Linear regression with multiple variables

Implementation and collecting the actual values of parameters respectively.

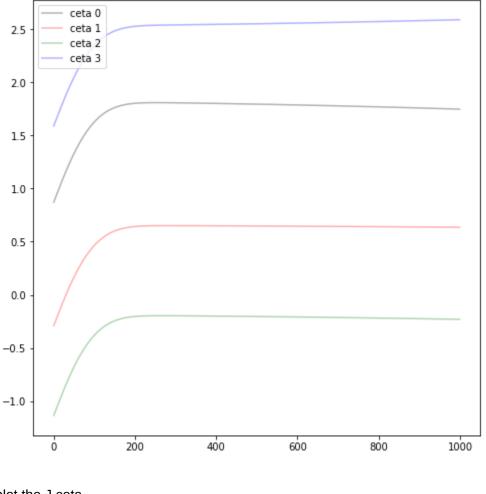
```
In [0]:
        import pandas as pd
        import matplotlib.pyplot as plt
        import torch
        import torch.optim as optim
        import numpy as np
        ### Load the data
        \# First we load the entire CSV file into an m \times 3
        D = torch.tensor(pd.read_csv("/content/drive/My Drive/Colab Notebooks/assignment 4/data_trai
        n.csv", header=None).values, dtype=torch.float)
        # We extract all rows and the first 2 columns, and then transpose it
        x_{dataset} = D[:, 0:3].t()
        # We extract all rows and the last column, and transpose it
        y_{dataset} = D[:, 3].t()
        # And make a convenient variable to remember the number of input columns
        n = 3
        iteration = 1000
        ### Model definition ###
        # First we define the trainable parameters A and b
        params = np.empty((1*3,iteration), dtype=float)
        B = np.empty((1*1, iteration), dtype=float)
        losses = []
        A = torch.randn((1, n), requires_grad=True)
        b = torch.randn(1, requires_grad=True)
        # Then we define the prediction model
        def model(x_input):
            return A.mm(x_input) + b
        ### Loss function definition ###
        def loss(y_predicted, y_target):
            return ((y_predicted - y_target)**2).sum()
        ### Training the model ###
        # Setup the optimizer object, so it optimizes a and b.
        optimizer = optim.Adam([A, b], lr=0.01)
        # Main optimization loop
        for t in range(iteration):
            # Set the gradients to 0.
            optimizer.zero_grad()
            # Compute the current predicted y's from x_dataset
            y_predicted = model(x_dataset)
            # See how far off the prediction is
            current_loss = loss(y_predicted, y_dataset)
            # Compute the gradient of the loss with respect to A and b.
            current_loss.backward()
            # Update A and b accordingly.
            optimizer.step()
            params[:, t] = A.detach().numpy()
            B[:, t] = b.item()
            losses.append(current_loss)
            \#print(f"t = \{t\}, loss = \{current\_loss\}, A = \{A.detach().numpy()\}, b = \{b.item()\}"\}
```

Plotting the actual values.

<Figure size 432x288 with 0 Axes>

#print(params[1,999]) #print(B[:, 999])

```
In [50]:
             import matplotlib.pyplot as plt
             print(params[:,999])
             print(params[1][999])
             plt.clf()
             plt.figure(figsize=(8, 8))
             plt.plot(range(0,iteration), B[0], c='black', label='ceta 0', alpha=0.3)
             plt.plot(range(0,iteration), params[0], c='r', label='ceta 1', alpha=0.3)
plt.plot(range(0,iteration), params[1], c='g', label='ceta 2', alpha=0.3)
plt.plot(range(0,iteration), params[2], c='b', label='ceta 3', alpha=0.3)
             plt.legend(loc='upper left')
             plt.show()
             [ 0.63614947 -0.23046547 2.59024858]
             -0.23046547174453735
```



plot the J ceta.

```
import matplotlib.pyplot as plt
In [56]:
         plt.clf()
         plt.figure(figsize=(8,8))
         plt.plot(range(0,iteration),losses,c='b', label='J ceta', alpha=0.3)
         plt.legend(loc='best')
         plt.show()
         <Figure size 432x288 with 0 Axes>
```

