C2_W2_Lab_1_training-basics

June 14, 2021

1 Custom Training Basics

In this ungraded lab you'll gain a basic understanding of building custom training loops. - It takes you through the underlying logic of fitting any model to a set of inputs and outputs. - You will be training your model on the linear equation for a straight line, wx + b. - You will implement basic linear regression from scratch using gradient tape. - You will try to minimize the loss incurred by the model using linear regression.

1.1 Imports

[1]:
```
from __future__ import absolute_import, division, print_function,␣
↪unicode_literals

try:
  # %tensorflow_version only exists in Colab.
  %tensorflow_version 2.x
except Exception:
    pass


import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
```

1.2 Define Model

You define your model as a class. - **x** is your input tensor. - The model should output values of **wx+b**. - You'll start off by initializing w and b to random values. - During the training process, values of w and b get updated in accordance with linear regression so as to minimize the loss incurred by the model. - Once you arrive at optimal values for w and b, the model would have been trained to correctly predict the values of wx+b.

Hence, - **w** and **b** are trainable weights of the model. - **x** is the input - **y** = wx + b is the output

[3]:
```
class Model(object):
    def __init__(self):
```

```
        # Initialize the weights to `2.0` and the bias to `1.0`
        # In practice, these should be initialized to random values (for␣
↪example, with `tf.random.normal`)
        self.w = tf.Variable(2.0)
        self.b = tf.Variable(1.0)

    def __call__(self, x):
        return self.w * x + self.b

model = Model()
```

1.2.1 Define a loss function

A loss function measures how well the output of a model for a given input matches the target output. - The goal is to minimize this difference during training. - Let's use the standard L2 loss, also known as the least square errors

$$Loss = \sum_{i} \left(y^i_{pred} - y^i_{target}\right)^2$$

[4]:
```
def loss(predicted_y, target_y):
    return tf.reduce_mean(tf.square(predicted_y - target_y))
```

1.2.2 Obtain training data

First, synthesize the training data using the "true" w and "true" b.

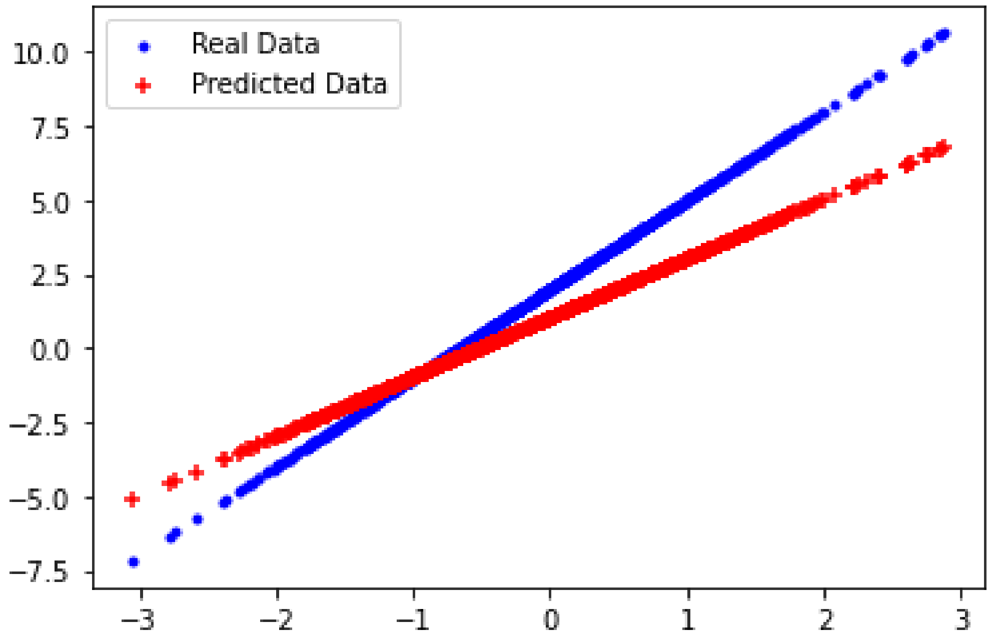
$$y = w_{true} \times x + b_{true}$$

[5]:
```
TRUE_w = 3.0
TRUE_b = 2.0
NUM_EXAMPLES = 1000

xs  = tf.random.normal(shape=[NUM_EXAMPLES])

ys = (TRUE_w * xs) + TRUE_b
```

Before training the model, visualize the loss value by plotting the model's predictions in red crosses and the training data in blue dots:

[6]:
```
def plot_data(inputs, outputs, predicted_outputs):
    real = plt.scatter(inputs, outputs, c='b', marker='.')
    predicted = plt.scatter(inputs, predicted_outputs, c='r', marker='+')
    plt.legend((real,predicted), ('Real Data', 'Predicted Data'))
    plt.show()
```

[7]:
```
plot_data(xs, ys, model(xs))
print('Current loss: %1.6f' % loss(model(xs), ys).numpy())
```




```
Current loss: 1.965352
```

1.2.3 Define a training loop

With the network and training data, train the model using gradient descent - Gradient descent updates the trainable weights **w** and **b** to reduce the loss.

There are many variants of the gradient descent scheme that are captured in `tf.train.Optimizer`—our recommended implementation. In the spirit of building from first principles, here you will implement the basic math yourself. - You'll use `tf.GradientTape` for automatic differentiation - Use `tf.assign_sub` for decrementing a value. Note that assign_sub combines `tf.assign` and `tf.sub`

[8]:
```
def train(model, inputs, outputs, learning_rate):
    with tf.GradientTape() as t:
        current_loss = loss(model(inputs), outputs)
    dw,db = t.gradient(current_loss, [model.w, model.b])
    model.w.assign_sub(learning_rate * dw)
    model.b.assign_sub(learning_rate * db)

    return current_loss
```

[9]:
```
# def train(model, inputs, outputs, learning_rate):
#   with tf.GradientTape() as t:
#     current_loss = loss(model(inputs), outputs)
#   dw, db = t.gradient(current_loss, [model.w, model.b])
#   model.w.assign_sub(learning_rate * dw)
#   model.b.assign_sub(learning_rate * db)

#   return current_loss
```

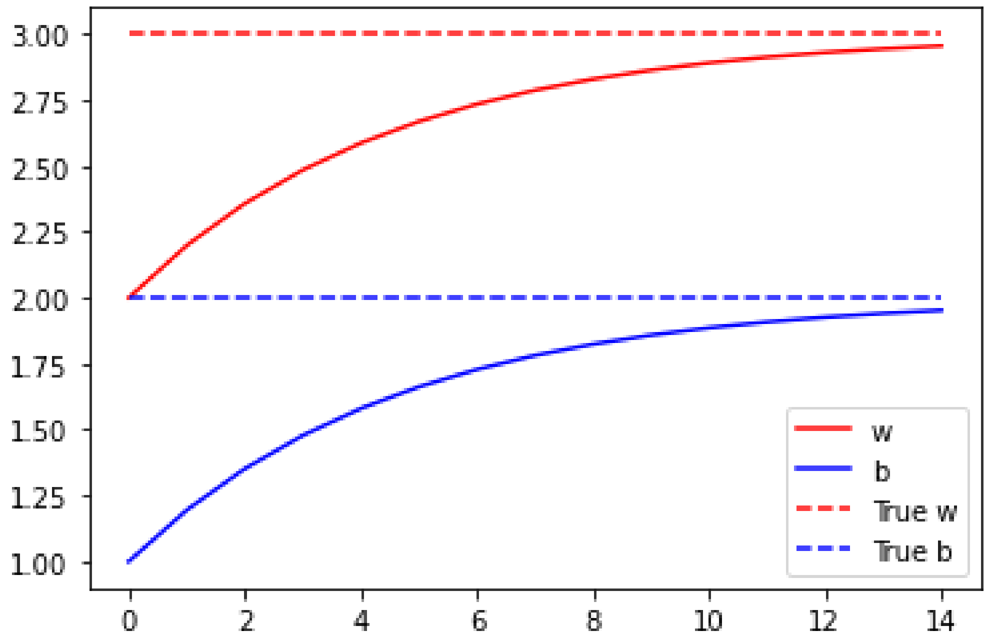
Finally, you can iteratively run through the training data and see how `w` and `b` evolve.

[11]:
```
model = Model()

# Collect the history of W-values and b-values to plot later
list_w, list_b = [], []
epochs = range(15)
losses = []
for epoch in epochs:
    list_w.append(model.w.numpy())
    list_b.append(model.b.numpy())
    current_loss = train(model, xs, ys, learning_rate=0.1)
    losses.append(current_loss)
    print('Epoch %2d: w=%1.2f b=%1.2f, loss=%2.5f' %
        (epoch, list_w[-1], list_b[-1], current_loss))
```

```
Epoch  0: w=2.00 b=1.00, loss=1.96535
Epoch  1: w=2.20 b=1.19, loss=1.26871
Epoch  2: w=2.36 b=1.35, loss=0.81901
Epoch  3: w=2.48 b=1.48, loss=0.52872
Epoch  4: w=2.59 b=1.58, loss=0.34133
Epoch  5: w=2.67 b=1.66, loss=0.22035
Epoch  6: w=2.73 b=1.73, loss=0.14226
Epoch  7: w=2.79 b=1.78, loss=0.09184
Epoch  8: w=2.83 b=1.82, loss=0.05929
Epoch  9: w=2.86 b=1.86, loss=0.03828
Epoch 10: w=2.89 b=1.89, loss=0.02471
Epoch 11: w=2.91 b=1.91, loss=0.01596
Epoch 12: w=2.93 b=1.93, loss=0.01030
Epoch 13: w=2.94 b=1.94, loss=0.00665
Epoch 14: w=2.95 b=1.95, loss=0.00429
```

In addition to the values for losses, you also plot the progression of trainable variables over epochs.

[12]:
```
plt.plot(epochs, list_w, 'r', epochs, list_b, 'b')
plt.plot([TRUE_w] * len(epochs), 'r--',[TRUE_b] * len(epochs), 'b--')
plt.legend(['w', 'b', 'True w', 'True b'])
plt.show()
```

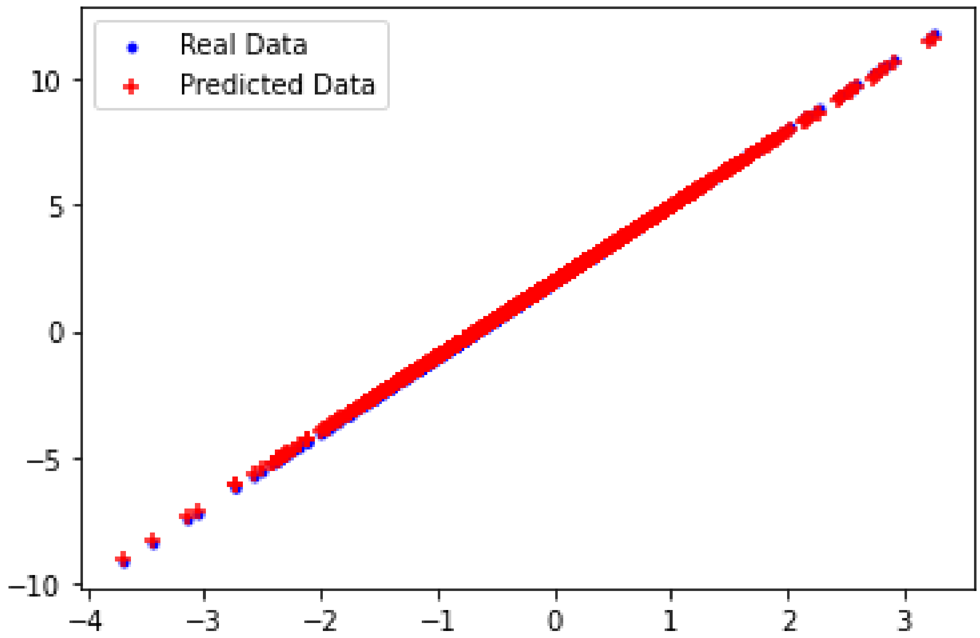


1.3 Plots for Evaluation

Now you can plot the actual outputs in red and the model's predictions in blue on a set of random test examples.

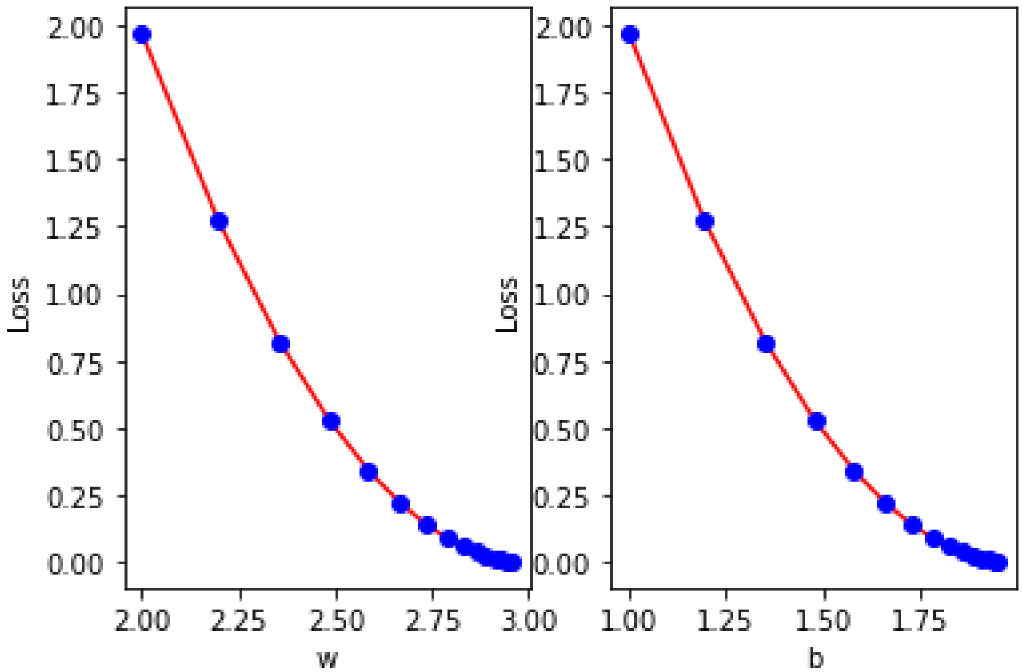
You can see that the model is able to make predictions on the test set fairly accurately.

[13]:
```
test_inputs  = tf.random.normal(shape=[NUM_EXAMPLES])
test_outputs = test_inputs * TRUE_w + TRUE_b

predicted_test_outputs = model(test_inputs)
plot_data(test_inputs, test_outputs, predicted_test_outputs)
```



Visualize the cost function against the values of each of the trainable weights the model approximated to over time.

[14]:
```
def plot_loss_for_weights(weights_list, losses):
    for idx, weights in enumerate(weights_list):
        plt.subplot(120 + idx + 1)
        plt.plot(weights['values'], losses, 'r')
        plt.plot(weights['values'], losses, 'bo')
        plt.xlabel(weights['name'])
        plt.ylabel('Loss')


weights_list = [{ 'name' : "w",
                  'values' : list_w
                },
                {
                  'name' : "b",
                  'values' : list_b
                }]

plot_loss_for_weights(weights_list, losses)
```


Loss
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
2.00
2.25
2.50
2.75
3.00
w
Loss
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
1.00
1.25
1.50
1.75
b