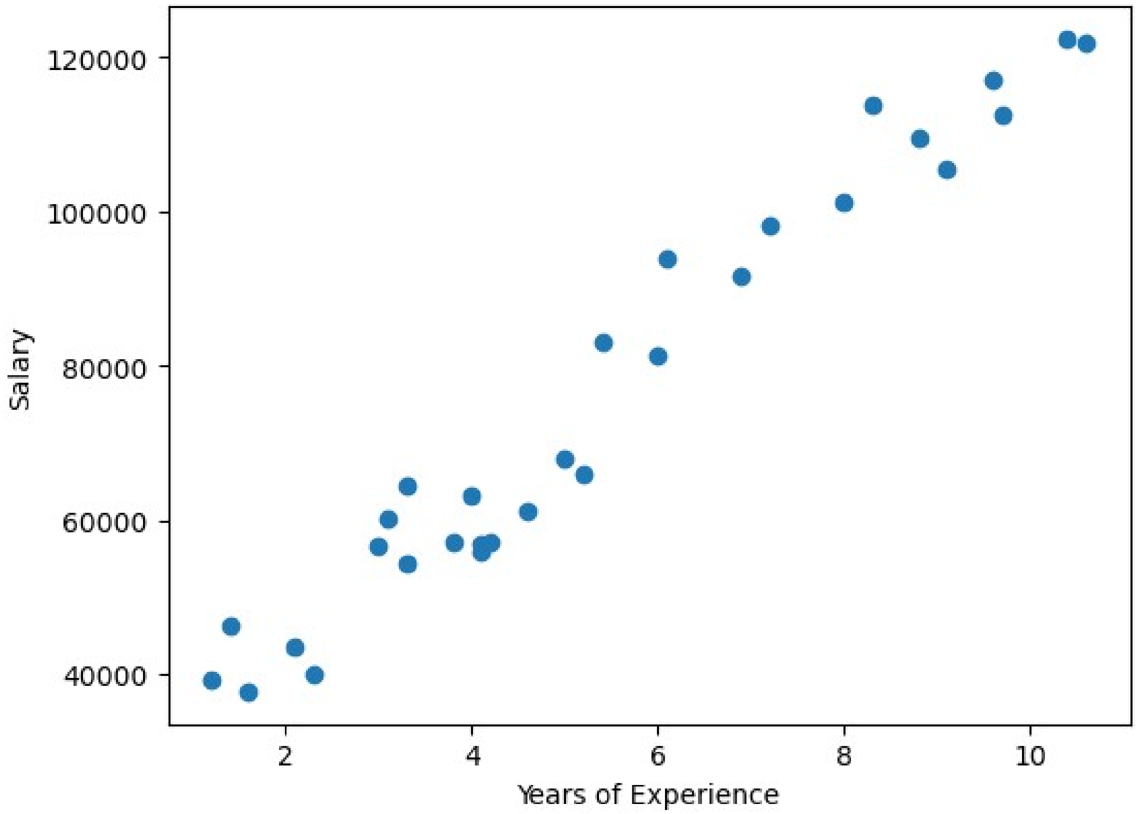
```
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score
from scipy.optimize import minimize
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
%matplotlib inline

# Read the CSV file
df = pd.read_csv('C:/Users/hp/Desktop/ABDUL/Salary_dataset.csv')

# Display the first few rows of the DataFrame
print(df.head())
```

	Unnamed: 0	YearsExperience	Salary
0	0	1.2	39344.0
1	1	1.4	46206.0
2	2	1.6	37732.0
3	3	2.1	43526.0
4	4	2.3	39892.0

```
df.describe()
```

	Unnamed: 0	YearsExperience	Salary
count	30.000000	30.000000	30.000000
mean	14.500000	5.413333	76004.000000
std	8.803408	2.837888	27414.429785
min	0.000000	1.200000	37732.000000
25%	7.250000	3.300000	56721.750000
50%	14.500000	4.800000	65238.000000
75%	21.750000	7.800000	100545.750000
max	29.000000	10.600000	122392.000000

```
plt.scatter(df['YearsExperience'], df['Salary'])
plt.xlabel('Years of Experience')
plt.ylabel('Salary')
plt.show()
```




```
X_train, X_test, y_train, y_test =
train_test_split(df['YearsExperience'], df['Salary'], test_size=0.2,
random_state=42)

regressor = LinearRegression()
regressor.fit(X_train.values.reshape(-1, 1), y_train)

def gradient_descent(X, y, learning_rate, num_iterations):
    # Initialize parameters
    theta0 = 0
    theta1 = 0
    m = len(X)

    # Perform gradient descent
    for iteration in range(num_iterations):
        y_pred = theta0 + theta1 * X

        # Calculate gradients
        gradient0 = (1/m) * np.sum(y_pred - y)
        gradient1 = (1/m) * np.sum((y_pred - y) * X)

        # Update parameters simultaneously
        theta0 -= learning_rate * gradient0
        theta1 -= learning_rate * gradient1
```

```
    return theta0, theta1

learning_rate = 0.01
num_iterations = 1000
theta0, theta1 = gradient_descent(X_train, y_train, learning_rate,
num_iterations)

print("Optimized Parameters:")
print("theta0:", theta0)
print("theta1:", theta1)
```

```
Optimized Parameters:
theta0: 21993.00196753751
theta1: 9774.098534264693
```

```
y_pred = theta0 + theta1 * X_test

# Evaluate the model's performance
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Print the evaluation metrics
print("Mean Squared Error:", mse)
print("Mean Absolute Error:", mae)
print("R-squared:", r2)
```

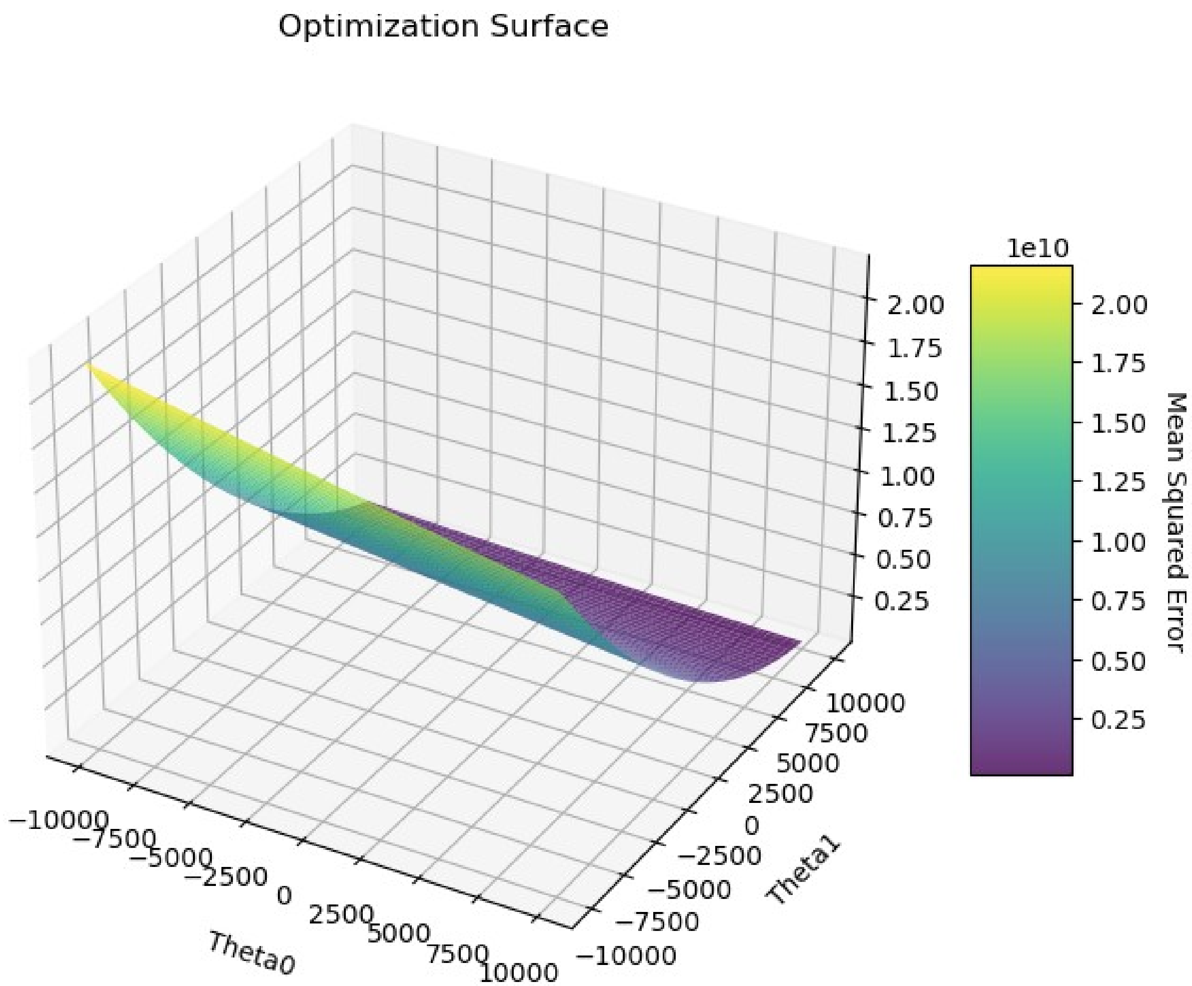
```
Mean Squared Error: 52872110.108439445
Mean Absolute Error: 6374.024633566171
R-squared: 0.8964907400447794
```

```
# Define the parameter grid for grid search
param_grid = {'fit_intercept': [True, False]}

# Perform grid search with cross-validation
grid_search = GridSearchCV(regressor, param_grid, cv=5)
grid_search.fit(X_train.values.reshape(-1, 1), y_train)

# Retrieve the best model and its parameters
best_regressor = grid_search.best_estimator_
best_params = grid_search.best_params_

# Make predictions on the testing set using the best model
y_pred_best = best_regressor.predict(X_test.values.reshape(-1, 1))

# Evaluate the best model's performance
mse_best = mean_squared_error(y_test, y_pred_best)
mae_best = mean_absolute_error(y_test, y_pred_best)
r2_best = r2_score(y_test, y_pred_best)
```

```
# Print the evaluation metrics and best parameters
print("\nOptimized Model Metrics:")
print("Mean Squared Error:", mse_best)
print("Mean Absolute Error:", mae_best)
print("R-squared:", r2_best)
print("Best Parameters:", best_params)
```

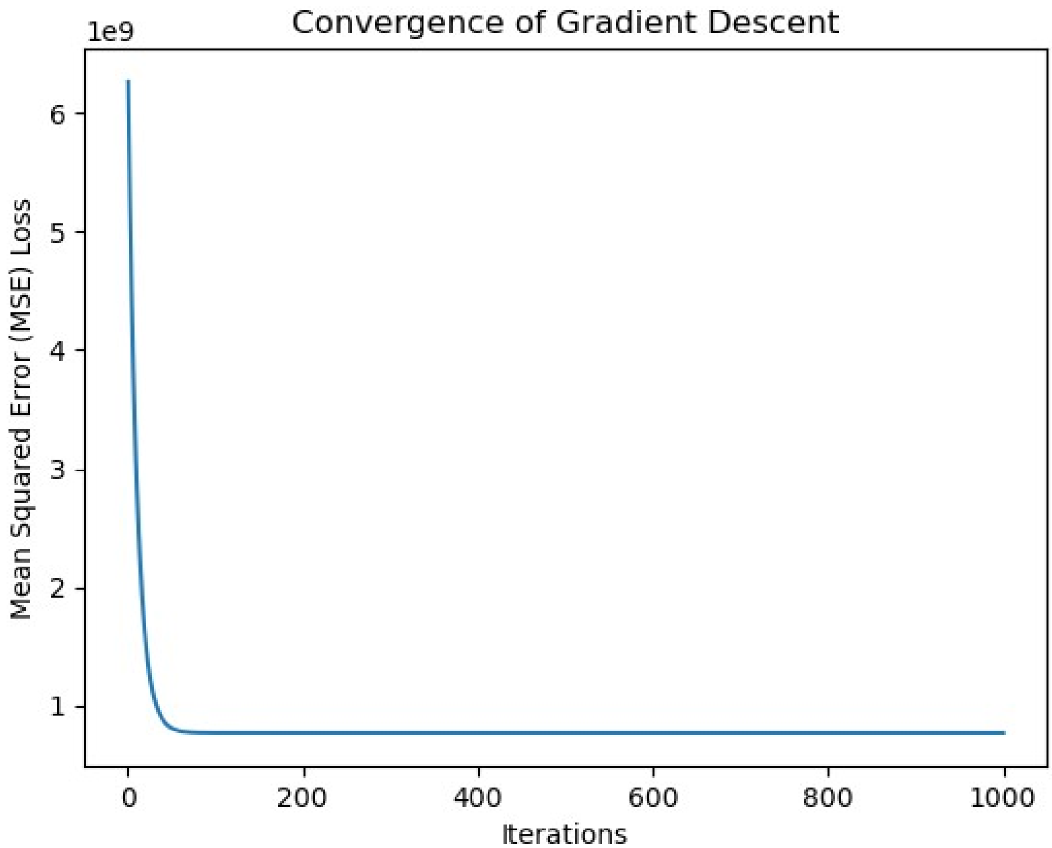
```
Optimized Model Metrics:
Mean Squared Error: 49830096.855908334
Mean Absolute Error: 6286.453830757745
R-squared: 0.9024461774180498
Best Parameters: {'fit_intercept': True}
```

```
# Create a range of parameter values for visualization
theta1_values = np.linspace(-10000, 10000, 100)
theta0_values = np.linspace(-10000, 10000, 100)

# Create a meshgrid of parameter values
Theta0, Theta1 = np.meshgrid(theta0_values, theta1_values)

# Initialize an array to store the mean squared error values
mse_values = np.zeros_like(Theta0)

# Calculate the mean squared error for each parameter combination
for i in range(len(theta0_values)):
    for j in range(len(theta1_values)):
        y_pred = Theta0[i][j] + Theta1[i][j] * X_train
        mse_values[i][j] = np.mean((y_pred - y_train)**2)

# Plot the optimization surface
fig = plt.figure(figsize=(8, 7))
ax = fig.add_subplot(111, projection='3d')
surf = ax.plot_surface(Theta0, Theta1, mse_values, cmap='viridis',
alpha=0.8)

# Add a color bar which maps values to colors
cbar = fig.colorbar(surf, shrink=0.5, aspect=5)
cbar.ax.set_ylabel('Mean Squared Error', rotation=270, labelpad=15)

ax.set_xlabel('Theta0', labelpad=10)  # Increase label padding
ax.set_ylabel('Theta1', labelpad=10)  # Increase label padding
ax.set_zlabel('Mean Squared Error', labelpad=10)  # Increase label
padding
ax.set_title('Optimization Surface')

plt.show()
```




```
# Scale the features (X) using StandardScaler
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y,
test_size=0.2, random_state=42)

def gradient_descent(X, y, learning_rate, num_iterations):
    # Initialize parameters
    theta0 = 0
    theta1 = 0
    m = len(X)
    losses = []  # To store the loss values at each iteration

    # Perform gradient descent
    for iteration in range(num_iterations):
        y_pred = theta0 + theta1 * X
```

```
        # Calculate gradients
        gradient0 = (2/m) * np.sum(y_pred - y)
        gradient1 = (2/m) * np.sum((y_pred - y) * X)

        # Update parameters
        theta0 -= learning_rate * gradient0
        theta1 -= learning_rate * gradient1

        # Calculate the MSE loss
        loss = np.mean((y_pred - y) ** 2)
        losses.append(loss)

    return theta0, theta1, losses

learning_rate = 0.001
num_iterations = 1000
theta0, theta1, losses = gradient_descent(X_train, y_train,
learning_rate, num_iterations)

# Plot the loss function over iterations
plt.plot(range(1, num_iterations + 1), losses)
plt.xlabel('Iterations')
plt.ylabel('Mean Squared Error (MSE) Loss')
plt.title('Convergence of Gradient Descent')
plt.show()
```




```
# Initialize parameters and other variables
theta0 = 0
theta1 = 0
m = len(X)
losses = []
convergence_threshold = 1e-6
converged = False

# Perform gradient descent
for iteration in range(num_iterations):
    y_pred = theta0 + theta1 * X  # Calculate y_pred for the current
parameters

    # Calculate gradients and update parameters (as before)
    # ...

    # Calculate the MSE loss
    loss = np.mean((y_pred - y) ** 2)
    losses.append(loss)

    # Check for convergence
    if iteration > 0:
        loss_change = losses[-2] - losses[-1]
```

```python
        if abs(loss_change) < convergence_threshold:
            converged = True
            break

if converged:
    print("Gradient Descent has converged.")
else:
    print("Gradient Descent has not converged.")
```

```
Gradient Descent has converged.
```

```python
# Assuming you have already loaded your dataset into a DataFrame named
'df'
correlation_matrix = df.corr()

# Print the correlation matrix
print(correlation_matrix)
```

```
                 Unnamed: 0  YearsExperience    Salary
Unnamed: 0         1.000000         0.986460  0.960826
YearsExperience    0.986460         1.000000  0.978242
Salary             0.960826         0.978242  1.000000
```

```python
# Access the correlation between 'YearsExperience' and 'Salary'
correlation = correlation_matrix.loc['YearsExperience', 'Salary']
print("Correlation between YearsExperience and Salary:", correlation)
```

```
Correlation between YearsExperience and Salary: 0.97824161848876
```