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 2 Alexander Koldy
 3 ECE 472 - Deep Learning
 4 Assignment 1
 5
 6
 7 import numpy as np
 8 import matplotlib.pyplot as plt
 9 import tensorflow as tf
10
11 | ' ' '
12 Code would not run without this:
13 ' ' '
14 tf.enable_eager_execution()
15
16 # Known parameters
17 \mid N = 50 \# number of discrete steps in function
18 | sigma_noise = 0.1
19 epsilon = np.random.normal(0, sigma noise, N) # noise
20
21 # Loop parameters
22 111
23 Editting these parameters may yield better results
25 \mid M = 10 \# number of gaussian basis functions
26 epochs = 1000 # loop iterations
27 learning_rate = 0.02 # step size
28
29 # Noisy sin wave
30 \times = \text{np.linspace}(0, 1, N)
31 y = np.sin(2*np.pi*x) + epsilon
32
33 # Parameters to estimate
34 w = []
35 \, \text{mu} = []
36 \text{ sigma} = []
37 b = []
38 for _ in range(M):
39
40
       Each parameter was established with a random value
41
       with no range. It may sometimes take more epochs to
42
       minimize the cost function due to this,
43
44
       w.append(tf.Variable(np.random.rand()))
45
       mu.append(tf.Variable(np.random.rand()))
46
       sigma.append(tf.Variable(np.random.rand()))
47
       b.append(tf.Variable(np.random.rand()))
48
49 # Gaussian
50 def phi(x, mu, sigma):
       return tf.exp(-(x - mu)**2 / sigma**2)
51
52
53 # Approximation of y
54 \text{ def y hat}(x):
55
       y_hat_i = 0
56
       for j in range(M):
57
           y hat i = y hat i + w[j]*phi(x, mu[j], sigma[j]) + b[j]
58
       return y hat i
59
60 # Cost function
```

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                                           assignment1.py
 61 def J(y, y_hat):
         return (1/2)*tf.square(y - y hat)
  62
 63
 64 # Gradient Descent
 65 ' ' '
 66 The following gradient descent code is editted from (1) to fit
  67 the scope of the assignment.
 68 ' ' '
 69 for epoch in range(epochs):
  70
         with tf.GradientTape() as tape:
  71
             loss = tf.reduce mean(J(y, y hat(x)))
  72
  73
         gradients = tape.gradient(loss, [w, mu, sigma, b])
  74
  75
         for i in range(M):
             w[j].assign sub(gradients[0][j]*learning rate)
  76
  77
             mu[j].assign sub(gradients[1][j]*learning rate)
  78
             sigma[j].assign sub(gradients[2][j]*learning rate)
  79
             b[j].assign sub(gradients[3][j]*learning rate)
  80
  81
  82
         Once again, this line is taken directly from (1). It helps visualize the
     loss as more iterations of the loop go through.
 83
         print(f"Epoch count {epoch}: Loss value: {loss.numpy()}")
  84
 85
 86 # Plot regression approximation
  87 plt.figure(1)
 88 plt.title("Fit")
 89 plt.xlabel("x")
  90 plt.ylabel("y", rotation="horizontal")
 91 plt.scatter(x, y, label="Noisy Sine Curve", color="green")
 92 plt.plot(x, np.sin(2*np.pi*x), label="Sine Curve", color="red")
 93 plt.plot(x, y_hat(x), '--', label="Approximation", color="blue")
  94 plt.legend()
 95 plt.show()
 96
 97 # Plot basis functions
 98 plt.figure(2)
 99 plt.title("Bases for Fit")
100 plt.xlabel("x")
 101 plt.ylabel("y", rotation="horizontal")
 102 for j in range(M):
         plt.plot(x, phi(x, mu[j], sigma[j]))
103
 104 plt.show()
105
106
107 '''
108 References:
 109 (1) https://www.machinelearningplus.com/deep-learning/linear-regression-
     tensorflow/
110 (2) Cooper Union ECE-472: Deep Learning - Learning Materials
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