**Dense (fully connected) layers**, which perform classification on the features extracted by the convolutional layers and downsampled by the pooling layers. In a dense layer, every node in the layer is connected to every node in the preceding layer.  
 密集（完全连接）层，对由卷积层提取和由池化层进行下采样的特征执行分类，。在密集层中，层中的每个节点都连接到前一层中的每个节点。

Logits Layer

The final layer in our neural network is the logits layer, which will return the raw values for our predictions. We create a dense layer with 10 neurons (one for each target class 0–9), with linear activation (the default):

logits = tf.layers.dense(inputs=dropout, units=10)

Our final output tensor of the CNN, logits, has shape [*batch\_size*, 10].

Logits层

我们神经网络的最后一层是logits层。他会返回我们预测值的未经加工的（raw）值。我们创建一个有10个神经元的使用默认的线性激活函数的全连接层。我们CNN最后的输出张量logits的shape是[*batch\_size*, 10].

### Calculate Loss

For both training and evaluation, we need to define a [loss function](https://en.wikipedia.org/wiki/Loss_function) that measures how closely the model's predictions match the target classes. For multiclass classification problems like MNIST, [cross entropy](https://en.wikipedia.org/wiki/Cross_entropy) is typically used as the loss metric. The following code calculates cross entropy when the model runs in either TRAIN or EVAL mode:

onehot\_labels = tf.one\_hot(indices=tf.cast(labels, tf.int32), depth=10)  
loss = tf.losses.softmax\_cross\_entropy(  
    onehot\_labels=onehot\_labels, logits=logits)

计算Loss

对于训练和评估，我们都需要定义一个loss函数用来衡量模型预测值与目标类别的距离。当不论模型是在运行TRAIN或者是EVAL模式时，上面的代码都计算cross entropy。 Our labels tensor contains a list of predictions for our examples, e.g. [1, 9, ...]. In order to calculate cross-entropy, first we need to convert labels to the corresponding [one-hot encoding](https://www.quora.com/What-is-one-hot-encoding-and-when-is-it-used-in-data-science):

[[0, 1, 0, 0, 0, 0, 0, 0, 0, 0],  
 [0, 0, 0, 0, 0, 0, 0, 0, 0, 1],  
 ...]

我们的labels张量包含一个预测值的列表。例如：[1, 9, …].为了计算交叉熵，我们首先需要将labels转换成相关的[one-hot encoding](https://www.quora.com/What-is-one-hot-encoding-and-when-is-it-used-in-data-science):

[[0, 1, 0, 0, 0, 0, 0, 0, 0, 0],  
 [0, 0, 0, 0, 0, 0, 0, 0, 0, 1],  
 ...] 列表中1就对应着[one-hot encoding](https://www.quora.com/What-is-one-hot-encoding-and-when-is-it-used-in-data-science)的[0, 1, 0, 0, 0, 0, 0, 0, 0, 0]，9对应着[0, 0, 0, 0, 0, 0, 0, 0, 0, 1]