In [1]: import pandas as pd import numpy as np import matplotlib.pyplot as plt import seaborn as sns from sklearn.preprocessing import StandardScaler from sklearn.preprocessing import PowerTransformer from sklearn.preprocessing import LabelEncoder from sklearn.model selection import train test split from sklearn.linear model import LogisticRegressionCV from sklearn.metrics import classification\_report, confusion\_matrix In [2]: df = pd.read\_csv("magic04.csv") df = df.drop\_duplicates() df = df.rename(columns = {"class":"Class"}) X = df.iloc[:,:10]y = df.iloc[:,10:]Class = y.Class.unique() le = LabelEncoder() y = pd.DataFrame(le.fit\_transform(np.ravel(y)), columns = y.columns) X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size = 0.20, random\_state = 101) scaler = StandardScaler() scaler.fit(X\_train) X\_train = pd.DataFrame(scaler.transform(X\_train), columns = X.columns)  $X_{test} = pd.DataFrame(scaler.transform(X_{test}), columns = X.columns)$ pt = PowerTransformer(method = "yeo-johnson") pt.fit(X\_train) X\_train = pd.DataFrame(pt.transform(X\_train), columns = X.columns) X\_test = pd.DataFrame(pt.transform(X\_test), columns = X.columns) **Logistic Regression** In [3]: Logit = LogisticRegressionCV(cv=10, scoring='accuracy', n jobs=-1, max iter = 100) Logit.fit(X\_train, np.ravel(y\_train)) y\_pred = Logit.predict(X\_test) In [4]: pd.DataFrame(data = Logit.coef\_, columns = X.columns) **fWidth** fConc1 fAsym fM3Long fM3Trans Out[4]: fLength **fConc** fDist **0** 1.383869 -0.189867 1.455469 1.421105 0.218006 -0.049338 -0.292599 -0.018409 1.586697 0.037657 Columns with Higher Coefficients are More Important (fLength, fSize, fConc, fAlpha). Others with low coefficient are less important. In [5]: print(confusion\_matrix(y\_test, y\_pred)) print(classification\_report(y\_test, y\_pred, target\_names=Class)) [[2292 201] [ 421 867]] precision recall f1-score support 0.84 0.92 0.88 2493 g 0.81 0.74 0.67 1288 0.84 3781 accuracy 0.83 macro avg 0.80 0.81 3781 weighted avg 0.83 0.84 0.83 3781 In [6]: from sklearn import metrics In [7]: fpr, tpr, \_ = metrics.roc\_curve(y\_test, Logit.predict\_proba(X\_test)[:,1]) In [8]: metrics.auc(fpr, tpr) 0.8745026446721628 Out[8]: In [9]: from sklearn.metrics import accuracy\_score In [10]: accuracy score (y test, y pred) 0.8354932557524465 Out[10]: In [11]: auc\_logit = pd.DataFrame(data = {"fpr":fpr,"tpr":tpr}) In [12]: plt.figure(figsize = (15,10))plot = sns.lineplot(x='fpr', y='tpr', data=auc\_logit).set(title='AUC ROC LOGIT') AUC ROC LOGIT 1.0 0.8 0.6 ă 0.4 0.2 0.0 0.2 0.6 0.8 1.0 0.0 **LDA** In [13]:  $\textbf{from} \ \, \text{sklearn.discriminant\_analysis} \ \, \textbf{import} \ \, \text{LinearDiscriminantAnalysis}$ In [14]: LDA = LinearDiscriminantAnalysis() In [15]: LDA.fit(X train, np.ravel(y\_train)) y pred = LDA.predict(X test) In [16]: print(confusion\_matrix(y\_test, y\_pred)) print(classification\_report(y\_test, y\_pred, target\_names=Class)) [[2290 203] [ 439 849]] precision recall f1-score support 0.92 0.88 0.84 2493 0.81 0.66 0.73 1288 3781 0.83 accuracy 0.82 0.79 0.80 3781 macro avg weighted avg 0.83 0.83 0.83 3781 In [17]: fpr, tpr, \_ = metrics.roc\_curve(y\_test, LDA.predict\_proba(X\_test)[:,1]) In [18]: metrics.auc(fpr, tpr) 0.8740526268583089 Out[18]: In [19]: accuracy score (y test, y pred) 0.8302036498280878 Out[19]: In [20]: auc LDA = pd.DataFrame(data = {"fpr":fpr,"tpr":tpr}) In [21]: plt.figure(figsize = (15,10)) plot = sns.lineplot(x='fpr', y='tpr', data=auc\_LDA).set(title='AUC ROC LDA') AUC ROC LDA 1.0 0.8 0.6 ğ 0.4 0.2 0.0 1.0 0.0 0.2 0.4 0.6 0.8 **KNN** In [22]: from sklearn.neighbors import KNeighborsClassifier In [ ]: | from sklearn.model\_selection import GridSearchCV from sklearn.metrics import make\_scorer scoring = {"AUC": "roc\_auc", "Accuracy": make\_scorer(accuracy\_score)} # Setting refit='AUC', refits an estimator on the whole dataset with the  $\ensuremath{\textit{\#}}$  parameter setting that has the best cross-validated AUC score. # That estimator is made available at ``gs.best\_estimator\_`` along with
# parameters like ``gs.best\_score\_``, ``gs.best\_params\_`` and # ``gs.best\_index\_`` gs = GridSearchCV( KNeighborsClassifier(), param\_grid={"n\_neighbors": range(1, 21), "weights":["uniform", "distance"], "p":[1, 2]}, scoring=scoring, refit="AUC", return\_train\_score=True, n jobs = -1, cv = 10,verbose = 3 gs.fit(X\_train, np.ravel(y\_train)) results = gs.cv\_results\_ In [ ]: gs.best\_params\_ In [23]: KNN = KNeighborsClassifier(n\_neighbors=20, p = 2, weights = "distance") KNN.fit(X\_train, np.ravel(y\_train)) y pred = KNN.predict(X test) In [24]: print(confusion\_matrix(y\_test, y\_pred)) print(classification\_report(y\_test, y\_pred, target\_names=Class)) [[2421 72] [ 457 831]] precision recall f1-score support 2493 0.84 0.97 0.90 0.92 0.65 0.76 1288 3781 accuracy 0.86 0.88 0.81 0.87 0.86 macro avg 0.83 3781 0.85 weighted avg 3781 In [25]: fpr, tpr, \_ = metrics.roc\_curve(y\_test, KNN.predict\_proba(X\_test)[:,1]) In [26]: metrics.auc(fpr, tpr) 0.9197065447850254 Out[26]: In [27]: accuracy\_score(y\_test, y\_pred) 0.8600899233007141 Out[27]: In [28]: auc\_KNN = pd.DataFrame(data = {"fpr":fpr,"tpr":tpr}) In [29]: plt.figure(figsize = (15,10)) sns.lineplot(x='fpr', y='tpr', data=auc\_KNN).set(title='AUC\_ROC\_KNN') AUC ROC KNN 1.0 0.8 0.6 ă 0.4 0.2 0.0 **Linear SVM** In [30]: from sklearn.svm import SVC In [ ]: C range = np.logspace(-2, 10, 13)param grid = dict(C=C range) from sklearn.model\_selection import StratifiedShuffleSplit cv = StratifiedShuffleSplit(n splits=30, test size=0.2, random state=101) In [ ]: grid = GridSearchCV(SVC(kernel = "linear", max\_iter=10000, probability=True), param\_grid=param\_grid, cv=cv, n\_ In [ grid.fit(X train, np.ravel(y train)) In [ ]: results = grid.cv\_results\_ grid.best\_params\_ In [31]: LSVC = SVC(kernel = "linear", max\_iter=10000, C = 0.1, probability = True) LSVC.fit(X train, np.ravel(y train)) y\_pred = LSVC.predict(X\_test) C:\Users\matth\anaconda3\lib\site-packages\sklearn\svm\\_base.py:255: ConvergenceWarning: Solver terminated earl y (max\_iter=10000). Consider pre-processing your data with StandardScaler or MinMaxScaler. warnings.warn('Solver terminated early (max\_iter=%i).' In [32]: print(confusion\_matrix(y\_test, y\_pred)) print(classification\_report(y\_test, y\_pred, target\_names=Class)) [[2329 164] [ 450 838]] precision recall f1-score support 0.84 0.93 0.88 2493 0.84 0.65 0.73 1288 0.84 3781 accuracy 0.84 0.79 0.81 3781 macro avg weighted avg 0.84 0.84 0.83 3781 In [33]: fpr, tpr, \_ = metrics.roc\_curve(y\_test, LSVC.predict\_proba(X\_test)[:,1]) In [34]: metrics.auc(fpr, tpr) 0.8726321900077983 Out[34]: In [35]: accuracy\_score(y\_test, y\_pred) 0.8376090981221899 Out[35]: In [36]: auc LSVC = pd.DataFrame(data = {"fpr":fpr,"tpr":tpr}) In [37]: plt.figure(figsize = (15,10))plot = sns.lineplot(x='fpr', y='tpr', data=auc\_LSVC).set(title='AUC ROC LINEAR SVC') AUC ROC LINEAR SVC 1.0 0.8 0.6 ğ 0.2 0.0 0.0 0.2 0.4 0.6 0.8 1.0 **Radial SVC** In [ ]: gamma\_range = np.logspace(-9, 3, 13) param\_grid = dict(gamma=gamma\_range, C=C\_range) cv = StratifiedShuffleSplit(n\_splits=3, test\_size=0.2, random\_state=101) grid = GridSearchCV(SVC(probability = True), param\_grid=param\_grid, cv=cv, n\_jobs = -1, verbose = 3) In [ ]: grid.fit(X\_train, np.ravel(y\_train)) results = grid.cv\_results\_ In [ ]: grid.best params In [38]: RSVC = SVC(C = 100, gamma = 0.1, probability = True) RSVC.fit(X\_train, np.ravel(y\_train)) y\_pred = RSVC.predict(X\_test) In [39]: print(confusion matrix(y test, y pred)) print(classification\_report(y\_test, y\_pred, target\_names=Class)) [[2389 104] [ 318 970]] precision recall f1-score g 0.88 0.96 0.92 2493 0.90 0.75 0.82 1288 h 0.89 3781 accuracy 3781 0.89 0.86 0.87 macro avg weighted avg 0.89 0.89 0.89 3781 In [40]: fpr, tpr, \_ = metrics.roc\_curve(y\_test, RSVC.predict\_proba(X\_test)[:,1]) In [41]: metrics.auc(fpr, tpr) 0.9290217578162955 Out[41]: In [42]: accuracy\_score(y\_test, y\_pred) 0.8883893149960328 Out[42]: In [43]: auc\_RSVC = pd.DataFrame(data = {"fpr":fpr,"tpr":tpr}) In [44]: plt.figure(figsize = (15,10))plot = sns.lineplot(x='fpr', y='tpr', data=auc\_RSVC).set(title='AUC\_ROC\_RADIAL\_SVC') AUC ROC RADIAL SVC 1.0 0.8 0.6 Ā 0.4 0.2 0.0 0.2 0.4 0.6 0.8 1.0 0.0 fpr