CH7. Working with Keras: A deep dive

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Working with Keras: A deep dive

A spectrum of workflows

Different ways to build Keras models

Using built-in training and evaluation loops

Writing your own training and evaluation loops

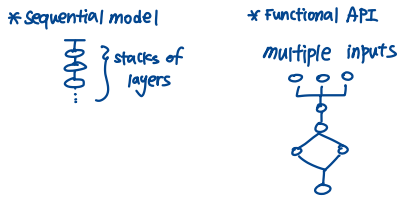
A spectrum of workflows

The design of the Keras API: make it easy to get started, yet make it possible to handle high-complexity use cases, only requiring incremental learning at each step

Simple use cases should be easy and approachable, and arbitrarily advanced workflows should be possible

Different ways to build Keras models

Three APIs for building models:



Sequential model: simple stacks of layers

Functional API: focuses on graph-like model architectures

Model subclassing: a low-level option where you write everything yourself.

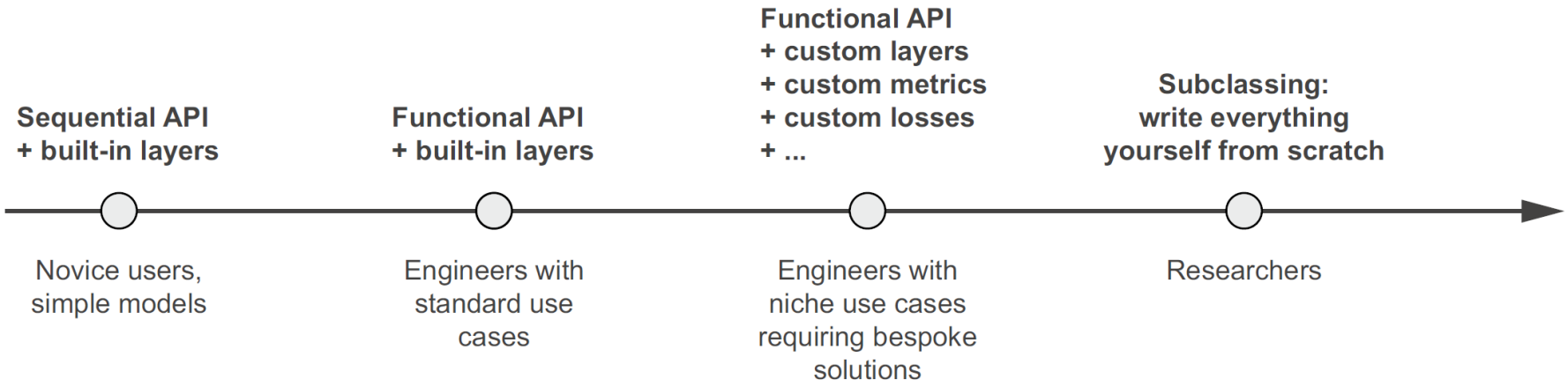


Figure 7.1 Progressive disclosure of complexity for model building

The Sequential model

Listing 7.1 The `Sequential` class

```
from tensorflow import keras
from tensorflow.keras import layers

model = keras.Sequential([
    layers.Dense(64, activation="relu"),
    layers.Dense(10, activation="softmax")
])
```

make sequential layers at once

Build the same model incrementally via the add() method

Listing 7.2 Incrementally building a Sequential model

```
model = keras.Sequential()
model.add(layers.Dense(64, activation="relu"))
model.add(layers.Dense(10, activation="softmax"))
```

add layers one by one

Sequential model does not have any weights until you actually call it on some data, or call its build() method with an input shape

If you do not specify input dimension, input weight then actually cannot calculate weight size.

Listing 7.3 Models that aren't yet built have no weights

```
>>> model.weights
ValueError: Weights for model sequential_1 have not yet been created.
```

At that point, the model isn't built yet.

Listing 7.4 Calling a model for the first time to build it

```
>>> model.build(input_shape=(None, 3))
>>> model.weights
[<tf.Variable "dense_2/kernel:0" shape=(3, 64) dtype=float32, ... >,
 <tf.Variable "dense_2/bias:0" shape=(64,) dtype=float32, ... >
 <tf.Variable "dense_3/kernel:0" shape=(64, 10) dtype=float32, ... >,
 <tf.Variable "dense_3/bias:0" shape=(10,) dtype=float32, ... >]
```

build로 input shape 지정해주면 weights 구할 수 있음

3x1

output dimension

Builds the model—now the model will expect samples of shape (3,). The None in the input shape signals that the batch size could be anything.

Now you can retrieve the model's weights.

$y = f_2(f_1(x))$

$f_1(x) = \sigma(W_1 x_1 + b_1)$ (nonlinear - activation)

64x3 3x1 64x1

If don't know about input shape x_1 → can't define the shape of W_1

After the model is built, you can display its contents via the summary()

Listing 7.5 The `summary()` method

```
>>> model.summary()
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_2 (Dense)              (None, 64)                256
_________________________________________________________________
dense_3 (Dense)              (None, 10)                650
=================================================================
Total params: 906
Trainable params: 906
Non-trainable params: 0
_________________________________________________________________
```

this model is constructed by two layers

$\sigma(x^0 W_1 + b_1) = x^1$ (3x64 1x64)

64x4

$\sigma(x^1 W_2 + b_2)$ (1x64 64x10 1x10)

65x10

This model happens to be named “sequential_1.” You can give names to everything in Keras—every model, every layer

Listing 7.6 Naming models and layers with the `name` argument

```
>>> model = keras.Sequential(name="my_example_model")
>>> model.add(layers.Dense(64, activation="relu", name="my_first_layer"))
>>> model.add(layers.Dense(10, activation="softmax", name="my_last_layer"))
>>> model.build((None, 3))
>>> model.summary()
Model: "my_example_model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
my_first_layer (Dense)       (None, 64)                256
_________________________________________________________________
my_last_layer (Dense)        (None, 10)                650
=================================================================
Total params: 906
Trainable params: 906
Non-trainable params: 0
_________________________________________________________________
```

If you'd like to print summary(), declare the shape of the model's inputs in advance

Listing 7.7 Specifying the input shape of your model in advance

```
model = keras.Sequential()
model.add(keras.Input(shape=(3,)))
model.add(layers.Dense(64, activation="relu"))
```

Use Input to declare the shape of the inputs. Note that the shape argument must be the shape of each sample, not the shape of one batch.

```
>>> model.summary()
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_4 (Dense)              (None, 64)                256
=================================================================
Total params: 256
Trainable params: 256
Non-trainable params: 0
_________________________________________________________________
>>> model.add(layers.Dense(10, activation="softmax"))
>>> model.summary()
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_4 (Dense)              (None, 64)                256
_________________________________________________________________
dense_5 (Dense)              (None, 10)                650
=================================================================
Total params: 906
Trainable params: 906
Non-trainable params: 0
_________________________________________________________________
```

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This is a companion notebook for the book Deep Learning with Python, Second Edition. For readability, it only contains runnable code blocks and section titles, and omits everything else in the book: text paragraphs, figures, and pseudocode.

If you want to be able to follow what's going on, I recommend reading the notebook side by side with your copy of the book.

This notebook was generated for TensorFlow 2.6.

Working with Keras: A deep dive

A spectrum of workflows

Different ways to build Keras models

The Sequential model

The `Sequential` class

```
[ ]  from tensorflow import keras
     from tensorflow.keras import layers
```

The Functional API

Sequential model only express models with single input and single output

& model is sequentially defined.

Functional API provide more power to define general model, graph-like structure

Listing 7.8 A simple Functional model with two `Dense` layers

```
inputs = keras.Input(shape=(3,), name="my_input")
features = layers.Dense(64, activation="relu")(inputs)
outputs = layers.Dense(10, activation="softmax")(features)
model = keras.Model(inputs=inputs, outputs=outputs)
```

inputs object holds information about the shape and dtype of the data

```
>>> inputs.shape
(None, 3)
>>> inputs.dtype
float32
```

The model will process batches where each sample has shape (3,). The number of samples per batch is variable (indicated by the None batch size).

These batches will have dtype float32.

symbolic information
Data is not provided.

We call such an object a symbolic tensor. It doesn't contain any actual data, but it encodes the specifications of the actual tensors of data that the model will see when you use it.

```
features = layers.Dense(64, activation="relu")(inputs)
```

real tensors of data or these symbolic tensors

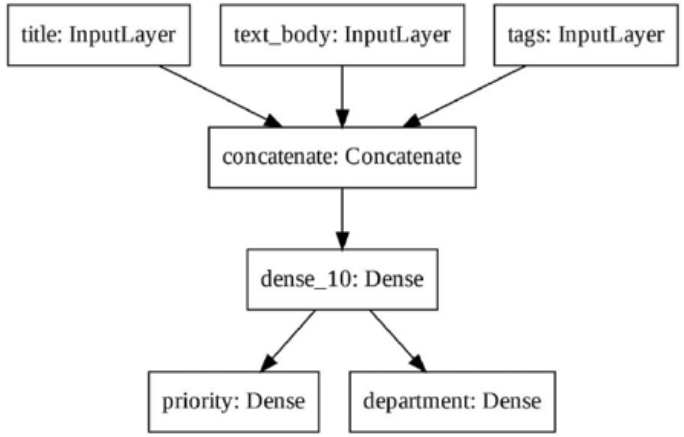
All Keras layers can be called both on real tensors of data and on these symbolic tensors. In the latter case, they return a new symbolic tensor, with updated shape and dtype information:

```
>>> features.shape
(None, 64)
```

After obtaining the final outputs, we instantiated the model by specifying its inputs and outputs in the Model constructor:

예를 들어 설명하다

```
outputs = layers.Dense(10, activation="softmax")(features)
model = keras.Model(inputs=inputs, outputs=outputs)
```



Multi-input, Multi-output models

→ cannot define sequential API
→ need to define functional API

Most deep learning models look like graphs.

Consider multi-input, multi-output model:

Listing 7.9 A multi-input, multi-output Functional model

```
vocabulary_size = 10000
num_tags = 100
num_departments = 4

title = keras.Input(shape=(vocabulary_size,), name="title")
text_body = keras.Input(shape=(vocabulary_size,), name="text_body")
tags = keras.Input(shape=(num_tags,), name="tags")

features = layers.Concatenate()([title, text_body, tags])
features = layers.Dense(64, activation="relu")(features)

priority = layers.Dense(1, activation="sigmoid", name="priority")(features)
department = layers.Dense(
    num_departments, activation="softmax", name="department")(features)

model = keras.Model(inputs=[title, text_body, tags],
                    outputs=[priority, department])
```

Define model inputs.

Combine input features into a single tensor, features, by concatenating them.

result shape → 20,100 vector

Define model outputs.

we have 3 inputs & 2 outputs

Apply an intermediate layer to recombine input features into richer representations.

Create the model by specifying its inputs and outputs.

Training a Multi-input, Multi-output model

Listing 7.10 Training a model by providing lists of input and target arrays

```
import numpy as np

num_samples = 1280

# Dummy input data
title_data = np.random.randint(0, 2, size=(num_samples, vocabulary_size))
text_body_data = np.random.randint(0, 2, size=(num_samples, vocabulary_size))
tags_data = np.random.randint(0, 2, size=(num_samples, num_tags))

# Dummy target data
priority_data = np.random.random(size=(num_samples, 1))
department_data = np.random.randint(0, 2, size=(num_samples, num_departments))

model.compile(optimizer="rmsprop",
              loss=["mean_squared_error", "categorical_crossentropy"],
              metrics=[["mean_absolute_error"], ["accuracy"]])
model.fit([title_data, text_body_data, tags_data],
          [priority_data, department_data],
          epochs=1)
model.evaluate([title_data, text_body_data, tags_data],
               [priority_data, department_data])
priority_preds, department_preds = model.predict(
    [title_data, text_body_data, tags_data])
```

dummy data

should be new data

You can also leverage the names you gave to the Input objects and the output layers, and pass data via dictionaries.

Listing 7.11 Training a model by providing dicts of input and target arrays

```
model.compile(optimizer="rmsprop",
              loss={"priority": "mean_squared_error", "department":
                    "categorical_crossentropy"},
              metrics={"priority": ["mean_absolute_error"], "department":
                       ["accuracy"]})
model.fit({"title": title_data, "text_body": text_body_data,
           "tags": tags_data},
          {"priority": priority_data, "department": department_data},
          epochs=1)
model.evaluate({"title": title_data, "text_body": text_body_data,
                "tags": tags_data},
               {"priority": priority_data, "department": department_data})
priority_preds, department_preds = model.predict(
    {"title": title_data, "text_body": text_body_data, "tags": tags_data})
```

The Power of the functional API: Access to layer connectivity

A Functional model is an explicit graph data structure. This makes it possible to inspect how layers are connected and reuse previous graph nodes as part of new models.

After carefully inspecting the model,
you can actually reuse previous graph nodes as part of new models.

```
keras.utils.plot_model(model, "ticket_classifier.png")
```

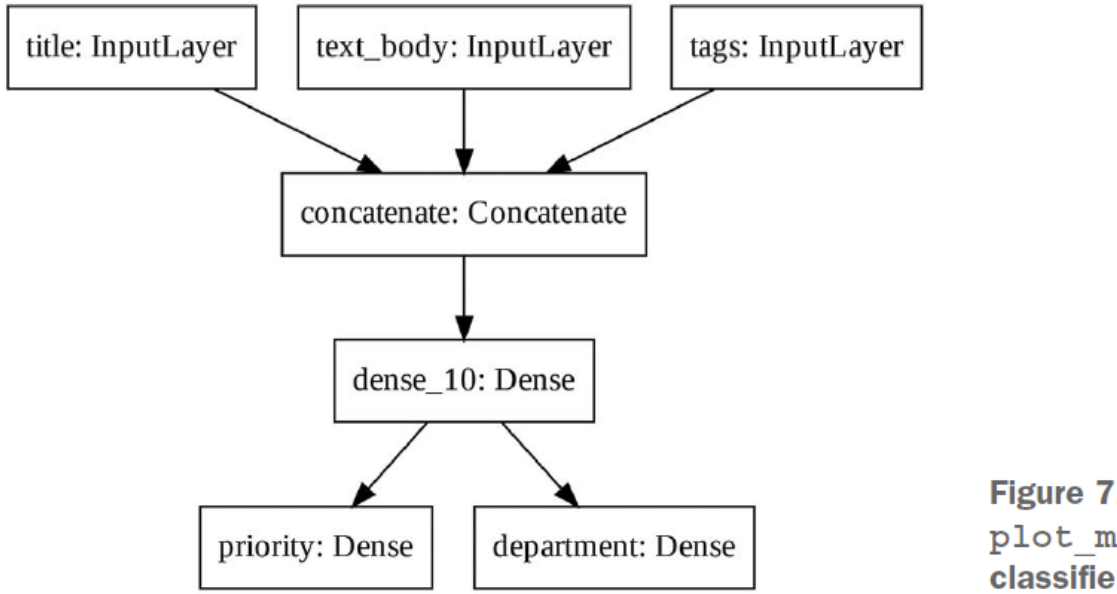


Figure 7.2 Plot generated by `plot_model()` on our ticket classifier model

```
keras.utils.plot_model(
    model, "ticket_classifier_with_shape_info.png", show_shapes=True)
```

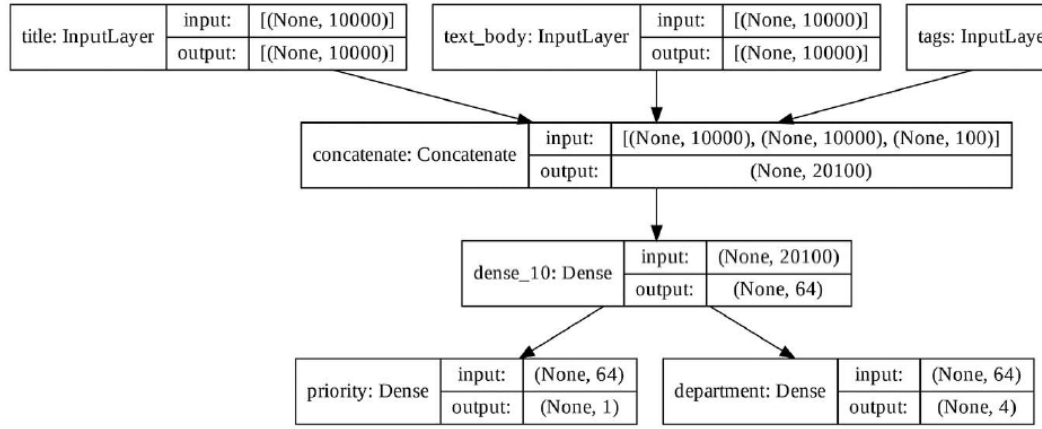


Figure 7.3 Model plot with shape information added

Access to layer connectivity also means that you can inspect and reuse individual nodes (layer calls) in the graph.

Listing 7.12 Retrieving the inputs or outputs of a layer in a Functional model

check layers

```
>>> model.layers
[<tensorflow.python.keras.engine.input_layer.InputLayer at 0x7fa963f9d358>,
 <tensorflow.python.keras.engine.input_layer.InputLayer at 0x7fa963f9d2e8>,
 <tensorflow.python.keras.engine.input_layer.InputLayer at 0x7fa963f9d470>,
 <tensorflow.python.keras.layers.merge.Concatenate at 0x7fa963f9d860>,
  <tensorflow.python.keras.layers.core.Dense at 0x7fa964074390>,
  <tensorflow.python.keras.layers.core.Dense at 0x7fa963f9d898>,
  <tensorflow.python.keras.layers.core.Dense at 0x7fa963f95470>]
>>> model.layers[3].input
[<tf.Tensor "title:0" shape=(None, 10000) dtype=float32>,
 <tf.Tensor "text_body:0" shape=(None, 10000) dtype=float32>,
 <tf.Tensor "tags:0" shape=(None, 100) dtype=float32>]
>>> model.layers[3].output
<tf.Tensor "concatenate/concat:0" shape=(None, 20100) dtype=float32>
```

concatenate layer

Enables us to do feature extraction, creating models that reuse intermediate features from another model.

How we reuse the model.

Listing 7.13 Creating a new model by reusing intermediate layer outputs

layers[4] is our intermediate Dense layer

```
features = model.layers[4].output
difficulty = layers.Dense(3, activation="softmax", name="difficulty")(features)

new_model = keras.Model(
    inputs=[title, text_body, tags],
    outputs=[priority, department, difficulty])
```

#new dense layer

output is added

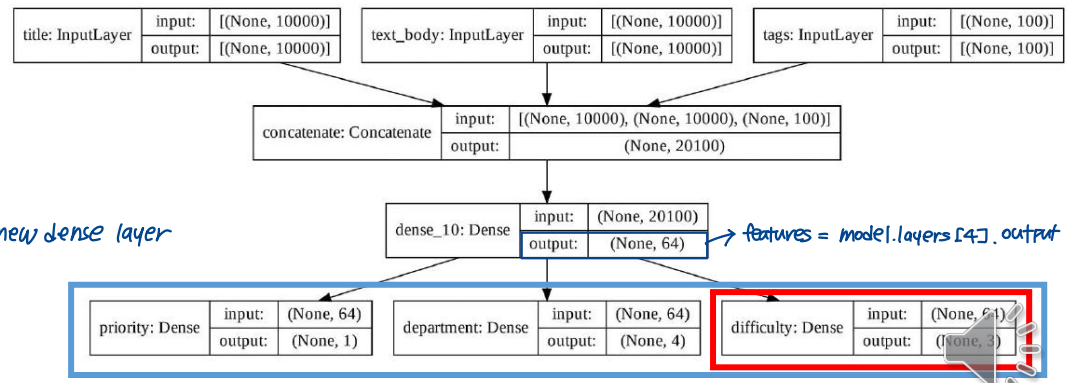


Figure 7.4 Plot of our new model

```
model.add(layers.Dense(10, activation="softmax"))
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_4 (Dense)             (None, 64)                256

 dense_5 (Dense)             (None, 10)                650

=================================================================
Total params: 906
Trainable params: 906
Non-trainable params: 0
_________________________________________________________________
```

The Functional API

A simple example

A simple Functional model with two `Dense` layers

```
inputs = keras.Input(shape=(3,), name="my_input")
features = layers.Dense(64, activation="relu")(inputs)
outputs = layers.Dense(10, activation="softmax")(features)
model = keras.Model(inputs=inputs, outputs=outputs)
```

Subclassing the Model class

In the __init__() method, define the layers the model will use

In the call() method, define the forward pass of the model

Instantiate your subclass, and call it on data to create its weights

Listing 7.14 A simple subclassed model

```
class CustomerTicketModel(keras.Model):                    # class created by keras

    def __init__(self, num_departments):                   # 생성자; constructor
        super().__init__()                                 # Don't forget to call the super() constructor!
        self.concat_layer = layers.Concatenate()           # Define sublayers in the constructor.
        self.mixing_layer = layers.Dense(64, activation="relu")
        self.priority_scorer = layers.Dense(1, activation="sigmoid")
        self.department_classifier = layers.Dense(
            num_departments, activation="softmax")

    def call(self, inputs):                                # should be dictionary type
        title = inputs["title"]                            # Define the forward pass in the call() method.
        text_body = inputs["text_body"]
        tags = inputs["tags"]

        features = self.concat_layer([title, text_body, tags])
        features = self.mixing_layer(features)
        priority = self.priority_scorer(features)
        department = self.department_classifier(features)
        return priority, department
```

Once you've defined the model, you can instantiate it.

```
model = CustomerTicketModel(num_departments=4)

priority, department = model(
    {"title": title_data, "text_body": text_body_data, "tags": tags_data})
```

You can compile and train a Model subclass just like a Sequential or Functional model:

The structure of what you pass as the loss and metrics arguments must match exactly what gets returned by call()—here, a list of two elements.

```
model.compile(optimizer="rmsprop",
              loss=["mean_squared_error", "categorical_crossentropy"],
              metrics=[["mean_absolute_error"], ["accuracy"]])
model.fit({"title": title_data,
           "text_body": text_body_data,
           "tags": tags_data},
          [priority_data, department_data],
          epochs=1)
model.evaluate({"title": title_data,
                "text_body": text_body_data,
                "tags": tags_data},
               [priority_data, department_data])
priority_preds, department_preds = model.predict({"title": title_data,
                                                  "text_body": text_body_data,
                                                  "tags": tags_data})
```

The structure of the target data must match exactly what is returned by the call() method—here, a list of two elements.

The structure of the input data must match exactly what is expected by the call() method—here, a dict with keys title, text_body, and tags.

Beware: what subclassed models don’t support

This freedom comes at a cost: with subclassed models, you are responsible for more of the model logic, which means your potential error surface is much larger

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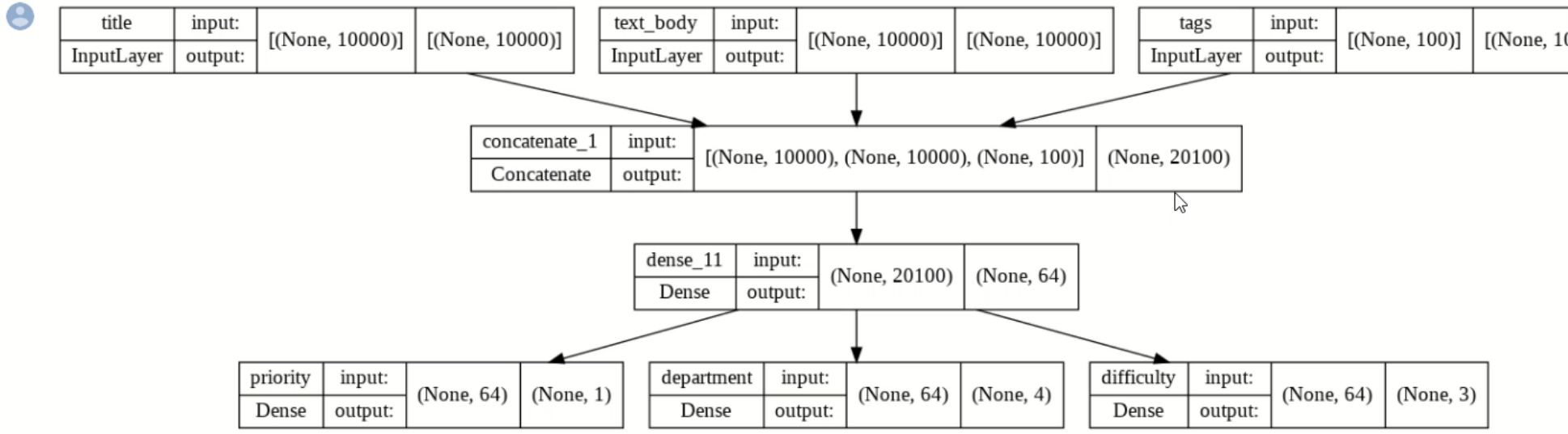
```
keras.utils.plot_model(new_model, "updated_ticket_classifier.png", show_shapes=True)
```



Subclassing the Model class

Rewriting our previous example as a subclassed model

A simple subclassed model

```
class CustomerTicketModel(keras.Model):
```

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Mixing and matching different components

All models in the Keras API can smoothly interoperate with each other, whether they're Sequential models, Functional models, or subclassed models

Listing 7.15 Creating a Functional model that includes a subclassed model

```
class Classifier(keras.Model):
```

↳ Subclass model

```
    def __init__(self, num_classes=2):
        super().__init__()
        if num_classes == 2:
            num_units = 1
            activation = "sigmoid"
        else:
            num_units = num_classes
            activation = "softmax"
        self.dense = layers.Dense(num_units, activation=activation)

    def call(self, inputs):
        return self.dense(inputs)

inputs = keras.Input(shape=(3,))
features = layers.Dense(64, activation="relu")(inputs)
outputs = Classifier(num_classes=10)(features)
model = keras.Model(inputs=inputs, outputs=outputs)
```

design of last layer (give outputs for the classification problem)

design functional model

Inversely, you can use a Functional model as part of a subclassed layer or model

Listing 7.16 Creating a subclassed model that includes a Functional model

```
inputs = keras.Input(shape=(64,))
outputs = layers.Dense(1, activation="sigmoid")(inputs)
binary_classifier = keras.Model(inputs=inputs, outputs=outputs)
class MyModel(keras.Model):

    def __init__(self, num_classes=2):
        super().__init__()
        self.dense = layers.Dense(64, activation="relu")
        self.classifier = binary_classifier

    def call(self, inputs):
        features = self.dense(inputs)
        return self.classifier(features)

model = MyModel()
```

← functional model in constructor

Using built-in training and evaluation loops

Listing 7.17 The standard workflow: `compile()`, `fit()`, `evaluate()`, `predict()`

```
from tensorflow.keras.datasets import mnist

def get_mnist_model():
    inputs = keras.Input(shape=(28 * 28,))
    features = layers.Dense(512, activation="relu")(inputs)
    features = layers.Dropout(0.5)(features)
    outputs = layers.Dense(10, activation="softmax")(features)
    model = keras.Model(inputs, outputs)
    return model

(images, labels), (test_images, test_labels) = mnist.load_data()
images = images.reshape((60000, 28 * 28)).astype("float32") / 255
test_images = test_images.reshape((10000, 28 * 28)).astype("float32") / 255
train_images, val_images = images[10000:], images[:10000]
train_labels, val_labels = labels[10000:], labels[:10000]

model = get_mnist_model()
model.compile(optimizer="rmsprop",
              loss="sparse_categorical_crossentropy",
              metrics=["accuracy"])
model.fit(train_images, train_labels,
          epochs=3,
          validation_data=(val_images, val_labels))
test_metrics = model.evaluate(test_images, test_labels)
predictions = model.predict(test_images)
```

Create a model (we factor this into a separate function so as to reuse it later).

create MNIST model using functional API

Load your data, reserving some for validation.

prepare our training and test (also labels) data sets

devide for normalization

Compile the model by specifying its optimizer, the loss function to minimize, and the metrics to monitor.

built-in training loop

Use fit() to train the model, optionally providing validation data to monitor performance on unseen data.

built-in evaluation loop

Use evaluate() to compute the loss and metrics on new data.

Use predict() to compute classification probabilities on new data.

Provide a custom metric after defining own versions

Pass callbacks to the fit() to schedule actions at specific points during training cf) early stopping

Writing your own metrics

A Keras metric is a subclass of the keras.metrics.Metric class

should overwrite

Write the state-update logic, which happens in the update_state() method.

Listing 7.18 Implementing a custom metric by subclassing the `Metric` class

```
import tensorflow as tf

class RootMeanSquaredError(keras.metrics.Metric):
    def __init__(self, name="rmse", **kwargs):
        super().__init__(name=name, **kwargs)
        self.mse_sum = self.add_weight(name="mse_sum", initializer="zeros")
        self.total_samples = self.add_weight(
            name="total_samples", initializer="zeros", dtype="int32")

    def update_state(self, y_true, y_pred, sample_weight=None):
        y_true = tf.one_hot(y_true, depth=tf.shape(y_pred)[1])
        mse = tf.reduce_sum(tf.square(y_true - y_pred))
        self.mse_sum.assign_add(mse)
        num_samples = tf.shape(y_pred)[0]
        self.total_samples.assign_add(num_samples)
```

Subclass the Metric class.

Define the state variables in the constructor. Like for layers, you have access to the add_weight() method.

To match our MNIST model, we expect categorical predictions and integer labels.

calculate MSE

→ It will add MSE one by one at every fitting stage (update)

→ Add # samples one by one, If batch size → 32 we add 32 times for total samples

Implement the state update logic in update_state(). The y_true argument is the targets (or labels) for one batch, while y_pred represents the corresponding predictions from the model. You can ignore the sample_weight argument—we won't use it here.

epoch 1 → → → → → → → ... each update

return current metric:

```
def result(self):
    return tf.sqrt(self.mse_sum / tf.cast(self.total_samples, tf.float32))
```

→ For each epoch, the current MSE will be updated by this method.

reset for each epoch:

```
def reset_state(self):
    self.mse_sum.assign(0.)
    self.total_samples.assign(0)
```

When I start new epoch, should reset the state.

Custom metrics can be used just like built-in ones

```
model = get_mnist_model()
model.compile(optimizer="rmsprop",
              loss="sparse_categorical_crossentropy",
              metrics=["accuracy", RootMeanSquaredError()])
model.fit(train_images, train_labels,
          epochs=3,
          validation_data=(val_images, val_labels))
test_metrics = model.evaluate(test_images, test_labels)
```

```
                                                "tags": tags_data})
```

```
40/40 [==============================] - 1s 8ms/step - loss: 35.1242 - output_1_loss: 0.3360 - output_2_loss: 34.7882 - output_1_mean_absolute_error:
40/40 [==============================] - 0s 6ms/step - loss: 35.1771 - output_1_loss: 0.3426 - output_2_loss: 34.8345 - output_1_mean_absolute_error:
```


Beware: What subclassed models don't support

Mixing and matching different components

Creating a Functional model that includes a subclassed model

```
[ ]  class Classifier(keras.Model):

        def __init__(self, num_classes=2):
            super().__init__()
            if num_classes == 2:
                num_units = 1
                activation = "sigmoid"
            else:
                num_units = num_classes
                activation = "softmax"
            self.dense = layers.Dense(num_units, activation=activation)

        def call(self, inputs):
            return self.dense(inputs)
```

Using callbacks

in traing stage

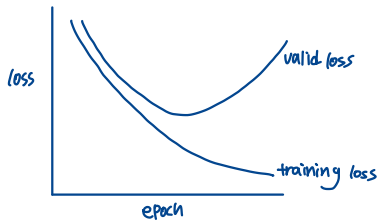
Launching a training run on a large dataset for tens of epochs using model.fit() can be a bit like launching a paper airplane: you don't have any control over its trajectory or its landing spot.

would like to have more controls on our training processes

A **callback** is an object (a class instance implementing specific methods) that is passed to the model in the call to fit()

Inside of the fit(), can define callback
→ It can make control eg) early stopping.

It has access to all the available data about the state of the model and its performance, and it can take action: interrupt training, save a model, load a different weight set, or otherwise alter the state of the model.



Using callbacks

Early stopping & Model checkpoint are widely used.

Model checkpointing—Saving the current state of the model at different points during training. keras.callbacks.ModelCheckpoint

Early stopping—Interrupting training when the validation loss is no longer improving (saving the best model obtained during training). keras.callbacks.EarlyStopping

Dynamically adjusting the value of certain parameters during training—Such as the learning rate of the optimizer. keras.callbacks.LearningRateScheduler, keras.callbacks.ReduceLROnPlateau

* Callbacks related to visualizing

Logging training and validation metrics during training, or visualizing the representations learned by the model as they're updated. keras.callbacks.CSVLogger

The EarlyStopping callback interrupts training once a target metric being monitored has stopped improving for a fixed number of epochs

ModelCheckpoint lets you continually save the model during training

Listing 7.19 Using the `callbacks` argument in the `fit()` method

Callbacks are passed to the model via the callbacks argument in fit(), which takes a list of callbacks. You can pass any number of callbacks.

```
callbacks_list = [
    keras.callbacks.EarlyStopping(
        monitor="val_accuracy",
        patience=2,
    ),
    keras.callbacks.ModelCheckpoint(
        filepath="checkpoint_path.keras",
        monitor="val_loss",
        save_best_only=True,
    )
]
model = get_mnist_model()
model.compile(optimizer="rmsprop",
              loss="sparse_categorical_crossentropy",
              metrics=["accuracy"])
model.fit(train_images, train_labels,
          epochs=10,
          callbacks=callbacks_list,
          validation_data=(val_images, val_labels))
```

Interrupts training when improvement stops

Monitors the model's validation accuracy

Interrupts training when accuracy has stopped improving for two epochs

Saves the current weights after every epoch

Path to the destination model file

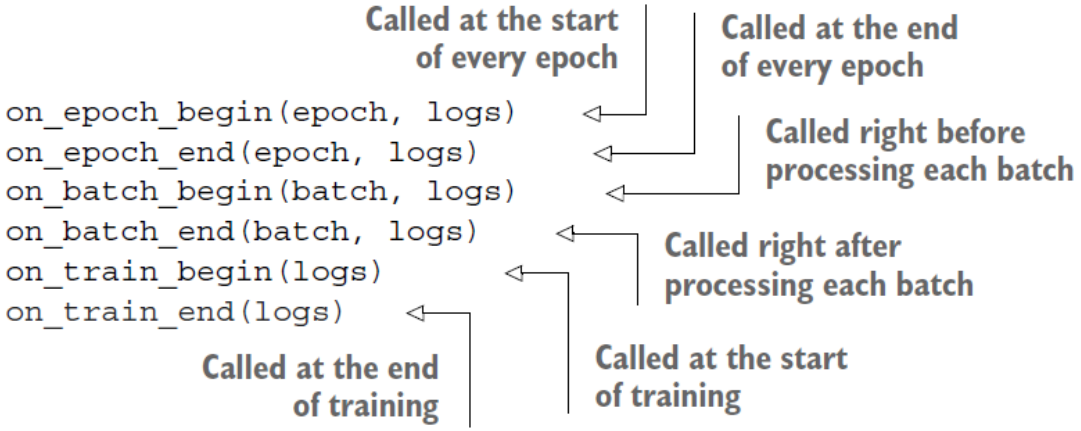
These two arguments mean you won't overwrite the model file unless val_loss has improved, which allows you to keep the best model seen during training.

You monitor accuracy, so it should be part of the model's metrics.

Note that because the callback will monitor validation loss and validation accuracy, you need to pass validation_data to the call to fit().

Writing your own callbacks

simple example that saves a list of per-batch loss values during training and saves a graph of these values at the end of each epoch.



Listing 7.20 Creating a custom callback by subclassing the `Callback` class

```
from matplotlib import pyplot as plt

class LossHistory(keras.callbacks.Callback):
    def on_train_begin(self, logs):
        self.per_batch_losses = []

    def on_batch_end(self, batch, logs):
        self.per_batch_losses.append(logs.get("loss"))

    def on_epoch_end(self, epoch, logs):
        plt.clf()
        plt.plot(range(len(self.per_batch_losses)), self.per_batch_losses,
                 label="Training loss for each batch")
        plt.xlabel(f"Batch (epoch {epoch})")
        plt.ylabel("Loss")
        plt.legend()
        plt.savefig(f"plot_at_epoch_{epoch}")
        self.per_batch_losses = []
```

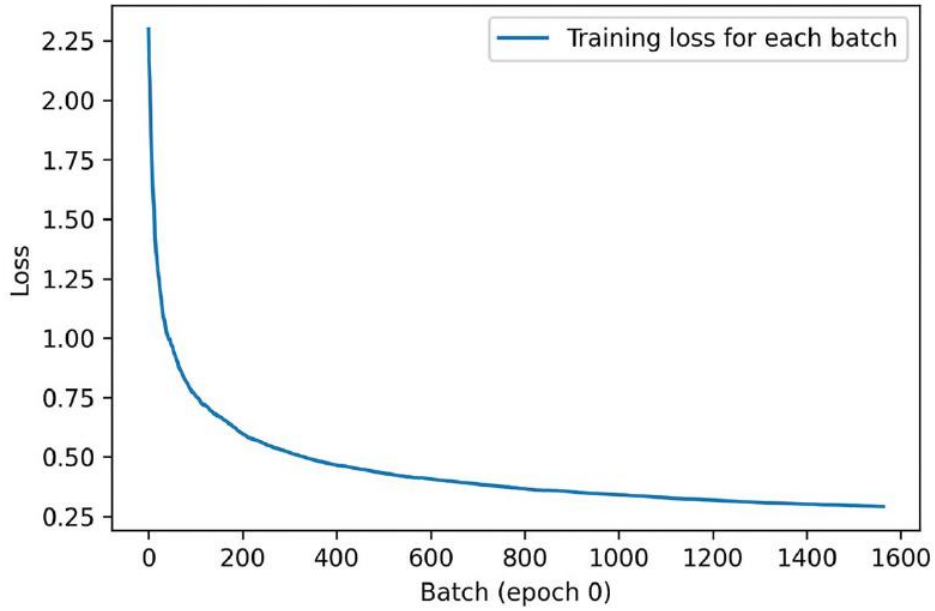


Figure 7.5 The output of our custom history plotting callback

The EarlyStopping and ModelCheckpoint callbacks

Using the `callbacks` argument in the `fit()` method

```
callbacks_list = [
    keras.callbacks.EarlyStopping(
        monitor="val_accuracy",
        patience=2,
    ),
    keras.callbacks.ModelCheckpoint(
        filepath="checkpoint_path.keras",
        monitor="val_loss",
        save_best_only=True,
    )
]
model = get_mnist_model()
model.compile(optimizer="rmsprop",
              loss="sparse_categorical_crossentropy",
              metrics=["accuracy"])
model.fit(train_images, train_labels,
          epochs=10,
          callbacks=callbacks_list,
          validation_data=(val_images, val_labels))
```

```
[ ]  model = keras.models.load_model("checkpoint_path.keras")
```

Monitoring and visualization with TensorBoard

TensorBoard (www.tensorflow.org/tensorboard) is a browser-based application that you can run locally

monitor training process of our model.

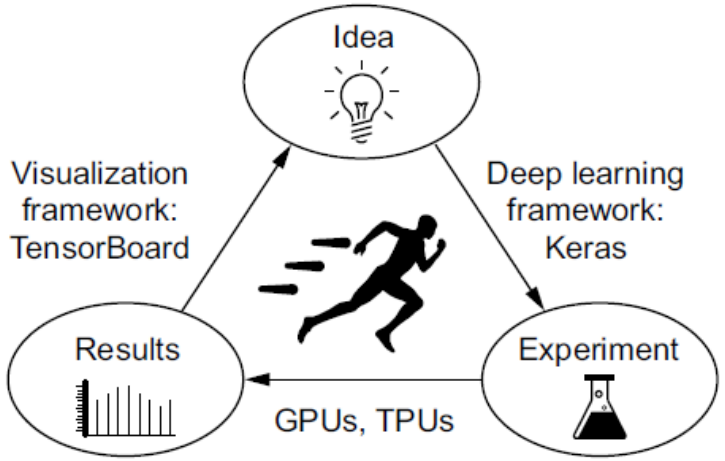


Figure 7.6 The loop of progress

- **Visually monitor metrics during training**
- **Visualize your model architecture**
- **Visualize histograms of activations and gradients**
- **Explore embeddings in 3D**

Easiest way to use TensorBoard with a Keras model and the fit() method is to use the keras.callbacks.TensorBoard callback.

```
model = get_mnist_model()
model.compile(optimizer="rmsprop",
              loss="sparse_categorical_crossentropy",
              metrics=["accuracy"])

tensorboard = keras.callbacks.TensorBoard(
    log_dir="/full_path_to_your_log_dir",
)
model.fit(train_images, train_labels,
          epochs=10,
          validation_data=(val_images, val_labels),
          callbacks=[tensorboard])
```

If you are running your script in a Colab notebook

```
%load_ext tensorboard
%tensorboard --logdir /full_path_to_your_log_dir
```

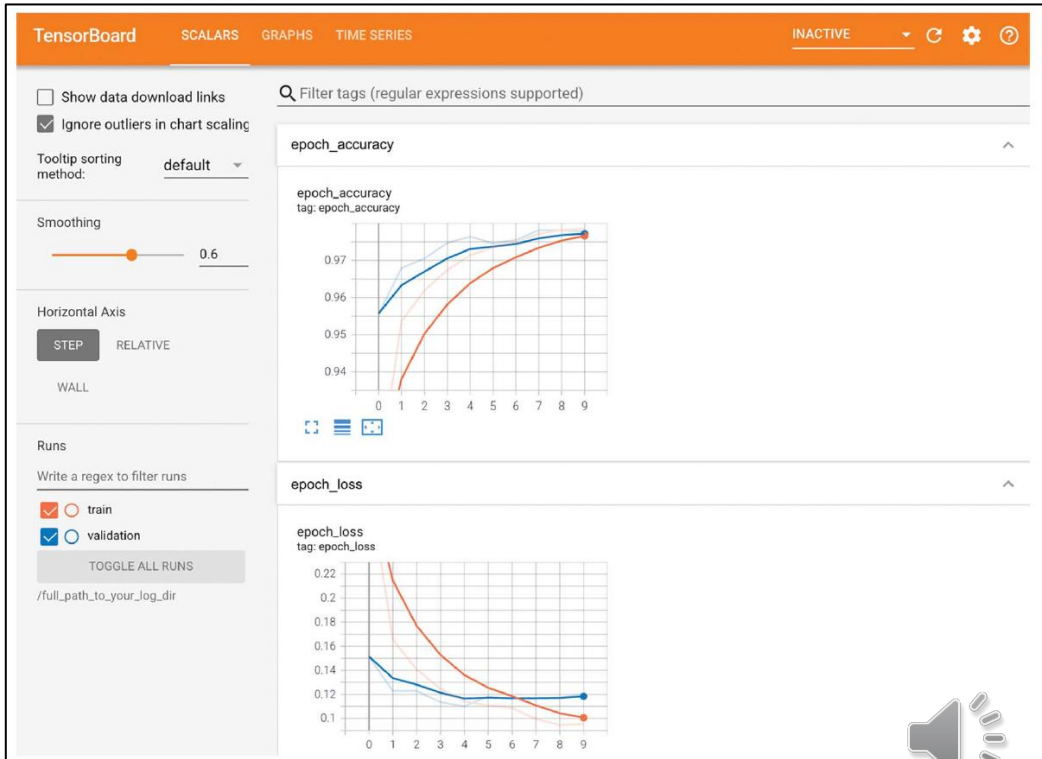


Figure 7.7 TensorBoard can be used for easy monitoring of training and evaluation metrics.

```
 'plot_at_epoch_0.png',
 'plot_at_epoch_2.png',
 'sample_data']
```

Monitoring and visualization with TensorBoard

```
[ ] model = get_mnist_model()
    model.compile(optimizer="rmsprop",
                  loss="sparse_categorical_crossentropy",
                  metrics=["accuracy"])

    tensorboard = keras.callbacks.TensorBoard(
        log_dir="/full_path_to_your_log_dir",
    )
    model.fit(train_images, train_labels,
              epochs=10,
              validation_data=(val_images, val_labels),
              callbacks=[tensorboard])
```

```
[ ] %load_ext tensorboard
    %tensorboard --logdir /full_path_to_your_log_dir
```

Writing your own training and evaluation loops

Training versus inference

Writing your own training and evaluation loops

Built-in fit() workflow is solely focused on supervised learning, However, not every form of machine learning falls into this category.

Typical training loop look like this:

1. **Run the forward pass inside a gradient tape to obtain a loss for the current batch of data.**
2. **Retrieve the gradients of the loss with regard to the model's weights.**
3. **Update the model's weights so as to lower the loss value on the current batch of data.**

We will learn to reimplement fit()

Supervised-learning training step ends up looking like this:

```
def train_step(inputs, targets):
    with tf.GradientTape() as tape:
        predictions = model(inputs, training=True)
        loss = loss_fn(targets, predictions)
    gradients = tape.gradients(loss, model.trainable_weights)
    optimizer.apply_gradients(zip(model.trainable_weights, gradients))
```

Set training = True: some Keras layers, such as the Dropout layer, have different behaviors during training and during inference

Layers and models own two kinds of weights: trainable weights, non-trainable weights → weights that automatically updated
No need to update myself

↑
only need to update trainable weights.

A complete training and evaluation loop

Training step function takes a batch of data and targets

Listing 7.21 Writing a step-by-step training loop: the training step function

```
model = get_mnist_model()

loss_fn = keras.losses.SparseCategoricalCrossentropy()
optimizer = keras.optimizers.RMSprop()
metrics = [keras.metrics.SparseCategoricalAccuracy()]
loss_tracking_metric = keras.metrics.Mean()

def train_step(inputs, targets):
    with tf.GradientTape() as tape:
        predictions = model(inputs, training=True)
        loss = loss_fn(targets, predictions)
    gradients = tape.gradient(loss, model.trainable_weights)
    optimizer.apply_gradients(zip(gradients, model.trainable_weights))

    logs = {}
    for metric in metrics:
        metric.update_state(targets, predictions)
        logs[metric.name] = metric.result()

    loss_tracking_metric.update_state(loss)
    logs["loss"] = loss_tracking_metric.result()
    return logs
```

Prepare the loss function.

Prepare the optimizer.

Prepare the list of metrics to monitor.

Prepare a Mean metric tracker to keep track of the loss average.

(10 number of inputs (batch), 10 number of outputs (batch))

How we defining training step

don't forget!

Run the forward pass. Note that we pass training=True.

Run the backward pass. Note that we use model.trainable_weights.

* dictionary

Keep track of metrics.

Keep track of the loss average.

we get the mean value of (10 (batch samples) losses.

Return the current values of the metrics and the loss.

eg) 1000 data point

batch size 10

100 batches

epoch 0 → traing updates 100 times

for each batch, it contains 10 number of samples

* train_step will apply for each batch

Reset the state of our metrics at the start of each epoch and before running evaluation.

Listing 7.22 Writing a step-by-step training loop: resetting the metrics

```
def reset_metrics():
    for metric in metrics:
        metric.reset_state()
    loss_tracking_metric.reset_state()
```

Our complete training loop

Listing 7.23 Writing a step-by-step training loop: the loop itself

```
training_dataset = tf.data.Dataset.from_tensor_slices(
    (train_images, train_labels))
training_dataset = training_dataset.batch(32)
epochs = 3
for epoch in range(epochs):
    reset_metrics()
    for inputs_batch, targets_batch in training_dataset:
        logs = train_step(inputs_batch, targets_batch)
    print(f"Results at the end of epoch {epoch}")
    for key, value in logs.items():
        print(f"...{key}: {value:.4f}")
```

The evaluation loop

Listing 7.24 Writing a step-by-step evaluation loop

```
def test_step(inputs, targets):
    predictions = model(inputs, training=False)
    loss = loss_fn(targets, predictions)

    logs = {}
    for metric in metrics:
        metric.update_state(targets, predictions)
        logs["val_" + metric.name] = metric.result()
    loss_tracking_metric.update_state(loss)
    logs["val_loss"] = loss_tracking_metric.result()
    return logs

val_dataset = tf.data.Dataset.from_tensor_slices((val_images, val_labels))
val_dataset = val_dataset.batch(32)
reset_metrics()
for inputs_batch, targets_batch in val_dataset:
    logs = test_step(inputs_batch, targets_batch)
print("Evaluation results:")
for key, value in logs.items():
    print(f"...{key}: {value:.4f}")
```

Note that we pass training=False.

Make it fast with tf.function

Listing 7.25 Adding a `@tf.function` decorator to our evaluation-step function

```
@tf.function
def test_step(inputs, targets):
    predictions = model(inputs, training=False)
    loss = loss_fn(targets, predictions)

    logs = {}
    for metric in metrics:
        metric.update_state(targets, predictions)
        logs["val_" + metric.name] = metric.result()

    loss_tracking_metric.update_state(loss)
    logs["val_loss"] = loss_tracking_metric.result()
    return logs

val_dataset = tf.data.Dataset.from_tensor_slices((val_images, val_labels))
val_dataset = val_dataset.batch(32)
reset_metrics()
for inputs_batch, targets_batch in val_dataset:
    logs = test_step(inputs_batch, targets_batch)
print("Evaluation results:")
for key, value in logs.items():
    print(f"...{key}: {value:.4f}")
```

using GPU, running codes below

This is the only line that changed.

On the Colab CPU, we go from taking 1.80 s to run the evaluation loop to only 0.8 s.

Leveraging fit() with a custom training loop

complicated

There's actually a middle ground between fit() and a training loop written from scratch: you can provide a custom training step function and let the framework do the rest.

Listing 7.26 Implementing a custom training step to use with `fit()`

```
loss_fn = keras.losses.SparseCategoricalCrossentropy()
loss_tracker = keras.metrics.Mean(name="loss")

class CustomModel(keras.Model):
    def train_step(self, data):
        inputs, targets = data
        with tf.GradientTape() as tape:
            predictions = self(inputs, training=True)
            loss = loss_fn(targets, predictions)
        gradients = tape.gradient(loss, model.trainable_weights)
        optimizer.apply_gradients(zip(gradients, model.trainable_weights))

        loss_tracker.update_state(loss)
        return {"loss": loss_tracker.result()}

    @property
    def metrics(self):
        return [loss_tracker]
```

This metric object will be used to track the average of per-batch losses during training and evaluation.

We override the train_step method.

We use self(inputs, training=True) instead of model(inputs, training=True), since our model is the class itself.

We update the loss tracker metric that tracks the average of the loss.

We return the average loss so far by querying the loss tracker metric.

Any metric you would like to reset across epochs should be listed here.

chapter07_working-with-keras.i

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Editing

Training versus inference

Low-level usage of metrics

+ Code + Text

```
metric = keras.metrics.SparseCategoricalAccuracy()
targets = [0, 1, 2]
predictions = [[1, 0, 0], [0, 1, 0], [0, 0, 1]]
metric.update_state(targets, predictions)
current_result = metric.result()
print(f"result: {current_result:.2f}")
```

```
result: 1.00
```

0s

```
[16] values = [0, 1, 2, 3, 4]
mean_tracker = keras.metrics.Mean()
for value in values:
    mean_tracker.update_state(value)
print(f"Mean of values: {mean_tracker.result():.2f}")
```

```
Mean of values: 2.00
```

A complete training and evaluation loop

Writing a step-by-step training loop: the training step function

0s completed at 4:56 PM

Thank you!