In [49]:

```
import pandas as pd
import numpy as np
from sklearn import preprocessing
import matplotlib.pyplot as plt
plt.rc("font", size=14)
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
import seaborn as sns
sns.set(style="white")
sns.set(style="whitegrid", color_codes=True)
```

In [50]:

```
data = pd.read_csv('banking.csv', header=0)
data = data.dropna()
print(data.shape)
print(list(data.columns))
```

```
(41188, 21)
['age', 'job', 'marital', 'education', 'default', 'housing', 'loan', 'contact', 'mon
th', 'day_of_week', 'duration', 'campaign', 'pdays', 'previous', 'poutcome', 'emp_va
r_rate', 'cons_price_idx', 'cons_conf_idx', 'euribor3m', 'nr_employed', 'y']
```

In [51]:

```
data.head()
```

Out[51]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_w
0	44	blue-collar	married	basic.4y	unknown	yes	no	cellular	aug	
1	53	technician	married	unknown	no	no	no	cellular	nov	
2	28	management	single	university.degree	no	yes	no	cellular	jun	
3	39	services	married	high.school	no	no	no	cellular	apr	
4	55	retired	married	basic.4y	no	yes	no	cellular	aug	

5 rows × 21 columns

Predict variable (desired target):

y - has the client subscribed a term deposit? (binary: '1','0')

The education column of the dataset has many categories and we need to reduce the categories for a better modelling. The education column has the following categories:

In [52]:

```
data['education'].unique()
```

Out[52]:

```
array(['basic.4y', 'unknown', 'university.degree', 'high.school',
       'basic.9y', 'professional.course', 'basic.6y', 'illiterate'],
      dtype=object)
```

Let us group "basic.4y", "basic.9y" and "basic.6y" together and call them "basic".

In [5]:

```
data['education']=np.where(data['education'] =='basic.9y', 'Basic', data['education'
data['education']=np.where(data['education'] =='basic.6y', 'Basic', data['education'
data['education']=np.where(data['education'] =='basic.4y', 'Basic', data['education'
```

After grouping, this is the columns.

In [6]:
```
data['education'].unique()
```

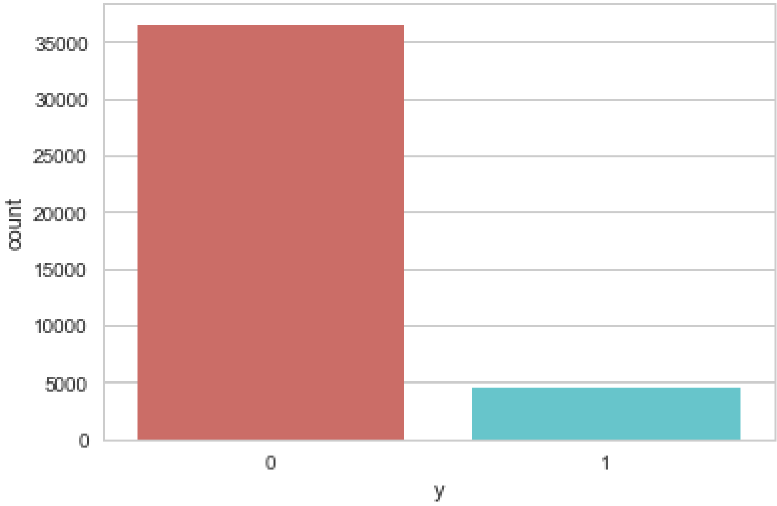
Out[6]:
```
array(['Basic', 'unknown', 'university.degree', 'high.school',
       'professional.course', 'illiterate'], dtype=object)
```

Data exploration

In [7]:
```
data['y'].value_counts()
```

Out[7]:
```
0    36548
1     4640
Name: y, dtype: int64
```

In [8]:
```
sns.countplot(x='y',data=data, palette='hls')
plt.show()
```



In [53]:
```
count_no_sub = len(data[data['y']==0])
count_sub = len(data[data['y']==1])
pct_of_no_sub = count_no_sub/(count_no_sub+count_sub)
print("percentage of no subscription is", pct_of_no_sub*100)
pct_of_sub = count_sub/(count_no_sub+count_sub)
print("percentage of subscription", pct_of_sub*100)
```

```
percentage of no subscription is 88.73458288821988
percentage of subscription 11.265417111780131
```

Our classes are imbalanced, and the ratio of no-subscription to subscription instances is 89:11. Before we go ahead to balance the classes, Let's do some more exploration.

In [13]:
```
data.groupby('y').mean()
```

Out[13]:

	age	duration	campaign	pdays	previous	emp_var_rate	cons_price_idx	cons_conf_i
y								
0	39.911185	220.844807	2.633085	984.113878	0.132374	0.248875	93.603757	-40.5930
1	40.913147	553.191164	2.051724	792.035560	0.492672	-1.233448	93.354386	-39.7897

Observations:

The average age of customers who bought the term deposit is higher than that of the customers who didn't. The pdays (days since the customer was last contacted) is understandably lower for the customers who bought it. The lower the pdays, the better the memory of the last call and hence the better chances of a sale. Surprisingly, campaigns (number of contacts or calls made during the current campaign) are lower for customers who bought the term deposit.

We can calculate categorical means for other categorical variables such as education and marital status to get a more detailed sense of our data.

In [10]:
```
data.groupby('job').mean()
```

Out[10]:

job	age	duration	campaign	pdays	previous	emp_var_rate	cons_price_idx
admin.	38.187296	254.312128	2.623489	954.319229	0.189023	0.015563	93.534054
blue-collar	39.555760	264.542360	2.558461	985.160363	0.122542	0.248995	93.656656
entrepreneur	41.723214	263.267857	2.535714	981.267170	0.138736	0.158723	93.605372
housemaid	45.500000	250.454717	2.639623	960.579245	0.137736	0.433396	93.676576
management	42.362859	257.058140	2.476060	962.647059	0.185021	-0.012688	93.522755
retired	62.027326	273.712209	2.476744	897.936047	0.327326	-0.698314	93.430786
self-employed	39.949331	264.142153	2.660802	976.621393	0.143561	0.094159	93.559982
services	37.926430	258.398085	2.587805	979.974049	0.154951	0.175359	93.634659
student	25.894857	283.683429	2.104000	840.217143	0.524571	-1.408000	93.331613
technician	38.507638	250.232241	2.577339	964.408127	0.153789	0.274566	93.561471
unemployed	39.733728	249.451677	2.564103	935.316568	0.199211	-0.111736	93.563781
unknown	45.563636	239.675758	2.648485	938.727273	0.154545	0.357879	93.718942

In [14]:
```
data.groupby('marital').mean()
```

Out[14]:

marital	age	duration	campaign	pdays	previous	emp_var_rate	cons_price_idx	cor
divorced	44.899393	253.790330	2.61340	968.639853	0.168690	0.163985	93.606563	
married	42.307165	257.438623	2.57281	967.247673	0.155608	0.183625	93.597367	
single	33.158714	261.524378	2.53380	949.909578	0.211359	-0.167989	93.517300	
unknown	40.275000	312.725000	3.18750	937.100000	0.275000	-0.221250	93.471250	

In [15]:
```
data.groupby('education').mean()
```

Out[15]:

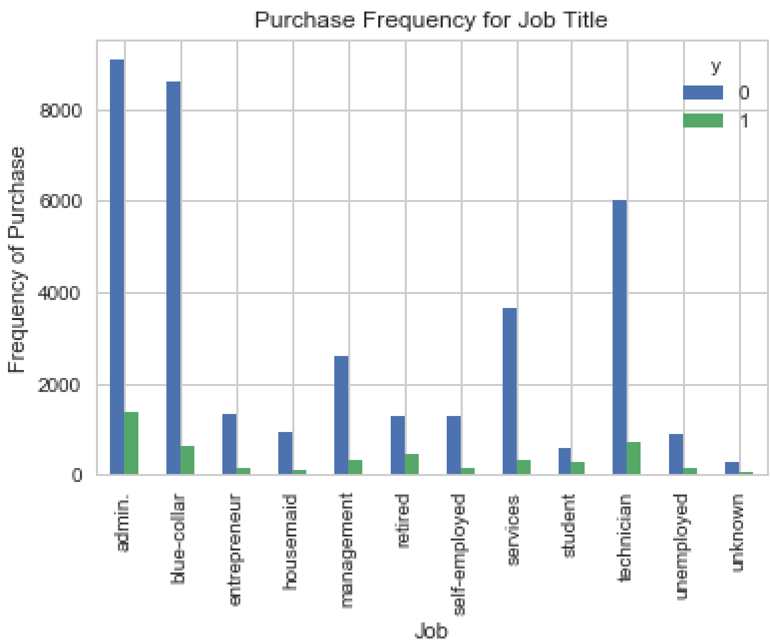
education	age	duration	campaign	pdays	previous	emp_var_rate	cons_pric

	age	duration	campaign	pdays	previous	emp_var_rate	cons_pric
education							
Basic	42.163910	263.043874	2.559498	974.877967	0.141053	0.191329	93.63
high.school	37.998213	260.886810	2.568576	964.358382	0.185917	0.032937	93.58
illiterate	48.500000	276.777778	2.277778	943.833333	0.111111	-0.133333	93.31
professional.course	40.080107	252.533855	2.586115	960.765974	0.163075	0.173012	93.56
university.degree	38.879191	253.223373	2.563527	951.807692	0.192390	-0.028090	93.49
unknown	43.481225	262.390526	2.596187	942.830734	0.226459	0.059099	93.65

Visualizations

In [16]:

```
%matplotlib inline
pd.crosstab(data.job,data.y).plot(kind='bar')
plt.title('Purchase Frequency for Job Title')
plt.xlabel('Job')
plt.ylabel('Frequency of Purchase')
```



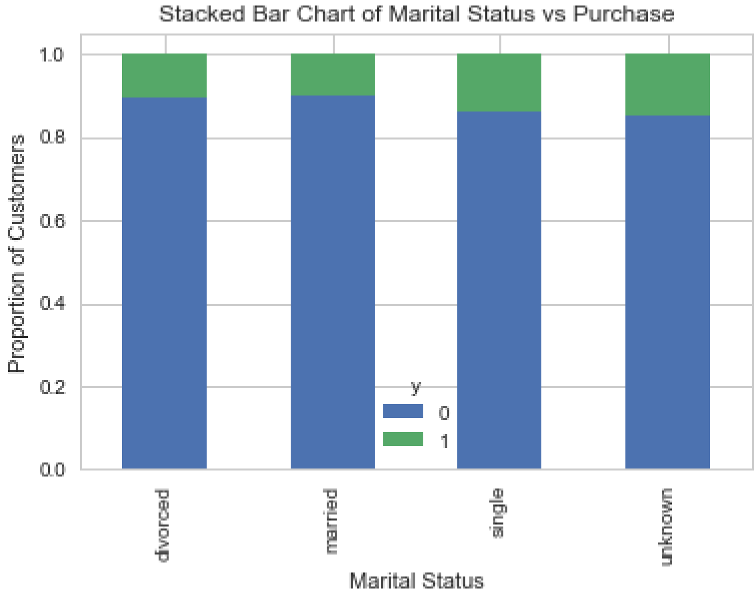
The frequency of purchase of the deposit depends a great deal on the job title. Thus, the job title can be a good predictor of the outcome variable.

In [17]:

```
table=pd.crosstab(data.marital,data.y)
table.div(table.sum(1).astype(float), axis=0).plot(kind='bar', stacked=True)
plt.title('Stacked Bar Chart of Marital Status vs Purchase')
plt.xlabel('Marital Status')
plt.ylabel('Proportion of Customers')
```

Out[17]:

```
Text(0,0.5,'Proportion of Customers')
```

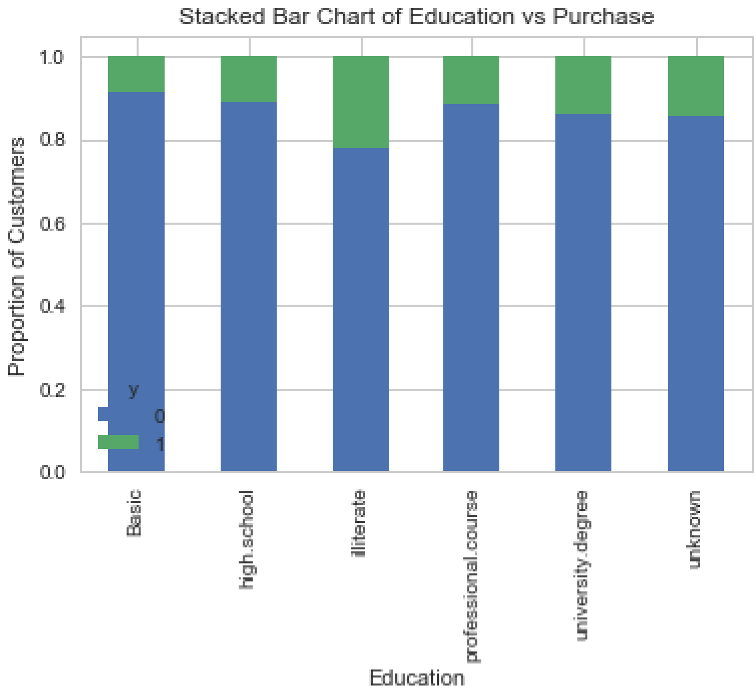


Hard to see, but the marital status does not seem a strong predictor for the outcome variable.

In [18]:

```
table=pd.crosstab(data.education,data.y)
table.div(table.sum(1).astype(float), axis=0).plot(kind='bar', stacked=True)
plt.title('Stacked Bar Chart of Education vs Purchase')
plt.xlabel('Education')
plt.ylabel('Proportion of Customers')
```

Out[18]: Text(0,0.5,'Proportion of Customers')

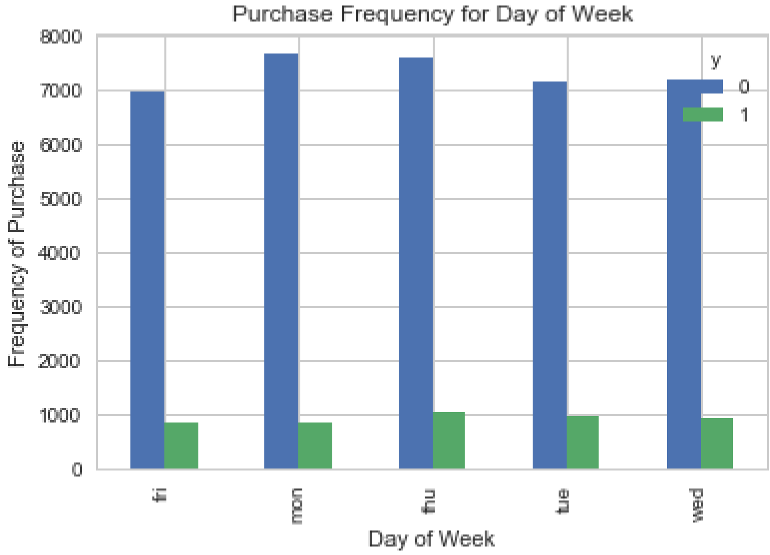


Education seems a good predictor of the outcome variable.

In [19]:

```
pd.crosstab(data.day_of_week,data.y).plot(kind='bar')
plt.title('Purchase Frequency for Day of Week')
plt.xlabel('Day of Week')
plt.ylabel('Frequency of Purchase')
```

Out[19]: Text(0,0.5,'Frequency of Purchase')

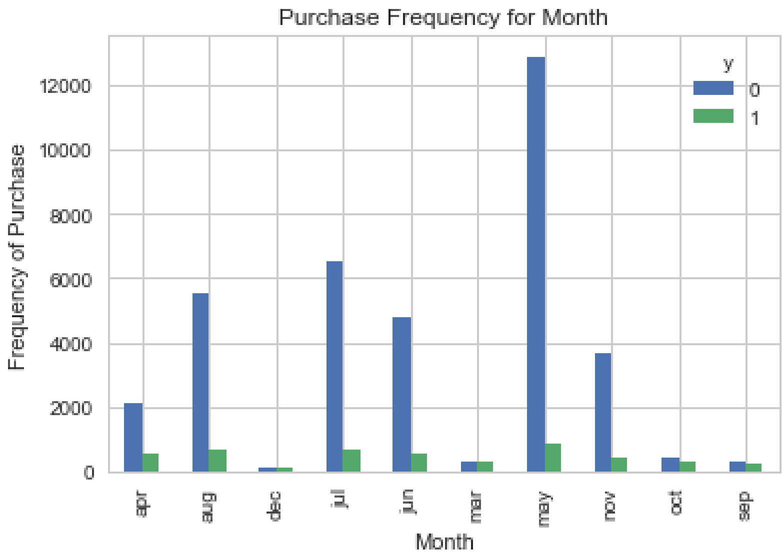


Day of week may not be a good predictor of the outcome.

In [20]:

```
pd.crosstab(data.month,data.y).plot(kind='bar')
plt.title('Purchase Frequency for Month')
plt.xlabel('Month')
plt.ylabel('Frequency of Purchase')
```

Out[20]: Text(0,0.5,'Frequency of Purchase')

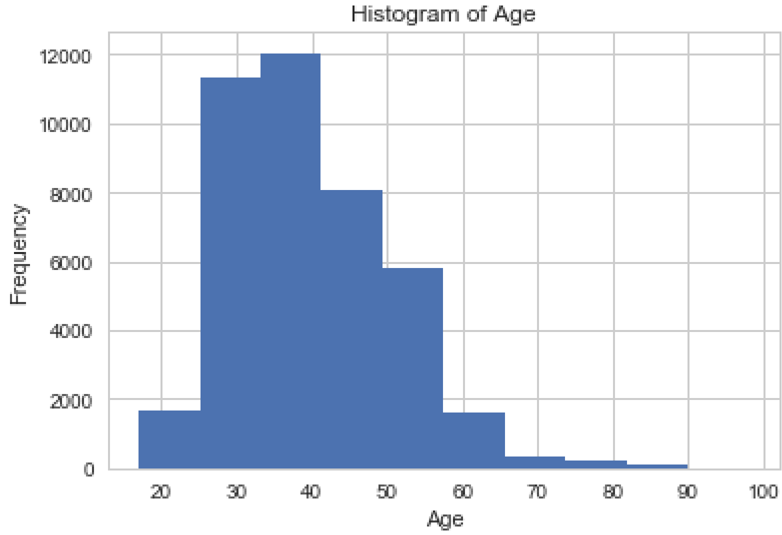


Month might be a good predictor of the outcome variable.

In [21]:

```
data.age.hist()
plt.title('Histogram of Age')
plt.xlabel('Age')
plt.ylabel('Frequency')
```

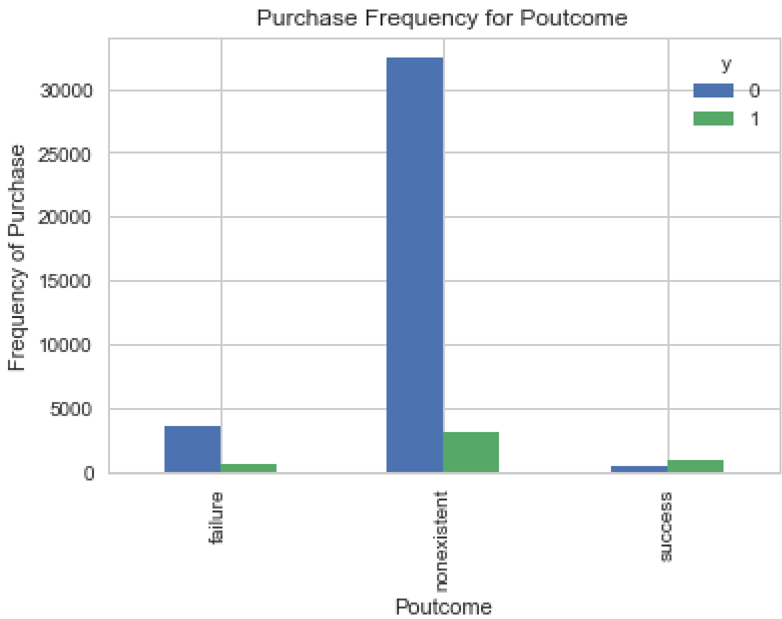
Out[21]: Text(0,0.5,'Frequency')



Most customers of the bank in this dataset are in the age range of 30-40.

In [22]:
```
pd.crosstab(data.poutcome,data.y).plot(kind='bar')
plt.title('Purchase Frequency for Poutcome')
plt.xlabel('Poutcome')
plt.ylabel('Frequency of Purchase')
```

Out[22]: Text(0,0.5,'Frequency of Purchase')



Poutcome seems to be a good predictor of the outcome variable.

Create dummy variables

In [68]:
```
cat_vars=['job','marital','education','default','housing','loan','contact','month','
for var in cat_vars:
    cat_list='var'+'_'+var
    cat_list = pd.get_dummies(data[var], prefix=var)
    data1=data.join(cat_list)
    data=data1

cat_vars=['job','marital','education','default','housing','loan','contact','month','
data_vars=data.columns.values.tolist()
to_keep=[i for i in data_vars if i not in cat_vars]
```

```
data_final=data[to_keep]
data_final.columns.values
```

Out[68]:
```
array(['age', 'duration', 'campaign', 'pdays', 'previous', 'emp_var_rate',
       'cons_price_idx', 'cons_conf_idx', 'euribor3m', 'nr_employed', 'y',
       'job_admin.', 'job_blue-collar', 'job_entrepreneur',
       'job_housemaid', 'job_management', 'job_retired',
       'job_self-employed', 'job_services', 'job_student',
       'job_technician', 'job_unemployed', 'job_unknown',
       'marital_divorced', 'marital_married', 'marital_single',
       'marital_unknown', 'education_basic.4y', 'education_basic.6y',
       'education_basic.9y', 'education_high.school',
       'education_illiterate', 'education_professional.course',
       'education_university.degree', 'education_unknown', 'default_no',
       'default_unknown', 'default_yes', 'housing_no', 'housing_unknown',
       'housing_yes', 'loan_no', 'loan_unknown', 'loan_yes',
       'contact_cellular', 'contact_telephone', 'month_apr', 'month_aug',
       'month_dec', 'month_jul', 'month_jun', 'month_mar', 'month_may',
       'month_nov', 'month_oct', 'month_sep', 'day_of_week_fri',
       'day_of_week_mon', 'day_of_week_thu', 'day_of_week_tue',
       'day_of_week_wed', 'poutcome_failure', 'poutcome_nonexistent',
       'poutcome_success'], dtype=object)
```

Over-sampling using SMOTE

In [78]:
```
X = data_final.loc[:, data_final.columns != 'y']
y = data_final.loc[:, data_final.columns == 'y']
```

In [80]:
```
from imblearn.over_sampling import SMOTE

os = SMOTE(random_state=0)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_stat
columns = X_train.columns

os_data_X,os_data_y=os.fit_sample(X_train, y_train)
os_data_X = pd.DataFrame(data=os_data_X,columns=columns )
os_data_y= pd.DataFrame(data=os_data_y,columns=['y'])
# we can Check the numbers of our data
print("length of oversampled data is ",len(os_data_X))
print("Number of no subscription in oversampled data",len(os_data_y[os_data_y['y']==
print("Number of subscription",len(os_data_y[os_data_y['y']==1]))
print("Proportion of no subscription data in oversampled data is ",len(os_data_y[os_
print("Proportion of subscription data in oversampled data is ",len(os_data_y[os_dat
```

```
C:\Users\SusanLi\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\utils\v
alidation.py:578: DataConversionWarning: A column-vector y was passed when a 1d arra
y was expected. Please change the shape of y to (n_samples, ), for example using rav
el().
  y = column_or_1d(y, warn=True)
length of oversampled data is  51134
Number of no subscription in oversampled data 25567
Number of subscription 25567
Proportion of no subscription data in oversampled data is  0.5
Proportion of subscription data in oversampled data is  0.5
```

Recursive feature elimination

In [82]:
```
data_final_vars=data_final.columns.values.tolist()
y=['y']
X=[i for i in data_final_vars if i not in y]
```

In [92]:
```
from sklearn import datasets
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression

logreg = LogisticRegression()

rfe = RFE(logreg, 20)
rfe = rfe.fit(os_data_X, os_data_y.values.ravel())
print(rfe.support_)
print(rfe.ranking_)
```

```
[False False False False False False False False  True False False  True
 False  True False False False False False False False False False False
 False  True False False False False  True False False False  True  True
 False False False False False False False  True  True  True  True  True
  True  True  True  True  True  True False False False False False False
  True False  True]
[39 38 26 42  9 12 24 36  1 35  8  1  7  1  5 32  2  4 31  3  6 10 23 21
 17  1 14 18 15 22  1 20 16 19  1  1 41 28 44 37 33 43 34  1  1  1  1  1
  1  1  1  1  1  1 29 30 11 27 40 25  1 13  1]
```

The Recursive Feature Elimination (RFE) has helped us select the following features: "previous", "euribor3m", "job_blue-collar", "job_retired", "job_services", "job_student", "default_no", "month_aug", "month_dec", "month_jul", "month_nov", "month_oct", "month_sep", "day_of_week_fri", "day_of_week_wed", "poutcome_failure", "poutcome_nonexistent", "poutcome_success".

In [99]:
```
cols=['euribor3m', 'job_blue-collar', 'job_housemaid', 'marital_unknown', 'education
      'contact_cellular', 'contact_telephone', 'month_apr', 'month_aug', 'month_dec'
      'month_may', 'month_nov', 'month_oct', "poutcome_failure", "poutcome_success"]
X=os_data_X[cols]
y=os_data_y['y']
```

Implementing the model

In [100…
```
import statsmodels.api as sm
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary2())
```

```
Warning: Maximum number of iterations has been exceeded.
         Current function value: 0.545891
         Iterations: 35
                              Results: Logit
==============================================================================
Model:                   Logit                 No. Iterations:      35.0000
Dependent Variable:      y                     Pseudo R-squared:    0.212
Date:                    2018-09-10 12:16      AIC:                 55867.1778
No. Observations:        51134                 BIC:                 56044.0219
Df Model:                19                    Log-Likelihood:      -27914.
Df Residuals:            51114                 LL-Null:             -35443.
Converged:               0.0000                Scale:               1.0000
------------------------------------------------------------------------------
                      Coef.    Std.Err.     z     P>|z|     [0.025     0.975]
------------------------------------------------------------------------------
euribor3m            -0.4634    0.0091 -50.9471 0.0000     -0.4813    -0.4456
job_blue-collar      -0.1736    0.0283  -6.1230 0.0000     -0.2291    -0.1180
job_housemaid        -0.3260    0.0778  -4.1912 0.0000     -0.4784    -0.1735
marital_unknown       0.7454    0.2253   3.3082 0.0009      0.3038     1.1870
education_illiterate  1.3156    0.4373   3.0084 0.0026      0.4585     2.1727
default_no           16.1521 5414.0744   0.0030 0.9976 -10595.2387 10627.5429
default_unknown      15.8945 5414.0744   0.0029 0.9977 -10595.4963 10627.2853
contact_cellular    -13.9393 5414.0744  -0.0026 0.9979 -10625.3302 10597.4515
```

```
contact_telephone    -14.0065 5414.0744  -0.0026 0.9979 -10625.3973 10597.3843
month_apr             -0.8356    0.0913  -9.1490 0.0000     -1.0145    -0.6566
month_aug             -0.6882    0.0929  -7.4053 0.0000     -0.8703    -0.5061
month_dec             -0.4233    0.1655  -2.5579 0.0105     -0.7477    -0.0990
month_jul             -0.4056    0.0935  -4.3391 0.0000     -0.5889    -0.2224
month_jun             -0.4817    0.0917  -5.2550 0.0000     -0.6614    -0.3021
month_mar              0.6638    0.1229   5.3989 0.0000      0.4228     0.9047
month_may             -1.4752    0.0874 -16.8815 0.0000     -1.6465    -1.3039
month_nov             -0.8298    0.0942  -8.8085 0.0000     -1.0144    -0.6451
month_oct              0.5065    0.1175   4.3111 0.0000      0.2762     0.7367
poutcome_failure      -0.5000    0.0363 -13.7706 0.0000     -0.5711    -0.4288
poutcome_success       1.5788    0.0618  25.5313 0.0000      1.4576     1.7000
==============================================================================

C:\Users\SusanLi\AppData\Local\Continuum\anaconda3\lib\site-packages\statsmodels\bas
e\model.py:496: ConvergenceWarning: Maximum Likelihood optimization failed to conver
ge. Check mle_retvals
  "Check mle_retvals", ConvergenceWarning)
```

The p-values for four variables are very high, therefore, we will remove them.

In [117…

```
cols=['euribor3m', 'job_blue-collar', 'job_housemaid', 'marital_unknown', 'education
      'month_apr', 'month_aug', 'month_dec', 'month_jul', 'month_jun', 'month_mar',
      'month_may', 'month_nov', 'month_oct', "poutcome_failure", "poutcome_success"]
X=os_data_X[cols]
y=os_data_y['y']
```

In [118…

```
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary2())
```

```
Optimization terminated successfully.
         Current function value: 0.555865
         Iterations 7
                           Results: Logit
=================================================================
Model:              Logit              No. Iterations:   7.0000
Dependent Variable: y                  Pseudo R-squared: 0.198
Date:               2018-09-10 12:38   AIC:              56879.2425
No. Observations:   51134              BIC:              57020.7178
Df Model:           15                 Log-Likelihood:   -28424.
Df Residuals:       51118              LL-Null:          -35443.
Converged:          1.0000             Scale:            1.0000
-----------------------------------------------------------------
                     Coef.  Std.Err.    z     P>|z|  [0.025 0.975]
-----------------------------------------------------------------
euribor3m           -0.4488   0.0074 -60.6837 0.0000 -0.4633 -0.4343
job_blue-collar     -0.2060   0.0278  -7.4032 0.0000 -0.2605 -0.1515
job_housemaid       -0.2784   0.0762  -3.6519 0.0003 -0.4278 -0.1290
marital_unknown      0.7619   0.2244   3.3956 0.0007  0.3221  1.2017
education_illiterate 1.3080   0.4346   3.0096 0.0026  0.4562  2.1598
month_apr            1.2863   0.0380  33.8180 0.0000  1.2118  1.3609
month_aug            1.3959   0.0411  33.9688 0.0000  1.3153  1.4764
month_dec            1.8084   0.1441  12.5483 0.0000  1.5259  2.0908
month_jul            1.6747   0.0424  39.5076 0.0000  1.5916  1.7578
month_jun            1.5574   0.0408  38.1351 0.0000  1.4773  1.6374
month_mar            2.8215   0.0908  31.0891 0.0000  2.6437  2.9994
month_may            0.5848   0.0304  19.2166 0.0000  0.5251  0.6444
month_nov            1.2725   0.0445  28.5720 0.0000  1.1852  1.3598
month_oct            2.7279   0.0816  33.4350 0.0000  2.5680  2.8878
poutcome_failure    -0.2797   0.0351  -7.9753 0.0000 -0.3485 -0.2110
poutcome_success     1.9617   0.0602  32.5939 0.0000  1.8438  2.0797
=================================================================
```

Logistic Regression Model Fitting

In [119…

```
from sklearn.linear_model import LogisticRegression
from sklearn import metrics

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_stat
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
```

Out[119…

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
```

In [120…

```
y_pred = logreg.predict(X_test)
print('Accuracy of logistic regression classifier on test set: {:.2f}'.format(logreg
```

```
Accuracy of logistic regression classifier on test set: 0.74
```

Confusion Matrix

In [122…

```
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(y_test, y_pred)
print(confusion_matrix)
```

```
[[6124 1542]
 [2505 5170]]
```

In [123…

```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

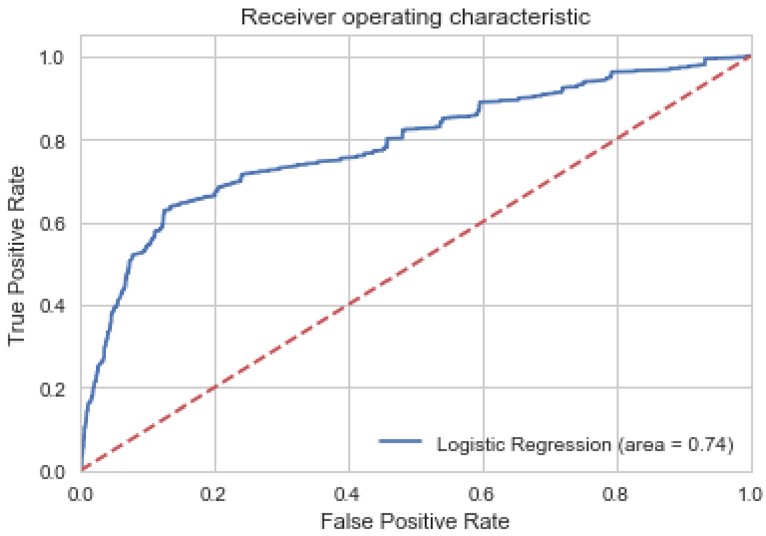
```
             precision    recall  f1-score   support

          0       0.71      0.80      0.75      7666
          1       0.77      0.67      0.72      7675

avg / total       0.74      0.74      0.74     15341
```

Interpretation:

Of the entire test set, 74% of the promoted term deposit were the term deposit that the customers liked. Of the entire test set, 74% of the customer's preferred term deposit were promoted.

In [124…

```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
logit_roc_auc = roc_auc_score(y_test, logreg.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, logreg.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % logit_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.savefig('Log_ROC')
plt.show()
```


Receiver operating characteristic
True Positive Rate
False Positive Rate
Logistic Regression (area = 0.74)
0.0
0.2
0.4
0.6
0.8
1.0