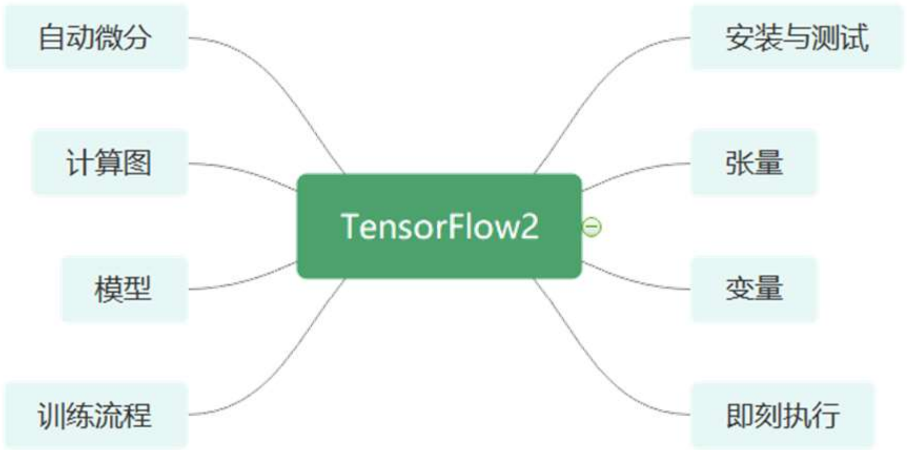
TensorFlow2

训练流程

Training loops

导学



TensorFlow2

自动微分

计算图

模型

训练流程

安装与测试

张量

变量

即刻执行

训练流程

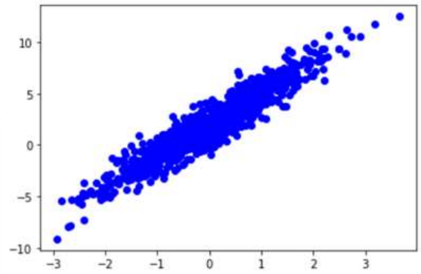
1. 获取训练数据。
2. 定义模型。
3. 定义一个损失函数。
4. 运行训练数据，从目标值计算损失。
5. 计算损失的梯度，并使用优化器来调整变量以适应数据。
6. 结果评估。

1. 获取数据

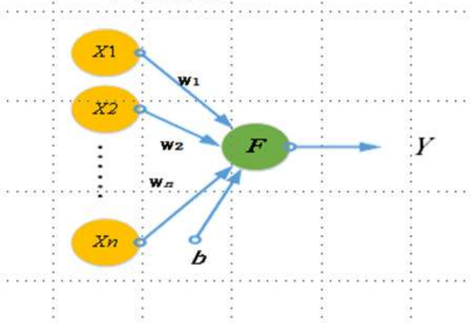
$$f(x) = x * W + b$$

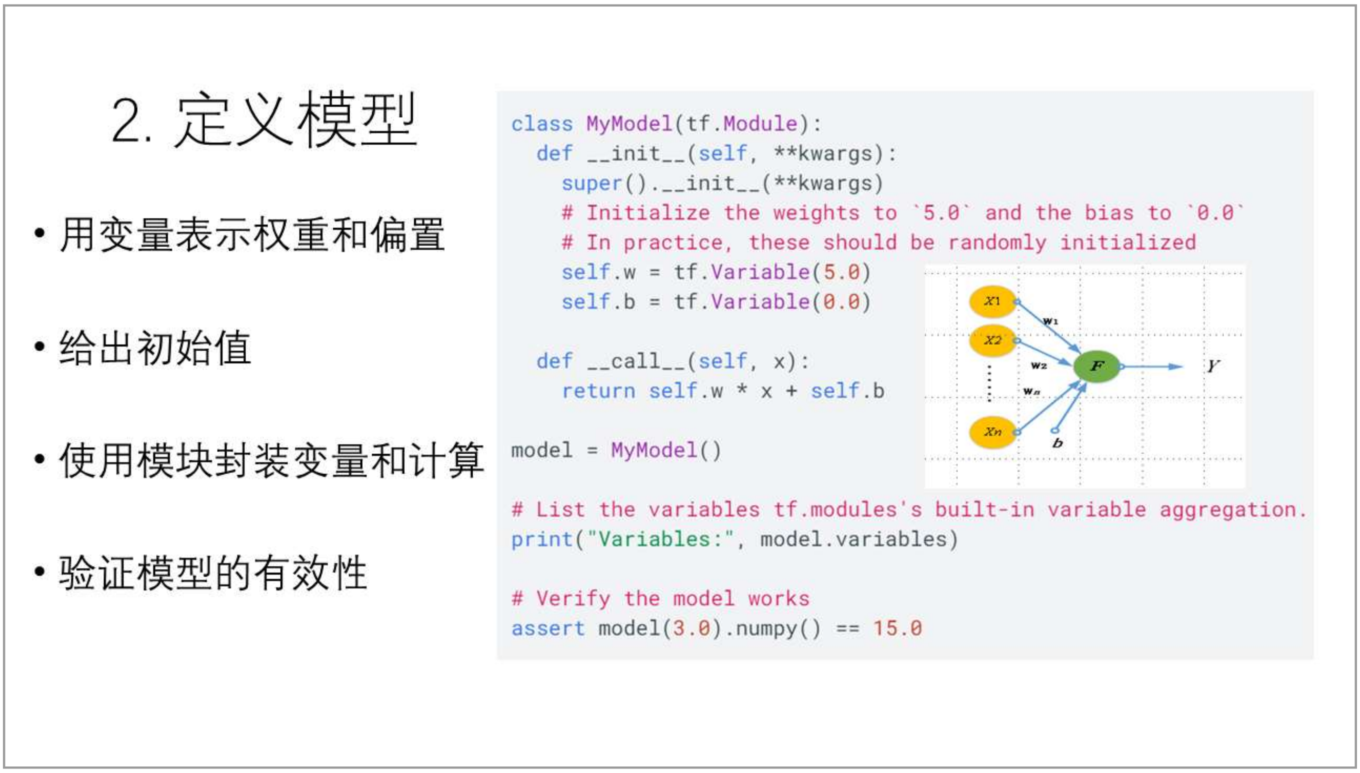
W: 权重

b: 偏置



```
# The actual line
TRUE_W = 3.0
TRUE_B = 2.0

NUM_EXAMPLES = 1000

# A vector of random x values
x = tf.random.normal(shape=[NUM_EXAMPLES])

# Generate some noise
noise = tf.random.normal(shape=[NUM_EXAMPLES])

# Calculate y
y = x * TRUE_W + TRUE_B + noise
```



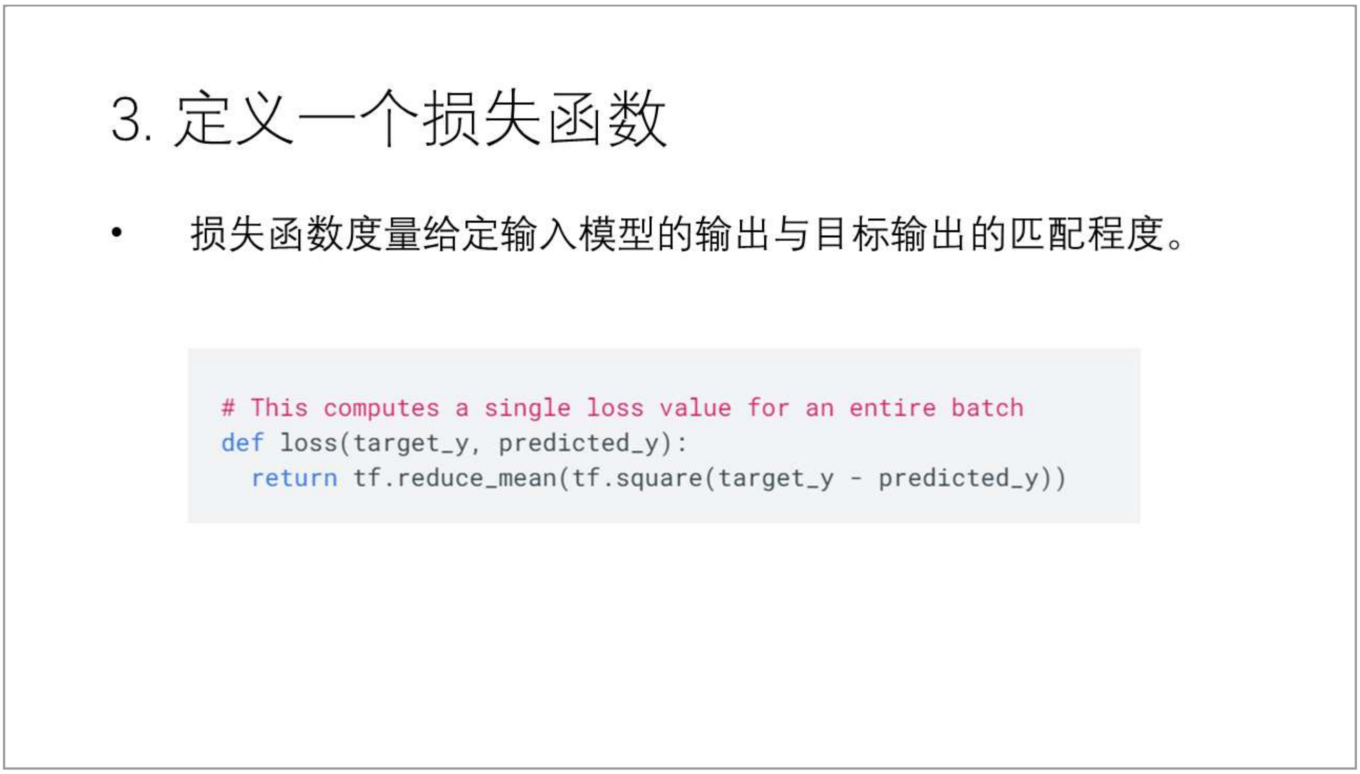


2. 定义模型

- 用变量表示权重和偏置
- 给出初始值
- 使用模块封装变量和计算
- 验证模型的有效性

```
class MyModel(tf.Module):
  def __init__(self, **kwargs):
    super().__init__(**kwargs)
    # Initialize the weights to `5.0` and the bias to `0.0`
    # In practice, these should be randomly initialized
    self.w = tf.Variable(5.0)
    self.b = tf.Variable(0.0)

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

model = MyModel()

# List the variables tf.modules's built-in variable aggregation.
print("Variables:", model.variables)

# Verify the model works
assert model(3.0).numpy() == 15.0
```

x1
x2
xn
w1
w2
wn
F
Y
b



3. 定义一个损失函数

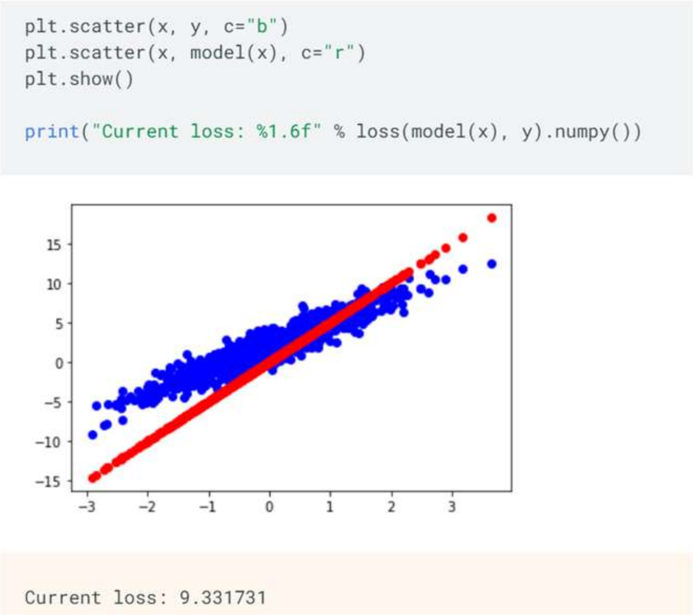
- 损失函数度量给定输入模型的输出与目标输出的匹配程度。

```
# This computes a single loss value for an entire batch
def loss(target_y, predicted_y):
  return tf.reduce_mean(tf.square(target_y - predicted_y))
```

3. 定义一个损失函数

- 可视化损失值

- 红色：模型的预测值
- 蓝色：训练数据



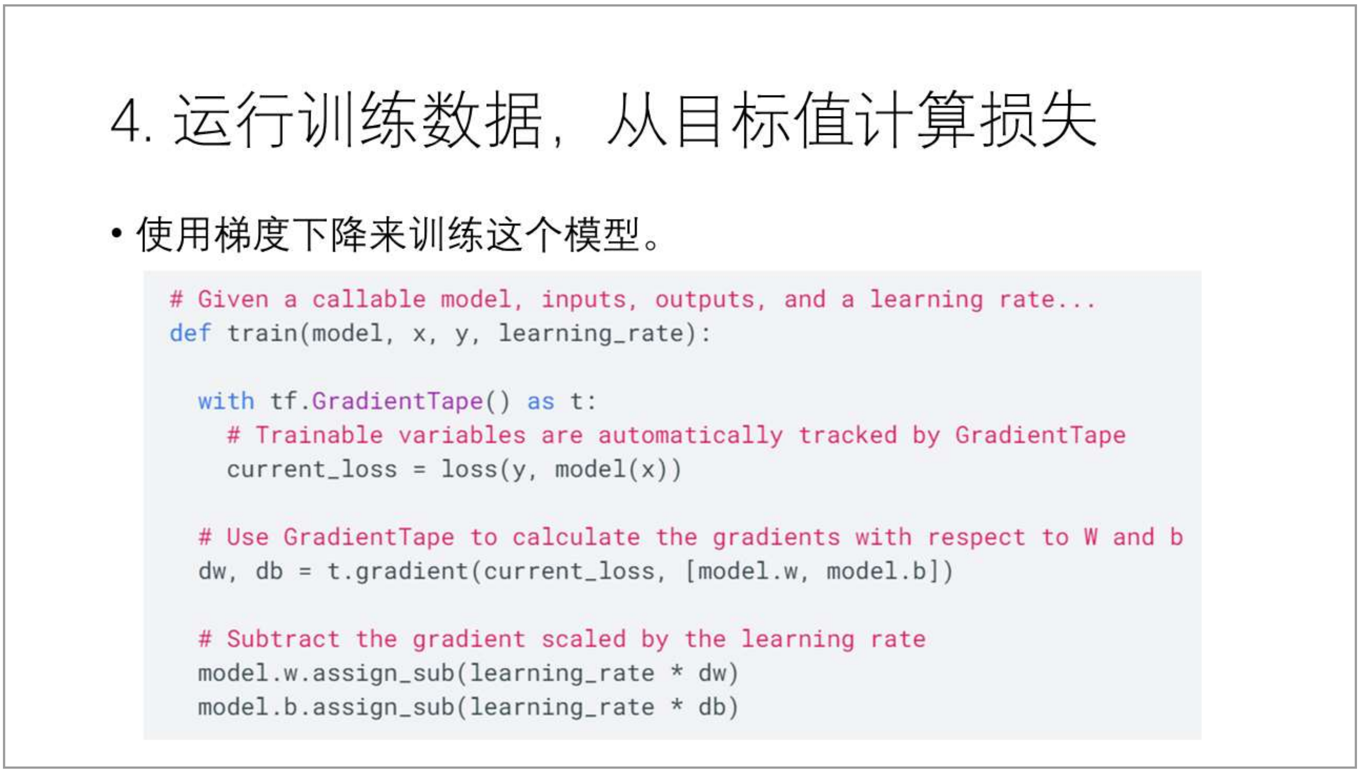
```
plt.scatter(x, y, c="b")
plt.scatter(x, model(x), c="r")
plt.show()

print("Current loss: %1.6f" % loss(model(x), y).numpy())
```

```
Current loss: 9.331731
```

4. 运行训练数据，从目标值计算损失

- 训练循环由重复执行的任务组成，依次为:

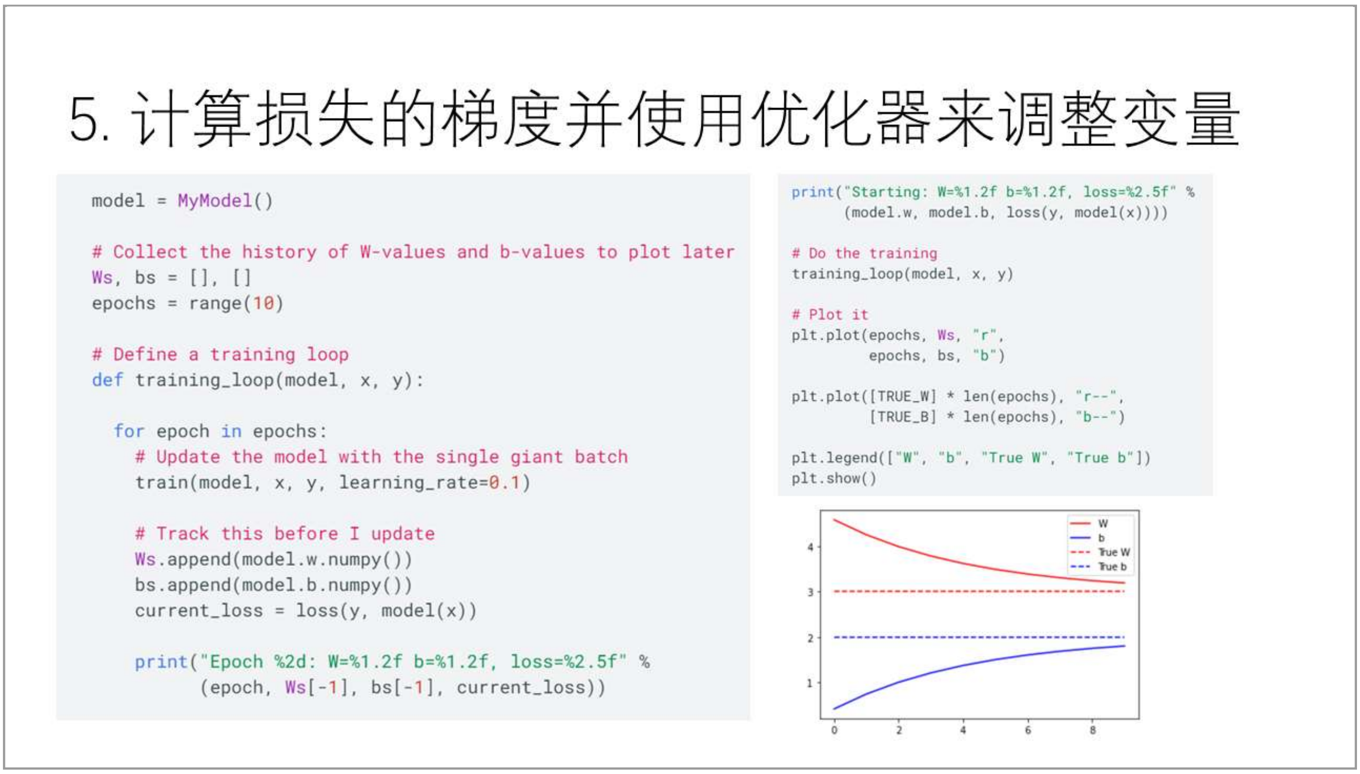
1. 通过发送一批输入到模型中以生成输出
2. 通过生成的输出与目标输出的比较来计算损失
3. 使用GradientTap计算损失loss对权重w的梯度
4. 用梯度优化变量w，b



4. 运行训练数据，从目标值计算损失

- 使用梯度下降来训练这个模型。

```
# Given a callable model, inputs, outputs, and a learning rate...
def train(model, x, y, learning_rate):

  with tf.GradientTape() as t:
    # Trainable variables are automatically tracked by GradientTape
    current_loss = loss(y, model(x))

  # Use GradientTape to calculate the gradients with respect to W and b
  dw, db = t.gradient(current_loss, [model.w, model.b])

  # Subtract the gradient scaled by the learning rate
  model.w.assign_sub(learning_rate * dw)
  model.b.assign_sub(learning_rate * db)
```

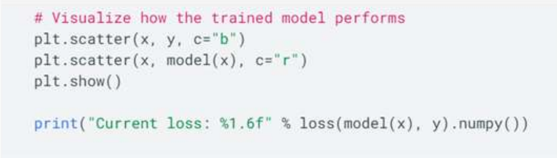


5. 计算损失的梯度并使用优化器来调整变量

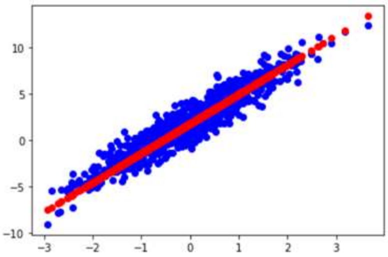
```
model = MyModel()

# Collect the history of W-values and b-values to plot later
Ws, bs = [], []
epochs = range(10)

# Define a training loop
def training_loop(model, x, y):

  for epoch in epochs:
    # Update the model with the single giant batch
    train(model, x, y, learning_rate=0.1)

    # Track this before I update
    Ws.append(model.w.numpy())
    bs.append(model.b.numpy())
    current_loss = loss(y, model(x))

    print("Epoch %2d: W=%1.2f b=%1.2f, loss=%2.5f" %
          (epoch, Ws[-1], bs[-1], current_loss))
```

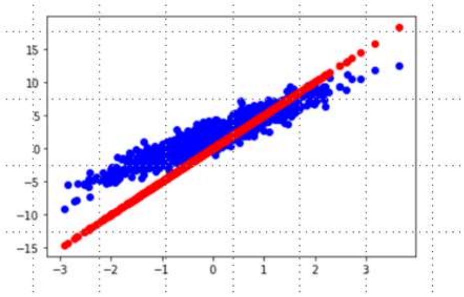
```
print("Starting: W=%1.2f b=%1.2f, loss=%2.5f" %
      (model.w, model.b, loss(y, model(x))))

# Do the training
training_loop(model, x, y)

# Plot it
plt.plot(epochs, Ws, "r",
         epochs, bs, "b")

plt.plot([TRUE_W] * len(epochs), "r--",
         [TRUE_B] * len(epochs), "b--")

plt.legend(["W", "b", "True W", "True b"])
plt.show()
```

6. 结果评估

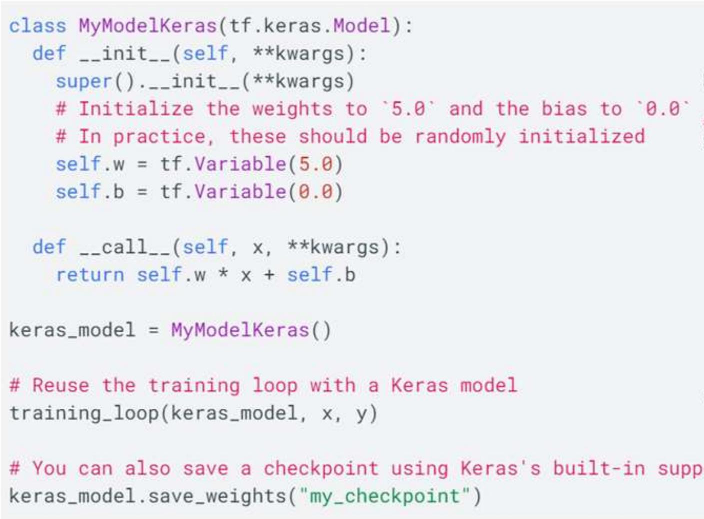


```
# Visualize how the trained model performs
plt.scatter(x, y, c="b")
plt.scatter(x, model(x), c="r")
plt.show()

print("Current loss: %1.6f" % loss(model(x), y).numpy())
```

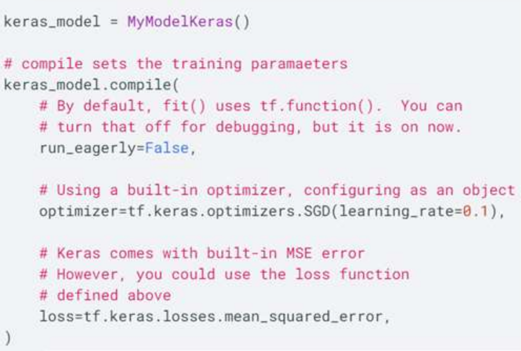




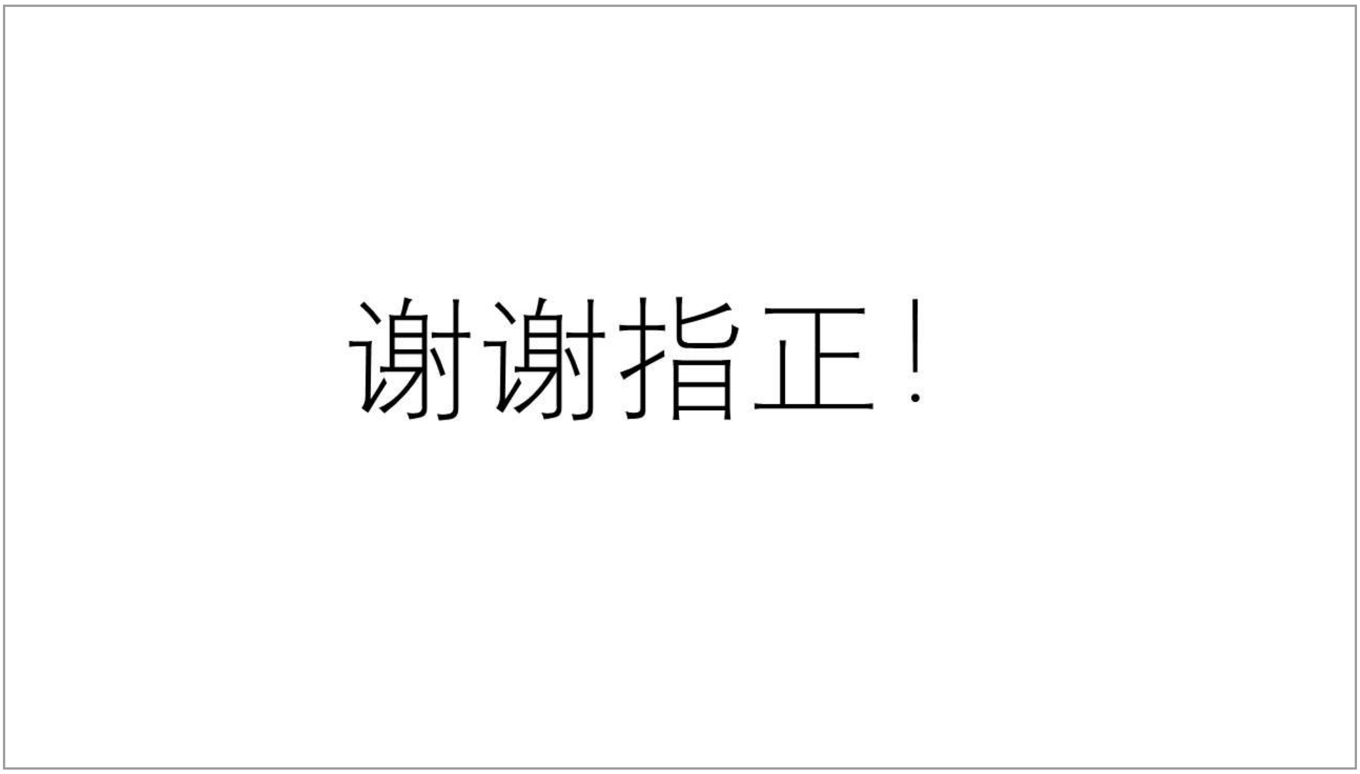
使用keras模型



```
class MyModelKeras(tf.keras.Model):
  def __init__(self, **kwargs):
    super().__init__(**kwargs)
    # Initialize the weights to `5.0` and the bias to `0.0`
    # In practice, these should be randomly initialized
    self.w = tf.Variable(5.0)
    self.b = tf.Variable(0.0)

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

keras_model = MyModelKeras()

# Reuse the training loop with a Keras model
training_loop(keras_model, x, y)

# You can also save a checkpoint using Keras's built-in support
keras_model.save_weights("my_checkpoint")
```



```
keras_model = MyModelKeras()

# compile sets the training paramaeters
keras_model.compile(
    # By default, fit() uses tf.function().  You can
    # turn that off for debugging, but it is on now.
    run_eagerly=False,

    # Using a built-in optimizer, configuring as an object
    optimizer=tf.keras.optimizers.SGD(learning_rate=0.1),

    # Keras comes with built-in MSE error
    # However, you could use the loss function
    # defined above
    loss=tf.keras.losses.mean_squared_error,
)
```



谢谢指正！