Logistic Regression Assignment

Dataset : bank_full

Objective - Whether the client has subscribed a term deposit or not

1. Import Necessary libraries

In [1]:
```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')
```

2. Import Data

In [2]:
```
bank_holder = pd.read_csv('bank-full.csv',sep = ';')
bank_holder
```

Out[2]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0	unknown	no
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	0	unknown	no
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1	0	unknown	no
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	0	unknown	no
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1	0	unknown	no
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
45206	51	technician	married	tertiary	no	825	no	no	cellular	17	nov	977	3	-1	0	unknown	yes
45207	71	retired	divorced	primary	no	1729	no	no	cellular	17	nov	456	2	-1	0	unknown	yes
45208	72	retired	married	secondary	no	5715	no	no	cellular	17	nov	1127	5	184	3	success	yes
45209	57	blue-collar	married	secondary	no	668	no	no	telephone	17	nov	508	4	-1	0	unknown	no
45210	37	entrepreneur	married	secondary	no	2971	no	no	cellular	17	nov	361	2	188	11	other	no

45211 rows × 17 columns

3. Data Understanding

a) Initial Analysis :

In [3]:
```
bank_holder.head()
```

Out[3]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0	unknown	no
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	0	unknown	no
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1	0	unknown	no
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	0	unknown	no
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1	0	unknown	no

In [4]:
```
bank_holder.shape
```

Out[4]:
```
(45211, 17)
```

In [5]:
```
bank_holder.info()
```

```
<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
```

In [6]:
```
bank_holder.isna().sum()
```

Out[6]:
```
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
```

In [7]:
```
bank_holder.dtypes
```

Out[7]:
```
age           int64
job          object
marital      object
education    object
default      object
balance       int64
housing      object
loan         object
contact      object
day           int64
month        object
duration      int64
campaign      int64
pdays         int64
previous      int64
poutcome     object
y            object
dtype: object
```

There is no Null value present in this data set and also the data types are appropriate in all attributes

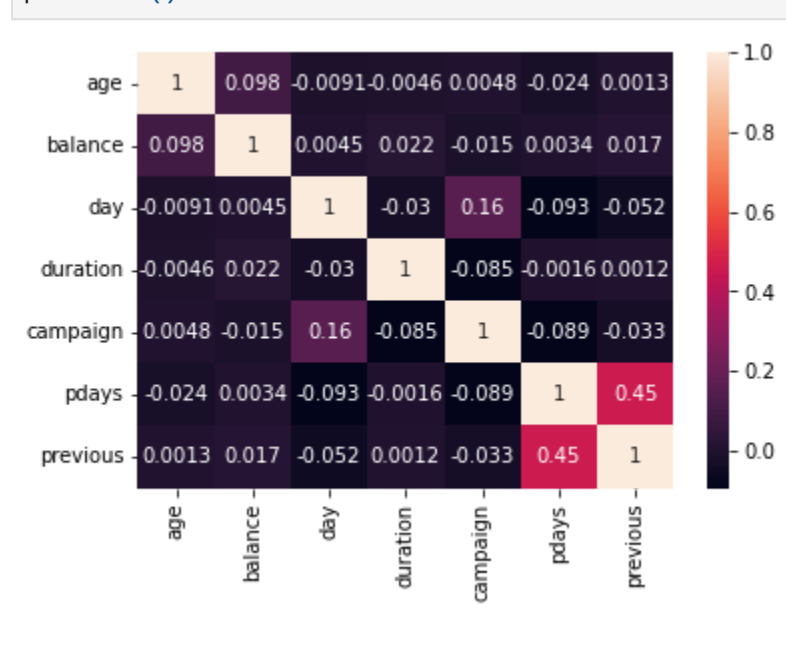
b) Correlation Matrix :

In [8]:
```
corr_matrix = bank_holder.corr()
corr_matrix
```

Out[8]:

	age	balance	day	duration	campaign	pdays	previous
age	1.000000	0.097783	-0.009120	-0.004648	0.004760	-0.023758	0.001288
balance	0.097783	1.000000	0.004503	0.021560	-0.014578	0.003435	0.016674
day	-0.009120	0.004503	1.000000	-0.030206	0.162490	-0.093044	-0.051710
duration	-0.004648	0.021560	-0.030206	1.000000	-0.084570	-0.001565	0.001203
campaign	0.004760	-0.014578	0.162490	-0.084570	1.000000	-0.088628	-0.032855
pdays	-0.023758	0.003435	-0.093044	-0.001565	-0.088628	1.000000	0.454820
previous	0.001288	0.016674	-0.051710	0.001203	-0.032855	0.454820	1.000000

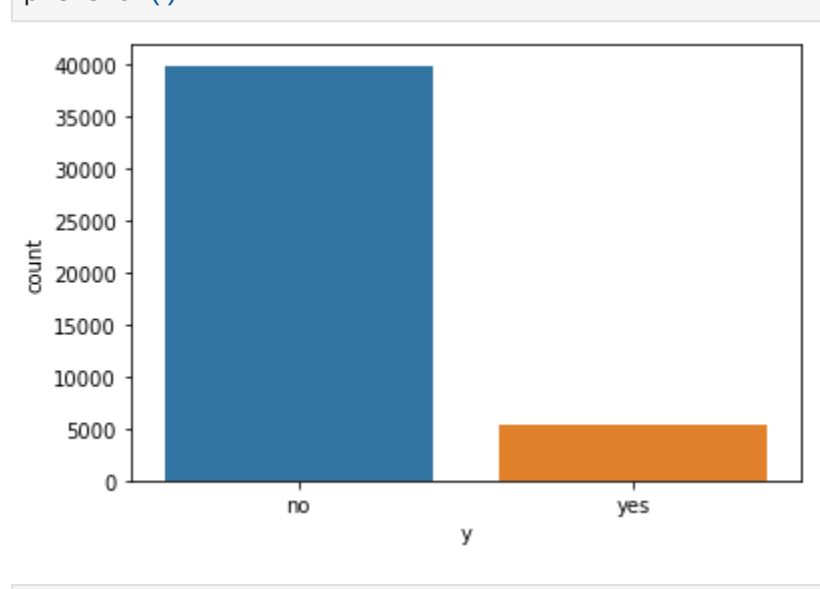
In [9]:
```
sns.heatmap(data = corr_matrix,annot = True)
plt.show()
```



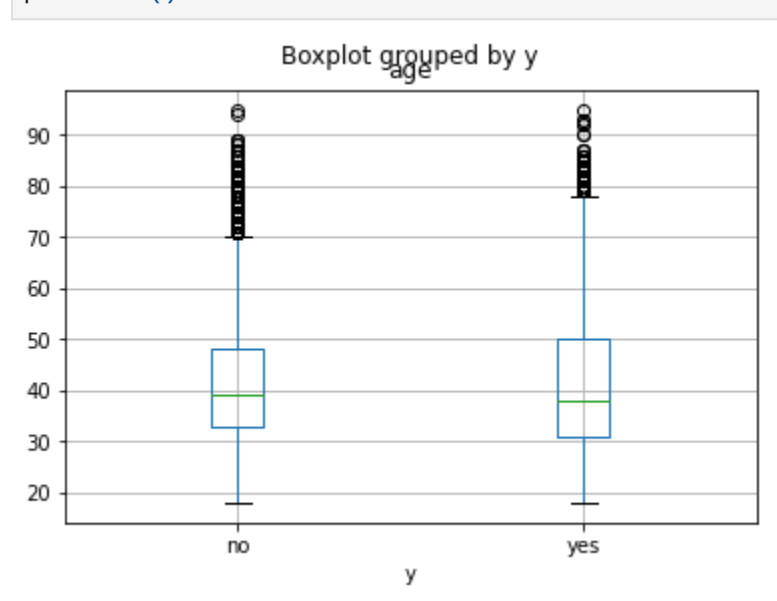
4. Perform Assumption Check

Checking which attributes have good impact to predict whether the cilent has subscribed a term deposit or not.

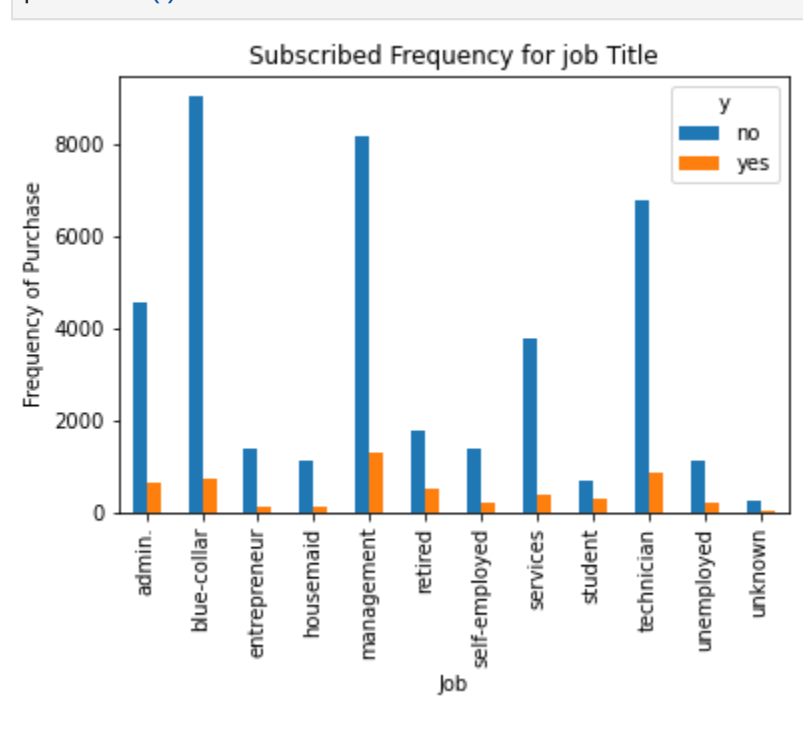
In [10]:
```
sns.countplot(x = 'y',data = bank_holder)
plt.show()
```



In [11]:
```
bank_holder.boxplot(column = 'age',by = 'y')
plt.show()
```

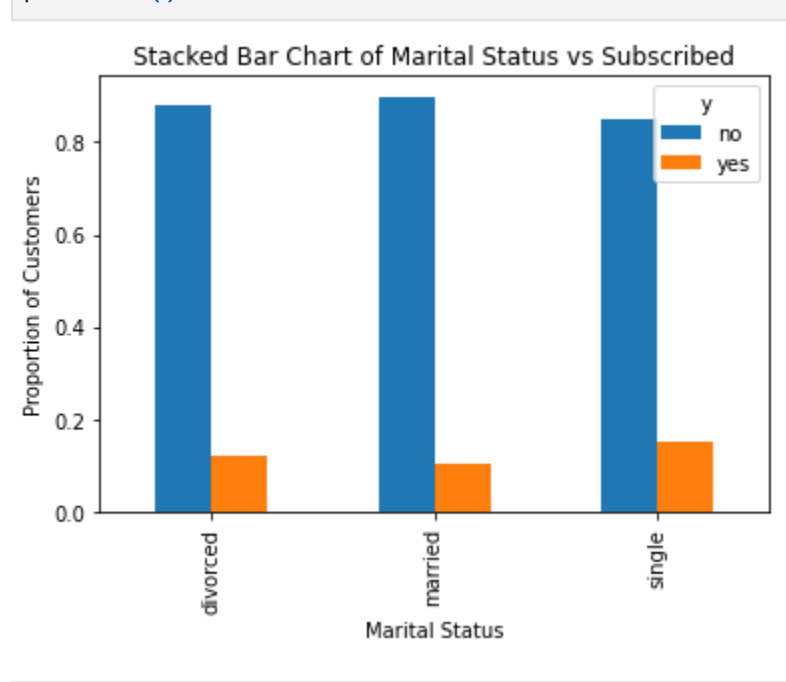


In [12]:
```
pd.crosstab(bank_holder.job,bank_holder.y).plot(kind = 'bar')

plt.title("Subscribed Frequency for job Title")
plt.xlabel('Job')
plt.ylabel('Frequency of Purchase')
plt.show()
```

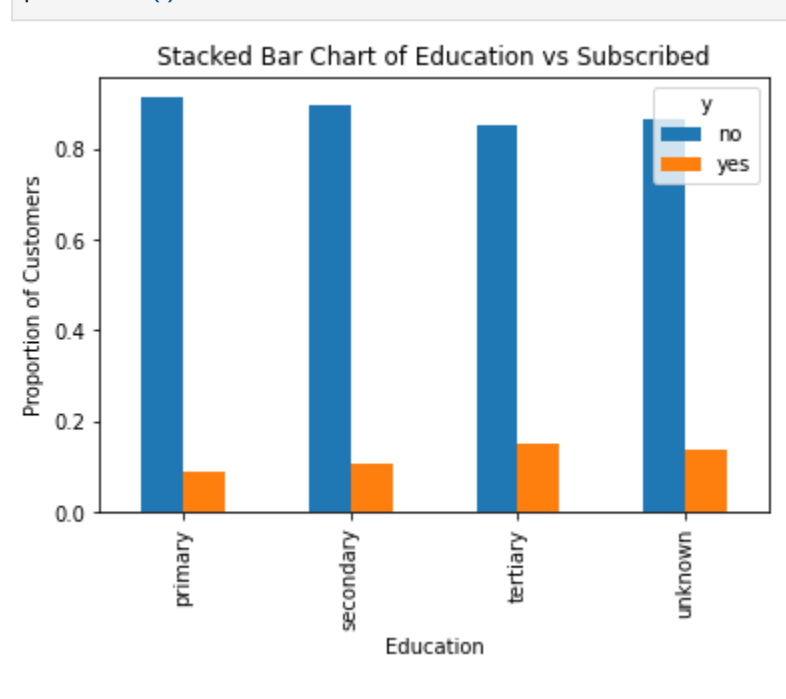


As per the above graph we can see that all occupation have diff types of subscriptions so it is a important features.

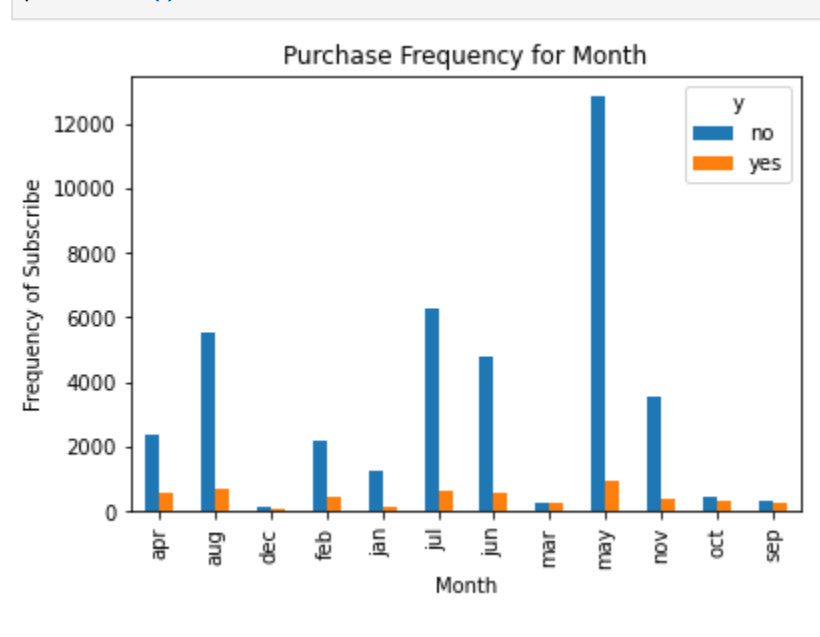
In [13]:
```
table1 = pd.crosstab(bank_holder.marital,bank_holder.y)
table1.div(table1.sum(1).astype(float),axis = 0).plot(kind = 'bar',stacked = False)

plt.title('Stacked Bar Chart of Marital Status vs Subscribed')
plt.xlabel('Marital Status')
plt.ylabel('Proportion of Customers')
plt.show()
```



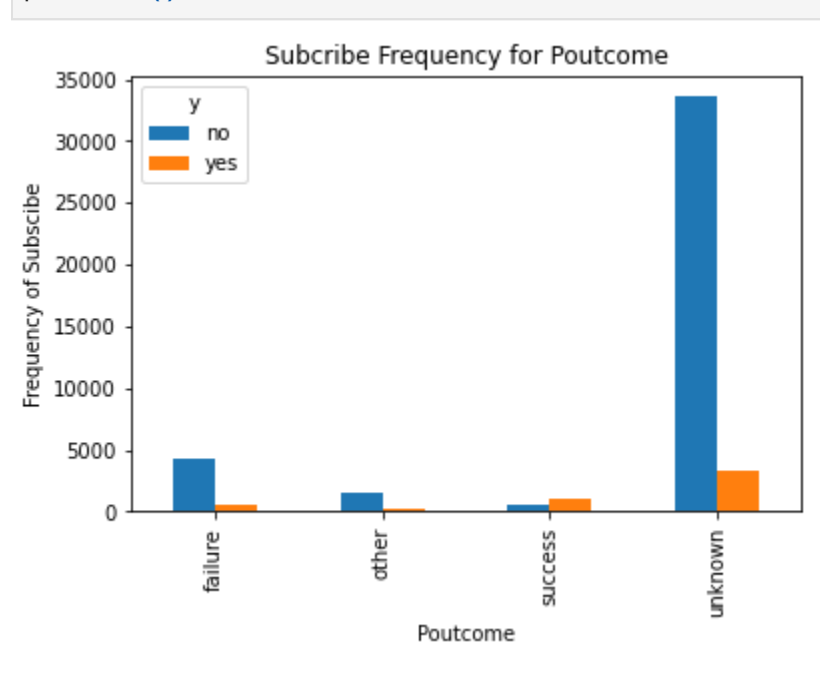
In [14]:
```
table2 = pd.crosstab(bank_holder.education,bank_holder.y)
table2.div(table2.sum(1).astype(float),axis = 0).plot(kind = 'bar')

plt.title('Stacked Bar Chart of Education vs Subscribed')
plt.xlabel('Education')
plt.ylabel('Proportion of Customers')
plt.show()
```



In [15]:
```
pd.crosstab(bank_holder.month,bank_holder.y).plot(kind = 'bar')

plt.title('Purchase Frequency for Month')
plt.xlabel('Month')
plt.ylabel('Frequency of Subscribe')
plt.show()
```



In [16]:
```
pd.crosstab(bank_holder.poutcome,bank_holder.y).plot(kind = 'bar')

plt.title('Subcribe Frequency for Poutcome')
plt.xlabel('Poutcome')
plt.ylabel('Frequency of Subscibe')
plt.show()
```



5. Creating Dummy Variable For Categorical Data

In [17]:
```
bank_holder_1 = pd.read_csv('bank-full.csv',sep = ';')
bank_holder_1.head()
```

Out[17]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0	unknown	no
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	0	unknown	no
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1	0	unknown	no
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	0	unknown	no
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1	0	unknown	no

In [18]:
```
bank_holder_1.columns
```

Out[18]:
```
Index(['age', 'job', 'marital', 'education', 'default', 'balance', 'housing',
       'loan', 'contact', 'day', 'month', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'y'],
      dtype='object')
```

In [19]:
```
df = pd.DataFrame(bank_holder_1)
df.head()
```

Out[19]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0	unknown	no
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	0	unknown	no
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1	0	unknown	no
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	0	unknown	no
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1	0	unknown	no

In [20]:
```
bank_holder_details = df.drop(columns = ['age','marital','education','housing','loan','day','month','campaign','pdays'])
bank_holder_details.head()
```

Out[20]:

	job	default	balance	contact	duration	previous	poutcome	y
0	management	no	2143	unknown	261	0	unknown	no
1	technician	no	29	unknown	151	0	unknown	no
2	entrepreneur	no	2	unknown	76	0	unknown	no
3	blue-collar	no	1506	unknown	92	0	unknown	no
4	unknown	no	1	unknown	198	0	unknown	no

In [21]:
```
job_dummy = pd.get_dummies(bank_holder_details['job'],drop_first = True)
job_dummy.columns
```

Out[21]:
```
Index(['blue-collar', 'entrepreneur', 'housemaid', 'management', 'retired',
       'self-employed', 'services', 'student', 'technician', 'unemployed',
       'unknown'],
      dtype='object')
```

In [22]:
```
default_dummy = pd.get_dummies(bank_holder_details['default'],drop_first = True)
default_dummy.columns
```

Out[22]:
```
Index(['yes'], dtype='object')
```

In [23]:
```
contact_dummy = pd.get_dummies(bank_holder_details['contact'],drop_first = True)
contact_dummy.columns
```

Out[23]:
```
Index(['telephone', 'unknown'], dtype='object')
```

In [24]:
```
poutcome_dummy = pd.get_dummies(bank_holder_details['poutcome'],drop_first = True)
poutcome_dummy.columns
```

Out[24]:
```
Index(['other', 'success', 'unknown'], dtype='object')
```

In [25]:
```
# Concate the dummy varibles
concat_details = pd.concat([bank_holder_details,job_dummy,default_dummy,contact_dummy,poutcome_dummy],axis = 1)
concat_details.head()
```

Out[25]:

	job	default	balance	contact	duration	previous	poutcome	y	blue-collar	entrepreneur	...	student	technician	unemployed	unknown	yes	telephone	unknown	other	success	unknown
0	management	no	2143	unknown	261	0	unknown	no	0	0	...	0	0	0	0	0	0	1	0	0	1
1	technician	no	29	unknown	151	0	unknown	no	0	0	...	0	1	0	0	0	0	1	0	0	1
2	entrepreneur	no	2	unknown	76	0	unknown	no	0	1	...	0	0	0	0	0	0	1	0	0	1
3	blue-collar	no	1506	unknown	92	0	unknown	no	1	0	...	0	0	0	0	0	0	1	0	0	1
4	unknown	no	1	unknown	198	0	unknown	no	0	0	...	0	0	0	1	0	0	1	0	0	1

5 rows × 25 columns

From the above table now drop the exist categorical columns from which we have made a dummy variables.

In [26]:
```
#droping categorical columns
df1 = pd.DataFrame(concat_details)
new_bank_details = df1.drop(columns = ['default','poutcome','job','contact'])
new_bank_details.head()
```

Out[26]:

	balance	duration	previous	y	blue-collar	entrepreneur	housemaid	management	retired	self-employed	...	student	technician	unemployed	unknown	yes	telephone	unknown	other	success	unknown
0	2143	261	0	no	0	0	0	1	0	0	...	0	0	0	0	0	0	1	0	0	1
1	29	151	0	no	0	0	0	0	0	0	...	0	1	0	0	0	0	1	0	0	1
2	2	76	0	no	0	1	0	0	0	0	...	0	0	0	0	0	0	1	0	0	1
3	1506	92	0	no	1	0	0	0	0	0	...	0	0	0	0	0	0	1	0	0	1
4	1	198	0	no	0	0	0	0	0	0	...	0	0	0	1	0	0	1	0	0	1

5 rows × 21 columns

6. Model Building

In [27]:
```
from sklearn.linear_model import LogisticRegression
```

In [28]:
```
## Map the output variable for converting categorical to numercal data & create new dataframe
new_bank_details_1 = new_bank_details.copy()
new_bank_details_1['y'] = new_bank_details_1['y'].map({'no':0,'yes':1})
new_bank_details_1.head(3)
```

Out[28]:

	balance	duration	previous	y	blue-collar	entrepreneur	housemaid	management	retired	self-employed	...	student	technician	unemployed	unknown	yes	telephone	unknown	other	success	unknown
0	2143	261	0	0	0	0	0	1	0	0	...	0	0	0	0	0	0	1	0	0	1
1	29	151	0	0	0	0	0	0	0	0	...	0	1	0	0	0	0	1	0	0	1
2	2	76	0	0	0	1	0	0	0	0	...	0	0	0	0	0	0	1	0	0	1

3 rows × 21 columns

In [29]:
```
#Assigning the input and output variables in x and y
X = new_bank_details_1.drop("y",axis = 1)
Y = new_bank_details_1["y"]
```

In [30]:
```
classifier = LogisticRegression()
classifier.fit(X,Y)
```

Out[30]:
```
LogisticRegression()
```

7. Model Prediction

In [31]:
```
y_pred = classifier.predict(X)
y_pred_prob = classifier.predict_proba(X)
y_pred_prob
```

Out[31]:
```
array([[0.97641599, 0.02358401],
       [0.98507741, 0.01492259],
       [0.99002721, 0.00997279],
       ...,
       [0.00853537, 0.99146463],
       [0.88227286, 0.11772714],
       [0.87910315, 0.12089685]])
```

In [32]:
```
pd.DataFrame({'actual_y':Y,'y_pred_prob':y_pred})
```

Out[32]:

	actual_y	y_pred_prob
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0
...	...	...
45206	1	1
45207	1	0
45208	1	1
45209	0	0
45210	0	0

45211 rows × 2 columns

8. Model Testing

In [33]:
```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
```

In [34]:
```
cm = confusion_matrix = confusion_matrix(Y,y_pred)
accuracy = accuracy_score(Y,y_pred)
```

In [35]:
```
print(cm)
print('Accuracy of a Model:',accuracy)
```

```
[[39005   917]
 [ 3605  1684]]
Accuracy of a Model: 0.8999800933401163
```

Accuracy of a Model is 90 % and it is a good Model

In [36]:
```
from sklearn.metrics import classification_report
print(classification_report(Y,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.92      0.98      0.95     39922
           1       0.65      0.32      0.43      5289

    accuracy                           0.90     45211
   macro avg       0.78      0.65      0.69     45211
weighted avg       0.88      0.90      0.88     45211
```

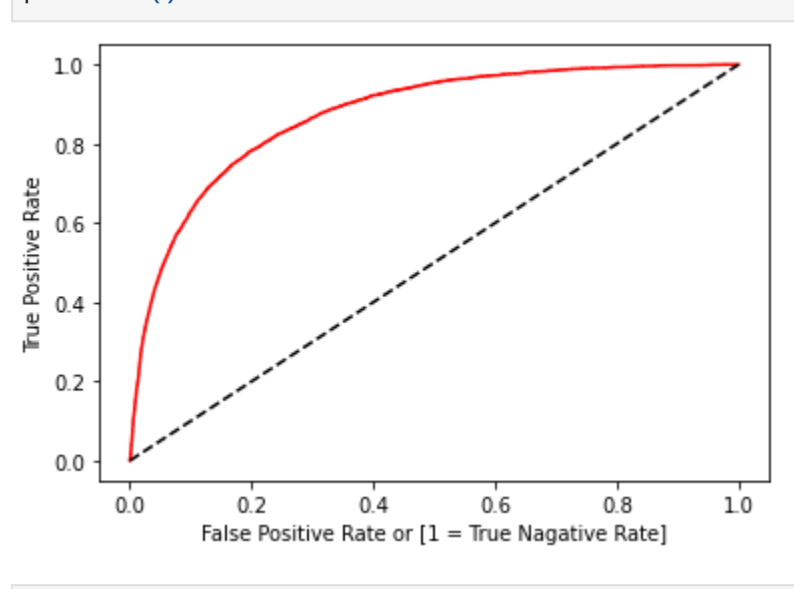
9. ROC Curve

In [37]:
```
from sklearn import preprocessing
```

In [38]:
```
label_encoder = preprocessing.LabelEncoder()

y_predict = label_encoder.fit_transform(y_pred)
y_actual = label_encoder.fit_transform(new_bank_details['y'])
```

In [39]:
```
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
```

In [40]:
```
fpr, tpr, thresholds = roc_curve(y_actual, classifier.predict_proba (X)[:,1])

auc = roc_auc_score(y_actual, y_predict)

import matplotlib.pyplot as plt
plt.plot(fpr,tpr,color = 'red', label = 'logit model(area = %0.2f)'%auc)

plt.plot([0,1],[0,1], 'k--')
plt.xlabel('False Positive Rate or [1 = True Nagative Rate]')
plt.ylabel('True Positive Rate')
plt.show()
```



In [41]:
```
print('AUC Value:',auc)
```

```
AUC Value: 0.6477134406230929
```

We have created a model with approprite feature and got around Accuracy of Model = 89.99% approx to 90% for prediction of client that the client will subsribe the term deposit or not.

But as per ROC curve we found that the area under curve AUC Value = 64.7% approx 65% that we can predict perfactly true positive rate and it is biased because our dataset has been a large frequency of negative result.

From classification table we got,

NO : 0.92, 0.98, 0.95, 39922

YES : 0.65, 0.32, 0.43, 5289

So we can say that this is average model prediction for client will be subscribed or not.