Lin_Reg

August 13, 2023

[ ]:
```python
import numpy as np
print(np.__version__)
import matplotlib.pylab as plt
```

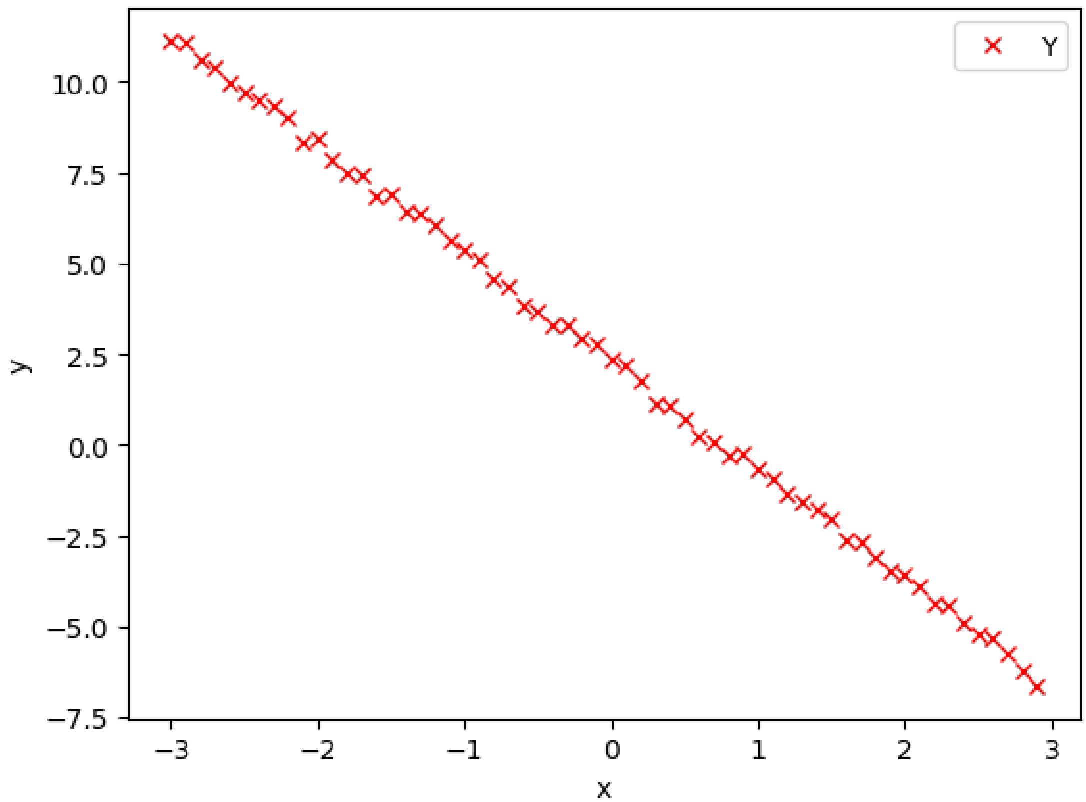
1.23.5

1 Linear Regression

you will train 1D linear regresion model with PyTorch by using data that you created. The model has two parameters: the slope `x` and bias `b`.

Model: $ y = wx+b $

[ ]:
```python
# Create the f(X) with a slope of -3
X = np.arange(-3, 3, 0.1)
f = -3 * X + 2
# Add some noise to f(X) and save it in Y
Y = f + 0.5 * np.random.rand(len(X))

# Plot the data points

plt.plot(X,Y, 'rx', label = 'Y')
plt.xlabel('x')
plt.ylabel('y')
plt.legend()
plt.show()
```



Your Task (Step 1): Initialize Model: $w = 2, b = -1$

[ ]:
```
w=2.0
b=-1.0
```

Your Task (Step 2): Define the function forward(x, w, b) makes the prediction as $y = wx + b$

[ ]:
```
def forward(x,w,b):
    # YOUR CODE STARTS HERE
    yhat = w*x+b
    # YOUR CODE ends HERE
    return yhat

# test: Try to make the prediction for multiple inputs: x1=1.0 and x2=2.0
x = np.array([[1.0], [2.0]])
yhat = forward(x,w,b)
print("The prediction: ", yhat)

assert yhat[0] == 1 # at x=1, predicted value should be 1
assert yhat[1] == 3 # at x=2, predicted value should be 3
```

```
The prediction:  [[1.]
```

```
[3.]]
```

Your Task (Step 3): Define the cost or criterion function using MSE (Mean Square Error):

```
[ ]: # Create the MSE function for evaluate the result.
def criterion(yhat, y):
    # YOUR CODE STARTS HERE
    loss = (y-yhat).T@(y-yhat)
    loss = loss/len(yhat)
    # YOUR CODE ends HERE
    return loss

# test cases:
y_true = np.array([3, -0.5, 2, 7])
y_pred = np.array([2.5, 0.0, 2, 8])
loss = criterion(y_pred,y_true)

assert loss.item() == 0.375
```

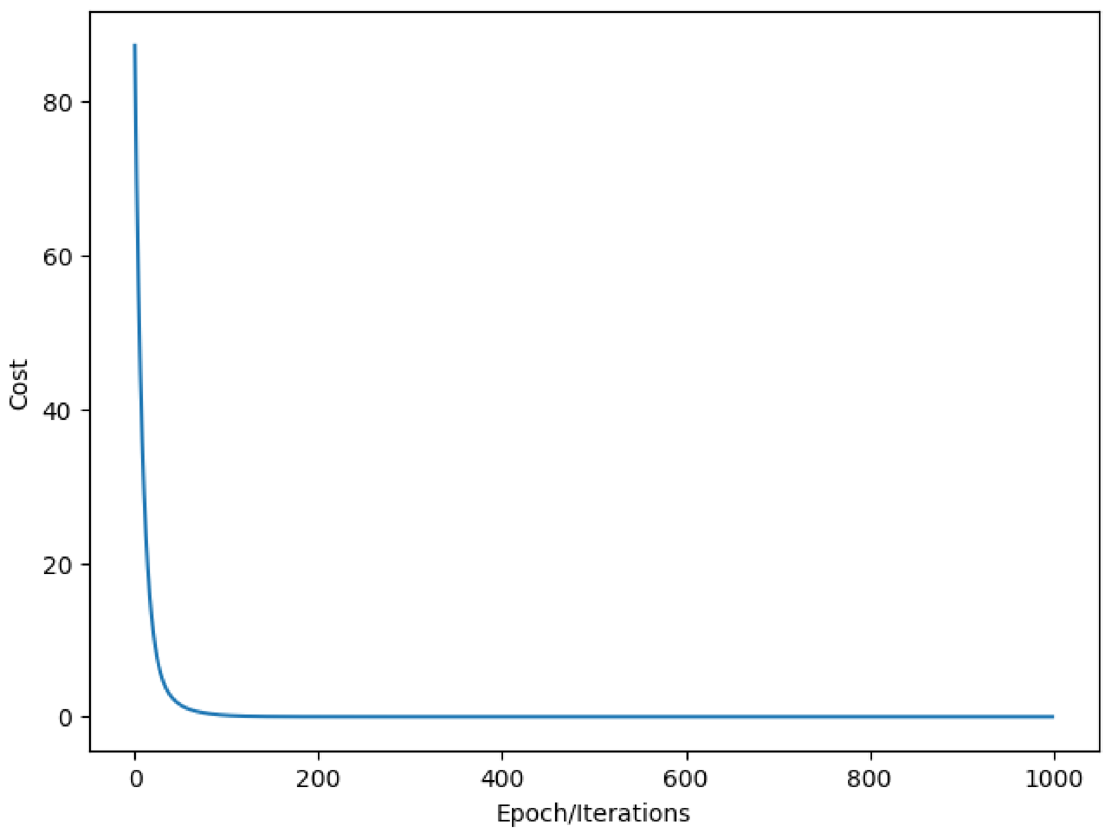
Your Task (Step 4): Train your model

```
[ ]: # Define a function for train the model
LOSS = []
def train_model(iter,w_init,b_init):
    w= w_init
    b= b_init
    for epoch in range(iter):

        # YOUR CODE STARTS HERE
        # make the prediction as we learned in the last lab
        # input data: X
        y_pred = forward(w, X, b)


        # calculate the loss between prediction Yhat and GT Y
        loss = criterion(y_pred, Y)
        # store the loss into list
        LOSS.append(loss)



        # backward pass: compute gradient of the loss with respect to all the␣
↪learnable parameters
        w_grad = 2*X.T@(y_pred-Y)/len(X)
        b_grad = 2*np.sum((y_pred-Y))/len(X)

        # updata parameters with learnign rate alpha=0.01
        # w = w - alpha * w_grad
        # b = b - alpha * b_grad
```

```
        alpha = 0.01
        w = w - alpha*w_grad
        b = b - alpha*b_grad

        # YOUR CODE ENDS HERE
    return w,b
```

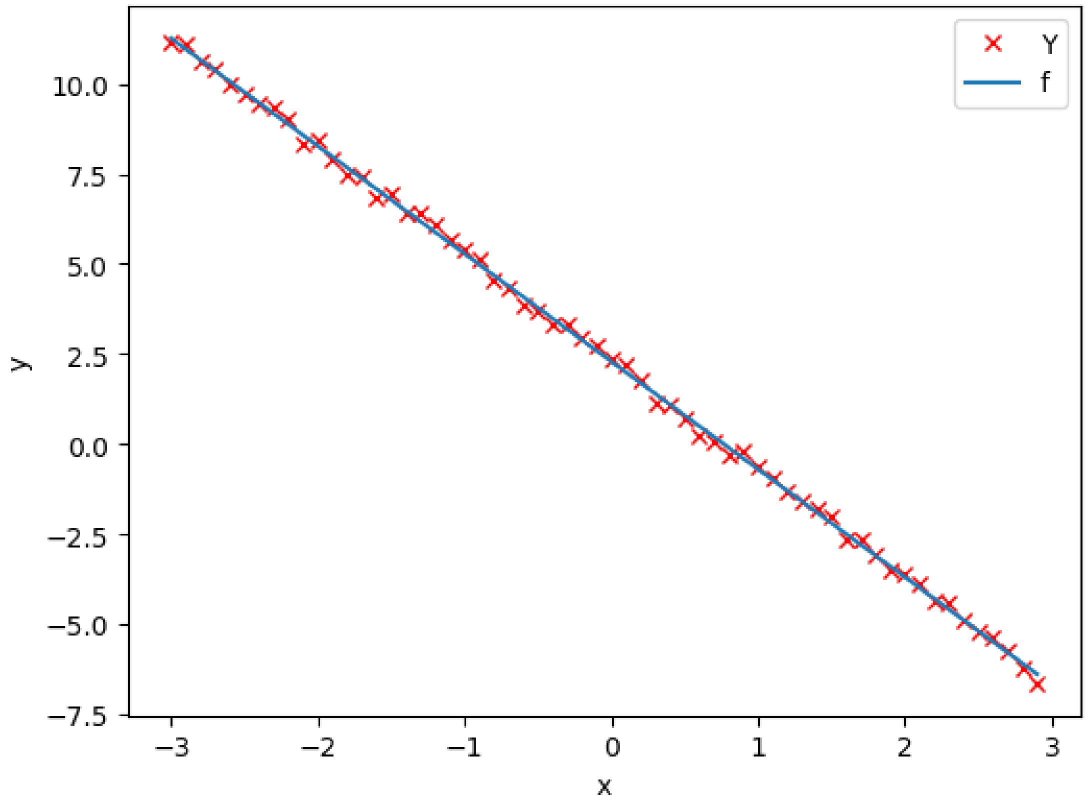
[ ]:
```
w_final,b_final = train_model(1000,w,b)

# Plot the loss for each iteration

plt.plot([x for x in LOSS])
plt.tight_layout()
plt.xlabel("Epoch/Iterations")
plt.ylabel("Cost")
```

[ ]:
```
Text(47.097222222222214, 0.5, 'Cost')
```



Clearly, there is no need for so many iterations. So, having a provision for early stopping might be useful.

```
[ ]: # Plot the data points
plt.plot(X, Y, 'rx', label = 'Y')
y_pred = forward(X,w_final,b_final)
plt.plot(X, y_pred, label = 'f')

plt.xlabel('x')
plt.ylabel('y')
plt.legend()
plt.show()
```




```
[ ]: print(f'True parameters: w=-3 and b=2')
print(f'Predicted parameters: w={w_final} and b={b_final}')
```

```
True parameters: w=-3 and b=2
Predicted parameters: w=-2.991377054448607 and b=2.289217099177737
```