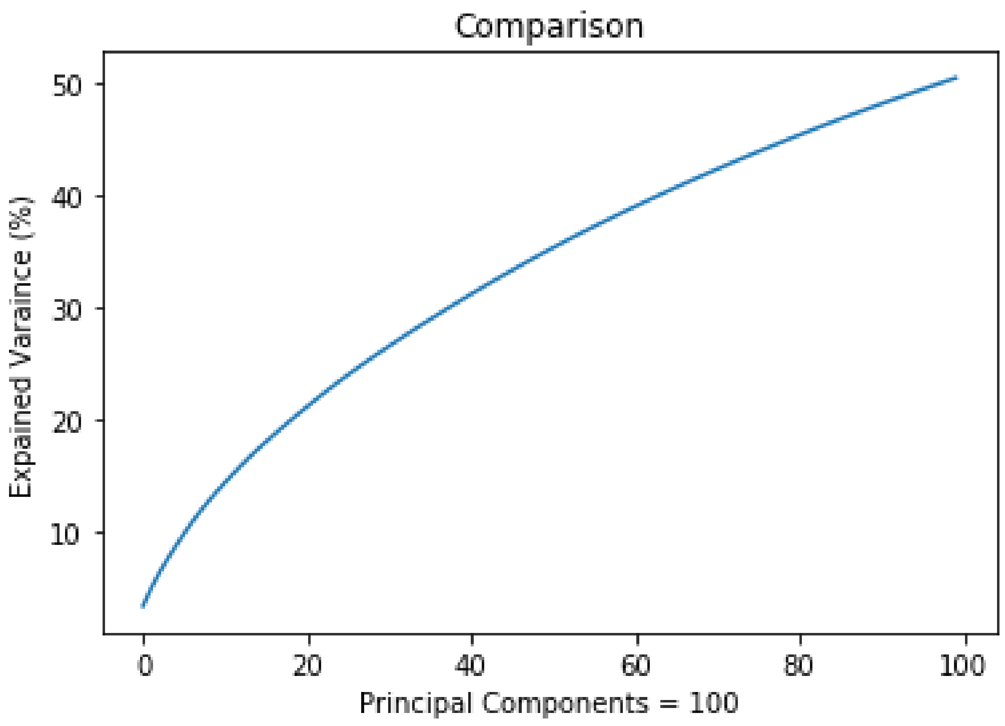
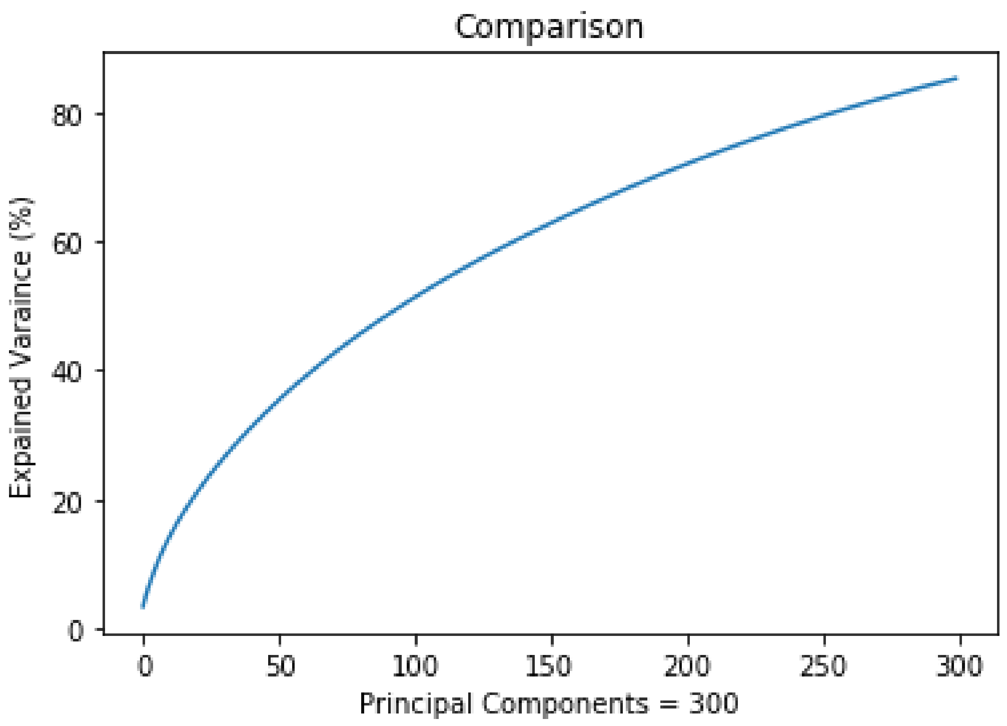
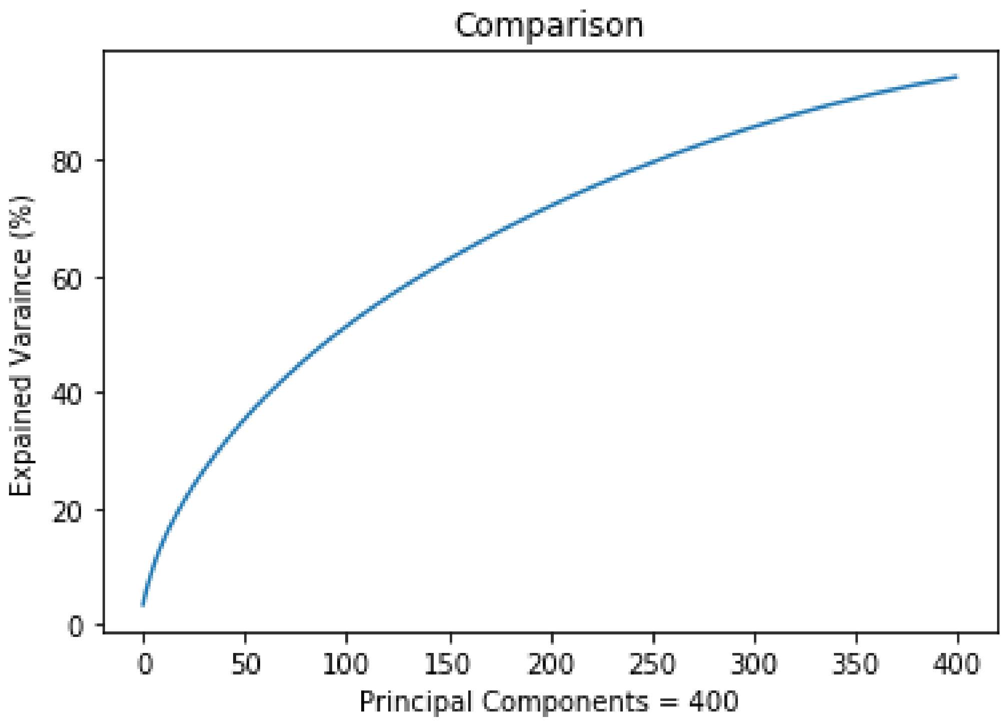
TempusCaseStudy_RohanDhamdhere

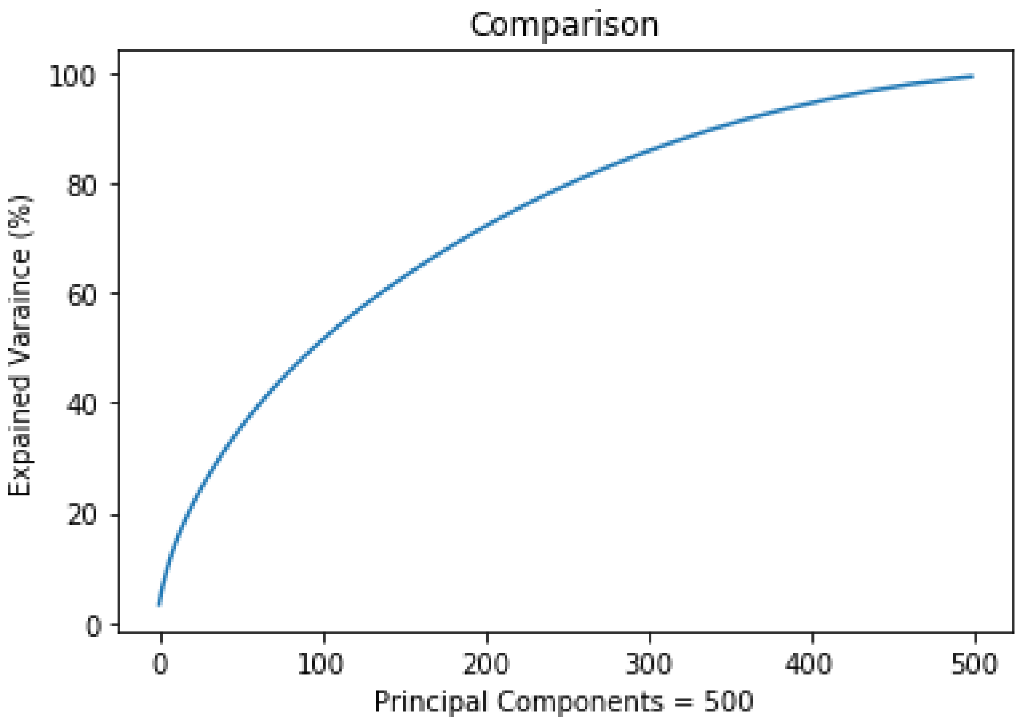
March 13, 2017

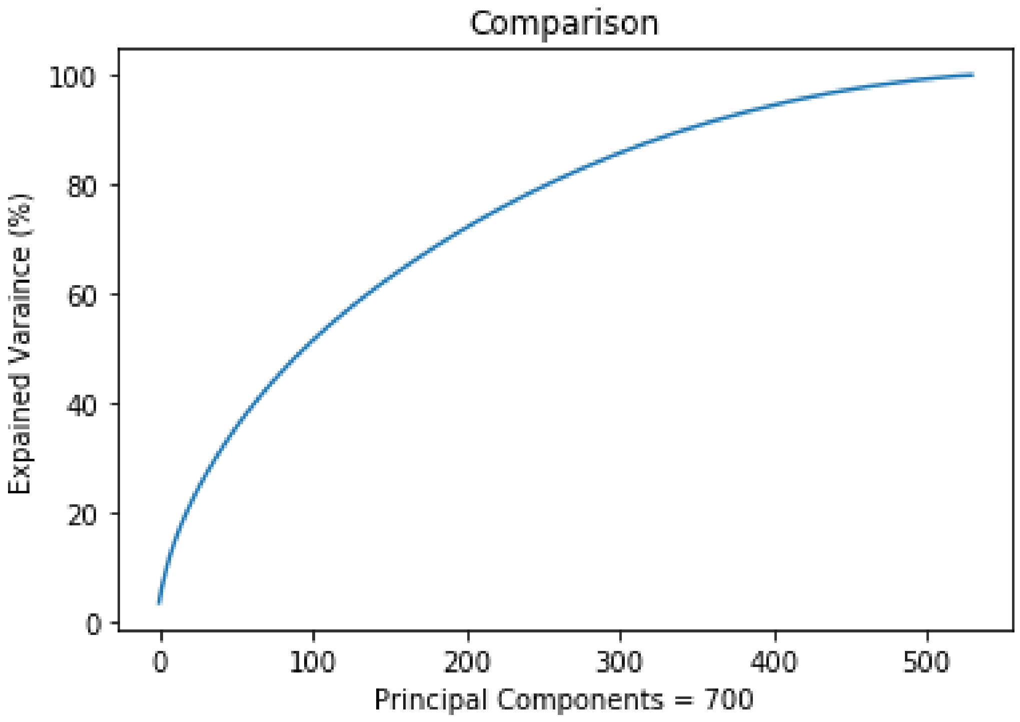
```
In [1]: import pandas as pd
        import  matplotlib.pyplot as plt
        import numpy as np

        #Loading Data (530 x 16563)
        df = pd.read_table('C:\Users\dcc\Desktop\Tempus/takehome1.txt')
        Data = df.values

        #Split the Feature data and Ground Truth data
        Xdata = Data[:,1:].copy()    # Copying to avoid damage to actual data
        GTdata = Data[:,0].copy()

In [ ]: '''
        Given the high number of Dimensions(16563), usage of some dimensionality
        reduction technique is a must, to remove highly correlated features.
        '''

In [2]: #Checking Proportion of Variance for various value of
        # components in PCA transformed data

        from sklearn.preprocessing import scale
        from sklearn.decomposition import PCA

        Data = scale(Data)             # Normalize data

        #Number of Output Components for PCA
        components = [100, 300, 400,500,700]
        i=1
        for component in components:
            pca = PCA(n_components=component, whiten= True)
            pca.fit(Data)

            #The amount of variance that each PC explains
            var= pca.explained_variance_ratio_

            #Cumulative Variance explains
            var1=np.cumsum(np.round(pca.explained_variance_ratio_, decimals=4)*100)
            plt.figure(i)
            plt.plot(var1)
            plt.xlabel('Principal Components = %d' % component)
            plt.ylabel('Expained Varaince (%)')
            plt.title('Comparison')
            plt.show()
            i = i+1

C:\Users\dcc\Anaconda2\lib\site-packages\sklearn\utils\validation.py:429: DataConve
  warnings.warn(msg, _DataConversionWarning)
```




Comparison
Expained Varaince (%)
0
20
40
60
80
0
50
100
150
200
250
300
Principal Components = 300


Comparison
Expained Varaince (%)
0
20
40
60
80
0
50
100
150
200
250
300
350
400
Principal Components = 400


Comparison
Expained Varaince (%)
Principal Components = 500
0
20
40
60
80
100
0
100
200
300
400
500


Comparison
Expained Varaince (%)
Principal Components = 700
0
20
40
60
80
100
0
100
200
300
400
500

```
In [ ]: '''
        -The above scree plots display the PCA Components needed to explian
        some percent variance in Data .
        -As it is evident from the plots, almost 100% variance in the data
        is explained by about 500 PCA components.
        -Thus the given 16563 varaibles are highly correlated and we can easily
        reduce the number of dimensions using PCA.
        - Almost 98% varaince in data is explained by 400 PCA components.
        -To avoid overfitting to the data, i use only 380 PCA components to
        predict the 'response' varaible.


        '''
```

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In [ ]: '''
        -Given varaible for prediction, 'response' is binary in nature.
        Thus, this is a 2-class classification problem.
        -After careful observation of data and Ground Truth(GT) values,
        it can be easily detected that there is a class imbalance, with 76%
        of the GT values being 0.
        -To avoid this problem, we divide our data into Training and Test sets
        using StratifiedKfold cross validation.
        -This method aplits the data, such that the ratio of number of
        elements of each class is equal in set of Data.
        -I split the data as follows: Train set - 75%, Test set - 25%
        -Further, i divide the Train set data as follows -
        Train_actual = 75% Train set, Validation = 25% Train set.

        '''
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In [ ]: '''
        -As explained in the case study document, no model is a perfect model.
        -So i provide a comparative analysis of 4 well known classification
        models:
        1] Linear SVM, 2] Logistic Regression, 3] Decision tree,
        4] Neural Nets.

        -As ovserved before, there is a class imbalance in data, with 76% of
        the GT values being 0.
        -As there is class imbalance in GT values, Accuracy is not the best
        metric to judge a classifier.
        -With predicting all zeros, a classifier can achieve an accuracy
        of 76%

        -Thus i use F-Measure of the classifer as a metric to judge the
        best classifier for the given data.
                F-Measure = 2*(Precision*Recall)/(Precision+Recall)
        -I have displayed the following metrics :
          -Accuracy
          -Precision
          -Recall
          -F-Measure

        Finally, i choose the best Classifier based of the F-measure.


        '''
```

```
In [3]: from sklearn.pipeline import Pipeline
        from sklearn.model_selection import StratifiedKFold, KFold

        #Importing Classifiers
        from sklearn import linear_model
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.svm import SVC
        from sklearn.tree import DecisionTreeClassifier
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.neural_network import MLPClassifier

        #Importing Classification Metrics
        from sklearn.metrics import precision_score
        from sklearn.metrics import recall_score
        from sklearn.metrics import f1_score
        from sklearn.metrics import accuracy_score

        names = ["Logistic Regression", "Linear SVM", "Decision Tree", "NNet"]
        classifiers = [
                                linear_model.LogisticRegression(C= 0.1),
                                SVC(kernel="linear", C=0.025),
                                DecisionTreeClassifier(max_depth=5),
                                MLPClassifier(alpha=0.9,hidden_layer_sizes=(20,20))

                                ]

        best_classifier = {}

        for name, classifier in zip(names, classifiers):

        #initialize metrics
            best_precision = 0.00
            best_recall = 0.00
            best_Fmeasure = 0.00
            best_accuracy = 0.00

        # Divide Data into Train and Test sets
            skf = StratifiedKFold(n_splits = 4)
```

```
    for Mtrain, test in skf.split(Xdata,GTdata):
        Xtrain = Xdata[Mtrain,:].copy()
        Xtest = Xdata[test,:].copy()
        GTtrain = GTdata[Mtrain]
        GTtest = GTdata[test]


# Divide Train data into Train_actual and Validation
        kf = KFold(n_splits = 4)
        for train, val in kf.split(Xtrain,GTtrain):
                Xtrain_actual = Xtrain[train,:].copy()
                Xval = Xtrain[val,:].copy()
                GTtrain_actual = GTtrain[train]
                GTval = GTtrain[val]

# PCA
                pca = PCA(n_components=380,whiten=True)

# Pipeline Model
                pipe = Pipeline([('pca', pca),
                                 ('classifier', classifier)])
                pipe.fit(Xtrain, GTtrain)
                predicted = pipe.predict(Xtest)

# Metrics
                precision = precision_score(GTtest, predicted)
                if precision > best_precision:  best_precision=precision
                recall = recall_score(GTtest, predicted)
                if recall > best_recall:  best_recall = recall
                accuracy = accuracy_score(GTtest, predicted)
                if accuracy > best_accuracy:  best_accuracy = accuracy
                Fmeasure = f1_score(GTtest, predicted)
                if Fmeasure > best_Fmeasure:  best_Fmeasure = Fmeasure
    best_classifier[best_Fmeasure] = name

    print ("Classifier: " +str(name))
    print ("Accuracy: " + str(round(best_accuracy,3)))
    print("Precision:" + str(round(best_precision,3)) + "\nRecall: " + str
    print("F-Measure = " + str(round(best_Fmeasure,3))+"\n")

best = best_classifier.keys()
Label = best_classifier.values()
r = np.arange(1,len(best)+1,1)
best_Fmeasure = max(best)
Fmeasure_of_best = best_classifier.keys()[best_classifier.values().index(be

print("Best Model is: " + str(best_classifier[best_Fmeasure]))
print("Fmeasure: "+ str(round(Fmeasure_of_best,3)))
Classifier: Logistic Regression
Accuracy: 0.887
Precision:0.864
Recall: 0.613
F-Measure = 0.717

Classifier: Linear SVM
Accuracy: 0.88
Precision:0.857
Recall: 0.581
F-Measure = 0.692

Classifier: Decision Tree
Accuracy: 0.805
Precision:0.857
Recall: 0.419
F-Measure = 0.491



C:\Users\dcc\Anaconda2\lib\site-packages\sklearn\neural_network\multilayer_perceptr
  % (), ConvergenceWarning)


Classifier: NNet
Accuracy: 0.895
Precision:1.0
Recall: 0.677
F-Measure = 0.75

Best Model is: NNet
Fmeasure: 0.75
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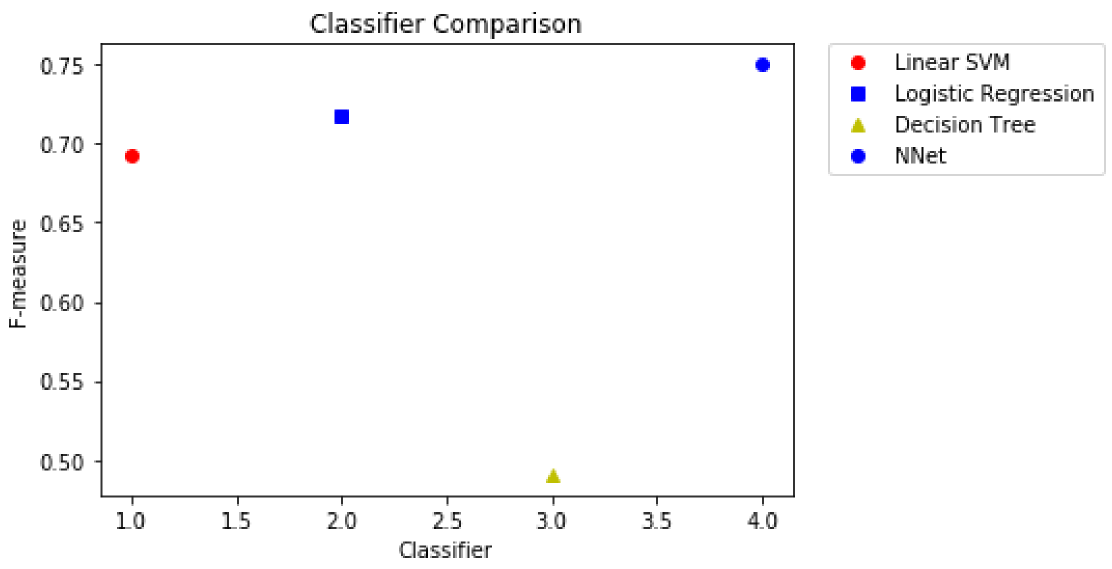
```
In [4]: #Plotting the Classifier Comparison
        import itertools
        marker = itertools.cycle(('ro', 'bs', 'y^', 'bo', 'y*','b^'))
        fig, ax = plt.subplots()
        for i in range(len(r)):
            ax.plot(r[i], best[i], marker.next(), label=Label[i])
        plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)
        plt.xlabel('Classifier')
        plt.ylabel('F-measure')
        plt.title('Classifier Comparison')
        plt.show()
```



```
In [ ]: '''
        - After careful observation, I had noted that 76% Ground Truth
        data is from class 0.
        - So even predicting all zeros will give me an accuracy of
        76% in prediction.
        - If any model that gives an accuracy less than 76%, is actually
        harming the prediction model.
        - Using my machine learning knowledge, i used a few classification
        models for prediction. All of them give an Accuracy > 77%.


        After observing the above metric based results and F-measure
        based plot for the different models,we can infer the following:


        F-Measure based Classifier ranking(1=worst):
        4]Neural Net (0.75)
        3]Logistic Regression(0717)
        2]Linear SVM(0.692)
        1]Decision Trees(0.491)

        Accuracy based Classifier ranking(1=worst):
        4]Neural Net (89.5%)
        3]Logistic Regression(88.7%)
        2]Linear SVM (88%)
        1]Decision Tree(80.5%)

        ** All these classifer metrics are naive, and their no
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hyperparameter tuning has been done.

-Except for Decision trees, all other classifiers have a
comparable F-measure.
-Thus, for me, the best model would be the one which would give
the best accuracy for a comparable F-measure.
From the above rankings, a model with maximum value after
summing the individual rankswould be the best model.

Here, undisputedly, it is Neural Network.
But if a simpler Model is required, Logistic Regression is a
Good bet!

Thus here the best model, Neural Net, has a predicts the data with
almost 90% accuracy.


'''
```