# 0097_ED_breach_prediction_pilot

October 30, 2018

## 1 97: Simple machine learning model to predict emergency department (ED) breaches of the four-hour target

In England emergency departments have a target that 95% of patients should be admitted or discharged from ED within four hours. Patients waiting more than four hours are known as 'breaches'

This notebook explores predicting emergency department (ED) breaches (patients taking more than 4 hours to be discharged or admitted).

The model receives data every 2 hours and predicts whether there will be a breach in the next 2 hours.

It uses some basic ED data alongside whole-hospital data (number of occupied beds and total beds) to try to predict whether there are likely to be breaches in the next two hours. It uses a simple logistic regression model to achieve 80% accuracy in predicting breaches. Sensitivity may be adjusted to balance accuracy in predicting beach and non-breaching episodes (80% accuracy may be be simultaneousness achieved in both).

### 1.1 Load and process data

Data is available at https://gitlab.com/michaelallen1966/1804_python_healthcare_wordpress/blob/master/dat

Download the data file and save it in the same directory as the python code file you will build up.

This code can also be downloaded:

py file: https://gitlab.com/michaelallen1966/1804_python_healthcare_wordpress/blob/master/py_files/00

jupyer-notebook: https://gitlab.com/michaelallen1966/1804_python_healthcare_wordpress/blob/master/j

```
In [1]: import pandas as pd
        data = pd.read_csv('ed_1.csv')
```

Show data columns:

```
In [2]: print (list(data))
```

```
['snapshot_id', 'snapshot_date', 'snapshot_time', 'Monday', 'Tuesday', 'Wednesday', 'Thursday'
```

Separate data into features (X) and label (Y) to predict. Y is whether there are breaches in the following 2 hours.

```
In [3]: X = data.loc[:,"Monday":"Free_beds"]
        y = data['Breach_in_next_timeslot']
```

Let's see what proportion of 2 hour epochs have a breach:

```
In [4]: print (data['Breach_in_next_timeslot'].mean())
```

```
0.6575510659671838
```

### 1.2 Split data in training and test sets

```
In [5]: from sklearn.model_selection import train_test_split
        X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.25)
```

### 1.3 Normalise data with standard scaling

```
In [6]: from sklearn.preprocessing import StandardScaler

        # Initialise a new scaling object for normalising input data
        sc=StandardScaler()

        # Set up the scaler just on the training set
        sc.fit(X_train)

        # Apply the scaler to the training and test sets
        X_train_std=sc.transform(X_train)
        X_test_std=sc.transform(X_test)
```

### 1.4 Build a logistic regression model

C=1000 sets low regularisation. If accuracy of training data is signficiantly higher than accuracy of test data this should be reduced in 10-fold or 3-fold steps to maximise accuracy of test data.

(Note: the ';' at the end of the last line suppresses model description output in the Jupyter Notebook)

```
In [7]: from sklearn.linear_model import LogisticRegression

        ml = LogisticRegression(C=1000)
        ml.fit(X_train_std,y_train);
```

### 1.5 Predict training and test set labels

Our model is now built. We can now predict breaches for training and test sets. The results for the test set gives the better description of accuracy, but it is useful to calculate both to look for 'over-fitting'. If the training data has significantly better accuracy than the test data then it is likely the emodel is 'over-fitted' to the training data, and the regularisation term (C) in the model fit above should be reduced step-wise - this will reduce accuracy of predicting the training data, but will increase the accuracy of the test data, though too high regularisation (low C) will reduce the accuracy of both predicting training and test data.

```
In [8]: # Predict training and test set labels
        y_pred_train = ml.predict(X_train_std)
        y_pred_test = ml.predict(X_test_std)
```

### 1.6 Test accuracy

```
In [9]: import numpy as np
        accuracy_train = np.mean(y_pred_train == y_train)
        accuracy_test = np.mean(y_pred_test == y_test)
        print ('Accuracy of predicting training data =', accuracy_train)
        print ('Accuracy of predicting test data =', accuracy_test)
```

```
Accuracy of predicting training data = 0.8109837773478196
Accuracy of predicting test data = 0.8084821428571428
```

### 1.7 Display weights (coefficients) of model

```
In [10]: # Create table of weights
         weights_table = pd.DataFrame()
         weights_table['feature'] = list(X)
         weights_table['weight'] = ml.coef_[0]
         print(weights_table)
```

```
                                              feature    weight
0                                              Monday  0.050776
1                                             Tuesday -0.017214
2                                           Wednesday -0.050666
3                                            Thursday  0.023890
4                                              Friday  0.004309
5                                            Saturday  0.004788
6                                              Sunday -0.015072
7          Number of Patients In department >= 4 Hours  1.544976
8           Total Number of Patients in the Department  0.702246
9                         Number of Patients in Resus  0.306031
10   Number of Patients Registered in Last 60 Minutes -0.539412
11                   Number of Patients Waiting Triage  0.047270
12          Number of Patients Waiting to be Seen (ED)  0.114584
13    Number of Patients Waiting to be Seen (Medical) -0.028709
14    Number of Patients Waiting to be Seen (Surgery) -0.000442
15                        Number of Patients > 3 Hours  1.193489
16                    Number of Patients Waiting a Bed -0.028263
17  Number of Patients Left Department in Last 60 ... -0.022188
18                                          Free_beds -0.369558
```

### 1.8 Define a function for sensitivity and specificity

Sensitivity = proportion of breaching periods correctly identified Specificity = proportion of breaching periods correctly identified

```
In [11]: def calculate_sensitivity_specificity(y_test, y_pred_test):
             # Note: More parameters are defined than necessary.
             # This would allow return of other measures other than sensitivity and specificit

             # Get true/false for whether a breach actually occurred
             actual_pos = y_test == 1
             actual_neg = y_test == 0

             # Get true and false test (true test match actual, false tests differ from actual
             true_pos = (y_pred_test == 1) & (actual_pos)
             false_pos = (y_pred_test == 1) & (actual_neg)
             true_neg = (y_pred_test == 0) & (actual_neg)
             false_neg = (y_pred_test == 0) & (actual_pos)

             # Calculate accuracy
             accuracy = np.mean(y_pred_test == y_test)

             # Calculate sensitivity and specificity
             sensitivity = np.sum(true_pos) / np.sum(actual_pos)
             specificity = np.sum(true_neg) / np.sum(actual_neg)

             return sensitivity, specificity, accuracy
```

Show sensitivty and specificity:

```
In [12]: sensitivity, specificity, accuracy = calculate_sensitivity_specificity(y_test, y_pred
         print ('Sensitivity:', sensitivity)
         print ('Specificity:', specificity)
         print ('Accuracy:', accuracy)
```

```
Sensitivity: 0.8430583501006036
Specificity: 0.739652870493992
Accuracy: 0.8084821428571428
```

So we are better at detecting breaches than non-breaches. This is likely because breaching sessions occur more often. Let's adjust our model cut-off to balance the accuracy out. We'll vary the cut-off we use and construct a sensitivity/specificity plot (very similar to a 'Receiver-Operator Curve' or 'ROC').

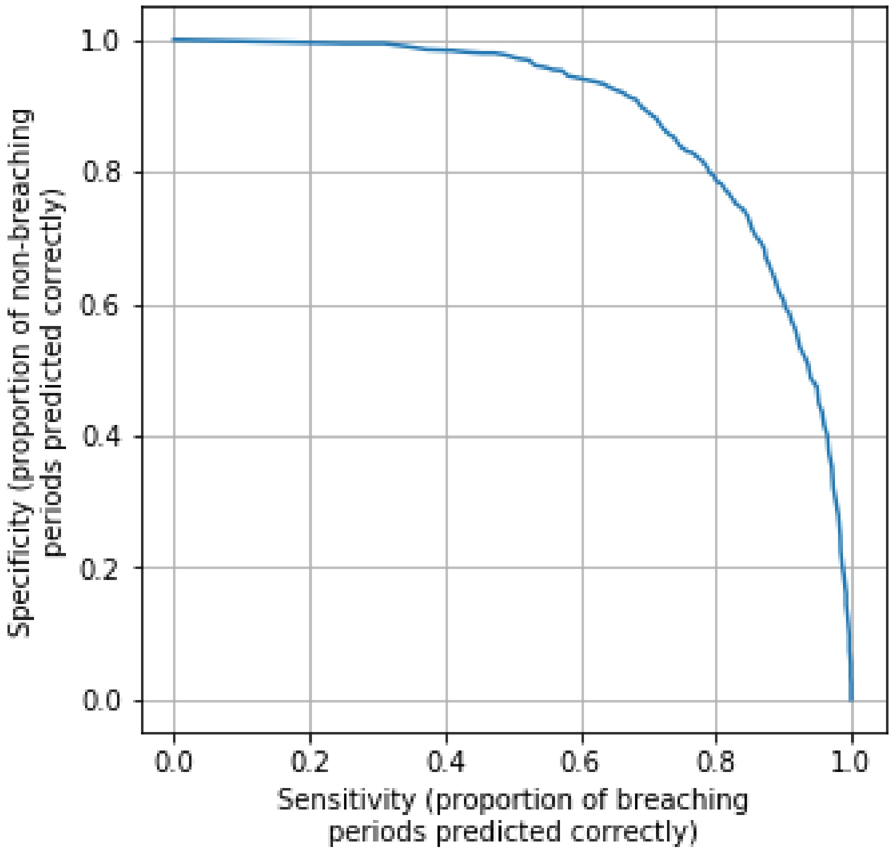
## 2 Balancing sensitivity and specificity

```
In [13]: cuttoff = np.arange (0.01,1.01,0.01)
         sensitivity_results = []
```

```
specificity_results = []


for threshold in cuttoff:
    # linear regression model has .predict+proba  method to return
    # probability of outcomes. Some methods such as svc use
    # .decision_function to return probability

    # Get test results
    y_pred_probability = ml.predict_proba(X_test_std)

    # Check probability of positive classification is >trhreshold
    y_pred_test = (y_pred_probability[:,1] >= threshold)

    # Convert boolean to 0/1 (could also simply multiple by 1)
    y_pred_test = y_pred_test.astype(int)

    # Get sensitivity and specificity
    sensitivity, specificity, accuracy = \
        calculate_sensitivity_specificity(y_test, y_pred_test)

    # Add results to list of results
    sensitivity_results.append(sensitivity)
    specificity_results.append(specificity)
```

Plotting specificity against sensitivity:

```
In [14]: import matplotlib.pyplot as plt

         %matplotlib inline

         fig = plt.figure(figsize=(5,5))
         ax1 = fig.add_subplot(111)

         x = sensitivity_results
         y = specificity_results

         ax1.grid(True, which='both')
         ax1.set_xlabel('Sensitivity (proportion of breaching\nperiods predicted correctly)')
         ax1.set_ylabel('Specificity (proportion of non-breaching\nperiods predicted correctly


         plt.plot(x,y)
         plt.show()
```




Plotting specificity against sensitivity shows we can adjust our machine learning cut-off to simultaneously achieve 80% accuracy in predicting likelihood of breaches in the next 2 hours.