Keras Functional API

Tensors: Mathematics vs TensorFlow

Different notions of tensors:

- Mathematical: N-D grid of values.
  - 1D: vector
  - 2D: matrix
- TensorFlow:
  - Data structure that can produce a mathematical tensor when “called”
  - Internals: tensor shape + a reference to the object that can produce the value
    - Forms the basis of the data-flow graph that represents the computation that your network performs

Data Flow Graphs

- Node: performs some computation or stores information
  - Inputs are TF tensors that link to the source of the inputs
  - Output(s) can be referenced by other nodes (as TF tensors)
- Some nodes take input from outside the graph (e.g., the input/output pairs used for training)
- Some nodes only provide output to outside the graph (e.g., an output layer)

Programming with TensorFlow Graphs

- Sequential class handles a lot of the details implicitly
  - Only allows us to specify particular types of networks
  - We must anticipate the correct order of the operations
- The Keras Model API to build our own networks with somewhat arbitrary topologies

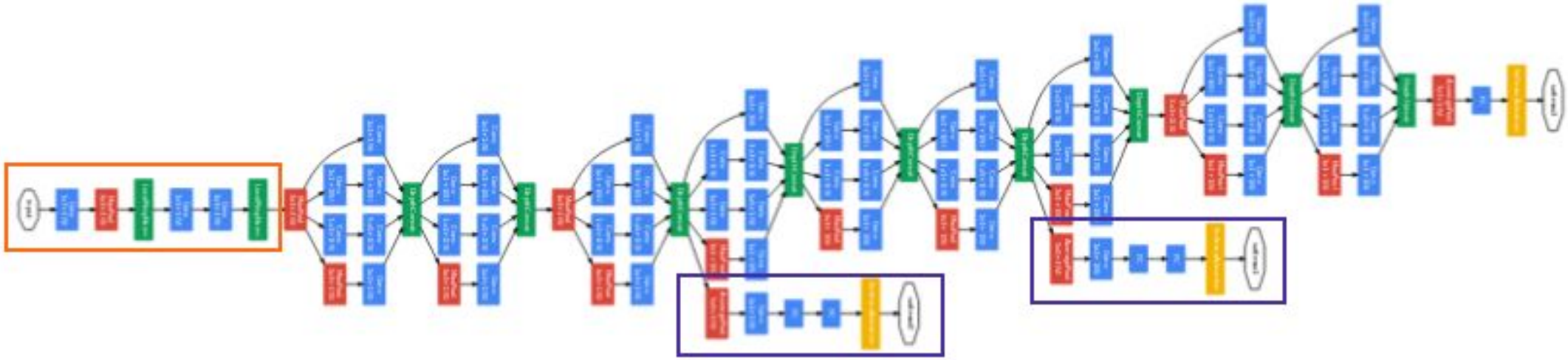
Key Magic of the Model API (#1)

An instantiated layer object is “callable”

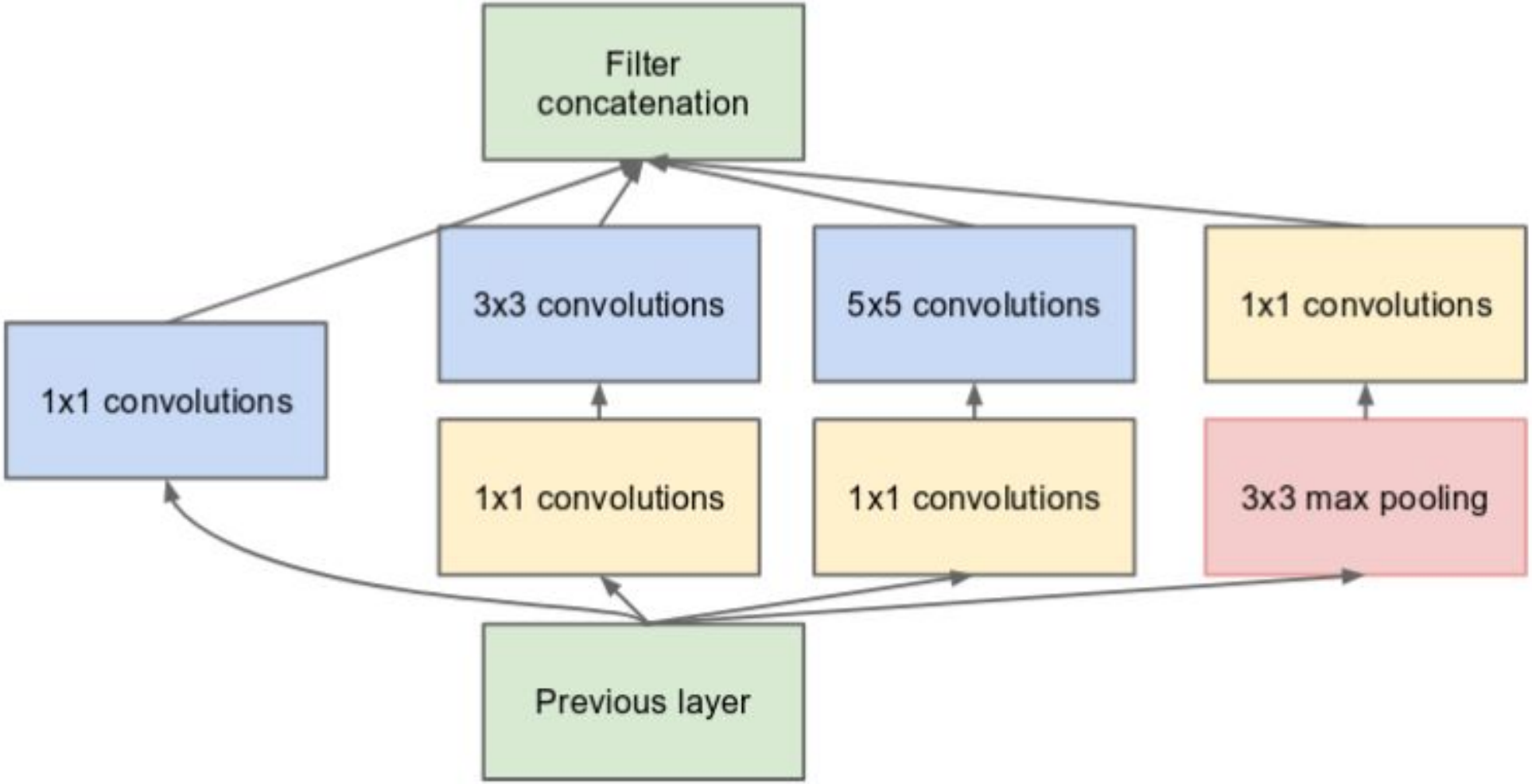
- Takes as input a TF tensor
- Returns a TF tensor

```
input_tensor = Input(shape=some_shape, name="input")
layer = Dense(50, …)
tensor = layer(input_tensor)
```

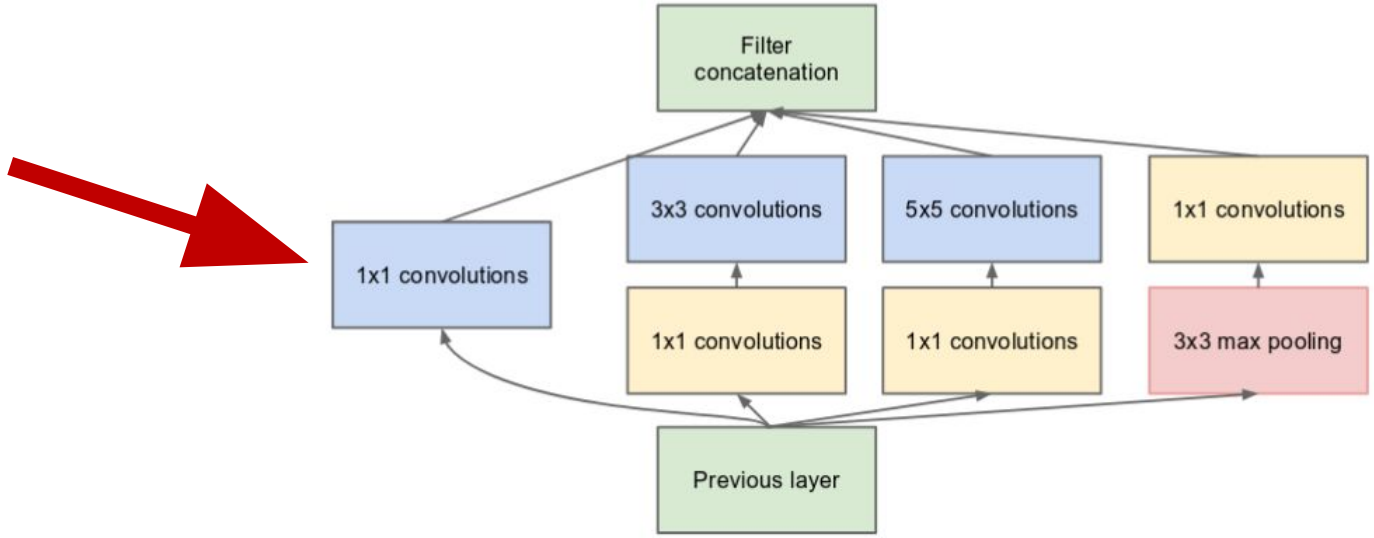
Example: Very Deep Networks (Inception)



Inception Module



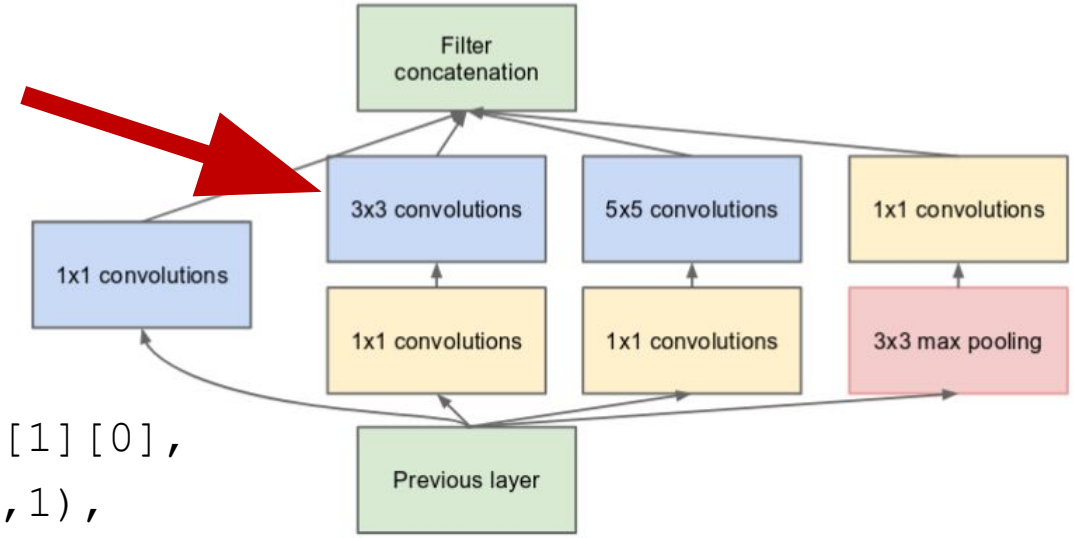
Branch A




```
def inception_module(input_tensor, nfilters, activation,
            lambda_regularization, name):

   convA_tensor = Convolution2D(filters=nfilters[0],
                                kernel_size=(1,1),
                                strides=(2,2),
                                padding='same',
                                name = 'convA_'+name,
                                activation=activation,
                                …  )(input_tensor)
```

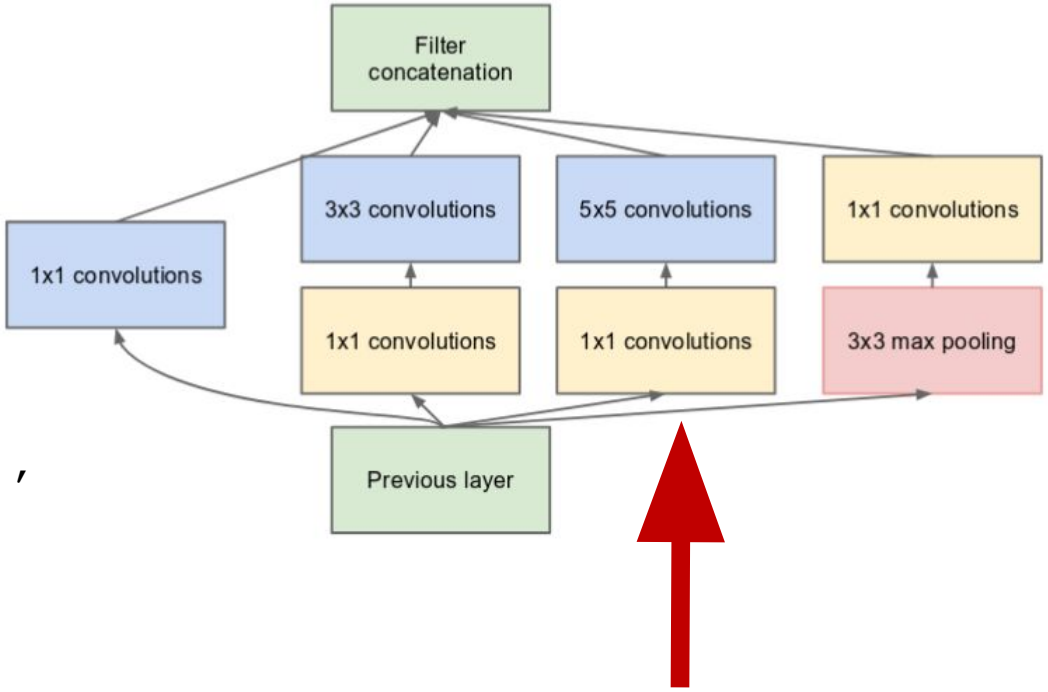
Branch B




```
convB0_tensor = Convolution2D(filters=nfilters[1][0],
                              kernel_size=(1,1),
                              strides=(1,1),
                              padding='same',
                            name = 'convB0_'+name,
                          activation=activation,
                          … ))(input_tensor)

convB1_tensor = Convolution2D(filters=nfilters[1][1],
                              kernel_size=(3,3),
                              strides=(2,2),
                              padding='same',
                            name = 'convB1_'+name,
                              activation=activation,
                              …  )(convB0_tensor)
```

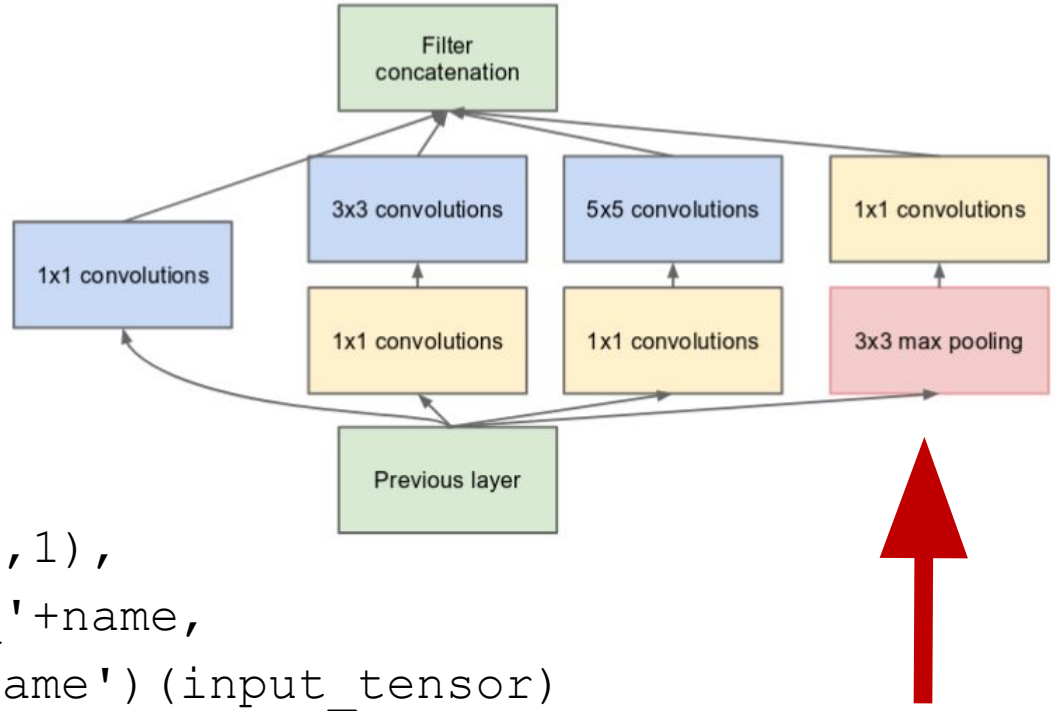
Branch C




```
convC0_tensor = Convolution2D(filters=nfilters[2][0],
                              kernel_size=(1,1),
                              strides=(1,1),
                              padding='same',
                            activation=activation,
                             name = 'convC0_'+name,
                             … ))(input_tensor)

convC1_tensor = Convolution2D(filters=nfilters[2][1],
                              kernel_size=(5,5),
                              strides=(2,2),
                              padding='same',
                            name = 'convC1_'+name,
                              activation=activation,
                            …  )(convC0_tensor)
```

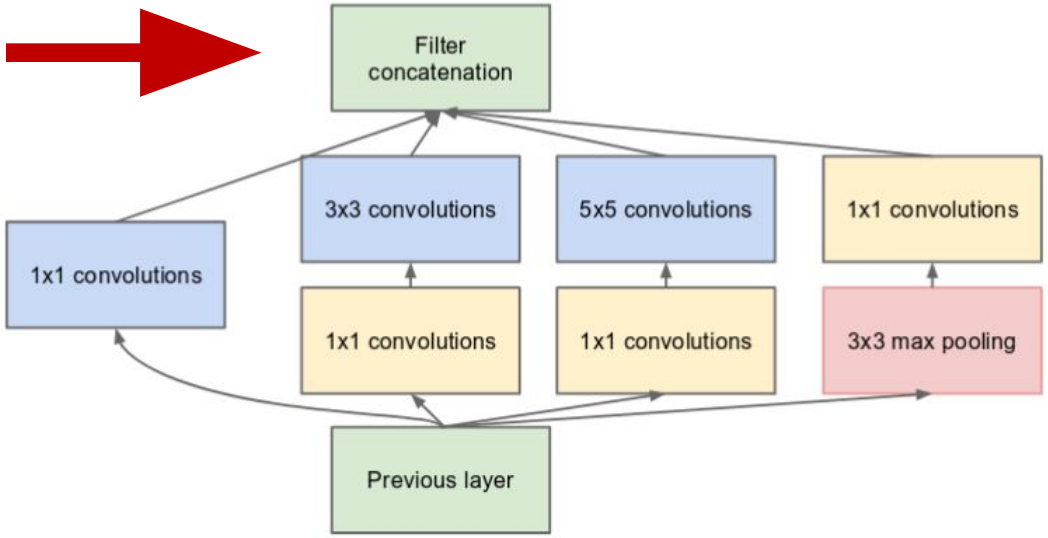
Branch D




```
max_tensor = MaxPooling2D(pool_size=(3,3),
                          strides=(1,1),
                          name='MAX_'+name,
                          padding='same')(input_tensor)

convD1_tensor = Convolution2D(filters=nfilters[3],
                              kernel_size=(1,1),
                              strides=(2,2),
                              padding='same',
                              name = 'convD0_'+name,
                              activation=activation,
                              … )(max_tensor)
```

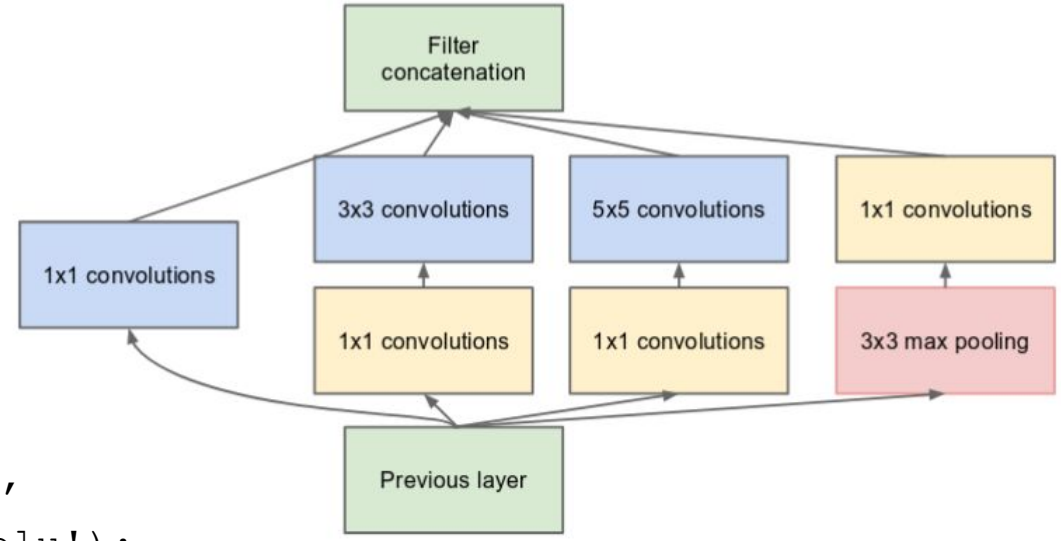
Concatenation




```
output_tensor = Concatenate()
    ([convA_tensor, convB1_tensor, convC1_tensor, convD1_tensor])

return output_tensor
```

Building an Image Classifier




```
def create_inception_network(image_size, n_channels,
                             lambda_regularization, activation='elu'):

    input_tensor = Input(shape=(image_size[0], image_size[1], n_channels), name="input")

    i1_tensor = inception_module(input_tensor, (10, (10,10), (10,10), 10), activation,
                                 lambda_regularization, name="i1")

    i2_tensor = inception_module(i1_tensor, (40, (40,40), (40,40), 40), activation,
                                 lambda_regularization, name="i2")

    flatten_tensor = GlobalMaxPooling2D()(i2_tensor)
```

Building an Image Classifier II

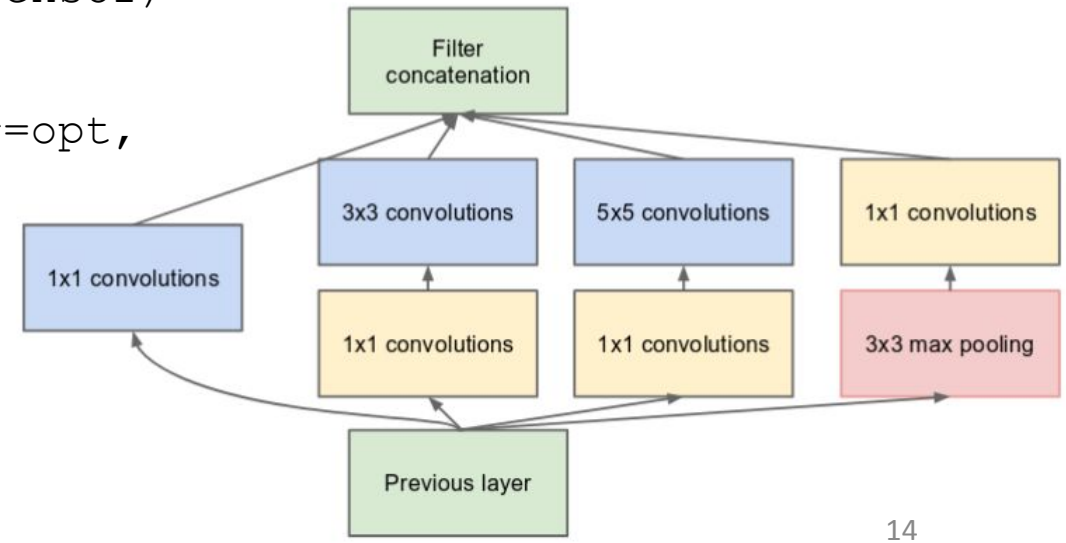
```
dense1_tensor = Dense(units=100, activation=activation, name = "D1", … ) (flatten_tensor)
dense2_tensor = Dense(units=20, activation=activation, name = "D2", … ) (dense1_tensor)
output_tensor = Dense(units=1, activation='sigmoid', name = "output", … ) (dense2_tensor)

opt = keras.optimizers.Adam(lr=0.0001, amsgrad=False)

model = Model(inputs=input_tensor, outputs=output_tensor)

model.compile(loss='binary_crossentropy', optimizer=opt,
                  metrics=['accuracy'])

print(model.summary())
return model
```



Layer (type)	Output Shape	Param #	Connected to
input (InputLayer)	(None, 32, 32, 3)	0	
convB0_i1 (Conv2D)	(None, 32, 32, 10)	40	input[0][0]
convC0_i1 (Conv2D)	(None, 32, 32, 10)	40	input[0][0]
MAX_i1 (MaxPooling2D)	(None, 32, 32, 3)	0	input[0][0]
convA_i1 (Conv2D)	(None, 16, 16, 10)	40	input[0][0]
convB1_i1 (Conv2D)	(None, 16, 16, 10)	910	convB0_i1[0][0]
convC1_i1 (Conv2D)	(None, 16, 16, 10)	2510	convC0_i1[0][0]
convD0_i1 (Conv2D)	(None, 16, 16, 10)	40	MAX_i1[0][0]
concatenate_14 (Concatenate)	(None, 16, 16, 40)	0	convA_i1[0][0] convB1_i1[0][0] convC1_i1[0][0] convD0_i1[0][0]
convB0_i2 (Conv2D)	(None, 16, 16, 40)	1640	concatenate_14[0][0]
convC0_i2 (Conv2D)	(None, 16, 16, 40)	1640	concatenate_14[0][0]
MAX_i2 (MaxPooling2D)	(None, 16, 16, 40)	0	concatenate_14[0][0]
convA_i2 (Conv2D)	(None, 8, 8, 40)	1640	concatenate_14[0][0]
convB1_i2 (Conv2D)	(None, 8, 8, 40)	14440	convB0_i2[0][0]
convC1_i2 (Conv2D)	(None, 8, 8, 40)	40040	convC0_i2[0][0]
convD0_i2 (Conv2D)	(None, 8, 8, 40)	1640	MAX_i2[0][0]
concatenate_15 (Concatenate)	(None, 8, 8, 160)	0	convA_i2[0][0] convB1_i2[0][0] convC1_i2[0][0] convD0_i2[0][0]
flatten_7 (Flatten)	(None, 10240)	0	concatenate_15[0][0]
D1 (Dense)	(None, 100)	1024100	flatten_7[0][0]
D2 (Dense)	(None, 20)	2020	D1[0][0]

Total params: 1,090,761

Inception Modules in Practice

In my implementation:

- No striding within the inception module
  - Perform striding only after the full module, if it is called for
- Padding=’same’
  - Keeps the dimensions the same across the different branches
- Allow for other parallel sequences
- Can specify all of these details at the command line, too!

Functional API: Multiple Input Tensors

Model construction:

- Create multiple Input objects
- Ideally, these are named

```
input_tensor1 = Input(shape=(image_size[0], image_size[1], n_channels),
                      name="input1")
input_tensor2 = Input(shape=(image_size[0], image_size[1], n_channels),
                      name="input2")
```

- Model creation: provide list of Input objects

```
model = Model(inputs=[input_tensor1, input_tensor2],
              outputs=output_tensor)
```

Functional API: Multiple Input Tensors

Model use:

- Provide list of inputs (in order):

```
model.fit([ins1, ins2], outs)
pred = model.predict([ins1, ins2])
```

- Or provide a dict:

```
ins_dict = {‘input1’: ins1, ‘input2’: ins2}
model.fit(ins_dict, outs)
pred = model.predict(ins_dict)
```

- Or provide a TF Dataset can be configured to generate the input tuples
  - The DataSet will be of this form ((in1, in2), out)

Functional API: Multiple Output Tensors

- model.fit/predict: mechanics are the same as for the multiple Input case
  - Provide a list or a dict in place of single numpy arrays
- model.compile():
  - desired output: one for each model output
  - loss: one for each output
  - Again, provide as list or a dict
  - loss_weights: weights for each loss in computing the aggregate loss. This aggregate loss is what is optimized

Functional API: Sharing Parameters of a Layer

- In some cases, we want to have the same sub-network placed in different locations within a larger network
- If these sub-networks perform the same function, but with different data, it makes sense for us to use the same parameters for both

Sharing Parameters of a Layer

```
input_tensor1 = Input(shape=(1000,), name="input1")
input_tensor2 = Input(shape=(1000,), name="input2")

# Create a dense layer
dense = Dense(units=100, activation='elu')

# Use the dense layer for two pathways
dense1_tensor = dense(input_tensor1)
dense2_tensor = dense(input_tensor2)

# Use dense1_tensor and dense2_tensor together to compute a model output
```

Gradients passing through both dense1/dense2_tensor will result in changes to the parameters of dense

Functional API: Models are Layers! (Magic #2)

- Any model can be used as a sub-component of a larger model
- Instantiated models are callable:
  - A model takes as input one or more tensors and returns one or more tensors
- During training, error information is propagated through these sub-components and trainable parameters are adjusted

Example: Two-Image Inception

Use our inception model as is, except cut off last dense layers:

- inception -> inception -> flatten -> dense(100)

New model:

- Takes two consecutive images as input
- Each image is passed through the same inception model
- Results are concatenated
- Several dense layers (down to classification)

Example: Modified Inception Model

```
def create_inception_subnetwork(image_size, n_channels, lambda_regularization,
activation='elu'):
    input_tensor = Input(shape=(image_size[0], image_size[1], n_channels), name="input")

    i1_tensor = inception_module(input_tensor, (10, (10,10), (10,10), 10), activation,
                                 lambda_regularization, name="i1")

    i2_tensor = inception_module(i1_tensor, (40, (40,40), (40,40), 40), activation,
                                 lambda_regularization, name="i2")

    flatten_tensor = Flatten()(i2_tensor)
    dense1_tensor = Dense(units=100, name = "D1", … )) (flatten_tensor)
    model = Model(inputs=input_tensor, outputs=dense1_tensor)

    return model
```

Example: Dual-Input Classifier

```
def create_dual_input_network(image_size, n_channels, lambda_regularization,
activation='elu'):
    # Create an instance of the inception model
    inception_model = create_inception_subnetwork(image_size, n_channels,
                                lambda_regularization, activation)

    input_tensor1 = Input(shape=(image_size[0], image_size[1], n_channels), name="input1")
    input_tensor2 = Input(shape=(image_size[0], image_size[1], n_channels), name="input2")

    # Use the  model twice
    dense1 = inception_model(input_tensor1)
    dense2 = inception_model(input_tensor2)

    # Combine the outputs
    concatenation_tensor = Concatenate()([dense1, dense2])
```

Example: Dual-Input Classifier

```
    :
dense3_tensor = Dense(units=20, name = "D3", … )(concatenation_tensor)

output_tensor = Dense(units=1, activation='sigmoid', name = "output", … )(dense3_tensor)

opt = keras.optimizers.Adam(lr=0.0001, amsgrad=False)

# Build the object model
model = Model(inputs=[input_tensor1, input_tensor2], outputs=output_tensor)

model.compile(loss='binary_crossentropy', optimizer=opt, metrics=['accuracy'])

return model
```

```
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input1 (InputLayer)             (None, 32, 32, 3)    0
__________________________________________________________________________________________________
input2 (InputLayer)             (None, 32, 32, 3)    0
__________________________________________________________________________________________________
model_5 (Model)                 (None, 100)          1088720     input1[0][0]
                                                                 input2[0][0]
__________________________________________________________________________________________________
concatenate_9 (Concatenate)     (None, 200)          0           model_5[1][0]
                                                                 model_5[2][0]
__________________________________________________________________________________________________
D3 (Dense)                      (None, 20)           4020        concatenate_9[0][0]
__________________________________________________________________________________________________
output (Dense)                  (None, 1)            21          D3[0][0]
==================================================================================================
Total params: 1,092,761
Trainable params: 1,092,761
Non-trainable params: 0
```

Nested Models for Model Instrumentation (Magic #3)

- After we train a model, we often want to break it open to observe how the individual components are contributing to solving the problem
  - Example: what is the response of the individual convolutional layers to a specific input?
- One option:
  - Create model as we have done so far
  - After training, create a new model:
    - Copy layers out of the original model into the new one
    - New model outputs: the tensors we wish to observe
  - Provide inputs to the new model & it returns the corresponding tensor values

Nested Models for Model Instrumentation

Another option: reverse these steps

- Create a model (A) that produces as output all tensors that we might care about
  - Class prediction
  - Convolutional layer states
  - …

- Wrap another model (B) around the first
  - Map inputs for B to inputs for A
  - Map just the class prediction output of A to the output of B
  - Perform training with model B
  - Can then ask model A to generate predictions for all of the internal tensors

Summary of Magic

1. Python object instances are “callable”
   - Including Layer instances, which take Tensors as inputs and return Tensors
   - A Layer can be used multiple times, with different inputs and outputs
2. Models are Layers
   - Recursive model structures
3. Models can be nested for instrumentation