Importing the packages This is a Binary classification Problem. In [1]: import numpy as np import pandas as pd import copy import matplotlib.pyplot as plt import seaborn as sns In [2]: data = pd.read\_excel(io = "Bank Data for case study assignment.xlsx", sheet\_name="Data") In [3]: df = copy.copy(data) In [4]: data.head(6) Out[4]: job | marital status education | credit default? | housing loan? | Personal loan age **0** 30 unemployed married primary no no no no 1 33 services married secondary no yes yes no **2** 35 management single tertiary no yes no no **3** 30 management married no yes no tertiary yes 4 59 blue-collar married no yes no no secondary **5** 35 management single tertiary no no no no In [5]: data.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 1021 entries, 0 to 1020 Data columns (total 8 columns): age 1021 non-null int64 job 1019 non-null object marital status 1020 non-null object education 1020 non-null object credit default? 1020 non-null object housing loan? 1019 non-null object Personal loan 1019 non-null object 1021 non-null object dtypes: int64(1), object(7) memory usage: 63.9+ KB In [6]: total\_null = data.isnull().sum().sort\_values(ascending=False) print(total null) Personal loan housing loan? job credit default? 1 education marital status age dtype: int64 There are 3 steps to proces further 1. Remove Missing Value 2. Replace missing value with Max occurance 3. Predict the Missing Value We will go with Removing the Missing values. Take backup if needed **Dropping NA Values** In [14]: data\_proc = copy.copy(data) In [15]: len(data) Out[15]: 1021 In [16]: len(data\_proc) Out[16]: 1021 In [17]: data\_proc = data\_proc.dropna(axis=0, inplace=False) In [18]: print(data\_proc.head()) job marital status education credit default? housing loan? \ age 0 30 unemployed married primary no no 1 33 services married secondary
2 35 management single tertiary
3 30 management married tertiary
4 59 blue-collar married secondary married secondary no single tertiary no married tertiary no married secondary no yes yes yes yes Personal loan y 0 no no 1 yes no no no yes no no no In [19]: len(data\_proc) Out[19]: 1013 Replacing NA with Most occuring Value In [20]: data['Personal loan'].describe() 1019 Out[20]: count 2 unique top no 869 freq Name: Personal loan, dtype: object In [21]: **for** i **in** data.columns: print('----{}----'.format(i)) print(data[i].describe()) print() ----age---count 1021.000000 41.066601 mean 10.400013 std min 19.000000 25% 33.000000 50% 39.000000 75% 48.000000 max 84.000000 Name: age, dtype: float64 ----job----count unique 12 blue-collar top freq 217 Name: job, dtype: object ----marital status -----1020 unique married top 617 freq Name: marital status , dtype: object ----education----1020 count 4 unique top secondary 524 freq Name: education, dtype: object ----credit default?---count 2 unique top no 998 Name: credit default?, dtype: object ----housing loan?---count 1019 3 unique top yes freq 583 Name: housing loan?, dtype: object ----Personal loan----1019 count unique 2 top no 869 freq Name: Personal loan, dtype: object ----y----1021 count unique 2 no top 897 freq Name: y, dtype: object In [22]: data = data.fillna({"Personal loan": "no"}) data = data.fillna({"housing loan?": "yes"}) data = data.fillna({"job": "blue-collar"}) data = data.fillna({"credit default?": "no"}) data = data.fillna({"education": "secondary"}) data = data.fillna({"marital status ": "married"}) In [24]: # Identifying no. of Unique Values for i in data.columns: **if** i == 'age': pass else: print("----{}----".format(i)) print(data[i].value counts()) print() -----job----blue-collar 219 management 212 technician 107 admin. 93 services self-employed 52 retired entrepreneur 32 29 unemployed 23 student housemaid unknown 10 Name: job, dtype: int64 -----marital status -----618 married 281 single divorced 122 Name: marital status , dtype: int64 ----education---secondary 525 tertiary 151 primary 42 unknown Name: education, dtype: int64 ----credit default?----999 no 22 yes Name: credit default?, dtype: int64 ----housing loan?----585 435 no 1 хххуу Name: housing loan?, dtype: int64 -----Personal loan----871 no 150 yes Name: Personal loan, dtype: int64 ----y----897 no 124 yes Name: y, dtype: int64 Housing Loan has extra variable as 'xxxyy', we replace it to max result 'yes' In [25]: data['housing loan?'].value\_counts() 585 Out[25]: yes 435 хххуу Name: housing loan?, dtype: int64 In [26]: data['housing loan?'] = data['housing loan?'].str.replace('xxxyy','yes') In [27]: data['housing loan?'].value\_counts() Out[27]: yes 586 435 no Name: housing loan?, dtype: int64 In [28]: # Find total Num after processing total\_null\_1 = data.isnull().sum().sort\_values(ascending=False) print(total null 1) Personal loan 0 housing loan? credit default? education marital status job 0 age dtype: int64 In [30]: dff = pd.DataFrame(data) In [31]: dff.head() Out[31]: job marital status education credit default? housing loan? Personal loan age **0** 30 unemployed married primary no no no no 1 33 services married secondary no yes yes no **2** 35 management single no tertiary no yes no **3** 30 management married no no tertiary yes yes **4** 59 blue-collar married secondary no no yes no In [32]: dff.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 1021 entries, 0 to 1020 Data columns (total 8 columns): 1021 non-null int64 1021 non-null object marital status 1021 non-null object 1021 non-null object education credit default? 1021 non-null object housing loan? 1021 non-null object Personal loan 1021 non-null object 1021 non-null object dtypes: int64(1), object(7) memory usage: 63.9+ KB Use one-hot-encoder or Manual inner-variable Conversion **Trying Label Encoding** In [33]: from sklearn.preprocessing import LabelEncoder In [34]: labelencoder = LabelEncoder() In [35]: dff.head() Out[35]: job marital status education credit default? Personal loan housing loan? age **0** 30 unemployed married primary no no no no 1 33 services secondary | no married yes yes no **2** 35 single management no no no tertiary yes **3** 30 married management tertiary no yes yes no **4** 59 blue-collar married secondary no yes no no In [36]: dff.iloc[:,1] = labelencoder.fit transform(dff.iloc[:,1]) dff.iloc[:,2] = labelencoder.fit\_transform(dff.iloc[:,2]) dff.iloc[:,3] = labelencoder.fit\_transform(dff.iloc[:,3]) dff.iloc[:,4] = labelencoder.fit\_transform(dff.iloc[:,4]) dff.iloc[:,5] = labelencoder.fit\_transform(dff.iloc[:,5]) dff.iloc[:,6] = labelencoder.fit\_transform(dff.iloc[:,6]) dff.iloc[:,7] = labelencoder.fit\_transform(dff.iloc[:,7]) In [37]: dff.head(10) Out[37]: age job marital status education credit default? housing loan? Personal loan y **0** 30 0 10 0 33 0 0 **2** 35 2 2 0 1 0 4 0 **3** 30 2 4 0 0 **4** 59 0 0 0 **5** 35 2 0 0 0 4 0 **6** 36 6 2 0 0 **7** 39 0 0 0 9 0 8 41 0 2 2 0 0 **9** 43 0 In [38]: Y\_data = dff['y'] In [39]: Y\_data.value\_counts() Out[39]: 0 897 124 Name: y, dtype: int64 In [40]: X\_data = dff.drop('y', axis = 1) In [41]: X\_data.head() Out[41]: age | job | marital status | education | credit default? | housing loan? | Personal loan **0** 30 10 0 33 0 **2** 35 4 2 2 0 1 0 **3** 30 2 4 0 **4** 59 0 0 In [42]: # Splitting the dataset into the Training set and Test set from sklearn.model\_selection import train\_test\_split X\_train, X\_test, y\_train, y\_test = train\_test\_split(X\_data, Y\_data, test\_size = 0.25, random\_state = In [43]: print(len(X\_train), len(X\_test), len(y\_train), len(y\_test)) 765 256 765 256 In [44]: len(y\_test) Out[44]: 256 In [45]: # Feature Scaling from sklearn.preprocessing import StandardScaler sc = StandardScaler() X\_train = sc.fit\_transform(X\_train) X test = sc.transform(X test) In [49]: print(X\_train[:2, :])  $[[-0.86139886 \quad 0.75242465 \quad 1.36016339 \quad -0.28501424 \quad -0.14615682 \quad -1.1760857 ]$  $[\ 1.27874623\ -1.05575815\ -0.26059205\ -0.28501424\ -0.14615682\ \ 0.85027817$ -0.40980353]] In [ ]: # Fitting Decision Tree Classification to the Training set from sklearn.tree import DecisionTreeClassifier dtclassifier = DecisionTreeClassifier(criterion = 'gini', random\_state =0) dtclassifier.fit(X\_train,y\_train) In [ ]: # Fitting Decision Tree Classification to the Training set from sklearn.ensemble import RandomForestClassifier rfclassifier = RandomForestClassifier(n estimators= 100, criterion = 'gini', random state =0) rfclassifier.fit(X\_train,y\_train) In [ ]: # Predicting the Test set results y\_pred = classifier.predict(X test) In [ ]: # Making the Confusion Matrix from sklearn.metrics import confusion matrix cm = confusion\_matrix(y\_test, y\_pred) In [ ]: cm In [ ]: acc\_random\_forest = round(classifier.score(X\_train, y\_train) \* 100, 2) print(acc random forest) In [ ]: logreg = LogisticRegression() In [ ]: logreg.fit(X\_train, y\_train) In [ ]: Y\_pred = logreg.predict(X\_test) In [ ]: acc\_log = round(logreg.score(X\_train, y\_train)\*100, 2) print(acc\_log) In [ ]: # Fitting Knn classifier to the Training set from sklearn.neighbors import KNeighborsClassifier  $knnclassifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)$ knnclassifier.fit(X\_train, y\_train) In [ ]: # Predicting the Test set results y\_pred = classifier.predict(X\_test) In [ ]: cmm = confusion\_matrix(y\_test, y\_pred) In [ ]: cmm In [ ]: # Fitting SVM to the Training set from sklearn.svm import SVC svmclassifier = SVC(kernel = 'linear', random state = 0) svmclassifier.fit(X\_train,y\_train) # Predicting the Test set results y\_pred = classifier.predict(X\_test) In [ ]: cmm = confusion matrix(y test, y pred) **Performing ML** In [ ]: from sklearn import linear\_model from sklearn.linear\_model import LogisticRegression  $\textbf{from sklearn.ensemble import} \ \texttt{RandomForestClassifier}$ from sklearn.linear\_model import Perceptron from sklearn.linear\_model import SGDClassifier from sklearn.tree import DecisionTreeClassifier from sklearn.neighbors import KNeighborsClassifier from sklearn.svm import SVC, LinearSVC from sklearn.naive\_bayes import GaussianNB In []: sgd = linear model.SGDClassifier(max iter=5, tol=None) In [ ]: sgd.fit(X train, Y train) In [ ]: y pred = sgd.predict(X test) In [ ]: sgd.score(X train, y train) In [ ]: # Merging the Values In [ ]: data[data['credit default?'].isna()] # Finding the NA Rows for i in data.columns: print(data[data[i].isna()]) In [ ]: # Identifying the Numerical stats data.age.describe() In [ ]: data["age"].value\_counts() In [ ]: # Binning the data age to make it Categorical data['agebin'] = pd.cut(data['age'], [10, 20, 30,40, 50, 60, 70, 80, 90], labels=['11-20', '21-30', '31-40', '41-50', '51-60', '61-70', '71-80', '81-90']) In [ ]: print(data[data['age'] <= 20])</pre> In [ ]: data['agebin'].value\_counts() In [ ]: # Finding the Unique value counts of data columns for i in data.columns: **if** i == "age": pass else:

print("-----".format(i))

print(data[i].value\_counts())

print(data[i].value counts())

print('')

In [ ]: data["job"].value counts()

In [ ]: for i in data.columns:

else:

if i == "age":
 pass

print('')

In [ ]: data["job"] = data["job"].astype('category')

In [ ]: data.apply(pd.value\_counts)

In [ ]: data["job"].describe()