

# THE NEURAL PERSPECTIVE

DEEP LEARNING SIMPLIFIED

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## LINEAR REGRESSION

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**Note:** This post will only cover the bare essentials of linear regression in order to understand its impact and use case to tackle more elaborate deep learning applications.

### I. OBJECTIVE:

Forward pass involves using our weights with X to determine the predictions y.

$$\hat{y} = \beta_0 + \beta_1 X + \epsilon$$

$\hat{y}$  = predicted response  
 $\beta$  = weights  
 $\epsilon$  = error

**Forward Pass:**

$$\hat{y} = \beta_0 + \beta_1 X + \epsilon$$

$$[NX1] = [1X1] + [NxD][DX1]$$

The objective is to accurately predict y using X. The bias and weights are values we need to determine with the objective to minimize the **mean squared error** function:

$$J(\theta) = \frac{1}{2n} \sum_i (\hat{y}_i - y_i)^2$$

y = actual y value

### II. BACKPROPAGATION:

#### STEPS:

1. Randomly initiate bias and weights.
2. Forward pass with weights and X to generate predictions y.
3. Calculate L2 loss J.
4. Determine gradient of J with respect to weights.
5. Update the weights based on gradient (which is a step towards decreasing the overall mean squared error (MSE)).

$$J(\theta) = \frac{1}{2} \sum_i (\hat{y}_i - y_i)^2$$

$$\frac{\partial J}{\partial \beta_1} = X(\hat{y} - y)$$

$$\frac{\partial J}{\partial \beta_0} = 1(\hat{y} - y)$$

→  $\beta_i = \beta_i - \alpha \frac{\partial J}{\partial \beta_i}$

### III. REGULARIZATION:

**Regularization** helps decrease over fitting. Below is L2 regularization. There are many forms of regularization but they all work to reduce overfitting in our models. With L2 regularization, we are penalizing the weights with large magnitudes because we want diffuse weights. Having certain weights with high magnitudes will lead to preferential bias with the inputs and we want the model to work with all the inputs and not just a select few. So applying the L2 penalty allows us to diffuse the weights by decaying them.

$$J(\theta) = \sum_i (\hat{y}_i - y_i)^2 + \frac{\lambda}{2} \sum_k \sum_l W_{kl}^2$$

$$\frac{\partial J}{\partial \beta_1} = X(\hat{y} - y) + \lambda W$$

$$\frac{\partial J}{\partial \beta_1} = 1(\hat{y} - y) + \lambda W$$

→  $\beta_i = \beta_i - \alpha \frac{\partial J}{\partial \beta_i}$

### IV. CODE ANALYSIS:

Our first few lines are the tensorflow and numpy dependencies that we need followed by a few hyperparameters. Learning rate, regularization coefficient should all be deduced empirically by testing across different ranges for optimal performance.

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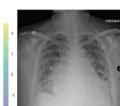
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Your model may be performing really well by incorrectly focusing on confounding features (extraneous influencers in the data that aren't accounted for). Check out [@johnrzech's](#) post where x-ray stickers unintentionally influenced the classifications: [medium.com/@jrzech/what-a...](#)



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```

1 import tensorflow as tf
2 import numpy as np
3
4 class parameters():
5
6     def __init__(self):
7         self.DATA_LENGTH = 10000
8         self.LEARNING_RATE = 1e-10
9         self.REG = 1e-10
10        self.NUM_EPOCHS = 2000
11        self.BATCH_SIZE = 5000
12        self.DISPLAY_STEP = 100 # epoch

```

The next part involves creating our data and separating into batches. Here in our dummy example, we generate a range x and get y by factoring in some linear noise to our inputs x. Using our data, we will split it into batches of length batch\_size so we can feed many batches simultaneously. Lastly, we will generate all batches in the set for multiple epochs for training.

```

1 def generate_data(data_length):
2 """
3     Load the data.
4 """
5     X = np.array(range(data_length))
6     y = 3.657*X + np.random.randn(*X.shape) * 0.33
7     return X, y
8
9 def generate_batches(data_length, batch_size):
10 """
11     Create <num_batches> batches from X and y
12 """
13     X, y = generate_data(data_length)
14
15     # Create batches
16     num_batches = data_length // batch_size
17     data_X = np.zeros([num_batches, batch_size], dtype=np.
18     data_y = np.zeros([num_batches, batch_size], dtype=np.
19     for batch_num in range(num_batches):
20         data_X[batch_num,:] = X[batch_num*batch_size:(batch_
21         data_y[batch_num,:] = y[batch_num*batch_size:(batch_
22         yield data_X[batch_num].reshape(-1, 1), data_y[batch_
23
24 def generate_epochs(num_epochs, data_length, batch_size):
25 """
26     Create batches for <num_epochs> epochs.
27 """
28     for epoch_num in range(num_epochs):
29         yield generate_batches(data_length, batch_size)

```

I'm going to assume you have some familiarity with tensorflow but if not check out this basics [video](#). First we will have placeholders for our inputs. The shape is [None, 1] where the None is batch\_size. In later examples you will see we will use shape=[None, None] to have complete freedom with batch\_size and seq\_len.

Next we will set out weights W and bias b. Our prediction will just be the forward pass with  $XW+b$ . We will then compute the MSE with L2 regularization and use this cost as the quantity to minimize using our optimizer.

We also have a `step()` function inside the model class. This will take in a batch of inputs and do one step of training.

We also have a `create_model()` function that will take in a tf session and a few parameters to initialize the model. We pass in session because in later example you will see that we want to save the model after training and reload later on. Here is the location that we will reload saved models if we have any.

```

1 class model(object):
2 """
3     Train the linear model to minimize L2 loss function.
4 """
5
6     def __init__(self, learning_rate, reg):
7         # Inputs
8         self.X = tf.placeholder(tf.float32, [None, 1], "X")
9         self.y = tf.placeholder(tf.float32, [None, 1], "y")
10
11         # Set model weights
12         with tf.variable_scope('weights'):
13             self.W = tf.Variable(tf.truncated_normal([1,1])
14             self.b = tf.Variable(tf.truncated_normal([1,1])
15
16         # Forward pass
17         self.prediction = tf.add(tf.matmul(self.X, self.W)
18
19         # L2 loss
20         self.cost = tf.reduce_mean(tf.pow(self.prediction-
21
22         # Gradient descent (backprop)
23         self.optimizer = tf.train.GradientDescentOptimizer(
24
25     def step(self, sess, batch_X, batch_y):
26
27         input_feed = {self.X:batch_X, self.y:batch_y}
28         output_feed = [self.prediction,
29                         self.cost,
30                         self.optimizer,
31                         self.W,
32                         self.b]
33
34         outputs = sess.run(output_feed, input_feed)
35
36         return outputs[0], outputs[1], outputs[2], outputs
37

```

```

38     def create_model(sess, FLAGS):
39         linear_model = model(FLAGS.LEARNING_RATE, FLAGS.REG)
40         sess.run(tf.initialize_all_variables())
41     return linear_model

```

Lastly, we will train for several epochs. Note that we chose an arbitrary number of epochs but later on in this blog, we will explore empirical techniques to use to determine when to stop training (gradient norm, etc.).

```

1  def train(FLAGS):
2
3      with tf.Session() as sess:
4
5          # Create the model
6          model = create_model(sess, FLAGS)
7
8          for epoch_num, epoch in enumerate(generate_epochs(
9              for simmult_batch_num, (input_X, labels_y) in e
10                 prediction, training_loss, _, W, b = model
11
12             # Display
13             if epoch_num%FLAGS.DISPLAY_STEP == 0:
14                 print "EPOCH %i: \n Training loss: %.3f, W
15                 epoch_num, training_loss, W, b)
16
17     if __name__ == '__main__':
18
19     FLAGS = parameters()
20     train(FLAGS)

```

## V. RESULTS:

```

EPOCH 0:
Training loss: 2228963328.000, W: 0.122, b:-0.007
EPOCH 100:
Training loss: 2534575.750, W: 3.538, b:-0.006
EPOCH 200:
Training loss: 2884.403, W: 3.653, b:-0.006
EPOCH 300:
Training loss: 3.820, W: 3.657, b:-0.006
EPOCH 400:
Training loss: 0.541, W: 3.657, b:-0.006

```

**results:** weights drop but the bias doesn't seem to change much from initial starting value. It might be better to combine bias with weights and append a 1 to all Xs.

## VI. RAW CODE:

[GitHub Repo](#) (Updating all repos, will be back up soon!)



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