Data Mining Assignment

Contributors:

Our group members have been incorrectly assigned to different group then what was originally given in the xls.

Name's

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Please note that everyone has contributed equally to each phase , but the above table is just for indication.

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Problem Statement

A bank wants to have a model that helps to predict whether a client will subscribe for a term deposit or not, based on the relevant data available with the bank.

As a data scientist, you are required to construct a classification model based on the available data and evaluate its efficacy. Your activities should include - performing various activities pertaining to the data such as, preparing the dataset for analysis; investigating the relationships in the data set with visualization; creating a model; evaluating the performance of the classification model.

Using the Bank's Dataset, construct a decision tree-based model, and use the model to predict whether a client will subscribe for a term deposit or not.

Exploratory Data Analysis and Statistical Analysis

Here we will be loading the given data-set into data frame and proceed with data analysis

In [91]:
```
import os
import numpy as np
import pandas as pd

#Visualizations
import matplotlib as mpl
from matplotlib import pyplot as plt
%matplotlib inline
import seaborn as sns

#Modeling
import sklearn
from sklearn.impute import SimpleImputer
from sklearn import preprocessing
from sklearn.externals import joblib
from sklearn import tree

from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn import preprocessing
from sklearn.metrics import classification_report, confusion_matrix, roc_curve
, auc, accuracy_score
```

In [3]:
```
df = pd.read_excel('bankData.xlsx', sheet_name='Data', header=0)
```

In [4]:
```
df.head()
```

Out[4]:

	age	job	marital status	education	credit default?	housing loan?	Personal loan	y
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	tertiary	no	yes	yes	no
4	59	blue-collar	married	secondary	no	yes	no	no

In [5]:
```
df.columns
```

Out[5]:
```
Index(['age', 'job', 'marital status ', 'education', 'credit default?',
       'housing loan?', 'Personal loan', 'y'],
      dtype='object')
```

Lets rename the columns and remove those special characters so that its easy to work with

In [7]:
```
df.rename(columns={'marital status ':'marital status','credit default?':'credi
t default','housing loan?':'housing loan',
                     'Personal loan':'personal loan' },inplace=True)
```

In [8]:
```
df.columns
```

Out[8]:
```
Index(['age', 'job', 'marital status', 'education', 'credit default',
       'housing loan', 'personal loan', 'y'],
      dtype='object')
```

In [9]:
```
df.head()
```

Out[9]:

	age	job	marital status	education	credit default	housing loan	personal loan	y
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	tertiary	no	yes	yes	no
4	59	blue-collar	married	secondary	no	yes	no	no

Now lets find the missing data in our data set

In [10]:
```
df.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
y                   1021 non-null object
dtypes: int64(1), object(7)
memory usage: 63.9+ KB
```

In [11]:
```
df.describe()
```

Out[11]:

	age
count	1021.000000
mean	41.066601
std	10.400013
min	19.000000
25%	33.000000
50%	39.000000
75%	48.000000
max	84.000000

In [12]:
```
df.isnull().values.any()
```

Out[12]:
```
True
```

Finding the null values in the dataset

In [13]:
```
df.isnull().sum()
```

Out[13]:
```
age               0
job               2
marital status    1
education         1
credit default    1
housing loan      2
personal loan     2
y                 0
dtype: int64
```

Finding the total count of null values in the data set (so there were 9 in total)

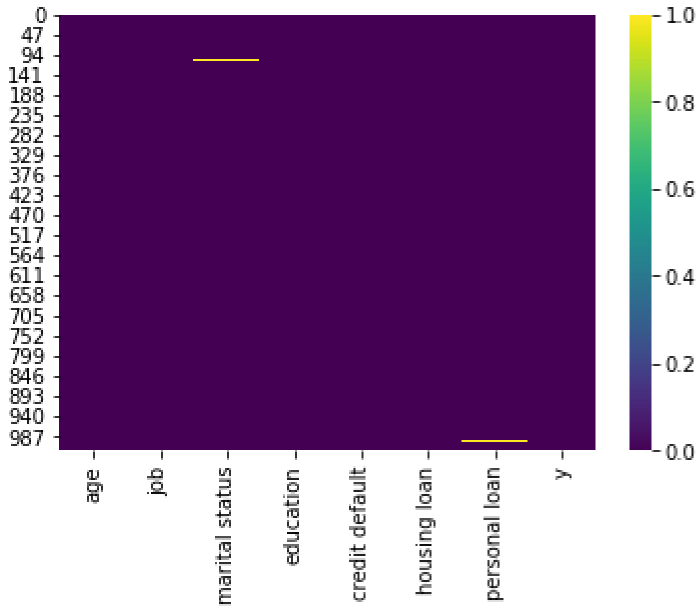
In [14]:
```
df.isnull().sum().sum()
```

Out[14]:
```
9
```

Lets generate the heatmap to visualize where the null values exist across data set

In [19]:
```
sns.heatmap(df.isnull(),  cmap='viridis', fmt='g')
```

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x2080767c860>



Preprocessing the data

Data preprocessing is a data mining technique that involves transforming raw data into an understandable format. Real-world data is often incomplete, inconsistent, and/or lacking in certain behaviors or trends, and is likely to contain many errors. Data preprocessing is a proven method of resolving such issues.

In [27]:
```
for col in df.columns:
    df[col].replace('unknown', np.nan, inplace=True)
    df[col].replace('xxxyy', np.nan, inplace=True)

education_count = df['education'].value_counts()
job_count = df['job'].value_counts()
house_loan_count = df['housing loan'].value_counts()

print("Job attribute :\n{0}".format(job_count))
print("--"*40)
print("Education attribute :\n{0}".format(education_count))
print("--"*40)
print("House loan attribute :\n{0}".format(house_loan_count))
```

```
Job attribute :
blue-collar      217
management       212
technician       178
admin.           107
services          93
self-employed     52
retired           46
entrepreneur      32
unemployed        29
student           23
housemaid         20
Name: job, dtype: int64
-----------------------------------------------------------------------------
---
Education attribute :
secondary    524
tertiary     303
primary      151
Name: education, dtype: int64
-----------------------------------------------------------------------------
---
House loan attribute :
yes    583
no     435
Name: housing loan, dtype: int64
```

In [50]:
```
# Missing columns list has a column names that have empty cell
missing_cols = [col for col in df if df[col].isnull().any()]
# Simple imputer object with replacement strategy as most frequent data
imputer = SimpleImputer(missing_values=np.nan, strategy='most_frequent')

sanitized_data = pd.DataFrame(imputer.fit_transform(df), columns=df.columns)
sanitized_data.info()
```

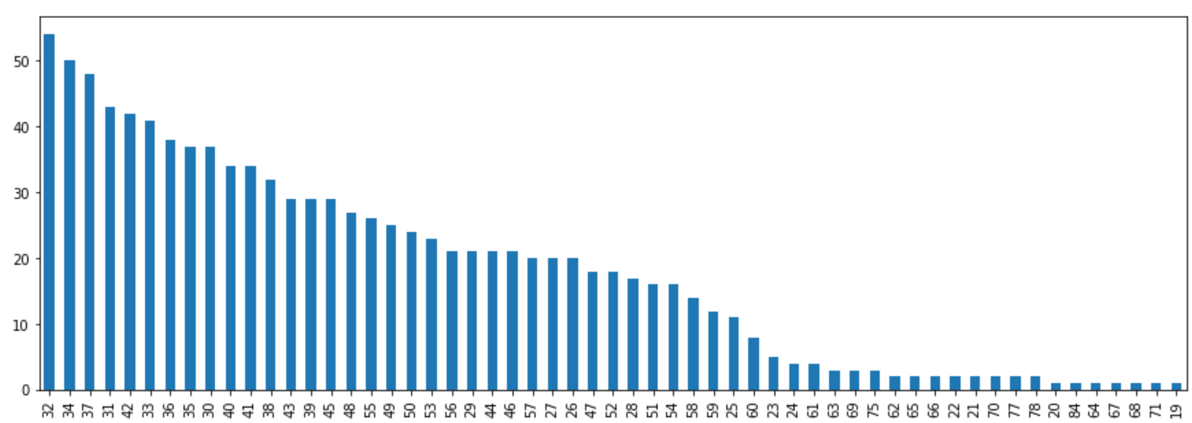
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1021 entries, 0 to 1020
Data columns (total 8 columns):
age                 1021 non-null object
job                 1021 non-null object
marital status      1021 non-null object
education           1021 non-null object
credit default      1021 non-null object
housing loan        1021 non-null object
personal loan       1021 non-null object
y                   1021 non-null object
dtypes: object(8)
memory usage: 63.9+ KB
```

In [29]:
```
df.columns
```

Out[29]:
```
Index(['age', 'job', 'marital status', 'education', 'credit default',
       'housing loan', 'personal loan', 'y'],
      dtype='object')
```

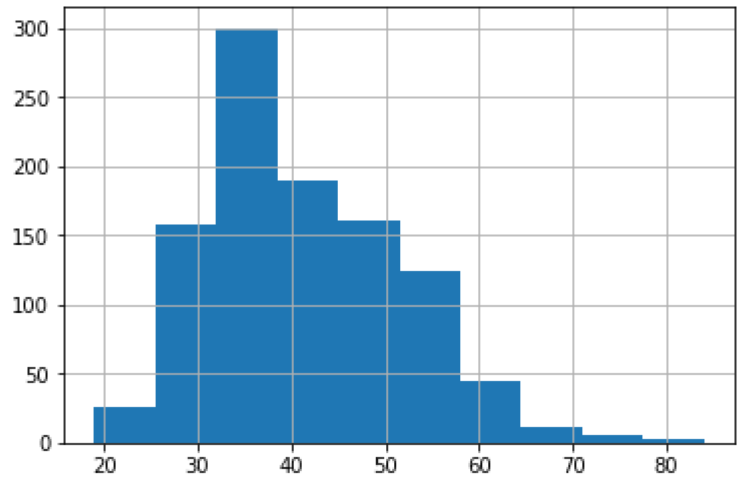
In [30]:
```
df['age'].value_counts().plot(kind='bar',figsize=(15,5))
```

Out[30]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2080b014a20>
```



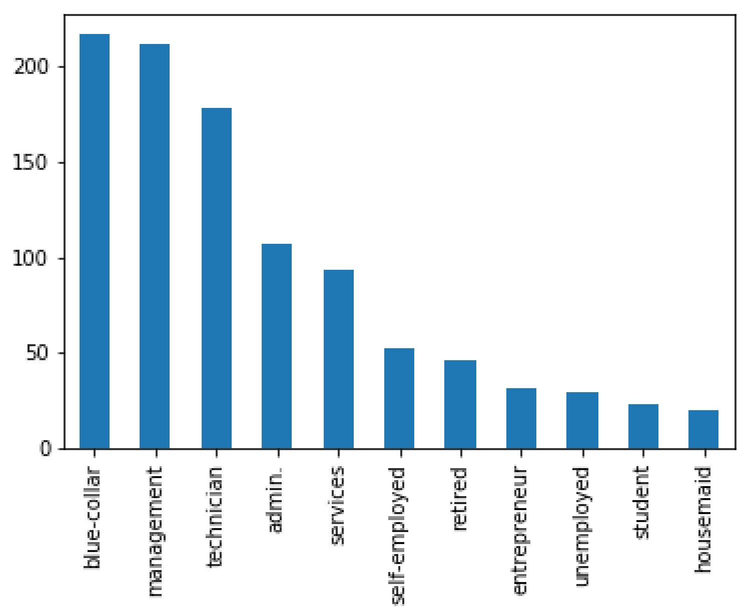
In [31]:
```
df['age'].hist()
```

Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x2080ae0f9b0>



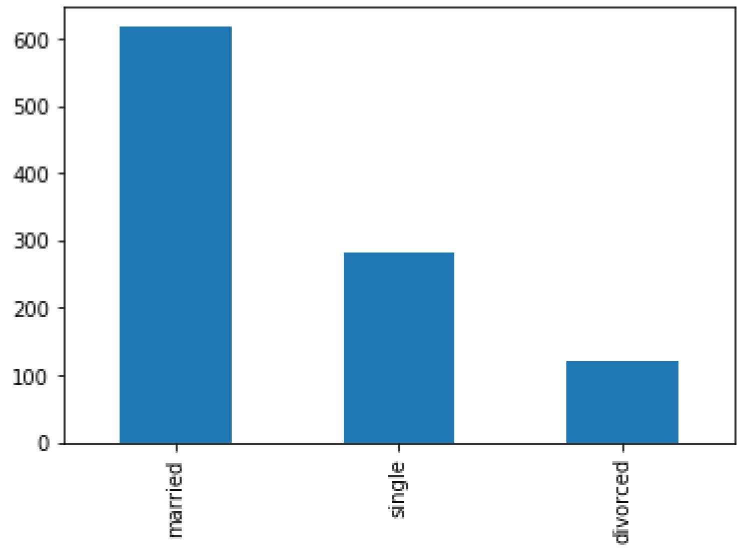
In [32]:
```
df['job'].value_counts().plot(kind='bar')
```

Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x2080ac856a0>



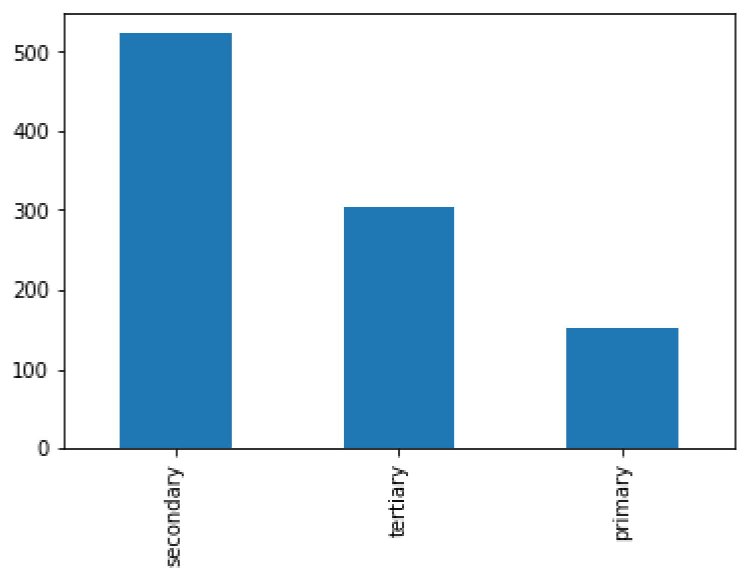
In [35]:
```
df['marital status'].value_counts().plot(kind='bar')
```

Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x2080ace9438>



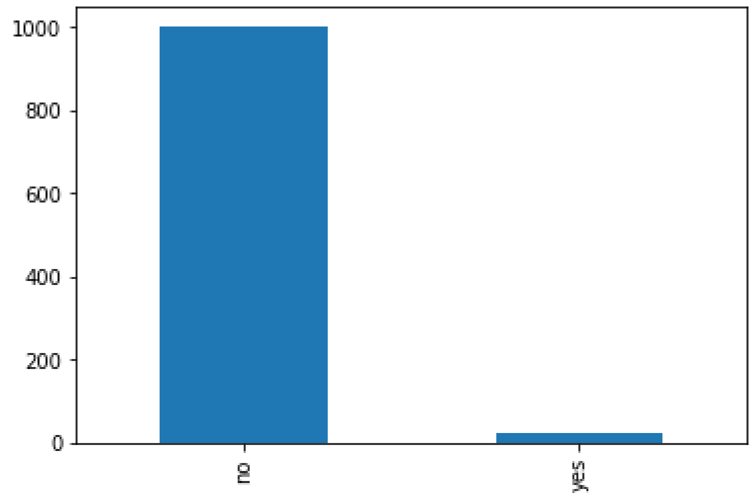
In [36]:
```
df['education'].value_counts().plot(kind='bar')
```

Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x2080ad49ac8>



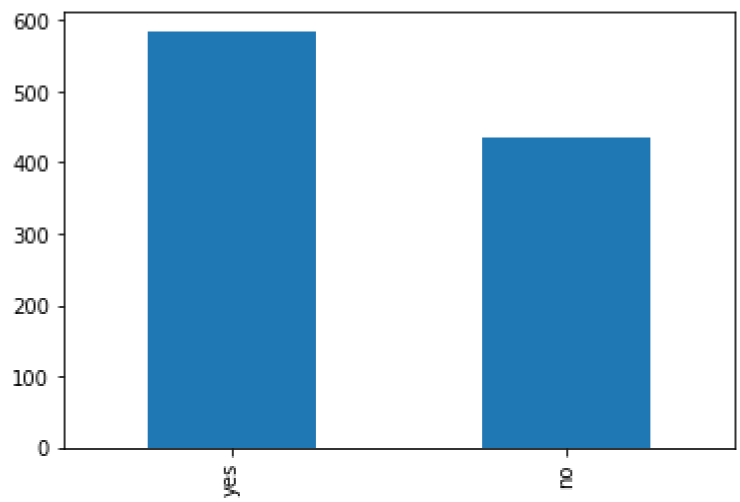
In [37]:
```
df['credit default'].value_counts().plot(kind='bar')
```

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x2080ad99b70>



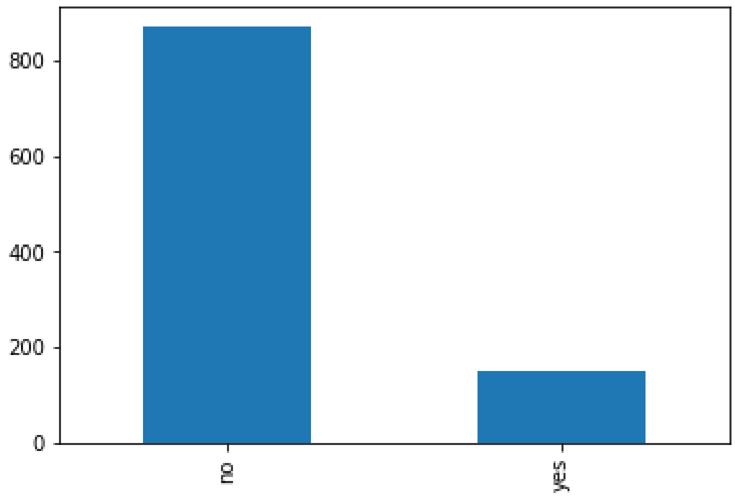
In [38]:
```
df['housing loan'].value_counts().plot(kind='bar')
```

Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x2080ae815f8>



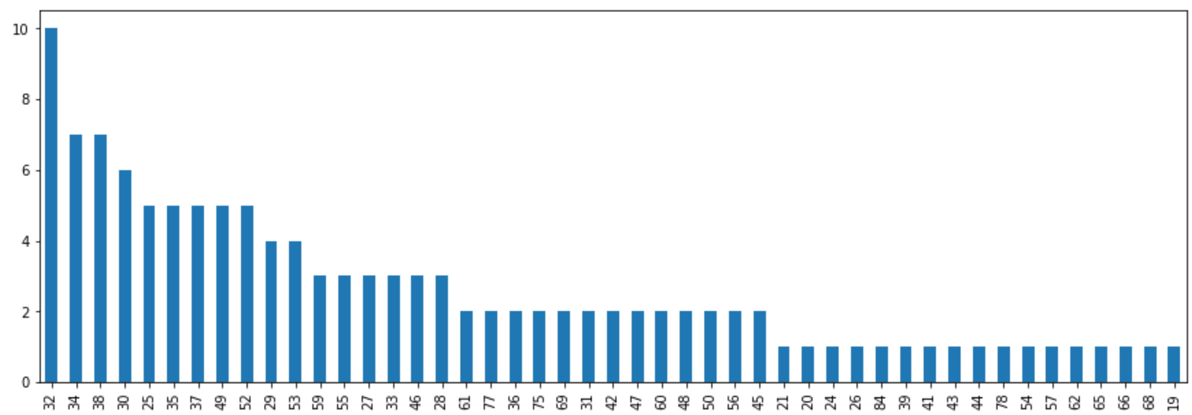
In [39]:
```
df['personal loan'].value_counts().plot(kind='bar')
```

Out[39]: <matplotlib.axes._subplots.AxesSubplot at 0x2080aed4f60>



In [40]:
```
df[df['y']=='yes']['age'].value_counts().plot(kind='bar',figsize=(15,5))
```

Out[40]: <matplotlib.axes._subplots.AxesSubplot at 0x2080af2dcf8>



In [41]:
```
df.head()
```

Out[41]:

	age	job	marital status	education	credit default	housing loan	personal loan	y
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	tertiary	no	yes	yes	no
4	59	blue-collar	married	secondary	no	yes	no	no

In [51]:
```
lbl_encoder = preprocessing.LabelEncoder()


non_num_cols = [col for col in df.columns if df[col].dtypes != np.int64]


for col in non_num_cols:
    sanitized_data[col] = lbl_encoder.fit_transform(sanitized_data[col])

sanitized_data.head(15)
```

Out[51]:

	age	job	marital status	education	credit default	housing loan	personal loan	y
0	30	10	1	0	0	0	0	0
1	33	7	1	1	0	1	1	0
2	35	4	2	2	0	1	0	0
3	30	4	1	2	0	1	1	0
4	59	1	1	1	0	1	0	0
5	35	4	2	2	0	0	0	0
6	36	6	1	2	0	1	0	0
7	39	9	1	1	0	1	0	0
8	41	2	1	2	0	1	0	0
9	43	7	1	0	0	1	1	0
10	39	7	1	1	0	1	0	0
11	43	0	1	1	0	1	0	0
12	36	9	1	2	0	0	0	0
13	20	8	2	1	0	0	0	1
14	31	1	1	1	0	1	1	0

In [118]:
```
sanitized_data.age = sanitized_data.age.astype(np.int32)
sanitized_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1021 entries, 0 to 1020
Data columns (total 8 columns):
age                 1021 non-null int32
job                 1021 non-null int32
marital status      1021 non-null int32
education           1021 non-null int32
credit default      1021 non-null int32
housing loan        1021 non-null int32
personal loan       1021 non-null int32
y                   1021 non-null int32
dtypes: int32(8)
memory usage: 32.0 KB
```

Select Training data, test data

training set—a subset to train a model.

test set—a subset to test the trained model.

Preparing train and test data

In [100]:
```
X = sanitized_data.drop(columns=['y'])
y = sanitized_data['y']

print("Predictors: {0}".format(X.columns.values))
```

```
Predictors: ['age' 'job' 'marital status' 'education' 'credit default' 'housi
ng loan'
 'personal loan']
```

In [120]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y , test_size=0.2)

print("Shape of Trainingset {0}".format(X_train.shape))
print("Shape of Testset {0}".format(X_test.shape))
```

```
Shape of Trainingset (816, 7)
Shape of Testset (205, 7)
```

Test the model (Predictions and reporting)

In [121]:
```
model = DecisionTreeClassifier()

model.fit(X_train, y_train)
print("Decision Tree model default parameters:\n")
print(model.get_params())
```

```
Decision Tree model default parameters:

{'class_weight': None, 'criterion': 'gini', 'max_depth': None, 'max_feature
s': None, 'max_leaf_nodes': None, 'min_impurity_decrease': 0.0, 'min_impurity
_split': None, 'min_samples_leaf': 1, 'min_samples_split': 2, 'min_weight_fra
ction_leaf': 0.0, 'presort': False, 'random_state': None, 'splitter': 'best'}
```

Test the model (Predicting data)

In [122]:
```
predictions = model.predict([[30,10,0,1,1,1,1]])
predictions
```

Out[122]:
```
array([0])
```

In [123]:
```
dt_pred = model.predict(X_test)
print("Accuracy of Decision Tree Classifier : {0}".format(accuracy_score(y_tes
t, dt_pred)))
```

```
Accuracy of Decision Tree Classifier : 0.8292682926829268
```

Update the training set and recheck the prediction

In [124]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y , test_size=0.3)

print("Shape of Trainingset {0}".format(X_train.shape))
print("Shape of Testset {0}".format(X_test.shape))
```

```
Shape of Trainingset (714, 7)
Shape of Testset (307, 7)
```

In [125]:
```
model = DecisionTreeClassifier()

model.fit(X_train, y_train)
print("Decision Tree model default parameters:\n")
print(model.get_params())
```

```
Decision Tree model default parameters:

{'class_weight': None, 'criterion': 'gini', 'max_depth': None, 'max_feature
s': None, 'max_leaf_nodes': None, 'min_impurity_decrease': 0.0, 'min_impurity
_split': None, 'min_samples_leaf': 1, 'min_samples_split': 2, 'min_weight_fra
ction_leaf': 0.0, 'presort': False, 'random_state': None, 'splitter': 'best'}
```

In [126]:
```
dt_pred = model.predict(X_test)
print("Accuracy of Decision Tree Classifier : {0}".format(accuracy_score(y_tes
t, dt_pred)))
```

```
Accuracy of Decision Tree Classifier : 0.8338762214983714
```

Evaluate the model performance

In [127]:
```
print("Confusion Matrix of Decision Tree: \n{0}".format(confusion_matrix(dt_pr
ed,y_test)))
```

```
Confusion Matrix of Decision Tree:
[[252  26]
 [ 25   4]]
```

In [128]:
```
print("Classification report of Decision Tree: \n{0}".format(classification_re
port(dt_pred,y_test)))
```

```
Classification report of Decision Tree:
              precision    recall  f1-score   support

           0       0.91      0.91      0.91       278
           1       0.13      0.14      0.14        29

   micro avg       0.83      0.83      0.83       307
   macro avg       0.52      0.52      0.52       307
weighted avg       0.84      0.83      0.84       307
```

Suggest ways of improving the model

Refitting the model with best/optimized parameters

Decision Tree Classifier

In [129]:
```
dtree_model = DecisionTreeClassifier(max_depth=3, min_samples_split=2, min_sam
ples_leaf=1, splitter='best')

dtree_model.fit(X_train, y_train)

# Predicting the test data
dt_preds = dtree_model.predict(X_test)
print("Decision Tree accuracy score: {0}".format(accuracy_score(y_test, dt_pre
ds)))
```

```
Decision Tree accuracy score: 0.8990228013029316
```

Save the model we created onto disk

In [114]:
```
joblib.dump(model,'bank_data.joblib')
```

Out[114]:
```
['bank_data.joblib']
```

Export the model to DOT file

In [115]:
```
sanitized_data.head()
```

Out[115]:

	age	job	marital status	education	credit default	housing loan	personal loan	y
0	30	10	1	0	0	0	0	0
1	33	7	1	1	0	1	1	0
2	35	4	2	2	0	1	0	0
3	30	4	1	2	0	1	1	0
4	59	1	1	1	0	1	0	0

Conclusion

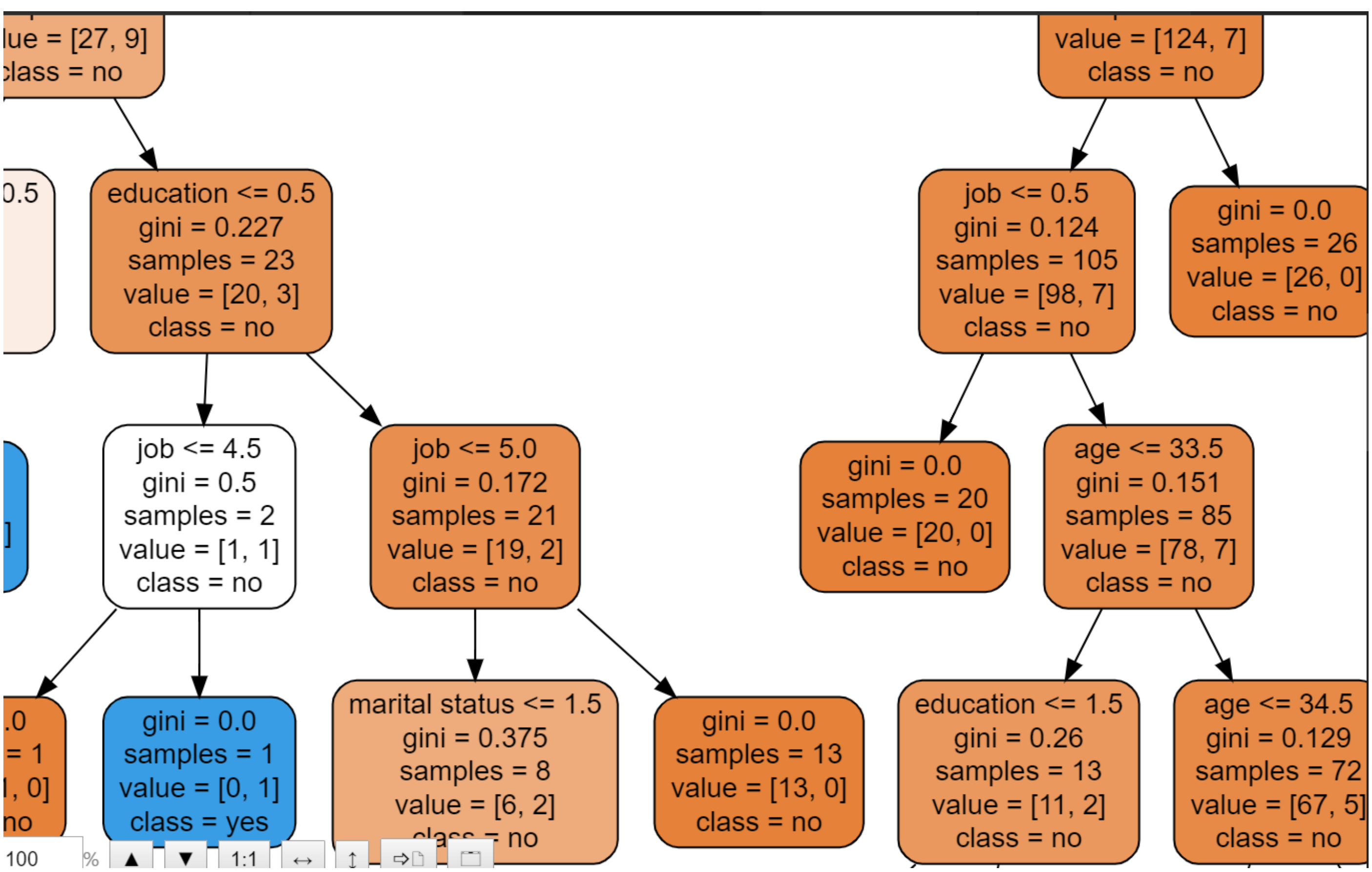
The bank term deposit data has been analysed, cleaned and prepared trainset and test for building a classification model.

Decision Tree Classifier

Accuracy score with default Parameter 83.3% Accuracy score after Optimization 89.9%

After optimization activity the best parameters are used to build a model. (decision tree classifier showed significant improvements)

Also we can dump the model as DOT file (using tree.export_graphviz call) to disk and visalize the chart as below.



In [ ]: