Importing the Data In [15]: import pandas as pd import matplotlib.pyplot as plt df = pd.read csv("car.data") df.head() Out[15]: vhigh vhigh.1 2 2.1 small low unacc vhigh 2 0 vhigh small med unacc 1 vhigh vhigh 2 small high unacc 2 vhigh vhigh 2 2 med low unacc 3 vhigh vhigh 2 2 med med unacc 4 vhigh vhigh 2 2 med high unacc In [16]: # Adding column labels df.columns = ["buying price", "maintenance", "doors", "persons", "lug boot", "safety", "class value"] df.head() Out[16]: buying_price maintenance doors persons lug_boot safety class_value 2 0 vhigh vhigh 2 small med unacc vhigh 2 2 high 1 vhigh small unacc vhigh vhigh 2 med low unacc 3 vhigh vhigh 2 2 med med unacc vhigh vhigh med high unacc In [17]: df.shape Out[17]: (1727, 7) **Exploratory Data Analysis and Preprocessing** In [18]: # Checking for any null values df.isnull().sum() Out[18]: buying_price 0 maintenance 0 doors persons lug_boot 0 safety class value 0 dtype: int64 In [19]: # Checking the distribution of every data column for col in list(df): print(df[col].value counts()) 432 med low 432 high 432 431 vhigh Name: buying price, dtype: int64 med 432 low 432 high 432 vhigh 431 Name: maintenance, dtype: int64 432 5more 432 432 431 Name: doors, dtype: int64 more 576 576 575 Name: persons, dtype: int64 576 576 big small 575 Name: lug boot, dtype: int64 576 high 576 575 low Name: safety, dtype: int64 1209 unacc 384 acc good 69 65 vgood Name: class_value, dtype: int64 In [20]: | X = df.drop(['buying price', 'persons'], axis=1) y = df[['buying_price']] In [21]: y.value_counts() Out[21]: buying_price 432 med 432 low high 432 vhigh 431 dtype: int64 In [22]: X.head() Out[22]: maintenance doors lug_boot safety class_value 0 vhigh small med unacc 1 vhigh small high unacc vhigh 2 med unacc 3 vhigh med med unacc vhigh high unacc med In [23]: X['class value'].value counts() Out[23]: unacc 1209 acc 384 69 good 65 vgood Name: class value, dtype: int64 In [24]: **def** maintenance safety encode (data): if data == "low": return 1 elif data == "med": return 2 elif data == "high": return 3 elif data == "vhigh": return 4 def lug encode(data): if data == "small": return 1elif data == "med": return 2 elif data == "big": return 3 def lug encode(data): if data == "small": return 1 elif data == "med": return 2 elif data == "big": return 3 def door encode(data): **if** data == "2": return 1 elif data == "3": return 2 elif data == "4": return 3 elif data == "5more": return 4 def class encode(data): if data == "unacc": return 1 elif data == "acc": return 2 elif data == "good": return 3 elif data == "vgood": return 4 In [25]: X.columns Out[25]: Index(['maintenance', 'doors', 'lug boot', 'safety', 'class value'], dtype='object') In [26]: X['maintenance'] = X['maintenance'].apply(maintenance safety encode) X['doors'] = X['doors'].apply(door encode) X['lug_boot'] = X['lug_boot'].apply(lug_encode) X['safety'] = X['safety'].apply(maintenance_safety_encode) X['class_value'] = X['class_value'].apply(class encode) X.head() Out[26]: maintenance doors lug_boot safety class_value 0 3 1 1 1 1 2 1 2 2 1 3 In [27]: X.hist() plt.show() maintenance doors 400 400 200 200 0 0 ľug_boots 2safety 3 500 500 250 250 class_value 1000 500 In [28]: import numpy as np X['class_value'] = X['class_value'].apply(lambda x: np.log(x+1)) X.hist() plt.show() maintenance doors 400 400 200 200 lug_boot 2safety 3 500 500 250 250 0 dass_value 1000 500 1.0 1.5 from sklearn.preprocessing import MinMaxScaler In [29]: scaler = MinMaxScaler() X = pd.DataFrame(scaler.fit transform(X), columns=list(X)) X.describe() Out[29]: maintenance doors lug_boot safety class_value 1727.000000 1727.000000 1727.000000 count 1727.000000 1727.000000 0.499710 0.500290 0.500290 0.500290 0.166253 mean 0.372699 0.372699 0.408307 0.408307 0.276485 0.000000 0.000000 0.000000 0.000000 0.000000 min 0.000000 0.000000 0.000000 0.166667 0.333333 25% 50% 0.333333 0.666667 0.500000 0.500000 0.000000 0.666667 0.833333 1.000000 0.442507 75% 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 max In [30]: from sklearn.model_selection import train test split # Split dataset into training set and test set X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=0) # 80% training and 20% test **Base Models** In [34]: #Import scikit-learn metrics module for accuracy calculation from sklearn import metrics from sklearn.metrics import accuracy score, fl score, precision score, recall score, classification rep ort, confusion matrix **Logistic Regression** In [35]: from sklearn.linear model import LogisticRegression logreg = LogisticRegression(random state = 100) logreg.fit(X_train, y_train) y_pred = logreg.predict(X_test) /Users/zentan/opt/anaconda3/lib/python3.7/site-packages/sklearn/utils/validation.py:72: DataConversio nWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for example using ravel(). return f(**kwargs) In [36]: # Model Accuracy, how often is the classifier correct? print("Accuracy:", metrics.accuracy_score(y_test, y_pred)) print("F1 Score", f1_score(y_test, y_pred, average="macro")) print("Precision", precision_score(y_test, y_pred, average="macro")) print("Recall", recall_score(y_test, y_pred, average="macro")) Accuracy: 0.3140655105973025 F1 Score 0.24243704045473213 Precision 0.2565921977627258 Recall 0.3182764284061994 KNN In [39]: from sklearn.neighbors import KNeighborsClassifier classifier = KNeighborsClassifier(n neighbors=5) classifier.fit(X_train, y_train) y pred knn = classifier.predict(X test) /Users/zentan/opt/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:4: DataConversionWarnin g: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samp les,), for example using ravel(). after removing the cwd from sys.path. In [40]: | # Model Accuracy, how often is the classifier correct? print("Accuracy:", metrics.accuracy score(y test, y pred)) print("F1 Score", f1_score(y_test, y_pred, average="macro")) print("Precision", precision score(y test, y pred, average="macro")) print("Recall", recall_score(y_test, y_pred, average="macro")) Accuracy: 0.3140655105973025 F1 Score 0.24243704045473213 Precision 0.2565921977627258 Recall 0.3182764284061994 Using pycaret to speed up the process In [41]: df pycaret = pd.read csv("car.data") df pycaret.columns = ["buying price", "maintenance", "doors", "persons", "lug boot", "safety", "class v df_pycaret.drop("persons", axis=1, inplace=True) df pycaret.head() Out[41]: buying_price maintenance doors lug_boot safety class_value 0 vhigh vhigh small med unacc vhigh 1 vhigh small high unacc vhigh vhigh low unacc 3 vhigh vhigh med med unacc vhigh vhigh high unacc In [42]: from pycaret.classification import * clf = setup(df pycaret, target='buying price', session id=1) Description **Value** 0 session_id Target buying_price 1 Target Type Multiclass 2 3 Label Encoded high: 0, low: 1, med: 2, vhigh: 3 Original Data (1727, 6)Missing Values False 5 Numeric Features 0 6 5 Categorical Features 7 Ordinal Features False High Cardinality Features False 9 High Cardinality Method None 10 Transformed Train Set (1208, 18)11 12 Transformed Test Set (519, 18)Shuffle Train-Test True 13 Stratify Train-Test False 14 Fold Generator StratifiedKFold 15 10 16 Fold Number **CPU Jobs** -1 17 Use GPU False 18 Log Experiment False 19 **Experiment Name** clf-default-name 20 USI 21 a3ca Imputation Type simple 22 23 Iterative Imputation Iteration None Numeric Imputer 24 mean Iterative Imputation Numeric Model None 25 Categorical Imputer constant 26 Iterative Imputation Categorical Model None 27 28 Unknown Categoricals Handling least_frequent Normalize False 29 Normalize Method None 30 Transformation False 31 Transformation Method 32 None **PCA** 33 False PCA Method None 34 **PCA Components** None 35 36 Ignore Low Variance False Combine Rare Levels False 37 Rare Level Threshold 38 None Numeric Binning False 39 40 Remove Outliers False **Outliers Threshold** None 41 Remove Multicollinearity False 42 43 Multicollinearity Threshold None 44 Remove Perfect Collinearity True False 45 Clustering Clustering Iteration None 46 Polynomial Features False 47 48 Polynomial Degree None Trignometry Features False 49 Polynomial Threshold None 50 **Group Features** False 51 52 Feature Selection False 53 Feature Selection Method classic Features Selection Threshold None 54 Feature Interaction False 55 56 Feature Ratio False Interaction Threshold None 57 58 Fix Imbalance False Fix Imbalance Method **SMOTE** 59 In [43]: compare_models() Model Accuracy AUC F1 MCC TT (Sec) Recall Prec. Kappa Naive Bayes 0.3179 0.5404 0.3180 0.3047 0.2500 0.0900 0.1123 0.1650 nb ada Ada Boost Classifier 0.3162 0.5757 0.3153 0.3701 0.0863 0.0903 0.0240 0.2963 0.0875 0.0050 ridge Ridge Classifier 0.3129 0.0000 0.3123 0.3435 0.0824 Linear Discriminant Analysis 0.3111 0.3702 0.2985 0.0808 0.0855 0.0060 lda 0.3121 0.5750 Logistic Regression 0.3055 0.3050 0.3311 0.2925 0.0726 0.0764 0.6340 lr SVM - Linear Kernel 0.2848 0.2906 0.2422 0.0454 0.0572 0.1520 svm gbc Gradient Boosting Classifier 0.2583 0.5740 0.2586 0.2818 0.2581 0.0100 0.0097 0.0770 0.0633 0.1012 0.0000 0.0000 Quadratic Discriminant Analysis 0.2517 0.0000 0.2500 0.0160 qda K Neighbors Classifier 0.1963 0.4402 0.1965 0.1978 0.1934 -0.0719 -0.0726 0.1890 knn Light Gradient Boosting Machine 0.1871 0.1877 0.1906 0.1864 -0.0842 -0.0849 2.5250 lightgbm Extreme Gradient Boosting 0.1722 0.4595 0.1728 0.1768 0.1722 -0.1041 -0.1051 1.2720 xgboost dt **Decision Tree Classifier** 0.1681 0.4297 0.1689 0.1545 0.1553 -0.1091 -0.1122 0.0060 -0.1155 Extra Trees Classifier 0.1656 0.1020 et Random Forest Classifier 0.1648 rf Out[43]: GaussianNB(priors=None, var smoothing=1e-09) In [44]: model = create model('nb') Accuracy AUC Recall Prec. Kappa MCC 0.3388 0.3347 0.2804 0.1209 0.5487 0.3417 0.2975 0.5287 0.3000 0.3278 0.2266 0.0659 0.2479 0.4794 0.2500 0.3039 0.1917 0.0000 0.0000 0.2975 0.5281 0.3000 0.2923 0.2195 0.0659 0.0872 0.3636 0.6000 0.3621 0.3274 0.3068 0.1471 0.1786 0.3140 0.5295 0.3087 0.2793 0.2437 0.0791 0.1000 0.3167 0.5451 0.3181 0.2925 0.2467 0.0896 0.1093 0.3583 0.5777 0.3601 0.3160 0.2838 0.1452 0.1793 9 0.3179 0.5404 0.3180 0.3047 0.2500 0.0900 0.1123 Mean 0.0315 0.0307 0.0311 0.0276 0.0342 0.0408 0.0498 SD In [48]: tuned nb = tune model(model) F1 Kappa MCC Accuracy AUC Recall Prec. 0.2975 0.5287 0.3000 0.3278 0.2266 0.0659 0.0847 0.2479 0.4794 0.2500 0.3039 0.1917 0.0000 0.0000 0.3636 0.6000 0.3621 0.3274 0.3068 0.1471 0.1786 0.3140 0.5295 0.3087 0.2793 0.2437 0.0791 0.1000 0.3167 0.5451 0.3181 0.2925 0.2467 0.0896 0.1093 0.3583 0.5777 0.3601 0.3160 0.2838 0.1452 0.1793 0.3179 0.5404 0.3180 0.3047 0.2500 0.0900 0.1123 Mean 0.0315 0.0307 0.0311 0.0276 0.0342 0.0408 0.0498 SD In [49]: test = pd.DataFrame([['High', '4', 'Big', 'High', 'Good']]) test.columns = ["maintenance", "doors", "lug boot", "safety", "class value"] test.head() Out[49]: maintenance doors lug_boot safety class_value Big High High Good unseen predictions = predict model(tuned nb, data=test) In [50]: unseen predictions.head() Out[50]: maintenance doors lug_boot safety class_value Label Score Big High Good 0 High low 0.9841 The predicted Buying Price would be low In []: