Convolutional Neural Networks

Microsoft London ML OpenHack

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youtube.com/machinelearningatmicrosoft

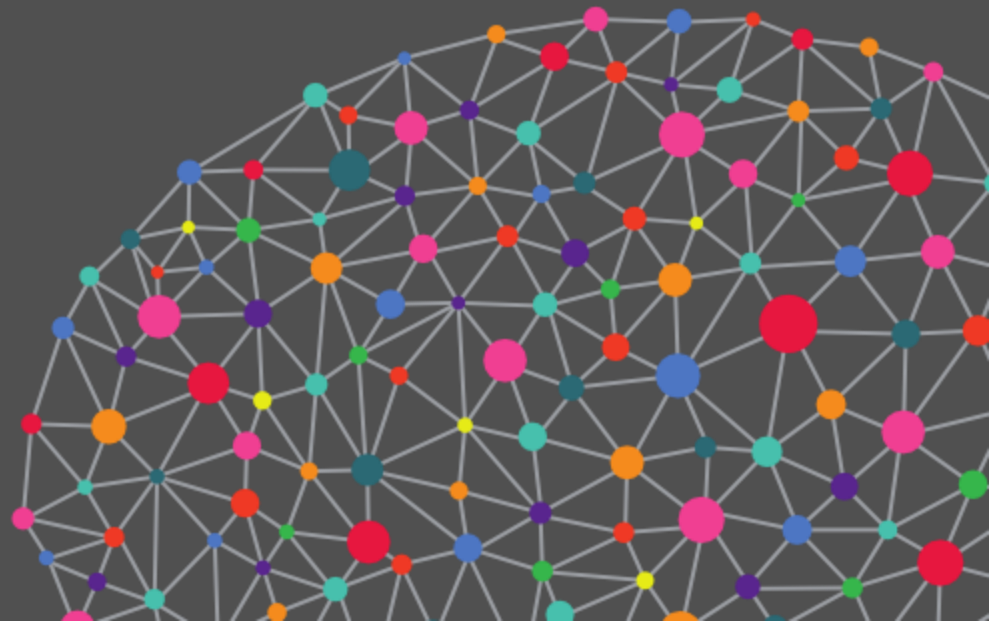
MACHINE LEARNING @ MICROSOFT

Azure

Microsoft

TALK OUTLINE

- High level concepts of deep learning
- Advanced topics
- Old days of vision
- How does convolution work?
- MNIST example in Keras code
- Data Augmentation on Cats+Dogs dataset
- Transfer Learning
- Visualising CNNs



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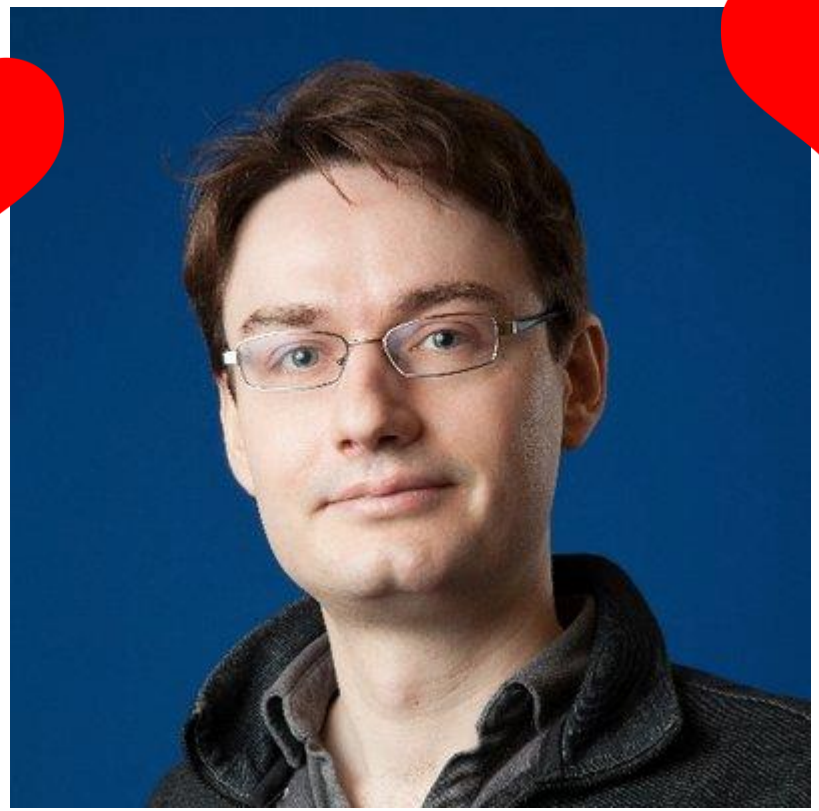
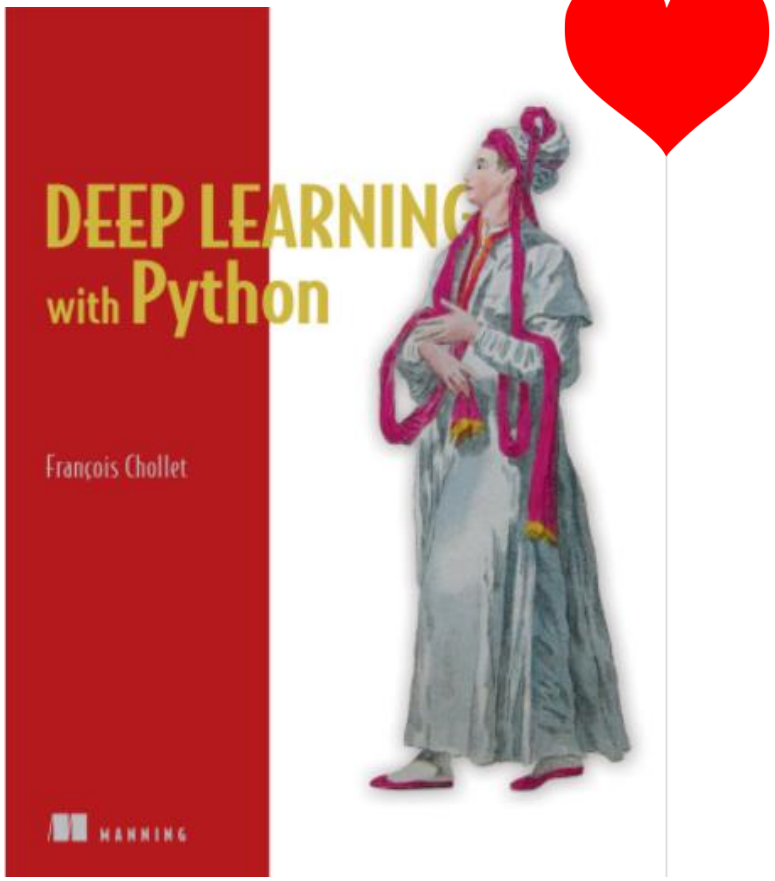
Francois Chollet. The man. The legend. Please buy his book!





https://github.com/fchollet/deep-learning-with-python-notebooks/
https://www.manning.com/books/deep-learning-with-python

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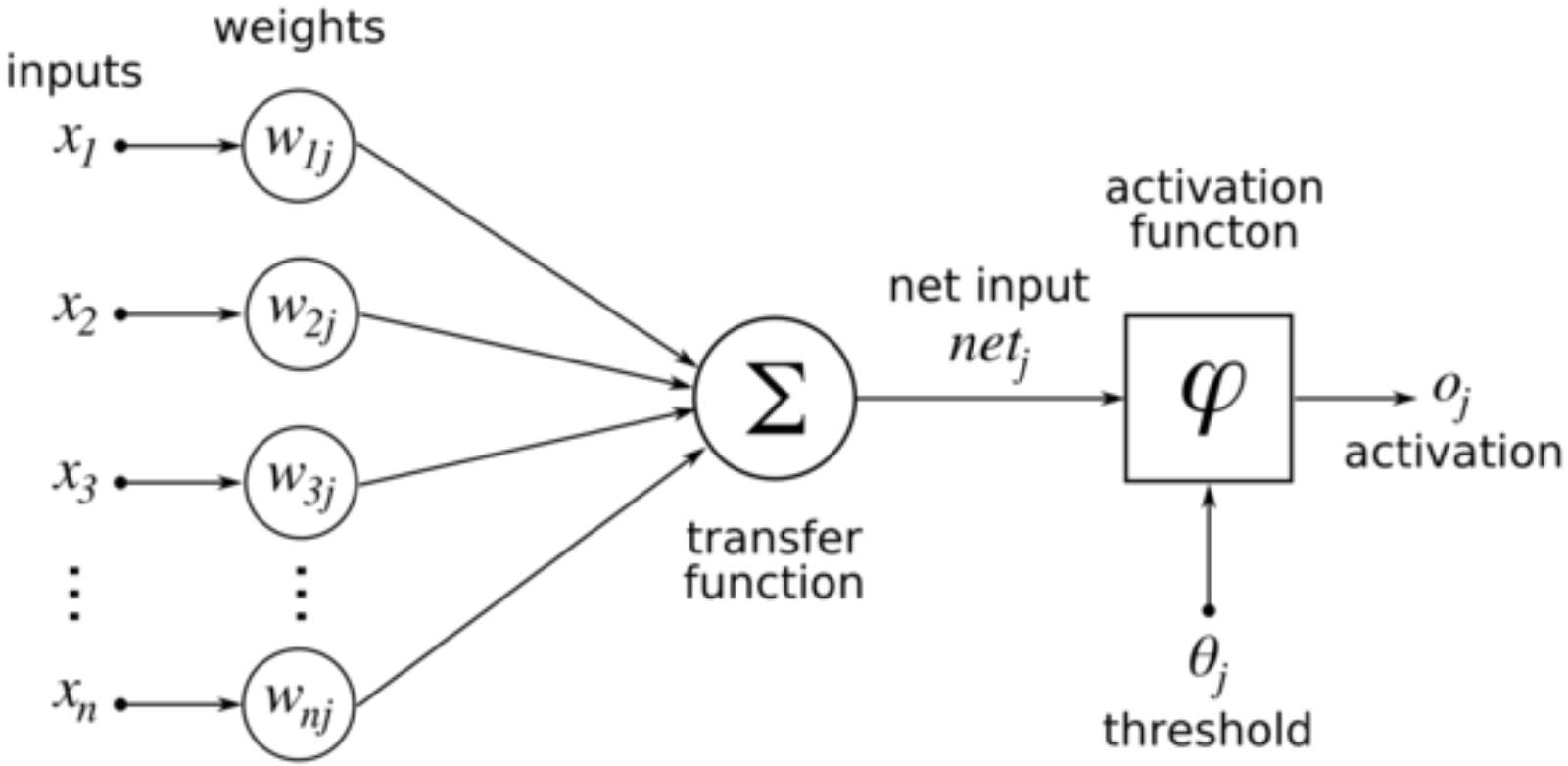
WHAT IS A NEURAL NETWORK?



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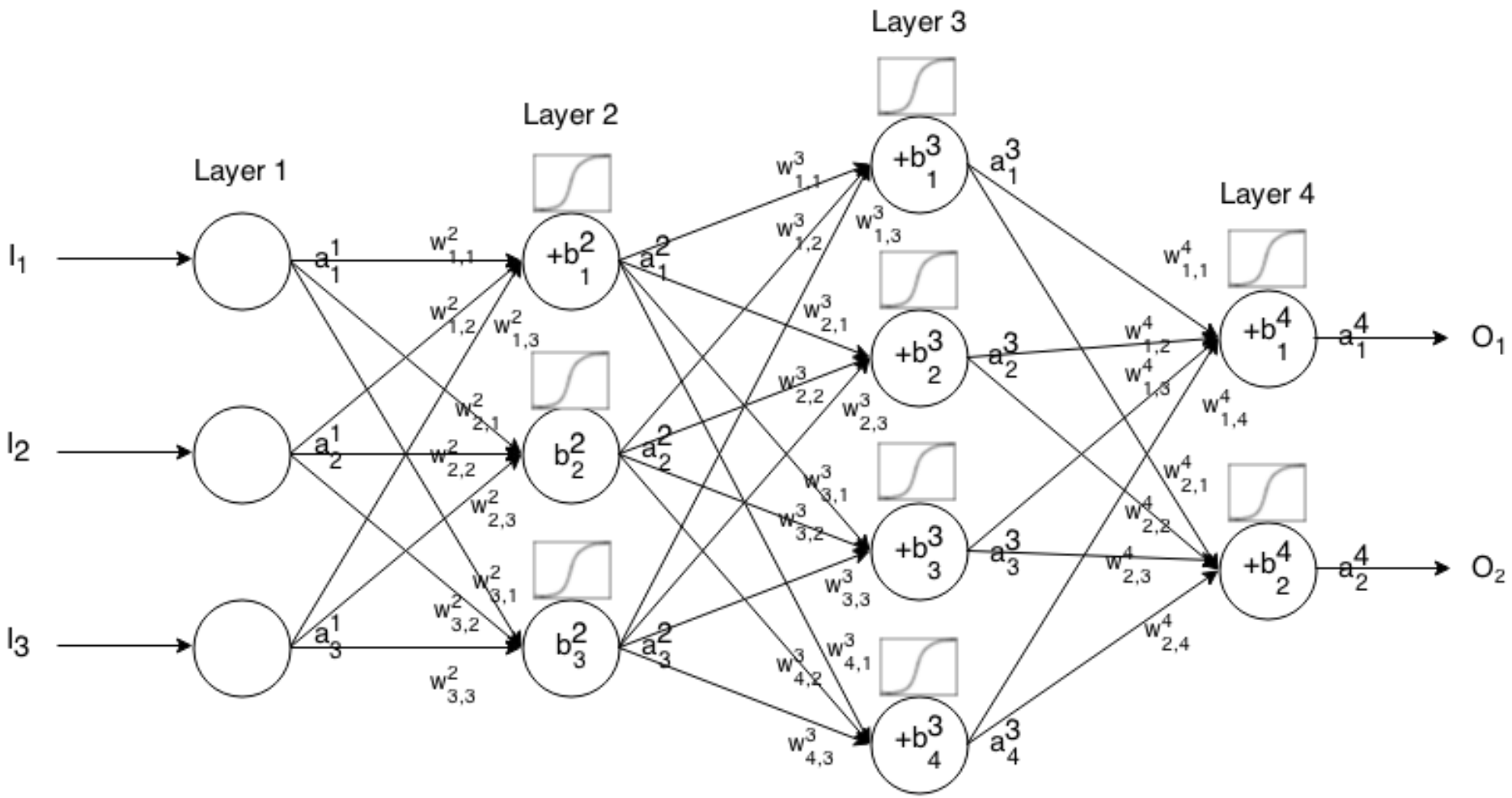
WHAT IS A (DENSE) DEEP NEURAL NETWORK?



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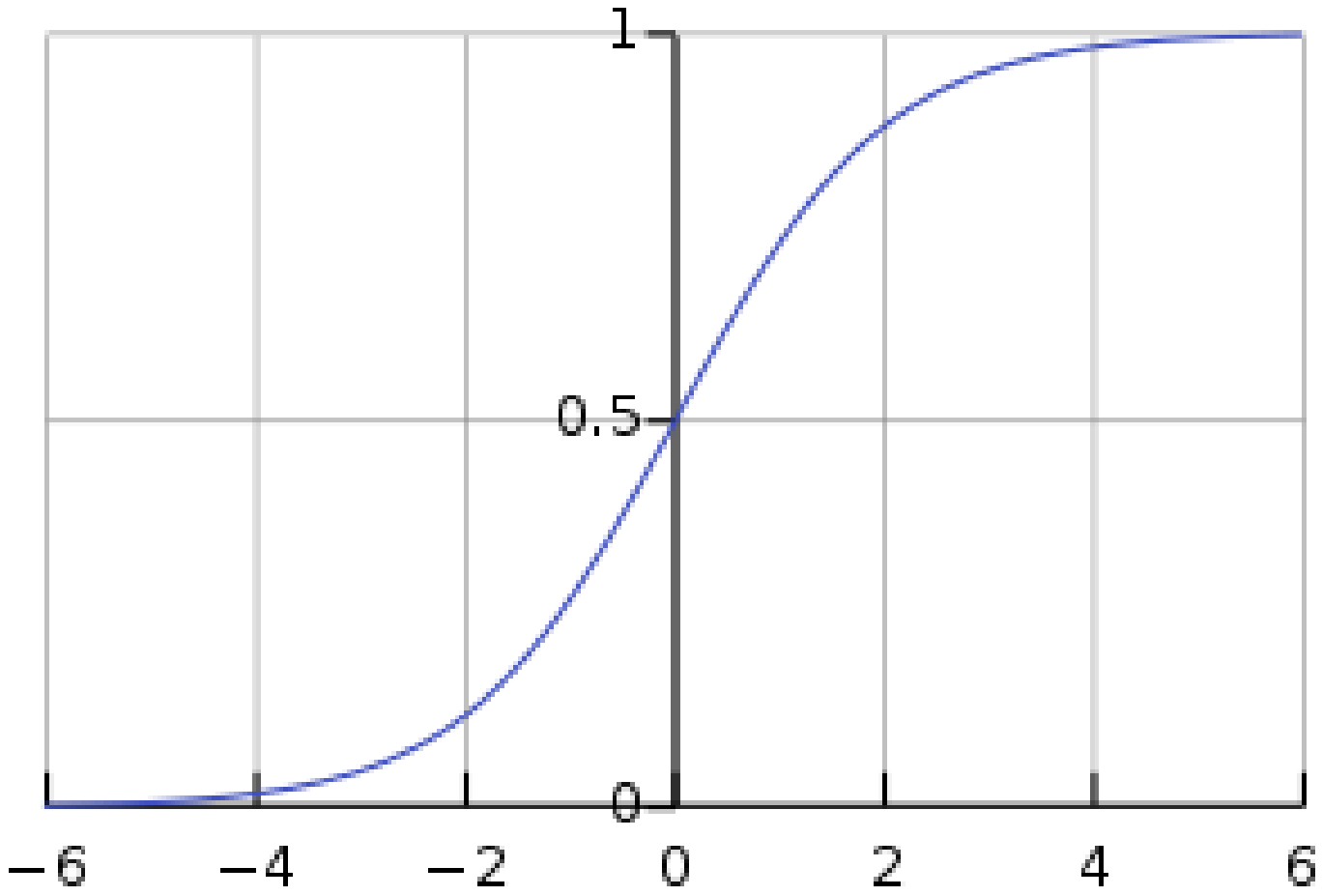
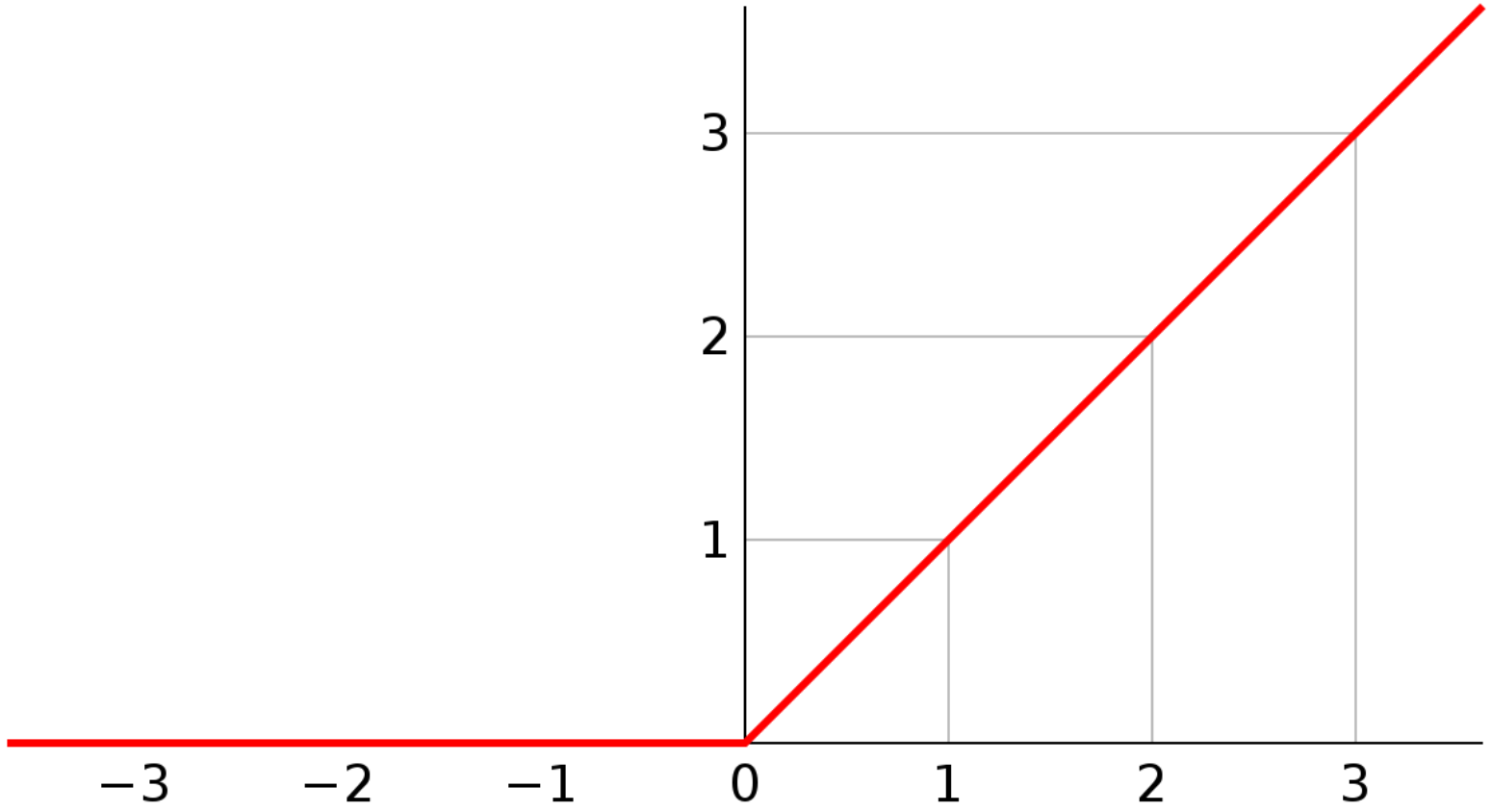
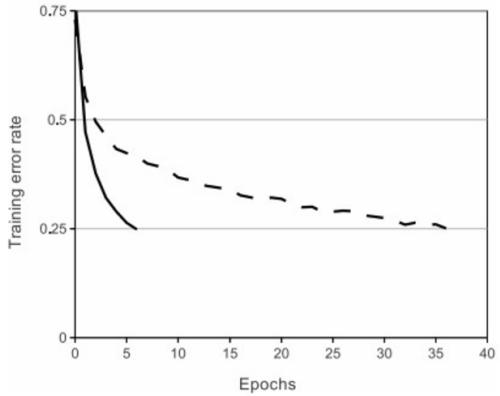


$$\frac{e^x}{e^x + 1}$$

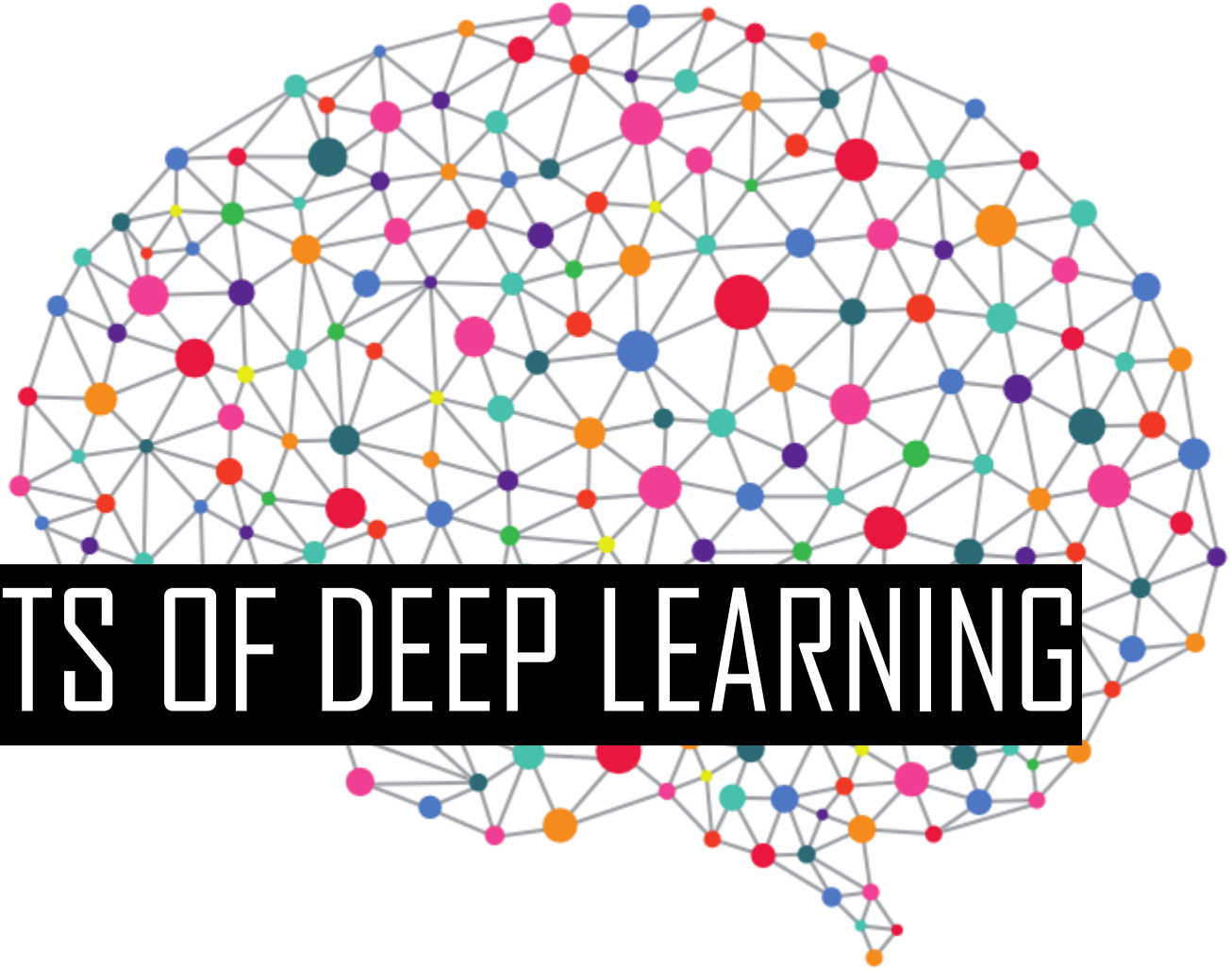
SIGMOID SQUASHING FUNCTION



$$f(x) = x^+ = \max(0, x)$$



RELU SQUASHING FUNCTION



DISTILLED CONCEPTS OF DEEP LEARNING

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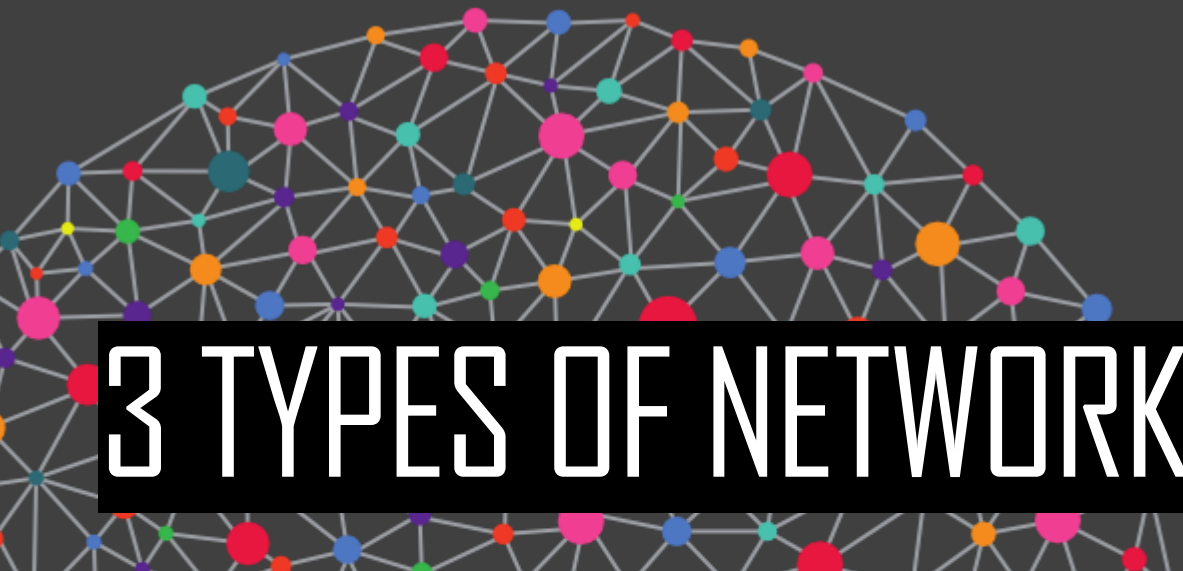
1. DENSELY CONNECTED NETWORKS
2. CONVOLUTIONAL NEURAL NETWORKS (MODEL SPACE)
3. RECURRENT NEURAL NETWORKS (MODEL TIME)



3 TYPES OF NETWORK ARCHITECTURE

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- The networks have **many levels** of depth
- Machine learns a hierarchy of representations i.e. **"representation learning"**
- **Less feature extraction** required (still need transposition, normalization etc)

Traditional ML

Hand crafted features

Feature Extractor → Trainable Classifier

Deep Learning

Representations are hierarchical and trained automatically

Low Level Features → Mid Level Features → High Level Features → Trainable Classifier

ENTIRE MACHINE IS TRAINABLE

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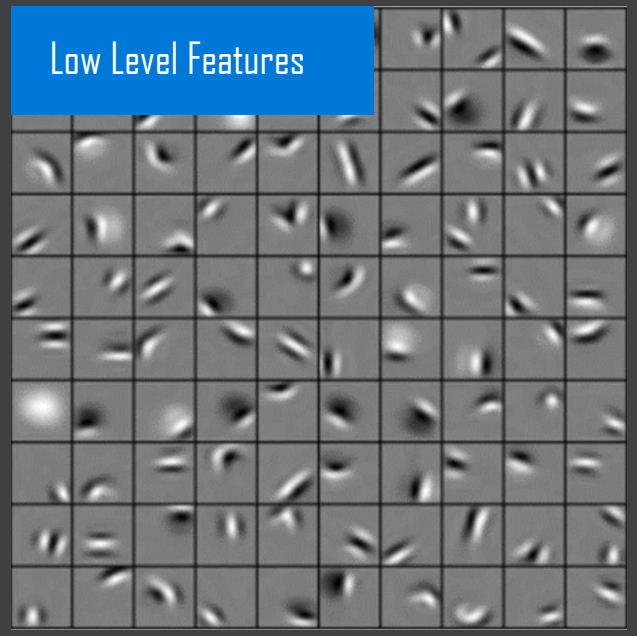

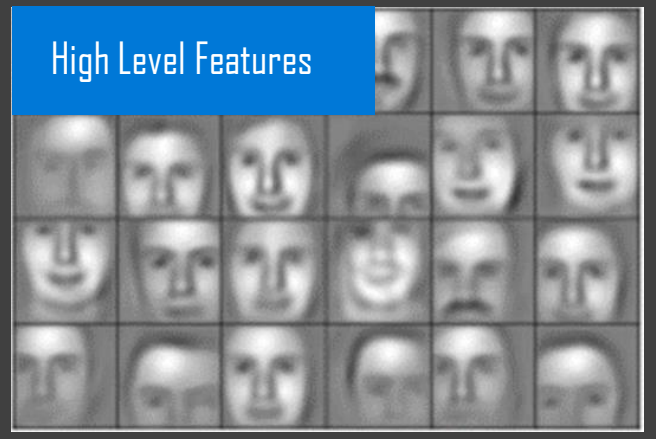

REPRESENTATIONS ARE LEARNED AUTOMATICALLY

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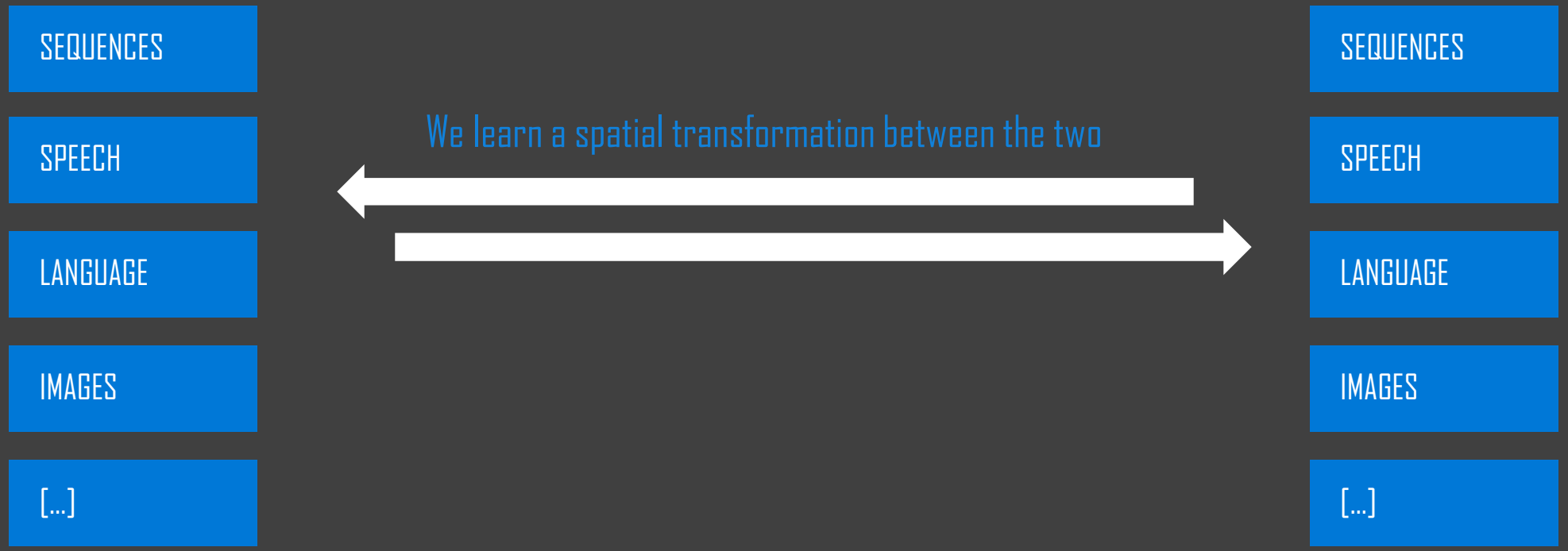
- Unlike other shallow ML algorithms; you can map *between data domains*
- **Generative** models are possible, not just **discriminative**
- You can have **multiple inputs** and **outputs**!

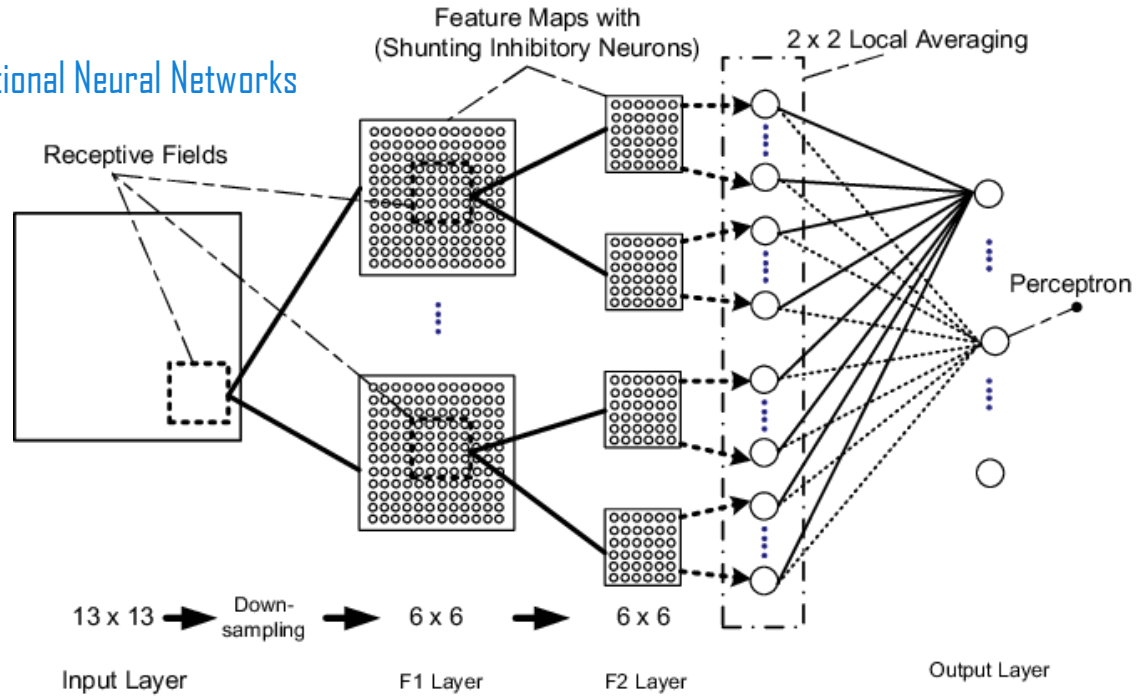


UNIVERSAL FUNCTION APPROXIMATORS

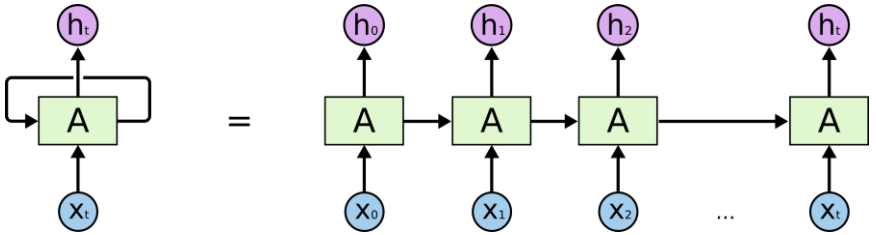
Unlike other algorithms, NNs can natively encode useful and obvious relationships in the data domain

- Local spatial dependencies (vision) i.e. CNNs
- Time dependencies (language, speech) i.e. RNNs

Convolutional Neural Networks



Recurrent Neural Networks



NATIVE DATA-DOMAIN FEATURES

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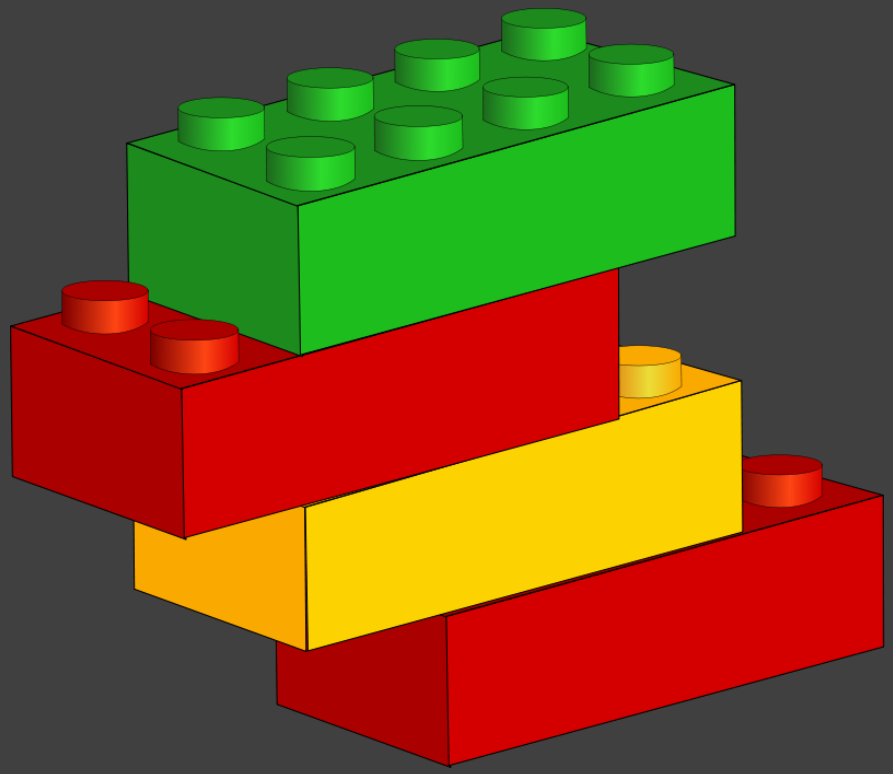
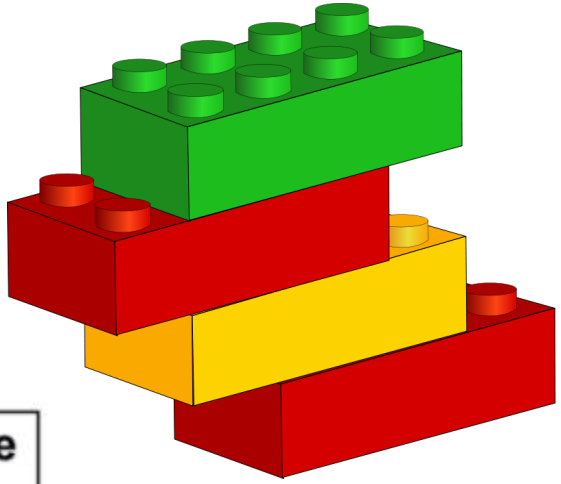
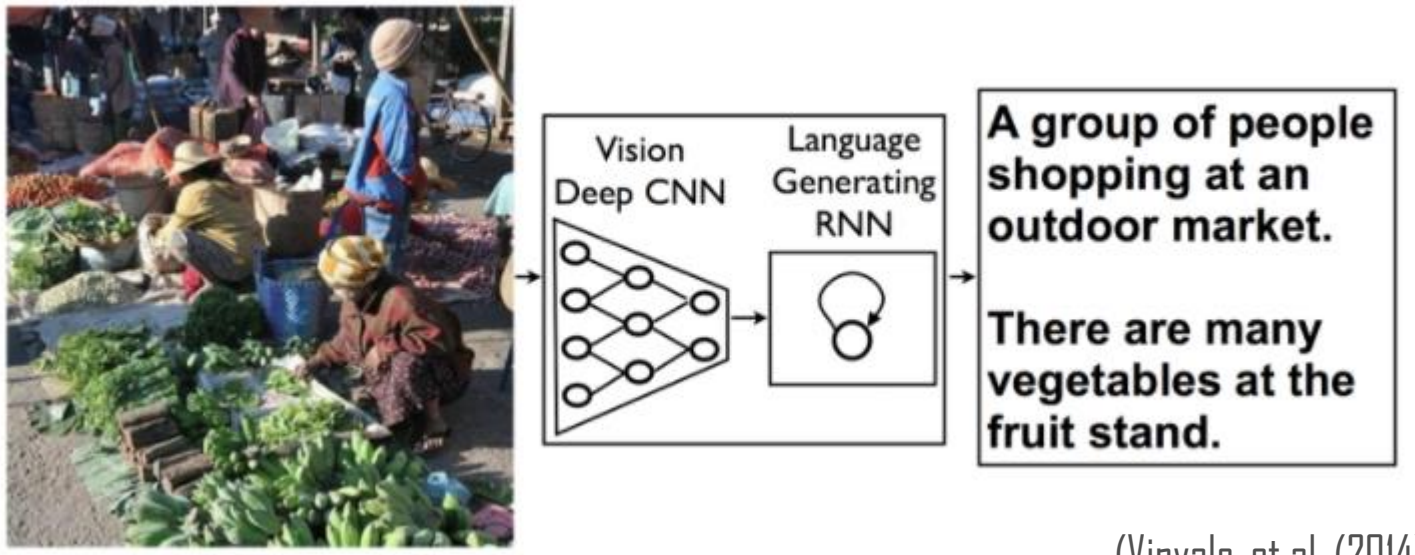
- ML is becoming a form of software development
- ML models are like software



COMPOSABILITY

BUILDING PREDICTIVE ARCHITECTURES LIKE LEGO BLOCKS





(Vinyals, et al. (2014))

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TWO INNOVATIVE DL ARCHITECTURES

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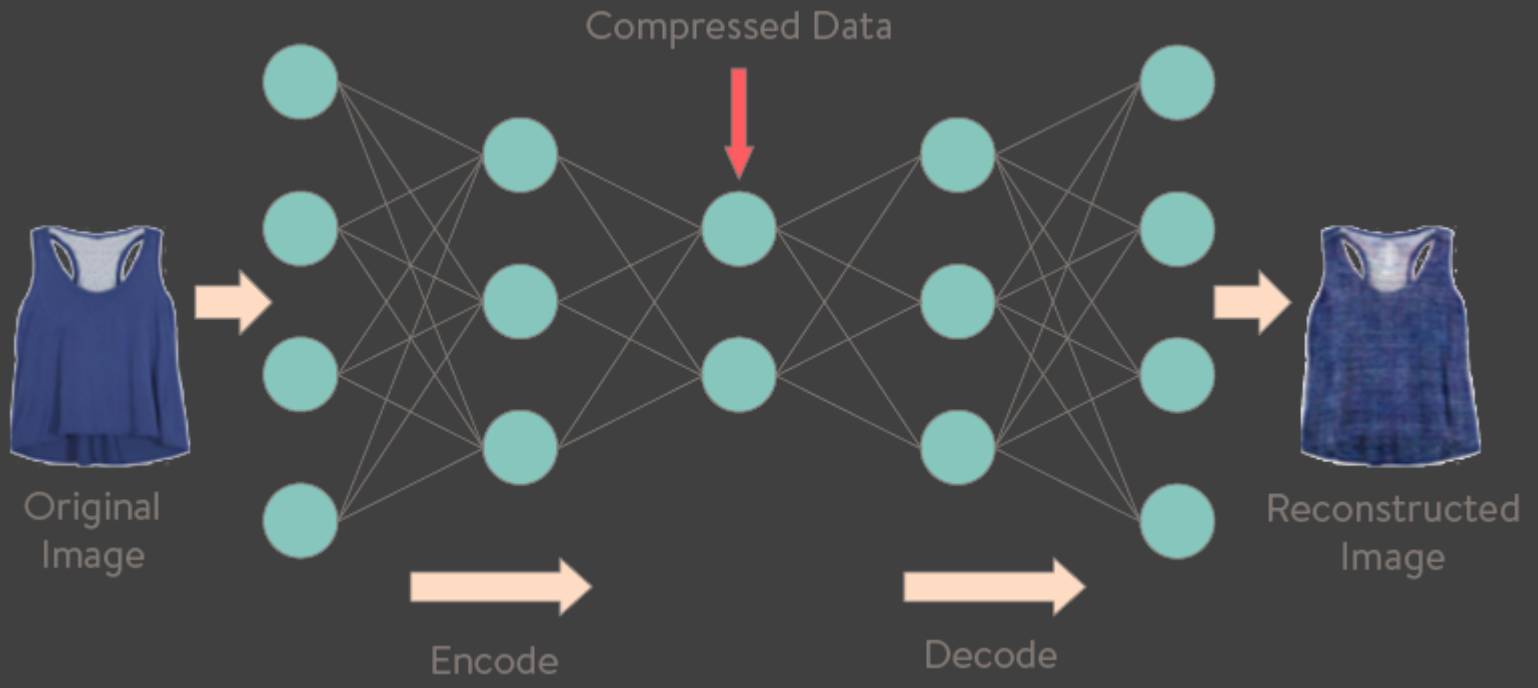
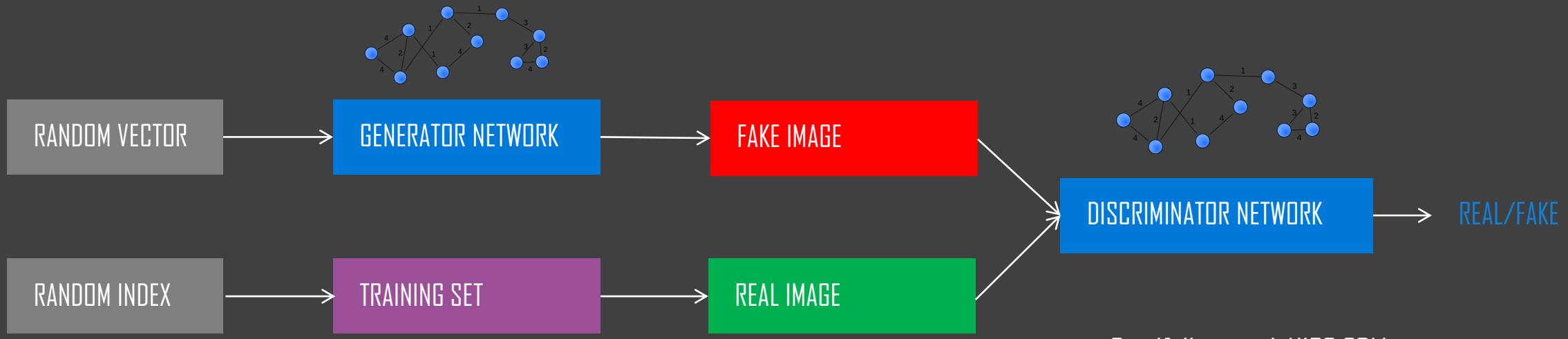
- Autoencoders are an unsupervised method to compress information into an "embedding" similar to unsupervised dimensionality reduction.



AUTOENCODERS

- An example; generative adversarial networks
- Game-theoretical approach to deep learning



Goodfellow et al. NIPS 2014

NOVEL ARCHITECTURES (GANS)

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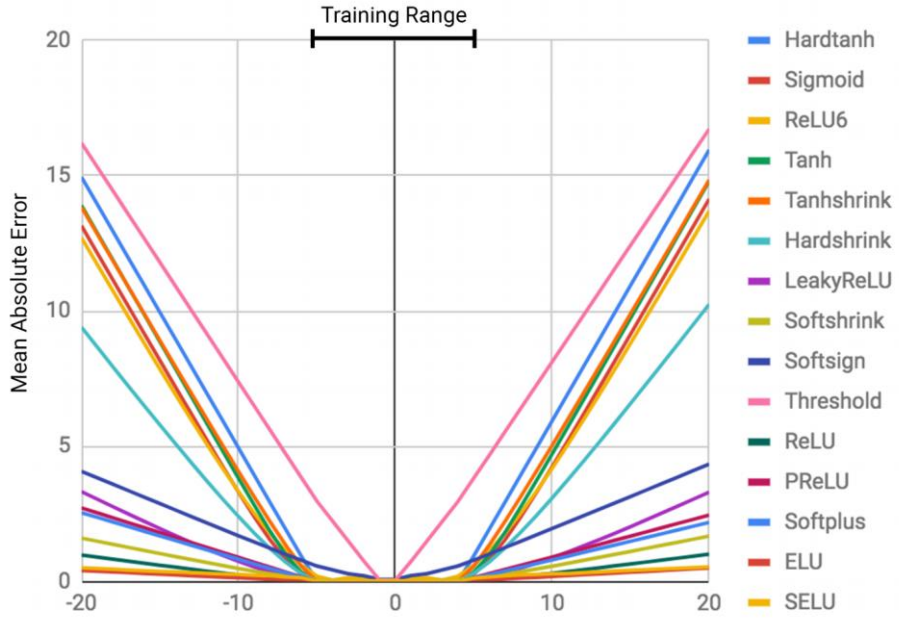
IMAGES GENERATED WITH GANS

INTERPOLATION VS EXTRAPOLATION

ML algorithms perform very, very badly on data out of range. They don't generalise as well as you think. Trask et al 2018 (DeepMind)



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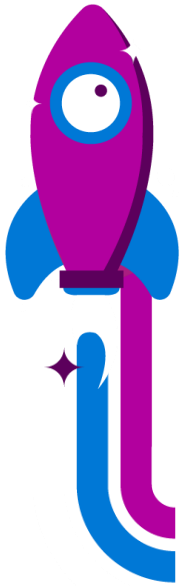

How did we used to do computer vision?

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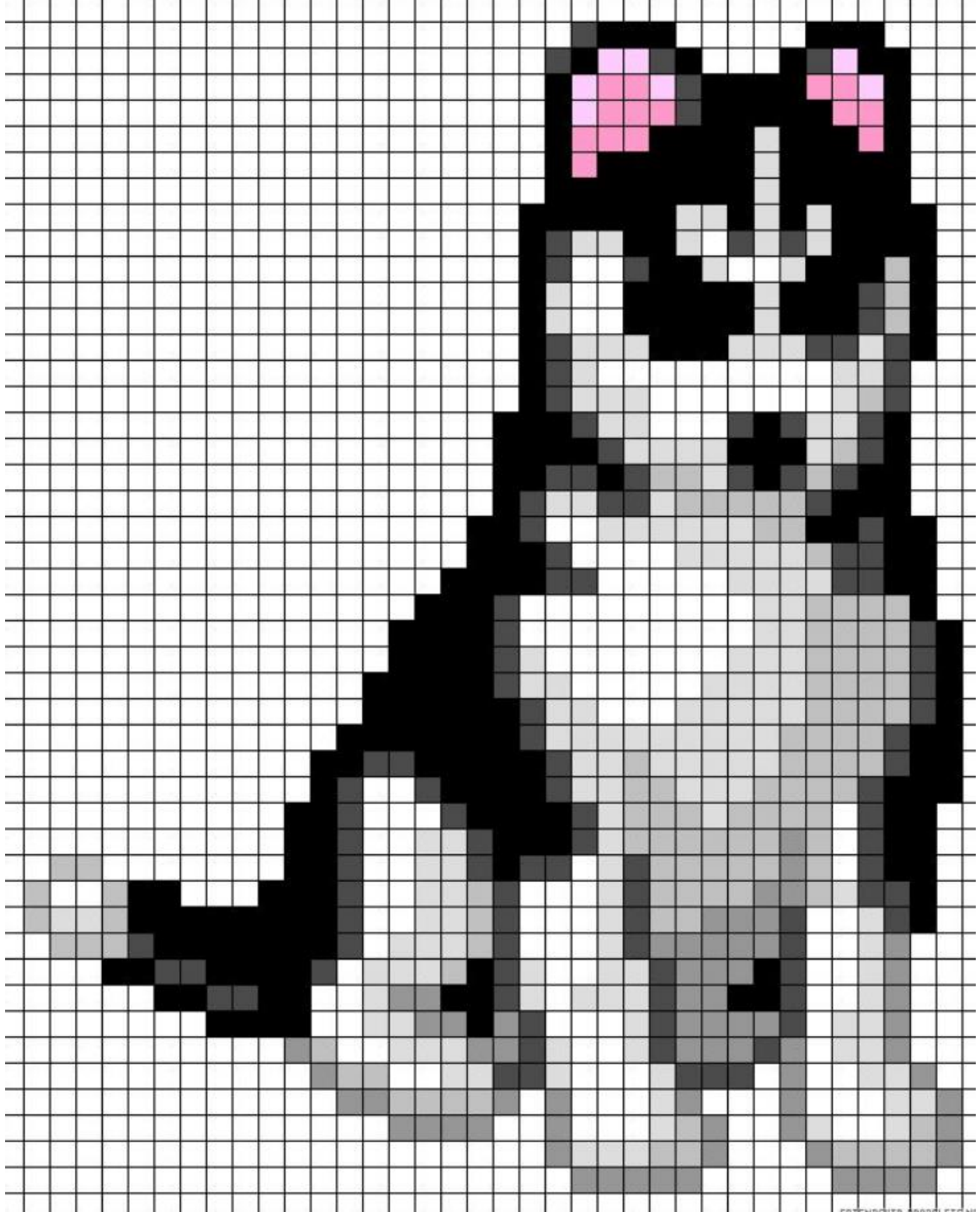
PIXEL-WISE LEARNING

- Not “translation” invariant
- Not scale invariant
- Not rotational invariant
- Affine transformations?



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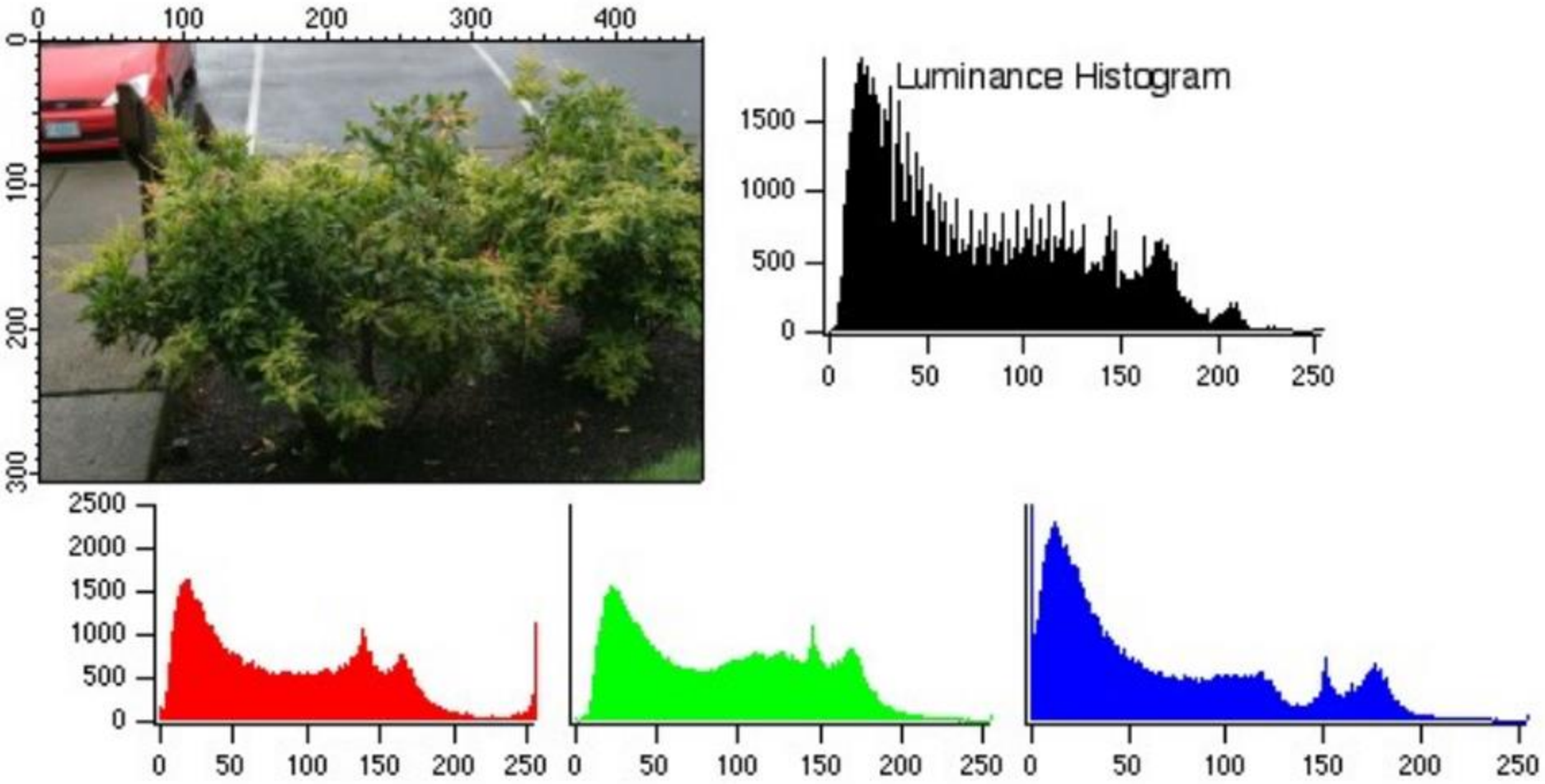
HISTOGRAMS A FEATURES



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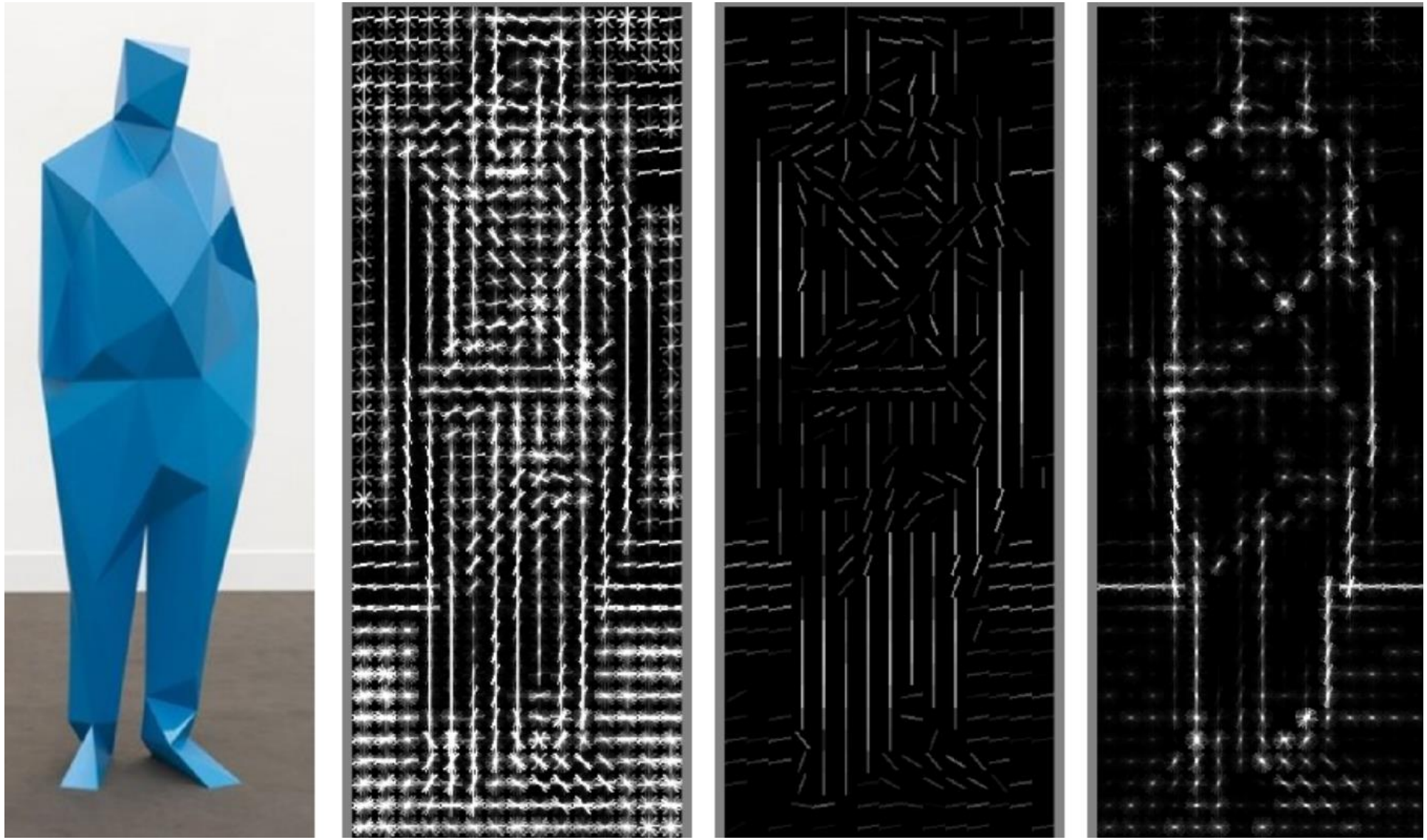
HISTOGRAMS OF GRADIENTS (HOG)



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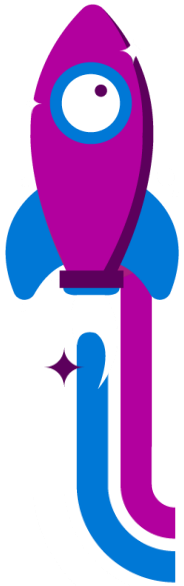
EDGE DETECTION (WITH CONVOLUTION)



How do convolutional neural networks work?

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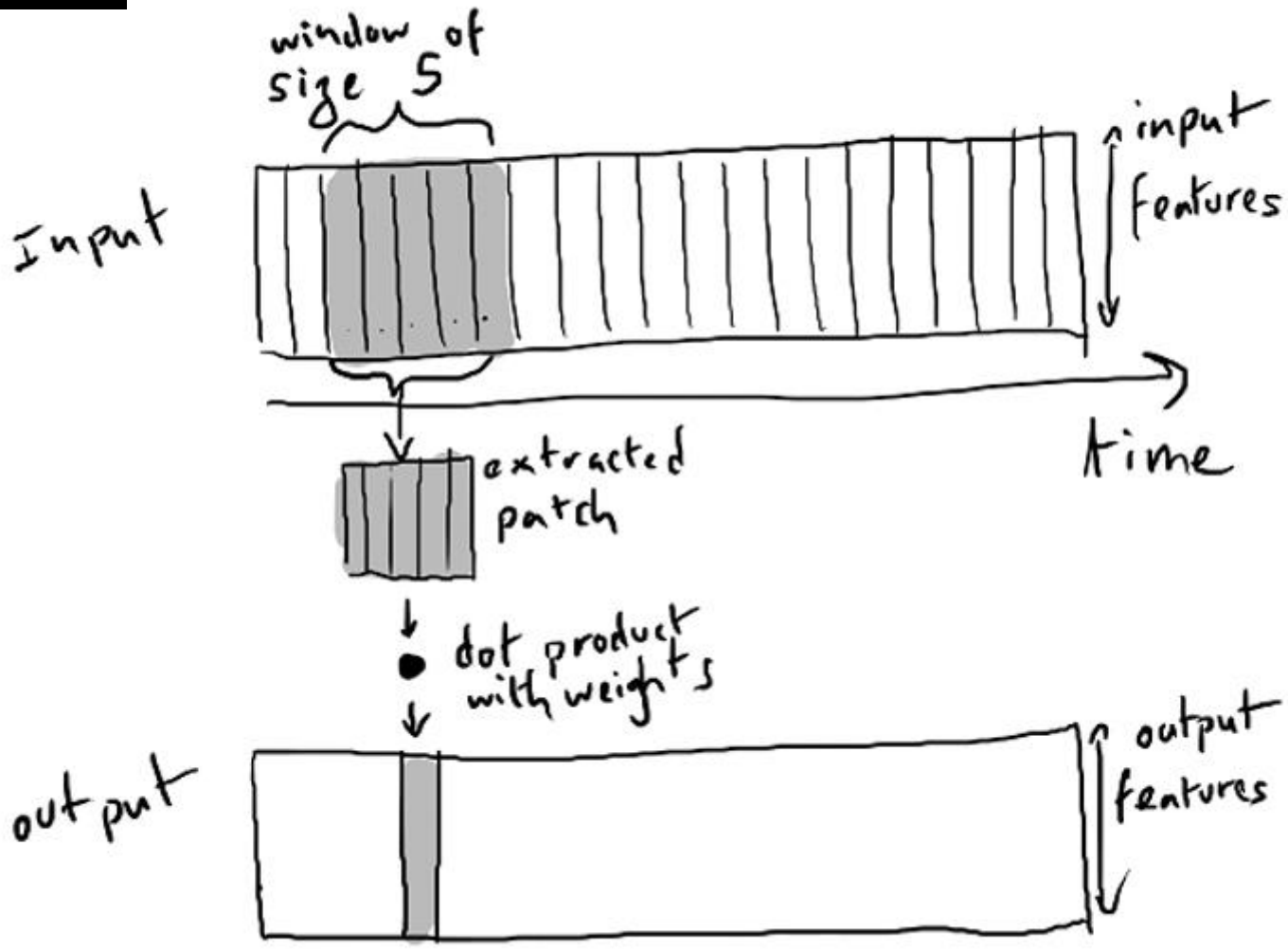
CONVOLUTION



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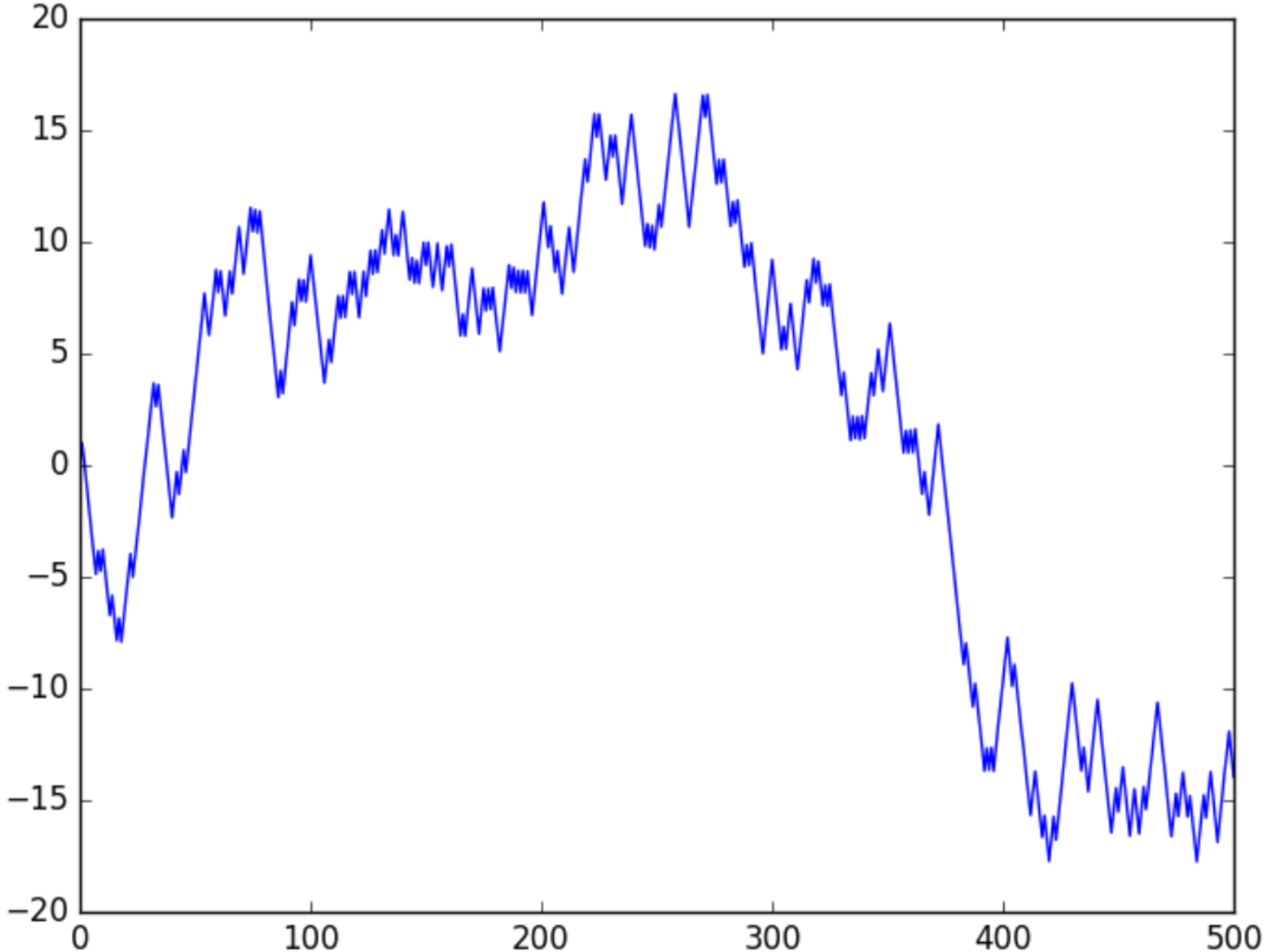
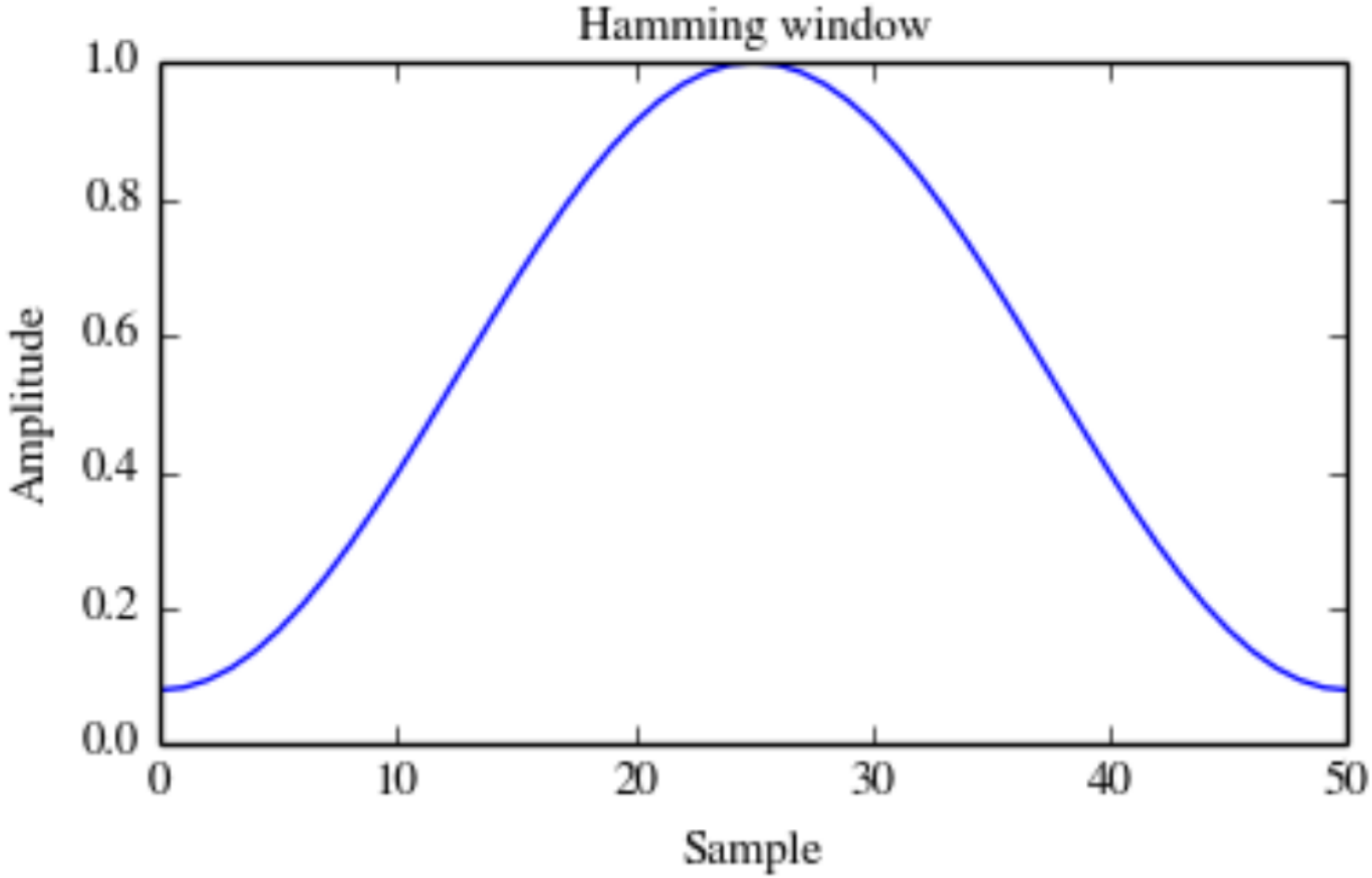
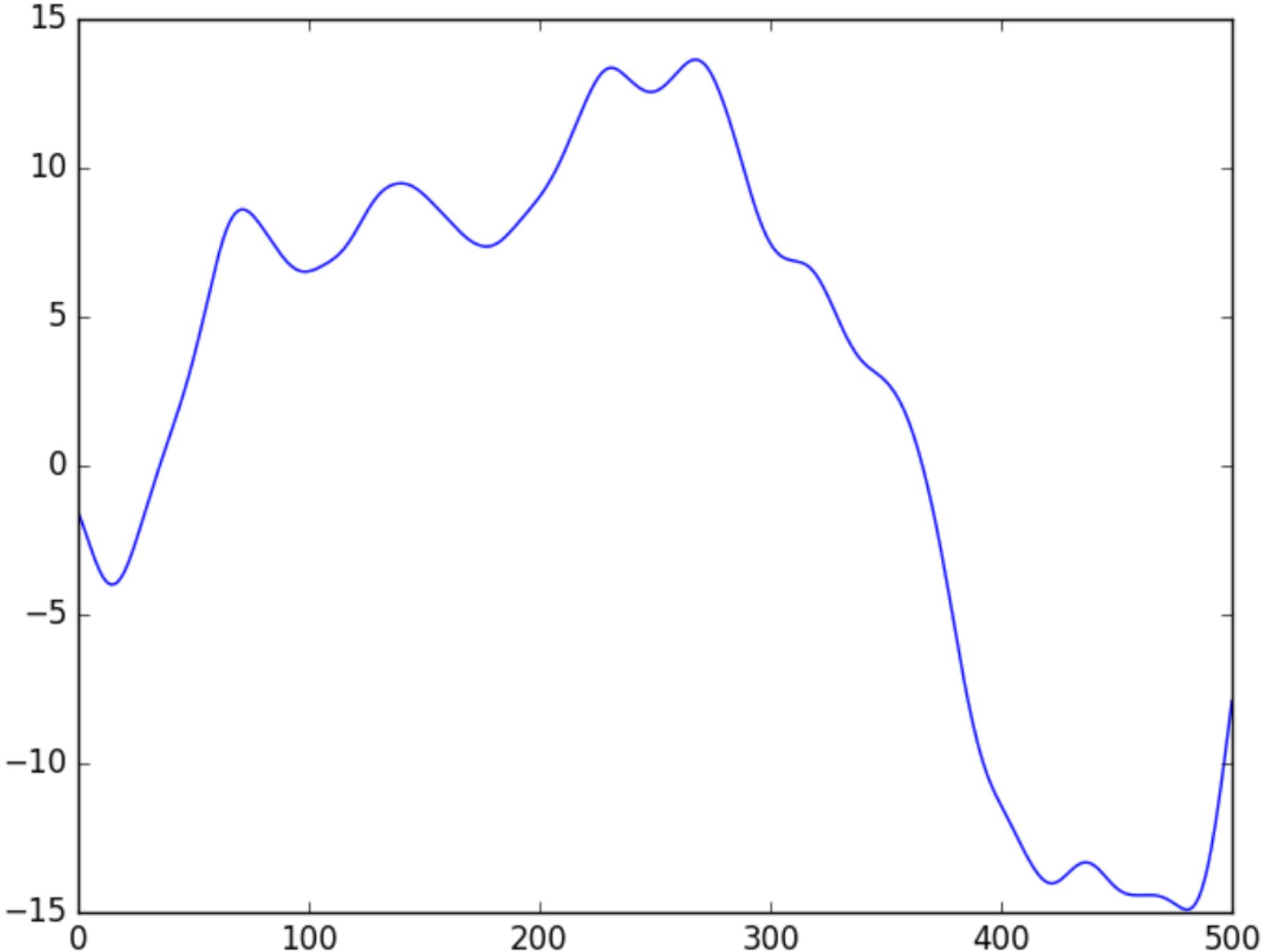
```
x = [0]

for j in range(500):
    step_x = random.randint(0,1)
    if step_x == 1:
        x.append(x[j] + 1 + 0.05*np.random.normal())
    else:
        x.append(x[j] - 1 + 0.05*np.random.normal())
```

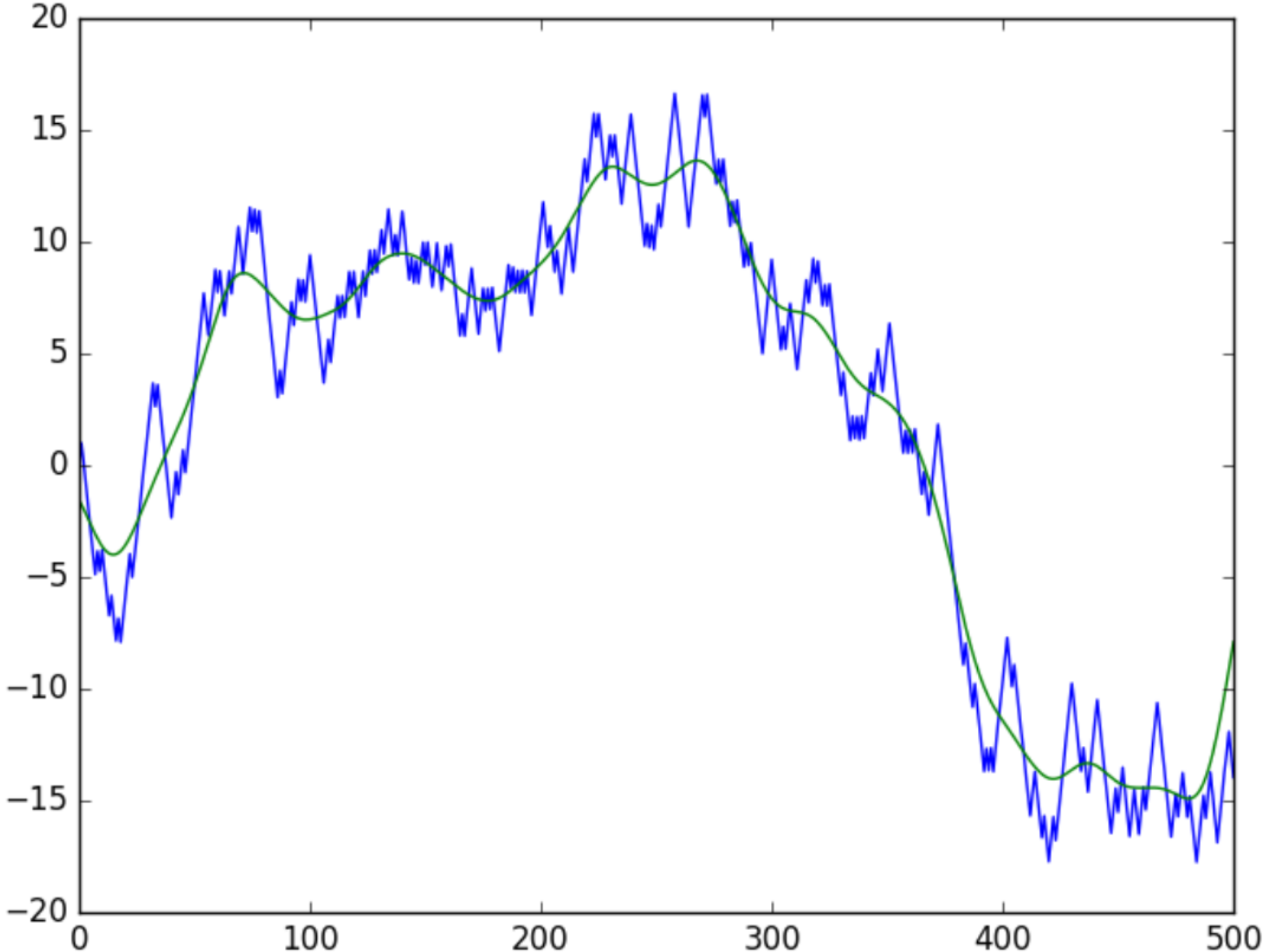


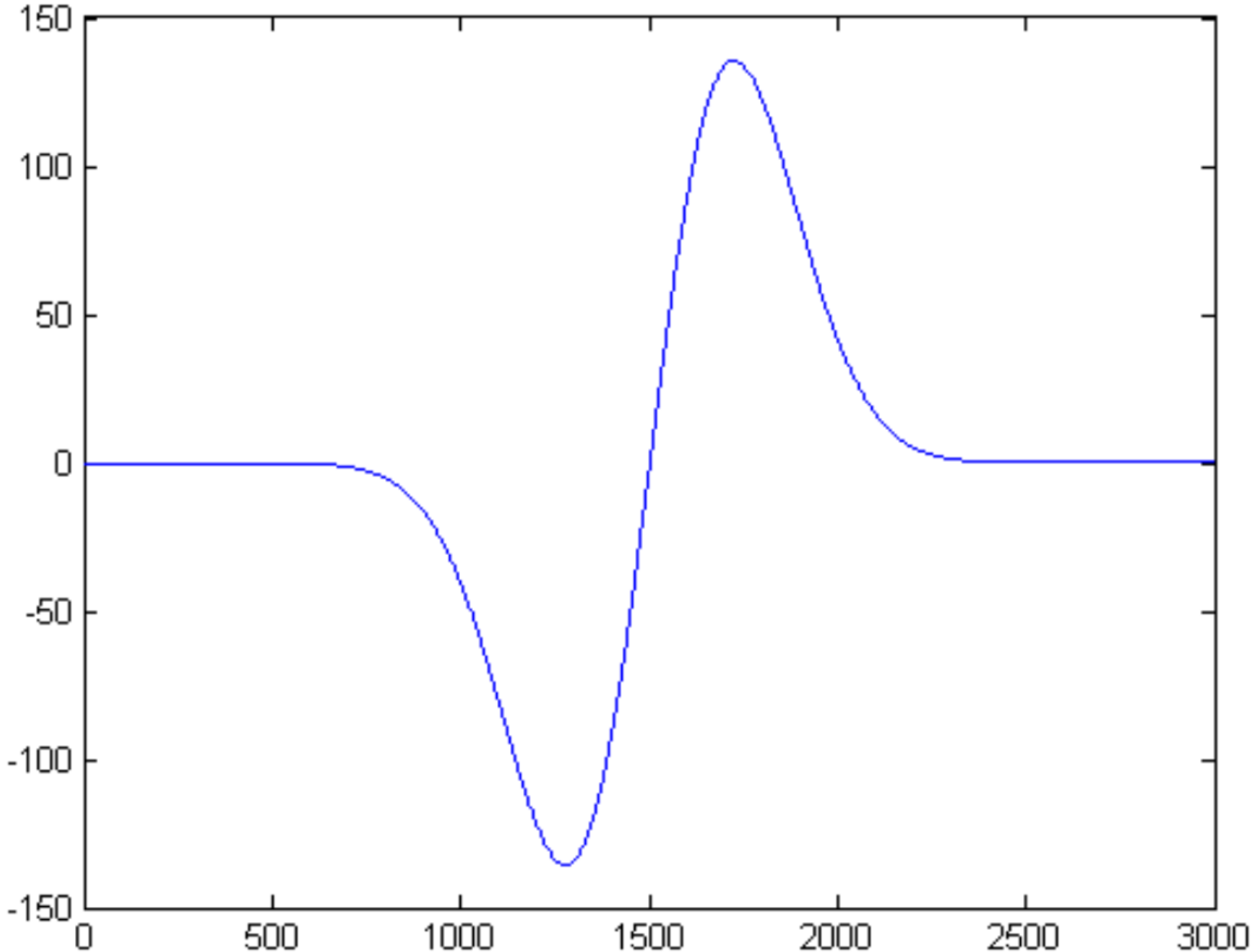


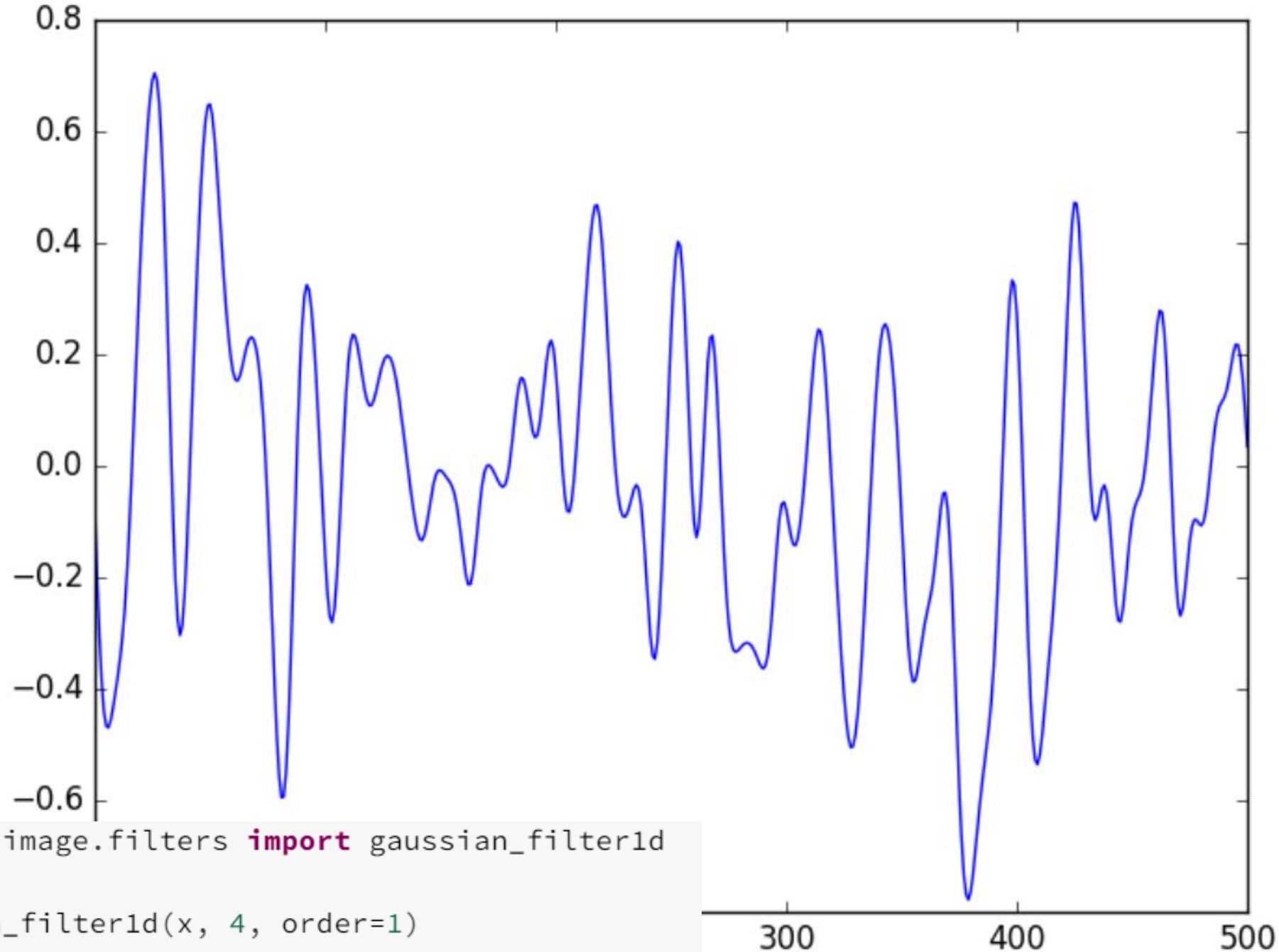
$$w(n) = 0.54 - 0.46\cos\left(2\pi\frac{n}{N}\right), \quad 0 \le n \le N.$$

```
from scipy import signal

win = signal.hann(50)
filtered = signal.convolve(x, win, mode='same') / sum(win)
```

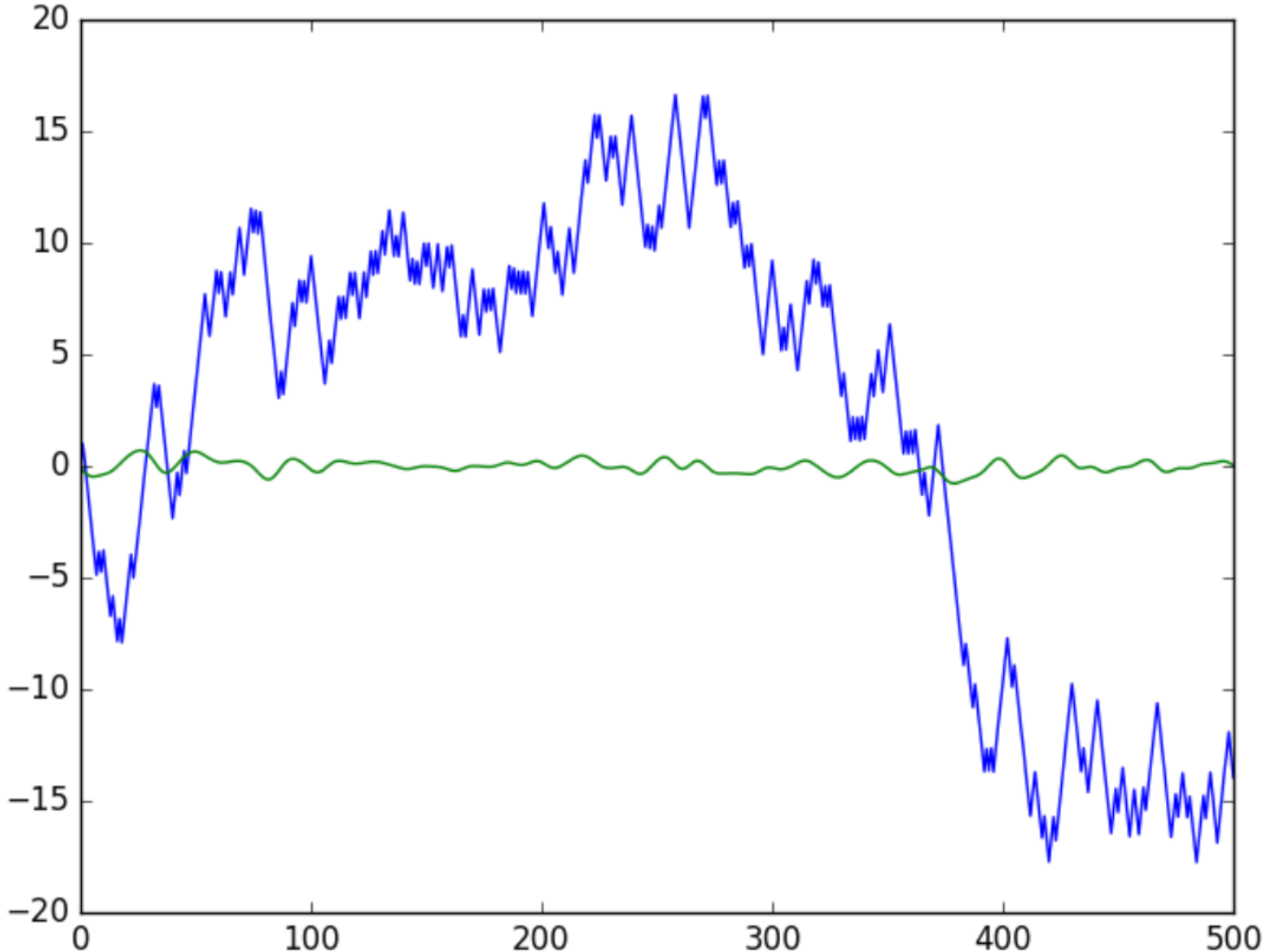




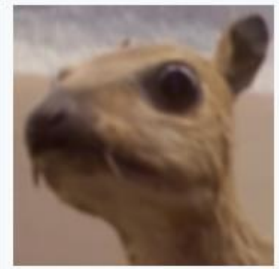
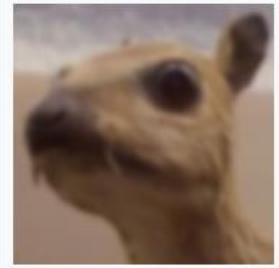




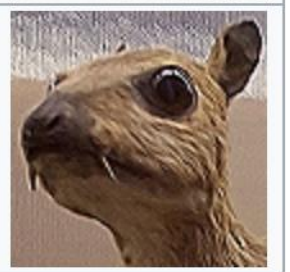

```
from scipy.ndimage.filters import gaussian_filter1d

x2 = gaussian_filter1d(x, 4, order=1)
```



Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	

Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Box blur (normalized)	$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	
Gaussian blur 3 × 3 (approximation)	$\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	
Gaussian blur 5 × 5 (approximation)	$\frac{1}{256}\begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}$	
Unsharp masking 5 × 5 Based on Gaussian blur with amount as 1 and threshold as 0 (with no image mask)	$\frac{-1}{256}\begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & -476 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}$	

DEMO

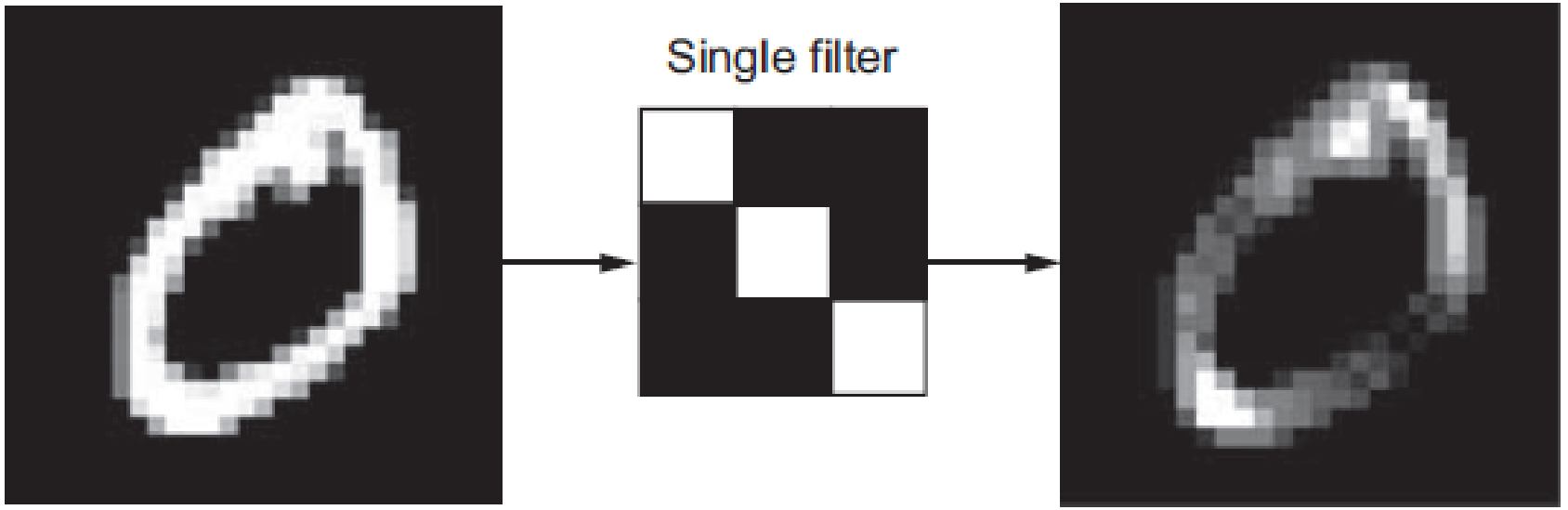
Operation	Kernel	Image result
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	

Microsoft

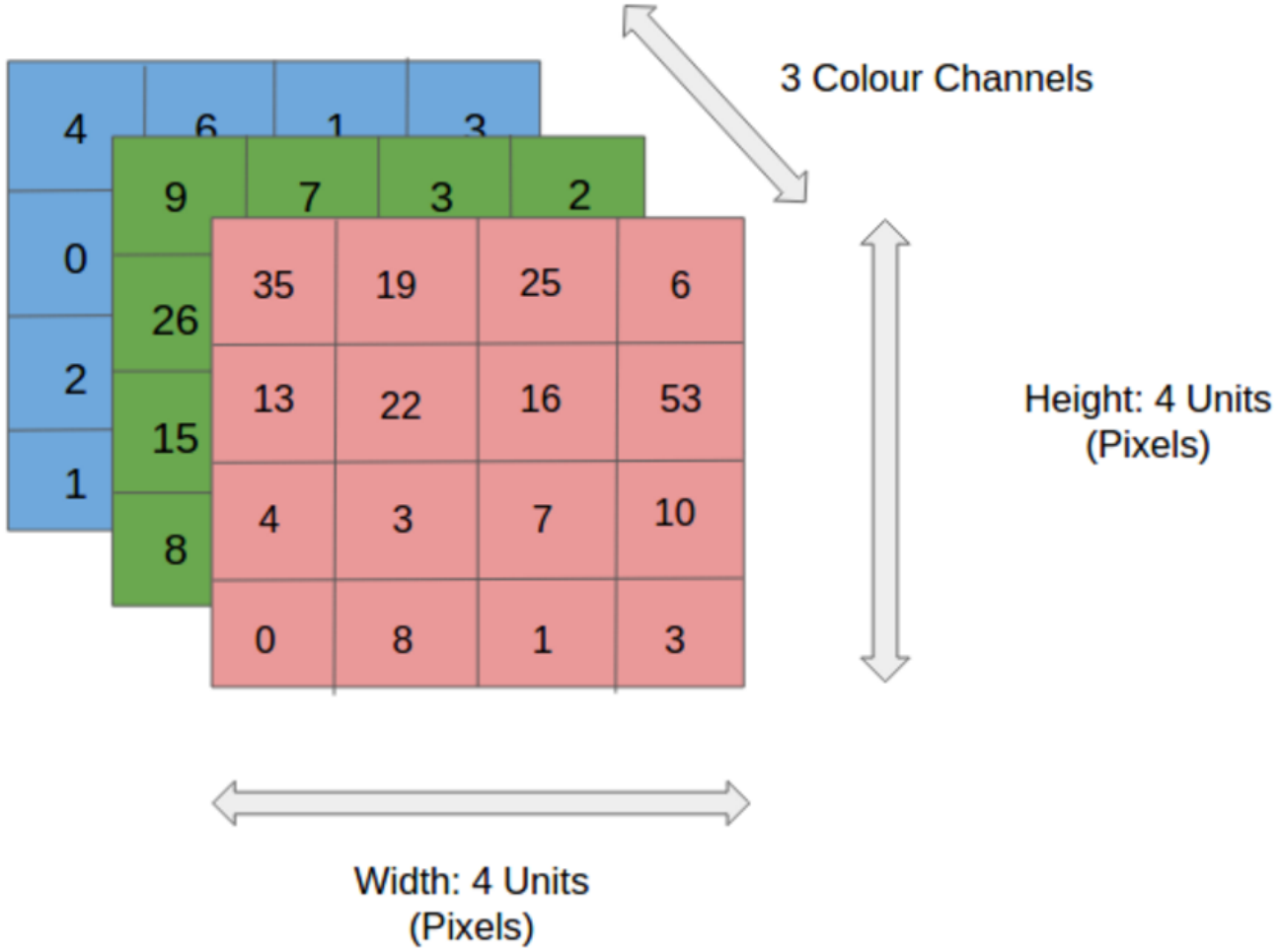
Original input

Single filter

Response map, quantifying the presence of the filter's pattern at different locations



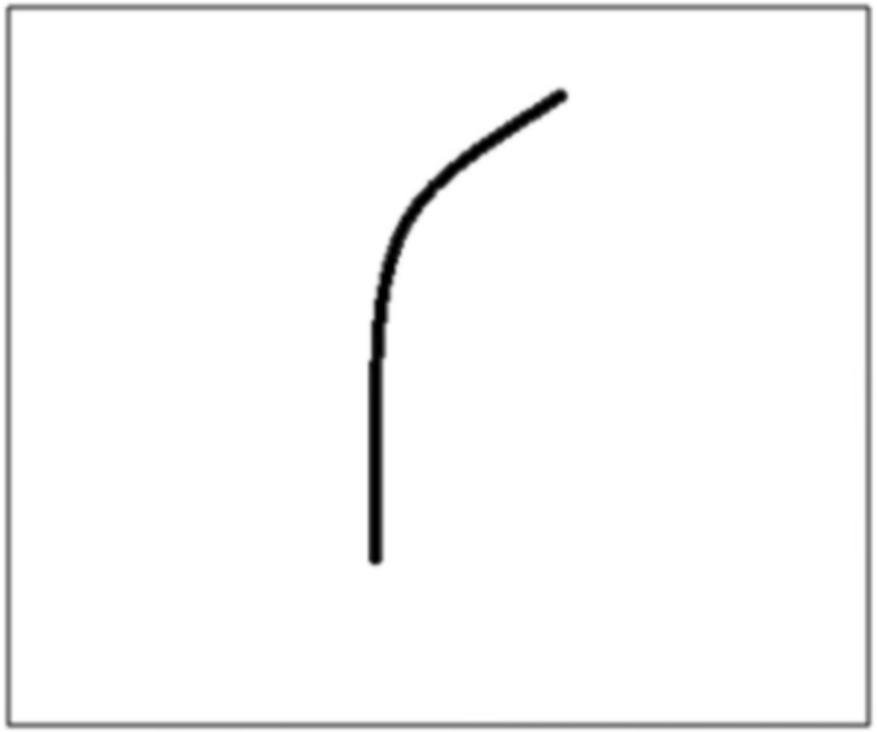
PREPARE DATASET OF IMAGES



Microsoft

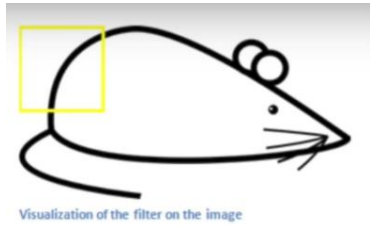
0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter



Visualization of a curve detector filter

CONVOLUTION FILTER



Visualization of the filter on the image

$$(50*30)+(50*30)+(50*30)+(20*30)+(50*30) = 6600$$

Visualization of the receptive field

0	0	0	0	0	0	30
0	0	0	0	50	50	50
0	0	0	20	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0

Pixel representation of the receptive field

*

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

CONVOLUTION FILTER MATCH

Visualization of the filter on the image

MULTIPLY AND SUMMATION = 0

0	0	0	0	0	0	0
0	40	0	0	0	0	0
40	0	40	0	0	0	0
40	20	0	0	0	0	0
0	50	0	0	0	0	0
0	0	50	0	0	0	0
25	25	0	50	0	0	0

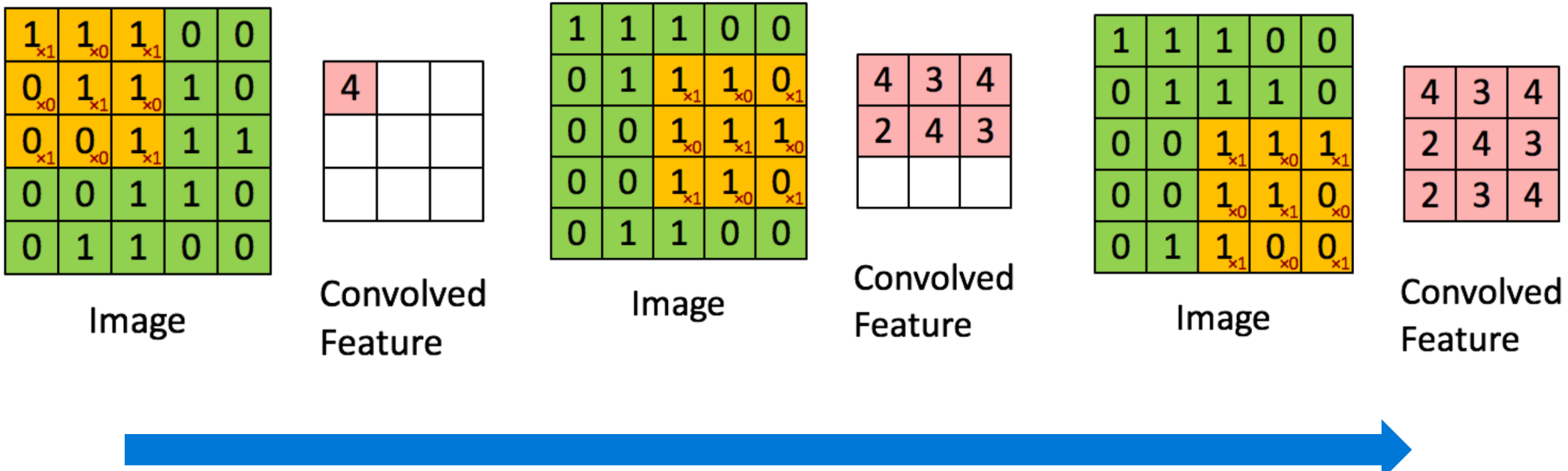
Pixel representation of receptive field

*

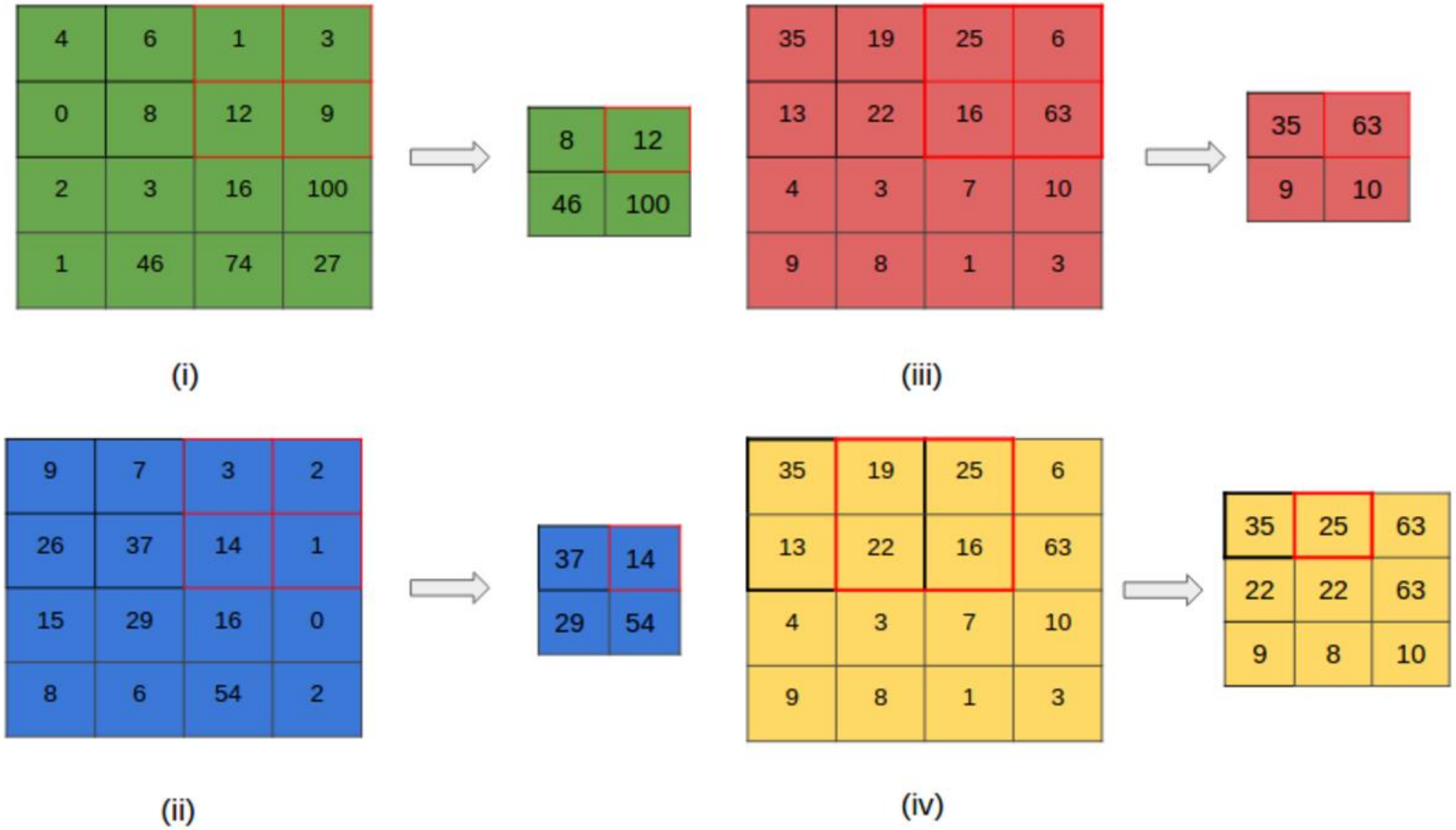
0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

CONVOLUTION FILTER NO MATCH

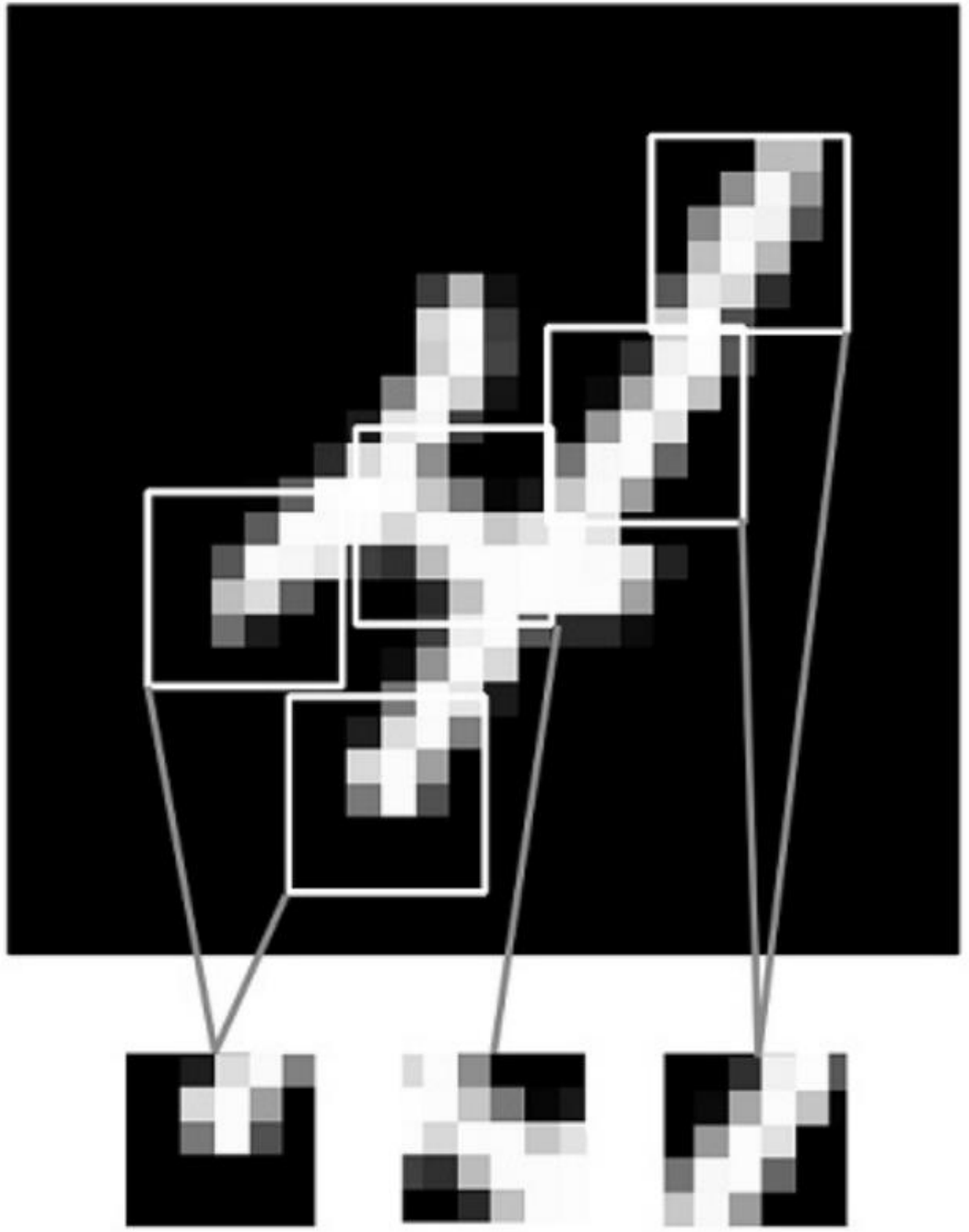


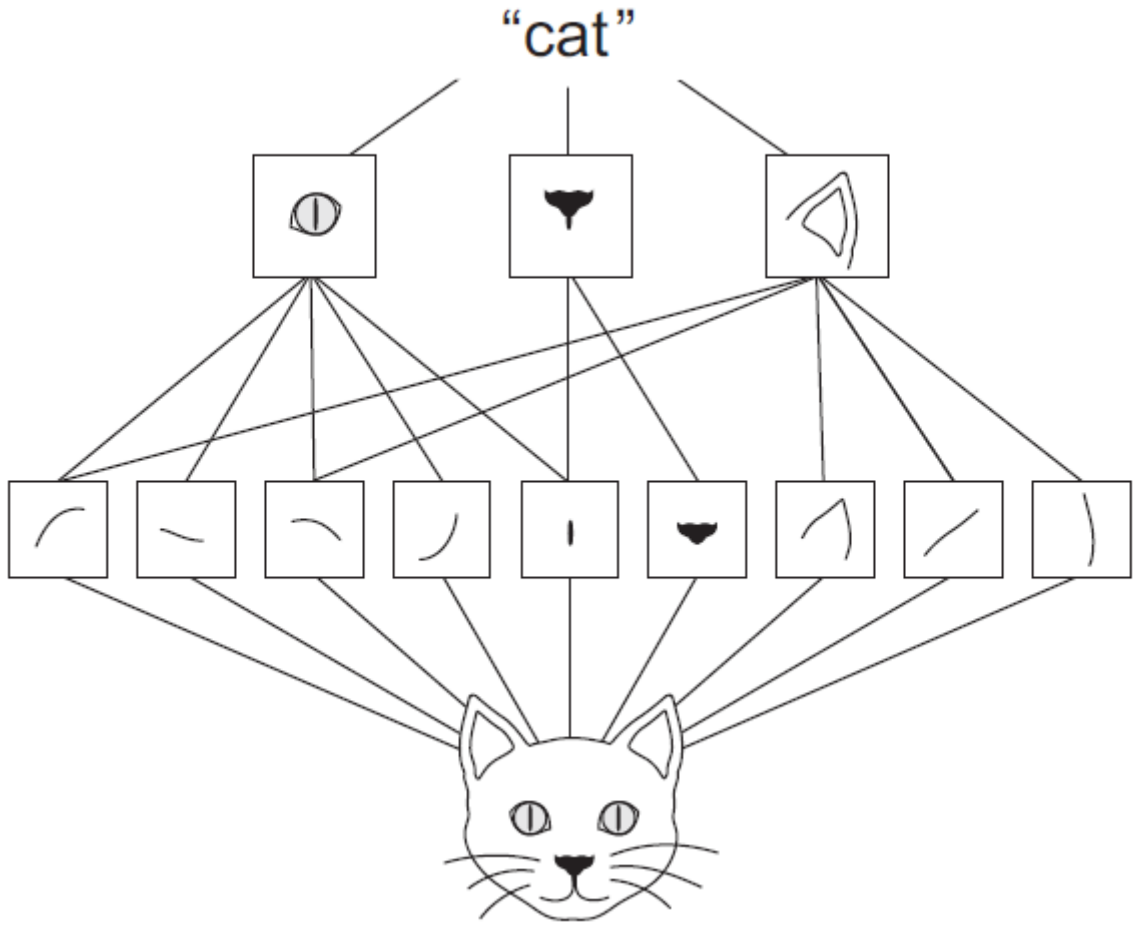
CONVOLUTION


4 6 1 3
0 8 12 9
2 3 16 100
1 46 74 27
8 12
46 100
(i)
35 19 25 6
13 22 16 63
4 3 7 10
9 8 1 3
35 63
9 10
(iii)
9 7 3 2
26 37 14 1
15 29 16 0
8 6 54 2
37 14
29 54
(ii)
35 19 25 6
13 22 16 63
4 3 7 10
9 8 1 3
35 25 63
22 22 63
9 8 10
(iv)

POOLING

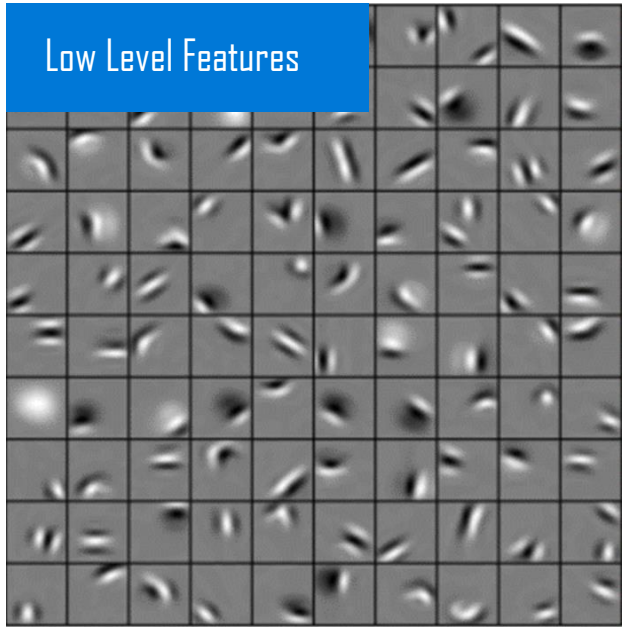
- Translation Invariant
- Spatial hierarchies of patterns
- Sort of scale invariant
- Not rotationally invariant!



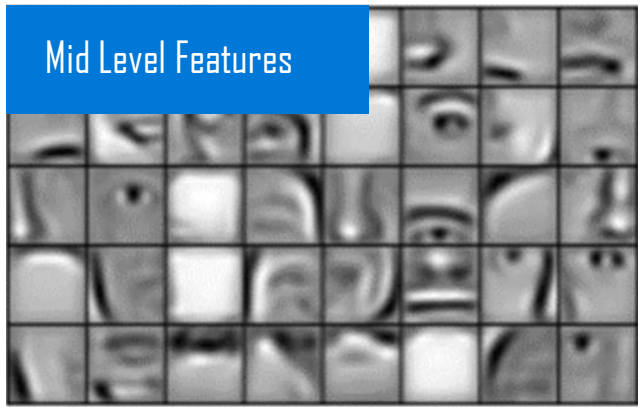


SPATIAL HIERARCHY OF PATTERNS

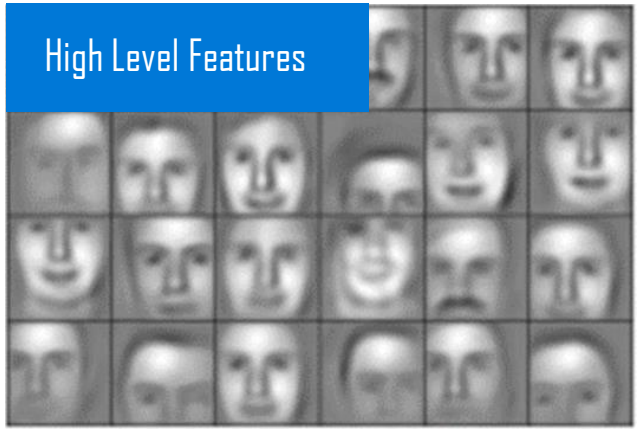
Low Level Features



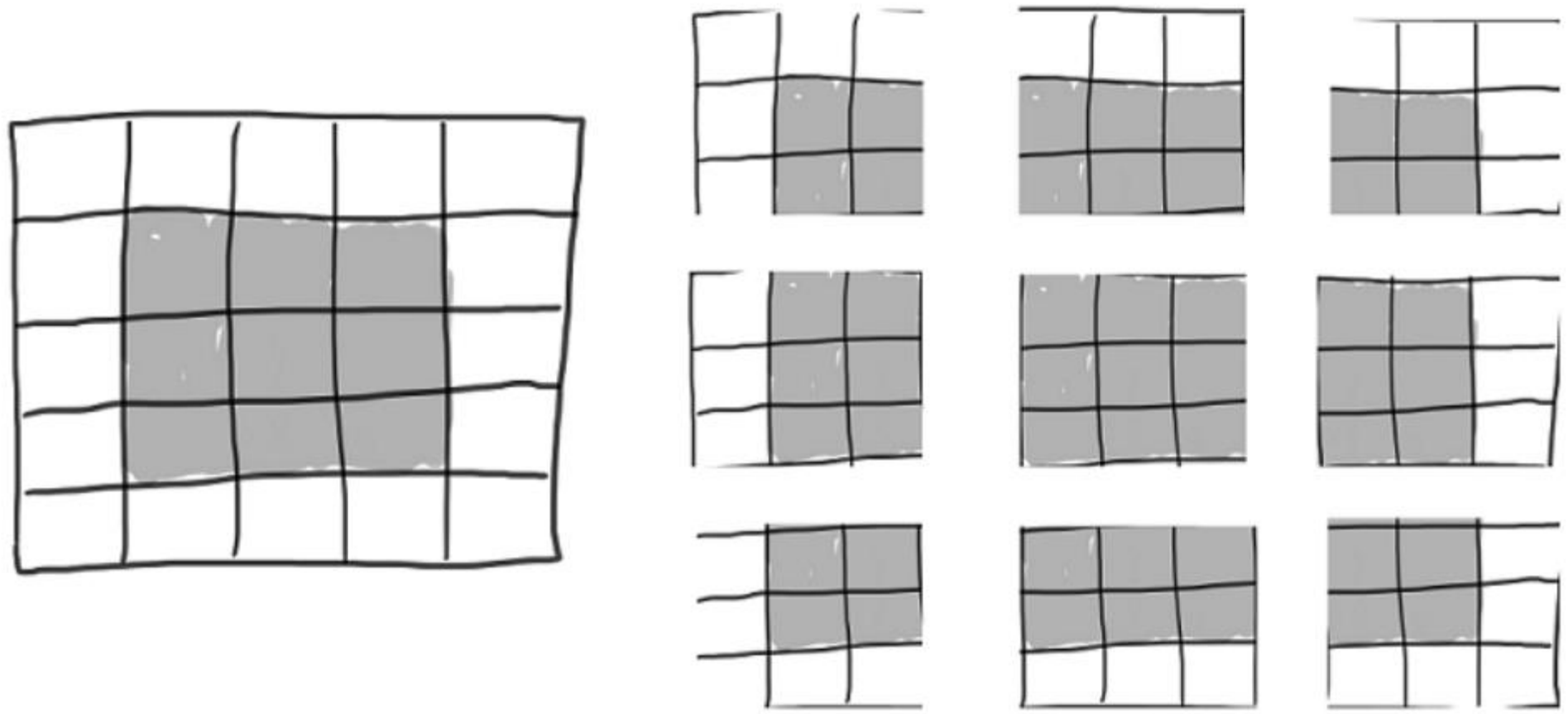
Mid Level Features



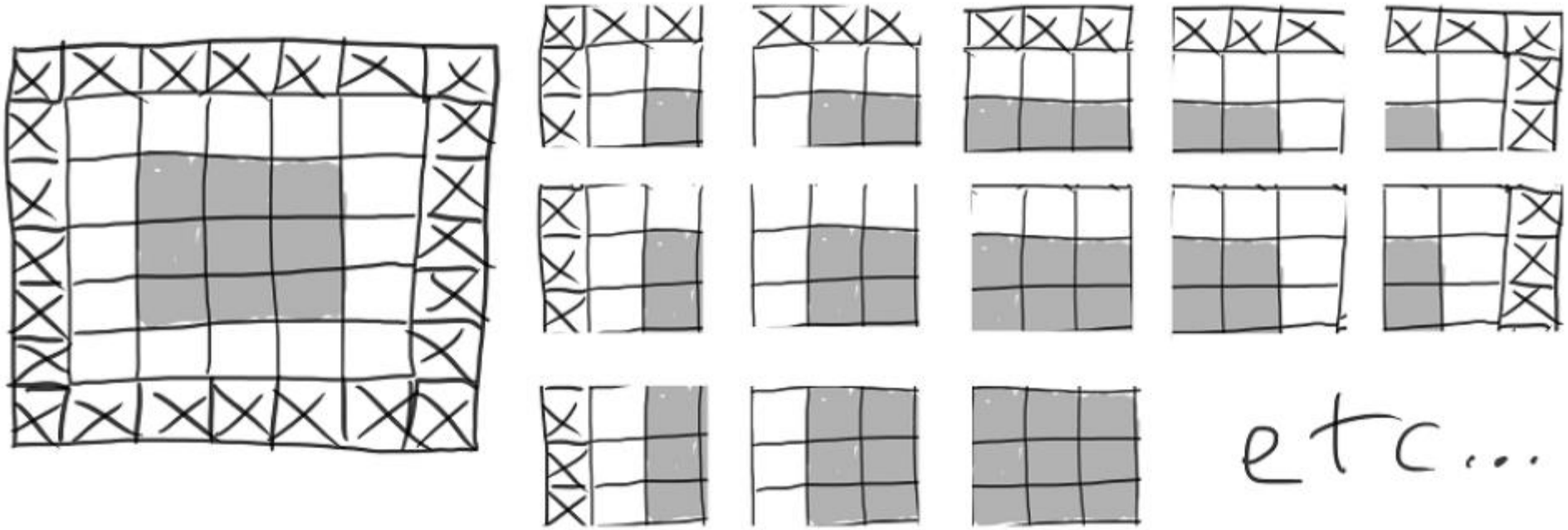
High Level Features



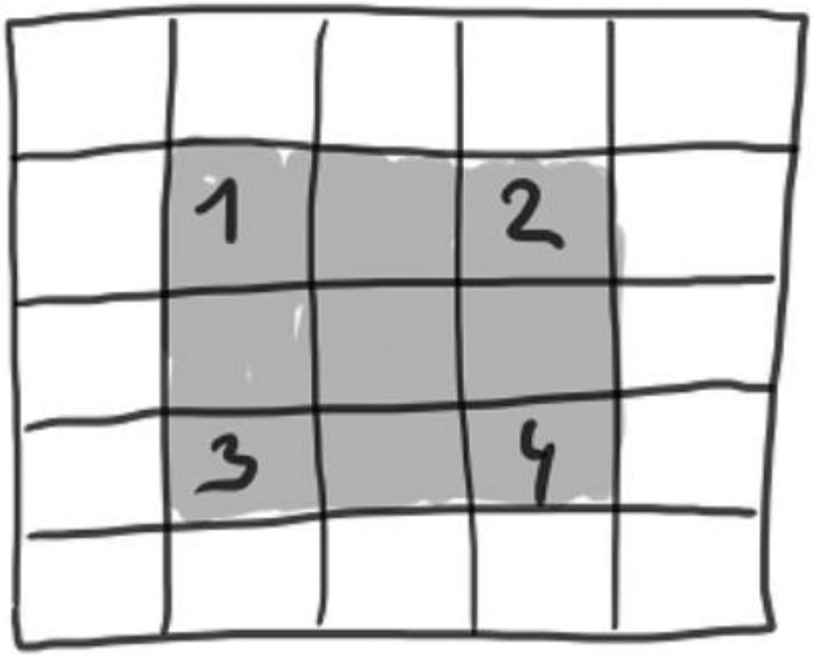
LEARNING REPRESENTATIONS

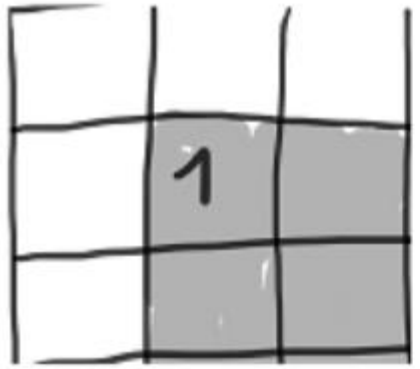


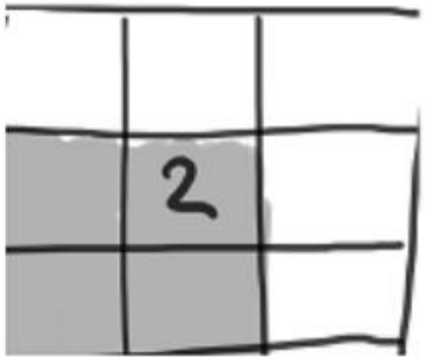
CONVOLUTION EXAMPLE

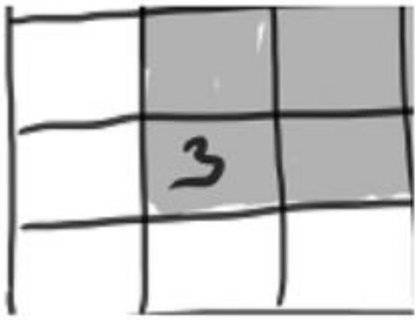


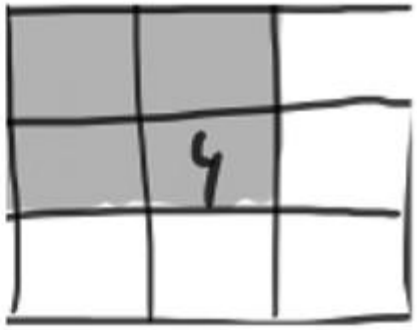
BORDER EFFECTS: 'VALID' VS 'SAME'



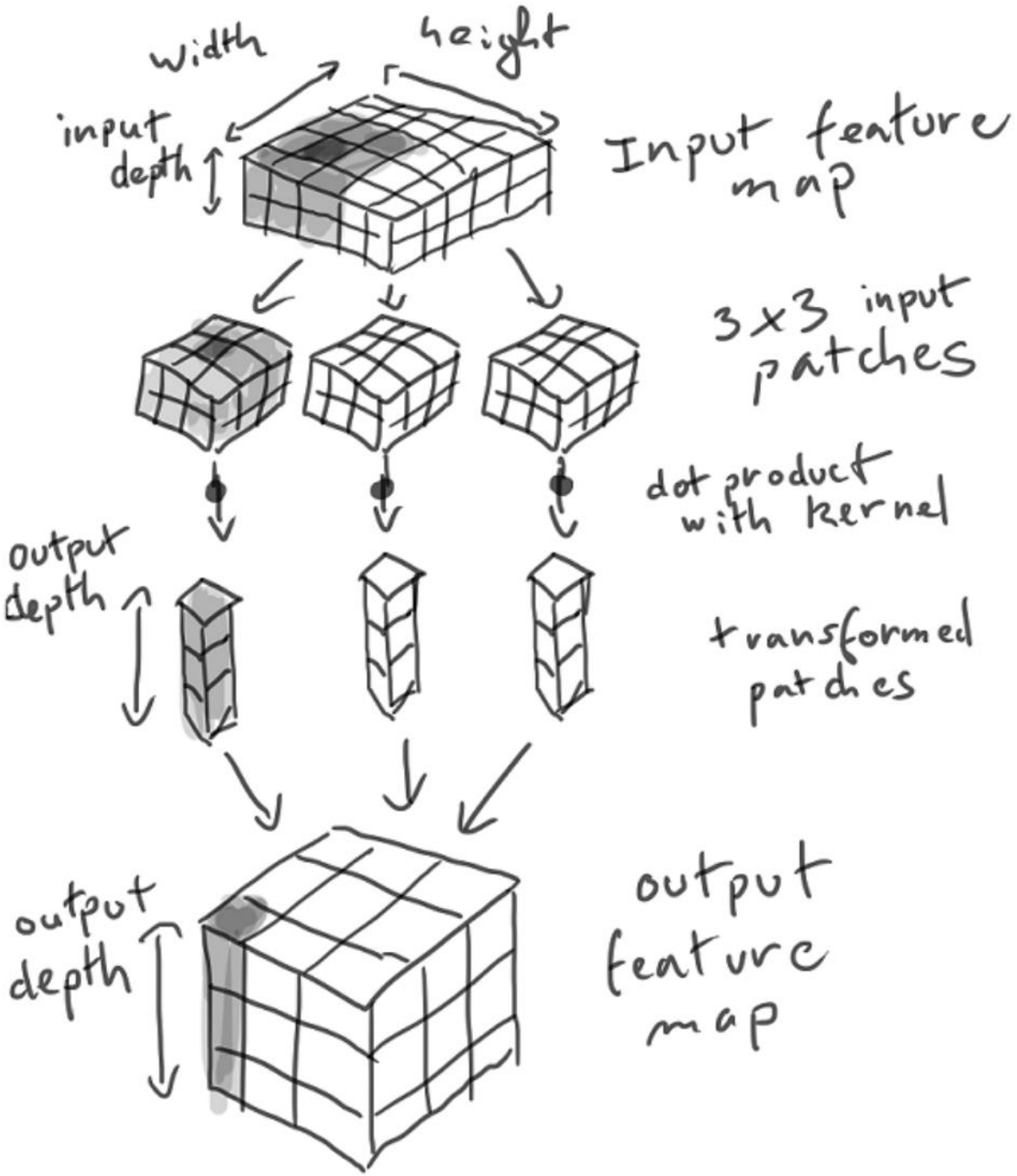








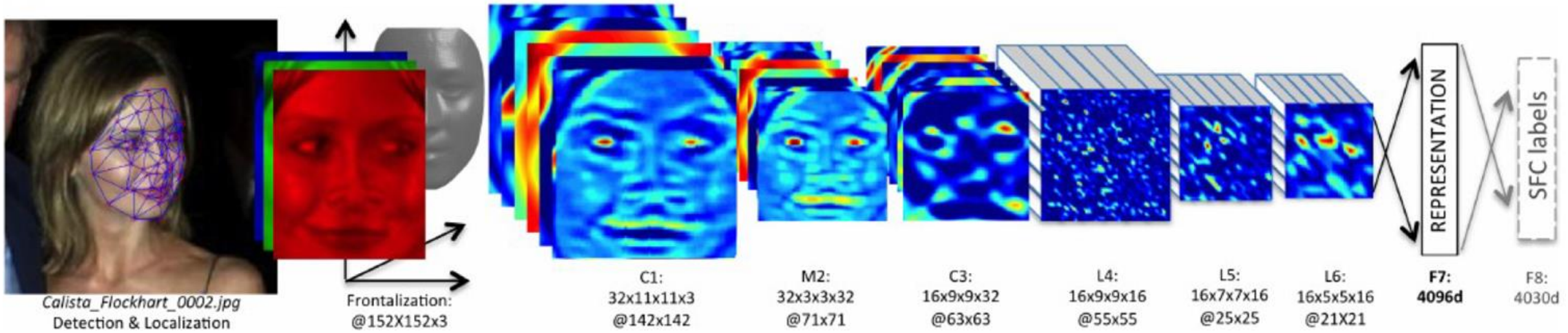
STRIDING



EACH LAYER DOES THIS

DEEP FACE

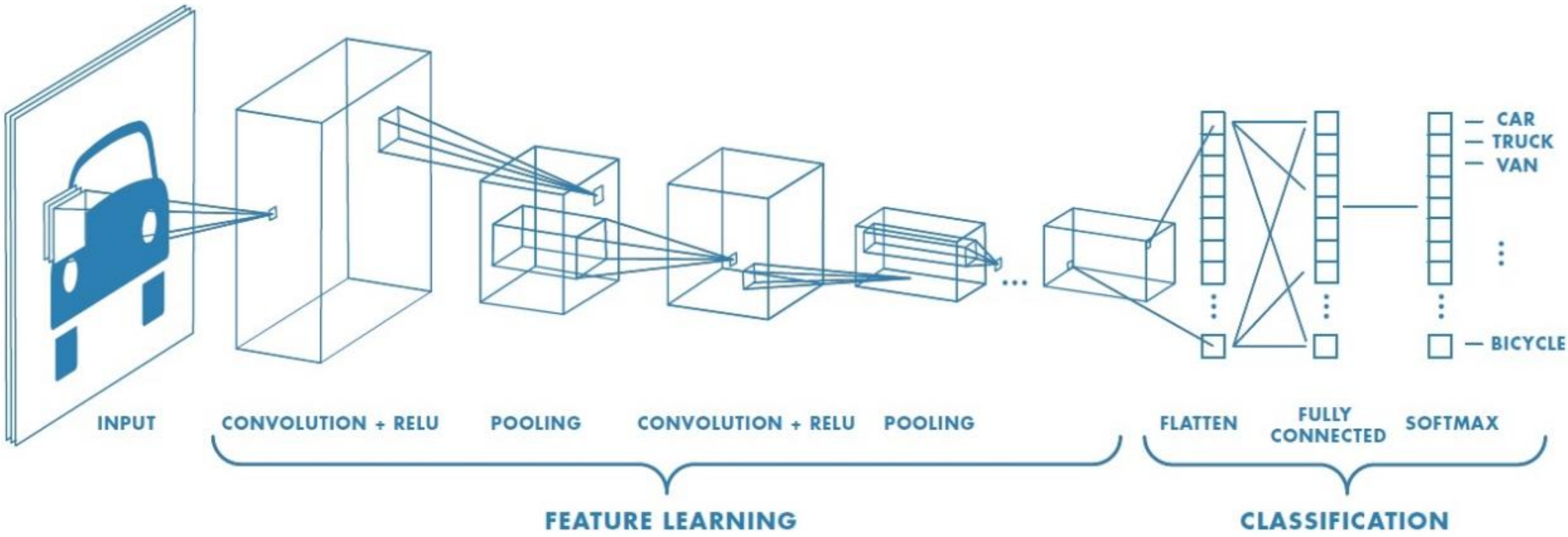
Taigman et al. CVPR 2014



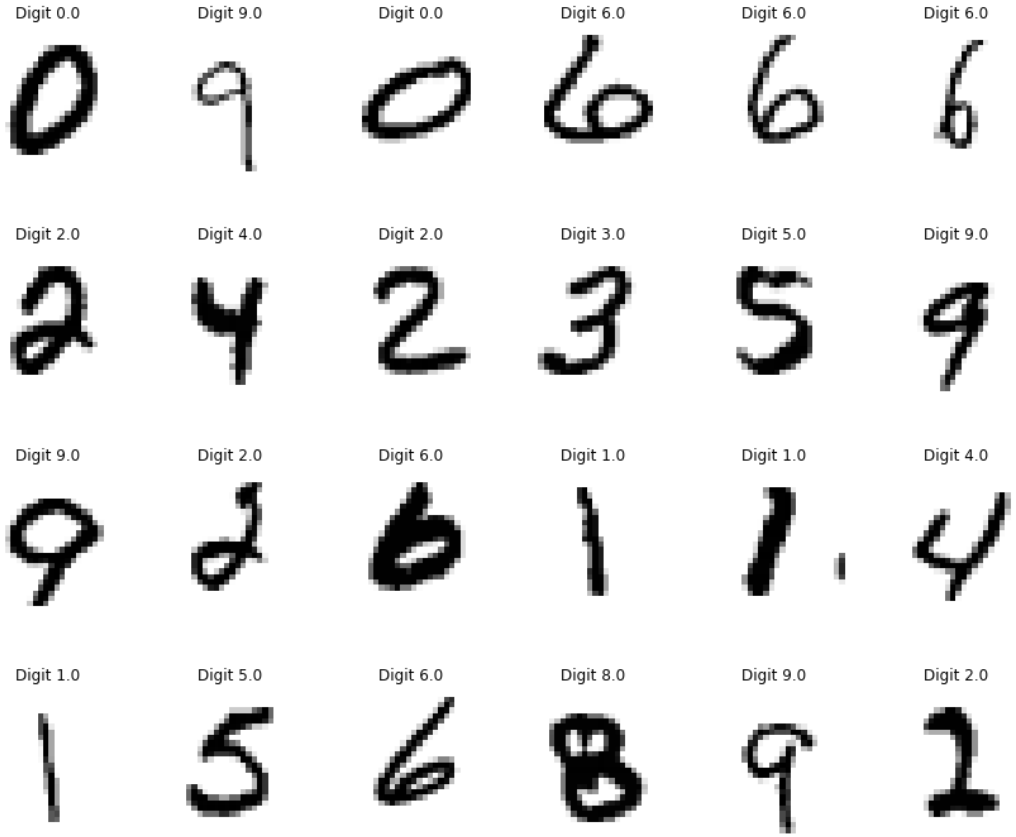
- Alignment
- CNN
- Metric Learning

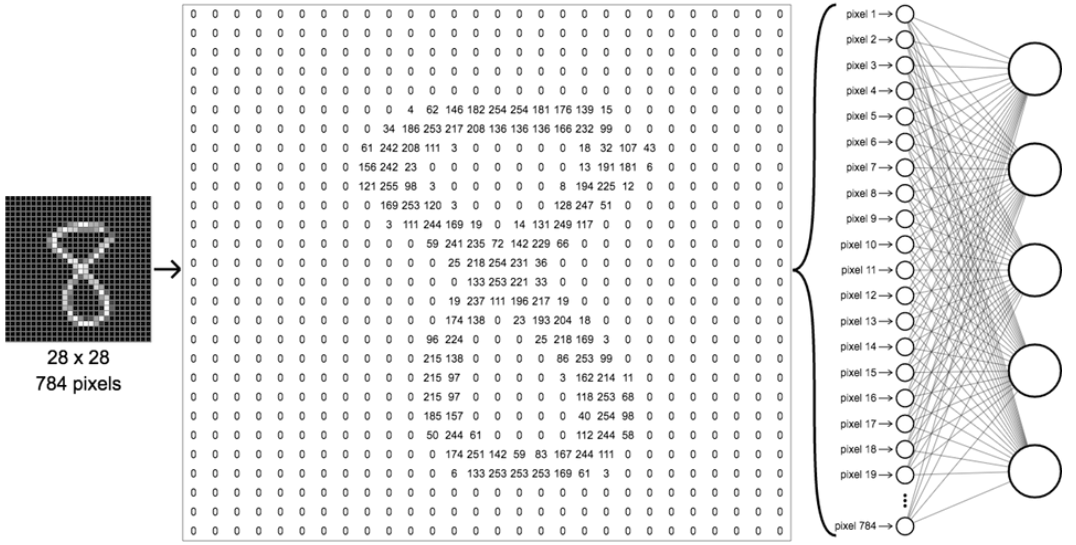
Microsoft

IMAGE CLASSIFICATION EXAMPLE



MNIST DIGIT CLASSIFICATION





Represent input image as a vector $\mathbf{x} \in \mathbb{R}^{784}$

Learn a classifier $f(\mathbf{x})$ such that,

$$f : \mathbf{x} \rightarrow \{0, 1, 2, 3, 4, 5, 6, 7, 8, 9\}$$

```
from keras import layers
from keras import models

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'))
```

```
model.summary()
```

```
_________________________________________________________________
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
_________________________________________________________________
```

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

```
model.summary()
```

```
_________________________________________________________________
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
_________________________________________________________________
```

```
from keras.datasets import mnist
from keras.utils import to_categorical

(train_images, train_labels), (test_images, test_labels) = mnist.load_data()

train_images = train_images.reshape((60000, 28, 28, 1))
train_images = train_images.astype('float32') / 255

test_images = test_images.reshape((10000, 28, 28, 1))
test_images = test_images.astype('float32') / 255

train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)
```

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

```
Epoch 1/5
60000/60000 [==============================] - 8s - loss: 0.1766 - acc: 0.9440
Epoch 2/5
60000/60000 [==============================] - 7s - loss: 0.0462 - acc: 0.9855
Epoch 3/5
60000/60000 [==============================] - 7s - loss: 0.0322 - acc: 0.9902
Epoch 4/5
60000/60000 [==============================] - 7s - loss: 0.0241 - acc: 0.9926
```

Let's evaluate the model on the test data:

In [8]:
```
test_loss, test_acc = model.evaluate(test_images, test_labels)
```

```
 9536/10000 [===========================>..] - ETA: 0s
```

In [9]:
```
test_acc
```

Out[9]:
```
0.9912999999999996
```

DOGS AND CATS DATASET

- 2000 Dogs
- 2000 Cats
- We use 2K for training

VISION ON SMALL DATA SETS

- "Deep learning only works on small datasets"
  - Only valid if you want to learn abstract representations
- Data Augmentation helps

DOGS CATS MODEL

```
from keras import layers
from keras import models

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.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 148, 148, 32)      896
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 74, 74, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 72, 72, 64)        18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 36, 36, 64)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 34, 34, 128)       73856
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 17, 17, 128)       0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 15, 15, 128)       147584
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 7, 7, 128)         0
_________________________________________________________________
flatten_1 (Flatten)          (None, 6272)              0
_________________________________________________________________
dense_1 (Dense)              (None, 512)               3211776
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 513
=================================================================
Total params: 3,453,121
Trainable params: 3,453,121
Non-trainable params: 0
_________________________________________________________________
```

:

```
from keras import optimizers

model.compile(loss='binary_crossentropy',
              optimizer=optimizers.RMSprop(lr=1e-4),
              metrics=['acc'])
```

```
from keras.preprocessing.image import ImageDataGenerator

# All images will be rescaled by 1./255
train_datagen = ImageDataGenerator(rescale=1./255)
test_datagen = ImageDataGenerator(rescale=1./255)

train_generator = train_datagen.flow_from_directory(
        # This is the target directory
        train_dir,
        # All images will be resized to 150x150
        target_size=(150, 150),
        batch_size=20,
        # Since we use binary_crossentropy loss, we need binary labels
        class_mode='binary')

validation_generator = test_datagen.flow_from_directory(
        validation_dir,
        target_size=(150, 150),
        batch_size=20,
        class_mode='binary')
```

```
Found 2000 images belonging to 2 classes.
Found 1000 images belonging to 2 classes.
```

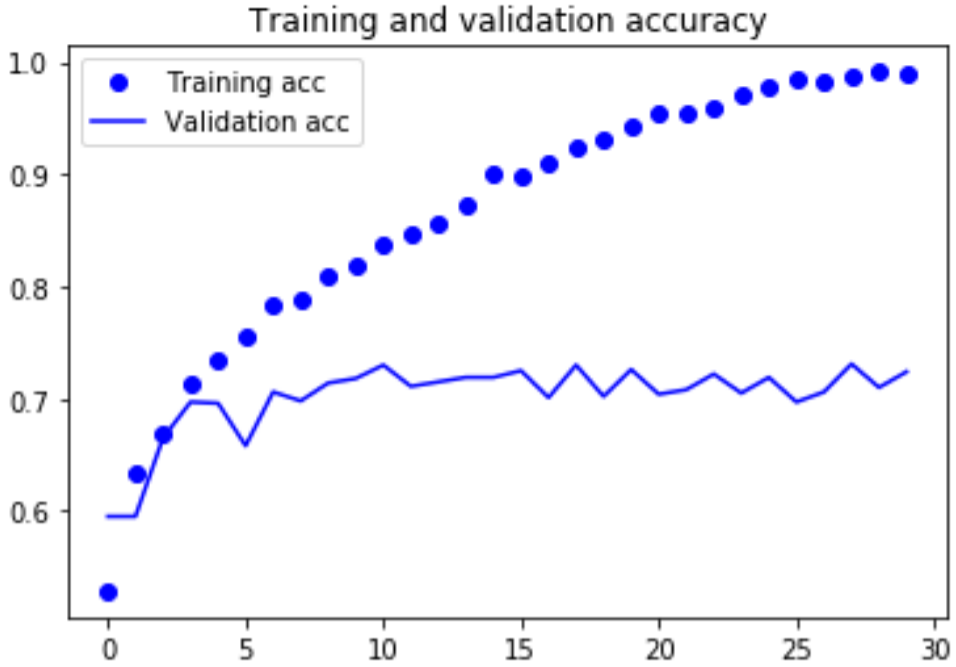
```
history = model.fit_generator(
      train_generator,
      steps_per_epoch=100,
      epochs=30,
      validation_data=validation_generator,
      validation_steps=50)
```

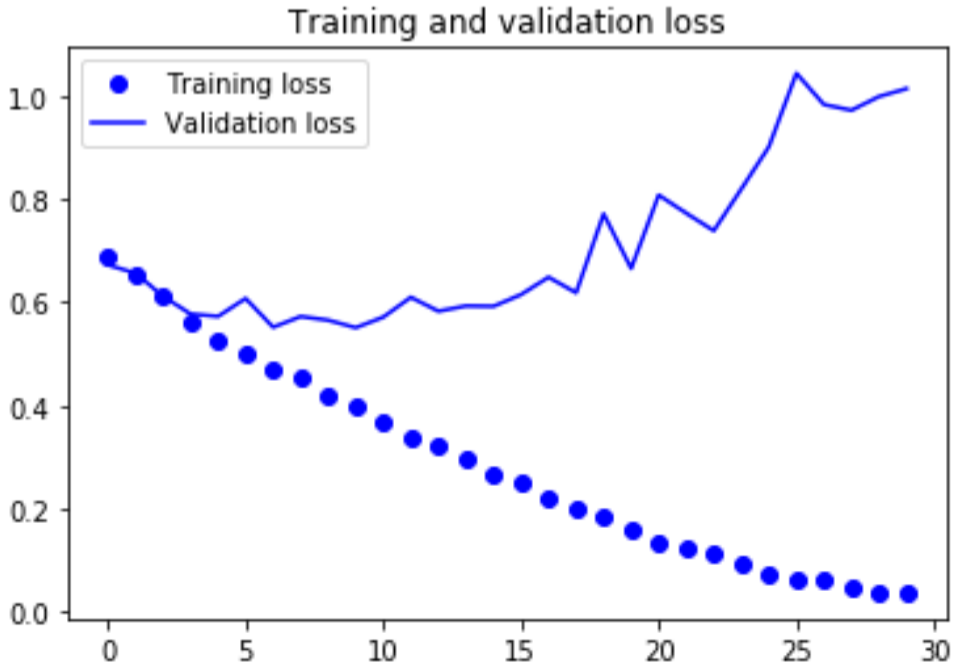
```
Epoch 1/30
100/100 [==============================] - 9s - loss: 0.6898 - acc: 0.5285 - val_loss: 0.6724 - val_acc:
0.5950
Epoch 2/30
100/100 [==============================] - 8s - loss: 0.6543 - acc: 0.6340 - val_loss: 0.6565 - val_acc:
0.5950
Epoch 3/30
100/100 [==============================] - 8s - loss: 0.6143 - acc: 0.6690 - val_loss: 0.6116 - val_acc:
0.6650
Epoch 4/30
100/100 [==============================] - 8s - loss: 0.5626 - acc: 0.7125 - val_loss: 0.5774 - val_acc:
0.6970
```

It is good practice to always save your models after training:

:
```
model.save('cats_and_dogs_small_1.h5')
```

```
import matplotlib.pyplot as plt

acc = history.history['acc']
val_acc = history.history['val_acc']
loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = range(len(acc))

plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.legend()

plt.figure()

plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```



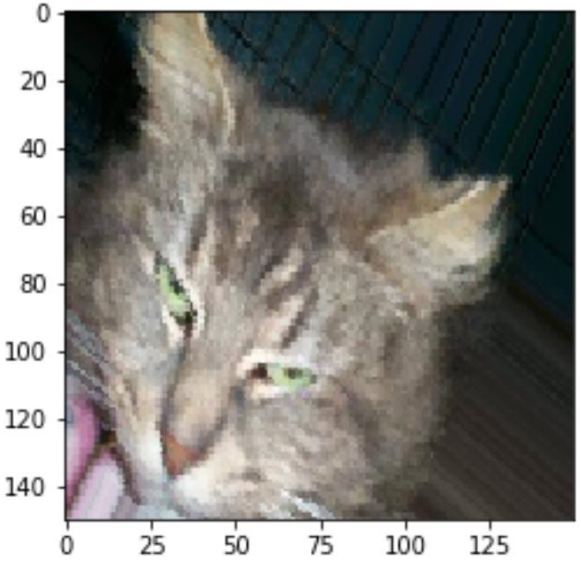


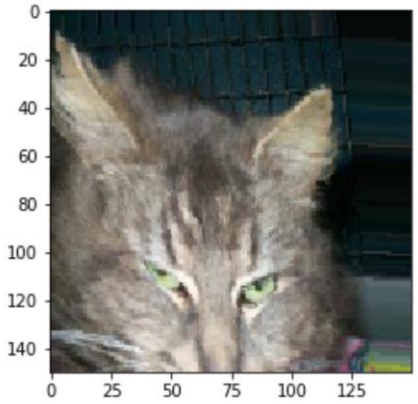
- Val acc of 70%
- Overfitting
- Dropout
- L2 regularisation
- Now... Augmentation

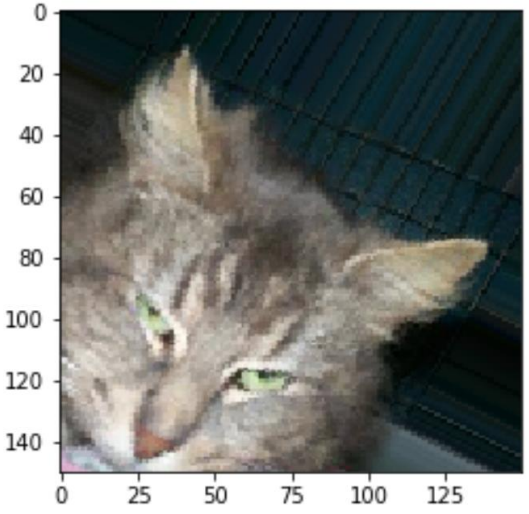
Overfitting is caused by having too few samples to learn from, rendering us unable to train a model able to generalize to new data

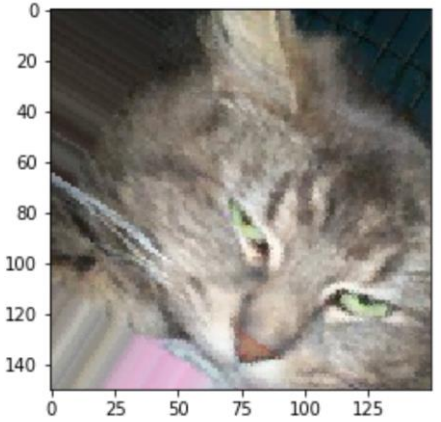
```
datagen = ImageDataGenerator(
        rotation_range=40,
        width_shift_range=0.2,
        height_shift_range=0.2,
        shear_range=0.2,
        zoom_range=0.2,
        horizontal_flip=True,
        fill_mode='nearest')
```

AUGMENTED IMAGES





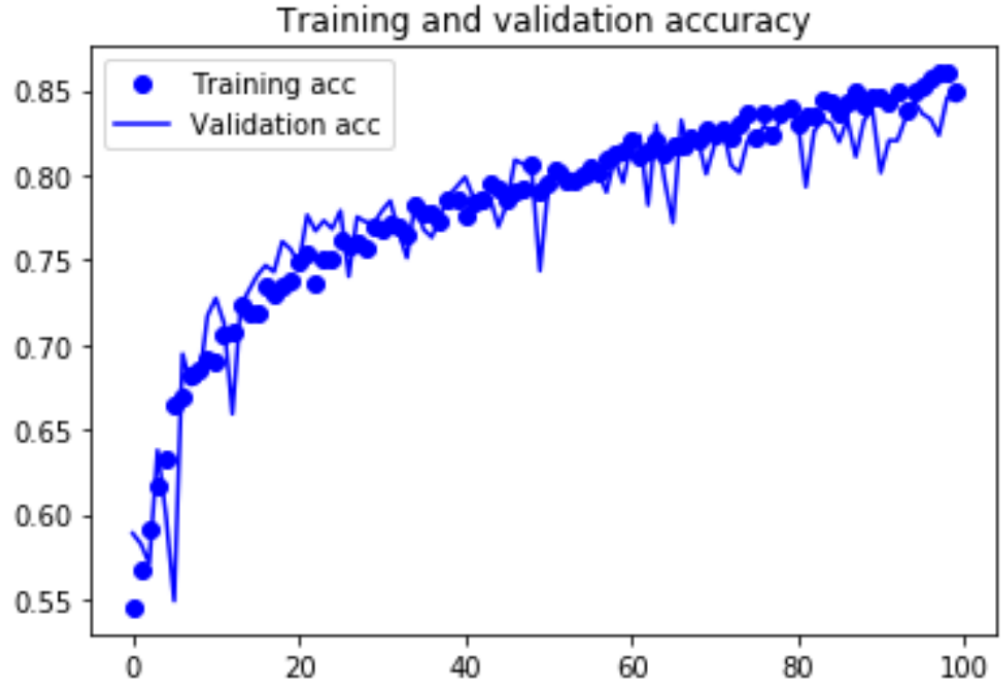


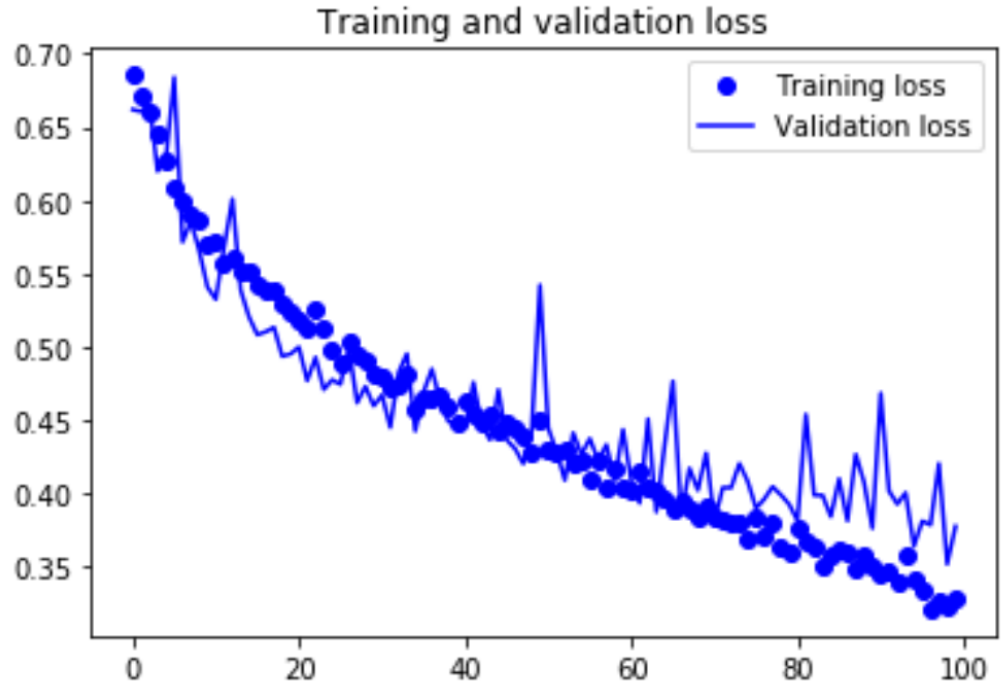


TRAIN AGAIN WITH DROPOUT AND AUGMENTATION

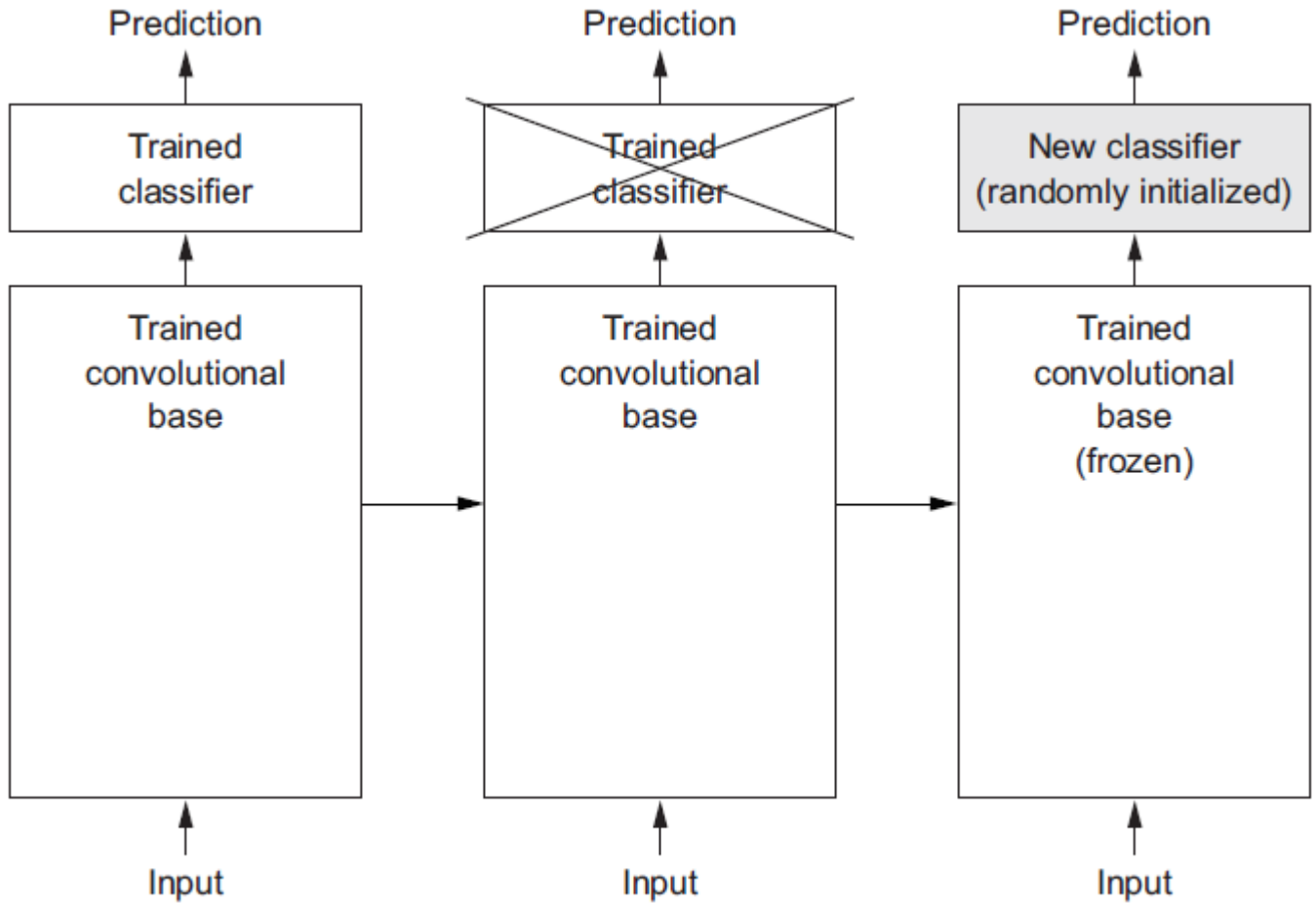
```
model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu',
                        input_shape=(150, 150, 3)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(128,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

model.compile(loss='binary_crossentropy',
              optimizer=optimizers.RMSprop(lr=1e-4),
              metrics=['acc'])
```

NO OVERFITTING!





- VAL acc of 82!
- 15% relative


Prediction
Trained classifier
Trained convolutional base
Input
Prediction
Trained classifier
Trained convolutional base
Input
Prediction
New classifier (randomly initialized)
Trained convolutional base (frozen)
Input

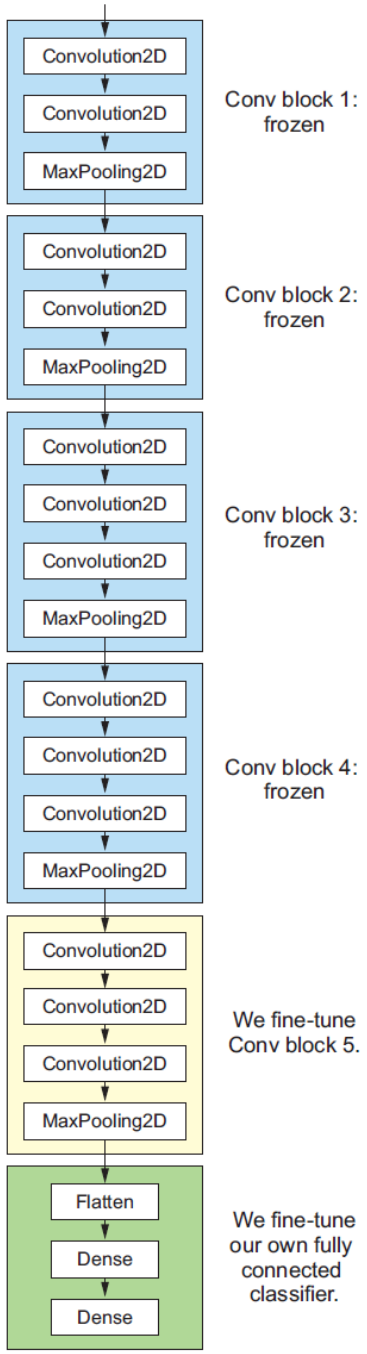


Figure 5.19 Fine-tuning the last convolutional block of the VGG16 network

- Xception
- InceptionV3
- ResNet50
- VGG16
- VGG19
- MobileNet

```
from keras.applications import VGG16

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

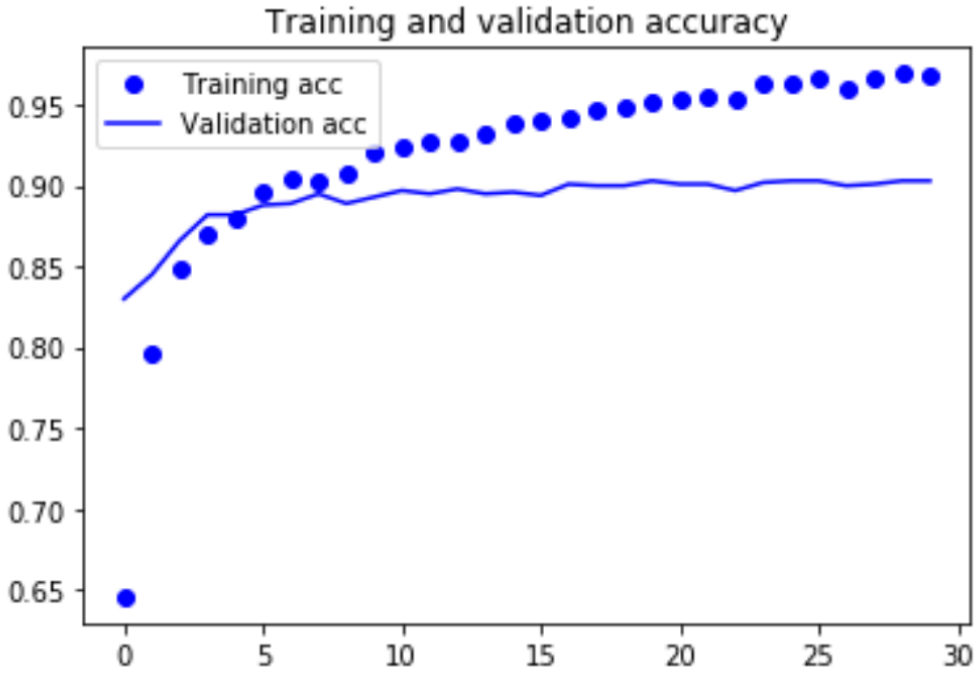
```
block2_pool (MaxPooling2D)   (None, 37, 37, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 37, 37, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 37, 37, 256)       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
_________________________________________________________________
```

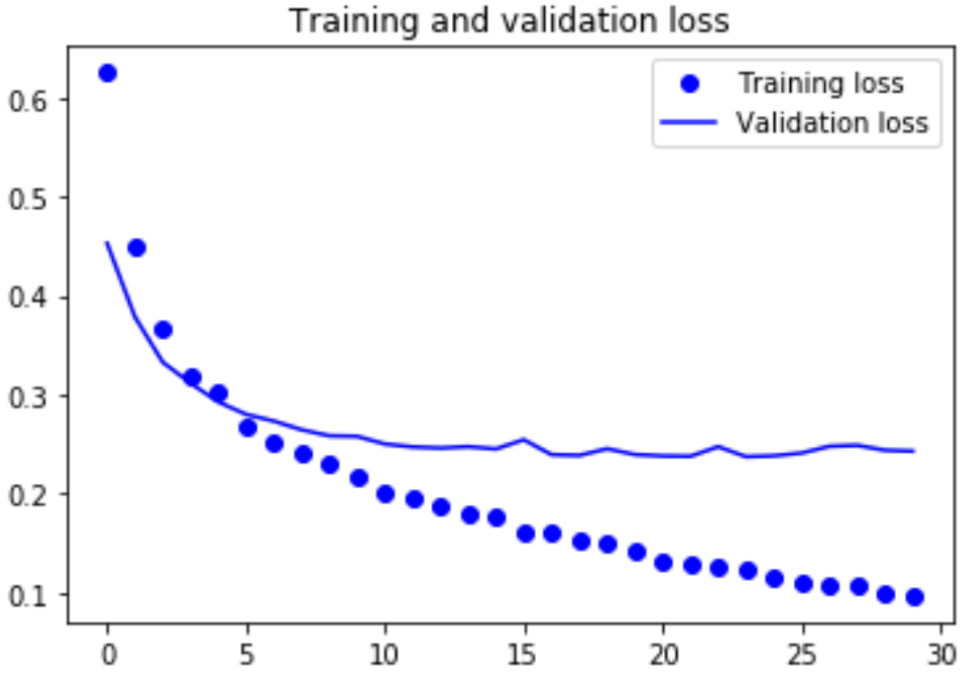
TWO WAYS TO PROCEED

- Precompute embeddings
- Create end-end artchitecture (needed with augmentation)

```
from keras import models
from keras import layers
from keras import optimizers

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'))

model.compile(optimizer=optimizers.RMSprop(lr=2e-5),
              loss='binary_crossentropy',
              metrics=['acc'])

history = model.fit(train_features, train_labels,
                    epochs=30,
                    batch_size=20,
                    validation_data=(validation_features, validation_labels))
```

```
Train on 2000 samples, validate on 1000 samples
Epoch 1/30
2000/2000 [==============================] - 1s - loss: 0.6253 - acc: 0.6455 - val_loss: 0.4
0.8300
Epoch 2/30
2000/2000 [==============================] - 0s - loss: 0.4490 - acc: 0.7965 - val_loss: 0.3
0.8450
Epoch 3/30
```





- Val now ~90%!
- Overfitting a lot

ADD THE CONV BASE TO MODEL

```
from keras import models
from keras import layers

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'))
```

```
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
vgg16 (Model)                (None, 4, 4, 512)         14714688
_________________________________________________________________
flatten_1 (Flatten)          (None, 8192)              0
_________________________________________________________________
dense_3 (Dense)              (None, 256)               2097408
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 257
=================================================================
Total params: 16,812,353
Trainable params: 16,812,353
Non-trainable params: 0
_________________________________________________________________
```

In [10]:
```
print('This is the number of trainable weights '
      'before freezing the conv base:', len(model.trainable_weights))
```

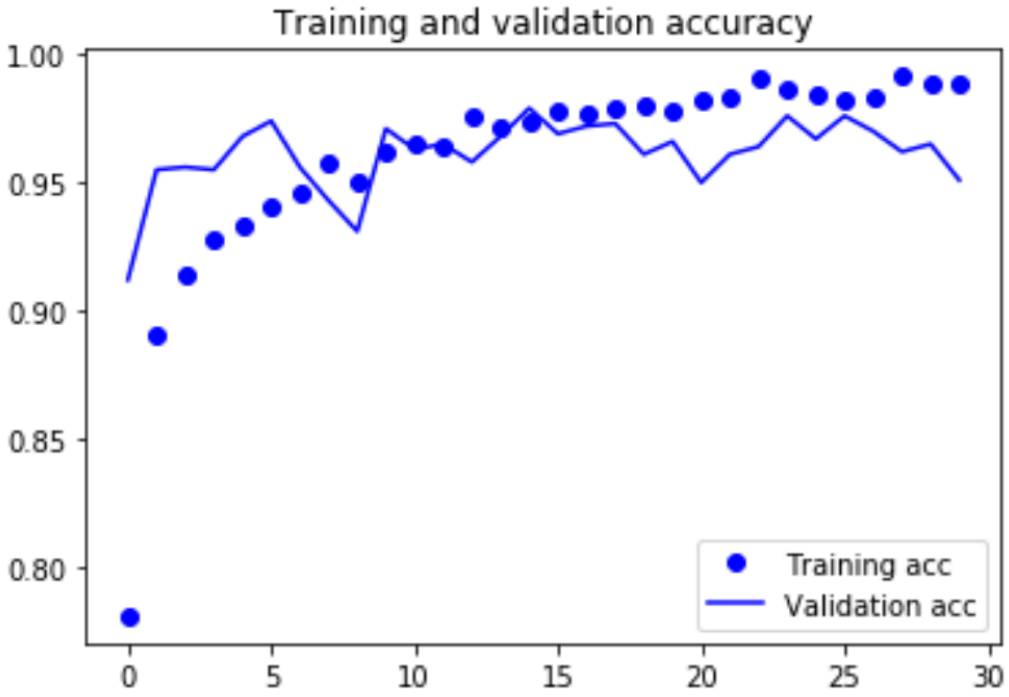
```
This is the number of trainable weights before freezing the conv base: 30
```

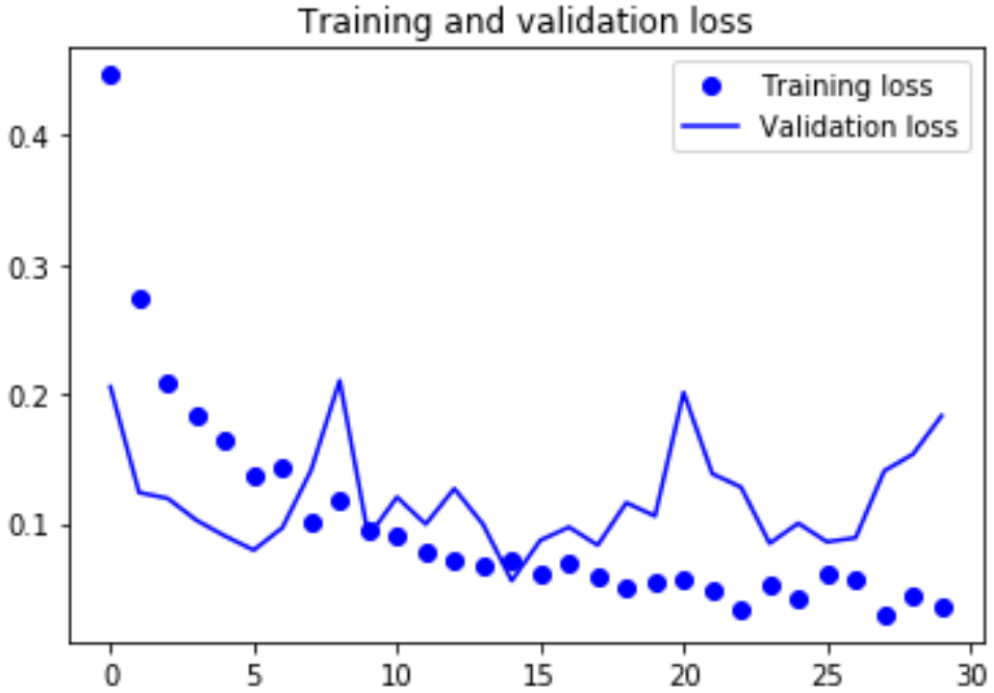
In [11]:
```
conv_base.trainable = False
```

In [12]:
```
print('This is the number of trainable weights '
      'after freezing the conv base:', len(model.trainable_weights))
```

```
This is the number of trainable weights after freezing the conv base: 4
```

"Since the dense layers are randomly initialized, very large weight updates would destroy the representations learned in the convolutional base!"





- Val now ~96%!
- Not overfitting

RECAP ON VALIDATION PERFORMANCE

- CATS AND DOGS
  - Basic model 72%
  - Dropout and augmentation 82%
  - Transfer learning 90% (overfitting)
  - Transfer with augmentation: 96% (not overfitting)

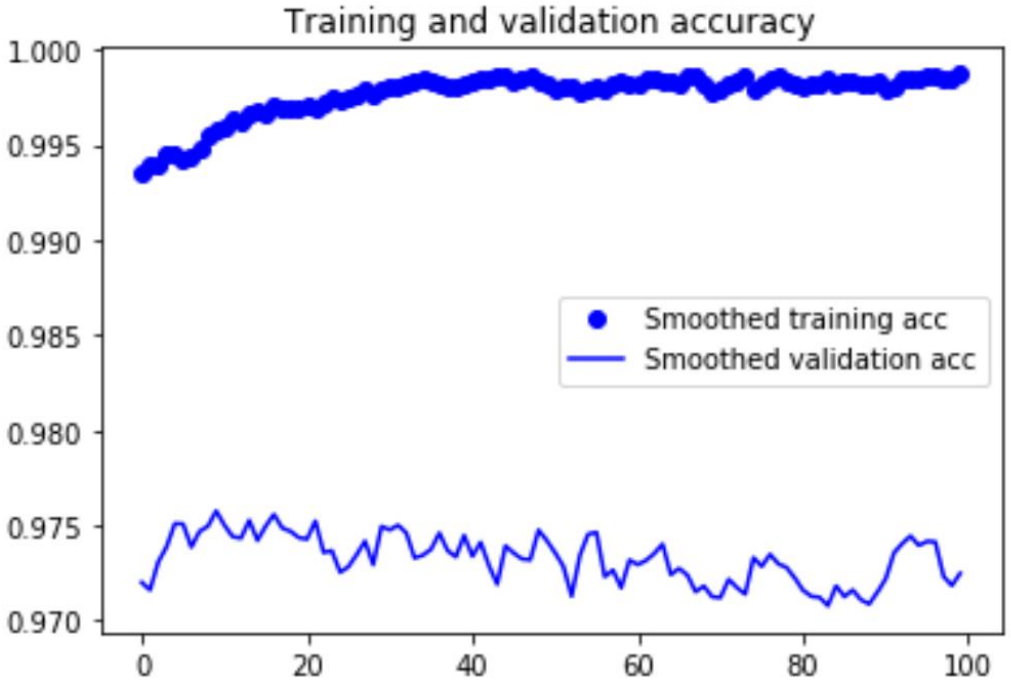
TRAINING INTO THE CONV BASE

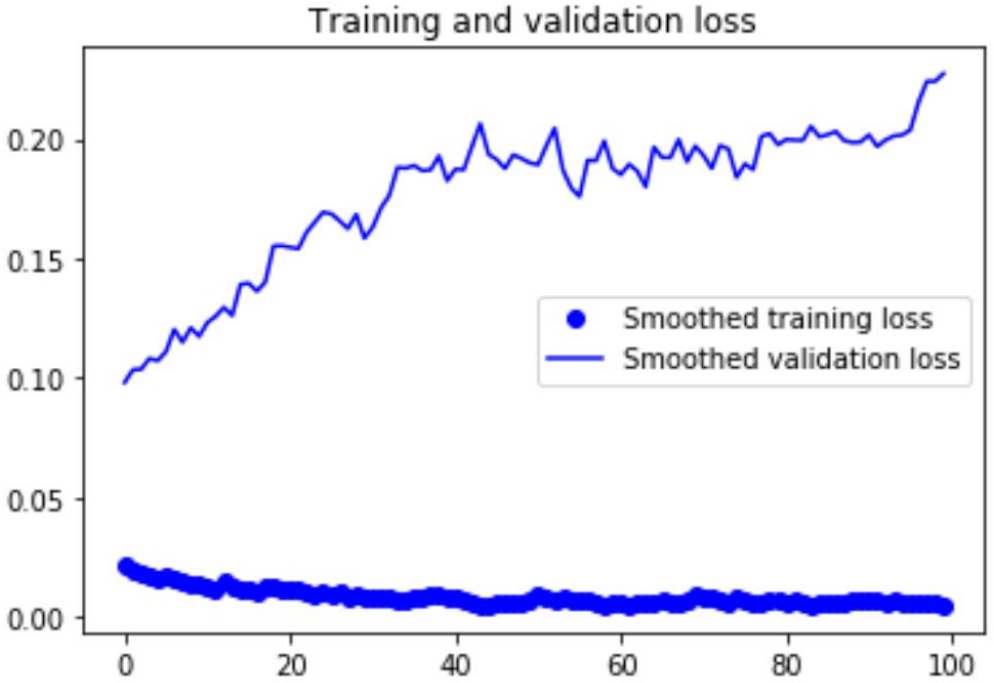
- Add your custom network on top of an already trained base network.
- Freeze the base network.
- Train the part you added.
- Unfreeze some layers in the base network.
- Jointly train both these layers and the part you added.

TRAINING INTO THE CONV BASE (2)

- Why not fine tune all layers?
  - More parameters == more overfitting
- Use a low learning rate == less chance of disaster
- How can loss get worse and accuracy go up?
  - Average of loss vs distribution of loss values might be different i.e. model might still be improving

```
conv_base.trainable = True

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



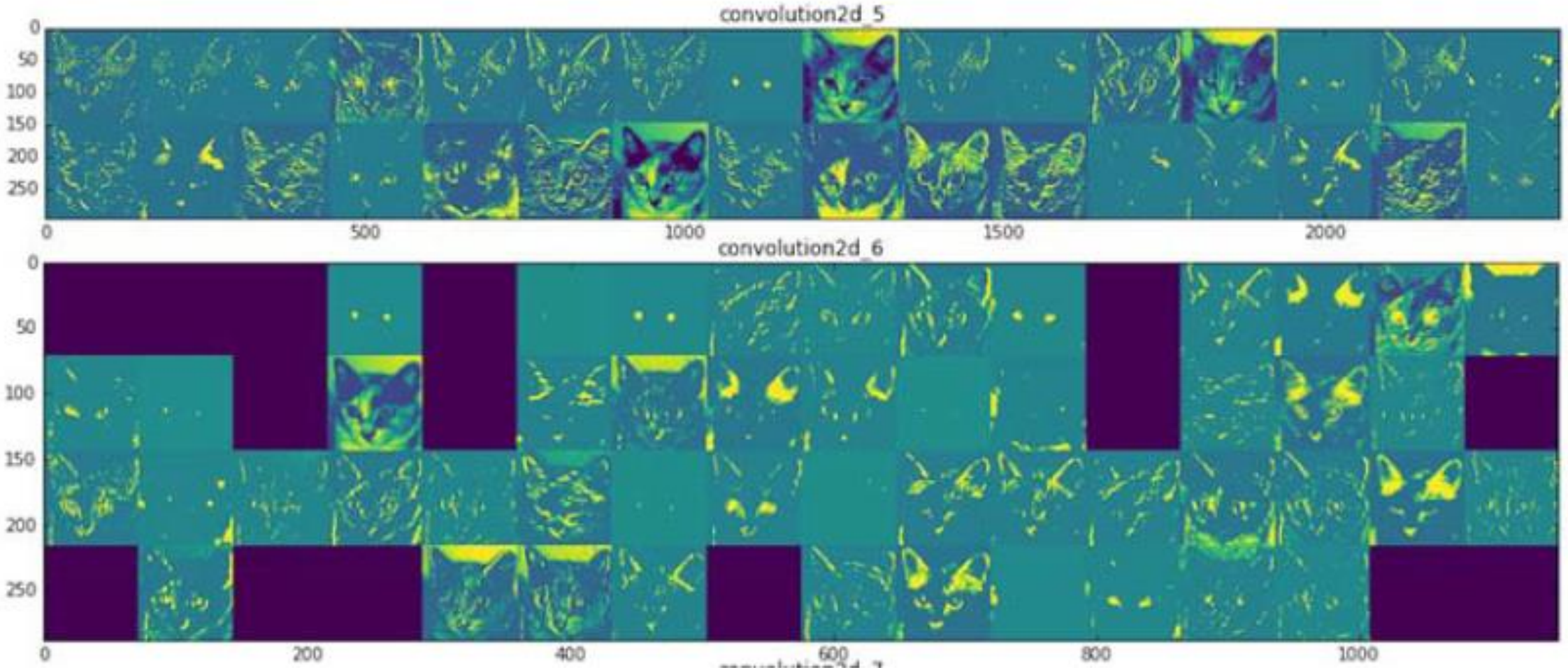


- 1% improvement
- 97% would have been a very good score on Kaggle in the day
- Done with only 2000 examples from the 4k!

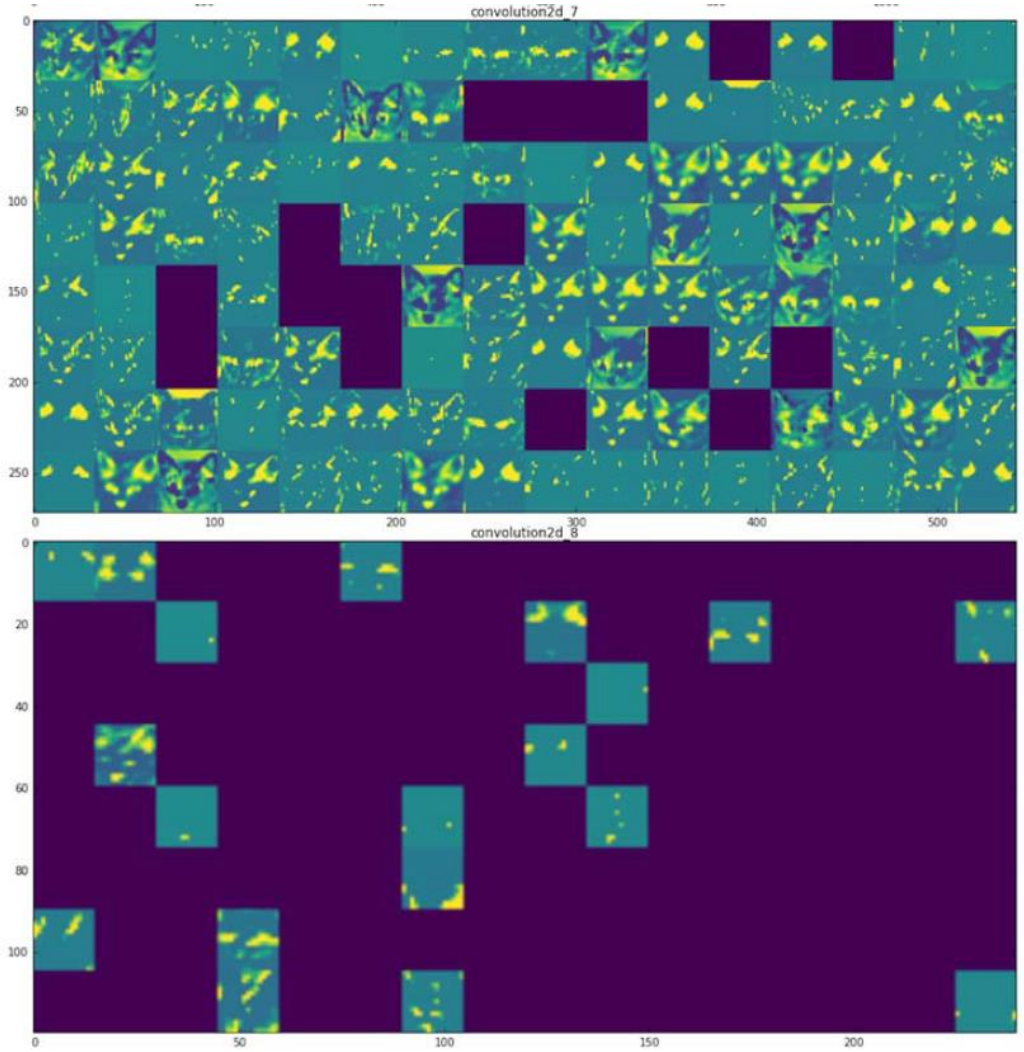
TAKE AWAYS

- Convnets best for vision tasks
- Can train from scratch even with small sets
- Overfitting is a huge issue, augmentation helps
- Reuse existing convnets (transfer)
- Can train into conv base but diminished returns

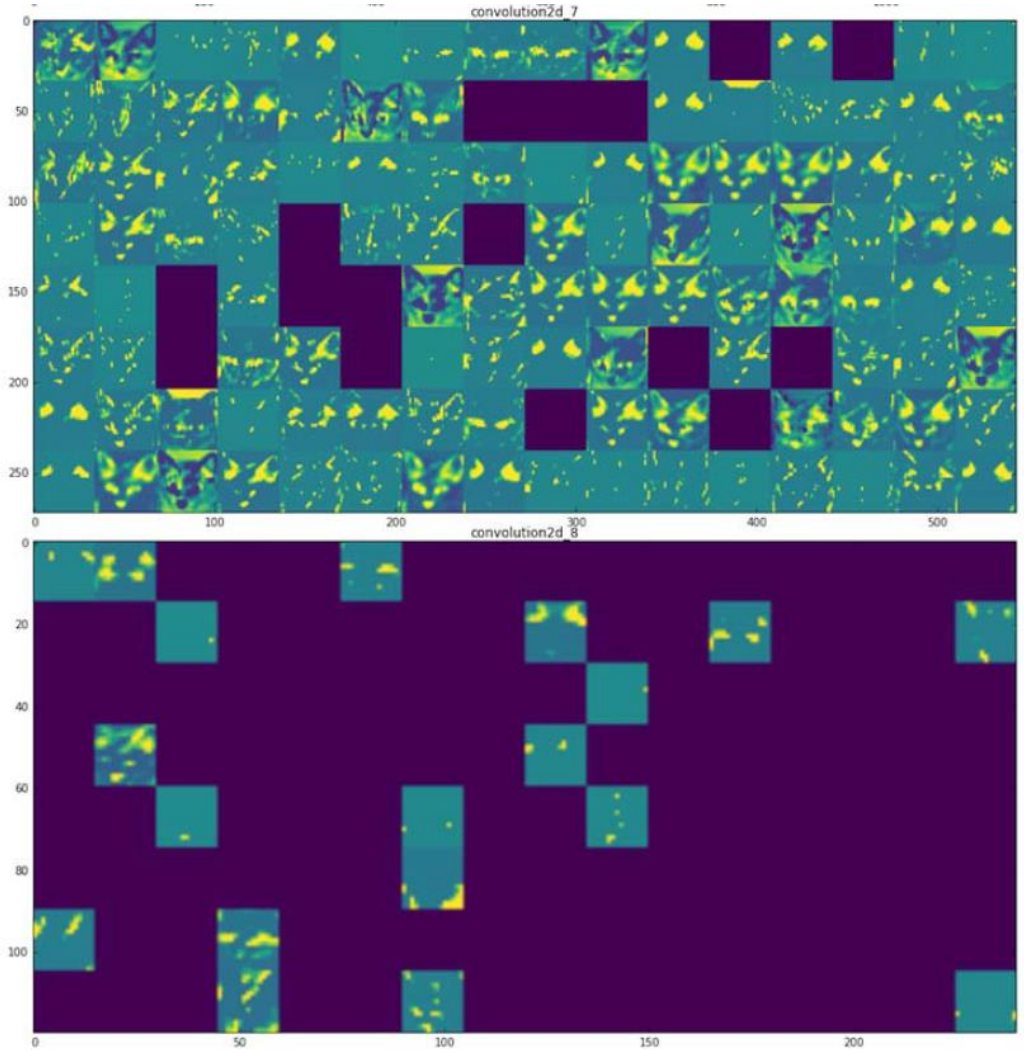
VISUALISING THE FILTERS (1)



VISUALISING THE FILTERS (2)

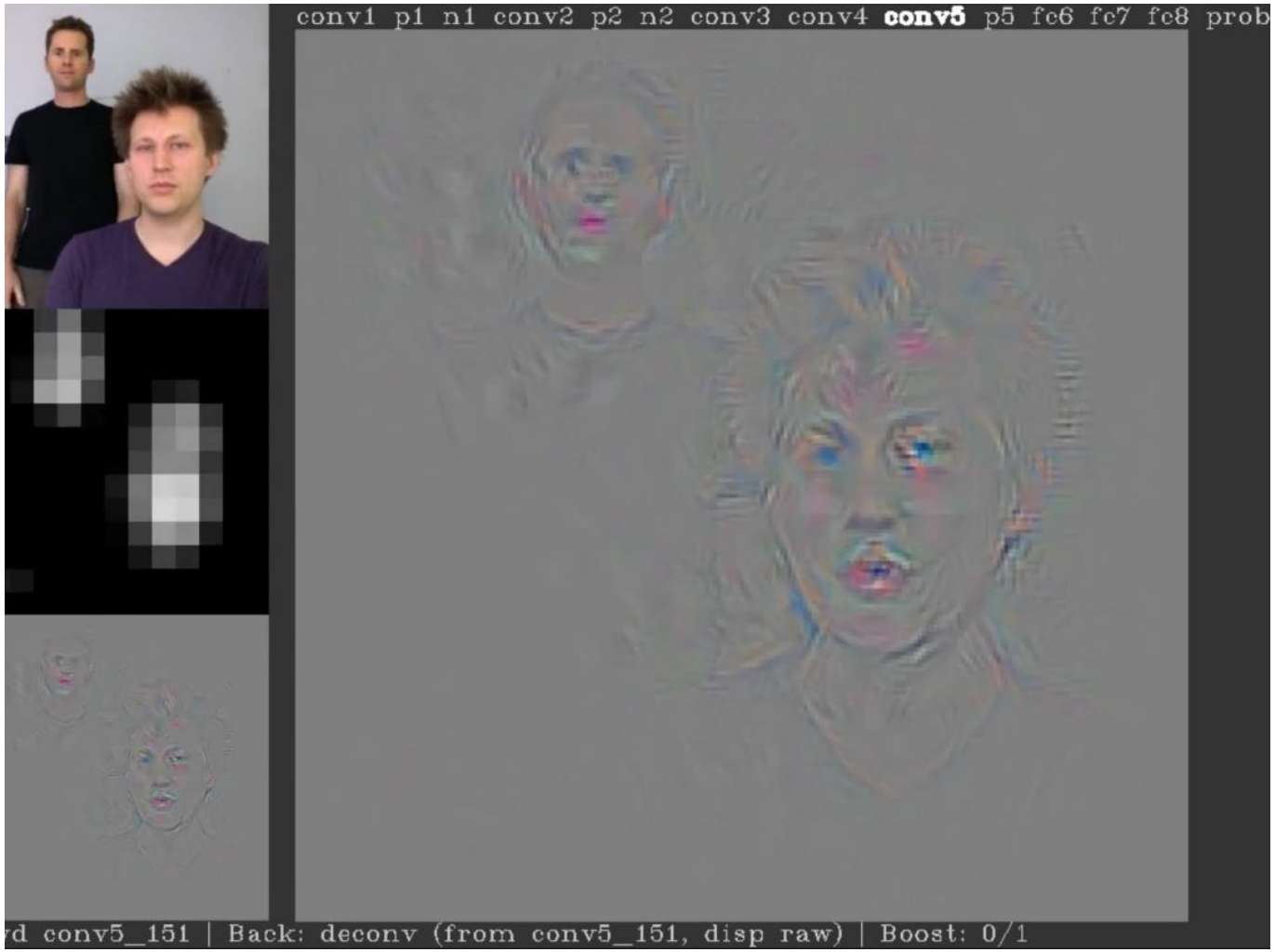


VISUALISING THE FILTERS (3)



- Early layers; content
- Later layers; class
- Sparsity

DEEP VISUALISATION TOOLBOX



https://www.youtube.com/watch?v=AgkfIQ4IGaM

Tim Scarfe

@ecsquendor

youtube.com/machinelearningatmicrosoft

THANK YOU!

Azure

Microsoft