ECGR_4105_HW5_Problem_3_Source_Code

November 16, 2024

[ ]:
```
# Link to Google Colab: https://colab.research.google.com/drive/
↪1iYPT-HOgODOv1s-hJMxslW3QpRj_bBi9?usp=sharing
```

[6]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
```

[7]:
```
file_url = 'https://raw.githubusercontent.com/lnguye782/ECGR-4105-Intro-to-ML/
↪refs/heads/main/HW2/Housing.csv'
data = pd.read_csv(file_url)

data.head(), data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 545 entries, 0 to 544
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   price             545 non-null    int64
 1   area              545 non-null    int64
 2   bedrooms          545 non-null    int64
 3   bathrooms         545 non-null    int64
 4   stories           545 non-null    int64
 5   mainroad          545 non-null    object
 6   guestroom         545 non-null    object
 7   basement          545 non-null    object
 8   hotwaterheating   545 non-null    object
 9   airconditioning   545 non-null    object
 10  parking           545 non-null    int64
 11  prefarea          545 non-null    object
 12  furnishingstatus  545 non-null    object
dtypes: int64(6), object(7)
memory usage: 55.5+ KB
```

[7]:
```
(      price  area  bedrooms  bathrooms  stories mainroad guestroom basement  \
 0  13300000  7420         4          2        3      yes        no       no
 1  12250000  8960         4          4        4      yes        no       no
 2  12250000  9960         3          2        2      yes        no      yes
 3  12215000  7500         4          2        2      yes        no      yes
 4  11410000  7420         4          1        2      yes       yes      yes

   hotwaterheating airconditioning  parking prefarea furnishingstatus
 0              no             yes        2      yes        furnished
 1              no             yes        3       no        furnished
 2              no              no        2      yes   semi-furnished
 3              no             yes        3      yes        furnished
 4              no             yes        2       no        furnished  ,
 None)
```

[9]:
```
# Preprocessing: Encode categorical features and normalize numerical features
categorical_columns = ['mainroad', 'guestroom', 'basement', 'hotwaterheating',
                       'airconditioning', 'prefarea', 'furnishingstatus']
numerical_columns = ['area', 'bedrooms', 'bathrooms', 'stories', 'parking']

# One-hot encode categorical features
encoder = OneHotEncoder(drop='first', sparse_output=False)
categorical_encoded = encoder.fit_transform(data[categorical_columns])

# Standardize numerical features
scaler = StandardScaler()
numerical_scaled = scaler.fit_transform(data[numerical_columns])

# Combine processed features
X_all_features = np.hstack((numerical_scaled, categorical_encoded))
y_all_features = data['price'].values

# Split the data into training and validation sets
X_train_all, X_val_all, y_train_all, y_val_all =␣
 ↪train_test_split(X_all_features, y_all_features, test_size=0.2,␣
 ↪random_state=42)
```

[11]:
```
# Linear Regression model with gradient descent
class LinearRegressionGD:
    def __init__(self, learning_rate=0.01, epochs=5000):
        self.learning_rate = learning_rate
        self.epochs = epochs
        self.weights = None
        self.bias = None

    def initialize_parameters(self, n_features):
        # Initialize weights and bias
```

```
        self.weights = np.zeros(n_features)
        self.bias = 0

    def compute_loss(self, y_true, y_pred):
        # Mean Squared Error
        return np.mean((y_true - y_pred) ** 2)

    def train(self, X, y, X_val, y_val):
        n_samples, n_features = X.shape
        self.initialize_parameters(n_features)

        train_loss = []
        val_loss = []

        # Training loop
        for epoch in range(self.epochs):
            # Predictions
            y_pred = np.dot(X, self.weights) + self.bias

            # Compute gradients
            dw = -(2 / n_samples) * np.dot(X.T, (y - y_pred))
            db = -(2 / n_samples) * np.sum(y - y_pred)

            # Update parameters
            self.weights -= self.learning_rate * dw
            self.bias -= self.learning_rate * db

            # Compute loss
            loss = self.compute_loss(y, y_pred)
            train_loss.append(loss)

            # Validation loss
            y_val_pred = np.dot(X_val, self.weights) + self.bias
            val_loss.append(self.compute_loss(y_val, y_val_pred))

            # Print progress every 500 epochs
            if (epoch + 1) % 500 == 0:
                print(f"Epoch {epoch + 1}/{self.epochs}: Train Loss = {loss:.
↪4f}, Validation Loss = {val_loss[-1]:.4f}")

        return train_loss, val_loss
```

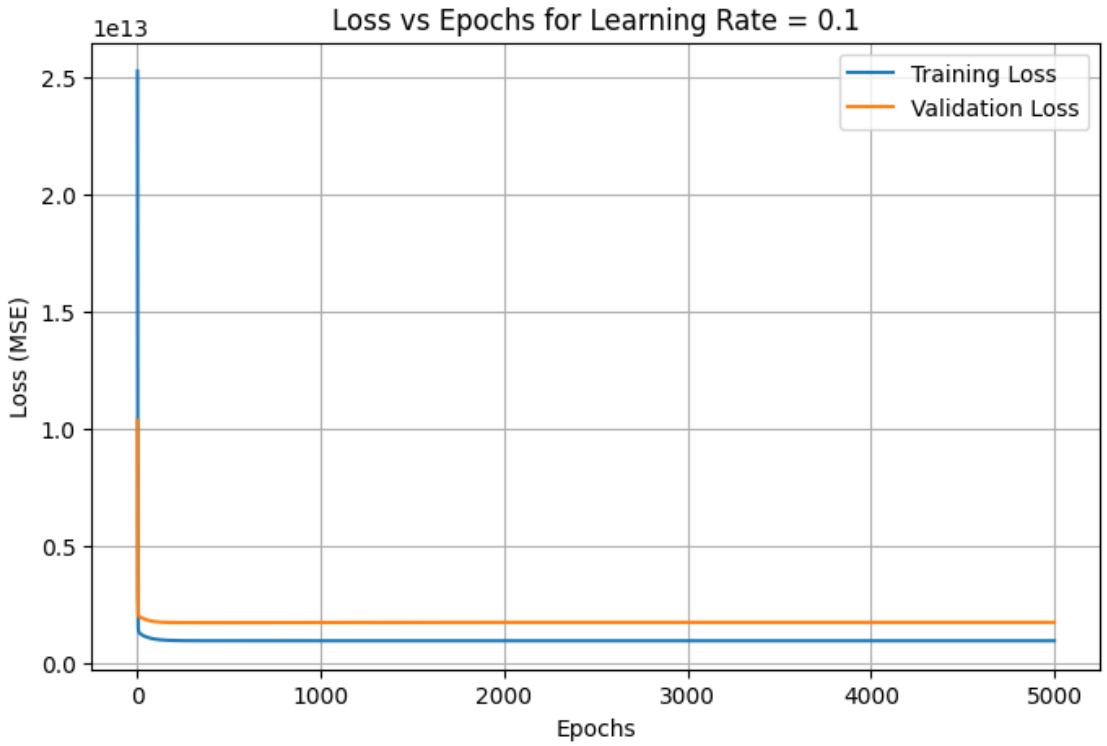
[12]:
```
# Train the model using different learning rates
learning_rates = [0.1, 0.01, 0.001, 0.0001]
results_all_features = {}

for lr in learning_rates:
```

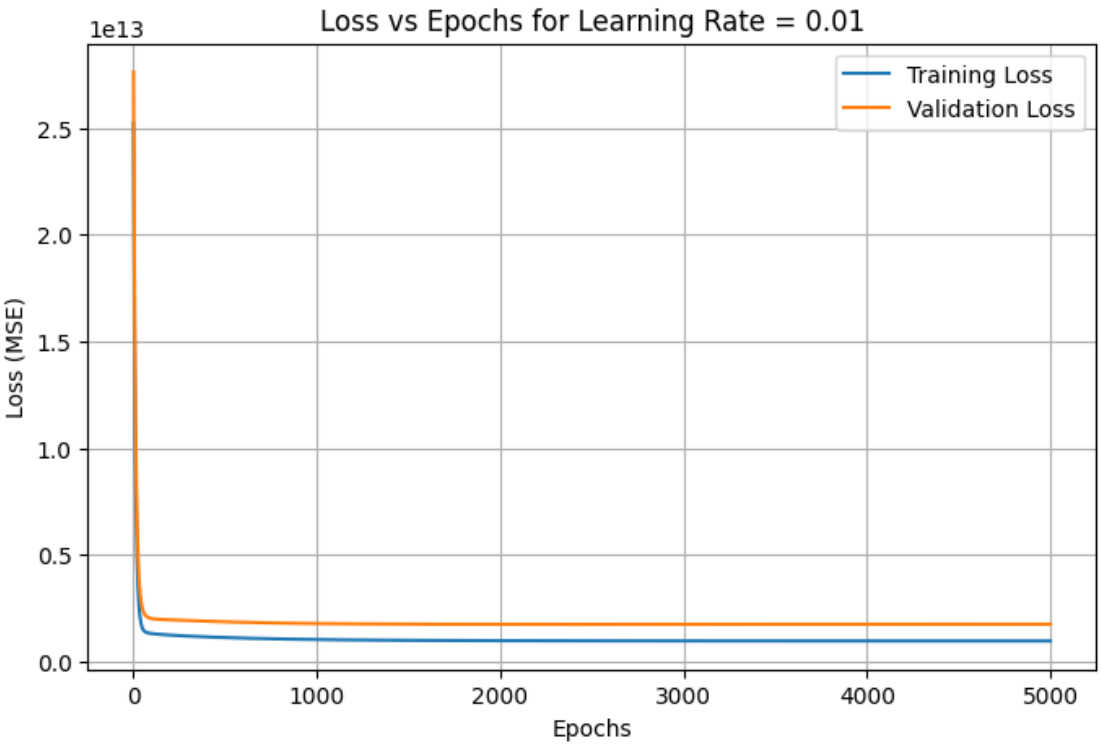
```
    print(f"\nTraining with Learning Rate: {lr}")
    model = LinearRegressionGD(learning_rate=lr, epochs=5000)
    train_loss, val_loss = model.train(X_train_all, y_train_all, X_val_all,␣
↪y_val_all)
    results_all_features[lr] = (train_loss, val_loss, model.weights, model.bias)
```

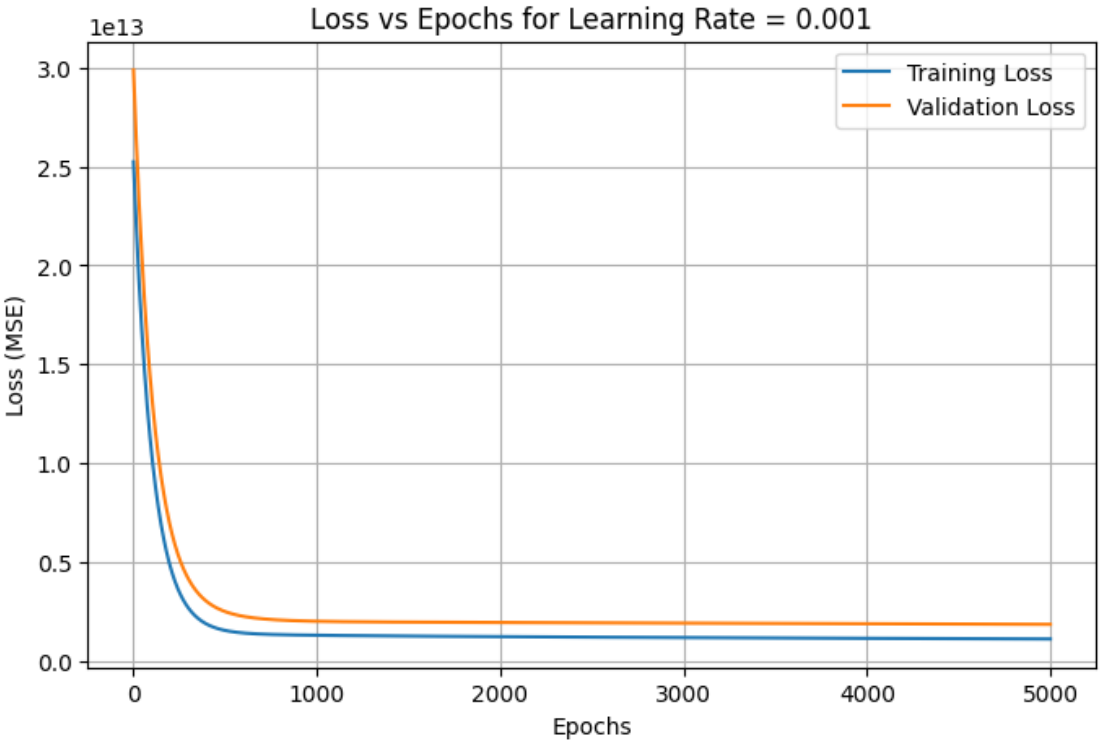
```
Training with Learning Rate: 0.1
Epoch 500/5000: Train Loss = 968434161689.2682, Validation Loss =
1752041921466.2380
Epoch 1000/5000: Train Loss = 968358211635.4539, Validation Loss =
1754267726692.2485
Epoch 1500/5000: Train Loss = 968358188448.7123, Validation Loss =
1754317676955.1101
Epoch 2000/5000: Train Loss = 968358188440.7271, Validation Loss =
1754318667921.8079
Epoch 2500/5000: Train Loss = 968358188440.7242, Validation Loss =
1754318686962.3716
Epoch 3000/5000: Train Loss = 968358188440.7242, Validation Loss =
1754318687323.7144
Epoch 3500/5000: Train Loss = 968358188440.7242, Validation Loss =
1754318687330.5369
Epoch 4000/5000: Train Loss = 968358188440.7242, Validation Loss =
1754318687330.6660
Epoch 4500/5000: Train Loss = 968358188440.7242, Validation Loss =
1754318687330.6667
Epoch 5000/5000: Train Loss = 968358188440.7242, Validation Loss =
1754318687330.6667

Training with Learning Rate: 0.01
Epoch 500/5000: Train Loss = 1126812705584.7939, Validation Loss =
1864882938866.8564
Epoch 1000/5000: Train Loss = 1034222523182.0872, Validation Loss =
1783095574037.8821
Epoch 1500/5000: Train Loss = 996025000245.2867, Validation Loss =
1754351165564.1201
Epoch 2000/5000: Train Loss = 980070937678.3365, Validation Loss =
1745953348499.3706
Epoch 2500/5000: Train Loss = 973352621383.3152, Validation Loss =
1744947959221.3137
Epoch 3000/5000: Train Loss = 970502319906.0071, Validation Loss =
1746298753364.7158
Epoch 3500/5000: Train Loss = 969284498205.9944, Validation Loss =
1748113942705.9753
Epoch 4000/5000: Train Loss = 968760708956.8226, Validation Loss =
1749750630628.0725
Epoch 4500/5000: Train Loss = 968534031375.7451, Validation Loss =
```

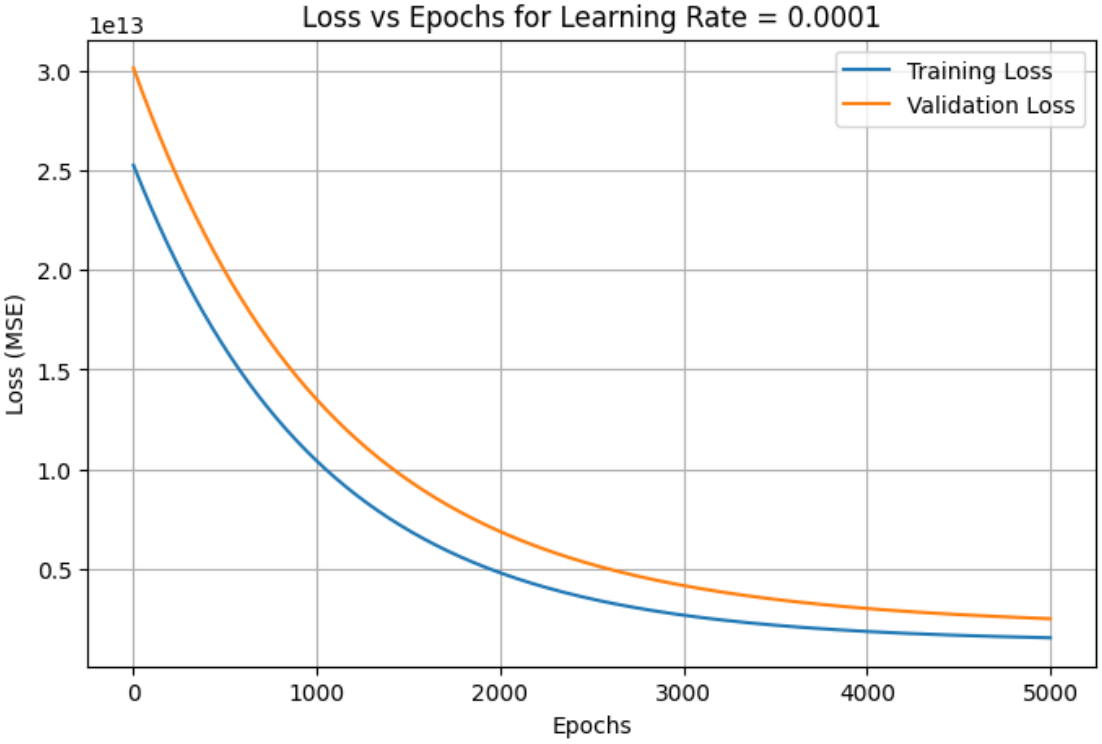
```
1751047495054.4617
Epoch 5000/5000: Train Loss = 968435375202.5380, Validation Loss =
1752015045436.3079

Training with Learning Rate: 0.001
Epoch 500/5000: Train Loss = 1557195750487.2029, Validation Loss =
2509610277593.2358
Epoch 1000/5000: Train Loss = 1312632078636.7546, Validation Loss =
2020294324473.3899
Epoch 1500/5000: Train Loss = 1271585921785.9302, Validation Loss =
1976872130463.8455
Epoch 2000/5000: Train Loss = 1241752937832.5464, Validation Loss =
1958062045888.1929
Epoch 2500/5000: Train Loss = 1216788563819.6497, Validation Loss =
1941054251011.5286
Epoch 3000/5000: Train Loss = 1194870094556.2161, Validation Loss =
1924266472406.2026
Epoch 3500/5000: Train Loss = 1175226584094.1443, Validation Loss =
1908000367923.1870
Epoch 4000/5000: Train Loss = 1157459618181.5737, Validation Loss =
1892582903948.4824
Epoch 4500/5000: Train Loss = 1141318144747.9006, Validation Loss =
1878198875281.1880
Epoch 5000/5000: Train Loss = 1126618061370.3796, Validation Loss =
1864920167418.7158

Training with Learning Rate: 0.0001
Epoch 500/5000: Train Loss = 16065928578311.4355, Validation Loss =
19911901612572.9141
Epoch 1000/5000: Train Loss = 10420133303641.8184, Validation Loss =
13497870348108.5254
Epoch 1500/5000: Train Loss = 6950225612638.8555, Validation Loss =
9450530187395.6895
Epoch 2000/5000: Train Loss = 4815665716233.3779, Validation Loss =
6880434797981.2031
Epoch 2500/5000: Train Loss = 3500842573130.8516, Validation Loss =
5236080909958.4600
Epoch 3000/5000: Train Loss = 2689419370649.0488, Validation Loss =
4174660009824.1914
Epoch 3500/5000: Train Loss = 2187283181208.8916, Validation Loss =
3482439958082.9482
Epoch 4000/5000: Train Loss = 1875294909295.2151, Validation Loss =
3025671940520.8364
Epoch 4500/5000: Train Loss = 1680311488942.8508, Validation Loss =
2720283851060.4966
Epoch 5000/5000: Train Loss = 1557412548047.2776, Validation Loss =
2513144177860.3071
```

[13]:
```python
# Plot training and validation loss for each learning rate
for lr, (train_loss, val_loss, _, _) in results_all_features.items():
    plt.figure(figsize=(8, 5))
    plt.plot(range(1, len(train_loss) + 1), train_loss, label="Training Loss")
    plt.plot(range(1, len(val_loss) + 1), val_loss, label="Validation Loss")
    plt.title(f"Loss vs Epochs for Learning Rate = {lr}")
    plt.xlabel("Epochs")
    plt.ylabel("Loss (MSE)")
    plt.legend()
    plt.grid()
    plt.show()
```




Loss vs Epochs for Learning Rate = 0.01
1e13
Training Loss
Validation Loss
Loss (MSE)
Epochs
0.0
0.5
1.0
1.5
2.0
2.5
0
1000
2000
3000
4000
5000


Loss vs Epochs for Learning Rate = 0.001
1e13
Training Loss
Validation Loss
Loss (MSE)
Epochs
0.0
0.5
1.0
1.5
2.0
2.5
3.0
0
1000
2000
3000
4000
5000


Loss vs Epochs for Learning Rate = 0.0001
1e13
3.0
2.5
2.0
1.5
1.0
0.5
Loss (MSE)
0
1000
2000
3000
4000
5000
Epochs
Training Loss
Validation Loss