Portuguese bank marketting analysis

In [1]:

```
# importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

%matplotlib inline

import seaborn as sns
sns.set()
from sklearn import preprocessing
from sklearn.preprocessing import LabelEncoder

# algorithms for supervised classification
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier,
GradientBoostingClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.linear_model import LogisticRegression

# evaluation
from sklearn import metrics
from sklearn.metrics import roc_auc_score, roc_curve, auc
from sklearn.metrics import confusion_matrix, mean_squared_error
```

EDA

In [2]:

```
df= pd.read_csv("bank-additional-full.csv", delimiter=";",header='infer')
df.head()
```

Out[2]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	...	campaign	pdays	previous	pou
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon	...	1	999	0	none
1	57	services	married	high.school	unknown	no	no	telephone	may	mon	...	1	999	0	none
2	37	services	married	high.school	no	yes	no	telephone	may	mon	...	1	999	0	none
3	40	admin.	married	basic.6y	no	no	no	telephone	may	mon	...	1	999	0	none
4	56	services	married	high.school	no	no	yes	telephone	may	mon	...	1	999	0	none

5 rows × 21 columns

In [3]:

```
df.columns
```

Out[3]:

```
Index(['age', 'job', 'marital', 'education', 'default', 'housing', 'loan',
       'contact', 'month', 'day_of_week', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'emp.var.rate', 'cons.price.idx',
       'cons.conf.idx', 'euribor3m', 'nr.employed', 'y'],
      dtype='object')
```

In [4]:

```
df.describe()
```

Out[4]:

	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m
count	41188.00000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.00000
mean	40.02406	258.285010	2.567593	962.475454	0.172963	0.081886	93.575664	-40.502600	3.62129
std	10.42125	259.279249	2.770014	186.910907	0.494901	1.570960	0.578840	4.628198	1.73444
min	17.00000	0.000000	1.000000	0.000000	0.000000	-3.400000	92.201000	-50.800000	0.63400
25%	32.00000	102.000000	1.000000	999.000000	0.000000	-1.800000	93.075000	-42.700000	1.34400
50%	38.00000	180.000000	2.000000	999.000000	0.000000	1.100000	93.749000	-41.800000	4.85700
75%	47.00000	319.000000	3.000000	999.000000	0.000000	1.400000	93.994000	-36.400000	4.96100
max	98.00000	4918.000000	56.000000	999.000000	7.000000	1.400000	94.767000	-26.900000	5.04500

In [5]:

```
df.shape
```

Out[5]:

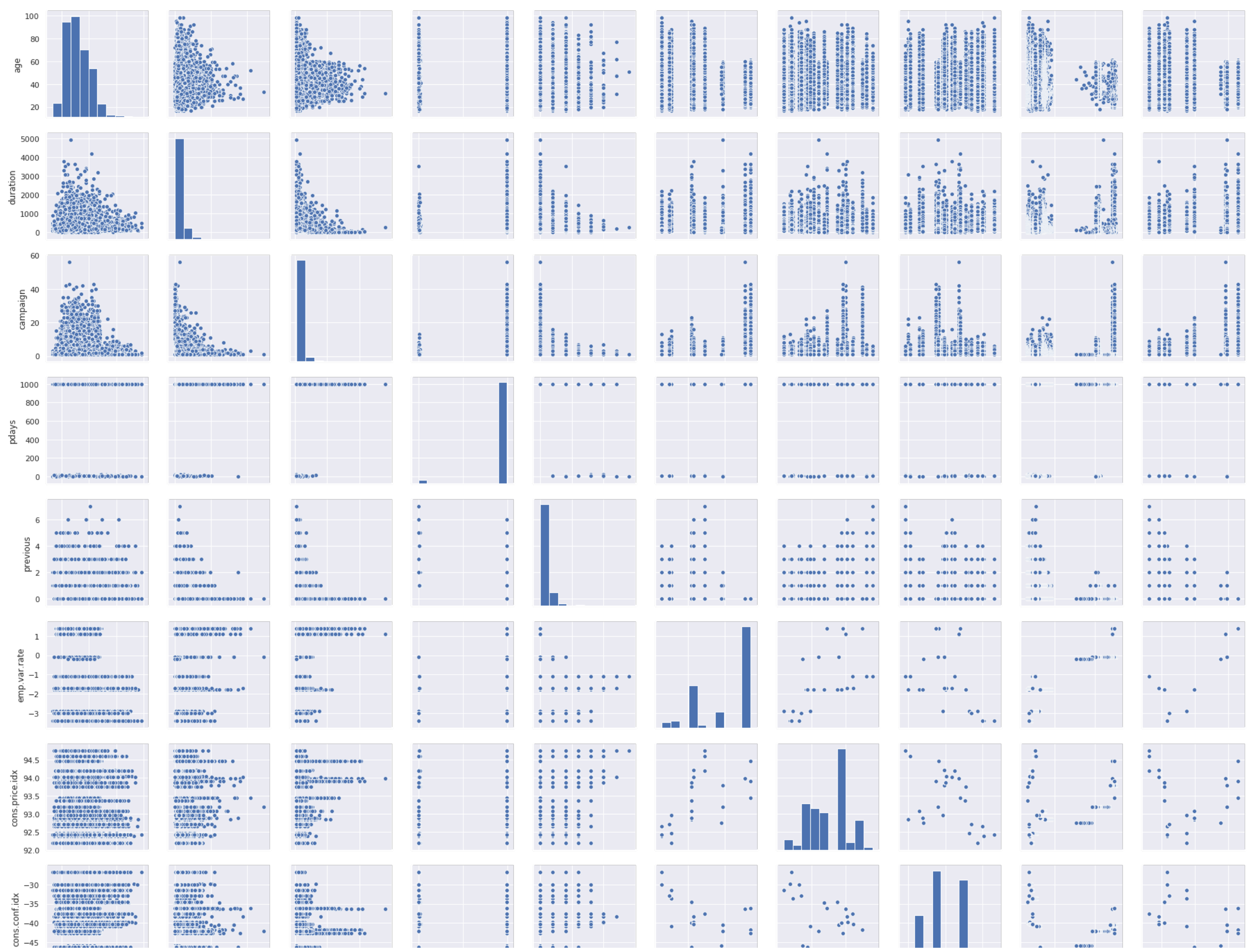
```
(41188, 21)
```

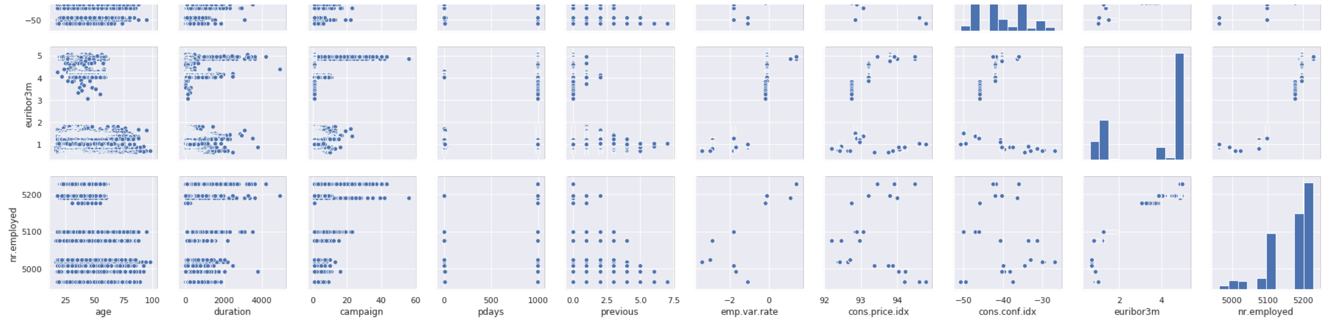
In [6]:

```
# to know the relationship between variables using pair-plot
sns.pairplot(df)
```

Out[6]:

```
<seaborn.axisgrid.PairGrid at 0x7f46639c9518>
```





In [7]:

```
df.dtypes
```

Out[7]:

```
age                  int64
job                 object
marital             object
education           object
default             object
housing             object
loan                object
contact             object
month               object
day_of_week         object
duration             int64
campaign             int64
pdays                int64
previous             int64
poutcome            object
emp.var.rate       float64
cons.price.idx     float64
cons.conf.idx      float64
euribor3m          float64
nr.employed        float64
y                   object
dtype: object
```

In [8]:

```
df_new= pd.get_dummies(df, columns=['job', 'marital', 'education', 'default','housing', 'loan', 'co
ntact', 'month', 'day_of_week', 'poutcome'])
```

In [9]:

```
df_new.y.head()
```

Out[9]:

```
0    no
1    no
2    no
3    no
4    no
Name: y, dtype: object
```

In [10]:

```
df_new.y.value_counts()
```

Out[10]:

```
no     36548
yes     4640
Name: y, dtype: int64
```

In [11]:

```
df_new.y.replace(('yes', 'no'), (1,0), inplace=True)
```

```
df_new.y.replace(('yes', 'no'),(1,0), inplace=True)
```

Conclusion:

1. It is an unbalanced dataset where the no. of no is more than yes
2. The datapoints are not much correlated

Modelling and evaluation

In [12]:

```
from sklearn.model_selection import train_test_split
import warnings
warnings.filterwarnings("ignore")
```

In [13]:

```
df_X = df_new.drop(['y'], axis=1)
df_y = pd.DataFrame(df_new['y'])
```

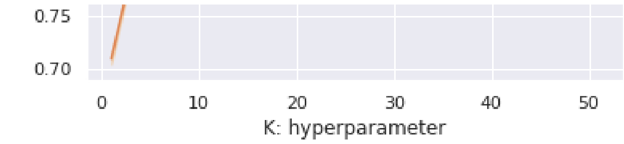
In [14]:

```
X_train, X_test, y_train, y_test = train_test_split(df_X, df_y, test_size=0.33, random_state=42)
```

using KNN algo.

In [15]:

```
# using Grid Search CV
# https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html
from sklearn.model_selection import GridSearchCV

neigh = KNeighborsClassifier()
parameters = {'n_neighbors':[1, 5, 10, 15, 21, 31, 41, 51]}
clf = GridSearchCV(neigh, parameters, cv=3, scoring='roc_auc')
clf.fit(X_train, y_train)

train_auc= clf.cv_results_['mean_train_score']
train_auc_std= clf.cv_results_['std_train_score']
cv_auc = clf.cv_results_['mean_test_score']
cv_auc_std= clf.cv_results_['std_test_score']

K= [1, 5, 10, 15, 21, 31, 41, 51]
plt.plot(K, train_auc, label='Train AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
plt.gca().fill_between(K,train_auc - train_auc_std,train_auc + train_auc_std,alpha=0.2,color='darkb
lue')

plt.plot(K, cv_auc, label='CV AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
plt.gca().fill_between(K,cv_auc - cv_auc_std,cv_auc + cv_auc_std,alpha=0.2,color='darkorange')
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
```



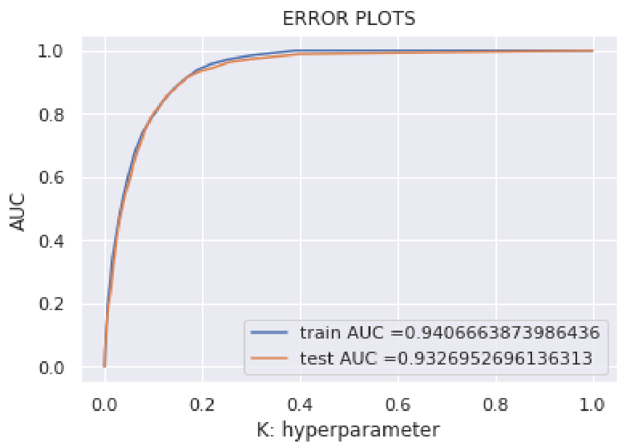
In [16]:

```
print('Best hyper parameter: ', clf.best_params_)
print('Best Accuracy: ', clf.best_score_*100)

best_k= int(clf.best_params_['n_neighbors'])
```

```
Best hyper parameter:  {'n_neighbors': 51}
Best Accuracy:  92.76068320009809
```

In [17]:

```
# https://scikit-
learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc


neigh = KNeighborsClassifier(n_neighbors=best_k)
neigh.fit(X_train, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive
class
# not the predicted outputs

train_fpr, train_tpr, thresholds = roc_curve(y_train, neigh.predict_proba(X_train)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_test, neigh.predict_proba(X_test)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()
print('AUC: ',roc_auc_score(y_test, neigh.predict(X_test)))

y_pred= neigh.predict(X_test)
print('Accuracy score: ',metrics.accuracy_score(y_test, y_pred ))
```




```
AUC:  0.7199298524042432
Accuracy score:  0.9125285073199441
```

In [18]:

```
from sklearn.metrics import confusion_matrix
print("Train confusion matrix")
print(confusion_matrix(y_train, neigh.predict(X_train)))
print("Test confusion matrix")
print(confusion_matrix(y_test, neigh.predict(X_test)))
```

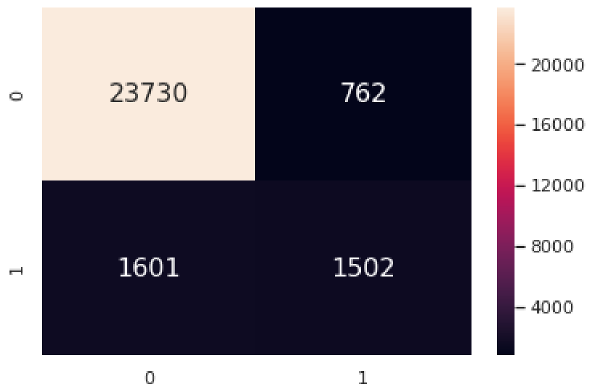
```
Train confusion matrix
[[23730   762]
 [ 1601  1502]]
Test confusion matrix
[[11680   376]
 [  813   724]]
```

In [19]:

```
# confusion_matrix using seaborn.heatmap
df_train= pd.DataFrame(confusion_matrix(y_train, neigh.predict(X_train)))

sns.heatmap(df_train, annot=True,annot_kws={"size": 16}, fmt='g')
```

Out[19]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4660f68c18>
```

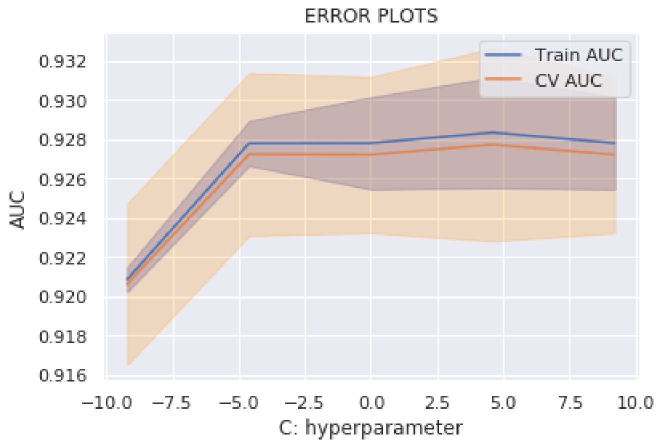


using Logistic Regression

In [20]:

```
# grid search CV
import math

ls=[10**-4, 10**-2, 10**0, 10**2, 10**4]
tuned_parameters = [{'C': ls}]

#Using GridSearchCV
model = GridSearchCV(LogisticRegression(), tuned_parameters, scoring = 'roc_auc', cv=5)
model.fit(X_train, y_train)

train_auc= model.cv_results_['mean_train_score']
train_auc_std= model.cv_results_['std_train_score']
cv_auc = model.cv_results_['mean_test_score']
cv_auc_std= model.cv_results_['std_test_score']


log_my_data = [math.log(x) for x in ls]

plt.plot(log_my_data, (train_auc), label='Train AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
plt.gca().fill_between(log_my_data,train_auc - train_auc_std,train_auc + train_auc_std,alpha=0.2,co
lor='darkblue')

plt.plot(log_my_data, cv_auc, label='CV AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
plt.gca().fill_between(log_my_data,cv_auc - cv_auc_std,cv_auc + cv_auc_std,alpha=0.2,color='darkora
nge')
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()

print('Best hyper parameter: ', model.best_params_)
print('Model Score: ', model.best_score_)
print('Model estimator: ', model.best_estimator_)
```

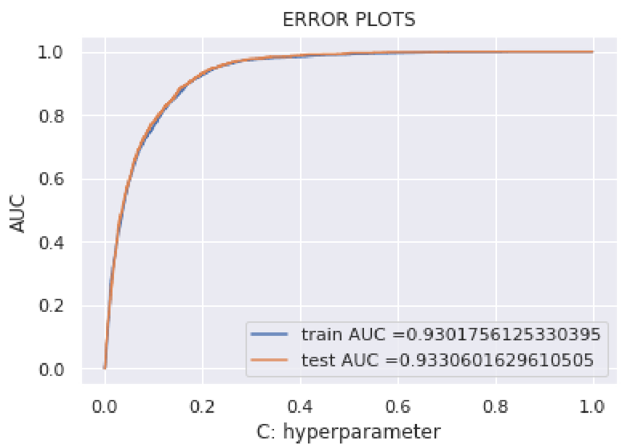
```
best_C= float(model.best_params_['C'])
```




```
Best hyper parameter:  {'C': 100}
Model Score:  0.9277432064461401
Model estimator:  LogisticRegression(C=100, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)
```

In [21]:

```
lr_model = LogisticRegression(C= best_C)
lr_model.fit(X_train, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive class
# not the predicted outputs

train_fpr, train_tpr, thresholds = roc_curve(y_train, lr_model.predict_proba(X_train)[:,1])
test_fpr, test_tpr, thresholds = roc_curve(y_test, lr_model.predict_proba(X_test)[:,1])

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.show()

print('AUC: ',roc_auc_score(y_train, lr_model.predict(X_train)))

y_pred= lr_model.predict(X_test)
print('Accuracy score: ',metrics.accuracy_score(y_test, y_pred ))
```




```
AUC:  0.6838742493356068
Accuracy score:  0.9101007871698669
```

In [22]:

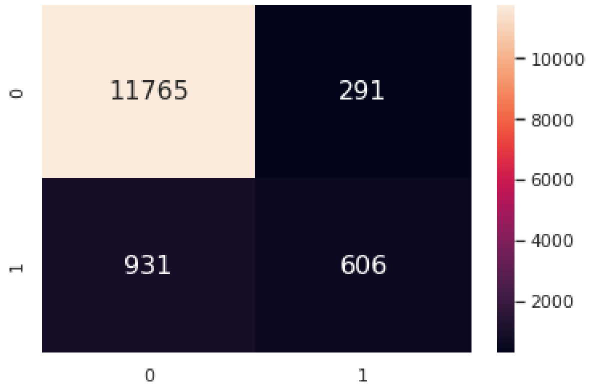
```
from sklearn.metrics import confusion_matrix
```

```
print("Test confusion matrix")
print(confusion_matrix(y_test, lr_model.predict(X_test)))

# conprint('AUC: ',roc_auc_score(Y_train, m_nb.predict(X_tr_bow)))fusion matrix visualization usin
g seaborn heatmap
df_test= pd.DataFrame(confusion_matrix(y_test, lr_model.predict(X_test)))
sns.heatmap(df_test, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
Test confusion matrix
[[11765   291]
 [  931   606]]
```

Out[22]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f465da340f0>
```



In [28]:

```
# http://zetcode.com/python/prettytable/
from prettytable import PrettyTable
x = PrettyTable()

x.field_names = ["Model", "Hyper parameter(Alpha)", "Model Score", "Train(%)", "Test(%)"]

x.add_row(["KNN", 51, .92, 94, 93])
x.add_row(["Logistic Reg.", 100, .93, 93, 93])

print(x)
```

```
+---------------+------------------------+-------------+----------+---------+
|     Model     | Hyper parameter(Alpha) | Model Score | Train(%) | Test(%) |
+---------------+------------------------+-------------+----------+---------+
|      KNN      |           51           |     0.92    |    94    |    93   |
| Logistic Reg. |          100           |     0.93    |    93    |    93   |
+---------------+------------------------+-------------+----------+---------+
```

In [24]:

```
from xgboost import XGBClassifier
classifiers = {
               'Adaptive Boosting Classifier':AdaBoostClassifier(),
               'Linear Discriminant Analysis':LinearDiscriminantAnalysis(),
               'Random Forest Classifier': RandomForestClassifier(),
               'Decision Tree Classifier':DecisionTreeClassifier(),
               'Gaussian Naive Bayes Classifier':GaussianNB(),
               'Support Vector Classifier':SVC(),
               }
```

In [25]:

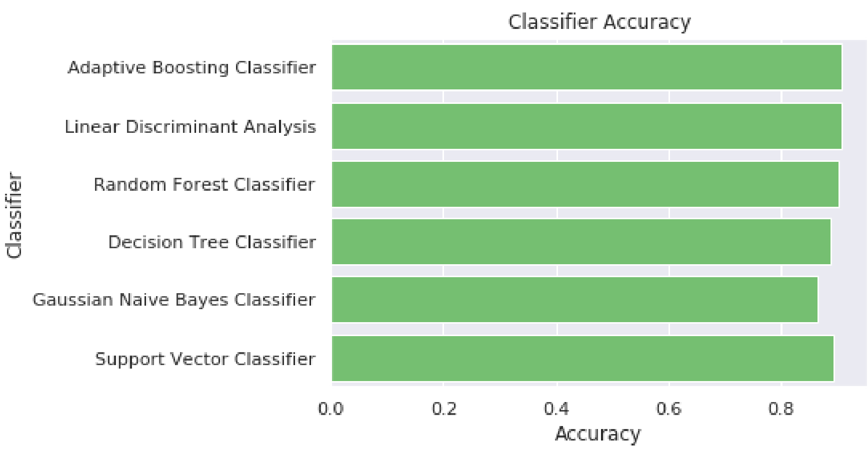
```
log_cols = ["Classifier", "Accuracy","Precision Score","Recall Score","F1-Score","roc-auc_Score"]
log = pd.DataFrame(columns=log_cols)
```

In [27]:

```
# ref. code: https://www.kaggle.com
```

```python
for Name,classify in classifiers.items():
    cls = classify
    cls =cls.fit(X_train,y_train)
    y_out = cls.predict(X_test)
    accuracy = metrics.accuracy_score(y_test,y_out)
    precision = metrics.precision_score(y_test,y_out,average='macro')
    recall = metrics.recall_score(y_test,y_out,average='macro')
    #roc_auc = roc_auc_score(y_out,y_test)
    f1_score = metrics.f1_score(y_test,y_out,average='macro')
    log_entry = pd.DataFrame([[Name,accuracy,precision,recall,f1_score,auc]], columns=log_cols)
    #metric_entry = pd.DataFrame([[precision,recall,f1_score,roc_auc]], columns=metrics_cols)
    log = log.append(log_entry)
        #metric = metric.append(metric_entry)

print(log)
plt.xlabel('Accuracy')
plt.title('Classifier Accuracy')
sns.set_color_codes("muted")
sns.barplot(x='Accuracy', y='Classifier', data=log, color="g")
plt.show()
```

```
                        Classifier  Accuracy  Precision Score  Recall Score  \
0     Adaptive Boosting Classifier  0.908482         0.791223      0.687846
0     Linear Discriminant Analysis  0.909659         0.780527      0.736762
0         Random Forest Classifier  0.904363         0.773697      0.682401
0         Decision Tree Classifier  0.887810         0.721296      0.728418
0  Gaussian Naive Bayes Classifier  0.866843         0.682651      0.717733
0        Support Vector Classifier  0.893990         0.741714      0.610704

   F1-Score                      roc-auc_Score
0  0.724218  <function auc at 0x7f46646c8a60>
0  0.755999  <function auc at 0x7f46646c8a60>
0  0.715306  <function auc at 0x7f46646c8a60>
0  0.724769  <function auc at 0x7f46646c8a60>
0  0.697603  <function auc at 0x7f46646c8a60>
0  0.642627  <function auc at 0x7f46646c8a60>
```



It works best with Logistic regression

Conclusion wrt the financial benefits

1) Months of Marketing Activity: We saw that the the month of highest level of marketing activity was the month of May. However, this was the month that potential clients tended to reject term deposits offers (Lowest effective rate: -34.49%). For the next marketing campaign, it will be wise for the bank to focus the marketing campaign during the months of March, September, October and December. (December should be under consideration because it was the month with the lowest marketing activity, there might be a reason why december is the lowest.)

2) Seasonality: Potential clients opted to suscribe term deposits during the seasons of fall and winter. The next marketing campaign should focus its activity throghout these seasons.

3) Campaign Calls: A policy should be implemented that states that no more than 3 calls should be applied to the same potential client in order to save time and effort in getting new potential clients. Remember, the more we call the same potential client, the likely he or she will decline to open a term deposit.

4) Age Category: The next marketing campaign of the bank should target potential clients in their 20s or younger and 60s or older. The youngest category had a 60% chance of suscribing to a term deposit while the eldest category had a 76% chance of suscribing to a term deposit. It will be great if for the next campaign the bank addressed these two categories and therefore, increase the likelihood of more term deposits suscriptions.

5) Occupation: Not surprisingly, potential clients that were students or retired were the most likely to suscribe to a term deposit. Retired individuals, tend to have more term deposits in order to gain some cash through interest payments. Remember, term deposits are short-term loans in which the individual (in this case the retired person) agrees not to withdraw the cash from the bank until a certain date agreed between the individual and the financial institution. After that time the individual gets its capital back and its interest made on the loan. Retired individuals tend to not spend bigly its cash so they are morelikely to put their cash to work by lending it to the financial institution. Students were the other group that used to suscribe term deposits.

6) House Loans and Balances: Potential clients in the low balance and no balance category were more likely to have a house loan than people in the average and high balance category. What does it mean to have a house loan? This means that the potential client has financial compromises to pay back its house loan and thus, there is no cash for he or she to suscribe to a term deposit account. However, we see that potential clients in the average and hih balances are less likely to have a house loan and therefore, more likely to open a term deposit. Lastly, the next marketing campaign should focus on individuals of average and high balances in order to increase the likelihood of suscribing to a term deposit.

7) Develop a Questionaire during the Calls: Since duration of the call is the feature that most positively correlates with whether a potential client will open a term deposit or not, by providing an interesting questionaire for potential clients during the calls the conversation length might increase. Of course, this does not assure us that the potential client will suscribe to a term deposit! Nevertheless, we don't loose anything by implementing a strategy that will increase the level of engagement of the potential client leading to an increase probability of suscribing to a term deposit, and therefore an increase in effectiveness for the next marketing campaign the bank will excecute.

By combining all these strategies and simplifying the market audience the next campaign should address, it is likely that the next marketing campaign of the bank will be more effective than the current one.

In [ ]:

```

```