Problem Statment:

Build a decision tree classifier to predict whether a customer will purchase a product or service based on their demographic and behavioral data. Use a dataset such as the Bank Marketing dataset from the UCI Machine Learning Repository.

[1]:
```
from google.colab import files
```

[4]:
```
data = files.upload()
```

```
<IPython.core.display.HTML object>
```

```
Saving bank-full.csv to bank-full.csv
```

IMPORTING LIBRARIES:

[5]:
```
import pandas as pd

import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

GETTING AND READING DATA:

[8]:
```
df = pd.read_csv('bank-full.csv', delimiter=';')
df.head()
```

[8]:
```
   age           job  marital  education default  balance housing loan  \
0   58    management  married   tertiary      no     2143     yes   no
1   44    technician   single  secondary      no       29     yes   no
2   33  entrepreneur  married  secondary      no        2     yes  yes
3   47   blue-collar  married    unknown      no     1506     yes   no
4   33       unknown   single    unknown      no        1      no   no

   contact  day month  duration  campaign  pdays  previous poutcome   y
0  unknown    5   may       261         1     -1         0  unknown  no
1  unknown    5   may       151         1     -1         0  unknown  no
2  unknown    5   may        76         1     -1         0  unknown  no
3  unknown    5   may        92         1     -1         0  unknown  no
4  unknown    5   may       198         1     -1         0  unknown  no
```

EDA AND PREPROCESSING:

[9]:
```
df.info()          #getting information about our data
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   age        45211 non-null  int64
 1   job        45211 non-null  object
 2   marital    45211 non-null  object
 3   education  45211 non-null  object
 4   default    45211 non-null  object
 5   balance    45211 non-null  int64
 6   housing    45211 non-null  object
 7   loan       45211 non-null  object
 8   contact    45211 non-null  object
 9   day        45211 non-null  int64
 10  month      45211 non-null  object
 11  duration   45211 non-null  int64
 12  campaign   45211 non-null  int64
 13  pdays      45211 non-null  int64
 14  previous   45211 non-null  int64
 15  poutcome   45211 non-null  object
 16  y          45211 non-null  object
dtypes: int64(7), object(10)
memory usage: 5.9+ MB
```

[10]:
```
df.isna().sum()          #checking foer null values
```

[10]:
```
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
```

[11]:
```
df.duplicated().sum()        #checking for duplicate values
```

[11]:
```
0
```

[12]:
```
#removing unnecessary columns from dataset
df = df[['age',␣
 ↪'job','marital','education','balance','housing','loan','campaign','pdays','previous','y']]
```

[13]:
```
df.head()
```

[13]:
```
   age           job  marital  education  balance housing loan  campaign  \
0   58    management  married   tertiary     2143     yes   no         1
1   44    technician   single  secondary       29     yes   no         1
2   33  entrepreneur  married  secondary        2     yes  yes         1
3   47   blue-collar  married    unknown     1506     yes   no         1
4   33       unknown   single    unknown        1      no   no         1

   pdays  previous   y
0     -1         0  no
1     -1         0  no
2     -1         0  no
3     -1         0  no
4     -1         0  no
```

[14]:
```
df['marital'].value_counts()                    #checks value by marital
```

[14]:
```
married     27214
single      12790
divorced     5207
Name: marital, dtype: int64
```

[15]:
```
df['job'].value_counts()       #checks value by job wise
```

[15]:
```
blue-collar      9732
management       9458
technician       7597
admin.           5171
services         4154
retired          2264
self-employed    1579
entrepreneur     1487
unemployed       1303
housemaid        1240
student           938
unknown           288
Name: job, dtype: int64
```

[16]:
```
df['education'].value_counts()          #checks value by education wise
```

[16]:
```
secondary    23202
tertiary     13301
primary       6851
unknown       1857
Name: education, dtype: int64
```

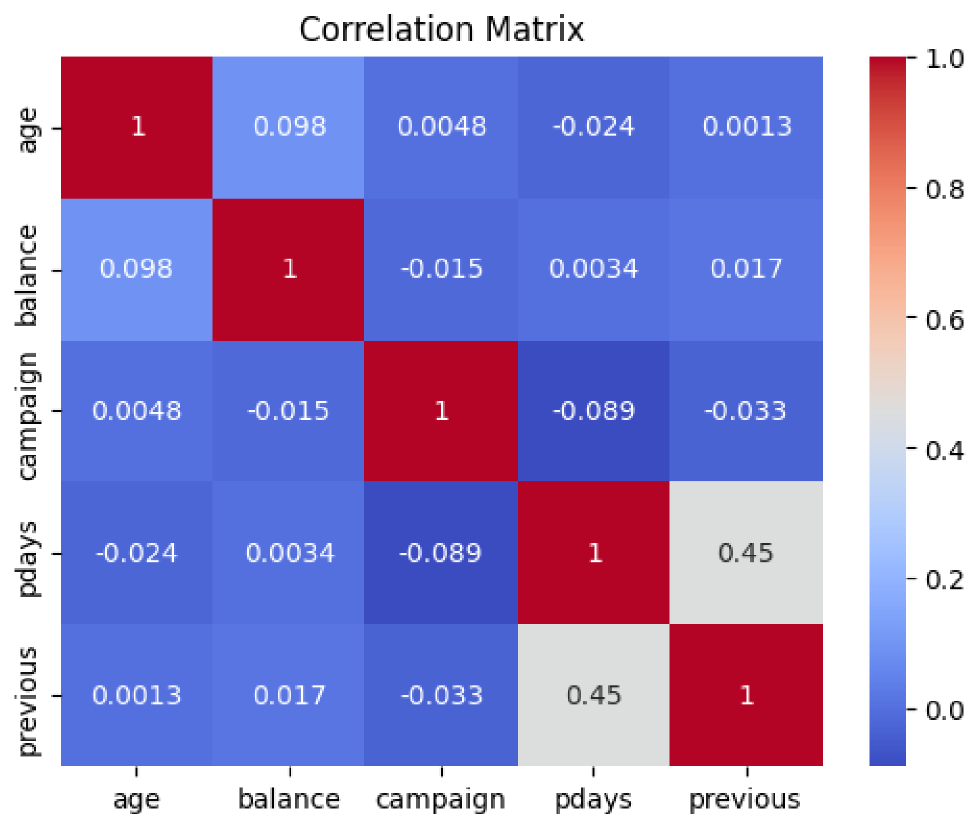
[17]:
```
df.describe().T                          #getting description of data
```

[17]:
```
            count         mean          std     min   25%    50%     75%  \
age       45211.0    40.936210    10.618762    18.0  33.0   39.0    48.0
balance   45211.0  1362.272058  3044.765829 -8019.0  72.0  448.0  1428.0
campaign  45211.0     2.763841     3.098021     1.0   1.0    2.0     3.0
pdays     45211.0    40.197828   100.128746    -1.0  -1.0   -1.0    -1.0
previous  45211.0     0.580323     2.303441     0.0   0.0    0.0     0.0

               max
age           95.0
balance   102127.0
campaign      63.0
pdays        871.0
previous     275.0
```

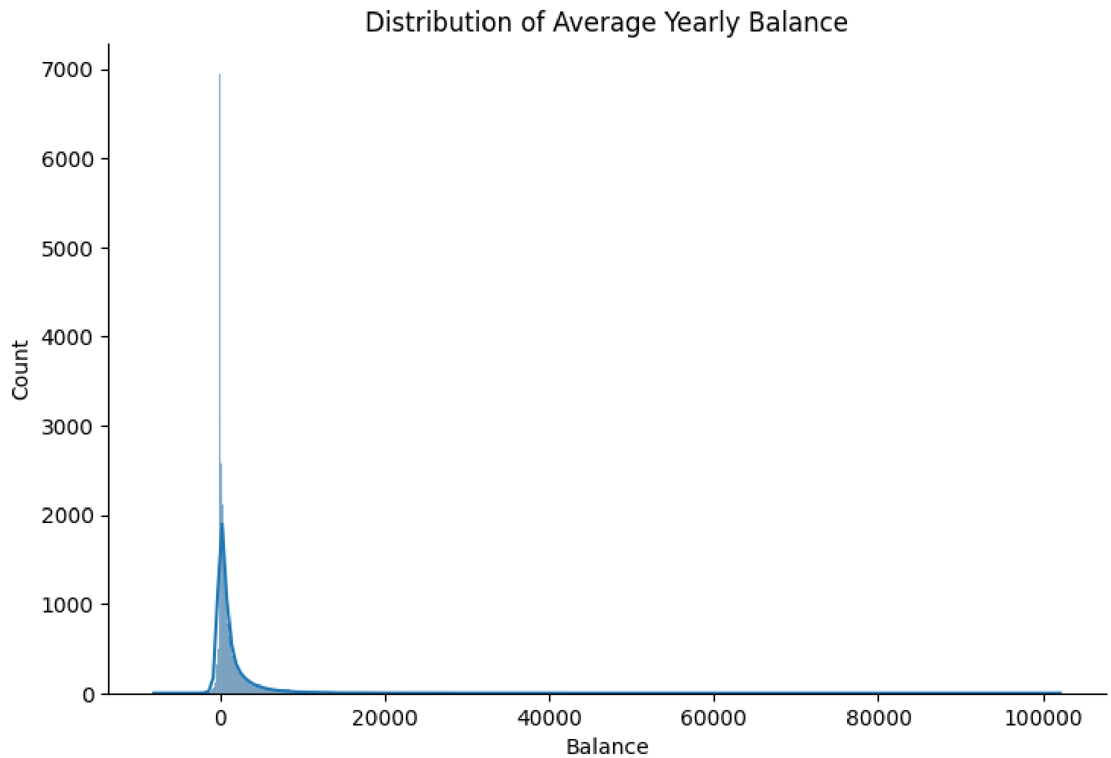
[18]:
```
df.corr(numeric_only=True)              #checking statistical correlation␣
 ↪between
```

[18]:
```
               age   balance  campaign     pdays  previous
age       1.000000  0.097783  0.004760 -0.023758  0.001288
balance   0.097783  1.000000 -0.014578  0.003435  0.016674
campaign  0.004760 -0.014578  1.000000 -0.088628 -0.032855
pdays    -0.023758  0.003435 -0.088628  1.000000  0.454820
previous  0.001288  0.016674 -0.032855  0.454820  1.000000
```

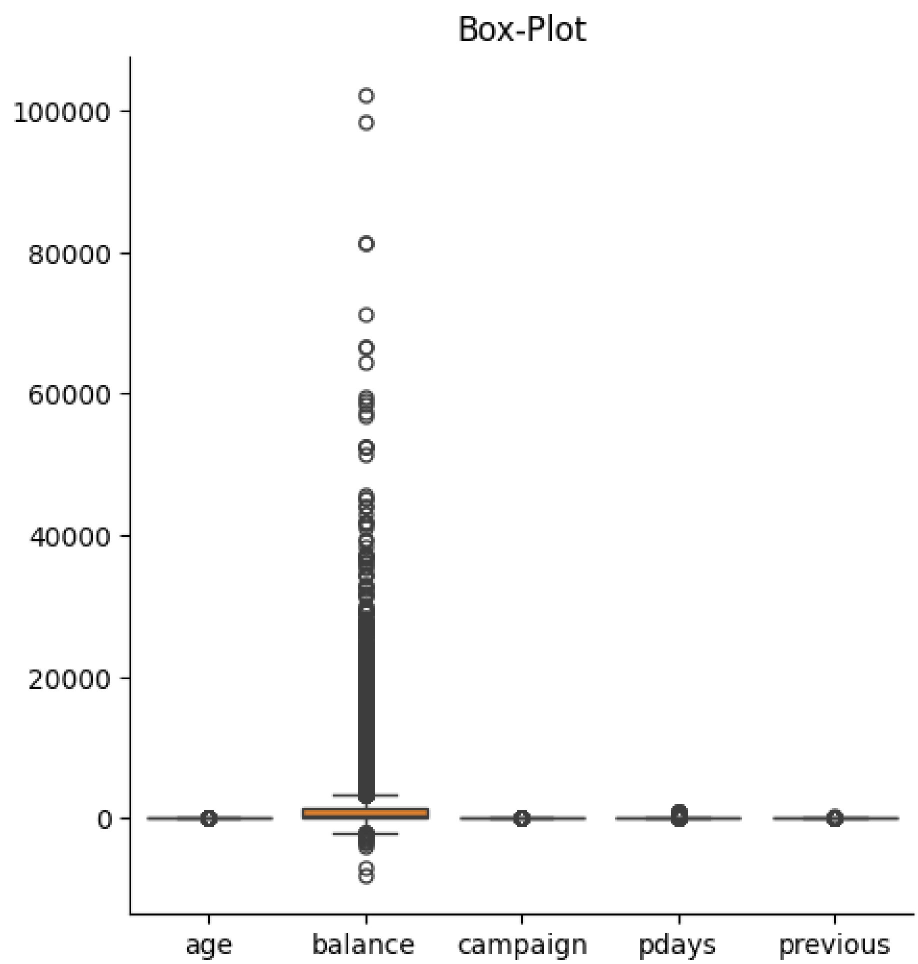
[19]:
```
# plotting correlation matrix by using heatmap
sns.heatmap(df.corr(numeric_only = True),annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



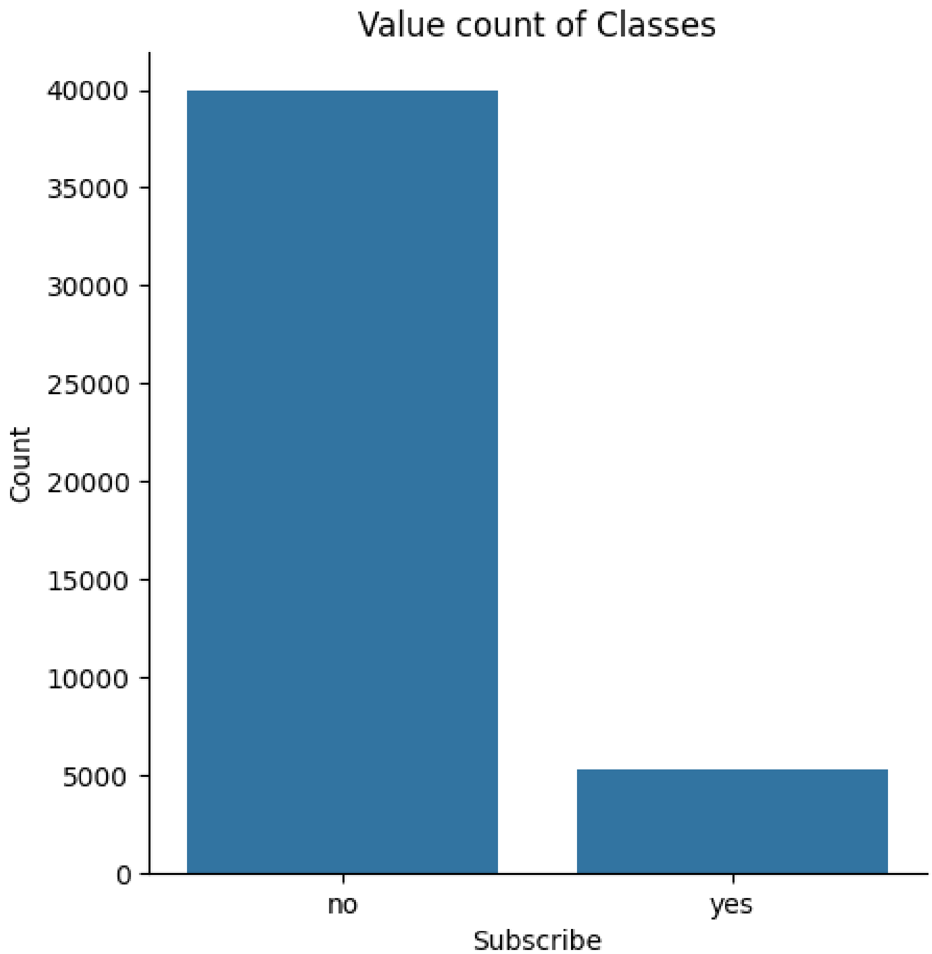
[20]:
```
# plotting histogram for average yearly balance
sns.displot(data = df, x='balance', kind ='hist', kde=True, aspect=1.5)
plt.title('Distribution of Average Yearly Balance')
plt.xlabel('Balance')
plt.ylabel('Count')
plt.show()
```



[21]:
```
# plotting box-plot to identify outliers
sns.catplot(data=df, kind='box')
plt.title('Box-Plot')
plt.show()
```



[22]:
```
# plotting countplot for target column
sns.catplot(data=df, x='y', kind='count')
plt.title('Value count of Classes')
plt.xlabel('Subscribe')
plt.ylabel('Count')
plt.show()
```



[23]:
```
pd.crosstab(df['y'],df['job']).T  #shows job wise distribution for target values
```

[23]:
```
y                no   yes
job
admin.         4540   631
blue-collar    9024   708
entrepreneur   1364   123
housemaid      1131   109
management     8157  1301
retired        1748   516
self-employed  1392   187
services       3785   369
student         669   269
technician     6757   840
unemployed     1101   202
unknown         254    34
```

[24]:
```
pd.crosstab(df['y'],df['education'])      #shows education wise class␣
 ↪distribution
```

[24]:
```
education  primary  secondary  tertiary  unknown
y
no            6260      20752     11305     1605
yes            591       2450      1996      252
```

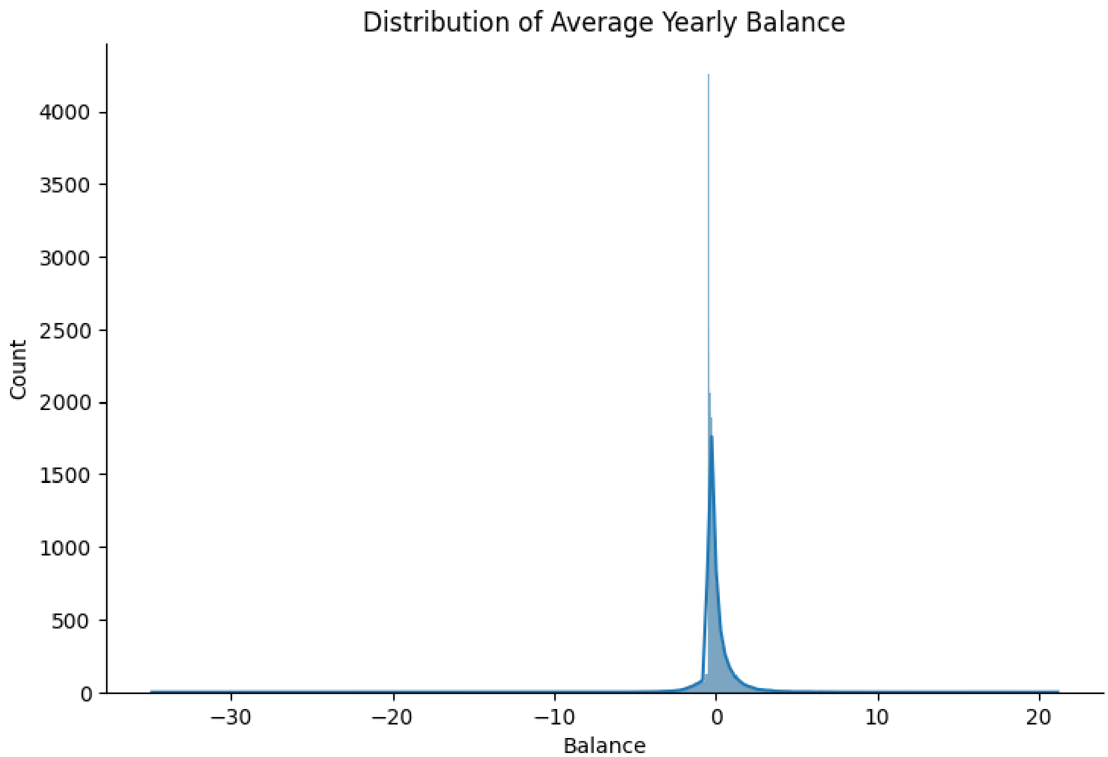
[25]:
```
df['balance'].skew()                # checking for skewness
```

[25]: 8.360308326166326

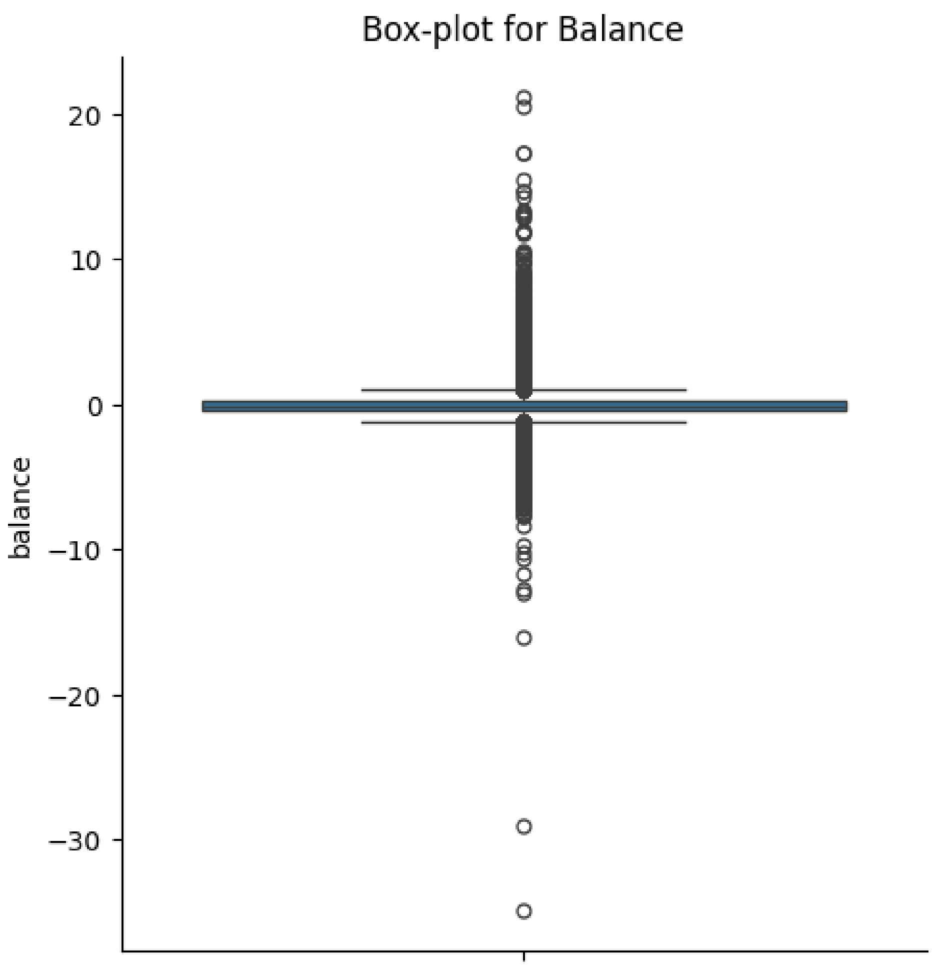
[26]:
```
# using Powertransformer to reduce skewness of the data
from sklearn.preprocessing import PowerTransformer

pt = PowerTransformer(method='yeo-johnson')
column_name = 'balance'

df.loc[:, column_name] = pt.fit_transform(df[[column_name]])

# Checking skewness after transformation
df[column_name].skew()
```

[26]: 1.0985820972305558

[27]:
```
# checking distribution of data
sns.displot(data = df, x='balance', kind ='hist', kde=True, aspect=1.5)
plt.title('Distribution of Average Yearly Balance')
plt.xlabel('Balance')
plt.ylabel('Count')
plt.show()
```



[28]:
```
# plotting bo-plot for balance column
sns.catplot(data=df, y='balance', kind='box')
plt.title('Box-plot for Balance')
plt.show()
```



[29]:
```
# Scaling balance coulmn by using standard scaler which scales data with␣
↪respect to mean
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

df.loc[:,'balance'] = scaler.fit_transform(df[['balance']])
```

[30]:
```
df['balance'].skew()
```

[30]: 1.0985820972305558

[31]:
```
del_rows = df[df['balance']<-5].index
len(del_rows)
```

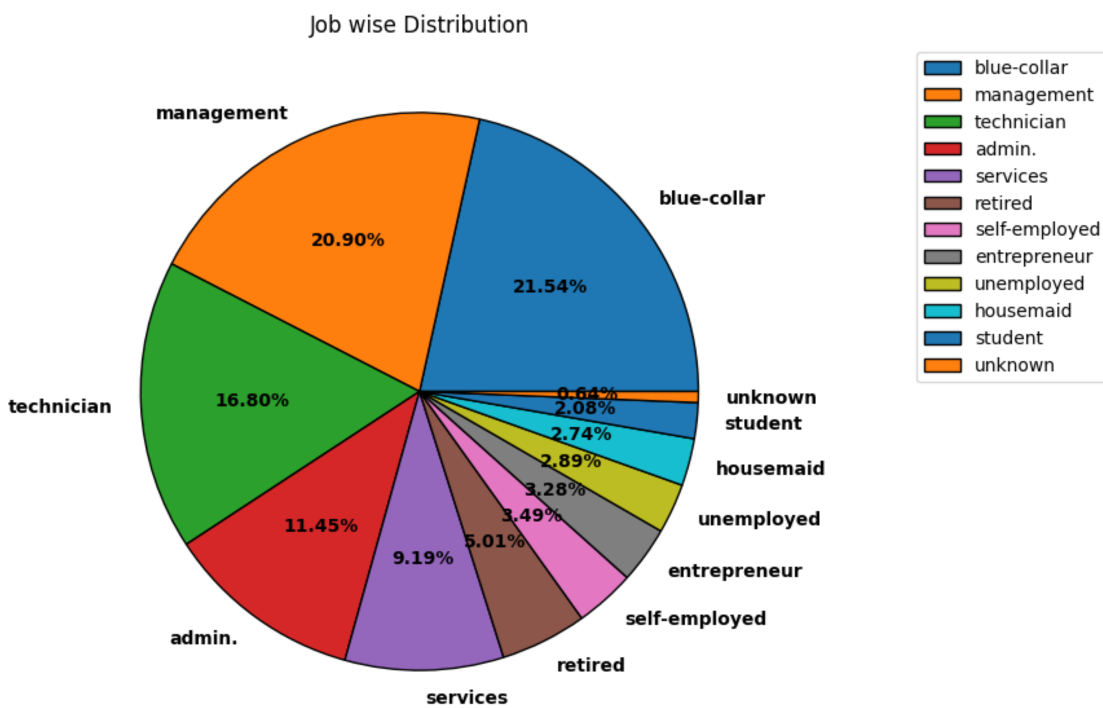
[31]: 62

[32]:
```
# droppping row which has balance lesser than -5
df.drop(del_rows, axis=0, inplace= True)
df.shape          # checks shape of data
```

[32]: (45149, 11)

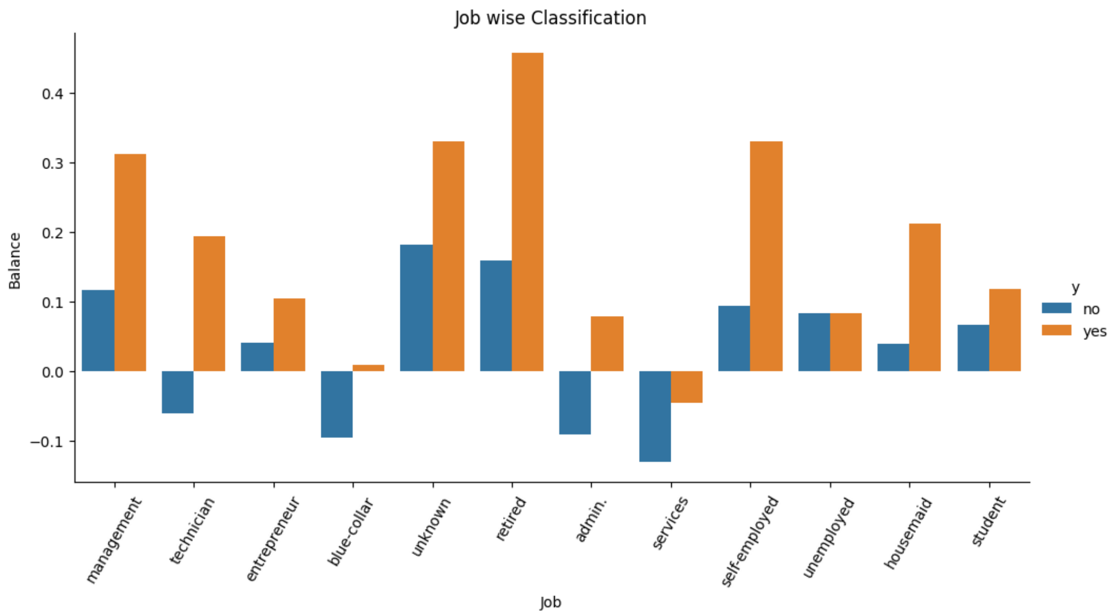
[33]:
```
job_count = df['job'].value_counts()
```

[34]:
```
#plotting pie chart to see destribution of data job wise
plt.figure(figsize=(10,7))

plt.pie(job_count, labels=job_count.index, autopct = '%.
 ↪2f%%',wedgeprops={'linewidth':1,'edgecolor': 'black'},
       textprops={'weight':'bold'})
plt.legend(bbox_to_anchor=(1.5, 1))
plt.title('Job wise Distribution')
plt.show()
```

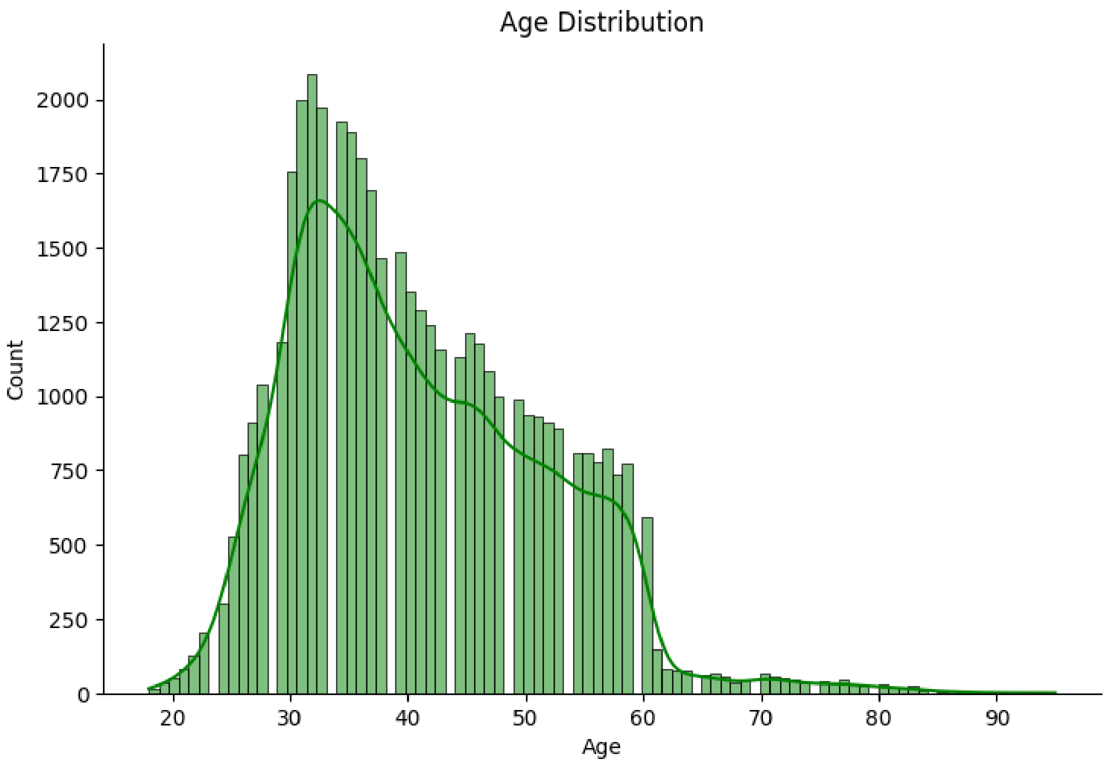


[35]:
```
#plotting bar chart
sns.catplot(data=df, x='job',y='balance',kind='bar',hue='y', aspect=2,␣
 ↪errorbar=('ci', False))
plt.title('Job wise Classification')
plt.xlabel('Job')
```

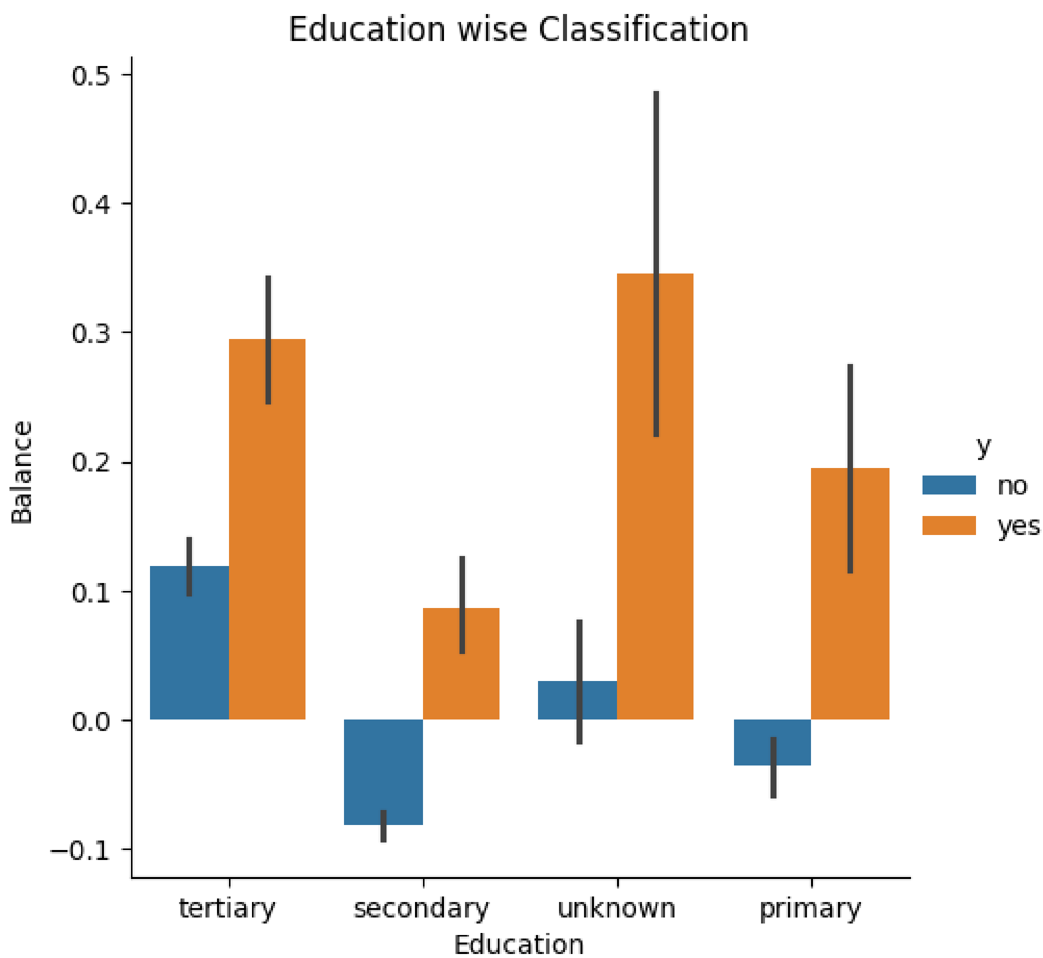
```
plt.xticks(rotation = 60)
plt.ylabel('Balance')
plt.show()
```



[36]:
```
#plotting histogram to see age distribution
sns.displot(data = df, x='age', kind ='hist', kde=True, aspect=1.5,␣
  ↪color='green')
plt.title('Age Distribution')
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()
```



[37]:
```
#plotting bar plot to see education wise distribution
sns.catplot(data=df, x='education',y='balance',kind='bar',hue='y')
plt.title('Education wise Classification')
plt.xlabel('Education')
plt.ylabel('Balance')
plt.show()
```



[38]:
```
df.shape
```

[38]: (45149, 11)

[39]:
```
df = df[df['balance']>-0.5]        #dropping rows which having budget lesser than␣
↪-0.5
```

[40]:
```
df.shape
```

[40]: (41925, 11)

OBSERVATIONS:

1. The dataset exhibits a significant imbalance, Hence we need to balnced it around somewhat manner to avoid biased predictions
2. The majority of individuals in the dataset fall within the age range of 25 to 60 years, indicating a concentration of data within this demographic

3. Notably, the dataset is dominated by individuals with a blue-collar job type. Interestingly, the data suggests that a substantial number of retired individuals have subscribed to the term deposit scheme.

4. The balance column displays a high skewness of approximately 8.36, indicating a non-uniform distribution. To enhance the model's performance, it is imperative to reduce this skewness.Also, there are outliers in the balance column. Heance we need to remove this outliers in somewhat manner.

[41]:
```
# encoding marital and education column by using one hot encoding.

df = pd.get_dummies(df,columns=['marital','education'])
```

[42]:
```
df.head()
```

[42]:
```
   age            job   balance housing loan  campaign  pdays  previous   y  \
0   58     management  0.414773     yes   no         1     -1         0  no
1   44     technician -0.410774     yes   no         1     -1         0  no
2   33   entrepreneur -0.431122     yes  yes         1     -1         0  no
3   47    blue-collar  0.197685     yes   no         1     -1         0  no
4   33        unknown -0.432119      no   no         1     -1         0  no

   marital_divorced  marital_married  marital_single  education_primary  \
0                 0                1               0                  0
1                 0                0               1                  0
2                 0                1               0                  0
3                 0                1               0                  0
4                 0                0               1                  0

   education_secondary  education_tertiary  education_unknown
0                    0                   1                  0
1                    1                   0                  0
2                    1                   0                  0
3                    0                   0                  1
4                    0                   0                  1
```

[43]:
```
#collecting all columns which having dtype as object
obj_cols = df.select_dtypes('object').columns
```

[44]:
```
#using label encoder
from sklearn.preprocessing import LabelEncoder

for i in obj_cols:
    encoder = LabelEncoder()
    df[i] = encoder.fit_transform(df[i])

df.dtypes      # checks dtype of columns
```

[44]:
```
age                    int64
job                    int64
balance              float64
housing                int64
loan                   int64
campaign               int64
pdays                  int64
previous               int64
y                      int64
marital_divorced       uint8
marital_married        uint8
marital_single         uint8
education_primary      uint8
education_secondary    uint8
education_tertiary     uint8
education_unknown      uint8
dtype: object
```

[45]:
```
df.head()
```

[45]:
```
   age  job   balance  housing  loan  campaign  pdays  previous  y  \
0   58    4  0.414773        1     0         1     -1         0  0
1   44    9 -0.410774        1     0         1     -1         0  0
2   33    2 -0.431122        1     1         1     -1         0  0
3   47    1  0.197685        1     0         1     -1         0  0
4   33   11 -0.432119        0     0         1     -1         0  0

   marital_divorced  marital_married  marital_single  education_primary  \
0                 0                1               0                  0
1                 0                0               1                  0
2                 0                1               0                  0
3                 0                1               0                  0
4                 0                0               1                  0

   education_secondary  education_tertiary  education_unknown
0                    0                   1                  0
1                    1                   0                  0
2                    1                   0                  0
3                    0                   0                  1
4                    0                   0                  1
```

[46]:
```
#splitting data into x and y
x= df.drop(columns = ['y'], axis = 1)
y = df['y']
```

[47]:
```
x.shape
```

[47]: (41925, 15)

[48]:
```
y.shape
```

[48]: (41925,)

[49]:
```
#splitting data into training and testing
from sklearn.model_selection import train_test_split

xtrain,xtest,ytrain,ytest = train_test_split(x,y, train_size=0.8,␣
↪random_state=4)
```

[50]:
```
from sklearn.tree import DecisionTreeClassifier

model = DecisionTreeClassifier()
```

[51]:
```
model.fit(xtrain,ytrain)  #training model on trining data
```

[51]: DecisionTreeClassifier()

DecisionTreeClassifier()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook. On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

[52]:
```
train_pred = model.predict(xtrain)    #predicating target based on training data
```

[53]:
```
from sklearn.metrics import classification_report      #checks metrics of␣
↪prediction
```

[54]:
```
print(classification_report(ytrain,train_pred))    #prints classification report
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     29457
           1       1.00      0.99      1.00      4083

    accuracy                           1.00     33540
   macro avg       1.00      1.00      1.00     33540
weighted avg       1.00      1.00      1.00     33540
```

[55]:
```
test_pred = model.predict(xtest)    #predicting based on test data

print(classification_report(ytest,test_pred))    #printing classification report
```

```
              precision    recall  f1-score   support

           0       0.90      0.88      0.89      7355
           1       0.25      0.28      0.27      1030

    accuracy                           0.81      8385
   macro avg       0.57      0.58      0.58      8385
weighted avg       0.82      0.81      0.81      8385
```

[56]:
```
from sklearn.ensemble import RandomForestClassifier     #importing random␣
↪forest classifier

model1 = RandomForestClassifier()
```

[57]:
```
model1.fit(xtrain,ytrain)
```

[57]: RandomForestClassifier()

RandomForestClassifier()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook. On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org

[58]:
```
trainpred = model1.predict(xtrain)

print(classification_report(ytrain,trainpred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     29457
           1       1.00      0.99      0.99      4083

    accuracy                           1.00     33540
   macro avg       1.00      0.99      1.00     33540
weighted avg       1.00      1.00      1.00     33540
```

[59]:
```
testpred = model1.predict(xtest)
print(classification_report(ytest,testpred))
```

```
              precision    recall  f1-score   support

           0       0.90      0.97      0.93      7355
           1       0.50      0.19      0.27      1030

    accuracy                           0.88      8385
   macro avg       0.70      0.58      0.60      8385
```

```
weighted avg       0.85      0.88      0.85      8385
```

CONCLUSION

1. As expected, decision trees exhibit a tendency to overfit the training data, achieving a perfect 100% accuracy during training. However, when applied to unseen data, the model's performance drops to around 81%.

2. To solve this problem, first we have tried to balance data in somewhat manner and used Random Forest Classifier to minimize overfiting of the model.

3. Random forest is forest of decision trees and it is ensemble technique which use Bagging. Random forest model has accuracy on training data 100% while on testing data it gives accuracy around 87%.