Assignment 04 - Multiple Regression and Gradient Descent

In this lab, you will implement multiple regression routines using both vectorized and non-vectorized approaches.

Outline

1.1 Goals

- Implement multiple regression model routines.
  - Write prediction, cost and gradient routines to support multiple features.
  - Utilize NumPy `np.dot` to vectorize their implementations for speed and simplicity.

In [ ]:
```
import copy, math
import numpy as np
import matplotlib.pyplot as plt
#plt.style.use('./deeplearning.mplstyle')
np.set_printoptions(precision=2)  # reduced display precision on numpy array
```

1.2 Notation

Here is a summary of some of the notation you will encounter, updated for multiple features.

General Notation	Description	Python (if applicable)
a	scalar, non bold	
$\mathbf{a}$	vector, bold	
$\mathbf{A}$	matrix, bold capital	
Regression		
$\mathbf{X}$	training example matrix	`X_train`
$\mathbf{y}$	training example targets	`y_train`
$\mathbf{x}^{(i)}$, $y^{(i)}$	i_{th} Training Example	`X[i]`, `y[i]`
m	number of training examples	`m`
n	number of features in each example	`n`
$\mathbf{w}$	parameter: weight,	`w`
b	parameter: bias	`b`
$f_{\mathbf{w},b}(\mathbf{x}^{(i)})$	The result of the model evaluation at $\mathbf{x^{(i)}}$ parameterized by $\mathbf{w},b$: $f_{\mathbf{w},b}(\mathbf{x}^{(i)}) = \mathbf{w} \cdot \mathbf{x}^{(i)}+b$	`f_wb`

2 Problem Statement

We will use the motivating example of housing price prediction. The training dataset contains three examples with four features (size, bedrooms, floors and, age) shown in the table below. Note that, unlike the earlier labs, size is in sqft rather than 1000 sqft. This causes an issue which we will see later in the lab, and which would be addressed through feature scaling, as discussed in the lectures.

Size (sqft)	Number of Bedrooms	Number of floors	Age of Home	Price (1000s dollars)
2104	5	1	45	460
1416	3	2	40	232
852	2	1	35	178

We will build a linear regression model using these values so we can then predict the price for other houses. For example, a house with 1200 sqft, 3 bedrooms, 1 floor, 40 years old.

Run the following code cell to create your `X_train` and `y_train` variables.

In [ ]:
```
X_train = np.array([[2104, 5, 1, 45], [1416, 3, 2, 40], [852, 2, 1, 35]])
y_train = np.array([460, 232, 178])
```

2.1 Matrix X containing our examples

Similar to the table above, examples are stored in a NumPy matrix `X_train`. Each row of the matrix represents one example. When there are m training examples (m is three in our example), and there are n features (four in our example), $\mathbf{X}$ is a matrix with dimensions (m, n) (m rows, n columns).

$$\mathbf{X} = \begin{pmatrix} x^{(0)}_0 & x^{(0)}_1 & \cdots & x^{(0)}_{n-1} \\ x^{(1)}_0 & x^{(1)}_1 & \cdots & x^{(1)}_{n-1} \\ \cdots \\ x^{(m-1)}_0 & x^{(m-1)}_1 & \cdots & x^{(m-1)}_{n-1} \end{pmatrix}$$

notation:

- $\mathbf{x}^{(i)}$ is vector containing example i. $\mathbf{x}^{(i)} = (x^{(i)}_0, x^{(i)}_1, \cdots, x^{(i)}_{n-1})$
- $x^{(i)}_j$ is element j in example i. The superscript in parenthesis indicates the example number while the subscript represents an element.

Display the input data.

In [ ]:
```
# data is stored in numpy array/matrix
print(f"X Shape: {X_train.shape}, X Type:{type(X_train)})")
print(X_train)
print(f"y Shape: {y_train.shape}, y Type:{type(y_train)})")
print(y_train)
```

```
X Shape: (3, 4), X Type:<class 'numpy.ndarray'>)
[[2104    5    1   45]
 [1416    3    2   40]
 [ 852    2    1   35]]
y Shape: (3,), y Type:<class 'numpy.ndarray'>)
[460 232 178]
```

2.2 Parameter vector w, b

- $\mathbf{w}$ is a vector with n elements.
  - Each element contains the parameter associated with one feature.
  - in our dataset, n is 4.
  - notionally, we draw this as a column vector

$$\mathbf{w} = \begin{pmatrix} w_0 \\ w_1 \\ \cdots \\ w_{n-1} \end{pmatrix}$$

- b is a scalar parameter.

For demonstration, $\mathbf{w}$ and b will be loaded with some initial selected values that are near the optimal. $\mathbf{w}$ is a 1-D NumPy vector.

In [ ]:
```
b_init = 785.1811367994083
w_init = np.array([ 0.39133535, 18.75376741, -53.36032453, -26.42131618])
print(f"w_init shape: {w_init.shape}, b_init type: {type(b_init)}")
```

```
w_init shape: (4,), b_init type: <class 'float'>
```

3 Model Prediction With Multiple Variables

The model's prediction with multiple variables is given by the linear model:

$$f_{\mathbf{w},b}(\mathbf{x}) = w_0x_0 + w_1x_1 + \ldots + w_{n-1}x_{n-1} + b \tag{1}$$

or in vector notation:

$$f_{\mathbf{w},b}(\mathbf{x}) = \mathbf{w} \cdot \mathbf{x} + b \tag{2}$$

where $\cdot$ is a vector `dot product`

To demonstrate the dot product, we will implement prediction using (1) and (2).

3.1 Exercise 1 - Make single prediction - Non-vectorized

[10 points]

Implement equation (1) above by looping over each element, performing the multiply with its parameter and then adding the bias parameter at the end.

In [ ]:
```
def predict_single_loop(x, w, b):
    """
    single predict using linear regression

    Args:
      x (ndarray): Shape (n,) example with multiple features
      w (ndarray): Shape (n,) model parameters
      b (scalar):  model parameter

    Returns:
      p (scalar):  prediction
    """

    ### START CODE HERE

    p = b
    for i in range(len(x)):
        p += x[i] * w[i]

    ### END CODE HERE

    return p
```

In [ ]:
```
# get a row from our training data
x_vec = X_train[0,:]
print(f"x_vec shape {x_vec.shape}, x_vec value: {x_vec}")

# make a prediction
f_wb = predict_single_loop(x_vec, w_init, b_init)
print(f"f_wb shape {f_wb.shape}, prediction: {f_wb}")
```

```
x_vec shape (4,), x_vec value: [2104    5    1   45]
f_wb shape (), prediction: 459.9999976194081
```

Note the shape of `x_vec`. It is a 1-D NumPy vector with 4 elements, (4,). The result, `f_wb` is a scalar.

3.2 Exercise 2 - Make single prediction - Vectorized

[10 points]

Noting that equation (1) above can be implemented using the dot product as in (2) above, make use of vector operations to speed up predictions by employing vectorization. That is, use [`np.dot()`] to perform a vector dot product.

In [ ]:
```
def predict(x, w, b):
    """
    single predict using linear regression
    Args:
      x (ndarray): Shape (n,) example with multiple features
      w (ndarray): Shape (n,) model parameters
      b (scalar):             model parameter

    Returns:
      p (scalar):  prediction
    """

    ### START CODE HERE

    p = np.dot(w, x) + b


    ### END CODE HERE

    return p
```

In [ ]:
```
# get a row from our training data
x_vec = X_train[0,:]
print(f"x_vec shape {x_vec.shape}, x_vec value: {x_vec}")

# make a prediction
f_wb = predict(x_vec,w_init, b_init)
print(f"f_wb shape {f_wb.shape}, prediction: {f_wb}")
```

```
x_vec shape (4,), x_vec value: [2104    5    1   45]
f_wb shape (), prediction: 459.9999976194083
```

The results and shapes are the same as the previous version which used looping. Going forward, `np.dot` will be used for these operations. The prediction is now a single statement.

4 Compute Cost With Multiple Variables

The equation for the cost function with multiple variables $J(\mathbf{w}, b)$ is:

$$J(\mathbf{w}, b) = \frac{1}{2m} \sum_{i=0}^{m-1} (f_{\mathbf{w},b}(\mathbf{x}^{(i)}) - y^{(i)})^2 \tag{3}$$

where:

$$f_{\mathbf{w},b}(\mathbf{x}^{(i)}) = \mathbf{w} \cdot \mathbf{x}^{(i)} + b \tag{4}$$

$\mathbf{w}$ and $\mathbf{x}^{(i)}$ are vectors supporting multiple features.

4.1 Exercise 3 - Compute Cost - Non-vectorized

[20 points]

Implement the compute_cost_nonvectorized() function. This function should *not* make use of vectorization.

In [ ]:
```
def compute_cost_nonvectorized(X, y, w, b):
    """
    compute cost
    Args:
      X (ndarray (m,n)): Data, m examples with n features
      y (ndarray (m,)) : target values
      w (ndarray (n,)) : model parameters
      b (scalar)       : model parameter

    Returns:
      cost (scalar): cost
    """

    ### START CODE HERE

    cost = 0
    for i in range(len(X)):
        cost += (predict_single_loop(X[i], w, b) - y[i])**2
    cost /= 2 * len(X)





    ### END CODE HERE

    return cost
```

In [ ]:
```
# Compute and display cost using our pre-chosen optimal parameters.
cost = compute_cost_nonvectorized(X_train, y_train, w_init, b_init)
print(f'Cost at optimal w : {cost}')
```

```
Cost at optimal w : 1.5578905850276372e-12
```

Expected Result: Cost at optimal w : 1.5578904045996674e-12

4.2 Exercise 4 - Compute Cost - Vectorized

[20 points]

Implement the compute_cost_vectorized() function. This function should use vectorization. Your implementation in the designated area for your code should consist of only one line of code.

In [ ]:
```
def compute_cost_vectorized(X, y, w, b):
    """
    compute cost
    Args:
      X (ndarray (m,n)): Data, m examples with n features
      y (ndarray (m,)) : target values
      w (ndarray (n,)) : model parameters
      b (scalar)       : model parameter

    Returns:
      cost (scalar): cost
    """

    m = X.shape[0]

    ### START CODE HERE


    cost = sum((predict(X[i], w, b) - y[i])**2 for i in range(m)) / (2 * m)



    ### END CODE HERE

    return cost
```

In [ ]:
```
# Compute and display cost using our pre-chosen optimal parameters.
cost = compute_cost_vectorized(X_train, y_train, w_init, b_init)
print(f'Cost at optimal w : {cost}')
```

```
Cost at optimal w : 1.5578904045996674e-12
```

Expected Result: Cost at optimal w : 1.5578904045996674e-12

5 Gradient Descent With Multiple Variables

Gradient descent for multiple variables:

$$\begin{align*} \text{repeat}&\text{ until convergence:} \; \lbrace \newline\;
& w_j = w_j - \alpha \frac{\partial J(\mathbf{w},b)}{\partial w_j} \tag{5} \; & \text{for j = 0..n-1}\newline
&b\ \ = b - \alpha \frac{\partial J(\mathbf{w},b)}{\partial b} \newline \rbrace
\end{align*}$$

where, n is the number of features, parameters w_j, b, are updated simultaneously and where

$$\begin{align}
\frac{\partial J(\mathbf{w},b)}{\partial w_j} &= \frac{1}{m} \sum\limits_{i = 0}^{m-1} (f_{\mathbf{w},b}(\mathbf{x}^{(i)}) - y^{(i)})x_{j}^{(i)} \tag{6} \\
\frac{\partial J(\mathbf{w},b)}{\partial b} &= \frac{1}{m} \sum\limits_{i = 0}^{m-1} (f_{\mathbf{w},b}(\mathbf{x}^{(i)}) - y^{(i)}) \tag{7}
\end{align}$$

- m is the number of training examples in the data set
- $f_{\mathbf{w},b}(\mathbf{x}^{(i)})$ is the model's prediction, while $y^{(i)}$ is the target value

5.1 Compute Gradient with Multiple Variables

An implementation for calculating the equations (6) and (7) is below. There are many ways to implement this.

For each feature j, where $j = 1 \ldots n$:

- outer loop over all n features.
  - inner loop over all m samples:
    - calculate $\frac{\partial J(\mathbf{w},b)}{\partial w_j}$ for each sample and accumulate.
  - divide by m to arrive at $\frac{\partial J(\mathbf{w},b)}{\partial w_j}$ for feature, j.

For b:

- loop over all m samples:
  - calculate $\frac{\partial J(\mathbf{w},b)}{\partial b}$ for each sample and accumulate.
- divide by m to arrive at $\frac{\partial J(\mathbf{w},b)}{\partial b}$.

5.2 Exercise 5 - Compute gradient - Non-vectorized

[20 points]

Implement the compute_gradient_nonvectorized() function. This function should *not* make use of vectorization.

In [ ]:
```
def compute_gradient_nonvectorized(X, y, w, b):
    """
    Computes the gradient for linear regression
    Args:
      X (ndarray (m,n)): Data, m examples with n features
      y (ndarray (m,)) : target values
      w (ndarray (n,)) : model parameters
      b (scalar)       : model parameter

    Returns:
      dj_db (scalar):       The gradient of the cost w.r.t. the parameter b.
      dj_dw (ndarray (n,)): The gradient of the cost w.r.t. the parameters w
    """
    m = X.shape[0]
    n = X.shape[1]

    ### START CODE HERE

    dj_db = 0
    dj_dw = np.zeros(n)
    for i in range(m):
        dj_db += predict_single_loop(X[i], w, b) - y[i]
        for j in range(n):
            dj_dw[j] += (predict_single_loop(X[i], w, b) - y[i]) * X[i][j]
    dj_db /= m
    dj_dw /= m


    ### END CODE HERE

    return dj_db, dj_dw
```

In [ ]:
```
#Compute and display gradient
tmp_dj_db, tmp_dj_dw = compute_gradient_nonvectorized(X_train, y_train, w_ir
print(f'dj_dw at initial w,b: {tmp_dj_dw}')
print(f'dj_db at initial w,b: {tmp_dj_db}')
```

```
dj_dw at initial w,b: [-2.73e-03 -6.27e-06 -2.22e-06 -6.92e-05]
dj_db at initial w,b: -1.6739251880911372e-06
```

Expected Result:

dj_dw at initial w,b: [-2.73e-03 -6.27e-06 -2.22e-06 -6.92e-05]

dj_db at initial w,b: -1.6739251122999121e-06

5.3 Exercise 6 - Compute gradient - Vectorized

[20 points]

Implement the compute_cost_vectorized() function. This function should use vectorization. Your code should consist of two lines of code - one for computing dj_dw and one for computing dj_db.

In [ ]:
```
def compute_gradient_vectorized(X, y, w, b):
    """
    Computes the gradient for linear regression
    Args:
      X (ndarray (m,n)): Data, m examples with n features
      y (ndarray (m,)) : target values
      w (ndarray (n,)) : model parameters
      b (scalar)       : model parameter

    Returns:
      dj_db (scalar):       The gradient of the cost w.r.t. the parameter b.
      dj_dw (ndarray (n,)): The gradient of the cost w.r.t. the parameters w
    """

    m, n = X.shape

    ### START CODE HERE

    dj_db = sum(predict(X[i], w, b) - y[i] for i in range(m)) / m
    dj_dw = np.zeros(n)
    for i in range(m):
        dj_dw += (predict(X[i], w, b) - y[i]) * X[i]
    dj_dw /= m


    ### END CODE HERE

    return dj_db, dj_dw
```

In [ ]:
```
#Compute and display gradient
tmp_dj_db, tmp_dj_dw = compute_gradient_vectorized(X_train, y_train, w_init,
print(f'dj_dw at initial w,b: {tmp_dj_dw}')
print(f'dj_db at initial w,b: {tmp_dj_db}')
```

```
dj_dw at initial w,b: [-2.73e-03 -6.27e-06 -2.22e-06 -6.92e-05]
dj_db at initial w,b: -1.6739251122999121e-06
```

Expected Result:
dj_dw at initial w,b: [-2.73e-03 -6.27e-06 -2.22e-06 -6.92e-05]
dj_db at initial w,b: -1.6739251122999121e-06

5.4 Gradient Descent Implementation

The routine below implements equation (5) above.

In [ ]:
```
def gradient_descent(X, y, w_in, b_in, cost_function, gradient_function, alp
    """
    Performs batch gradient descent to learn w and b. Updates w and b by tak
    num_iters gradient steps with learning rate alpha

    Args:
      X (ndarray (m,n))   : Data, m examples with n features
      y (ndarray (m,))    : target values
      w_in (ndarray (n,)) : initial model parameters
      b_in (scalar)       : initial model parameter
      cost_function       : function to compute cost
      gradient_function   : function to compute the gradient
      alpha (float)       : Learning rate
      num_iters (int)     : number of iterations to run gradient descent

    Returns:
      w (ndarray (n,)) : Updated values of parameters
      b (scalar)       : Updated value of parameter
      """

    # An array to store cost J and w's at each iteration primarily for graph
    J_history = []
    w = copy.deepcopy(w_in)  #avoid modifying global w within function
    b = b_in

    for i in range(num_iters):

        # Calculate the gradient and update the parameters
        dj_db,dj_dw = gradient_function(X, y, w, b)   ##None

        # Update Parameters using w, b, alpha and gradient
        w = w - alpha * dj_dw               ##None
        b = b - alpha * dj_db               ##None

        # Save cost J at each iteration
        if i<100000:      # prevent resource exhaustion
            J_history.append( cost_function(X, y, w, b))

        # Print cost every at intervals 10 times or as many iterations if <
        if i% math.ceil(num_iters / 10) == 0:
            print(f"Iteration {i:4d}: Cost {J_history[-1]:8.2f}   ")

    return w, b, J_history #return final w,b and J history for graphing
```

In the next cell you will test the implementation.

In [ ]:
```
## initialize parameters
initial_w = np.zeros_like(w_init)
initial_b = 0.
# some gradient descent settings
iterations = 1000
alpha = 5.0e-7
# run gradient descent
w_final, b_final, J_hist = gradient_descent(X_train, y_train, initial_w, ini
                                            compute_cost_vectorized,
                                            alpha, iterations)
print(f"b,w found by gradient descent: {b_final:0.2f},{w_final} ")
m,_ = X_train.shape
for i in range(m):
    print(f"prediction: {np.dot(X_train[i], w_final) + b_final:0.2f}, target
```

```
Iteration    0: Cost  2529.46
Iteration  100: Cost   695.99
Iteration  200: Cost   694.92
Iteration  300: Cost   693.86
Iteration  400: Cost   692.81
Iteration  500: Cost   691.77
Iteration  600: Cost   690.73
Iteration  700: Cost   689.71
Iteration  800: Cost   688.70
Iteration  900: Cost   687.69
b,w found by gradient descent: -0.00,[ 0.2   0.   -0.01 -0.07]
prediction: 426.19, target value: 460
prediction: 286.17, target value: 232
prediction: 171.47, target value: 178
```

Expected Result:

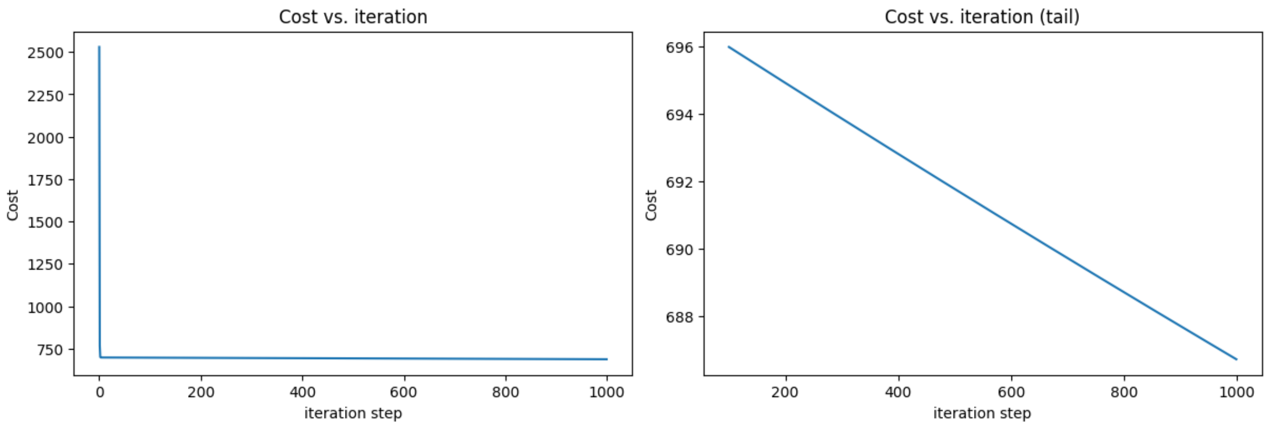
b,w found by gradient descent: -0.00,[0.2 0. -0.01 -0.07]

prediction: 426.19, target value: 460

prediction: 286.17, target value: 232

prediction: 171.47, target value: 178

In [ ]:
```
# plot cost versus iteration
fig, (ax1, ax2) = plt.subplots(1, 2, constrained_layout=True, figsize=(12, 4
ax1.plot(J_hist)
ax2.plot(100 + np.arange(len(J_hist[100:])), J_hist[100:])
ax1.set_title("Cost vs. iteration");  ax2.set_title("Cost vs. iteration (tai
ax1.set_ylabel('Cost')             ;  ax2.set_ylabel('Cost')
ax1.set_xlabel('iteration step')   ;  ax2.set_xlabel('iteration step')
plt.show()
```



These results are not inspiring! Cost is still declining and our predictions are not very accurate. Feature scaling, as discussed in the lectures, would help, here.

6 Congratulations!

In this lab you:

- Developed routines for linear regression with multiple variables.
- Utilized NumPy `np.dot` to vectorize the implementations

In [ ]: