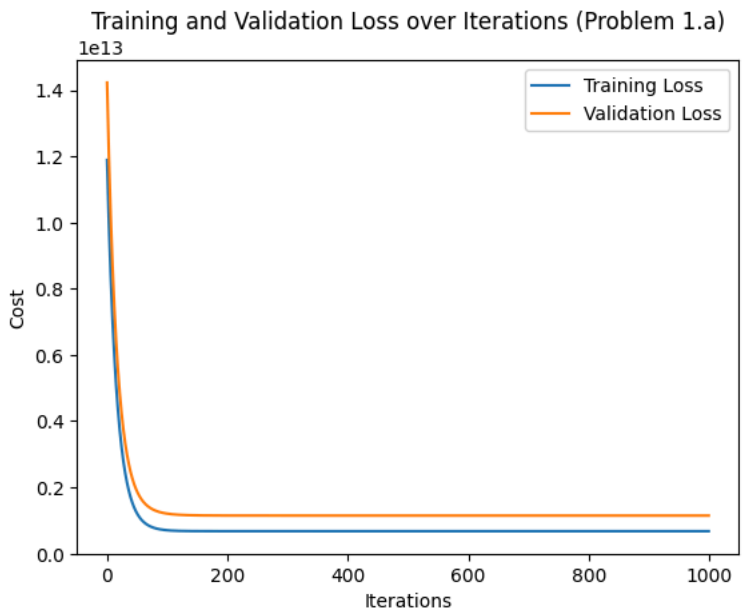
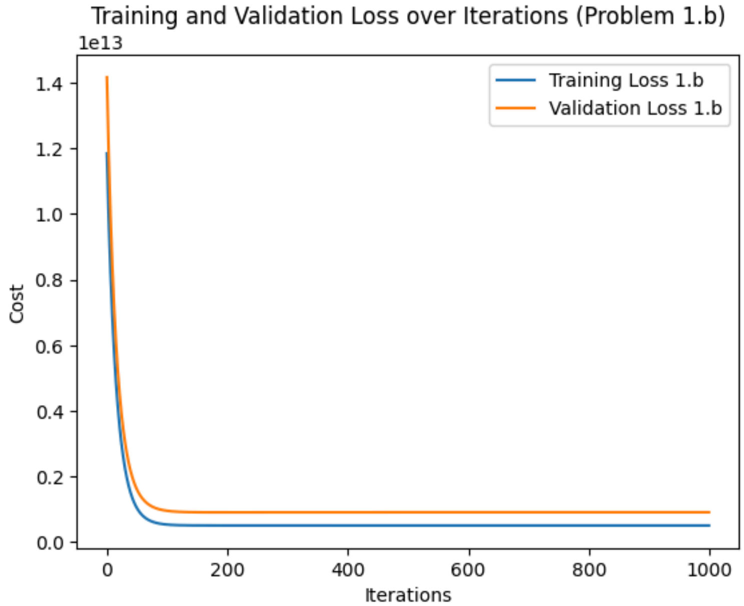
```
import pandas as pd

file_path = '/content/drive/MyDrive/HW2/Housing.csv'
data = pd.read_csv(file_path)
data.head()

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split

# Feature selection for 1.a (Area, bedrooms, bathrooms, stories, parking)
features = data[['area', 'bedrooms', 'bathrooms', 'stories', 'parking']]
target = data['price']

# Normalize the features
def normalize_features(X):
    return (X - X.mean()) / X.std()

# Prepare the data
X = normalize_features(features).values
y = target.values

# Add a column of ones to X for the bias term (intercept)
X = np.c_[np.ones(X.shape[0]), X]

# Split the data into training (80%) and validation (20%) sets
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize theta (weights) to zero
theta = np.zeros(X_train.shape[1])

# Hypothesis function (linear regression model)
def hypothesis(X, theta):
    return np.dot(X, theta)

# Compute cost function (Mean Squared Error)
def compute_cost(X, y, theta):
    m = len(y)
    return (1 / (2 * m)) * np.sum((hypothesis(X, theta) - y) ** 2)

# Gradient Descent Algorithm
def gradient_descent(X, y, X_val, y_val, theta, alpha, iterations):
    m = len(y)
    cost_history_train = []
    cost_history_val = []

    for _ in range(iterations):
        theta -= (alpha / m) * np.dot(X.T, (hypothesis(X, theta) - y))
        cost_history_train.append(compute_cost(X, y, theta))
        cost_history_val.append(compute_cost(X_val, y_val, theta))  # Compute validation loss

    return theta, cost_history_train, cost_history_val

# Hyperparameters
alpha = 0.03  # Learning rate
iterations = 1000  # Number of iterations

# Train the model using gradient descent
theta, cost_history_train, cost_history_val = gradient_descent(X_train, y_train, X_val, y_val, theta, alpha, iterations)

# Plot the cost function over iterations (Training and Validation loss in a single graph with two lines)
plt.plot(range(iterations), cost_history_train, label='Training Loss')
plt.plot(range(iterations), cost_history_val, label='Validation Loss')
plt.xlabel('Iterations')
plt.ylabel('Cost')
plt.title('Training and Validation Loss over Iterations (Problem 1.a)')
plt.legend()
plt.show()

# Output the final theta (parameters)
print("Final Parameters (Problem 1.a):", theta)
```



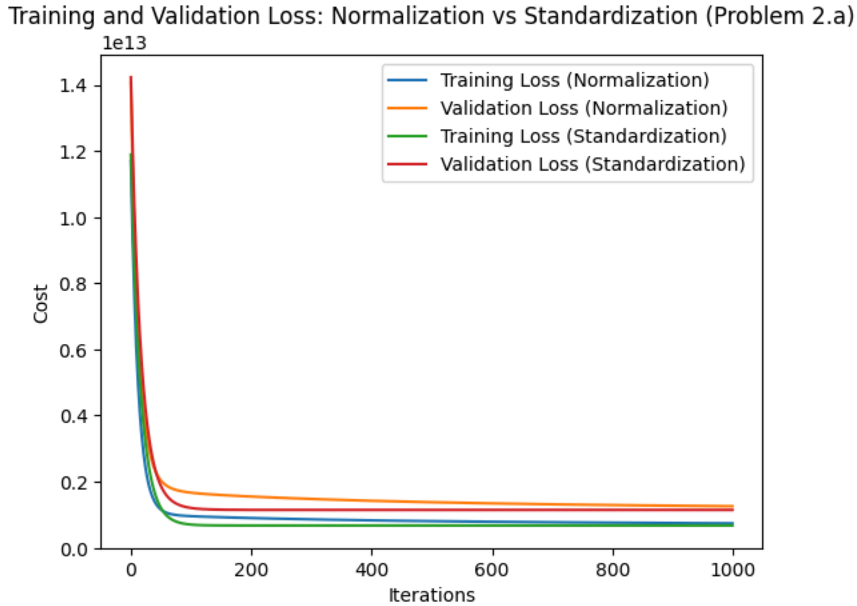

```
Final Parameters (Problem 1.a): [4744533.74764539  670284.85213657  111629.77893579  595794.1445517
  429496.17221722  290923.7607207 ]
```

```
# Feature selection for 1.b (adding more features)
features_1b = data[['area', 'bedrooms', 'bathrooms', 'stories', 'mainroad', 'guestroom',
                    'basement', 'hotwaterheating', 'airconditioning', 'parking', 'prefarea']]

# Convert non-numeric features to numeric representations
features_1b = features_1b.replace({'yes': 1, 'no': 0}) # Replace 'yes' with 1 and 'no' with 0

# Normalize the features
X_1b = normalize_features(features_1b).values

# Add the intercept term
X_1b = np.c_[np.ones(X_1b.shape[0]), X_1b]

# Split the data into training and validation sets
X_train_1b, X_val_1b, y_train_1b, y_val_1b = train_test_split(X_1b, y, test_size=0.2, random_state=42)

# Initialize theta for 1.b
theta_1b = np.zeros(X_train_1b.shape[1])

# Train the model using gradient descent
theta_1b, cost_history_train_1b, cost_history_val_1b = gradient_descent(X_train_1b, y_train_1b, X_val_1b, y_val_1b, theta_1b, al

# Plot the cost function over iterations (Training and Validation loss in a single graph with two lines)
plt.plot(range(iterations), cost_history_train_1b, label='Training Loss 1.b')
plt.plot(range(iterations), cost_history_val_1b, label='Validation Loss 1.b')
plt.xlabel('Iterations')
plt.ylabel('Cost')
plt.title('Training and Validation Loss over Iterations (Problem 1.b)')
plt.legend()
plt.show()

# Output the final theta (parameters)
print("Final Parameters for 1.b:", theta_1b)
```



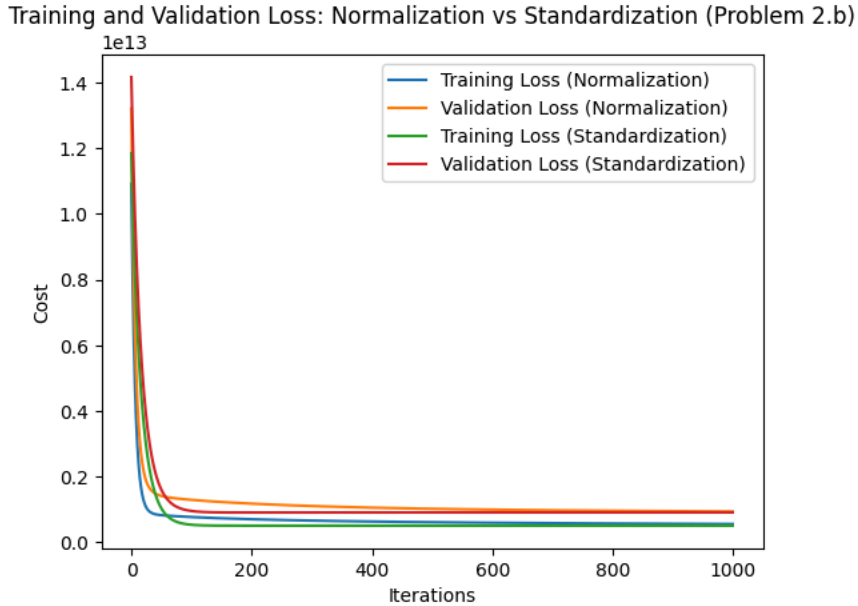

```
Final Parameters for 1.b: [4741436.23490171  515864.9682071    57926.44299725  557402.85078684
  370339.92834663  143874.03862123   93264.79774406  207737.03235415
  149147.39835038  376058.98307566  213193.39236965  270190.49520021]
```

```
# Normalize features
X_1a_normalized = normalize_features(features_1a).values
X_1a_standardized = standardize_features(features_1a).values

# Add the intercept term
X_1a_normalized = np.c_[np.ones(X_1a_normalized.shape[0]), X_1a_normalized]
X_1a_standardized = np.c_[np.ones(X_1a_standardized.shape[0]), X_1a_standardized]

# Split the data for normalization
X_train_norm_1a, X_val_norm_1a, y_train_norm_1a, y_val_norm_1a = train_test_split(X_1a_normalized, y, test_size=0.2, random_stat

# Split the data for standardization
X_train_std_1a, X_val_std_1a, y_train_std_1a, y_val_std_1a = train_test_split(X_1a_standardized, y, test_size=0.2, random_state=

# Initialize theta
theta_norm_1a = np.zeros(X_train_norm_1a.shape[1])
theta_std_1a = np.zeros(X_train_std_1a.shape[1])

# Train the model using gradient descent with normalized data
theta_norm_1a, cost_history_train_norm_1a, cost_history_val_norm_1a = gradient_descent(X_train_norm_1a, y_train_norm_1a, X_val_r

# Train the model using gradient descent with standardized data
theta_std_1a, cost_history_train_std_1a, cost_history_val_std_1a = gradient_descent(X_train_std_1a, y_train_std_1a, X_val_std_1a

# Plot both normalization and standardization training losses in the same graph
plt.plot(range(iterations), cost_history_train_norm_1a, label='Training Loss (Normalization)')
plt.plot(range(iterations), cost_history_val_norm_1a, label='Validation Loss (Normalization)')
plt.plot(range(iterations), cost_history_train_std_1a, label='Training Loss (Standardization)')
plt.plot(range(iterations), cost_history_val_std_1a, label='Validation Loss (Standardization)')
plt.xlabel('Iterations')
plt.ylabel('Cost')
plt.title('Training and Validation Loss: Normalization vs Standardization (Problem 2.a)')
plt.legend()
plt.show()

# Output the final theta (parameters)
print("Final Parameters for Normalized 2.a:", theta_norm_1a)
print("Final Parameters for Standardized 2.a:", theta_std_1a)
```




```
Final Parameters for Normalized 2.a: [2592517.61822269 2583174.55235088 1438330.56298223 2052774.50341065
 1614728.23276501 1470955.15607116]
Final Parameters for Standardized 2.a: [4744533.74764539  670284.85213657  111629.77893579  595794.1445517
  429496.17221722  290923.7607207 ]
```

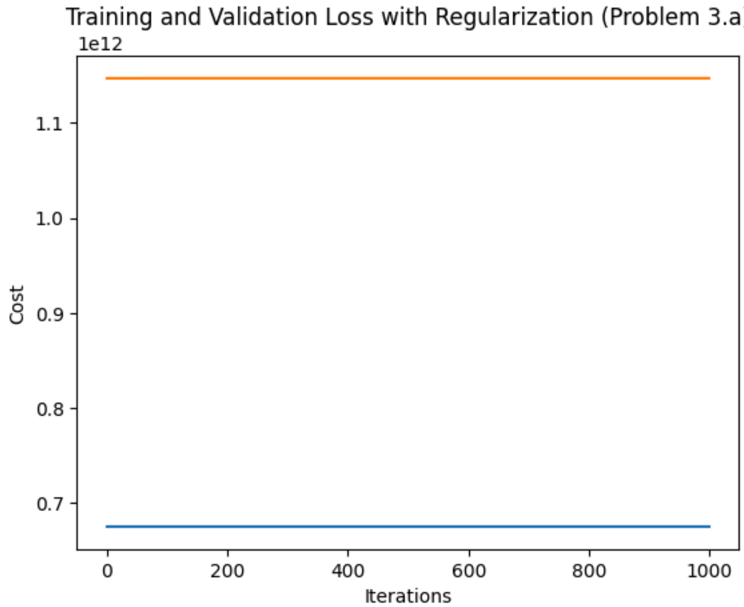
```
# Feature selection for 2.b (extended feature set used in 1.b)
features_2b = data[['area', 'bedrooms', 'bathrooms', 'stories', 'mainroad', 'guestroom',
                    'basement', 'hotwaterheating', 'airconditioning', 'parking', 'prefarea']]
target = data['price']

# Convert non-numeric features to numeric representations
features_2b = features_2b.replace({'yes': 1, 'no': 0}) # Replace 'yes' with 1 and 'no' with 0

# Normalize and standardize the features
X_2b_normalized = normalize_features(features_2b).values
X_2b_standardized = standardize_features(features_2b).values
y = target.values

# Add the intercept term (bias) for both normalization and standardization
X_2b_normalized = np.c_[np.ones(X_2b_normalized.shape[0]), X_2b_normalized]
X_2b_standardized = np.c_[np.ones(X_2b_standardized.shape[0]), X_2b_standardized]

# Split the data into training (80%) and validation (20%) sets for both normalization and standardization
X_train_norm_2b, X_val_norm_2b, y_train_norm_2b, y_val_norm_2b = train_test_split(X_2b_normalized, y, test_size=0.2, random_stat
X_train_std_2b, X_val_std_2b, y_train_std_2b, y_val_std_2b = train_test_split(X_2b_standardized, y, test_size=0.2, random_state=

# Initialize theta (weights) for both normalization and standardization
theta_norm_2b = np.zeros(X_train_norm_2b.shape[1])
theta_std_2b = np.zeros(X_train_std_2b.shape[1])

# Train the model using gradient descent with normalized data
theta_norm_2b, cost_history_train_norm_2b, cost_history_val_norm_2b = gradient_descent(X_train_norm_2b, y_train_norm_2b, X_val_r

# Train the model using gradient descent with standardized data
theta_std_2b, cost_history_train_std_2b, cost_history_val_std_2b = gradient_descent(X_train_std_2b, y_train_std_2b, X_val_std_2t

# Plot both normalization and standardization training losses in the same graph
plt.plot(range(iterations), cost_history_train_norm_2b, label='Training Loss (Normalization)')
plt.plot(range(iterations), cost_history_val_norm_2b, label='Validation Loss (Normalization)')
plt.plot(range(iterations), cost_history_train_std_2b, label='Training Loss (Standardization)')
plt.plot(range(iterations), cost_history_val_std_2b, label='Validation Loss (Standardization)')
plt.xlabel('Iterations')
plt.ylabel('Cost')
plt.title('Training and Validation Loss: Normalization vs Standardization (Problem 2.b)')
plt.legend()
plt.show()

# Output the final theta (parameters)
print("Final Parameters for Normalized 2.b:", theta_norm_2b)
print("Final Parameters for Standardized 2.b:", theta_std_2b)
```




```
Final Parameters for Normalized 2.b: [1860237.89557848 1821725.9976172  1123300.3595822  1851455.22508541
 1301815.68611924  634364.96159425  358250.81663099  410696.67337187
  640951.30019278  922028.04653103 1056205.89920216  651130.13250584]
Final Parameters for Standardized 2.b: [4741436.23490171  515864.9682071    57926.44299725  557402.85078684
  370339.92834663  143874.03862123   93264.79774406  207737.03235415
  149147.39835038  376058.98307566  213193.39236965  270190.49520021]
```

```
# Regularized cost function
def compute_cost_with_penalty(X, y, theta, lambda_):
    m = len(y)
    regularization_term = (lambda_ / (2 * m)) * np.sum(np.square(theta[1:]))  # Regularization excludes bias
    return (1 / (2 * m)) * np.sum((hypothesis(X, theta) - y) ** 2) + regularization_term

# Modify gradient descent to include the penalty term
def gradient_descent_with_penalty(X, y, X_val, y_val, theta, alpha, iterations, lambda_):
    m = len(y)
    cost_history_train = []
    cost_history_val = []

    for _ in range(iterations):
        # Apply regularization only to the non-intercept terms
        gradient = np.dot(X.T, (hypothesis(X, theta) - y)) / m
        gradient[1:] += (lambda_ / m) * theta[1:]
        theta -= alpha * gradient
        cost_history_train.append(compute_cost_with_penalty(X, y, theta, lambda_))
        cost_history_val.append(compute_cost_with_penalty(X_val, y_val, theta, lambda_))  # Validation loss

    return theta, cost_history_train, cost_history_val

# Set regularization parameter (lambda)
lambda_ = 0.1

# Train the model using gradient descent with regularization
theta_reg_1a, cost_history_train_reg_1a, cost_history_val_reg_1a = gradient_descent_with_penalty(X_train_1a, y_train_1a, X_val_1

# Plot the regularized cost function for both training and validation loss
plt.plot(range(iterations), cost_history_train_reg_1a, label='Training Loss (Regularized)')
plt.plot(range(iterations), cost_history_val_reg_1a, label='Validation Loss (Regularized)')
plt.xlabel('Iterations')
plt.ylabel('Cost')
plt.title('Training and Validation Loss with Regularization (Problem 3.a)')
plt
```

```
<module 'matplotlib.pyplot' from '/usr/local/lib/python3.10/dist-packages/matplotlib/pyplot.py'>
```




```
# Feature selection for 3.b (same as 2.b)
features_3b = data[['area', 'bedrooms', 'bathrooms', 'stories', 'mainroad', 'guestroom',
                    'basement', 'hotwaterheating', 'airconditioning', 'parking', 'prefarea']]
target = data['price']

# Convert non-numeric features to numeric representations
features_3b = features_3b.replace({'yes': 1, 'no': 0}) # Replace 'yes' with 1 and 'no' with 0

# Normalize and standardize the features
X_3b_normalized = normalize_features(features_3b).values
X_3b_standardized = standardize_features(features_3b).values
y = target.values

# Add the intercept term for both normalization and standardization
X_3b_normalized = np.c_[np.ones(X_3b_normalized.shape[0]), X_3b_normalized]
X_3b_standardized = np.c_[np.ones(X_3b_standardized.shape[0]), X_3b_standardized]

# Split the data into training and validation sets for normalization and standardization
X_train_norm_3b, X_val_norm_3b, y_train_norm_3b, y_val_norm_3b = train_test_split(X_3b_normalized, y, test_size=0.2, random_stat
X_train_std_3b, X_val_std_3b, y_train_std_3b, y_val_std_3b = train_test_split(X_3b_standardized, y, test_size=0.2, random_state=

# Initialize theta for both normalization and standardization
theta_norm_3b = np.zeros(X_train_norm_3b.shape[1])
theta_std_3b = np.zeros(X_train_std_3b.shape[1])

# Set regularization parameter (lambda)
lambda_ = 0.1

# Train the model with regularization for normalized data
theta_norm_3b, cost_history_train_norm_3b, cost_history_val_norm_3b = gradient_descent_with_penalty(X_train_norm_3b, y_train_nor

# Train the model with regularization for standardized data
theta_std_3b, cost_history_train_std_3b, cost_history_val_std_3b = gradient_descent_with_penalty(X_train_std_3b, y_train_std_3b,

# Plot both normalization and standardization training losses with regularization
plt.plot(range(iterations), cost_history_train_norm_3b, label='Training Loss (Normalization with Regularization)')
plt.plot(range(iterations), cost_history_val_norm_3b, label='Validation Loss (Normalization with Regularization)')
plt.plot(range(iterations), cost_history_train_std_3b, label='Training Loss (Standardization with Regularization)')
plt.plot(range(iterations), cost_history_val_std_3b, label='Validation Loss (Standardization with Regularization)')
plt.xlabel('Iterations')
plt.ylabel('Cost')
plt.title('Training and Validation Loss: Normalization vs Standardization with Regularization (Problem 3.b)')
plt.legend()
plt.show()

# Output the final theta (parameters) for both normalized and standardized models with regularization
print("Final Parameters for Normalized 3.b (with Regularization):", theta_norm_3b)
```


Training and Validation Loss: Normalization vs Standardization with Regularization (Problem 3.b)
1e13
1.4
1.2
1.0
0.8
0.6
0.4
Cost
Training Loss (Normalization with Regularization)
Validation Loss (Normalization with Regularization)
Training Loss (Standardization with Regularization)
Validation Loss (Standardization with Regularization)