Code:

import tensorflow as tf

```
import numpy as np

class parameters():

def __init__(self):
    self.DATA_LENGTH = 10000
    self.LEARNING_RATE = 1e-10
    self.REG = 1e-10
    self.NUM_EPOCHS = 500
    self.NUM_BATCHES = 10
    self.DISPLAY_STEP = 100 # epoch
```

dependencies: implementation in tensorflow and numpy

hyperparameters: the learning rate and regularization rates are very important. Should be finalized using empirical evidence.

```
def generate_data(config):
    Load the data.
   X = np.array(range(config.DATA LENGTH))
   y = 3.657*X + np.random.randn(*X.shape) * 0.33
    return X, y
def generate batches(config):
    Create <num batches> batches from X and y
   X, y = generate_data(config)
    # Create batches
   batch size = config.DATA LENGTH // config.NUM BATCHES
    data X = np.zeros([config.NUM BATCHES, batch size], dtype=np.float32)
    data y = np.zeros([config.NUM BATCHES, batch size], dtype=np.float32)
    for batch_num in range(config.NUM_BATCHES):
        data X[batch num,:] = X[batch num*batch size:(batch num+1)*batch size]
        data y[batch num,:] = y[batch num*batch size:(batch num+1)*batch size]
   yield data X.reshape(-1, 1), data y.reshape(-1, 1)
def generate epochs(config)
    Create batches for <num epochs> epochs.
    for epoch num in range(config.NUM EPOCHS):
       yield generate batches(config)
```

data: X is sequential and y is a linear output with a big of noise added in.

batches: Separating the data into batches, each of length batch_size and feeding in all batches simultaneously.

epochs: Feed in same data for num_epochs in order to continuously train and update the weights to minimize the cost function

placeholders: X and y are of size (?, 1)

```
def model(config):
                                                                weights: should be initialize to different
   Train the linear model to minimize L2 loss function.
   # Inputs
                                                                random values so they don't all update
   X = tf.placeholder(tf.float32, [None, 1], "X")
   y = tf.placeholder(tf.float32, [None, 1], "y")
                                                                same way
   # Set model weights
   with tf.variable scope('weights'):
       W = tf.Variable(tf.truncated_normal([1,1], stddev=0.01), name="W", dtype=tf.float32)
       b = tf.Variable(tf.truncated normal([1,1], stddev=0.01), name="b", dtype=tf.float32)
                                                       prediction: get y_hat via forward pass
   # Forward pass
   prediction = tf.add(tf.matmul(X, W), b)
   # L2 loss
                                                                                                   MSE +
   batch size = config.DATA LENGTH // config.NUM BATCHES
   cost = tf.reduce sum(tf.pow(prediction-y, 2))/(2*batch size) + config.REG * np.sum(W
                                                                                                   L2 Reg
   # Gradient descent (backprop)
   optimizer = tf.train.GradientDescentOptimizer(config.LEARNING RATE).minimize(cost)
   return dict(
       X=X, y=y, W=W, b=b,
       prediction=prediction,
       cost=cost, optimizer=optimizer)
```

optimizer: takes care of backprop and updates our weights.

train: run the optimizer to update the weights. Call for other variables for performance indication.

if __name__ == '__main__':
 import time
 start = time.time()
 config = parameters()
 g = model(config)
 train(g)
 print time.time() - start

execute: it is faster to use simultaneous batches than one batch at a time, depending on the size of the batch based on your CPU/GPU constraints