Importing Libraries

```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
from matplotlib import cm # For colors in scatterplots
import seaborn as sns # For plotting
import warnings # Ignore Warnings
warnings.filterwarnings('ignore')

from sklearn.datasets import make_regression # To create synthetic dataset
from sklearn.datasets import fetch_california_housing # To import california_hou
from xgboost import XGBClassifier # XG Boost Model
from sklearn.linear_model import LinearRegression # Linear Regression Model
from sklearn.linear_model import LogisticRegression # Logistic Regression Model
from sklearn.model_selection import train_test_split # Split into train and test
from sklearn.neighbors import KNeighborsRegressor # For K Neighbors
from sklearn.neighbors import KNeighborsClassifier # For K Neighbors
from sklearn.metrics import r2_score # R^2
from sklearn.metrics import accuracy_score
from sklearn.metrics import f1_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score

from sklearn import preprocessing # Label encoder
from sklearn.preprocessing import OneHotEncoder # One Hot Encoder

# Set scale of the scatter plots
SPLOTSCALE = .8

# Set scale of outlier plots
PLOTSCALE = .4

# Sets the random state (seed) so results can be replicated
RANDOM_STATE=7

# K Neighbours - # of neighbors
KREG = 3
KCLASS = 2

# Names of each Model
NAMES = ['Linear Regression',
         'Logistic Regression',
         'XGBoost Regressor',
         'K Neighbor Regressor',
```

```
          'K Neighbor Classifier']

# Code for each Model
MODELS = [LinearRegression(),
          LogisticRegression(solver='liblinear'),
          XGBClassifier(eval_metric='mlogloss'),
          KNeighborsRegressor(n_neighbors=KREG),
          KNeighborsClassifier(n_neighbors=KCLASS)]
```

Scatterplot Function

```
XList = {}
for i in range(6):
    XList[i-1] = 'Feature %s' % i

def scatterPlot(title="Title",plotType=""):
    # Synthetic Plot Features
    if plotType == 's':
        colors = iter(cm.rainbow(np.linspace(0, 1, len(XList)))) # For the color
        f, ax = plt.subplots(3, 2, figsize=(12*SPLOTSCALE, 15*SPLOTSCALE))
        f.suptitle(title, fontsize=16), f.delaxes(ax[2,1]) # Removing index in p

        a=[0,0,1,1,2] # For the 'y' positions
        b=[0,1,0,1,0] # For the 'x' positions
        n = 5
        labels = XList

    # Housing Plot Features
    else:
        colors = iter(cm.rainbow(np.linspace(0, 1, len(housing.feature_names))))
        f, ax = plt.subplots(4, 2, figsize=(12*SPLOTSCALE, 15*SPLOTSCALE))
        f.suptitle(title, fontsize=16)

        a=[0,0,1,1,2,2,3,3] # For the 'y' positions
        b=[0,1,0,1,0,1,0,1] # For the 'x' positions
        n = 8
        labels = housing.feature_names

    # Code to plot
    for i in range(0,n):
        plt.sca(ax[a[i], b[i]])
        plt.scatter(X[:,i], y, color=next(colors), marker='.', label=labels[i])
        plt.xlabel(labels[i])
        if b[i] == 0:
            plt.ylabel('y axis')
        plt.legend(loc='upper right')
```

Outliers Function

```
def comparePlot(df,dfnew,feature,title,type1='capping'):
    # compare the distribution after capping/trimming
    print(title + ': Comparing the distribution of',feature, 'after', type1)
    plt.figure(figsize=(12*PLOTSCALE,6*PLOTSCALE))
    plt.subplot(2,2,1)
    sns.distplot(df[feature])
    plt.subplot(2,2,2)
```

```
    sns.boxplot(df[feature])
    plt.subplot(2,2,3)
    sns.distplot(dfnew[feature])
    plt.subplot(2,2,4)
    sns.boxplot(dfnew[feature])
    plt.show()


def outliers(feature,df,df_z,df_iqr,df_per,df_win):
    # Z-score

    # finding the boundary values
    threshold = 10 # Was 3
    HA = df_z['y'].mean() + threshold*df_z['y'].std()
    LA = df_z['y'].mean() - threshold*df_z['y'].std()

    # trimming of Outliers
    df_z = df_z[(df_z['y'] < HA) & (df_z['y'] > LA)]
    df_z.head()

    # capping on Outliers
    UL = df_z['y'].mean() + threshold*df_z['y'].std()
    LL = df_z['y'].mean() - threshold*df_z['y'].std()

    # apply the capping
    df_z['y'] = np.where(
        df_z['y']>UL, UL,
        np.where(
            df_z['y']<LL, LL,
            df_z['y']
        )
    )

    #--------------------------------------------------------------------------
    # IQR based filtering

    # finding the IQR
    Q1 = df_iqr[feature].quantile(0.25)
    Q3 = df_iqr[feature].quantile(0.75)
    IQR = Q3 - Q1

    # finding upper and lower limit
    # 1.5 is the general consensis
    UL2 = Q3 + 1.5 * IQR
    LL2 = Q1 - 1.5 * IQR

    # finding Outliers
    df_iqr[df_iqr[feature] > UL2]
```

```
    df_iqr[df_iqr[feature] < LL2]

    # trimming
    new_df_iqr = df_iqr[df_iqr[feature] < UL2]
    new_df_iqr.shape

    # capping
    new_df_cap = df_iqr.copy()
    new_df_cap[feature] = np.where(
        new_df_cap[feature] > UL2, UL2,
        np.where(
            new_df_cap[feature] < LL2, LL2,
            new_df_cap[feature]
        )
    )
    df_iqr = new_df_iqr

    #---------------------------------------------------------------------------
    # Percentile

    # upper and lower limit
    # can play with the parameters
    UL3 = df_per[feature].quantile(0.90)
    LL3 = df_per[feature].quantile(0.10)

    # apply trimming
    new_df_per = df_per[(df_per[feature] <= UL3) & (df[feature] >= LL3)]
    df_per = new_df_per

    #---------------------------------------------------------------------------
    # Winsorization
    # apply capping (Winsorization)
    df_win[feature] = np.where(df_win[feature] >= UL3, UL3,
            np.where(df_win[feature] <= LL3, LL3,
            df_win[feature]))

    return df_z, df_iqr, df_per, df_win
```

Function to print model results

```
def print_results(input_model, model_name, XTrain, yTrain, XTest, yTest,
                                           XTrainZ, yTrainZ, XTestZ, yTestZ,
                                           XTrainIQR, yTrainIQR, XTestIQR, yTest
                                           XTrainPER, yTrainPER, XTestPER, yTest
                                           XTrainWIN, yTrainWIN, XTestWIN, yTest
    # Creating the model
```

```
model = z_model = iqr_model = per_model = win_model = input_model

# Fitting the model to the data
model.fit(XTrain, yTrain)
z_model.fit(XTrainZ, yTrainZ)
iqr_model.fit(XTrainIQR, yTrainIQR)
per_model.fit(XTrainPER, yTrainPER)
win_model.fit(XTrainWIN, yTrainWIN)

# Make predictions (assign class labels)
y_pred = model.predict(XTest)
y_predZ = z_model.predict(XTestZ)
y_predIQR = iqr_model.predict(XTestIQR)
y_predPER = per_model.predict(XTestPER)
y_predWIN = win_model.predict(XTestWIN)

# Dataframe for Scores
if model_name != 'Linear Regression' and model_name != 'K Neighbor Regressor
  df_scores = pd.DataFrame({'Score': ['Training Accuracy',
                                      'Test Accuracy',
                                      'R\u00b2',
                                      'Accuracy',
                                      'Weighted F1',
                                      'Weighted Precision',
                                      'Weighted Recall'],

                            'Train/Test': [model.score(XTrain, yTrain),
                                           model.score(XTest, yTest),
                                           r2_score(yTest, y_pred),
                                           accuracy_score(yTest, y_pred),
                                           f1_score(yTest, y_pred, average='
                                           precision_score(yTest, y_pred, av
                                           recall_score(yTest, y_pred, avera

                            'Z-Score': [z_model.score(XTrainZ, yTrainZ),
                                        z_model.score(XTestZ, yTestZ),
                                        r2_score(yTestZ, y_predZ),
                                        accuracy_score(yTestZ, y_predZ),
                                        f1_score(yTestZ, y_predZ, average='w
                                        precision_score(yTestZ, y_predZ, ave
                                        recall_score(yTestZ, y_predZ, averag

                            'IQR': [iqr_model.score(XTrainIQR, yTrainIQR),
                                    iqr_model.score(XTestIQR, yTestIQR),
                                    r2_score(yTestIQR, y_predIQR),
                                    accuracy_score(yTestIQR, y_predIQR),
                                    f1_score(yTestIQR, y_predIQR, average='w
                                    precision_score(yTestIQR, y_predIQR, ave
```

```
                                    recall_score(yTestIQR, y_predIQR, averag

                                'Percentile': [per_model.score(XTrainPER, yTrain
                                               per_model.score(XTestPER, yTestPE
                                               r2_score(yTestPER, y_predPER),
                                               accuracy_score(yTestPER, y_predPE
                                               f1_score(yTestPER, y_predPER, ave
                                               precision_score(yTestPER, y_predP
                                               recall_score(yTestPER, y_predPER,

                                'Winsorization': [win_model.score(XTrainWIN, yTr
                                                  win_model.score(XTestWIN, yTes
                                                  r2_score(yTestWIN, y_predWIN),
                                                  accuracy_score(yTestWIN, y_pre
                                                  f1_score(yTestWIN, y_predWIN,
                                                  precision_score(yTestWIN, y_pr
                                                  recall_score(yTestWIN, y_predW
    else:
      df_scores = pd.DataFrame({'Score': ['Training Accuracy',
                                         'Test Accuracy',
                                         'R\u00b2'],

                                'Train/Test': [model.score(XTrain, yTrain),
                                               model.score(XTest, yTest),
                                               r2_score(yTest, y_pred)],

                                'Z-Score': [z_model.score(XTrainZ, yTrainZ),
                                            z_model.score(XTestZ, yTestZ),
                                            r2_score(yTestZ, y_predZ)],

                                'IQR': [iqr_model.score(XTrainIQR, yTrainIQR),
                                        iqr_model.score(XTestIQR, yTestIQR),
                                        r2_score(yTestIQR, y_predIQR)],

                                'Percentile': [per_model.score(XTrainPER, yTrain
                                               per_model.score(XTestPER, yTestPE
                                               r2_score(yTestPER, y_predPER)],

                                'Winsorization': [win_model.score(XTrainWIN, yTr
                                                  win_model.score(XTestWIN, yTes
                                                  r2_score(yTestWIN, y_predWIN)]

    return df_scores
```

K Classifier Plot

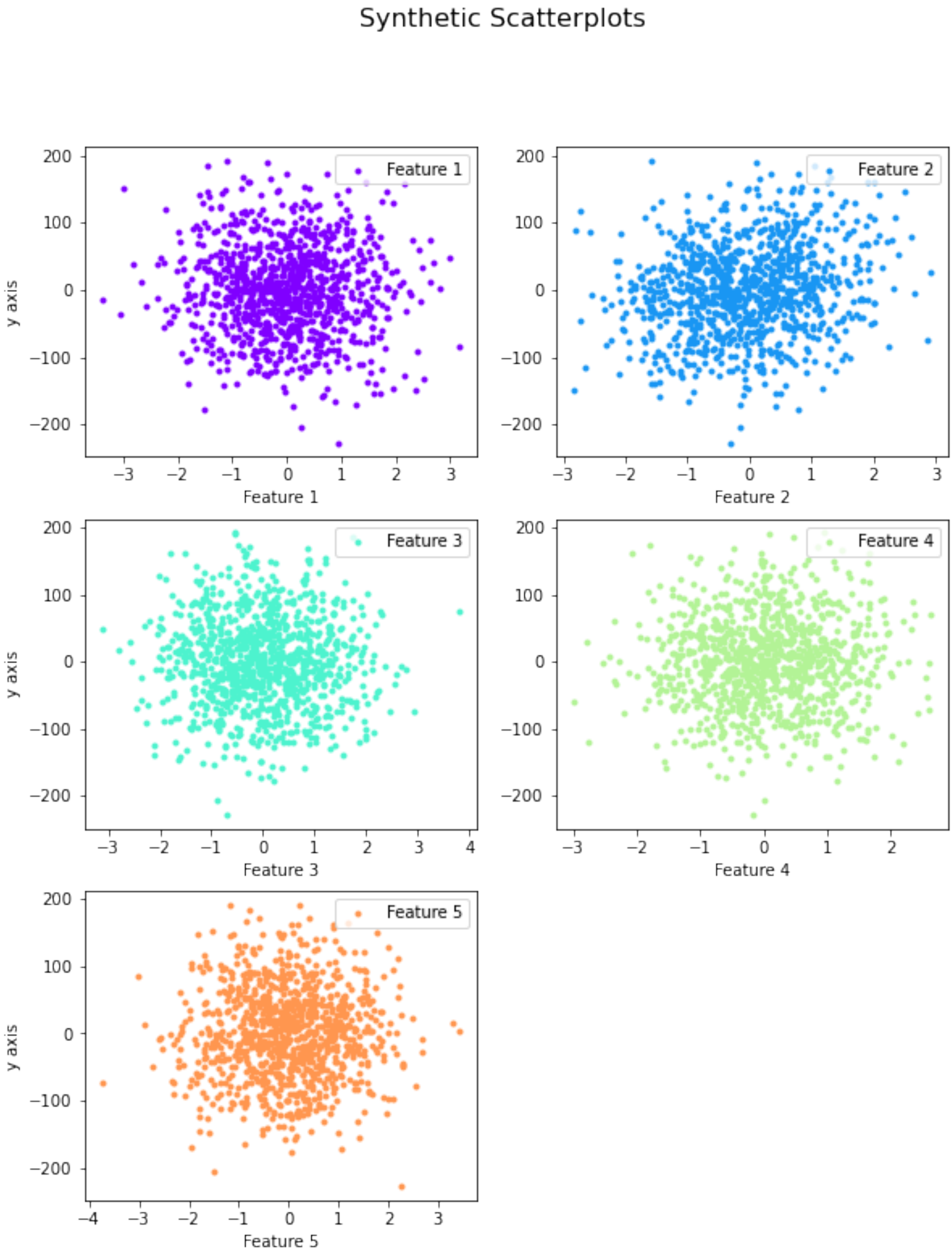
```
def kClassPlot(XTrain, yTrain, XTest, yTest,
               XTrainZ, yTrainZ, XTestZ, yTestZ,
               XTrainIQR, yTrainIQR, XTestIQR, yTestIQR,
               XTrainPER, yTrainPER, XTestPER, yTestPER,
               XTrainWIN, yTrainWIN, XTestWIN, yTestWIN):

    techniqueName = ['Train/Test','Z-Score','IQR','Percentile','Winsorization']
    techniqueName = [i + " # of neighbors" for i in techniqueName]

    XTrainArray = [XTrain,XTrainZ,XTrainIQR,XTrainPER,XTrainWIN]
    XTestArray = [XTest,XTestZ,XTestIQR,XTestPER,XTestWIN]
    yTrainArray = [yTrain,yTrainZ,yTrainIQR,yTrainPER,yTrainWIN]
    yTestArray = [yTest,yTestZ,yTestIQR,yTestPER,yTestWIN]

    colors = iter(cm.rainbow(np.linspace(0, 1, 10))) # For the color of the each
    f, ax = plt.subplots(3, 2, figsize=(12*SPLOTSCALE, 15*SPLOTSCALE))
    f.suptitle('K Classification Plots', fontsize=16), f.delaxes(ax[2,1]) # Remo

    a=[0,0,1,1,2,2] # For the 'y' positions
    b=[0,1,0,1,0,1] # For the 'x' positions

    for i in range(5):
        plt.sca(ax[a[i], b[i]])
        training_accuracy = []
        test_accuracy = []
        # try n_neighbors from 1 to 10
        neighbors_settings = range(1, 11)

        for n_neighbors in neighbors_settings:
            # build the model
            knn = KNeighborsClassifier(n_neighbors=n_neighbors)
            knn.fit(XTrainArray[i], yTrainArray[i])
            # record training set accuracy
            training_accuracy.append(knn.score(XTrainArray[i], yTrainArray[i]))
            # record test set accuracy
            test_accuracy.append(knn.score(XTestArray[i], yTestArray[i]))
        plt.plot(neighbors_settings, training_accuracy, label="Training accuracy
        plt.plot(neighbors_settings, test_accuracy, label="Test accuracy", color
        plt.ylabel("Accuracy"), plt.xlabel(techniqueName[i])
        plt.legend()
```

Dataset 1: Synthetic

1.1 Creating the Dataset & Detecting NANs

```
n_samples = 1000
X, y = make_regression(n_samples=n_samples,
                       n_features=5,
                       n_informative=1,
                       noise=65,
                       random_state=0)

# Checking for NANs
print('Data has NANs:', np.isnan(np.sum(X)))

# Plotting
scatterPlot('Synthetic Scatterplots','s')
```

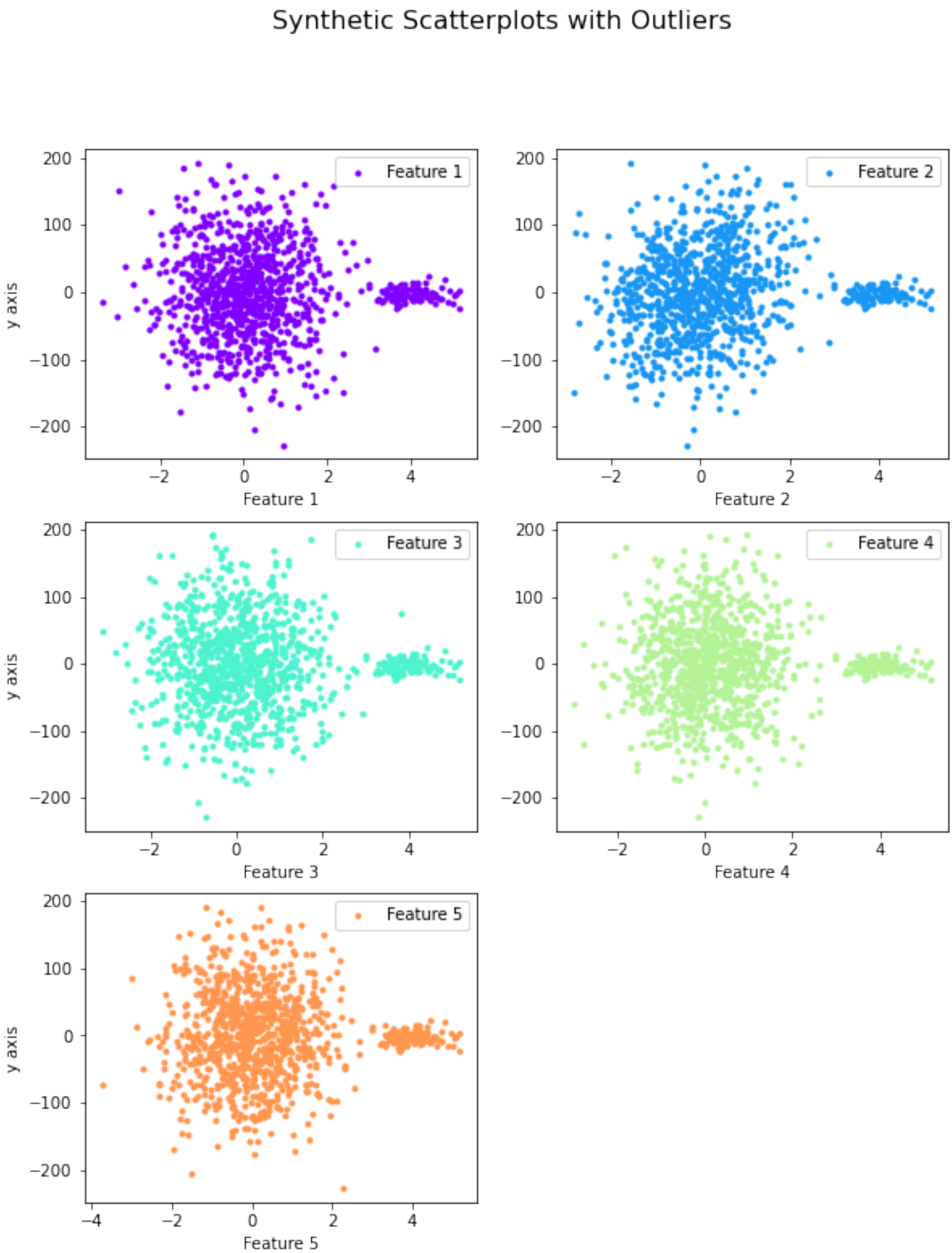
```
Data has NANs: False
```



1.2 Adding Outliers

```
n_outliers = int(np.round(n_samples*0.1))
```

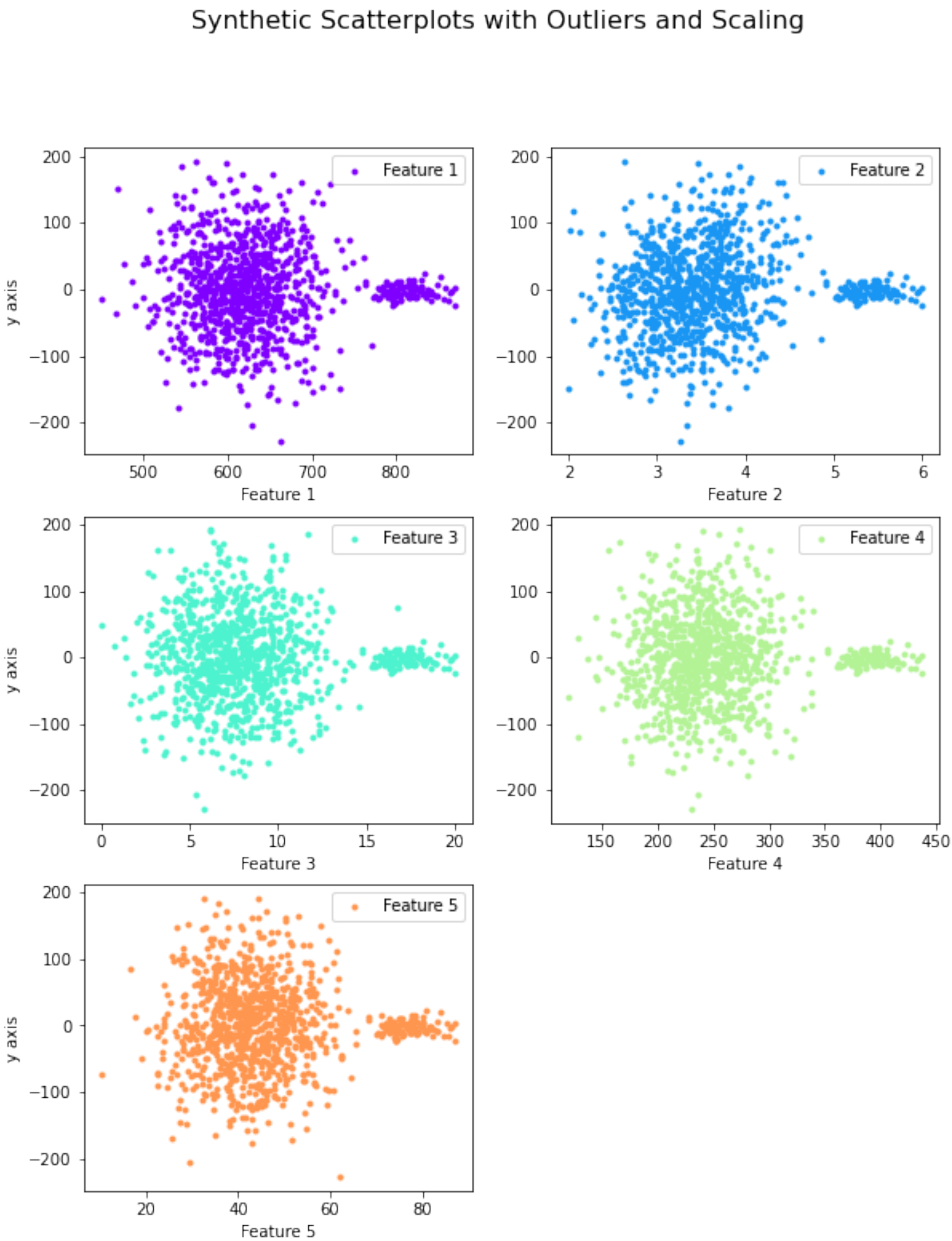
```
n_outliers = int(np.round(n_samples*0.1))
th = 4
X[:n_outliers] = th + 0.5 * np.random.normal(size=(n_outliers, 1))
y[:n_outliers] = -th + 10 * np.random.normal(size=n_outliers)


# Plotting
scatterPlot('Synthetic Scatterplots with Outliers','s')
```



1.3 Scaling the Data

```
# Scale Feature 1: 450-870 (float)
```

```
f1_l, f1_u = float(450), float(870)
X[:,0] = np.interp(X[:,0], (X[:,0].min(), X[:,0].max()), (f1_l, f1_u))

# Scale Feature 2: 2-6 (integer)
f2_l, f2_u = 2, 6
X[:,1] = np.interp(X[:,1], (X[:,1].min(), X[:,1].max()), (f2_l, f2_u))

# Scale Feature 3: 0-20 (integer)
f3_l, f3_u = 0, 20
X[:,2] = np.interp(X[:,2], (X[:,2].min(), X[:,2].max()), (f3_l, f3_u))

# Scale Feature 4: 120.56-436.92 (float)
f4_l, f4_u = float(120.56), float(436.92)
X[:,3] = np.interp(X[:,3], (X[:,3].min(), X[:,3].max()), (f4_l, f4_u))

# Scale Feature 5: 10.22-87.15 (float)
f5_l, f5_u = float(10.22), float(87.15)
X[:,4] = np.interp(X[:,4], (X[:,4].min(), X[:,4].max()), (f5_l, f5_u))

# Scale Output Var: 150000-2000000 (integer)
# Not sure about this??


# Plotting
scatterPlot('Synthetic Scatterplots with Outliers and Scaling','s')
```

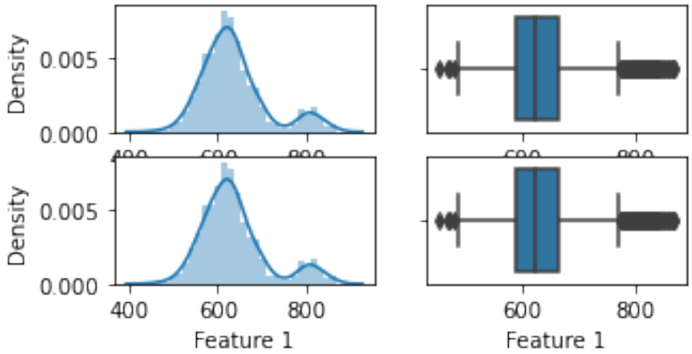


1.4 Detect and Remove Outliers

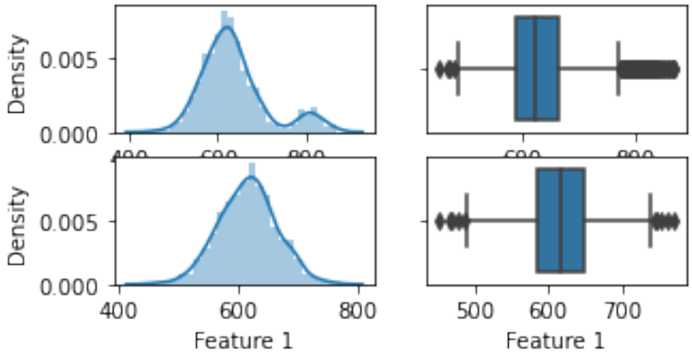
```
# Converting y to multiclass (5 classes)
```

```
c1, c2, c3, c4 = np.percentile(y, [20, 40, 60, 80])
pos = 0
for i in y:
    if i < c1:
        y[pos] = 0
    elif i < c2:
        y[pos] = 1
    elif i < c3:
        y[pos] = 2
    elif i < c4:
        y[pos] = 3
    else:
        y[pos] = 4
    pos+=1

# Convert to DataFrame
df = pd.DataFrame({'Feature 1': X[:,0].flatten(),
                   'Feature 2': X[:,1].flatten(),
                   'Feature 3': X[:,2].flatten(),
                   'Feature 4': X[:,3].flatten(),
                   'Feature 5': X[:,4].flatten(),
                   'y': y})

# Initializing dfs
df_z = df_iqr = df_per = df_win = df.copy()
for i in range(0,5):
    df_z,df_iqr,df_per,df_win = outliers(df.columns[i], df, df_z,df_iqr,df_per,d

# Plotting One Feature
DFLIST = [df_z,df_iqr,df_per,df_win]
DFNAMES = ['Z-Score','IQR Based Filtering','Percentile','Winsorization']
feature = 'Feature 1'
for i,name in zip(DFLIST, DFNAMES):
    if name == 'Percentile':
        comparePlot(df,i,feature,name,type1='trimming')
    else:
        comparePlot(df,i,feature,name)

# Converting to numpy
df_z = df_z.to_numpy()
df_iqr = df_iqr.to_numpy()
df_per = df_per.to_numpy()
df_win = df_win.to_numpy()
```

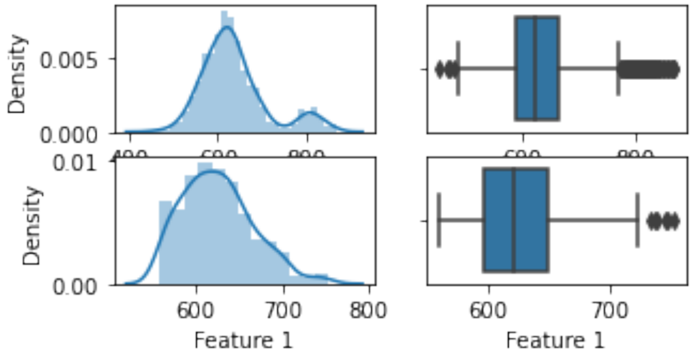
```
Z-Score: Comparing the distribution of Feature 1 after capping
```



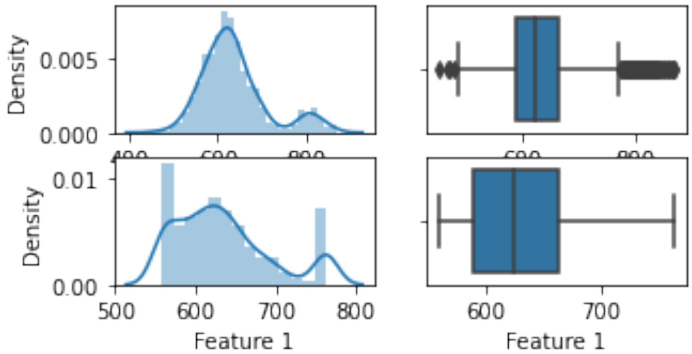

```
IQR Based Filtering: Comparing the distribution of Feature 1 after capping
```




```
Percentile: Comparing the distribution of Feature 1 after trimming
```




```
Winsorization: Comparing the distribution of Feature 1 after capping
```



1.5 Apply sampling strategies

```
# Training: 70%, Test 30%
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, shuffle
XTrainZ, XTestZ, yTrainZ,  yTestZ = train_test_split(df_z[:,0:5], df_z[:,-1], te
XTrainIQR, XTestIQR, yTrainIQR, yTestIQR = train_test_split(df_iqr[:,0:5], df_iq
XTrainPER, XTestPER, yTrainPER, yTestPER = train_test_split(df_per[:,0:5], df_pe
XTrainWIN, XTestWIN, yTrainWIN, yTestWIN = train_test_split(df_win[:,0:5], df_wi
```

1.6 Models

```
for name,model in zip(NAMES, MODELS):
  print(name)
  display(print_results(model, name, X_train, y_train, X_test, y_test,
                                     XTrainZ, yTrainZ, XTestZ, yTestZ,
                                     XTrainIQR, yTrainIQR, XTestIQR, yTestIQR,
                                     XTrainPER, yTrainPER, XTestPER, yTestPER,
                                     XTrainWIN, yTrainWIN, XTestWIN, yTestWIN))
  print('\n')

kClassPlot(X_train, y_train, X_test, y_test,
           XTrainZ, yTrainZ, XTestZ, yTestZ,
           XTrainIQR, yTrainIQR, XTestIQR, yTestIQR,
           XTrainPER, yTrainPER, XTestPER, yTestPER,
           XTrainWIN, yTrainWIN, XTestWIN, yTestWIN)
```

Linear Regression

	Score	Train/Test	Z-Score	IQR	Percentile	Winsorization
0	Training Accuracy	0.01	0.01	0.02	0.03	0.04
1	Test Accuracy	-0.06	-0.06	0.03	0.02	-0.02
2	R^2	-0.06	-0.06	0.03	0.02	-0.02

Logistic Regression

	Score	Train/Test	Z-Score	IQR	Percentile	Winsorization
0	Training Accuracy	0.32	0.32	0.24	0.24	0.31
1	Test Accuracy	0.27	0.27	0.28	0.26	0.26
2	R^2	-1.03	-1.03	-0.80	-0.83	-1.09
3	Accuracy	0.27	0.27	0.28	0.26	0.26
4	Weighted F1	0.25	0.25	0.27	0.24	0.24
5	Weighted Precision	0.27	0.27	0.28	0.29	0.25

6	Weighted Recall	0.27	0.27	0.28	0.26	0.26

XGBoost Regressor

	Score	Train/Test	Z-Score	IQR	Percentile	Winsorization
0	Training Accuracy	0.98	0.98	0.75	0.75	0.98
1	Test Accuracy	0.25	0.25	0.78	0.79	0.25
2	R^2	-0.95	-0.95	0.49	0.42	-0.95
3	Accuracy	0.25	0.25	0.78	0.79	0.25
4	Weighted F1	0.25	0.25	0.78	0.79	0.25
5	Weighted Precision	0.25	0.25	0.78	0.79	0.25
6	Weighted Recall	0.25	0.25	0.78	0.79	0.25

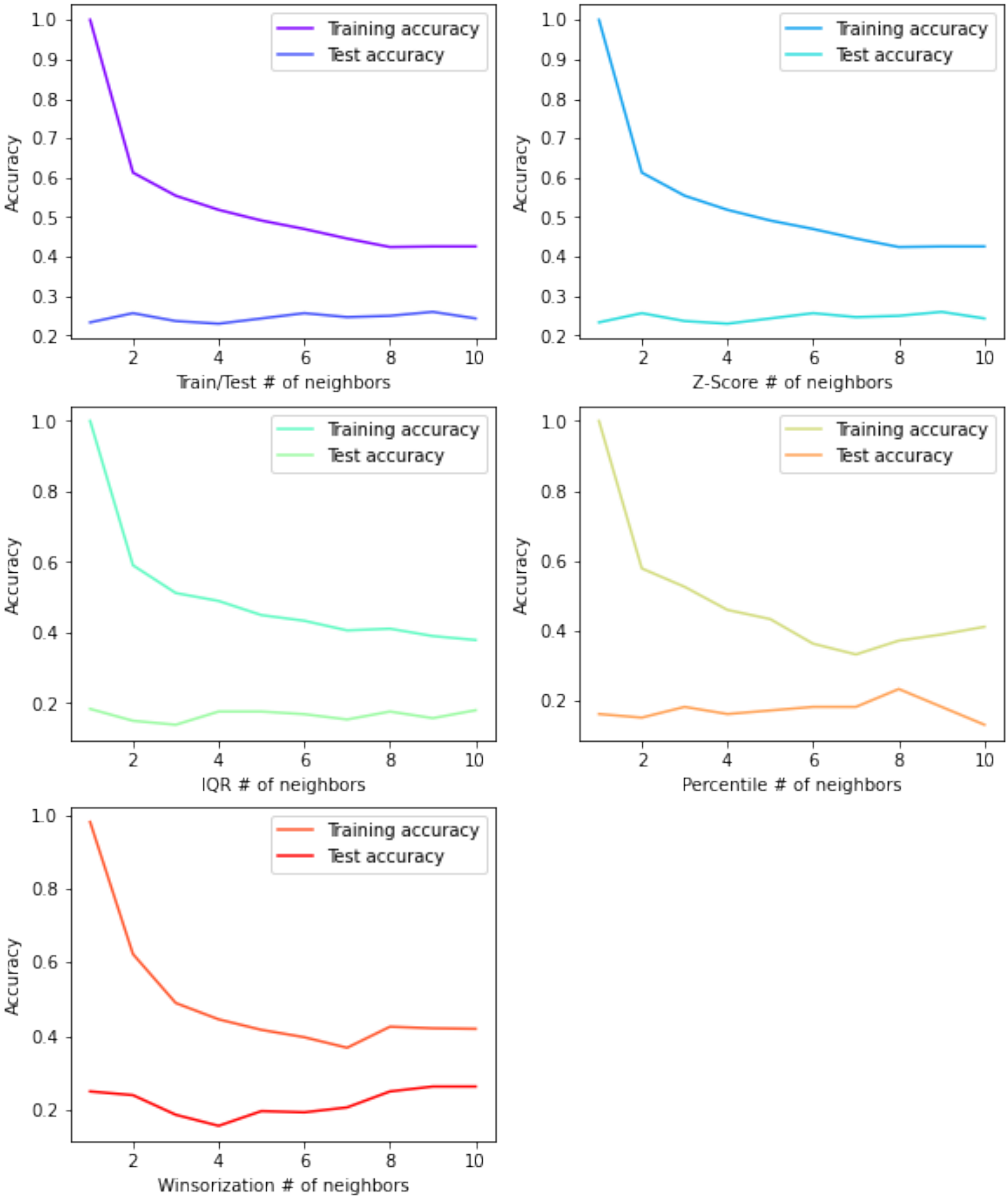
K Neighbor Regressor

	Score	Train/Test	Z-Score	IQR	Percentile	Winsorization
0	Training Accuracy	0.28	0.28	0.09	0.10	0.31
1	Test Accuracy	-0.37	-0.37	0.03	0.35	-0.36
2	R^2	-0.37	-0.37	0.03	0.35	-0.36

K Neighbor Classifier

	Score	Train/Test	Z-Score	IQR	Percentile	Winsorization
0	Training Accuracy	0.61	0.61	0.48	0.45	0.62
1	Test Accuracy	0.25	0.25	0.45	0.52	0.24
2	R^2	-1.04	-1.04	-0.64	-0.19	-1.03
3	Accuracy	0.25	0.25	0.45	0.52	0.24
4	Weighted F1	0.22	0.22	0.42	0.49	0.22
5	Weighted Precision	0.23	0.23	0.54	0.63	0.23
6	Weighted Recall	0.25	0.25	0.45	0.52	0.24

K Classification Plots



Dataset 2: California Housing

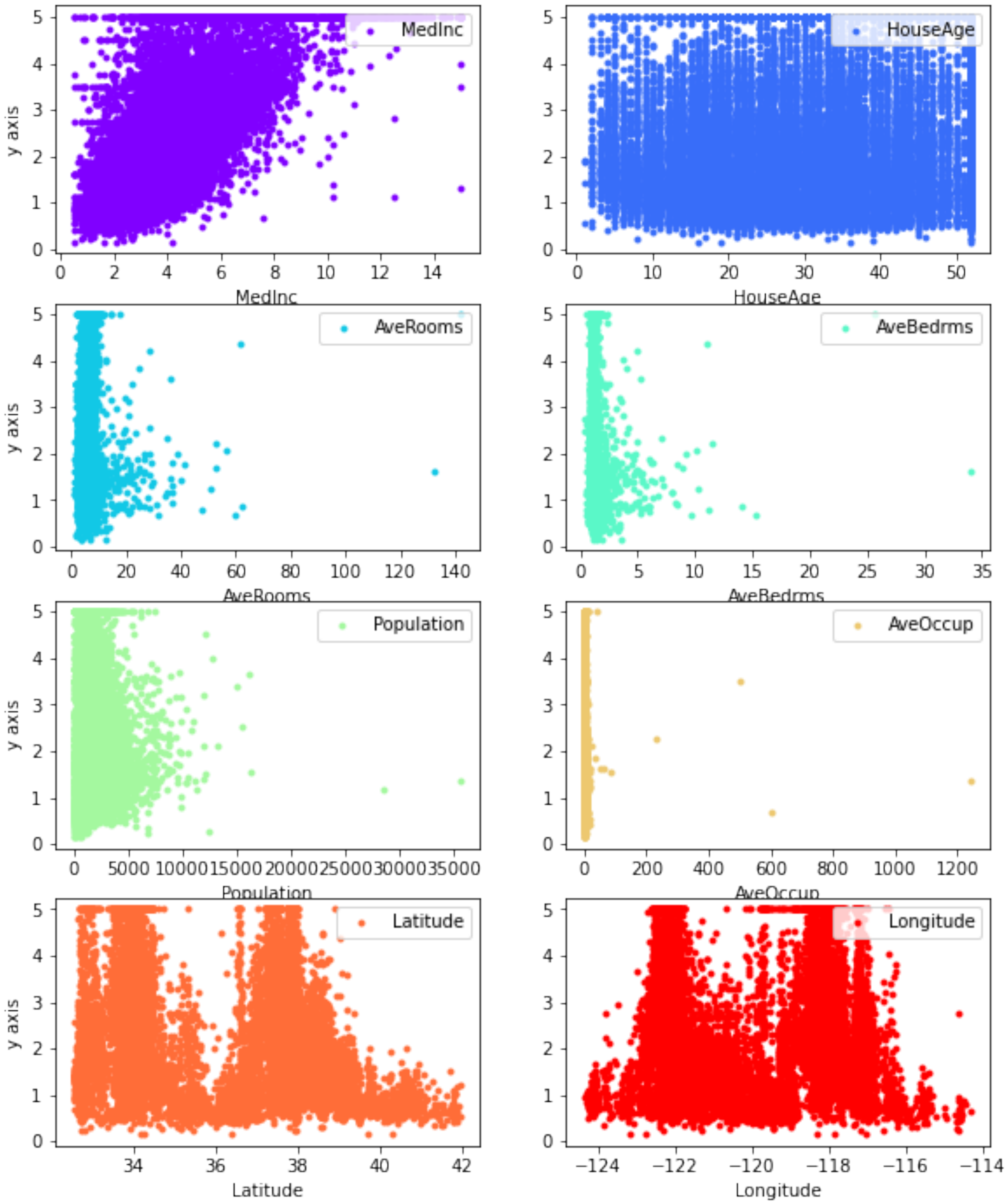
2.1 Loading the Dataset & Detecting NANs

```
housing = fetch_california_housing()
```

```
X = housing.data
y = housing.target
scatterPlot('Housing Scatterplots')

# Checking for NANs
print('Data has NANs:', pd.isna(housing))
```

```
Data has NANs: False
```

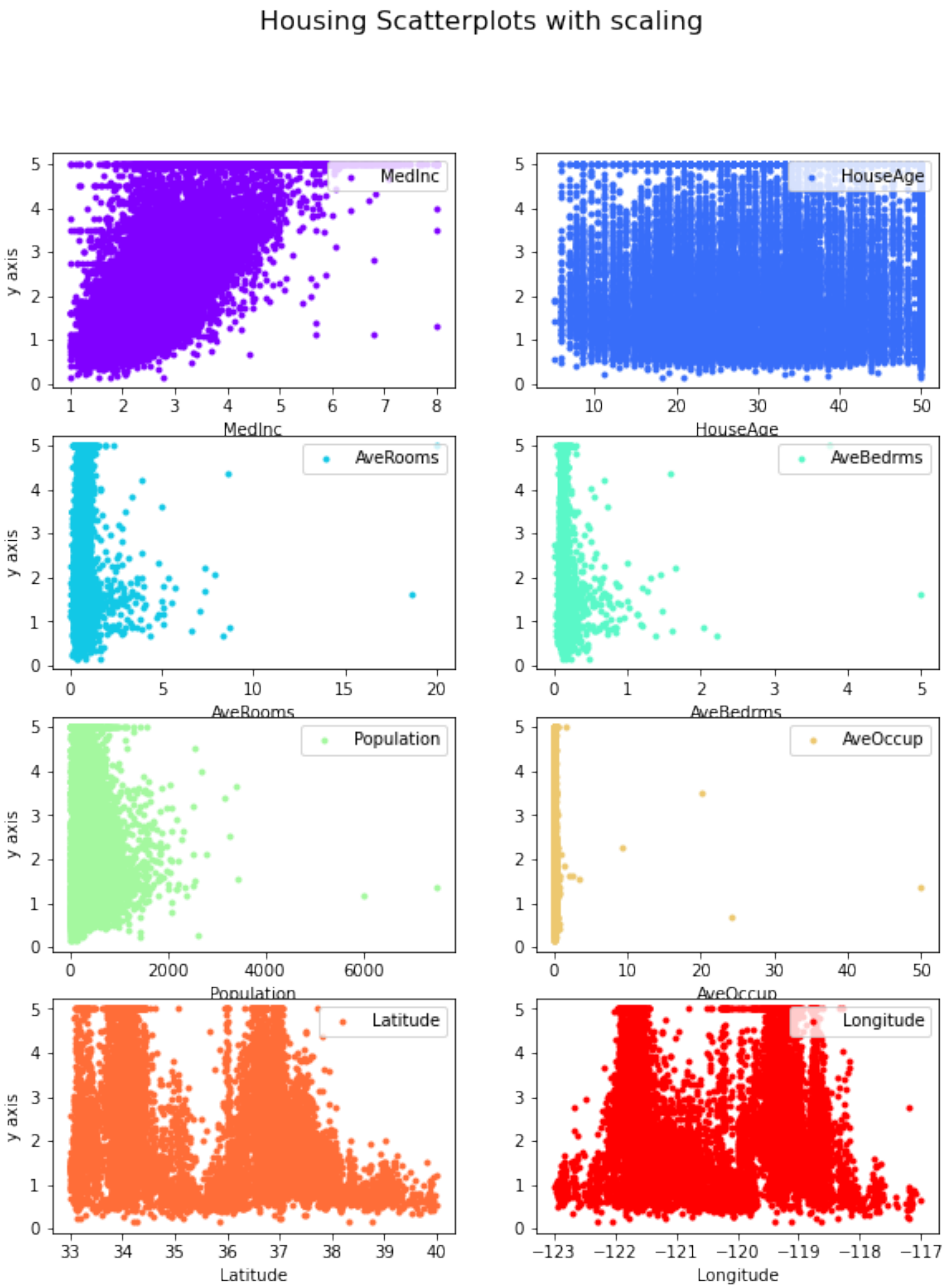
Housing Scatterplots



2.2 Scaling the data

```
# Scale MedInc: 1-8 (float)
```

```
# Scale MedInc: 1-8 (float)
f1_l, f1_u = float(1), float(8)
X[:,0] = np.interp(X[:,0], (X[:,0].min(), X[:,0].max()), (f1_l, f1_u))

# Scale HouseAge: 5-50 (integer)
f2_l, f2_u = 5, 50
X[:,1] = np.interp(X[:,1], (X[:,1].min(), X[:,1].max()), (f2_l, f2_u))

# Scale AveRooms: 0-20 (integer)
f3_l, f3_u = 0, 20
X[:,2] = np.interp(X[:,2], (X[:,2].min(), X[:,2].max()), (f3_l, f3_u))

# Scale AveBedrms: 0-5 (float)
f4_l, f4_u = float(0), float(5)
X[:,3] = np.interp(X[:,3], (X[:,3].min(), X[:,3].max()), (f4_l, f4_u))

# Scale Population: 0-7500 (float)
f5_l, f5_u = float(0), float(7500)
X[:,4] = np.interp(X[:,4], (X[:,4].min(), X[:,4].max()), (f5_l, f5_u))

# Scale AveOccup: 0-50 (float)
f6_l, f6_u = float(0), float(50)
X[:,5] = np.interp(X[:,5], (X[:,5].min(), X[:,5].max()), (f6_l, f6_u))

# Scale Lattitude: 33-40 (float)
f7_l, f7_u = float(33), float(40)
X[:,6] = np.interp(X[:,6], (X[:,6].min(), X[:,6].max()), (f7_l, f7_u))

# Scale Longitude: -123-(-117) (float)
f8_l, f8_u = float(-123), float(-117)
X[:,7] = np.interp(X[:,7], (X[:,7].min(), X[:,7].max()), (f8_l, f8_u))

scatterPlot('Housing Scatterplots with scaling')
```

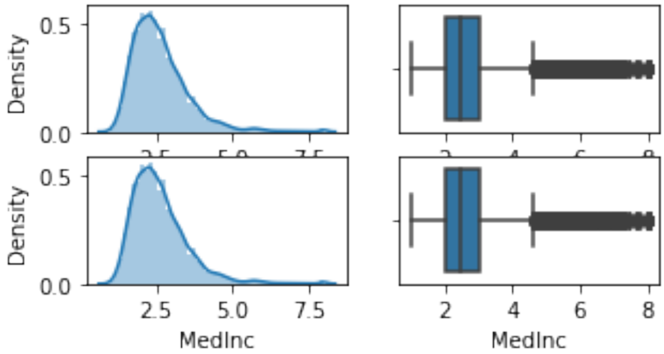


2.3 Detect and Remove Outliers

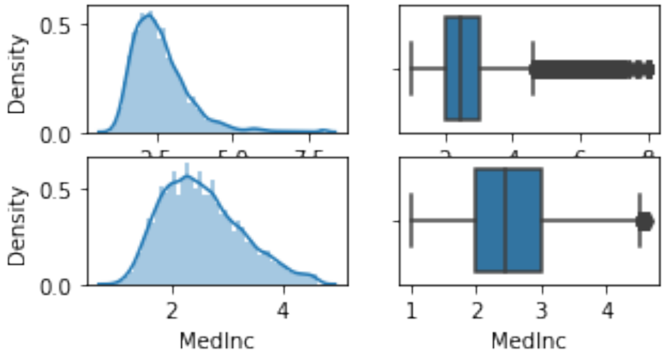
```
# Converting y to multiclass (5 classes)
```

```
c1, c2, c3, c4 = np.percentile(y, [20, 40, 60, 80])
pos = 0
for i in y:
    if i < c1:
        y[pos] = 0
    elif i < c2:
        y[pos] = 1
    elif i < c3:
        y[pos] = 2
    elif i < c4:
        y[pos] = 3
    else:
        y[pos] = 4
    pos+=1


# Convert to DataFrame
df = pd.DataFrame({housing.feature_names[0]: X[:,0].flatten(),
                   housing.feature_names[1]: X[:,1].flatten(),
                   housing.feature_names[2]: X[:,2].flatten(),
                   housing.feature_names[3]: X[:,3].flatten(),
                   housing.feature_names[4]: X[:,4].flatten(),
                   housing.feature_names[5]: X[:,5].flatten(),
                   housing.feature_names[6]: X[:,6].flatten(),
                   housing.feature_names[7]: X[:,7].flatten(),
                   'y': y})

# Initializing dfs
df_z = df_iqr = df_per = df_win = df.copy()
for i in range(0,8):
    df_z,df_iqr,df_per,df_win = outliers(df.columns[i], df, df_z,df_iqr,df_per,d

# Plotting One Feature
DFLIST = [df_z,df_iqr,df_per,df_win]
DFNAMES = ['Z-Score','IQR Based Filtering','Percentile','Winsorization']
feature = housing.feature_names[0]
for i,name in zip(DFLIST, DFNAMES):
    if name == 'Percentile':
        comparePlot(df,i,feature,name,type1='trimming')
    else:
        comparePlot(df,i,feature,name)

# Converting to numpy
df_z = df_z.to_numpy()
df_iqr = df_iqr.to_numpy()
df_per = df_per.to_numpy()
df_win = df_win.to_numpy()
```

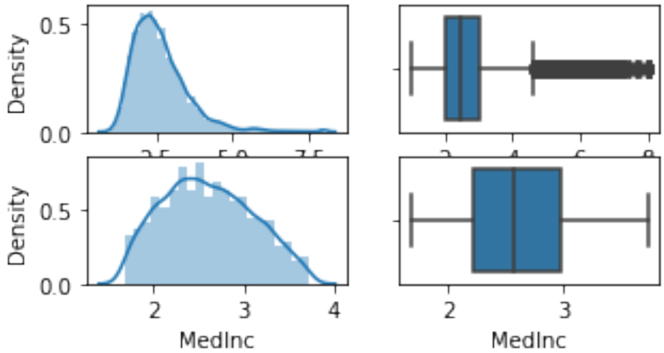
```
Z-Score: Comparing the distribution of MedInc after capping
```



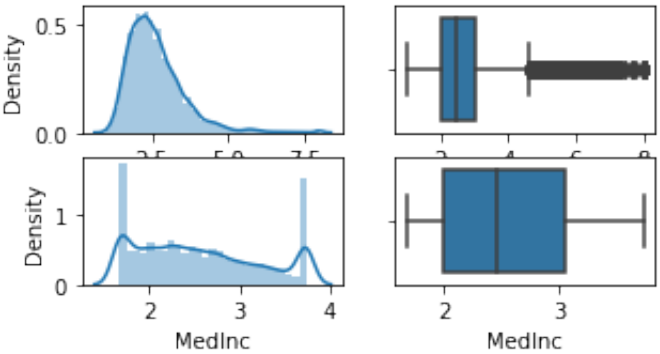

```
IQR Based Filtering: Comparing the distribution of MedInc after capping
```




```
Percentile: Comparing the distribution of MedInc after trimming
```




```
Winsorization: Comparing the distribution of MedInc after capping
```



2.4 Apply sampling strategies

```
# Training: 70%, Test 30%
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, shuffle
XTrainZ, XTestZ, yTrainZ,  yTestZ = train_test_split(df_z[:,0:8], df_z[:,-1], te
XTrainIQR, XTestIQR, yTrainIQR, yTestIQR = train_test_split(df_iqr[:,0:8], df_iq
XTrainPER, XTestPER, yTrainPER, yTestPER = train_test_split(df_per[:,0:8], df_pe
XTrainWIN, XTestWIN, yTrainWIN, yTestWIN = train_test_split(df_win[:,0:8], df_wi
```

2.5 Models

```
for name,model in zip(NAMES, MODELS):
  print(name)
  display(print_results(model, name, X_train, y_train, X_test, y_test,
                                    XTrainZ, yTrainZ, XTestZ, yTestZ,
                                    XTrainIQR, yTrainIQR, XTestIQR, yTestIQR,
                                    XTrainPER, yTrainPER, XTestPER, yTestPER,
                                    XTrainWIN, yTrainWIN, XTestWIN, yTestWIN))
  print('\n')

kClassPlot(X_train, y_train, X_test, y_test,
          XTrainZ, yTrainZ, XTestZ, yTestZ,
          XTrainIQR, yTrainIQR, XTestIQR, yTestIQR,
          XTrainPER, yTrainPER, XTestPER, yTestPER,
          XTrainWIN, yTrainWIN, XTestWIN, yTestWIN)
```

Linear Regression

	Score	Train/Test	Z-Score	IQR	Percentile	Winsorization
0	Training Accuracy	-7.38	-7.38	0.64	0.63	0.64
1	Test Accuracy	-40.56	-40.56	0.63	0.63	0.64
2	R^2	-40.56	-40.56	0.63	0.63	0.64

Logistic Regression

	Score	Train/Test	Z-Score	IQR	Percentile	Winsorization
0	Training Accuracy	0.47	0.47	0.45	0.41	0.46
1	Test Accuracy	0.47	0.47	0.45	0.41	0.46
2	R^2	0.34	0.34	0.29	0.23	0.31
3	Accuracy	0.47	0.47	0.45	0.41	0.46
4	Weighted F1	0.44	0.44	0.41	0.38	0.43
5	Weighted Precision	0.44	0.44	0.42	0.42	0.43

6	Weighted Recall	0.47	0.47	0.45	0.41	0.46

```
XGBoost Regressor
```

	Score	Train/Test	Z-Score	IQR	Percentile	Winsorization
0	Training Accuracy	0.94	0.94	0.86	0.87	0.94
1	Test Accuracy	0.67	0.67	0.86	0.86	0.67
2	R^2	0.73	0.73	0.88	0.89	0.73
3	Accuracy	0.67	0.67	0.86	0.86	0.67
4	Weighted F1	0.67	0.67	0.86	0.86	0.67
5	Weighted Precision	0.67	0.67	0.86	0.86	0.67
6	Weighted Recall	0.67	0.67	0.86	0.86	0.67

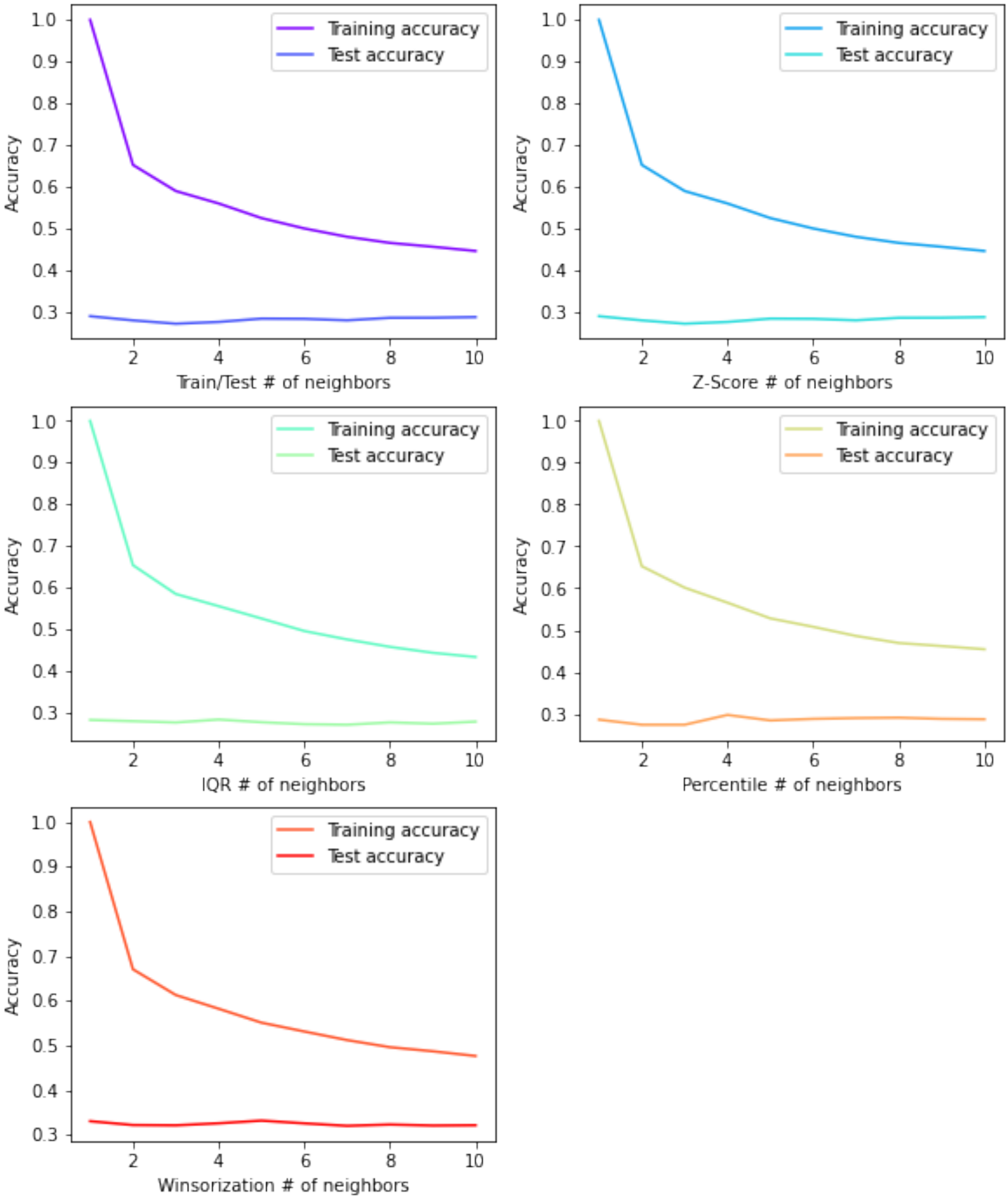
```
K Neighbor Regressor
```

	Score	Train/Test	Z-Score	IQR	Percentile	Winsorization
0	Training Accuracy	0.63	0.63	0.46	0.38	0.62
1	Test Accuracy	0.22	0.22	0.48	0.36	0.19
2	R^2	0.22	0.22	0.48	0.36	0.19

```
K Neighbor Classifier
```

	Score	Train/Test	Z-Score	IQR	Percentile	Winsorization
0	Training Accuracy	0.68	0.68	0.56	0.52	0.67
1	Test Accuracy	0.33	0.33	0.56	0.50	0.32
2	R^2	-0.13	-0.13	0.27	-0.00	-0.17
3	Accuracy	0.33	0.33	0.56	0.50	0.32
4	Weighted F1	0.32	0.32	0.54	0.49	0.31
5	Weighted Precision	0.37	0.37	0.60	0.57	0.36
6	Weighted Recall	0.33	0.33	0.56	0.50	0.32

K Classification Plots


Training accuracy
Test accuracy
Accuracy
Train/Test # of neighbors
Z-Score # of neighbors
IQR # of neighbors
Percentile # of neighbors
Winsorization # of neighbors

Summary