Import Necessary libraries In [45]: import pandas as pd import numpy as np import seaborn as sns from sklearn.model_selection import train_test_split from sklearn.neighbors import KNeighborsClassifier from sklearn.metrics import accuracy_score from sklearn.model_selection import cross_val_score **Data Collection** In [9]: # Import Dataset glassdata=pd.read_csv('glass.csv') glassdata RI ΑI Si K Ca Na Mg Ba Fe **Type** Out[9]: 1.52101 13.64 4.49 1.10 0.06 8.75 0.00 0.0 1 71.78 1.51761 13.89 3.60 1.36 72.73 0.48 7.83 0.00 0.0 1 1.51618 13.53 3.55 1.54 72.99 0.39 7.78 0.00 0.0 1 1.51766 13.21 3.69 1.29 72.61 0.57 8.22 0.00 0.0 1 1.51742 13.27 3.62 1.24 73.08 0.55 8.07 0.00 0.0 1 209 1.51623 14.14 0.00 2.88 72.61 0.08 9.18 1.06 0.0 7 7 1.51685 14.92 0.00 1.99 73.06 0.00 8.40 1.59 0.0 1.52065 7 211 14.36 0.00 2.02 73.42 0.00 8.44 1.64 0.0 8.48 1.51651 14.38 0.00 1.94 73.61 0.00 1.57 7 73.36 7 213 1.51711 14.23 0.00 2.08 0.00 8.62 1.67 0.0 214 rows × 10 columns In [5]: glassdata.head() Mg ΑI Si K Ca Ba Fe Out[5]: Na **Type** 1.52101 13.64 4.49 1.10 71.78 0.06 8.75 0.0 0.0 1 1.51761 13.89 3.60 1.36 72.73 0.48 7.83 0.0 0.0 1 1.51618 13.53 3.55 72.99 0.0 1.54 0.39 7.78 0.0 1 1.51766 13.21 3.69 1.29 72.61 0.57 8.22 0.0 0.0 1 1.51742 13.27 3.62 1.24 73.08 0.55 8.07 0.0 1 In [6]: glassdata.describe() Na Mg Si Out[6]: 214.000000 214.000000 214.000000 214.000000 count 214.000000 214.000000 214.000000 mean 72.650935 0.497056 8.956963 1.518365 13.407850 2.684533 1.444907 0.003037 1.442408 0.774546 std 0.816604 0.499270 0.652192 1.423153 min 1.511150 10.730000 0.000000 0.290000 69.810000 0.000000 5.430000 25% 2.115000 1.190000 8.240000 1.516522 12.907500 72.280000 0.122500 50% 1.517680 13.300000 3.480000 1.360000 72.790000 0.555000 8.600000 max 1.533930 17.380000 4.490000 3.500000 75.410000 6.210000 16.190000 In [13]: import warnings warnings.filterwarnings('ignore') In [14]: sns.factorplot('Type', data=glassdata, kind="count", size = 5, aspect = 2) <seaborn.axisgrid.FacetGrid at 0x20b3094a6d0> 70 60 50 40 30 20 10 Туре In [15]: glassdata.plot(kind='density', subplots=True, layout=(4,5), figsize=(13,26 plt.show() 200 0.6 RI Na 1.0 0.5 175 0.6 0.5 150 0.8 0.4 0.5 0.4 125 Density 0.6 0.4 0.3 100 0.3 E.0 B 75 0.2 0.4 0.2 0.2 50 0.1 0.2 0.1 25 0.1 0.0 1.54 15 1.52 5.0 1.50 20 -2.50.0 2.5 Ca 2.00 — к Fe 0.30 Ba Туре 8 1.0 .75 0.4 0.25 1.50 0.8 d.20 0.3 .25 0.6 1.00 d.15 0.2 **0**.75 0.4 0.10 **0**.50 0.1 0.2 d.05 **0**.25 0.0 0.0 **d**.00 10 0.0 In [16]: glassdata.plot(kind='box', subplots=**True**, layout=(4,5), figsize=(13,20), s plt.show() 1.535 3.5 17 75 3.0 16 74 2.5 3 15 1.525 73 2.0 14 2 1.520 13 1 1.0 12 0.5 8 11 70 Αİ Mg 0 0 16 0.5 6 3.0 0 8 14 2.5 0.4 0 5 8 4 2.0 12 0.3 1.5 000 10 0.2 2 1.0 8 0.1 2 1 0.5 6 0.0 0.0 Finding correlation between the variables in data In [17]: cor = glassdata.corr(method='pearson') In [18]: cor.style.background_gradient(cmap='coolwarm') RI Out[18]: Na Mg ΑI Ca Ва 1.000000 -0.191885 -0.122274 -0.407326 -0.542052 -0.289833 0.810403 -0.000386 RI-0.273732 -0.069809 -0.266087 0.326603 -0.191885 1.000000 0.156794 -0.275442 Na -0.481799 -0.492262 -0.122274 -0.273732 1.000000 -0.165927 0.005396 -0.443750 Mg 1.000000 0.325958 -0.407326 0.156794 -0.481799 -0.005524 -0.259592 0.479404 -0.193331 -0.005524 Si -0.542052 -0.069809 -0.165927 1.000000 -0.208732 -0.102151 0.005396 Κ -0.289833 -0.266087 0.325958 -0.193331 1.000000 -0.317836 -0.042618 0.810403 -0.275442 -0.443750 -0.259592 -0.208732 -0.317836 -0.112841 1.000000 Ca -0.000386 0.326603 -0.492262 0.479404 -0.102151 -0.042618 -0.112841 1.000000 Ba 0.143010 -0.241346 0.083060 -0.074402 -0.007719 -0.058692 Fe -0.094201 0.124968 -0.164237 0.502898 -0.744993 0.598829 0.151565 -0.010054 0.000952 0.575161 **Type** KNN Finding optimal number of K In [21]: X = np.array(glassdata.iloc[:,3:5]) y = np.array(glassdata['Type']) In [24]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, r In [25]: $k_values = np.arange(1,25)$ train_accuracy = [] test_accuracy = [] In [29]: for i, k in enumerate(k_values): knn = KNeighborsClassifier(n_neighbors=k) knn.fit(X_train,y_train) train_accuracy.append(knn.score(X_train, y_train)) test_accuracy.append(knn.score(X_test, y_test)) In [30]: plt.figure(figsize=[13,8]) plt.plot(k_values, test_accuracy, label = 'Testing Accuracy') plt.plot(k_values, train_accuracy, label = 'Training Accuracy') plt.legend() plt.title('-value VS Accuracy') plt.xlabel('Number of Neighbors') plt.ylabel('Accuracy') plt.xticks(k_values) plt.show() -value VS Accuracy Testing Accuracy 1.0 Training Accuracy 0.9 0.8 0.7 0.6 0.5 15 10 13 14 16 **Applying Algorithm** In [47]: knn = KNeighborsClassifier(n_neighbors=4) In [48]: knn.fit(X_train, y_train) y_pred_KNeighborsClassifier = knn.predict(X_test) In [49]: scores = [] cv_scores = [] In [50]: score = accuracy_score(y_pred_KNeighborsClassifier,y_test) scores.append(score) In [51]: score_knn=cross_val_score(knn, X,y, cv=10) In [53]: score_knn.mean() 0.6127705627705629 Out[53]: In [54]: score_knn.std()*2 0.23547117559816877 Out[54]: In [55]: cv_score = score_knn.mean() In [56]: cv_scores.append(cv_score) In [57]: cv_scores

Out[57]: [0.6127705627705629]