October 1, 2020

```
[6]: import numpy as np
import matplotlib.pyplot as plt
def cost_function(b0, b1, x, y):
    # assume x and y are in vector form
    # x = np.array([[1], [2], [3]])
    # y = np.array([[1], [2], [3]])
    # x = x.reshape(-1,1)
    m = len(x)
    a = np.ones(np.shape(x))
    x = np.hstack((a, x))
    theta = np.array([b0, b1])

    h_x = x.dot(theta).reshape(-1,1)
    cost = (1/(2*m))* np.sum(np.square(h_x-y))
    return cost
```

```
[7]: def gradient_function(b0, b1, x, y):
    # assum x and y are in vector form
    # x = np.array([[1], [2], [3]])
    m = len(x)
    a = np.ones(np.shape(x))
    X = np.hstack((a, x))
    theta = np.array([b0, b1])

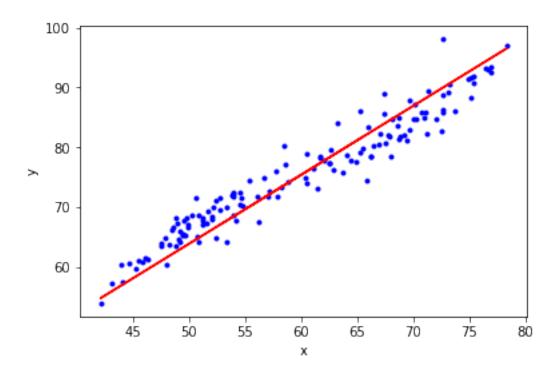
    h_x = X.dot(theta).reshape(-1,1)

    gradient = (1/m)*(x.T.dot(h_x-y))
    return gradient[0][0]
```

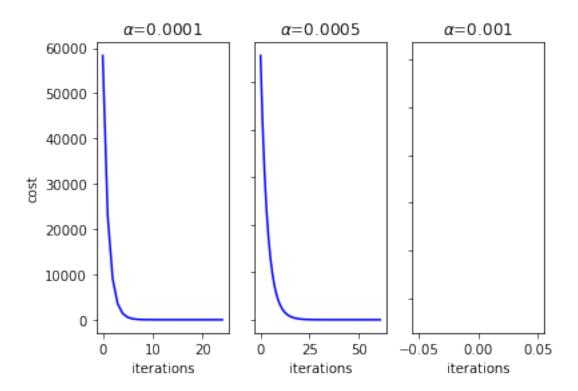
```
if c_prev-cost < 5e-7:
    return theta, cost_hist, i
    c_prev = cost
    cost_hist.append(cost)

return theta, cost_hist, i</pre>
```

```
[29]: def import_data(filename:str):
    #imports data from a numpy file (.npy) and returns data
    #Here filename should have a .npy extension
    data = np.load(filename, allow_pickle=True)
    return data
```



```
[31]: theta_1, cost_hist_1, itr_1 = gradient_descent(x, y, b0, b1, learning_rate=0.
       \rightarrow0005, iterations=10000)
      theta_2, cost_hist_2, itr_2 = gradient_descent(x, y, b0, b1, learning_rate=0.
      \rightarrow001, iterations=10000)
      figure, axes = plt.subplots(nrows=1, ncols=3)
      axes[0].plot(np.arange(len(cost_hist)), cost_hist, 'b-')
      axes[0].set_title(r'$\alpha$=0.0001')
      axes[1].plot(np.arange(len(cost_hist_1)), cost_hist_1, 'b-')
      axes[1].set_title(r'$\alpha$=0.0005')
      axes[2].plot(np.arange(len(cost_hist_2)), cost_hist_2, 'b-')
      axes[2].set_title(r'$\alpha$=0.001')
      #the learning rate is too high, so we are taking too large steps and jumping \Box
      →over global minim
      # axes[0].plot(x, Y, 'r')
      for ax in axes.flat:
          ax.set(xlabel='iterations', ylabel='cost')
      for ax in axes.flat:
          ax.label_outer()
      plt.show()
```



The learning rate at 0.0001 seems to be the best because it converges with a shorter number of iterations. The learning rate at 0.001 is the worst here because of //if c_prev-cost < 5e-7: // return theta, cost_hist, i//

This was not able to progress because the cost was increasing. The jump steps were too high and the gradient exploded.

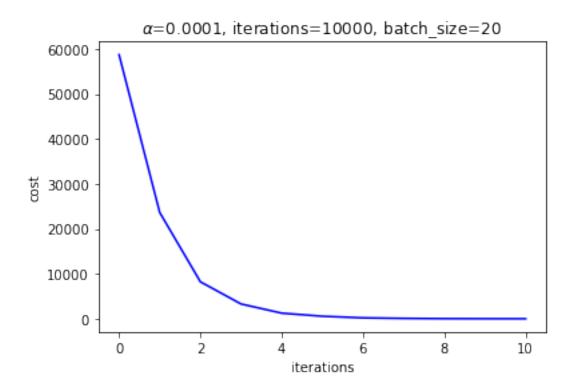
```
[34]: def mini_batch_gradient_descent(x, y, b0, b1, learning_rate, iterations,_
       →batch_size):
          theta = np.array([b0, b1])
          m = len(x)
          # batch_num = int(m/batch_size)
          cost_hist = []
          c_prev = np.inf
          for j in range(iterations):
              idx = np.random.randint(0, m, size=(20))
              x_j = x[idx]
              y_j = y[idx]
              theta = theta - (learning rate*gradient function(theta[0], theta[1],
       \rightarrow x_j, y_j)
              cost = cost_function(theta[0], theta[1], x_j, y_j)
              if c_prev-cost < 5e-7:</pre>
                  return theta, cost_hist, j
              c_prev = cost
```

```
cost_hist.append(cost)
return theta, cost_hist, j
```

```
[36]: data = import_data('data.npy')
    x = data[:, 0].reshape(-1,1)
    y = data[:, 1].reshape(-1,1)
    b0, b1 = 15, 10

theta, cost_hist, it = mini_batch_gradient_descent(x, y, b0, b1, \( \to \) \( \to \) learning_rate=0.0001, iterations=10000, batch_size=20)
    plt.figure()
    plt.plot(np.arange(len(cost_hist)), cost_hist, 'b-')
    plt.title(r'$\alpha$=0.0001, iterations=10000, batch_size=20')
    plt.xlabel('iterations')
    plt.ylabel('cost')
```

[36]: Text(0, 0.5, 'cost')



The mini batch reduces the number of iterations till convergence than the regular gradient descent function.