roozara_hw4

March 3, 2019

- **ECE 657A: Data and Knowledge Modelling and Analysis**
- **Winter 2019**
- **WATIAM:roozara ID: 20801583**
- **Homework 4:Classification I**

Reference used :https://archive.ics.uci.edu/ml/datasets/Bank+Marketing

In [27]:
```
# Importing the required Python Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler   # Standardize the data for same sc
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier # Imports KNN Classifier
from sklearn.svm import SVC # Imports Support Vector Classifier
from sklearn.metrics import classification_report, confusion_matrix # Imports Classif

# Initial Setup for the Jupyter Notebook
from IPython import get_ipython
get_ipython().run_line_magic('matplotlib', 'inline')       # Instead of %matplotlib i
plt.style.use('ggplot')                # Uses a pre-defined style, which emulates the
sns.set_style('whitegrid')             # whitegrid is a Personal Style Preference
```

1 Load the dataset and store it as a DataFrame.

In [28]:
```
# Reading the "Bank Marketing" Dataset from "https://archive.ics.uci.edu/ml/datasets/
df = pd.read_csv('data/bank-additional.csv', sep=';')
df.head()
```

Out[28]:

	age	job	marital	education	default	housing	loan	\
0	30	blue-collar	married	basic.9y	no	yes	no	
1	39	services	single	high.school	no	no	no	
2	25	services	married	high.school	no	yes	no	
3	38	services	married	basic.9y	no	unknown	unknown	
4	47	admin.	married	university.degree	no	yes	no	

```
     contact month day_of_week ...  campaign  pdays  previous     poutcome  \
0   cellular   may         fri ...         2    999         0  nonexistent
1  telephone   may         fri ...         4    999         0  nonexistent
2  telephone   jun         wed ...         1    999         0  nonexistent
3  telephone   jun         fri ...         3    999         0  nonexistent
4   cellular   nov         mon ...         1    999         0  nonexistent

  emp.var.rate  cons.price.idx  cons.conf.idx  euribor3m  nr.employed   y
0         -1.8          92.893          -46.2      1.313       5099.1  no
1          1.1          93.994          -36.4      4.855       5191.0  no
2          1.4          94.465          -41.8      4.962       5228.1  no
3          1.4          94.465          -41.8      4.959       5228.1  no
4         -0.1          93.200          -42.0      4.191       5195.8  no

[5 rows x 21 columns]
```

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

Out[29]:
```
(4119, 21)
```

2 Formulate the problem as kNN and SVM (linear) problem and run using standard libraries in your language or choice.

In [30]:
```
# Change y column to numeric
df['y'] = df['y'].astype('category')
cat_columns = df.select_dtypes(['category']).columns
df[cat_columns] = df[cat_columns].apply(lambda x: x.cat.codes)
df.head()
```

Out[30]:
```
   age          job  marital          education default  housing     loan  \
0   30  blue-collar  married           basic.9y      no      yes       no
1   39     services   single        high.school      no       no       no
2   25     services  married        high.school      no      yes       no
3   38     services  married           basic.9y      no  unknown  unknown
4   47       admin.  married  university.degree      no      yes       no

     contact month day_of_week ...  campaign  pdays  previous     poutcome  \
0   cellular   may         fri ...         2    999         0  nonexistent
1  telephone   may         fri ...         4    999         0  nonexistent
2  telephone   jun         wed ...         1    999         0  nonexistent
3  telephone   jun         fri ...         3    999         0  nonexistent
4   cellular   nov         mon ...         1    999         0  nonexistent

  emp.var.rate  cons.price.idx  cons.conf.idx  euribor3m  nr.employed  y
0         -1.8          92.893          -46.2      1.313       5099.1  0
1          1.1          93.994          -36.4      4.855       5191.0  0
2          1.4          94.465          -41.8      4.962       5228.1  0
3          1.4          94.465          -41.8      4.959       5228.1  0
```

```
4         -0.1          93.200          -42.0      4.191       5195.8  0

[5 rows x 21 columns]
```

```
In [31]: # Choose only Numeric columns
         df = df.select_dtypes(exclude=['object'])
         df.shape
```

```
Out[31]: (4119, 11)
```

3 KNN for Classification

Splitting the data into train and test data. The test data size chosen to be 30%.

```
In [32]: # Train Test Split for KNN:
         X = df.loc[:, df.columns != 'y']
         y = df['y']
         X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.30, random_state=
```

```
In [33]: # Using KNN: (Instantiate  Train  Predict)
         # We are trying to come up with a model to predict whether someone will be a TARGET C
         knn = KNeighborsClassifier(n_neighbors=1)
         knn.fit(X_train,y_train)
         knn_predictions = knn.predict(X_test)

         # Evaluation
         print(classification_report(y_test,knn_predictions))
         print(confusion_matrix(y_test,knn_predictions))
```

```
              precision    recall  f1-score   support

           0       0.93      0.93      0.93      1081
           1       0.49      0.50      0.49       155

   micro avg       0.87      0.87      0.87      1236
   macro avg       0.71      0.71      0.71      1236
weighted avg       0.87      0.87      0.87      1236

[[1001   80]
 [  78   77]]
```

Improving the model by choosing a better k value. A plot has to be constructed (elbow method plot) for the error rate Vs. K Value (range from 1 to 40)

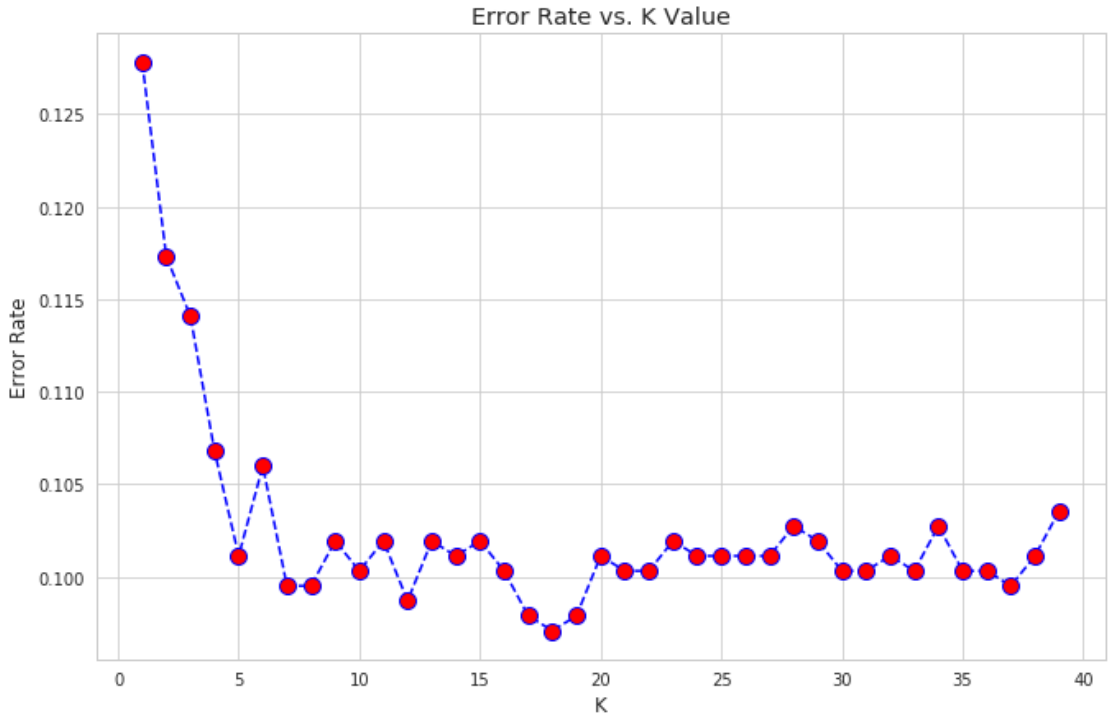
```
In [34]: # Use the elbow method to pick the best K Value:
         error_rate = [] # Define Error Rate as empty list
         for i in range(1,40):
```

```
            knn = KNeighborsClassifier(n_neighbors=i)
            knn.fit(X_train,y_train)
            pred_i = knn.predict(X_test)
            error_rate.append(np.mean(pred_i != y_test)) # Average Error Rate

        plt.figure(figsize=(11,7)) # Plot the K Value' (X-axis) (1-40) vs. 'Error Rate (Y-axi
        plt.plot(range(1,40), error_rate, color='blue', linestyle='dashed', marker='o', marke
        plt.title('Error Rate vs. K Value')
        plt.xlabel('K')
        plt.ylabel('Error Rate')

        knn = KNeighborsClassifier(n_neighbors=1) # FIRST A QUICK COMPARISON TO OUR ORIGINAL
        knn.fit(X_train,y_train)
        knn_predictions = knn.predict(X_test)
        print('WITH K=1')
        print('\n')
        print(confusion_matrix(y_test,knn_predictions))
        print('\n')
        print(classification_report(y_test,knn_predictions))

        knn = KNeighborsClassifier(n_neighbors=18) # NOW WITH K=18
        knn.fit(X_train,y_train)
        knn_predictions = knn.predict(X_test)
        print('WITH K=18')
        print('\n')
        print(confusion_matrix(y_test,knn_predictions))
        print('\n')
        print(classification_report(y_test,knn_predictions)) # We were able to squeeze some m
```

```
WITH K=1


[[1001   80]
 [  78   77]]


              precision    recall  f1-score   support

           0       0.93      0.93      0.93      1081
           1       0.49      0.50      0.49       155

   micro avg       0.87      0.87      0.87      1236
   macro avg       0.71      0.71      0.71      1236
weighted avg       0.87      0.87      0.87      1236

WITH K=18
```

```
[[1051   30]
 [  90   65]]
```

	precision	recall	f1-score	support
0	0.92	0.97	0.95	1081
1	0.68	0.42	0.52	155
micro avg	0.90	0.90	0.90	1236
macro avg	0.80	0.70	0.73	1236
weighted avg	0.89	0.90	0.89	1236

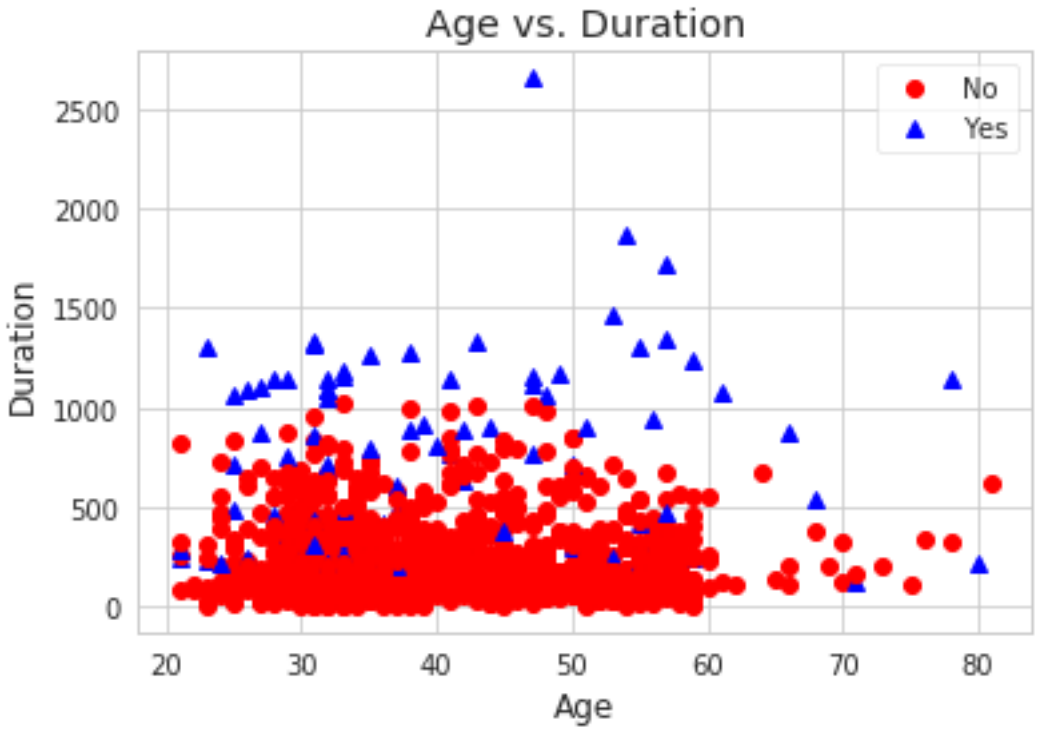


we can see with better K values the f measure improved. An f1 score of 0.49 when k = 1 and an improved f1 score of 0.52 when k = 18 using the elbow method

```
In [35]: plt.xlabel('Age')
         plt.ylabel('Duration')
         plt.title('Age vs. Duration')

         # Iterating on all test samples. range changes index from 0 to (number of test sample
         for index in range(X_test.shape[0]):
             if knn_predictions.ravel()[index] == 0:
```

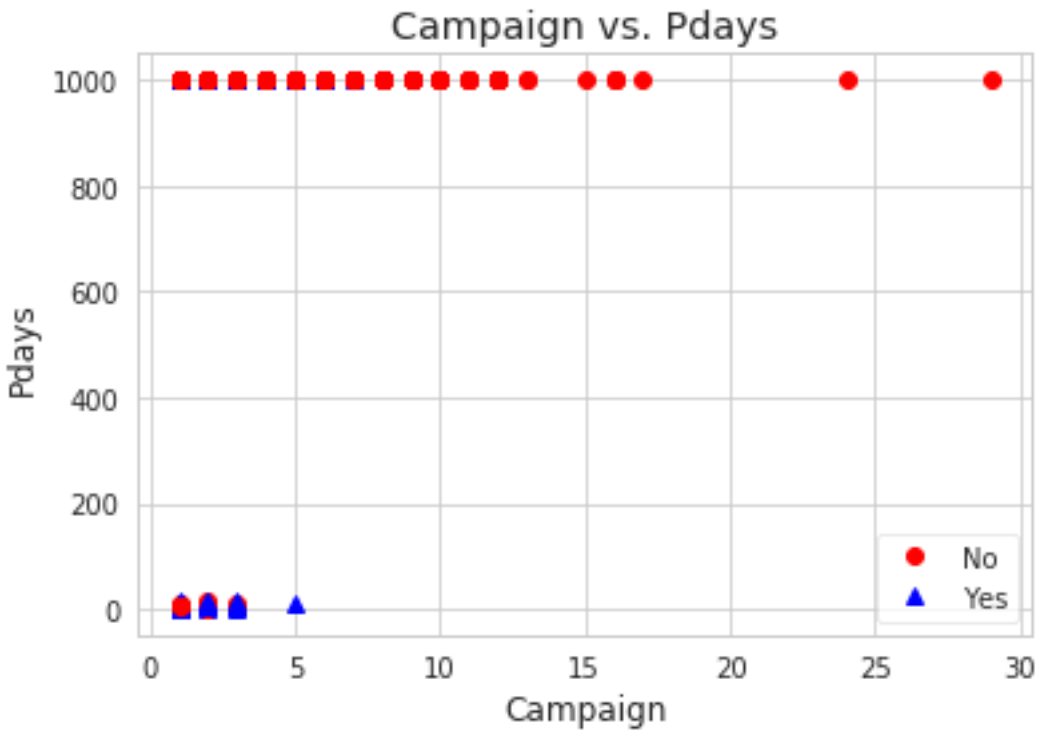
```
            plt0, = plt.plot(X_test.iloc[index, 0], X_test.iloc[index, 1], 'ro', label='No
        else:
            plt1, = plt.plot(X_test.iloc[index, 0], X_test.iloc[index, 1], '^b', label='Ye
    plt.legend(handles = [plt0, plt1])
```

Out[35]: <matplotlib.legend.Legend at 0x7fe08c5abd68>

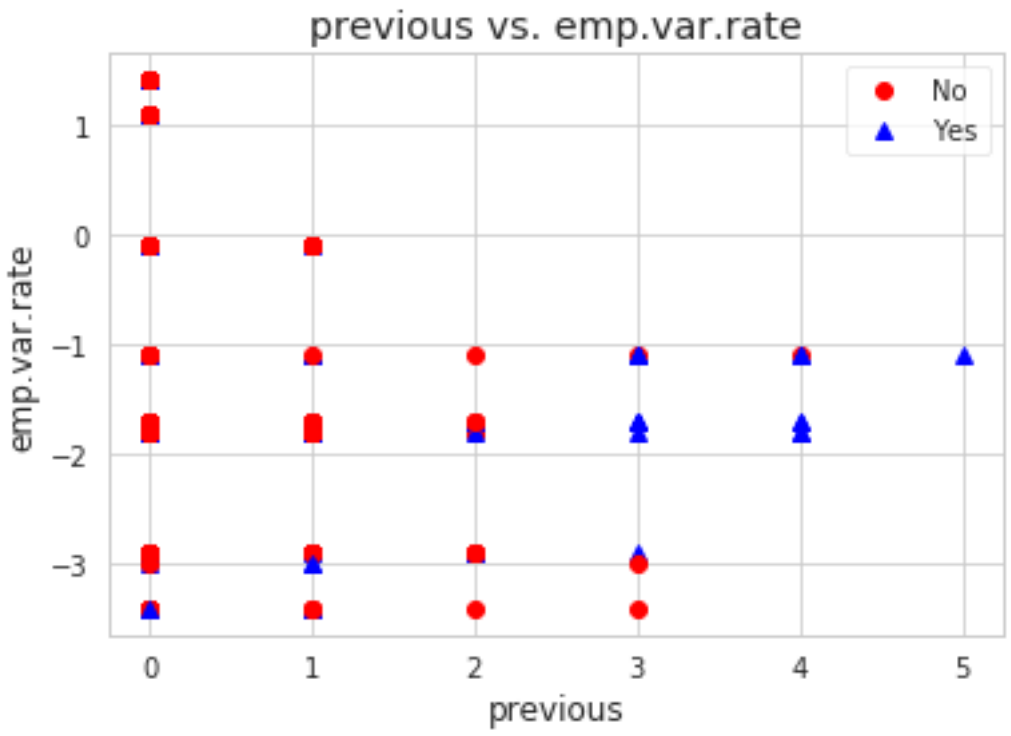


In [36]:
```
plt.xlabel('Campaign')
plt.ylabel('Pdays')
plt.title('Campaign vs. Pdays')

# Iterating on all test samples. range changes index from 0 to (number of test sample
for index in range(X_test.shape[0]):
    if knn_predictions.ravel()[index] == 0:
        plt0, = plt.plot(X_test.iloc[index, 2], X_test.iloc[index, 3], 'ro', label='No
    else:
        plt1, = plt.plot(X_test.iloc[index, 2], X_test.iloc[index, 3], '^b', label='Ye
plt.legend(handles = [plt0, plt1])
```

Out[36]: <matplotlib.legend.Legend at 0x7fe08b95abe0>




```
In [37]: plt.xlabel('previous')
         plt.ylabel('emp.var.rate')
         plt.title('previous vs. emp.var.rate')

         # Iterating on all test samples. range changes index from 0 to (number of test sample
         for index in range(X_test.shape[0]):
             if knn_predictions.ravel()[index] == 0:
                 plt0, = plt.plot(X_test.iloc[index, 4], X_test.iloc[index, 5], 'ro', label='N
             else:
                 plt1, = plt.plot(X_test.iloc[index, 4], X_test.iloc[index, 5], '^b', label='Ye
         plt.legend(handles = [plt0, plt1])

Out[37]: <matplotlib.legend.Legend at 0x7fe08adf4940>
```



4 SVM for Classification

```
In [38]: # Train Test Split for SVM:
         X = df.drop('y',axis=1) # All columns except y
         y = df['y']
         X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.30, random_state=

         # SVM
         model = SVC(kernel='linear')
         model.fit(X_train,y_train)

         # Predictions and Evaluations using default values
         SVM_predictions = model.predict(X_test)
         print(confusion_matrix(y_test,SVM_predictions))
         print(classification_report(y_test,SVM_predictions))
```

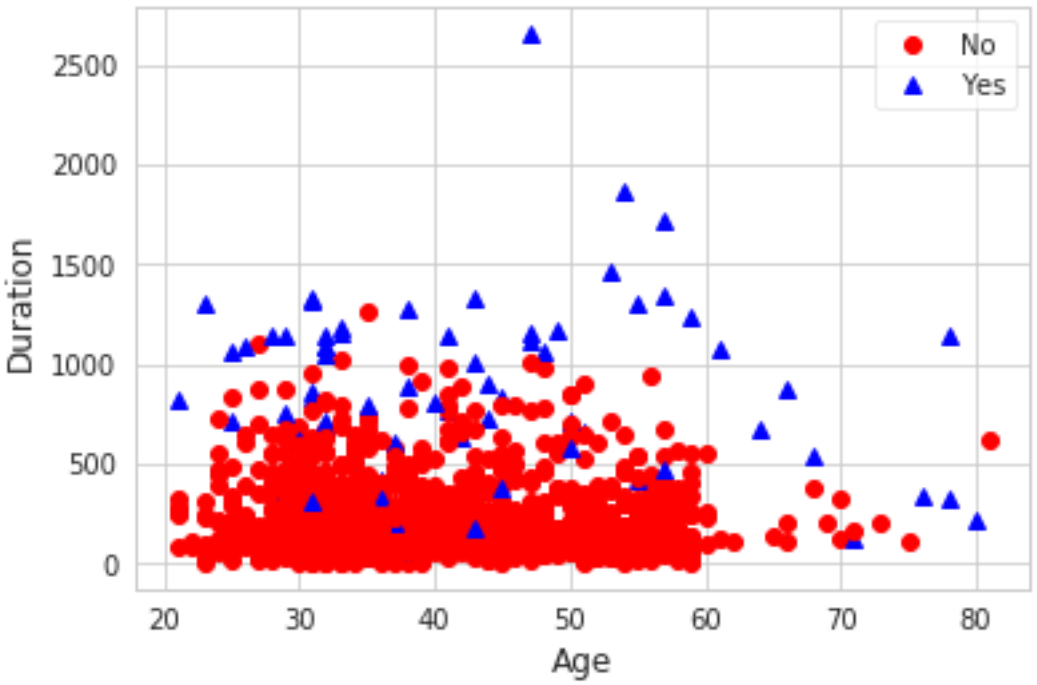
```
[[1060   21]
 [ 100   55]]
              precision    recall  f1-score   support

           0       0.91      0.98      0.95      1081
           1       0.72      0.35      0.48       155
```

```
   micro avg       0.90      0.90      0.90      1236
   macro avg       0.82      0.67      0.71      1236
weighted avg       0.89      0.90      0.89      1236
```

SVM records an f1-score of 0.48

```
In [39]: plt.xlabel('Age')
         plt.ylabel('Duration')

         # Iterating on all test samples. range changes index from 0 to (number of test sample
         for index in range(X_test.shape[0]):
             if SVM_predictions.ravel()[index] == 0:
                 plt0, = plt.plot(X_test.iloc[index, 0], X_test.iloc[index, 1], 'ro', label='N
             else:
                 plt1, = plt.plot(X_test.iloc[index, 0], X_test.iloc[index, 1], '^b', label='Y
         plt.legend(handles = [plt0, plt1])
```

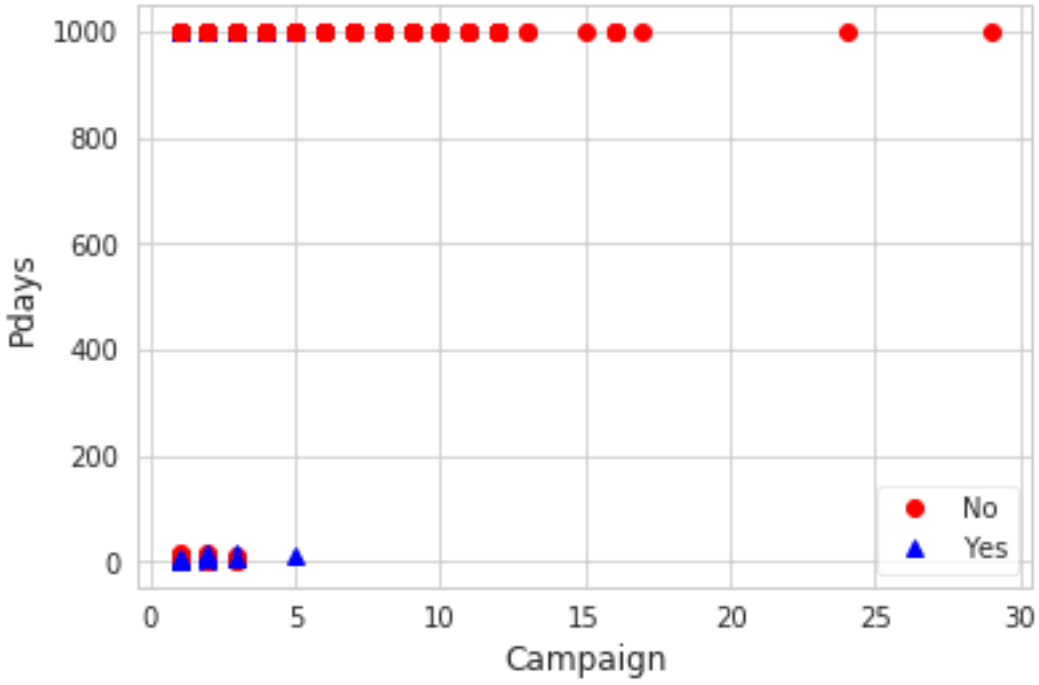
```
Out[39]: <matplotlib.legend.Legend at 0x7fe08a1a3780>
```




```
In [40]: plt.xlabel('Campaign')
         plt.ylabel('Pdays')

         # Iterating on all test samples. range changes index from 0 to (number of test sample
```

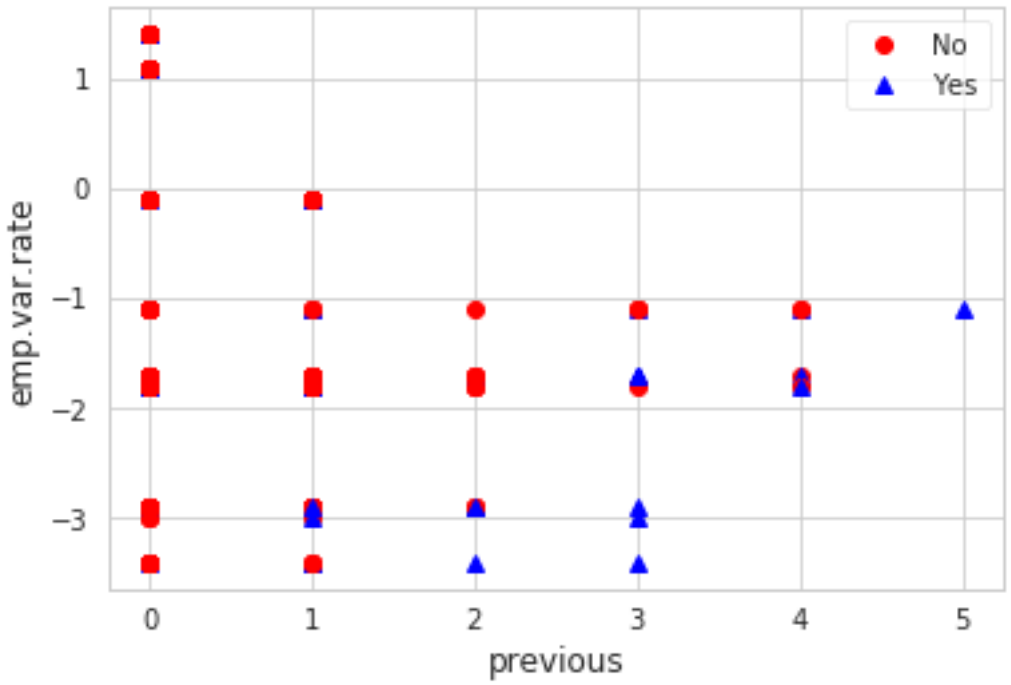
```
for index in range(X_test.shape[0]):
    if SVM_predictions.ravel()[index] == 0:
        plt0, = plt.plot(X_test.iloc[index, 2], X_test.iloc[index, 3], 'ro', label='No
    else:
        plt1, = plt.plot(X_test.iloc[index, 2], X_test.iloc[index, 3], '^b', label='Ye
plt.legend(handles = [plt0, plt1])
```

Out[40]: <matplotlib.legend.Legend at 0x7fe08951a860>



In [41]:
```
plt.xlabel('previous')
plt.ylabel('emp.var.rate')

# Iterating on all test samples. range changes index from 0 to (number of test sample
for index in range(X_test.shape[0]):
    if SVM_predictions.ravel()[index] == 0:
        plt0, = plt.plot(X_test.iloc[index, 4], X_test.iloc[index, 5], 'ro', label='No
    else:
        plt1, = plt.plot(X_test.iloc[index, 4], X_test.iloc[index, 5], '^b', label='Ye
plt.legend(handles = [plt0, plt1])
```

Out[41]: <matplotlib.legend.Legend at 0x7fe0889be780>



- We cannot see a clear separation in three plots, each is between two features
- Two features out of 20 are not enough to separate two classes
- There may be a combination of more than two features that have a better separation between classes
- I think, the plot of Age vs. Duration is the most clear separation between the classes in my three plots
- As we can see the plots of the KNN and SVM are similar, probably due to both working based on distance