

Understanding Neurons

The Building Blocks of Deep Learning



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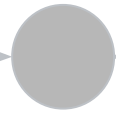
```
model = keras.Sequential([keras.layers.Dense(units=1, input_shape=[1])])  
model.compile(optimizer='sgd', loss='mean_squared_error')
```

```
xs = np.array([-1.0, 0.0, 1.0, 2.0, 3.0, 4.0], dtype=float)  
ys = np.array([-3.0, -1.0, 1.0, 3.0, 5.0, 7.0], dtype=float)
```

```
model.fit(xs, ys, epochs=500)
```

```
print(model.predict([10.0]))
```

X



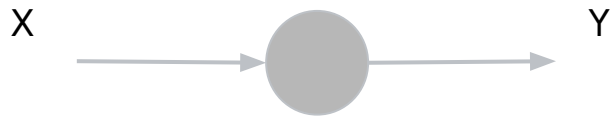
Y

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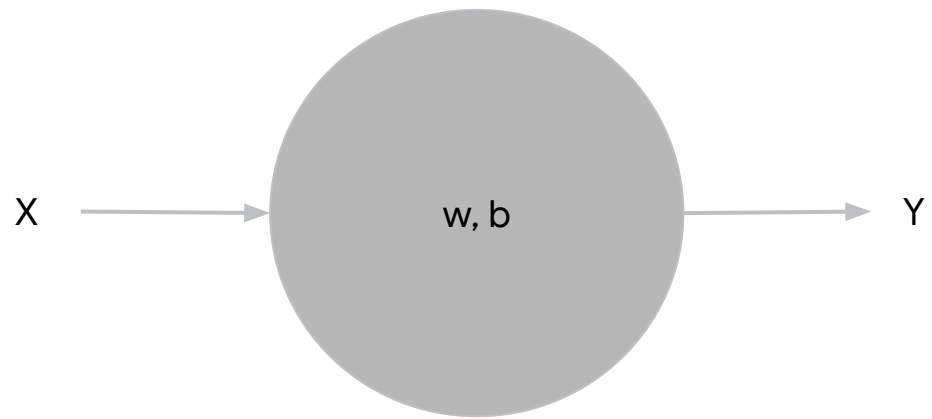
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```

```
model.fit(xs, ys, epochs=500)
```

```
print(model.predict([10.0]))
```



$$y = f(x) = wx + b$$



```
class Model(object):  
    def __init__(self):  
        self.w = tf.Variable(10.0)  
        self.b = tf.Variable(10.0)  
  
    def __call__(self, x):  
        return self.w * x + self.b
```

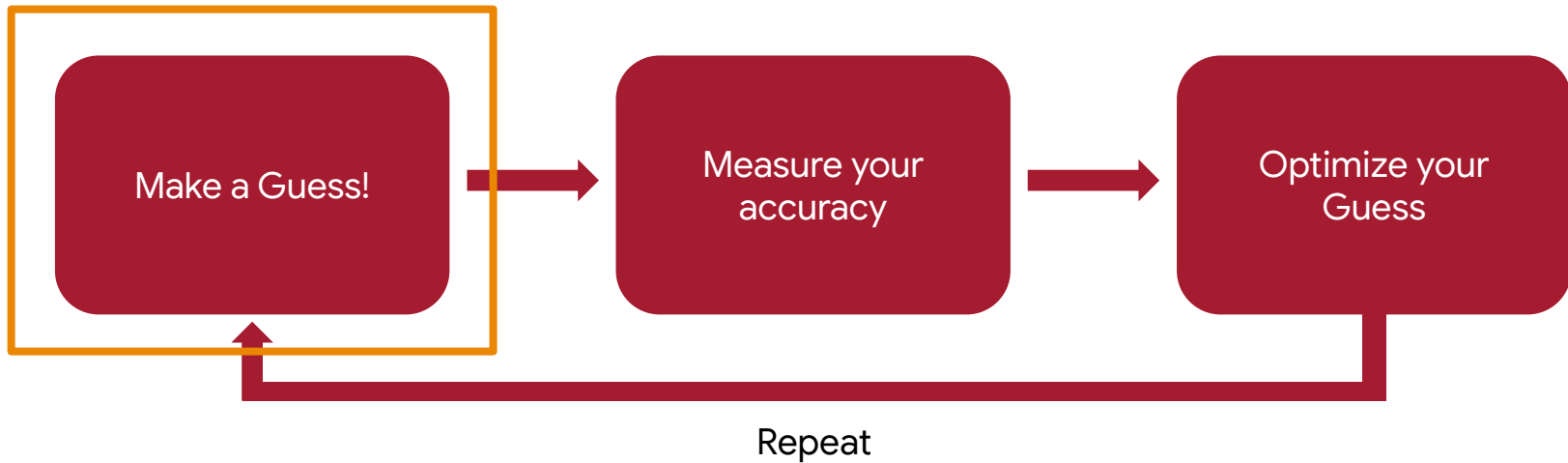
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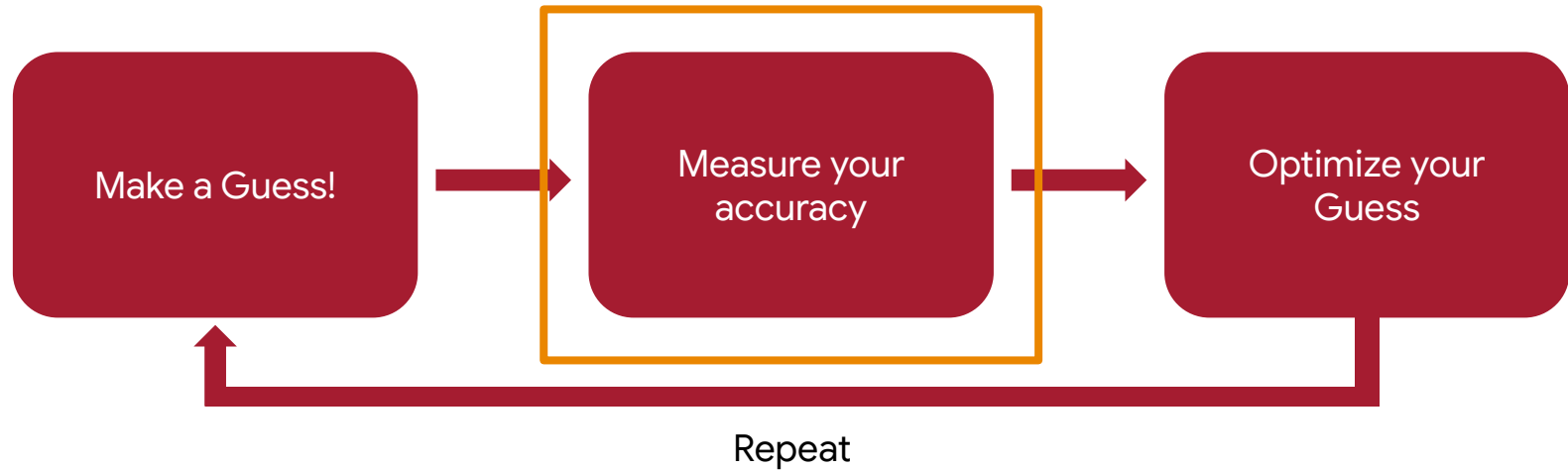
```
model = Model()  
xs = [-1.0, 0.0, 1.0, 2.0, 3.0, 4.0]  
ys = [-3.0, -1.0, 1.0, 3.0, 5.0, 7.0]  
print(model(xs))
```

```
[ 0. 10. 20. 30. 40. 50.]
```

The Machine Learning Paradigm



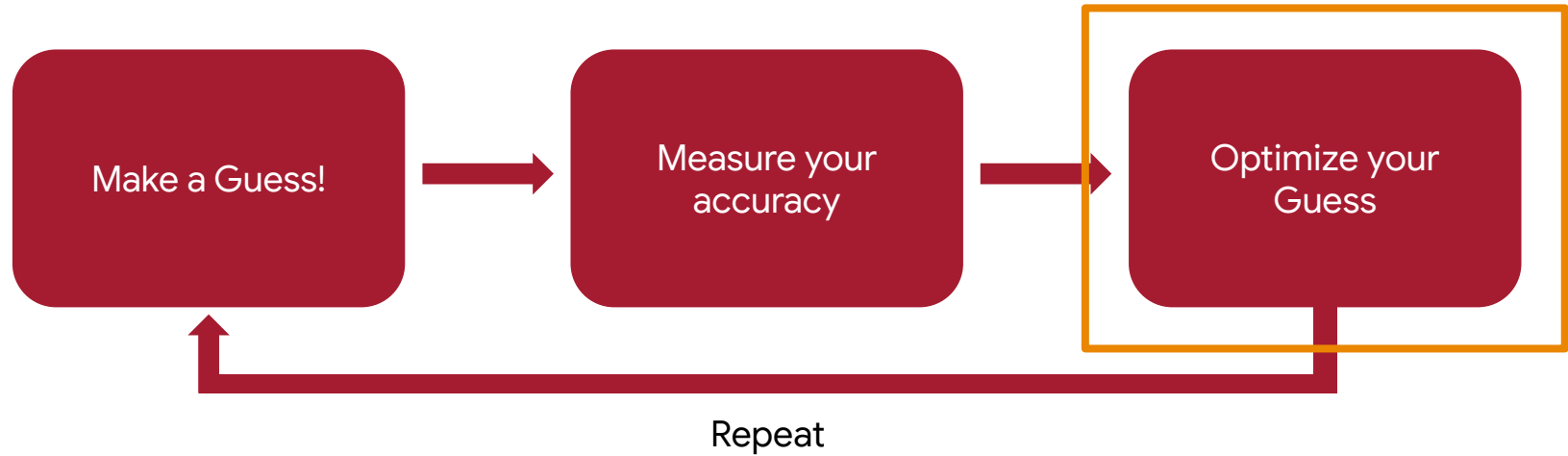
The Machine Learning Paradigm



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

```
def train(model, xs, ys, learning_rate):  
    with tf.GradientTape() as t:  
        current_loss = loss(model(xs), ys)  
  
        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
```

The Machine Learning Paradigm



```
def train(model, xs, ys, learning_rate):
```

```
    with tf.GradientTape() as t:
```

```
        current_loss = loss(model(xs), ys)
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    dw, db = t.gradient(current_loss, [model.w, model.b])
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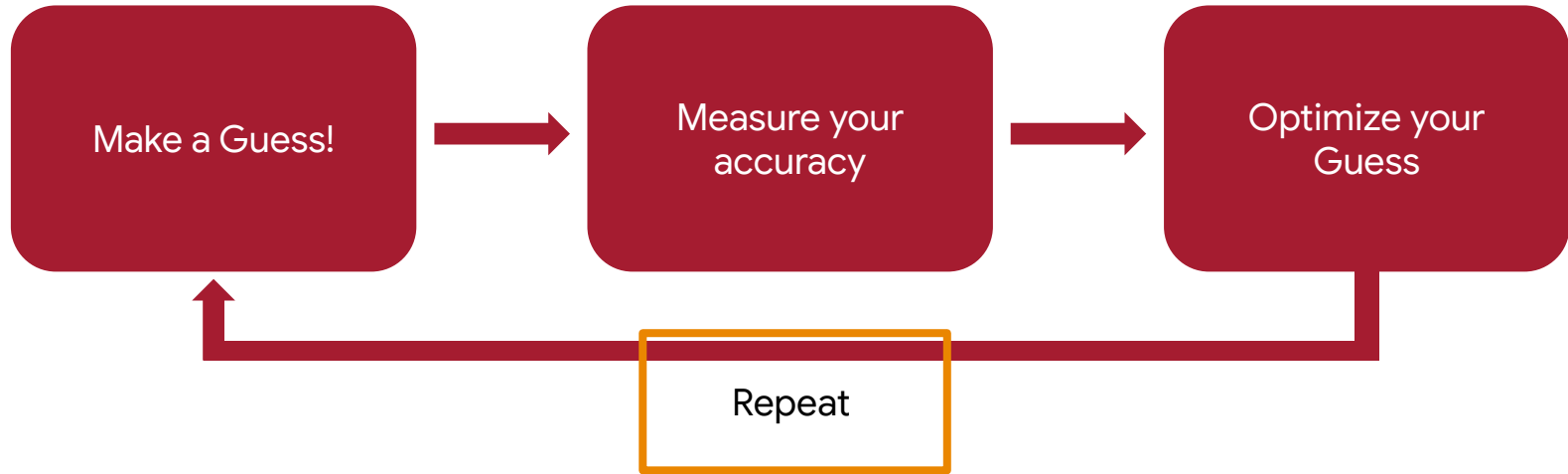
```
    model.w.assign_sub(learning_rate * dw)
```

```
    model.b.assign_sub(learning_rate * db)
```

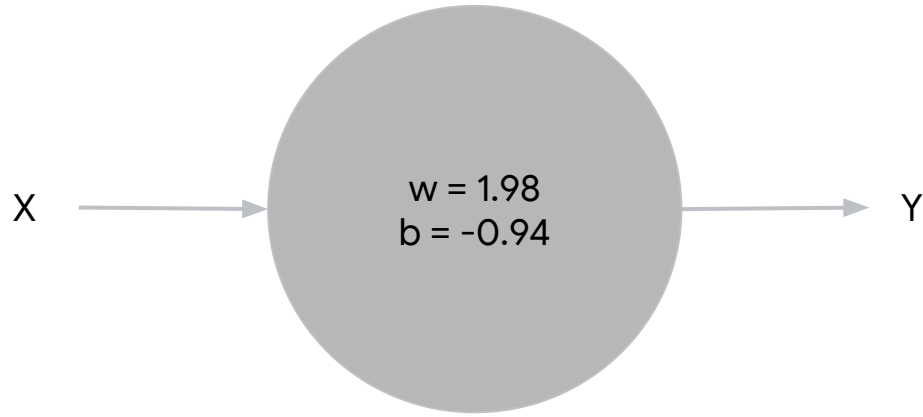
```
    return current_loss
```

```
def train(model, xs, ys, learning_rate):  
    with tf.GradientTape() as t:  
        current_loss = loss(model(xs), ys)  
  
        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
```


The Machine Learning Paradigm



```
for epoch in range(50):  
    current_loss = train(model, xs, ys, learning_rate=0.1)
```



$$y = 1.98x - 0.94$$



Your turn!