```python
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import math

cols = ["Year", "Min_val", "Max_Val"]

df = pd.read_csv("./data/X.csv", names=cols)

df.head() #get the first five rows to make sure its orking
```

	Year	Min_val	Max_Val
0	2024	32750	55620
1	2023	27400	40950
2	2022	25980	39739
3	2021	24840	39035
4	2020	24110	38675

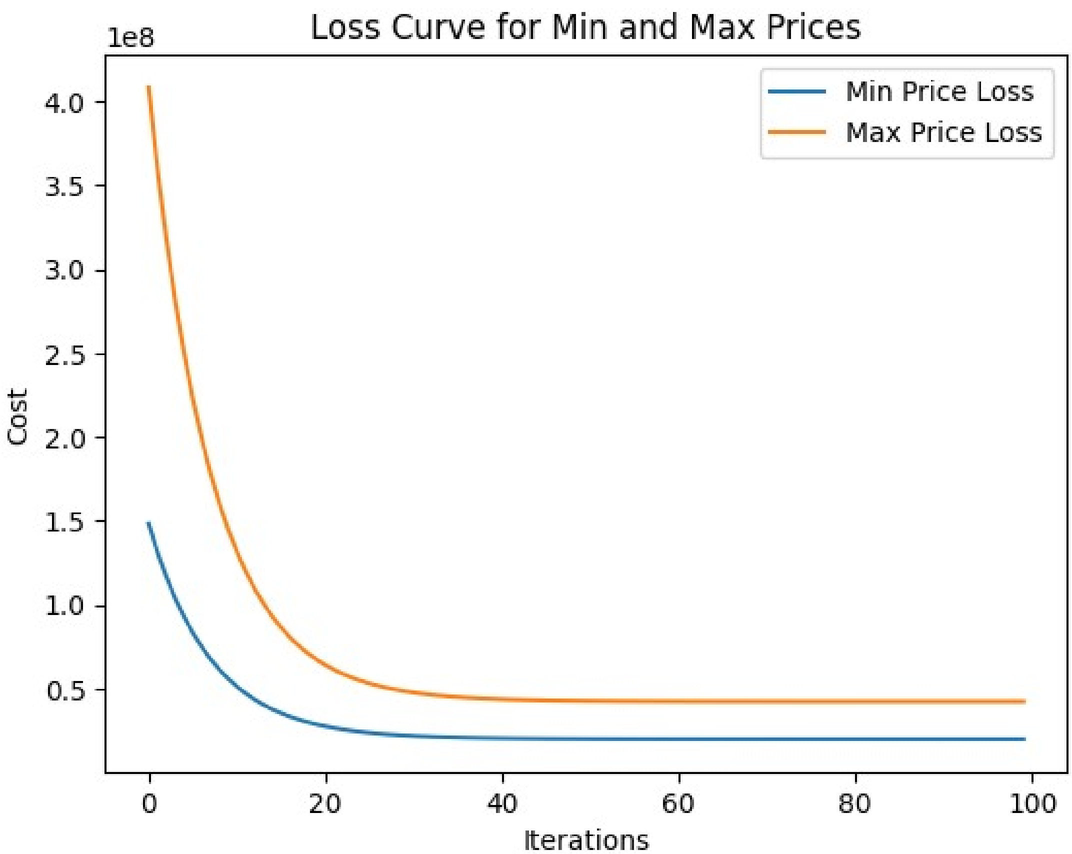
```python
X = df["Year"].values
y_min = df["Min_val"].values
y_max = df["Max_Val"].values


#assign the values in dataset


def LinearRegression(X, y, alpha, iter,missing_years):

    m = len(y)
    #m = X.shape[0] will get 26 which is the dataset rows

    b = 0#dont know why it worked
    w = 0

    costs =[]

    #iteration count for loop
    for i in range(iter):

        y_hat = [] #to store the predicted values z
        cost_sum = 0
        for i in range(m):
            #model hypothesis and adding it to the list my
predicitions

            pred = (w*X[i]) +b
            y_hat.append(pred)


            #calcultte cost
            cost = (pred - y[i]) **2
```

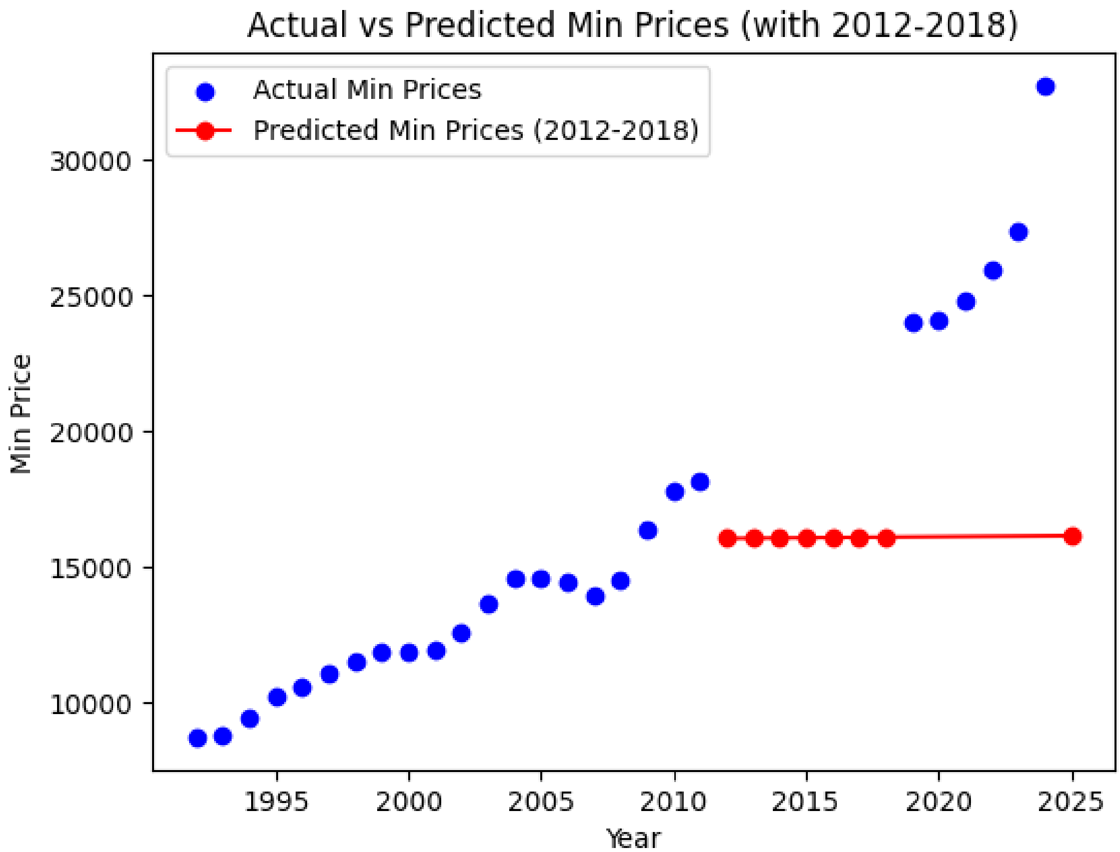
```
            cost_sum += cost

        avg_cost = cost_sum /(2*m) #MSE
        costs.append(avg_cost) #store my losses through iterations


        #COMPUTE GRADIENTS AND CALCULATE SGD

        b_gradient = 0
        w_gradient = 0

        for i in range(m):
            b_gradient += (y_hat[i] - y[i]) #bias terms gradient so no
X feature
            w_gradient += (y_hat[i] - y[i] ) * X[i] #computing the
weight term so there is X feature to multiply

        #to get the average for gradient based on the equation
        b_gradient /= m
        w_gradient /= m

        #UPDATE PARAMETERS AT THE SAME TIME
        b = b - alpha *b_gradient
        w = w - alpha * w_gradient

        pred_missing_years = [(w * year + b) for year in
missing_years]
        #Missing years prediction inside missing years come from
driver code under


    return b,w, costs, pred_missing_years


#initilaze the alpha and iterations
alpha = 0.00000048
iterations = 100

# missing years
missing_years = np.array([2012, 2013, 2014, 2015, 2016, 2017, 2018,
2025])

# Train the model for max prices
b_min, w_min, cost_min, pred_min = LinearRegression(X, y_min, alpha,
iterations, missing_years)

# Train the model for min prices
b_max, w_max, cost_max, pred_max = LinearRegression(X, y_max, alpha,
iterations, missing_years)
```

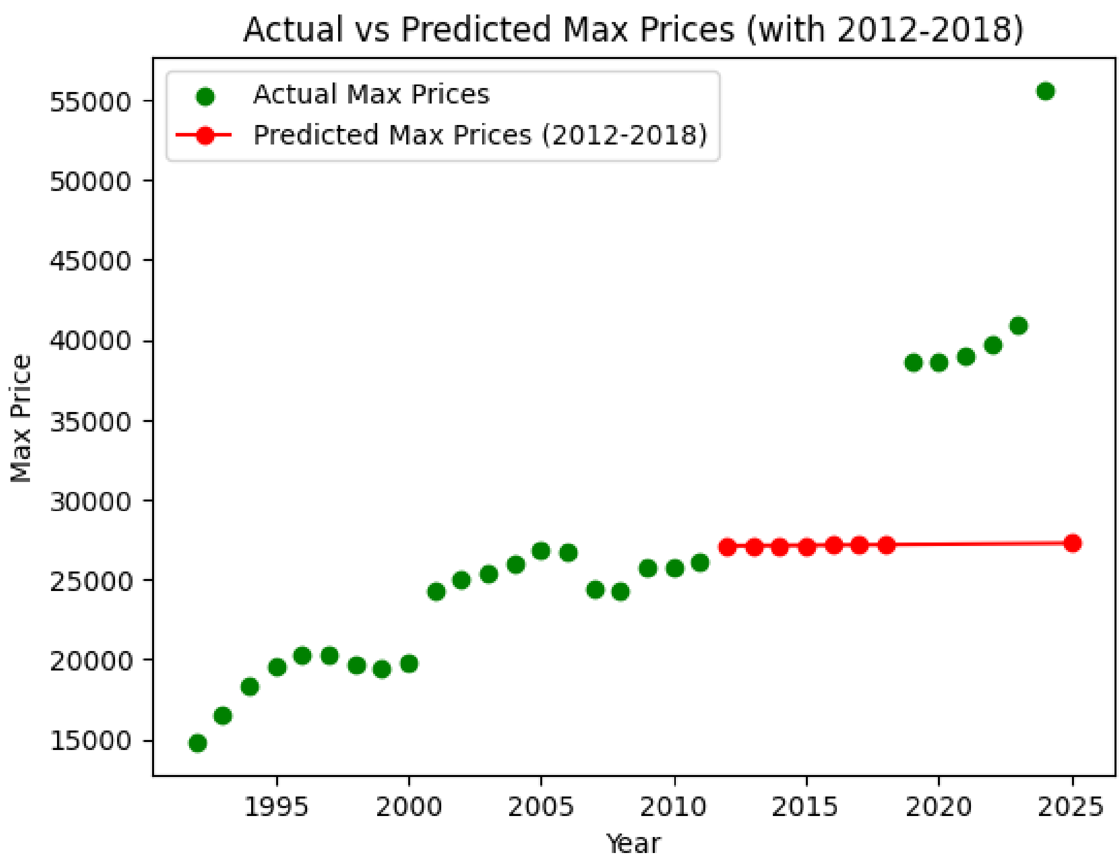
```
# missing years prediction min and max
print(f"Predicted Min Prices for 2012-2018, 2025: {pred_min}")
print(f"Predicted Max Prices for 2012-2018, 2025: {pred_max}")

# see the w and b for min and max prices
print("Weight of w after 100 iter ","for min ",w_min, "for max
",w_min)
print("Bias term after 100 iter", "for min ", b_min, "for max ",
b_max)

plt.plot(range(iterations), cost_min, label='Min Price Loss')
plt.plot(range(iterations), cost_max, label='Max Price Loss')
print(cost_max[-1], cost_min[-1])

#labels
plt.xlabel('Iterations')
plt.ylabel('Cost')
plt.title('Loss Curve for Min and Max Prices')
plt.legend()
plt.show()


# plot the model and actual data for min prices
plt.scatter(X, y_min, color='blue', label='Actual Min Prices')
plt.plot(missing_years, pred_min, color='red', marker='o',
label='Predicted Min Prices (2012-2018)')
plt.xlabel('Year')
plt.ylabel('Min Price')
plt.legend()
plt.title('Actual vs Predicted Min Prices (with 2012-2018)')
plt.show()

# plot the model and actual data for max prices
plt.scatter(X, y_max, color='green', label='Actual Max Prices')
plt.plot(missing_years, pred_max, color='red', marker='o',
label='Predicted Max Prices (2012-2018)')
plt.xlabel('Year')
plt.ylabel('Max Price')
plt.legend()
plt.title('Actual vs Predicted Max Prices (with 2012-2018)')
plt.show()
```

```
Predicted Min Prices for 2012-2018, 2025: [16052.92951333097,
16060.90810527031, 16068.88669720965, 16076.86528914899,
16084.843881088327, 16092.822473027667, 16100.801064967007,
16156.65120854238]
Predicted Max Prices for 2012-2018, 2025: [27102.77928076572,
```

```
27116.249844676448, 27129.720408587178, 27143.19097249791,
27156.66153640864, 27170.13210031937, 27183.602664230097,
27277.896611605207]
Weight of w after 100 iter  for min  7.978591939339243 for max
7.978591939339243
Bias term after 100 iter for min  0.002531380414541902 for max
0.004692377376449123
42368150.995645486 19946843.051590238
```




Actual vs Predicted Min Prices (with 2012-2018)
Actual Min Prices
Predicted Min Prices (2012-2018)
Min Price
30000
25000
20000
15000
10000
1995
2000
2005
2010
2015
2020
2025
Year



QUESTION: why did my initial w and b worked but if its other then this its not working?

```
#scale the data calcualte mean and std

def scale_features(data):

    mean = np.mean(data)
    std = np.std(data)

    scaled_data = (data - mean) / std
    return scaled_data, mean ,std



#unscale the data to see the prediction actually make sense
def unscale_data(scaled_data, mean, std):

    scaled_data = np.array(scaled_data) #convert it into nunpy array

    return (scaled_data * std) + mean
```

NOTE: Do the code more clean and do a function for scaling data and inverse it to make sense and be more clean

```
def ScaledLinearRegression(X, y, alpha, iter,missing_years, c):


    #length of the dataset and the initial weight and bias
    m = len(y)

    w = 1
    b = 1


    costs = []

    #Scaling the features and labels and missing years(as in feature 
inputs)

    X_scaled, X_mean, X_std = scale_features(X)
    y_scaled, y_mean, y_std = scale_features(y)
    missing_years_scaled = (missing_years - X_mean) / X_std


    for i in range(iter):

        y_hat = [] #store the prediction values
        cost_sum = 0
        for j in range(m):
            #model hypothesis
            pred = (w * X_scaled[j]) + b
            y_hat.append(pred)

            #calculate the cost

            cost = (pred - y_scaled[j]) ** 2
            cost_sum += cost

        avg_cost = cost_sum / (2*m) #Mean sqaurred error
        costs.append(avg_cost) #store the costs

        #Compute gradients and optimize

        b_gradient = 0
        w_gradient = 0


        for z in range(m):

            b_gradient += (y_hat[z] - y_scaled[z]) #compute bias terms 
gradient
            w_gradient += (y_hat[z] - y_scaled[z]) * X_scaled[z] 
#compute weight terms gradient
```

```
        #to get the average for gradient based on the equation as in
equations head 1/m
        b_gradient /= m
        w_gradient /= m


        #dynamic learning rate according to equation

        dynamic_alpha = alpha / (1 + c * i)


        #update the parameters bias and weight

        b = b - dynamic_alpha * b_gradient
        w = w - dynamic_alpha * w_gradient

        pred_missing_years = [(w * year + b) for year in
missing_years_scaled] #predict the missing years 2012-2018

        pred_missing_years_unscaled = unscale_data(pred_missing_years,
y_mean, y_std) #unscale the data to make sense


    return b, w, costs, pred_missing_years_unscaled
```

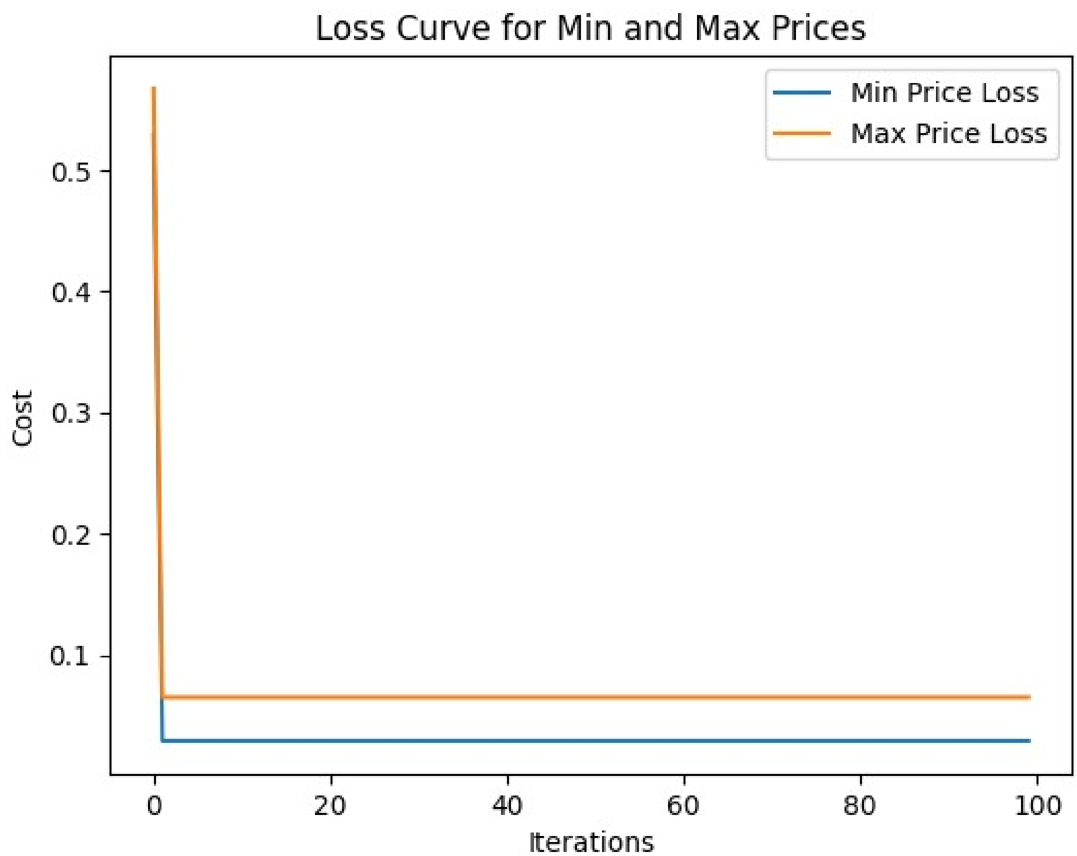
more clean code and do the driver code with plots clean like above

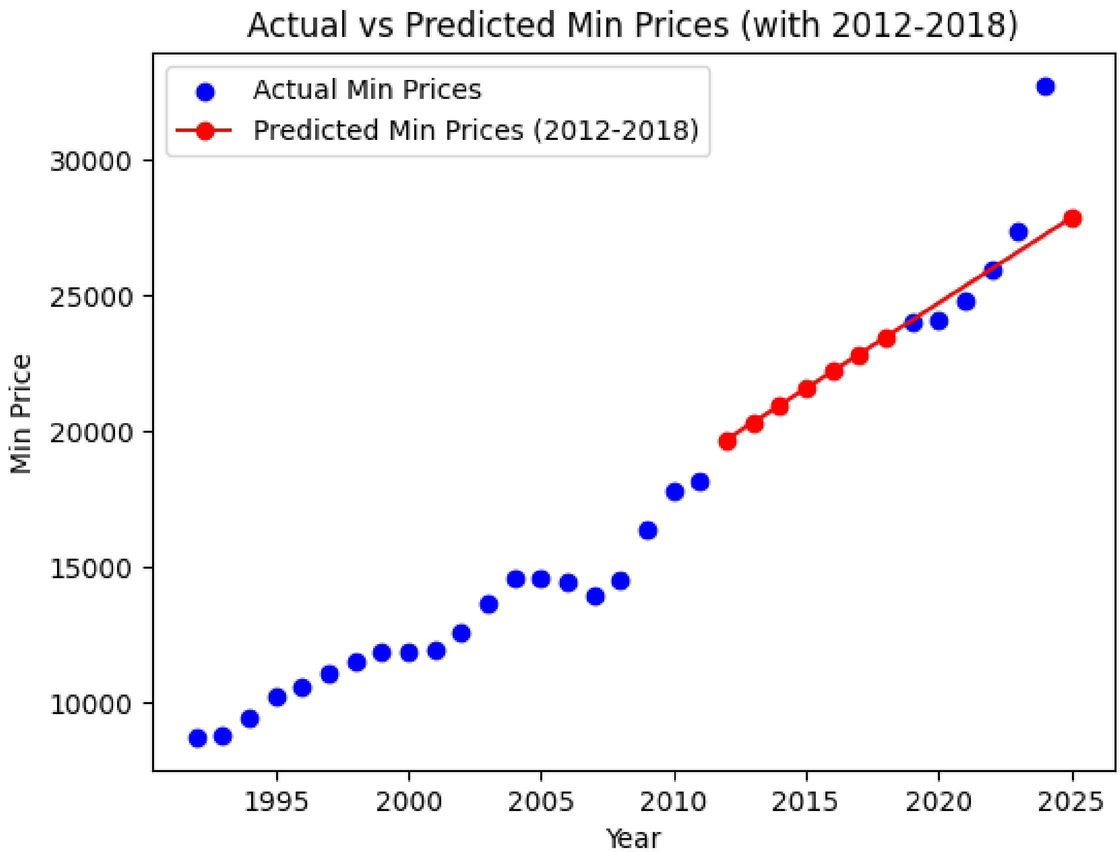
```
#initilaze the alpha and iterations
alpha = 0.999
iterations = 100
c = 10


# missing years
missing_years = np.array([2012, 2013, 2014, 2015, 2016, 2017, 2018,
2025])

# Train the model for max prices
b_min, w_min, cost_min, pred_min = ScaledLinearRegression(X, y_min,
alpha, iterations, missing_years, c)


# Train the model for min prices
b_max, w_max, cost_max, pred_max = ScaledLinearRegression(X, y_max,
alpha, iterations, missing_years, c)

# missing years prediction min and max
```

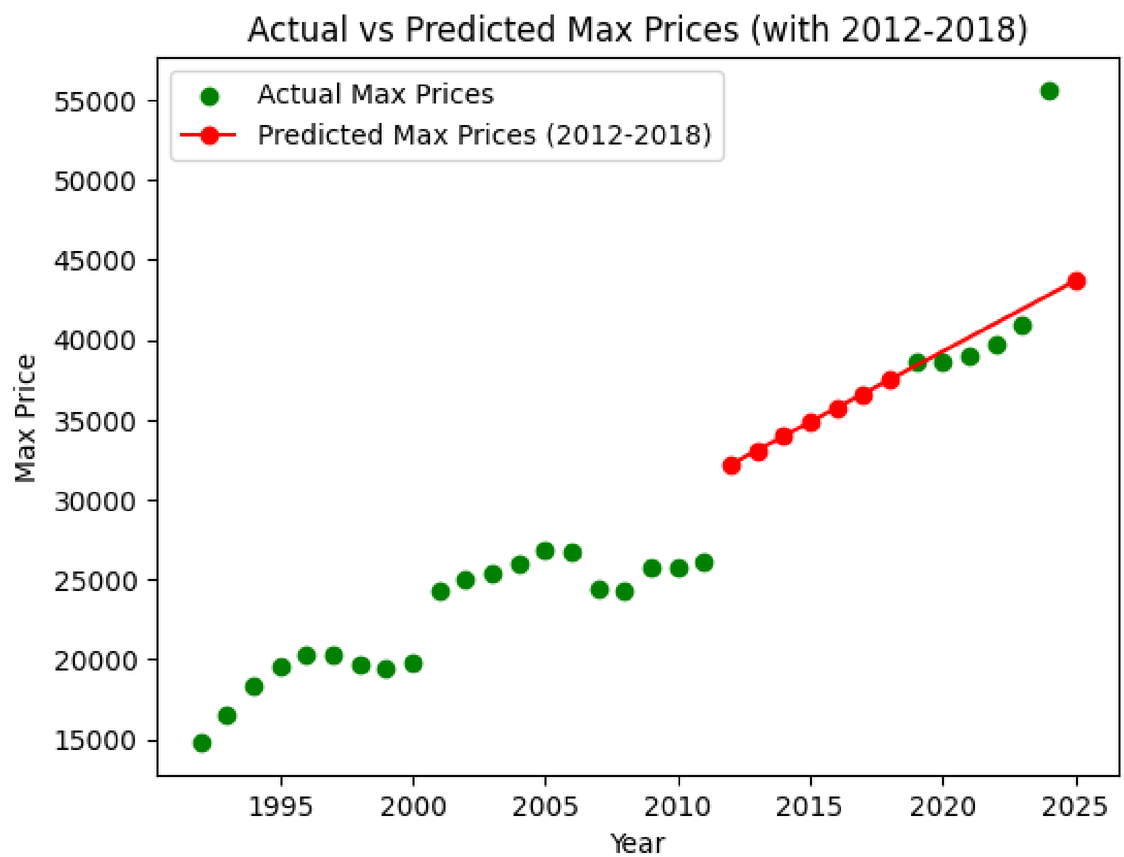
```python
print(f"Predicted Min Prices for 2012-2018, 2025: {pred_min}")
print(f"Predicted Max Prices for 2012-2018, 2025: {pred_max}")

# see the w and b for min and max prices
print("Weight of w after 100 iter ","for min ",w_min, "for max
",w_min)
print("Bias term after 100 iter", "for min ", b_min, "for max ",
b_max)

# see the costs throguh iterations
plt.plot(range(iterations), cost_min, label='Min Price Loss')
plt.plot(range(iterations), cost_max, label='Max Price Loss')

#labels
plt.xlabel('Iterations')
plt.ylabel('Cost')
plt.title('Loss Curve for Min and Max Prices')
plt.legend()
plt.show()


# plot the model and actual data for min prices
plt.scatter(X, y_min, color='blue', label='Actual Min Prices')
plt.plot(missing_years, pred_min, color='red', marker='o',
label='Predicted Min Prices (2012-2018)')
plt.xlabel('Year')
plt.ylabel('Min Price')
plt.legend()
plt.title('Actual vs Predicted Min Prices (with 2012-2018)')
plt.show()

# plot the model and actual data for max prices
plt.scatter(X, y_max, color='green', label='Actual Max Prices')
plt.plot(missing_years, pred_max, color='red', marker='o',
label='Predicted Max Prices (2012-2018)')
plt.xlabel('Year')
plt.ylabel('Max Price')
plt.legend()
plt.title('Actual vs Predicted Max Prices (with 2012-2018)')
plt.show()
```

```
Predicted Min Prices for 2012-2018, 2025: [19696.27632686
20325.52025985 20954.76419284 21584.00812583
 22213.25205882 22842.49599181 23471.7399248  27876.44745573]
Predicted Max Prices for 2012-2018, 2025: [32203.49788988
33086.02866094 33968.559432   34851.09020306
 35733.62097412 36616.15174518 37498.68251624 43676.39791365]
Weight of w after 100 iter  for min  0.9707515438470152 for max
0.9707515438470152
```

```
Bias term after 100 iter for min  0.0006008432877295687 for max
0.0006008432877299006
```




Actual vs Predicted Min Prices (with 2012-2018)
Actual Min Prices
Predicted Min Prices (2012-2018)
30000
25000
20000
15000
10000
Min Price
1995
2000
2005
2010
2015
2020
2025
Year



Summary

For 2025 my models predcits different prices normalized linear regression my model predicted for min prices: 27876.44745573 and the without feature scaled linear regression predicted 16156.65120854238 as min for max normalized linear regression predicted:43676.39791365 and base linear regression predcited: 27277.896611605207

Without the feature scaled and dynamic learning rated linear regression my bias is: for min 0.0006008432877295687 for max 0.0006008432877299006 and weight term is: for min 7.978591939339243 for max 7.978591939339243

For the scaled linear regression model and dynamic learning rate my bias is: or min 0.0006008432877295687 for max 0.0006008432877299006 and weight term is for min 0.9707515438470152 for max 0.9707515438470152

My thoughts on my models are that it is under performs due to a lack of the features with scaling the performance and accuracy has increased but the prediction is still not as good as it should be. With scaling and dynamic learning rate the models best accuracy achieved faster and the loss function decreased drastically but still underfits it won't be good in the unseen data as well as normal linear regression that has not scaling and dynamic learning rate. With more features and more data like thoosands of data the models performance could be better as well as using vectorization and dot product formulas also divide the dataset with %60 training %20 test and %20 for cross validation (optional)

The comparisons of the models are the normalized and dynamic learning rate linear regression has better performance it reaches the global minimum faster and i think it could have better performance in unseen data.

I would buy 2025 ford ranger because my model predicts the price will decrase and it alligns with the real world data.