



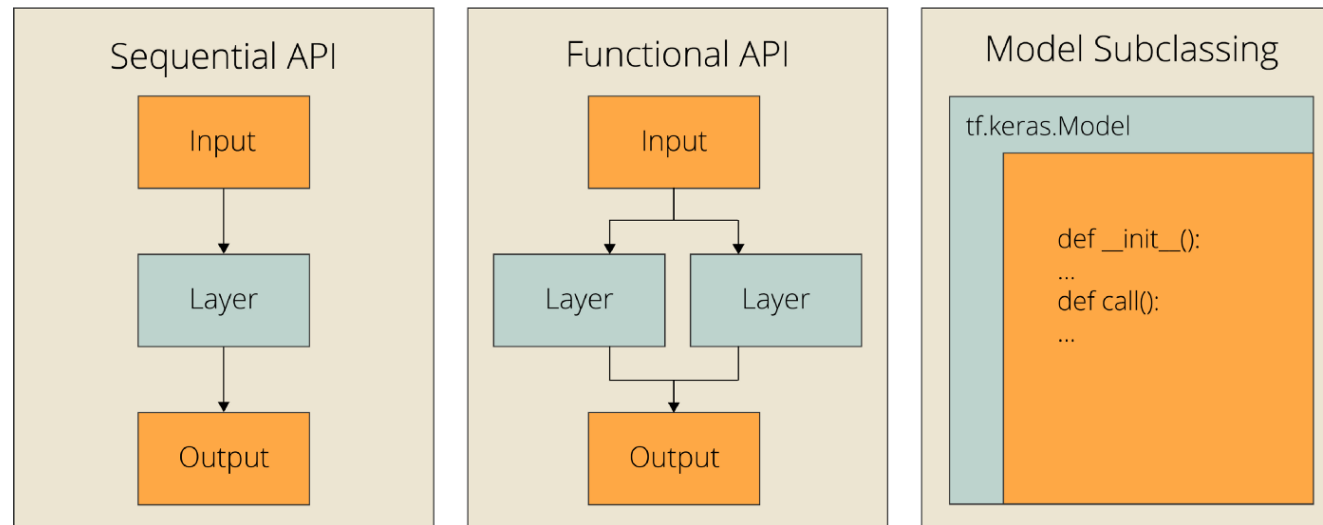
Intro to Neural Nets

Week 5: Functional API

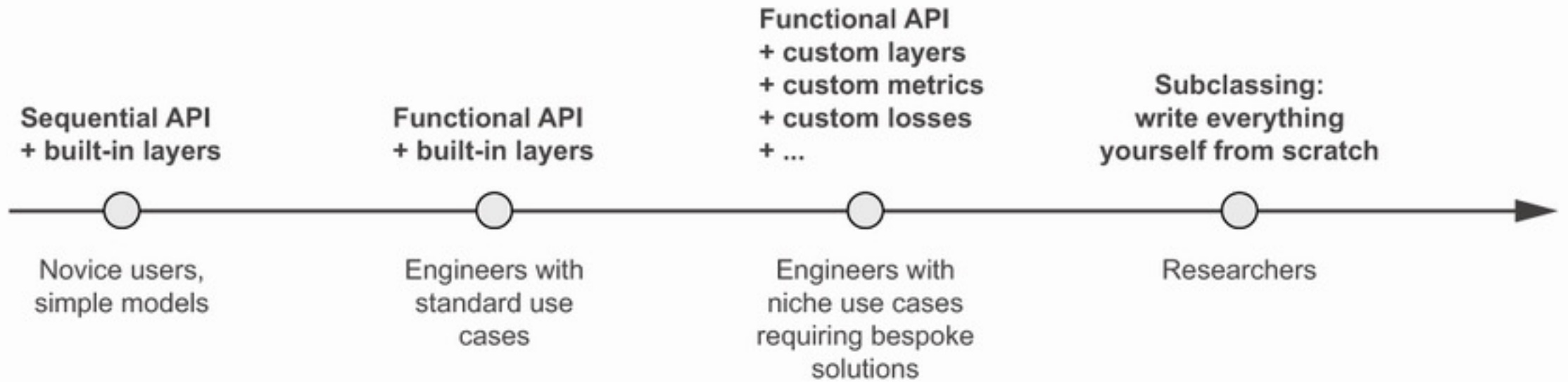
Today's Agenda

Functional vs. Sequential API (vs. Subclassing)

- Creating Keras models with the Sequential class vs. the Functional API
- Custom Loss functions
- Using TensorBoard to monitor training and evaluation metrics
- Writing training and evaluation loops from scratch



Alternative Options /w Keras



Sequential API: Topology

Listing 7.1 The `Sequential` class

```
1 from tensorflow import keras
2 from tensorflow.keras import layers
3
4 model = keras.Sequential([
5     layers.Dense(64, activation="relu"),
6     layers.Dense(10, activation="softmax")
7 ])
```

Same Thing, but Adding Layers Dynamically

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

Sequential API: Initialization

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

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

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

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

Listing 7.7 Specifying the input shape of your model in advance

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

Sequential API: Summary

Listing 7.5 The `summary()` method

```
1 >>> model.summary()
2 Model: "sequential_1"
3
4 Layer (type) Output Shape Param #
5 =====
6 dense_2 (Dense) (None, 64) 256
7
8 dense_3 (Dense) (None, 10) 650
9 =====
10 Total params: 906
11 Trainable params: 906
12 Non-trainable params: 0
13
```

Functional API: Topology

Define Each Layer and its Linkages (If Any)

- When you specify a given layer, you state what input it takes (if any).
- This lets you build more complicated topologies (e.g., branches, multi-outputs, letting earlier layers feed into later layers in the network, and so on).

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

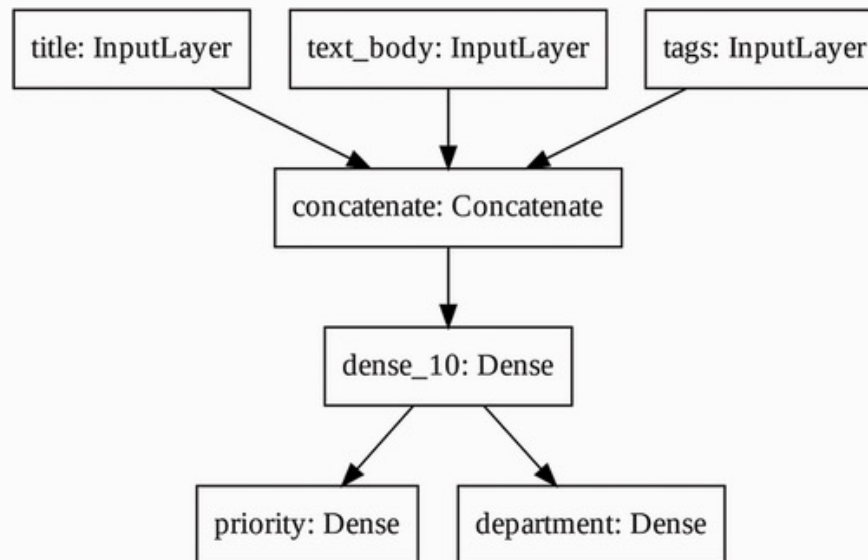
```
1 inputs = keras.Input(shape=(3,), name="my_input")
2 features = layers.Dense(64, activation="relu")(inputs)
3 outputs = layers.Dense(10, activation="softmax")(features)
4 model = keras.Model(inputs=inputs, outputs=outputs)
```

Complex Topologies

We Can Define a Multi-Input (Branches) to Multi-Output (Labels) Topology

- This because useful for multi-modal data, or for introducing feedback loops, etc. into the network.

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



Complex Topologies

We Can Define a Multi-Input (Branches) to Multi-Output (Labels) Topology

- This is useful for multi-modal data, residual links, or feedback loops, etc.

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

```
1 vocabulary_size = 10000
2 num_tags = 100
3 num_departments = 4
4
5 title = keras.Input(shape=(vocabulary_size,), name="title")
6 text_body = keras.Input(shape=(vocabulary_size,), name="text_body")
7 tags = keras.Input(shape=(num_tags,), name="tags")
8
9 features = layers.Concatenate()([title, text_body, tags])
10 features = layers.Dense(64, activation="relu")(features)
11
12 priority = layers.Dense(1, activation="sigmoid", name="priority")(features)
13 department = layers.Dense(
14     num_departments, activation="softmax", name="department")(features)
15
16 model = keras.Model(inputs=[title, text_body, tags],
17                      outputs=[priority, department])
```

Functional API: Training

Pass Lists of Input Arrays, and Specify Lists of Loss Functions / Metrics

- We need to pass in a list of arrays addressing all inputs, as well as a list of labels for all outputs.
- We can also provide a list of loss functions and metrics, one of each for each output label.

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

```
1 import numpy as np
2
3 num_samples = 1280
4
5 title_data = np.random.randint(0, 2, size=(num_samples, vocabulary_size))
6 text_body_data = np.random.randint(0, 2, size=(num_samples, vocabulary_size))
7 tags_data = np.random.randint(0, 2, size=(num_samples, num_tags))
8
9 priority_data = np.random.random(size=(num_samples, 1))
10 department_data = np.random.randint(0, 2, size=(num_samples, num_departments))
11
12 model.compile(optimizer="rmsprop",
13               loss=["mean_squared_error", "categorical_crossentropy"],
14               metrics=[["mean_absolute_error"], ["accuracy"]])
15 model.fit([title_data, text_body_data, tags_data],
16         [priority_data, department_data],
17         epochs=1)
18 model.evaluate([title_data, text_body_data, tags_data],
19               [priority_data, department_data])
20 priority_preds, department_preds = model.predict(
21     [title_data, text_body_data, tags_data])
```

Functional API: Training

Pass Lists of Input Arrays, and Specify Lists of Loss Functions / Metrics

- Use dictionaries rather than argument positional indexing (you are less likely to make a mistake this way!)

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

```
1  model.compile(optimizer="rmsprop",
2                loss={"priority": "mean_squared_error", "department":
3                      "categorical_crossentropy"},
4                metrics={"priority": ["mean_absolute_error"], "department":
5                                ["accuracy"]})
6  model.fit({"title": title_data, "text_body": text_body_data,
7            "tags": tags_data,
8            {"priority": priority_data, "department": department_data},
9            epochs=1)
10 model.evaluate({"title": title_data, "text_body": text_body_data,
11                "tags": tags_data,
12                {"priority": priority_data, "department": department_data})
13 priority_preds, department_preds = model.predict(
14     {"title": title_data, "text_body": text_body_data, "tags": tags_data})
```

Functional API: Pre-Trained Weights

We Can Use Pre-Weights From Another Trained Model

- Query the layer of an existing model, to extract its weights / bias term.
- Then feed them into a new model.

Let's Say We Want to Extract Weights from First Dense Layer...

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

```
1 >>> model.layers
2 [<tensorflow.python.keras.engine.input_layer.InputLayer at 0x7fa963f9d358>,
3  <tensorflow.python.keras.engine.input_layer.InputLayer at 0x7fa963f9d2e8>,
4  <tensorflow.python.keras.engine.input_layer.InputLayer at 0x7fa963f9d470>,
5  <tensorflow.python.keras.layers.merge.Concatenate at 0x7fa963f9d860>,
6  <tensorflow.python.keras.layers.core.Dense at 0x7fa964074390>,
7  <tensorflow.python.keras.layers.core.Dense at 0x7fa963f9d898>,
8  <tensorflow.python.keras.layers.core.Dense at 0x7fa963f95470>]
9 >>> model.layers[3].input
10 [<tf.Tensor "title:0" shape=(None, 10000) dtype=float32>,
11  <tf.Tensor "text_body:0" shape=(None, 10000) dtype=float32>,
12  <tf.Tensor "tags:0" shape=(None, 100) dtype=float32>]
13 >>> model.layers[3].output
14 <tf.Tensor "concatenate/concat:0" shape=(None, 20100) dtype=float32>
```

Custom Loss Functions

We Can Write a Custom Loss Function

- Many application-specific situations where we might want a custom metric (or loss function).
- One example I will show you is image-sharpening – MSE or MAE are okay, but there are better metrics for image-wide alignment of pixel values.

Function That Accepts Predicted and Actual as Input

```
def psnrLoss(y_true, y_pred, max_pixel=255.0):  
    psnr = tf.image.psnr(y_true, y_pred, max_val=max_pixel)  
    return psnr  
  
def ssim_msLoss(y_true, y_pred, max_val=255.0):  
    ssim = tf.image.ssim_multiscale(y_true, y_pred, max_val)  
    return ssim
```

Custom Loss Functions

We Can Write a Custom Loss Function

- Many application-specific situations where we might want a custom metric (or loss function).
- One example I will show you is image-sharpening – MSE or MAE are okay, but there are better metrics for image-wide alignment of pixel values.

Function That Accepts Predicted and Actual as Input

```
def psnrLoss(y_true, y_pred, max_pixel=255.0):  
    psnr = tf.image.psnr(y_true, y_pred, max_val=max_pixel)  
    return psnr  
  
def ssim_msLoss(y_true, y_pred, max_val=255.0):  
    ssim = tf.image.ssim_multiscale(y_true, y_pred, max_val)  
    return ssim
```

Callbacks in the Fit Method

We Can Enforce Some Rules During Fitting

- For example, we can tell the fit method to stop the training process early based on $<$ threshold improvements in our objective function.

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

```
1  callbacks_list = [  
2      keras.callbacks.EarlyStopping(  
3          monitor="val_accuracy",  
4          patience=2,  
5      ),  
6      keras.callbacks.ModelCheckpoint(  
7          filepath="checkpoint_path.keras",  
8          monitor="val_loss",  
9          save_best_only=True,  
10     )  
11 ]  
12 model = get_mnist_model()  
13 model.compile(optimizer="rmsprop",  
14               loss="sparse_categorical_crossentropy",  
15               metrics=["accuracy"])  
16 model.fit(train_images, train_labels,  
17           epochs=10,  
18           callbacks=callbacks_list,  
19           validation_data=(val_images, val_labels))
```


Save / Load a Trained Model

We Can Save and Re-load Models with Trained Weights for Later Use

- This enables transfer learning, picking up where we left off...

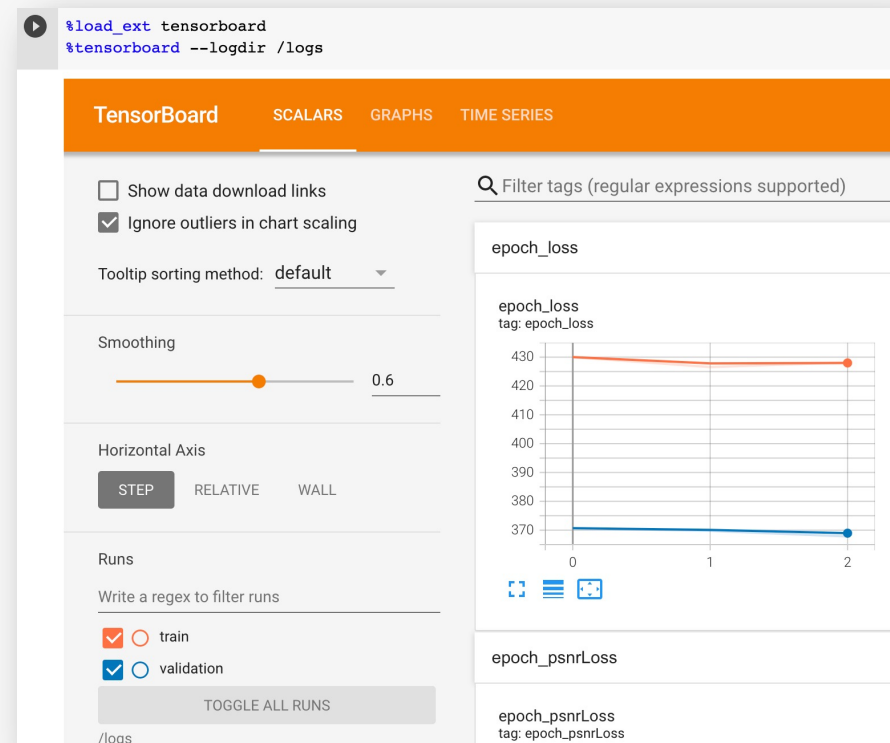
```
model.save('my_model')  
model = keras.models.load_model("my_model.keras")
```

- We might load an old model, extract the first 5 layers, and then stack new layers on the end.
- We might also fix the old model's layers as non-trainable ('calibrate' a new model 'end' on top of the pre-trained model).
- More on this shortly...

Tensorboard

Load in Keras, then add Callback to `model.fit()`

```
%load_ext tensorboard
%tensorboard --logdir /logs ,callbacks=keras.callbacks.TensorBoard(log_dir='/logs')
```



Questions?