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Get Started with Eager Execution (入门)
      o 在线运行
      o 鸢尾花分类教程,使用eager execution完成: (1)构建模型; (2)训练模型; (3)利用模型预测
         未知数据。
      o TensorFlow编程
      o TensorFlow高级概念: (1) 启动一个 eager execution开发环境; (2) 使用Datasets API导入数据;
          (3) 使用Keras API构建模型
      ○ 教程涉及APIs: (1) 导入和解析数据集; (2) 选择模型类型; (3) 训练模型; (4) 评估模型有
        效性;(5)使用训练好的模型进行预测
      ○ 机器学习基础: 机器学习速成课程
      o 运行notebook: (1) Connect to runtime; (2) run
      o 安装tensorflow最新版本(需要版本1.7.0,注意notebook需要重新启动代码执行程序)
      o 一旦启动了 eager execution,将不能在同一程序中禁用。详见eager execution guide。
import os
import matplotlib.pyplot as plt
import tensorflow as tf
import tensorflow.contrib.eager as tfe
tf.enable_eager_execution()
print("TensorFlow version: {}".format(tf.VERSION))
print("Eager execution: {}".format(tf.executing_eagerly()))
# result
# TensorFlow version: 1.7.0
# Eager execution: True
       鸢尾花分类问题:根据萼片和花瓣的长度和宽度来对鸢尾花进行分类
      o 鸢尾花三种类别: (1) Iris setosa (2) Iris virginica (3) Iris versicolor
      ○ 鸢尾花数据集: 120条数据
      。 导入和解析训练数据集
      。 下载数据
train_dataset_url = "http://download.tensorflow.org/data/iris_training.csv"
train_dataset_fp = tf.keras.utils.get_file(fname=os.path.basename(train_dataset_url),
                                     origin=train_dataset_url)
print("Local copy of the dataset file: {}".format(train_dataset_fp))
      o 检查数据
def load_iris_data():
    csv_path = "data/iris_training.csv"
    data = pd.read_csv(csv_path)
    return data
data = load_iris_data()
print(data.head()) # 查看前五行
      。 前五行内容:
                setosa versicolor virginica
     120
    6.4 2.8
                    5.6
                                  2.2
    5.0 2.3
                   3.3
                                  1.0
                                                 2
 2
    4.9 2.5
                   4.5
                                 1.7
 3
    4.9 3.1
                    1.5
                                  0.1
                                                 0
    5.7 3.8
                    1.7
                                  0.3
                                                 0
      o 类别标签编码: 0—setosa, 1—versicolor, 2—virginica
      o 特征与标签更多学习: ML Terminology section of the Machine Learning Crash Course
      ○ 解析数据集:将文本数据转为特征和标签张量
def parse_csv(line):
   example_defaults = [[0.], [0.], [0.], [0.], [0]] # sets field types
   parsed_line = tf.decode_csv(line, example_defaults)
   features = tf.reshape(parsed_line[:-1], shape=(4,)) # 抽取前四列特征
   label = tf.reshape(parsed_line[-1], shape=()) # 抽取最后一列标签
   return features, label
      o 创建训练集: <u>Dataset API</u>, 更多参见<u>Datasets Quick Start guide</u>
      o 训练数据最好是随机顺序的,利用【tf.data.Dataset.shuffle】随机化。
      o 设置buffer_size > 数据个数 (120), 设置batch_size=32
           "data/iris_training.csv"
data_path
train_dataset
              tf.data.TextLineDataset(data_path)
train_dataset
              train_dataset.skip(1) # skip the first header row
train_dataset
              train_dataset.map(parse_csv) # parse each row
train_dataset
              train_dataset.shuffle(buffer_size 1000) # randomize
train_dataset
              train_dataset.batch(32)
# View a single example entry from a batch
features, label = tfe.Iterator(train_dataset).next()
print("example features:", features 0)
print("example label:", label 0 )
        选择模型的类型
        模型是特征和标签的关系
      o 神经网络模型,全连接神经网络 (dense, or fully-connected neural network)
                                                                   Probability of this type of Iris
    SepalLength
                                                                   0.02
                                                                             Setosa
    SepalWidth
                                                                   0.95
                                                                             Versicolor
    PetalLength
                             2
                                                                   0.03
                                                                            Virginica
    PetalWidth
                                 Hidden Layers
    Input Layer
                                                                       Output Layer
      o 使用Keras构建模型: tf.keras API
model = tf.keras.Sequential(
   tf.keras.layers.Dense(10, activation "relu", input_shape (4,)), # input shape required
   tf.keras.layers.Dense(10, activation="relu"),
   tf.keras.layers.Dense(3)
 )
      。 训练模型
      o 过拟合问题 (overfitting)
      o <u>监督学习</u>, <u>非监督学习</u>
      o 定义损失(loss)和梯度函数
      o tf.losses.sparse_softmax_cross_entropy
def loss(model, x, y):
    y_{-} = model(x)
    return tf.losses.sparse_softmax_cross_entropy(labels=y, logits=y_)
def grad(model, inputs, targets):
    with tfe.GradientTape() as tape:
      loss_value = loss(model, inputs, targets)
    return tape.gradient(loss_value, model.variables)
      o 创建优化器 (optimizer): 优化算法,最小化损失函数,找到最低点
                                    SGD
                                    Momentum
                                    NAG
                                    Adagrad
                                    Adadelta
 4
                                    Rmsprop
 2
  0
  -2
  -4
                                        1.0
   1.0
      0.5
                                    0.5
         0.0
                                0.0
           -0.5
              -1.0
                           -0.5
                 -1.5
      学习率(超参数)
        随机梯度下降优化算法: tf.train.GradientDescentOptimizer
optimizer = tf.train.GradientDescentOptimizer(learning_rate=0.01)
      。 循环训练
      o num_epochs (轮次, 超参数)
# keep results for plotting
train_loss_results = []
train_accuracy_results = []
num_epochs = 201
for epoch in range(num_epochs)
    epoch_loss_avg = tfe.metrics.Mean()
    epoch_accuracy = tfe.metrics.Accuracy()
    # Training loop - using batches of 32
   for x, y in tfe.Iterator(train_dataset)
        # Optimize the model
       grads
              grad(model, x, y)
        optimizer.apply_gradients(zip(grads, model.variables),
                              global_step_tf.train.get_or_create_global_step())
        # Track progress
       epoch_loss_avg(loss(model, x, y)) # add current batch loss
       # compare predicted label to actual label
       epoch_accuracy(tf.argmax(model(x), axis=1, output_type tf.int32), y)
   # end epoch
   train_loss_results.append(epoch_loss_avg.result())
    train_accuracy_results.append(epoch_accuracy.result())
    if epoch % 50 == 0
        print("Epoch {:03d}: Loss: {:.3f}, Accuracy: {:.3%}".format(epoch,
                                                            epoch_loss_avg.result(),
                                                            epoch_accuracy.result()))
```

```
可视化损失函数: TensorBoard, mathplotlib
            plt.subplots(2, sharex=True, figsize=(12, 8))
fig.suptitle('Training Metrics')
axes 0 .set_ylabel("Loss", fontsize 14)
axes 0 .plot(train_loss_results)
axes 1 .set_ylabel("Accuracy", fontsize 14)
axes 1 .set_xlabel("Epoch", fontsize 14)
axes 1 .plot(train_accuracy_results)
plt.show()
                                      Training Metrics
 1.2
 1.0
Loss
0.6
 0.4
 0.2
 1.0
```

```
0.9
 0.8
 0.5
 0.4
              25
                      50
                               75
                                       100
                                               125
                                                       150
                                                               175
                                                                       200
                                      Epoch
      • 评估模型有效性
      ○ 设置测试集: iris_test.csv
test_fp
         "data/iris_test.csv"
test_dataset
             tf.data.TextLineDataset(test_fp)
test_dataset
             test_dataset.skip(1) # skip header row
test_dataset
             test_dataset.map(parse_csv) # parse each row with the funcition created earlier
             test_dataset.shuffle(1000) # randomize
test_dataset
```

test_dataset.batch(32) # use the same batch size as the training set

o 在测试集上评估模型: Test set accuracy: 96.667%

```
test_accuracy tfe.metrics.Accuracy()
for (x, y) in tfe.Iterator(test_dataset)
    prediction tf.argmax(model(x), axis 1, output_type tf.int32)
    test_accuracy(prediction, y)
print("Test set accuracy: {:.3%}".format(test_accuracy.result()))
      。 使用训练好的模型预测未知数据
print("Test set accuracy: {:.3%}".format(test_accuracy.result()))
```

"Iris setosa", "Iris versicolor", "Iris virginica"

```
predict_dataset tf.convert_to_tensor(
      5.1, 3.3, 1.7, 0.5,
     5.9, 3.0, 4.2, 1.5,
     6.9, 3.1, 5.4, 2.1
 )
              model(predict_dataset)
predictions
 for i, logits in enumerate(predictions)
     class_idx tf.argmax(logits).numpy()
            class_ids class_idx
     name
     print("Example {} prediction: {}".format(i, name))
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```

test_dataset

class_ids