24MDT0184_experiment3 -assessment

January 17, 2025

1 Experiment 3

1.1 8 January

1.2 Multiple Linear Regression

1.2.1 Q1-Download the dataset 'Book1.csv' from moodle. This dataset has information regarding the house price and many features depending on it. Open the CSV file and see the different features and the target variable Y (house price) also.

[86]:
```python
## Importing the necessary libraries
import numpy as np
import pandas as pd
from sklearn.metrics import mean_squared_error
from sklearn import preprocessing
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
##  Load the dataset to a dataframe.
df = pd.read_csv(r'D:\study material\VIT_Data_Science\Winter_Sem\Data Mining␣
 ↪and Machine Learning Lab\Class_notes\ML_exp2\Book1.csv')
df
```

[86]:
```
        price  area  bedrooms  bathrooms  stories  parking furnishingstatus
0    13300000  7420         4          2        3        2        furnished
1    12250000  8960         4          4        4        3        furnished
2    12250000  9960         3          2        2        2   semi-furnished
3    12215000  7500         4          2        2        3        furnished
4    11410000  7420         4          1        2        2        furnished
..        …     …         …          …        …        …              …
244   4550000  5320         3          1        2        0   semi-furnished
245   4550000  5360         3          1        2        2      unfurnished
246   4550000  3520         3          1        1        0   semi-furnished
247   4550000  8400         4          1        4        3      unfurnished
248   4543000  4100         2          2        1        0   semi-furnished

[249 rows x 7 columns]
```

1.3 Drop the furnishing status column and then we will be left out with 5 features (X1, X2, X3, X4, X5) to predict the house price (Y)

[87]:
```
df.drop('furnishingstatus',axis = 1,inplace = True)
df
```

[87]:

	price	area	bedrooms	bathrooms	stories	parking
0	13300000	7420	4	2	3	2
1	12250000	8960	4	4	4	3
2	12250000	9960	3	2	2	2
3	12215000	7500	4	2	2	3
4	11410000	7420	4	1	2	2
..	…	…	…	…	…	…
244	4550000	5320	3	1	2	0
245	4550000	5360	3	1	2	2
246	4550000	3520	3	1	1	0
247	4550000	8400	4	1	4	3
248	4543000	4100	2	2	1	0

[249 rows x 6 columns]

1.4 Use MinMaxScaler() to scale the data to 0 to 1 range.

[88]:
```
MM = preprocessing.MinMaxScaler()
x = MM.fit_transform(df)
print(x)
```

```
[[1.00000000e+00 3.56776557e-01 5.00000000e-01 3.33333333e-01
  6.66666667e-01 6.66666667e-01]
 [8.80095923e-01 4.69597070e-01 5.00000000e-01 1.00000000e+00
  1.00000000e+00 1.00000000e+00]
 [8.80095923e-01 5.42857143e-01 2.50000000e-01 3.33333333e-01
  3.33333333e-01 6.66666667e-01]
 …
 [7.99360512e-04 7.10622711e-02 2.50000000e-01 0.00000000e+00
  0.00000000e+00 0.00000000e+00]
 [7.99360512e-04 4.28571429e-01 5.00000000e-01 0.00000000e+00
  1.00000000e+00 1.00000000e+00]
 [0.00000000e+00 1.13553114e-01 0.00000000e+00 3.33333333e-01
  0.00000000e+00 0.00000000e+00]]
```

1.5 Split the data into training and testing sets using appropriate functions. Use a 80:20 split.

[89]:
```
X = x[:,1:]
Y = x[:,0]
```

[90]:
```
X.shape
```

[90]: (249, 5)

[91]:
```
Y.shape
```

[91]: (249,)

[92]:
```
x_train,x_test,y_train,y_test = train_test_split(X,Y,test_size = 0.2, random_state = 0)
```

1.6 Also, use the inbuilt LinearRegression class and create an object of this class and fit the model using training data and check for the values of the parameters of your model. If you print the intercept and coefficients as you did in the previous lab you will get the model parameters 0, 1, ..., 5

[93]:
```
model = LinearRegression()
model.fit(x_train,y_train)
print("optimized m:",model.coef_)
print("optimized n:",model.intercept_)
```

```
optimized m: [0.32033532 0.09007501 0.3199135  0.13202285 0.14958391]
optimized n: -0.06121183786718576
```

[94]:
```
Y_pred = model.predict(x_test)

# Evaluating the model performance using Mean Squared Error
mse = mean_squared_error(y_test, Y_pred)
print(f"Mean Squared Error on test data: {mse}")
```

```
Mean Squared Error on test data: 0.020077937566470735
```

2 Q2

2.1 Gradient descent algorithm for multiple regression

[95]:
```
def gd(X, Y, m, n, L):
    Dm = np.zeros(X.shape[1])
    Dn = 0
    m_len = len(X)

    for i in range(m_len):
        prediction_error = np.dot(X[i], m) + n - Y[i]
        Dm += (2 / m_len) * prediction_error * X[i]
        Dn += (2 / m_len) * prediction_error
    m = m - L * Dm
    n = n - L * Dn
    return m, n
m = np.zeros(x_train.shape[1])
n = 0
```

```
L = 0.3
epochs = 1000

for epoch in range(epochs):
    m, n = gd(x_train, y_train, m, n, L)

print(f"Optimized m: {m}")
print(f"Optimized n (intercept): {n}")

# Making predictions using the learned parameters on the test data
Y_pred = np.dot(x_test, m) + n

# Evaluating the model performance using Mean Squared Error
mse = mean_squared_error(y_test, Y_pred)
print(f"Mean Squared Error on test data: {mse}")
```

```
Optimized m: [0.32033458 0.09007431 0.31991389 0.13202283 0.14958395]
Optimized n (intercept): -0.061211484565910086
Mean Squared Error on test data: 0.020077925354191114
```

2.1.1 Vectorized approach

[96]:
```
def gd(X, Y, m, n, L):
    m_len = len(X)
    prediction_error = np.dot(X, m) + n - Y
    Dm = (2 / m_len) * np.dot(X.T, prediction_error)
    Dn = (2 / m_len) * np.sum(prediction_error)
    m = m - L * Dm
    n = n - L * Dn
    return m, n

m = np.zeros(x_train.shape[1])
n = 0
L = 0.3
epochs = 1000

for epoch in range(epochs):
    m, n = gd(x_train, y_train, m, n, L)

print(f"Optimized m: {m}")
print(f"Optimized n (intercept): {n}")

# Making predictions using the learned parameters on the test data
Y_pred = np.dot(x_test, m) + n

# Evaluating the model performance using Mean Squared Error
mse = mean_squared_error(y_test, Y_pred)
```

```
print(f"Mean Squared Error on test data: {mse}")
```

```
Optimized m: [0.32033458 0.09007431 0.31991389 0.13202283 0.14958395]
Optimized n (intercept): -0.06121148456591006
Mean Squared Error on test data: 0.020077925354191114
```

2.2 Alternate approach

[97]:
```
z = np.ones(len(x_train))
new_X_train = np.concatenate((np.array(z)[:, np.newaxis], x_train), axis=1)
print(new_X_train)
```

```
[[1.         0.05054945 0.5        0.         0.66666667 0.33333333]
 [1.         0.15018315 0.25       0.33333333 0.33333333 0.66666667]
 [1.         0.27472527 0.25       0.         0.         0.66666667]
 …
 [1.         0.08424908 0.5        0.         0.33333333 0.        ]
 [1.         0.2967033  0.25       0.         1.         1.        ]
 [1.         0.42857143 0.25       0.         0.33333333 0.66666667]]
```

[98]:
```
def gd(data,yt,parameters,lrate):
    slopes = np.zeros(6)
    for j in range(len(data)):
        for k in range(6):
            slopes[k]+= (1/len(data))*((data[j]*parameters).
 ↪sum()-yt[j])*data[j][k]
    parameters = parameters-lrate*slopes
    return parameters
parameters = np.zeros(6)
lrate = 0.9
iter_value = 1500
for i in range(iter_value):
    parameters = gd(new_X_train,y_train,parameters,lrate)
print(parameters)
```

```
[-0.06121184  0.32033532  0.09007501  0.3199135   0.13202285  0.14958391]
```

3 Q3

3.0.1 Implement the Linear regression problem what we attempted using the house-pricedata set in the last lab using stochastic gradient descent and mini batch gradient descent and present the results and plots of your model. Also find the testing error in both the cases. (Use the learning rate to be 0.5 and Hint: you can use random module and random.sample function can be used to generate say 30 (a mini batch) of indices and the derivative can be calculated for only those data points and summed. which can be used to update the model parameters values.

[99]:
```
## loading the dataset
data = pd.read_csv(r'D:\study material\VIT_Data_Science\Winter_Sem\Data Mining␣
↪and Machine Learning Lab\Class_notes\ML_exp2\Training_set_heights200.csv')
data
```

[99]:
```
       Height    Weight
0    127.8296  67.63371
1    123.4114  65.95421
2    134.4043  66.14316
3    155.9981  73.45251
4    136.1354  69.30943
..        …         …
194  135.2500  68.41222
195  109.5143  66.49607
196  139.6043  67.84894
197  134.3672  67.27839
198  130.3869  68.48742

[199 rows x 2 columns]
```

[100]:
```
#  Use MinMaxScaler() to scale the data to 0 to 1 range.
MM = preprocessing.MinMaxScaler()
x = MM.fit_transform(data)
```

[101]:
```
X = x[:,0]
Y = x[:,1]
```

[102]:
```
# splitting the data into train and test

x_train,x_test,y_train,y_test = train_test_split(X,Y,test_size = 0.
↪2,random_state= 0)
```

[103]:
```
# Creating linear regression model and fitting the data
reg = LinearRegression()
reg.fit(x_train.reshape(-1,1),y_train)
m = reg.intercept_
n = reg.coef_
```

```python
print(m,n)
# Making predictions using the learned parameters on the test data
Y_pred = reg.predict(x_test.reshape(-1,1))

# Evaluating the model performance using Mean Squared Error
mse = mean_squared_error(y_test, Y_pred)
print(f"Mean Squared Error on test data: {mse}")
```

```
0.3187097588547204 [0.42917335]
Mean Squared Error on test data: 0.028299747771811332
```

[104]:
```python
def gd(xt,yt,mb,nb,L):
    Dm=0
    Dn=0
    for i in range(len(xt)):
        Dm=Dm+(2/len(xt))*((mb*xt[i]+nb-yt[i])*xt[i])
        Dn=Dn+(2/len(xt))*(mb*xt[i]+nb-yt[i])
    mb=mb-L*Dm
    nb=nb-L*Dn
    return mb,nb
m=0
n=0
L=0.5
epochs=900
for i in range(epochs):
    m,n=gd(x_train,y_train,m,n,L)
print(m,n)
```

```
0.42917326798919886 0.3187098016324925
```

3.1 Stochastic gradient descent

[105]:
```python
def sgd(x,y,m,n,L):
    ## randomly shuffling the data
    i = np.random.randint(len(x))
    dm = 2*(m*x[i]+n - y[i])*x[i]
    dn = 2*(m*x[i]+n - y[i])
    m -= L*dm
    n -= L*dn
    return m,n

m_sgd = 0
n_sgd = 0
L = 0.3
epochs = 1500

for epoch in range(epochs):
    m_sgd, n_sgd = sgd(x_train, y_train, m, n, L)
```

```
print(f"Optimized m: {m_sgd}")
print(f"Optimized n (intercept): {n_sgd}")

# Making predictions using the learned parameters on the test data
Y_pred = np.dot(x_test,m_sgd) + n_sgd

# Evaluating the model performance using Mean Squared Error
mse = mean_squared_error(y_test, Y_pred)
print(f"Mean Squared Error on test data: {mse}")
```

```
Optimized m: 0.443281943852369
Optimized n (intercept): 0.34806297724312585
Mean Squared Error on test data: 0.027451015932419075
```

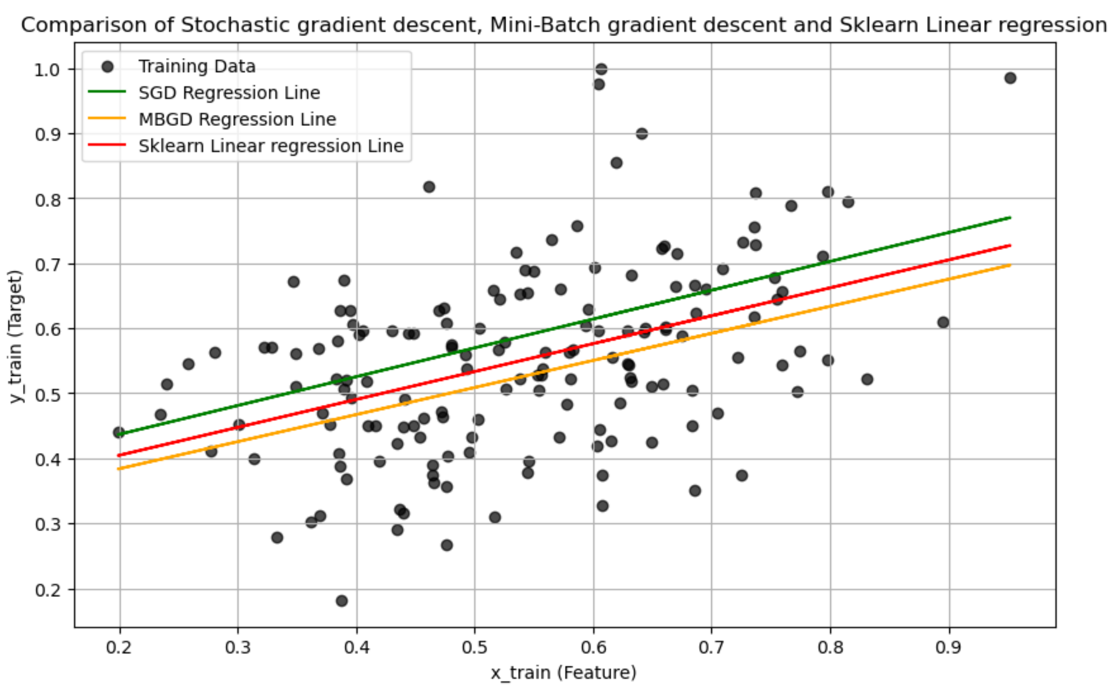
3.2 Minibatch gradient descent

[106]:
```
def mbgd(x,y,m,n,l,batchsize):
    indices = np.random.permutation(len(x))
    x,y = x[indices],y[indices]
    for i in range(0,len(x),batchsize):
        x_batch = x[i:i+batchsize]
        y_batch = y[i:i+batchsize]
        grad_m = np.sum(2*(m*x_batch+n-y_batch)*x_batch/len(x_batch))
        grad_n = np.sum(2*(m*x_batch+n-y_batch)/len(x_batch))
        m-= l*grad_m
        n-=l*grad_n
    return m,n

m_mbgd = 0
n_mbgd = 0
L = 0.5
batchsize = 30
epochs = 1500

for epoch in range(epochs):
    m_mbgd, n_mbgd = mbgd(x_train, y_train, m, n, L,batchsize)

print(f"Optimized m: {m_mbgd}")
print(f"Optimized n (intercept): {n_mbgd}")

# Making predictions using the learned parameters on the test data
Y_pred = np.dot(x_test,m_mbgd) + n_mbgd

# Evaluating the model performance using Mean Squared Error
mse = mean_squared_error(y_test, Y_pred)
print(f"Mean Squared Error on test data: {mse}")
```

```
Optimized m: 0.41640933750720044
Optimized n (intercept): 0.3005646943825705
Mean Squared Error on test data: 0.03055277822325292
```

3.3 Plotting the regression lines for both models

[109]:
```python
plt.figure(figsize=(10, 6))
plt.scatter(x_train, y_train, color='black', label='Training Data',alpha=0.7)
plt.plot(x_train, m_sgd * x_train + n_sgd, color='green', label='SGD Regression Line')
plt.plot(x_train, m_mbgd * x_train + n_mbgd, color='orange', label='MBGD Regression Line')
plt.plot(x_train, m * x_train + n, color='red', label='Sklearn Linear regression Line')
plt.title("Comparison of Stochastic gradient descent, Mini-Batch gradient descent and Sklearn Linear regression")
plt.xlabel("x_train (Feature)")
plt.ylabel("y_train (Target)")
plt.legend()
plt.grid(True)
plt.show()
```



4 Polynomial Regression

Q4. When we look at the scatter plot of the data in trainingheights200.csv. It can be identified that there is a quadratic nature for the data. So it would be good we can go for such a model.Let us try to now implement polynomial regression in the case of same dataset training heights200.csv. Let us say we want to fit a polynomial of degree 3 to this data we can do so. That is the model we are trying to fit is h (x) = 0 + 1x+ 2x2 + 3x3 So here we need to model the variable Y in terms of the features X,X2,X3. We can take Y has weight and X as height from the data set

[110]:
```
# importing the libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import PolynomialFeatures, MinMaxScaler
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
```

[111]:
```
## reading the dataset
training_dataset = pd.read_csv(r'D:\study␣
↪material\VIT_Data_Science\Winter_Sem\Data Mining and Machine Learning␣
↪Lab\Class_notes\ML_exp2\Training_set_heights200.csv')
```

[112]:
```
training_dataset
```

[112]:

	Height	Weight
0	127.8296	67.63371
1	123.4114	65.95421
2	134.4043	66.14316
3	155.9981	73.45251
4	136.1354	69.30943
..	…	…
194	135.2500	68.41222
195	109.5143	66.49607
196	139.6043	67.84894
197	134.3672	67.27839
198	130.3869	68.48742

[199 rows x 2 columns]

[113]:
```
#  Use MinMaxScaler() to scale the data to 0 to 1 range.
MM = preprocessing.MinMaxScaler()
x = MM.fit_transform(training_dataset)
```

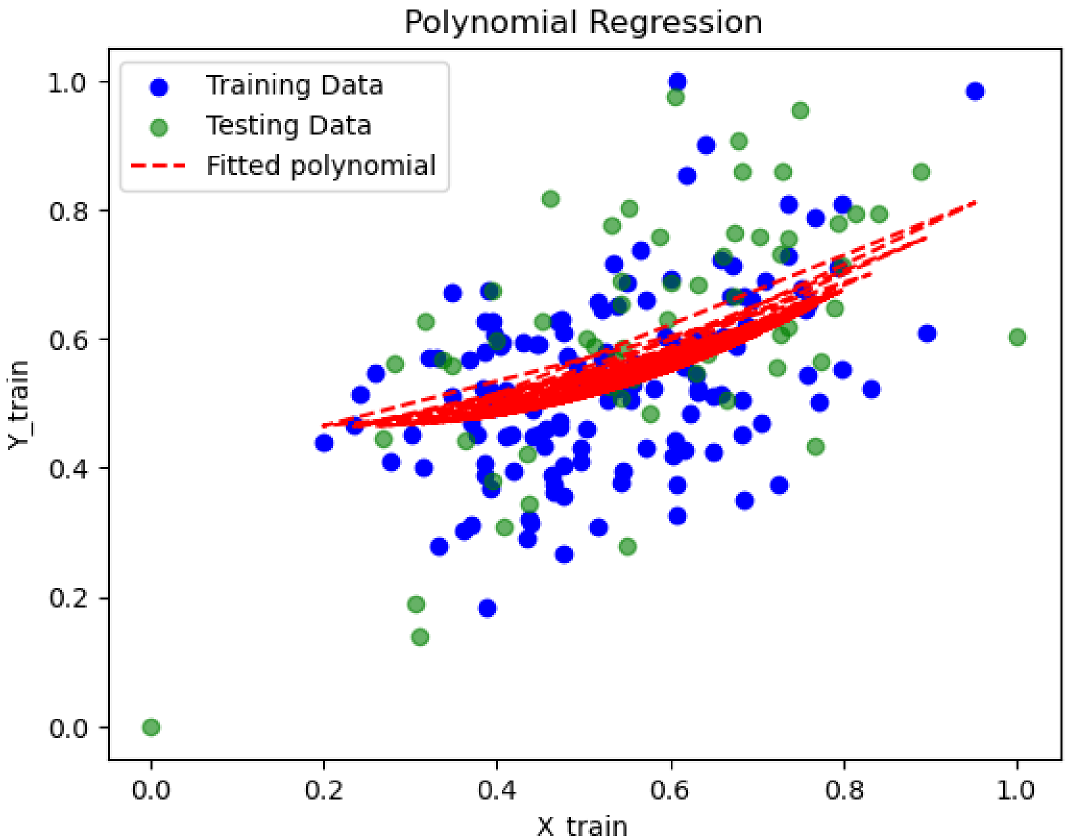
[114]:
```
x_train,x_test,y_train,y_test = train_test_split(x[:,0].reshape(-1,1),x[:
↪,1],test_size=0.3,random_state=0)
```

```
[115]: poly = PolynomialFeatures(degree=3,include_bias=True)
x_train_poly = poly.fit_transform(x_train)
x_test_poly = poly.transform(x_test)

model = LinearRegression()
model.fit(x_train_poly,y_train)

y_train_pred = model.predict(x_train_poly)
y_test_pred = model.predict(x_test_poly)

train_mse = mean_squared_error(y_train,y_train_pred)
test_mse = mean_squared_error(y_test,y_test_pred)

print("Training MSE:",train_mse)
print("Testing MSE:",test_mse)

print("polynomial coefficients:",model.coef_)
print("Intercept:",model.intercept_)
```

```
Training MSE: 0.015123017896174455
Testing MSE: 0.031124085897679937
polynomial coefficients: [ 0.         -0.27208909  0.55389291  0.08276656]
Intercept: 0.4963572481217523
```

4.1 Plotting

```
[116]: plt.scatter(x_train,y_train,label = "Training Data",color = 'blue')
plt.scatter(x_test,y_test,label = "Testing Data",color = 'green',alpha=0.6)
plt.plot(x_train,y_train_pred,linestyle='--',color = 'red',label = "Fitted␣
 ↪polynomial")
plt.xlabel("X_train")
plt.ylabel("Y_train")
plt.legend()
plt.title("Polynomial Regression")
plt.show()
```


Polynomial Regression
Training Data
Testing Data
Fitted polynomial
1.0
0.8
0.6
0.4
0.2
0.0
Y_train
0.0
0.2
0.4
0.6
0.8
1.0
X_train