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Machine Learning with Python-From Linear Models to Deep Learning

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[Unit 2 Nonlinear Classification](#),  
[Linear regression, Collaborative](#)

2. Linear Regression with Closed

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## 2. Linear Regression with Closed Form Solution

After seeing the problem, your classmate Alice immediately argues that we can apply a linear regression model, as the labels are numbers from 0-9, very similar to the example we learned from the lecture. Though being a little doubtful, you decide to have a try and start simple by using the raw pixel values of each image as features.

Alice wrote a skeleton code `run_linear_regression_on_MNIST` in `main.py`, but she needs your help to complete the code and make the model work.

### Closed Form Solution of Linear Regression

5/5 points (graded)

To solve the linear regression problem, you recall the linear regression has a closed form solution:

$$\theta = (X^T X + \lambda I)^{-1} X^T Y$$

Write a function `closed_form` that computes this closed form solution given the features  $X$ , labels  $Y$  and the regularization parameter  $\lambda$ .

**Available Functions:** You have access to the NumPy python library as `np`; No need to import anything.

```
1 def closed_form(X, Y, lambda_factor):
2     """
3     Computes the closed form solution of linear regression with L2 regularization
4
5     Args:
6     X - (n, d + 1) NumPy array (n datapoints each with d features plus the bias feature in the first dimension)
7     Y - (n, ) NumPy array containing the labels (a number from 0-9) for each
8         data point
9     lambda_factor - the regularization constant (scalar)
```

```
10 Returns:
11     theta - (d + 1, ) NumPy array containing the weights of linear regression. Note that theta[0]
12     represents the y-axis intercept of the model and therefore X[0] = 1
13     """
14     # YOUR CODE HERE
15     return np.linalg.inv(X.T@X + lambda_factor*np.eye(X.shape[1]))@(X.T@Y)
16
```

Press ESC then TAB or click outside of the code editor to exit

Correct

## Test results

**CORRECT**[Hide output](#)

Test: output

Output:

```
X: [[0.51261794 0.70242204]
 [0.74943563 0.74858527]
 [0.89390655 0.89801078]
 [0.09047841 0.29687843]
 [0.50363122 0.64924333]
 [0.10424944 0.71019987]
 [0.93943595 0.95494293]
 [0.92742283 0.14598462]
 [0.45884661 0.26049004]
 [0.91260513 0.35158453]
 [0.56993027 0.20429471]]
Y: [0.96510048 0.85659104 0.77623373 0.34989444 0.34228261 0.22196316
 0.32790104 0.85882415 0.98712346 0.98605459 0.73846034]
lambda_factor: 0.8373422026379005
Submission output: [0.70702669 0.21486756]
```

Test: size

Output:

```
Output size: (3,)
```

[Submit](#)

You have used 1 of 20 attempts

✓ Correct (5/5 points)

## Test Error on Linear Regression

1/1 point (graded)

Apply the linear regression model on the test set. For classification purpose, you decide to round the predicted label into numbers 0-9.

**Note:** For this project we will be looking at the error rate defined as the fraction of labels that don't match the target labels, also known as the "gold labels" or ground truth. In other contexts, you might want to consider other performance measures we've learned about in this class, including precision and recall.

Please enter the **test error** of your linear regression algorithm for different  $\lambda$  (copy the output from the `main.py` run).

 $\text{Error}|_{\lambda=1} =$ 

0.744

 $\text{Error}|_{\lambda=0.1} =$ 

0.7442

 $\text{Error}|_{\lambda=0.01} =$ 

0.744

[Submit](#)

You have used 1 of 20 attempts

✓ Correct (1/1 point)

## What went Wrong?

1/1 point (graded)

Alice and you find that no matter what lambda factor you try, the test error is large. With some thinking, you realize that something is wrong with this approach.

☐ Gradient descent should be used instead of the closed form solution.

☒ The loss function related to the closed-form solution is inadequate for this problem.

☐ Regularization should not be used here.



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You have used 1 of 2 attempts

✓ Correct (1/1 point)

Discussion

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**Topic:** Unit 2 Nonlinear Classification, Linear regression, Collaborative Filtering (2 weeks):Project 2: Digit recognition (Part 1) / 2. Linear Regression with Closed Form Solution

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