Lecture 9: Convolutional Neural Networks

Handling image data

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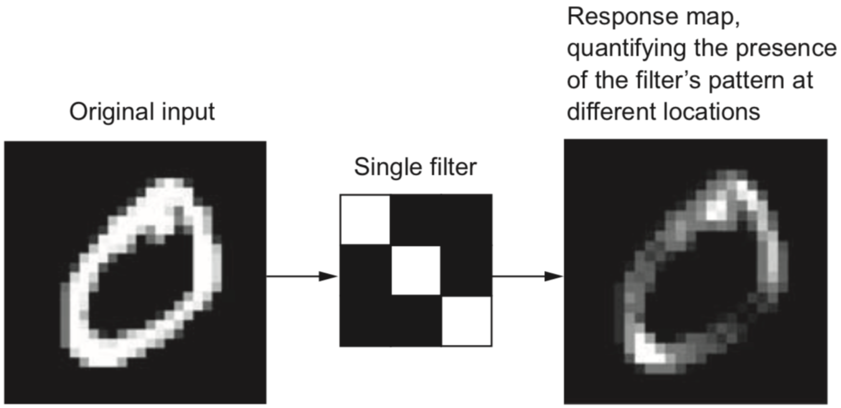
Overview

- Image convolution
- Convolutional neural networks
- Data augmentation
- Model interpretation
- Using pre-trained networks (transfer learning)

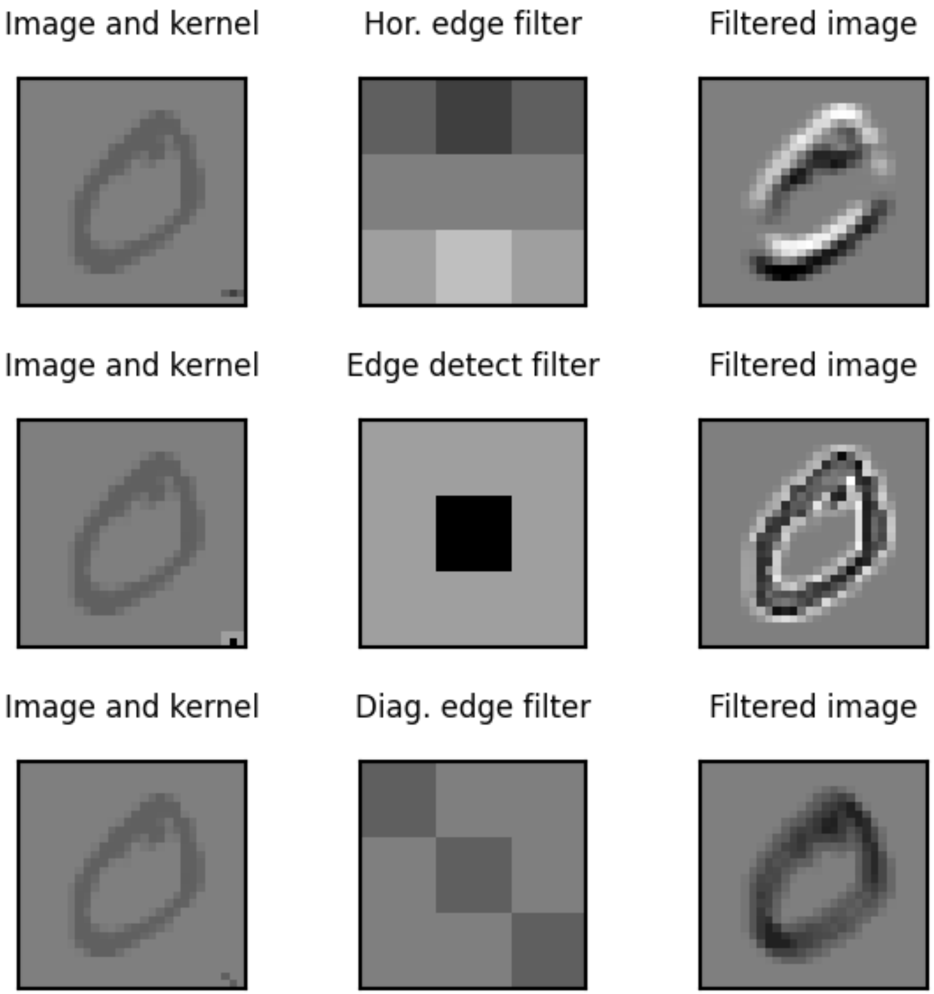
Convolution

- Operation that transforms an image by sliding a smaller image (called a *filter* or *kernel*) over the image and multiplying the pixel values
  - Slide an n x n filter over n x n *patches* of the original image
  - Every pixel is replaced by the *sum* of the *element-wise products* of the values of the image patch around that pixel and the kernel

```python
# kernel and image_patch are n x n matrices
pixel_out = np.sum(kernel * image_patch)
```

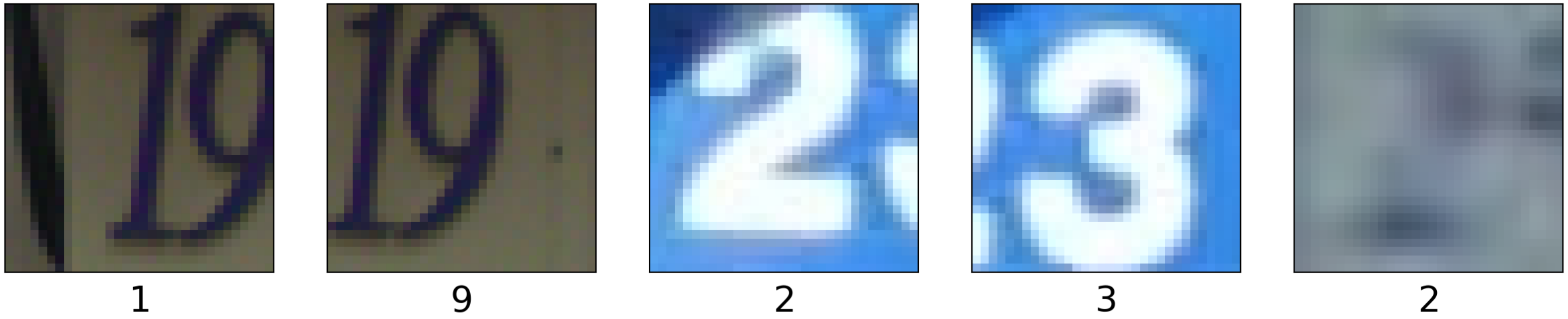


- Different kernels can detect different types of patterns in the image

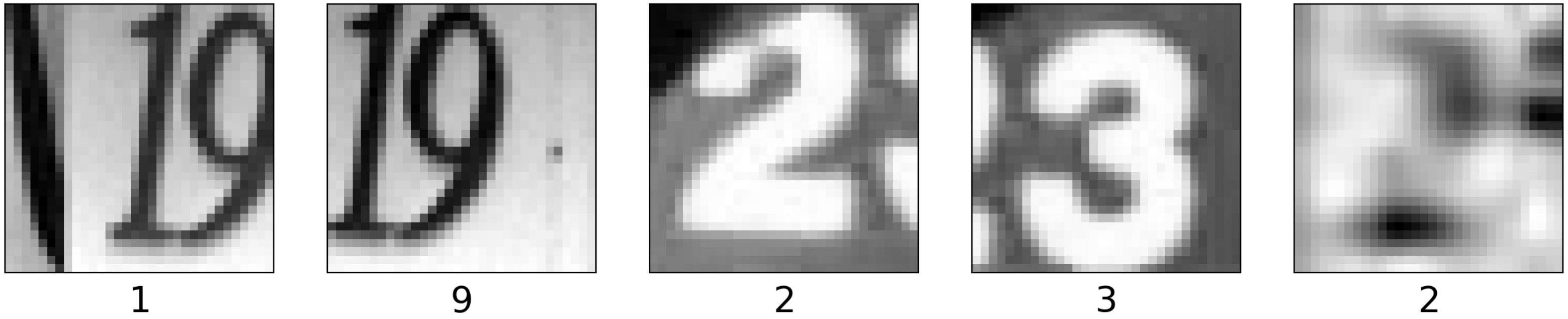


Demonstration on Google streetview data

House numbers photographed from Google streetview imagery, cropped and centered around digits, but with neighboring numbers or other edge artifacts.



For recognizing digits, color is not important, so we grayscale the images



Demonstration

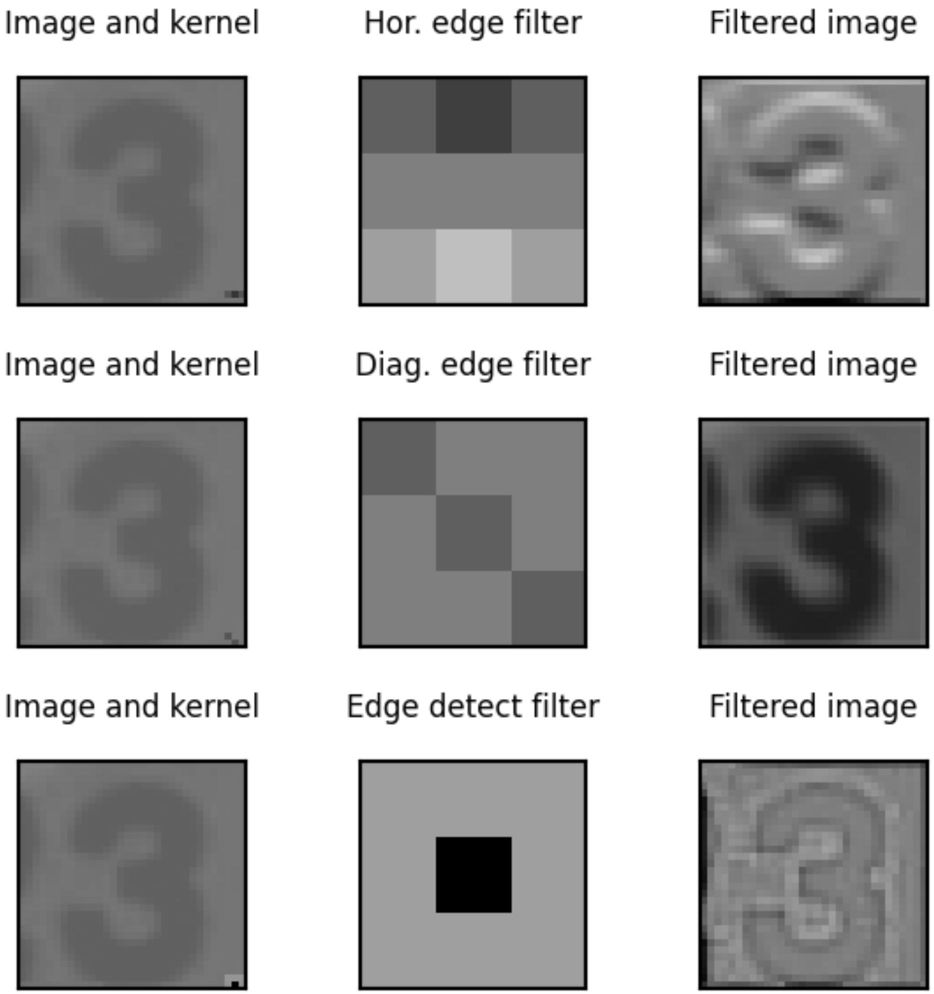
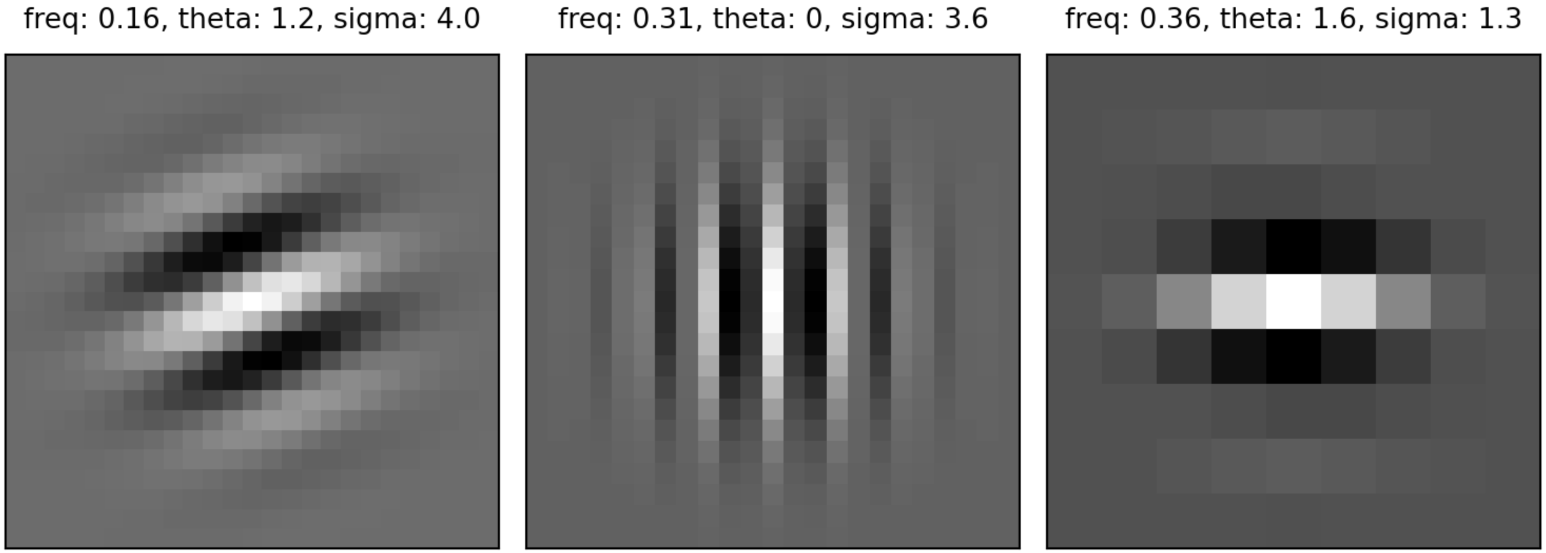


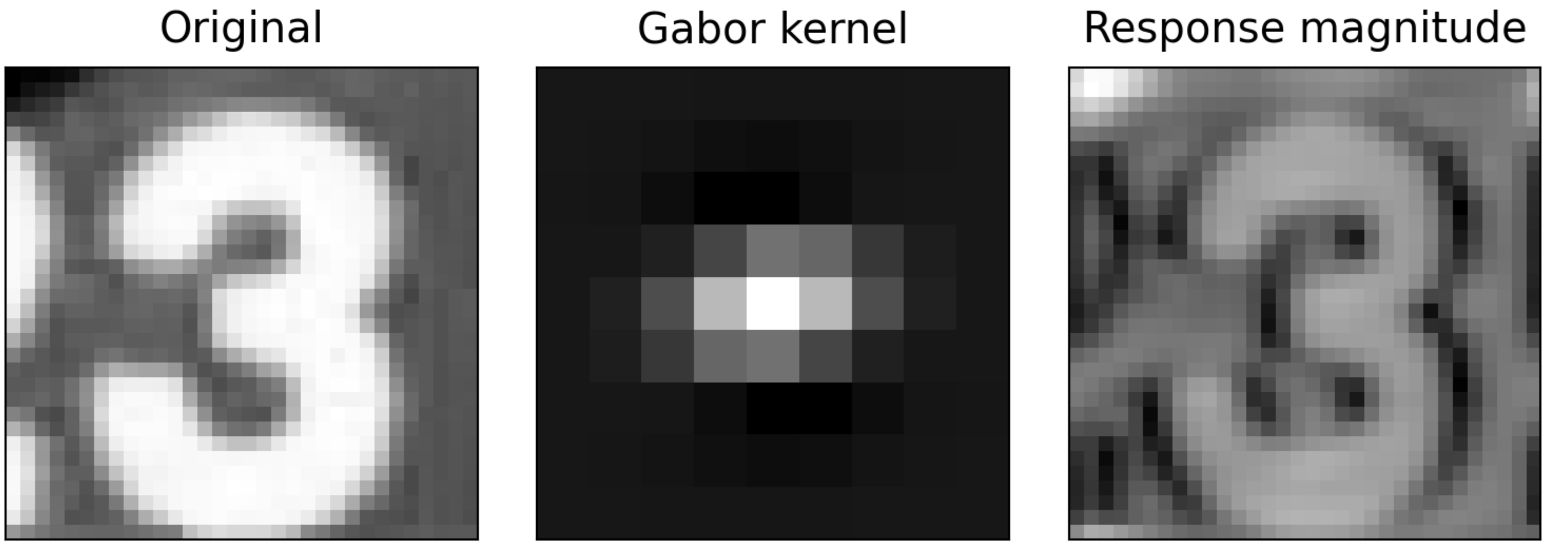
Image convolution in practice

- How do we know which filters are best for a given image?
- *Families* of kernels (or *filter banks*) can be run on every image
    - Gabor, Sobel, Haar Wavelets,...
- Gabor filters: Wave patterns generated by changing:
    - Frequency: narrow or wide ondulations
    - Theta: angle (direction) of the wave
    - Sigma: resolution (size of the filter)

Demonstration

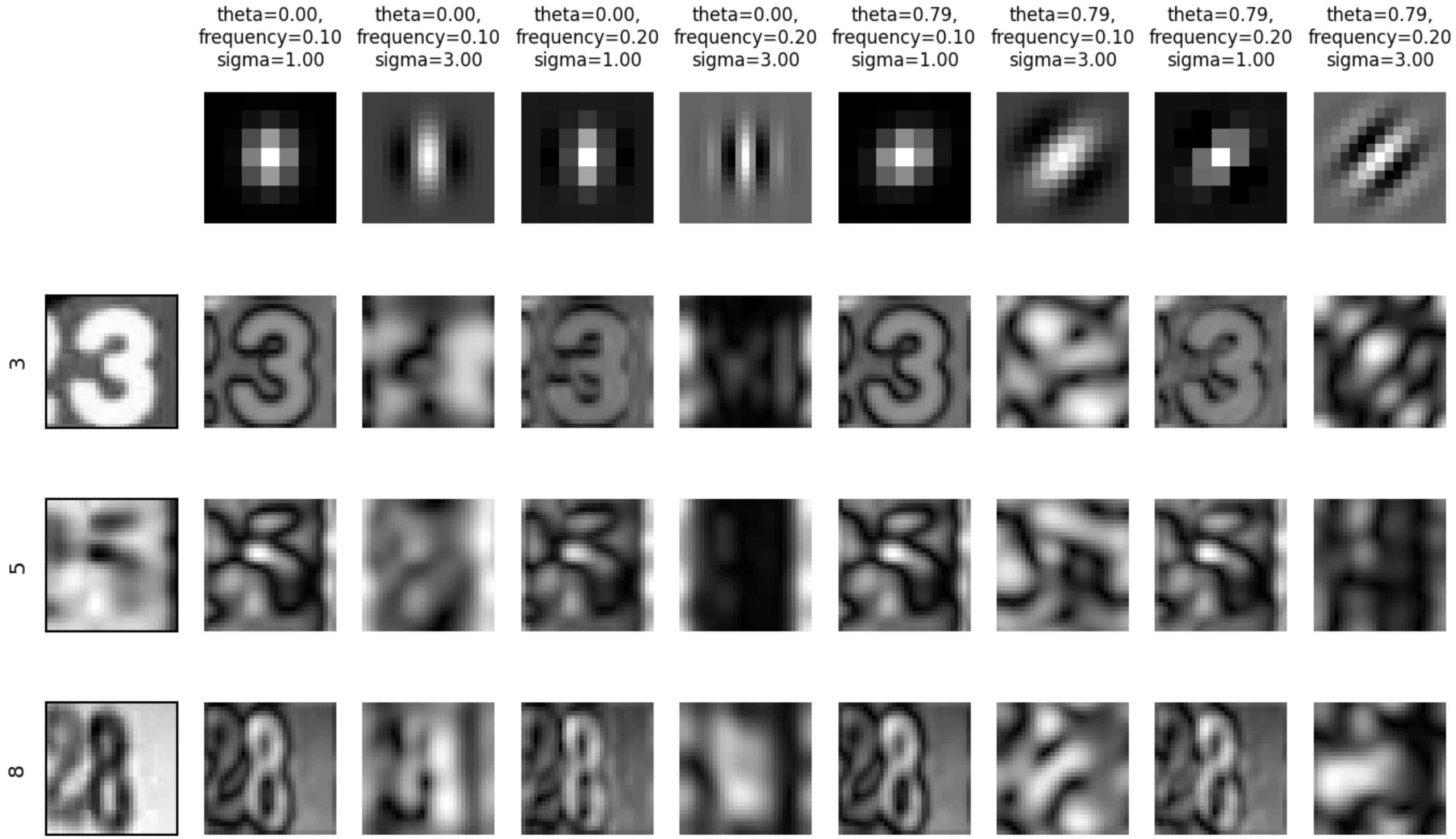


Demonstration on the streetview data

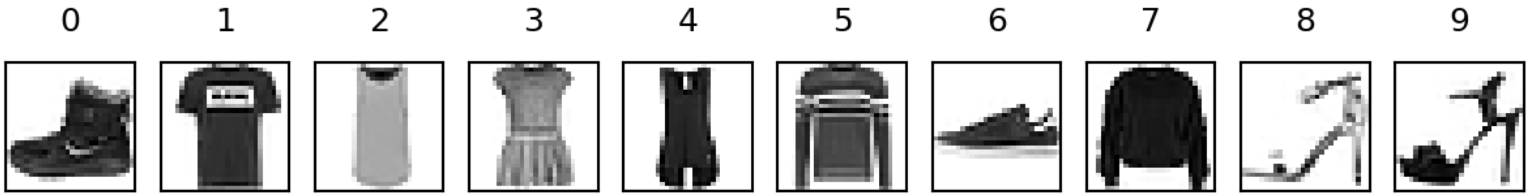


Filter banks

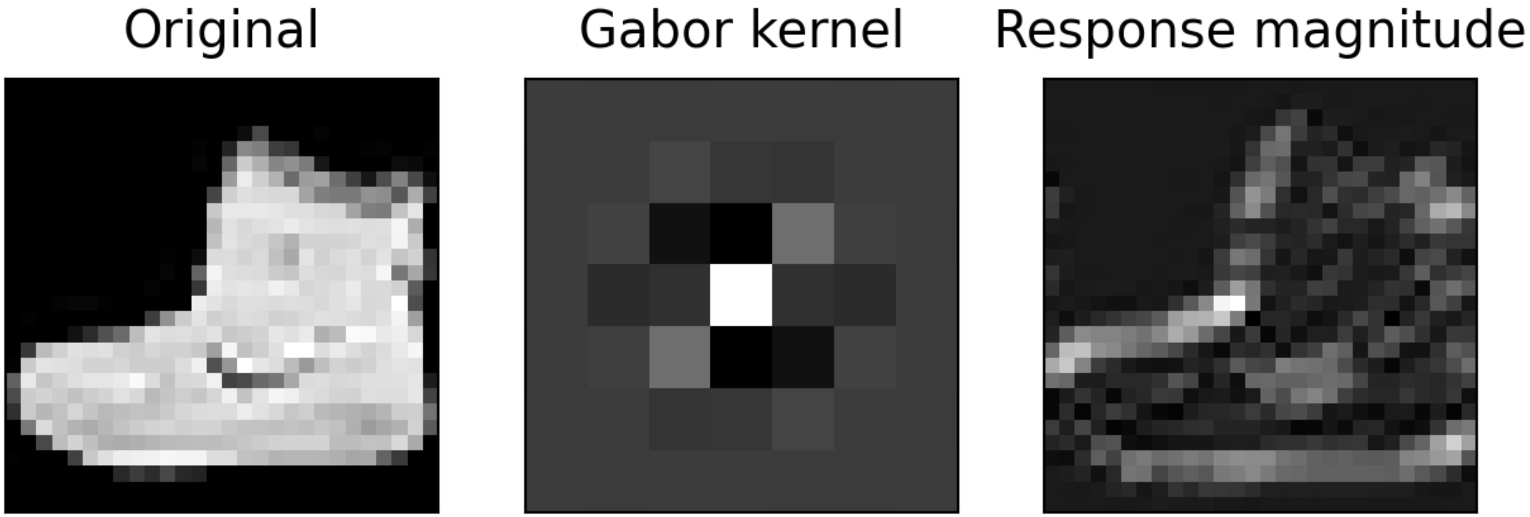
- Different filters detect different edges, shapes,...
- Not all seem useful



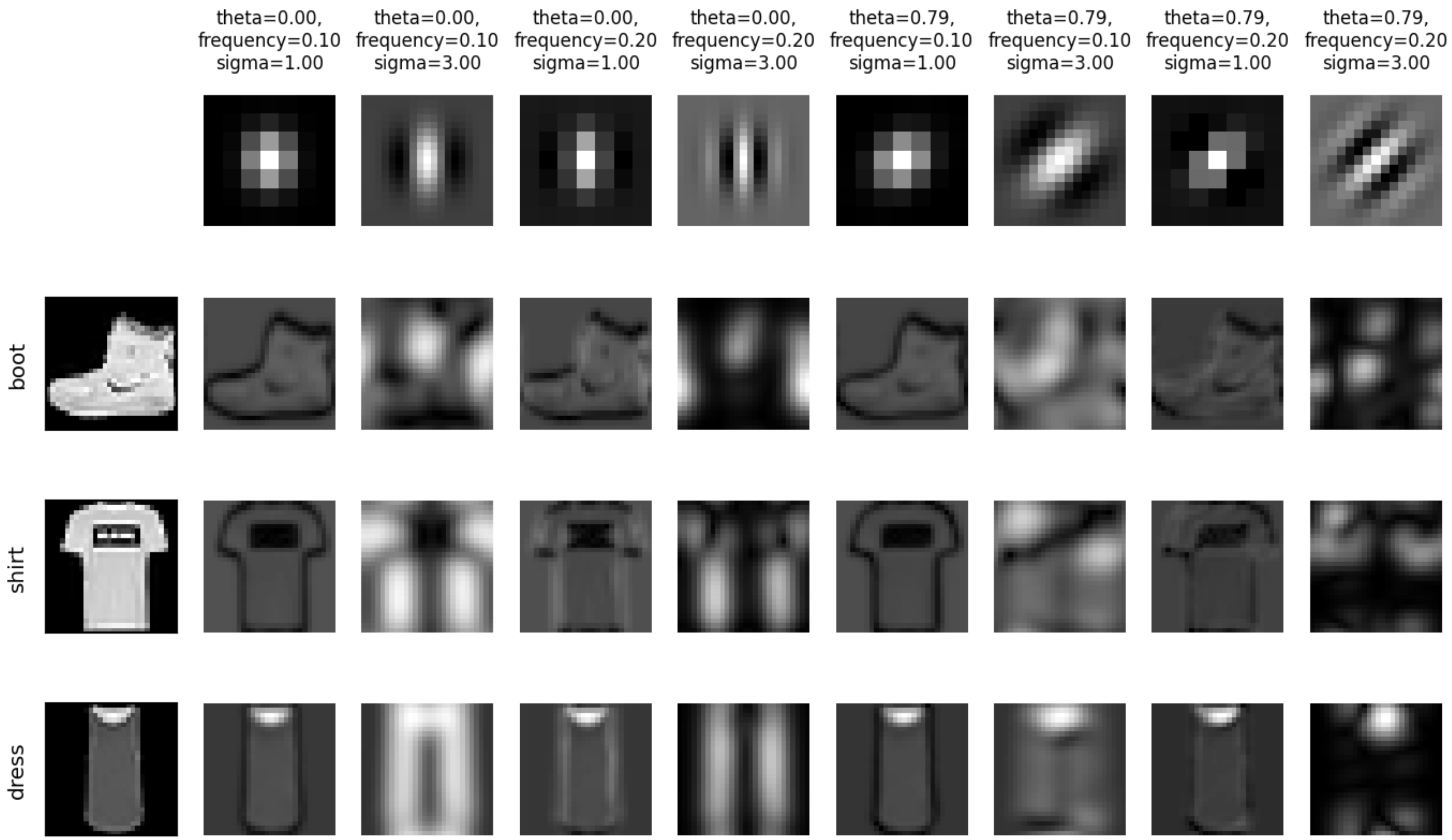
Another example: Fashion MNIST



Demonstration

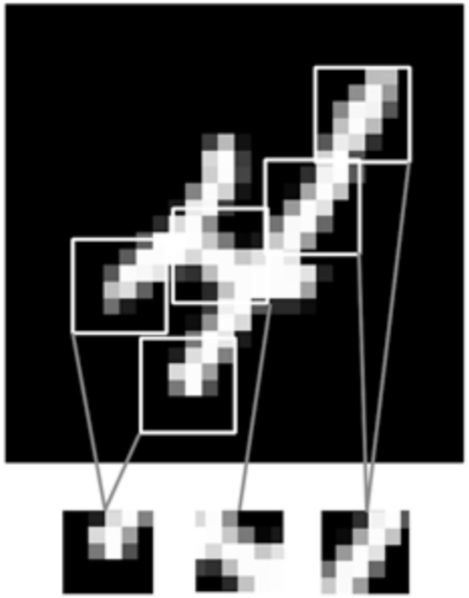


Fashion MNIST with multiple filters (filter bank)



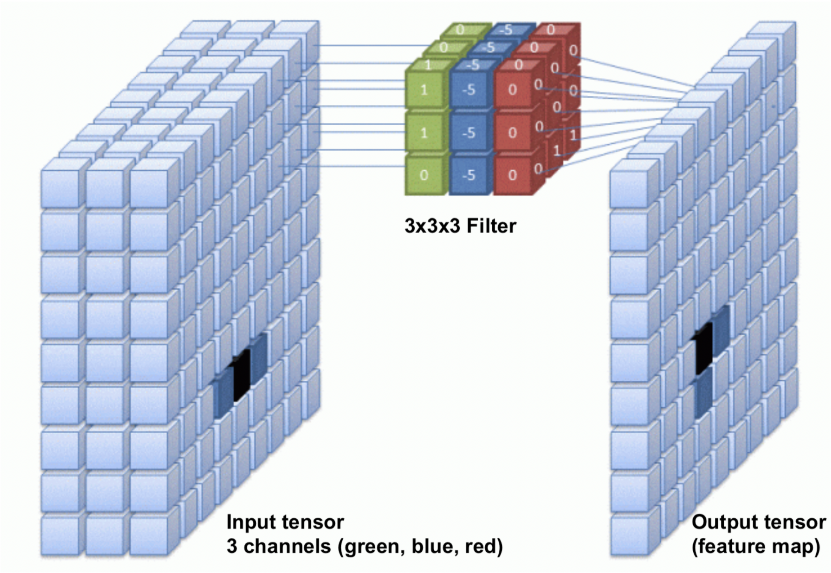
Convolutional neural nets

- Finding relationships between individual pixels and the correct class is hard
- We want to discover 'local' patterns (edges, lines, endpoints)
- Representing such local patterns as features makes it easier to learn from them
- We could use convolutions, but how to choose the filters?



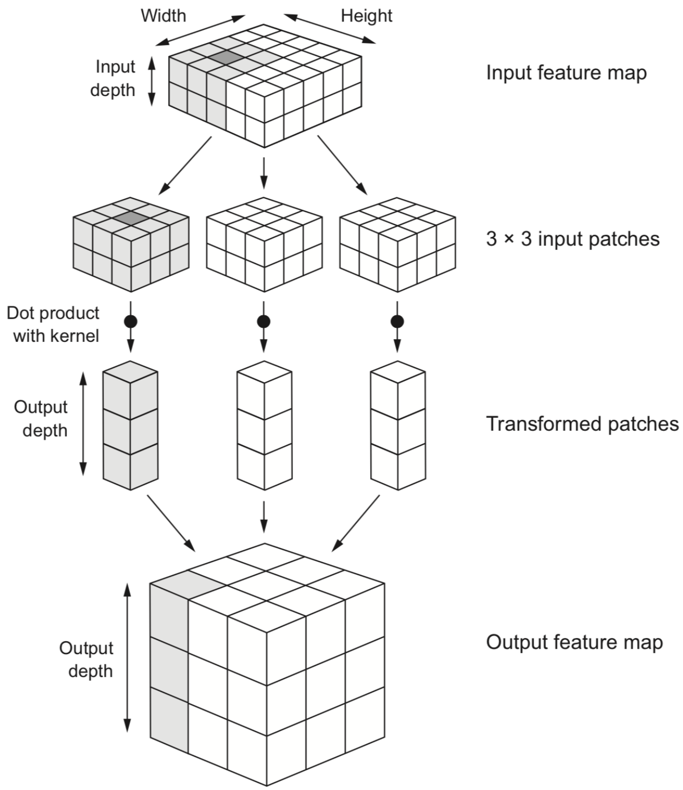
Convolutional Neural Networks (ConvNets)

- Instead of manually designing the filters, we can also *learn* them based on data
    - Choose filter sizes (manually), initialize with small random weights
- Forward pass: Convolutional layer slides the filter over the input, generates the output
- Backward pass: Update the filter weights according to the loss gradient
- Illustration for 1 filter:



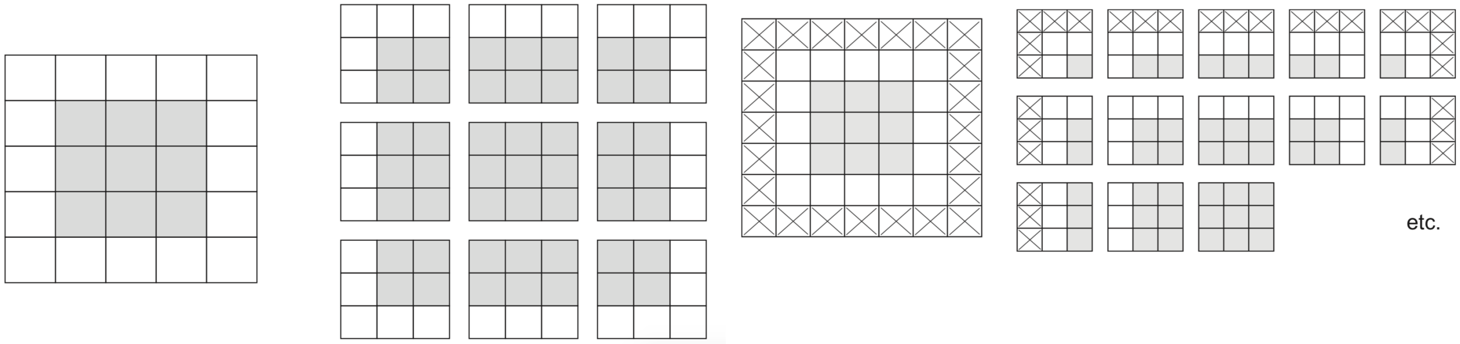
Convolutional layers: Feature maps

- One filter is not sufficient to detect all relevant patterns in an image
- A convolutional layer applies and learns d filter in parallel
- Slide d filters across the input image (in parallel) -> a (1x1xd) output per patch
- Reassemble into a *feature map* with d 'channels', a (width x height x d) tensor.



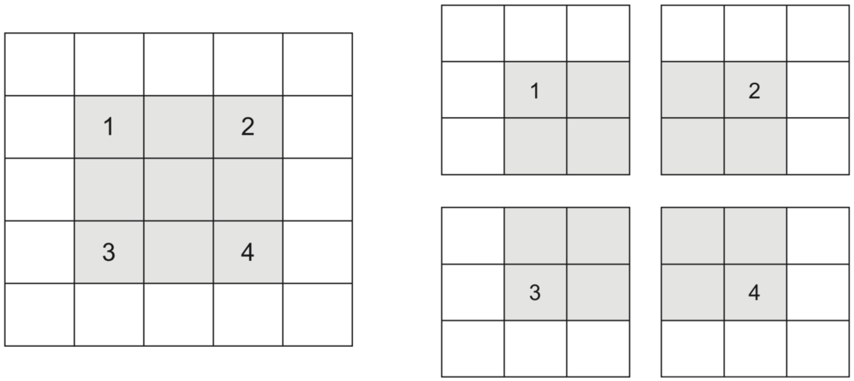
Border effects (zero padding)

- Consider a 5x5 image and a 3x3 filter: there are only 9 possible locations, hence the output is a 3x3 feature map
- If we want to maintain the image size, we use *zero-padding*, adding 0's all around the input tensor.



Undersampling (striding)

- Sometimes, we want to *downsample* a high-resolution image
    - Faster processing, less noisy (hence less overfitting)
- One approach is to *skip* values during the convolution
    - Distance between 2 windows: *stride length*
- Example with stride length 2 (without padding):



Max-pooling

- Another approach to shrink the input tensors is *max-pooling* :
    - Run a filter with a fixed stride length over the image
        - Usually 2x2 filters and stride lenght 2
    - The filter simply returns the *max* (or *avg*) of all values
- Agressively reduces the number of weights (less overfitting)
- Information from every input node spreads more quickly to output nodes
    - In `pure` convnets, one input value spreads to 3x3 nodes of the first layer, 5x5 nodes of the second, etc.
    - Without maxpooling, you need much deeper networks, harder to train
- Increases *translation invariance* : patterns can affect the predictions no matter where they occur in the image

Convolutional nets in practice

- Use multiple convolutional layers to learn patterns at different levels of abstraction
    - Find local patterns first (e.g. edges), then patterns across those patterns
- Use MaxPooling layers to reduce resolution, increase translation invariance
- Use sufficient filters in the first layer (otherwise information gets lost)
- In deeper layers, use increasingly more filters
    - Preserve information about the input as resolution descreases
    - Avoid decreasing the number of activations (resolution x nr of filters)
- For very deep nets, add *skip connections* to preserve information (and gradients)
    - Sums up outputs of earlier layers to those of later layers (with same dimensions)

Example with Keras:

- `Conv2D` for 2D convolutional layers
    - 32 filters (default), randomly initialized (from uniform distribution)
    - Deeper layers use 64 filters
    - Filter size is 3x3
    - ReLU activation to simplify training of deeper networks
- `MaxPooling2D` for max-pooling
    - 2x2 pooling reduces the number of inputs by a factor 4

```
model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu',
                        input_shape=(28, 28, 1)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
```

Observe how the input image on 28x28x1 is transformed to a 3x3x64 feature map

- Convolutional layer:
  - No zero-padding: every output 2 pixels less in every dimension
  - 320 weights: (3x3 filter weights + 1 bias) * 32 filters
- After every MaxPooling, resolution halved in every dimension

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 26, 26, 32)        320

 max_pooling2d (MaxPooling2D  (None, 13, 13, 32)       0
 )

 conv2d_1 (Conv2D)           (None, 11, 11, 64)        18496

 max_pooling2d_1 (MaxPooling  (None, 5, 5, 64)         0
 2D)

 conv2d_2 (Conv2D)           (None, 3, 3, 64)          36928

=================================================================
Total params: 55,744
Trainable params: 55,744
Non-trainable params: 0
_________________________________________________________________
```

Completing the network

- To classify the images, we still need a Dense and Softmax layer.
- We need to flatten the 3x3x64 feature map to a vector of size 576

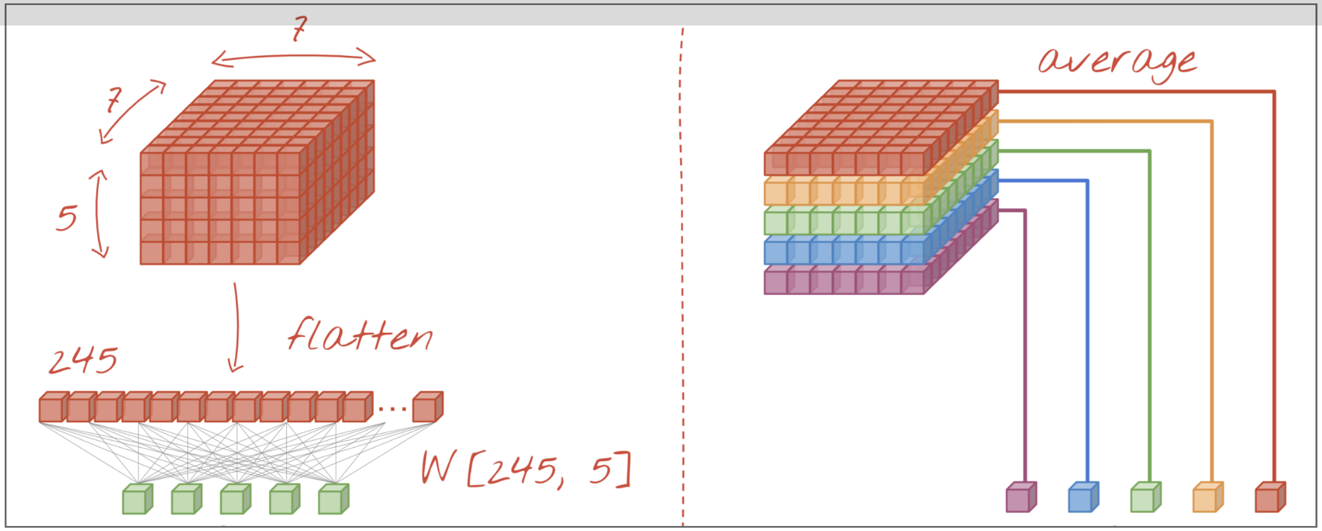
```
model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))
```

Complete network

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 26, 26, 32)        320

 max_pooling2d (MaxPooling2D  (None, 13, 13, 32)       0
 )

 conv2d_1 (Conv2D)           (None, 11, 11, 64)        18496

 max_pooling2d_1 (MaxPooling  (None, 5, 5, 64)         0
 2D)

 conv2d_2 (Conv2D)           (None, 3, 3, 64)          36928

 flatten (Flatten)           (None, 576)               0

 dense (Dense)               (None, 64)                36928

 dense_1 (Dense)             (None, 10)                650

=================================================================
Total params: 93,322
Trainable params: 93,322
Non-trainable params: 0
_________________________________________________________________
```

- `Flatten` adds a lot of weights
- Instead, we can do `GlobalAveragePooling`: returns average of each activation map
- This sometimes works even without adding a dense layer (the number of outputs is similar to the number of classes)

```
model.add(layers.GlobalAveragePooling2D())
model.add(layers.Dense(10, activation='softmax'))
```



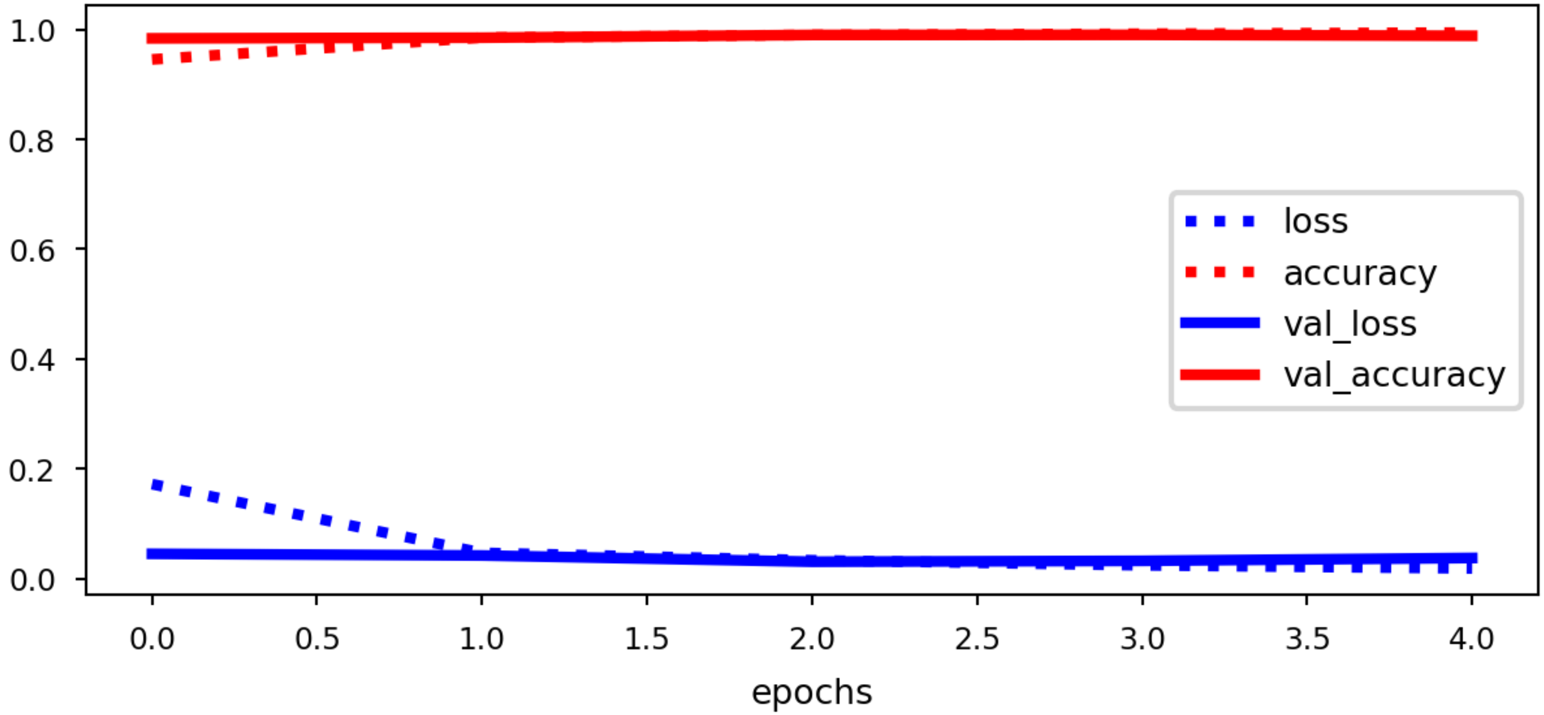
- With `GlobalAveragePooling`: much fewer weights to learn
- Use with caution: this destroys the location information learned by the CNN
- Not ideal for tasks such as object localization

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_3 (Conv2D)           (None, 26, 26, 32)        320

 max_pooling2d_2 (MaxPooling  (None, 13, 13, 32)       0
 2D)

 conv2d_4 (Conv2D)           (None, 11, 11, 64)        18496

 max_pooling2d_3 (MaxPooling  (None, 5, 5, 64)         0
 2D)

 conv2d_5 (Conv2D)           (None, 3, 3, 64)          36928

 global_average_pooling2d (G  (None, 64)               0
 lobalAveragePooling2D)

 dense_2 (Dense)             (None, 10)                650

=================================================================
Total params: 56,394
Trainable params: 56,394
```

Run the model on MNIST dataset

- Train and test as usual: 99% accuracy
    - Compared to 97,8% accuracy with the dense architecture

```
Accuracy:  0.988800048828125
```



Tip:

- Training ConvNets can take a lot of time
- Save the trained model (and history) to disk so that you can reload it later

```
model.save(os.path.join(model_dir, 'mnist.h5'))
with open(os.path.join(model_dir, 'mnist_history.p'), 'wb') as
file_pi:
    pickle.dump(history.history, file_pi)
```

Cats vs Dogs

- A more realistic dataset: Cats vs Dogs
    - Colored JPEG images, different sizes
    - Not nicely centered, translation invariance is important
- Preprocessing
    - Create balanced subsample of 4000 colored images
        - 3000 for training, 1000 validation
    - Decode JPEG images to floating-point tensors
    - Rescale pixel values to [0,1]
    - Resize images to 150x150 pixels

Data generators

- `ImageDataGenerator` : allows to encode, resize, and rescale JPEG images
- Returns a Python *generator* we can endlessly query for batches of images
- Separately for training, validation, and validation set

```
train_generator =
ImageDataGenerator(rescale=1./255).flow_from_directory(
        train_dir,                    # Directory with images
        target_size=(150, 150),       # Resize images
        batch_size=20,                # Return 20 images at a time
        class_mode='binary')          # Binary labels
```

Since the images are larger and more complex, we add another convolutional layer and increase the number of filters to 128.

```
model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu',
                        input_shape=(150, 150, 3)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(128, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(128, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Flatten())
model.add(layers.Dense(512, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_3 (Conv2D)           (None, 148, 148, 32)      896

 max_pooling2d_2 (MaxPooling  (None, 74, 74, 32)       0
 2D)

 conv2d_4 (Conv2D)           (None, 72, 72, 64)        18496

 max_pooling2d_3 (MaxPooling  (None, 36, 36, 64)       0
 2D)

 conv2d_5 (Conv2D)           (None, 34, 34, 128)       73856

 max_pooling2d_4 (MaxPooling  (None, 17, 17, 128)      0
 2D)

 conv2d_6 (Conv2D)           (None, 15, 15, 128)       147584

 max_pooling2d_5 (MaxPooling  (None, 7, 7, 128)        0
 2D)

 flatten_1 (Flatten)         (None, 6272)              0

 dense_2 (Dense)             (None, 512)               3211776

 dense_3 (Dense)             (None, 1)                 513

=================================================================
Total params: 3,453,121
Trainable params: 3,453,121
Non-trainable params: 0
_________________________________________________________________
```

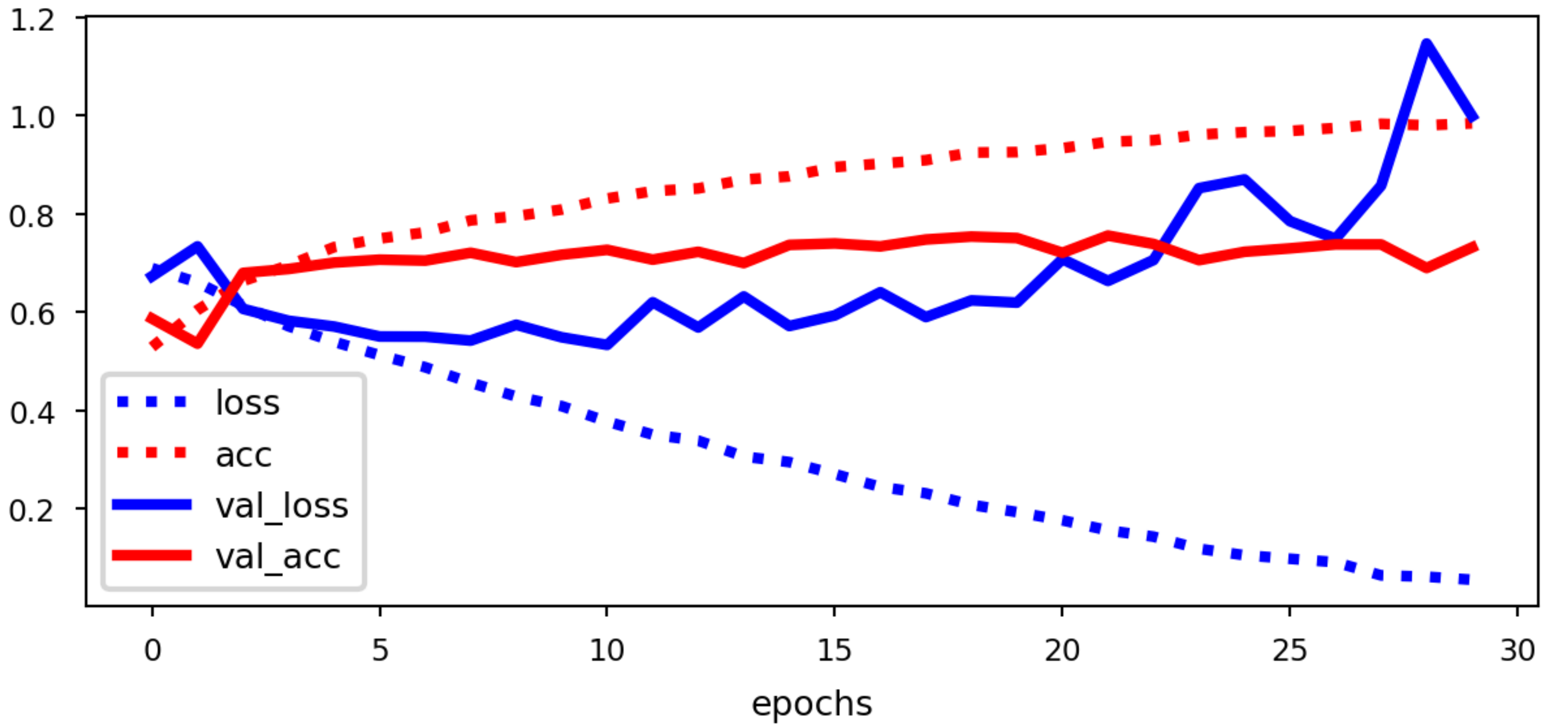
Training

- The `fit` function also supports generators
    - 100 steps per epoch (batch size: 20 images per step), for 30 epochs
    - Provide a separate generator for the validation data

```
model.compile(loss='binary_crossentropy',
              optimizer=optimizers.RMSprop(lr=1e-4),
              metrics=['acc'])
history = model.fit(
      train_generator, steps_per_epoch=100,
      epochs=30, verbose=0,
      validation_data=validation_generator,
      validation_steps=50)
```

Results

- The network seems to be overfitting. Validation accuracy is stuck at 75% while the training accuracy reaches 100%
- There are many things we can do:
    - Regularization (e.g. Dropout, L1/L2, Batch Normalization,...)
    - Generating more training data
    - Meta-learning: Use pretrained rather than randomly initialized filters



Data augmentation

- Generate new images via image transformations
    - Images will be randomly transformed *every epoch*
- We can again use a data generator to do this

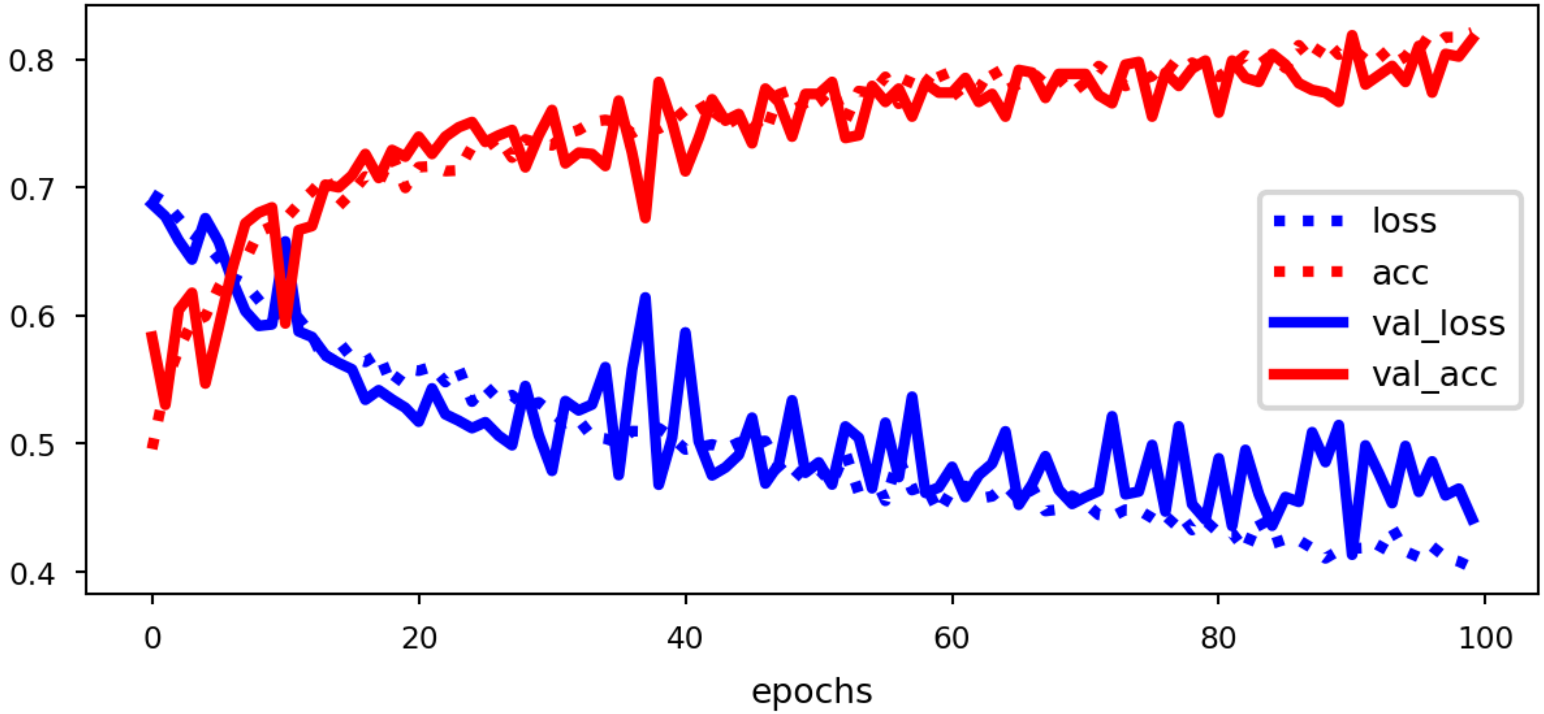
```
datagen = ImageDataGenerator(
      rotation_range=40,     # Rotate image up to 40 degrees
      width_shift_range=0.2, # Shift image left-right up to 20% of
image width
      height_shift_range=0.2,# Shift image up-down up to 20% of
image height
      shear_range=0.2,       # Shear (slant) the image up to 0.2
degrees
      zoom_range=0.2,        # Zoom in up to 20%
      horizontal_flip=True,  # Horizontally flip the image
      fill_mode='nearest')
```

Example

We also add Dropout before the Dense layer

```
model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu',
                        input_shape=(150, 150, 3)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(128, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(128, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Flatten())
model.add(layers.Dropout(0.5))
model.add(layers.Dense(512, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))
```

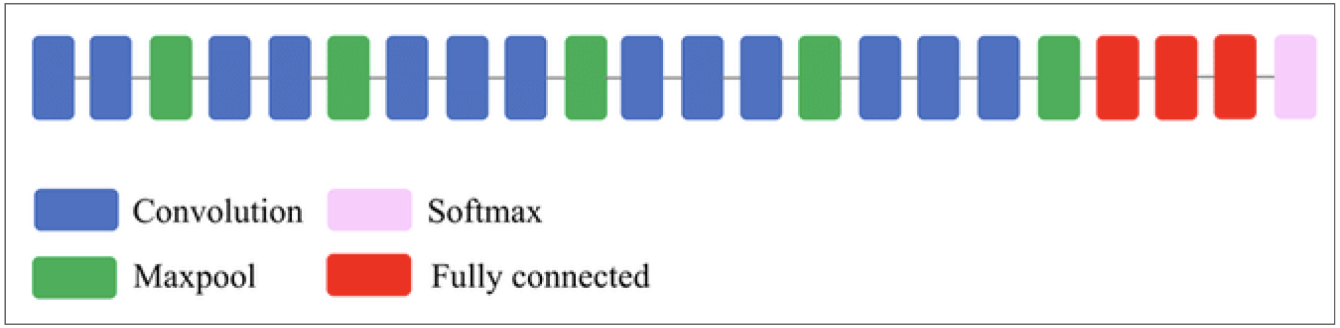
(Almost) no more overfitting!



Real-world CNNs

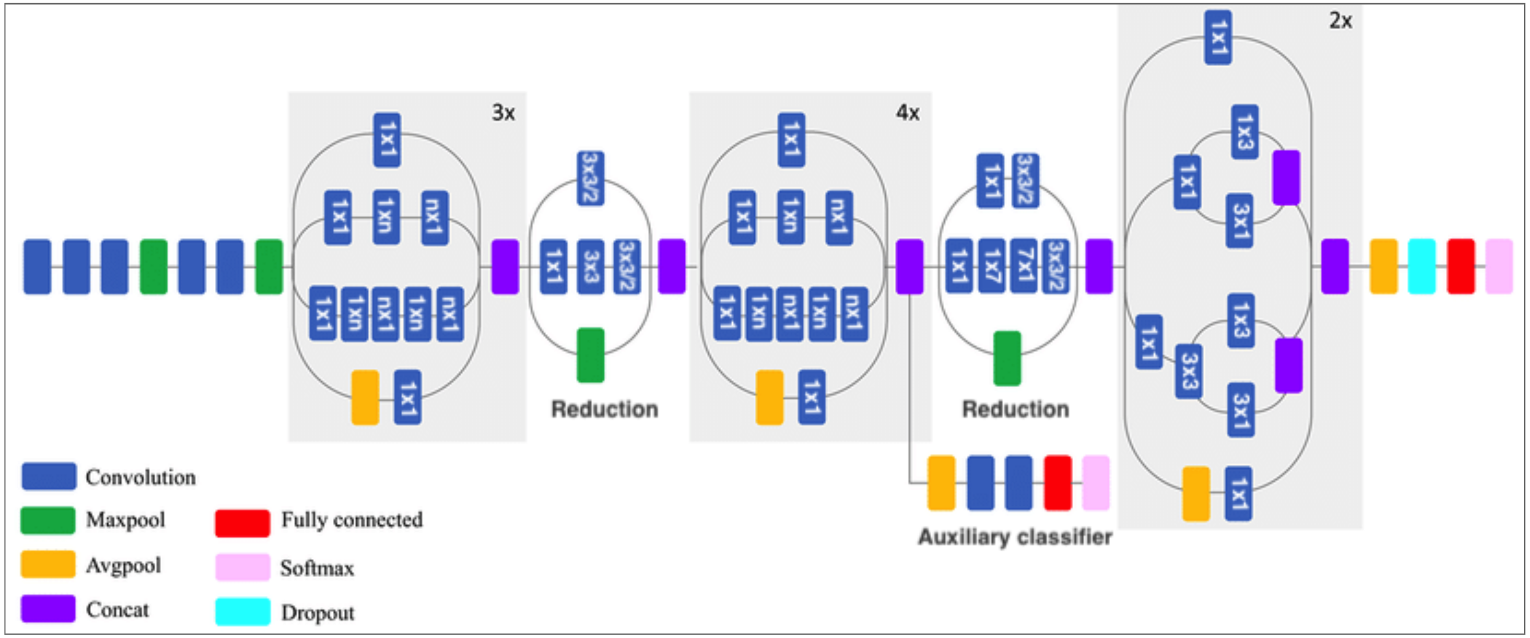
VGG16

- Deeper architecture (16 layers): allows it to learn more complex high-level features
    - Textures, patterns, shapes,...
- Small filters (3x3) work better: capture spatial information while reducing number of parameters
- Max-pooling (2x2): reduces spatial dimension, improves translation invariance
    - Lower resolution forces model to learn robust features (less sensitive to small input changes)
    - Only after every 2 layers, otherwise dimensions reduce too fast
- Downside: too many parameters, expensive to train



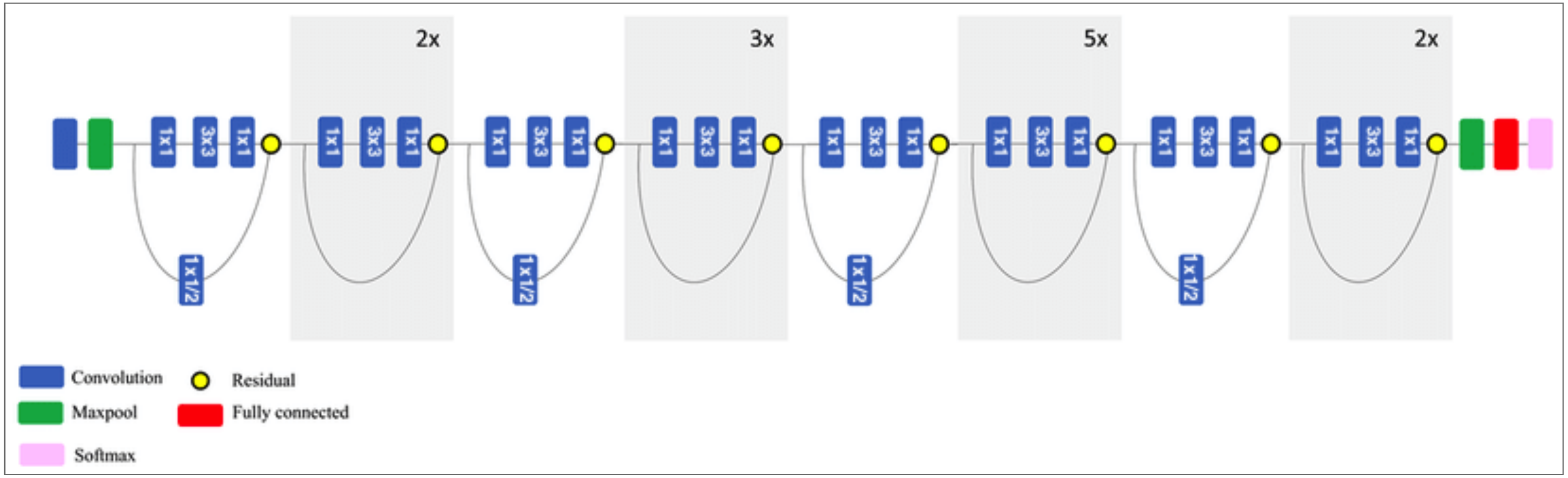
Inceptionv3

- Inception modules: parallel branches learn features of different sizes and scales (3x3, 5x5, 7x7,...)
    - Add reduction blocks that reduce dimensionality via convolutions with stride 2
- Factorized convolutions: a 3x3 conv. can be replaced by combining 1x3 and 3x1, and is 33% cheaper
    - A 5x5 can be replaced by combining 3x3 and 3x3, which can in turn be factorized as above
- 1x1 convolutions, or Network-In-Network (NIN) layers help reduce the number of channels: cheaper
- An auxiliary classifier adds an additional gradient signal deeper in the network



ResNet50

- Residual (skip) connections: add earlier feature map to a later one (dimensions must match)
    - Information can bypass layers, reduces vanishing gradients, allows much deeper nets
- Residual blocks: skip small number or layers and repeat many times
    - Match dimensions though padding and 1x1 convolutions
    - When resolution drops, add 1x1 convolutions with stride 2
- Can be combined with Inception blocks



Interpreting the model

- Let's see what the convnet is learning exactly by observing the intermediate feature maps
    - A layer's output is also called its *activation*
- We can choose a specific test image, and observe the outputs
- We can retrieve and visualize the activation for every filter for every layer

- Layer 0: has activations of resolution 148x148 for each of its 32 filters
- Layer 2: has activations of resolution 72x72 for each of its 64 filters
- Layer 4: has activations of resolution 34x34 for each of its 128 filters
- Layer 6: has activations of resolution 15x15 for each of its 128 filters

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d_10 (Conv2D)          (None, 148, 148, 32)      896       
                                                                 
 max_pooling2d_8 (MaxPooling  (None, 74, 74, 32)       0         
 2D)                                                             
                                                                 
 conv2d_11 (Conv2D)          (None, 72, 72, 64)        18496     
                                                                 
 max_pooling2d_9 (MaxPooling  (None, 36, 36, 64)       0         
 2D)                                                             
                                                                 
 conv2d_12 (Conv2D)          (None, 34, 34, 128)       73856     
                                                                 
 max_pooling2d_10 (MaxPoolin  (None, 17, 17, 128)      0         
 g2D)                                                            
                                                                 
 conv2d_13 (Conv2D)          (None, 15, 15, 128)       147584    
                                                                 
 max_pooling2d_11 (MaxPoolin  (None, 7, 7, 128)        0         
 g2D)                                                            
                                                                 
 flatten_2 (Flatten)         (None, 6272)              0         
                                                                 
 dropout (Dropout)           (None, 6272)              0         
                                                                 
 dense_4 (Dense)             (None, 512)               3211776   
                                                                 
 dense_5 (Dense)             (None, 1)                 513       
                                                                 
=================================================================
Total params: 3,453,121
Trainable params: 3,453,121
Non-trainable params: 0
_________________________________________________________________
```

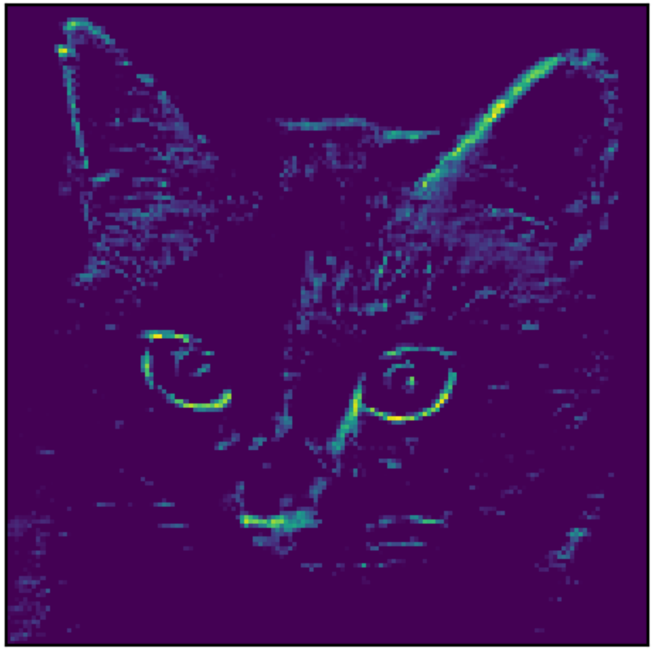
- To extract the activations, we create a new model that outputs the trained layers
    - 8 output layers in total (only the convolutional part)
- We input a test image for prediction and then read the relevant outputs

```
layer_outputs = [layer.output for layer in model.layers[:8]]
activation_model = models.Model(inputs=model.input,
outputs=layer_outputs)
activations = activation_model.predict(img_tensor)
```

Output of the first Conv2D layer, 3rd channel (filter):

- Similar to a diagonal edge detector
- Your own channels may look different

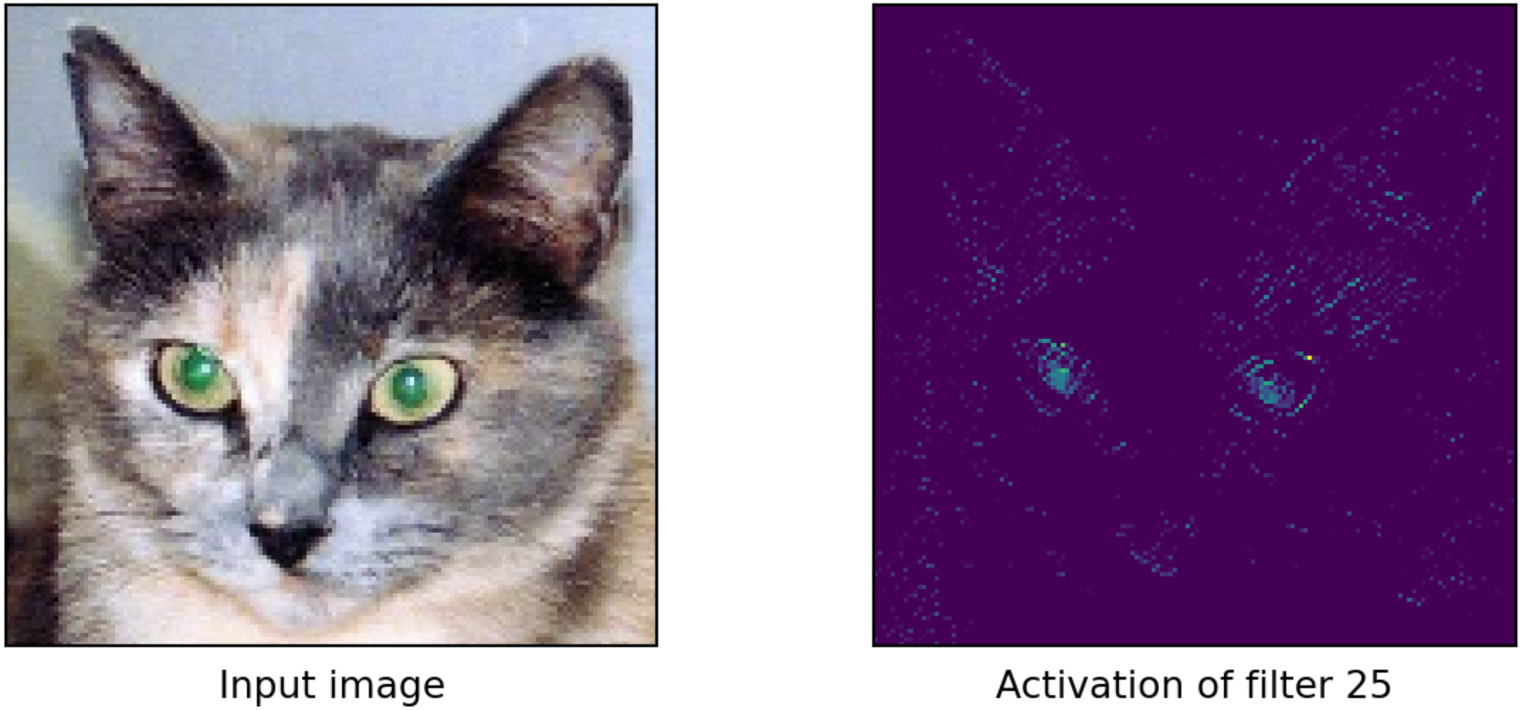
Input image



Activation of filter 6

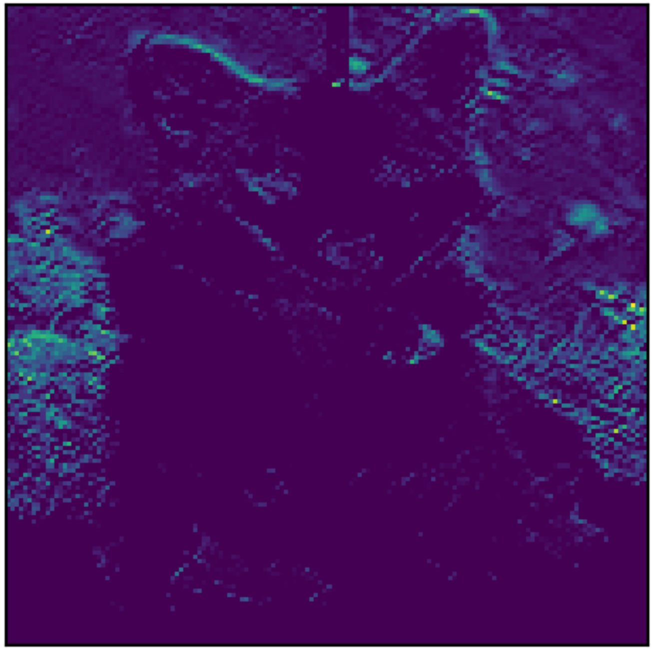
Output of filter 16:

- Cat eye detector?



The same filter responds quite differently for other inputs (green detector?).

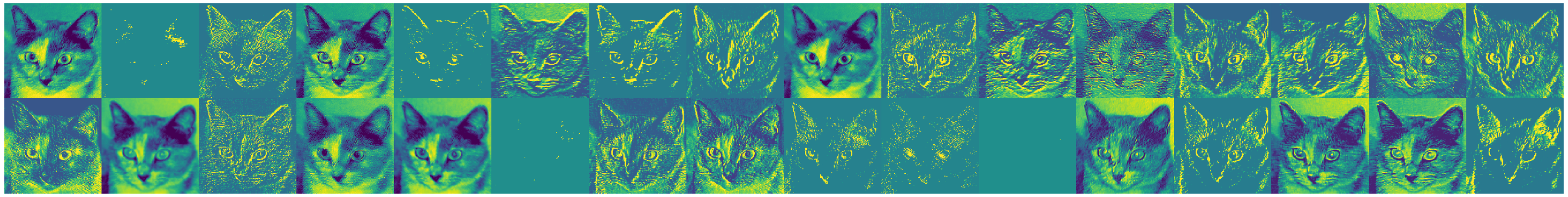
Input image



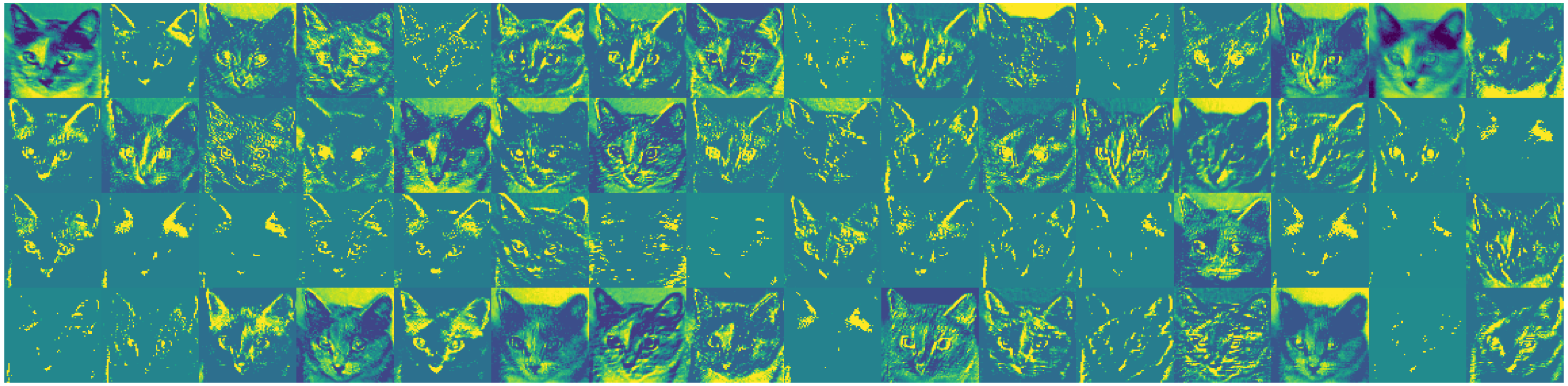
Activation of filter 25

- First 2 convolutional layers: various edge detectors

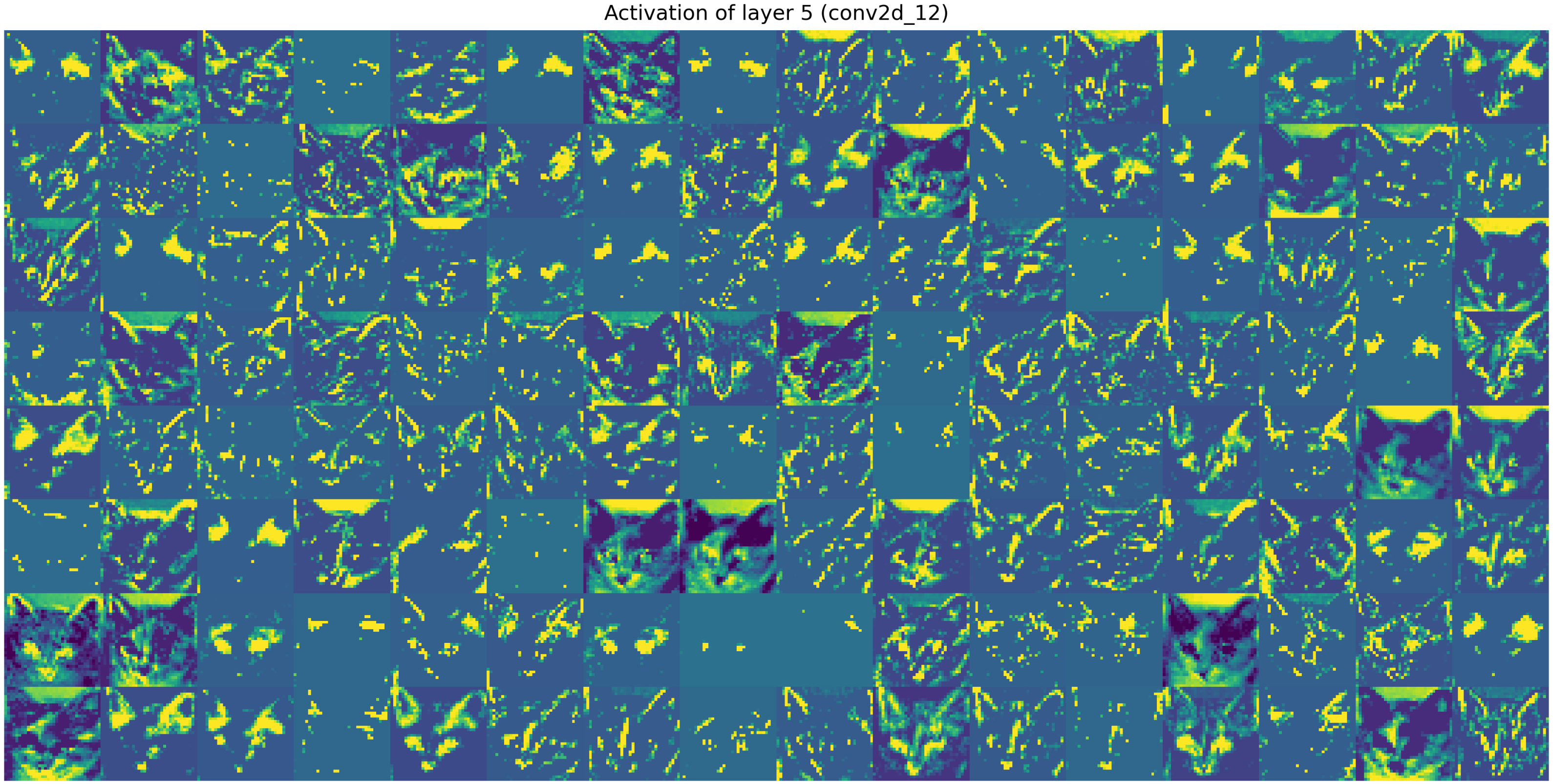
Activation of layer 1 (conv2d_10)



Activation of layer 3 (conv2d_11)

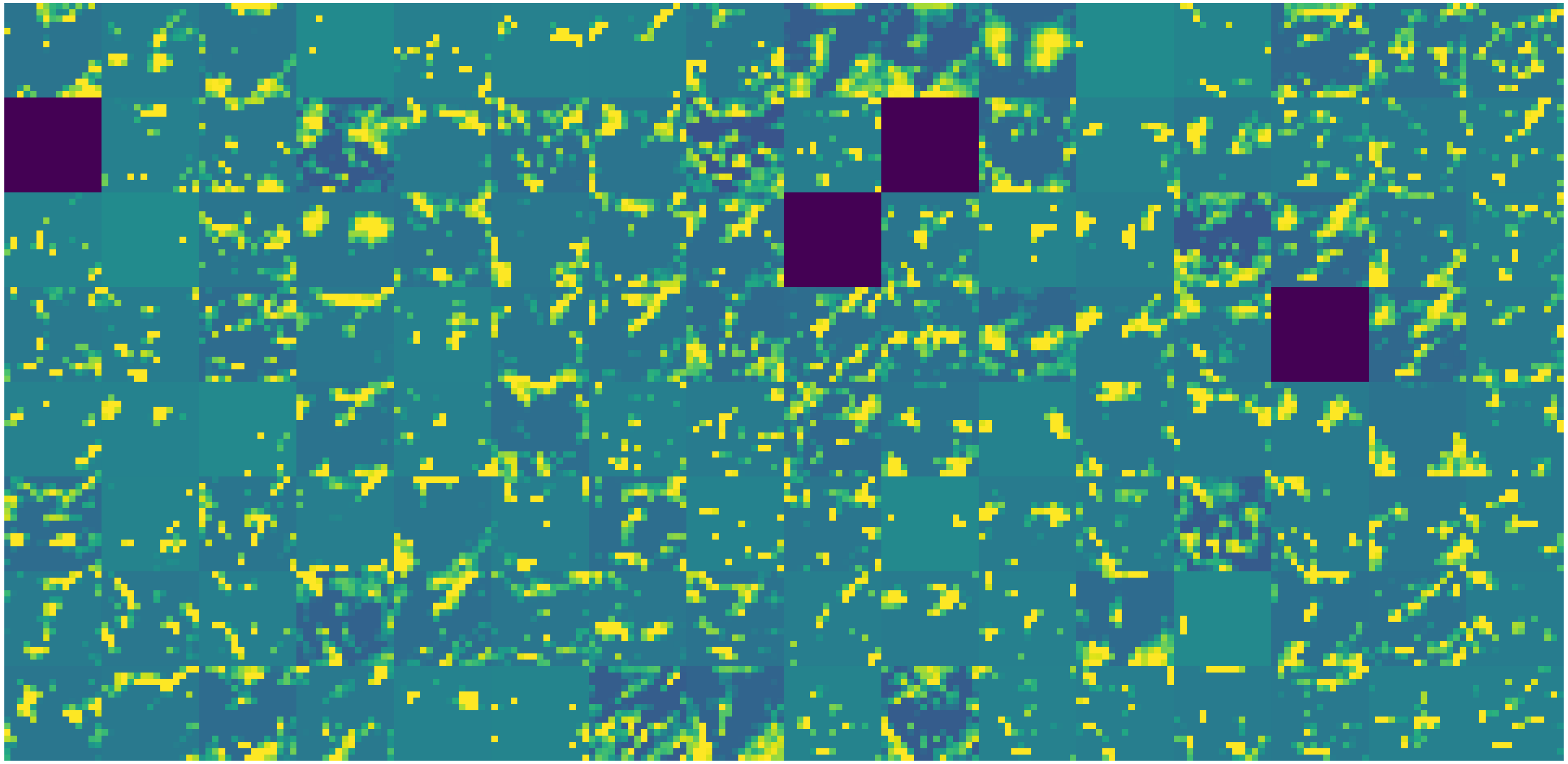


- 3rd convolutional layer: increasingly abstract: ears, eyes



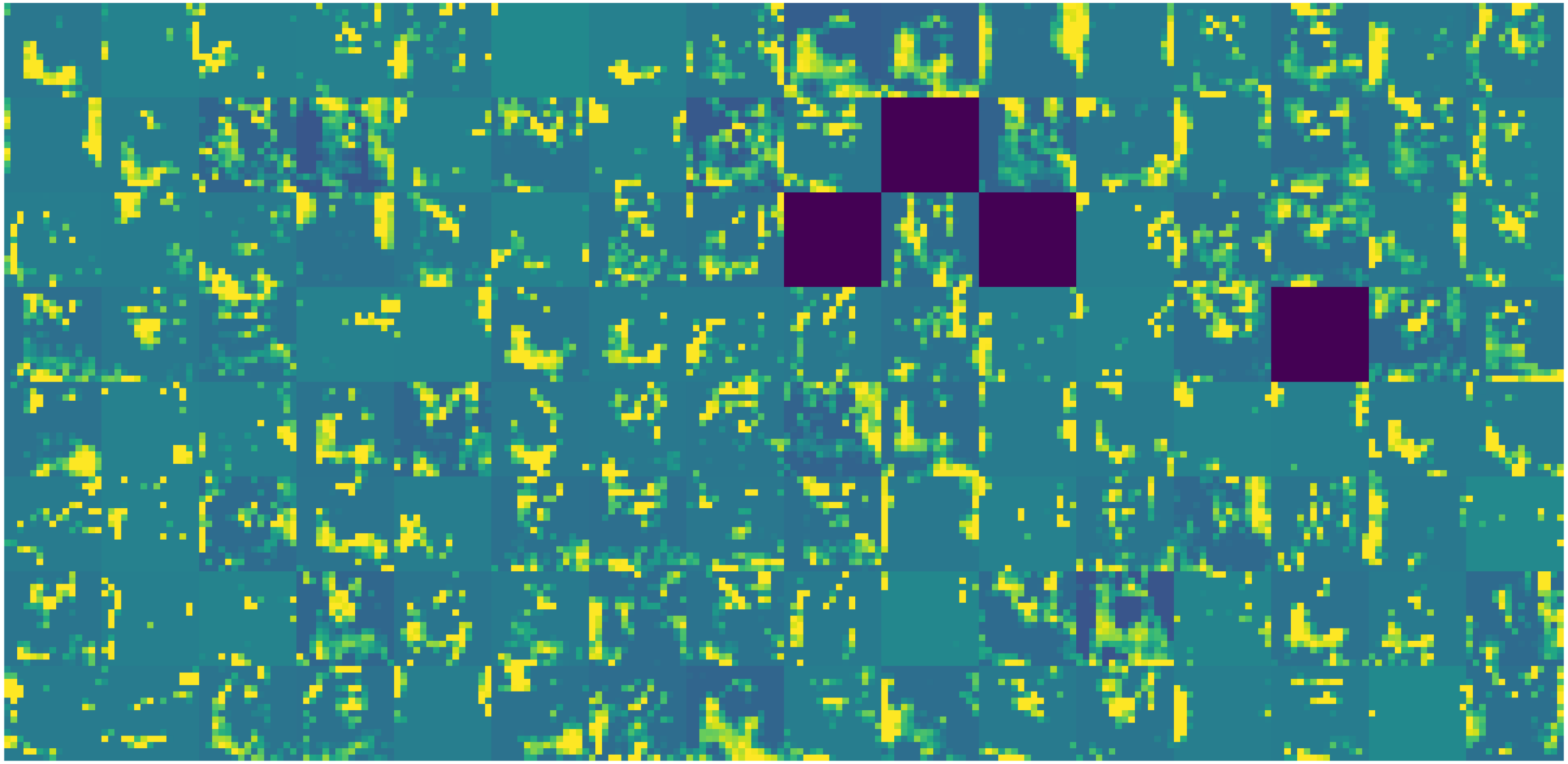
- Last convolutional layer: more abstract patterns
- Empty filter activations: input image does not have the information that the filter was interested in

Activation of layer 7 (conv2d_13)



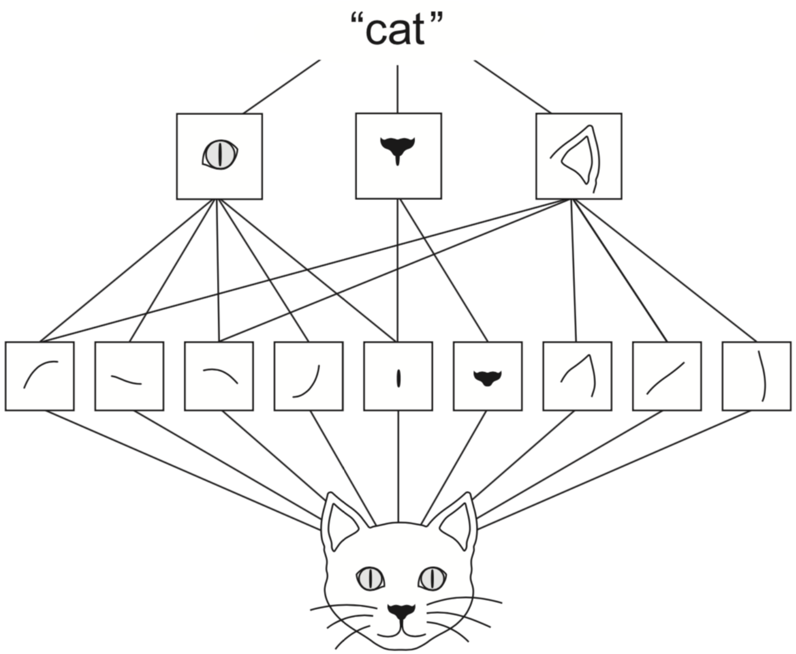
- Same layer, with dog image input
    - Very different activations

Activation of layer 7 (conv2d_13)



Spatial hierarchies

- Deep convnets can learn *spatial hierarchies* of patterns
    - First layer can learn very local patterns (e.g. edges)
    - Second layer can learn specific combinations of patterns
    - Every layer can learn increasingly complex *abstractions*

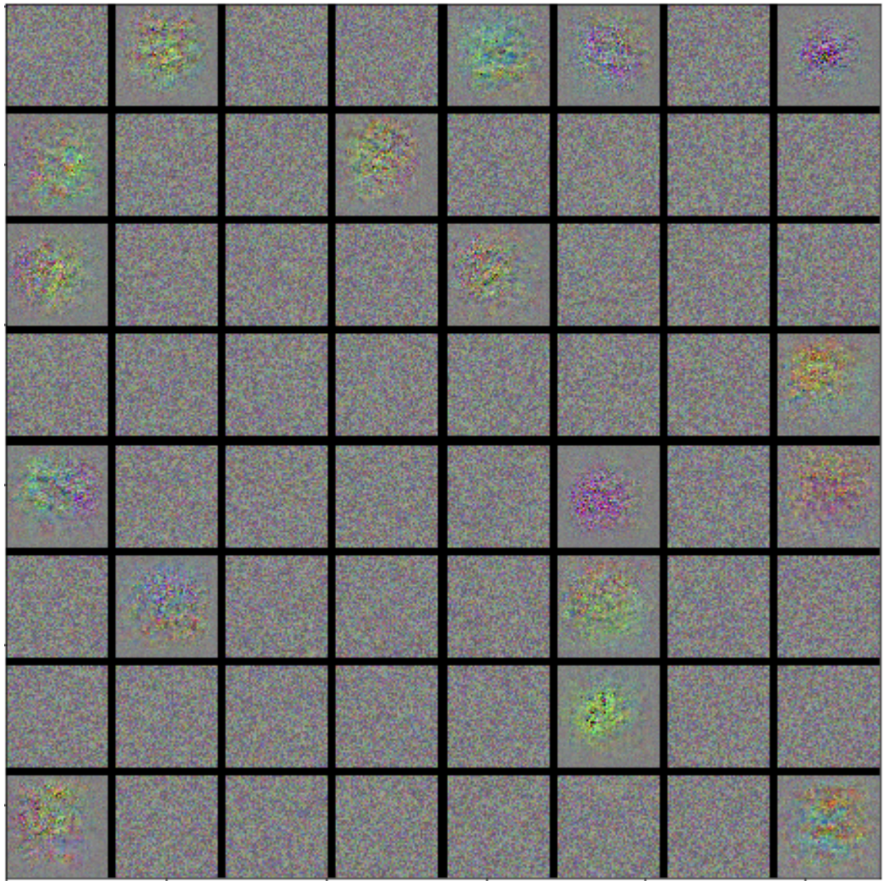


Visualizing the learned filters

- Visualize filters by finding the input image that they are maximally responsive to
- *gradient ascent in input space* : start from a random image x, use loss to update the **input values** to values that the filter responds to more strongly (keep weights fixed)
  - $X_{(i+1)} = X_{(i)} + \frac{\partial L(x, X_{(i)})}{\partial X} * \eta$

```
from keras import backend as K
    input_img = np.random.random((1, size, size, 3)) * 20 + 128.
    loss = K.mean(layer_output[:, :, :, filter_index])
    grads = K.gradients(loss, model.input)[0] # Compute gradient
    for i in range(40): # Run gradient ascent for 40 steps
        loss_v, grads_v = K.function([input_img], [loss, grads])
        input_img_data += grads_v * step
```

- Learned filters of last convolutional layer
- More focused on center, some vague cat/dog head shapes



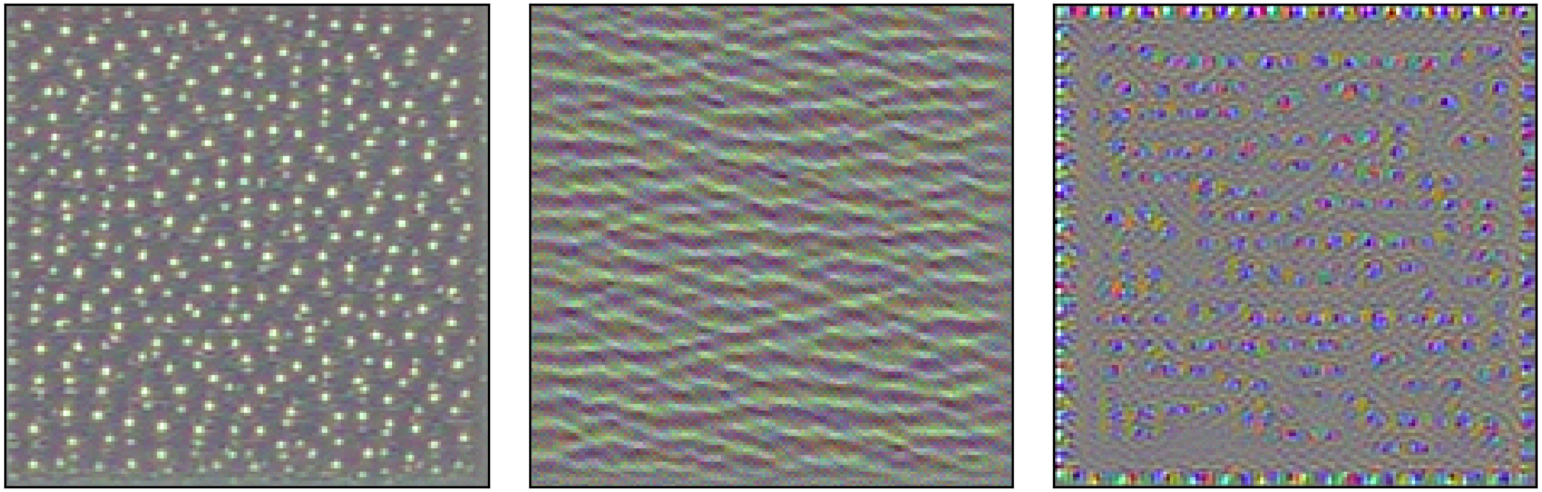
Let's do this again for the `VGG16` network pretrained on `ImageNet` (much larger)

```
model = VGG16(weights='imagenet', include_top=False)
```

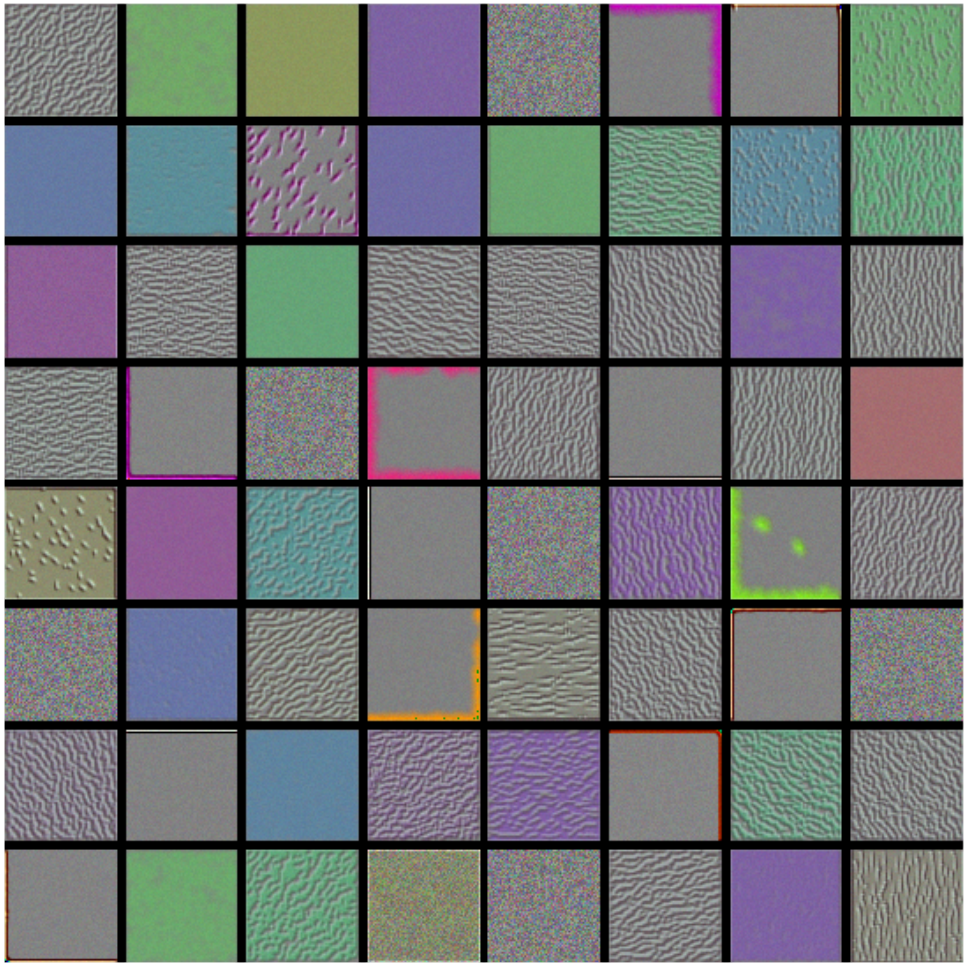
```
Model: "vgg16"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, None, None, 3)]   0

 block1_conv1 (Conv2D)       (None, None, None, 64)    1792

 block1_conv2 (Conv2D)       (None, None, None, 64)    36928

 block1_pool (MaxPooling2D)  (None, None, None, 64)    0

 block2_conv1 (Conv2D)       (None, None, None, 128)   73856

 block2_conv2 (Conv2D)       (None, None, None, 128)   147584

 block2_pool (MaxPooling2D)  (None, None, None, 128)   0

 block3_conv1 (Conv2D)       (None, None, None, 256)   295168

 block3_conv2 (Conv2D)       (None, None, None, 256)   590080

 block3_conv3 (Conv2D)       (None, None, None, 256)   590080

 block3_pool (MaxPooling2D)  (None, None, None, 256)   0

 block4_conv1 (Conv2D)       (None, None, None, 512)   1180160

 block4_conv2 (Conv2D)       (None, None, None, 512)   2359808

 block4_conv3 (Conv2D)       (None, None, None, 512)   2359808

 block4_pool (MaxPooling2D)  (None, None, None, 512)   0

 block5_conv1 (Conv2D)       (None, None, None, 512)   2359808

 block5_conv2 (Conv2D)       (None, None, None, 512)   2359808

 block5_conv3 (Conv2D)       (None, None, None, 512)   2359808
```

```
 block5_pool (MaxPooling2D)  (None, None, None, 512)   0

=================================================================
Total params: 14,714,688
Trainable params: 14,714,688
Non-trainable params: 0
_________________________________________________________________
```

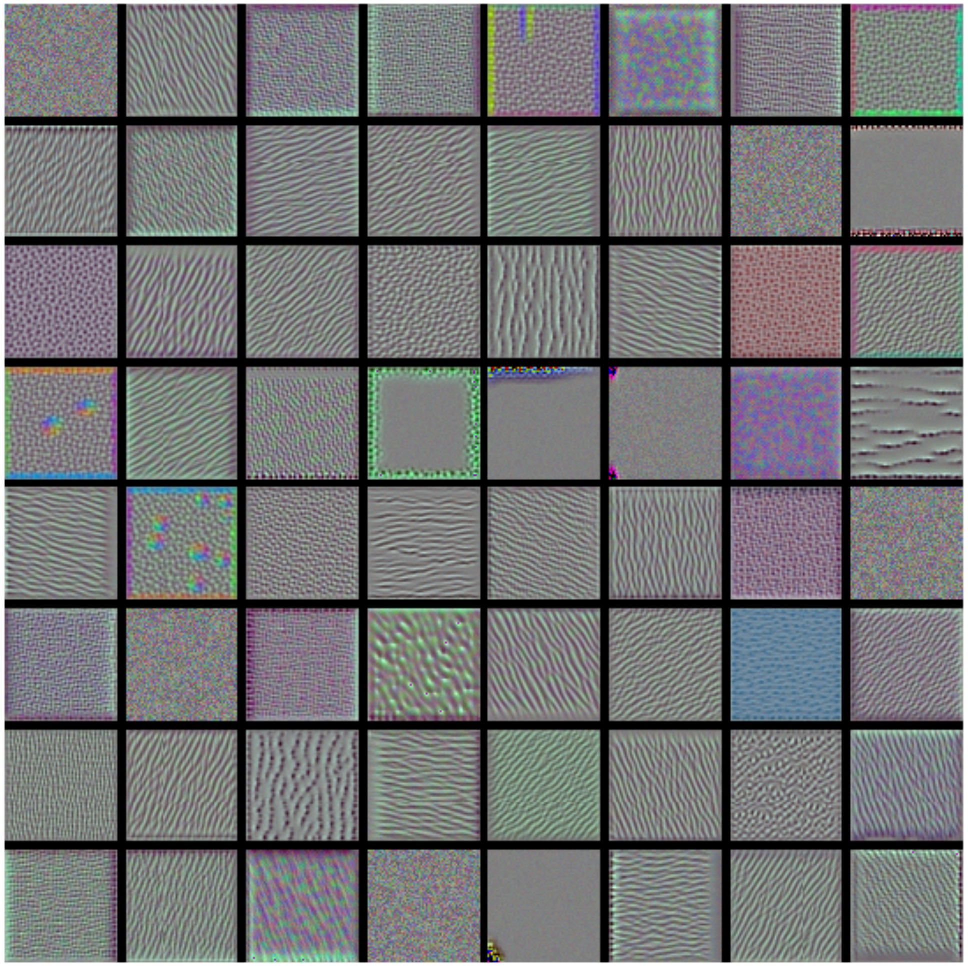
- Visualize convolution filters 0-2 from layer 5 of the VGG network trained on ImageNet
- Some respond to dots or waves in the image



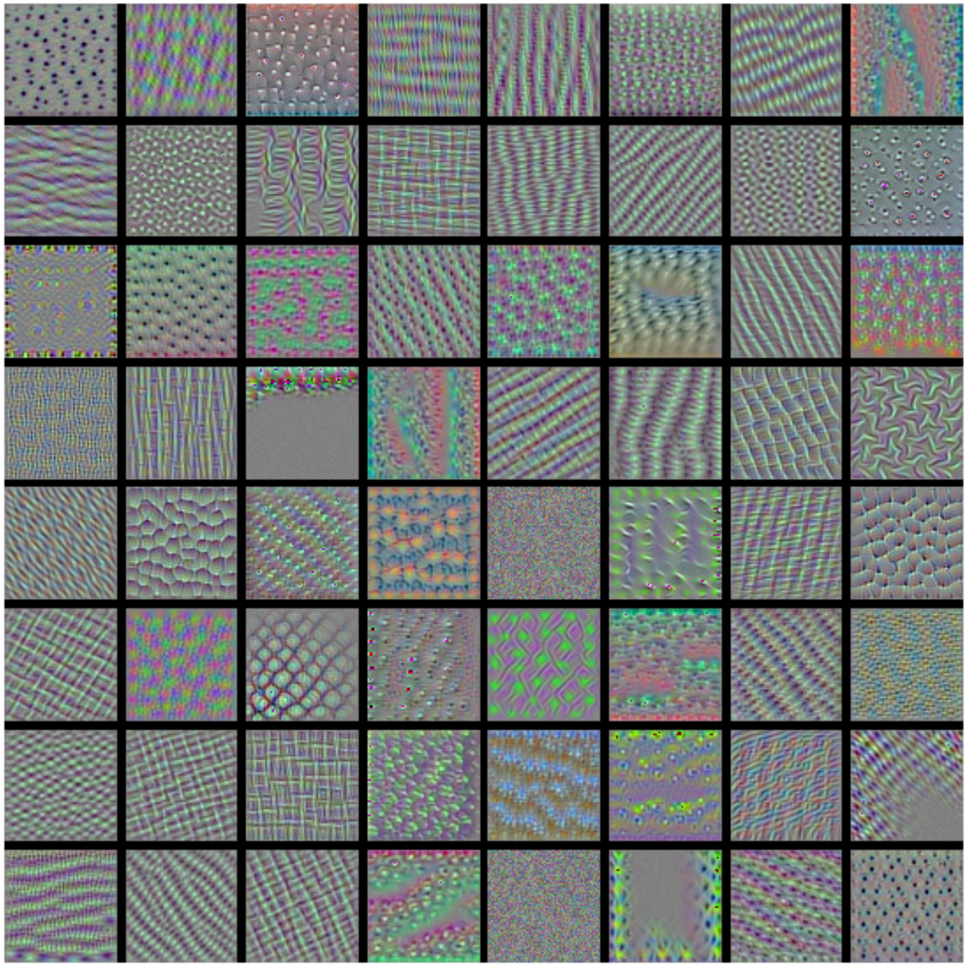
First 64 filters for 1st convolutional layer in block 1: simple edges and colors



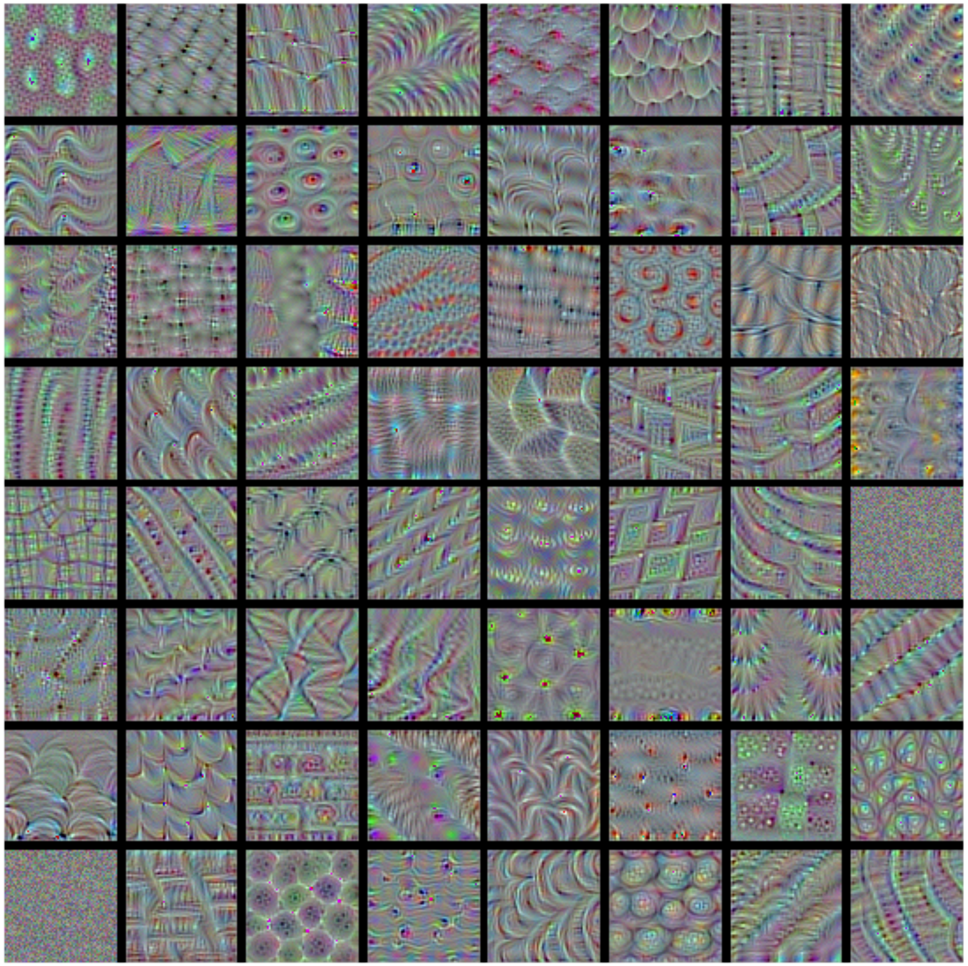
Filters in 2nd block of convolution layers: simple textures (combined edges and colors)



Filters in 3rd block of convolution layers: more natural textures

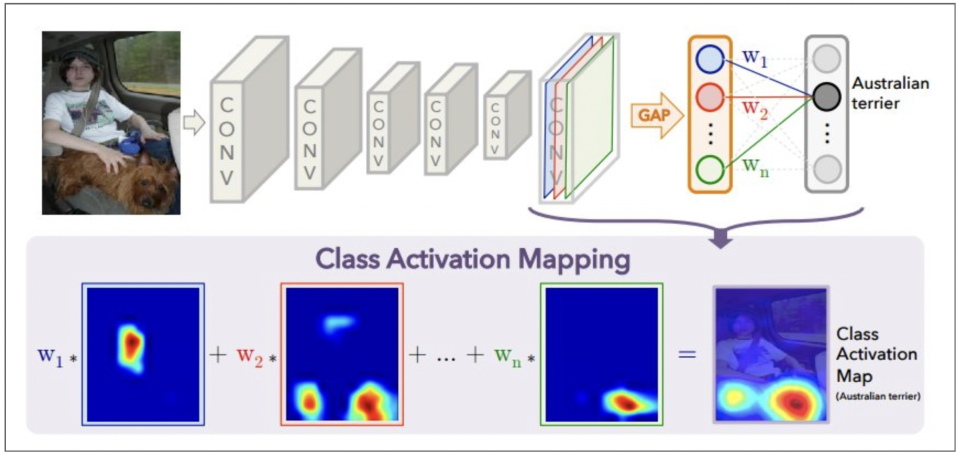


Filters in 4th block of convolution layers: feathers, eyes, leaves,...



Visualizing class activation

- We can also visualize which part of the input image had the greatest influence on the final classification. Helps to interpret what the model is paying attention to.
- *Class activation maps* : produces a heatmap over the input image
  - Choose a convolution layer, do Global Average Pooling (GAP) to get one output per filter
  - Get the weights between those outputs and the class of interest
  - Compute the weighted sum of all filter activations: combines what each filter is responding to and how much this affects the class prediction



Example on VGG with a specific input image

- Take the last convolutional layer of VGG pretrained on ImageNet
    - It consists of 512 filters of size 14x14

```
model = VGG16(weights='imagenet')
last_conv_layer = model.get_layer('block5_conv3')
```

```
Last conv layer shape: (None, 14, 14, 512)
```

- Choose an input image and preprocess it so we can feed it to the model

```
img = image.load_img(img_path, target_size=(224, 224))
```

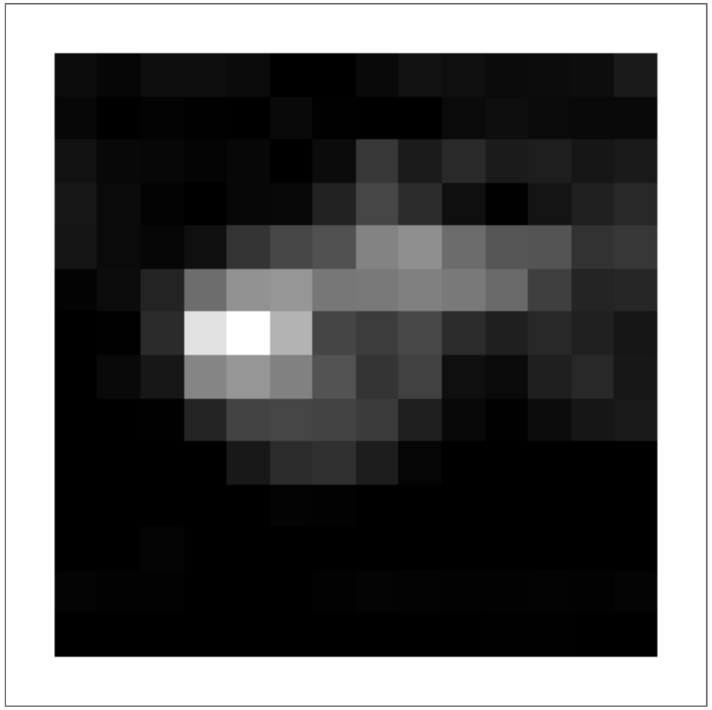
- Find the output node for its class ('african elephant', class 386)

```
african_elephant_output = model.output[:, 386]
```

- VGG doesn't use GAP. Compute the average gradient from the output node to the conv layer
- Multiply (channel-wise) with the activations of the conv layer

```
grads = K.gradients(african_elephant_output, last_conv_layer.output)[0]
pooled_grads = K.mean(grads, axis=(0, 1, 2))
for i in range(512): # 512 filters
    conv_layer_output_value[:, :, i] *= pooled_grads_value[i]
heatmap = np.mean(conv_layer_output_value, axis=-1)
```

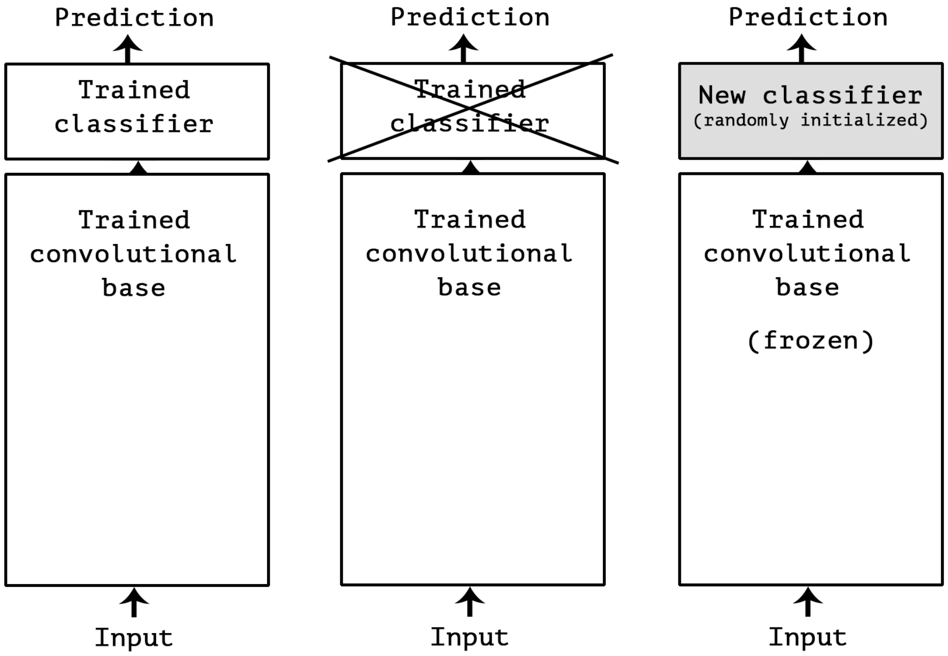
- Visualize `heatmap`. It's 14x14 since that's the output dimension of the conv layer



- Upscaled and superimposed on the original image
- The model looked at the face of the baby elephant and the trunk of the large elephant

Using pretrained networks

- We can re-use pretrained networks instead of training from scratch
- Learned features can be a generic model of the visual world
- Use *convolutional base* to contruct features, then train any classifier on new data
- Also called *transfer learning* , which is a kind of *meta-learning*



- Let's instantiate the VGG16 model (without the dense layers)
- Final feature map has shape (4, 4, 512)

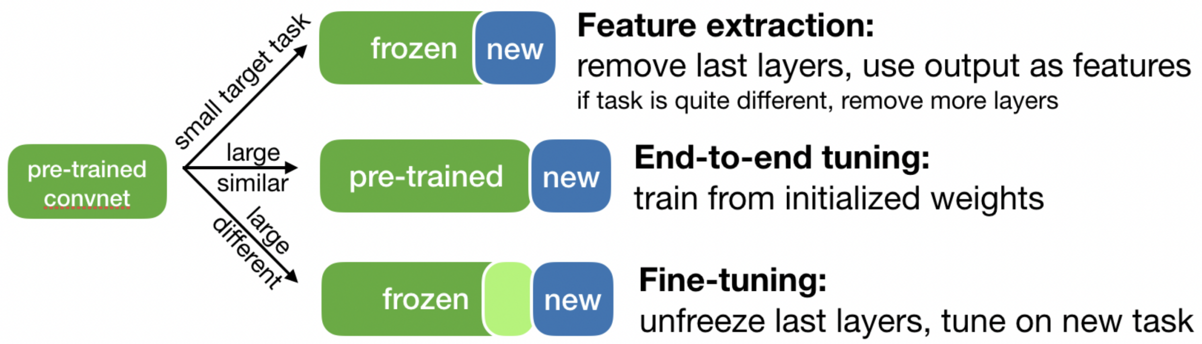
```
conv_base = VGG16(weights='imagenet', include_top=False,
input_shape=(150, 150, 3))
```

```
Model: "vgg16"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_2 (InputLayer)        [(None, 150, 150, 3)]     0

 block1_conv1 (Conv2D)       (None, 150, 150, 64)      1792

 block1_conv2 (Conv2D)       (None, 150, 150, 64)      36928

 block1_pool (MaxPooling2D)  (None, 75, 75, 64)        0

 block2_conv1 (Conv2D)       (None, 75, 75, 128)       73856

 block2_conv2 (Conv2D)       (None, 75, 75, 128)       147584

 block2_pool (MaxPooling2D)  (None, 37, 37, 128)       0

 block3_conv1 (Conv2D)       (None, 37, 37, 256)       295168

 block3_conv2 (Conv2D)       (None, 37, 37, 256)       590080

 block3_conv3 (Conv2D)       (None, 37, 37, 256)       590080

 block3_pool (MaxPooling2D)  (None, 18, 18, 256)       0

 block4_conv1 (Conv2D)       (None, 18, 18, 512)       1180160

 block4_conv2 (Conv2D)       (None, 18, 18, 512)       2359808

 block4_conv3 (Conv2D)       (None, 18, 18, 512)       2359808

 block4_pool (MaxPooling2D)  (None, 9, 9, 512)         0

 block5_conv1 (Conv2D)       (None, 9, 9, 512)         2359808
```

```
 block5_conv2 (Conv2D)       (None, 9, 9, 512)         2359808

 block5_conv3 (Conv2D)       (None, 9, 9, 512)         2359808

 block5_pool (MaxPooling2D)  (None, 4, 4, 512)         0

=================================================================
Total params: 14,714,688
Trainable params: 14,714,688
Non-trainable params: 0
_________________________________________________________________
```

Using pre-trained networks: 3 ways

- Fast feature extraction (similar task, little data)
  - Call `predict` from the convolutional base to build new features
  - Use outputs as input to a new neural net (or other algorithm)
- End-to-end tuning (similar task, lots of data + data augmentation)
  - Extend the convolutional base model with a new dense layer
  - Train it end to end on the new data (expensive!)
- Fine-tuning (somewhat different task)
  - Unfreeze a few of the top convolutional layers, and retrain
    - Update only the more abstract representations



Fast feature extraction (without data augmentation)

- Run every batch through the pre-trained convolutional base

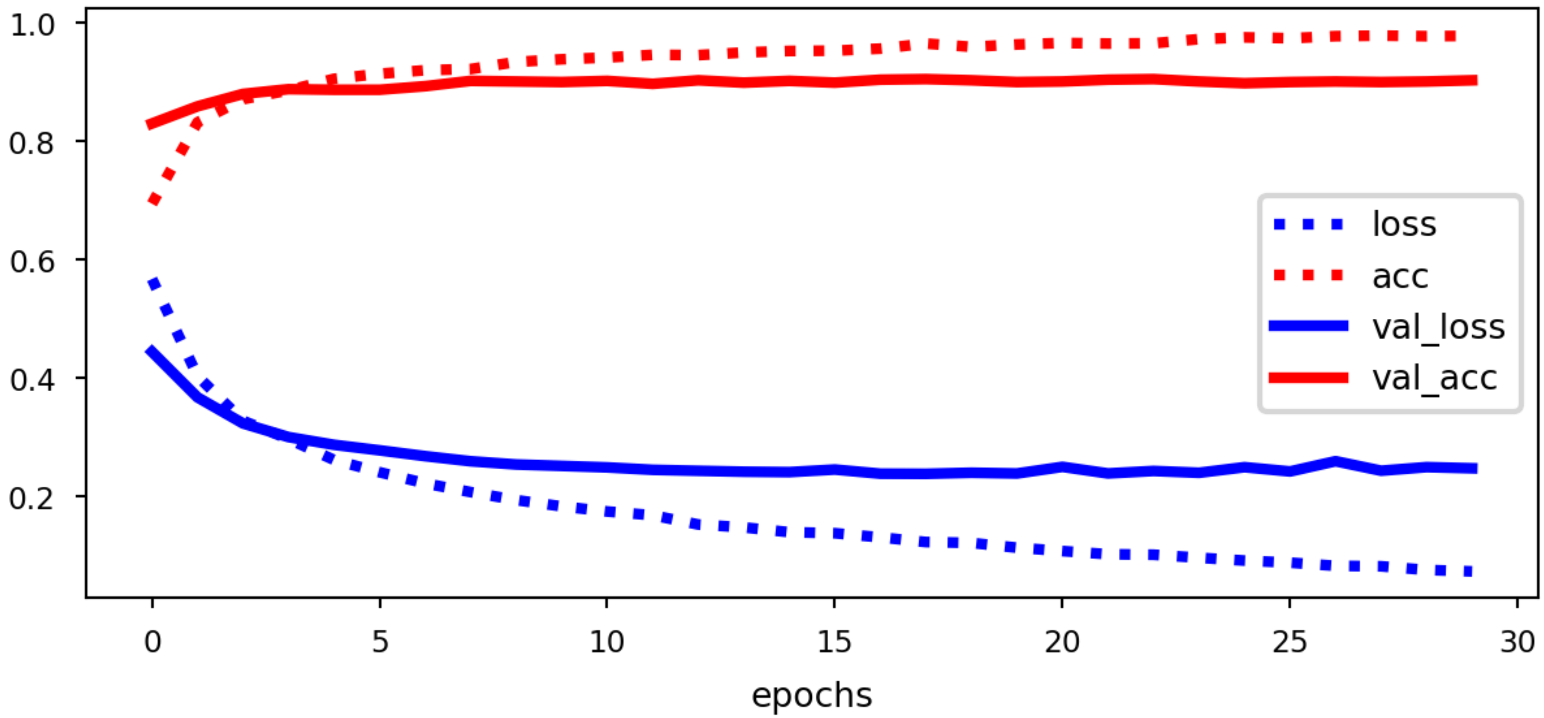
```
generator = datagen.flow_from_directory(dir, target_size=(150, 150),
        batch_size=batch_size, class_mode='binary')
for inputs_batch, labels_batch in generator:
    features_batch = conv_base.predict(inputs_batch)
```

- Build Dense neural net (with Dropout)
- Train and evaluate with the transformed examples

```
model = models.Sequential()
model.add(layers.Dense(256, activation='relu', input_dim=4 * 4 *
512))
model.add(layers.Dropout(0.5))
model.add(layers.Dense(1, activation='sigmoid'))
```

- Validation accuracy around 90%, much better!
- Still overfitting, despite the Dropout: not enough training data

```
Max val_acc 0.90500003
```



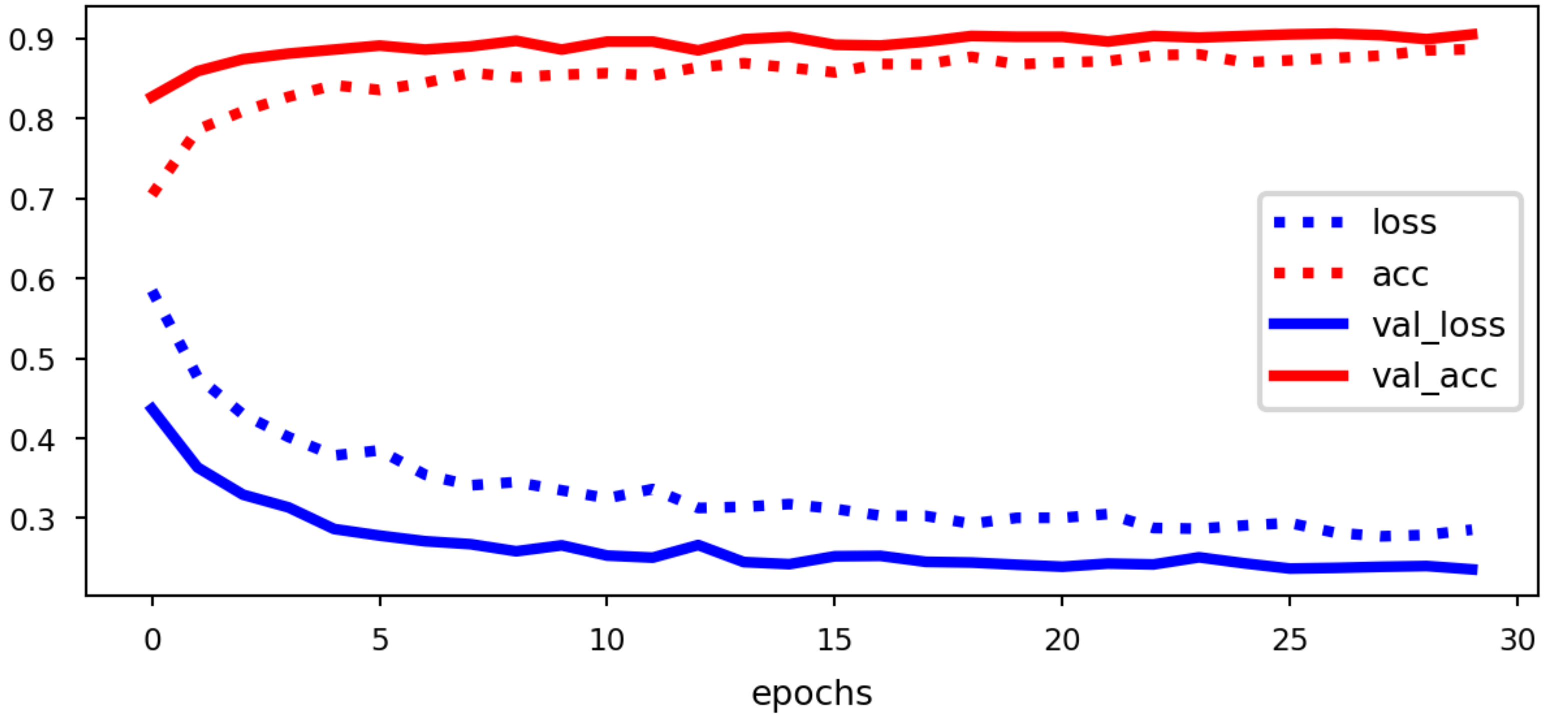
Fast feature extraction (with data augmentation)

- Simply add the Dense layers to the convolutional base
- *Freeze* the convolutional base (before you compile)
    - Without freezing, you train it end-to-end (expensive)

```
model = models.Sequential()
model.add(conv_base)
model.add(layers.Flatten())
model.add(layers.Dense(256, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))
conv_base.trainable = False
```

We now get about 90% accuracy again, and very little overfitting

```
Max val_acc 0.906
```

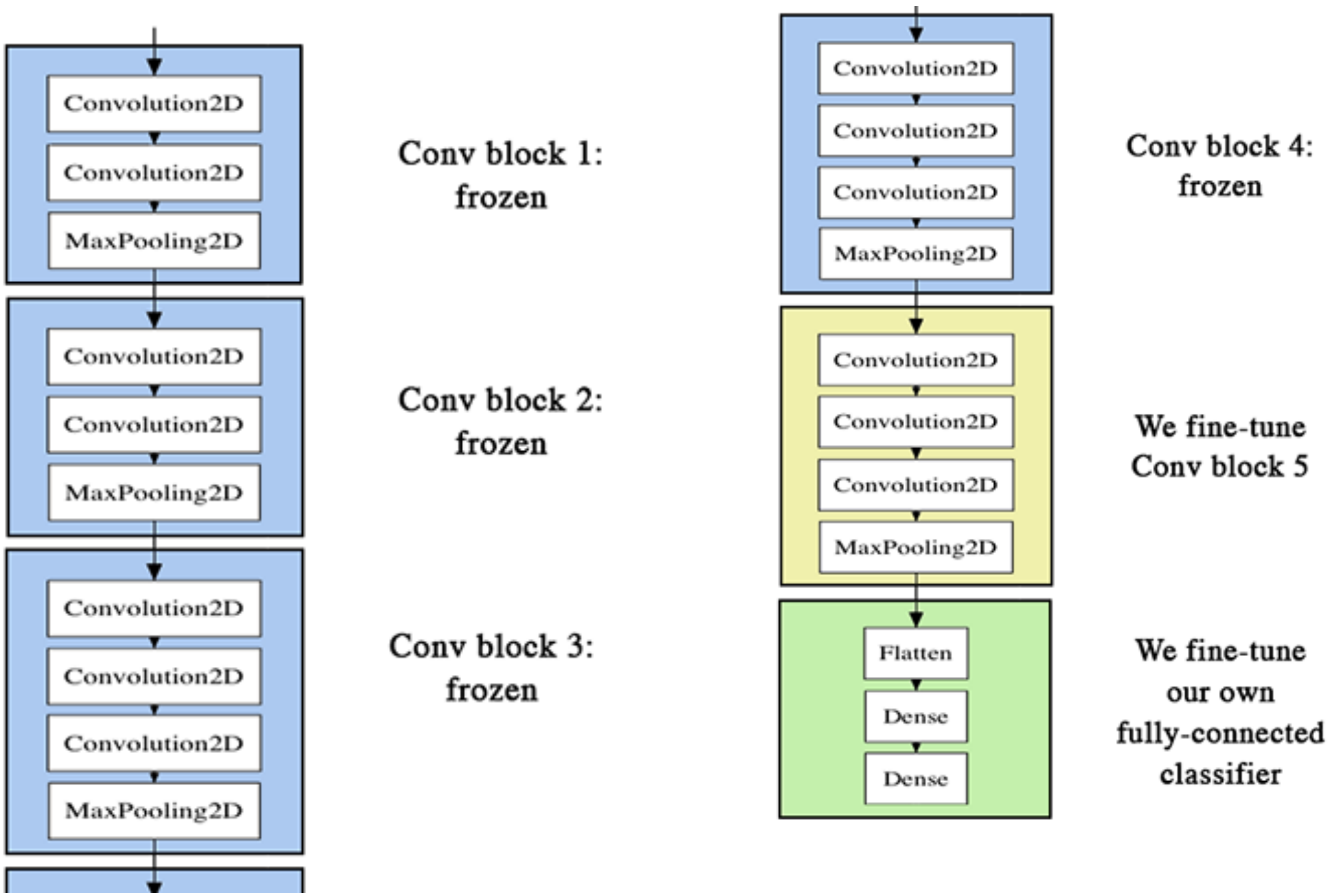


Fine-tuning

- Add your custom network on top of an already trained base network.
- Freeze the base network, but unfreeze the last block of conv layers.

```
for layer in conv_base.layers:
    if layer.name == 'block5_conv1':
        layer.trainable = True
    else:
        layer.trainable = False
```

Visualized



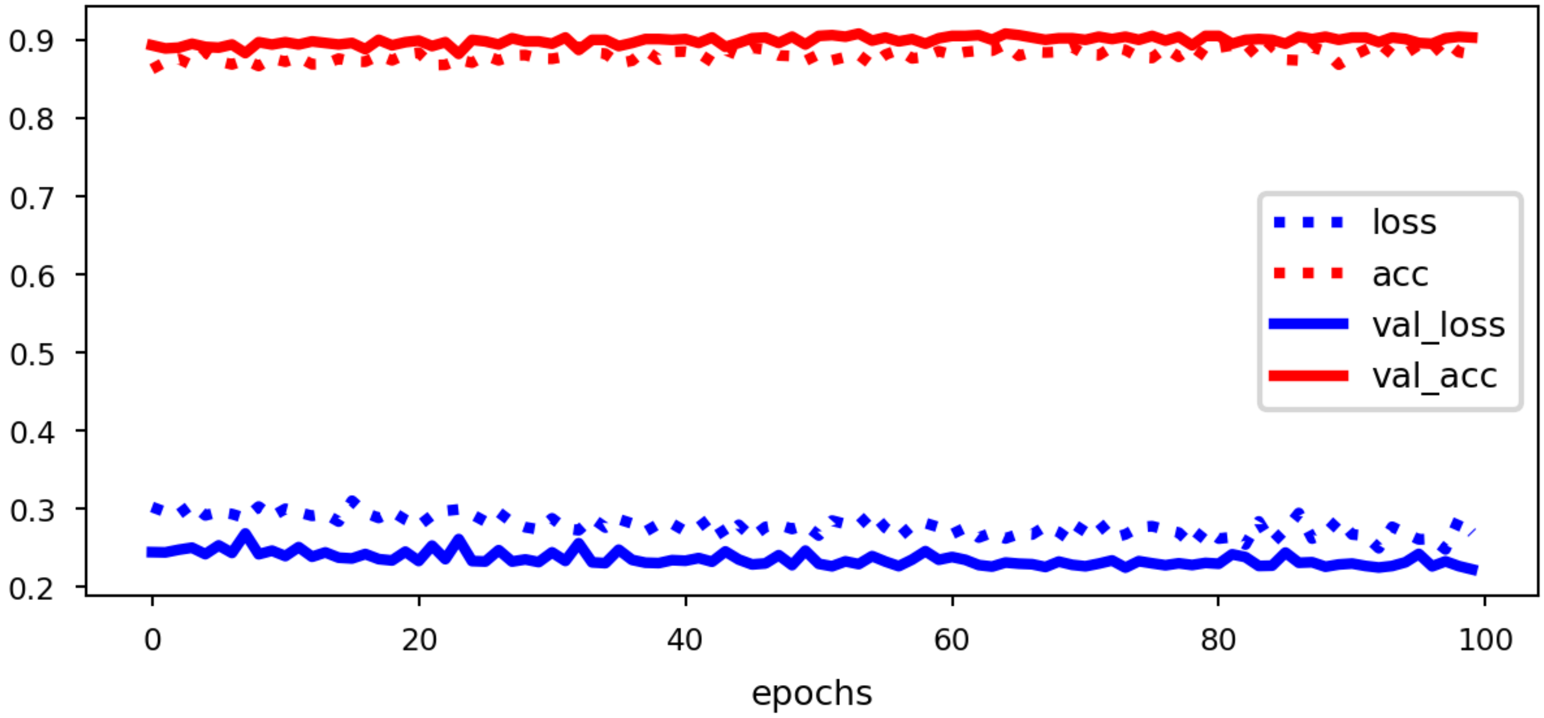
Convolution2D
Convolution2D
MaxPooling2D
Conv block 1: frozen
Convolution2D
Convolution2D
MaxPooling2D
Conv block 2: frozen
Convolution2D
Convolution2D
Convolution2D
MaxPooling2D
Conv block 3: frozen
Convolution2D
Convolution2D
Convolution2D
MaxPooling2D
Conv block 4: frozen
Convolution2D
Convolution2D
Convolution2D
MaxPooling2D
We fine-tune Conv block 5
Flatten
Dense
Dense
We fine-tune our own fully-connected classifier

- Load trained network, finetune
    - Use a small learning rate, large number of epochs
    - You don't want to unlearn too much: *catastrophic forgetting*

```
model = load_model(os.path.join(model_dir,
'cats_and_dogs_small_3b.h5'))
model.compile(loss='binary_crossentropy',
              optimizer=optimizers.RMSprop(lr=1e-5),
              metrics=['acc'])
history = model.fit(
      train_generator, steps_per_epoch=100, epochs=100,
      validation_data=validation_generator,
      validation_steps=50)
```

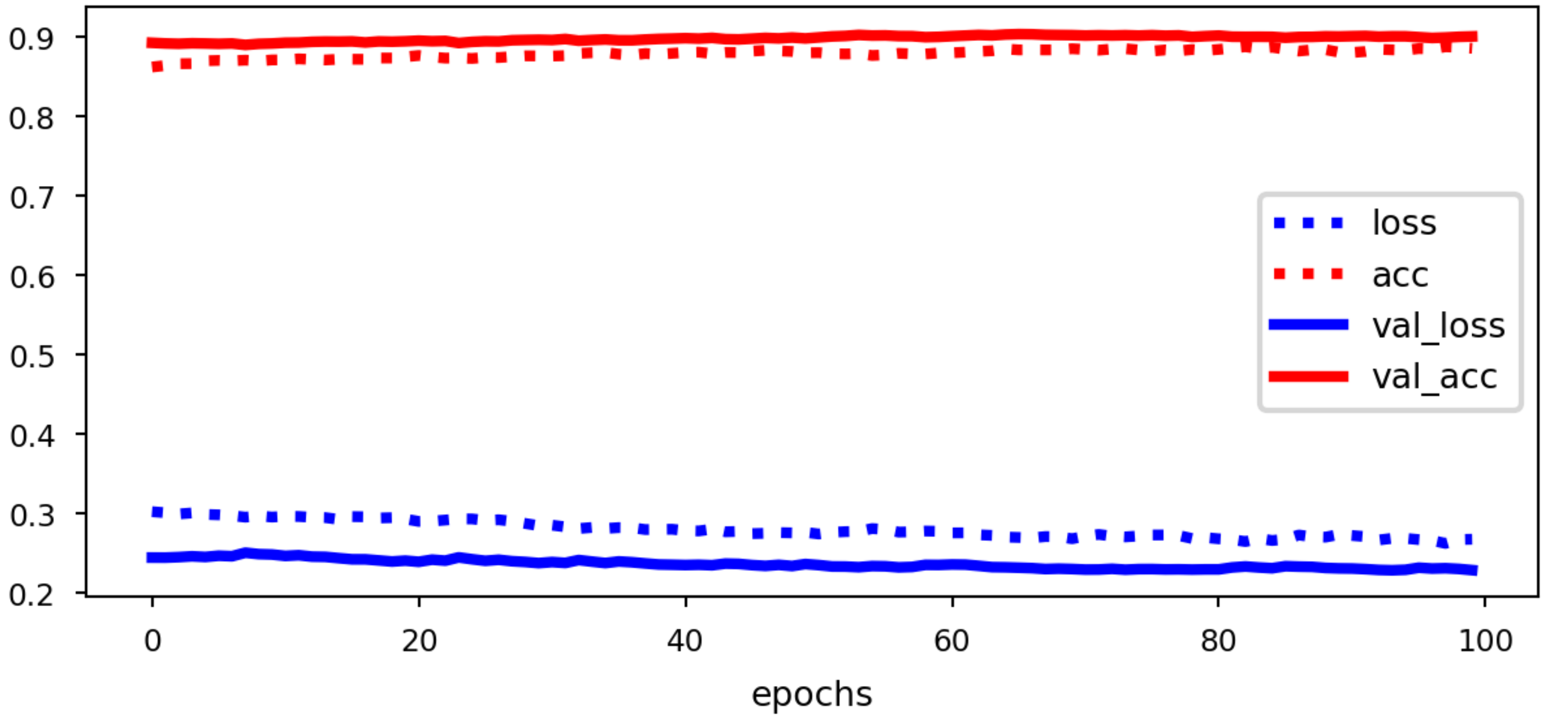
Almost 95% accuracy. The curves are quite noisy, though.

```
Max val_acc 0.90800005
```



- We can smooth the learning curves using a running average

```
Max val_acc 0.9039536851123335
```



Take-aways

- Convnets are ideal for attacking visual-classification problems.
- They learn a hierarchy of modular patterns and concepts to represent the visual world.
- Representations are easy to inspect
- Data augmentation helps fight overfitting
- You can use a pretrained convnet to build better models via transfer learning