homework5

November 15, 2024

[3]:
```
#ORIGINAL CODE FROM LECTURE NOTES

import torch
import torch.optim as optim

# Training data
t_c = [0.5, 14.0, 15.0, 28.0, 11.0, 8.0, 3.0, -4.0, 6.0, 13.0, 21.0]
t_u = [35.7, 55.9, 58.2, 81.9, 56.3, 48.9, 33.9, 21.8, 48.4, 60.4, 68.4]
t_c = torch.tensor(t_c)
t_u = torch.tensor(t_u)

# Normalize the input
t_un = 0.1 * t_u

def model(t_u, w, b):
    return w * t_u + b

def loss_fn(t_p, t_c):
    squared_diffs = (t_p - t_c)**2
    return squared_diffs.mean()

params = torch.tensor([1.0, 0.0], requires_grad=True)
optimizer = optim.Adam([params], lr=1e-2)

n_epochs = 5000
for epoch in range(n_epochs):
    t_p = model(t_un, *params)
    loss = loss_fn(t_p, t_c)

    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

    if epoch % 500 == 0:
        print(f'Epoch {epoch}, Loss {loss.item():.4f}')

print(f'\nFinal Parameters: w={params[0].item():.4f}, b={params[1].item():.4f}')
```

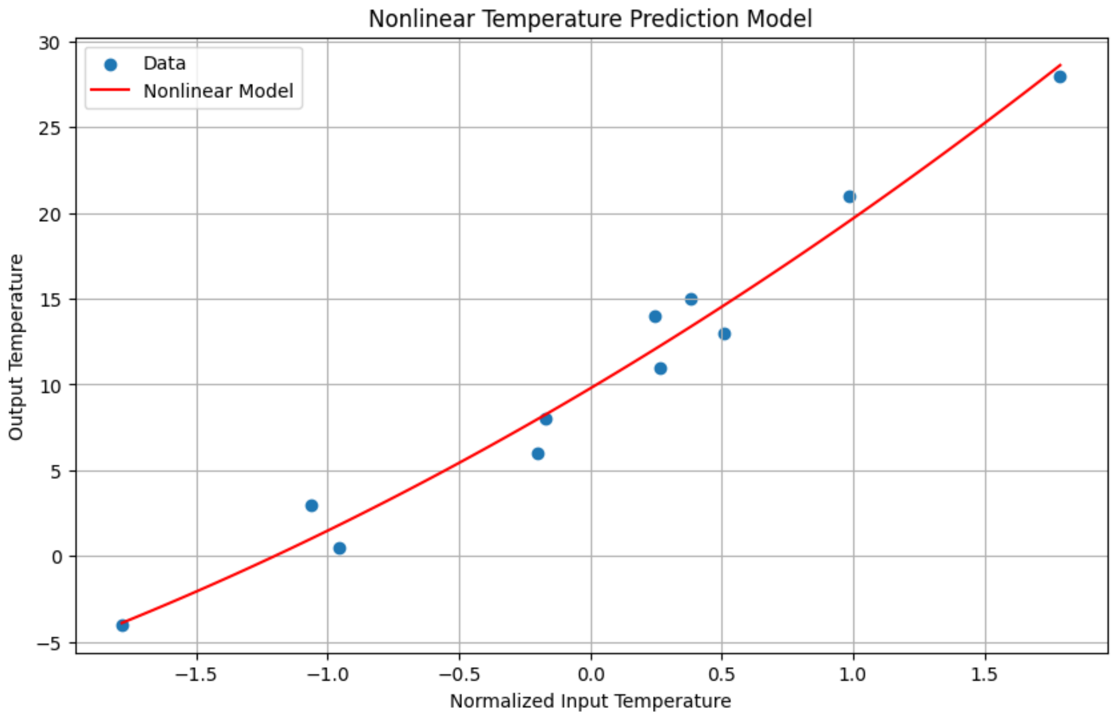
```
Epoch 0, Loss 80.3643
Epoch 500, Loss 24.9258
Epoch 1000, Loss 15.7372
Epoch 1500, Loss 9.4454
Epoch 2000, Loss 5.7623
Epoch 2500, Loss 3.9305
Epoch 3000, Loss 3.1960
Epoch 3500, Loss 2.9770
Epoch 4000, Loss 2.9332
Epoch 4500, Loss 2.9280

Final Parameters: w=5.3660, b=-17.2952
```

[7]:
```python
##Problem 1
#1a and 1b

import torch
import torch.optim as optim
import matplotlib.pyplot as plt

# Training data
t_c = [0.5, 14.0, 15.0, 28.0, 11.0, 8.0, 3.0, -4.0, 6.0, 13.0, 21.0]
t_u = [35.7, 55.9, 58.2, 81.9, 56.3, 48.9, 33.9, 21.8, 48.4, 60.4, 68.4]
t_c = torch.tensor(t_c, dtype=torch.float)
t_u = torch.tensor(t_u, dtype=torch.float)

# Normalize input
t_un = (t_u - torch.mean(t_u)) / torch.std(t_u)

def model(t_u, w2, w1, b):
    return w2 * t_u**2 + w1 * t_u + b

def loss_fn(t_p, t_c):
    squared_diffs = (t_p - t_c)**2
    return squared_diffs.mean()

learning_rates = [0.1, 0.01, 0.001, 0.0001]
final_losses = []
all_params = []

for lr in learning_rates:
    params = torch.tensor([0.1, 0.1, 0.0], requires_grad=True)
    optimizer = optim.Adam([params], lr=lr)

    print(f"\nTraining with learning rate: {lr}")
    for epoch in range(5000):
        t_p = model(t_un, *params)
```

```
        loss = loss_fn(t_p, t_c)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        if epoch % 500 == 0:
            print(f'Epoch {epoch}, Loss {loss.item():.4f}')

    final_losses.append(loss.item())
    all_params.append(params.detach().clone())
    print(f'Final parameters: w2={params[0].item():.4f}, w1={params[1].item():.
 ↪4f}, b={params[2].item():.4f}')

# Find best model
best_lr_index = final_losses.index(min(final_losses))
best_params = all_params[best_lr_index]

# Plot results
plt.figure(figsize=(10, 6))
t_u_range = torch.linspace(min(t_un), max(t_un), 100)
predictions = model(t_u_range, *best_params)

plt.scatter(t_un.numpy(), t_c.numpy(), label='Data')
plt.plot(t_u_range.numpy(), predictions.detach().numpy(), 'r-',␣
 ↪label='Nonlinear Model')
plt.xlabel('Normalized Input Temperature')
plt.ylabel('Output Temperature')
plt.legend()
plt.title('Nonlinear Temperature Prediction Model')
plt.grid(True)
plt.show()

print(f"\nBest learning rate: {learning_rates[best_lr_index]}")
print(f"Best final loss: {min(final_losses):.4f}")
```

```
Training with learning rate: 0.1
Epoch 0, Loss 183.7949
Epoch 500, Loss 2.0907
Epoch 1000, Loss 2.0907
Epoch 1500, Loss 2.0907
Epoch 2000, Loss 2.0907
Epoch 2500, Loss 2.0907
Epoch 3000, Loss 2.0907
Epoch 3500, Loss 2.0907
Epoch 4000, Loss 2.0907
```

```
Epoch 4500, Loss 2.0907
Final parameters: w2=0.8019, w1=9.1033, b=9.7710

Training with learning rate: 0.01
Epoch 0, Loss 183.7949
Epoch 500, Loss 44.1960
Epoch 1000, Loss 12.4033
Epoch 1500, Loss 3.9486
Epoch 2000, Loss 2.3267
Epoch 2500, Loss 2.1083
Epoch 3000, Loss 2.0913
Epoch 3500, Loss 2.0907
Epoch 4000, Loss 2.0907
Epoch 4500, Loss 2.0907
Final parameters: w2=0.8019, w1=9.1034, b=9.7710

Training with learning rate: 0.001
Epoch 0, Loss 183.7949
Epoch 500, Loss 157.5642
Epoch 1000, Loss 135.0377
Epoch 1500, Loss 115.7226
Epoch 2000, Loss 99.2051
Epoch 2500, Loss 85.1278
Epoch 3000, Loss 73.1675
Epoch 3500, Loss 63.0144
Epoch 4000, Loss 54.3578
Epoch 4500, Loss 46.8837
Final parameters: w2=3.0189, w1=4.6637, b=4.2439

Training with learning rate: 0.0001
Epoch 0, Loss 183.7949
Epoch 500, Loss 180.9931
Epoch 1000, Loss 178.2315
Epoch 1500, Loss 175.5074
Epoch 2000, Loss 172.8189
Epoch 2500, Loss 170.1641
Epoch 3000, Loss 167.5414
Epoch 3500, Loss 164.9497
Epoch 4000, Loss 162.3881
Epoch 4500, Loss 159.8559
Final parameters: w2=0.5891, w1=0.5965, b=0.4937
```



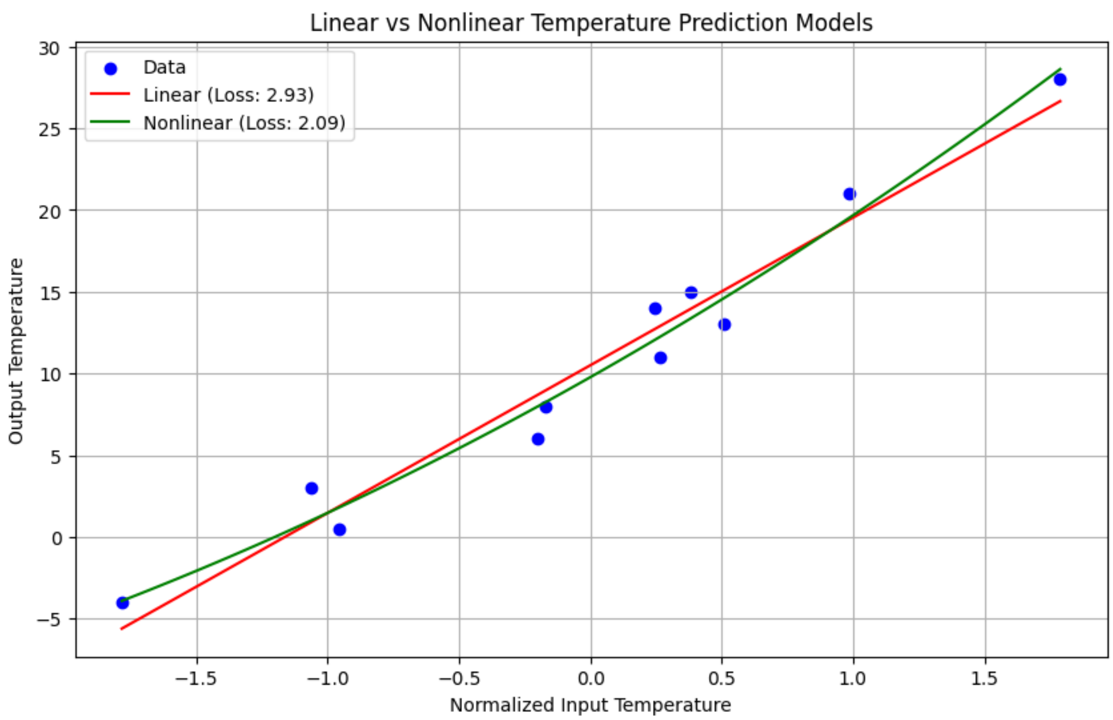

```
Best learning rate: 0.1
Best final loss: 2.0907
```

[10]:

```python
## Problem 1
## 1c

import torch
import torch.optim as optim
import matplotlib.pyplot as plt

# Training data
t_c = [0.5, 14.0, 15.0, 28.0, 11.0, 8.0, 3.0, -4.0, 6.0, 13.0, 21.0]
t_u = [35.7, 55.9, 58.2, 81.9, 56.3, 48.9, 33.9, 21.8, 48.4, 60.4, 68.4]
t_c = torch.tensor(t_c, dtype=torch.float)
t_u = torch.tensor(t_u, dtype=torch.float)

# Normalize input
t_un = (t_u - torch.mean(t_u)) / torch.std(t_u)

# Linear model
def linear_model(t_u, w, b):
    return w * t_u + b
```

```
# Nonlinear model
def nonlinear_model(t_u, w2, w1, b):
    return w2 * t_u**2 + w1 * t_u + b

def loss_fn(t_p, t_c):
    squared_diffs = (t_p - t_c)**2
    return squared_diffs.mean()

# Train linear model
linear_params = torch.tensor([0.1, 0.0], requires_grad=True)
linear_optimizer = optim.Adam([linear_params], lr=0.01)

for epoch in range(5000):
    t_p = linear_model(t_un, *linear_params)
    loss = loss_fn(t_p, t_c)
    linear_optimizer.zero_grad()
    loss.backward()
    linear_optimizer.step()

linear_final_loss = loss.item()

# Train nonlinear model
nonlinear_params = torch.tensor([0.1, 0.1, 0.0], requires_grad=True)
nonlinear_optimizer = optim.Adam([nonlinear_params], lr=0.01)

for epoch in range(5000):
    t_p = nonlinear_model(t_un, *nonlinear_params)
    loss = loss_fn(t_p, t_c)
    nonlinear_optimizer.zero_grad()
    loss.backward()
    nonlinear_optimizer.step()

nonlinear_final_loss = loss.item()

# Plotting
plt.figure(figsize=(10, 6))
t_u_range = torch.linspace(min(t_un), max(t_un), 100)

# Plot data points
plt.scatter(t_un.numpy(), t_c.numpy(), label='Data', color='blue')

# Plot linear model predictions
linear_predictions = linear_model(t_u_range, *linear_params.detach())
plt.plot(t_u_range.numpy(), linear_predictions.numpy(), 'r-', label=f'Linear␣
 ↪(Loss: {linear_final_loss:.2f})')

# Plot nonlinear model predictions
```

```
nonlinear_predictions = nonlinear_model(t_u_range, *nonlinear_params.detach())
plt.plot(t_u_range.numpy(), nonlinear_predictions.numpy(), 'g-',␣
↪label=f'Nonlinear (Loss: {nonlinear_final_loss:.2f})')

plt.xlabel('Normalized Input Temperature')
plt.ylabel('Output Temperature')
plt.legend()
plt.title('Linear vs Nonlinear Temperature Prediction Models')
plt.grid(True)
plt.show()

print(f"\nLinear Model Final Loss: {linear_final_loss:.4f}")
print(f"Nonlinear Model Final Loss: {nonlinear_final_loss:.4f}")
print(f"Improvement: {((linear_final_loss - nonlinear_final_loss) /␣
↪linear_final_loss * 100):.2f}%")
```




```
Linear Model Final Loss: 2.9276
Nonlinear Model Final Loss: 2.0907
Improvement: 28.59%
```

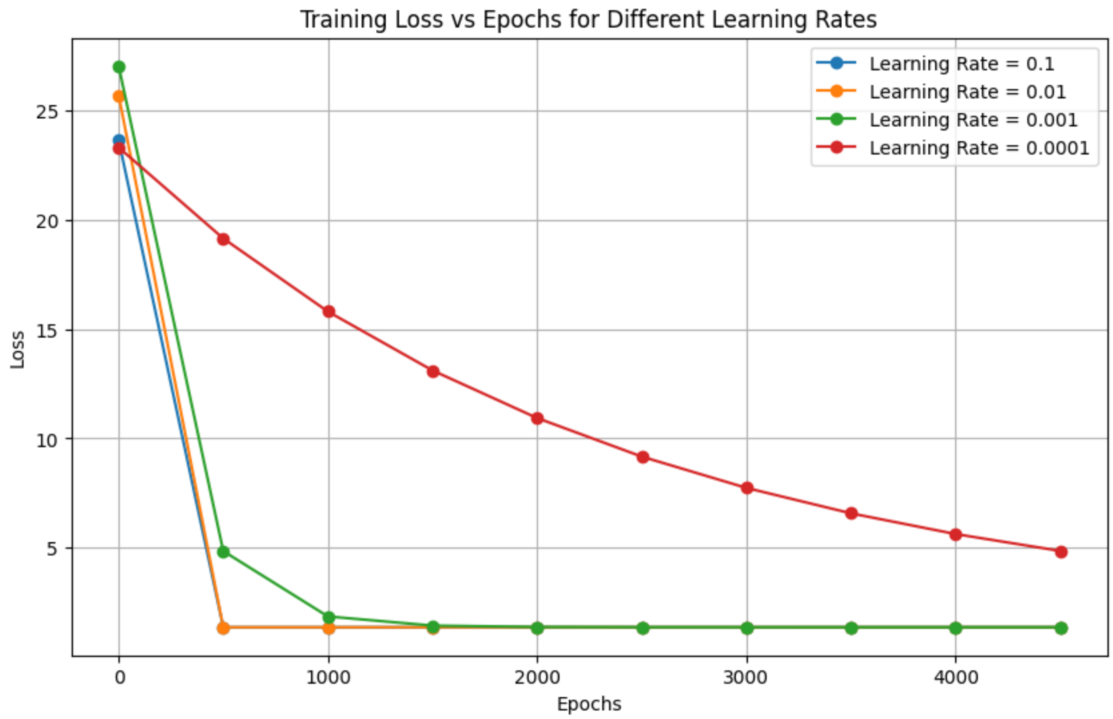
[17]:
```
import torch
import torch.optim as optim
import pandas as pd
```

```python
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

# Load and preprocess data
data = pd.read_csv('assets/Housing.csv')
features = ['area', 'bedrooms', 'bathrooms', 'stories', 'parking']
X = data[features]
y = data['price'] / 1e6  # Convert to millions for better scaling

# Split and scale
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Convert to tensors
X_train_tensor = torch.FloatTensor(X_train_scaled)
y_train_tensor = torch.FloatTensor(y_train.values)
X_test_tensor = torch.FloatTensor(X_test_scaled)
y_test_tensor = torch.FloatTensor(y_test.values)

class LinearRegression(torch.nn.Module):
    def __init__(self):
        super().__init__()
        self.linear = torch.nn.Linear(5, 1)

    def forward(self, x):
        return self.linear(x)

# Training function with loss tracking
def train_and_plot(learning_rate):
    model = LinearRegression()
    criterion = torch.nn.MSELoss()
    optimizer = optim.SGD(model.parameters(), lr=learning_rate)

    train_losses = []
    epochs = []

    for epoch in range(5000):
        optimizer.zero_grad()
        outputs = model(X_train_tensor)
        loss = criterion(outputs, y_train_tensor.reshape(-1, 1))
        loss.backward()
        optimizer.step()
```

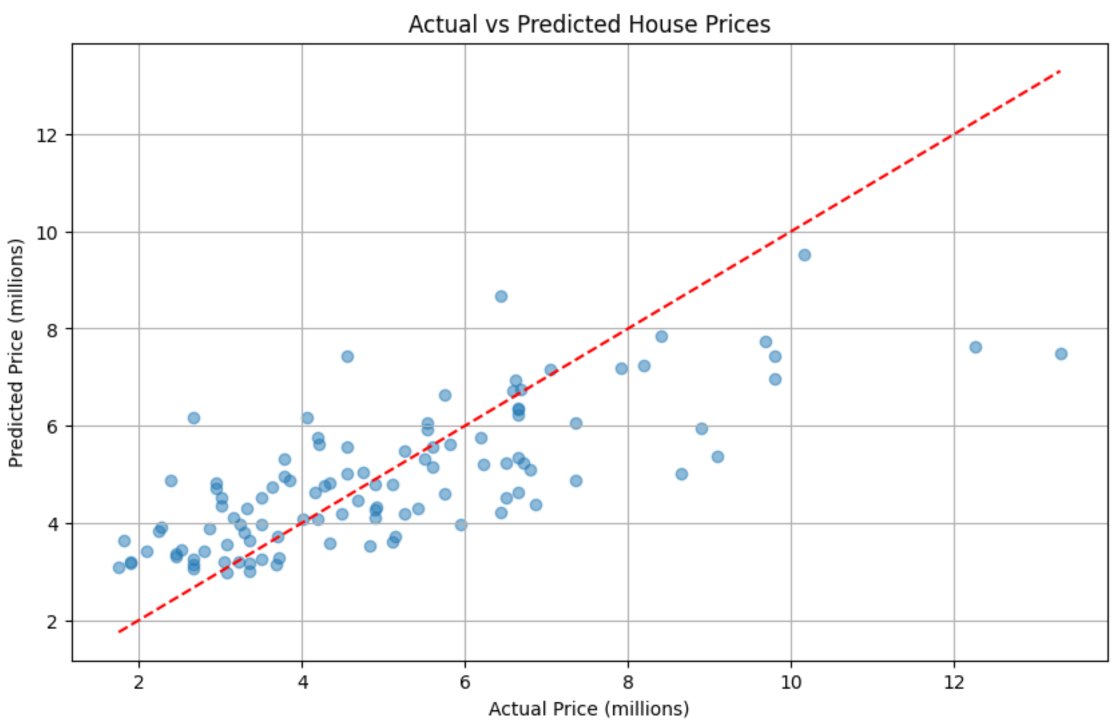
```python
        if epoch % 500 == 0:
            epochs.append(epoch)
            train_losses.append(loss.item())
            print(f'Epoch {epoch}, Loss: {loss.item():.4f}')

    return epochs, train_losses, model

# Plot training curves for different learning rates
plt.figure(figsize=(10, 6))
learning_rates = [0.1, 0.01, 0.001, 0.0001]
best_loss = float('inf')
best_model = None

for lr in learning_rates:
    epochs, losses, model = train_and_plot(lr)
    plt.plot(epochs, losses, marker='o', label=f'Learning Rate = {lr}')
    if losses[-1] < best_loss:
        best_loss = losses[-1]
        best_model = model

plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training Loss vs Epochs for Different Learning Rates')
plt.legend()
plt.grid(True)
plt.show()

# Plot actual vs predicted prices
with torch.no_grad():
    y_pred = best_model(X_test_tensor)

plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred.numpy(), alpha=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')
plt.xlabel('Actual Price (millions)')
plt.ylabel('Predicted Price (millions)')
plt.title('Actual vs Predicted House Prices')
plt.grid(True)
plt.show()
```

```
Epoch 0, Loss: 23.6618
Epoch 500, Loss: 1.3500
Epoch 1000, Loss: 1.3500
Epoch 1500, Loss: 1.3500
Epoch 2000, Loss: 1.3500
Epoch 2500, Loss: 1.3500
Epoch 3000, Loss: 1.3500
```

```
Epoch 3500, Loss: 1.3500
Epoch 4000, Loss: 1.3500
Epoch 4500, Loss: 1.3500
Epoch 0, Loss: 25.7232
Epoch 500, Loss: 1.3500
Epoch 1000, Loss: 1.3500
Epoch 1500, Loss: 1.3500
Epoch 2000, Loss: 1.3500
Epoch 2500, Loss: 1.3500
Epoch 3000, Loss: 1.3500
Epoch 3500, Loss: 1.3500
Epoch 4000, Loss: 1.3500
Epoch 4500, Loss: 1.3500
Epoch 0, Loss: 27.0583
Epoch 500, Loss: 4.8386
Epoch 1000, Loss: 1.8445
Epoch 1500, Loss: 1.4244
Epoch 2000, Loss: 1.3625
Epoch 2500, Loss: 1.3524
Epoch 3000, Loss: 1.3506
Epoch 3500, Loss: 1.3502
Epoch 4000, Loss: 1.3501
Epoch 4500, Loss: 1.3500
Epoch 0, Loss: 23.3274
Epoch 500, Loss: 19.1591
Epoch 1000, Loss: 15.8106
Epoch 1500, Loss: 13.1122
Epoch 2000, Loss: 10.9317
Epoch 2500, Loss: 9.1656
Epoch 3000, Loss: 7.7323
Epoch 3500, Loss: 6.5671
Epoch 4000, Loss: 5.6183
Epoch 4500, Loss: 4.8448
```



Training Loss vs Epochs for Different Learning Rates
Learning Rate = 0.1
Learning Rate = 0.01
Learning Rate = 0.001
Learning Rate = 0.0001
Loss
Epochs
0
1000
2000
3000
4000
5
10
15
20
25



Actual vs Predicted House Prices
Predicted Price (millions)
Actual Price (millions)
2
4
6
8
10
12

[4]:

```python
##Problem 2
## 2a 2b 2c

import torch
import torch.optim as optim
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

# Load and preprocess data
data = pd.read_csv('assets/Housing.csv')
features = ['area', 'bedrooms', 'bathrooms', 'stories', 'parking']
X = data[features]
y = data['price']

# Split and scale
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
scaler_X = StandardScaler()
scaler_y = StandardScaler()

X_train_scaled = scaler_X.fit_transform(X_train)
X_test_scaled = scaler_X.transform(X_test)
y_train_scaled = scaler_y.fit_transform(y_train.values.reshape(-1, 1)).flatten()
y_test_scaled = scaler_y.transform(y_test.values.reshape(-1, 1)).flatten()

# Convert to tensors
X_train_tensor = torch.FloatTensor(X_train_scaled)
y_train_tensor = torch.FloatTensor(y_train_scaled)
X_test_tensor = torch.FloatTensor(X_test_scaled)
y_test_tensor = torch.FloatTensor(y_test_scaled)

class LinearRegression(torch.nn.Module):
    def __init__(self):
        super().__init__()
        self.linear = torch.nn.Linear(5, 1)  # 5 features -> 1 output

    def forward(self, x):
        return self.linear(x)

def train_model(lr):
    model = LinearRegression()
    criterion = torch.nn.MSELoss()
    optimizer = optim.SGD(model.parameters(), lr=lr)
```

```
    train_losses = []
    val_losses = []

    print(f"\nTraining with learning rate: {lr}")
    for epoch in range(5000):
        # Training
        model.train()
        outputs = model(X_train_tensor)
        loss = criterion(outputs, y_train_tensor.reshape(-1, 1))

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        # Validation
        model.eval()
        with torch.no_grad():
            val_outputs = model(X_test_tensor)
            val_loss = criterion(val_outputs, y_test_tensor.reshape(-1, 1))

        if (epoch + 1) % 500 == 0:
            print(f'Epoch {epoch+1}:')
            print(f'Training Loss: {loss.item():.6f}')
            print(f'Validation Loss: {val_loss.item():.6f}')
            train_losses.append(loss.item())
            val_losses.append(val_loss.item())

    return model, train_losses, val_losses

# Train with different learning rates
learning_rates = [0.1, 0.01, 0.001, 0.0001]
all_models = []
all_train_losses = []
all_val_losses = []

for lr in learning_rates:
    model, train_losses, val_losses = train_model(lr)
    all_models.append(model)
    all_train_losses.append(train_losses)
    all_val_losses.append(val_losses)

# Find best model
best_model_idx = np.argmin([losses[-1] for losses in all_val_losses])
best_model = all_models[best_model_idx]
best_lr = learning_rates[best_model_idx]

print("\nBest Model Parameters:")
```

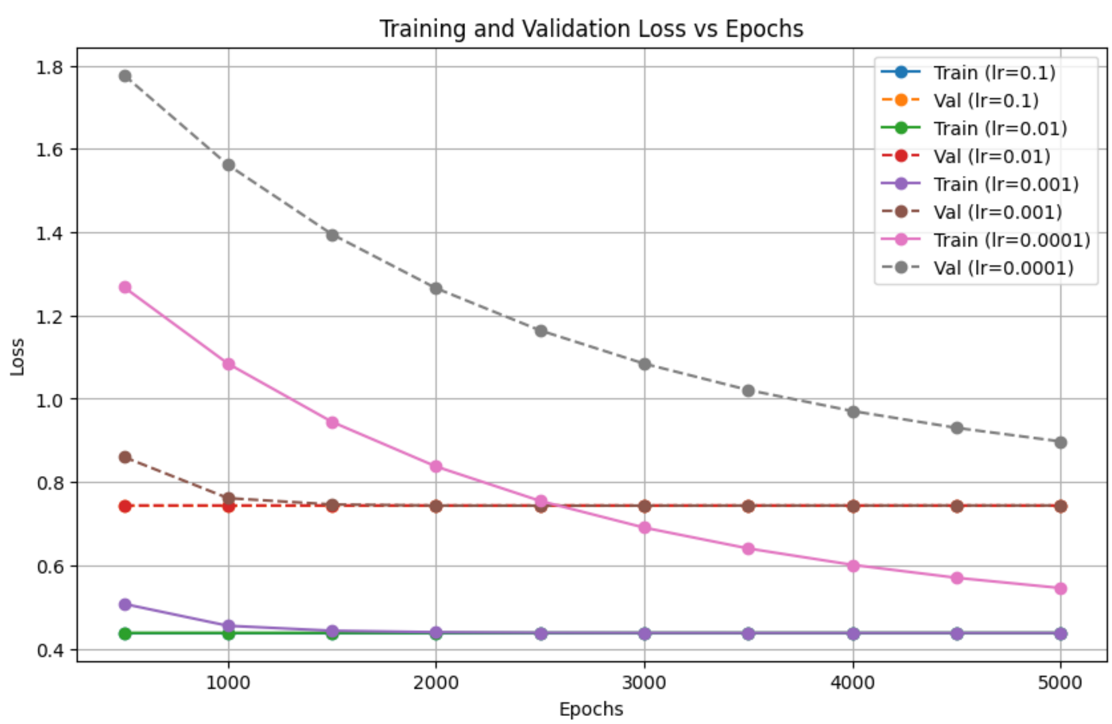
```python
for name, param in best_model.named_parameters():
    if name == 'linear.weight':
        print("\nFeature weights:")
        for feature, weight in zip(features, param.data.numpy().flatten()):
            print(f"{feature}: {weight:.6f}")
    elif name == 'linear.bias':
        print(f"\nBias: {param.data.numpy()[0]:.6f}")

print(f"\nBest learning rate: {best_lr}")
print(f"Final validation loss: {all_val_losses[best_model_idx][-1]:.6f}")

# Plot training curves
plt.figure(figsize=(10, 6))
epochs = np.arange(500, 5001, 500)
for i, lr in enumerate(learning_rates):
    plt.plot(epochs, all_train_losses[i], label=f'Train (lr={lr})', marker='o')
    plt.plot(epochs, all_val_losses[i], label=f'Val (lr={lr})', marker='o',␣
↪linestyle='--')

plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training and Validation Loss vs Epochs')
plt.legend()
plt.grid(True)
plt.show()
```

```
Training with learning rate: 0.1
Epoch 500:
Training Loss: 0.437832
Validation Loss: 0.743571
Epoch 1000:
Training Loss: 0.437832
Validation Loss: 0.743571
Epoch 1500:
Training Loss: 0.437832
Validation Loss: 0.743571
Epoch 2000:
Training Loss: 0.437832
Validation Loss: 0.743571
Epoch 2500:
Training Loss: 0.437832
Validation Loss: 0.743571
Epoch 3000:
Training Loss: 0.437832
Validation Loss: 0.743571
Epoch 3500:
Training Loss: 0.437832
```

```
Validation Loss: 0.743571
Epoch 4000:
Training Loss: 0.437832
Validation Loss: 0.743571
Epoch 4500:
Training Loss: 0.437832
Validation Loss: 0.743571
Epoch 5000:
Training Loss: 0.437832
Validation Loss: 0.743571

Training with learning rate: 0.01
Epoch 500:
Training Loss: 0.437834
Validation Loss: 0.743727
Epoch 1000:
Training Loss: 0.437832
Validation Loss: 0.743571
Epoch 1500:
Training Loss: 0.437832
Validation Loss: 0.743571
Epoch 2000:
Training Loss: 0.437832
Validation Loss: 0.743571
Epoch 2500:
Training Loss: 0.437832
Validation Loss: 0.743571
Epoch 3000:
Training Loss: 0.437832
Validation Loss: 0.743571
Epoch 3500:
Training Loss: 0.437832
Validation Loss: 0.743571
Epoch 4000:
Training Loss: 0.437832
Validation Loss: 0.743571
Epoch 4500:
Training Loss: 0.437832
Validation Loss: 0.743571
Epoch 5000:
Training Loss: 0.437832
Validation Loss: 0.743571

Training with learning rate: 0.001
Epoch 500:
Training Loss: 0.507405
Validation Loss: 0.860031
Epoch 1000:
```

```
Training Loss: 0.454805
Validation Loss: 0.761232
Epoch 1500:
Training Loss: 0.442914
Validation Loss: 0.746025
Epoch 2000:
Training Loss: 0.439387
Validation Loss: 0.743386
Epoch 2500:
Training Loss: 0.438311
Validation Loss: 0.743124
Epoch 3000:
Training Loss: 0.437980
Validation Loss: 0.743258
Epoch 3500:
Training Loss: 0.437878
Validation Loss: 0.743394
Epoch 4000:
Training Loss: 0.437846
Validation Loss: 0.743481
Epoch 4500:
Training Loss: 0.437837
Validation Loss: 0.743528
Epoch 5000:
Training Loss: 0.437834
Validation Loss: 0.743551

Training with learning rate: 0.0001
Epoch 500:
Training Loss: 1.267752
Validation Loss: 1.776989
Epoch 1000:
Training Loss: 1.084056
Validation Loss: 1.561130
Epoch 1500:
Training Loss: 0.944256
Validation Loss: 1.394576
Epoch 2000:
Training Loss: 0.837147
Validation Loss: 1.265131
Epoch 2500:
Training Loss: 0.754547
Validation Loss: 1.163834
Epoch 3000:
Training Loss: 0.690446
Validation Loss: 1.084043
Epoch 3500:
Training Loss: 0.640401
```

```
Validation Loss: 1.020803
Epoch 4000:
Training Loss: 0.601103
Validation Loss: 0.970388
Epoch 4500:
Training Loss: 0.570075
Validation Loss: 0.929978
Epoch 5000:
Training Loss: 0.545447
Validation Loss: 0.897418

Best Model Parameters:

Feature weights:
area: 0.387517
bedrooms: 0.065551
bathrooms: 0.321314
stories: 0.241037
parking: 0.163968

Bias: 0.000001

Best learning rate: 0.001
Final validation loss: 0.743551
```



[7]:

```python
##PROBLEM 3

import torch
import torch.optim as optim
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
import matplotlib.pyplot as plt

# Load data
data = pd.read_csv('assets/Housing.csv')

# Convert categorical variables to numeric
categorical_columns = ['mainroad', 'guestroom', 'basement', 'hotwaterheating',
                      'airconditioning', 'prefarea', 'furnishingstatus']
label_encoders = {}

for column in categorical_columns:
    label_encoders[column] = LabelEncoder()
    data[column] = label_encoders[column].fit_transform(data[column])

# Prepare features and target
X = data.drop('price', axis=1)
y = data['price']

# Split and scale
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
scaler_X = StandardScaler()
scaler_y = StandardScaler()

X_train_scaled = scaler_X.fit_transform(X_train)
X_test_scaled = scaler_X.transform(X_test)
y_train_scaled = scaler_y.fit_transform(y_train.values.reshape(-1, 1)).flatten()
y_test_scaled = scaler_y.transform(y_test.values.reshape(-1, 1)).flatten()

# Convert to tensors
X_train_tensor = torch.FloatTensor(X_train_scaled)
y_train_tensor = torch.FloatTensor(y_train_scaled)
X_test_tensor = torch.FloatTensor(X_test_scaled)
y_test_tensor = torch.FloatTensor(y_test_scaled)

class LinearRegression(torch.nn.Module):
    def __init__(self, input_size):
        super().__init__()
        self.linear = torch.nn.Linear(input_size, 1)
```

```python
    def forward(self, x):
        return self.linear(x)

def train_model(lr):
    model = LinearRegression(X_train.shape[1])
    criterion = torch.nn.MSELoss()
    optimizer = optim.SGD(model.parameters(), lr=lr)

    train_losses = []
    val_losses = []

    print(f"\nTraining with learning rate: {lr}")
    for epoch in range(5000):
        # Training
        model.train()
        outputs = model(X_train_tensor)
        loss = criterion(outputs, y_train_tensor.reshape(-1, 1))

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        # Validation
        model.eval()
        with torch.no_grad():
            val_outputs = model(X_test_tensor)
            val_loss = criterion(val_outputs, y_test_tensor.reshape(-1, 1))

        if (epoch + 1) % 500 == 0:
            print(f'Epoch {epoch+1}:')
            print(f'Training Loss: {loss.item():.6f}')
            print(f'Validation Loss: {val_loss.item():.6f}')
            train_losses.append(loss.item())
            val_losses.append(val_loss.item())

    return model, train_losses, val_losses

# Train with different learning rates
learning_rates = [0.1, 0.01, 0.001, 0.0001]
all_models = []
all_train_losses = []
all_val_losses = []

for lr in learning_rates:
    model, train_losses, val_losses = train_model(lr)
    all_models.append(model)
```

```
    all_train_losses.append(train_losses)
    all_val_losses.append(val_losses)

# Find best model
best_model_idx = np.argmin([losses[-1] for losses in all_val_losses])
best_model = all_models[best_model_idx]
best_lr = learning_rates[best_model_idx]

print("\nBest Model Parameters:")
for name, param in best_model.named_parameters():
    if name == 'linear.weight':
        print("\nFeature weights:")
        for feature, weight in zip(X_train.columns, param.data.numpy().
 ↪flatten()):
            print(f"{feature}: {weight:.6f}")
    elif name == 'linear.bias':
        print(f"\nBias: {param.data.numpy()[0]:.6f}")

print(f"\nBest learning rate: {best_lr}")
print(f"Final validation loss: {all_val_losses[best_model_idx][-1]:.6f}")

# Plot training curves
plt.figure(figsize=(12, 6))
epochs = np.arange(500, 5001, 500)
for i, lr in enumerate(learning_rates):
    plt.plot(epochs, all_train_losses[i], label=f'Train (lr={lr})', marker='o')
    plt.plot(epochs, all_val_losses[i], label=f'Val (lr={lr})', marker='o',␣
 ↪linestyle='--')

plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training and Validation Loss vs Epochs')
plt.legend()
plt.grid(True)
plt.show()

# Plot feature importance
plt.figure(figsize=(12, 6))
weights = best_model.linear.weight.data.numpy().flatten()
feature_importance = pd.DataFrame({
    'Feature': X_train.columns,
    'Weight': np.abs(weights)
}).sort_values('Weight', ascending=True)

plt.barh(feature_importance['Feature'], feature_importance['Weight'])
plt.xlabel('Absolute Weight Value')
plt.ylabel('Features')
```

```python
plt.title('Feature Importance in Housing Price Prediction')
plt.tight_layout()
plt.show()
```

```
Training with learning rate: 0.1
Epoch 500:
Training Loss: 0.314557
Validation Loss: 0.574611
Epoch 1000:
Training Loss: 0.314557
Validation Loss: 0.574611
Epoch 1500:
Training Loss: 0.314557
Validation Loss: 0.574611
Epoch 2000:
Training Loss: 0.314557
Validation Loss: 0.574611
Epoch 2500:
Training Loss: 0.314557
Validation Loss: 0.574611
Epoch 3000:
Training Loss: 0.314557
Validation Loss: 0.574611
Epoch 3500:
Training Loss: 0.314557
Validation Loss: 0.574611
Epoch 4000:
Training Loss: 0.314557
Validation Loss: 0.574611
Epoch 4500:
Training Loss: 0.314557
Validation Loss: 0.574611
Epoch 5000:
Training Loss: 0.314557
Validation Loss: 0.574611

Training with learning rate: 0.01
Epoch 500:
Training Loss: 0.314575
Validation Loss: 0.574551
Epoch 1000:
Training Loss: 0.314557
Validation Loss: 0.574610
Epoch 1500:
Training Loss: 0.314557
Validation Loss: 0.574611
Epoch 2000:
```

```
Training Loss: 0.314557
Validation Loss: 0.574611
Epoch 2500:
Training Loss: 0.314557
Validation Loss: 0.574611
Epoch 3000:
Training Loss: 0.314557
Validation Loss: 0.574611
Epoch 3500:
Training Loss: 0.314557
Validation Loss: 0.574611
Epoch 4000:
Training Loss: 0.314557
Validation Loss: 0.574611
Epoch 4500:
Training Loss: 0.314557
Validation Loss: 0.574611
Epoch 5000:
Training Loss: 0.314557
Validation Loss: 0.574611

Training with learning rate: 0.001
Epoch 500:
Training Loss: 0.399782
Validation Loss: 0.658702
Epoch 1000:
Training Loss: 0.342636
Validation Loss: 0.584102
Epoch 1500:
Training Loss: 0.325162
Validation Loss: 0.573324
Epoch 2000:
Training Loss: 0.318813
Validation Loss: 0.572084
Epoch 2500:
Training Loss: 0.316341
Validation Loss: 0.572587
Epoch 3000:
Training Loss: 0.315328
Validation Loss: 0.573241
Epoch 3500:
Training Loss: 0.314897
Validation Loss: 0.573739
Epoch 4000:
Training Loss: 0.314709
Validation Loss: 0.574071
Epoch 4500:
Training Loss: 0.314626
```

```
Validation Loss: 0.574280
Epoch 5000:
Training Loss: 0.314588
Validation Loss: 0.574409

Training with learning rate: 0.0001
Epoch 500:
Training Loss: 0.880955
Validation Loss: 1.466555
Epoch 1000:
Training Loss: 0.710533
Validation Loss: 1.219520
Epoch 1500:
Training Loss: 0.598023
Validation Loss: 1.048471
Epoch 2000:
Training Loss: 0.522442
Validation Loss: 0.928042
Epoch 2500:
Training Loss: 0.470674
Validation Loss: 0.841833
Epoch 3000:
Training Loss: 0.434458
Validation Loss: 0.779115
Epoch 3500:
Training Loss: 0.408556
Validation Loss: 0.732782
Epoch 4000:
Training Loss: 0.389608
Validation Loss: 0.698062
Epoch 4500:
Training Loss: 0.375439
Validation Loss: 0.671705
Epoch 5000:
Training Loss: 0.364620
Validation Loss: 0.651461

Best Model Parameters:

Feature weights:
area: 0.293081
bedrooms: 0.036938
bathrooms: 0.298370
stories: 0.192993
mainroad: 0.074730
guestroom: 0.053281
basement: 0.103163
hotwaterheating: 0.086414
```

```
airconditioning: 0.208585
parking: 0.109573
prefarea: 0.152070
furnishingstatus: -0.090537

Bias: 0.000001

Best learning rate: 0.001
Final validation loss: 0.574409
```