Advanced Keras API

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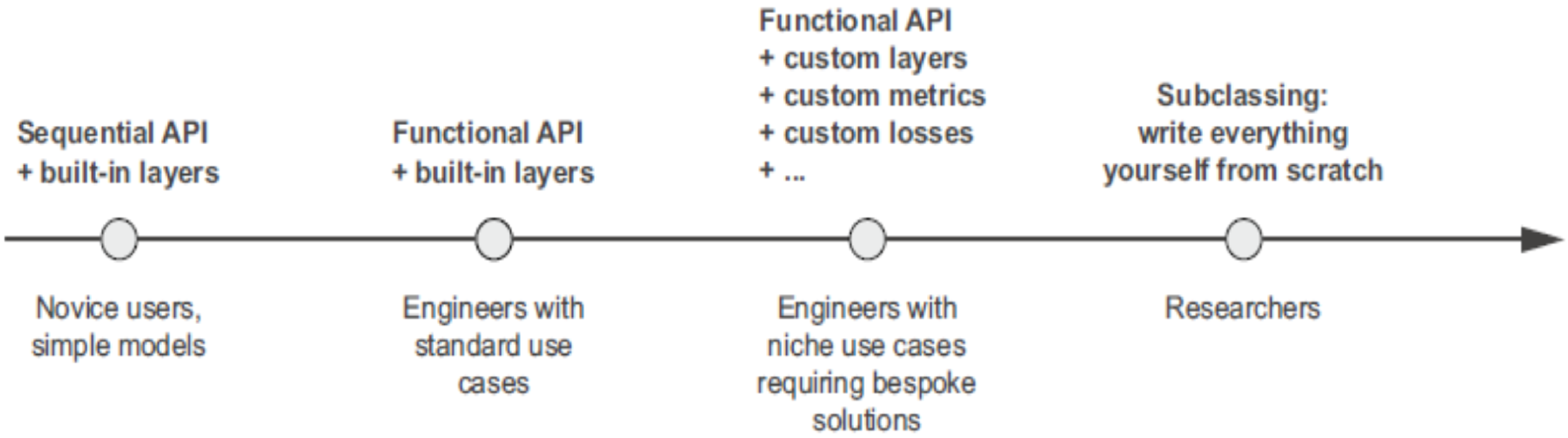
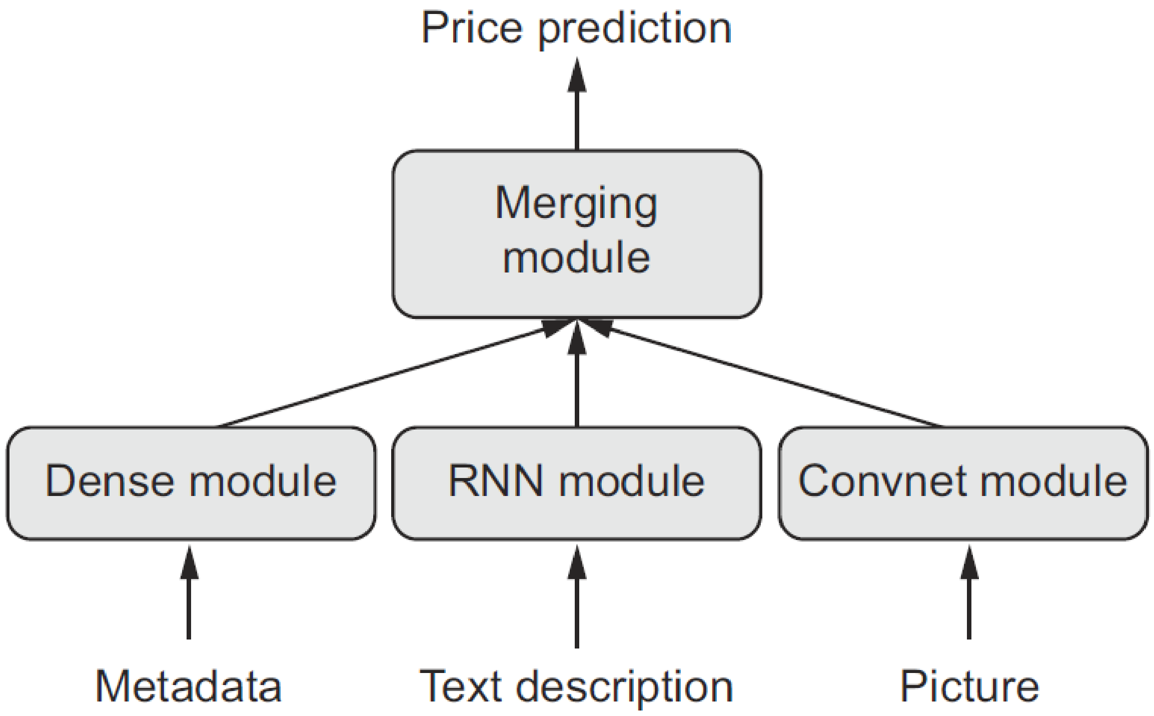
Keras Learning Stages

- Progressive complexity

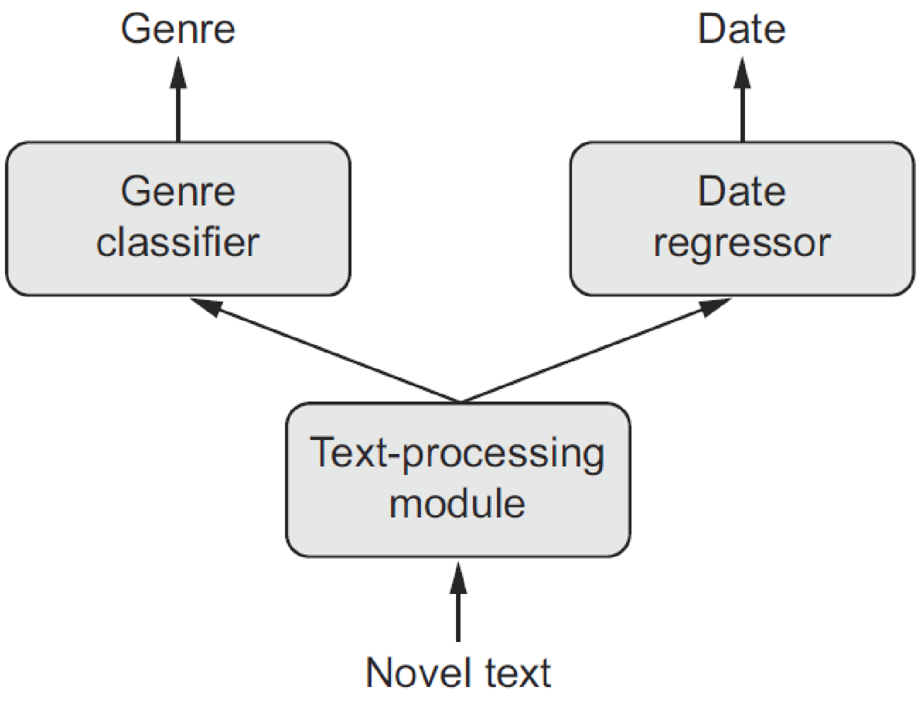


Going Beyond Sequential Model

Multi-input Model

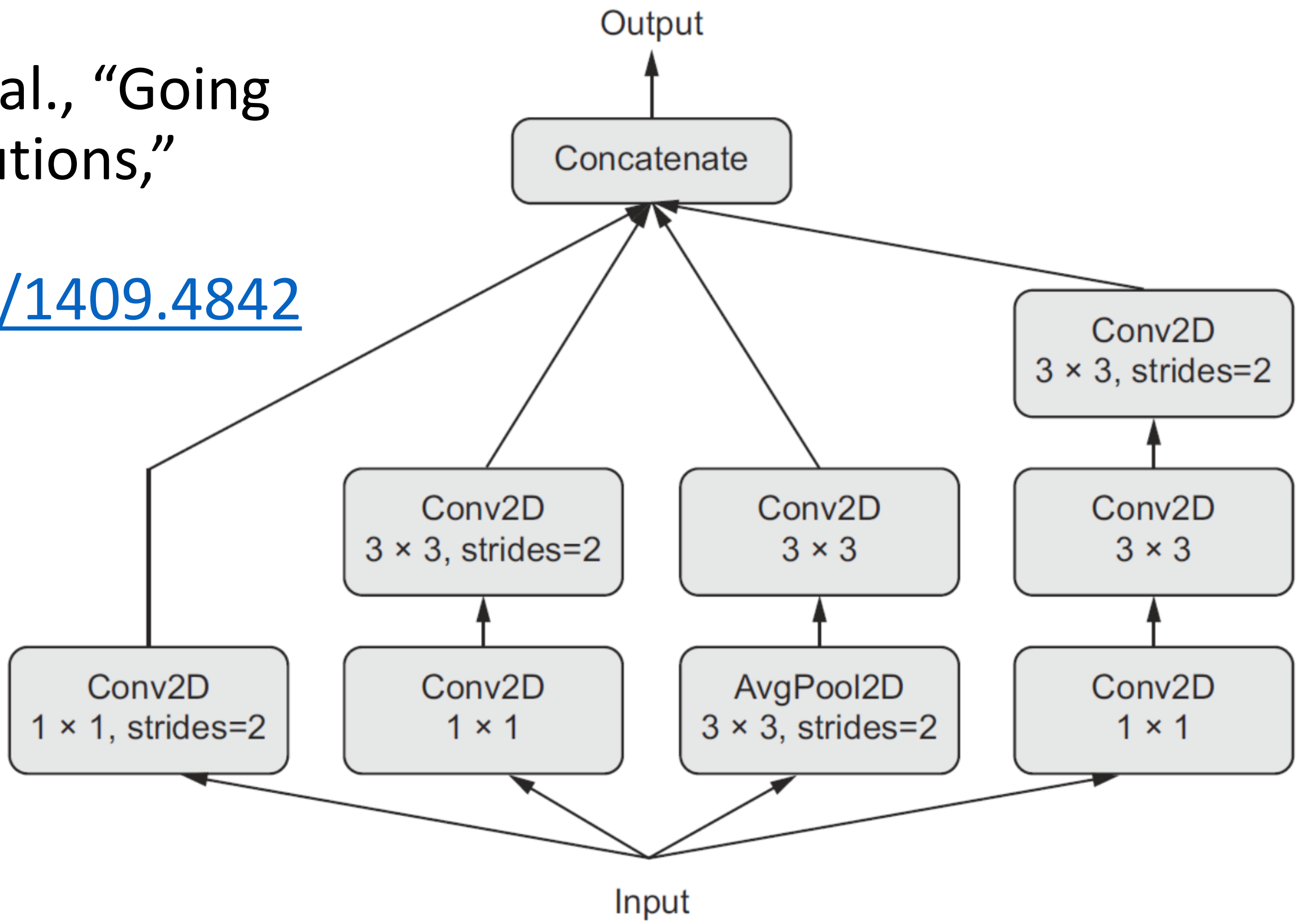


Multi-output Model



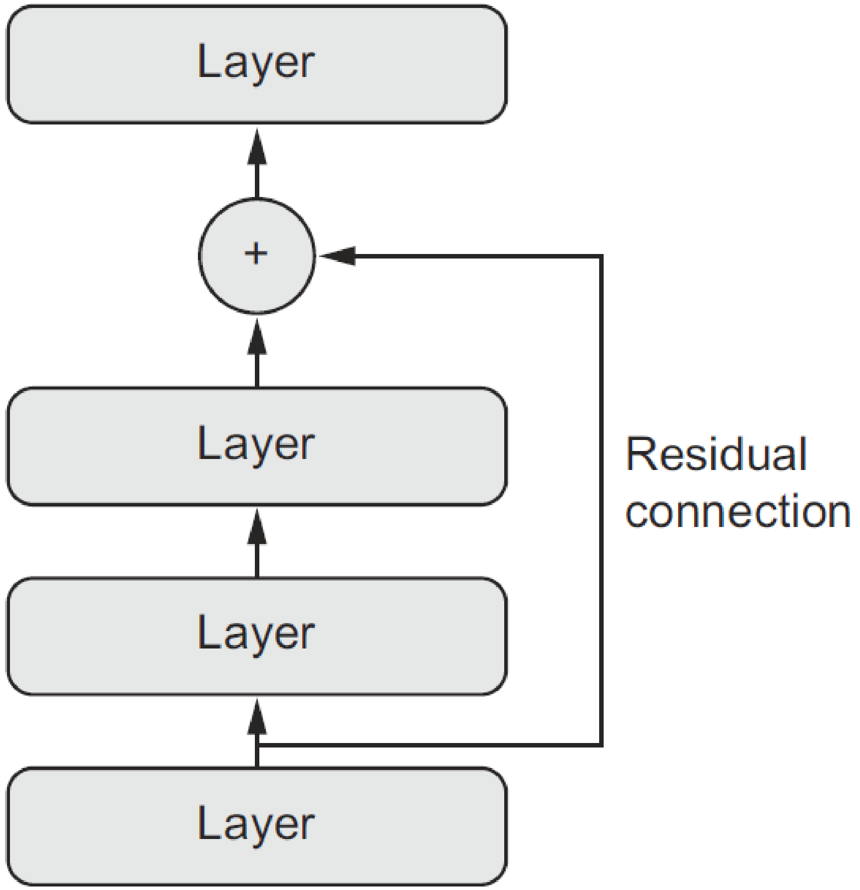
Inception Module

- Christian Szegedy et al., “Going Deeper with Convolutions,” *CVPR*, 2014. https://arxiv.org/abs/1409.4842



Residual Connection

- Kaiming He et al., “Deep Residual Learning for Image Recognition,” CVPR (2015), https://arxiv.org/abs/1512.03385



Functional API

```
from keras import Input, layers

input_tensor = Input(shape=(32,))

dense = layers.Dense(32, activation='relu')

output_tensor = dense(input_tensor)
```

A layer is a function

A layer may be called on a tensor, and it returns a tensor

Functional API vs. Sequential Model

- Create a Model object using only an input tensor and an output tensor

```
input_tensor = Input(shape=(64,))
x = layers.Dense(32, activation='relu')(input_tensor)
x = layers.Dense(32, activation='relu')(x)
output_tensor = layers.Dense(10, activation='softmax')(x)
model = Model(input_tensor, output_tensor)
```

Functional API vs. Sequential Model

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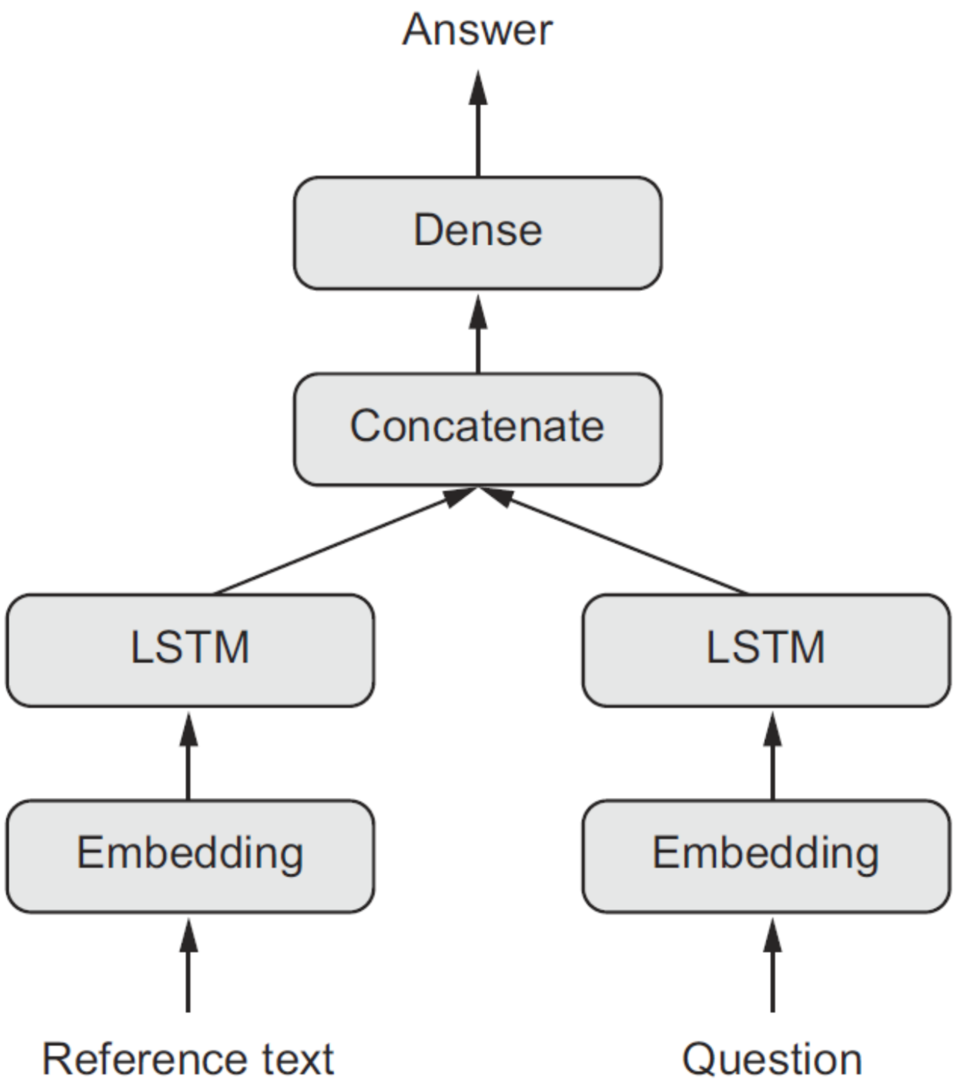
output_tensor = layers.Dense(10, activation='softmax')(x)
model = Model(input_tensor, output_tensor)
```

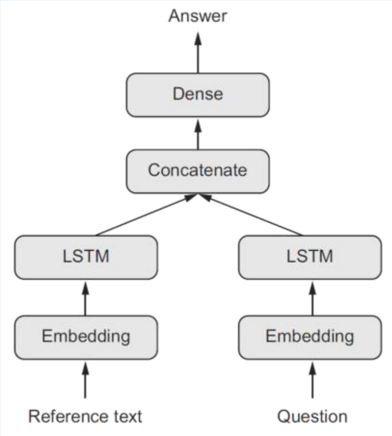
```
seq_model = Sequential()
seq_model.add(layers.Dense(32, activation='relu’,
              input_shape=(64,)))
seq_model.add(layers.Dense(32, activation='relu'))
seq_model.add(layers.Dense(10, activation='softmax'))
```

Question-answering Model

- Two inputs:
  1. A natural-language question
  2. Reference text snippet (such as a news article)
- One output: answer
  - One-word answer obtained via a SoftMax over some predefined vocabulary



```python
text_vocabulary_size = 10000
question_vocabulary_size = 10000
answer_vocabulary_size = 500

### Reference text ###
text_input = Input(shape=(None,), dtype='int32', name='text')
embedded_text = layers.Embedding(64, text_vocabulary_size)(text_input)
encoded_text = layers.LSTM(32)(embedded_text)

### Question ###
question_input = Input(shape=(None,), dtype='int32', name='question')
embedded_question = layers.Embedding(32, question_vocabulary_size)(question_input)
encoded_question = layers.LSTM(16)(embedded_question)

### Concatenate ###
concatenated = layers.concatenate([encoded_text, encoded_question], axis=-1)
answer = layers.Dense(answer_vocabulary_size, activation='softmax')(concatenated)

model = Model([text_input, question_input], answer)
model.compile(optimizer='rmsprop', loss='categorical_crossentropy’, metrics=['acc'])
```



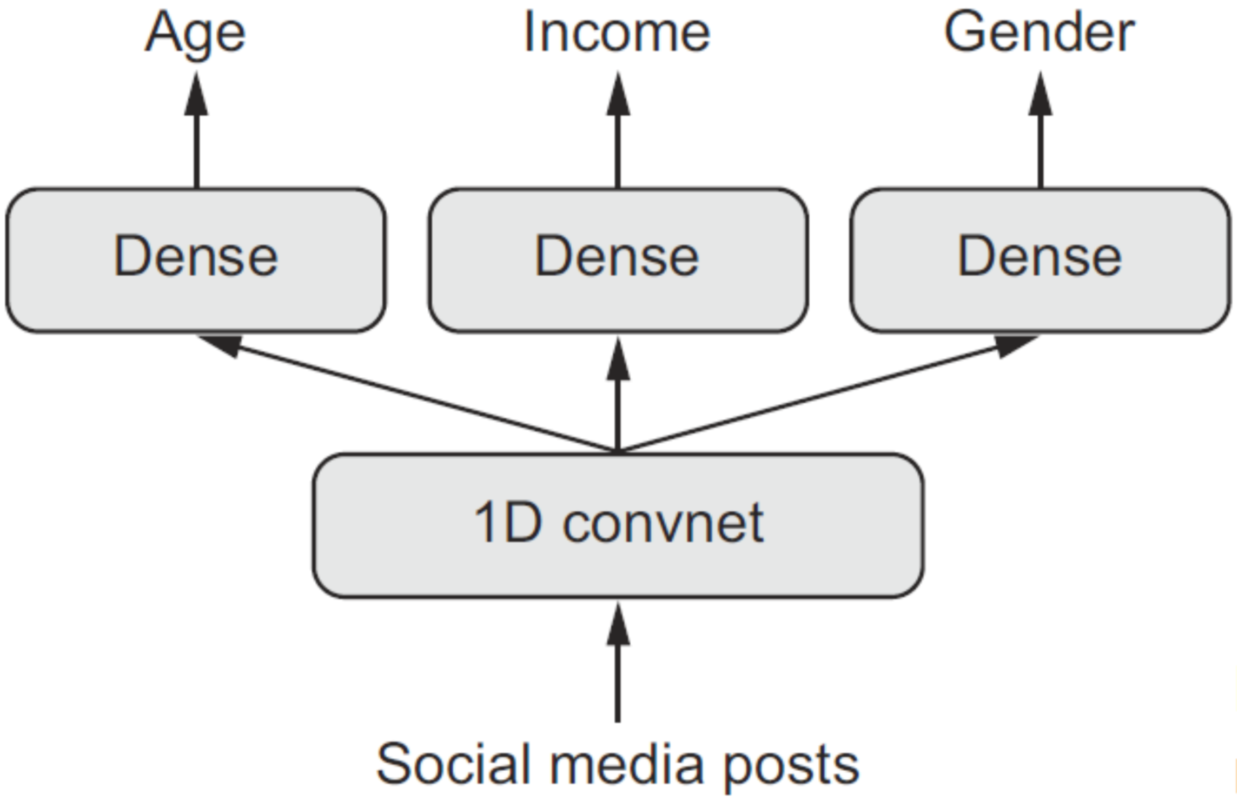
Train Two-input Models

- Training data can be array or dictionary

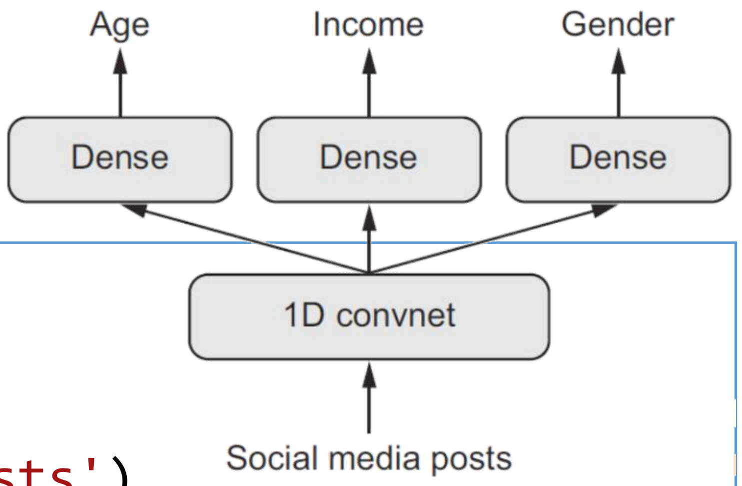
```
text = np.random.randint(1, text_vocabulary_size, size=(num_samples, max_length))
question = np.random.randint(1, question_vocabulary_size, size=(num_samples,
                            max_length))
answers = np.random.randint(0, 1, size=(num_samples, answer_vocabulary_size))

### Option 1 ###
model.fit([text, question], answers, epochs=10, batch_size=128)

### Option 2 ###
model.fit({'text': text, 'question': question}, answers, epochs=10, batch_size=128)
```

Multi-output Model

- Predict age, income, gender based on the contents of posts



Multi-output Model




```
vocabulary_size = 50000
num_income_groups = 10

posts_input = Input(shape=(None,), dtype='int32', name='posts')
embedded_posts = layers.Embedding(256, vocabulary_size)(posts_input)
x = layers.Conv1D(128, 5, activation='relu')(embedded_posts)
x = layers.MaxPooling1D(5)(x)
x = layers.Conv1D(256, 5, activation='relu')(x)
...
x = layers.Dense(128, activation='relu')(x)

age_prediction = layers.Dense(1, name='age')(x)
income_prediction = layers.Dense(num_income_groups, activation='softmax',
                                 name='income')(x)
gender_prediction = layers.Dense(1, activation='sigmoid', name='gender')(x)

model = Model(posts_input, [age_prediction, income_prediction, gender_prediction])
```

Compiling Model with Multiple Losses

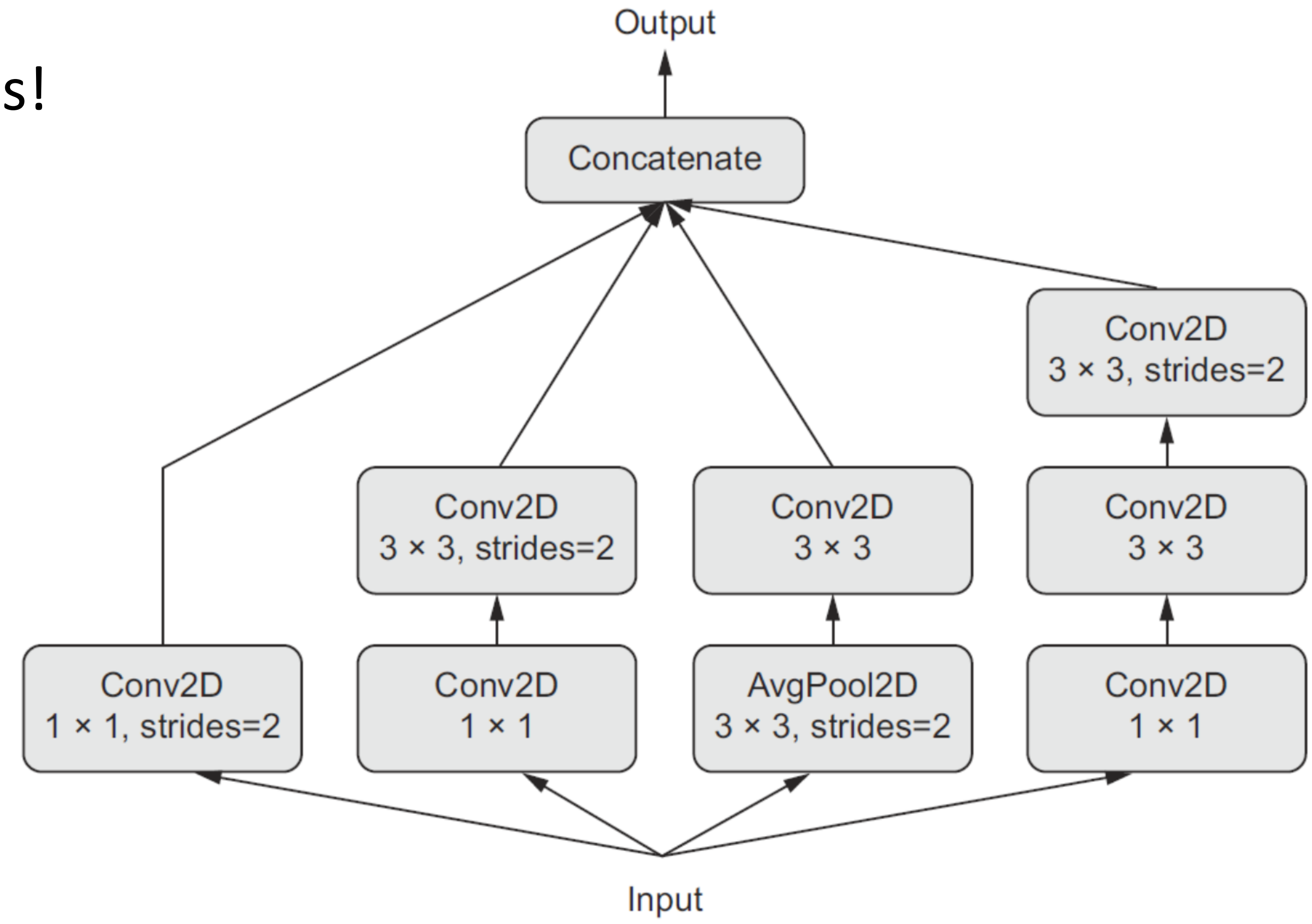
```
### Option 1 ###
model.compile(optimizer='rmsprop',
              loss=['mse', 'categorical_crossentropy', 'binary_crossentropy'])

### Option 2 ###
model.compile(optimizer='rmsprop',
                loss={'age': 'mse',
                      'income': 'categorical_crossentropy',
                      'gender': 'binary_crossentropy'})
```

Compile Model with Loss Weighting

```
model.compile(optimizer='rmsprop',
                loss=['mse', 'categorical_crossentropy', 'binary_crossentropy'],
                loss_weights=[0.25, 1., 10.])

model.compile(optimizer='rmsprop',
                loss={'age': 'mse',
                'income': 'categorical_crossentropy',
                'gender': 'binary_crossentropy'},
                loss_weights={'age': 0.25,
                'income': 1.,
                'gender': 10.})
```

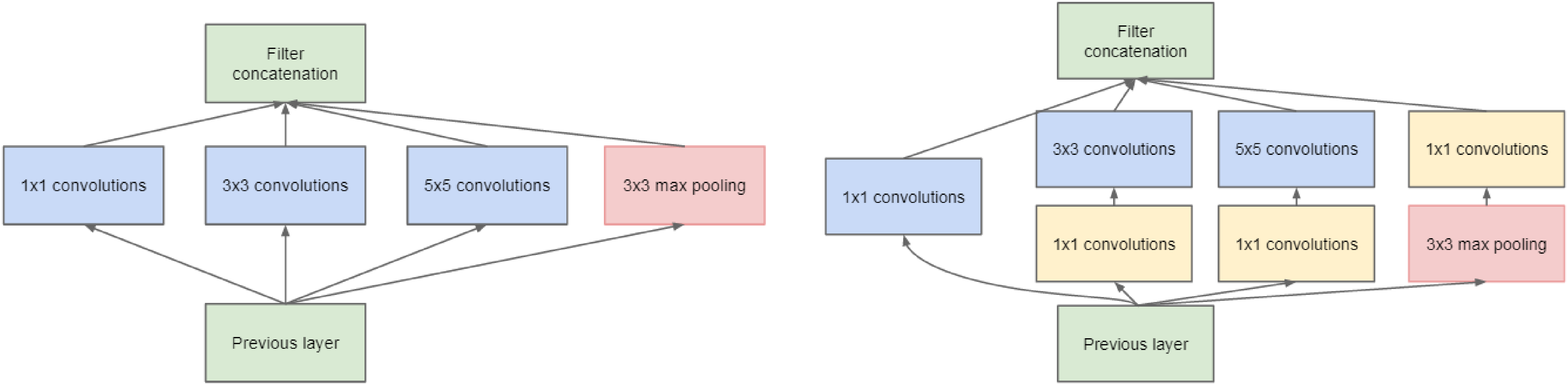
Directed Acyclic Graph of Layers

- Graph can't have cycles!



The Purpose of 1x1 Convolutions

- Reduce the channel dimension



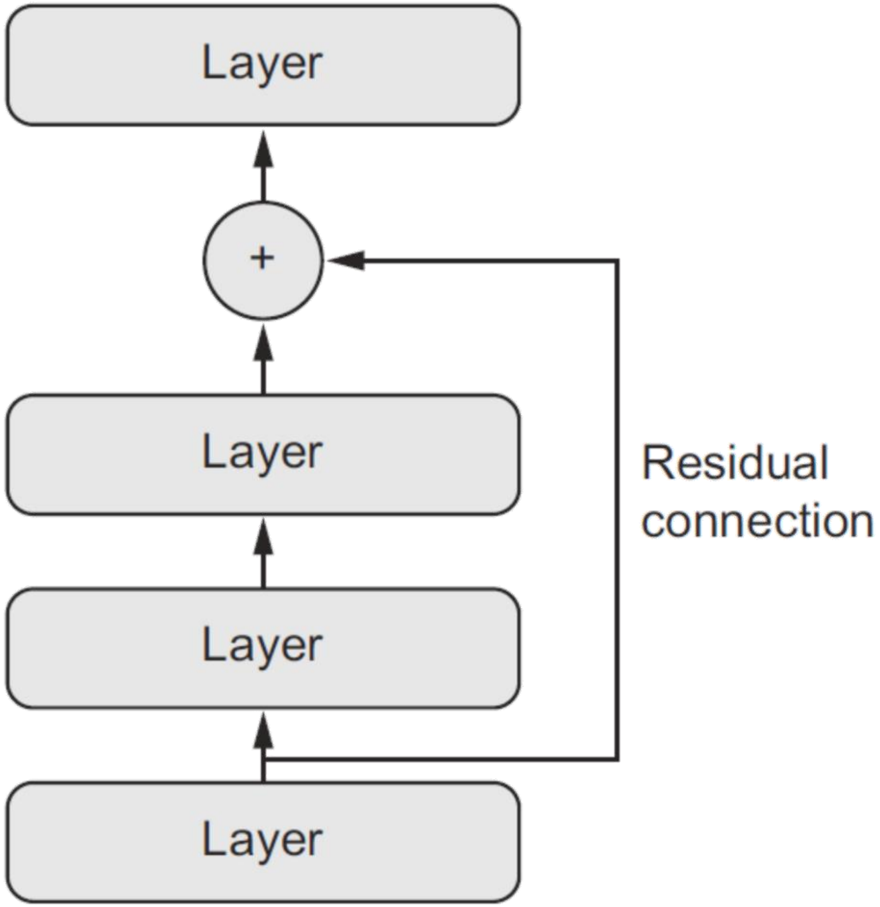
(a) Inception module, naïve version (b) Inception module with dimension reductions

Implement Inception Module

```
from keras import layers
branch_a = layers.Conv2D(128, 1, activation='relu', strides=2)(x)

branch_b = layers.Conv2D(128, 1, activation='relu')(x)
branch_b = layers.Conv2D(128, 3, activation='relu', strides=2)(branch_b)

branch_c = layers.AveragePooling2D(3, strides=2)(x)
branch_c = layers.Conv2D(128, 3, activation='relu')(branch_c)

branch_d = layers.Conv2D(128, 1, activation='relu')(x)
branch_d = layers.Conv2D(128, 3, activation='relu')(branch_d)
branch_d = layers.Conv2D(128, 3, activation='relu', strides=2)(branch_d)

output = layers.concatenate([branch_a, branch_b, branch_c, branch_d], axis=-1)
```

Residual Connection

```
from keras import layers

x = ...
y = layers.Conv2D(128, 3,
                  activation='relu',
                  padding='same')(x)
y = layers.Conv2D(128, 3,
                  activation='relu',
                  padding='same')(y)
y = layers.Conv2D(128, 3,
                  activation='relu',
                  padding='same')(y)

y = layers.add([y, x])
```



Vanishing Gradients in Deep Learning

- A signal becomes smaller after propagated through multi-layers, and may be lost (vanished)

- Solutions:
  - LSTM: using carry track to propagate signal parallel to main track
  - Residual: simple jump connection

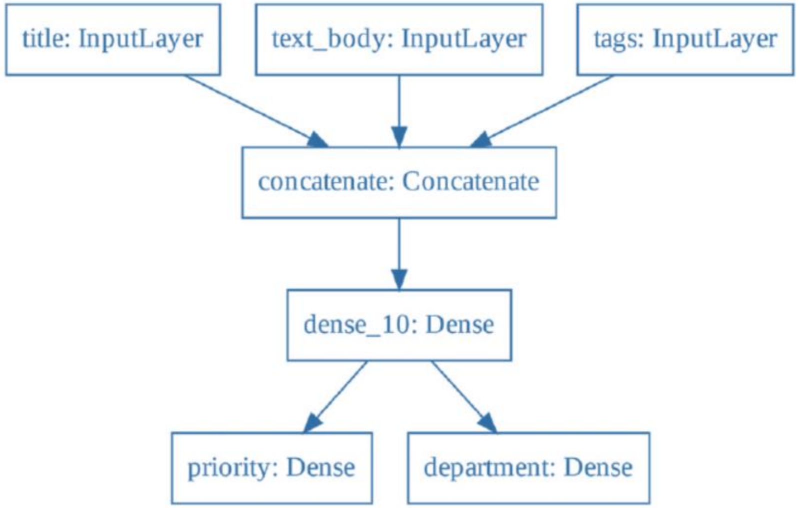
Share layers and models

- Example: dual-camera

```
from keras import layers
from keras import applications
from keras import Input

xception_base = applications.Xception(weights=None, include_top=False)

left_input = Input(shape=(250, 250, 3))
right_input = Input(shape=(250, 250, 3))
# Extract features from left and right cameras
left_features = xception_base(left_input)
right_features = xception_base(right_input)

merged_features = layers.concatenate([left_features, right_ features], axis=-1)
```

Inheriting the Model Class

- Train a model to rank customer support tickets by priority
- In the call() method, define the forward pass of the model




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

    def __init__(self, num_departments):
        super().__init__()
        self.concat_layer = layers.Concatenate()
        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):
        title = inputs["title"]
        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
```

Test Our Custom Model

```
model = CustomerTicketModel(num_departments=4)

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

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})
```

Monitoring Model Training

- Model checkpoint saving
  - Saving the current weights of the model during training
- Early stopping
- Dynamically adjusting parameters
  - Adaptive learning rate during training
- Visualizing the model and data

Using Callbacks

- `EarlyStopping` - interrupts training when accuracy has stopped improving for more than one epoch
- `ModelCheckpoint` - Saves the current weights after every epoch

```
from keras import callbacks

callbacks_list = [
    callbacks.EarlyStopping(monitor='acc', patience=1),
    callbacks.ModelCheckpoint(filepath='my_model.h5', monitor='val_loss',
                                  save_best_only=True)
]

model.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['acc'])
model.fit(x, y, epochs=10, batch_size=32, callbacks=callbacks_list,
          validation_data=(x_val, y_val))
```

ReduceLROnPlateau Callback

- factor – the learning rate is multiplied by factor after pre-defined epochs
- patience – epochs before callback is triggered

```
callbacks_list = [
     callbacks.ReduceLROnPlateau(monitor='val_loss', factor=0.1, patience=10)
]
model.fit(x, y, epochs=10, batch_size=32,
        callbacks=callbacks_list,
        validation_data=(x_val, y_val))
```

Implement Your Own Callback Function

- Inherit keras.callbacks.Callback and implement any number of the following methods
  - on_epoch_begin
  - on_epoch_end
  - on_batch_begin
  - on_batch_end
  - on_train_begin
  - on_train_end

Exmaple: Creating Your Own Logger

```
class ActivationLogger(keras.callbacks.Callback):
    def set_model(self, model):
        self.model = model
        layer_outputs = [layer.output for layer in model.layers]
        self.activations_model = keras.models.Model(model.input, layer_outputs)

    def on_epoch_end(self, epoch, logs=None):
        if self.validation_data is None:
            raise RuntimeError('Requires validation_data.')
        validation_sample = self.validation_data[0][0:1]
        activations = self.activations_model.predict(validation_sample)
        f = open('activations_at_epoch_' + str(epoch) + '.npz', 'w')
        np.savez(f, activations)
        f.close()
```

Tensor Board

- Add TensorBoard callback function and assign log_dir

```
callbacks = [
    keras.callbacks.TensorBoard(log_dir='my_log_dir', histogram_freq=1,
                                embeddings_freq=1)
]

history = model.fit(x_train, y_train, epochs=20, batch_size=128,
                    validation_split=0.2, callbacks=callbacks)
```

- Run command => $ tensorboard --logdir=`my_log_dir` --host localhost

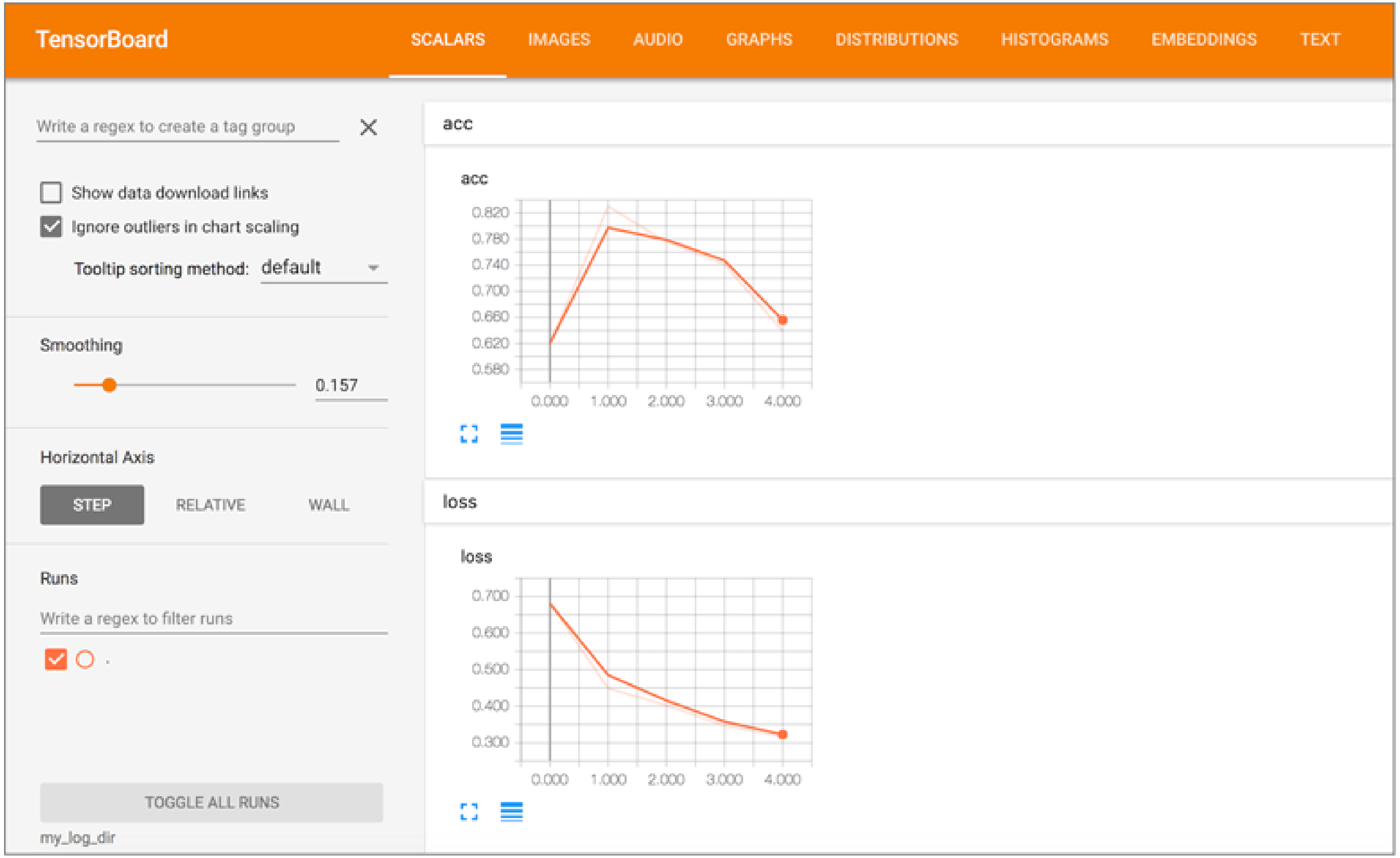
Example: Text Classification with TensorBoard (2-1)

```
import keras
import numpy as np
from keras import layers
from keras.datasets import imdb
from keras.preprocessing import sequence
max_features = 2000
max_len = 500
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=max_features)
x_train = sequence.pad_sequences(x_train, maxlen=max_len)
x_test = sequence.pad_sequences(x_test, maxlen=max_len)

model = keras.models.Sequential()
model.add(layers.Embedding(max_features, 128, input_length=max_len, name='embed'))
model.add(layers.Conv1D(32, 7, activation='relu'))
model.add(layers.MaxPooling1D(5))
model.add(layers.Conv1D(32, 7, activation='relu'))
model.add(layers.GlobalMaxPooling1D())
model.add(layers.Dense(1))
model.summary()
```

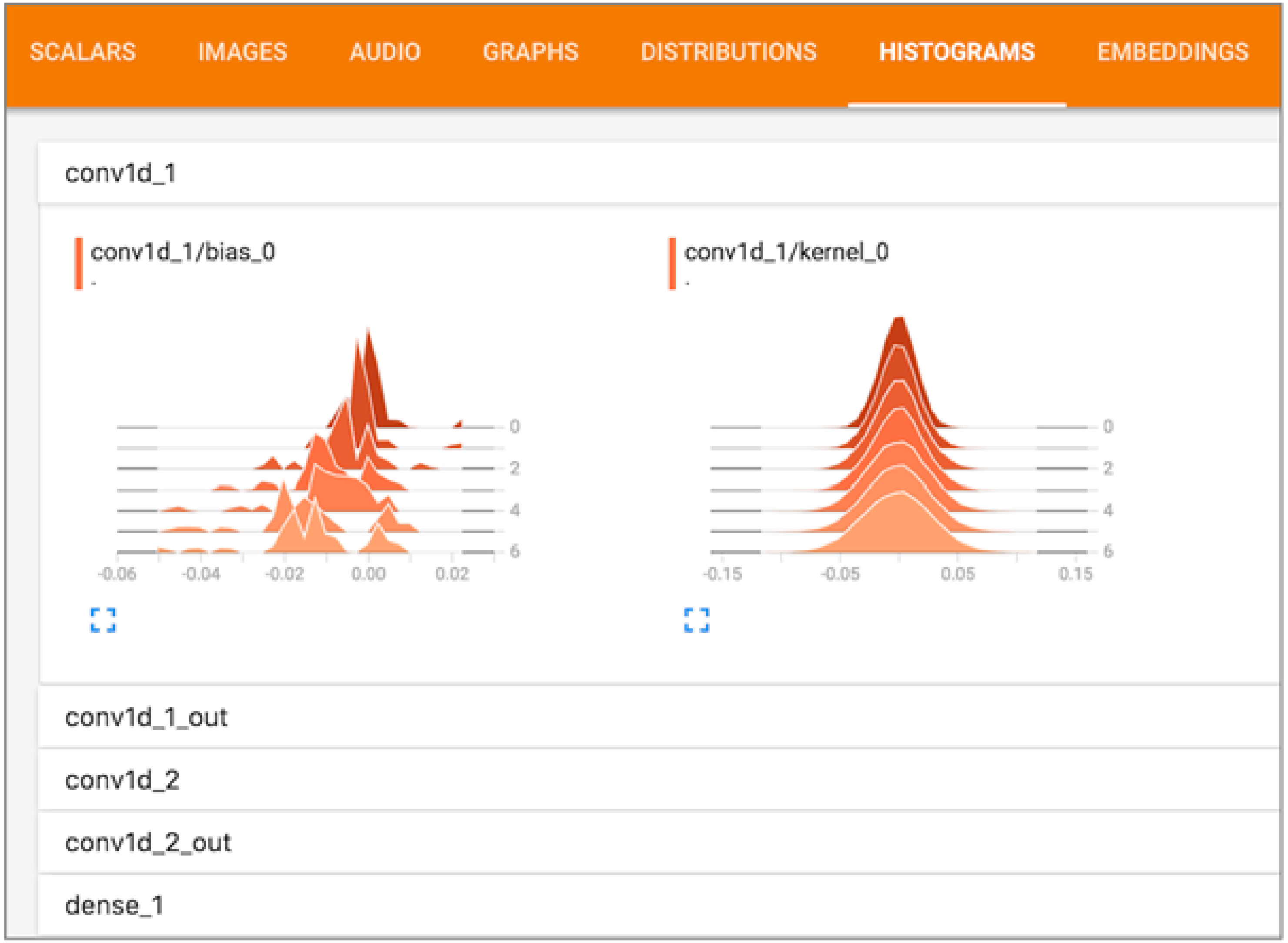
Example: Text Classification with TensorBoard (2-2)

```
…
model.compile(optimizer='rmsprop',
                loss='binary_crossentropy',
                metrics=['acc'])

callbacks = [
    keras.callbacks.TensorBoard(
        log_dir='my_log_dir',
        histogram_freq=1,
        embeddings_freq=1,
        embeddings_data = np.arange(0, max_len).reshape((1, max_len)),
    )
]
history = model.fit(x_train, y_train,
        epochs=20,
        batch_size=128,
        validation_split=0.2,
        callbacks=callbacks)
```

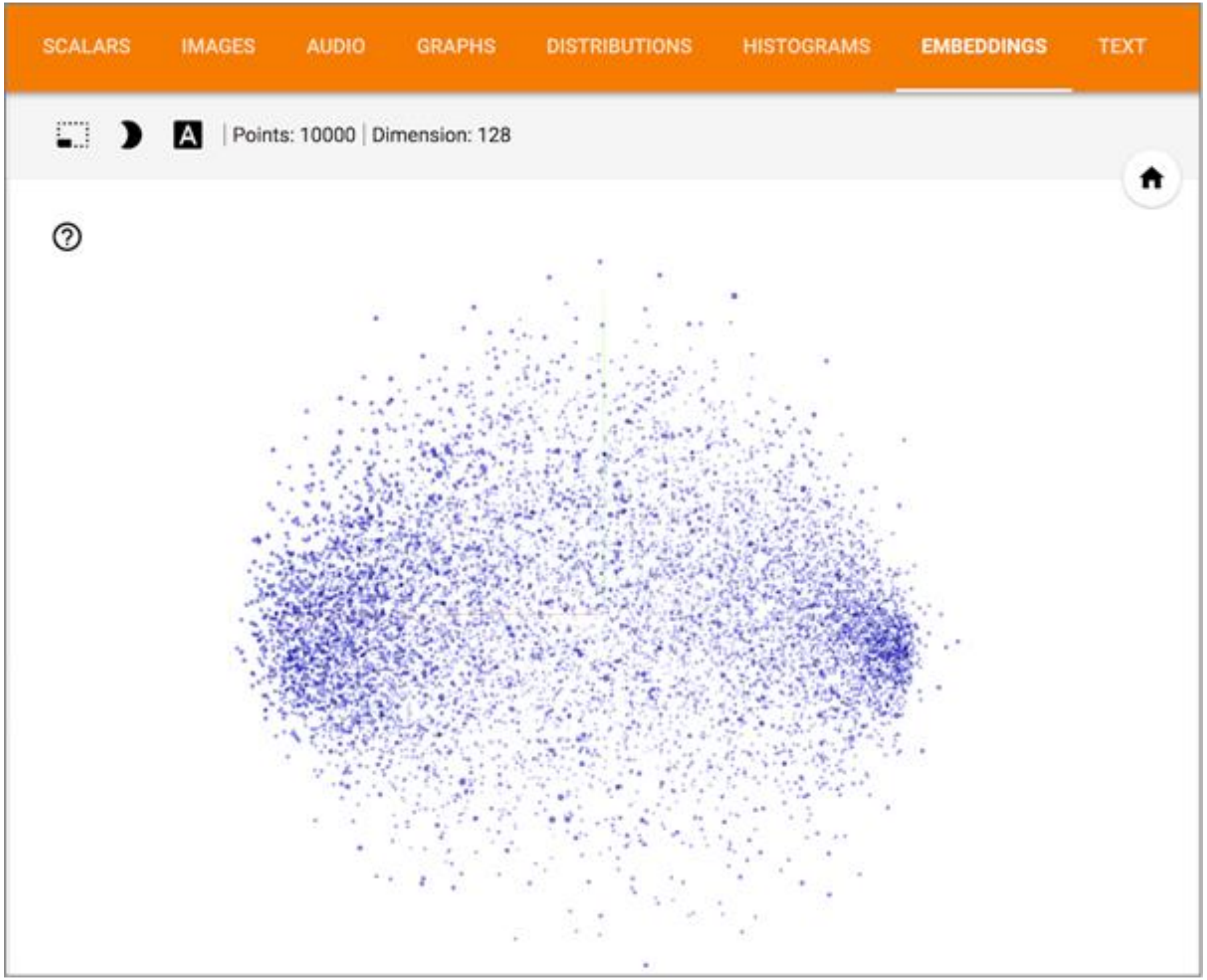
TensorBoard: Accuracy and Loss



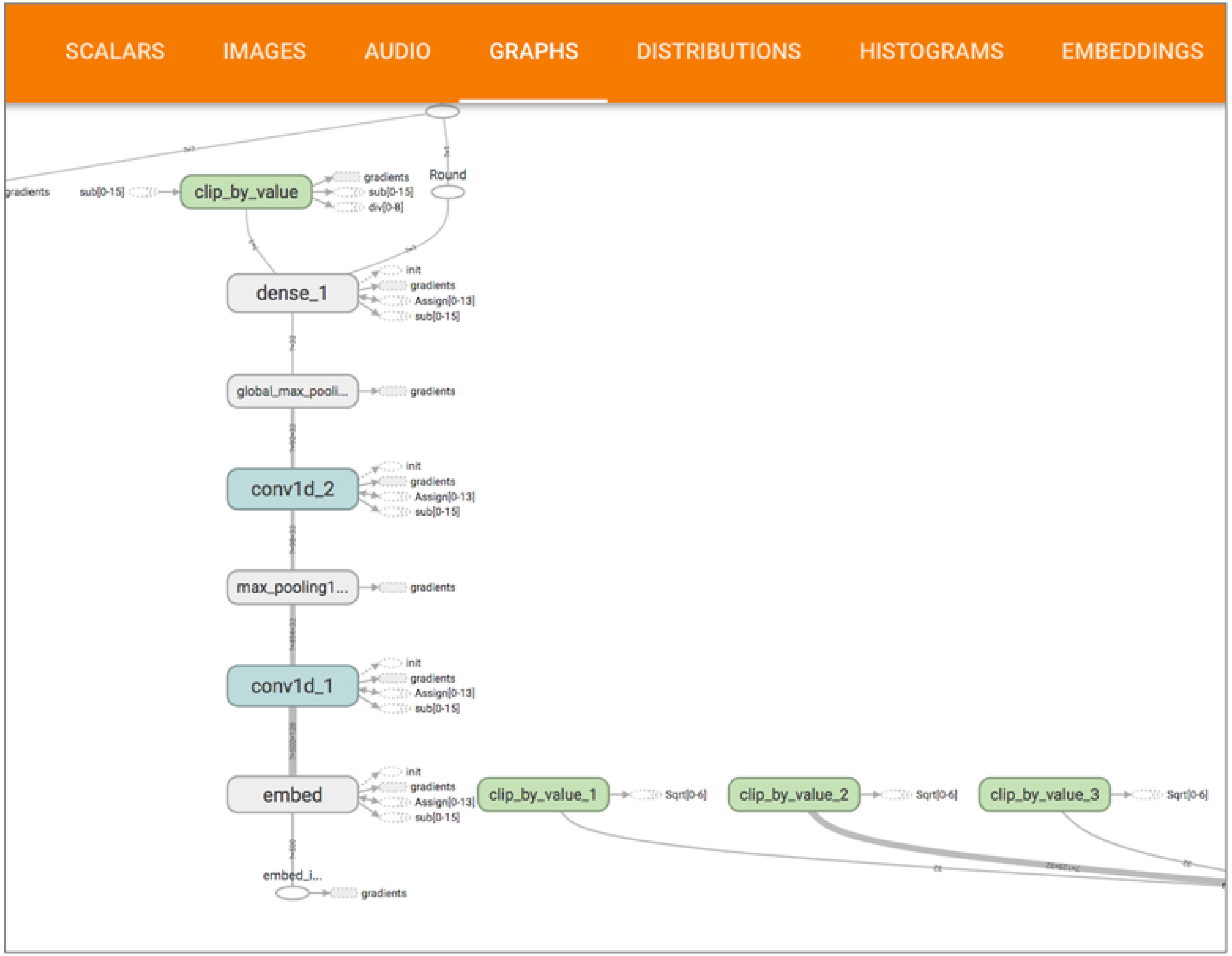
TensorBoard: Activation Histograms



TensorBoard: Word-embedding Visualization

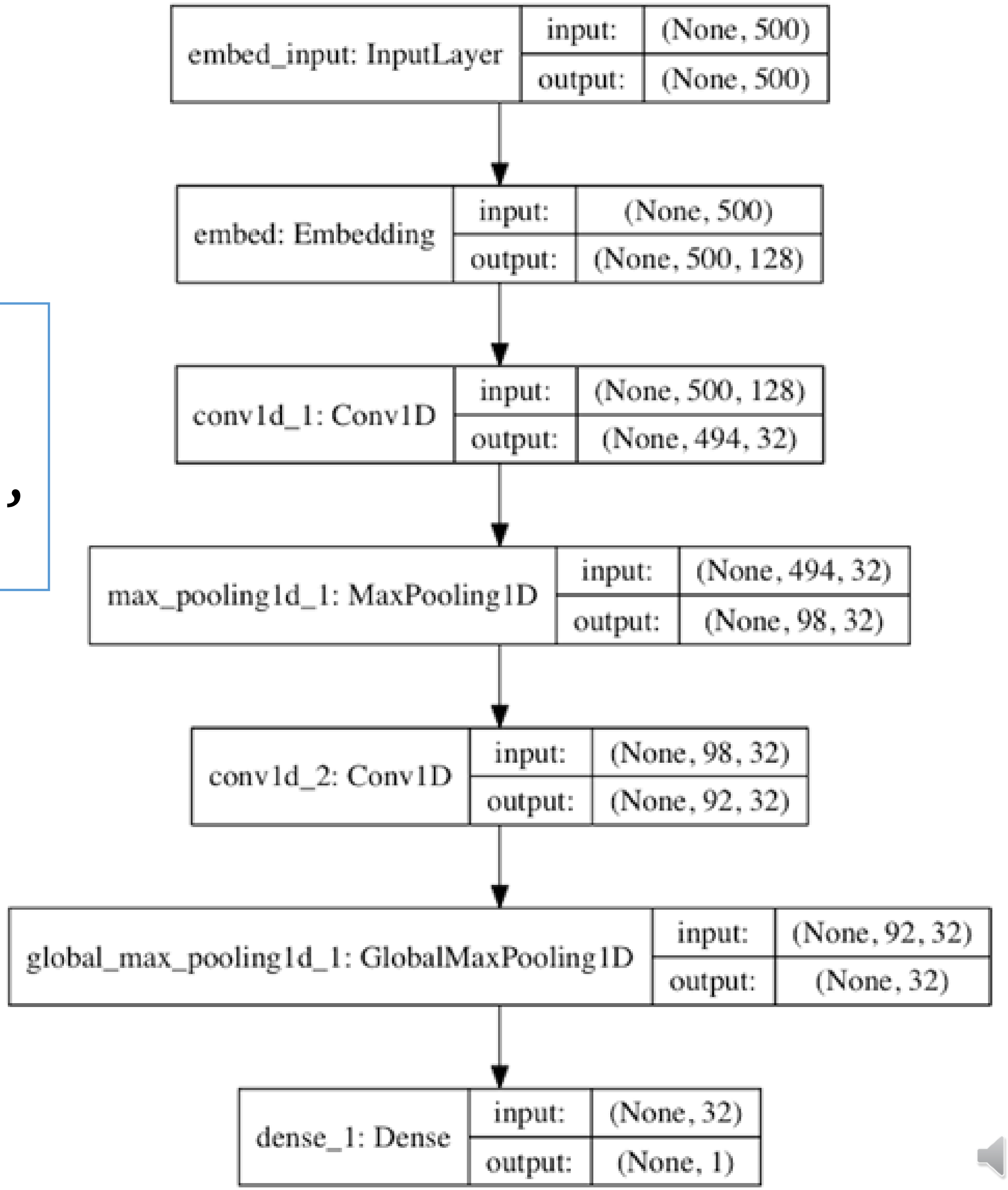


TensorBoard: Network Graph Visualization



Keras plot_model

```
from keras.utils import plot_model

plot_model(model, show_shapes=True,
              to_file='model.png')
```



Batch Normalization

- Sergey Ioffe and Christian Szegedy, "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift," *ICML,* 2015 (https://arxiv.org/abs/1502.03167).
- Normalizing data after every transformation
- Enhance back propagation
- Some deep networks can only be trained with batch normalization

```
conv_model.add(layers.Conv2D(32, 3, activation='relu'))
conv_model.add(layers.BatchNormalization())

dense_model.add(layers.Dense(32, activation='relu'))
dense_model.add(layers.BatchNormalization())
```

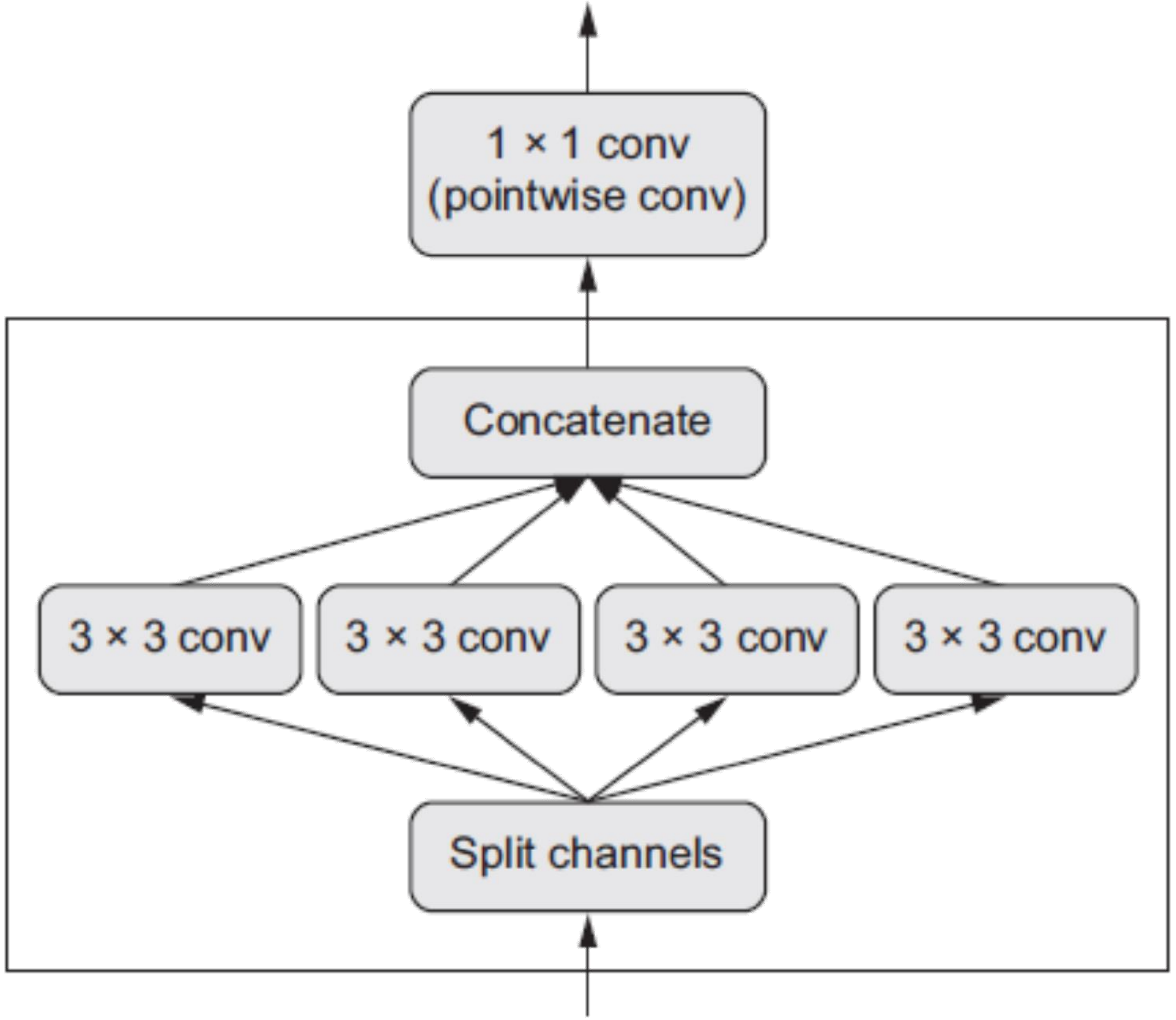
Batch Renormalization

- Sergey Ioffe, “Batch Renormalization: Towards Reducing Minibatch Dependence in Batch-Normalized Models,” 2017, https://arxiv.org/abs/1702.03275.

- Günter Klambauer et al., “Self-Normalizing Neural Networks,” *NIPS*, 2017, https://arxiv.org/abs/1706.02515 .

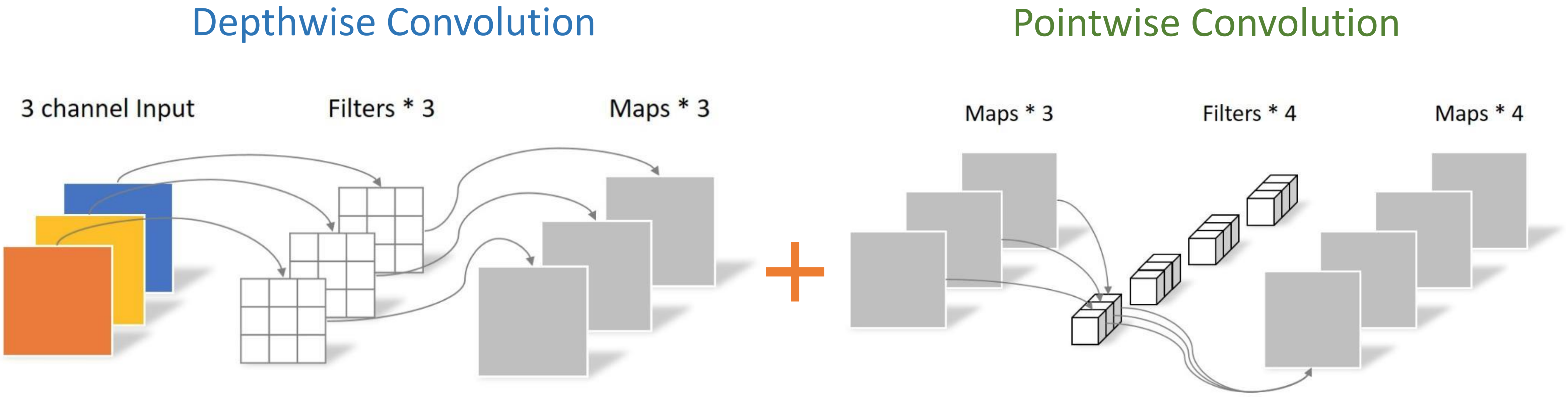
Depthwise Separable Convolution

- Separating the learning of spatial features and channel-wise features
- Less parameters, slightly better accuracy
- Francois Chollet, "Xception: Deep Learning with Depthwise Separable Convolutions," *CVPR*, 2018



Xception - Separable Convolution (2017)

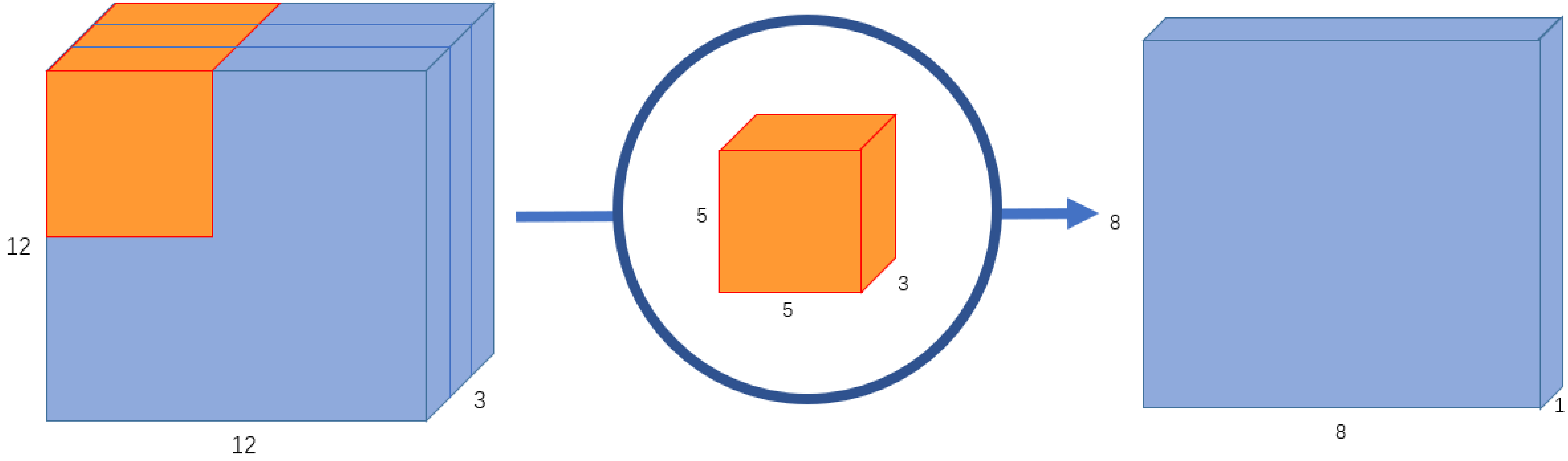
- Assume that cross-channel correlations and spatial correlations can be mapped completely separately



https://towardsdatascience.com/a-basic-introduction-to-separable-convolutions-b99ec3102728

Normal Convolution of 1 Kernel

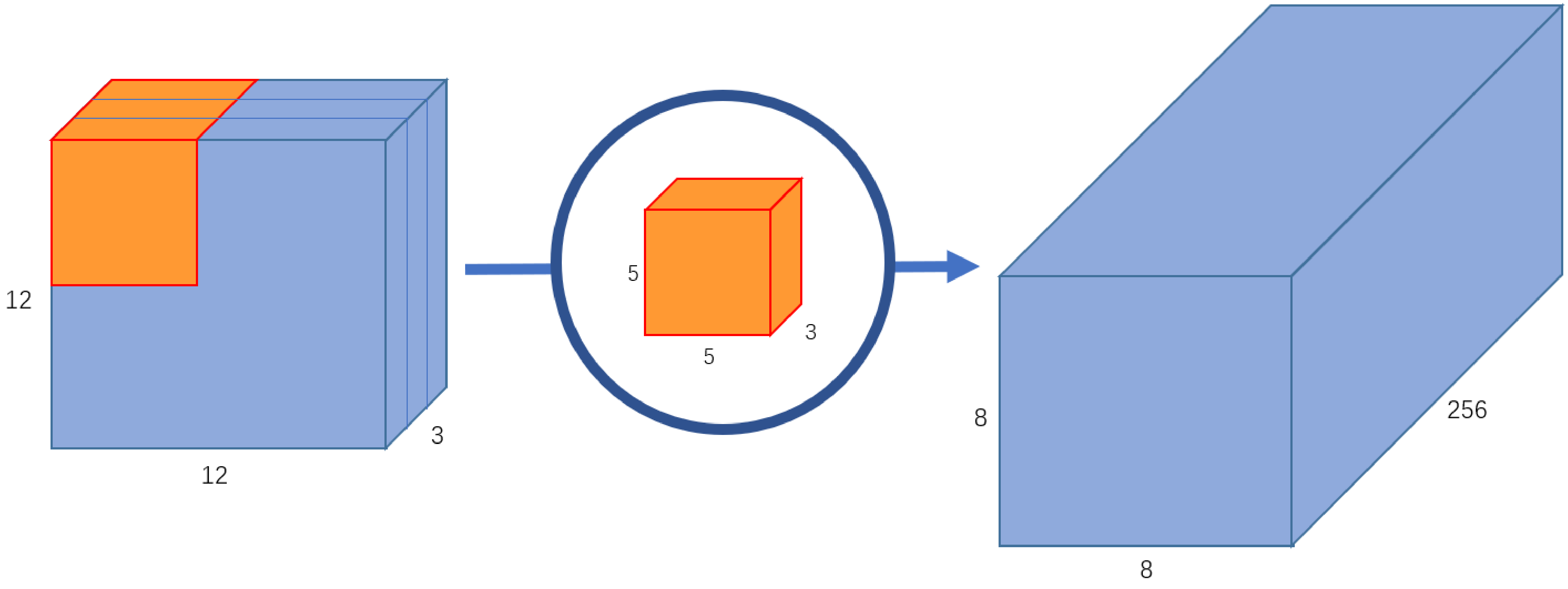
- Normal Convolution of 5*5*3 kernel



https://towardsdatascience.com/a-basic-introduction-to-separable-convolutions-b99ec3102728

Normal Convolution of 256d Output Channels

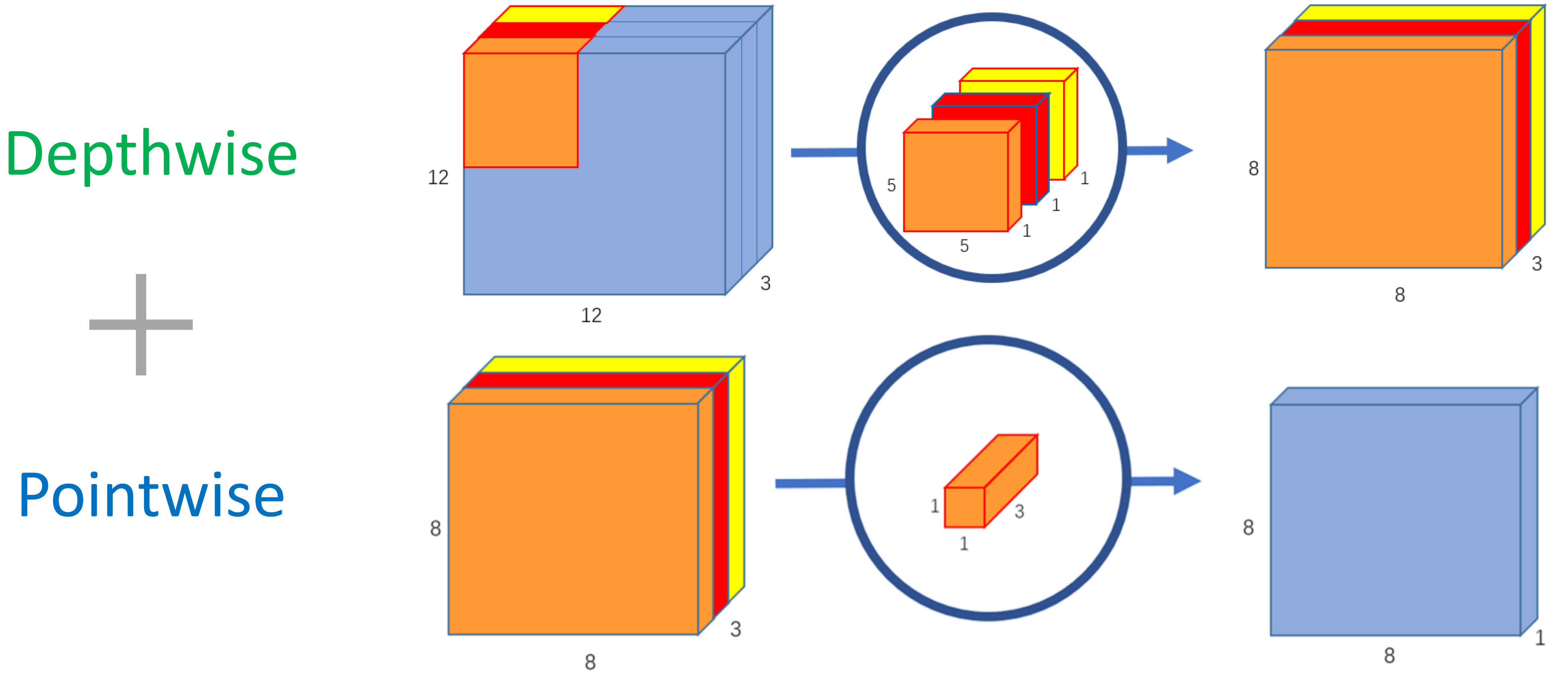
- Require 256 * (5*5*3+1) = 19,456 parameters!



https://towardsdatascience.com/a-basic-introduction-to-separable-convolutions-b99ec3102728

Separable Convolution

- Two steps:
  1. Depthwise: (5*5*1)*3
  2. Pointwise: (1*1*3+1)*256

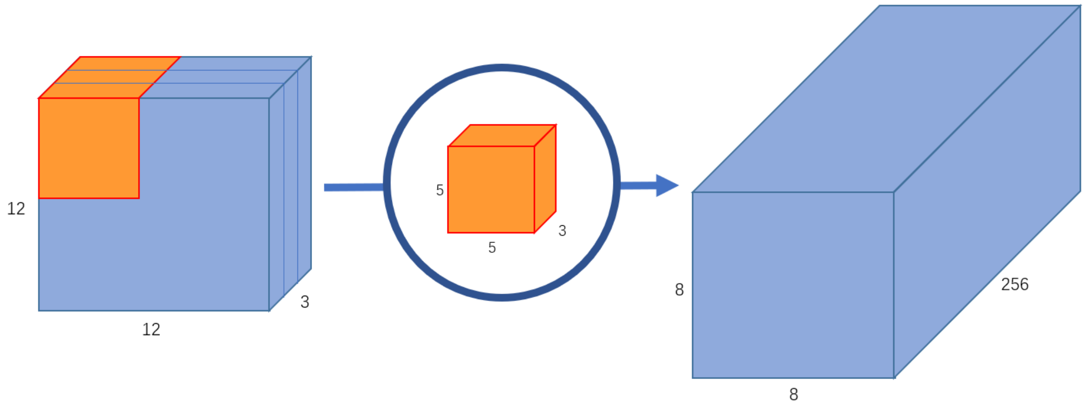


Normal Convolution vs. Depthwise Separable

- Normal filer size:

$$(5*5*3 + {\color{red}1})*256$$
$$=19,456$$

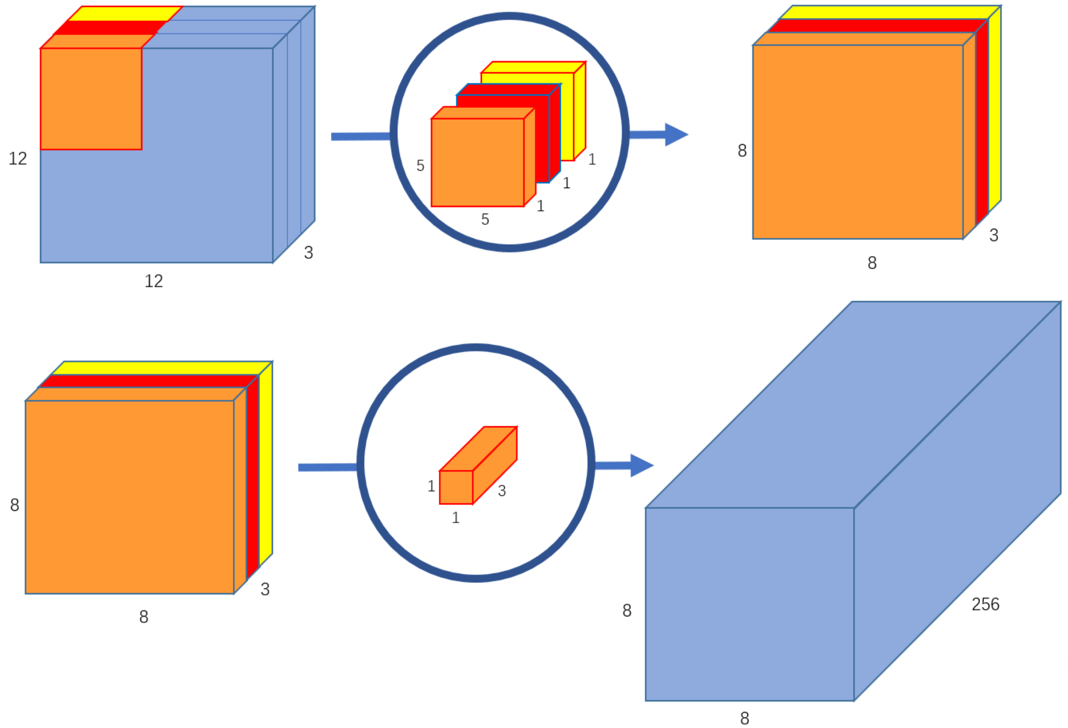
*Bias=1



- Depthwise + Pointwise filter size:

$$(5*5*1)*3 + (1*1*3+{\color{red}1})*256$$
$$=1099$$

*Bias=1



Test Separable Convolution in Colab

- SeparableConv2D()

```
import tensorflow as tf
from tensorflow.keras import layers
```

[11]
```
model = tf.keras.Sequential()
model.add(layers.SeparableConv2D(256, (5, 5), use_bias=True, input_shape=(12, 12, 3)))
model.add(layers.Flatten())
model.add(layers.Dense(10, activation="Softmax"))
model.summary()
```

```
Model: "sequential_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
separable_conv2d_3 (Separabl (None, 8, 8, 256)         1099
_________________________________________________________________
flatten_5 (Flatten)          (None, 16384)             0
_________________________________________________________________
dense_5 (Dense)              (None, 10)                163850
=================================================================
Total params: 164,949
Trainable params: 164,949
Non-trainable params: 0
_________________________________________________________________
```

[12]
```
model = tf.keras.Sequential()
model.add(layers.Conv2D(256, (5, 5), activation='relu', input_shape=(12, 12, 3)))
model.add(layers.Flatten())
model.add(layers.Dense(10, activation="Softmax"))
model.summary()
```

```
Model: "sequential_6"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_2 (Conv2D)            (None, 8, 8, 256)         19456
_________________________________________________________________
flatten_6 (Flatten)          (None, 16384)             0
_________________________________________________________________
dense_6 (Dense)              (None, 10)                163850
=================================================================
Total params: 183,306
Trainable params: 183,306
Non-trainable params: 0
_________________________________________________________________
```

Hyperparameter Optimization

- Use random search, genetic algorithm, Bayesian optimization to find best parameters for your model
- Hyperopt (https://github.com/hyperopt/hyperopt)
- Hyperas (https://github.com/maxpumperla/hyperas)
  - Varying dropout probabilities, sampling from a uniform distribution
  - Different layer output sizes
  - Different optimization algorithms to use
  - Varying choices of activation functions
  - Conditionally adding layers depending on a choice
  - Swapping whole sets of layers

Model Ensembling

- Combine the outputs of multiple models (a.k.a late fusion)
  - Random forest
  - Gadient-boosted trees
  - Wide and deep model

Key Takeaways

- Use Keras API to go beyond Sequential().
- Keras callbacks provide a simple way to monitor model training.
- You can control what fit() does by overriding the train_step() method.
- Beyond fit(), researchers can write their own training loops entirely from scratch for brand-new training algorithms.
- Separable convolution can reduce model parameters with same accuracy.

References

- Francois Chollet, “Deep Learning with Python,” Chapter 7
- Francois Chollet, “Deep Learning with Python, 2nd Edition” Chapter 7
- https://towardsdatascience.com/a-basic-introduction-to-separable-convolutions-b99ec3102728