Advanced Neural Networks

Joaquin Vanschoren, Eindhoven University of Technology

Overview

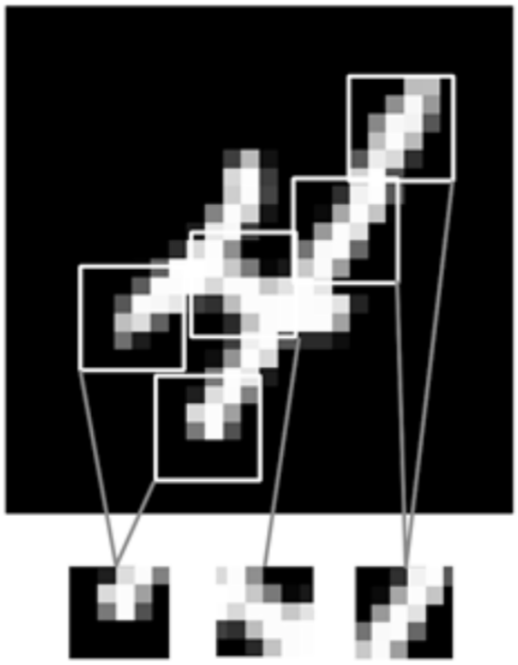
- Convolutional neural networks
- Data augmentation
- Using pre-trained networks
- Batch normalization

Some lessons from Assignment 1

- We saw that greyscaling the image helps, but not a lot
- Problem: numbers can be dark on a light background, or vice versa
    - We care about where the boundaries are, not the exact pixel values
- Problem: the location within the image matters, but not exactly
    - We care about the center, but not exactly where in the center
- In short, we care about shapes (relationships between nearby pixels) much more than the actual pixel values

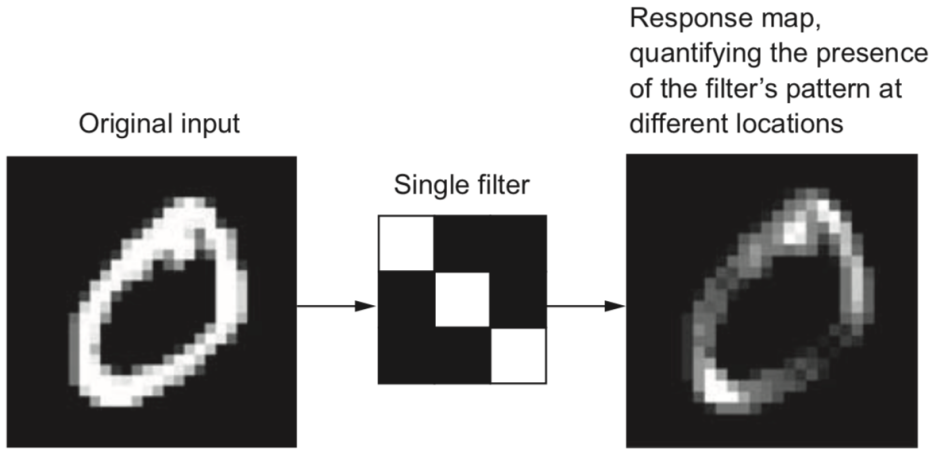
Convolutional neural nets

- When processing image data, we want to discover 'local' patterns (between nearby pixels)
    - edges, lines, structures
- Consider *windows* (or *patches*) of pixels (e.g 5x5)



Convolution

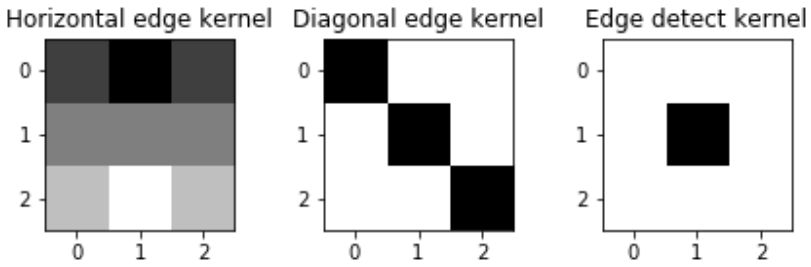
- Slide an *n* x *n filter* (or *kernel*) over *n* x *n patches* of the input feature map
- Replace pixel values with the convolution of the kernel with the underlying image patch



- The convolution operation itself takes the sum of the values of the element-wise product of the image patch with the kernel

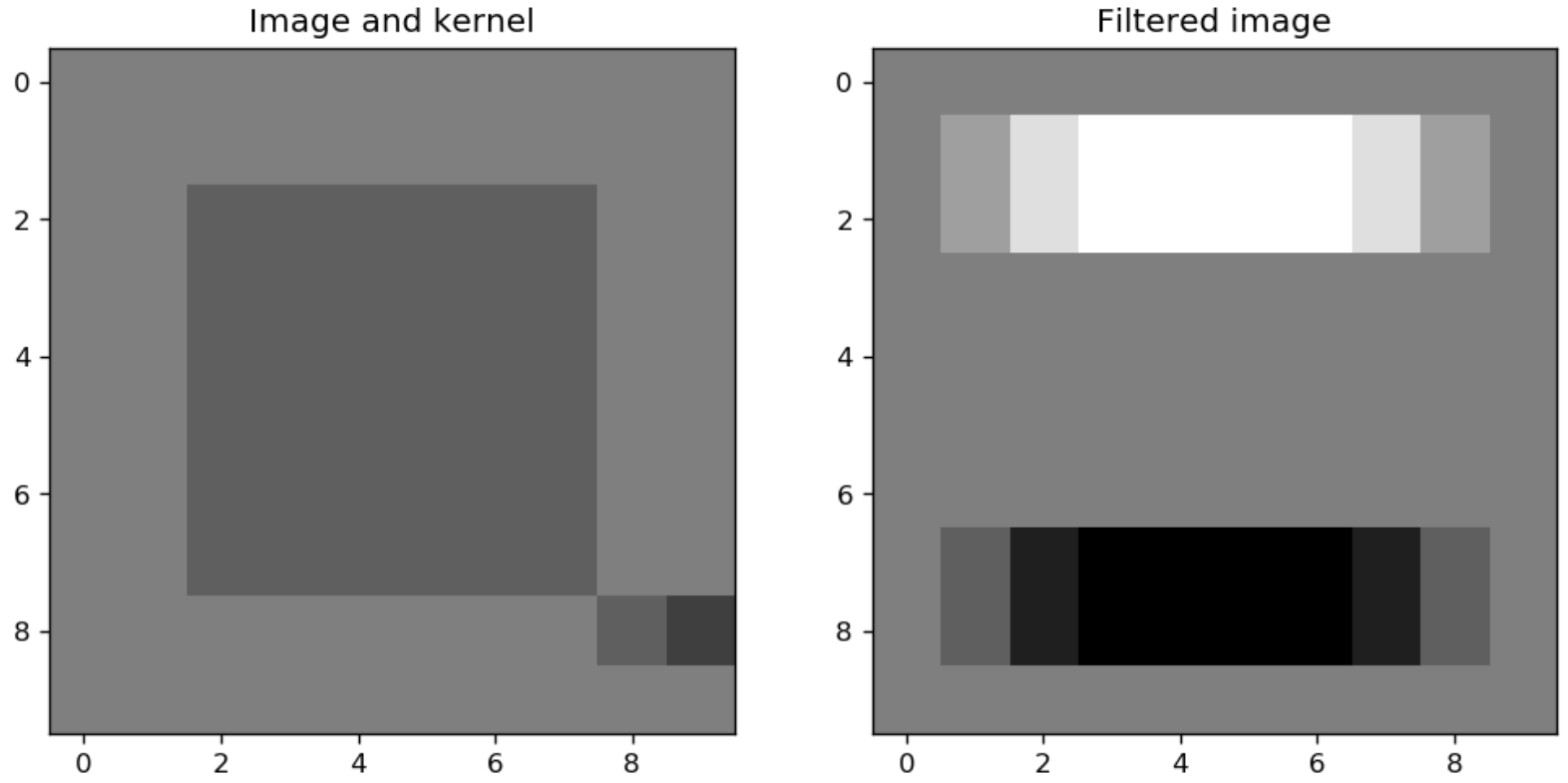
```
def apply_kernel(center, kernel, orig_image):
    image_patch = orig_image[window_slice(center, kernel)]
    # An element-wise multiplication followed by the sum
    return np.sum(kernel * image_patch)
```

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

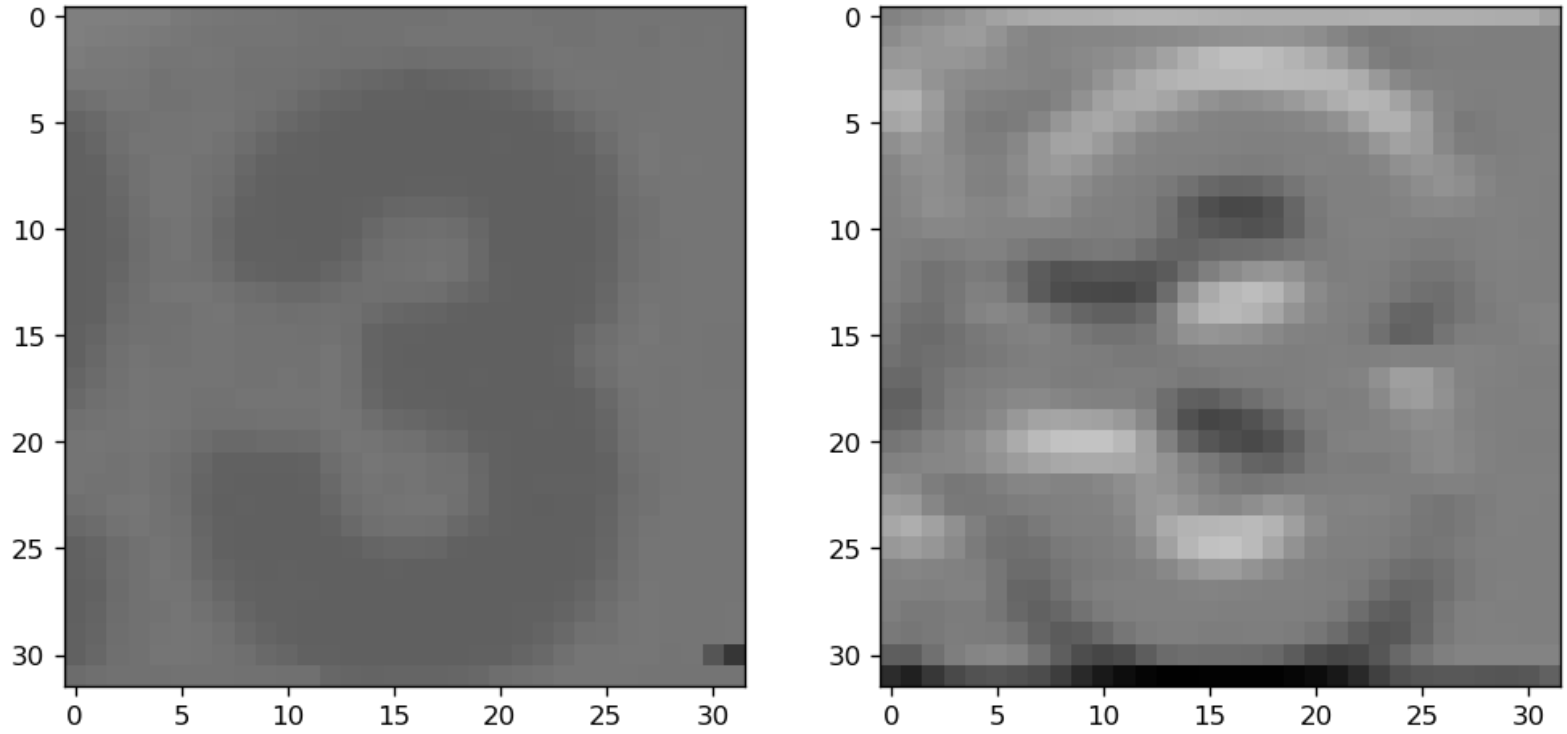


Demonstration: horizontal edge filter

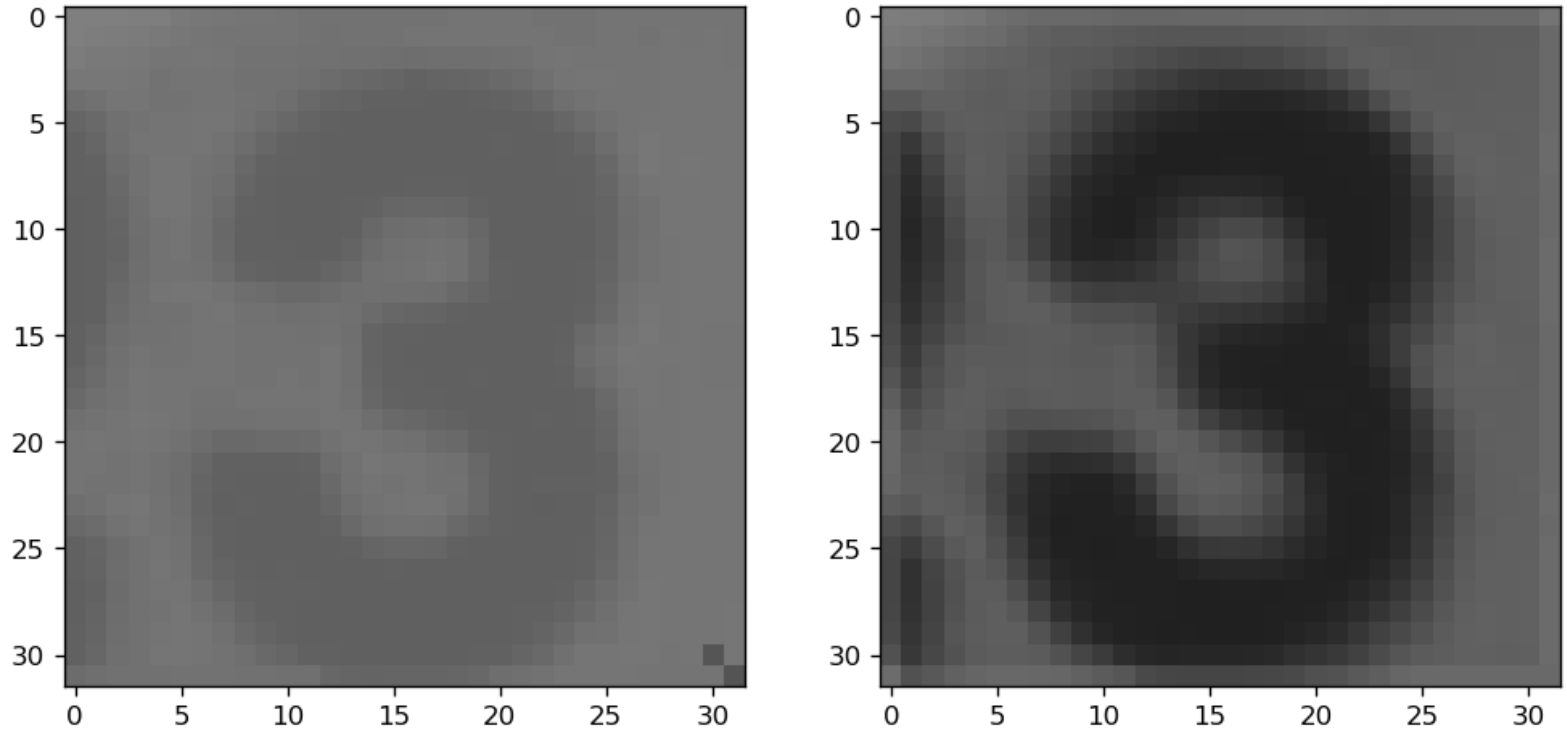
- Responds only to horizontal edges, sensitive to the 'direction' of the edge



Demonstration: horizontal edge filter



MNIST Demonstration: diagonal edge filter



MNIST Demonstration: edge detect filter

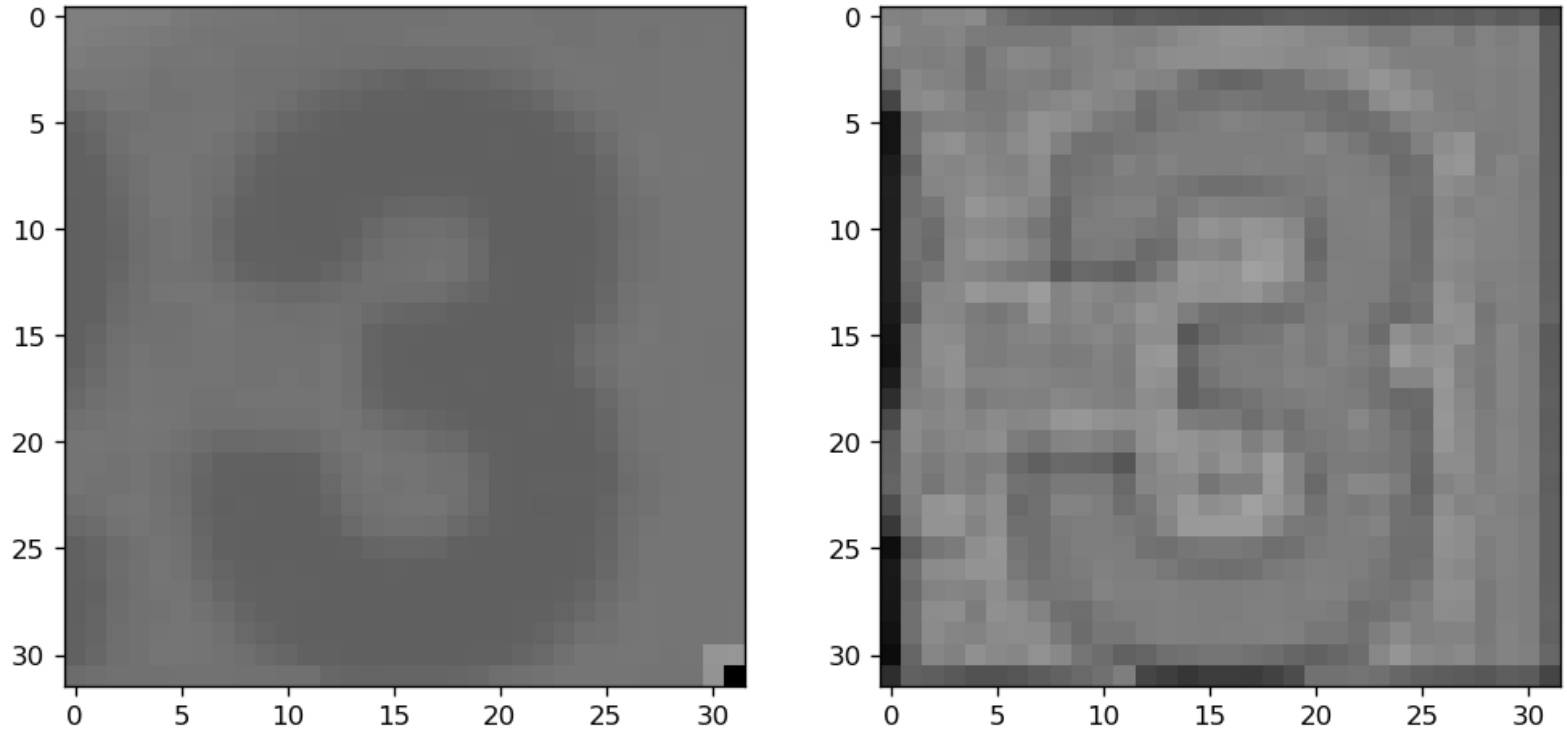
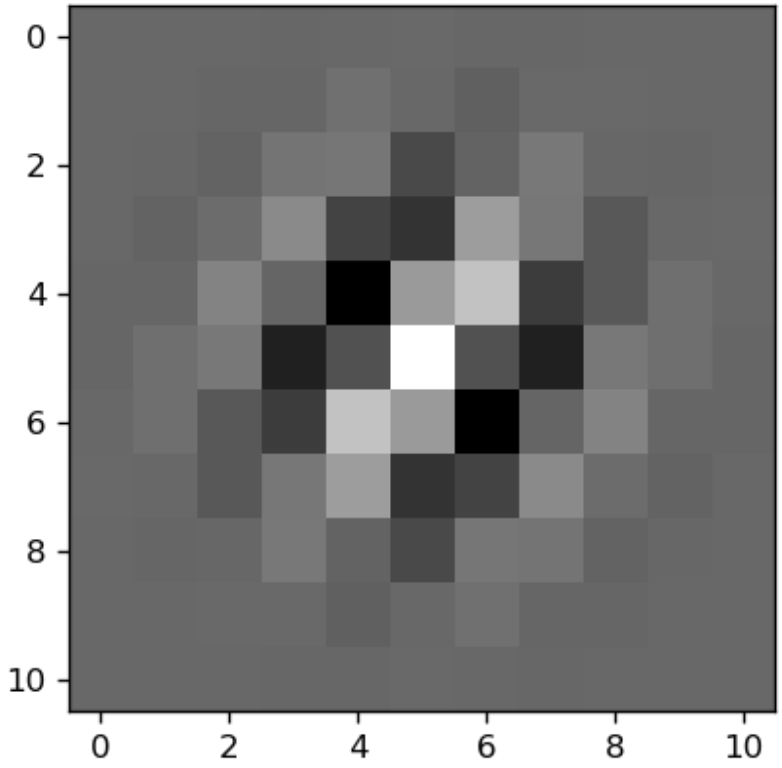
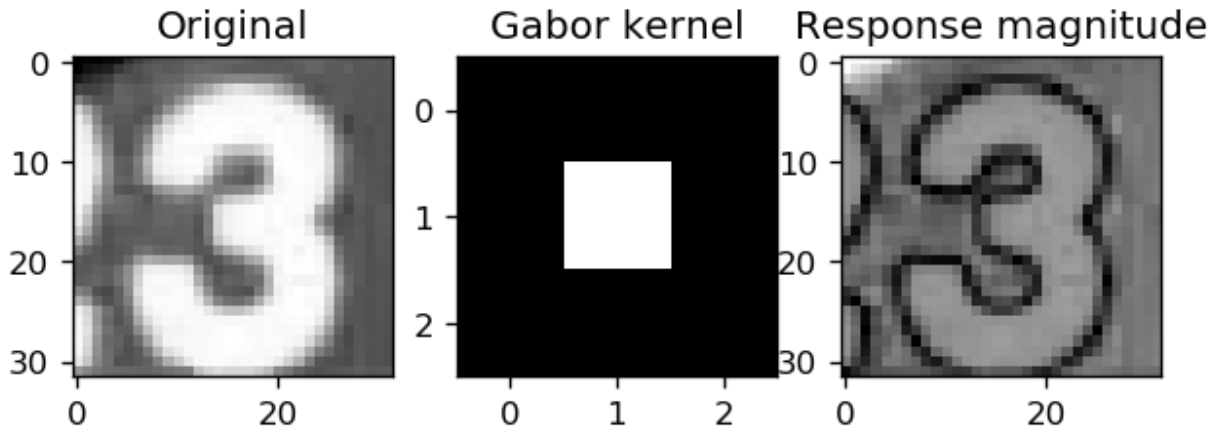


Image convolution in practice

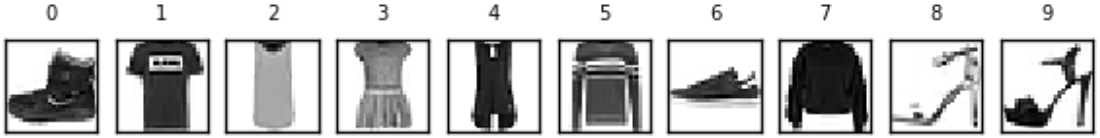
- Convolutions have always been used to preprocess image data
- *Families* of kernels were run on every image (e.g. Gabor filters)



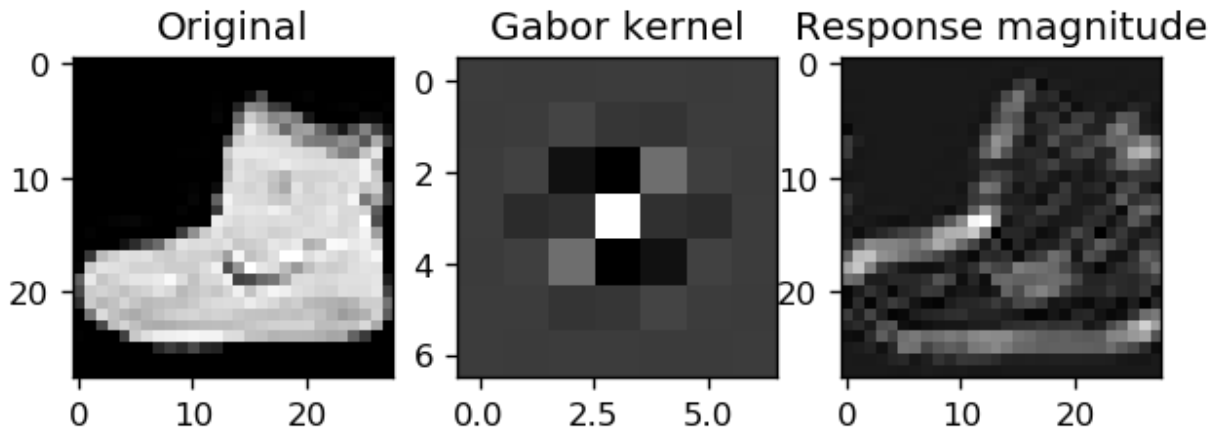
Demonstration on the streetview data

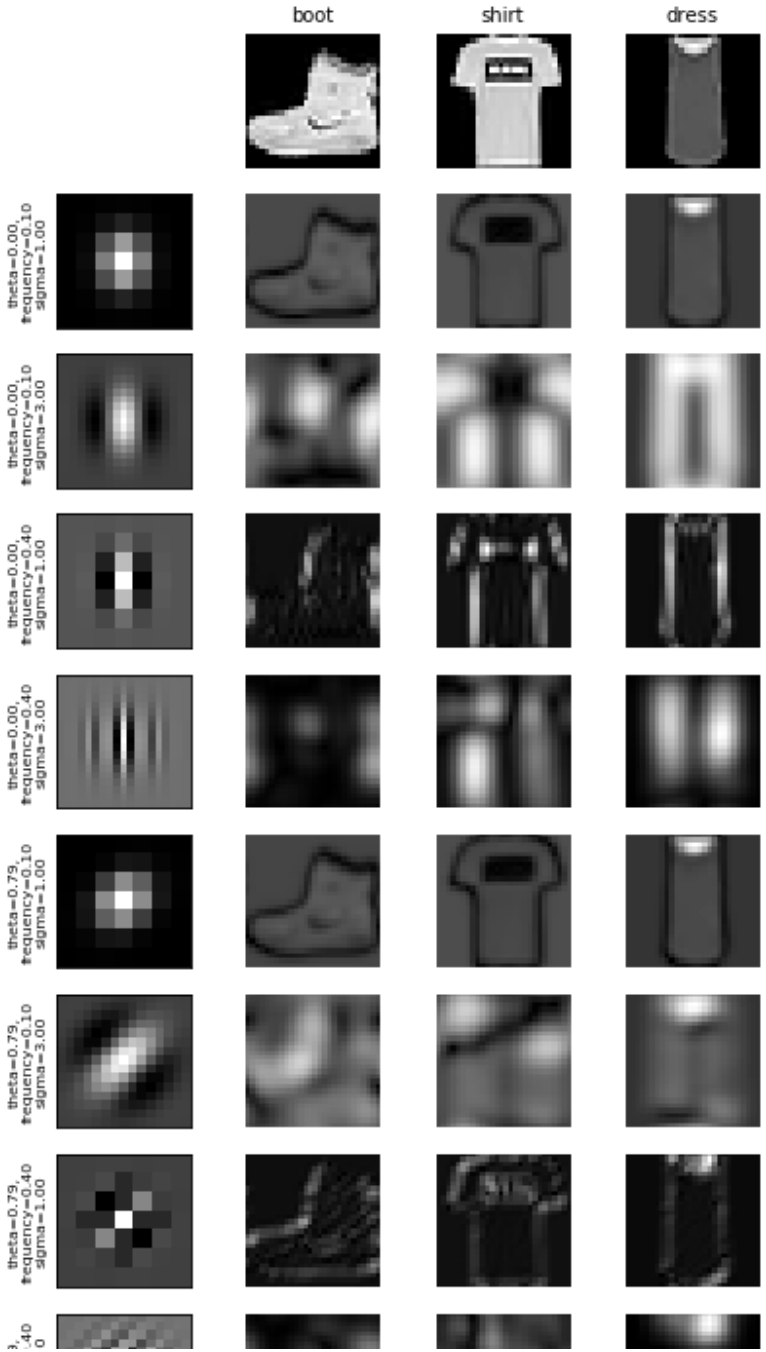


- It also works for general images
- Toy example: Fashion-MNIST

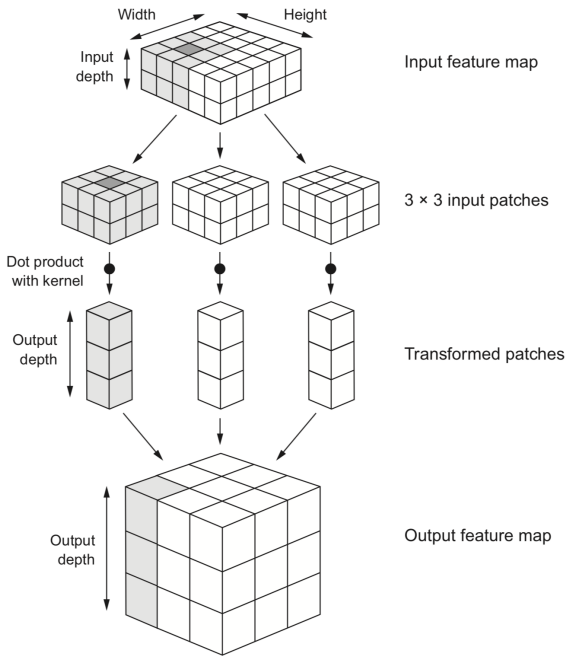


Demonstration: Fashion MNIST




boot
shirt
dress
theta=0.00, frequency=0.10 sigma=1.00
theta=0.00, frequency=0.10 sigma=3.00
theta=0.00, frequency=0.40 sigma=1.00
theta=0.00, frequency=0.40 sigma=3.00
theta=0.79, frequency=0.10 sigma=1.00
theta=0.79, frequency=0.10 sigma=3.00
theta=0.79, frequency=0.40 sigma=1.00

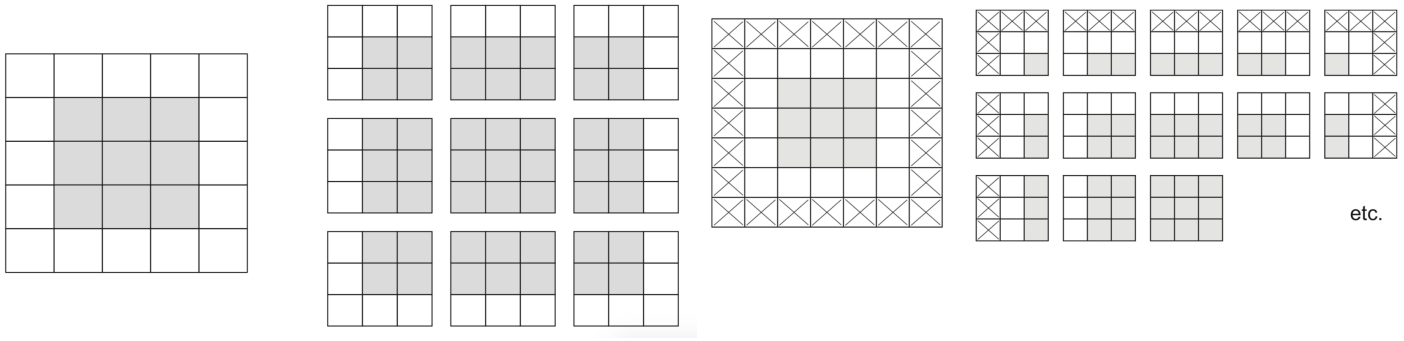
Convolutional layers: Feature maps



- We slide *d* filters across the input image in parallel, producing a (1x1xd) output per patch, reassembled into the final *feature map* with *d* 'channels', a (width x height x d) tensor.
- The filters are randomly initialized, we want to *learn* the optimal values for the input data

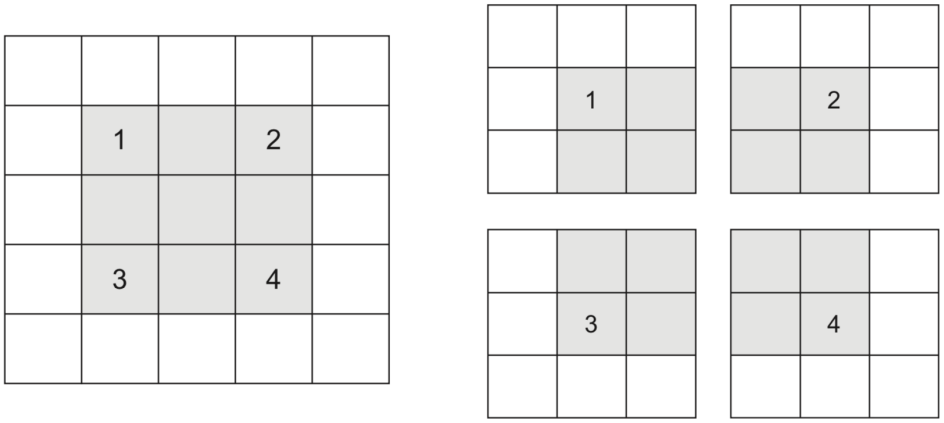
Border effects

- 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

- 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 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.
    - You'd need much deeper networks, which are much harder to train

Convolutional nets in practice

- Let's model MNIST again, this time using convnets
- `Conv2D` for 2D convolutional layers
    - Default: 32 filters, randomly initialized (from uniform distribution)
- `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 is reduced to a 3x3x64 feature map

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 26, 26, 32)        320
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 13, 13, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 11, 11, 64)        18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 5, 5, 64)          0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 3, 3, 64)          36928
=================================================================
Total params: 55,744
Trainable params: 55,744
Non-trainable params: 0
_________________________________________________________________
```

Compare to the architecture without max-pooling:

- Output layer is a 22x22x64 feature map!

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_4 (Conv2D)            (None, 26, 26, 32)        320
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 24, 24, 64)        18496
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 22, 22, 64)        36928
=================================================================
Total params: 55,744
Trainable params: 55,744
Non-trainable params: 0
_________________________________________________________________
```

- To classify the images, we still need a Dense and Softmax layer.
- We need to flatten the 3x3x36 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'))
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 26, 26, 32)        320
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 13, 13, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 11, 11, 64)        18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 5, 5, 64)          0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 3, 3, 64)          36928
_________________________________________________________________
flatten_1 (Flatten)          (None, 576)               0
_________________________________________________________________
dense_1 (Dense)              (None, 64)                36928
_________________________________________________________________
dense_2 (Dense)              (None, 10)                650
=================================================================
Total params: 93,322
Trainable params: 93,322
Non-trainable params: 0
_________________________________________________________________
```

- Train and test as usual (takes about 5 minutes):
- Compare to the 97,8% accuracy of the earlier dense architecture

```
model.compile(optimizer='rmsprop',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
model.fit(train_images, train_labels, epochs=5, batch_size=64)
test_loss, test_acc = model.evaluate(test_images, test_labels)
```

```
10000/10000 [==============================] - 2s 217us/step
Accuracy:  0.991599977016449
```

Convnets on small datasets

- Let's move to a more realistic dataset: Cats vs Dogs
    - We take a balanced subsample of 4000 real colored images
    - 2000 for training, 1000 validation, 1000 testing
- Convnets learn local patterns, which is highly efficient
- *Translation invariant*: a pattern can be recognized even if it is shifted to another part of the image
    - More robust, efficient to train (with fewer examples)
- We can use tricks such as *data augmentation*
- We can re-use *pre-trained* networks

Data preprocessing

- We use Keras' ImageDataGenerator to:
    - Decode JPEG images to floating-point tensors
    - Rescale pixel values to [0,1]
    - Resize images to 150x150 pixels
- Returns a Python *generator* we can endlessly query for images
    - Batches of 20 images per query
- Separately for training, validation, and test set

```
train_generator = train_datagen.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
```

Build from scratch

```
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_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_7 (Conv2D)            (None, 148, 148, 32)      896
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 74, 74, 32)        0
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 72, 72, 64)        18496
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 36, 36, 64)        0
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 34, 34, 128)       73856
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 17, 17, 128)       0
_________________________________________________________________
conv2d_10 (Conv2D)           (None, 15, 15, 128)       147584
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 7, 7, 128)         0
_________________________________________________________________
flatten_2 (Flatten)          (None, 6272)              0
_________________________________________________________________
dense_3 (Dense)              (None, 512)               3211776
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 513
=================================================================
Total params: 3,453,121
Trainable params: 3,453,121
Non-trainable params: 0
_________________________________________________________________
```

Training

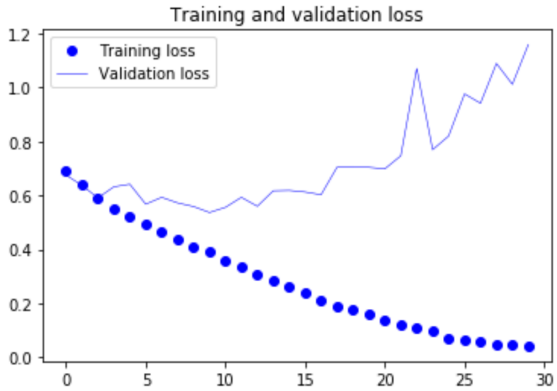
- Since the data comes from a generator, we use `fit_generator`
  - 100 steps per epoch (of 20 images each), for 30 epochs
  - Also provide sa generator for the validation data

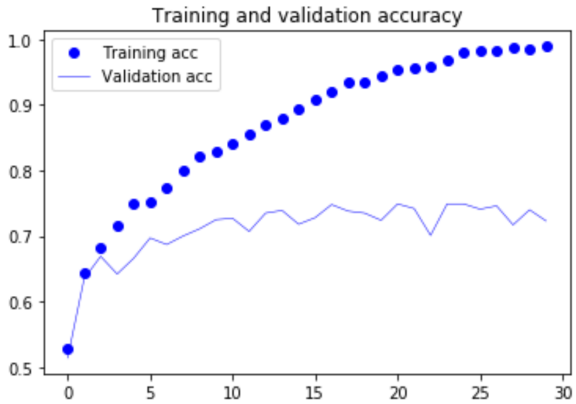
```
model.compile(loss='binary_crossentropy',
              optimizer=optimizers.RMSprop(lr=1e-4),
              metrics=['acc'])
history = model.fit_generator(
      train_generator, steps_per_epoch=100,
      epochs=30, verbose=0,
      validation_data=validation_generator,
      validation_steps=50)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

- Training takes more than an hour (on CPU)
- We save the trained model (and history) to disk so that we can reload it later

```
model.save(os.path.join(model_dir, 'cats_and_dogs_small_1.h5'))
with open(os.path.join(model_dir, 'cats_and_dogs_small_1_history.p'), 'w
b') as file_pi:
    pickle.dump(history.history, file_pi)
```

Our model is overfitting: we need more training examples, more regularization



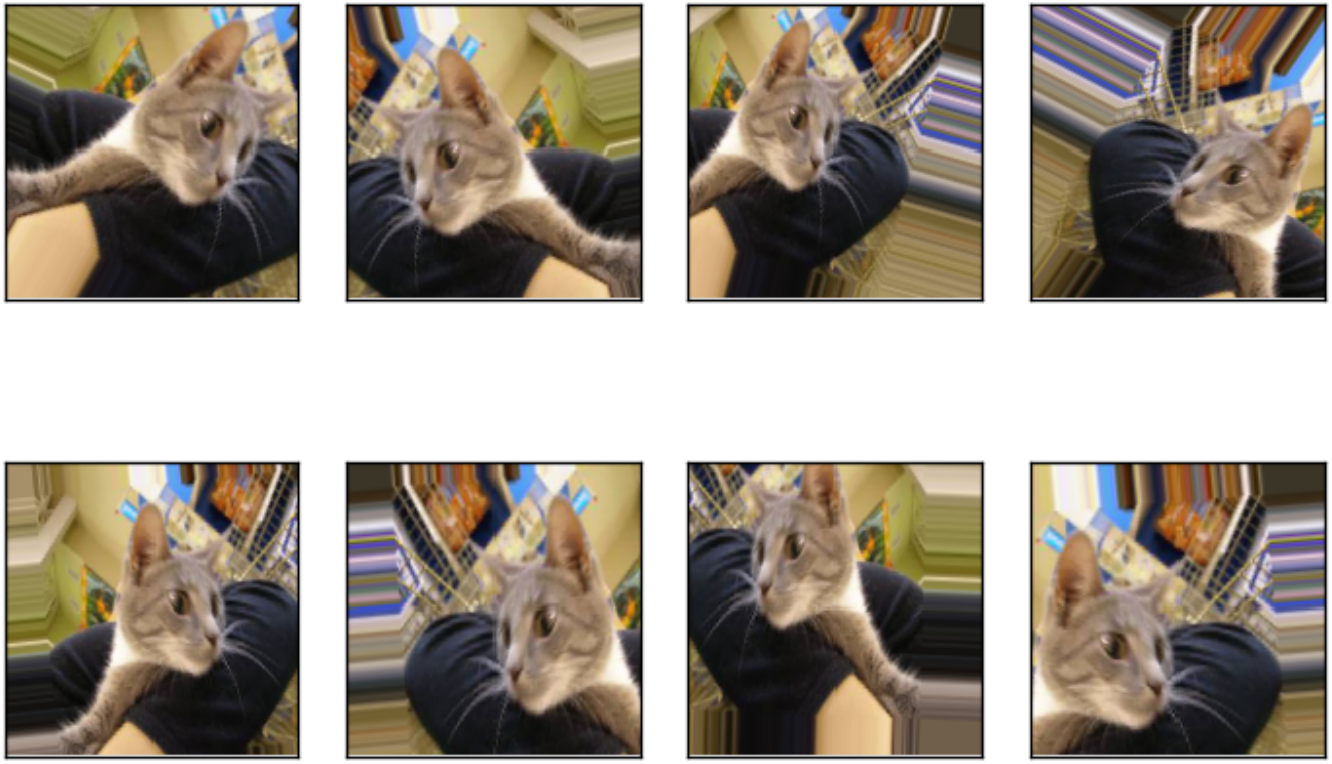


Data augmentation

- Generate new images via image transformations
  - Rotation, translation, shear, zoom, horizontal flip,...
- Keras has a tool for this:

```
datagen = ImageDataGenerator(
      rotation_range=40, width_shift_range=0.2,
      height_shift_range=0.2, shear_range=0.2,
      zoom_range=0.2, horizontal_flip=True,
      fill_mode='nearest')
```

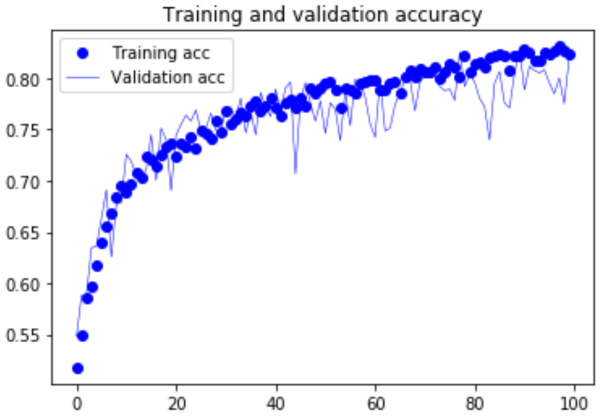
Example

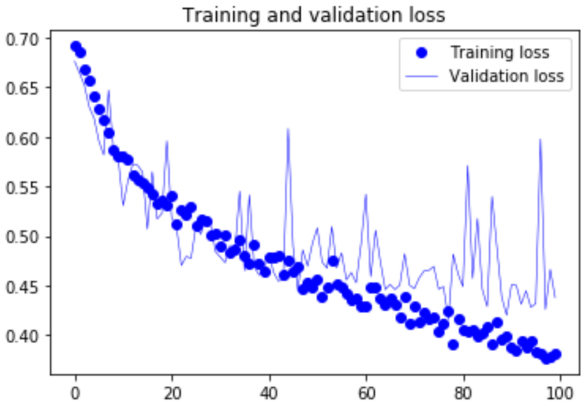


We also add Dropout before the Dense layer

```
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'))
```

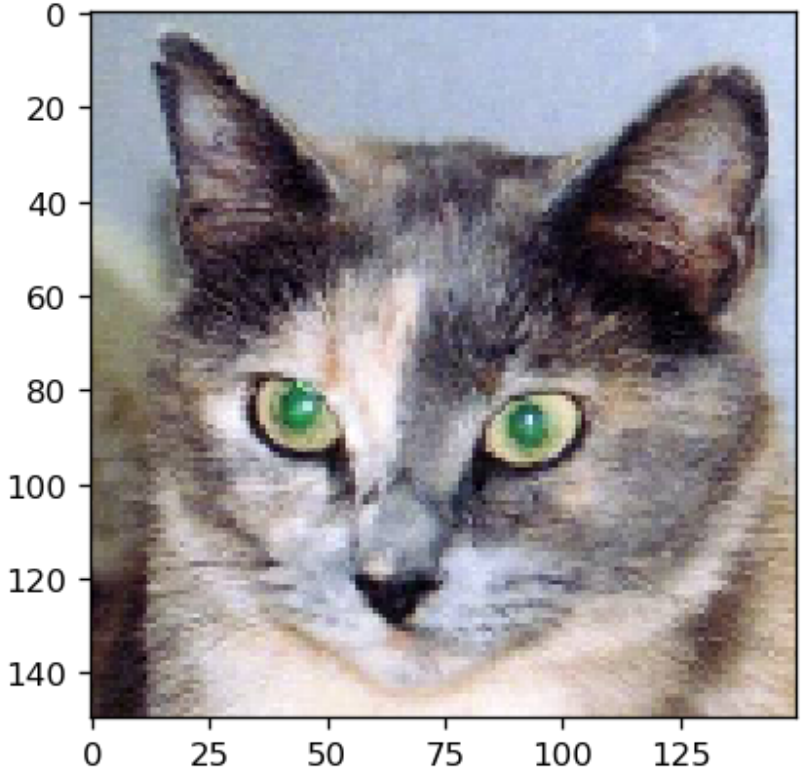
(Almost) no more overfitting!





Visualizing the intermediate outputs

- Let's see what the convnet is learning exactly by observing the intermediate feature maps
    - A layer's output is also called its *activation*
- Since our feature maps have depth 32/64/128, we need to visualize *all*
- We choose a specific input image, and observe the outputs

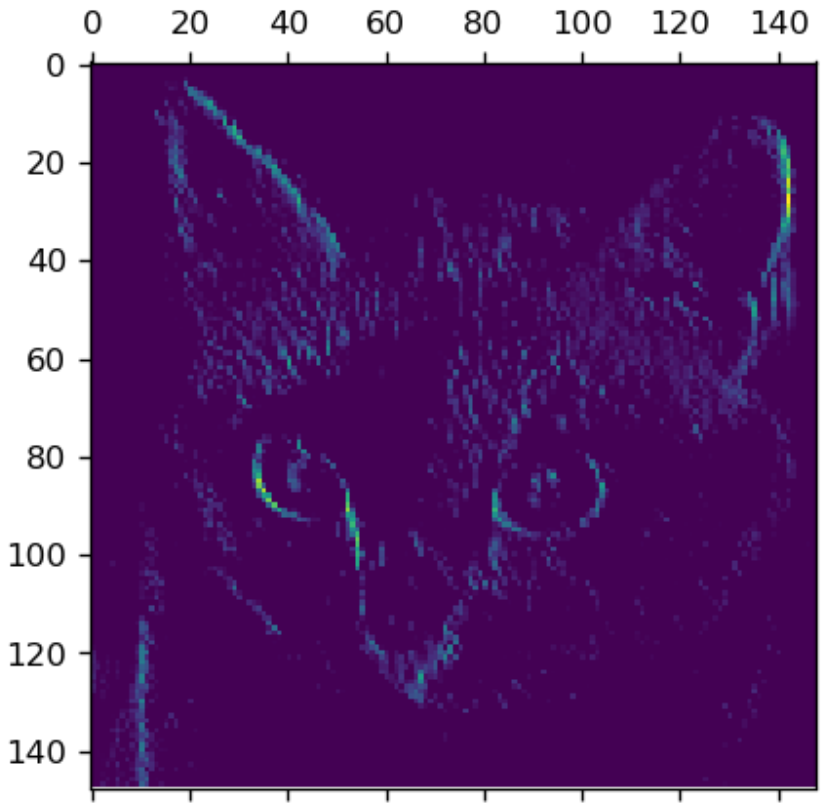

0
20
40
60
80
100
120
140
0
25
50
75
100
125

- We create a new model that is composed of the first 8 layers (the convolutional part)
- We input our example image and read the output

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

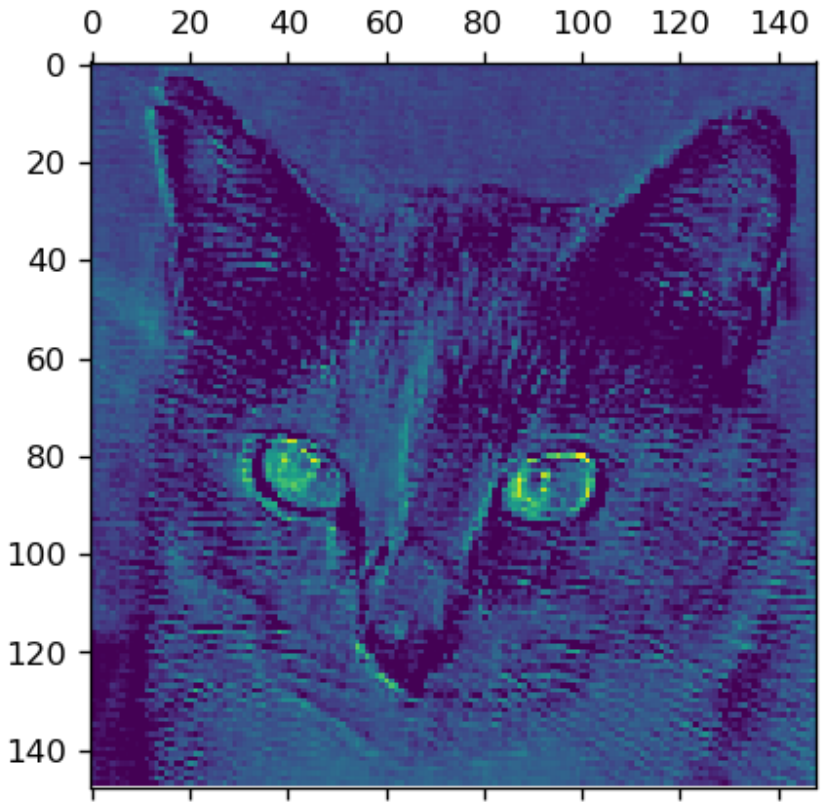
Output of the first Conv2D layer, 4th channel (filter):

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

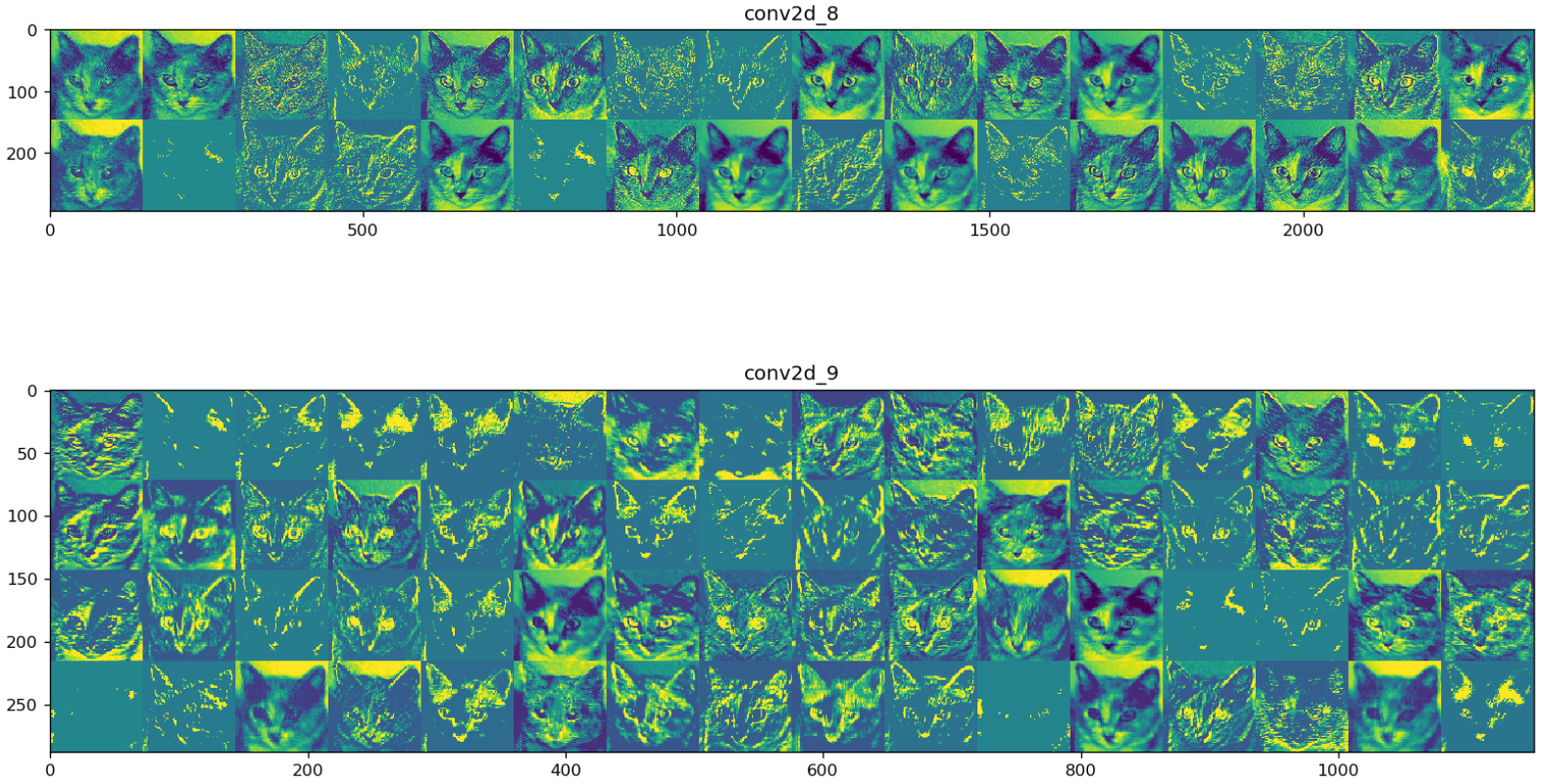


Output of the 22th channel (filter):

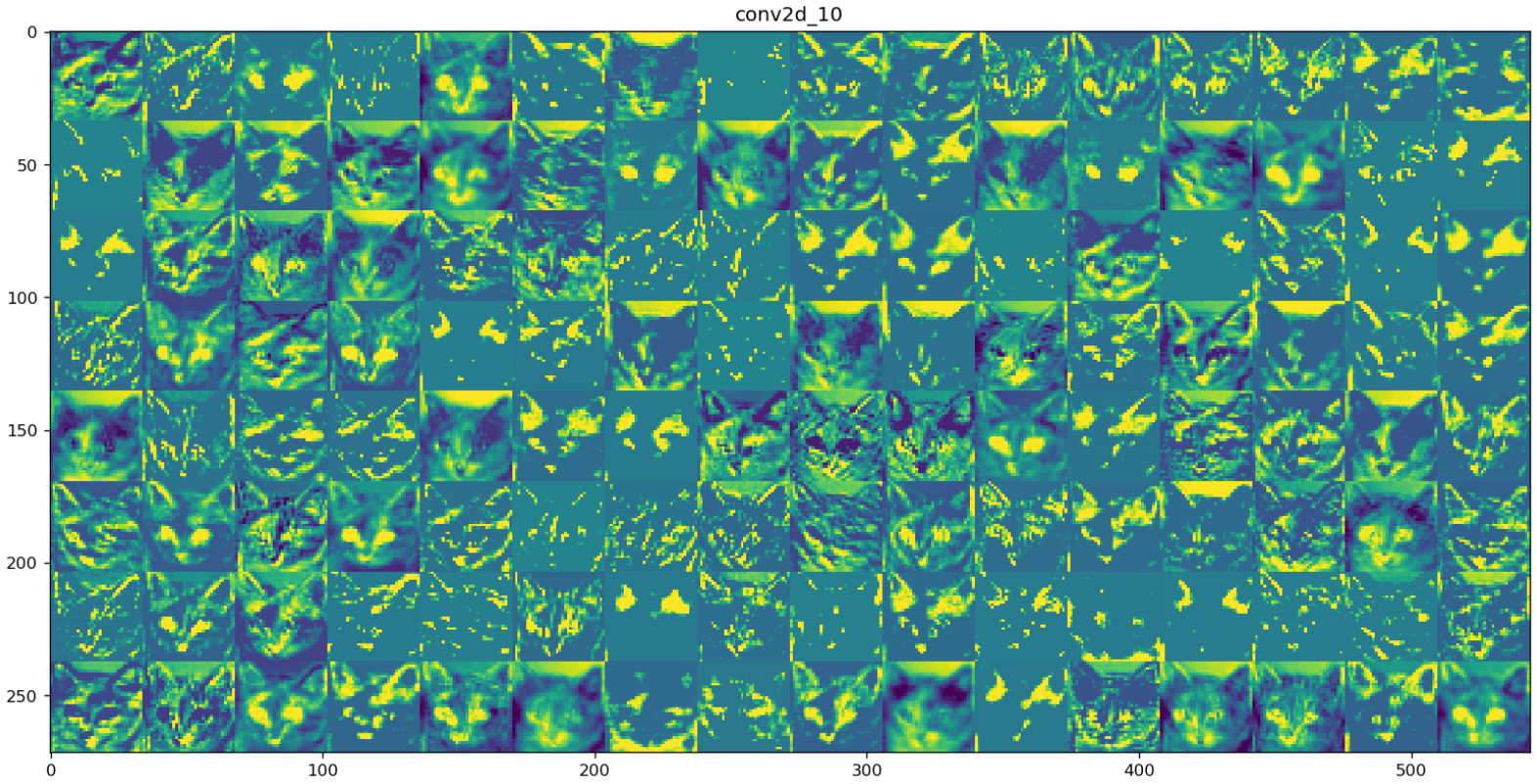
- Cat eye detector?



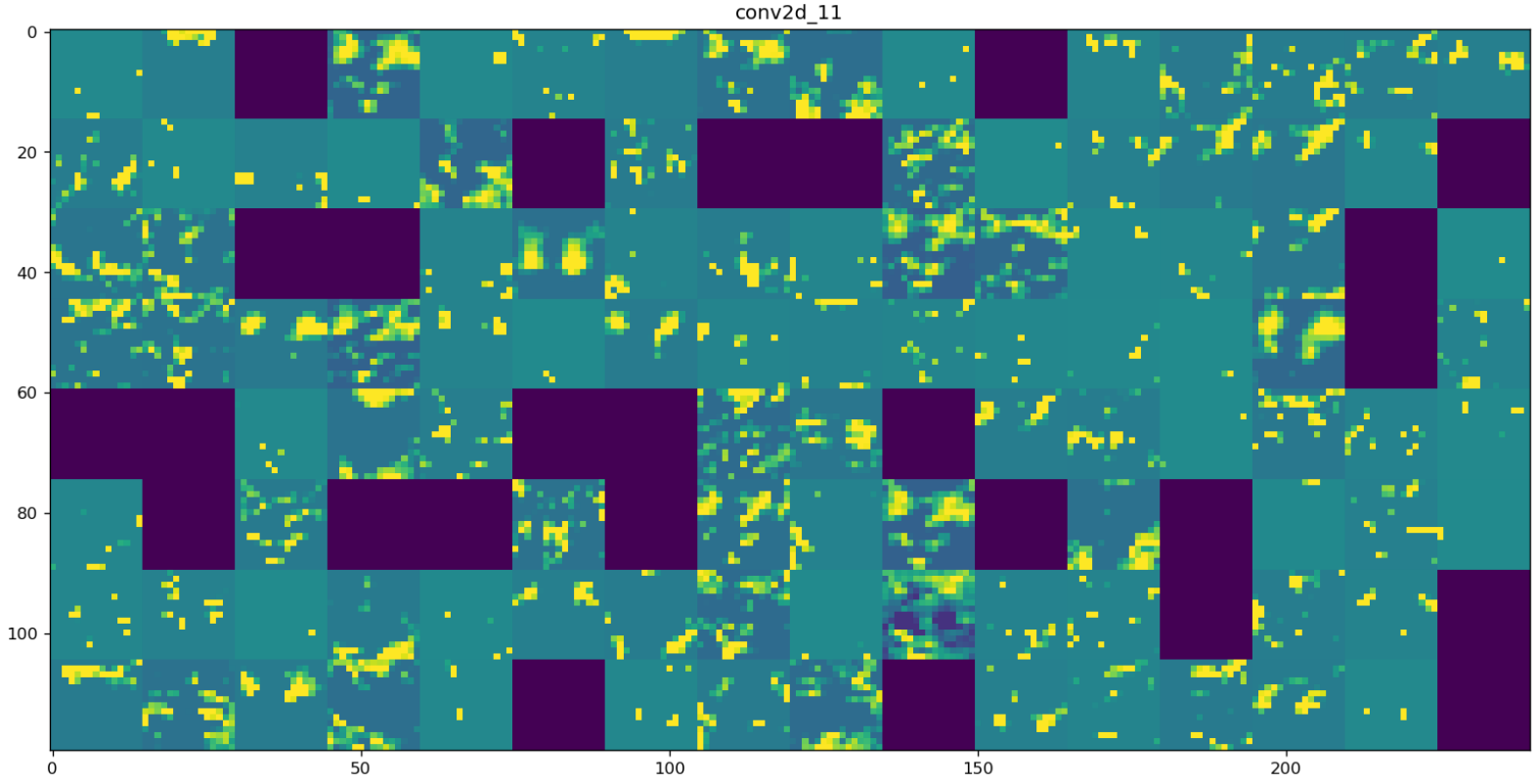
- First 2 convolutional layers: various edge detectors



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

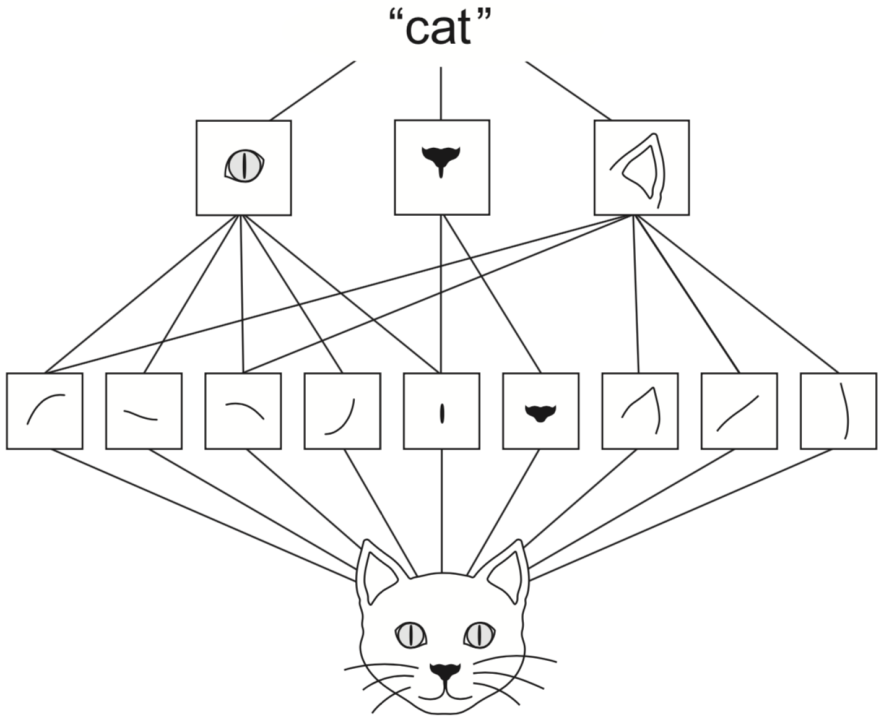


- Last convolutional layer: increasing sparsity. The learned patterns don't exist in the training data



Spacial hierarchies

- Deep convnets can learn *spacial 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

- The filters themselves can be visualized by finding the input image that they are maximally responsive to
- *gradient ascent in input space*: start from a blank image, use loss to update the pixel values to values that the filter responds to more strongly

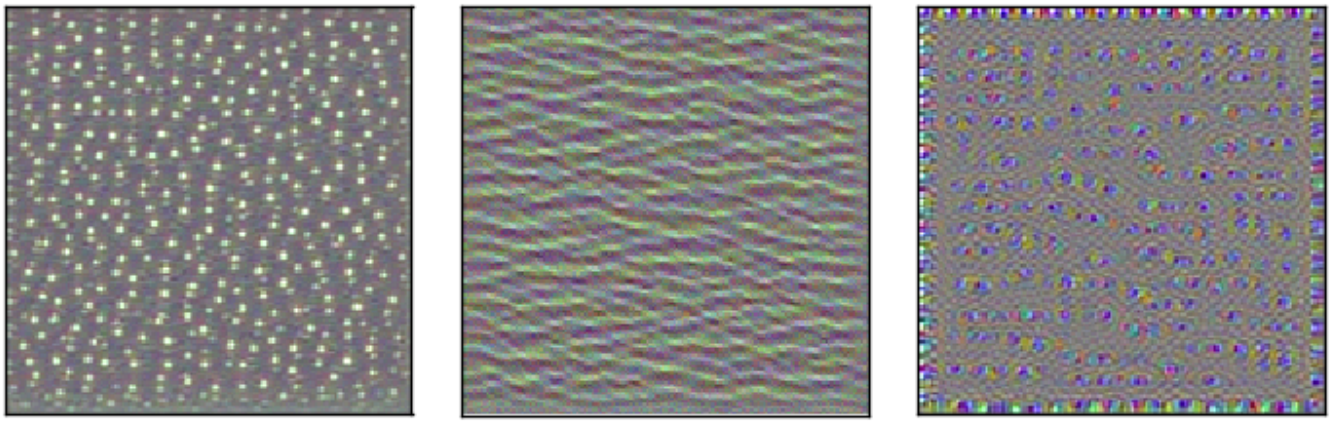
```
from keras import backend as K
    input_img = np.random.random((1, size, size, 3)) * 20 + 128.
    loss = K.mean(layer_output[:, :, :, filter_index])
    grads = K.gradients(loss, model.input)[0] # Compute gradient
    for i in range(40): # Run gradient ascent for 40 steps
        loss_v, grads_v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

Let's do this for the `VGG16` network pretrained on `ImageNet`

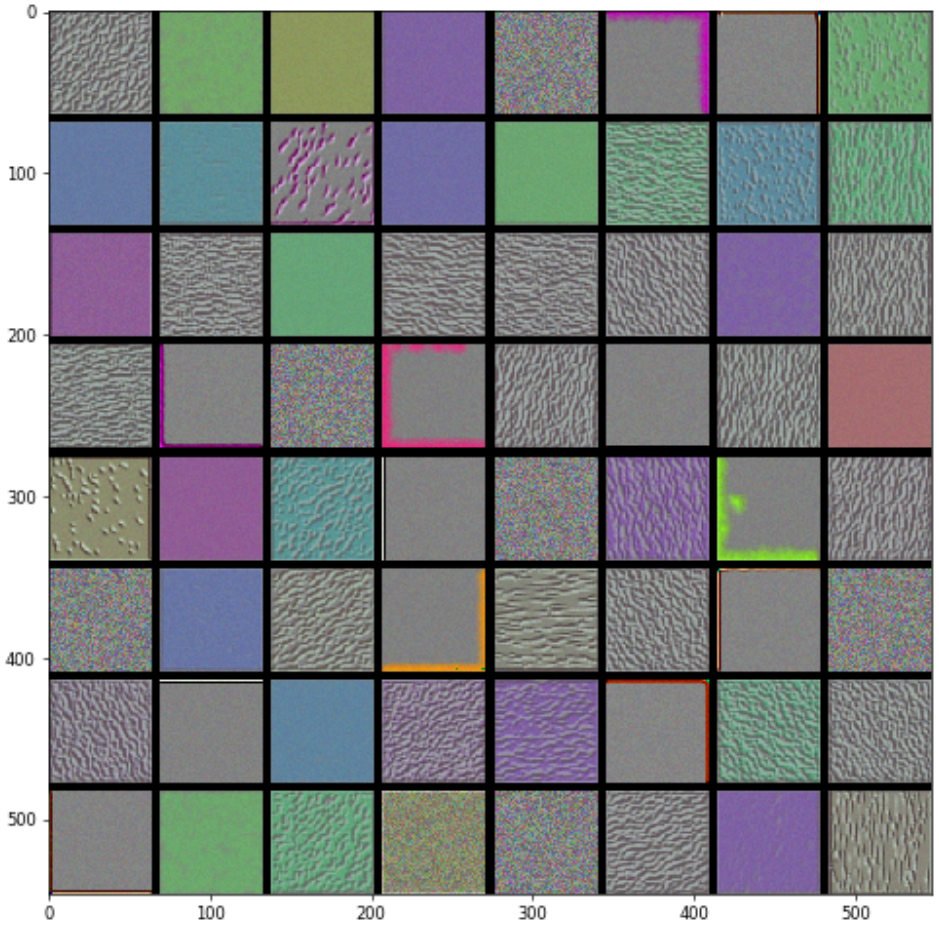
```
model = VGG16(weights='imagenet', include_top=False)
```

```
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
```

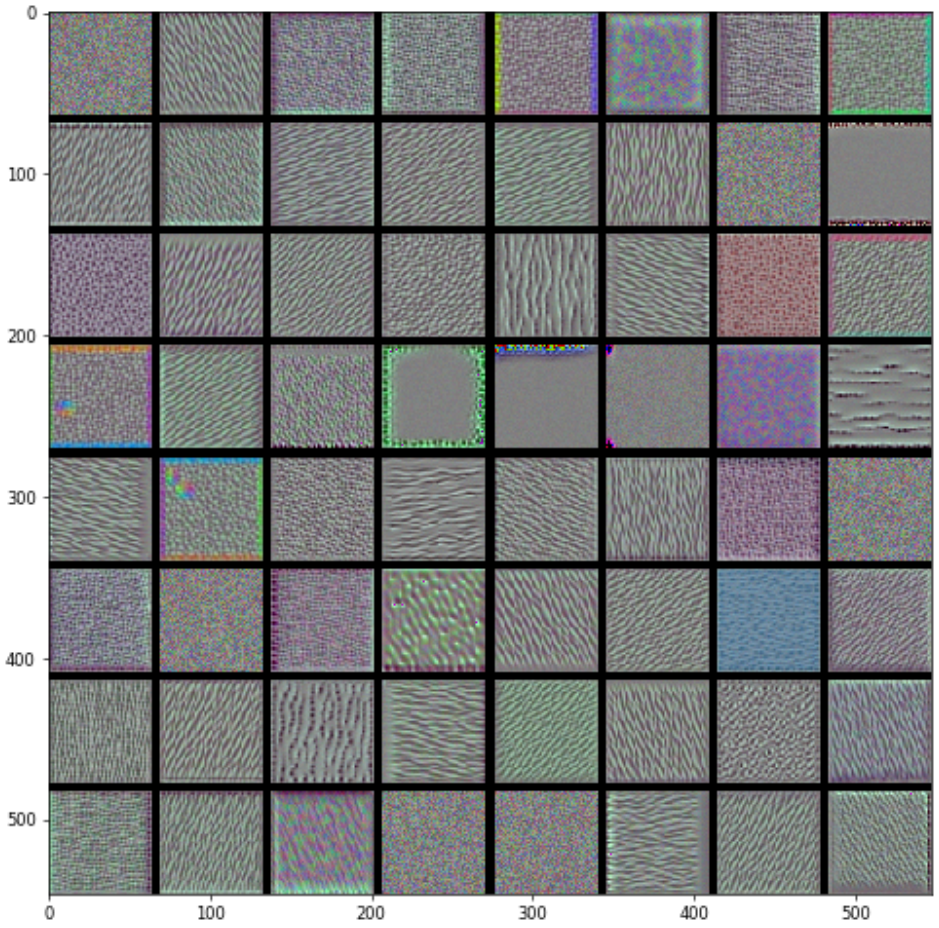
- Visualize convolution filters 0-2 from layer 5 of the VGG network trained on ImageNet



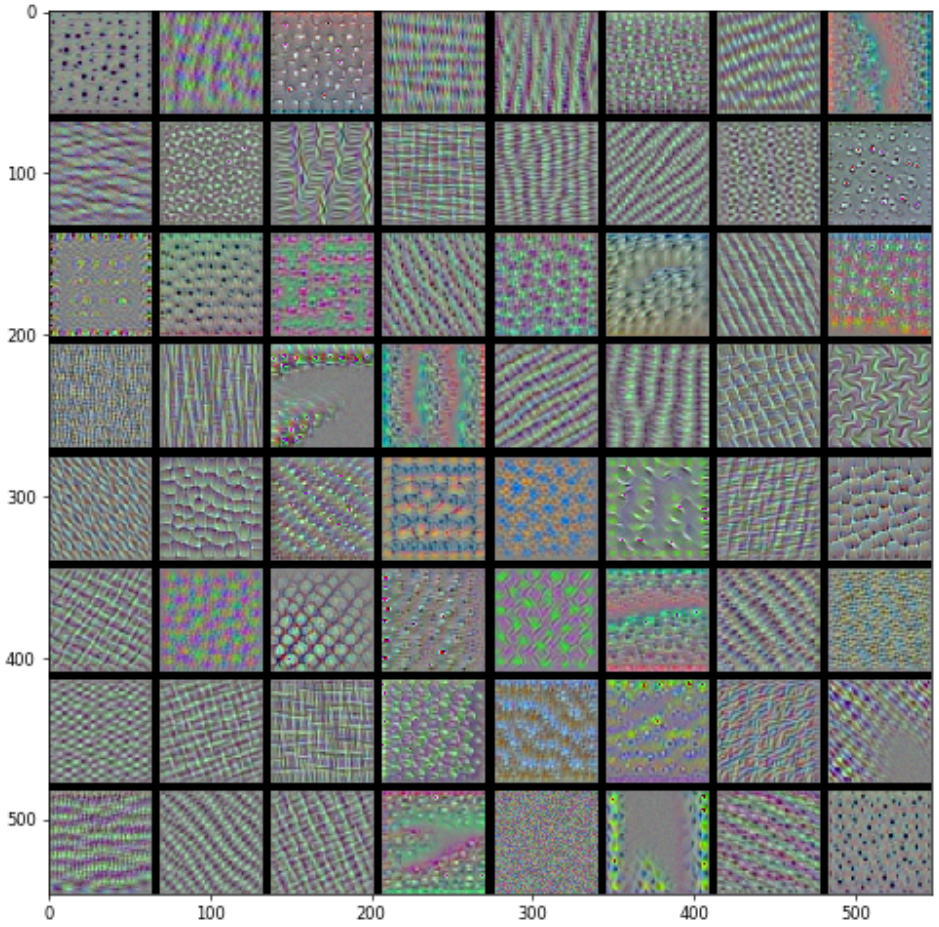
First 64 filters for 1st convolutional layer in block 1: simple edges and colors



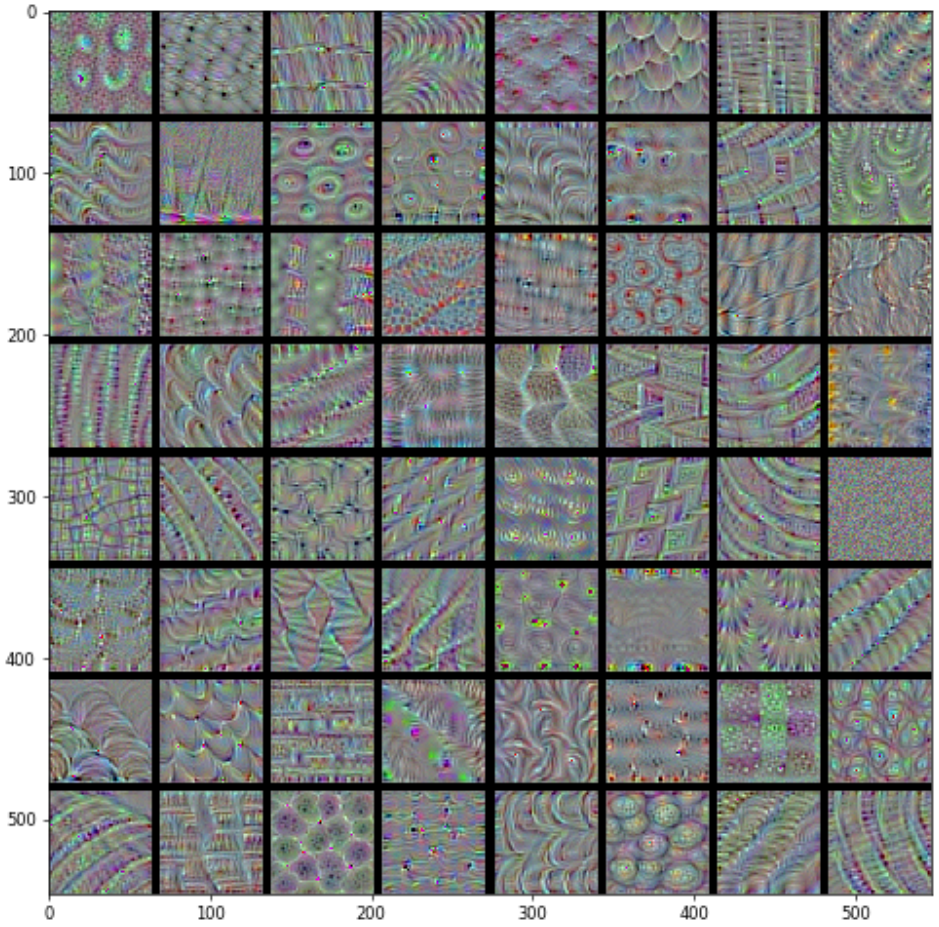
Filters in 2nd block of convolution layers: simple textures (combined edges and colors)



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

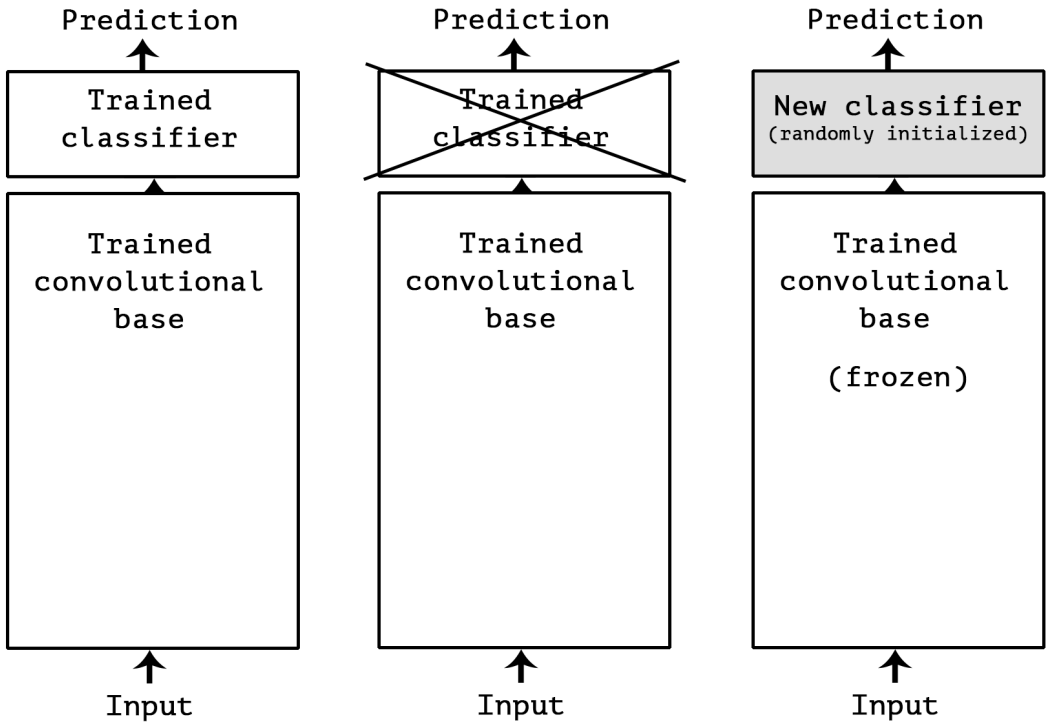


Filters in 4th block of convolution layers: feathers, eyes, leaves,...



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



- 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_sha
pe=(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

Using pre-trained networks: 3 ways

- Fast feature extraction without data augmentation
  - Call `predict` from the convolutional base
  - Use results to train a dense neural net
- Feature extraction with data augmentation
  - Extend the convolutional base model with a Dense layer
  - Run it end to end on the new data (expensive!)
- Fine-tuning
  - Do any of the above two to train a classifier
  - Unfreeze a few of the top convolutional layers
    - Updates only the more abstract representations
  - Jointly train all layers on the new data

Fast feature extraction without data augmentation

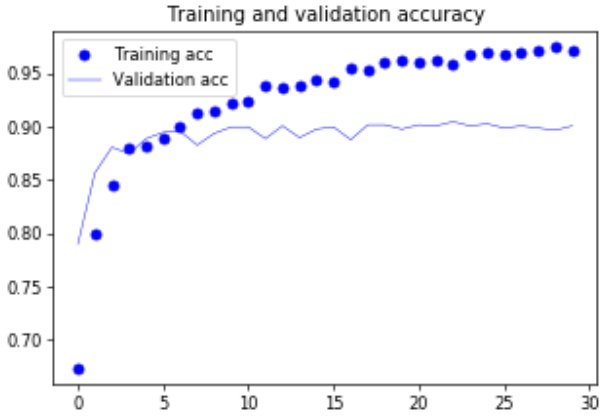
- Extract filtered images and their labels
  - You can use a data generator again

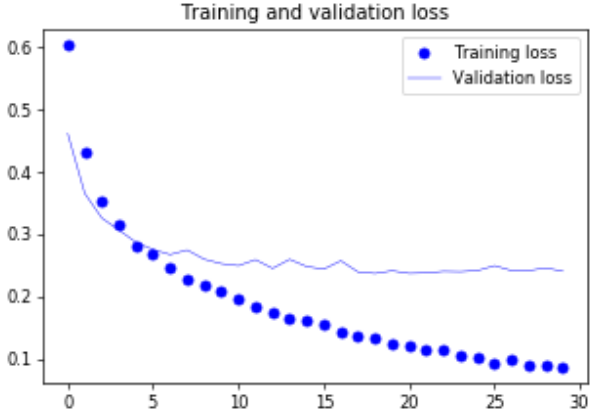
```
generator = datagen.flow_from_directory(dir, target_size=(150, 150),
        batch_size=batch_size, class_mode='binary')
for inputs_batch, labels_batch in generator:
    features_batch = conv_base.predict(inputs_batch)
```

- 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





Feature extraction with data augmentation

- Use data augmentation to get more training data
- Simply add the Dense layers to the convolutional base
- *Freeze* the convolutional base (before you compile)

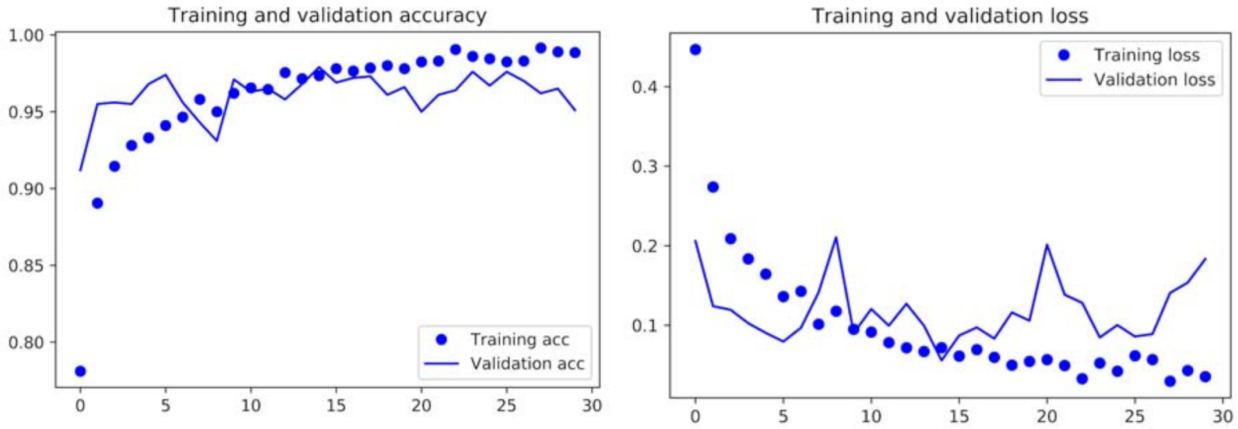
```
model = models.Sequential()
model.add(conv_base)
model.add(layers.Flatten())
model.add(layers.Dense(256, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))
conv_base.trainable = False
```

```
Model: "sequential_7"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
vgg16 (Model)                (None, 4, 4, 512)         14714688
_________________________________________________________________
flatten_4 (Flatten)          (None, 8192)              0
_________________________________________________________________
dense_9 (Dense)              (None, 256)               2097408
_________________________________________________________________
dense_10 (Dense)             (None, 1)                 257
=================================================================
Total params: 16,812,353
Trainable params: 2,097,665
Non-trainable params: 14,714,688
_________________________________________________________________
```

Data augmentation and training (takes a LONG time)

```
train_datagen = ImageDataGenerator(
      rescale=1./255, rotation_range=40, width_shift_range=0.2,
      height_shift_range=0.2, shear_range=0.2, zoom_range=0.2,
      horizontal_flip=True, fill_mode='nearest')
train_generator = train_datagen.flow_from_directory(dir,
      target_size=(150, 150), batch_size=20, class_mode='binary')
history = model.fit_generator(
      train_generator, steps_per_epoch=100, epochs=30,
      validation_data=validation_generator, validation_steps=50)
model.save(os.path.join(model_dir, 'cats_and_dogs_small_3.h5'))
with open(os.path.join(model_dir, 'cats_and_dogs_small_3_history.p'), 'w
b') as file_pi:
    pickle.dump(history.history, file_pi)
```

We now get about 96% accuracy, and very little overfitting

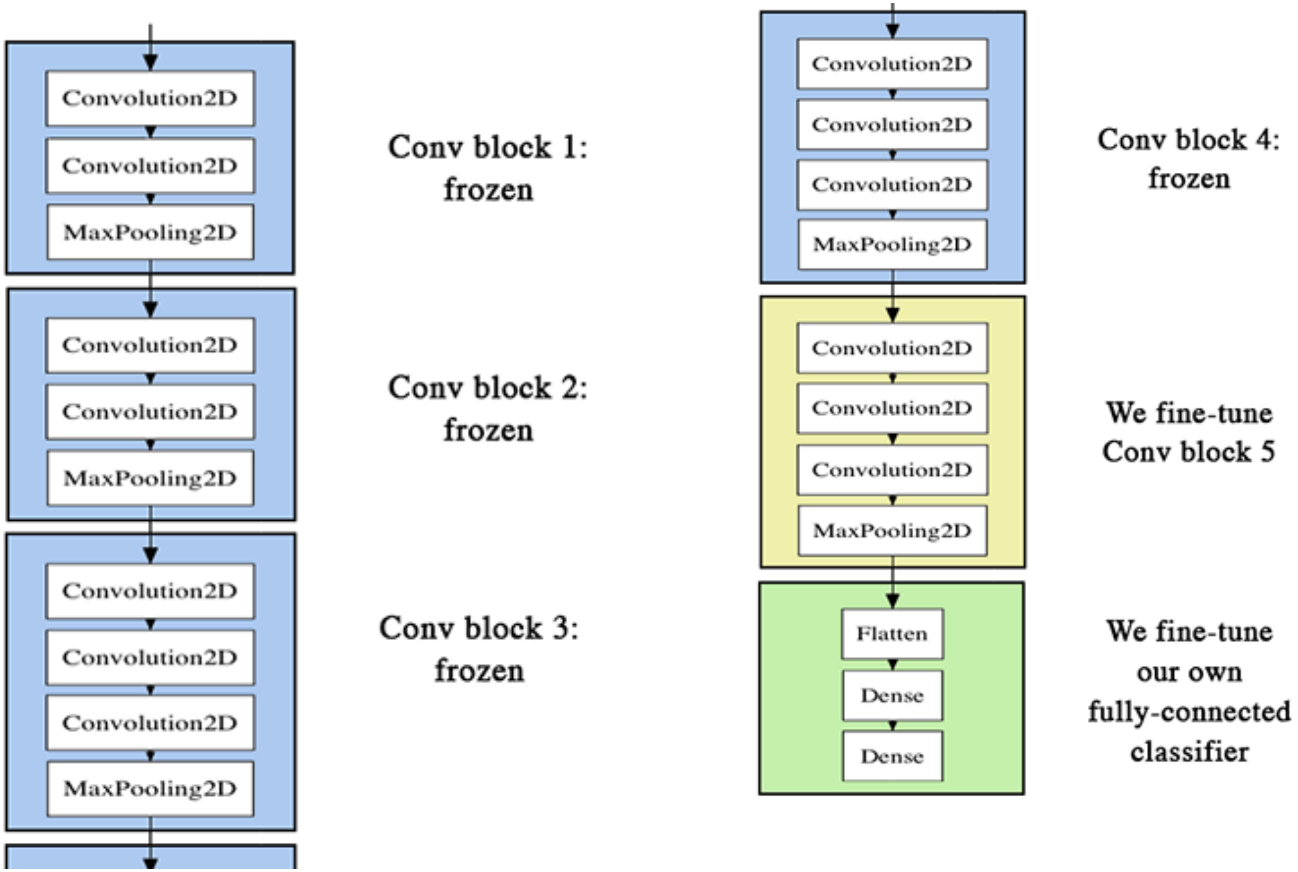


Fine-tuning

- Add your custom network on top of an already trained base network.
- Freeze the base network.
- Train the part you added.
- Unfreeze some layers in the base network.
- Jointly train both these layers and the part you added.

```
for layer in conv_base.layers:
    if layer.name == 'block5_conv1':
        set_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

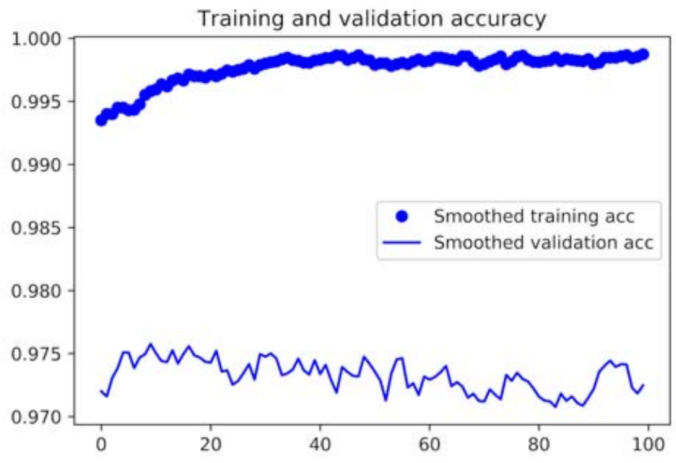
- Load trained network, finetune
  - Use a small learning rate, large number of epochs
  - You don't want to unlearn too much

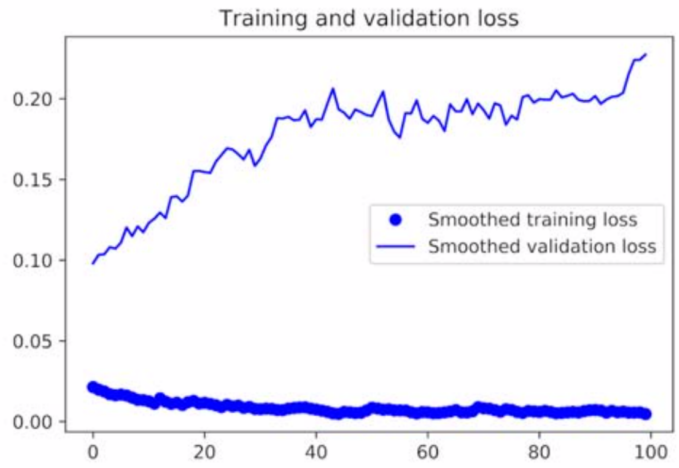
```
model = load_model(os.path.join(model_dir, 'cats_and_dogs_small_3.h5'))
model.compile(loss='binary_crossentropy',
              optimizer=optimizers.RMSprop(lr=1e-5),
              metrics=['acc'])
history = model.fit_generator(
      train_generator, steps_per_epoch=100, epochs=100,
      validation_data=validation_generator,
      validation_steps=50)
```

- Learning curves are a bit noisy, smooth them using a running average

```
def smooth_curve(points, factor=0.8):
  smoothed = []
  for point in points:
    if smoothed:
      previous = smoothed[-1]
      smoothed.append(previous * factor + point * (1 - factor))
    else:
      smoothed.append(point)
  return smoothed
```

- Results: 97% accuracy (1% better)
- Better validation accuracy, worse validation loss





Visualizing class activation

- We can also visualize which part of the input image had the greatest influence on the final classification
    - Helpful for interpreting what is learned (or misclassified)
- *Class activation maps*: produce heatmap over the input image
    - Take the output feature map of a convolution layer
    - Weigh every channel (filter) by the gradient of the class with respect to the channel
- Find important channels, see what activates those

- Try VGG (including the dense layers) and an image from ImageNet

```
model = VGG16(weights='imagenet')
```

- Load image
- Resize to 224 x 224 (what VGG was trained on)
- Do the same preprocessing (Keras VGG utility)

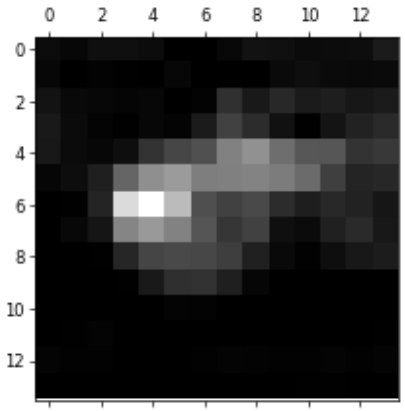
```
from keras.applications.vgg16 import preprocess_input
img_path = '../images/10_elephants.jpg'
img = image.load_img(img_path, target_size=(224, 224))
x = image.img_to_array(img)
x = np.expand_dims(x, axis=0) # Transform to batch of size (1, 224, 224,
3)
x = preprocess_input(x)
```

- Sanity test: do we get the right prediction?

```
preds = model.predict(x)
```

```
Predicted: [('n02504458', 'African_elephant', 0.909421), ('n01871265', 'tu
sker', 0.086182885), ('n02504013', 'Indian_elephant', 0.0043545826)]
```

Visualize the class activation map



- Superimpose on our image

One more thing: Batch Normalization

- Normalization (in general) aims to make different examples more similar to each other
    - Easier to learn and generalize
- Standardization (centering the data to 0 and scaling to 1 stddev)
    - This assumes that the data is normalliy distributed
- Batch normalization layer adaptively normalize data, even as the mean and variance change over time during training.
    - It works by internally maintaining an exponential moving average of the batch-wise mean and variance of training data
    - Helps with gradient propagation, allows for deeper networks.

BatchNormalization layer is typically used after a convolutional or densely connected layer:

```
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())
```

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
- Batch normalization helps train deeper networks
- You can use a pretrained convnet to do feature extraction and fine-tuning