lab11

November 12, 2024

1 STOR 320: Introduction to Data Science

1.1 Lab 11

[2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.linear_model import Ridge, Lasso
from sklearn.metrics import mean_squared_error
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
import warnings
warnings.filterwarnings('ignore')
```

Diabetes dataset:

We use the dataset from last lab to perform cross validation.

[3]:
```
# Load the dataset
diabetes = datasets.load_diabetes()
X = diabetes.data
y = diabetes.target
```

[4]:
```
df = pd.DataFrame(data=diabetes.data, columns=diabetes.feature_names)

# Add the target variable to the DataFrame
df['target'] = diabetes.target
df
```

[4]:
```
        age       sex       bmi        bp        s1        s2        s3  \
0  0.038076  0.050680  0.061696  0.021872 -0.044223 -0.034821 -0.043401
1 -0.001882 -0.044642 -0.051474 -0.026328 -0.008449 -0.019163  0.074412
2  0.085299  0.050680  0.044451 -0.005670 -0.045599 -0.034194 -0.032356
```

```
3   -0.089063 -0.044642 -0.011595 -0.036656  0.012191  0.024991 -0.036038
4    0.005383 -0.044642 -0.036385  0.021872  0.003935  0.015596  0.008142
..        …         …         …         …         …         …         …
437  0.041708  0.050680  0.019662  0.059744 -0.005697 -0.002566 -0.028674
438 -0.005515  0.050680 -0.015906 -0.067642  0.049341  0.079165 -0.028674
439  0.041708  0.050680 -0.015906  0.017293 -0.037344 -0.013840 -0.024993
440 -0.045472 -0.044642  0.039062  0.001215  0.016318  0.015283 -0.028674
441 -0.045472 -0.044642 -0.073030 -0.081413  0.083740  0.027809  0.173816

           s4        s5        s6  target
0   -0.002592  0.019907 -0.017646   151.0
1   -0.039493 -0.068332 -0.092204    75.0
2   -0.002592  0.002861 -0.025930   141.0
3    0.034309  0.022688 -0.009362   206.0
4   -0.002592 -0.031988 -0.046641   135.0
..        …         …         …       …
437 -0.002592  0.031193  0.007207   178.0
438  0.034309 -0.018114  0.044485   104.0
439 -0.011080 -0.046883  0.015491   132.0
440  0.026560  0.044529 -0.025930   220.0
441 -0.039493 -0.004222  0.003064    57.0

[442 rows x 11 columns]
```

[5]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

[6]:
```python
# Create polynomial features of second order
poly = PolynomialFeatures(degree=2, include_bias=False)
X_train_poly = poly.fit_transform(X_train)
X_test_poly = poly.transform(X_test)

# Convert to DataFrame for better understanding
feature_names = poly.get_feature_names_out(input_features=datasets.load_diabetes().feature_names)
X_train_poly_df = pd.DataFrame(X_train_poly, columns=feature_names)
X_test_poly_df = pd.DataFrame(X_test_poly, columns=feature_names)

# Display the first few rows of the new training set
X_train_poly_df
```

[6]:
```
          age       sex       bmi        bp        s1        s2        s3  \
0    0.070769  0.050680  0.012117  0.056301  0.034206  0.049416 -0.039719
1   -0.009147  0.050680 -0.018062 -0.033213 -0.020832  0.012152 -0.072854
2    0.005383 -0.044642  0.049840  0.097615 -0.015328 -0.016345 -0.006584
3   -0.027310 -0.044642 -0.035307 -0.029770 -0.056607 -0.058620  0.030232
4   -0.023677 -0.044642 -0.065486 -0.081413 -0.038720 -0.053610  0.059685
```

```
..        …         …         …         …         …         …         …
348 -0.096328 -0.044642 -0.076264 -0.043542 -0.045599 -0.034821  0.008142
349  0.005383  0.050680  0.030440  0.083844 -0.037344 -0.047347  0.015505
350  0.030811 -0.044642 -0.020218 -0.005670 -0.004321 -0.029497  0.078093
351 -0.012780 -0.044642 -0.023451 -0.040099 -0.016704  0.004636 -0.017629
352 -0.092695 -0.044642  0.028284 -0.015999  0.036958  0.024991  0.056003

           s4        s5        s6  …      s3^2     s3 s4     s3 s5  \
0    0.034309  0.027364 -0.001078  …  0.001578 -0.001363 -0.001087
1    0.071210  0.000272  0.019633  …  0.005308 -0.005188 -0.000020
2   -0.002592  0.017036 -0.013504  …  0.000043  0.000017 -0.000112
3   -0.039493 -0.049872 -0.129483  …  0.000914 -0.001194 -0.001508
4   -0.076395 -0.037129 -0.042499  …  0.003562 -0.004560 -0.002216
..        …         …         …  …       …         …         …
348 -0.039493 -0.059471 -0.083920  …  0.000066 -0.000322 -0.000484
349 -0.039493  0.008641  0.015491  …  0.000240 -0.000612  0.000134
350 -0.039493 -0.010903 -0.001078  …  0.006099 -0.003084 -0.000851
351 -0.002592 -0.038460 -0.038357  …  0.000311  0.000046  0.000678
352 -0.039493 -0.005142 -0.001078  …  0.003136 -0.002212 -0.000288

        s3 s6      s4^2     s4 s5     s4 s6          s5^2     s5 s6      s6^2
0    0.000043  0.001177  0.000939 -0.000037  7.487912e-04 -0.000029  0.000001
1   -0.001430  0.005071  0.000019  0.001398  7.424434e-08  0.000005  0.000385
2    0.000089  0.000007 -0.000044  0.000035  2.902277e-04 -0.000230  0.000182
3   -0.003915  0.001560  0.001970  0.005114  2.487261e-03  0.006458  0.016766
4   -0.002537  0.005836  0.002836  0.003247  1.378551e-03  0.001578  0.001806
..        …         …         …         …           …         …         …
348 -0.000683  0.001560  0.002349  0.003314  3.536821e-03  0.004991  0.007043
349  0.000240  0.001560 -0.000341 -0.000612  7.465999e-05  0.000134  0.000240
350 -0.000084  0.001560  0.000431  0.000043  1.188809e-04  0.000012  0.000001
351  0.000676  0.000007  0.000100  0.000099  1.479150e-03  0.001475  0.001471
352 -0.000060  0.001560  0.000203  0.000043  2.644212e-05  0.000006  0.000001

[353 rows x 65 columns]
```

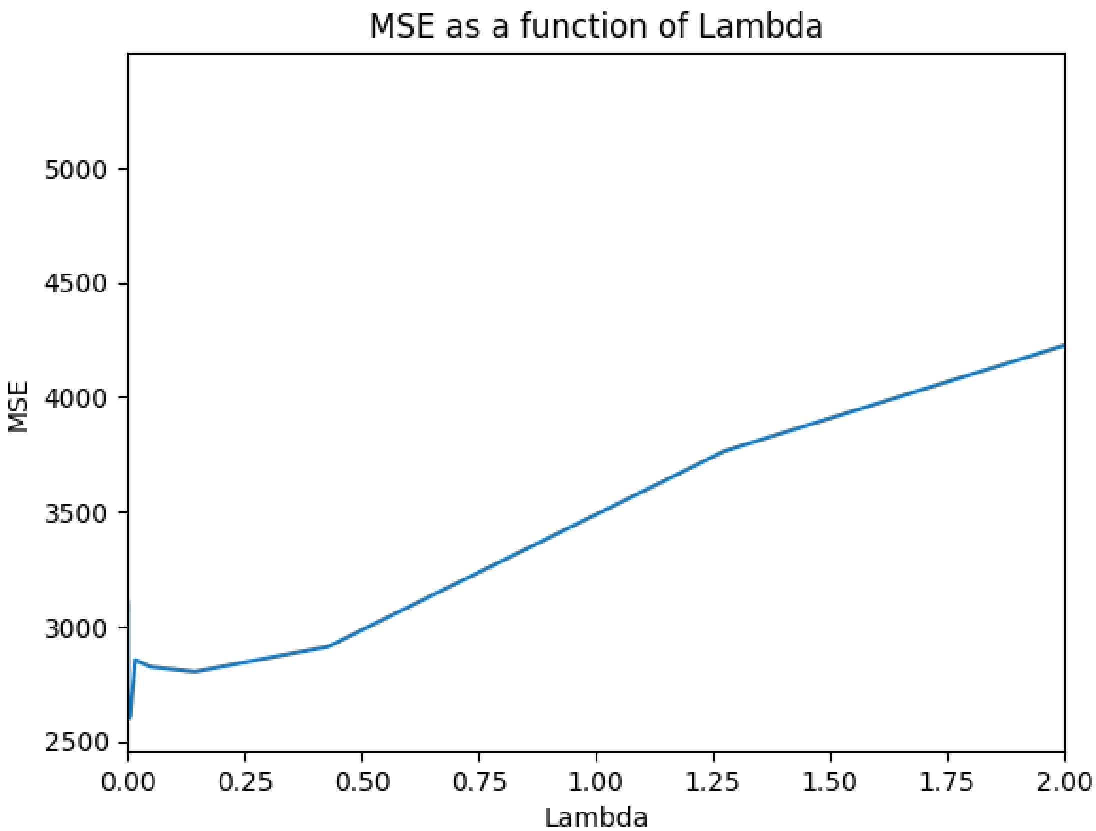
1.2 1. Based on the LASSO model from last lab, use 10-fold cross validation to find the best value of labmda for the LASSO.

1.2.1 The search grid is `np.logspace(-7, 2, num=20, base=10)`. The metric is MSE.

1.2.2 Visualize the MSE as a function of the value of lamda. What is the best value of lambda? What is its corresponding MSE?

[12]:
```python
MSE = []
for lamda in np.logspace(-7, 2, num=20, base=10):
    lasso = Lasso(alpha=lamda, random_state=88)
    lasso.fit(X_train_poly, y_train)
    y_pred_train = lasso.predict(X_train_poly)
```

```
    y_pred_test = lasso.predict(X_test_poly)
    MSE.append(mean_squared_error(y_test, y_pred_test))

plt.plot(np.logspace(-7, 2, num=20, base=10), MSE)
plt.xlim(0, 2)
plt.xlabel("Lambda")
plt.ylabel("MSE")
plt.title("MSE as a function of Lambda")
plt.show()
```



[15]:
```
best_lambda = np.logspace(-7, 2, num=20, base=10)[np.argmin(MSE)]
print(f"The best value of lambda is {best_lambda} with corresponding MSE␣
 ↪{MSE[np.argmin(MSE)]}")
```

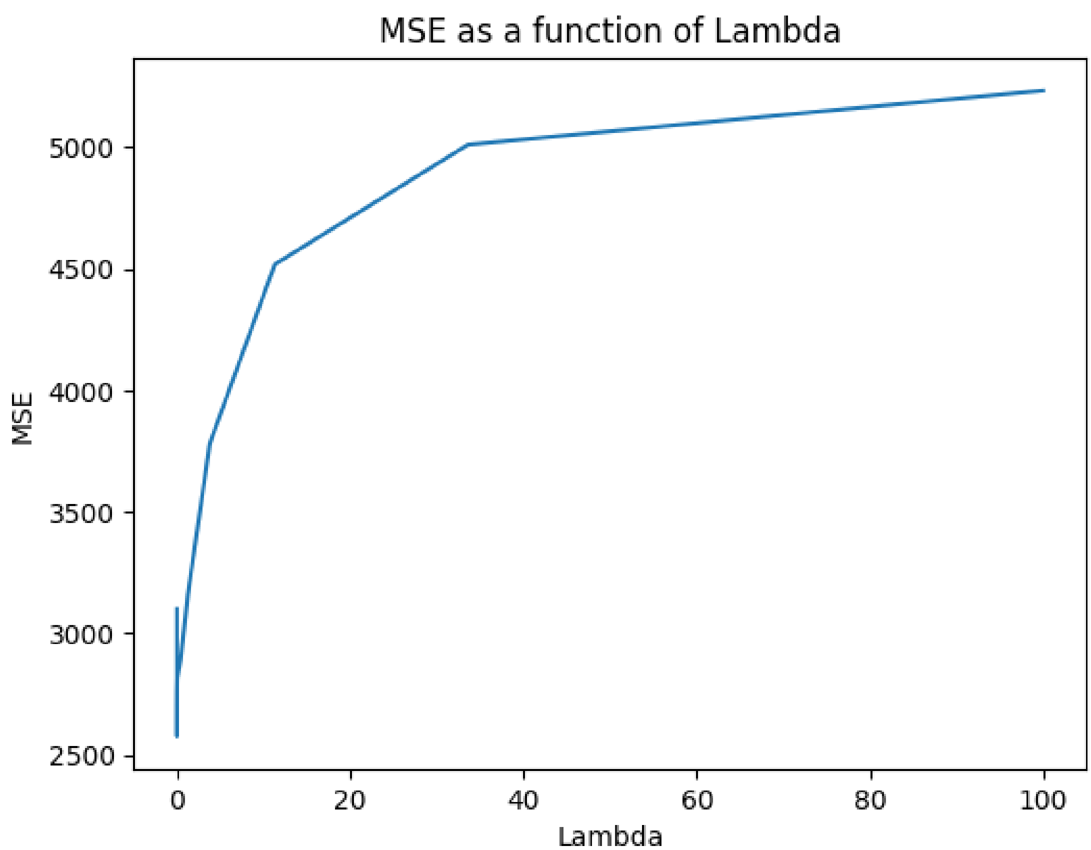
```
The best value of lambda is 0.0018329807108324338 with corresponding MSE
2595.6511270490687
```

1.3 2. Based on the Ridge model from last lab, use 5-fold cross validation to find the best value of labmda for the Ridge.

1.3.1 The search grid is `np.logspace(-4, 2, num=50, base=10)`. The metric is MSE.

1.3.2 Visualize the MSE as a function of the value of lamda. What is the best value of lambda? What is its corresponding MSE?

[18]:
```
MSE = []
for lamda in np.logspace(-7, 2, num=20, base=10):
    ridge = Ridge(alpha=lamda, random_state=88)
    ridge.fit(X_train_poly, y_train)
    y_pred_train = ridge.predict(X_train_poly)
    y_pred_test = ridge.predict(X_test_poly)
    MSE.append(mean_squared_error(y_test, y_pred_test))

plt.plot(np.logspace(-7, 2, num=20, base=10), MSE)
plt.xlabel("Lambda")
plt.ylabel("MSE")
plt.title("MSE as a function of Lambda")
plt.show()
```



[19]:
```
best_lambda = np.logspace(-7, 2, num=20, base=10)[np.argmin(MSE)]
print(f"The best value of lambda is {best_lambda} with corresponding MSE␣
↪{MSE[np.argmin(MSE)]}")
```

```
The best value of lambda is 0.0006158482110660261 with corresponding MSE
2576.5139825764113
```

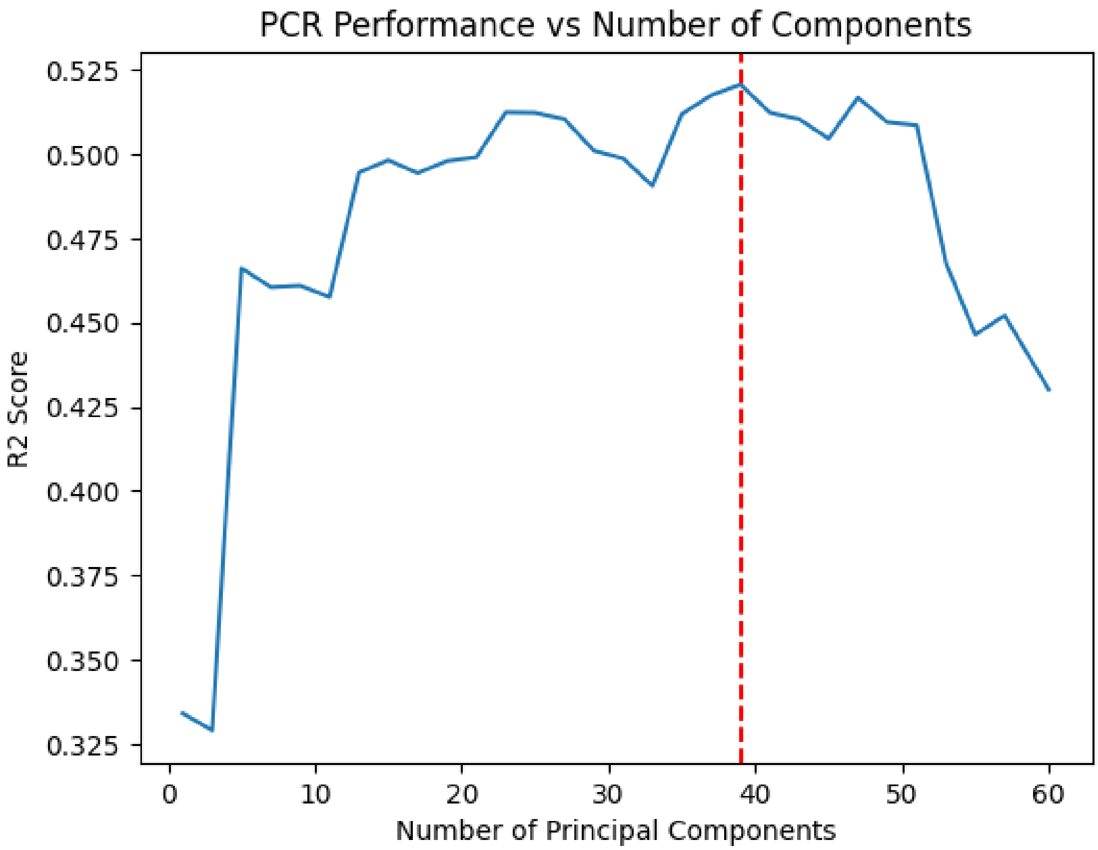
1.4 3. Based on the PCR model from last lab, use 5-fold cross validation to find the best value of number of PC.

1.4.1 The search grid is `np.linspace(1, 60, 30).astype('int')`. The metric is R2.

1.4.2 Visualize the R2 as a function of the value of number of PC. What is the best value of PC? What is its corresponding R2?

[20]:
```
def OSR2(y_train, y_test, y_pred):

    SSE = np.sum((y_test - y_pred)**2)
    SST = np.sum((y_test - np.mean(y_train))**2)

    return (1 - SSE/SST)
```

[26]:
```
PCR = []
for num_pc in np.linspace(1, 60, 30).astype("int"):

    pca = PCA(n_components=num_pc)
    X_train_pca = pca.fit_transform(X_train_poly)
    X_test_pca = pca.transform(X_test_poly)

    lr = LinearRegression()
    lr.fit(X_train_pca, y_train)

    y_pred = lr.predict(X_test_pca)

    PCR.append(OSR2(y_train, y_test, y_pred))

best_num_pc = np.linspace(1, 60, 30).astype('int')[np.argmax(PCR)]

plt.axvline(x=best_num_pc, color="red", linestyle="--")
plt.plot(np.linspace(1, 60, 30).astype("int"), PCR)
plt.xlabel("Number of Principal Components")
plt.ylabel("R2 Score")
plt.title("PCR Performance vs Number of Components")
plt.show()
```



[25]:
```
print(f"The best value of number of principal components is {best_num_pc} with␣
↪corresponding R²= {PCR[np.argmax(PCR)]}")
```

```
The best value of number of principal components is 39 with corresponding R²=
0.5205752756407203
```