```
# importing needed libraries and packages
import numpy as np
import pandas as pd
```

```
data = pd.read_csv('/content/bank-full.csv',sep=';')
```

```
data2=data
```

```
# getting a glimpse of the data
data
```

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	pre
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1	
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
45206	51	technician	married	tertiary	no	825	no	no	cellular	17	nov	977	3	-1	
45207	71	retired	divorced	primary	no	1729	no	no	cellular	17	nov	456	2	-1	
45208	72	retired	married	secondary	no	5715	no	no	cellular	17	nov	1127	5	184	
45209	57	blue-collar	married	secondary	no	668	no	no	telephone	17	nov	508	4	-1	
45210	37	entrepreneur	married	secondary	no	2971	no	no	cellular	17	nov	361	2	188	

45211 rows × 17 columns

```
# we use value_counts() to display how many instances are present in the
# categorical feature/class variable
data['y'].value_counts()
```

```
no     39922
yes     5289
Name: y, dtype: int64
```

Preprocessing Data

Preprocessing data includes handling missing values and outliers, applying feature coding techniques if needed, scale & standardize features.

Checking for Missing values

```
# isnull() method can be used to check each cell in the dataset
data.isnull()
```

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previou
0	False	False	False	False	False	False	False	False	False	False	False	False	False	False	Fals
1	False	False	False	False	False	False	False	False	False	False	False	False	False	False	Fals
2	False	False	False	False	False	False	False	False	False	False	False	False	False	False	Fals
3	False	False	False	False	False	False	False	False	False	False	False	False	False	False	Fals
4	False	False	False	False	False	False	False	False	False	False	False	False	False	False	Fals
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
45206	False	False	False	False	False	False	False	False	False	False	False	False	False	False	Fals
45207	False	False	False	False	False	False	False	False	False	False	False	False	False	False	Fals
45208	False	False	False	False	False	False	False	False	False	False	False	False	False	False	Fals
45209	False	False	False	False	False	False	False	False	False	False	False	False	False	False	Fals
45210	False	False	False	False	False	False	False	False	False	False	False	False	False	False	Fals

45211 rows × 17 columns

isnull() returns True if the cell contains a missing value and False otherwise. However, since the dataset is large, it is impractical for us to manually check all True, False values. Therefore, we will try to get a summary of the missing values in the dataset as follows.

```
# Finding total standard missing values for each feature
print(data.isnull().sum())
```

```
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
y            0
dtype: int64
```

When using Pandas, we can find the standard missing values (missing values that Pandas can detect) using isnull() and get a summary of the missing values using isnull().sum().

```
# Making a list of missing value types
missing_values = ["unknown"]

# reading the data again, with the defined non-standard missing value
new_data = pd.read_csv('/content/bank-full.csv',sep=';', na_values = missing_values)

print(new_data.isnull().sum())
```

```
age              0
job            288
marital          0
education     1857
default          0
balance          0
housing          0
loan             0
contact      13020
day              0
month            0
duration         0
campaign         0
pdays            0
previous         0
poutcome     36959
y                0
dtype: int64
```

According to the above output, we can see that 4 features contain values as 'unknown', which is a non-standard missing value. However, I have not removed them. These 'unknown' missing values were treated as separate feature values in my model creation. This is because these missing values may not be random and may themselves be information.

Handling Outliers

We check for outliers only in the features that contain numerical values.

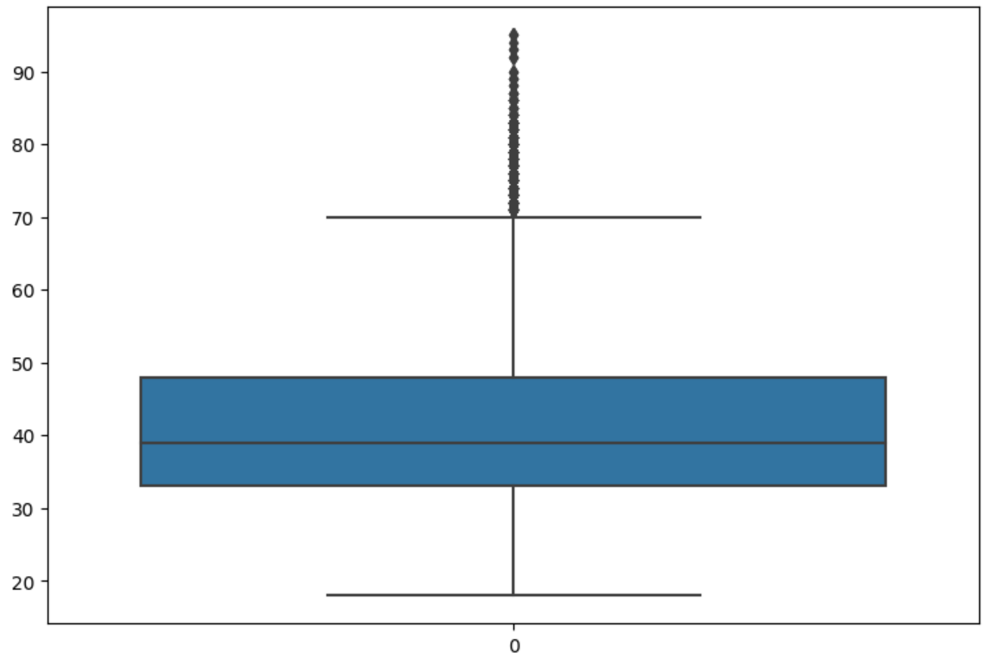
1. Checking the 'age' feature for outliers

```
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
import pandas as pd
warnings.filterwarnings("ignore")
fig, axes = plt.subplots(figsize=(9, 6))

# Checking the box plot for age feature
print("Age Shape:",data.shape)
## Max and Min Quantile
max_val = data.age.quantile(0.75)
min_val = data.age.quantile(0.25)

sns.boxplot(data['age'])
plt.show()
```

```
Age Shape: (45211, 17)
```



When checking the boxplot for the age feature, we can see that there are no significant outliers, and that there are many datapoints that are outside the boxplot. Therefore, i will not be removing the datapoints that are identified here as outliers, since they can carry information in them.

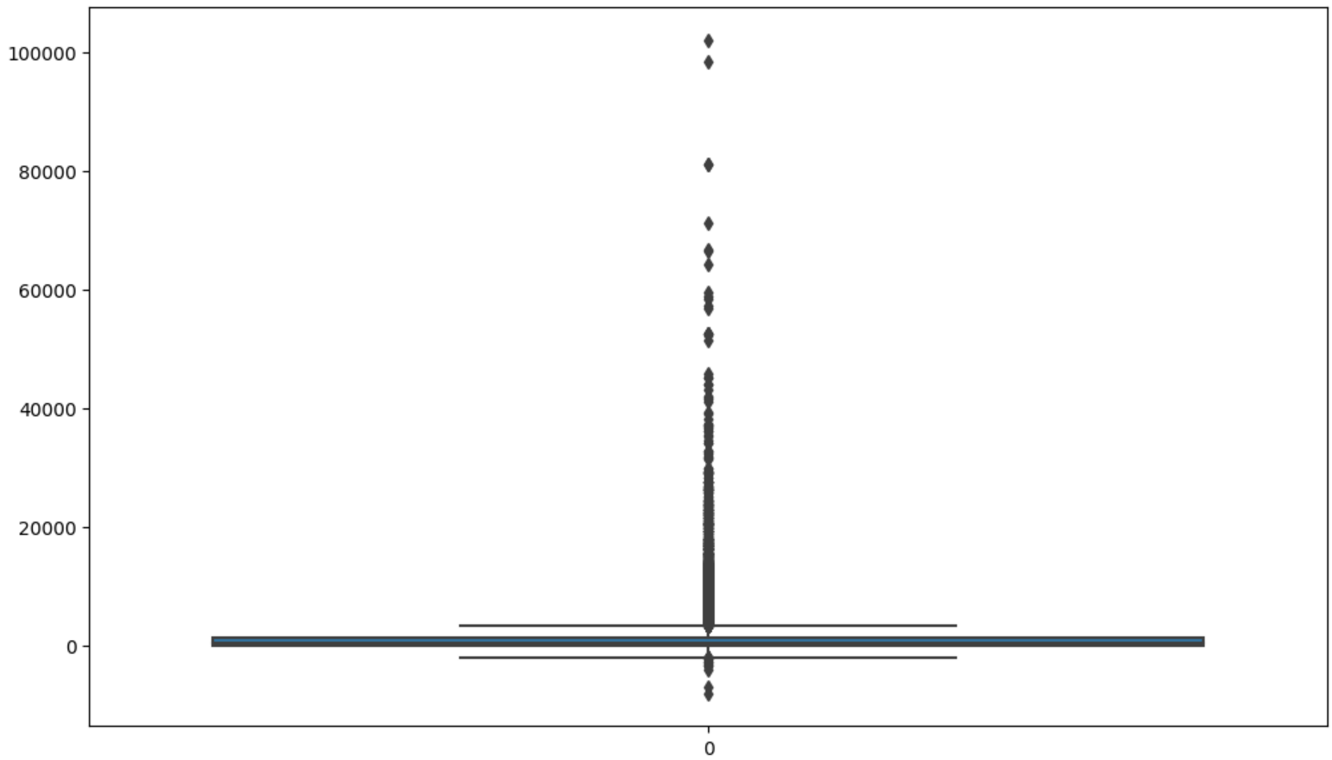
2. Checking the balance feature for outliers

```
fig, axes = plt.subplots(figsize=(12, 7))

# Checking the box plot for balance feature
print("Balance Shape:",data.shape)
## Max and Min Quantile
max_val = data.balance.quantile(0.75)
min_val = data.balance.quantile(0.25)

sns.boxplot(data['balance'])
plt.show()
print(min_val)
```

```
Balance Shape: (45211, 17)
```




```
72.0
```

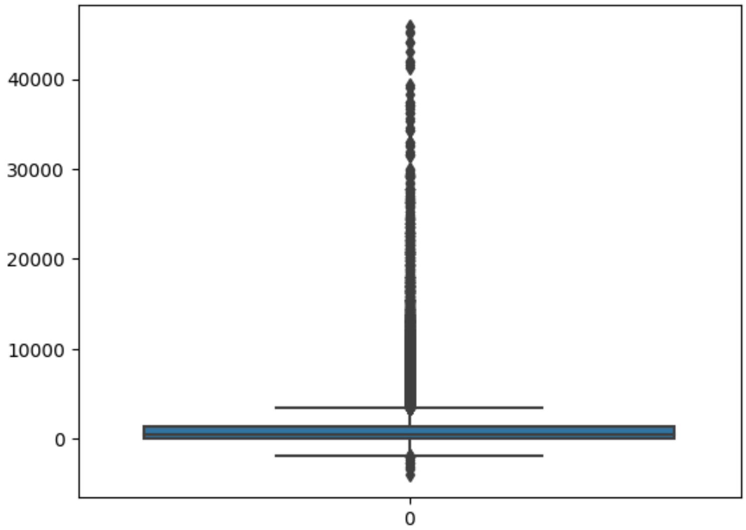
When checking the above visualized boxplot for the balance feature, we can see that eventhough there are many data points outside the boxplot as in the age boxplot, we can point out a range where the datapoints start to spread wider. Therefore, i will manually set the cutoff region for outliers as balance < -6000 and balance > 50000, which is purely out of my discretion.

```
# removing datapoints that have balance values greater than 50000 and less than -6000
data = data[(data['balance']>-6000) & (data['balance']<50000)]

print("After Balance Shape:",data.shape)

sns.boxplot(data['balance'])
plt.show()
```

```
After Balance Shape: (45191, 17)
```



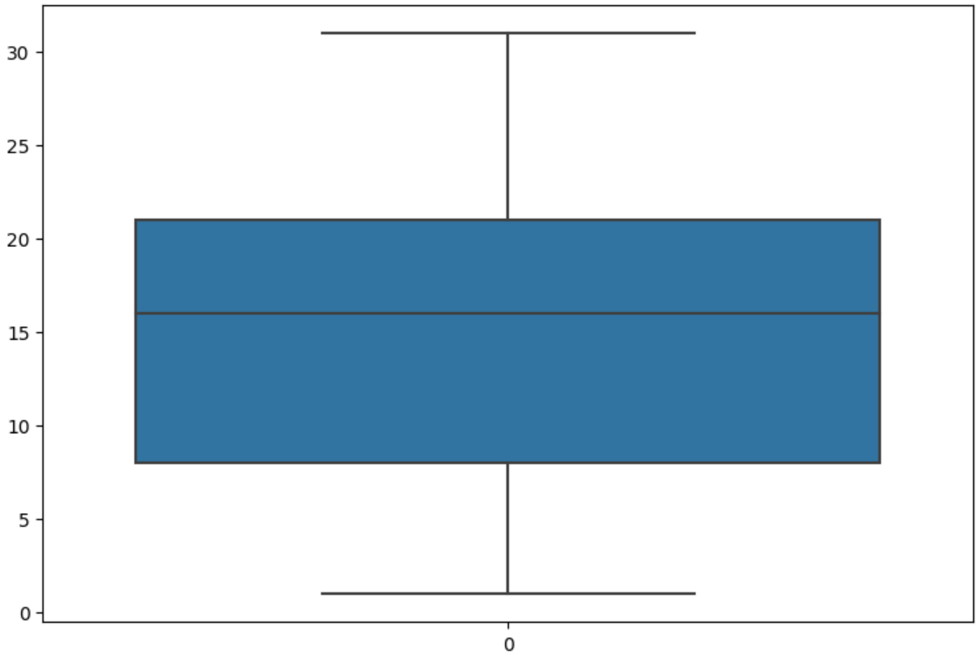
3. Checking outliers for day feature

```
fig, axes = plt.subplots(figsize=(9, 6))

# Checking the box plot for day feature
print("Day Shape:",data.shape)
## Max and Min Quantile
max_val = data.balance.quantile(0.75)
min_val = data.balance.quantile(0.25)

sns.boxplot(data['day'])
plt.show()
```

```
Day Shape: (45191, 17)
```



There are no outliers in the day feature.

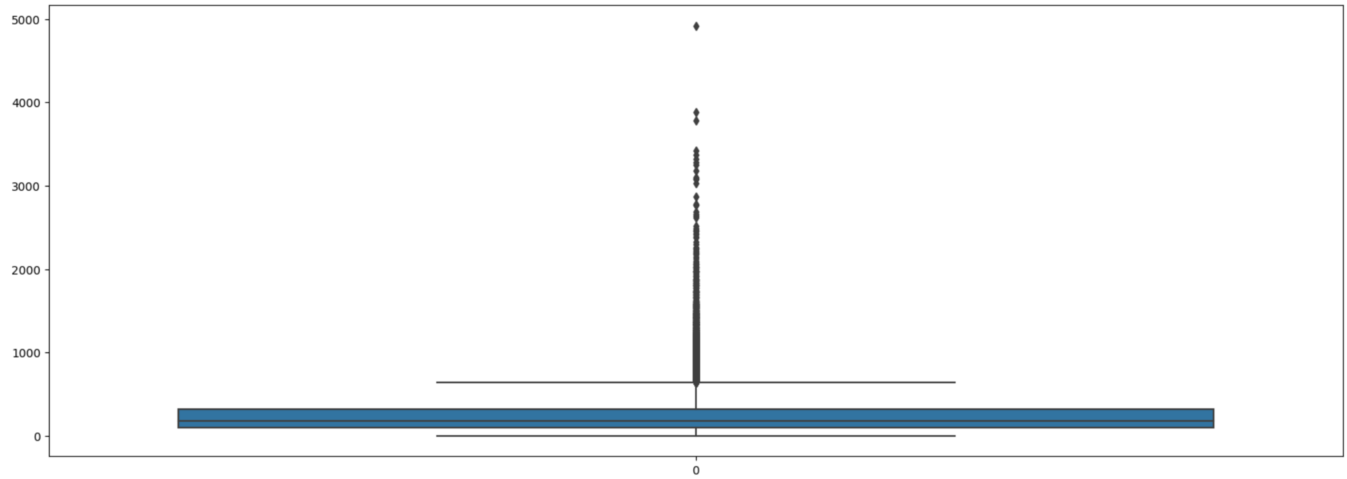
4. Checking outliers for duration feature

```
fig, axes = plt.subplots(figsize=(20, 7))

# Checking the box plot for duration feature
print("Duration Shape:",data.shape)
## Max and Min Quantile
max_val = data.balance.quantile(0.75)
min_val = data.balance.quantile(0.25)

sns.boxplot(data['duration'])
plt.show()
```

```
Duration Shape: (45191, 17)
```



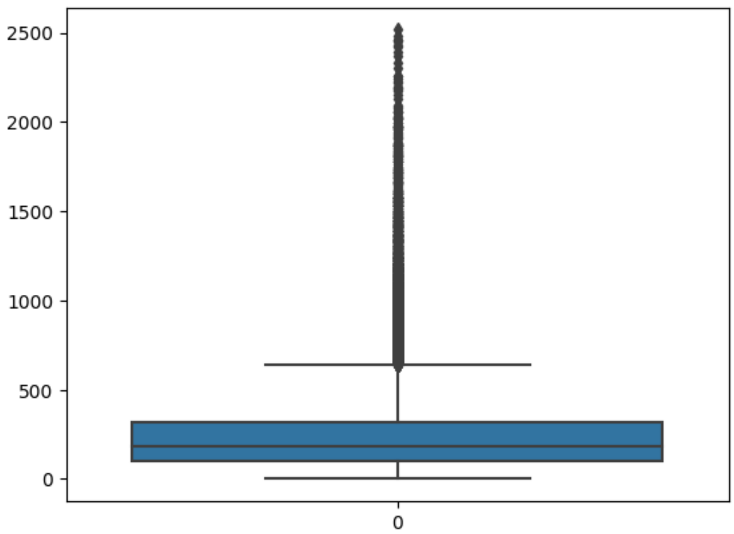
When checking the above box plot, we can see that, there a significant gap has first occured around the duration value 2600. Therefore i decided to clear the datapoints after duration 2600 as handling outliers in this feature

```
# removing datapoints that have duration values greater than 2600
data = data[(data['duration']<2600)]

print("After Duration Shape:",data.shape)

sns.boxplot(data['duration'])
plt.show()
```

```
After Duration Shape: (45169, 17)
```



We can see that after removing the aforesaid outliers, the number of datapoints in the dataset has been educed to 45169.

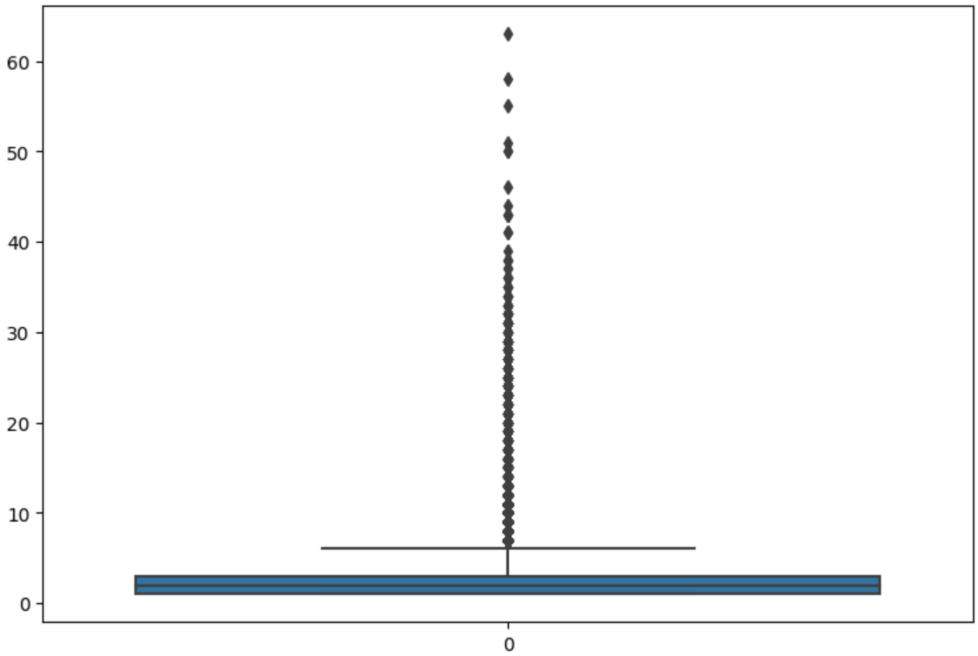
5. Checking outliers in campaign feature

```
fig, axes = plt.subplots(figsize=(9, 6))

# Checking the box plot for campaign feature
print("Campaign Shape:",data.shape)
## Max and Min Quantile
max_val = data.campaign.quantile(0.75)
min_val = data.campaign.quantile(0.25)

sns.boxplot(data['campaign'])
plt.show()
```

```
Campaign Shape: (45169, 17)
```



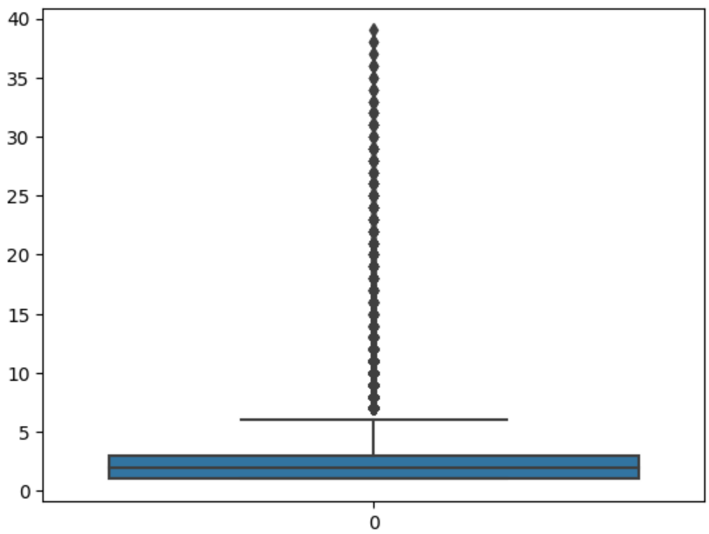
When checking the boxplot visualization, we can see that a break has occured in the datapoints outside the boxplot aroung the campaign count 40. Therefore, i will be clearing the datapoints that has campaign contact count more than 40.

```
# removing datapoints that have campaign values greater than 2600
data = data[(data['campaign']<40)]

print("After Campaign Shape:",data.shape)

sns.boxplot(data['campaign'])
plt.show()
```

```
After Campaign Shape: (45156, 17)
```



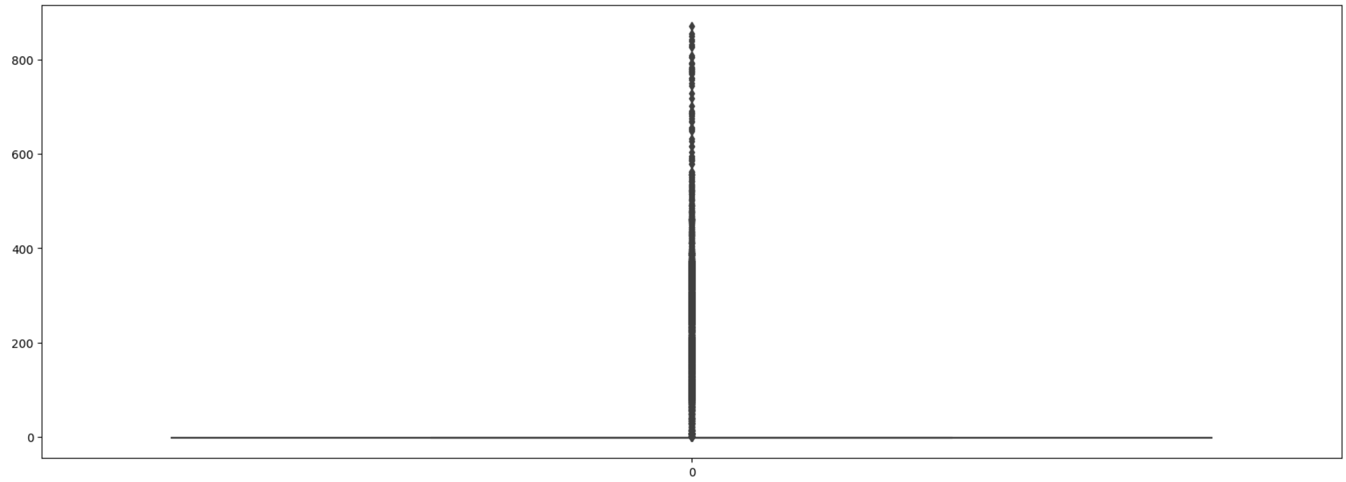
6. Checking outliers in pdays feature

```
fig, axes = plt.subplots(figsize=(20, 7))

# Checking the box plot for pdays feature
print("pdays Shape:",data.shape)
## Max and Min Quantile
max_val = data.pdays.quantile(0.75)
min_val = data.pdays.quantile(0.25)

sns.boxplot(data['pdays'])
plt.show()
```

```
pdays Shape: (45156, 17)
```



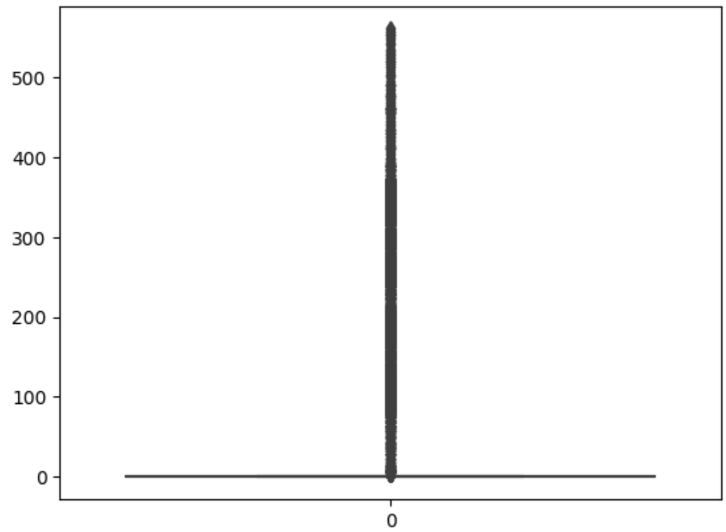
We can see that the values has started breaking from a point aroung 580 pdays. Therefore i will be removing the outliers after pdays = 575

```
# removing datapoints that have pdays values greater than 575
data = data[(data['pdays']<575)]

print("After pdays Shape:",data.shape)

sns.boxplot(data['pdays'])
plt.show()
```

```
After pdays Shape: (45095, 17)
```



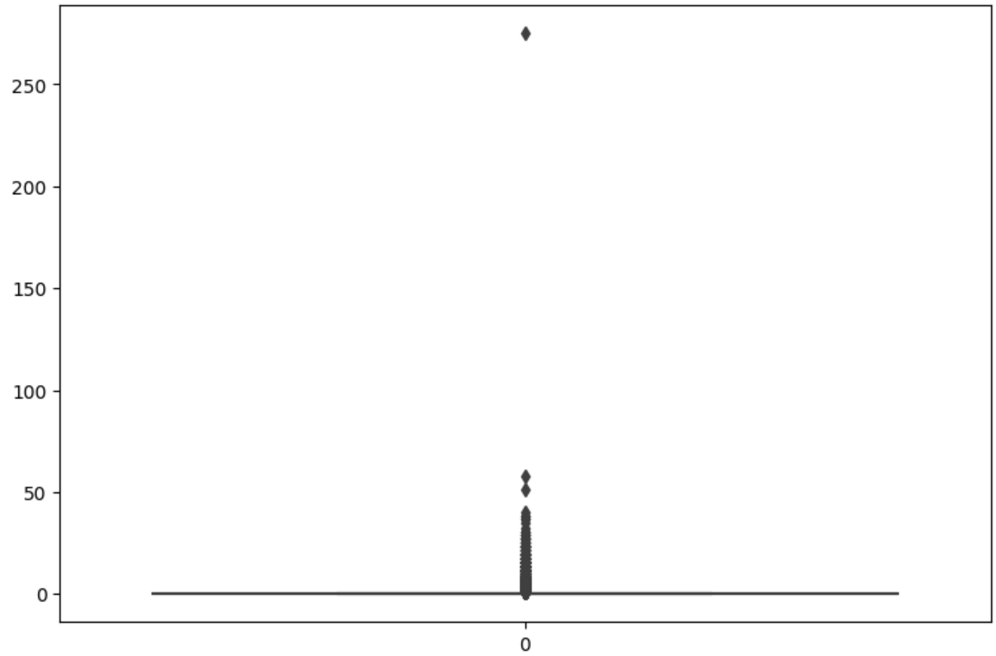
7. Checking outliers in the previous feature

```
fig, axes = plt.subplots(figsize=(9, 6))

# Checking the box plot for previous feature
print("previous Shape:",data.shape)
## Max and Min Quantile
max_val = data.previous.quantile(0.75)
min_val = data.previous.quantile(0.25)

sns.boxplot(data['previous'])
plt.show()
```

```
previous Shape: (45095, 17)
```



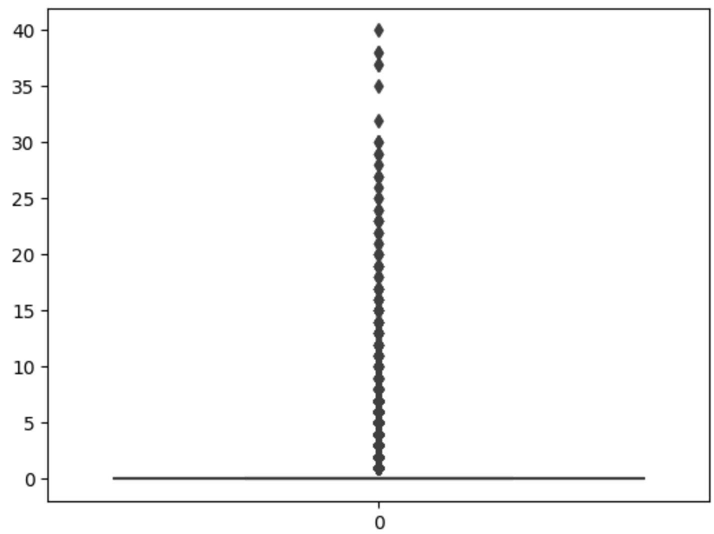
We can see 3 clear outliers after 50 range. Therefore, i will be removing outliers after previous = 50

```
# removing datapoints that have previous values greater than 50
data = data[(data['previous']<50)]

print("After previous Shape:",data.shape)

sns.boxplot(data['previous'])
plt.show()
```

```
After previous Shape: (45092, 17)
```



Now, after careful inspection of all the numerical fields (features) in the dataset, i have removed outliers and the remaining number datapoints of datapoints is 45092. Therefore, we have removed 45211 - 45092 = 119 outliers.

Feature Enoding

In this process, the categorical data are encoded into numerical data. The LabelEncoder is used to encode the class values to integers accordingly as follows.

```
from sklearn.preprocessing import LabelEncoder

# encode strings to integer
data['y'] = LabelEncoder().fit_transform(data['y'])
data['y']
```

```
0        0
1        0
2        0
3        0
4        0
        ..
45206    1
45207    1
45208    1
45209    0
45210    0
Name: y, Length: 45092, dtype: int64
```

There was one feature that can be considered as having Categorical Ordinal data type; education. This is because when considering the values present in this field, an order can be seen as secondary, tertiary etc. This feature was converted to numerical representation using mapping as follows.

```
from sklearn.preprocessing import OrdinalEncoder

# checking the values in education field
data['education'].value_counts()

education_mapper = {"unknown":-1, "primary":1, "secondary":2, "tertiary":3}
data["education"] = data["education"].replace(education_mapper)
data
```

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	pre
0	58	management	married	3	no	2143	yes	no	unknown	5	may	261	1	-1	
1	44	technician	single	2	no	29	yes	no	unknown	5	may	151	1	-1	
2	33	entrepreneur	married	2	no	2	yes	yes	unknown	5	may	76	1	-1	
3	47	blue-collar	married	-1	no	1506	yes	no	unknown	5	may	92	1	-1	
4	33	unknown	single	-1	no	1	no	no	unknown	5	may	198	1	-1	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
45206	51	technician	married	3	no	825	no	no	cellular	17	nov	977	3	-1	
45207	71	retired	divorced	1	no	1729	no	no	cellular	17	nov	456	2	-1	
45208	72	retired	married	2	no	5715	no	no	cellular	17	nov	1127	5	184	
45209	57	blue-collar	married	2	no	668	no	no	telephone	17	nov	508	4	-1	
45210	37	entrepreneur	married	2	no	2971	no	no	cellular	17	nov	361	2	188	

45092 rows × 17 columns

Removing Unwanted Features

The feature **duration** contains last contact duration, in seconds.

As said by the data source, this attribute highly affects the output target (e.g., if duration=0 then y='no'). Yet, the duration is not known before a call is performed. Also, after the end of the call y is obviously known. Thus, this input should only be included for benchmark purposes and should be discarded if the intention is to have a realistic predictive model.

Therefore, i have decided to remove the feature **duration** from the dataset used for prediction.

```
# data.drop(['duration', 'contact','month','day'], inplace=True, axis = 1)
data.drop(['duration'], inplace=True, axis = 1)

# inplace=True means the operation would work on the original object. axis=1 means we are dropping the column, not the row.

data
```

	age	job	marital	education	default	balance	housing	loan	contact	day	month	campaign	pdays	previous	pou
0	58	management	married	3	no	2143	yes	no	unknown	5	may	1	-1	0	un
1	44	technician	single	2	no	29	yes	no	unknown	5	may	1	-1	0	un
2	33	entrepreneur	married	2	no	2	yes	yes	unknown	5	may	1	-1	0	un
3	47	blue-collar	married	-1	no	1506	yes	no	unknown	5	may	1	-1	0	un
4	33	unknown	single	-1	no	1	no	no	unknown	5	may	1	-1	0	un
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
45206	51	technician	married	3	no	825	no	no	cellular	17	nov	3	-1	0	un
45207	71	retired	divorced	1	no	1729	no	no	cellular	17	nov	2	-1	0	un
45208	72	retired	married	2	no	5715	no	no	cellular	17	nov	5	184	3	su
45209	57	blue-collar	married	2	no	668	no	no	telephone	17	nov	4	-1	0	un
45210	37	entrepreneur	married	2	no	2971	no	no	cellular	17	nov	2	188	11	

45092 rows × 16 columns

OneHot Encoding is used to encode the categorical features - 'job', 'marital', 'contact', 'month', 'poutcome' as follows

```
#  Using OneHotEncoding pandas.get_dummies

# listing down the features that has categorical data
categorial_features = ['job', 'marital', 'contact', 'month', 'poutcome']
# categorial_features = ['job', 'marital', 'poutcome']
for item in categorial_features:
    # assigning the encoded data into a new DataFrame object
    df = pd.get_dummies(data[item], prefix=item)
    data = data.drop(item, axis=1)
    for categorial_feature in df.columns:
        #Set the new column in data to have corresponding df values
        data[categorial_feature] = df[categorial_feature]


binary_valued_features = ['default','housing', 'loan']
bin_dict = {'yes':1, 'no':0}

#Replace binary values in data using the provided dictionary
for item in binary_valued_features:
    data.replace({item:bin_dict},inplace=True)
```

After this point, we have encoded all the values in the dataset into numerical values

```
# rearrange the columns in the dataset to contain the y (target/label) at the end

cols = list(data.columns.values)
cols.pop(cols.index('y')) # pop y out of the list
data = data[cols+['y']] #Create new dataframe with columns in new order
```

The above code fragment was written because while encoding the categorical data using OneHotEncoding, the new columns were appended to the end of the dataset and the y (target) column was not at the end anymore.

```
# checking the final info about the dataset
data.describe()
```

	age	education	default	balance	housing	loan	day	campaign	pdays
75%	48.000000	3.000000	0.000000	1425.000000	1.000000	0.000000	21.000000	3.000000	-1.000000

Splitting the Data

```
y = data['y']
X = data.values[:, :-1] # get all columns except the last column

# spliting training and testing data
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state=50)
```

Here when using train_test_split, we use a random_state initializing value to make sure that the data splitting is done in the same way even in a different run of the code.

Feature Scaling

After encoding categorical data, the dataset consists of features with different data ranges. These values are standardized and feature scaling is done as follows. Numerical features were scaled by removing the mean and by scaling to unit variance (StandardScaler) as follows

```
from sklearn.preprocessing import StandardScaler

# Feature scaling
scaler = StandardScaler()
scaler.fit(X)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)


X_train = pd.DataFrame(X_train)
X_test = pd.DataFrame(X_test)
```

Feature Engineering

Feature Selection is one of the core concepts in machine learning which hugely impacts the performance of your model. The data features that you use to train your machine learning models have a huge influence on the performance you can achieve. Irrelevant or partially relevant features can negatively impact model performance.

Drawing the Correlation Matrix

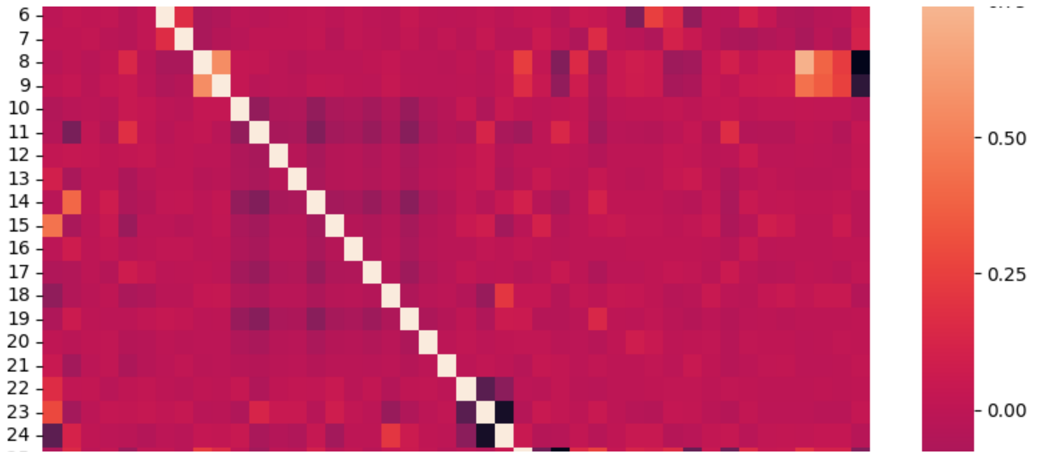
Therefore I will be performing the Correlation Coefficient checking mechanism in order to check the relationship between the different features with the output.

Each of those correlation types can exist in a spectrum represented by values from 0 to 1 where slightly or highly positive correlation features can be something like 0.5 or 0.7. If there is a strong and perfect positive correlation, then the result is represented by a correlation score value of 0.9 or 1.

```
# draw the correlation matrix
correlation_matrix = pd.DataFrame(X_train).corr()
fig, ax = plt.subplots(figsize=(10,10))         # Sample figsize in inches
sns.heatmap(correlation_matrix, ax=ax)
correlation_matrix
```

	0	1	2	3	4	5	6	7	8	9	...	34	
0	1.000000	-0.164160	-0.015227	0.086632	-0.179804	-0.016287	-0.007087	0.005524	-0.026688	0.002297	...	0.052429	0.0228
1	-0.164160	1.000000	-0.008288	0.046873	-0.021548	0.015159	0.018139	0.001410	0.006897	0.026724	...	-0.068824	0.0181
2	-0.015227	-0.008288	1.000000	-0.071413	-0.004733	0.070133	0.005912	0.016081	-0.027990	-0.020866	...	0.006028	-0.0140
3	0.086632	0.046873	-0.071413	1.000000	-0.064539	-0.090828	0.009663	-0.016481	0.003927	0.025602	...	0.033259	0.0296
4	-0.179804	-0.021548	-0.004733	-0.064539	1.000000	0.041551	-0.030964	-0.029192	0.133308	0.043427	...	-0.106072	-0.0680
5	-0.016287	0.015159	0.070133	-0.090828	0.041551	1.000000	0.010779	0.012088	-0.019148	-0.011602	...	-0.025250	-0.0298
6	-0.007087	0.018139	0.005912	0.009663	-0.030964	0.010779	1.000000	0.167007	-0.094614	-0.061620	...	-0.196811	-0.0194
7	0.005524	0.001410	0.016081	-0.016481	-0.029192	0.012088	0.167007	1.000000	-0.088567	-0.037563	...	0.039771	-0.0186
8	-0.026688	0.006897	-0.027990	0.003927	0.133308	-0.019148	-0.094614	-0.088567	1.000000	0.555006	...	-0.117551	0.0282
9	0.002297	0.026724	-0.020866	0.025602	0.043427	-0.011602	-0.061620	-0.037563	0.555006	1.000000	...	-0.075735	0.0323
10	-0.053430	-0.022010	-0.010927	-0.026260	0.042950	0.029686	-0.012678	-0.023276	0.027819	0.023313	...	-0.005793	0.0178
11	-0.046026	-0.306875	0.012105	-0.051600	0.178240	0.022484	-0.023268	0.004331	0.020462	-0.023915	...	0.022677	-0.0431
12	0.021753	0.030001	0.026482	0.004680	0.015230	0.035442	-0.001262	0.002232	-0.013604	-0.011141	...	0.014141	-0.0166
13	0.089869	-0.091424	0.000637	0.007631	-0.079964	-0.015702	0.003409	0.003350	-0.033692	-0.016842	...	0.057443	0.0002
14	-0.024640	0.399608	0.002399	0.068451	-0.068157	-0.038554	0.015127	0.018818	-0.008165	0.018705	...	-0.035616	0.0191
15	0.447124	-0.092202	-0.010992	0.042482	-0.154723	-0.012232	-0.008760	-0.030499	-0.007012	0.009722	...	0.011126	0.0452
16	-0.007664	0.072204	-0.000147	0.017995	-0.027450	-0.004260	0.009912	0.010929	-0.010990	-0.004148	...	0.007724	-0.0024
17	-0.059451	-0.057029	-0.005781	-0.039262	0.069399	0.031589	-0.007507	-0.001459	0.007129	-0.014046	...	0.010280	-0.0183
18	-0.199933	-0.057469	-0.018181	0.005053	-0.085552	-0.058513	-0.016856	-0.020584	0.025585	0.035139	...	-0.014274	0.0459
19	-0.071419	0.062998	-0.003457	-0.012946	-0.012886	0.011318	0.034591	0.017365	-0.013921	-0.000897	...	-0.038083	-0.0130
20	0.003076	-0.014289	0.007834	0.008774	-0.043150	-0.034810	-0.003070	-0.015414	-0.009360	-0.008714	...	0.002679	0.0080
21	0.049217	-0.118527	-0.008266	0.013908	-0.074612	-0.031852	-0.008336	0.012993	-0.017314	-0.012345	...	0.051110	0.0014
22	0.167251	0.010131	0.018405	-0.024636	0.001098	0.017297	-0.000222	-0.019078	0.003481	-0.003226	...	0.012696	-0.0052
23	0.284552	-0.112360	-0.012556	0.023283	0.018429	0.035055	0.009161	0.033837	-0.028798	-0.018549	...	0.017731	-0.0172
24	-0.427703	0.114895	0.000596	-0.007835	-0.020800	-0.050346	-0.009796	-0.023241	0.028820	0.022440	...	-0.028263	0.0224
25	-0.070286	0.151680	-0.009017	0.016282	-0.153160	0.012107	0.020149	-0.023260	0.236325	0.162039	...	-0.391858	0.0488
26	0.167962	-0.072612	-0.015262	0.033222	-0.078778	-0.006640	0.025289	0.054327	0.015339	0.037591	...	-0.073749	0.0237
27	-0.016785	-0.120673	0.017772	-0.035156	0.204181	-0.009175	-0.034941	-0.004875	-0.257556	-0.191251	...	0.453215	-0.0643
28	-0.028933	0.005041	-0.026545	0.017947	0.081377	-0.024016	0.050078	-0.069444	0.149295	0.070211	...	-0.096051	-0.0275
29	0.075142	0.095718	-0.007383	0.006771	-0.306417	-0.070639	0.033704	0.159575	-0.112173	-0.064303	...	-0.146913	-0.0421
30	0.019249	0.000377	-0.008984	0.016632	-0.051110	-0.020362	-0.009908	-0.010558	0.048476	0.050632	...	-0.024562	-0.0070
31	-0.004771	0.021399	-0.007702	-0.006904	-0.060830	-0.009667	-0.284591	-0.028424	0.074104	0.071945	...	-0.090389	-0.0259
32	-0.007162	0.010511	-0.006785	-0.026823	-0.066789	-0.006500	0.248698	-0.062673	0.056908	0.055307	...	-0.065249	-0.0187
33	0.003489	-0.014431	0.039730	-0.068199	-0.059941	0.168922	0.147445	0.108861	-0.140985	-0.101605	...	-0.154839	-0.0443
34	0.052429	-0.068824	0.006028	0.033259	-0.106072	-0.025250	-0.196811	0.039771	-0.117551	-0.075735	...	1.000000	-0.0383
35	0.022825	0.018169	-0.014019	0.029632	-0.068011	-0.029853	-0.019449	-0.018677	0.028234	0.032310	...	-0.038330	1.0000
36	-0.125761	-0.068977	-0.002881	-0.073507	0.426129	-0.025027	-0.026958	-0.074723	0.088779	0.004265	...	-0.243090	-0.0696
37	0.029050	0.051460	0.009799	0.124019	0.003226	0.015810	0.095247	-0.087845	0.013275	0.052001	...	-0.113645	-0.0325
38	0.061120	0.010865	-0.017395	0.045353	-0.089980	-0.030357	0.028929	-0.053320	0.053665	0.066291	...	-0.047560	-0.0136
39	0.033475	0.001384	-0.012491	0.018811	-0.074278	-0.031792	-0.053488	-0.035423	0.054546	0.071680	...	-0.039547	-0.0113
40	-0.008377	0.020024	-0.023488	0.016565	0.112398	0.000931	-0.069878	-0.088182	0.715263	0.436729	...	-0.097473	0.0099
41	-0.021871	0.008748	-0.015419	0.008178	0.037032	-0.007114	-0.033025	-0.018895	0.384932	0.360163	...	-0.053934	0.0182
42	0.032141	0.028548	-0.023613	0.033107	-0.087610	-0.052044	-0.028486	-0.059563	0.234780	0.252633	...	-0.024131	0.0611
43	0.002919	-0.033866	0.037753	-0.032908	-0.068683	0.027069	0.086364	0.108394	-0.881427	-0.652595	...	0.117210	-0.0457

44 rows × 44 columns



After generating the correlation matrix, we can see that to the right side of the matrix, there are features that has a very high correlation. We usually remove such features that have high correlations because, they are some what linearly dependent with other features. These features contribute very less in predicting the output but increses the computational cost. In order to find the exact columns that has the high correlation values, i perform the below code. I am checking the upper triangle of the correlation matrux because the uppoer and lower traingles are mirrors of each other that are divided by the diagonal in the correlation matrix. Here i am checking the columns that has correlations values more than 0.95 with the hope of removing them.


```
# getting the upper triangle of the correlation matrix
upper_tri = correlation_matrix.where(np.triu(np.ones(correlation_matrix.shape),k=1).astype(np.bool))
print(upper_tri)

# checking which columns can be dropped
to_drop = [column for column in upper_tri.columns if any(upper_tri[column] > 0.95)]
print('\nTo drop')
print(to_drop)

# removing the selected columns
X_train = X_train.drop(X_train.columns[to_drop], axis=1)
X_test = X_test.drop(X_test.columns[to_drop], axis=1)
print(X_train.head())
```

```
     0        1         2         3         4         5         6         7  \
0  NaN -0.16416 -0.015227  0.086632 -0.179804 -0.016287 -0.007087  0.005524
1  NaN      NaN -0.008288  0.046873 -0.021548  0.015159  0.018139  0.001410
2  NaN      NaN       NaN -0.071413 -0.004733  0.070133  0.005912  0.016081
3  NaN      NaN       NaN       NaN -0.064539 -0.090828  0.009663 -0.016481
4  NaN      NaN       NaN       NaN       NaN  0.041551 -0.030964 -0.029192
5  NaN      NaN       NaN       NaN       NaN       NaN  0.010779  0.012088
6  NaN      NaN       NaN       NaN       NaN       NaN       NaN  0.167007
7  NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
8  NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
9  NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
10 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
11 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
12 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
13 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
14 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
15 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
16 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
17 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
18 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
19 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
20 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
21 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
22 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
23 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
24 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
25 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
26 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
27 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
28 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
29 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
30 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
31 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
32 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
33 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
34 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
35 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
36 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
37 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
38 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
39 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
40 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
41 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
42 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN
```

```
43 NaN      NaN       NaN       NaN       NaN       NaN       NaN       NaN

          8         9   ...        34        35        36        37        38  \
0  -0.026688  0.002297  ...  0.052429  0.022825 -0.125761  0.029050  0.061120
1   0.006897  0.026724  ... -0.068824  0.018169 -0.068977  0.051460  0.010865
2  -0.027990 -0.020866  ...  0.006028 -0.014019 -0.002881  0.009799 -0.017395
3   0.003927  0.025602  ...  0.033259  0.029632 -0.073507  0.124019  0.045353
4   0.133308  0.043427  ... -0.106072 -0.068011  0.426129  0.003226 -0.089980
5  -0.019148 -0.011602  ... -0.025250 -0.029853 -0.025027  0.015810 -0.030357
6  -0.094614 -0.061620  ... -0.196811 -0.019449 -0.026958  0.095247  0.028929
7  -0.088567 -0.037563  ...  0.039771 -0.018677 -0.074723 -0.087845 -0.053320
8        NaN  0.555006  ... -0.117551  0.028234  0.088779  0.013275  0.053665
9        NaN       NaN  ... -0.075735  0.032310  0.004265  0.052001  0.066291
```

However, after performing the above code, we can see that there are no columns that has more than 0.95 correlation and that therefore, there are no columns to be removed.

Applying PCA

Principal Component Analysis, or PCA, is a dimensionality-reduction method that is often used to reduce the dimensionality of large data sets, by transforming a large set of variables into a smaller one that still contains most of the information in the large set.

```
from sklearn.decomposition import PCA

# apply the PCA for feature for feature reduction
pca = PCA(n_components=0.95)
pca.fit(X_train)
PCA_X_train = pca.transform(X_train)
PCA_X_test = pca.transform(X_test)

X_train
```

	0	1	2	3	4	5	6	
0	-0.558648	-1.128982	-0.135502	-0.479519	0.893548	-0.436770	-0.097025	-0.250
1	1.796571	-0.021201	-0.135502	-0.484989	-1.119134	2.289535	0.263477	0.748
2	0.666066	-0.021201	-0.135502	0.085987	-1.119134	-0.436770	-1.298699	-0.584
3	-0.841275	-1.128982	-0.135502	-0.491552	0.893548	-0.436770	1.344984	-0.584
4	-0.181813	-0.021201	-0.135502	-0.001518	0.893548	2.289535	1.585319	-0.250
...	...	...	...	...	...	...	...	
36068	-0.747066	1.086579	-0.135502	0.232195	-1.119134	-0.436770	-0.217193	-0.250
36069	-0.558648	1.086579	-0.135502	-0.387274	0.893548	-0.436770	1.104649	0.748
36070	-1.123901	-3.344543	-0.135502	-0.233045	-1.119134	-0.436770	-0.938197	-0.584
36071	-1.312319	-0.021201	-0.135502	-0.358834	0.893548	-0.436770	-0.097025	-0.584
36072	-0.087605	-0.021201	-0.135502	-0.433214	0.893548	-0.436770	-0.577695	-0.584

36073 rows × 44 columns

Here, I have not manually set the n_components of the PCA model. We want the explained variance to be between 95–99%. Therefore, i have set the PCA's n_components to 0.95

Developing the MultiLayer Perceptron Model

```
from sklearn.neural_network import MLPClassifier

# define and train an MLPClassifier named mlp on the given data
mlp = MLPClassifier(hidden_layer_sizes=(50,200,50), max_iter=300, activation='relu', solver='adam', random_state=1)
mlp.fit(PCA_X_train, y_train)
```

```
MLPClassifier
MLPClassifier(hidden_layer_sizes=(50, 200, 50), max_iter=300, random_state=1)
```

```
PCA_X_train
```

```
array([[ 3.17428136,  2.9417411 ,  1.10190984, ..., -0.7581117 ,
         -0.06754851, -0.08753574],
       [-0.45357695, -2.77266654,  2.74546928, ...,  0.35935679,
         -0.51365627, -0.72655917],
       [-0.28609767, -1.77098747,  0.85752515, ..., -1.11515942,
```

```
        -0.22941411, -0.16754282],
       ...,
       [ 0.32611861, -0.83789589, -1.5608128 , ...,  0.96349741,
         1.89423924,  3.23526765],
       [-0.2452907 ,  0.84814249, -2.59078885, ..., -0.11918013,
        -0.39904162, -0.09239883],
       [-0.34673753, -0.82099457,  0.23221502, ..., -1.23767651,
        -0.6650229 , -0.04314375]])
```

Confusion Matrix

Using confusion matrix, we can find how many true positives, false postives, false negatives and true negatives are there.

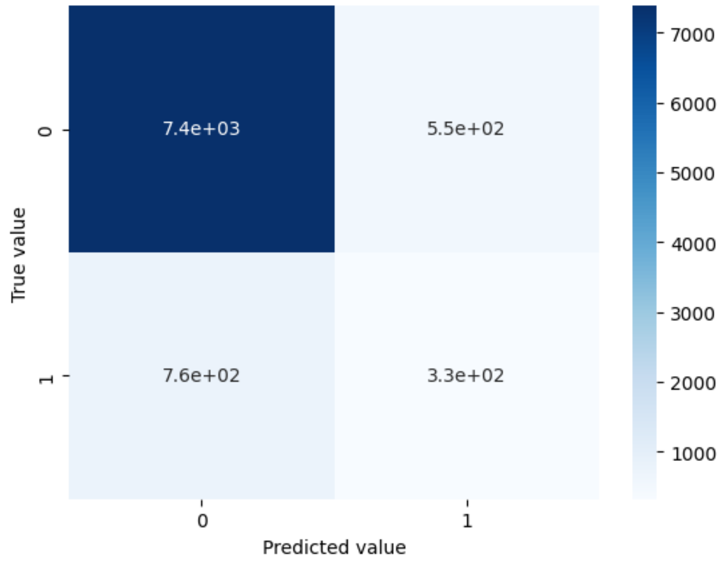
```
print('Accuracy')
print(mlp.score(PCA_X_test, y_test))

# draw the confusion matrix
predict = mlp.predict(PCA_X_test)

from sklearn.metrics import confusion_matrix

confusion_matrix = confusion_matrix(y_test, predict)
fig, ax = plt.subplots(1)
ax = sns.heatmap(confusion_matrix, ax=ax, cmap=plt.cm.Blues, annot=True)
plt.ylabel('True value')
plt.xlabel('Predicted value')
plt.show()
```

```
Accuracy
0.8546402040137487
```



The above confusion matrix shows that there are 340 true positives and 7400 false negatives, which is still good for an imbalanced dataset. The number of false positives are 570 and true negatives are 750.

We can find the Mean Squared Error (MSE) and other scores as follows

```
from sklearn.metrics import accuracy_score, mean_squared_error

# print the training error and MSE
print("Training error: %f" % mlp.loss_curve_[-1])
print("Training set score: %f" % mlp.score(PCA_X_train, y_train))
print("Test set score: %f" % mlp.score(PCA_X_test, y_test))
print(accuracy_score(y_test, predict))

print("MSE: %f" % mean_squared_error(y_test, predict))
```

```
Training error: 0.089994
Training set score: 0.972001
Test set score: 0.854640
0.8546402040137487
MSE: 0.145360
```