<u>ASSIGNMENT 3- Applied Machine Learning</u>
(BUAN 6341.501)

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I. Student Dataset – Binary Classification problem of predicting the Grade of the student based on the 30 independent variables of demographics data

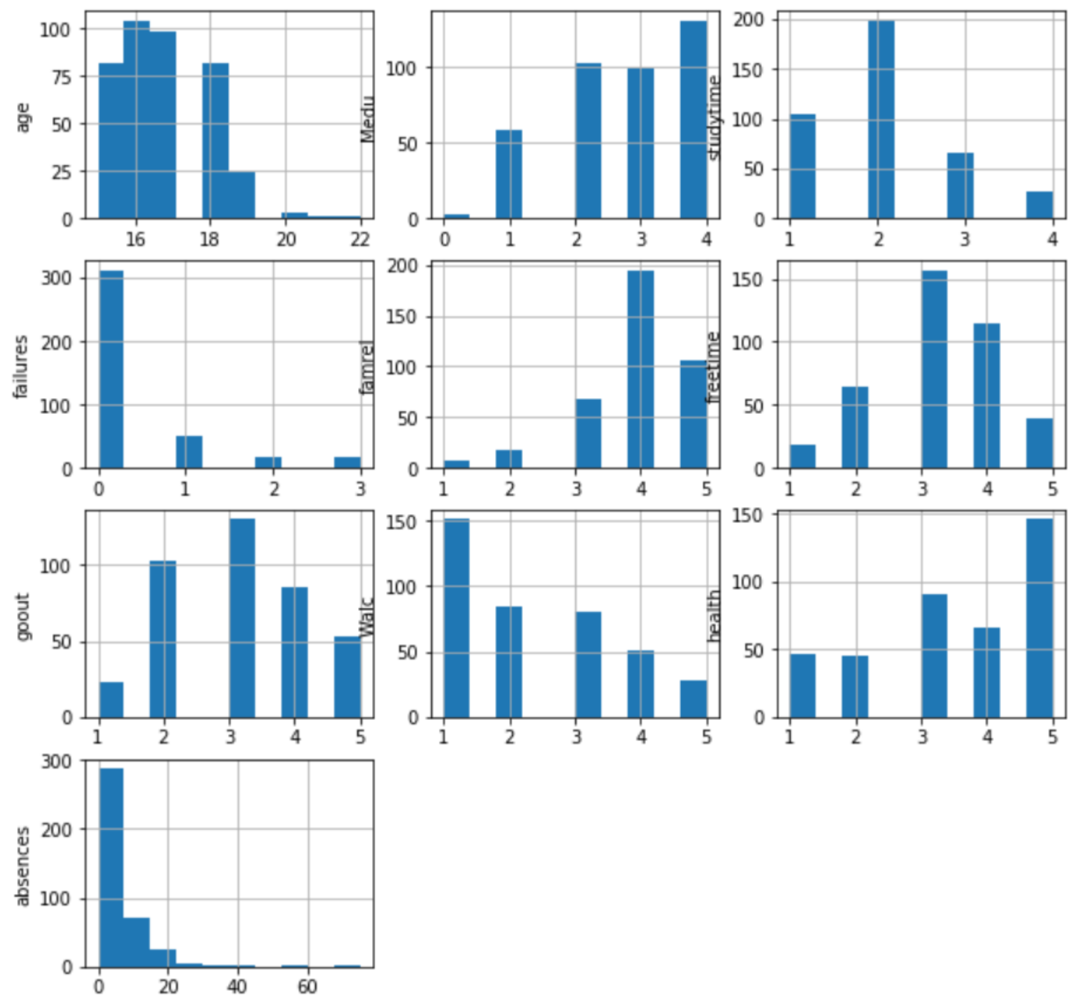
Step 1: **Variable Modifications** (dummy variables of categorical independent variables data)

Step 2: **Feature selection** using Recursive Feature Elimination. We are left with 10 independent variables after using this technique to find the significant variables out of 30

```
In [74]: rf_random.best_estimator_

Out[74]: RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=100,
                    max_features='auto', max_leaf_nodes=None,
                    min_impurity_decrease=0.0, min_impurity_split=None,
                    min_samples_leaf=4, min_samples_split=5,
                    min_weight_fraction_leaf=0.0, n_estimators=1000, n_jobs=1,
                    oob_score=False, random_state=None, verbose=0, warm_start=False)

In [75]: rfe_estimation = RFE(rf,n_features_to_select=10)
         rfe_estimation = rfe_estimation.fit(new_X, Y)

         C:\Users\VisualBI\Anaconda3\lib\site-packages\sklearn\utils\validation.py:578: DataConversionWarning: A column-vector y was pas
         sed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
           y = column_or_1d(y, warn=True)

In [76]: rfe_estimation.get_support
         features_bool = np.array(rfe_estimation.support_)
         features = np.array(new_X.columns)
         result = features[features_bool]
         print(result)

         ['age' 'Fedu' 'studytime' 'failures' 'famrel' 'freetime' 'goout' 'Walc'
          'health' 'absences']
```

These are those 10 features: `'age' ,'Fedu', 'studytime', 'failures', 'famrel', 'freetime', 'goout', 'Walc', 'health', 'absences'`

Step 3: **Data Wrangling**: There is a lot of skewness in the data as per the histograms and describing the mean and median of the data



Further, to tackle the outliers and skewness of 10 features, we perform various types of scaling (scaling, minmax scaler, normalization, standardization). We find normalization providing the best results:

```
The training score with normalization is : 0.15901409890395124
The testing score with normalization is 0.03729454204864402
```

Step 4**: Transforming Target variable into binary form**

```
################ binary classification of G3 i.e target variable #########
def f(row):
    if row['G3'] > 10 :
        val = 1
```

```
    else:
        val = 0
    return val
df['Grade'] = df.apply(f, axis=1)
df.head()
```

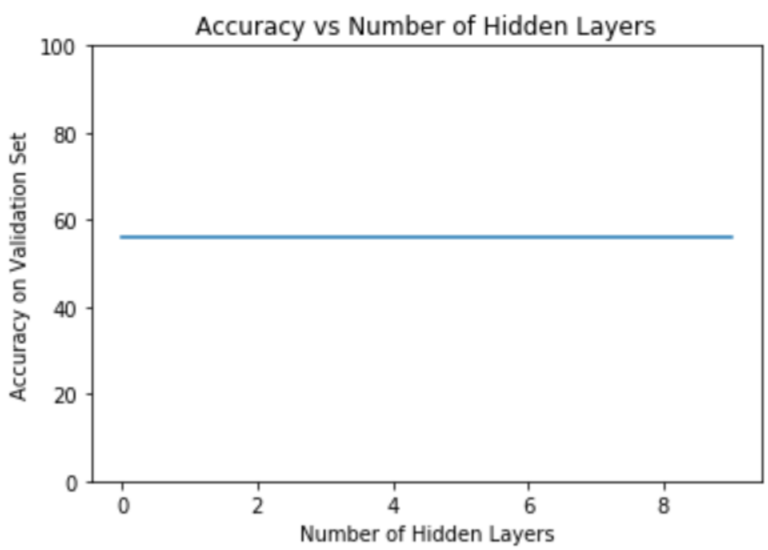
Step 5: Splitting the features into X and Y and further classifying the records into train and test

```
X = df_10[['age', 'Medu', 'studytime', 'failures', 'famrel', 'freetime', 'goout', 'Walc', 'health', 'absences']]
Y= df['Grade']
## Randomly grouping data into train and test
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, random_state = 5)
```

Step 6: Applying Artificial Neural Networks with changing parameters and identifying the better parameter by looking at Accuracy_score and Error metrics (ROC curve)

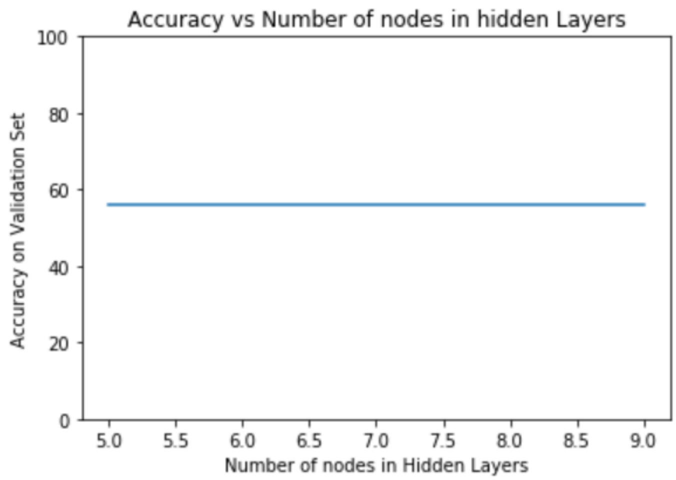
a. Experimentation with 'No. of hidden layers': checking the accuracy score

```
Out[59]: Text(0,0.5,'Accuracy on Validation Set')
```



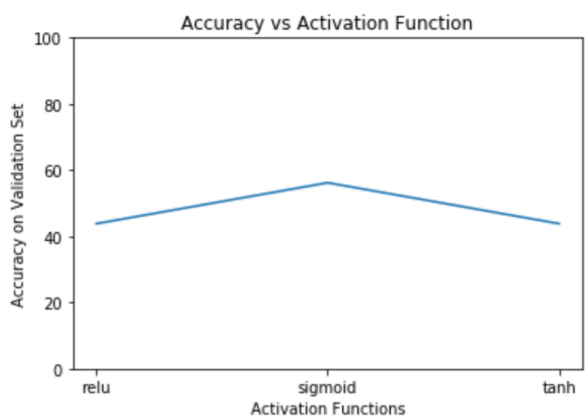
b. Experimentation with No. of nodes in hidden layer:

```
Out[65]: Text(0,0.5,'Accuracy on Validation Set')
```



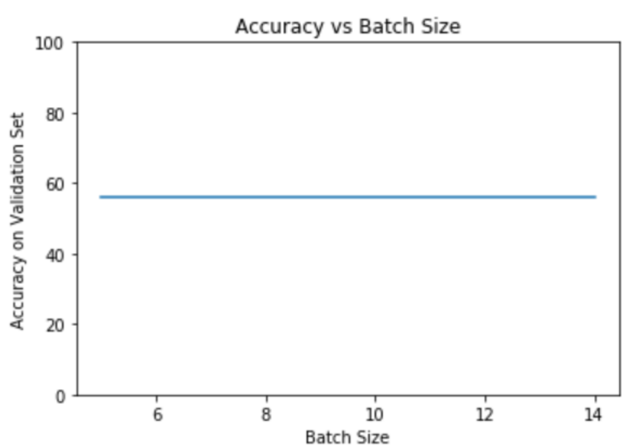
c. Experimentation with Activation function:

```
Out[68]: Text(0,0.5,'Accuracy on Validation Set')
```



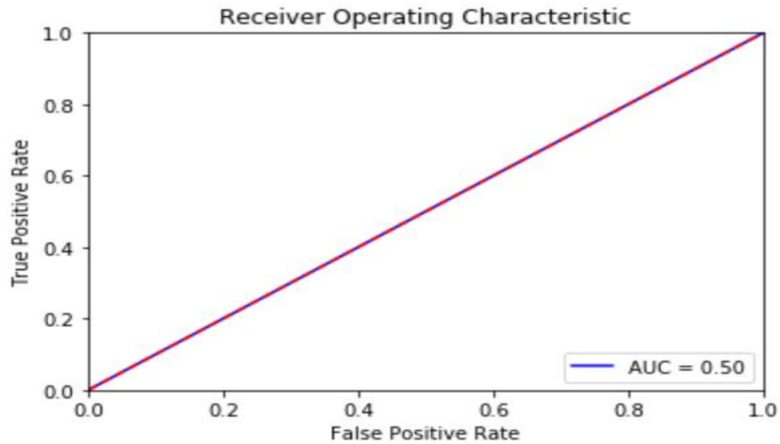
d. Experimentation with the Batch Size

```
Out[72]: Text(0,0.5,'Accuracy on Validation Set')
```



e. Final model with One Hidden Layer, 6 nodes and 'sigmoid' function:

```
Train accuracy = 53.14%
Test accuracy = 49.49%
Validation accuracy = 56.18%
```




```
ROC_AUC Score : 0.5
```

Step 7: KNN Algorithm

Identifying no. of neighbors:

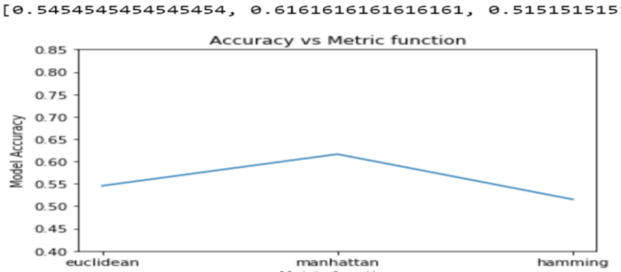
```
# What k works best? Let's try several ...
for k in range(5,15):
        KNN = KNeighborsClassifier(n_neighbors=k)
        KNN.fit(X_train,y_train)
        print(k, KNN.score(X_test,y_test))
```

```
5 0.5050505050505051
6 0.5555555555555556
7 0.5858585858585859
8 0.5454545454545454
9 0.5252525252525253
10 0.5555555555555556
11 0.5252525252525253
12 0.494949494949495
13 0.48484848484848486
14 0.5151515151515151
```

Identifying the distance metric:

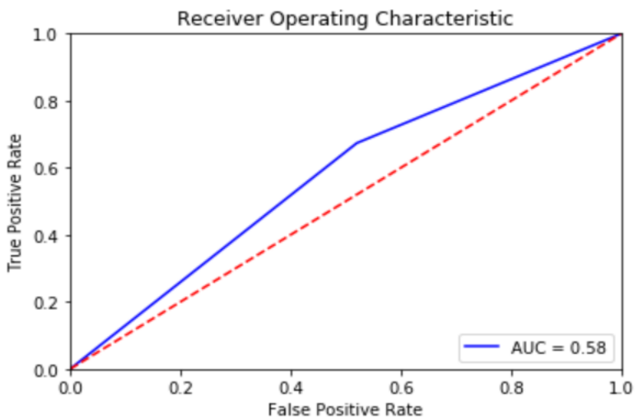
```
plt.ylim([0.40,0.85])
plt.plot(metric,accuracy)
plt.title("Accuracy vs Metric function")
plt.xlabel("Metric function")
plt.ylabel("Model Accuracy")
print(accuracy)
```

```
[0.5454545454545454, 0.6161616161616161, 0.5151515151515151]
```



Final KNN model with "manhattan" distance metric and 7 neighbors

```
Training Score:0.7198067632850241
Test Accuracy Score:0.5757575757575758
Confusion Matrix:
[[24 26]
 [16 33]]
```




```
ROC_AUC Score : 0.576734693877551
```

Step 8: COMPARISON OF ALGORITHMS

Model	Accuracy_Score	Error (ROC_AUC Score)
1. SVM classification with linear kernel	49.495%	0.49
2. SVM classification with rbf kernel	52.525%	0.528
3. SVM classification with sigmoid kernel	49.495%	0.5
4. Decision Tree with 'Gini' metric without pruning	51.515%	0.51
5. Decision Treee with 'Gini' metric with pruning with tree depth = 8	52.525%	0.52
6. Boosting Ensemble methods with Decision tree without boosting	54.545%	0.54
7. Boosting Ensemble methods with Decision tree with pruning considering depth as 2	64.646%	0.64
8. Artifical Neural Networks (sigmoid activation, one hidden layer)	49.49%	0.5
9. K Nearest Neighbors	57.57%	0.5767

Step 7: Interpretations: Boosting Ensemble methods with Decision tree with pruning performs the best in terms of Accuracy_Score of 64.64%. The low accuracy in ANN is due to small size of dataset. ANN requires huge dataset for large computations. This is not the perfect use case for ANN

II. Loan Dataset: Predict whether the person should be granted a loan or not based on his income, credit history and other demographics features.

Target variable: Loan_Status

Predictors: Loan_ID, Gender, Married, Dependents, Education, Self-Employed, AppliantIncome, CoAppliantIncome, LoanAmount, LoanAmountTurn, Credit History, Property Area

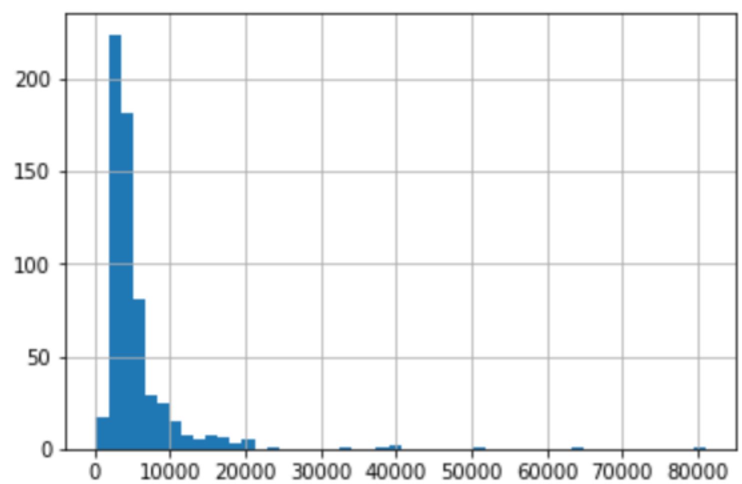
Step 1: Data Exploratory Analysis

:n [126]:

```
## Plotting histogram and box plots to study the distributions of num
df['ApplicantIncome'].hist(bins=50)
```

)ut[126]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1e3988e0828>
```

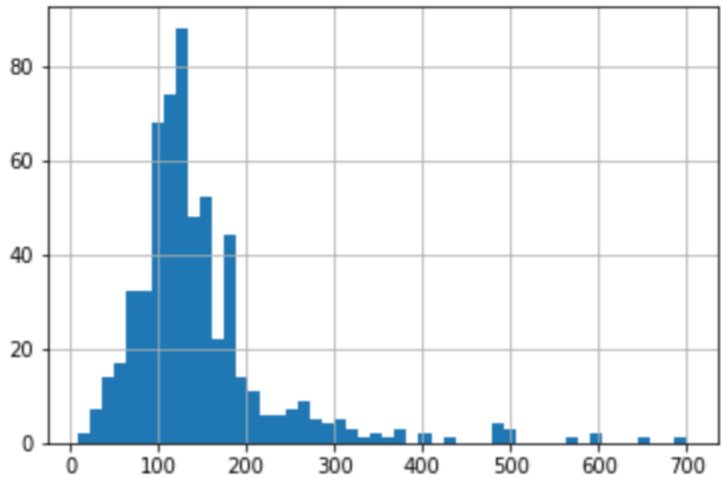


:n [127]:

```
df.boxplot(column='ApplicantIncome')
```

```
: df['LoanAmount'].hist(bins=50)
```

```
: <matplotlib.axes._subplots.AxesSubplot at 0x1e398bc6dd8>
```




```
: df.boxplot(column='LoanAmount')
```

```
: <matplotlib.axes._subplots.AxesSubplot at 0x1e399d0d438>
```

Step 2: Data Wrangling:

1. **Imputing missing values** in the variables

Reidentifying the missing values:

df.apply(lambda x: sum(x.isnull()),axis=0)

imputing 'LoanAmount' with it's mean

df['LoanAmount'].fillna(df['LoanAmount'].mean(), inplace=True)

Since more than 80% values are “No”, it is safe to impute the missing values as “No”

df['Self_Employed'].fillna('No',inplace=True)

imputing others

df['Gender'].fillna(df['Gender'].mode()[0], inplace=True)

df['Married'].fillna(df['Married'].mode()[0], inplace=True)

df['Dependents'].fillna(df['Dependents'].mode()[0], inplace=True)

df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].mode()[0], inplace=True) df['Credit_History'].fillna(df['Credit_History'].mode()[0], inplace=True)

Data Transformation 2:

let’s try a **log transformation** to nullify the skewed histograms of LoanAmount and ApplicantIncome

Step 3: **Data Modifications**:

CONVERTING all categorical variables to numerical before starting with predictions

```
var_mod =
['Gender','Married','Dependents','Education','Self_Employed','Property_Area','Loan_Status']

le = LabelEncoder()

for i in var_mod:

   df[i] = le.fit_transform(df[i])

df.dtypes
```

Step 4**: Checking for cross-validation score error as the dataset is small.**

Performing k-fold cross-validation with 5 folds as it will help generalize the model better, help the model become skilled and test different types of models

#Generic function for making a cross validation model and accessing performance:

def cross_validation(model, data, X_train, Y_train):

{ …………..

}

Step 5: ## Splitting data into X and Y

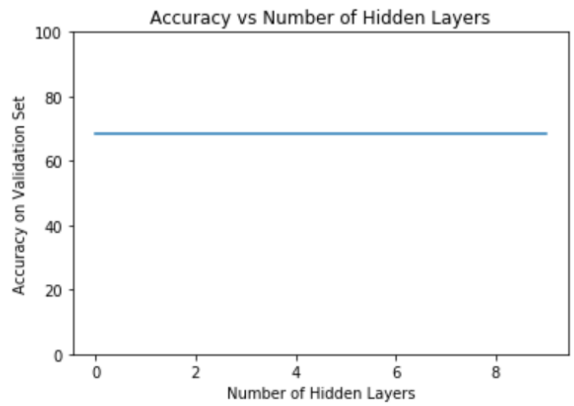
Grouping data into Train and Test

X_train, X_test, Y_train, Y_test = train_test_split(X, Y,test_size = 0.20, random_state =0)

Step 6: Applying Artificial Neural Networks with changing parameters and identifying the better parameter by looking at Accuracy_score and Error metrics (ROC curve)

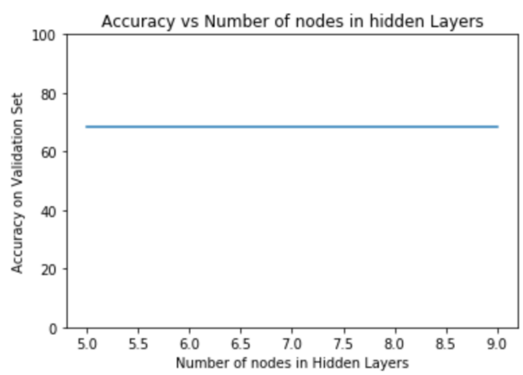
a. Experimentation with 'No. of hidden layers': checking the accuracy score

```
Out[37]: Text(0,0.5,'Accuracy on Validation Set')
```



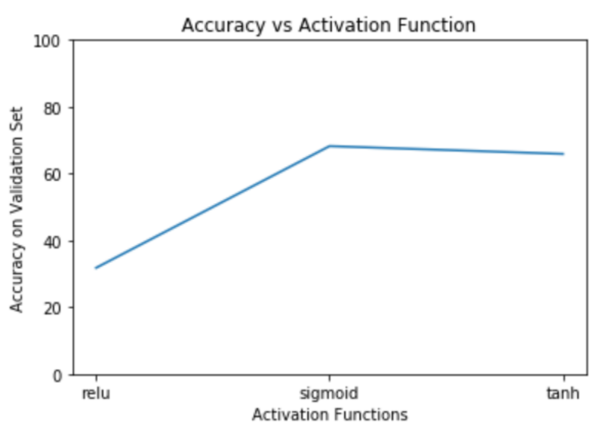
b. Experimentation with No. of nodes in hidden layer:

```
Out[48]: Text(0,0.5,'Accuracy on Validation Set')
```



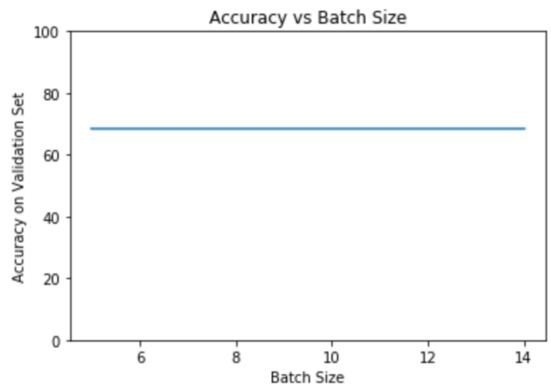
c. Experimentation with Activation function:

```
Out[52]: Text(0,0.5,'Accuracy on Validation Set')
```



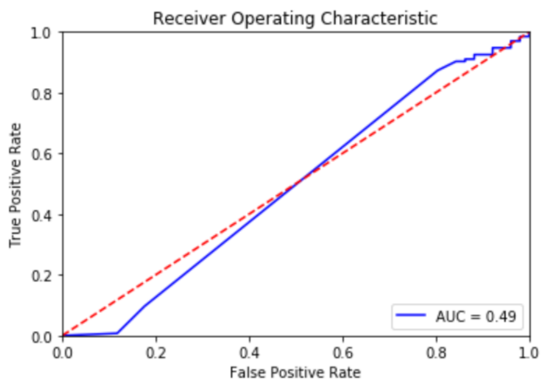
d. Experimentation with the Batch Size

```
Out[62]: Text(0,0.5,'Accuracy on Validation Set')
```



e. Final model with One Hidden Layer, 6 nodes and 'sigmoid' function:

```
Train accuracy = 66.67%
Test accuracy = 72.43%
Validation accuracy = 68.22%
```




```
ROC_AUC Score : 0.490049751243781
```

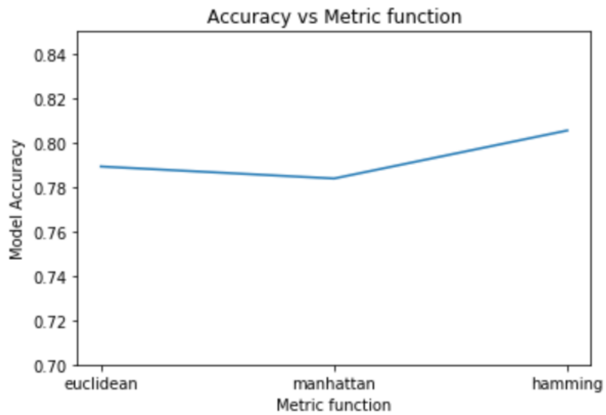
Step 7: KNN Algorithm

Identifying no. of neighbors:

```
1 0.7297297297297297
2 0.6324324324324324
3 0.745945945945946
4 0.6972972972972973
5 0.7621621621621621
6 0.7513513513513513
7 0.7837837837837838
8 0.7891891891891892
9 0.7783783783783784
10 0.7675675675675676
11 0.7675675675675676
12 0.7675675675675676
```

Identifying the distance metric:

```
[0.7891891891891892, 0.7837837837837838, 0.8054054054054054]
```

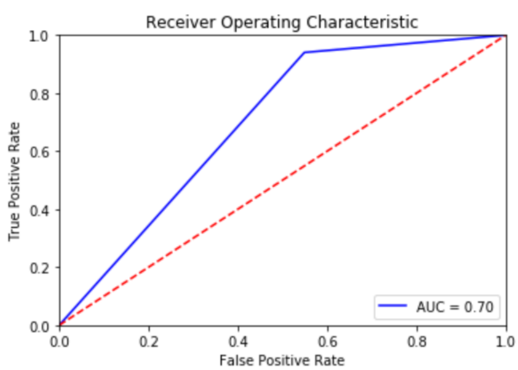


Final KNN model with “hamming” distance metric and 8 neighbors

```
Training Score:0.8066666666666666
Test Accuracy Score:0.8054054054054054
Confusion Matrix:
[[ 23  28]
 [  8 126]]
```

Folder

```
C:\Users\VisualBI\Anaconda3\lib\site-packages\ipykernel_launcher.py:4: DataConversionWarning:
a 1d array was expected. Please change the shape of y to (n_samples, ), for example using rav
  after removing the cwd from sys.path.
```




```
ROC_AUC Score : 0.6956394498097747
```

Step 8: COMPARISON OF ALGORITHMS

Model	Accuracy_Score	Error (ROC_AUC Score)	Cross-Validation Score
1. SVM classification with linear kernel	82.927%	0.70	80.946%
2. SVM classification with rbf kernel	80.488%	0.67	77.528%
3. SVM classification with sigmoid kernel	73.171%	0.5	68.729%
4. Decision Tree with 'Gini' metric without pruning	64.228%	0.62	69.058%
5. Decision Treee with 'Gini' metric with pruning with tree depth = 8	75.610%	0.67	77.361%
6. Boosting Ensemble methods with Decision tree without boosting	66.667%	0.65	69.544%
7. Boosting Ensemble methods with Decision tree with pruning considering depth as 2	72.358%	0.647	74.926%
8. Artificial Neural Network (sigmoid activation, one hidden layer)	72.43%	0.49	68.22%
9. K Nearest Neighbors	80.54%	0.6956	80.66%

Step 7: Interpretations:

SVM has higher accuracy_score compared to Decision Tree, Ensemble Boosting method and ANN, but it carries the burden of high error metric. Except for the sigmoid kernel SVM model which has highest accuracy and lowest error score.

Here, KNN performs better than ANN because we don't have sufficient data to conduct high computational ANN predictions.