lab10

November 5, 2024

1 STOR 320: Introduction to Data Science

1.1 Lab 10

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
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
```

Diabetes dataset:

- age: This feature represents the normalized age of the patient. The values are scaled and centered around the mean, which means they don't represent actual ages but rather relative differences.
- sex: The normalized gender information of the patient. Like the age feature, this is a numerical value that has been scaled and centered.
- bmi: The Body Mass Index (BMI) of the patient, which is a measure of body fat based on weight and height. This feature is also normalized and centered.
- bp: The average blood pressure of the patient. It has been measured and normalized to represent a scaled version, not an absolute pressure in mmHg.
- s1: This is a measure related to serum cholesterol levels. The value is normalized and represents the blood serum measurement, not an actual cholesterol count.
- s2: A measure related to low-density lipoproteins (LDL), another cholesterol-related measure, which is scaled and centered.
- s3: This feature is related to high-density lipoproteins (HDL), known as "good" cholesterol. Again, it is a normalized measure.

- s4: This column represents the level of serum triglycerides, a type of fat (lipid) in the blood. The value is scaled and normalized.
- s5: A measure related to the level of serum insulin, normalized and centered to represent relative differences between patients.
- s6: A measure related to the blood sugar level (glucose). The feature is scaled and centered, like the other measurements.
- target: The response variable, representing the progression of diabetes one year after the baseline measurements. This is a continuous value indicating how much the disease has progressed.

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

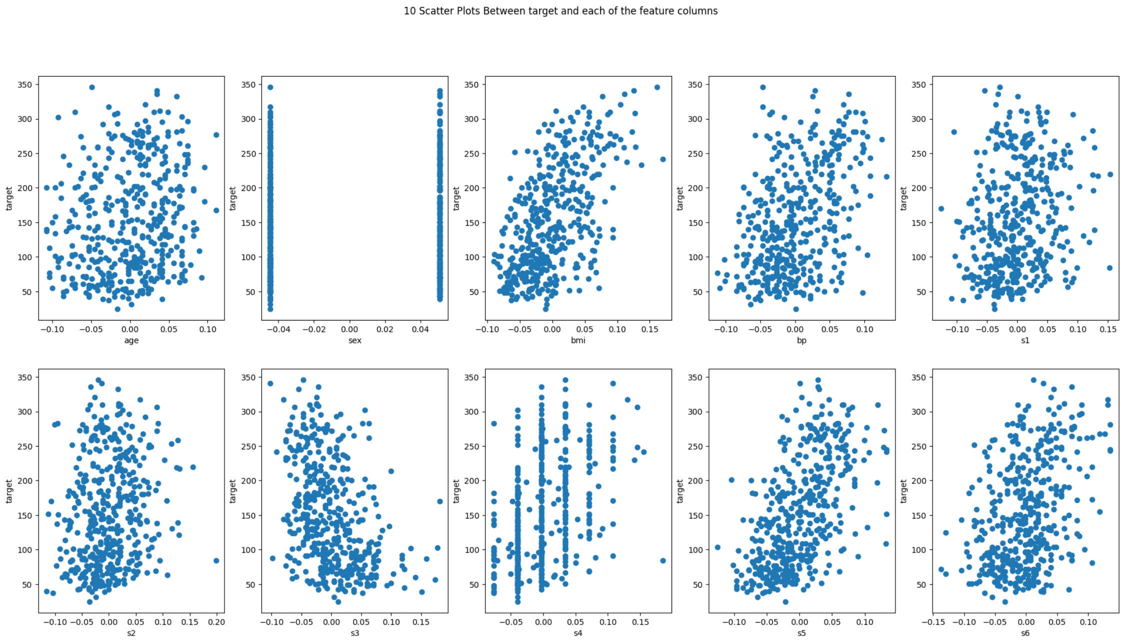
[ ]:
```python
df = pd.DataFrame(data=diabetes.data, columns=diabetes.feature_names)

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

[ ]:
```
        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

         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
```

1. Present 10 scatter plots between target and each of the feature columns

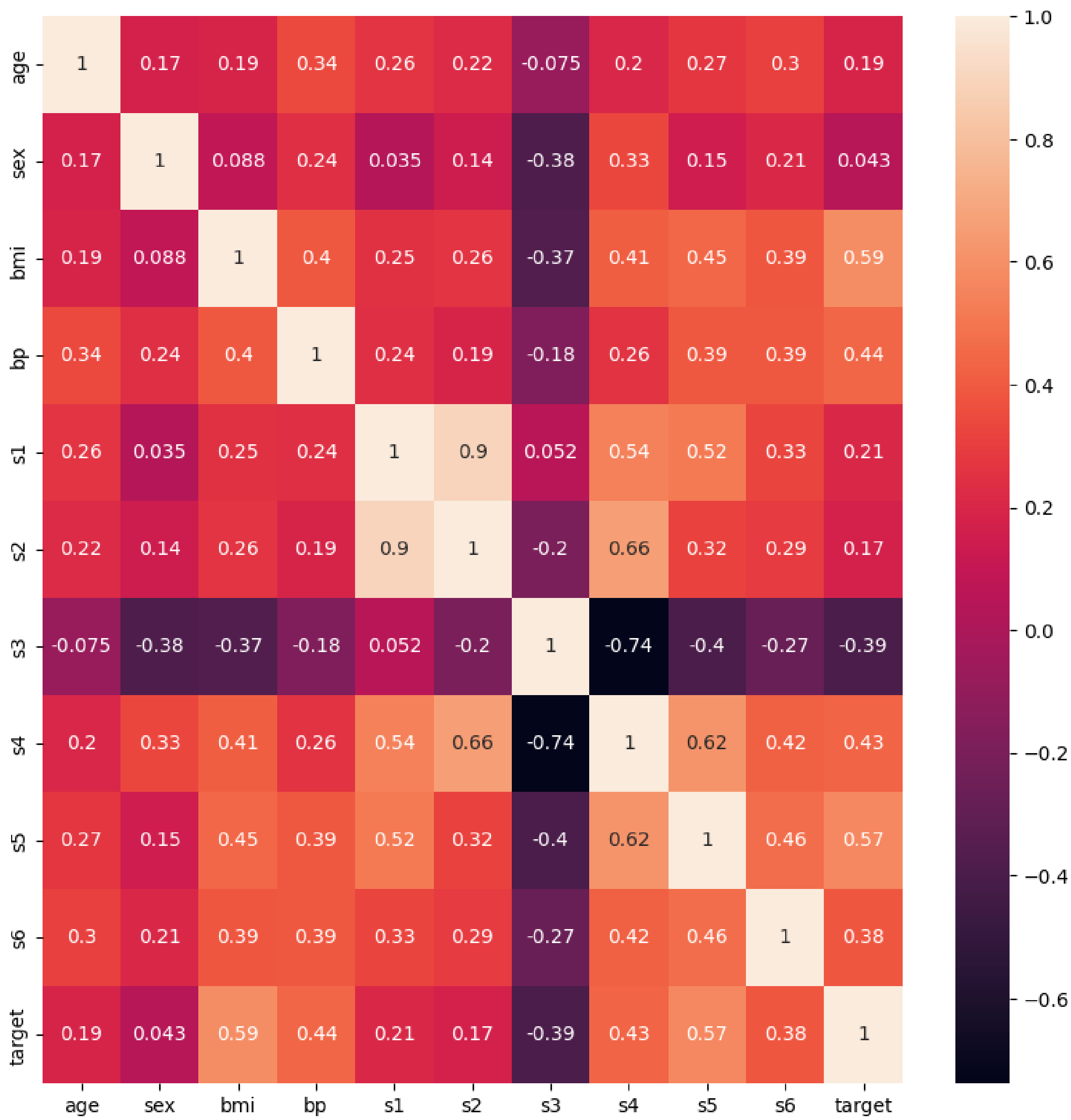
[ ]:
```python
fig, axes = plt.subplots(2, 5, figsize=(24, 12))

for i, ax in enumerate(axes.flatten()):
    feature = df.columns[i]
    ax.scatter(df[feature], df["target"])
    ax.set_xlabel(feature)
    ax.set_ylabel("target")

fig.suptitle("10 Scatter Plots Between target and each of the feature columns")
```

```python
plt.show()
```



2. Present the pair plot to check correlations. Do you find any correlation?

[ ]:
```python
plt.figure(figsize=(10,10))
sns.heatmap(df.corr(), annot=True)
plt.show()
```



s3 seems to be correlated in some way with all other factors, especially s4.

3. Split the data (X and y) into a training set (80%) and a test set (20%)

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

4. For both training and testing dataset, add second-order features and their interactions.

Hint: you can use PolynomialFeatures.

[ ]:
```
degree = PolynomialFeatures(degree=2)
```

```
X_train_poly = degree.fit_transform(X_train)
X_test_poly = degree.fit_transform(X_test)
```

5. Build a linear regression model using all the features including the second order term and interaction term. Calculate the R2 and OSR2.

[ ]:
```
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)
```

[ ]:
```
X_train_poly = sm.add_constant(X_train_poly)
model1 = sm.OLS(y_train, X_train_poly).fit()
y_pred_train = model1.predict(X_train_poly)
y_pred_test = model1.predict(X_test_poly)

print(f"R2 for training set: {OSR2(y_train, y_train, y_pred_train)}")
print(f"OSR2 for test set: {OSR2(y_train, y_test, y_pred_test)}")
```

```
R2 for training set: 0.6061583502354679
OSR2 for test set: 0.42254798332640486
```

6. Build a PCR model. Set the number of PC as 6. Calculate R2 and OSR2. Is OSR2 better than the linear regression?

[ ]:
```
scaler = StandardScaler()
pca = PCA(random_state=88)
lr = LinearRegression()
pipe = Pipeline(steps=[('scaler', scaler), ('pca', pca), ('lr', lr)])
pipe.set_params(pca__n_components=6)
pipe.fit(X_train_poly, y_train)

y_pred_train = pipe.predict(X_train_poly)
y_pred_test = pipe.predict(X_test_poly)
```

[ ]:
```
print(f"R2 = {OSR2(y_train, y_train, y_pred_train)}")
print(f"OSR2 = {OSR2(y_train, y_test, y_pred_test)}")
```

```
R2 = 0.3215596900597456
OSR2 = 0.31448386917472626
```

no

7. Build a Ridge model. Set the regularization parameter as 0.1. Calculate R2 and OSR2. Is OSR2 better than the linear regression?

[ ]:
```
alpha_max = 10**-1
rr = Ridge(alpha=alpha_max, random_state=88)
```

```
rr.fit(X_train_poly, y_train)

y_pred_train = rr.predict(X_train_poly)
y_pred_test = rr.predict(X_test_poly)
```

[ ]:
```
print(f"R2 = {OSR2(y_train, y_train, y_pred_train)}")
print(f"OSR2 = {OSR2(y_train, y_test, y_pred_test)}")
```

```
R2 = 0.5238444895115633
OSR2 = 0.47223847551796905
```

OSR^2 is slightly better than linear regression.

8. Build a Lasso model. Set the regularization parameter as 0.1. Calculate R2 and OSR2. Is OSR2 better than the linear regression?

[ ]:
```
lasso = Lasso(alpha=0.1, 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)
```

[ ]:
```
print(f"R2 = {OSR2(y_train, y_train, y_pred_train)}")
print(f"OSR2 = {OSR2(y_train, y_test, y_pred_test)}")
```

```
R2 = 0.5169410847799543
OSR2 = 0.47809828895277584
```

OSR2 is marginally better than the Ridge, much better than linear regression.