M6-L1-P2

October 16, 2023

1 Problem 2 (6 Points)

In this problem you'll learn how to make a 'pipeline' in SciKit-Learn. A pipeline chains together multiple sklearn modules and runs them in series. For example, you can create a pipeline to perform feature scaling and then regression. For more information see https://machinelearningmastery.com/standardscaler-and-minmaxscaler-transforms-in-python/

First, run the cell below to import modules and load data. Note the data axis scaling.

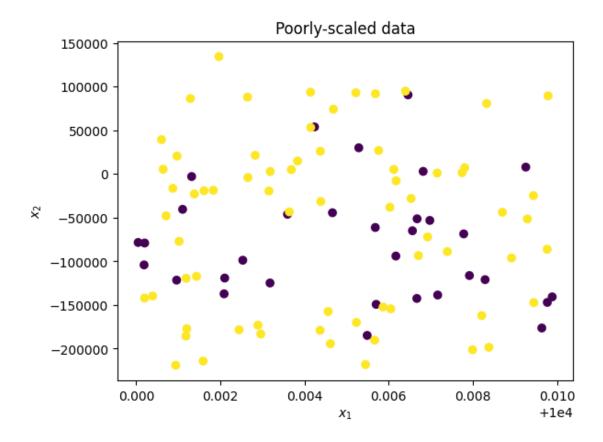
```
[]: import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
```

```
x1 = np.array([10000.00548814, 10000.00715189, 10000.00602763, 10000.00544883]
 410000.00423655, 10000.00645894, 10000.00437587, 10000.00891773, 10000.
 400963663, 10000.00383442, 10000.00791725, 10000.00528895, 10000.00568045, I
 410000.00925597, 10000.00071036, 10000.00087129, 10000.00020218, 10000.
 40083262 , 10000.00778157, 10000.00870012, 10000.00978618, 10000.00799159, L
 →10000.00461479, 10000.00780529, 10000.00118274, 10000.00639921, 10000.
 400143353, 10000.00944669, 10000.00521848, 10000.00414662, 10000.00264556, I
 →10000.00774234, 10000.0045615 , 10000.00568434, 10000.0001879 , 10000.
 400617635, 10000.00612096, 10000.00616934, 10000.00943748, 10000.0068182
 410000.00359508, 10000.00437032, 10000.00697631, 10000.00060225, 10000.
 400666767, 10000.00670638, 10000.00210383, 10000.00128926, 10000.00315428, I
 410000.00363711, 10000.00570197, 10000.00438602, 10000.00988374, 10000.
 →00102045, 10000.00208877, 10000.0016131 , 10000.00653108, 10000.00253292, □
 410000.00466311, 10000.00244426, 10000.0015897, 10000.00110375, 10000.
 40065633 , 10000.00138183 , 10000.00196582 , 10000.00368725 , 10000.00820993 , I
 410000.00097101, 10000.00837945, 10000.00096098, 10000.00976459, 10000.
 400468651, 10000.00976761, 10000.00604846, 10000.00739264, 10000.00039188, L
 →10000.00282807, 10000.00120197, 10000.0029614, 10000.00118728, 10000.
 400317983, 10000.00414263, 10000.00064147, 10000.00692472, 10000.00566601, I
 410000.00265389, 10000.00523248, 10000.00093941, 10000.00575946, 10000.
 →00929296, 10000.00318569, 10000.0066741 , 10000.00131798, 10000.00716327, ⊔
 410000.00289406, 10000.00183191, 10000.00586513, 10000.00020108, 10000.
 →0082894 , 10000.00004695])
```

```
x2 = np.array([-184863.4856705, 1074.38382588, -38090.38042426, -218261.
 ⇒93176495, 53942.6974416,
                              90630.02584275, 26090.16140437, -96193.
 423522311, -176367.73593595, 14900.6554238, -116285.92522759, 30020.
 →05633442, -61255.25197308, 7897.51328353, -47927.0242543, -16408.
 41486272, -79054.99813513, 80728.34445153, -68577.91165667, -43820.
 △95728998, 89483.56273506, -201298.31550282, -194343.64986372,
 470373422, -185581.10646027, 94925.90670844, -117225.70826838, -147270.
 →93302967, 93064.78238323, 53246.3312291, 88080.30643839,
 ↔01924478, -157510.31165492, 91905.84577891, -104120.30338562,
 492437832, 5252.67709964, -93950.90837818, -24732.85666885, 2998.60044099, II
                                                    39374.73070183...
 →-46121.70219599, -178946.07115258, -53158.56432145,
 ¬-142511.10737582, -93467.10862949, -119163.81965495, 86433.73556314, ц
 ¬-19493.47186888, -43328.4347383 , -149292.44670008, -31467.57278374, ц
 ¬-140689.93945916, -77135.24975531, -137226.1470541 , -19121.00345482, ц
 →-28106.82650466, -98746.88800202, -44359.39586045, -178375.53578575, I
 →-214213.1833435 , -40454.74688619, -64999.38541647, -22847.17067971, ⊔
                    5003.15382914, -162154.00028997, 20531.46592863,
 →134483.02973775,
 →-198431.66694604, -121542.61443332, -86141.74447922,
                                                      74200.84494844,
 →-147027.93398436, -154379.46847931, -88860.72719829, -139713.04577259, ⊔
 421397.23298959, -177193.83575271, -183272.178717 , -119403.804027 , L
 →-124822.92056231, 93657.88484353, 5447.87262332, -72120.38827533, ⊔
4-190289.19669472, -4007.33212386, -170019.38126506, -219029.39870999, III
 →26922.68131171, -51475.16492676, 2877.29414027, -51314.51123513, -2885.
424492876, -138592.30339701, -173081.8557606, -18656.49335465, -152306.
→86977565, -142059.47999752, -120997.92531656, -78426.87568774])
X = np.vstack([x1,x2]).T
y = np.array([0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1]
 \hookrightarrow 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, _{\perp}
↔0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, ⊔
41, 0, 0]
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0,_

strain size=0.8)

plt.figure()
plt.scatter(x1,x2,c=y,cmap="viridis")
plt.xlabel("$x 1$")
plt.ylabel("$x 2$")
plt.title("Poorly-scaled data")
plt.show()
```



1.1 Creating a pipeline

In this section, code to set up a pipeline has been given. Make note of how each step works: 1. Create a scaler and classifier 2. Put the scaler and classifier into a new pipeline 3. Fit the pipeline to the training data 4. Make predictions with the pipeline

Training accuracy: 0.825 Testing accuracy: 0.6

1.2 Testing several pipelines

Now, complete the code to create a new pipeline for every combination of scalers and models below:

Scalers: - None - MinMax - Standard

Classifiers: - Logistic Regression - Support Vector Machine - KNN Classifier, 1 neighbor

Within the loop, a scaler and model are created. You will create a pipeline, fit it to the training data, and make predictions on testing and training data.

```
[]: def get_scaler(i):
         if i == 0:
             return ("No Scaler", None)
         elif i == 1:
             return ("MinMax Scaler", MinMaxScaler())
         elif i == 2:
             return ("Standard Scaler", StandardScaler())
     def get_model(i):
         if i == 0:
             return ("Logistic Regression", LogisticRegression())
         elif i == 1:
             return ("Support Vector Classifier", SVC())
         elif i == 2:
             return ("1-NN Classifier", KNeighborsClassifier(n_neighbors=1))
     for scaler_index in range(3):
         for model_index in range(3):
             scaler = get_scaler(scaler_index)
             model = get_model(model_index)
             pipeline = Pipeline([scaler, model])
             pipeline.fit(X_train, y_train)
             acc_train = accuracy_score(y_train, pipeline.predict(X_train))
             acc_test = accuracy_score(y_test, pipeline.predict(X_test))
             print(f"{scaler[0]:>15}, {model[0]:>26}:
                                                        Train Acc. = {100*acc train:
      5.1f}%
                 Test Acc. = {100*acc_test:5.1f}%")
```

```
No Scaler,
                      Logistic Regression:
                                             Train Acc. = 67.5%
                                                                    Test Acc.
  70.0%
     No Scaler, Support Vector Classifier:
                                             Train Acc. = 78.8%
                                                                    Test Acc.
  65.0%
     No Scaler,
                          1-NN Classifier:
                                             Train Acc. = 100.0%
                                                                    Test Acc.
= 50.0%
 MinMax Scaler, Logistic Regression:
                                             Train Acc. = 67.5%
                                                                   Test Acc.
= 70.0%
```

```
MinMax Scaler, Support Vector Classifier:
                                                                      Test Acc.
                                               Train Acc. = 67.5%
= 70.0%
 MinMax Scaler,
                           1-NN Classifier:
                                               Train Acc. = 100.0%
                                                                      Test Acc.
= 85.0%
                      Logistic Regression:
Standard Scaler,
                                               Train Acc. = 67.5%
                                                                      Test Acc.
= 70.0%
Standard Scaler, Support Vector Classifier:
                                               Train Acc. = 68.8%
                                                                      Test Acc.
= 70.0%
Standard Scaler,
                           1-NN Classifier:
                                               Train Acc. = 100.0%
                                                                      Test Acc.
= 85.0%
```

1.3 Questions

Answer the following questions:

- Which model's testing accuracy was improved the most by scaling data?
 The support vector classifier had marginal increase, but the 1-NN classifier improved the most with scaling.
- 2. Which performs better on this data: MinMax scaler, Standard scaler, or neither? Neither