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.

Imports

In [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
```

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

In [2]:
```
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()
```

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

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

In [3]:
```
def loss(predicted_y, target_y):
  return tf.reduce_mean(tf.square(predicted_y - target_y))
```

Obtain training data

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

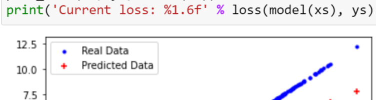
$$y = w_{true} \times x + b_{true}$$

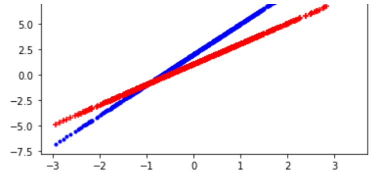
In [4]:
```
TRUE_w = 3.0
TRUE_b = 2.0
NUM_EXAMPLES = 1000

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:

In [5]:
```
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()
```

In [6]:
```
plot_data(xs, ys, model(xs))
print('Current loss: %1.6f' % loss(model(xs), ys).numpy())
```






```
Current loss: 2.051971
```

Define a training loop

With the network and training data, train the model using [gradient descent](https://en.wikipedia.org/wiki/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`

In [7]:

```
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.

In [8]:

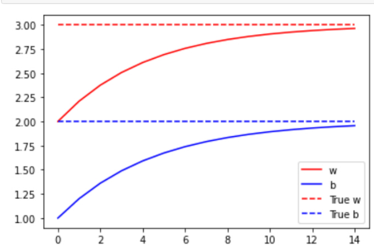
```
model = Model()

# 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=2.05197
Epoch  1: w=2.21 b=1.20, loss=1.29597
Epoch  2: w=2.38 b=1.36, loss=0.81860
Epoch  3: w=2.51 b=1.49, loss=0.51714
Epoch  4: w=2.61 b=1.59, loss=0.32674
Epoch  5: w=2.69 b=1.67, loss=0.20647
Epoch  6: w=2.76 b=1.74, loss=0.13048
Epoch  7: w=2.81 b=1.79, loss=0.08248
Epoch  8: w=2.85 b=1.83, loss=0.05214
Epoch  9: w=2.88 b=1.87, loss=0.03296
Epoch 10: w=2.91 b=1.89, loss=0.02084
Epoch 11: w=2.92 b=1.91, loss=0.01318
Epoch 12: w=2.94 b=1.93, loss=0.00834
Epoch 13: w=2.95 b=1.95, loss=0.00527
Epoch 14: w=2.96 b=1.96, loss=0.00334
```

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

In [9]:

```
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()
```



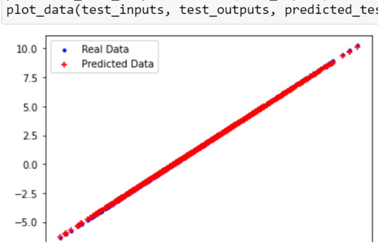
Plots for Evaluation

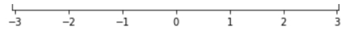
Now you can plot the actual outputs in red and the model's predictions in blue on a set of random test examples.

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

In [10]:

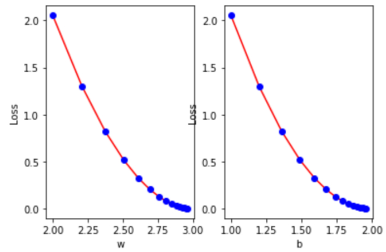
```
test_inputs  = tf.random.normal(shape=[NUM_EXAMPLES])
test_outputs = test_inputs * TRUE_w + TRUE_b

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.

In [11]:
```
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)
```



In [ ]: