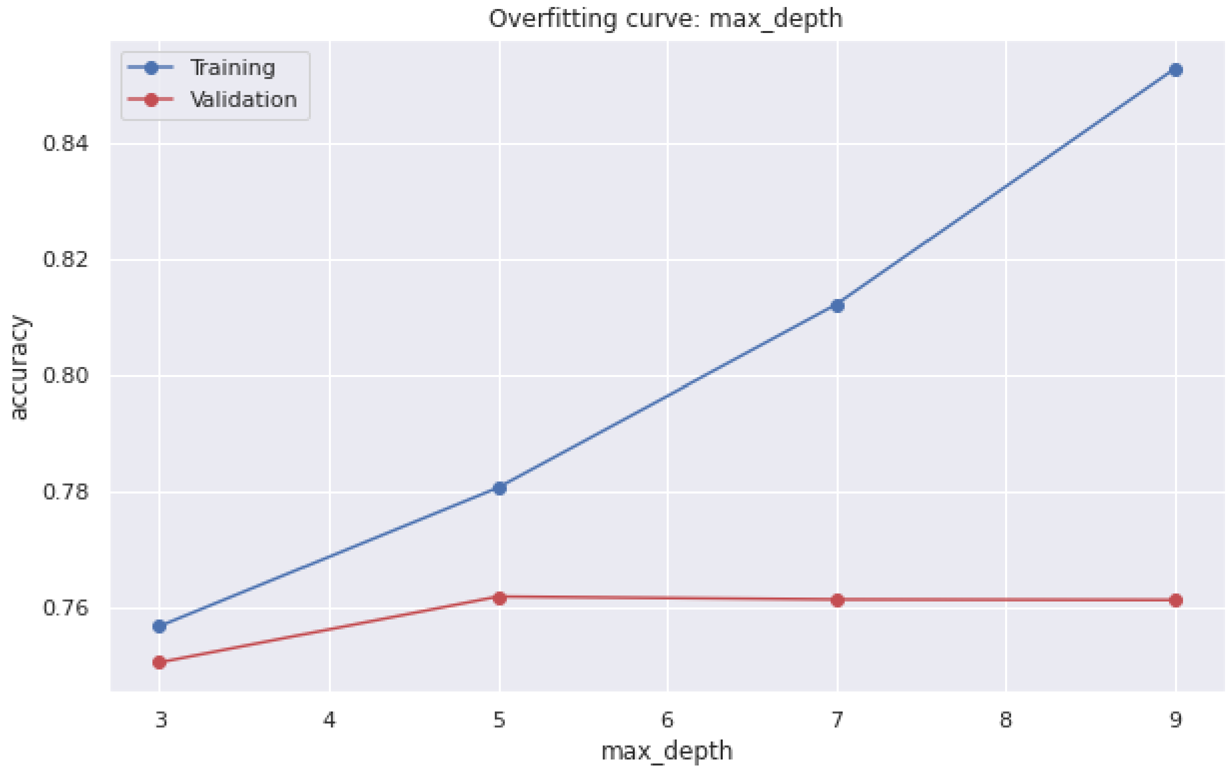


Hyperparameter Tuning (XGBoost Classifier)

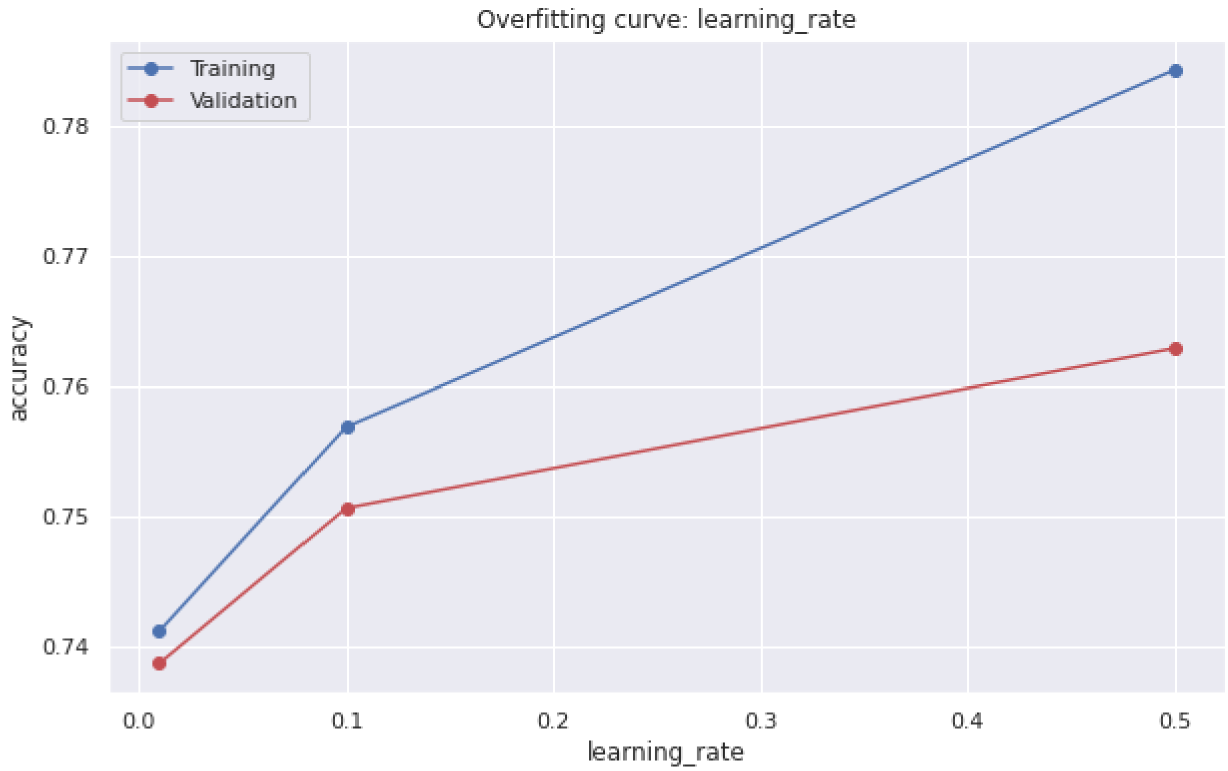
```
#Importing required library
from xgboost import XGBClassifier

def test_params(**params):
    model = XGBClassifier(**params).fit(X_train, Y_train)
    train_acc = accuracy_score(model.predict(X_train), Y_train)
    val_acc = accuracy_score(model.predict(X_val), Y_val)
    return train_acc, val_acc
```

```
def test_param_and_plot(param_name, param_values):
    train_accs, val_accs = [], []
    for value in param_values:
        params = {param_name: value}
        train_acc, val_acc = test_params(**params)
        train_accs.append(train_acc)
        val_accs.append(val_acc)
    plt.figure(figsize=(10,6))
    plt.title('Overfitting curve: ' + param_name)
    plt.plot(param_values, train_accs, 'b-o')
    plt.plot(param_values, val_accs, 'r-o')
    plt.xlabel(param_name)
    plt.ylabel('accuracy')
    plt.legend(['Training', 'Validation'])
```

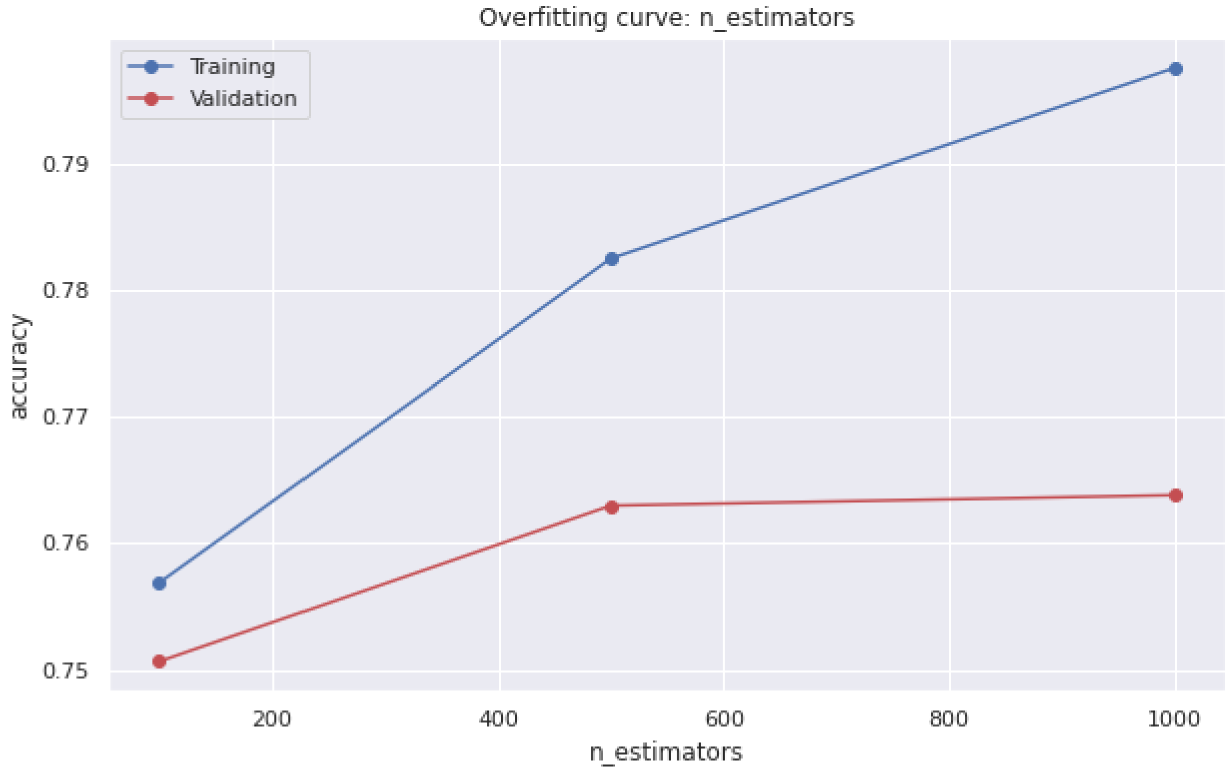
```
test_param_and_plot('max_depth', [3, 5, 7, 9])
```



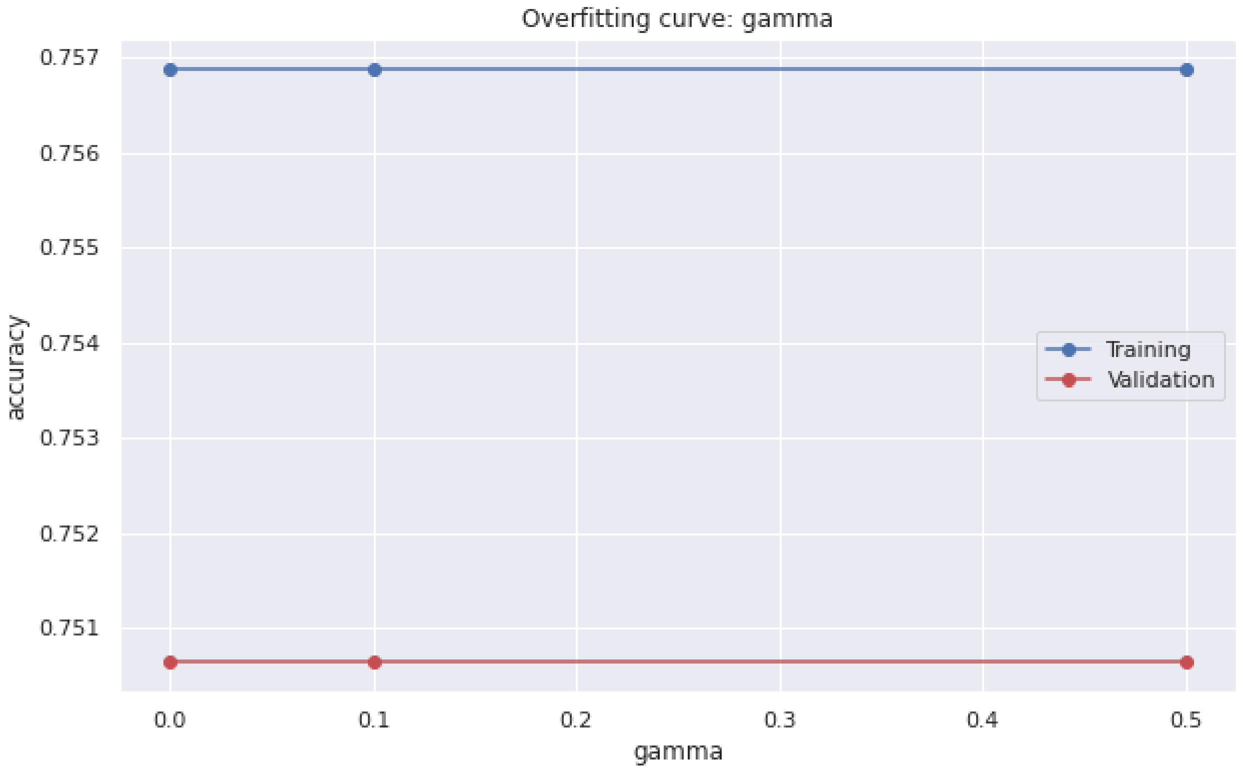

```
test_param_and_plot("learning_rate" , [0.01, 0.1, 0.5])
```



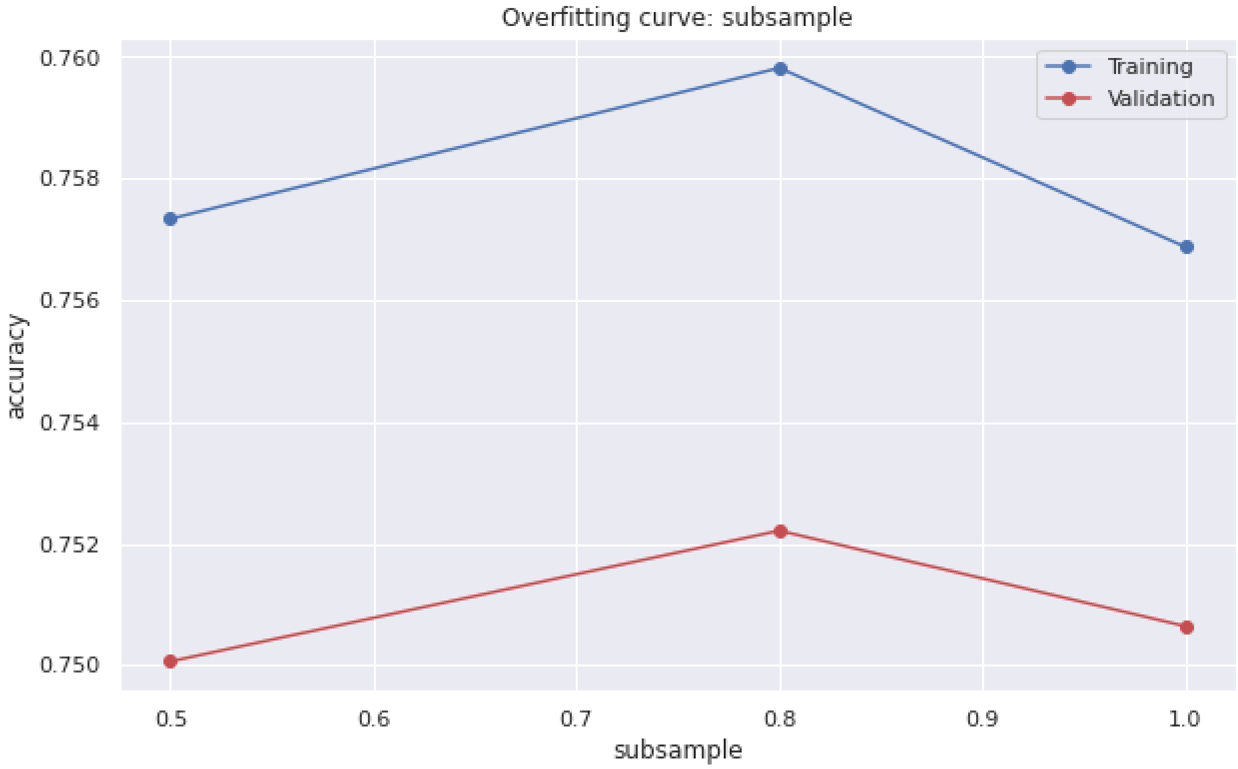

```
test_param_and_plot("n_estimators" , [100, 500, 1000])
```




```
test_param_and_plot("gamma" , [0, 0.1, 0.5])
```




```
test_param_and_plot("subsample" , [0.5, 0.8, 1.0],)
```



So, we can see that in case of improving, **learning_rate** and **n_estimators** these two parameters wroked well.

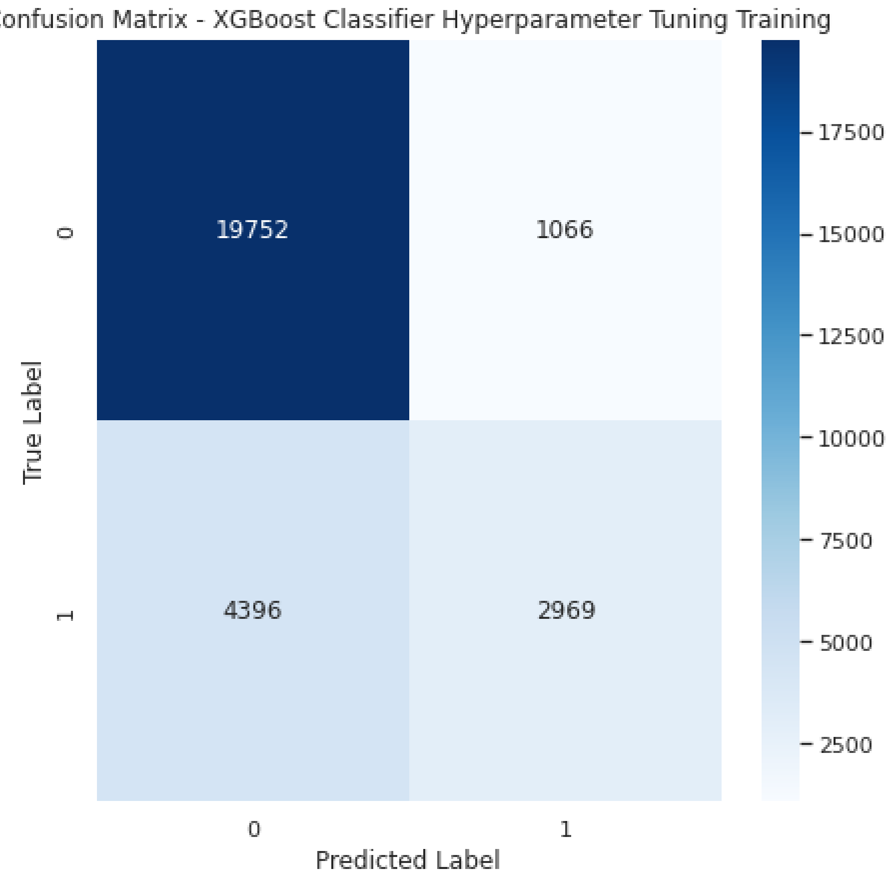
```
%%time
xgb_model = XGBClassifier(learning_rate = 0.1, n_estimators = 450, max_depth = 4, subsa
```

```
CPU times: user 12.9 s, sys: 34.7 ms, total: 12.9 s
Wall time: 13.1 s
```

```
def predict_and_plot(inputs, targets, name=''):
  # predict the target variable on the test set
  preds3 = xgb_model.predict(inputs)

  # evaluate the accuracy of the classifier
  acc3 = accuracy_score(targets, preds3)
  print("XGBoost classifier accuracy:", acc3)

  # create a confusion matrix
  cm = confusion_matrix(targets, preds3)

  # plot the confusion matrix
  sns.heatmap(cm, annot=True, cmap="Blues", fmt="d")
  plt.title("Confusion Matrix - XGBoost Classifier Hyperparameter Tuning {}".format(nam
  plt.xlabel("Predicted Label")
  plt.ylabel("True Label")
  plt.show()

  return preds3
```

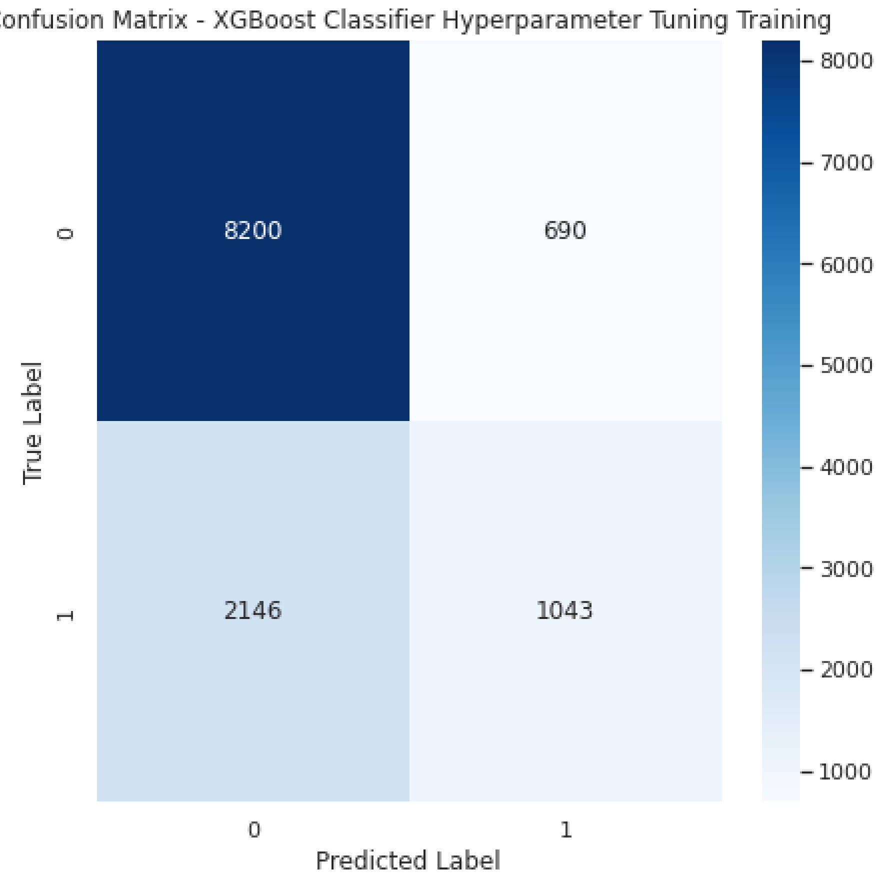
```
train_preds3 = predict_and_plot(X_train, Y_train, 'Training')
```

```
XGBoost classifier accuracy: 0.8061952240712487
```




```
test_preds3 = predict_and_plot(X_val, Y_val, 'Training')
```

```
XGBoost classifier accuracy: 0.7652123520158953
```



We can see after hyperparameter tuning, training & validation accuracy of XGBoost Classifier slightly increased. We can also try different parameters and analyse which parameters are the best to provide a satisfactory accuracy.

Moreover, we can say that among Decision Tree and XGBoost, The **XGBoost** model perfomred better.

```
jovian.commit()
```

```
[jovian] Detected Colab notebook...
[jovian] Uploading colab notebook to Jovian...
Committed successfully! https://jovian.com/kowshikchakraborty6/photo-quality-prediction
```

```
'https://jovian.com/kowshikchakraborty6/photo-quality-prediction'
```