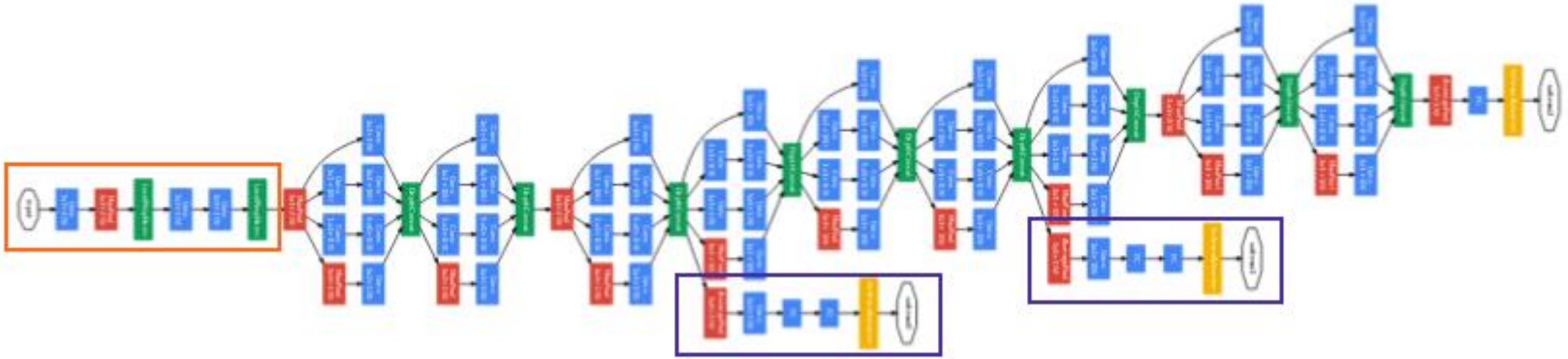
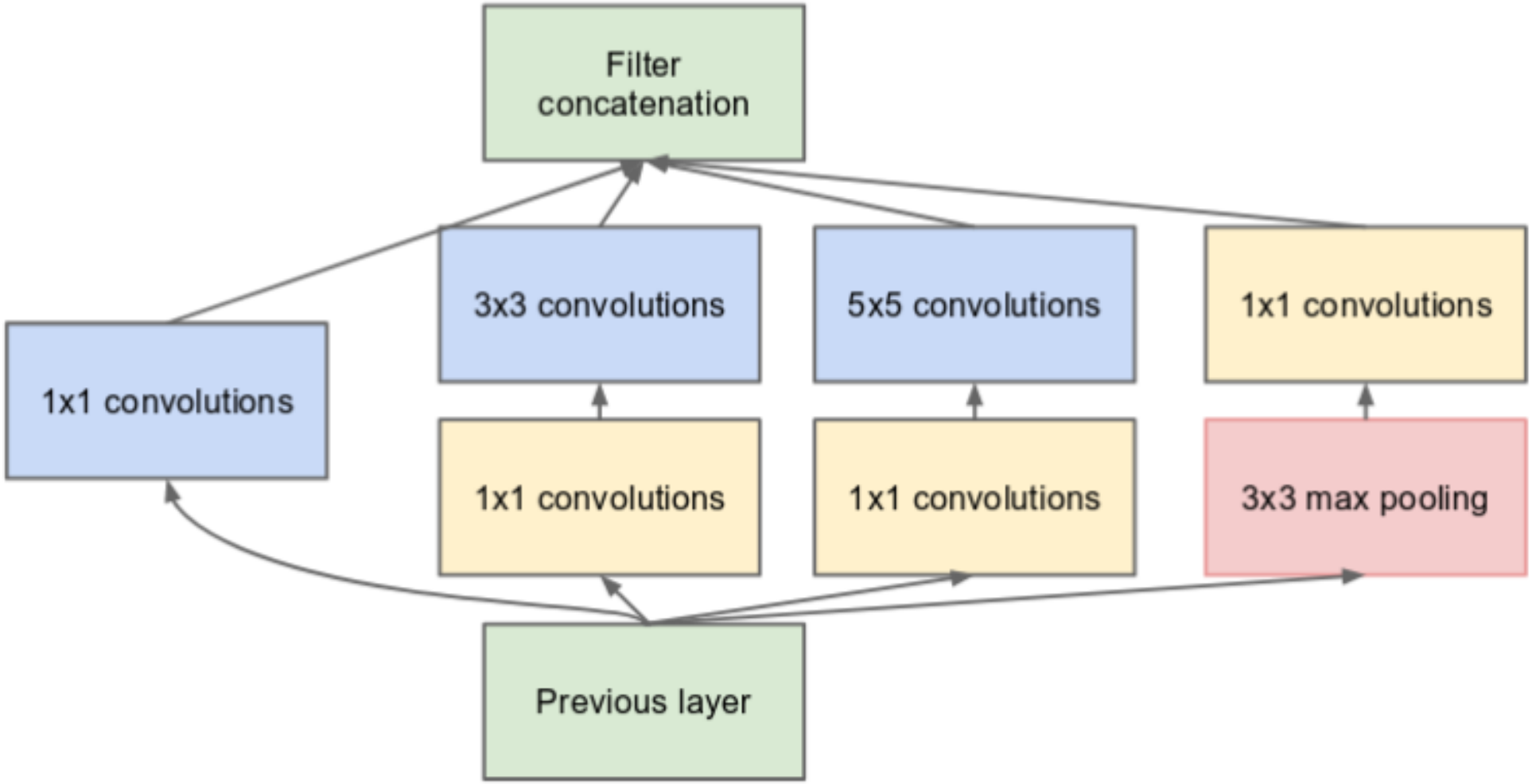
Keras Functional API

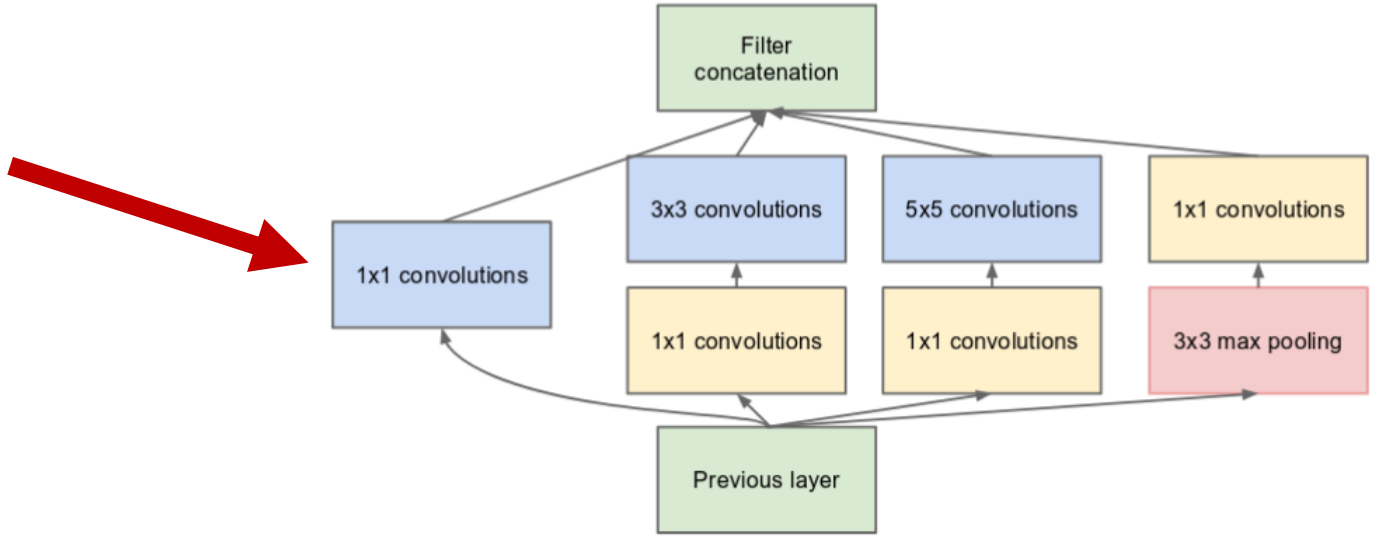
Example: Very Deep Networks (Inception)



Inception Module



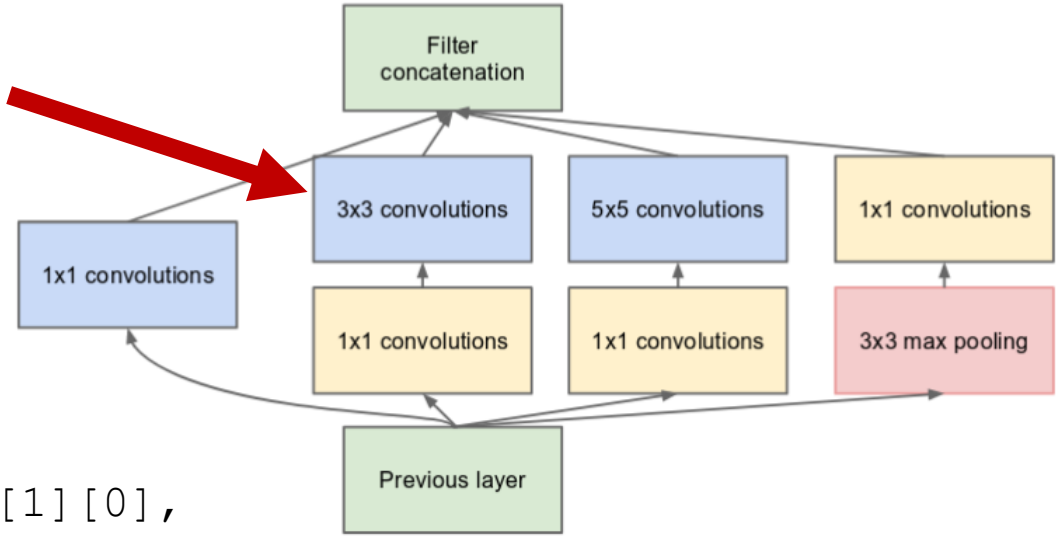
Branch A




```
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,
                                   …   )(input_tensor)
```

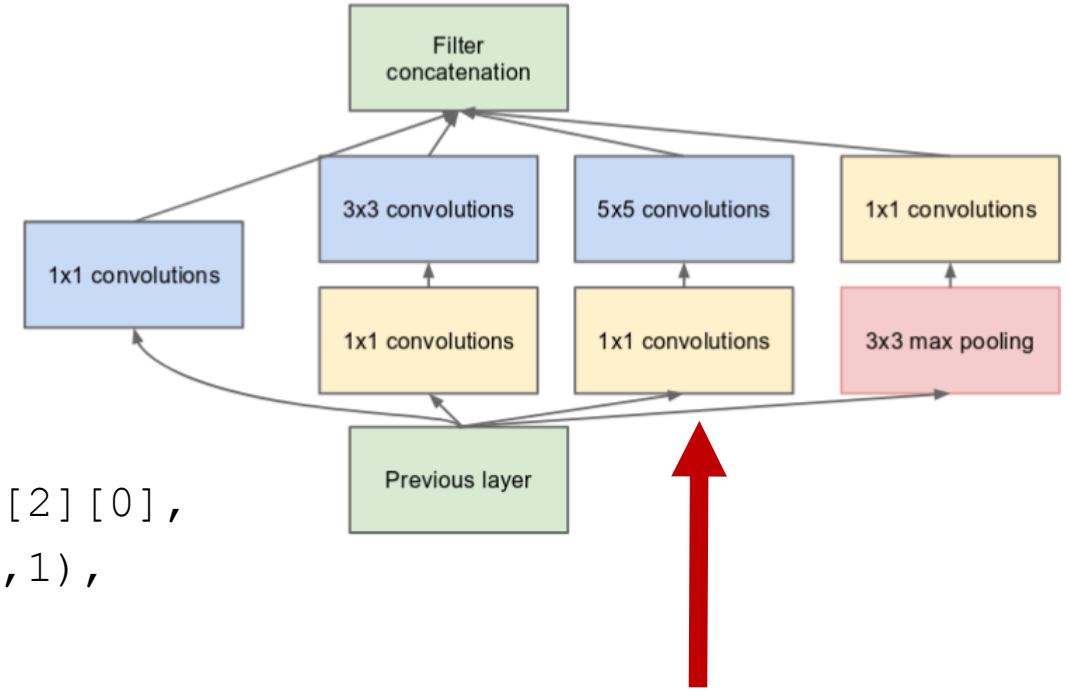
Branch B




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

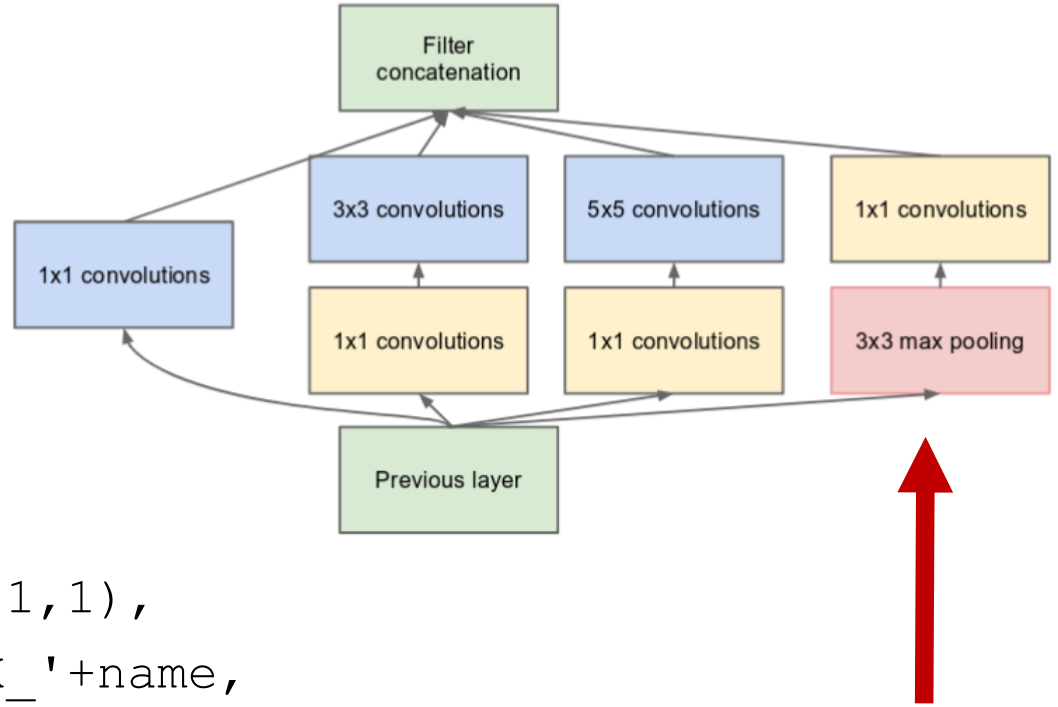
Branch C




```
convC0_tensor = Convolution2D(filters=nfilters[2][0],
                              kernel_size=(1,1),
                              strides=(1,1),
                              padding='same',
                              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)
```

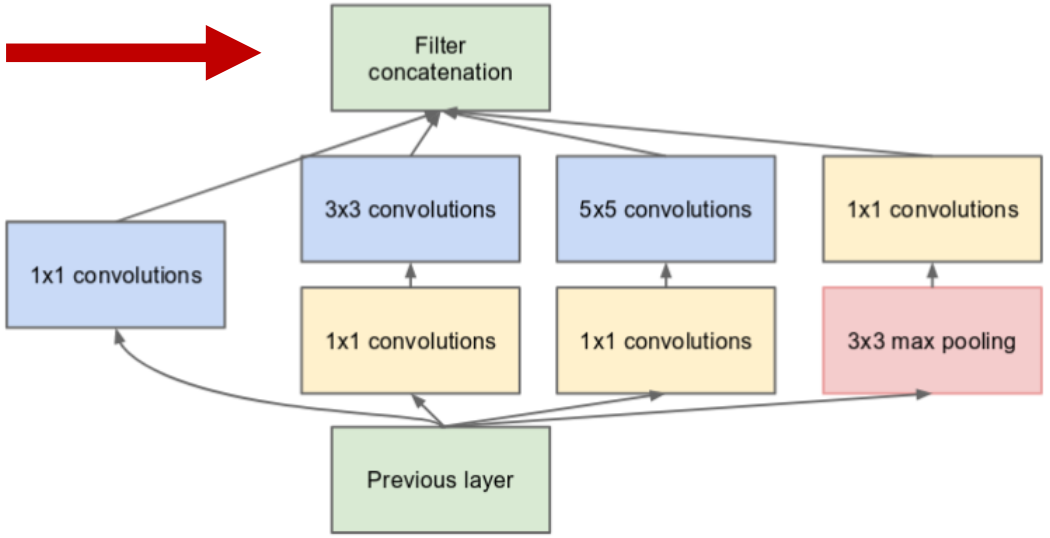
Branch D




```
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)
```

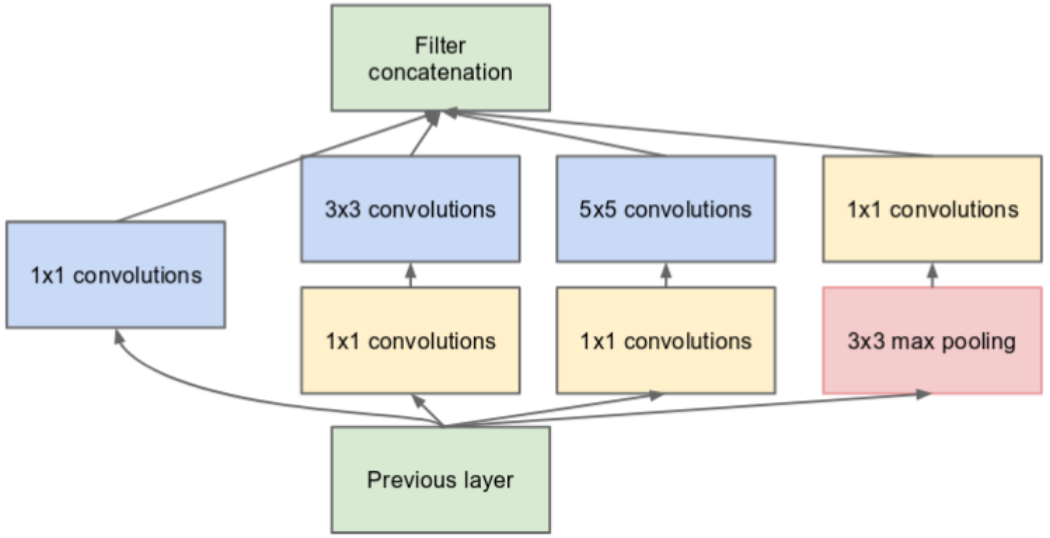
Concatenation




```
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 = Flatten()(i2_tensor)
```

Building an Image Classifier II

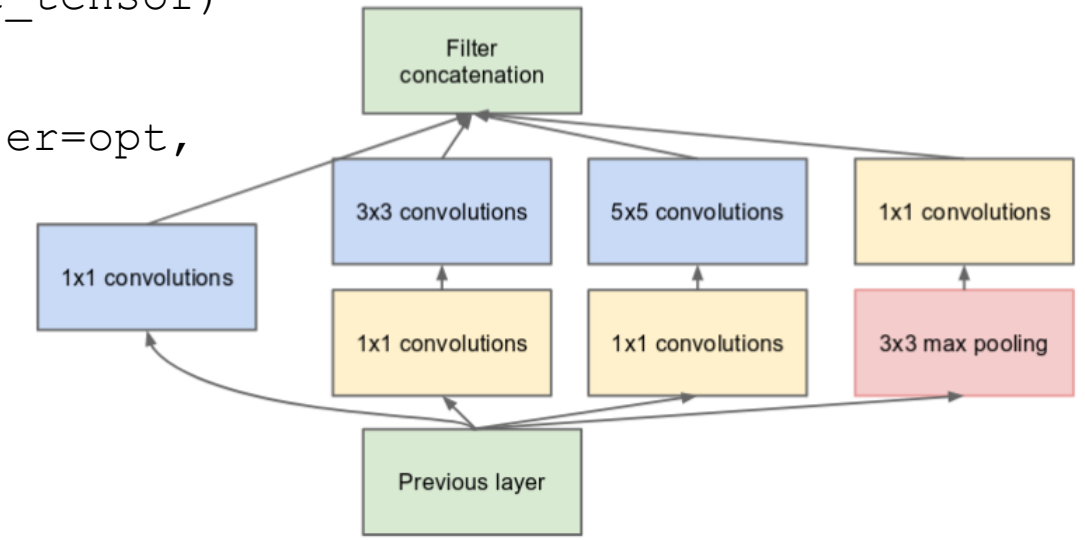
```
dense1_tensor = Dense(units=100, activation=activation, name = "D1", … ) (flatten_tensor)
dense2_tensor = Dense(units=20, activation=activation, name = "D2", … ) (dense1_tensor)
output_tensor = Dense(units=1, activation='sigmoid', name = "output", … ) (dense2_tensor)

opt = keras.optimizers.Adam(lr=0.0001, beta_1=0.9, beta_2=0.999,
                            epsilon=None, decay=0.0, amsgrad=False)

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

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

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



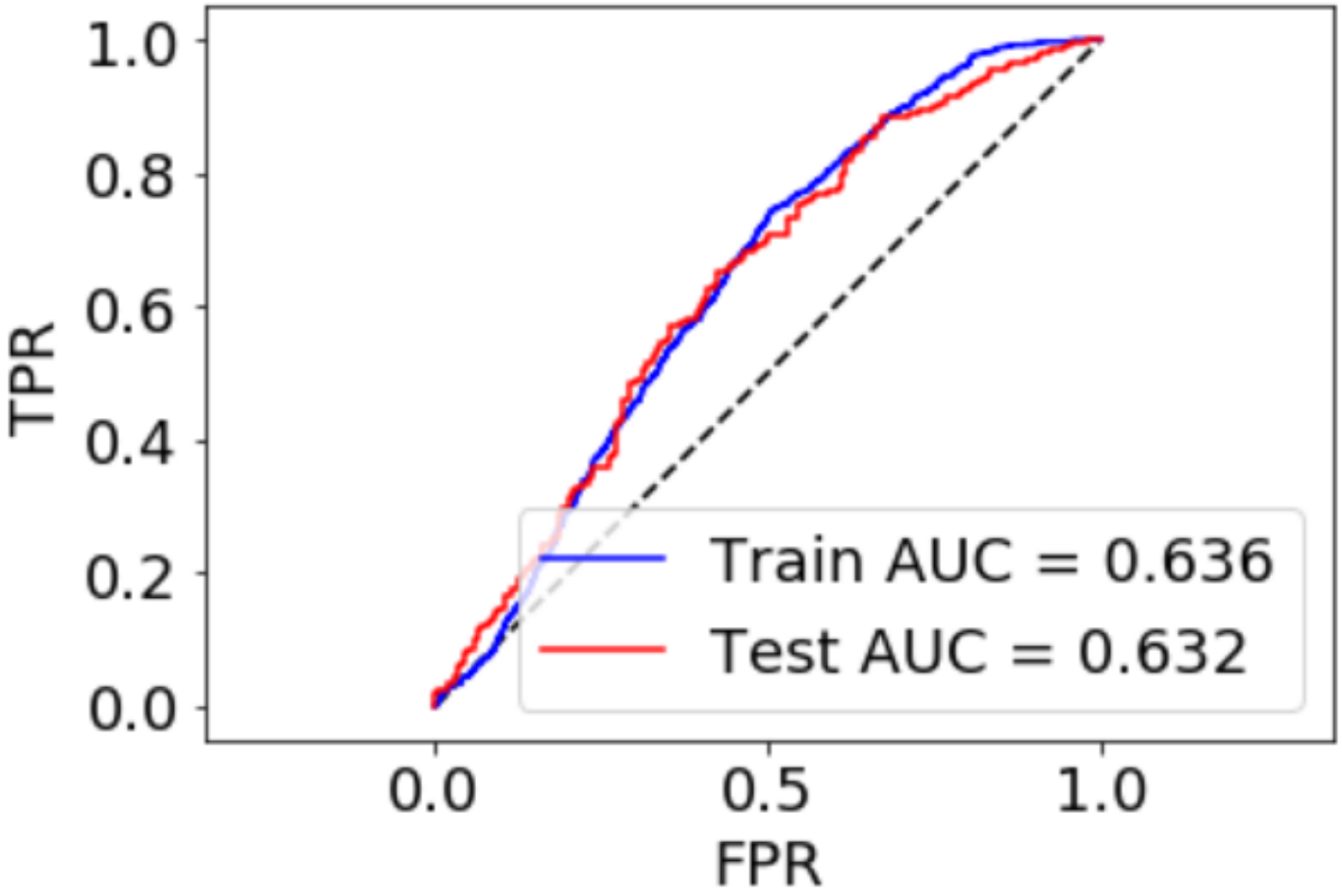
Layer (type)	Output Shape	Param #	Connected to
input (InputLayer)	(None, 32, 32, 3)	0	
convB0_i1 (Conv2D)	(None, 32, 32, 10)	40	input[0][0]
convC0_i1 (Conv2D)	(None, 32, 32, 10)	40	input[0][0]
MAX_i1 (MaxPooling2D)	(None, 32, 32, 3)	0	input[0][0]
convA_i1 (Conv2D)	(None, 16, 16, 10)	40	input[0][0]
convB1_i1 (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

Performance: Mugs vs Cans

Caveats:

- 32x32 images
- Little training
- No tuning



Multiple Input or Output Tensors

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)
```

Functional API: Multiple Output Tensors

- model.fit/predict: mechanics are the same as for multiple Input tensors
  - Provide a list or a dict in place of single numpy arrays
- model.compile():
  - 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=(image_size[0], image_size[1], n_channels),
                                                          name="input1")
input_tensor2 = Input(shape=(image_size[0], image_size[1], n_channels),
                                                          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)

# Concatenate dense1_tensor and dense2_tensor and (through multiple layers),
make a single prediction
```

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

Functional API: Models are Layers!

- Any model can be used as a sub-component of a larger model
- 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, beta_1=0.9, beta_2=0.999,
                            epsilon=None, decay=0.0, 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

Example: Split Inputs

```
# 1/2 are consecutive images (making this assumption for simplicity
ins_training1 = ins_training[0::2,:,:,:]
ins_training2 = ins_training[1::2,:,:,:]
# Just take label from the first half
outs_training_new = outs_training[0::2]

ins_validation1 = ins_validation[0::2,:,:,:]
ins_validation2 = ins_validation[1::2,:,:,:]
outs_validation_new = outs_validation[0::2]
```

Example: Generator with Two Inputs

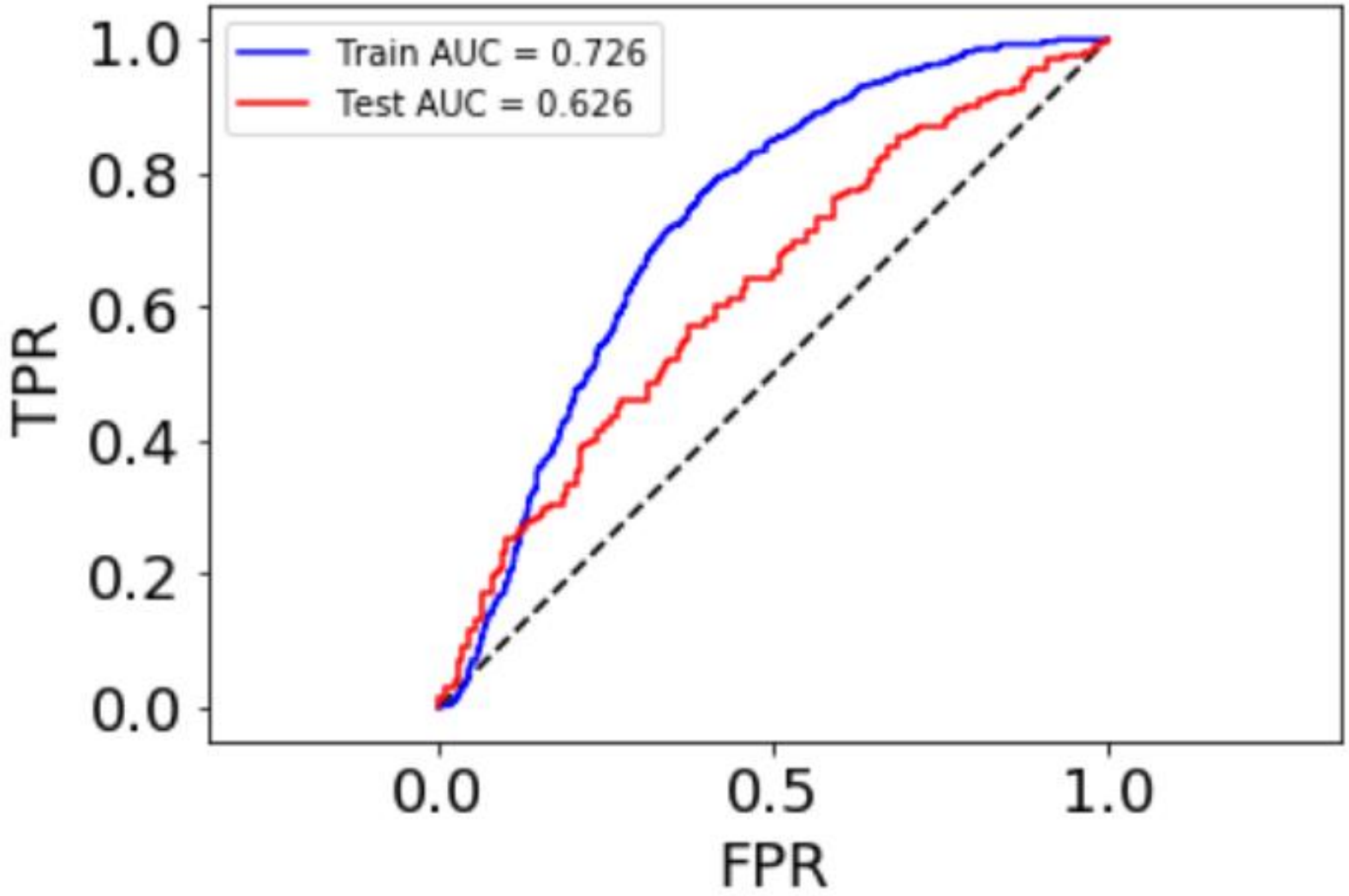
```
def training_set_generator_dual_input(ins1, ins2, outs, batch_size=10,
                                      input_name1='input1',
                                      input_name2='input2',
                                      output_name='output'):
    while True:
        example_indices = [random.choice(range(ins1.shape[0]))
                                         for k in range(batch_size)]

        yield({input_name1: ins1[example_indices,:,:,:],
               input_name2: ins2[example_indices,:,:,:]},
              {output_name: outs[example_indices]})
```

Performance: Mugs vs Cans

Caveats (again):

- Little training
- No tuning



Model within a Model

A very powerful idea

- Use a single sub-model in multiple ways (we just did this)
  - This effectively increases the training set size that the model has available to it
- Instrumenting a model vs training it

Instrumentation vs Training

For our classifier models:

- Training: input is a model; output is a probability
- But, after training, it is sometimes useful to look inside the different layers to see how they are participating in the computation
  - We did this in a class demo by creating a second model that was a copy of the trained model (including parameters), but with different layers as outputs
  - This allowed us to ask: what does channel k look like when the input is a specific image?

Instrumentation vs Training

An alternative approach with nested models:

- Inner model: instrumentation
  - Input: image
  - Output: all of the output layers that are of interest, including the class probability vector
- Outer model: training
  - Input: image
  - Output: class probability vector
  - In between: include an instance of the Inner model, but output only selects the class probability vector (all other outputs are ignored
- Our model building function returns both. Training of the outer model selects parameters of both. The inner model can then be queried with new images!

HW 5 Proposal

- Same classification problem
- Two model types are possible
  - Inception-like branching structures
  - Take multiple images of the same object (in sequential order) and predict one class label for the set