EC9630 MACHINE LEARNING LABORATORY 2

TASK: LINEAR REGRESSION

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EC9630 Machine Learning - LAboratory 2

Task : LINEAR REGRESSION

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Reg No: 2020/E/082

Date : 2024 / 07/ 19

Time : 08.00 a.m.

Download the dataset

References:

Kaggle Learn - https://www.kaggle.com/learn

Pandas Tutorial - https://pandas.pydata.org/docs/getting_started/intro_tutorials/

```
# Step : Download the dataset
!wget https://archive.ics.uci.edu/ml/machine-learning-databases/00275/Bike-Sharing-Dataset.zip
!unzip Bike-Sharing-Dataset.zip
```

```
--2024-07-25 06:08:52--  https://archive.ics.uci.edu/ml/machine-learning-databases/00275/Bike-Sharing-Dataset.zip
Resolving archive.ics.uci.edu (archive.ics.uci.edu)... 128.195.10.252
Connecting to archive.ics.uci.edu (archive.ics.uci.edu)|128.195.10.252|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: unspecified
Saving to: 'Bike-Sharing-Dataset.zip'

Bike-Sharing-Datase     [  <=>               ] 273.43K  1.01MB/s    in 0.3s

2024-07-25 06:08:52 (1.01 MB/s) - 'Bike-Sharing-Dataset.zip' saved [279992]

Archive:  Bike-Sharing-Dataset.zip
  inflating: Readme.txt
  inflating: day.csv
  inflating: hour.csv
```

Read the data as a CSV file

```
import pandas as pd

# Step : Read the data
df = pd.read_csv('day.csv')
df.head()
```

	instant	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	casual	registered	cnt
0	1	2011-01-01	1	0	1	0	6	0	2	0.344167	0.363625	0.805833	0.160446	331	654	985
1	2	2011-01-02	1	0	1	0	0	0	2	0.363478	0.353739	0.696087	0.248539	131	670	801
2	3	2011-01-03	1	0	1	0	1	1	1	0.196364	0.189405	0.437273	0.248309	120	1229	1349
3	4	2011-01-04	1	0	1	0	2	1	1	0.200000	0.212122	0.590435	0.160296	108	1454	1562
4	5	2011-01-05	1	0	1	0	3	1	1	0.226957	0.229270	0.436957	0.186900	82	1518	1600

Preprocessing

References:

Data cleaning - https://www.kaggle.com/learn/data-cleaning

```
# Step : Preprocessing
# Check for missing values
print(df.isnull().sum())

# Convert categorical variables using one-hot encoding
df = pd.get_dummies(df, columns=['season', 'weathersit'])

# Drop unnecessary columns
df.drop(['instant', 'dteday', 'casual', 'registered'], axis=1, inplace=True)

# Standardize the features
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
df[df.columns] = scaler.fit_transform(df[df.columns])
```

```
instant       0
dteday        0
season        0
yr            0
mnth          0
holiday       0
weekday       0
workingday    0
weathersit    0
temp          0
atemp         0
hum           0
windspeed     0
casual        0
registered    0
cnt           0
dtype: int64
```

Split the Data

```python
from sklearn.model_selection import train_test_split

# Split the data
X = df.drop('cnt', axis=1)
y = df['cnt']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Fit Linear Regression Model

References:

Linear Regression Scikit-learn - https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LinearRegression.html

Evaluation Score - https://scikit-learn.org/stable/modules/model_evaluation.html

```python
from sklearn.linear_model import LinearRegression

# Fit the model
model = LinearRegression()
model.fit(X_train, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

Calculate Errors

```python
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np

# Predict on test data
y_pred = model.predict(X_test)

# Calculate errors
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)

print(f'MAE: {mae}')
print(f'MSE: {mse}')
print(f'RMSE: {rmse}')
```

```
MAE: 0.3120796879071219
MSE: 0.17463177521162723
RMSE: 0.4178896687064987
```

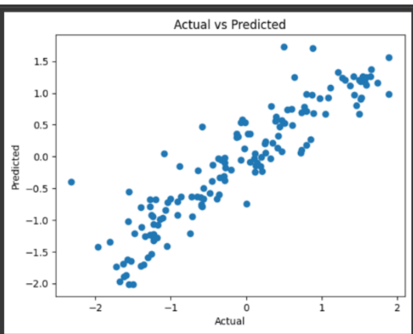
Compare Actual vs Predicted Values

References:

Data Visualization - https://www.kaggle.com/learn/data-visualization

```python
import matplotlib.pyplot as plt

# Compare actual vs predicted values
plt.scatter(y_test, y_pred)
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('Actual vs Predicted')
plt.show()
```



Implement Regularization

References:

Regression - https://scikit-learn.org/stable/supervised_learning.html#supervised-

Evaluation Score - https://scikit-learn.org/stable/modules/model_evaluation.html

```python
from sklearn.linear_model import Lasso, Ridge

# Lasso Regression
lasso = Lasso(alpha=0.1)
lasso.fit(X_train, y_train)
y_pred_lasso = lasso.predict(X_test)
mse_lasso = mean_squared_error(y_test, y_pred_lasso)

# Ridge Regression
ridge = Ridge(alpha=0.1)
ridge.fit(X_train, y_train)
y_pred_ridge = ridge.predict(X_test)
mse_ridge = mean_squared_error(y_test, y_pred_ridge)

print(f'Lasso MSE: {mse_lasso}')
print(f'Ridge MSE: {mse_ridge}')
```

```
Lasso MSE: 0.24008102790382765
Ridge MSE: 0.17338423072582856
```

Analyze the impact of regularization on model performance and coefficients.

```python
from sklearn.linear_model import Lasso, Ridge
from sklearn.metrics import mean_squared_error

# Fit Lasso regression model
lasso = Lasso(alpha=0.1)
lasso.fit(X_train, y_train)
y_pred_lasso = lasso.predict(X_test)
mse_lasso = mean_squared_error(y_test, y_pred_lasso)

# Fit Ridge regression model
ridge = Ridge(alpha=0.1)
ridge.fit(X_train, y_train)
y_pred_ridge = ridge.predict(X_test)
mse_ridge = mean_squared_error(y_test, y_pred_ridge)

# Print MSE for Lasso and Ridge
print(f'Lasso MSE: {mse_lasso}')
print(f'Ridge MSE: {mse_ridge}')

# Compare coefficients
print(f'Linear Regression Coefficients: {model.coef_}')
print(f'Lasso Regression Coefficients: {lasso.coef_}')
print(f'Ridge Regression Coefficients: {ridge.coef_}')
```

```
Lasso MSE: 0.24008102790382765
Ridge MSE: 0.17338423072582856
Linear Regression Coefficients: [ 5.30922334e-01 -2.12603499e-02 -4.17838600e-02  7.21078386e-02
  3.66009295e-02  4.27087255e-01  7.06263188e-02 -7.66212077e-02
 -9.28234286e-02 -9.30255973e+11 -9.35372096e+11 -9.42021196e+11
 -9.25026985e+11  1.35200323e+13  1.32706133e+13  4.68660832e+12]
Lasso Regression Coefficients: [ 0.43592816  0.          -0.          0.          0.          0.05395207
  0.27481367 -0.         -0.00406872 -0.26384906  0.          0.
  0.          0.08265311 -0.         -0.06165527]
Ridge Regression Coefficients: [ 0.51612747 -0.02987371 -0.03710704  0.07354324  0.0345674   0.4184837
  0.0763692  -0.07488397 -0.09650969 -0.20677185  0.05693397 -0.02216466
  0.17294186  0.08451638 -0.04171908 -0.1256829 ]
```

Recursive Least Squares (SelfLearning)

References:

Regression - https://scikit-learn.org/stable/supervised_learning.html#supervised-learning

Evaluation Score - https://scikit-learn.org/stable/modules/model_evaluation.html

```python
#Implement and compare the Recursive Least Squares algorithm.
import numpy as np
from sklearn.metrics import mean_squared_error

# Recursive Least Squares (RLS) function
def recursive_least_squares(X, y, lambda_factor=1.0):
    n_features = X.shape[1]
    P = np.eye(n_features) * 1000  # Large initial value
    theta = np.zeros(n_features)

    for i in range(len(y)):
        x_i = X[i, :].reshape(-1, 1)
        y_i = y[i]

        K = P @ x_i / (lambda_factor + x_i.T @ P @ x_i)
        theta = theta + K.flatten() * (y_i - x_i.T @ theta)
        P = (P - K @ x_i.T @ P) / lambda_factor

    return theta

# Prepare the training data
X_train_with_intercept = np.hstack((np.ones((X_train.shape[0], 1)), X_train))
y_train_np = y_train.values

# Fit the RLS model
theta_rls = recursive_least_squares(X_train_with_intercept, y_train_np)

# Prepare the test data
X_test_with_intercept = np.hstack((np.ones((X_test.shape[0], 1)), X_test))

# Predict using the RLS model
y_pred_rls = X_test_with_intercept @ theta_rls
```

```
# Calculate Mean Squared Error for RLS
mse_rls = mean_squared_error(y_test, y_pred_rls)
print(f'RLS MSE: {mse_rls}')
```

```
RLS MSE: 0.17340567092786865
```

Compare the performance of RLS with the traditional linear regression model.(Self Learning)

```
import numpy as np
from sklearn.metrics import mean_squared_error

# Recursive Least Squares (RLS) function
def recursive_least_squares(X, y, lambda_factor=1.0):
    n_features = X.shape[1]
    P = np.eye(n_features) * 1000  # Large initial value
    theta = np.zeros(n_features)

    for i in range(len(y)):
        x_i = X[i, :].reshape(-1, 1)
        y_i = y[i]

        K = P @ x_i / (lambda_factor + x_i.T @ P @ x_i)
        theta = theta + K.flatten() * (y_i - x_i.T @ theta)
        P = (P - K @ x_i.T @ P) / lambda_factor

    return theta

# Prepare the training data
X_train_with_intercept = np.hstack((np.ones((X_train.shape[0], 1)), X_train))
y_train_np = y_train.values
```

```
# Fit the RLS model
theta_rls = recursive_least_squares(X_train_with_intercept, y_train_np)

# Prepare the test data
X_test_with_intercept = np.hstack((np.ones((X_test.shape[0], 1)), X_test))

# Predict using the RLS model
y_pred_rls = X_test_with_intercept @ theta_rls

# Calculate Mean Squared Error for RLS
mse_rls = mean_squared_error(y_test, y_pred_rls)
print(f'RLS MSE: {mse_rls}')

# Compare with traditional linear regression
mse_lr = mean_squared_error(y_test, y_pred)
print(f'Traditional Linear Regression MSE: {mse_lr}')
```

```
RLS MSE: 0.17340567092786865
Traditional Linear Regression MSE: 0.17463177521162723
```

LAB02_2020E082.ipynb

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Gradient Descent (Self Learning)

```
# Import necessary library
from sklearn.linear_model import SGDRegressor

# Implement Gradient Descent
sgd = SGDRegressor(max_iter=1000, tol=1e-3)
sgd.fit(X_train, y_train)
y_pred_sgd = sgd.predict(X_test)
mse_sgd = mean_squared_error(y_test, y_pred_sgd)

print(f'SGD MSE: {mse_sgd}')
```

```
SGD MSE: 0.17127480964373695
```