Development of intelligent systems (RInS)

Object recognition with Convolutional Neural Networks

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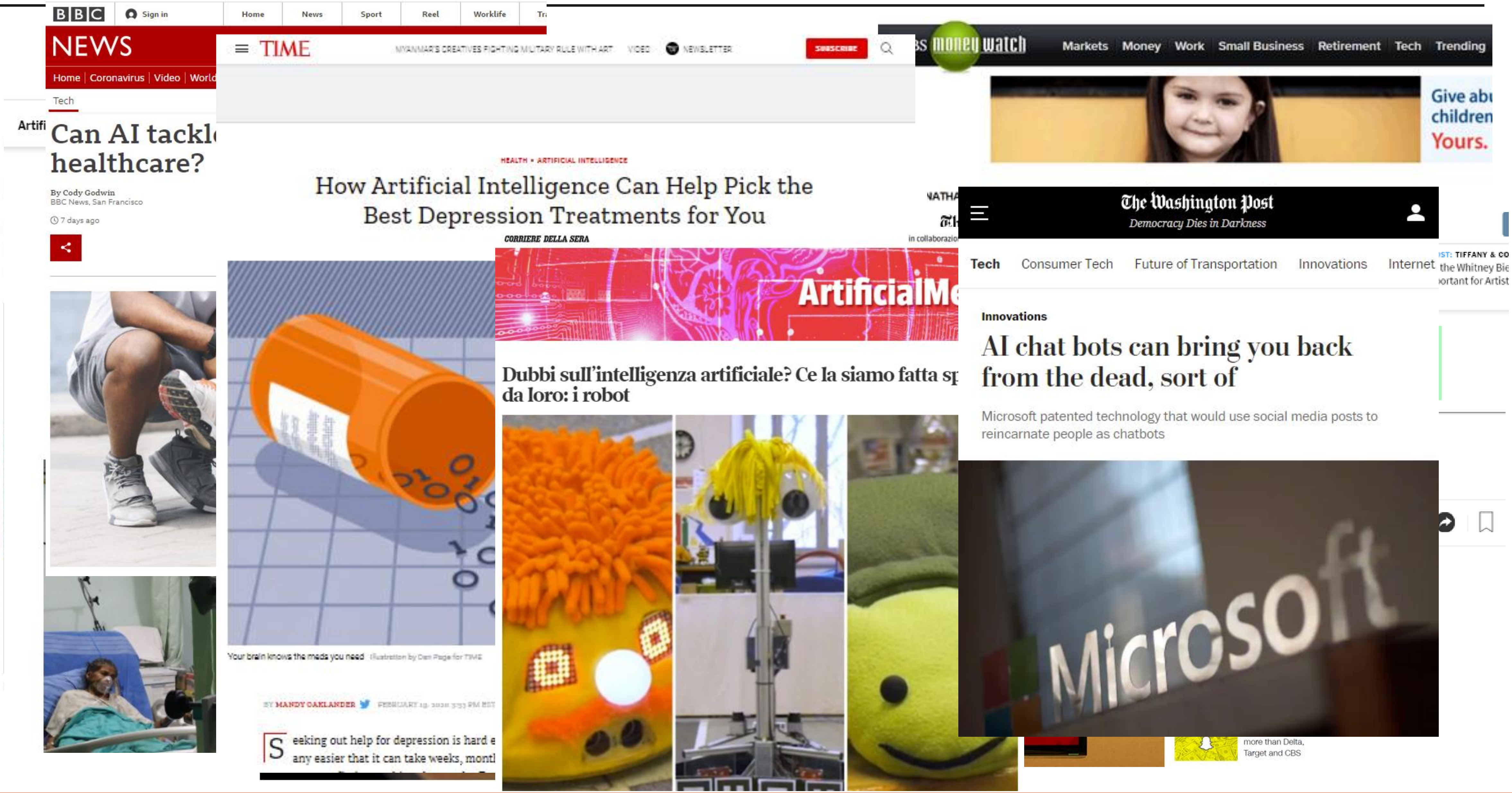
Media hype



BBC NEWS
Can AI tackl
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By Cody Godwin
BBC News, San Francisco
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How Artificial Intelligence Can Help Pick the Best Depression Treatments for You
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Give abu
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Yours.
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Democracy Dies in Darkness
Tech Consumer Tech Future of Transportation Innovations Internet
Innovations
AI chat bots can bring you back from the dead, sort of
Microsoft patented technology that would use social media posts to reincarnate people as chatbots
Microsoft

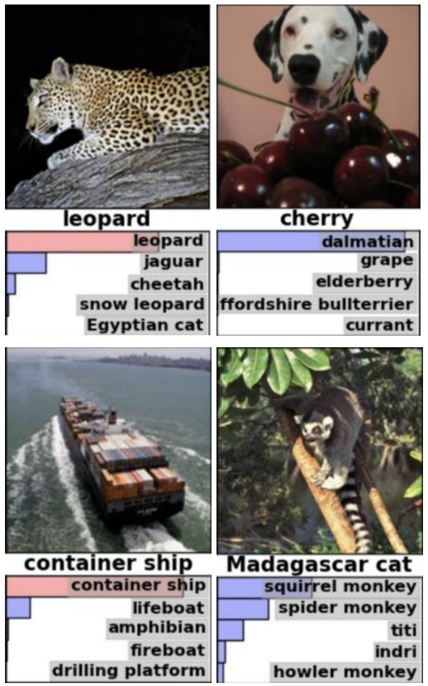
Superior perfomance

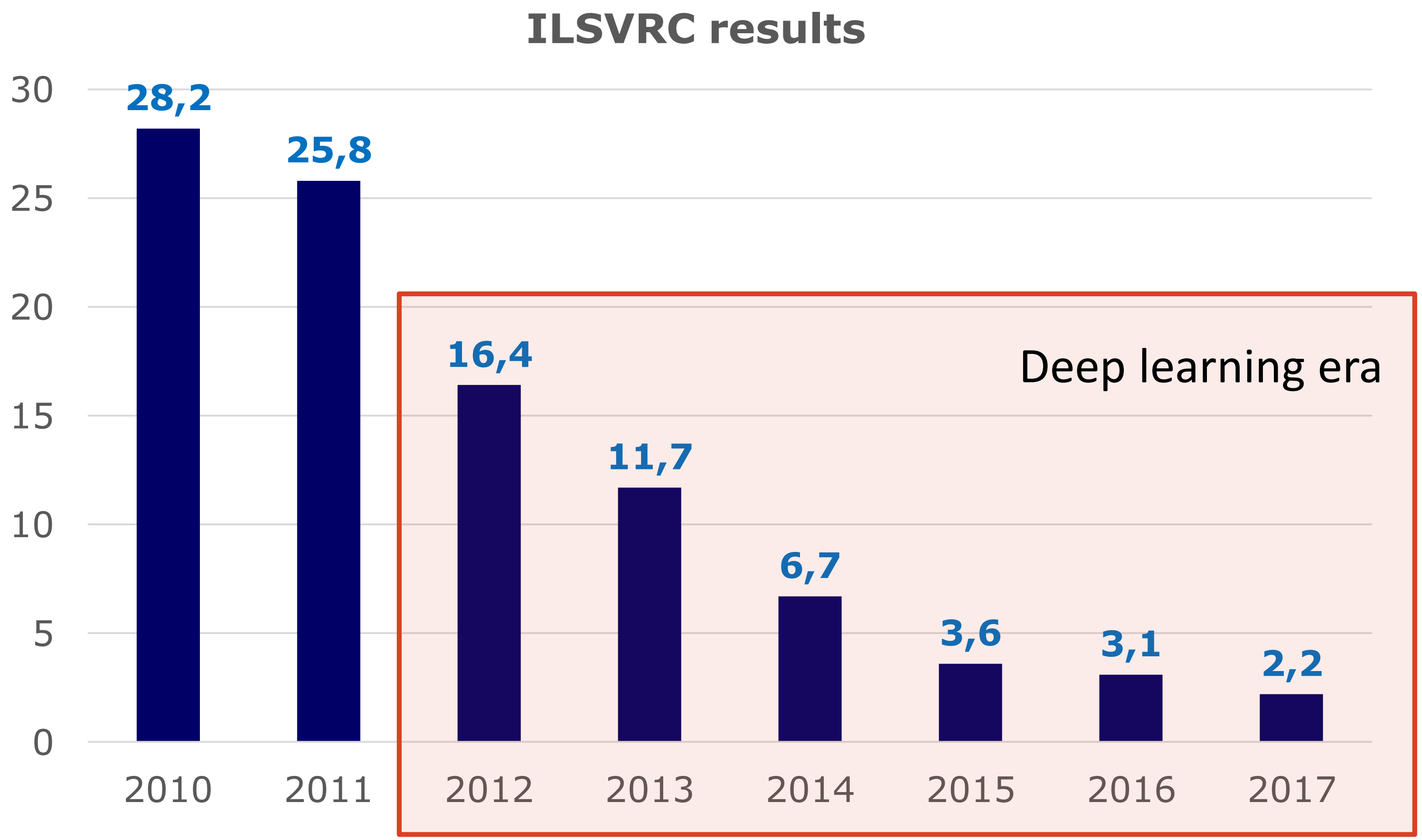
IMAGENET

1k categories

1,3M images

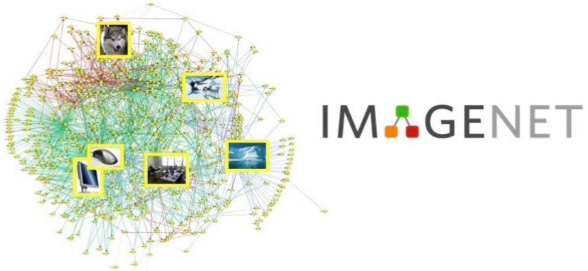
Top5 classification

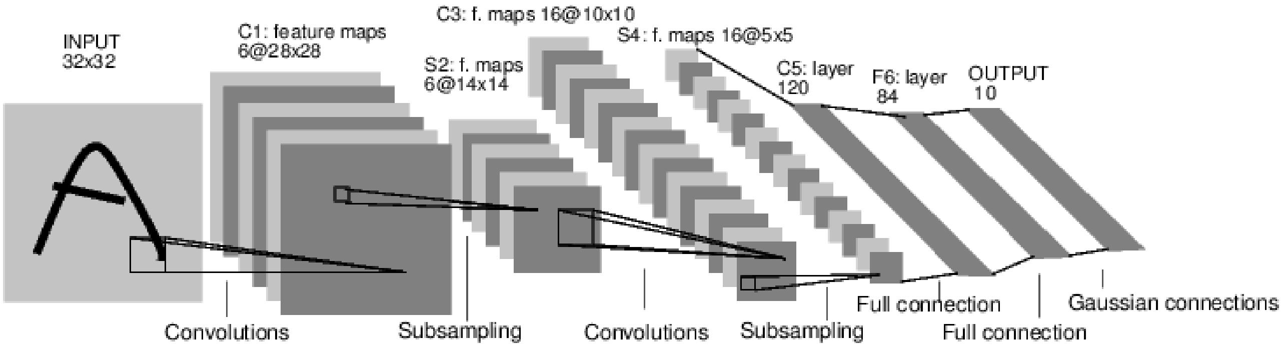




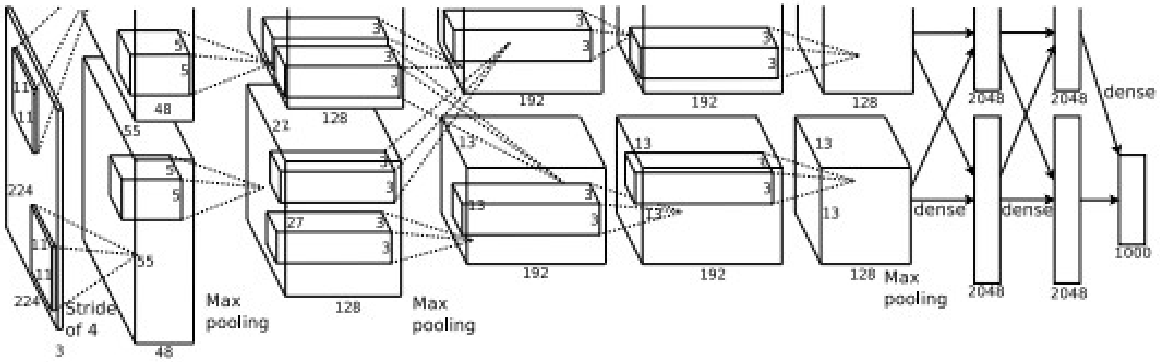
New deep learning era

- More data!



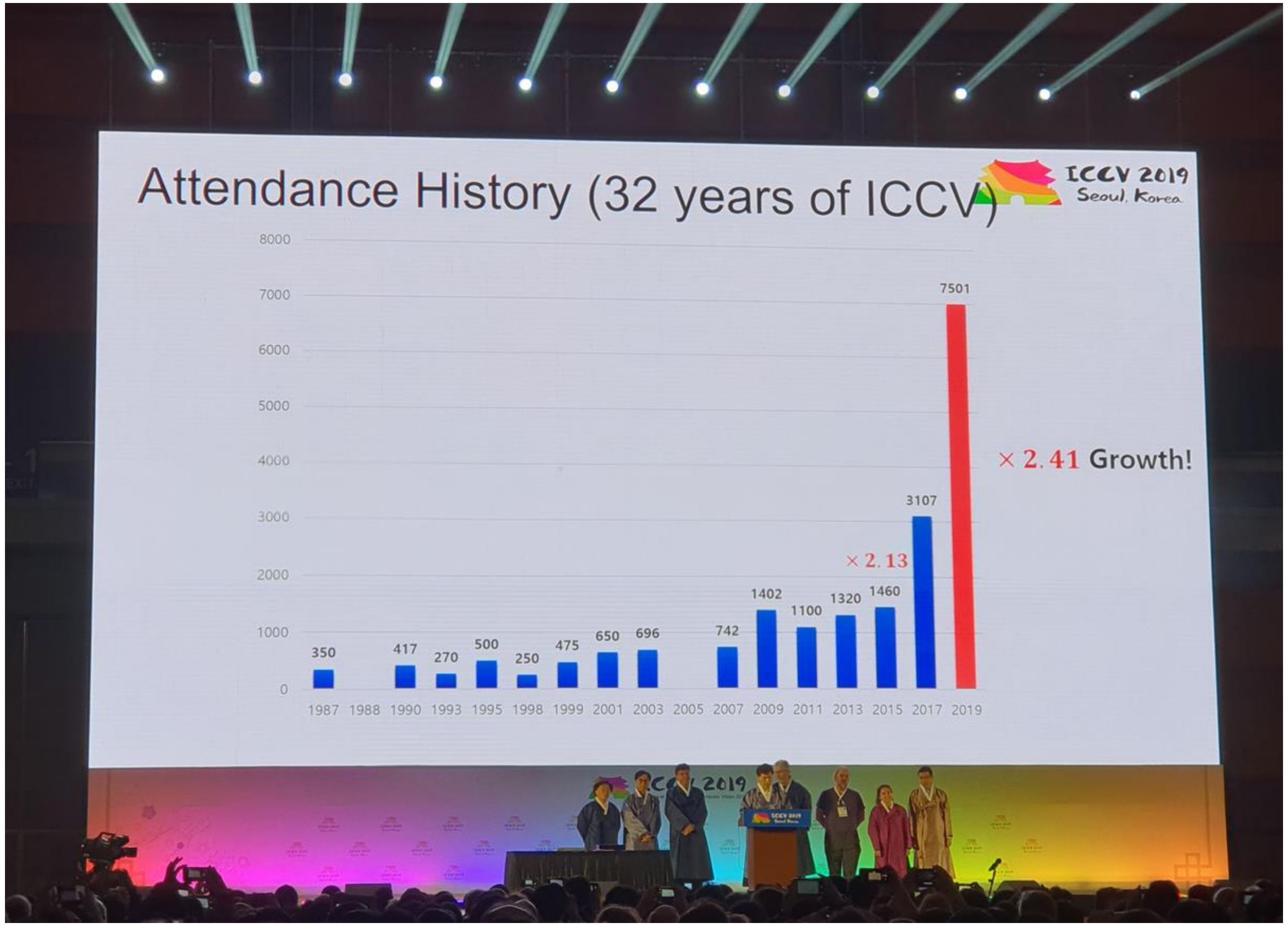


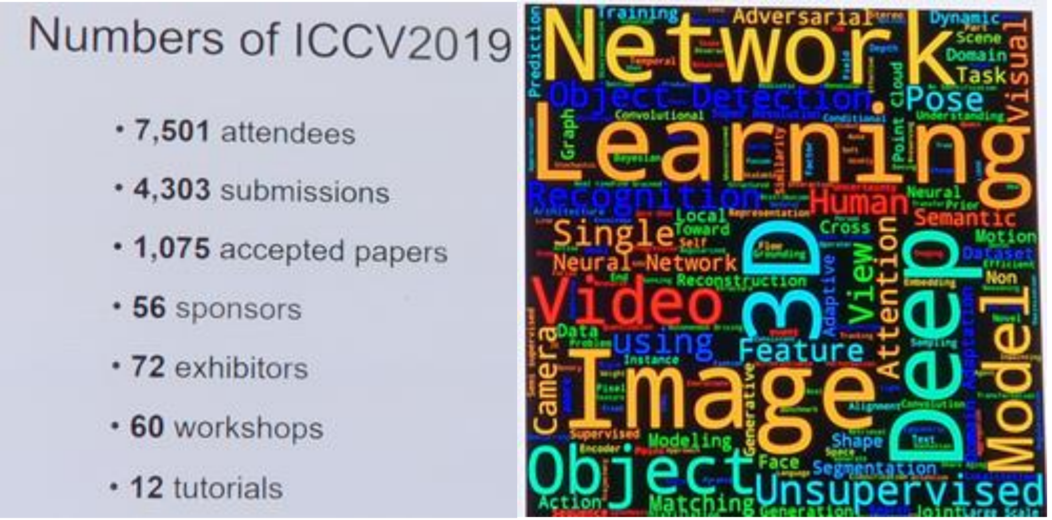
- More computing power - GPU!



- Better learning algorithms!

New deep learning era

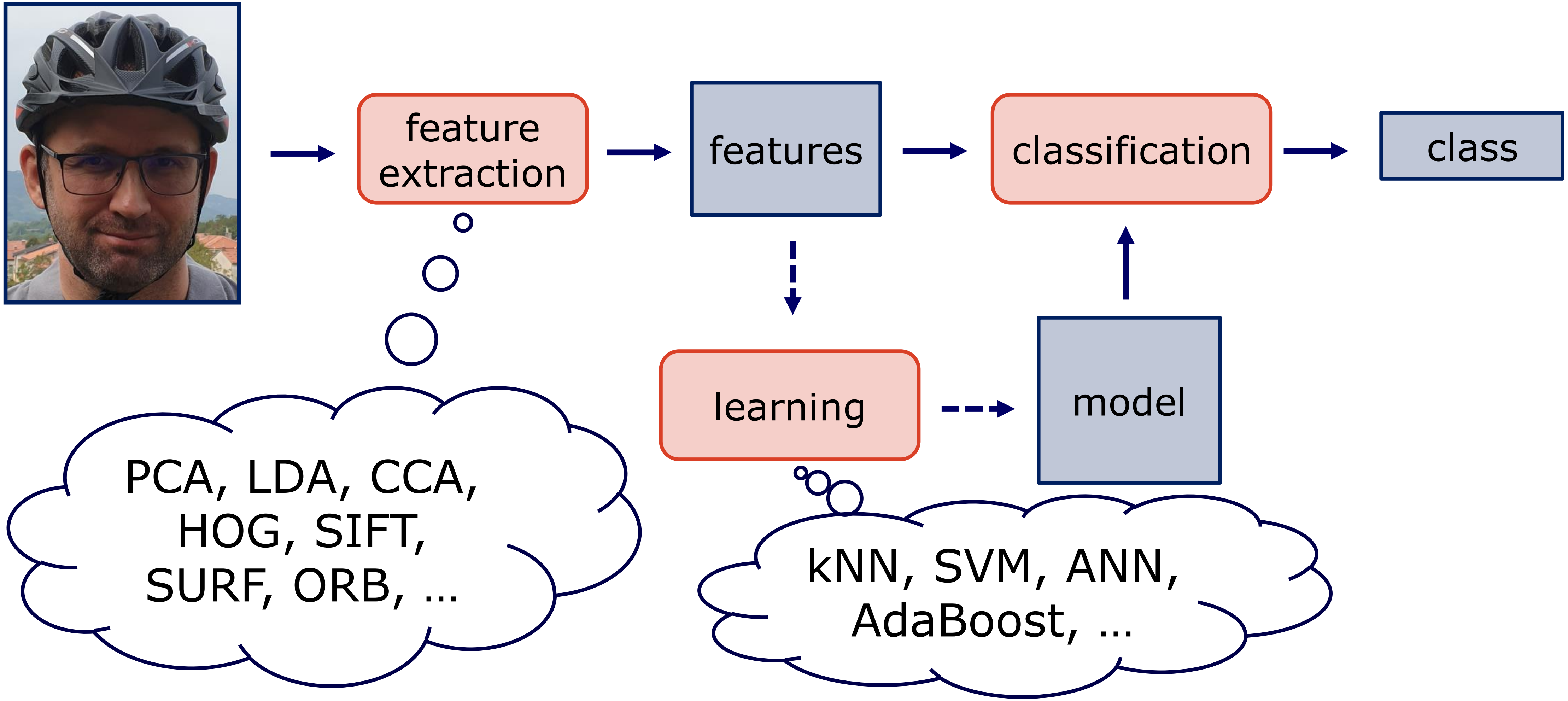




ICCV 2019, Seoul, Korea, 27. 10. - 2. 11. 2019

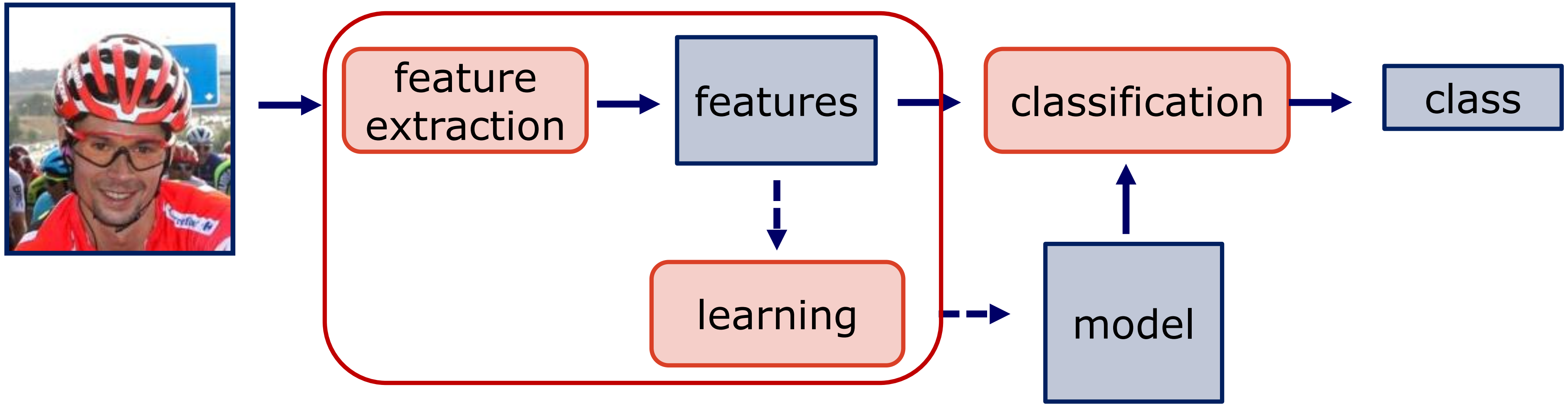
Machine learning in computer vision

- Conventional approach

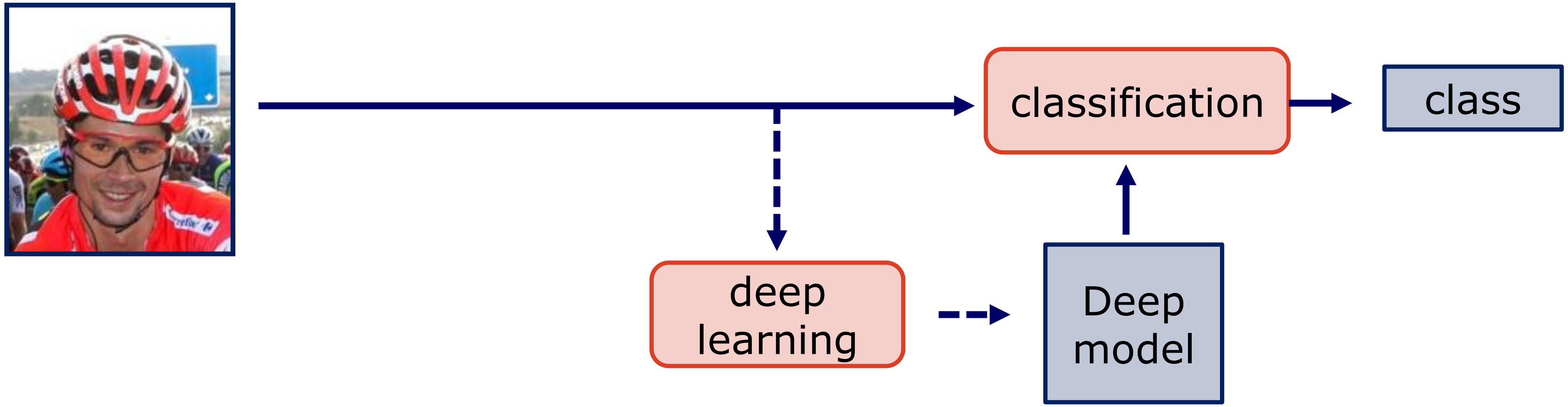


Deep learning in computer vision

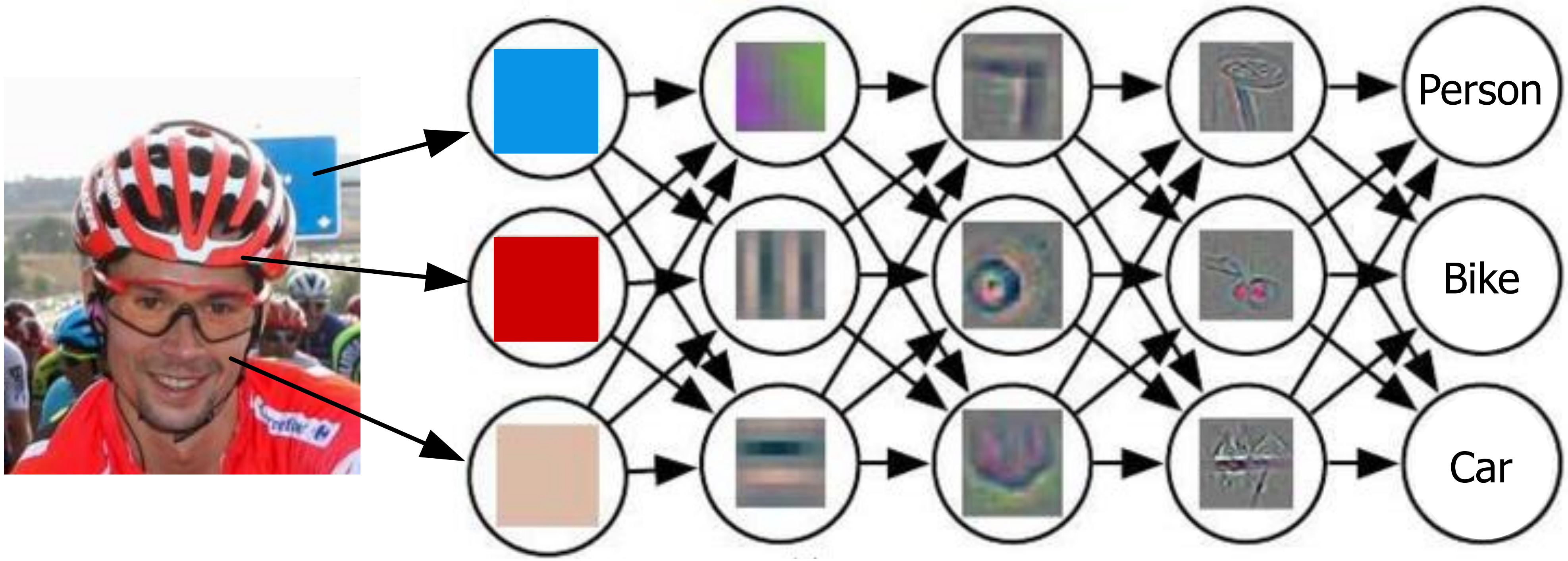
- Conventional machine learning approach in computer vision



- Deep learing approach

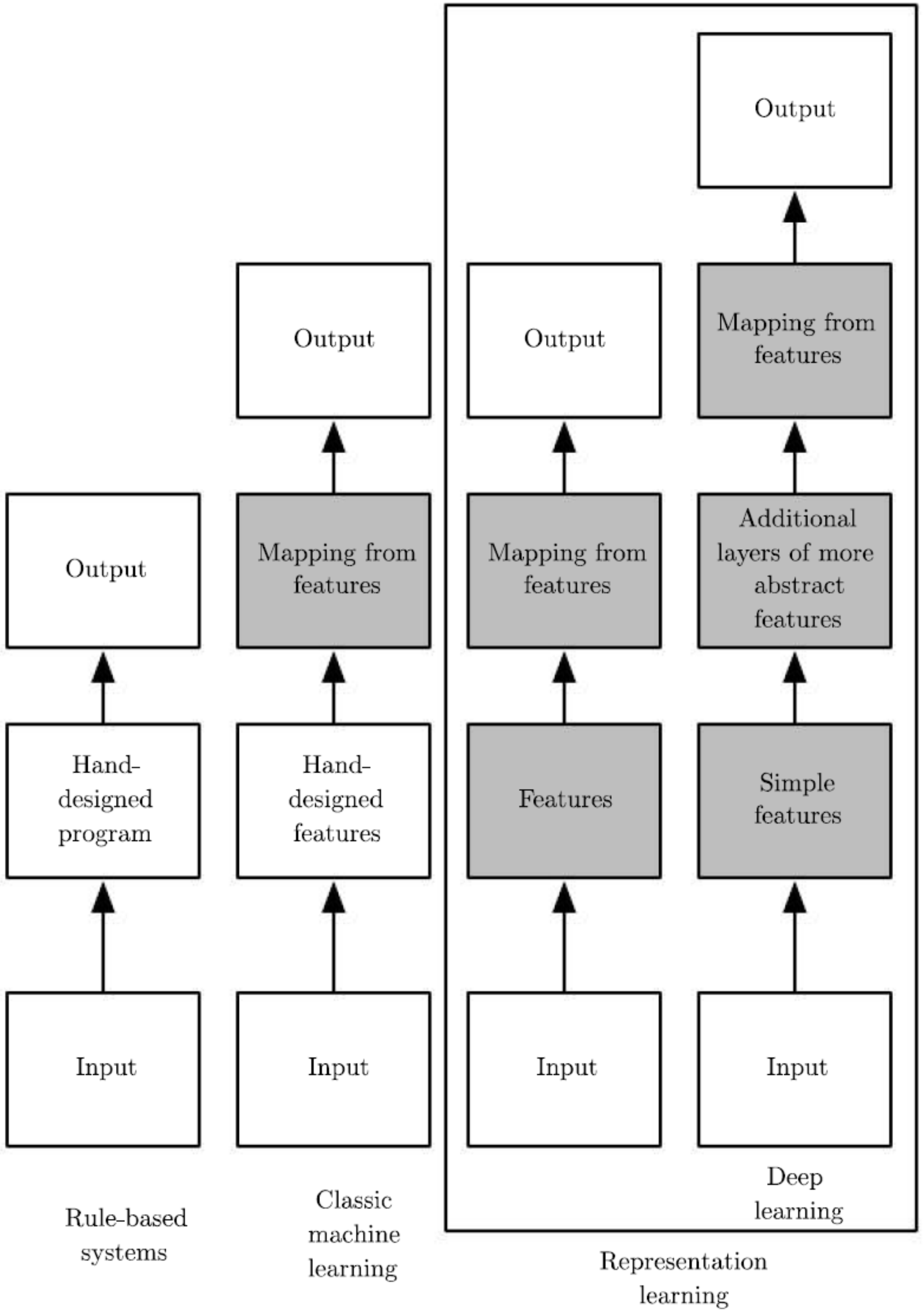


Deep learning – the main concept



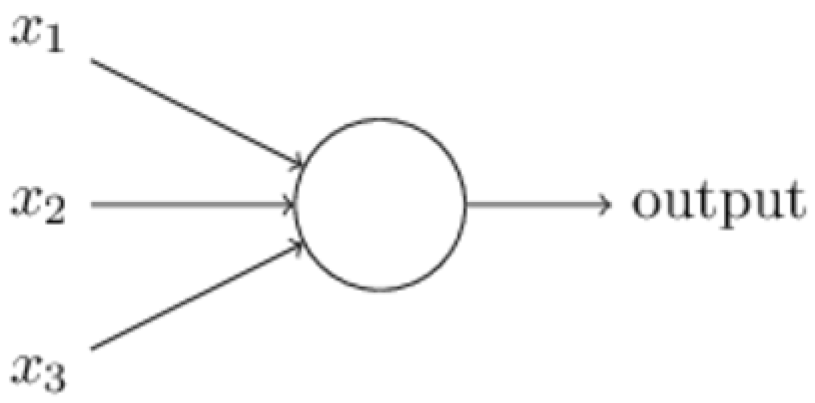
End to end learning

- Representations as well as classifier are being learned



Perceptron

- Rosenblatt, 1957
- Binary inputs and output
- Weights
- Threshold
- Bias
- Very simple!

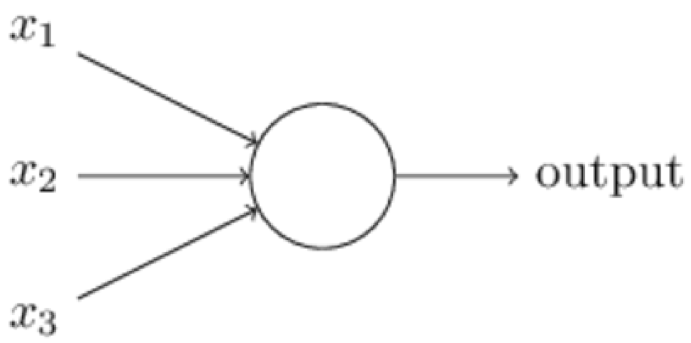


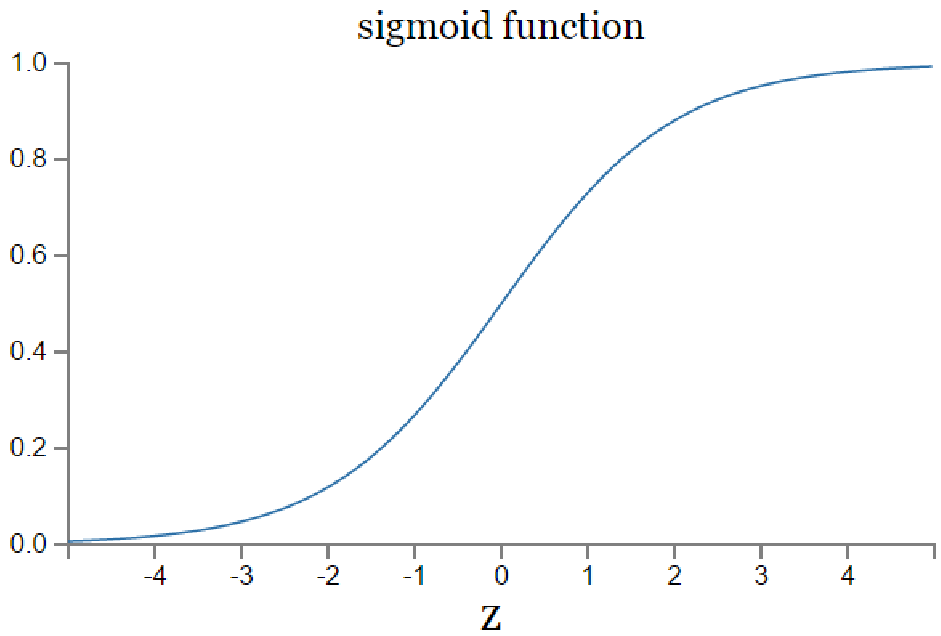
$$\text{output} = \begin{cases} 0 & \text{if } \sum_j w_j x_j \leq \text{ threshold} \\ 1 & \text{if } \sum_j w_j x_j > \text{ threshold} \end{cases}$$

$$\text{output} = \begin{cases} 0 & \text{if } w \cdot x + b \leq 0 \\ 1 & \text{if } w \cdot x + b > 0 \end{cases}$$

Sigmoid neurons

- Real inputs and outputs from interval [0,1]





- Activation function: sgimoid function

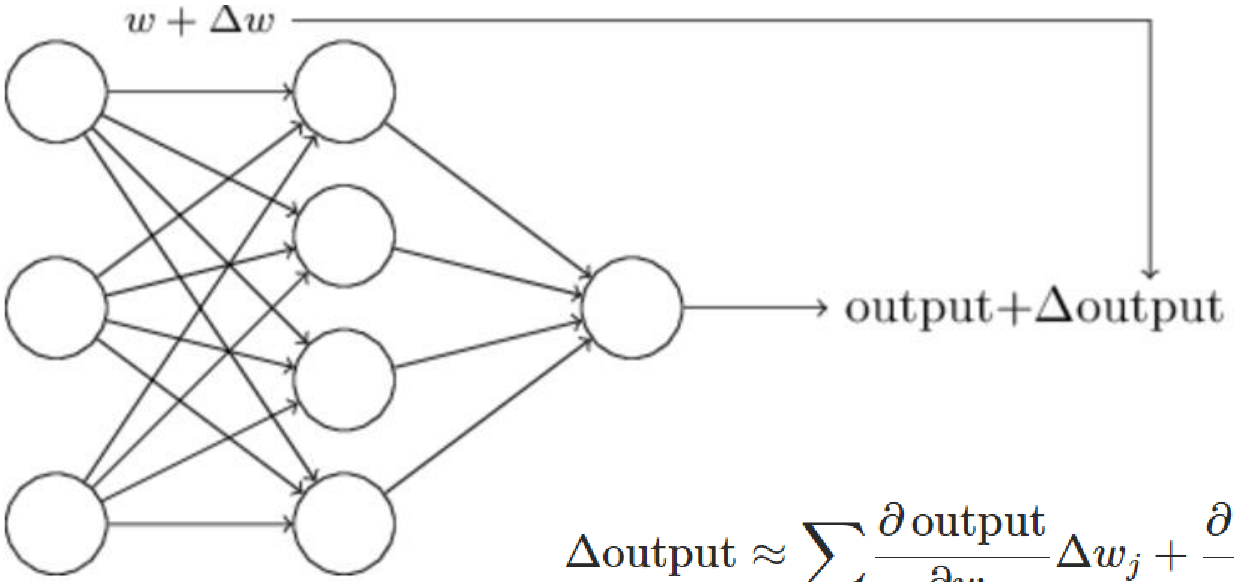
- *output* = $\dfrac{1}{1+\exp(-\sum_j w_j x_j - b)}$

$$\sigma(z) \equiv \frac{1}{1+e^{-z}}$$

$$\sigma(w \cdot x + b)$$

Sigmoid neurons

- Small changes in weights and biases causes small change in output

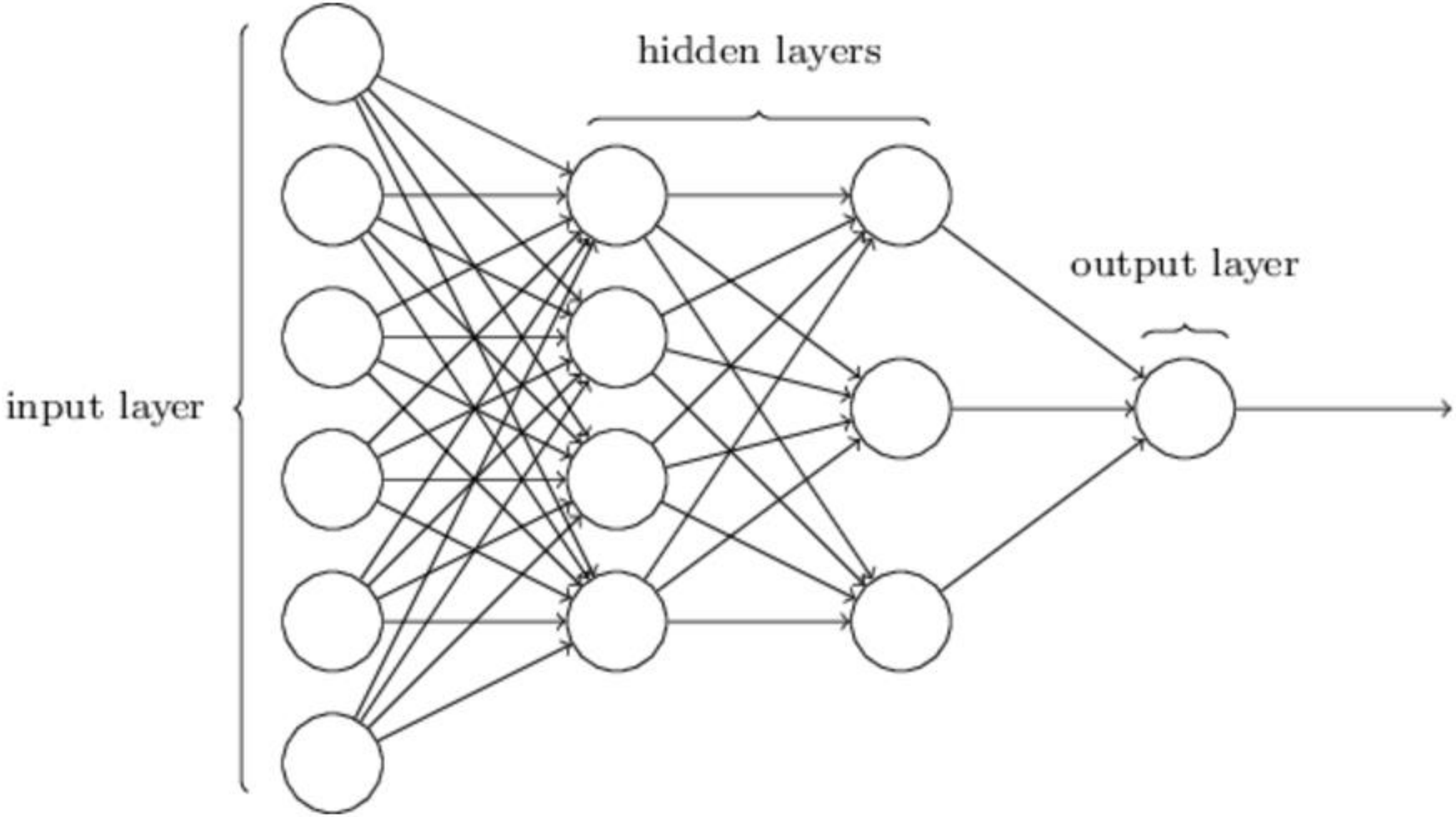


$$\Delta \text{output} \approx \sum_j \frac{\partial\, \text{output}}{\partial w_j} \Delta w_j + \frac{\partial\, \text{output}}{\partial b} \Delta b$$

- Enables learning!

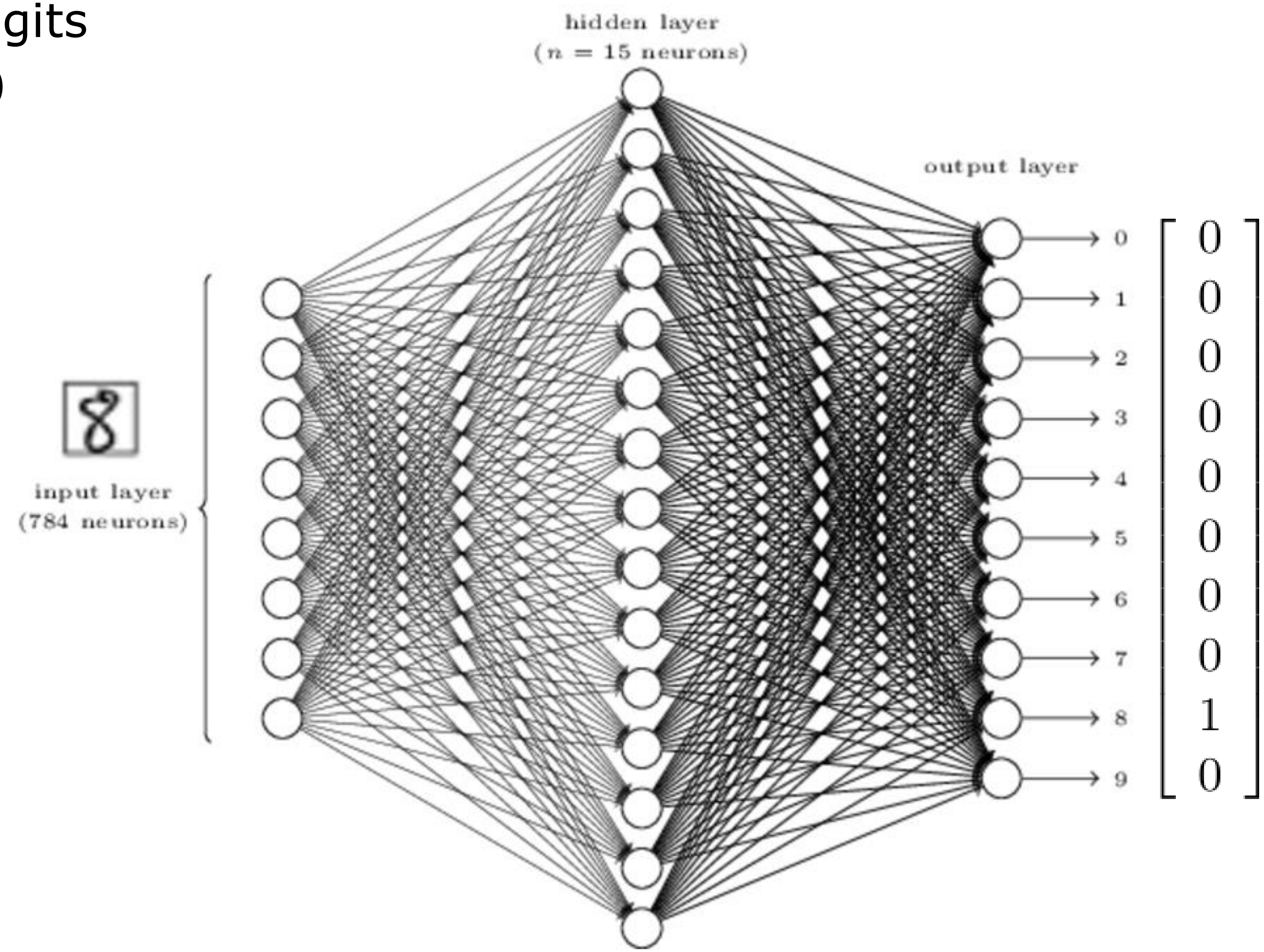
Feedfoward neural networks

- Network architecture:



Example: recognizing digits

- MNIST database of handwritten digits
  - 28x28 pixes (=784 input neurons)
  - 10 digits
  - 50.000 training images
  - 10.000 validation images
  - 10.000 test images



Example code: Feedforward

- Code from https://github.com/mnielsen/neural-networks-and-deep-learning/archive/master.zip
  or *https://github.com/mnielsen/neural-networks-and-deep-learning*
  git clone https://github.com/mnielsen/neural-networks-and-deep-learning.git
- or *https://github.com/chengfx/neural-networks-and-deep-learning-for-python3* (for Python 3)

```
class Network(object):

    def __init__(self, sizes):
        self.num_layers = len(sizes)
        self.sizes = sizes
        self.biases = [np.random.randn(y, 1) for y in sizes[1:]]
        self.weights = [np.random.randn(y, x)
                        for x, y in zip(sizes[:-1], sizes[1:])]

    def feedforward(self, a):
        for b, w in zip(self.biases, self.weights):
            a = sigmoid(np.dot(w, a)+b)
        return a


def sigmoid(z):
    return 1.0/(1.0+np.exp(-z))
```

```
net = network.Network([784, 30, 10])
net.SGD(training_data, 5, 10, 3.0, test_data=test_data)
```

```
In [55]: x,y=test_data[0]

In [56]: net.feedforward(x)
Out[56]:
array([[  1.83408119e-03],
       [  5.94472468e-08],
       [  1.84785949e-03],
       [  6.85718810e-04],
       [  1.41399919e-05],
       [  5.40491233e-06],
       [  4.74332685e-09],
       [  9.97920007e-01],
       [  8.19370561e-05],
       [  6.65086583e-05]])

In [57]: y
Out[57]: 7
```

Loss function

- Given:

$y\Big($  $\Big) = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$ for all training images

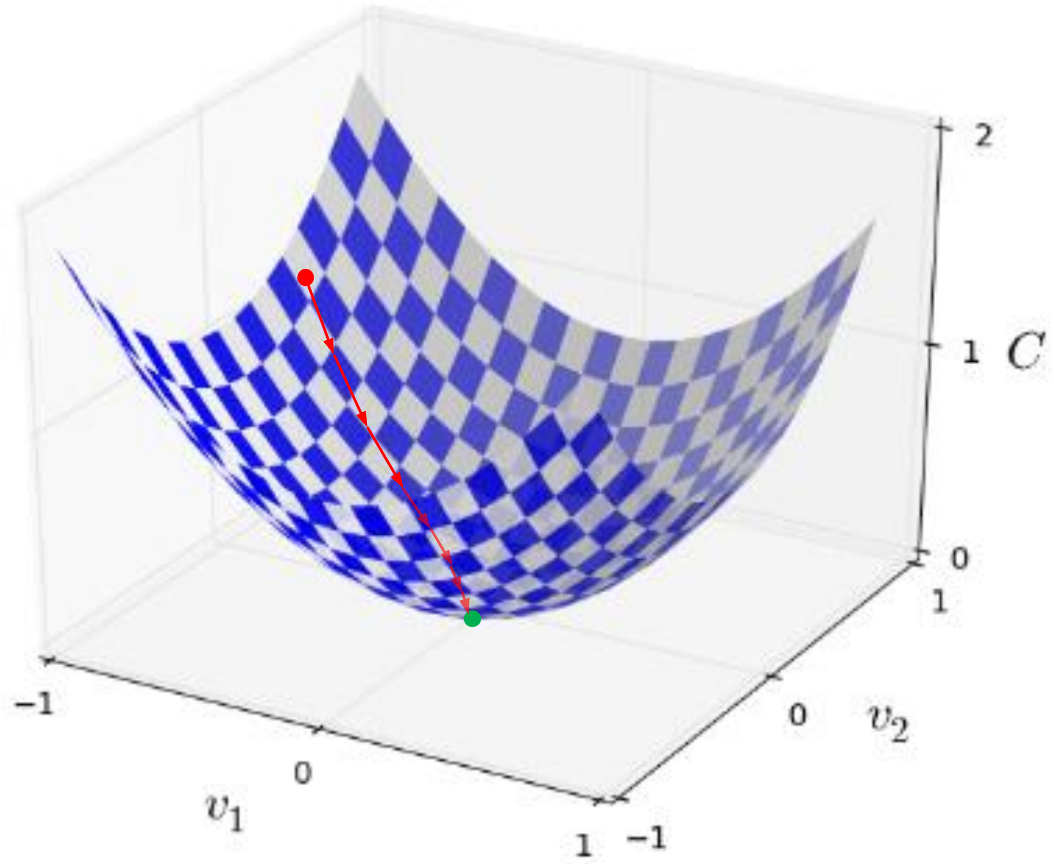
- Loss function: $C(w,b) \equiv \frac{1}{2n} \sum_x \|y(x) - a\|^2$
  - (mean sqare error – quadratic loss function)

- Find weigths w and biases b that for given input x produce output a that minimizes Loss function C

Gradient descend

- Find minimum of $C(v_1, v_2)$
- Change of C: $\Delta C \approx \frac{\partial C}{\partial v_1}\Delta v_1 + \frac{\partial C}{\partial v_2}\Delta v_2 = \nabla C \cdot \Delta v = -\eta \|\nabla C\|^2$
- Gradient of C: $\nabla C \equiv \left(\frac{\partial C}{\partial v_1}, \frac{\partial C}{\partial v_2}\right)^T$
- *Change v in the opposite direction of the gradient:* $\Delta v = -\eta \nabla C$

  Learning rate
- Algorithm:
  - Initialize v
  - Until stopping criterium riched
    - Apply udate rule $v \rightarrow v' = v - \eta \nabla C.$



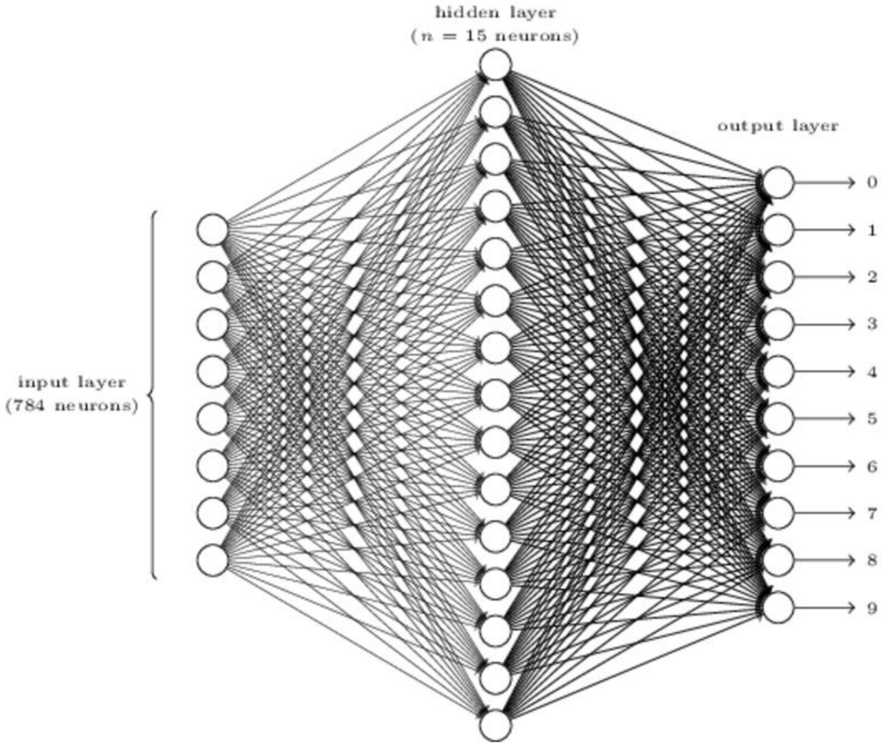
Gradient descend in neural networks

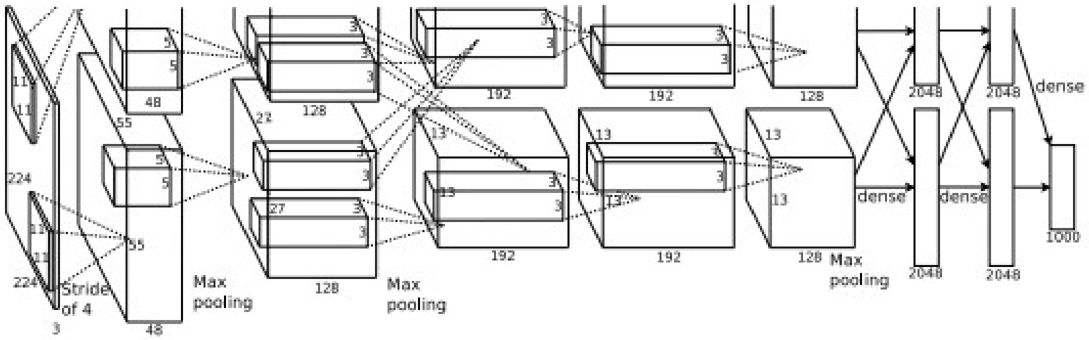
- Loss function $C(w,b)$
- Update rules:

$$w_k \rightarrow w_k' = w_k - \eta \frac{\partial C}{\partial w_k}$$

$$b_l \rightarrow b_l' = b_l - \eta \frac{\partial C}{\partial b_l}$$

- Consider all training samples
- Very many parameters
  => computationaly very expensive
- Use Stochastic gradient descend instead





Stochastic gradient descend

- Compute gradient only for a subset of m training samples:
  - *Mini-batch*: $X_1, X_2, \ldots, X_m$
  - Approximate gradient: $\frac{\sum_{j=1}^{m} \nabla C_{X_j}}{m} \approx \frac{\sum_x \nabla C_x}{n} = \nabla C$

$$\nabla C \approx \frac{1}{m} \sum_{j=1}^{m} \nabla C_{X_j}$$

  - Update rules:

$$w_k \rightarrow w'_k = w_k - \frac{\eta}{m} \sum_j \frac{\partial C_{X_j}}{\partial w_k}$$

$$b_l \rightarrow b'_l = b_l - \frac{\eta}{m} \sum_j \frac{\partial C_{X_j}}{\partial b_l},$$

- Training:
  1. Initialize w and b
  2. In one *epoch* of training keep randomly selecting one mini-batch of m samples at a time (and train) until all training images are used
  3. Repeat for several epochs

Example code: SGD

```python
def SGD(self, training_data, epochs, mini_batch_size, eta):
    n = len(training_data)
    for j in xrange(epochs):
        random.shuffle(training_data)
        mini_batches = [
            training_data[k:k+mini_batch_size]
            for k in xrange(0, n, mini_batch_size)]
        for mini_batch in mini_batches:
            self.update_mini_batch(mini_batch, eta)


def update_mini_batch(self, mini_batch, eta):
    nabla_b = [np.zeros(b.shape) for b in self.biases]
    nabla_w = [np.zeros(w.shape) for w in self.weights]
    for x, y in mini_batch:
        delta_nabla_b, delta_nabla_w = self.backprop(x, y)
        nabla_b = [nb+dnb for nb, dnb in zip(nabla_b, delta_nabla_b)]
        nabla_w = [nw+dnw for nw, dnw in zip(nabla_w, delta_nabla_w)]
    self.weights = [w-(eta/len(mini_batch))*nw
                     for w, nw in zip(self.weights, nabla_w)]
    self.biases = [b-(eta/len(mini_batch))*nb
                    for b, nb in zip(self.biases, nabla_b)]
```

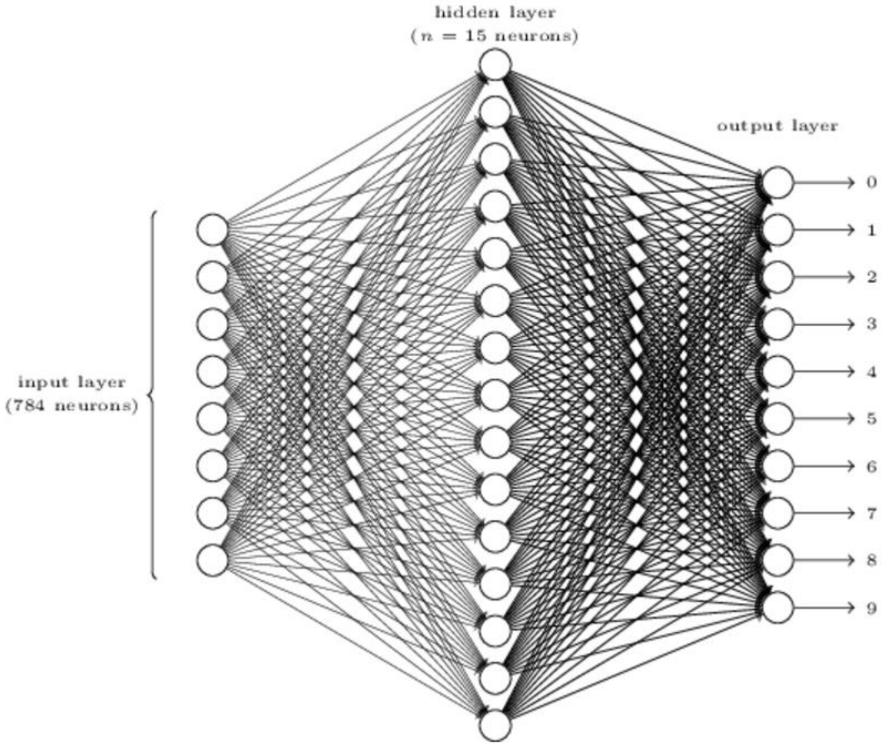
Backpropagation

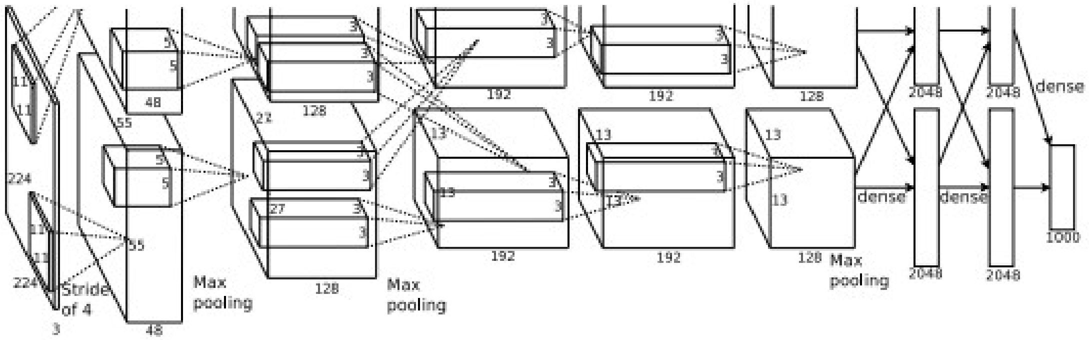
- All we need is gradient of loss function ∇C
  - Rate of change of C wrt. to change in any weigt
  - Rate of change of C wrt. to change in any biase

$$\frac{\partial C}{\partial b^l_j} \qquad \frac{\partial C}{\partial w^l_{jk}}$$

- How to compute gradient?
  - Numericaly
    - Simple, approximate, extremely slow ☹
  - Analyticaly for entire C
    - Fast, exact, nontractable ☹
  - Chain individual parts of netwok
    - Fast, exact, doable ☺

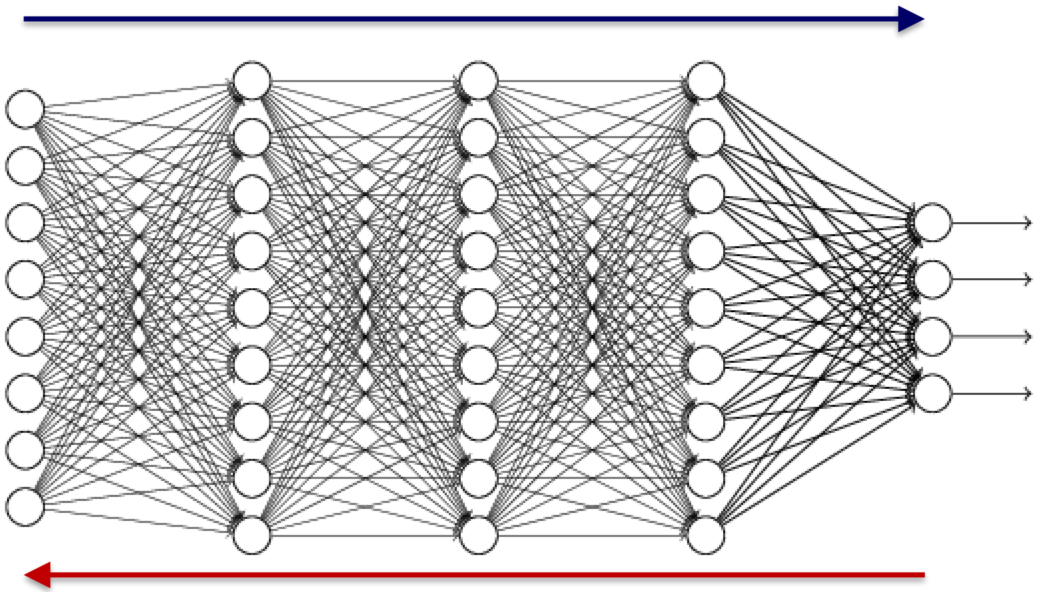
Backpropagation!





Main principle

- We need the gradient of the Loss function ∇C $\frac{\partial C}{\partial b^l_j}$ $\frac{\partial C}{\partial w^l_{jk}}$
- Two phases:
  - Forward pass; propagation: the input sample is propagated through the network and the error at the final layer is obtained



  - Backward pass; weight update: the error is backpropagated to the individual levels, the contribution of the individual neuron to the error is calculated and the weights are updated accordingly

Learning strategy

- To obtain the gradient of the Loss function ∇C : $\frac{\partial C}{\partial b_j^l}$ $\frac{\partial C}{\partial w_{jk}^l}$
  - For every neuron in the network calculate error of this neuron

    $$\delta_j^l \equiv \frac{\partial C}{\partial z_j^l}$$

    - This error propagates through the netwok causing the final error
    - Backpropagate the final error to get all δ_j^l
  - Obtain all $\frac{\partial C}{\partial b_j^l}$ and $\frac{\partial C}{\partial w_{jk}^l}$ from δ_j^l

Equations of backpropagation

- BP1: Error in the output layer:

$$\delta_j^L = \frac{\partial C}{\partial a_j^L}\sigma'(z_j^L) \qquad\qquad \delta^L = \nabla_a C \odot \sigma'(z^L)$$

- BP2: Error in terms of the error in the next layer:

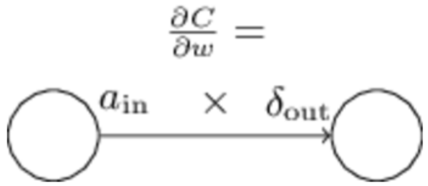
$$\delta_j^l = \sum_k w_{kj}^{l+1}\delta_k^{l+1}\sigma'(z_j^l) \qquad\qquad \delta^l = ((w^{l+1})^T\delta^{l+1}) \odot \sigma'(z^l)$$

- BP3: Rate of change of the cost wrt. to any bias:

$$\frac{\partial C}{\partial b_j^l} = \delta_j^l \qquad\qquad \frac{\partial C}{\partial b} = \delta$$

- BP4: Rate of change of the cost wrt. to any weight:

$$\frac{\partial C}{\partial w_{jk}^l} = a_k^{l-1}\delta_j^l \qquad\qquad \frac{\partial C}{\partial w} = a_{\text{in}}\delta_{\text{out}}$$



Backpropagation algorithm

- **Input** x: Set the corresponding activation a^1 for the input layer
- **Feedforward**: For each $l = 2, 3, \ldots, L$
  compute $z^l = w^l a^{l-1} + b^l$ and $a^l = \sigma(z^l)$
- **Output error** δ^L: Compute the output error $\delta^L = \nabla_a C \odot \sigma'(z^L)$
- **Backpropagate the error**:
  For each $l = L-1, L-2, \ldots, 2$
  compute $\delta^l = ((w^{l+1})^T \delta^{l+1}) \odot \sigma'(z^l)$
- **Output the gradient**:

$$\frac{\partial C}{\partial w^l_{jk}} = a^{l-1}_k \delta^l_j \qquad \frac{\partial C}{\partial b^l_j} = \delta^l_j$$

Backpropagation and SGD

For a number of **epochs**

Until all training images are used

Select a **mini-batch** of m training samples

For each training sample x in the mini-batch

Input: set the corresponding activation $a^{x,1}$

Feedforward: for each $l = 2, 3, \ldots, L$

compute $z^{x,l} = w^l a^{x,l-1} + b^l$ and $a^{x,l} = \sigma(z^{x,l})$

Output error: compute $\delta^{x,L} = \nabla_a C_x \odot \sigma'(z^{x,L})$

Backpropagation: for each $l = L-1, L-2, \ldots, 2$

compute $\delta^{x,l} = ((w^{l+1})^T \delta^{x,l+1}) \odot \sigma'(z^{x,l})$

Gradient descend: for each $l = L, L-1, \ldots, 2$ and x update:

$$w^l \rightarrow w^l - \frac{\eta}{m} \sum_x \delta^{x,l} (a^{x,l-1})^T$$

$$b^l \rightarrow b^l - \frac{\eta}{m} \sum_x \delta^{x,l}$$

Example code: Backpropagation

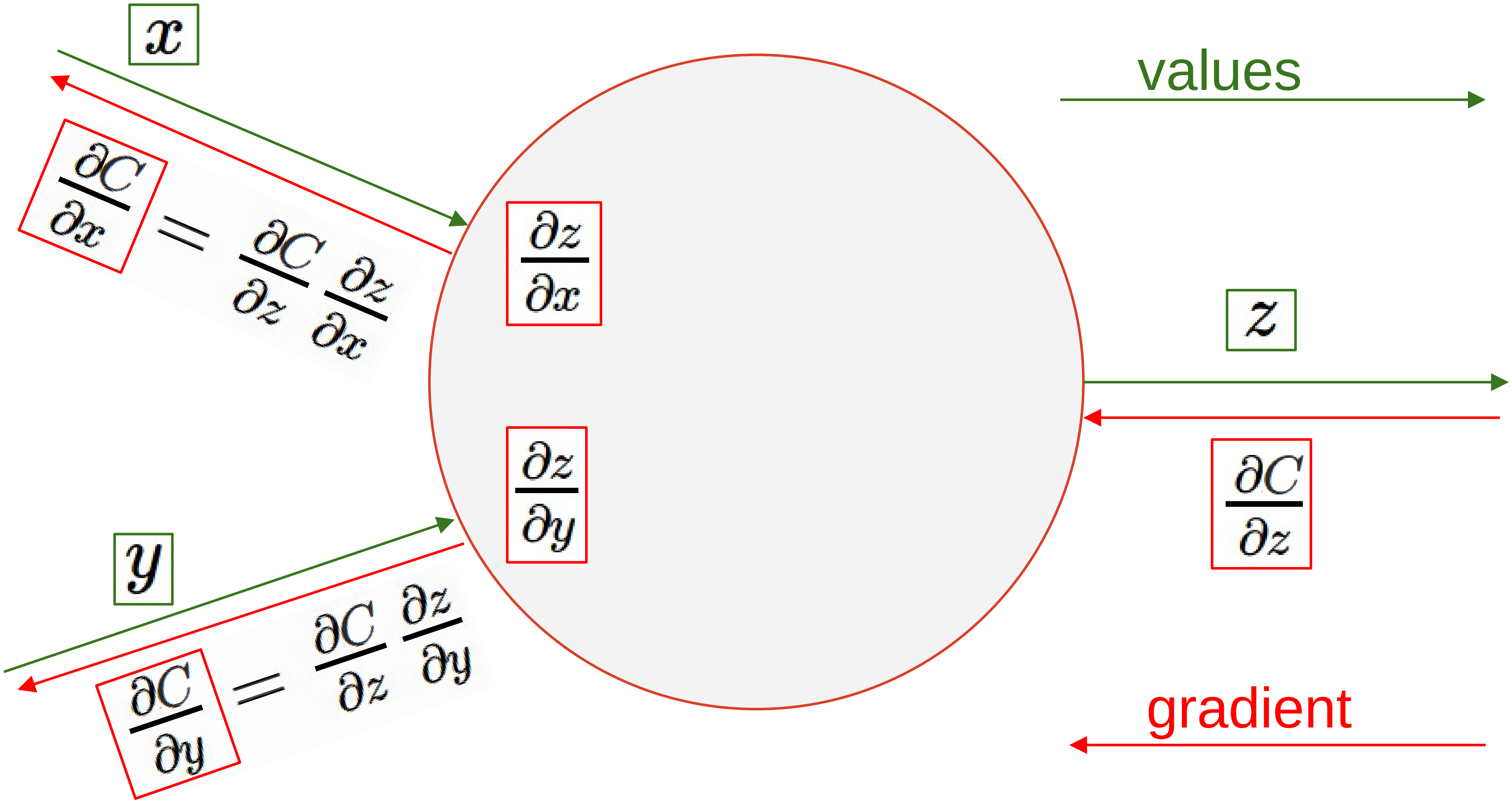
```
def backprop(self, x, y):
        nabla_b = [np.zeros(b.shape) for b in self.biases]
        nabla_w = [np.zeros(w.shape) for w in self.weights]
        # feedforward
        activation = x
        activations = [x] # list to store all the activations, layer by layer
        zs = [] # list to store all the z vectors, layer by layer
        for b, w in zip(self.biases, self.weights):
            z = np.dot(w, activation)+b
            zs.append(z)
            activation = sigmoid(z)
            activations.append(activation)
        # backward pass
        delta = self.cost_derivative(activations[-1], y) * \
            sigmoid_prime(zs[-1])
        nabla_b[-1] = delta
        nabla_w[-1] = np.dot(delta, activations[-2].transpose())
        for l in xrange(2, self.num_layers):
            z = zs[-l]
            sp = sigmoid_prime(z)
            delta = np.dot(self.weights[-l+1].transpose(), delta) * sp
            nabla_b[-l] = delta
            nabla_w[-l] = np.dot(delta, activations[-l-1].transpose())
        return (nabla_b, nabla_w)
```

```
def cost_derivative(self, output_activations, y):
    return (output_activations-y)
```

```
def sigmoid(z):
    return 1.0/(1.0+np.exp(-z))
```

```
def sigmoid_prime(z):
    return sigmoid(z)*(1-sigmoid(z))
```

Local computation



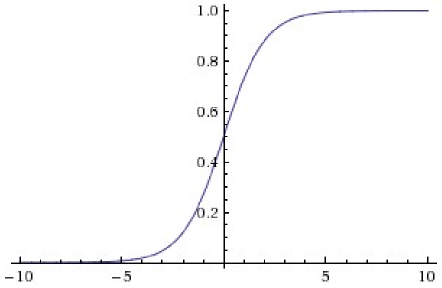
Activation and loss functions

Activation function	Loss function
Linear $$a_j^L = z_j^L$$	Quadratic $$C(w,b) \equiv \frac{1}{2n} \sum_x \|y(x) - a\|^2$$
Sigmoid $$\sigma(z) \equiv \frac{1}{1+e^{-z}}$$	Binary cross-entropy $$C = -\frac{1}{n} \sum_x \sum_j \left[y_j \ln a_j^L + (1 - y_j) \ln(1 - a_j^L) \right]$$
Softmax $$a_j^L = \frac{e^{z_j^L}}{\sum_k e^{z_k^L}}$$	Categorical Cross-entropy $$C = -\frac{1}{n} \sum_x \sum_j y_j \ln a_j^L$$
Other	Custom

Activation functions

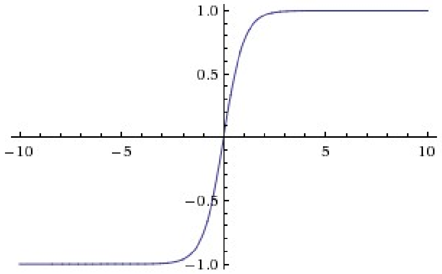
Sigmoid

$$\sigma(x) = 1/(1 + e^{-x})$$



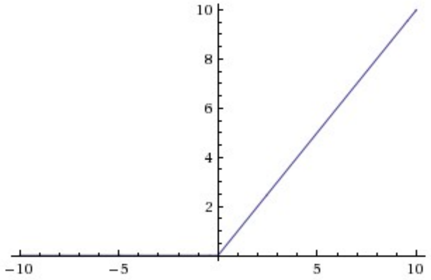
tanh

tanh(x)



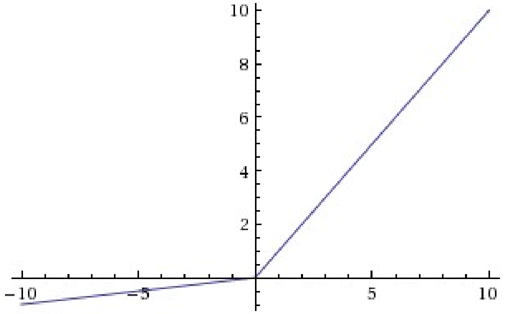
ReLU

max(0,x)



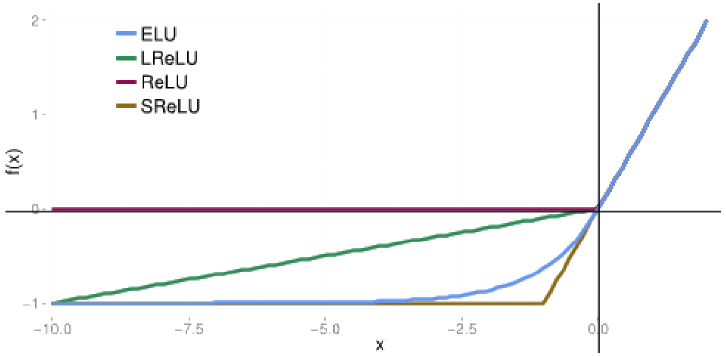
Leaky ReLU

max(0.1x, x)

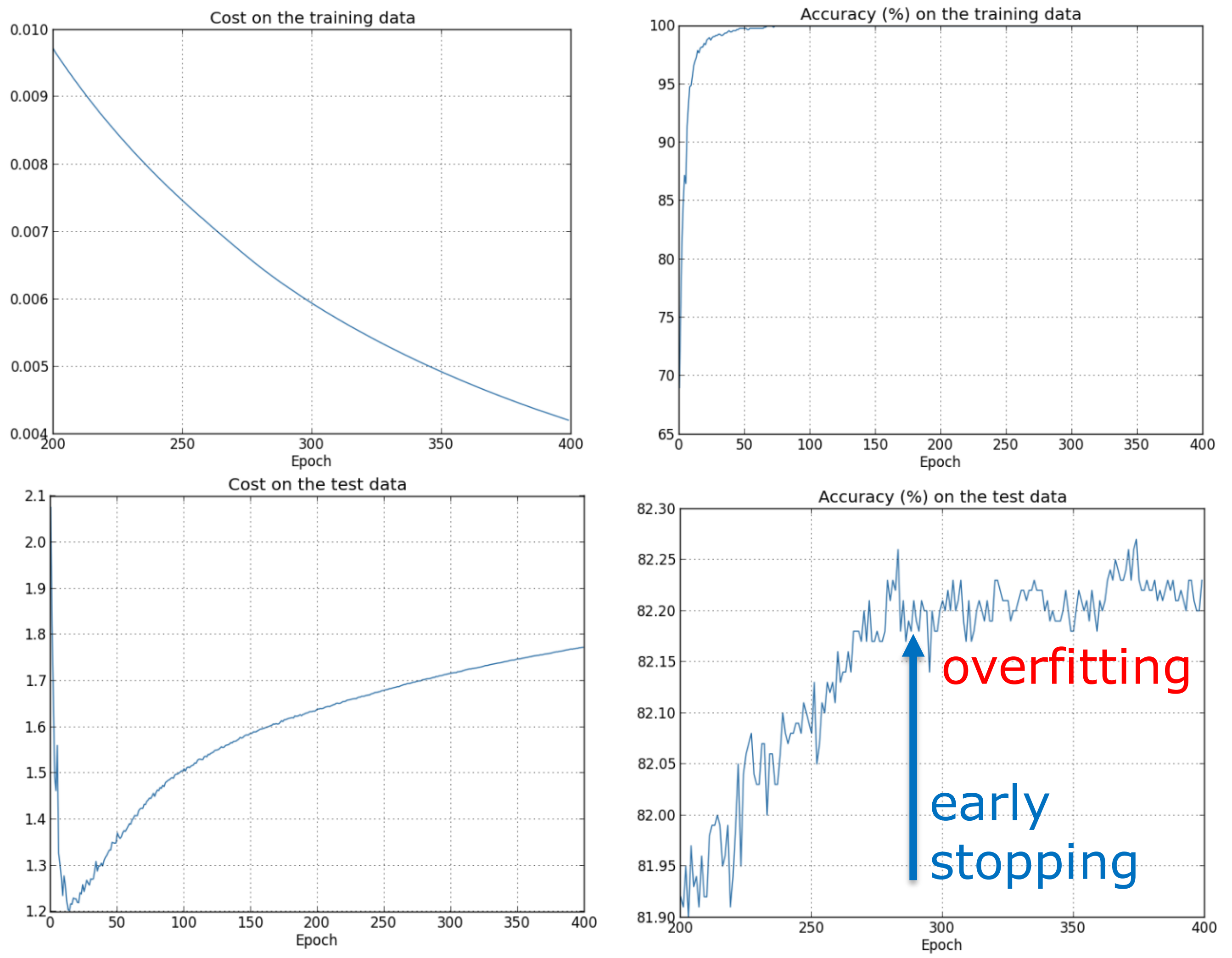


ELU

$$f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha\,(\exp(x) - 1) & \text{if } x \leq 0 \end{cases}$$

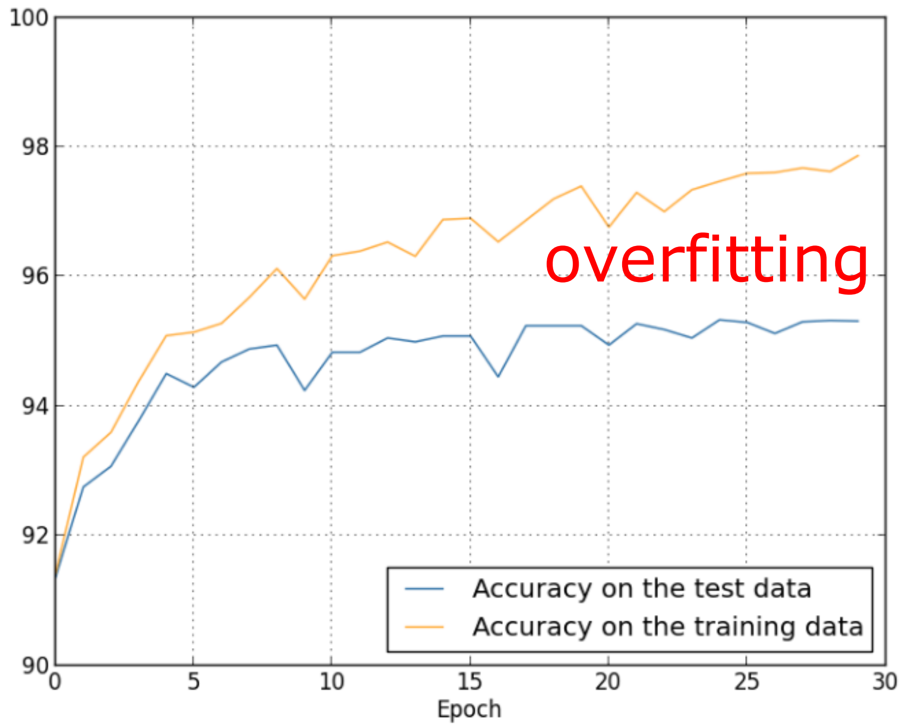


Overfitting



1,000 MNIST training images

- Huge number of parameters -> danger of overfitting
- Use validation set to determine overfitting and early stopping
  - Hold out method



50,000 MNIST training images

Regularization

- How to avoid overfitting:
  - Increase the number of training images ☹
  - Decrease the number of parameters ☹
  - Regularization ☺

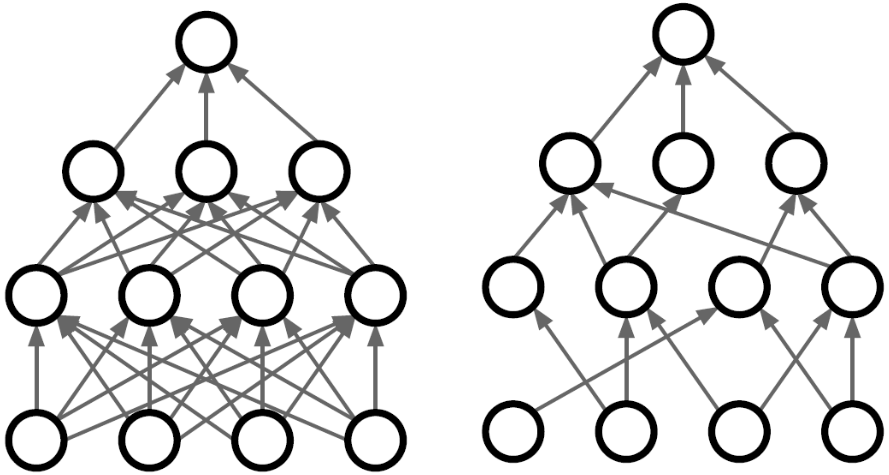
- Regularization:
  - L2 regularization
  - L1 regularization
  - Dropout
  - Data augmentation

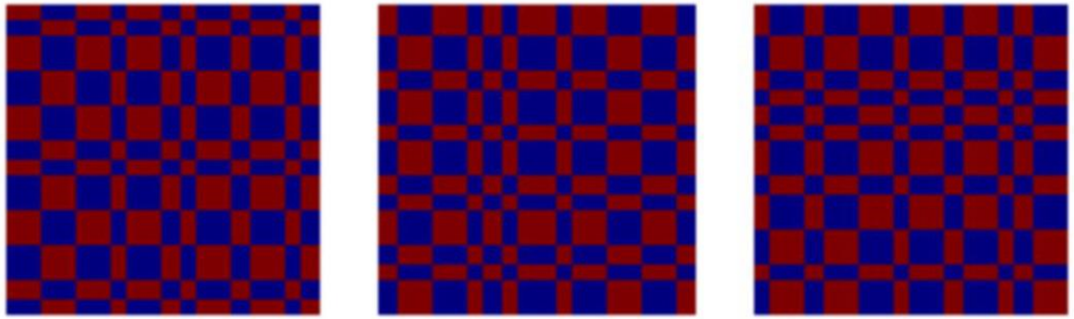
Regularisation

- How to avoid overfitting:
  - Increase the number of training images ☹
  - Decrease the number of parameters ☹
  - Regularization ☺

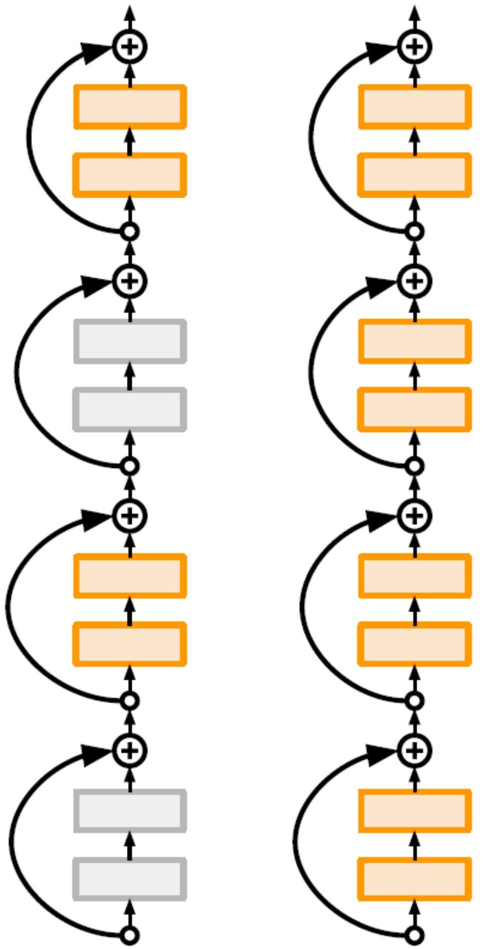
- Data Augmentation
- L1 regularisation
- L2 regularisation
- Dropout
- Batch Normalization
- DropConnect
- Fractional Max Pooling
- Stochastic Depth
- Cutout / Random Crop
- Mixup

[Wan et al. 2013]





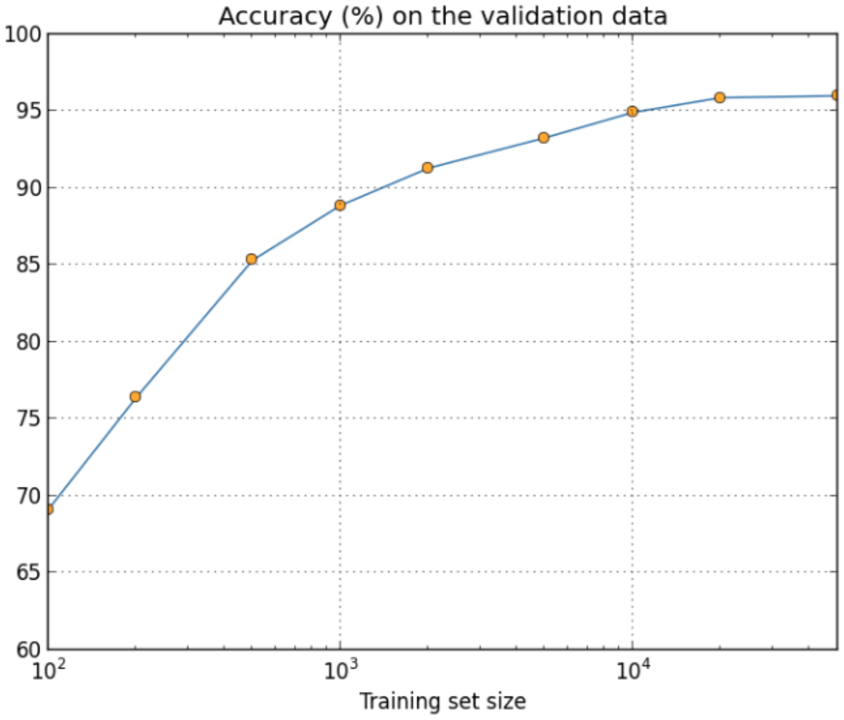
[Graham, 2014]



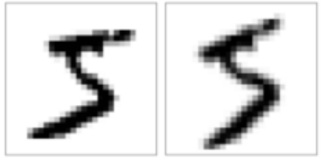
[Huang et al. 2016]

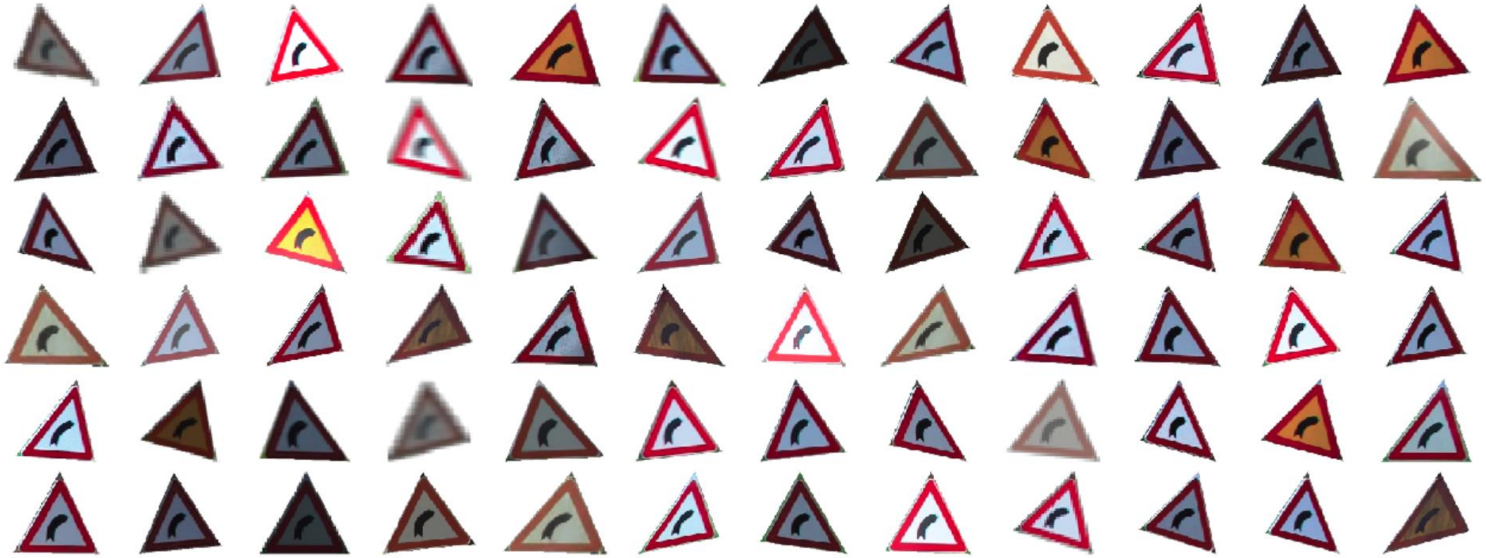
Data augmentation

- Use more data!



- Synthetically generate new data
- Apply different kinds of transformations: translations, rotations, elastic distortions, appearance modifications (intensity, blur)
- Operations should reflect real-world variation





Parameter updates

- Different schemes for updating gradient
  - Gradient descend
  - Momentum update
  - Nesterov momentum
  - AdaGrad update
  - RMSProp update
  - Adam update

  - Learning rate decay

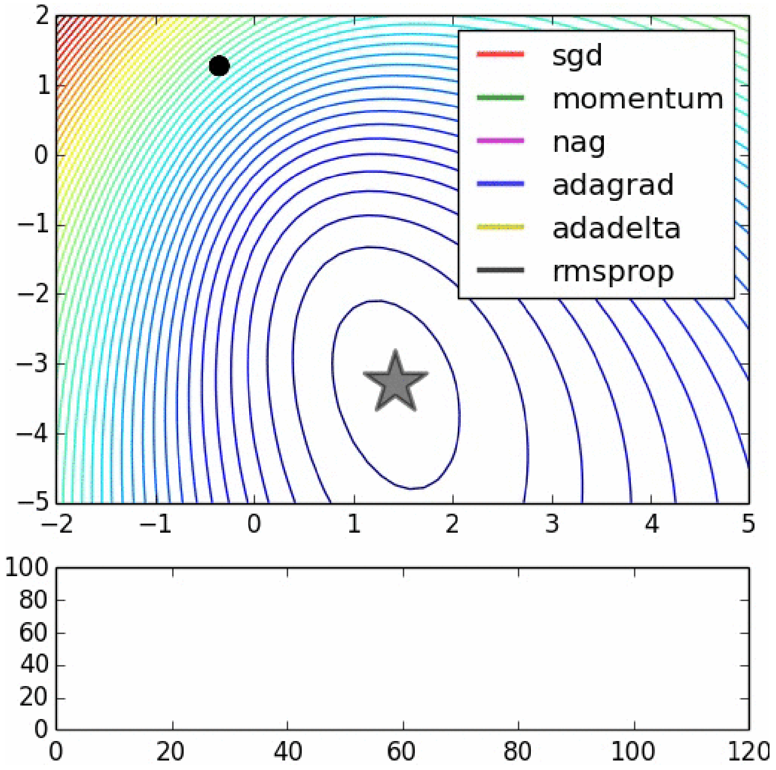
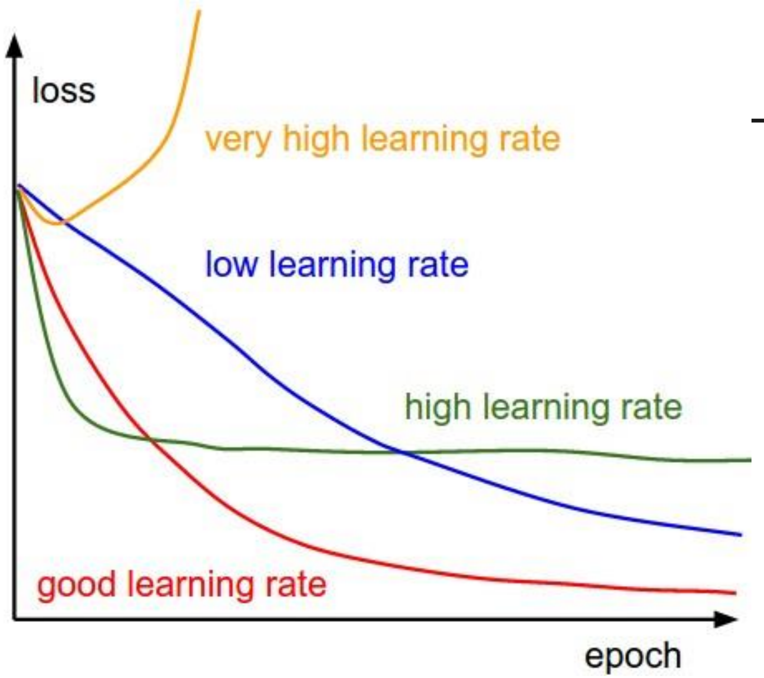
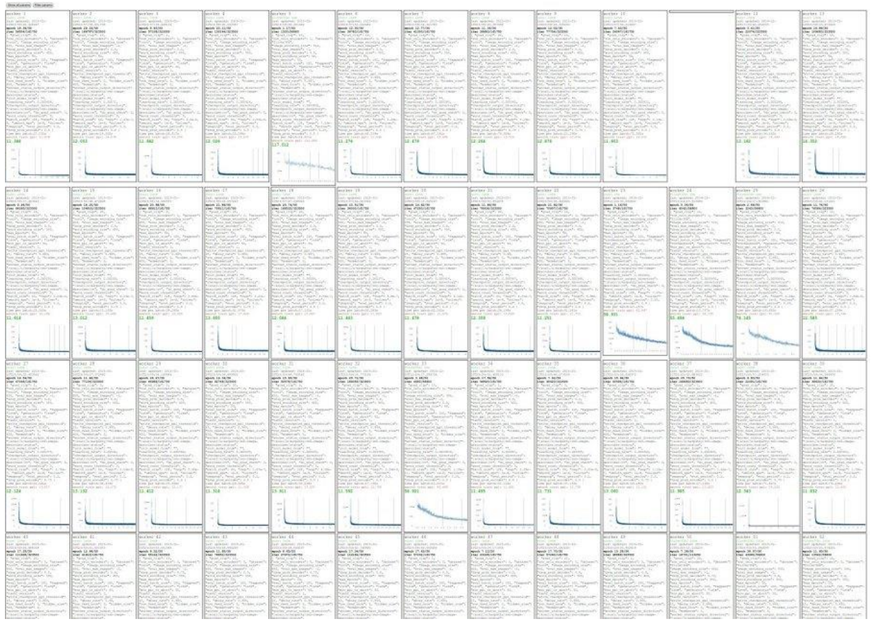


Image credits: Alec Radford

Setting up the network

- Set up the network
- Coarse-fine cross-validation in stages
  - Only a few epochs to get a rough idea
  - Even on a smaller problem
    to speed up the process
  - Longer running time, finer search,…
- Cross-validation strategy
  - Check various parameter settings
  - Always sample parameters
- Check the results, adjust the range
- Hyperparameters to play with:
  - network architecture
  - learning rate, its decay schedule, update type
  - regularization (L2/Dropout strength)…
- Run multiple validations simultaneously
- Actively observe the learning progress

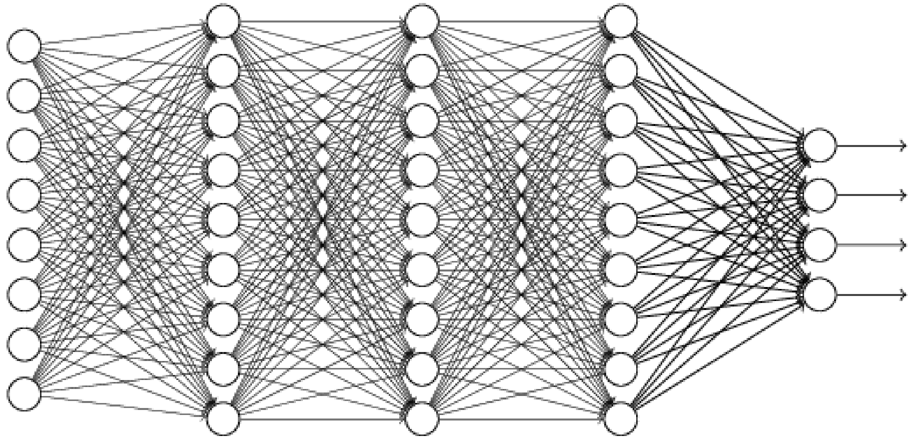




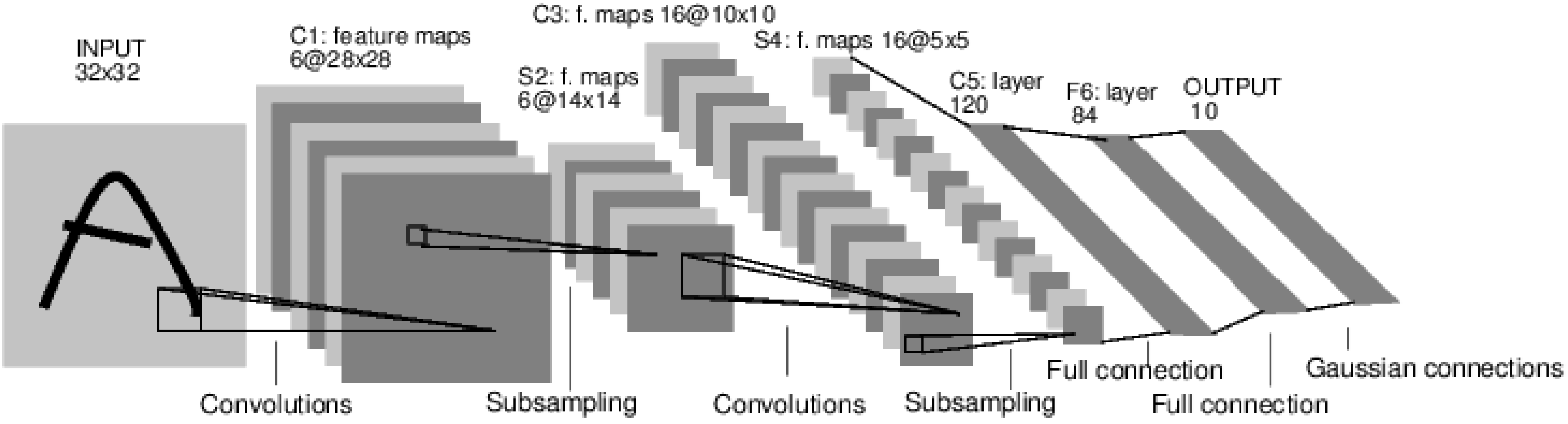
Slide credit: Fei-Fei Li, Andrej Karpathy, Justin Johnson

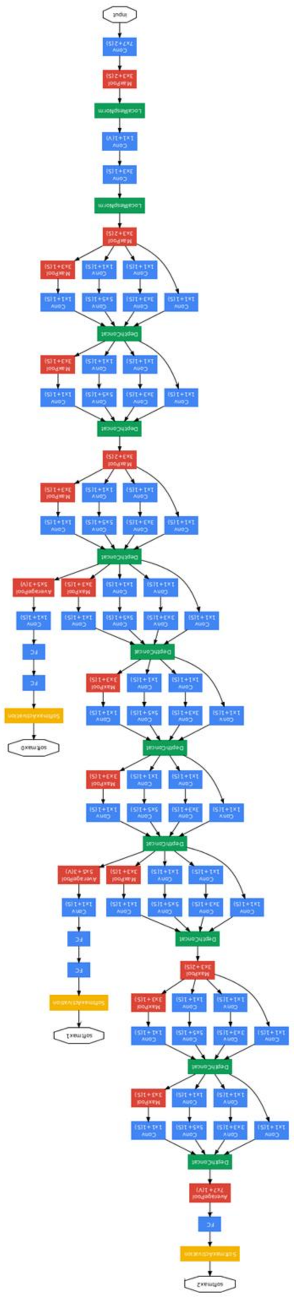
Convolutional neural networks

- From feedforward fully-connected neural networks



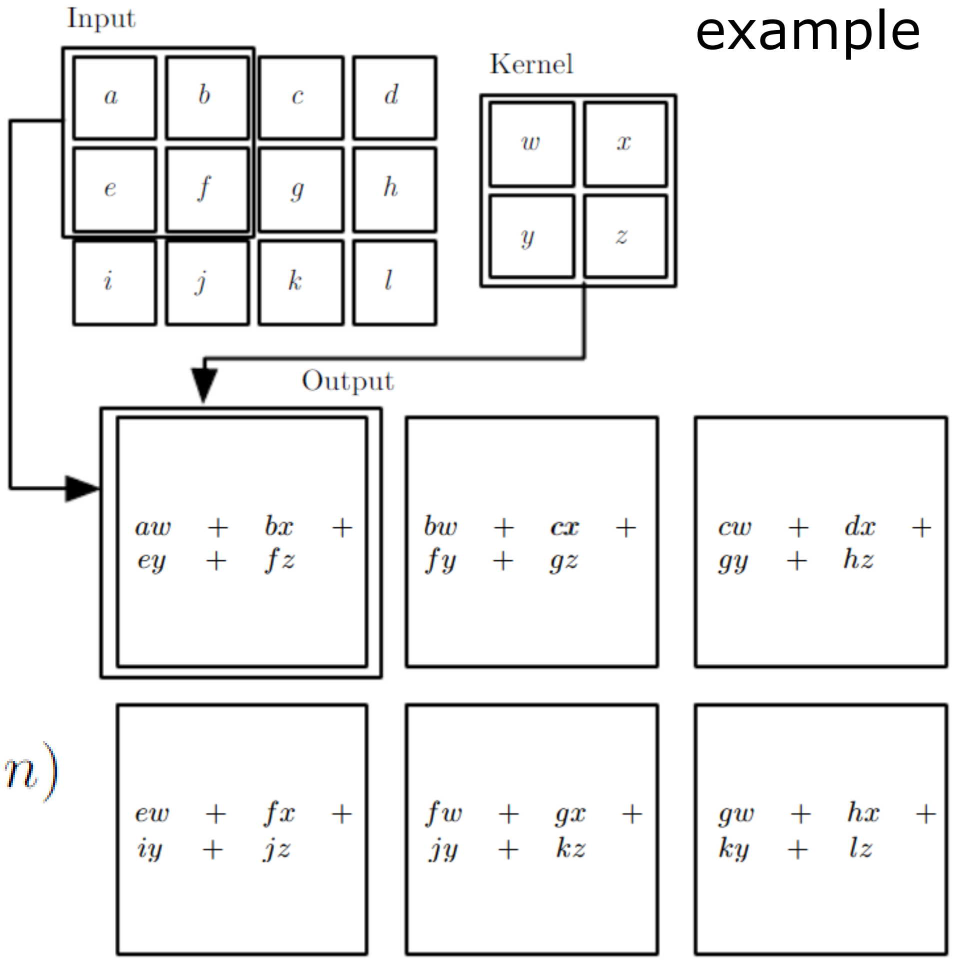
- To convolutional neural networks





Convolution

example



- Convolution operation:

$$s(t) = \int x(a)w(t-a)da \qquad s(t) = (x * w)(t)$$

- Discrete convolution:

$$s(t) = (x * w)(t) = \sum_{a=-\infty}^{\infty} x(a)w(t-a)$$

- Two-dimensional convolution:

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(m,n)K(i-m, j-n)$$

- Convolution is commutative:

$$S(i,j) = (K * I)(i,j) = \sum_m \sum_n I(i-m, j-n)K(m,n)$$

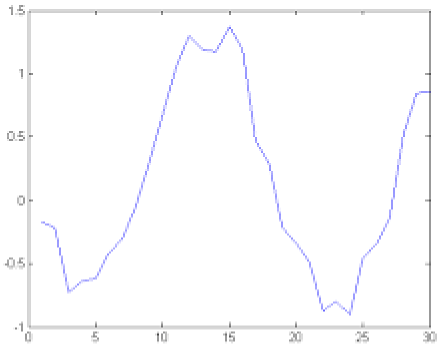
flipped kernel

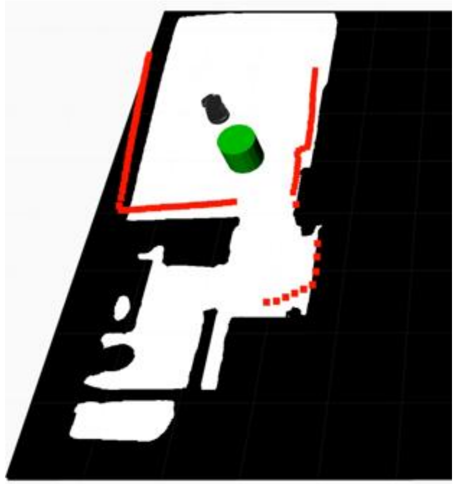
- Cross-correlation:

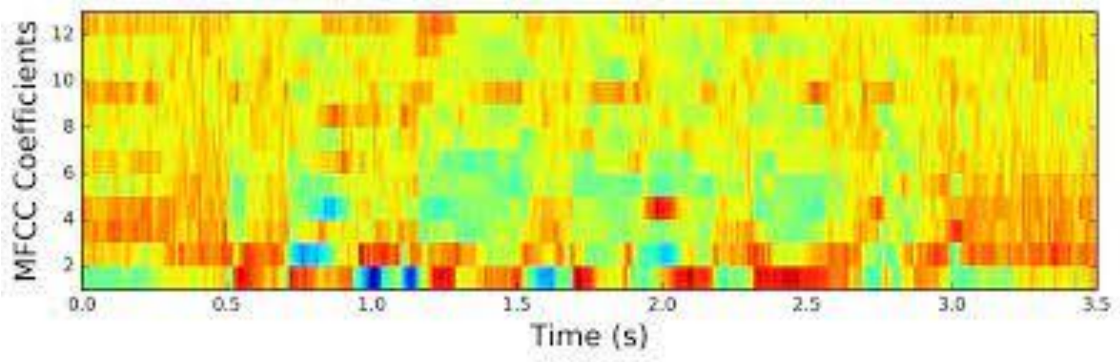
$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(i+m, j+n)K(m,n)$$

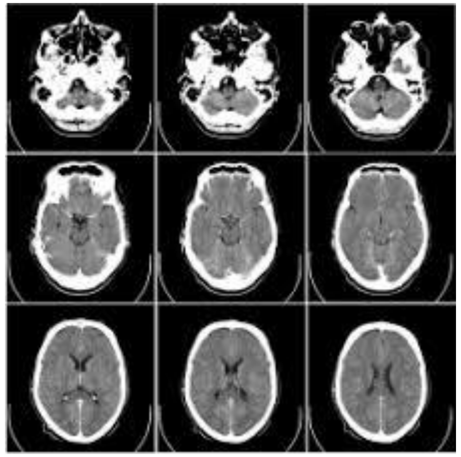
Convolutional neural networks

- Data in vectors, matrices, tensors
- Neigbourhood, spatial arrangement
- 2D: Images,time-fequency representations



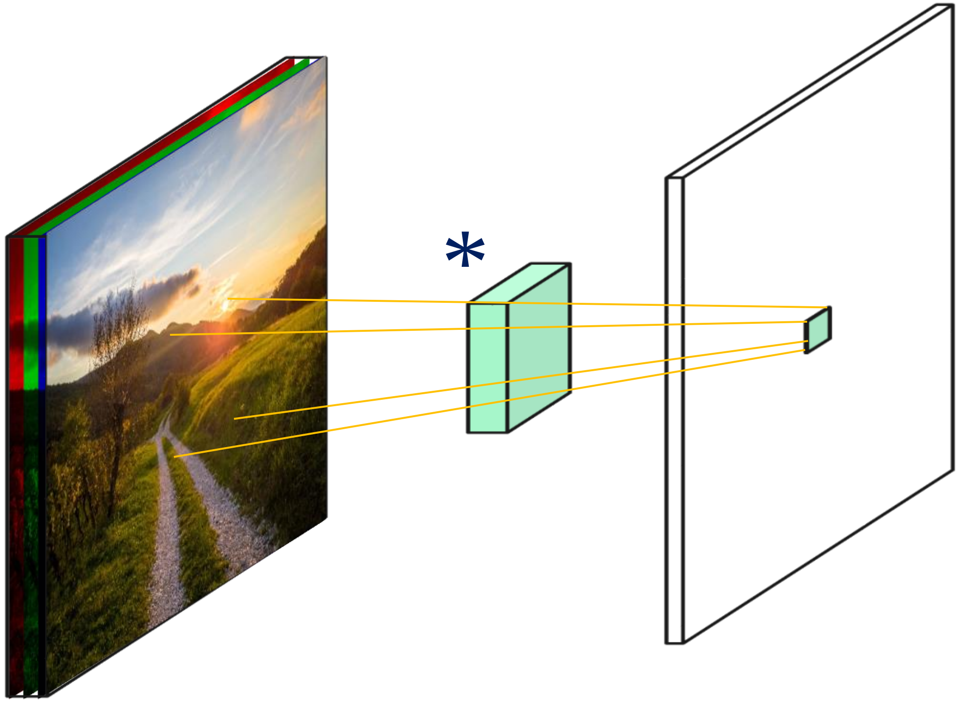




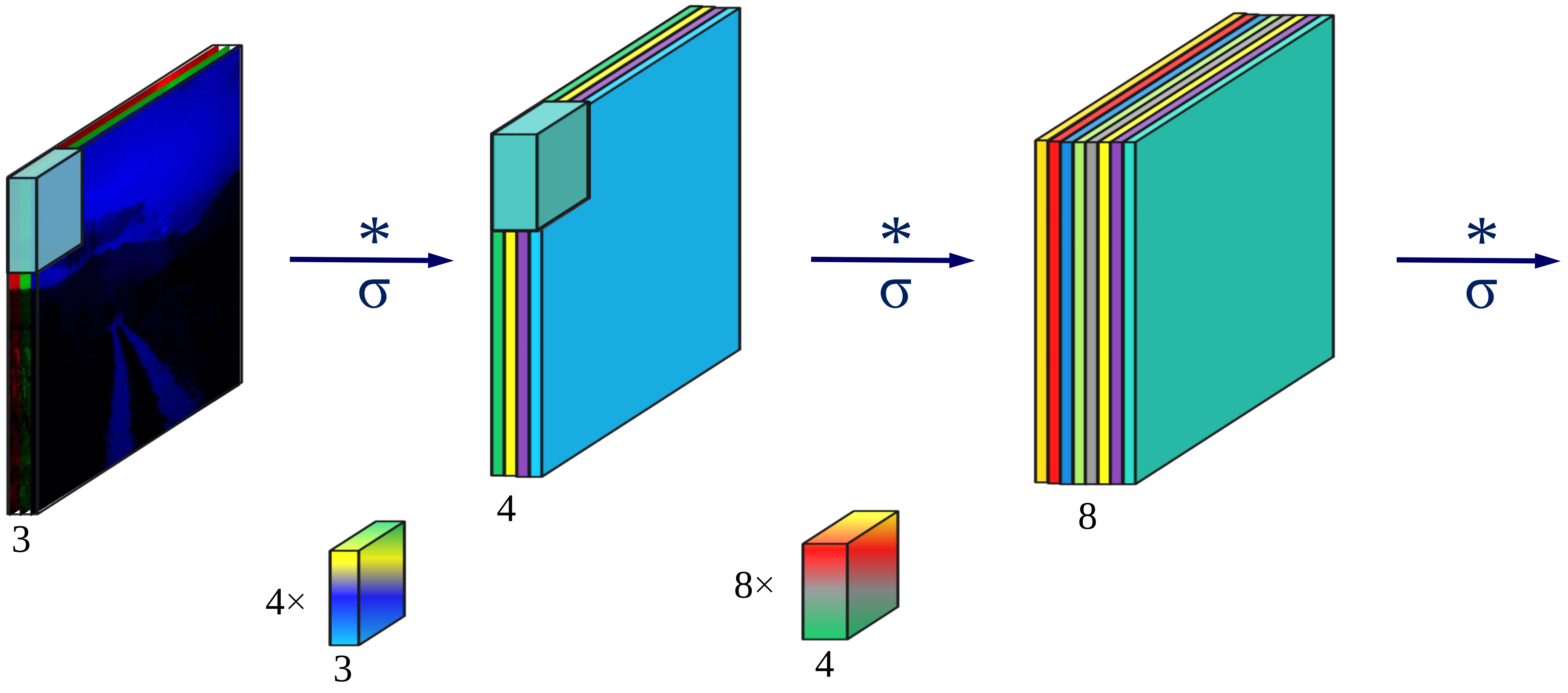


- 1D: sequential signals, text, audio, speech, time series,…
- 3D: volumetric images, video, 3D grids

Convolution layer

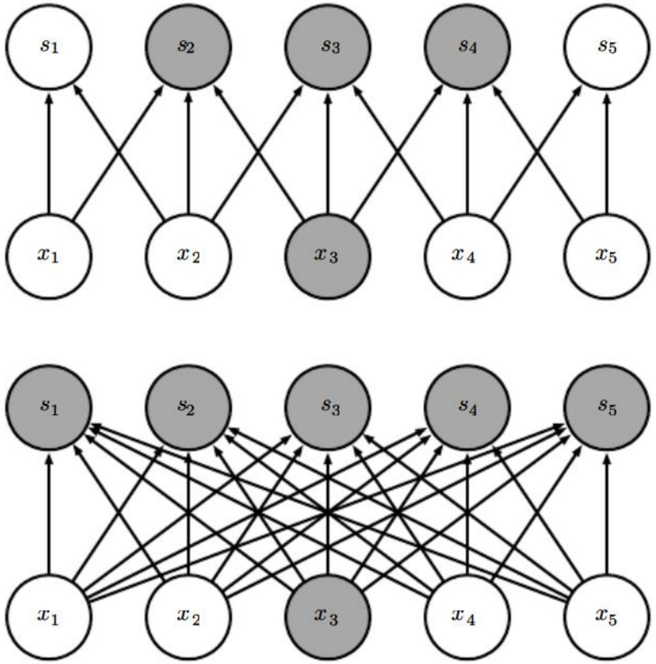


Convolution layer

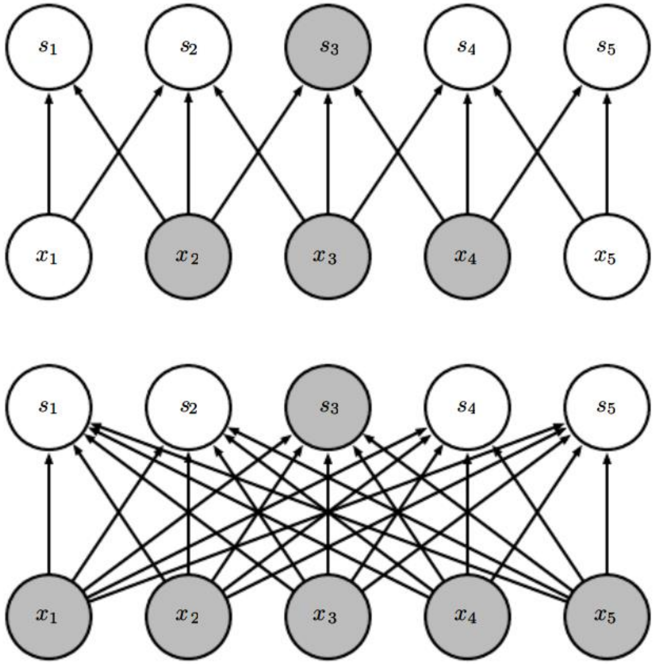


Sparse connectivity

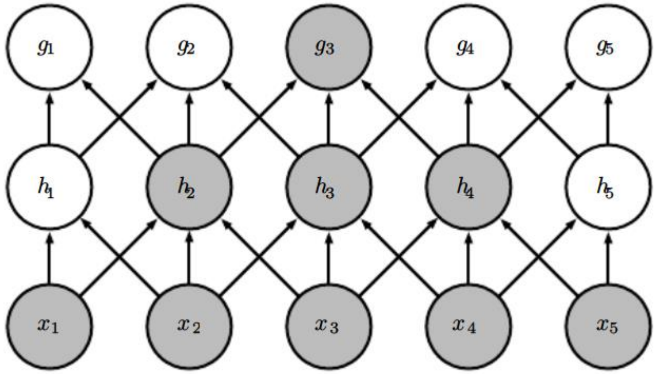
- Local connectivity – neurons are only locally connected (**receptive field**)
  - Reduces memory requirements
  - Improves statistical efficiency
  - Requires fewer operations



from below



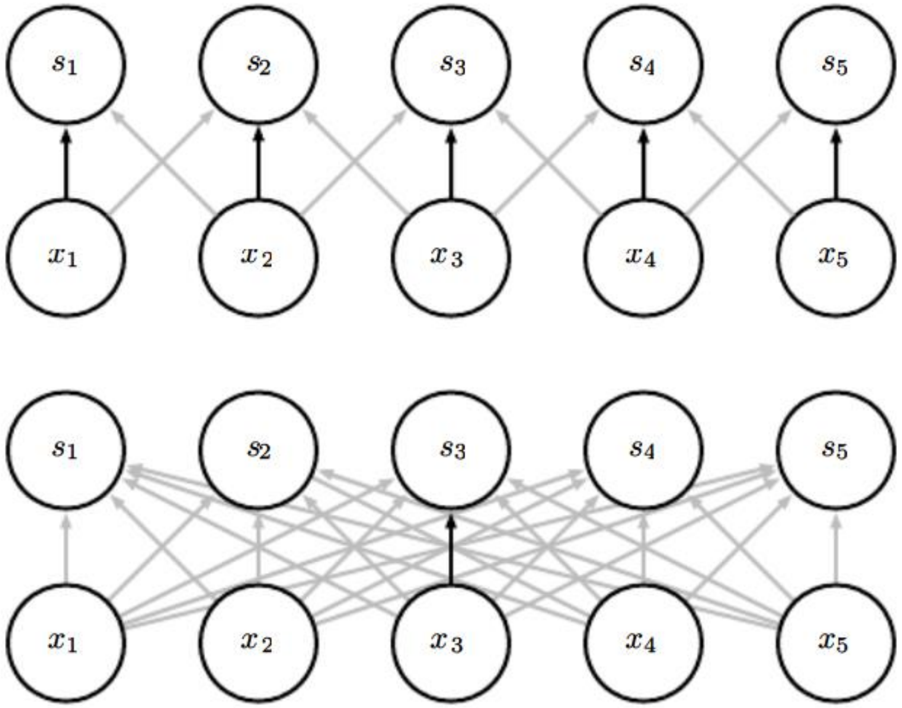
from above



The receptive field of the units in the deeper layers is large
=> Indirect connections!

Parameter sharing

- **Neurons share weights!**
  - Tied weights
- Every element of the kernel is used at every position of the input
- All the neurons at the same level detect the same feature (everywhere in the input)
- Greatly reduces the number of parameters!



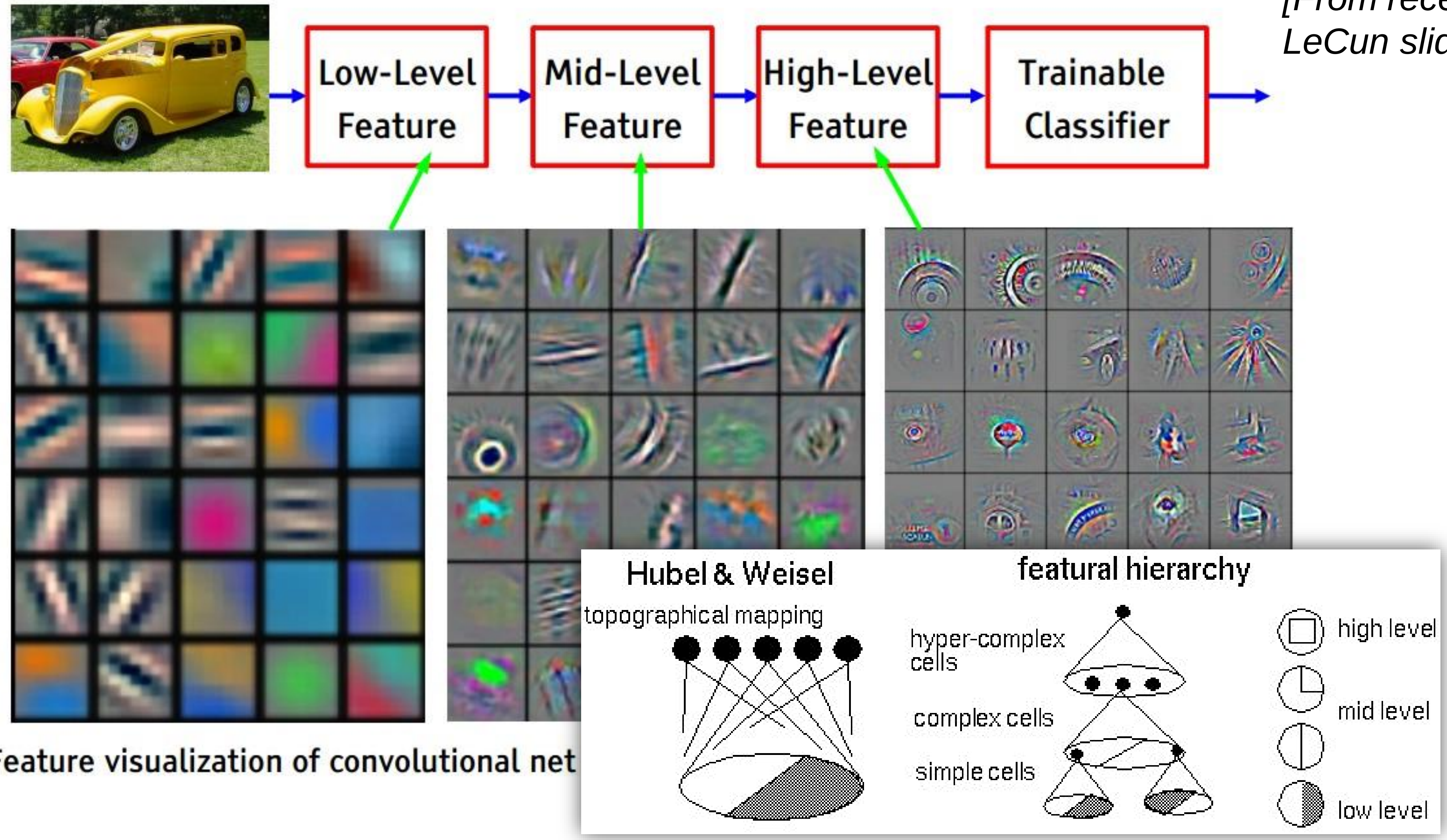
- **Equivariance to translation**
  - Shift, convolution = convolution, shift
  - Object moves => representation moves

- Fully connected network with an infinitively strong prior over its weights
  - Tied weights
  - Weights are zero outside the kernel region

  => learns only local interactions and is equivariant to translations

Convolutional neural network

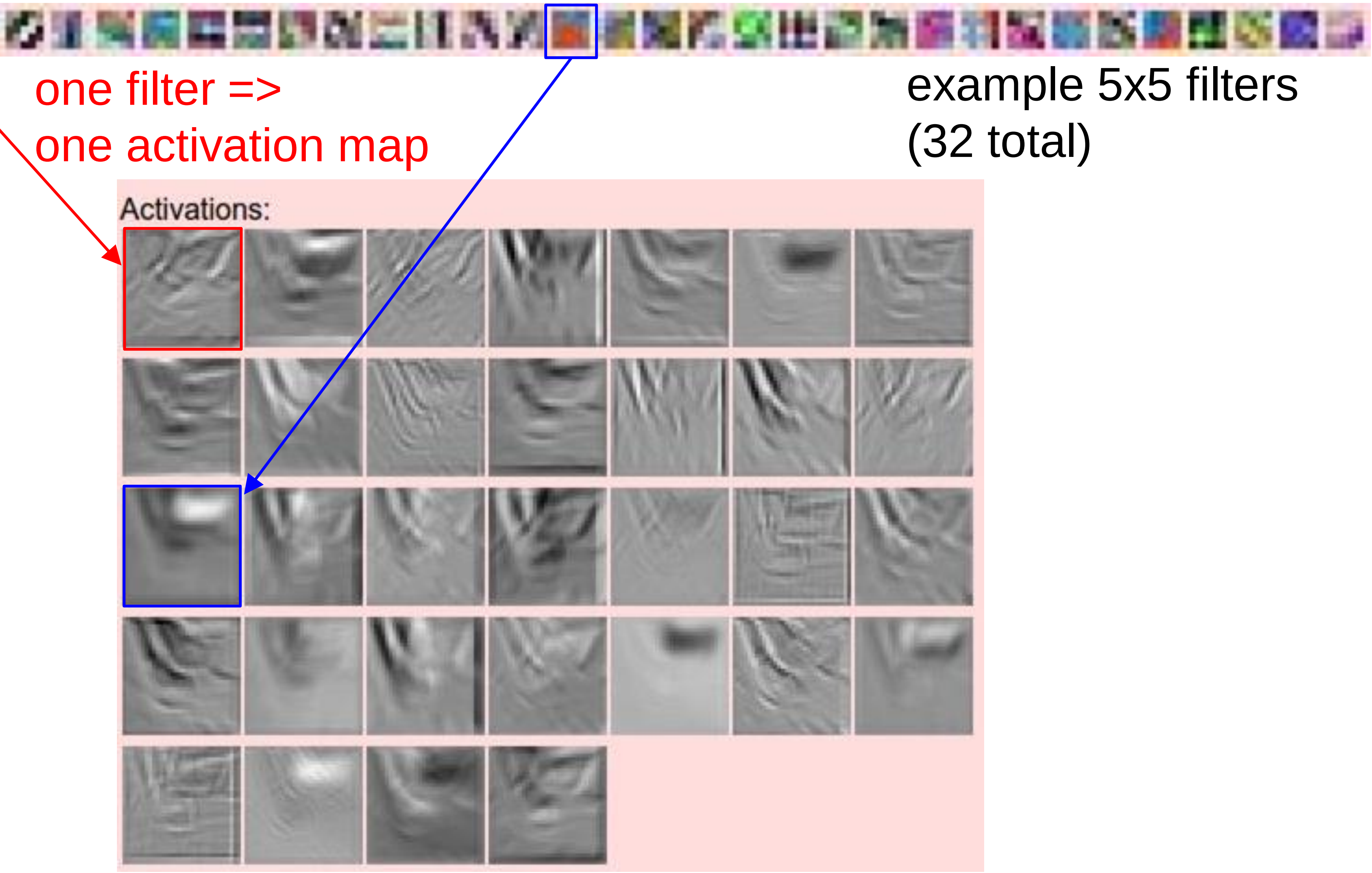
[From recent Yann LeCun slides]



Feature visualization of convolutional net

Slide credit: Fei-Fei Li, Andrej Karpathy, Justin Johnson

Convolutional neural network



one filter =>
one activation map

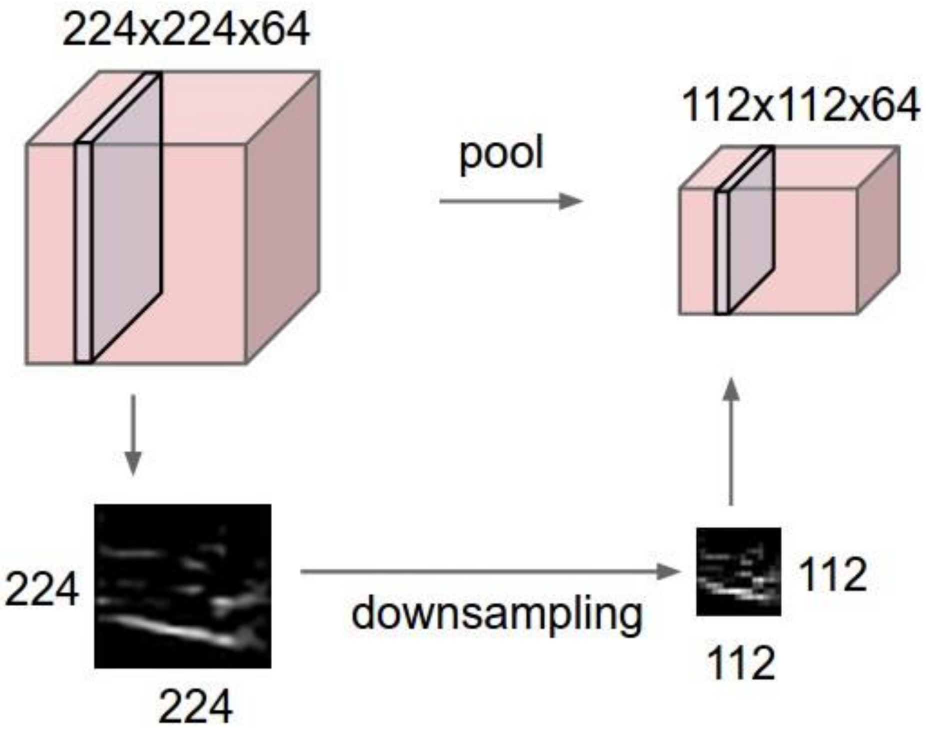
example 5x5 filters
(32 total)

input
image:

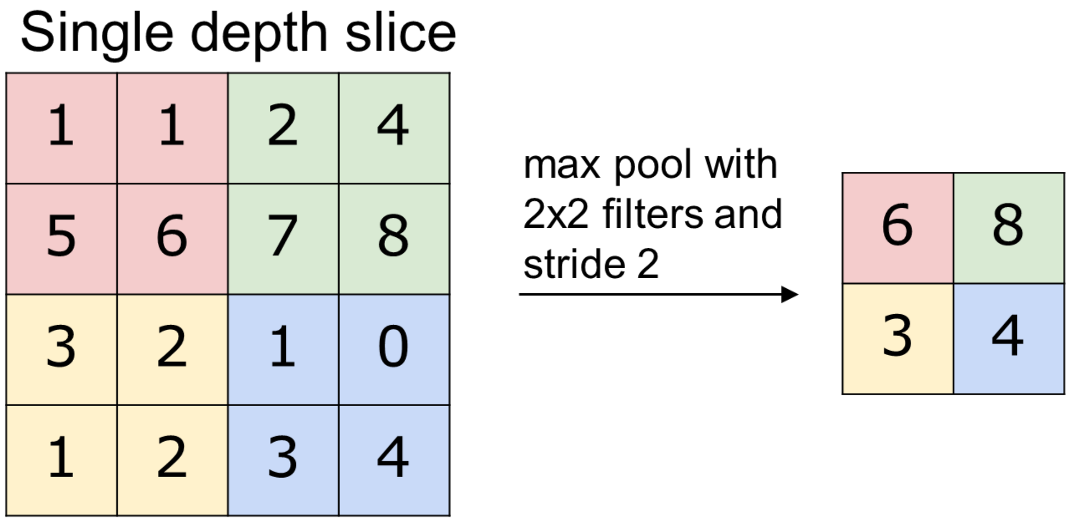
Slide credit: Fei-Fei Li, Andrej Karpathy, Justin Johnson

Pooling layer

- makes the representations smaller and more manageable
- operates over each activation map independently
- downsampling

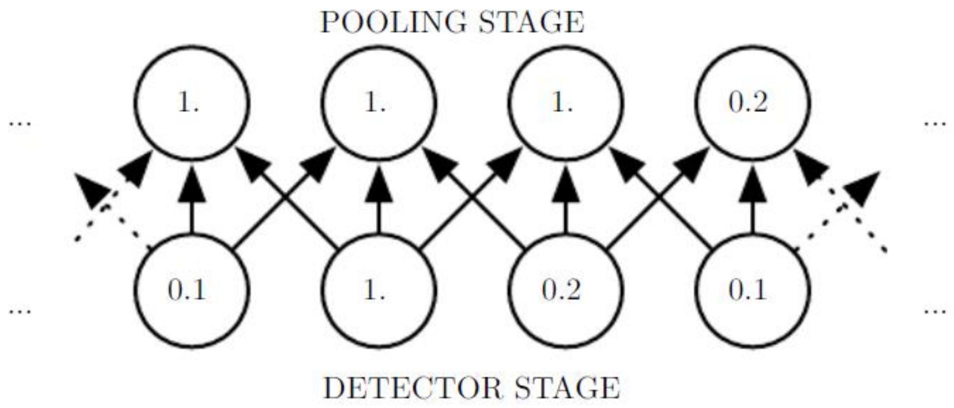


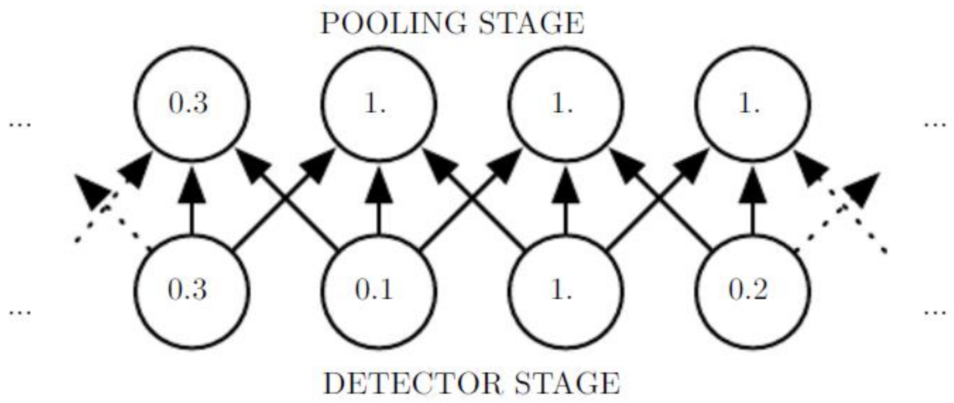
Example: **Max pooling**



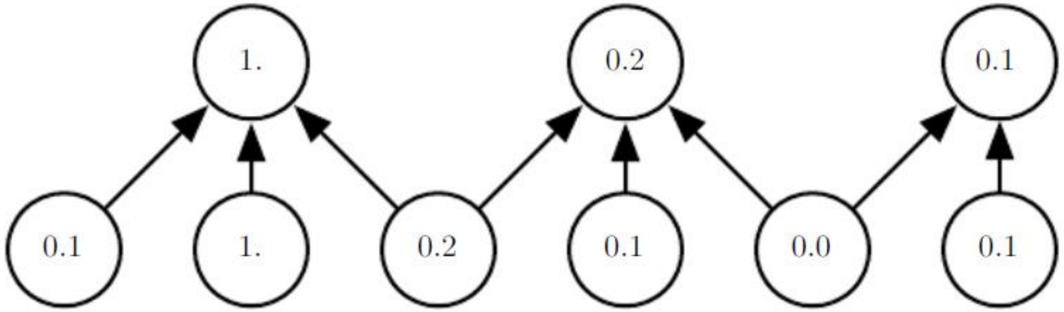
Pooling

- Max pooling introduces translation invariance

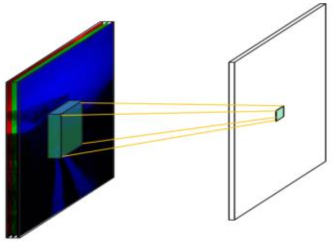
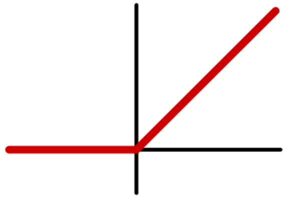
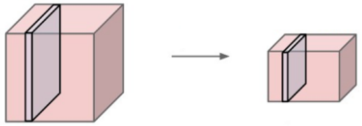
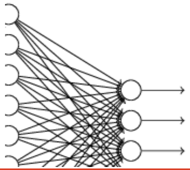


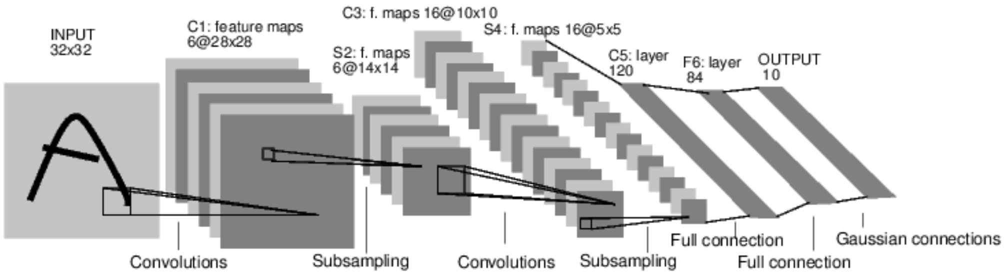


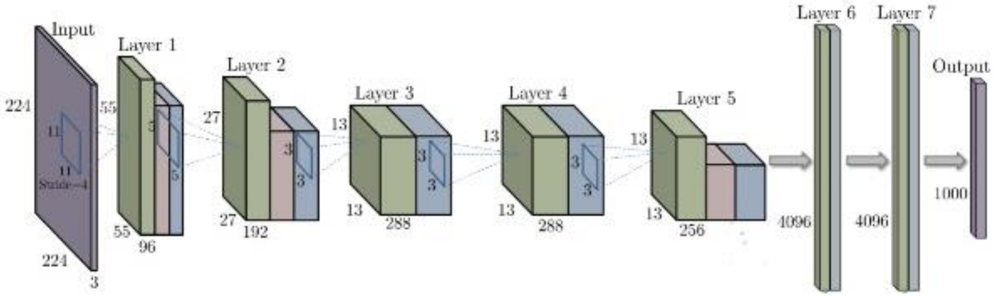
- Pooling with downsampling
  - Reduces the representation size
  - Reduces computational cost
  - Increases statistical efficiency

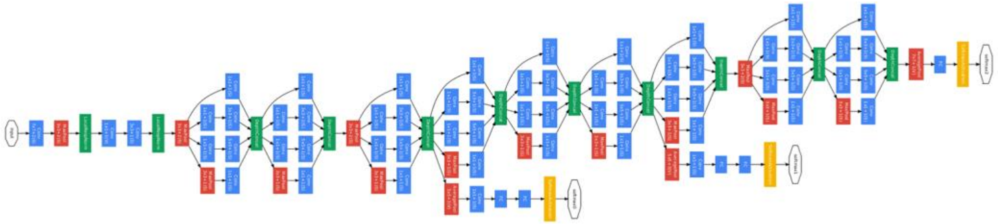


CNN layers

- Layers used to build ConvNets:
  - INPUT:
    raw pixel values
    
  - CONV:
    convolutional layer
    
  - (BN: batch nornalisation)
  - (ReLU:)
    introducing nonlinearity
    
  - POOL:
    downsampling
    
  - FC:
    for computing class scores
    
  - SoftMax

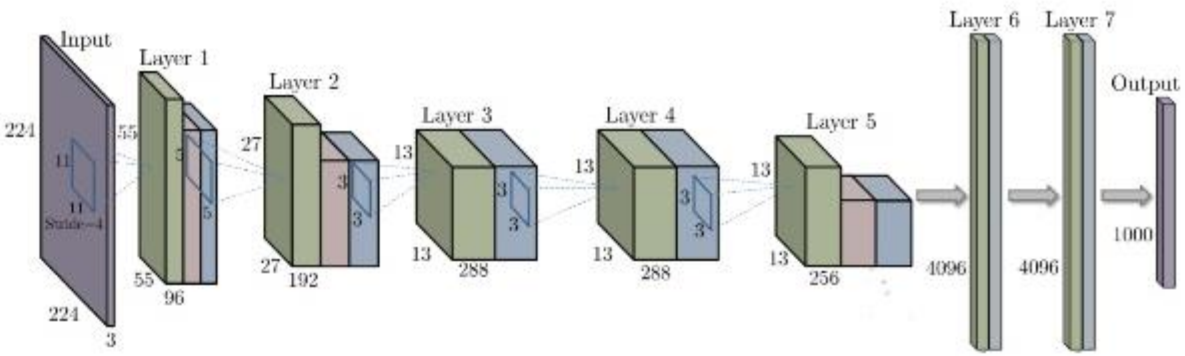




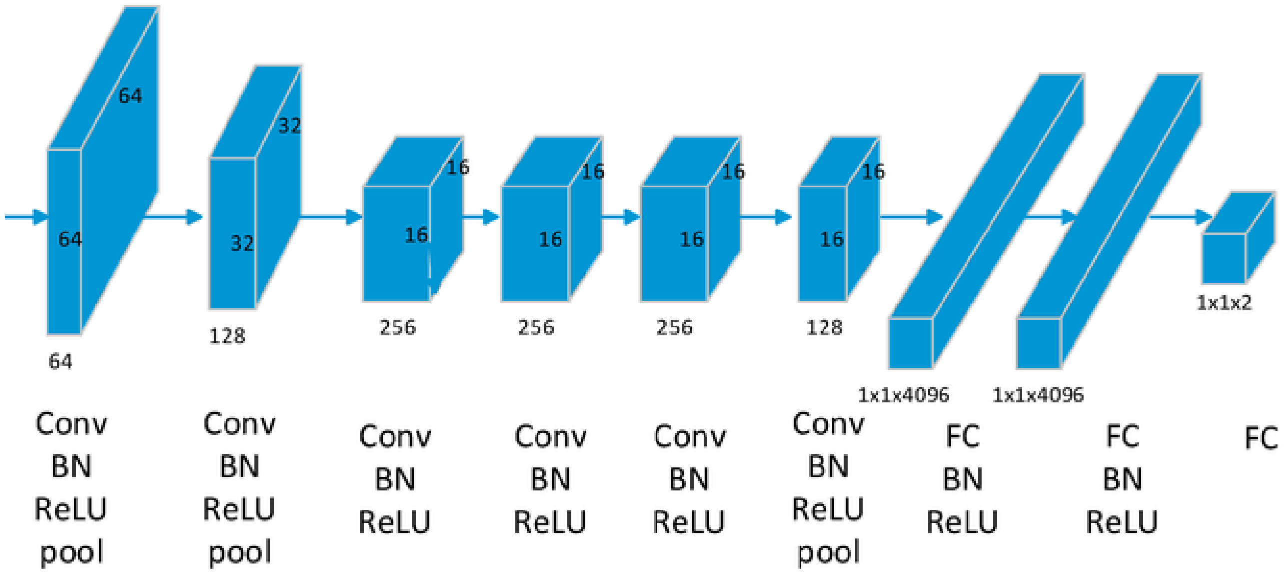


CNN architecture

- Stack the layers in an appropriate order

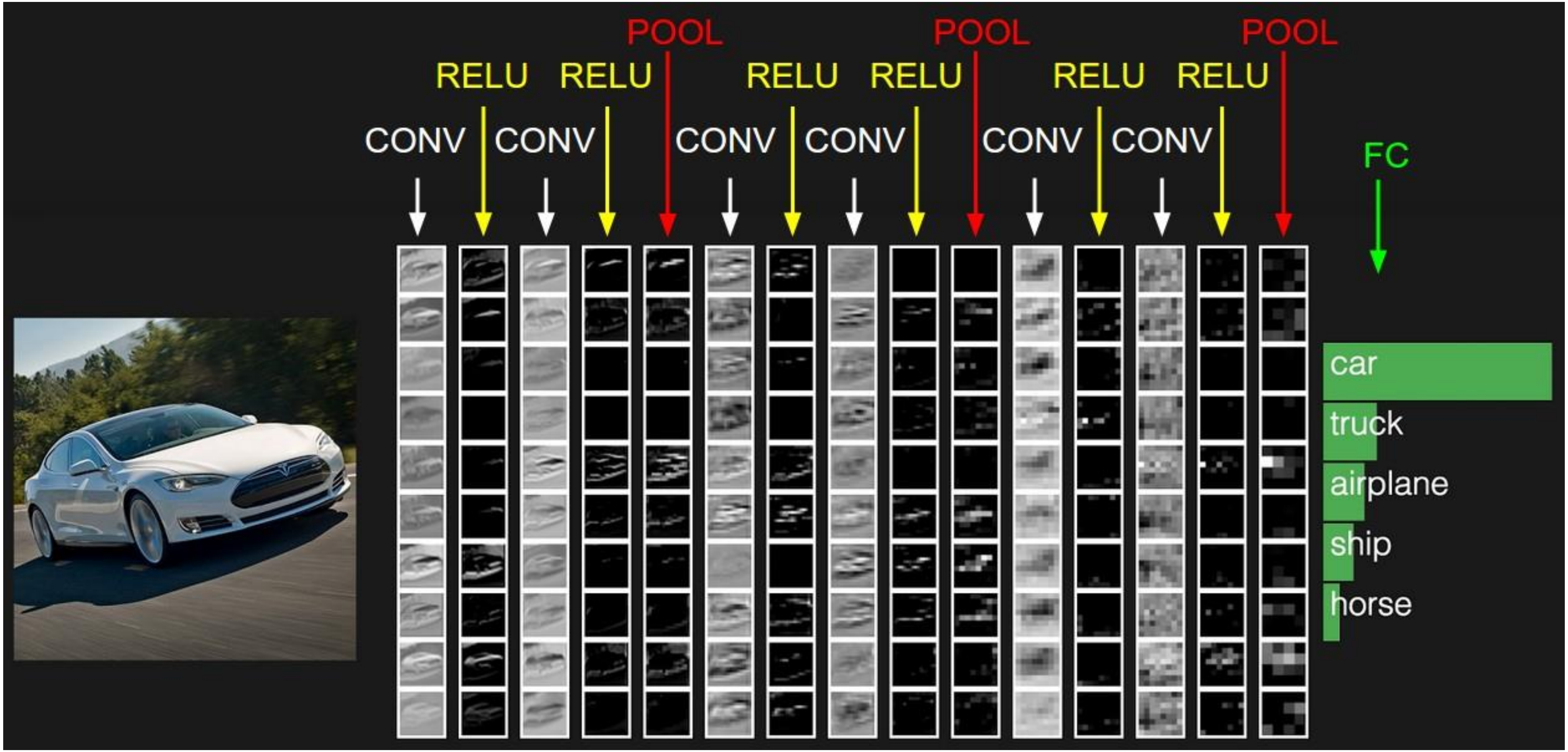


Babenko et. al.



Hu et. al.

CNN architecture



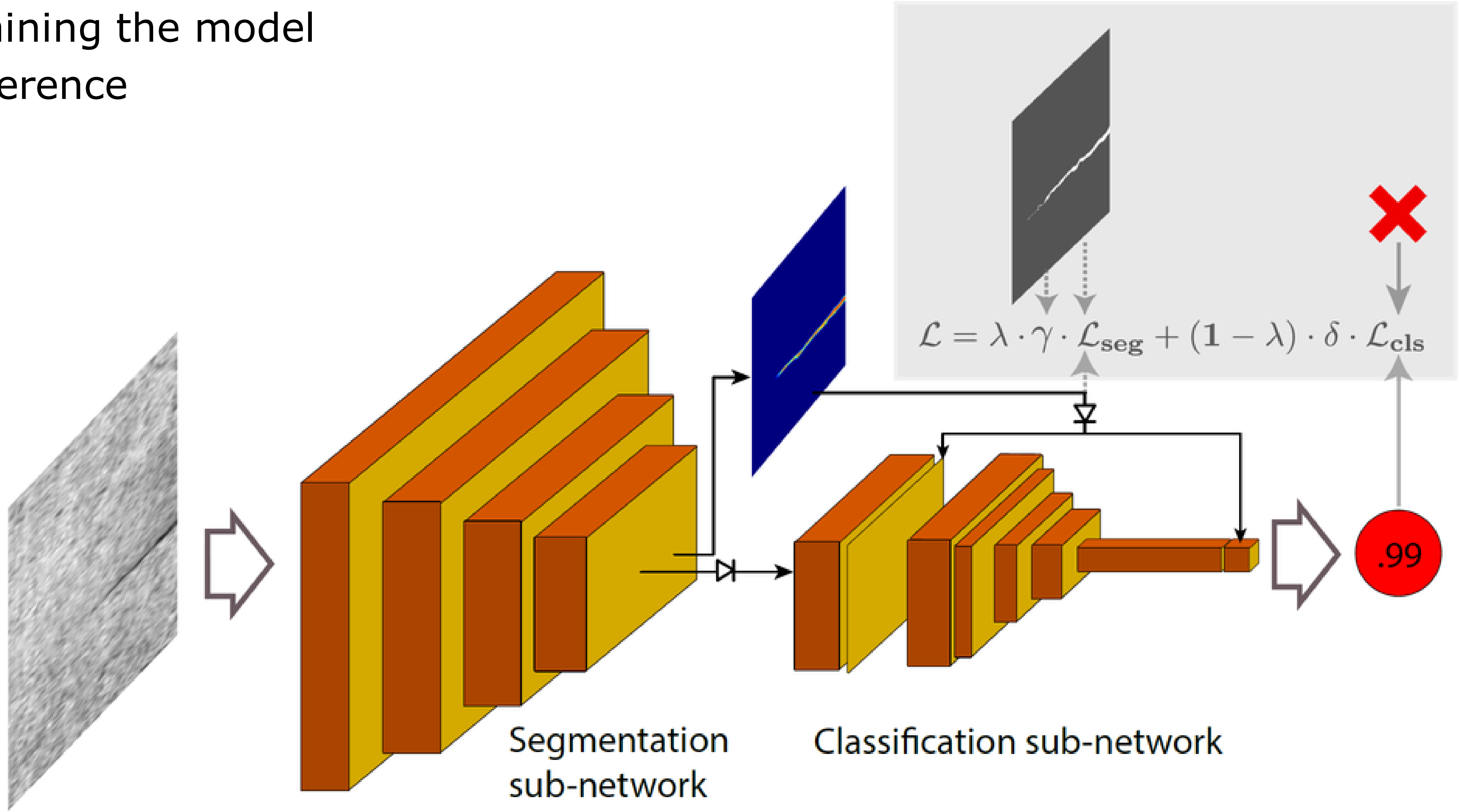
Slide credit: Fei-Fei Li, Andrej Karpathy, Justin Johnson

Typical solution

Korak 1: Zajem podatkov

Network architecture

- Training the model
- Inference



Example implementation in TensorFlow

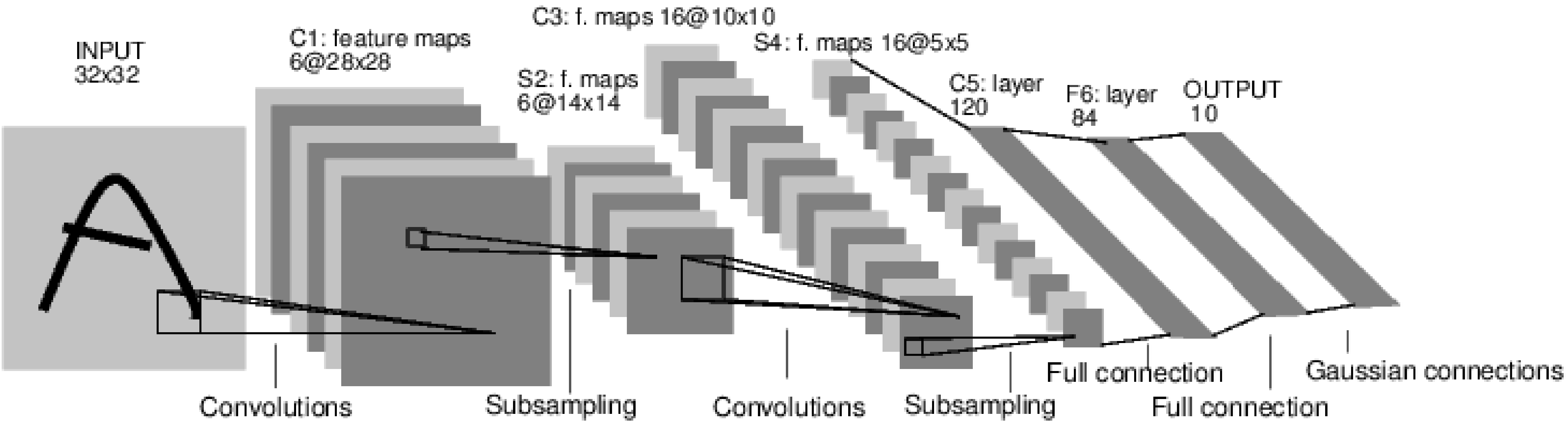
```
with variable_scope.variable_scope(scope, 'SegDecNet', [inputs]) as sc:
    end_points_collection = sc.original_name_scope + '_end_points'
    # Collect outputs for conv2d, max_pool2d
    with arg_scope([layers.conv2d, layers.fully_connected, layers_lib.max_pool2d, layers.batch_norm],
                   outputs_collections=end_points_collection):
        # Apply specific parameters to all conv2d layers (to use batch norm and relu - relu is by default)
        with arg_scope([layers.conv2d, layers.fully_connected],
                       weights_initializer= lambda shape,dtype=tf.float32, partition_info=None: tf.random_normal(shape, mean=0,stddev=0.01, dtype=dtype),
                       biases_initializer=None,
                       normalizer_fn=layers.batch_norm,
                       normalizer_params={'center': True,'scale': True, 'decay': self.BATCHNORM_MOVING_AVERAGE_DECAY,'epsilon': 0.001}):

            net = layers_lib.repeat(inputs, 2, layers.conv2d, 32, [5, 5], scope='conv1')
            net = layers_lib.max_pool2d(net, [2, 2], scope='pool1')
            net = layers_lib.repeat(net, 3, layers.conv2d, 64, [5, 5], scope='conv2')
            net = layers_lib.max_pool2d(net, [2, 2], scope='pool2')
            net = layers_lib.repeat(net, 4, layers.conv2d, 64, [5, 5], scope='conv3')
            net = layers_lib.max_pool2d(net, [2, 2], scope='pool3')
            net = layers.conv2d(net, 1024, [15, 15], padding='SAME', scope='conv4')
            net_prob_mat = layers.conv2d(net, 1, [1, 1], scope='conv5', activation_fn=None)

            with tf.name_scope('decision'):
               net_prob_mat = tf.nn.relu(net_prob_mat)
               decision_net = tf.concat([net, net_prob_mat],axis=3)
               decision_net = layers_lib.max_pool2d(decision_net, [2, 2], scope='decision/pool4')
               decision_net = layers.conv2d(decision_net, 8, [5, 5], padding='SAME', scope='decision/conv6')
               decision_net = layers_lib.max_pool2d(decision_net, [2, 2], scope='decision/pool5')
               decision_net = layers.conv2d(decision_net, 16, [5, 5], padding='SAME', scope='decision/conv7')
               decision_net = layers_lib.max_pool2d(decision_net, [2, 2], scope='decision/pool6')
               decision_net = layers.conv2d(decision_net, 32, [5, 5], scope='decision/conv8')

               with tf.name_scope('decision/global_avg_pool'):
                   avg_decision_net = keras.layers.GlobalAveragePooling2D()(decision_net)
               with tf.name_scope('decision/global_max_pool'):
                   max_decision_net = keras.layers.GlobalMaxPooling2D()(decision_net)
               with tf.name_scope('decision/global_avg_pool'):
                   avg_prob_net = keras.layers.GlobalAveragePooling2D()(net_prob_mat)
               with tf.name_scope('decision/global_max_pool'):
                   max_prob_net = keras.layers.GlobalMaxPooling2D()(net_prob_mat)

               # adding avg_prob_net and max_prob_net may not be needed, but it doesen't hurt
               decision_net = tf.concat([avg_decision_net, max_decision_net, avg_prob_net, max_prob_net], axis=1)
               decision_net = layers.fully_connected(decision_net, 1, scope='decision/FC9',normalizer_fn=None,
                                                     biases_initializer=tf.constant_initializer(0), activation_fn=None)
return decision_net
```

Segmentation network

Classification network

Case study – LeNet-5

[LeCun et al., 1998]



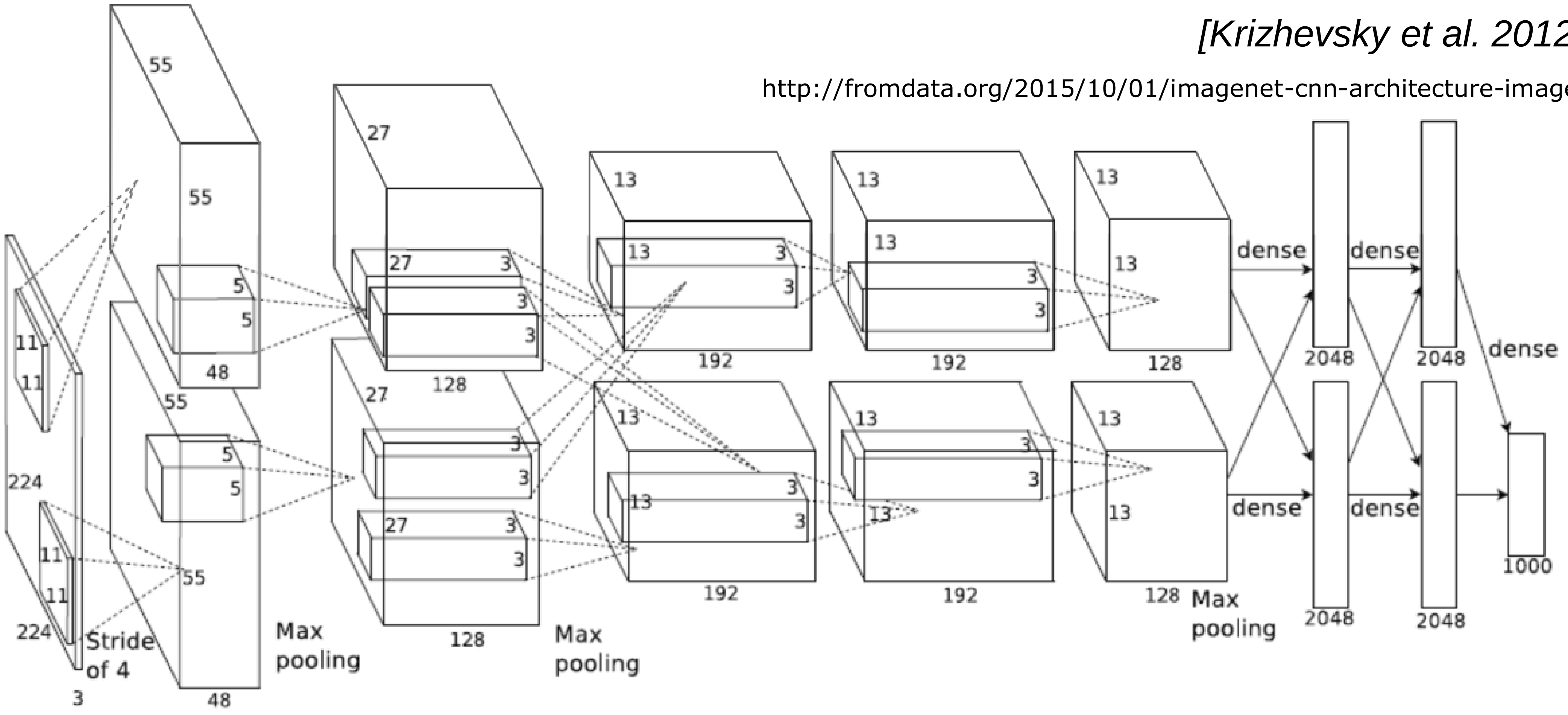
Conv filters were 5x5, applied at stride 1
Subsampling (Pooling) layers were 2x2 applied at stride 2
i.e. architecture is [CONV-POOL-CONV-POOL-CONV-FC]

Slide credit: Fei-Fei Li, Andrej Karpathy, Justin Johnson

Case study - AlexNet

[Krizhevsky et al. 2012]

http://fromdata.org/2015/10/01/imagenet-cnn-architecture-image/

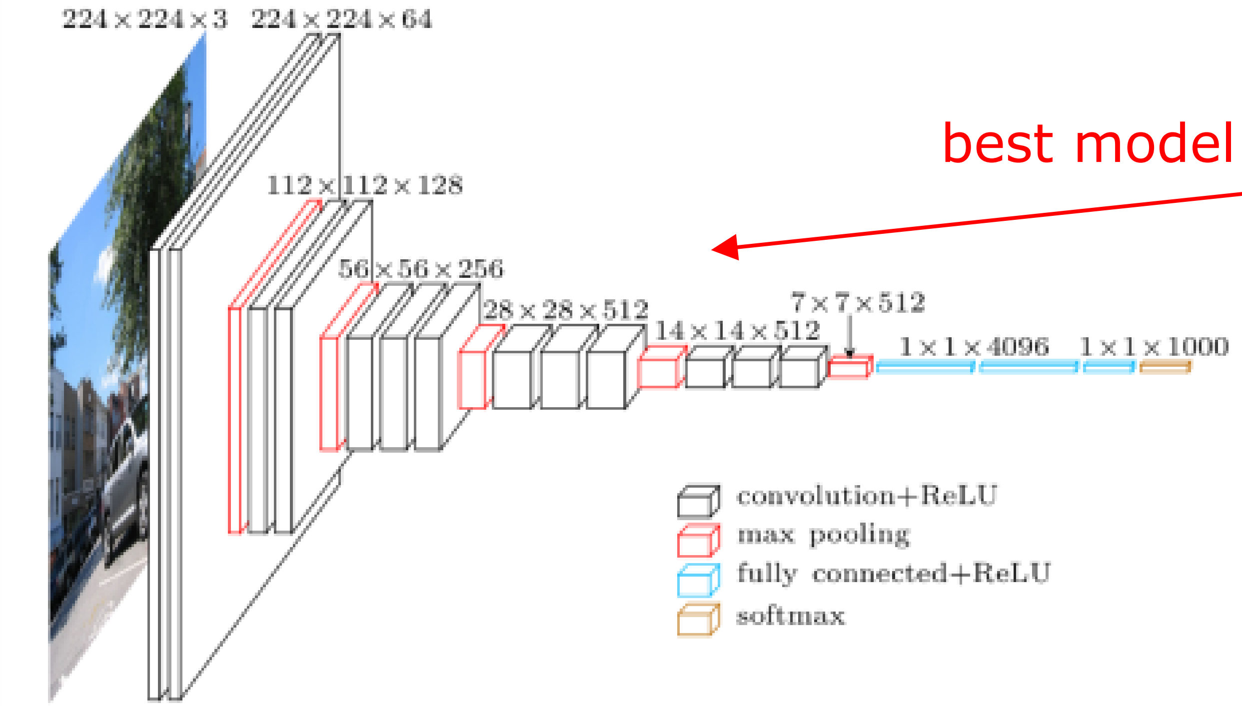


INPUT CONV1 POOL1 NORM1 CONV2 POOL2 NORM2 CONV3 CONV4 CONV5 POOL3 FC6 FC7 FC8

Slide credit: Fei-Fei Li, Andrej Karpathy, Justin Johnson

Case studay - VGGNet

[Simonyan and Zisserman, 2014]



best model

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Only 3x3 CONV stride 1, pad 1
and 2x2 MAX POOL stride 2

11.2% top 5 error in ILSVRC 2013
-> 7.3% top 5 error

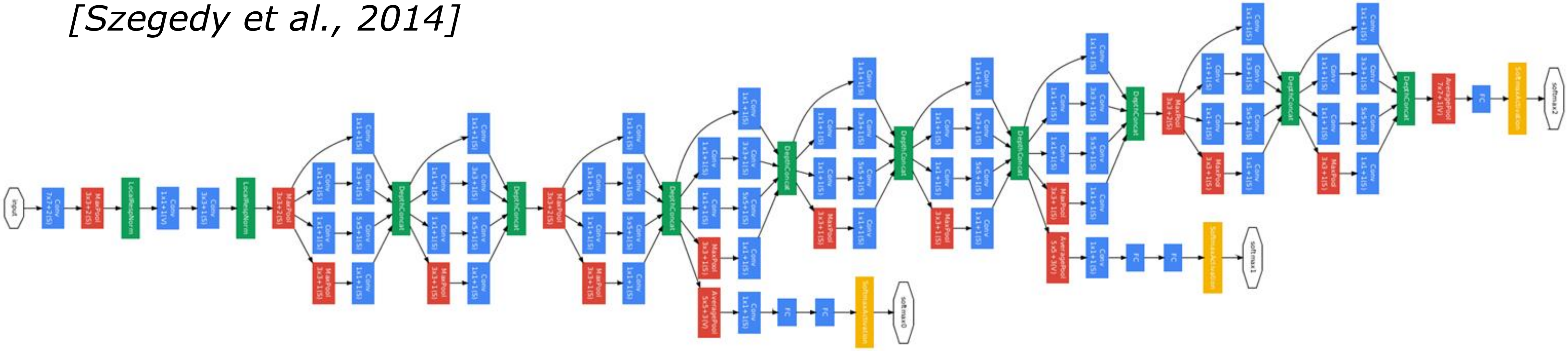
Table 2: **Number of parameters** (in millions).

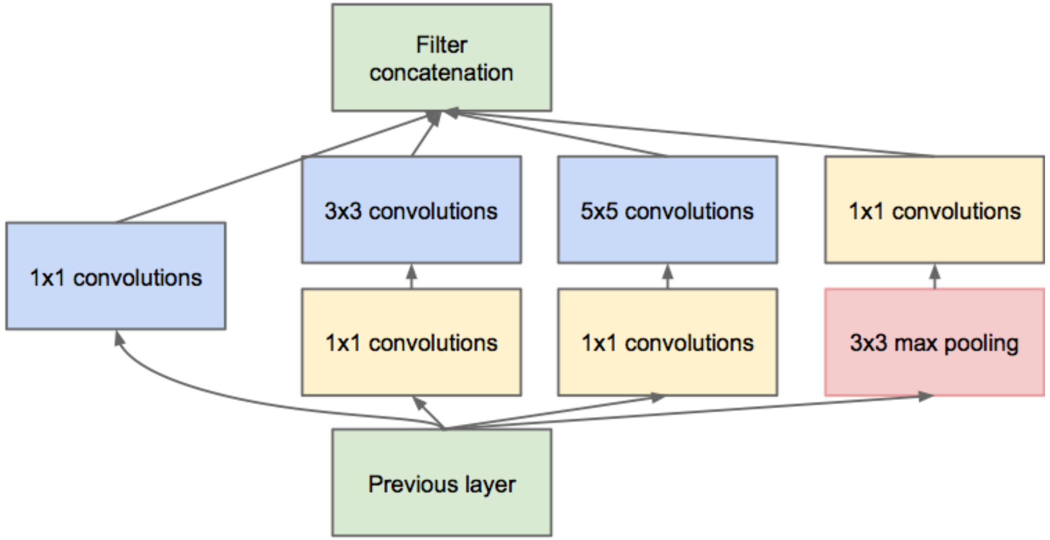
Network	A,A-LRN	B	C	D	E
Number of parameters	133	133	134	138	144

Slide credit: Fei-Fei Li, Andrej Karpathy, Justin Johnson

Case study - GoogLeNet

[Szegedy et al., 2014]

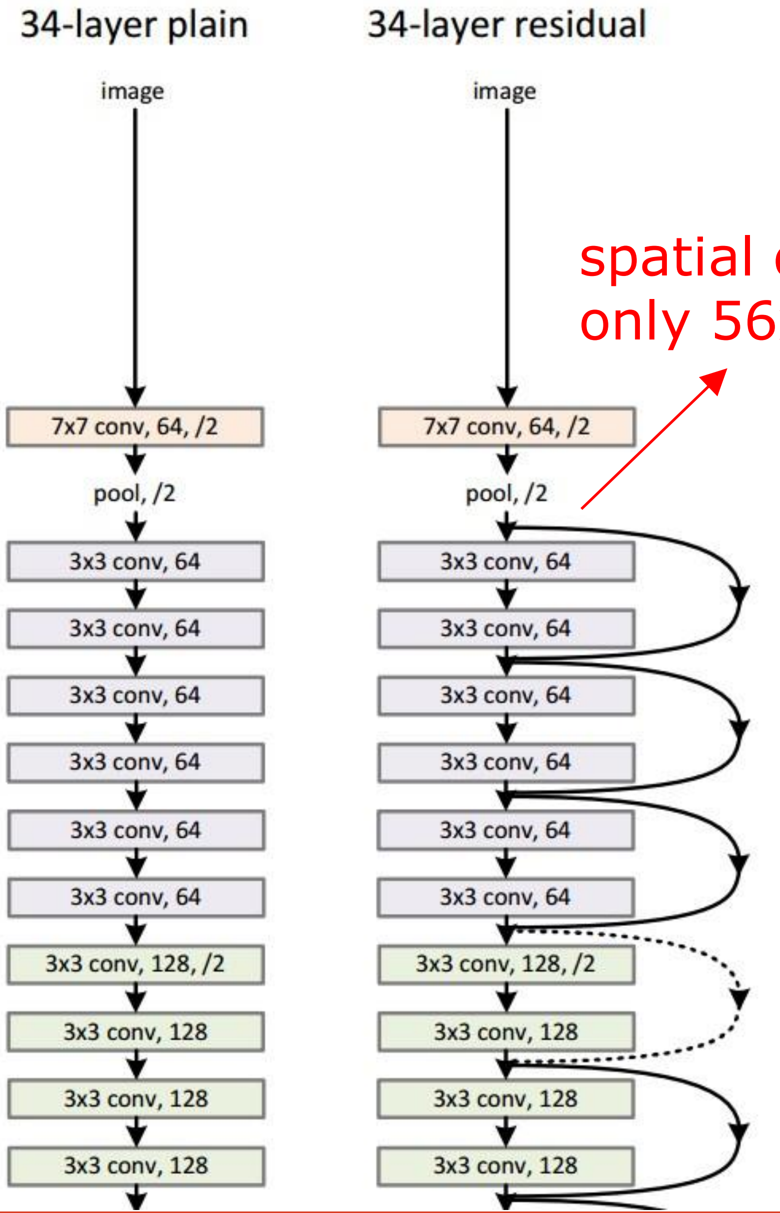




Inception module

ILSVRC 2014 winner (6.7% top 5 error)

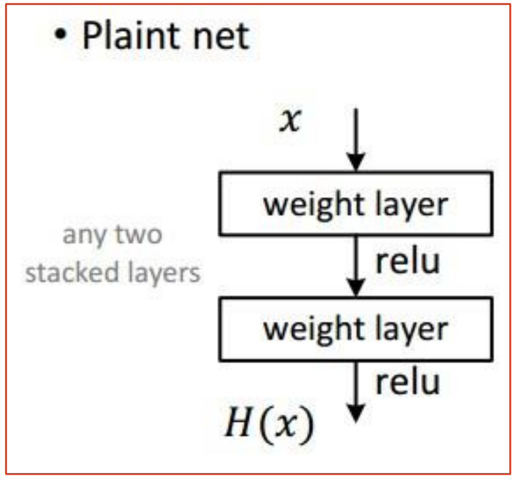
Case study - ResNet

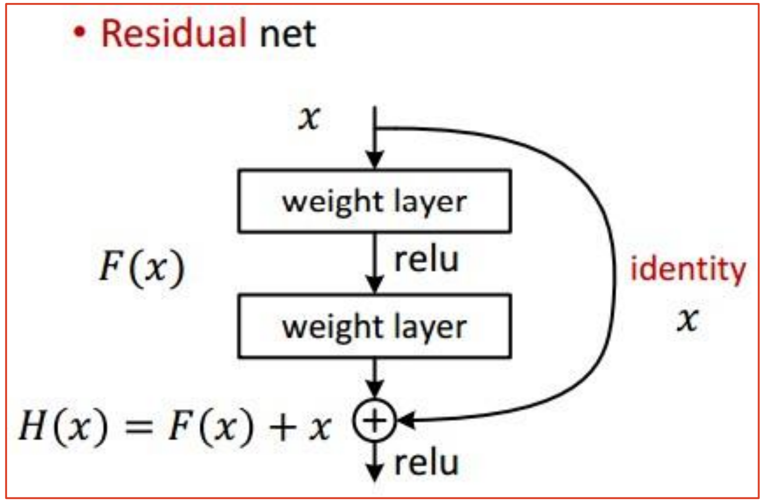


spatial dim.
only 56x56!

- Batch Normalization after every CONV layer
- Xavier/2 initialization from He et al.
- SGD + Momentum (0.9)
- Learning rate: 0.1, divided by 10 when validation error plateaus
- Mini-batch size 256
- Weight decay of 1e-5
- No dropout used

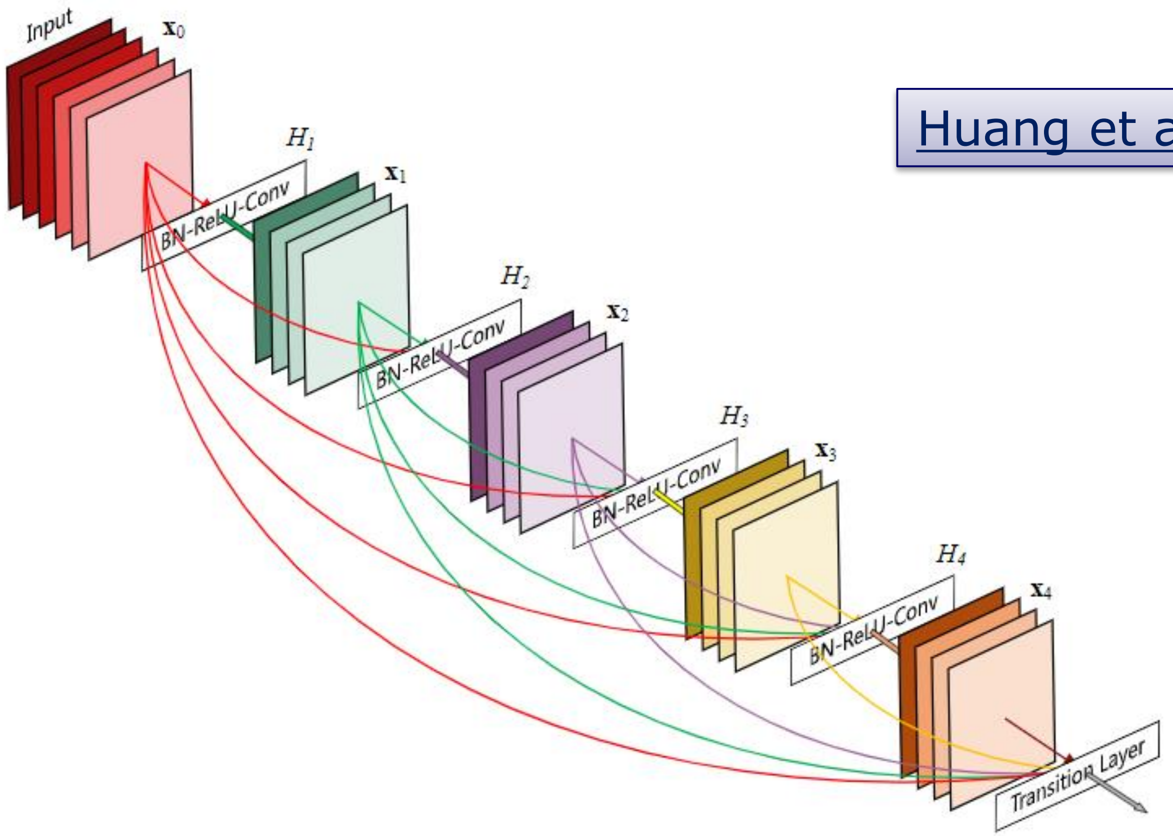
ILSVRC 2015 winner
(3.6% top 5 error)



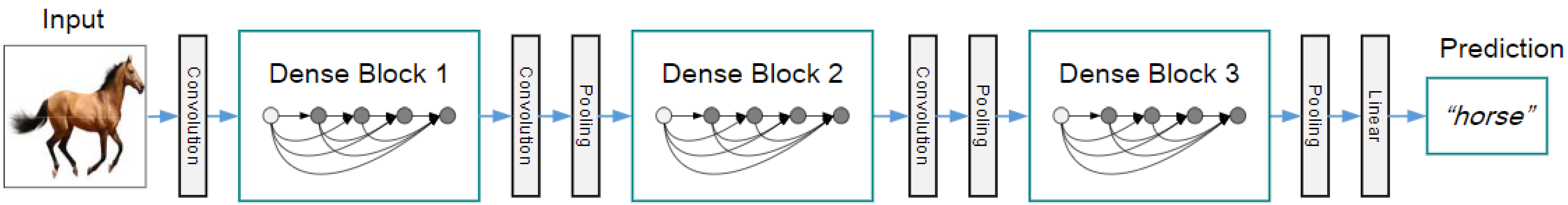


DenseNet

- Densely Connected Convolutional Networks
  - Every layer connected to every other layer in a feed-forward fashion
  - Dense connectivity
  - Model compactness
  - Strong gradient flow
  - Implicit deep supervision
  - Feature reuse



Huang et al. 2017

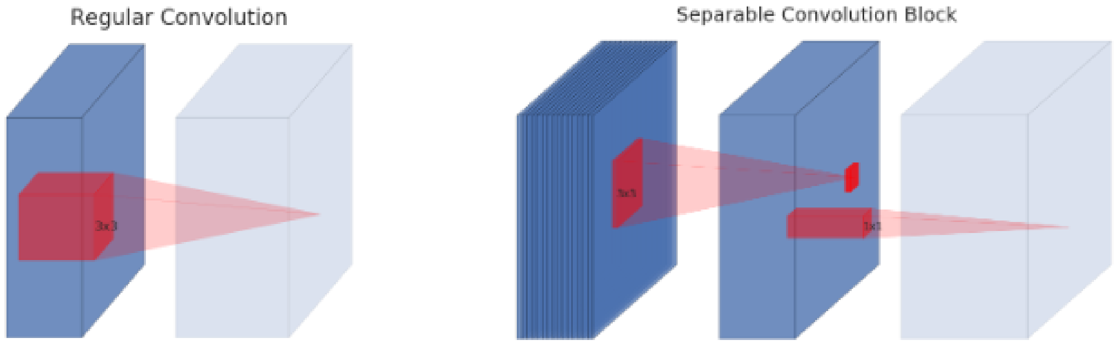


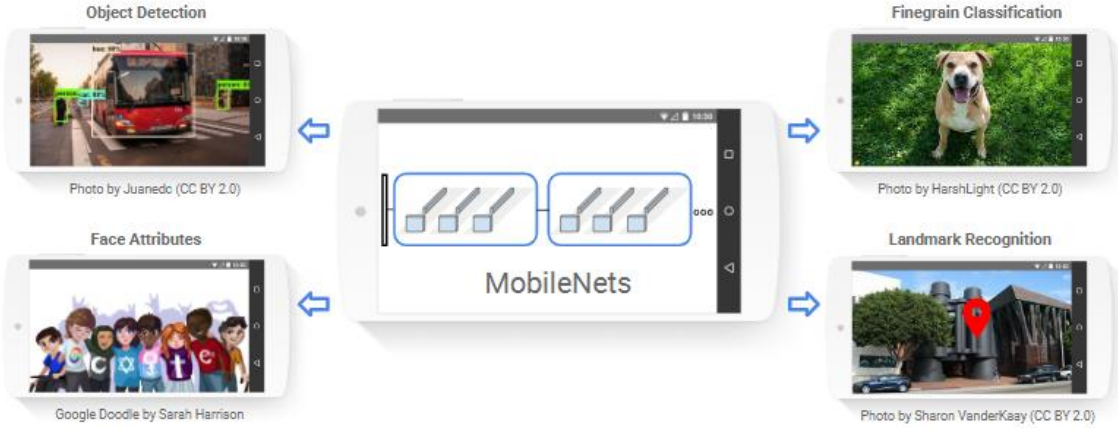
MobileNets

- Efficient Convolutional Neural Networks for Mobile Applications
- Efficient models for mobile and embedded vision applications

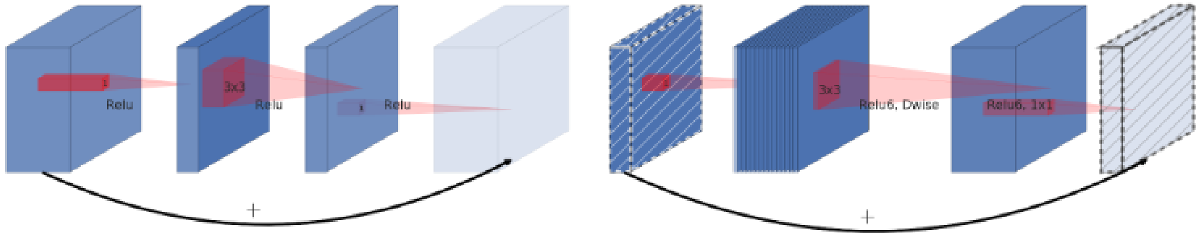
Howard et al. 2017

- Depthwise separable convolution:
  - Depthwise convolution
  - Pointwise (1x1) convolution





- MobileNetV2: Inverted Residuals and Linear Bottlenecks



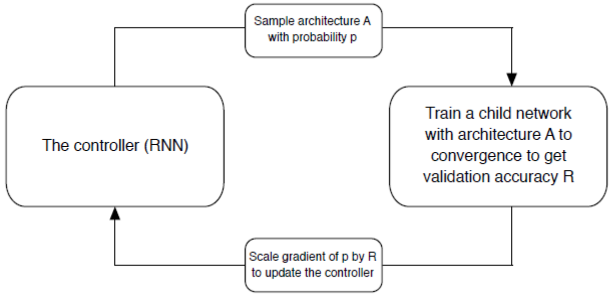
Sandler et al. 2018

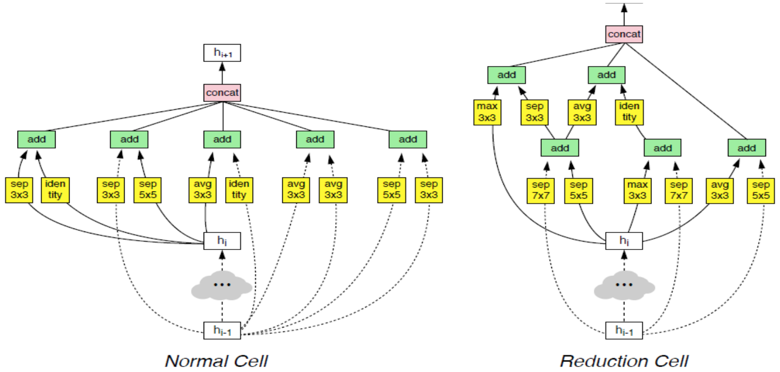
- MobileNetV3: NAS+ NetAdapt

Howard et al. 2019

NASNet

- Neural Architecure Search *[Zoph et al. 2018]*
  - Search the space of architetures to find the optimal one given available resources
  - 500 GPUs across 4 days resulting in 2,000 GPU-hours on NVidia P100

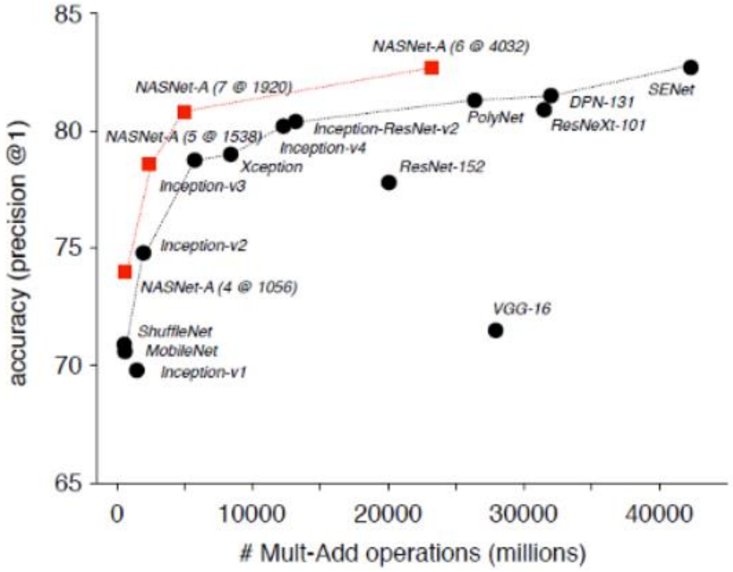


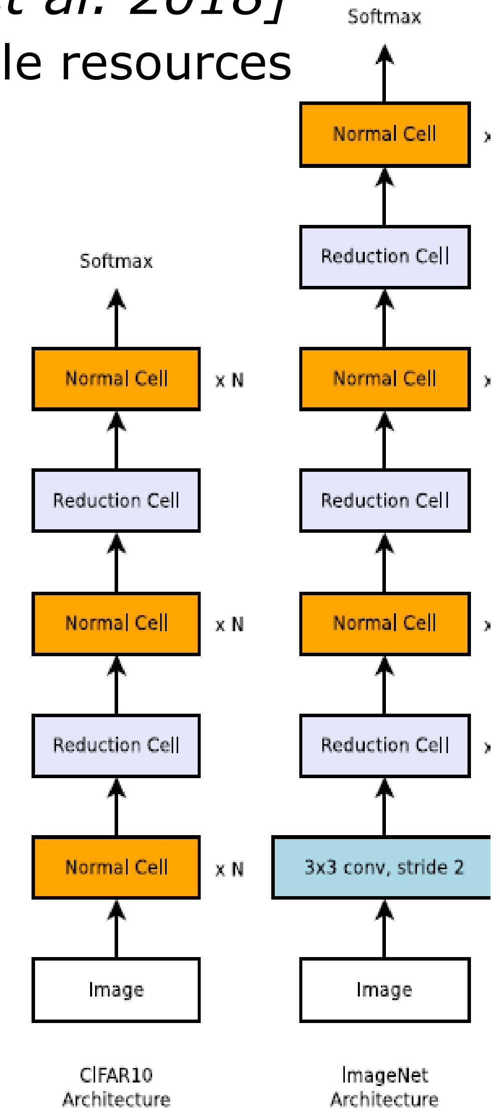


Best convolutional cells (NASNet-A) for CIFAR-10

Available operations to select from:

- identity
- 1x7 then 7x1 convolution
- 3x3 average pooling
- 5x5 max pooling
- 1x1 convolution
- 3x3 depthwise-separable conv
- 7x7 depthwise-separable conv
- 1x3 then 3x1 convolution
- 3x3 dilated convolution
- 3x3 max pooling
- 7x7 max pooling
- 3x3 convolution
- 5x5 depthwise-seperable conv





- Other architecture search methods:
  - AmoebaNet, Real et al., 2018
  - MoreMNAS, Chu et. al, 2019, …

EfficientNet

- Scaling the network in

$$\text{depth: } d = \alpha^{\phi}$$

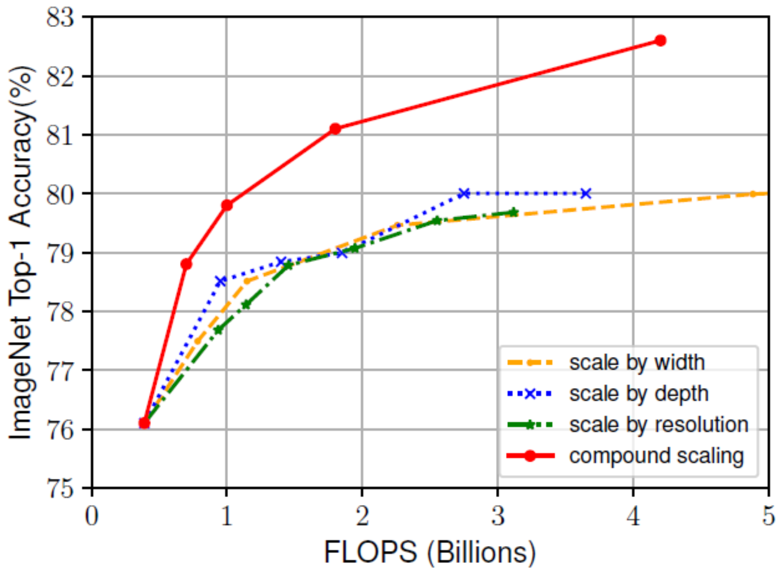
$$\text{width: } w = \beta^{\phi}$$

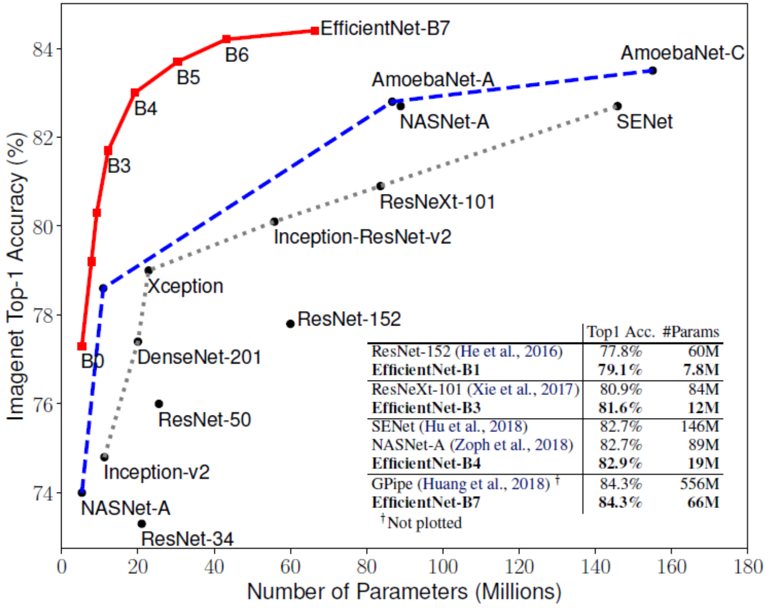
$$\text{resolution: } r = \gamma^{\phi}$$

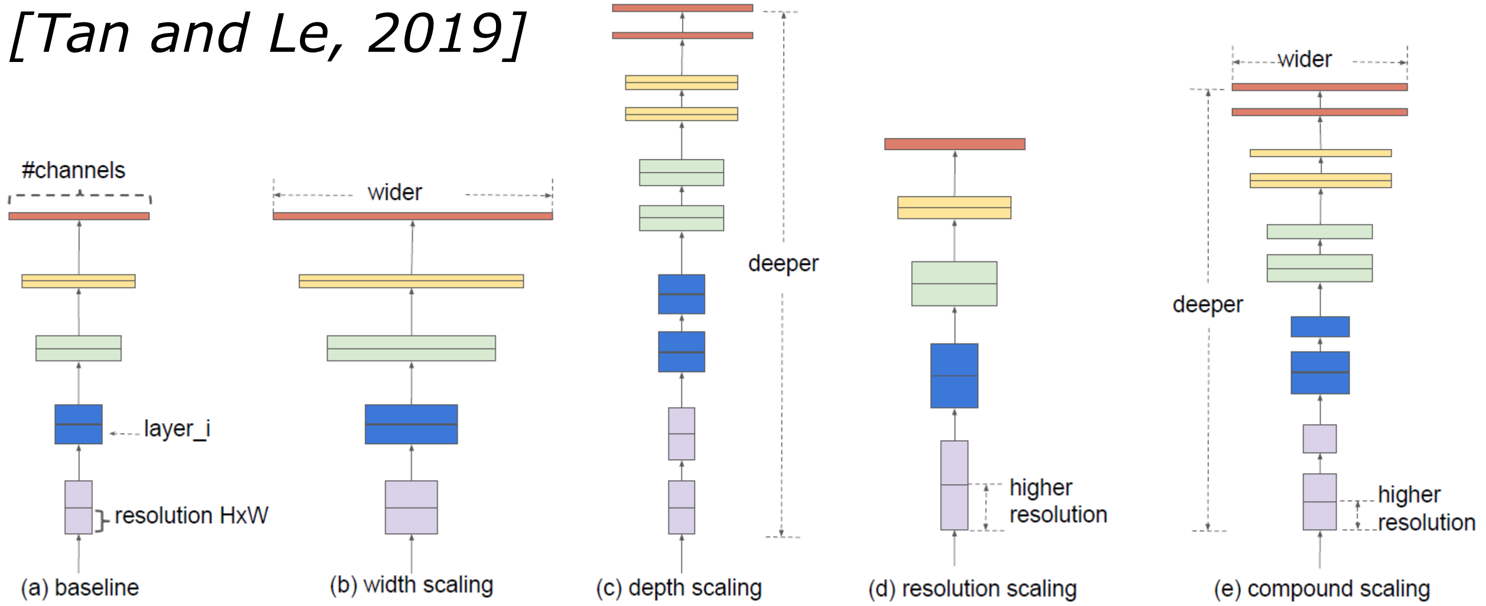
$$\text{s.t. } \alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$$

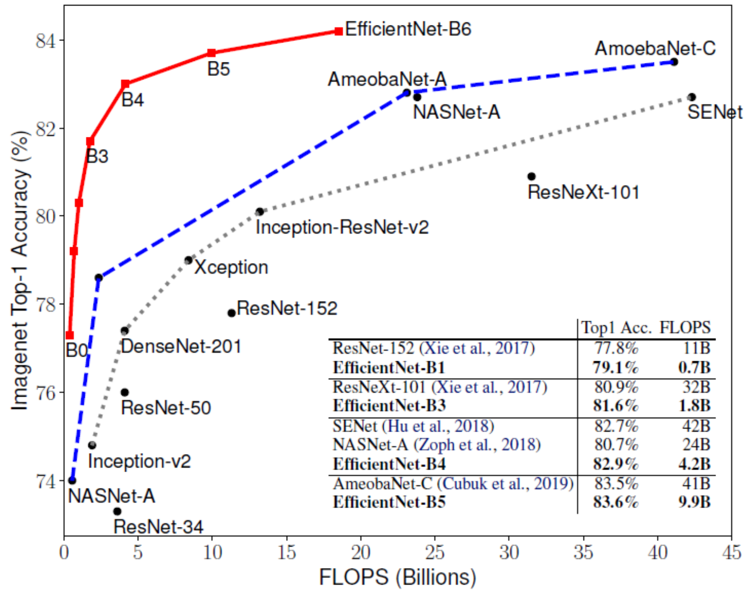
$$\alpha \geq 1, \beta \geq 1, \gamma \geq 1$$

[Tan and Le, 2019]



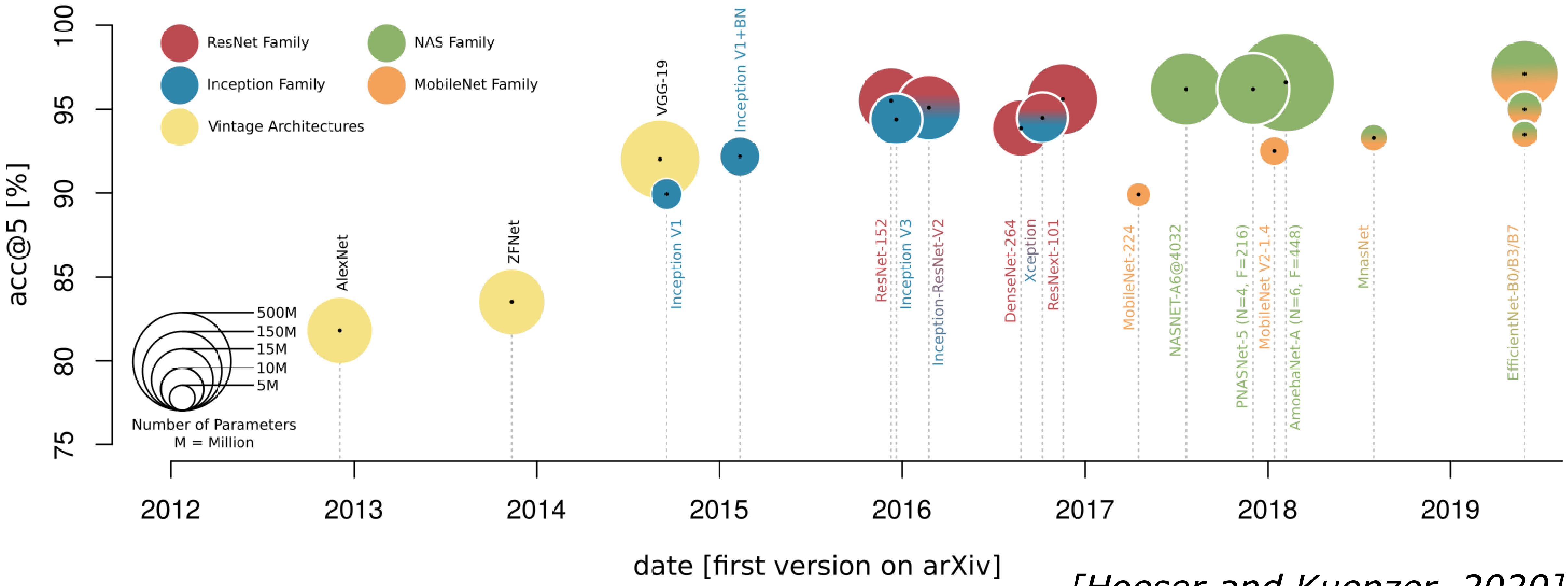






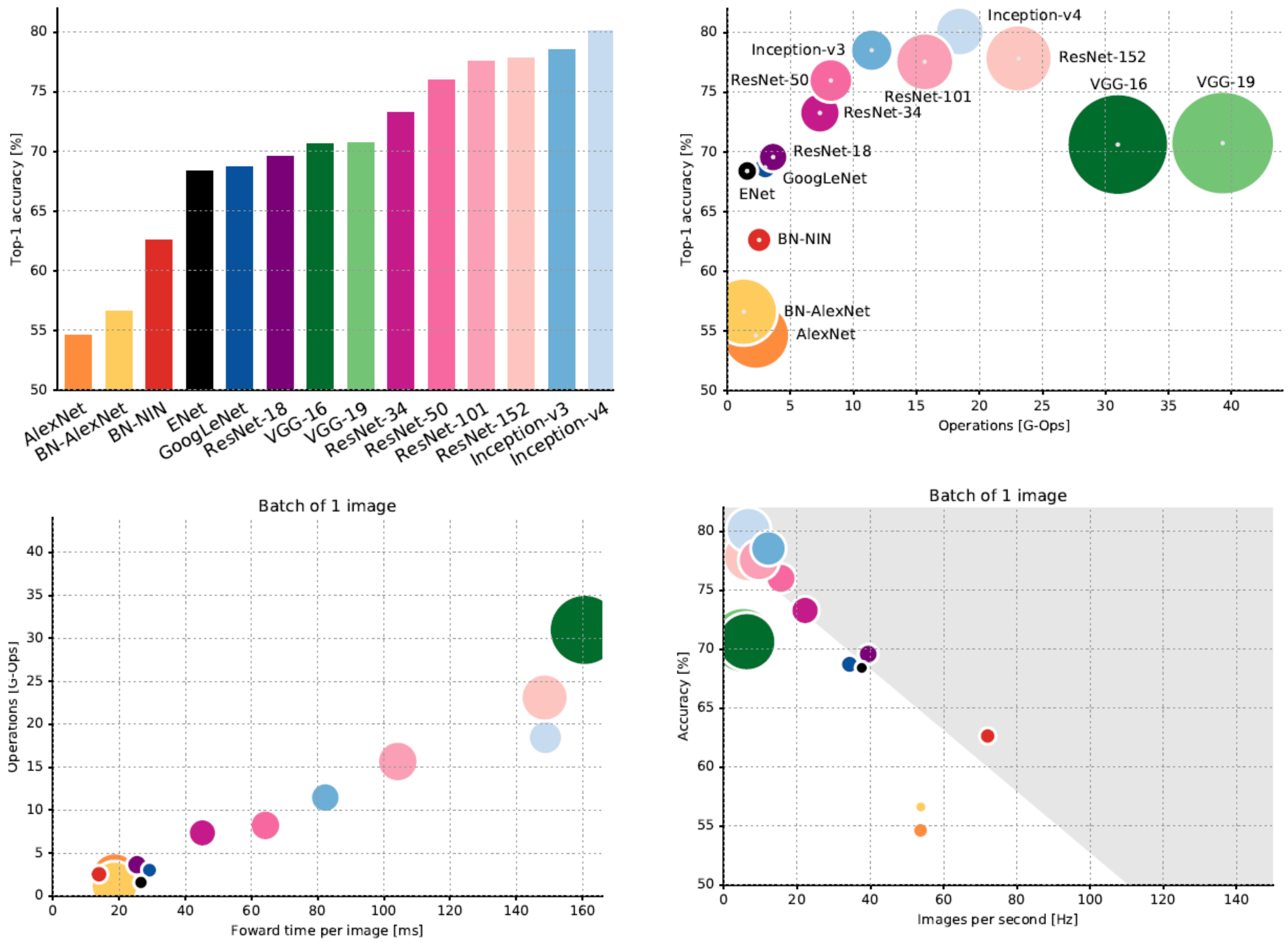
Architectures overview

- Date of publication, main type



[Hoeser and Kuenzer, 2020]

Analysis of DNN models

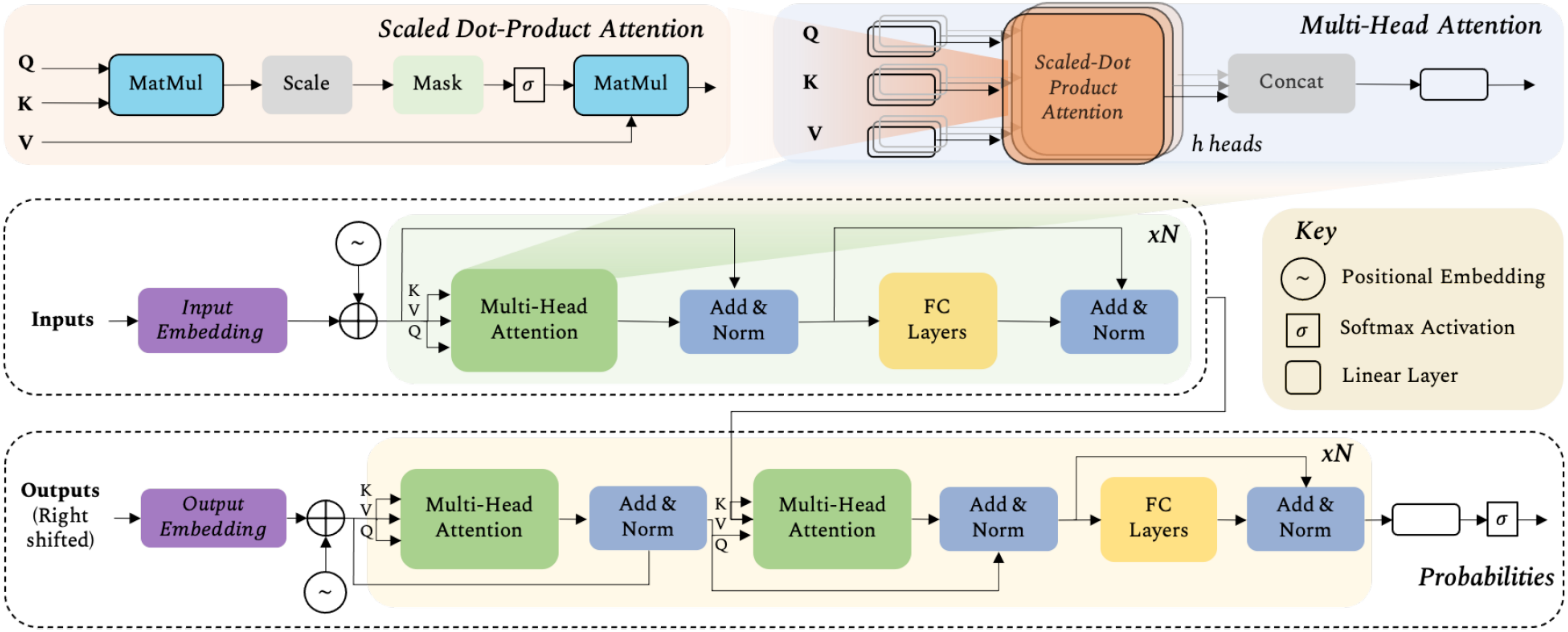


[Canziani et al., 2017]

Pretrained models

```python
import torchvision.models as models
resnet18 = models.resnet18(pretrained=True)
alexnet = models.alexnet(pretrained=True)
squeezenet = models.squeezenet1_0(pretrained=True)
vgg16 = models.vgg16(pretrained=True)
densenet = models.densenet161(pretrained=True)
inception = models.inception_v3(pretrained=True)
googlenet = models.googlenet(pretrained=True)
shufflenet = models.shufflenet_v2_x1_0(pretrained=True)
mobilenet_v2 = models.mobilenet_v2(pretrained=True)
mobilenet_v3_large = models.mobilenet_v3_large(pretrained=True)
mobilenet_v3_small = models.mobilenet_v3_small(pretrained=True)
resnext50_32x4d = models.resnext50_32x4d(pretrained=True)
wide_resnet50_2 = models.wide_resnet50_2(pretrained=True)
mnasnet = models.mnasnet1_0(pretrained=True)
```

Transformers



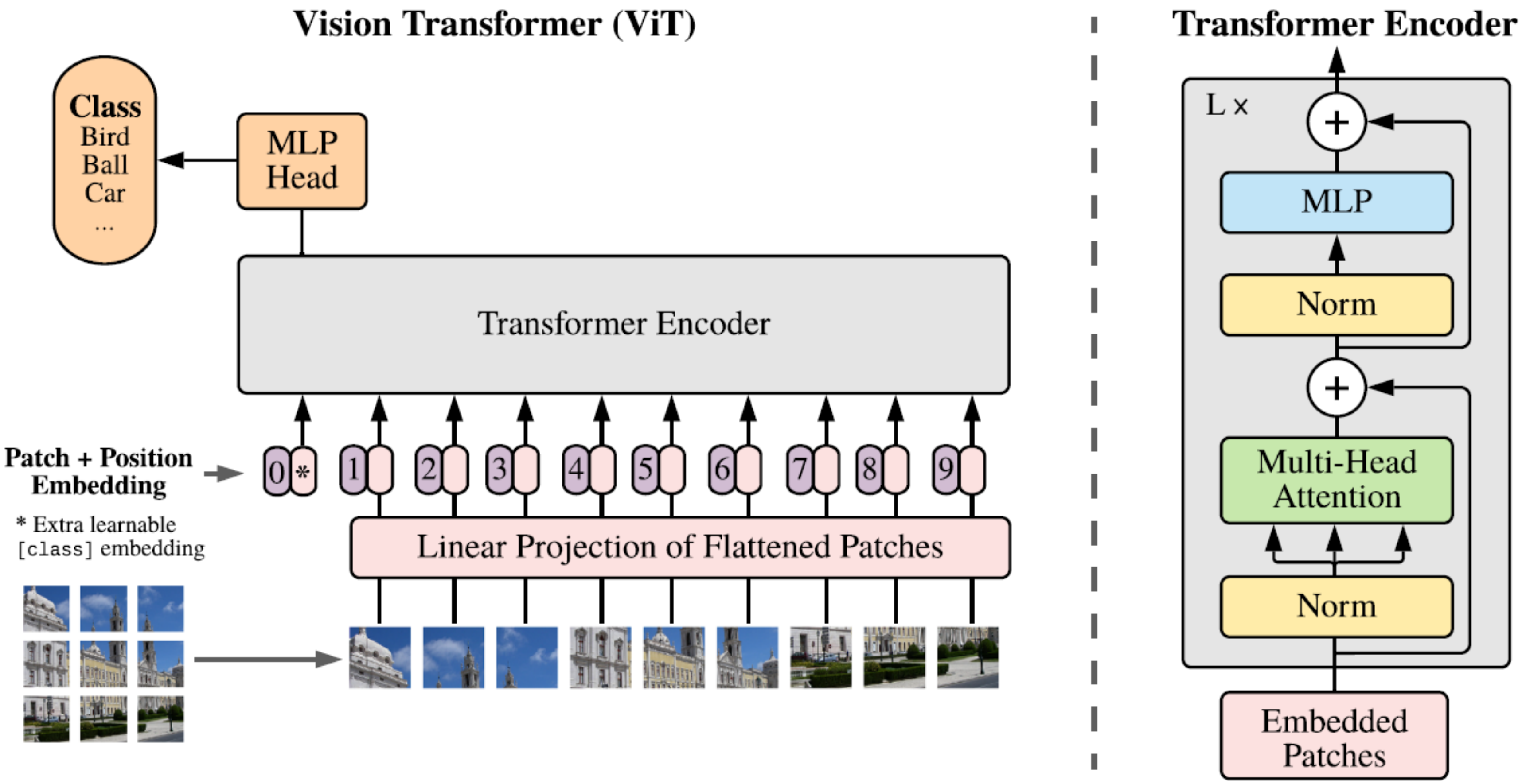
[Vaswani et.al, NIPS 2017]

[Khan et.al, 2021]

ViT - Vision Transformer

$$\mathbf{z}_0 = [\mathbf{x}_{\text{class}};\, \mathbf{x}_p^1\mathbf{E};\, \mathbf{x}_p^2\mathbf{E}; \cdots;\, \mathbf{x}_p^N\mathbf{E}] + \mathbf{E}_{pos}$$
$$\mathbf{z'}_\ell = \mathrm{MSA}(\mathrm{LN}(\mathbf{z}_{\ell-1})) + \mathbf{z}_{\ell-1},$$
$$\mathbf{z}_\ell = \mathrm{MLP}(\mathrm{LN}(\mathbf{z'}_\ell)) + \mathbf{z'}_\ell,$$
$$\mathbf{y} = \mathrm{LN}(\mathbf{z}_L^0)$$

- AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE

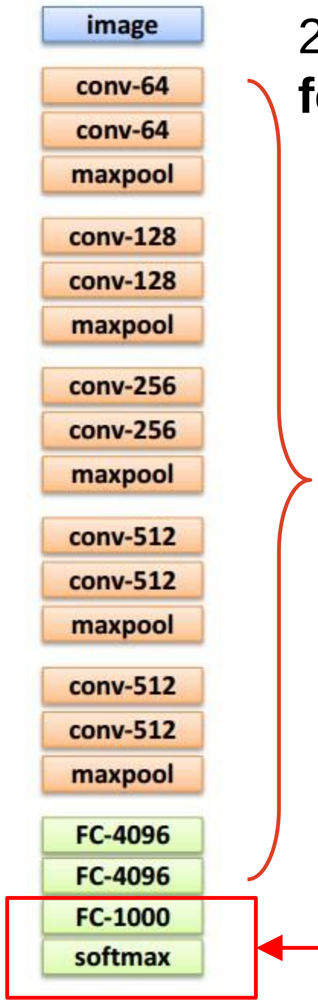


[Dosovitskiy et.al, Google, 2020, ICLR 2021]

Transfer learning

- If you don‵t have enough data use pretrained models!

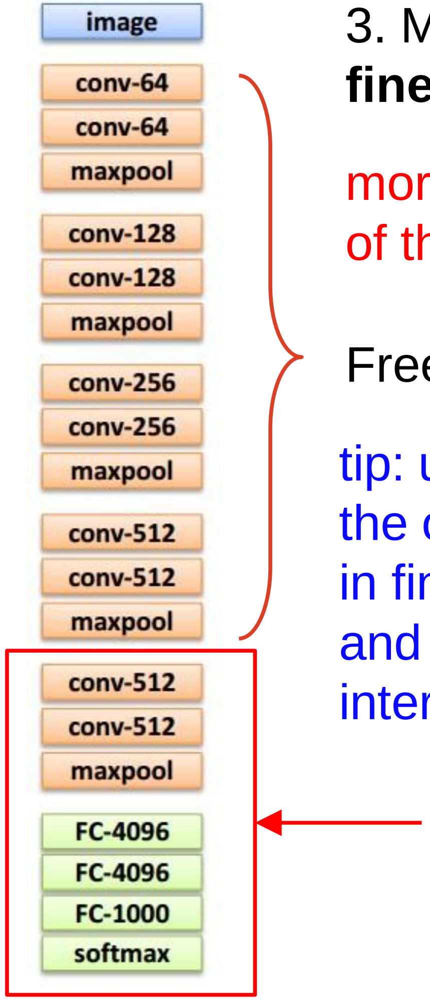
1. Train on Imagenet



2. Small dataset: **feature extractor**

Freeze these

Train this



3. Medium dataset: **finetuning**

more data = retrain more of the network (or all of it)

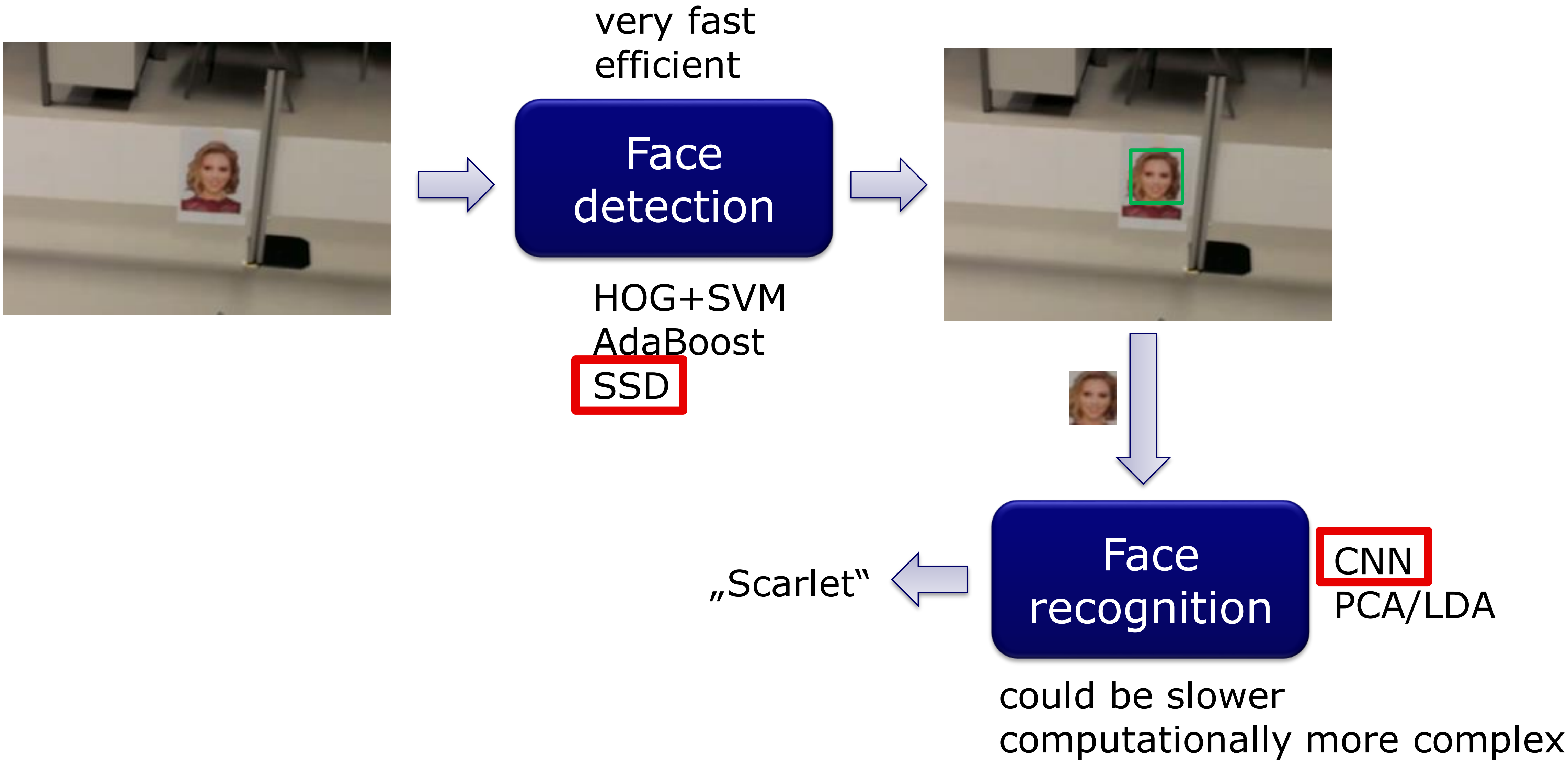
Freeze these

tip: use only ~1/10th of the original learning rate in finetuning top layer, and ~1/100th on intermediate layers

Train this

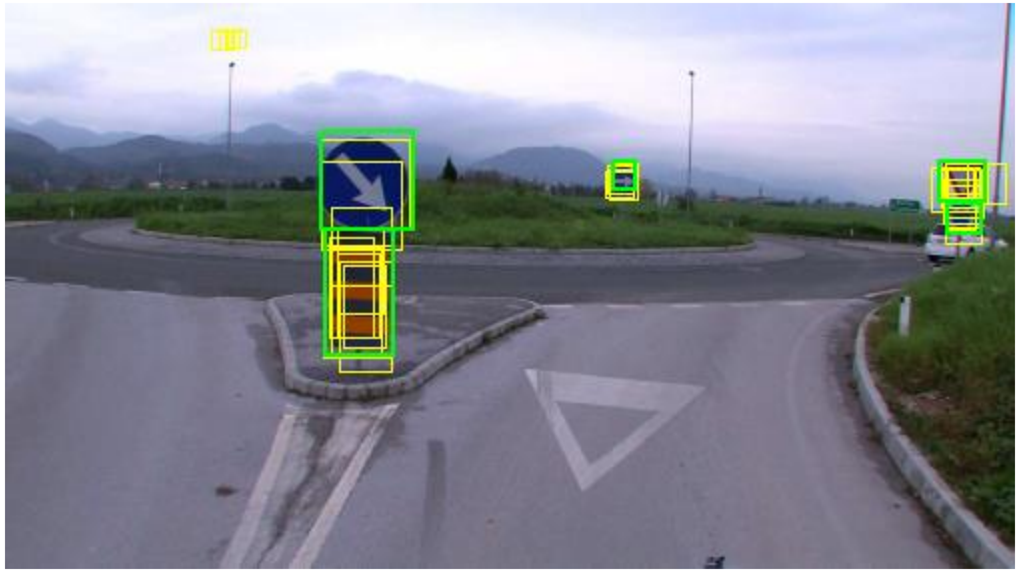
Slide credit: Fei-Fei Li, Andrej Karpathy, Justin Johnson

Two stage object detection and recognition



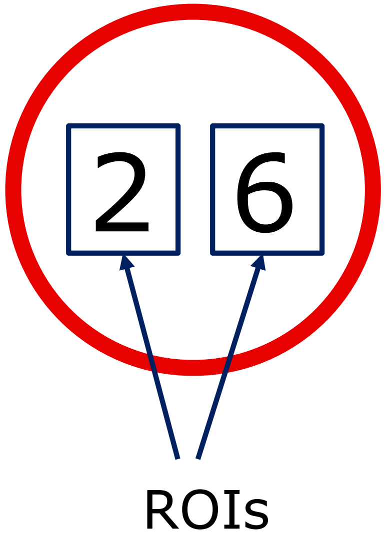
Object detection and recognition

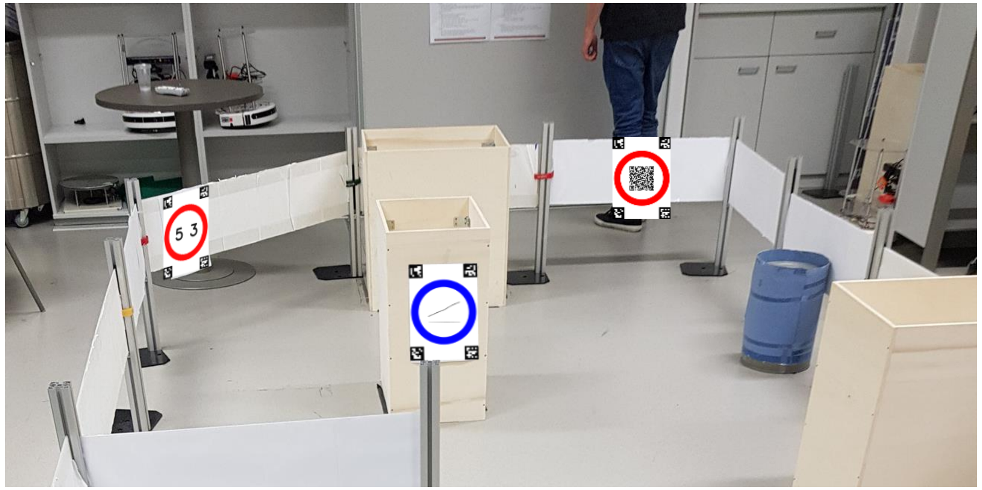
- Two stage approach:
  - Detection of region proposals
  - Recognition of the individual region proposals



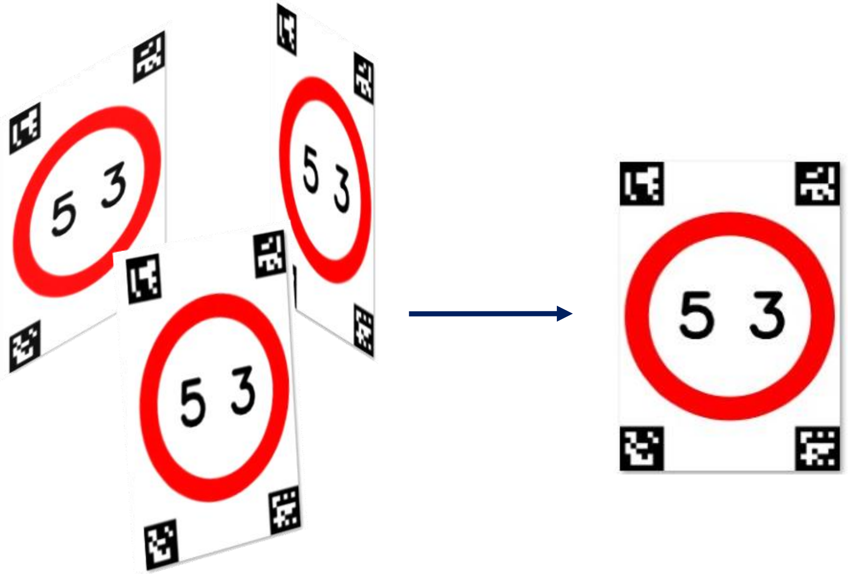
Object detection in RInS

- Information in circles
  - -> detecting circles as region proposals (Region Of Interests)
- Rectify ROIs
- Recognize the content of ROIs



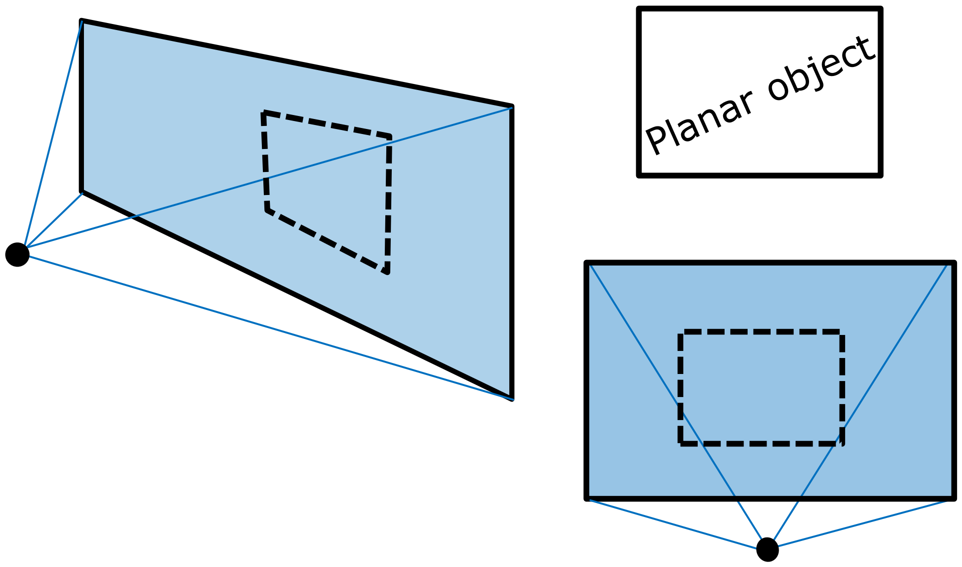


- Rectification using homography



Homography

- Two views on the same (planar) object:

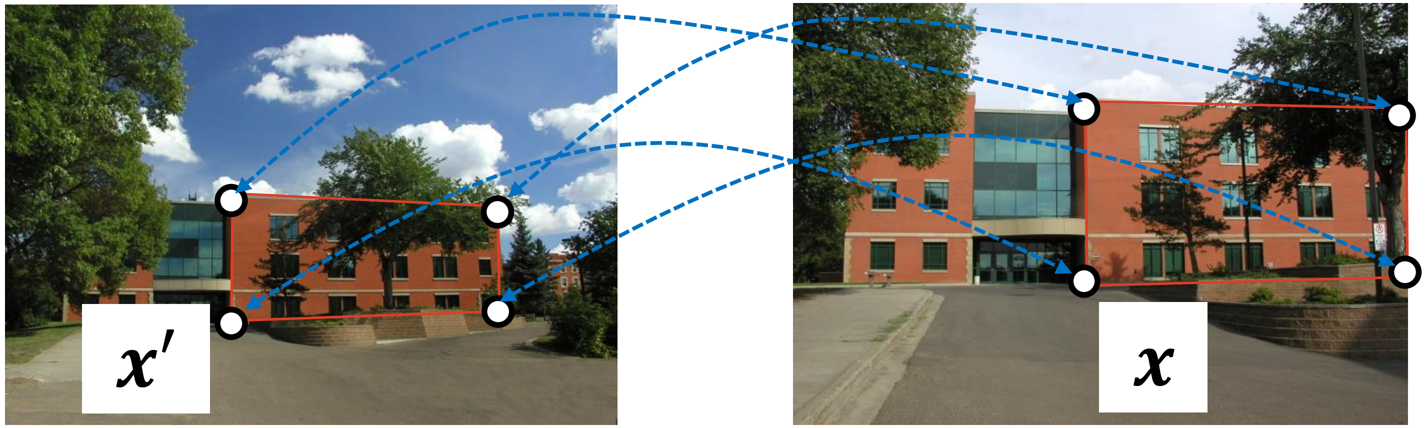


- Homography: plane to plane mapping

Slide credit: Matej Kristan

Computing homography

- Four corresponding points:



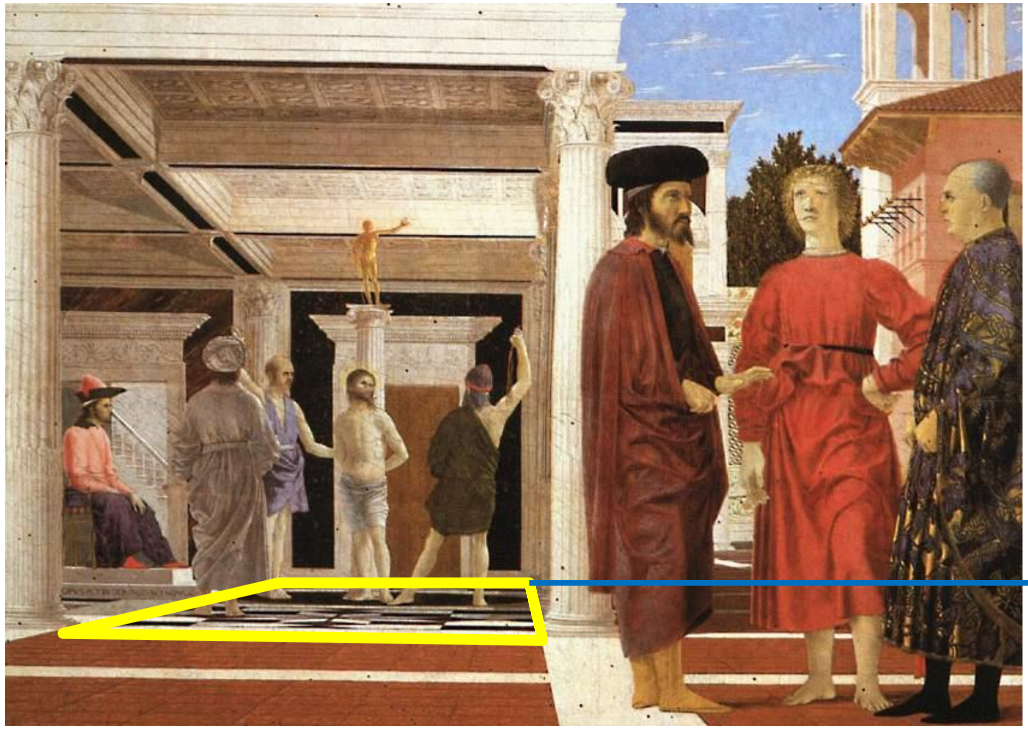
$$wx' = Hx$$

$$w\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} H_{11} & H_{12} & H_{13} \\ H_{21} & H_{22} & H_{23} \\ H_{31} & H_{32} & H_{33} \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

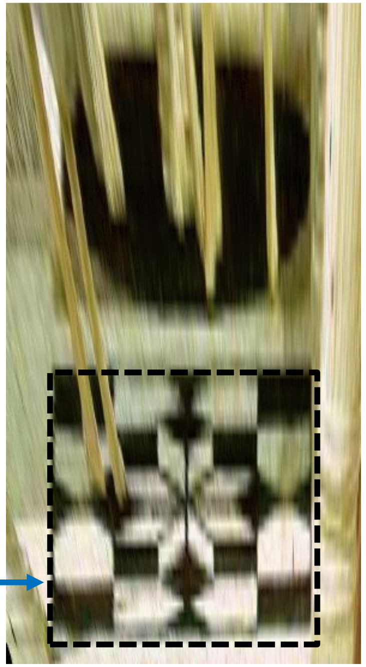
- The elements of the matrix $\boldsymbol{H}$ can be computed using Direct Linear Transform (DLT)!

Slide credit: Matej Kristan

Application of homography



Homography mapping between part of the image and a sqare



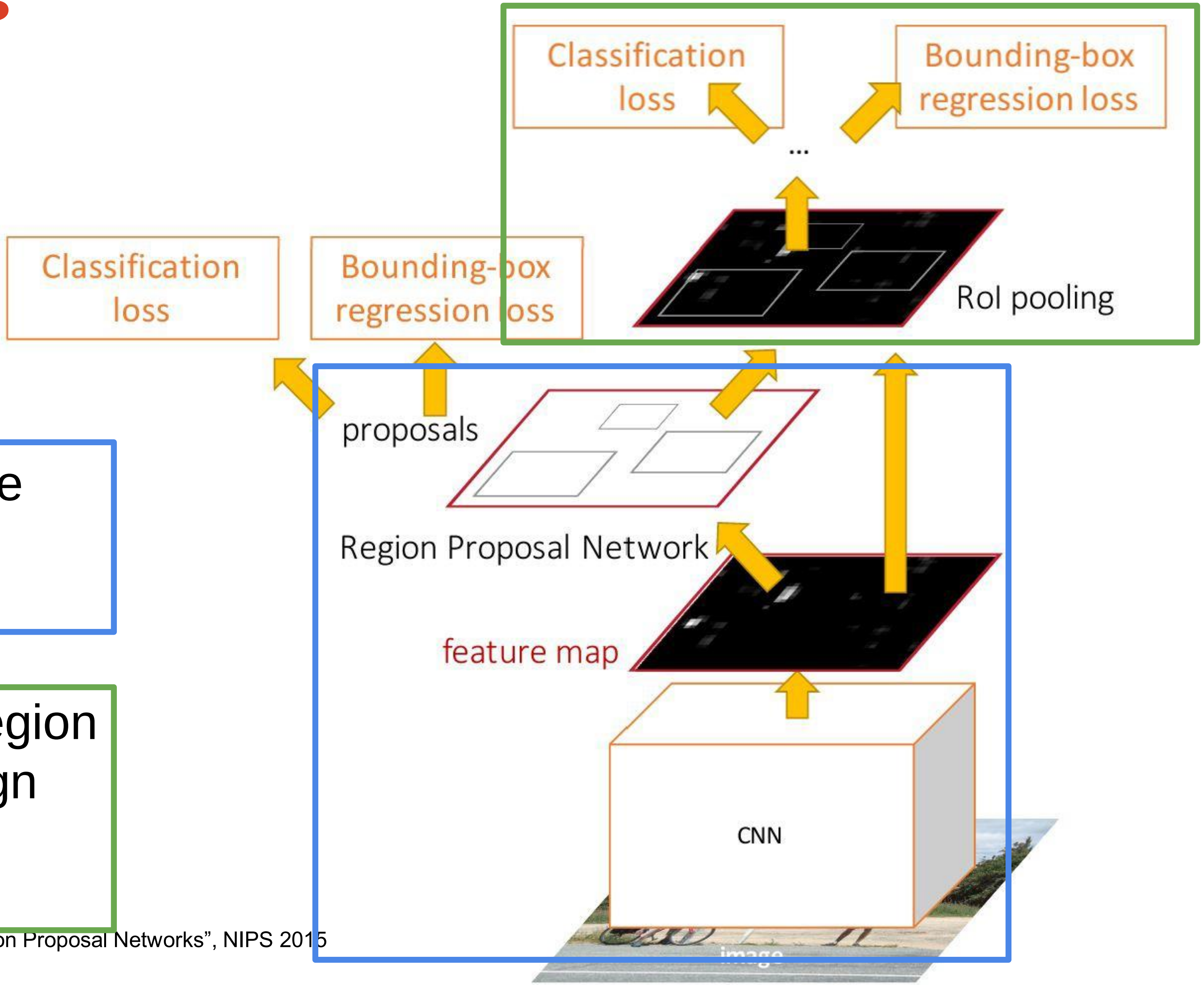
Flagellation of Christ (Piero della Francesca)

Slide credit: Antonio Criminisi

Two-stage detectors

First stage: Run once per image
- Backbone network
- Region proposal network

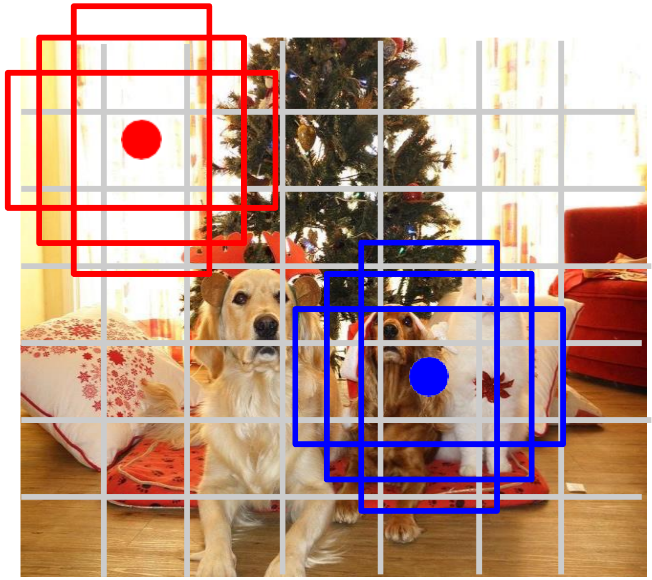
Second stage: Run once per region
- Crop features: RoI pool / align
- Predict object class
- Prediction bbox offset



Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015
Figure copyright 2015, Ross Girshick; reproduced with permission

Single-Stage Object Detectors

Input image
3 x H x W



Divide image into grid
7 x 7

Image a set of **base boxes** centered at each grid cell
Here B = 3

Within each grid cell:

- Regress from each of the B base boxes to a final box with 5 numbers: (dx, dy, dh, dw, confidence)
- Predict scores for each of C classes (including background as a class)
- Looks a lot like RPN, but category-specific!

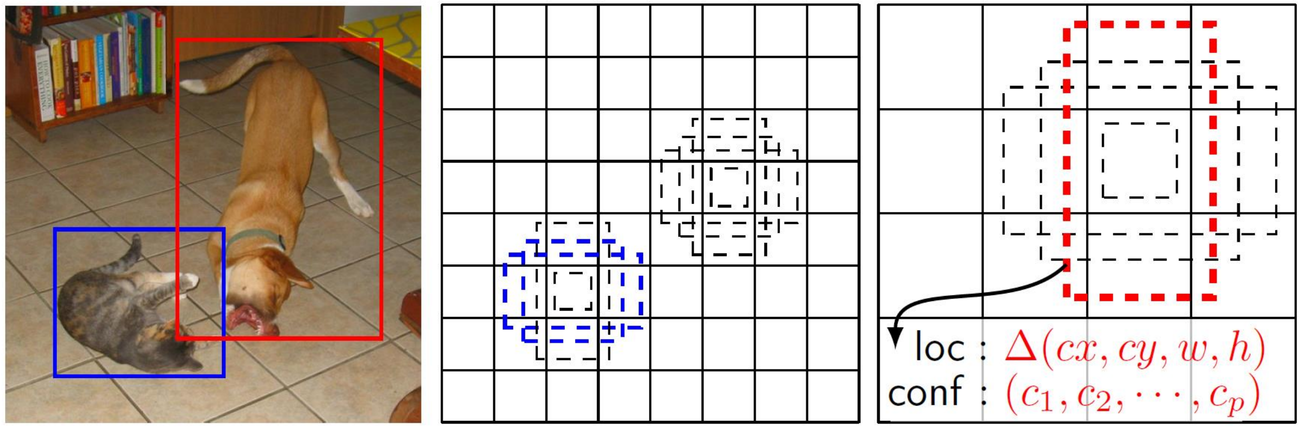
Output:
7 x 7 x (5 * B + C)

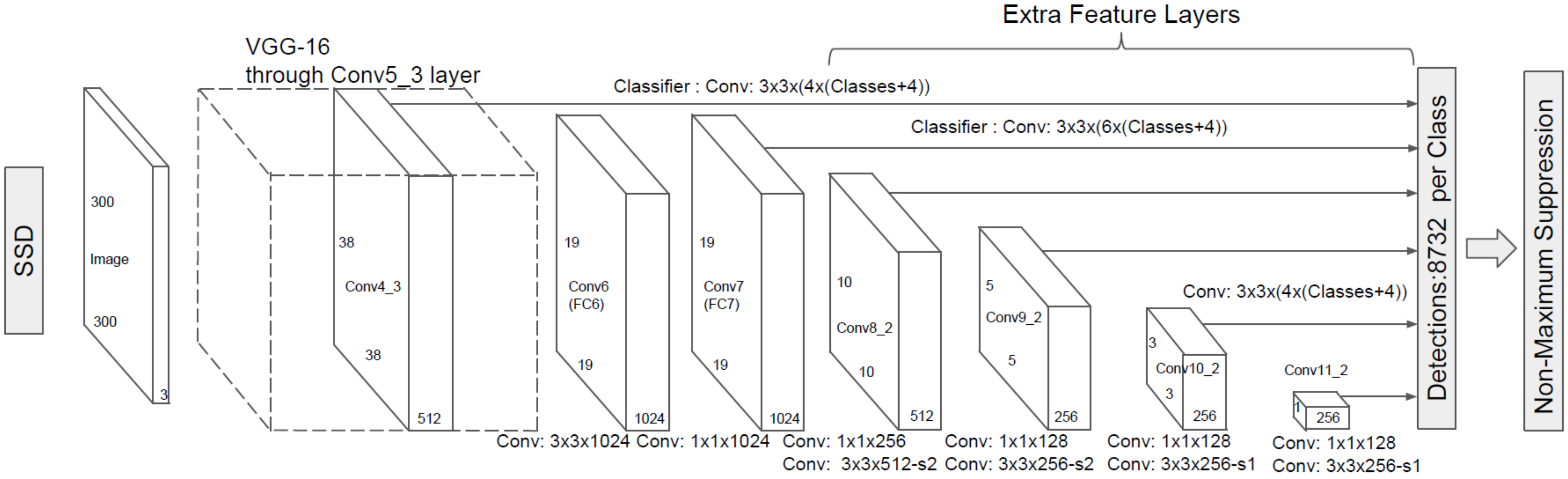
Redmon et al, "You Only Look Once: Unified, Real-Time Object Detection", CVPR 2016
Liu et al, "SSD: Single-Shot MultiBox Detector", ECCV 2016
Lin et al, "Focal Loss for Dense Object Detection", ICCV 2017

SSD: Single Shot MultiBox Detector

- Multi-scale feature maps for detection
- Convolutional predictors for detection
- Default boxes and aspect ratios
- Real time operation

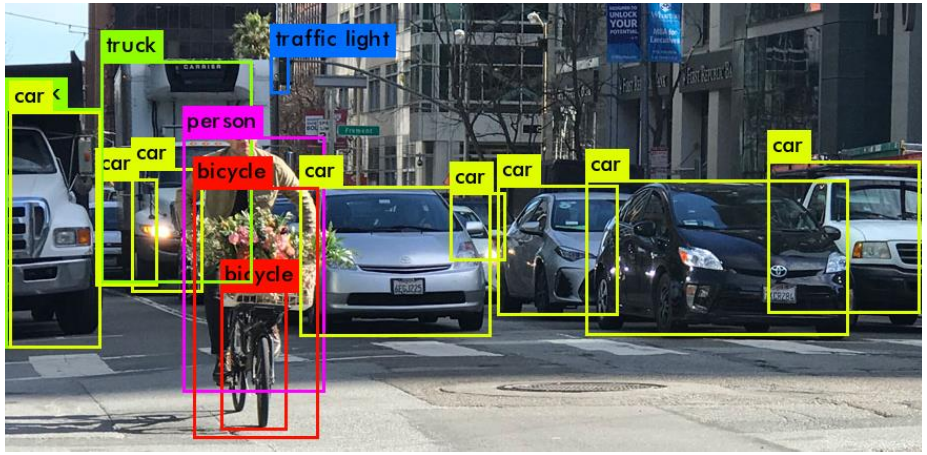
[Liu et al., ECCV 2016]





Wide usabilty of ConvNets

Detection



[Redmon, Yolo, 2018]

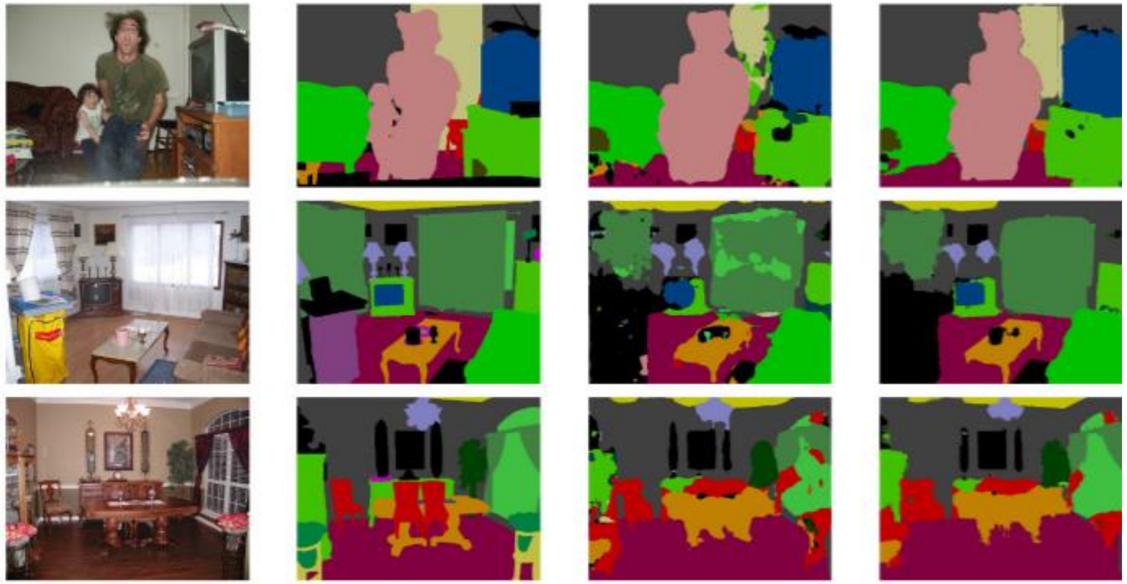
[Liu, SSD, 2015]

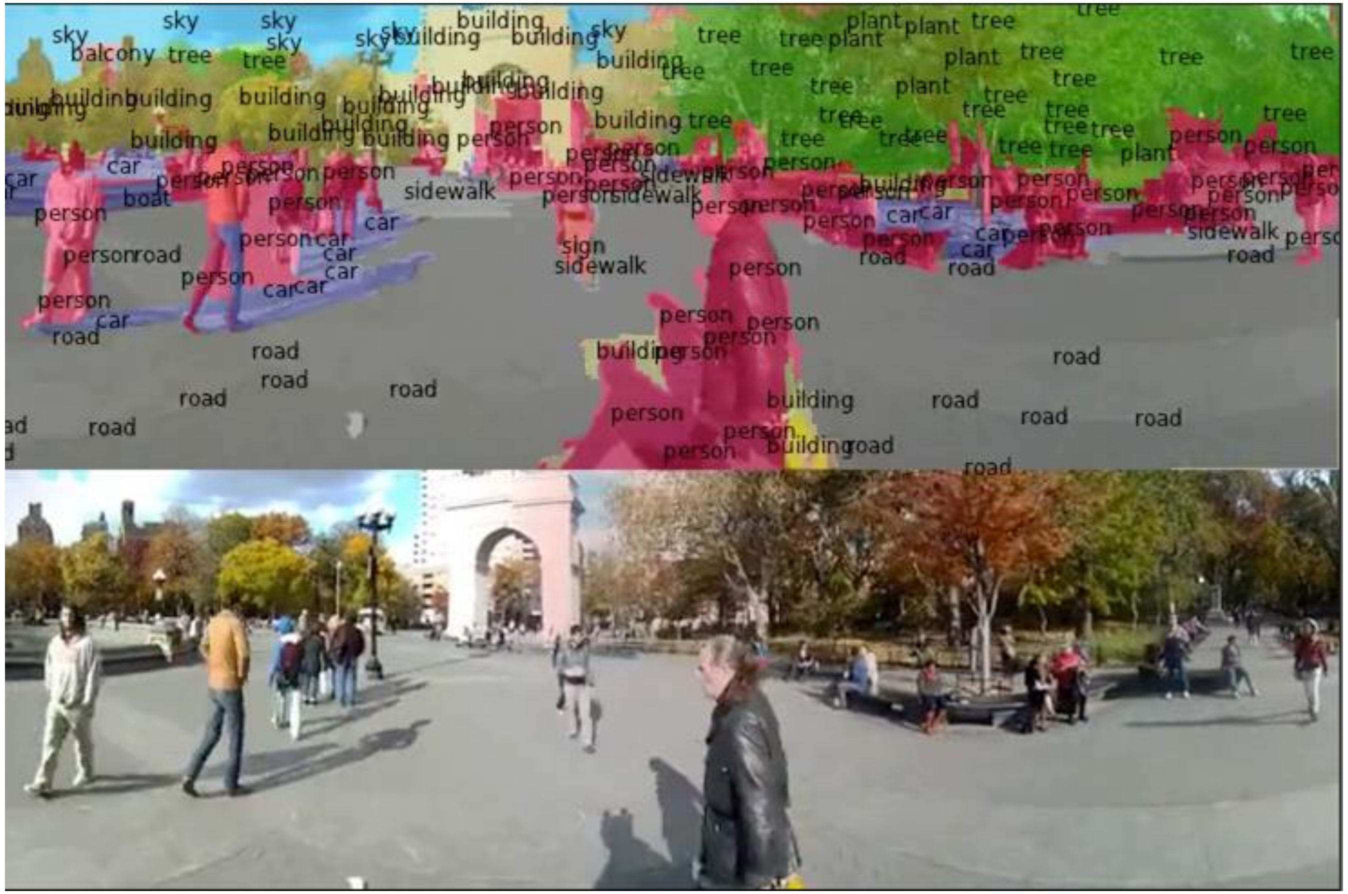
Instance segmentation

[He, Mask R-CNN, 2012]

Wide usabilty of ConvNets

Semantic segmentation



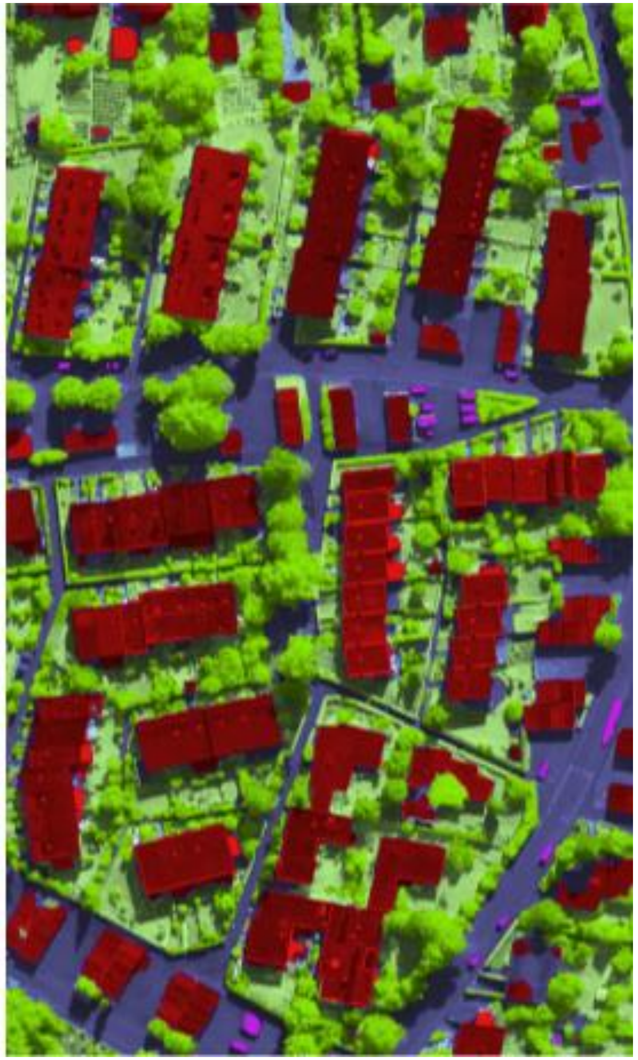


[Chen, DeepLab 2017]

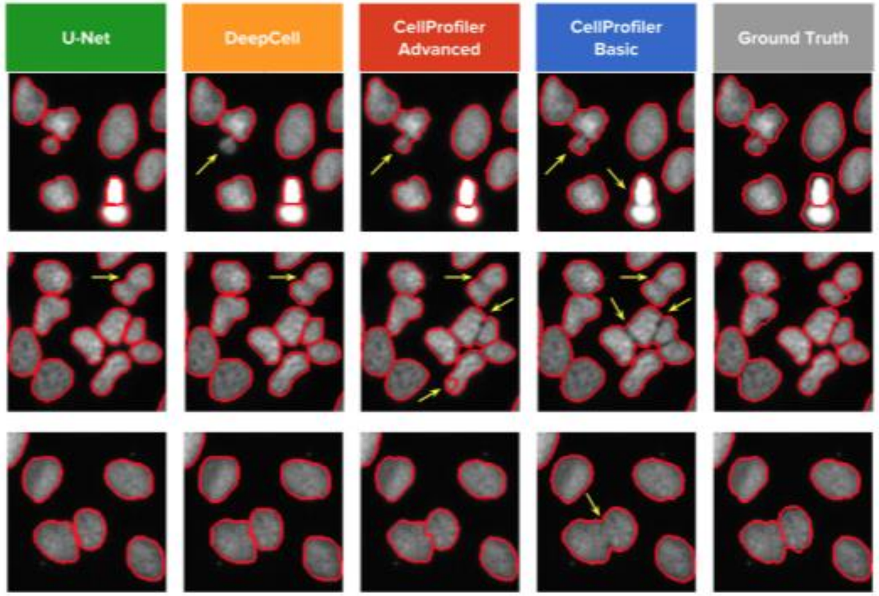
[Farabet et al., 2012]

Wide usabilty of ConvNets

- Image segmentation

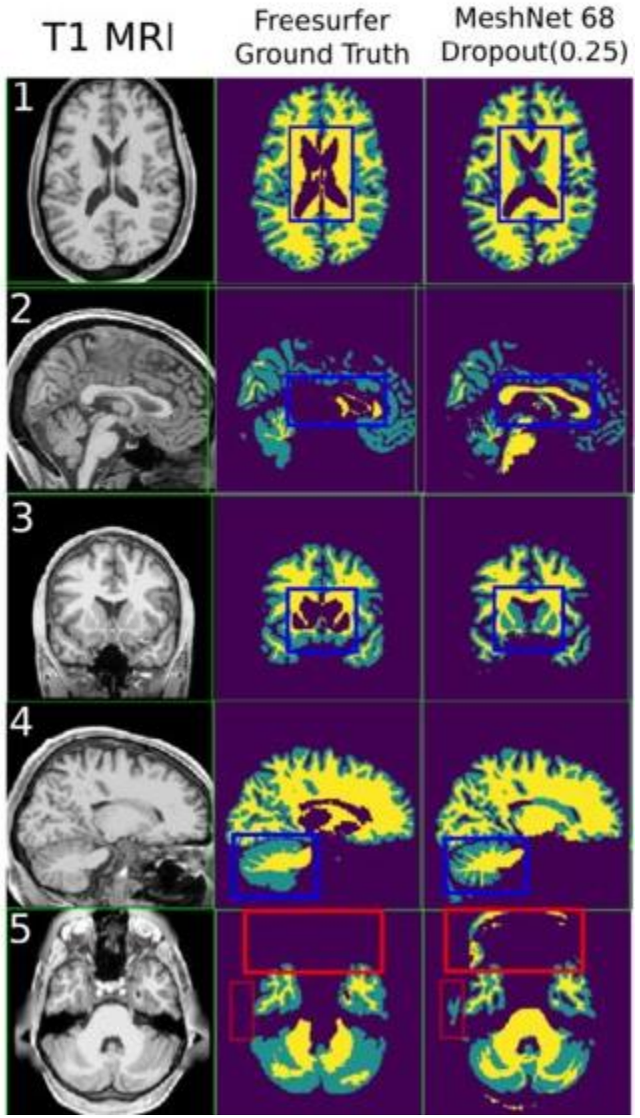


[Marmanis, 2016]



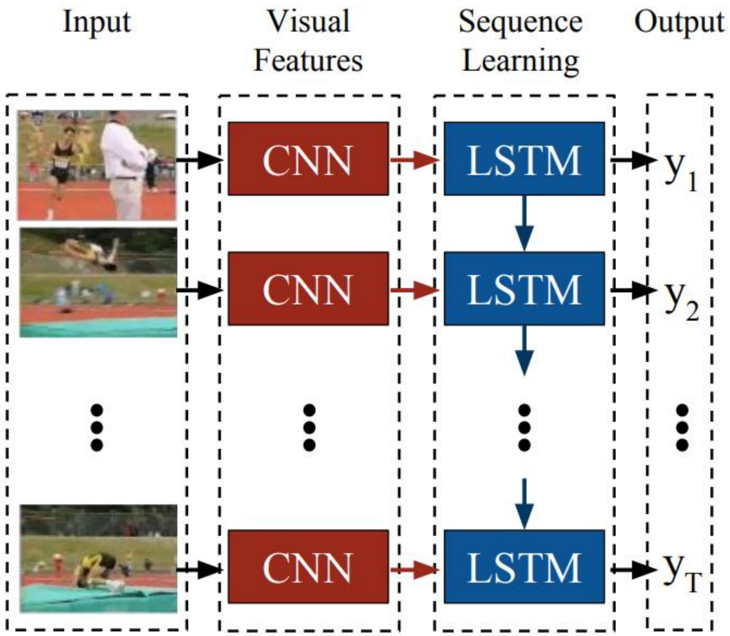
[Caicedo, 2018]

[Jonson, 2016]

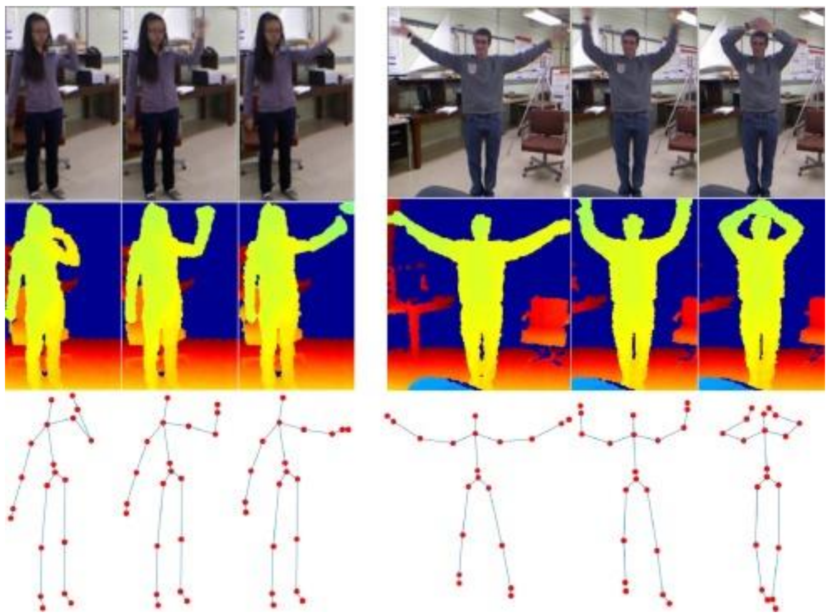


Wide usabilty of ConvNets

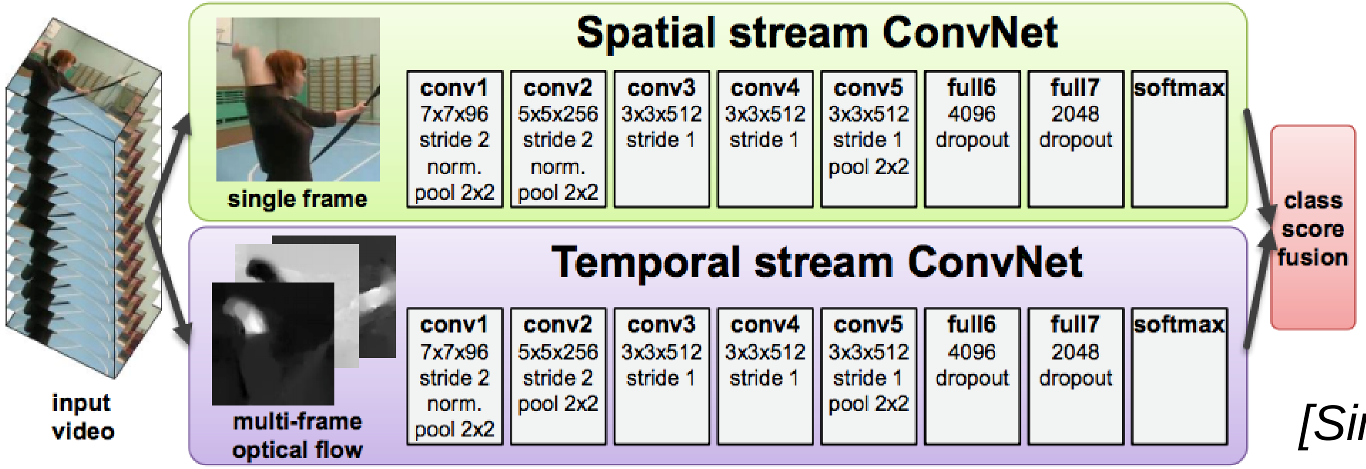
- Action recognition



[Donahue et al. 2016]



[Luvizon et al. 2016]

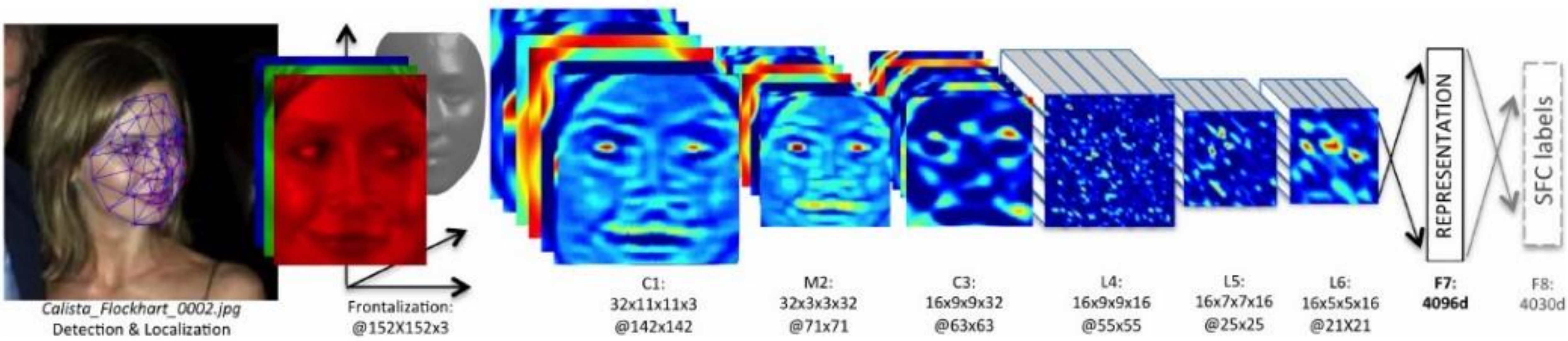


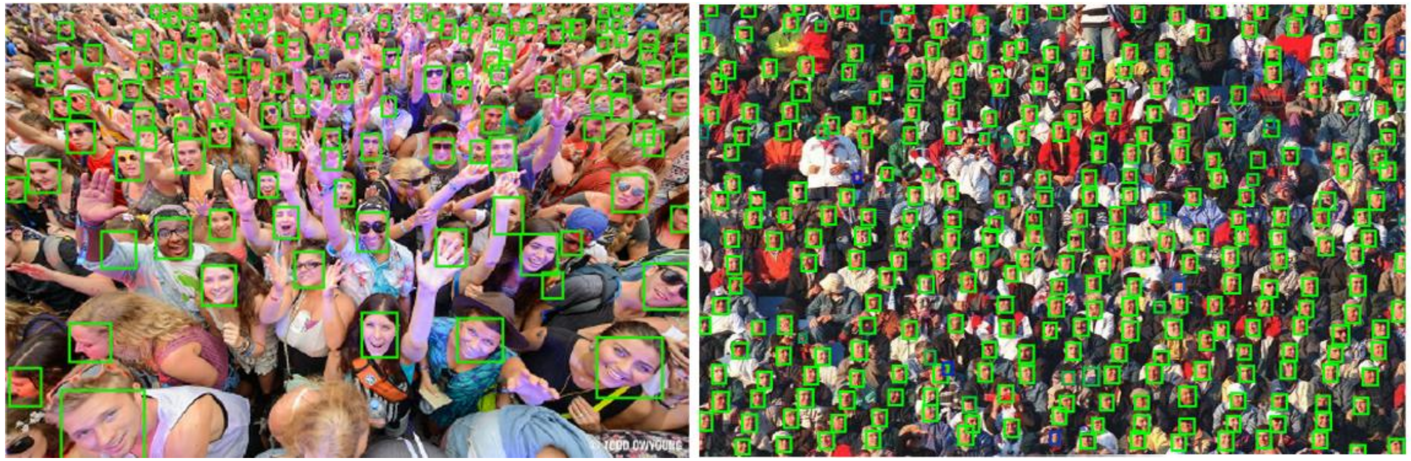
[Simonyan et al. 2014]

Wide usabilty of ConvNets

- Biometry

[Taigman et al. 2014]





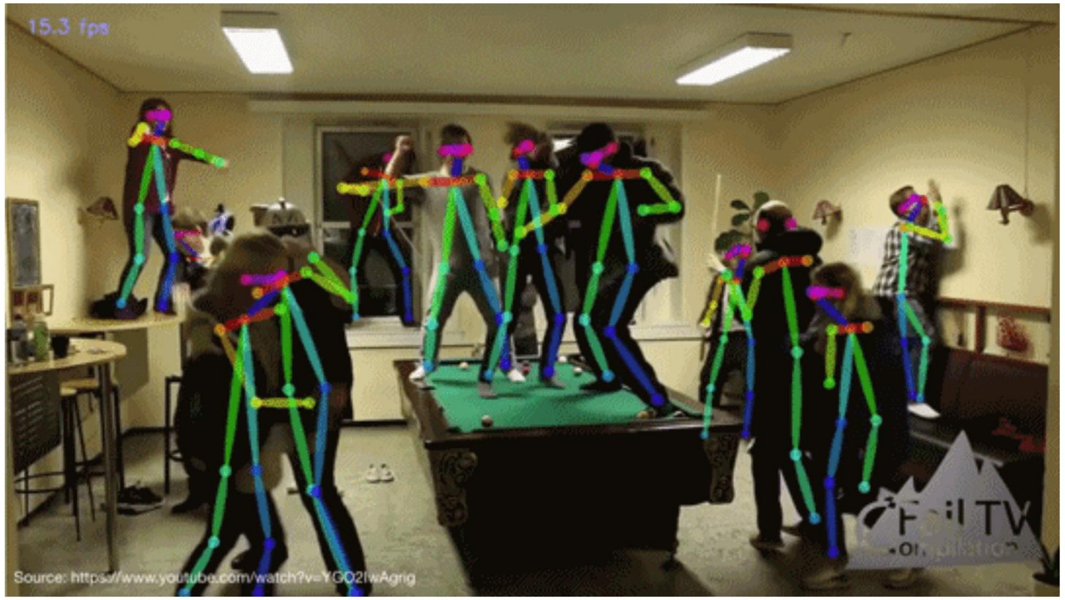
[Najibi, SSH, 2017]

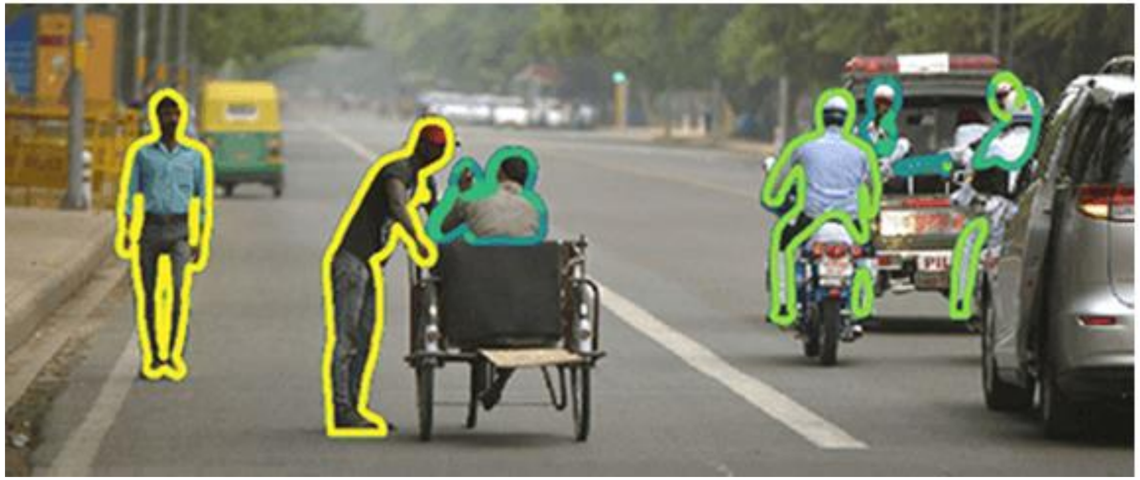
[Emeršič, 2017]

Wide usabilty of ConvNets

[Güler, DensePose, 2018]

- Person/pose detection

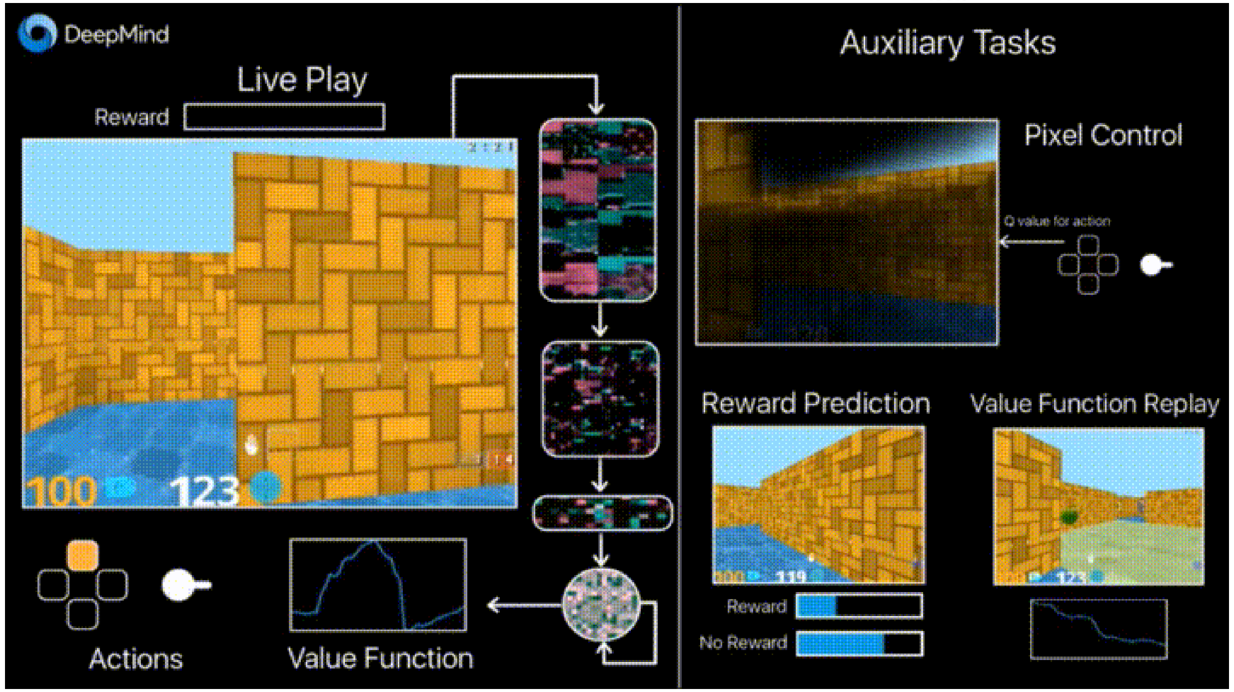




[Cao 2017]

Wide usabilty of ConvNets

- Reinforcement learning for game playing



[Google DeepMind]

Wide usabilty of ConvNets

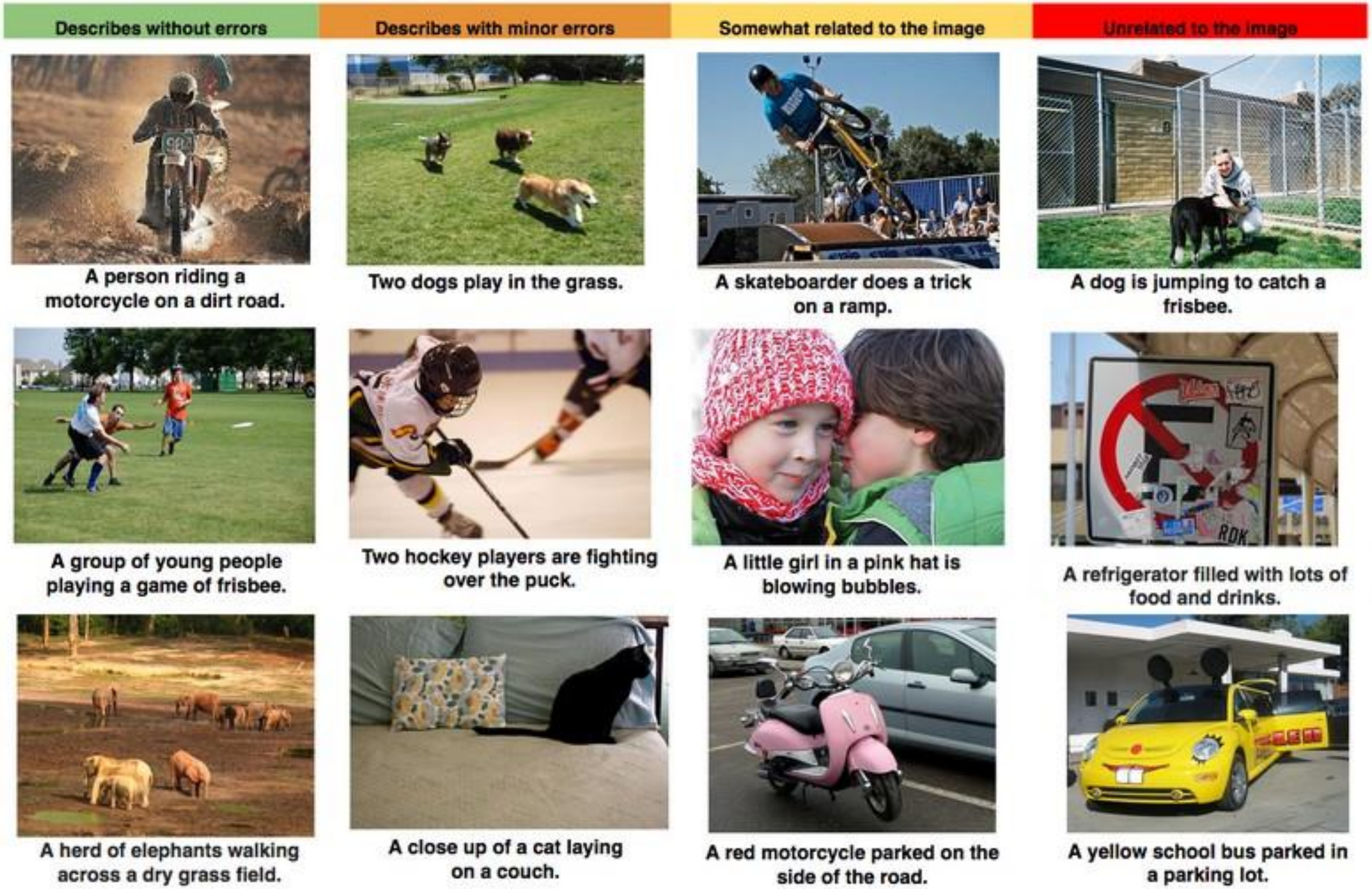
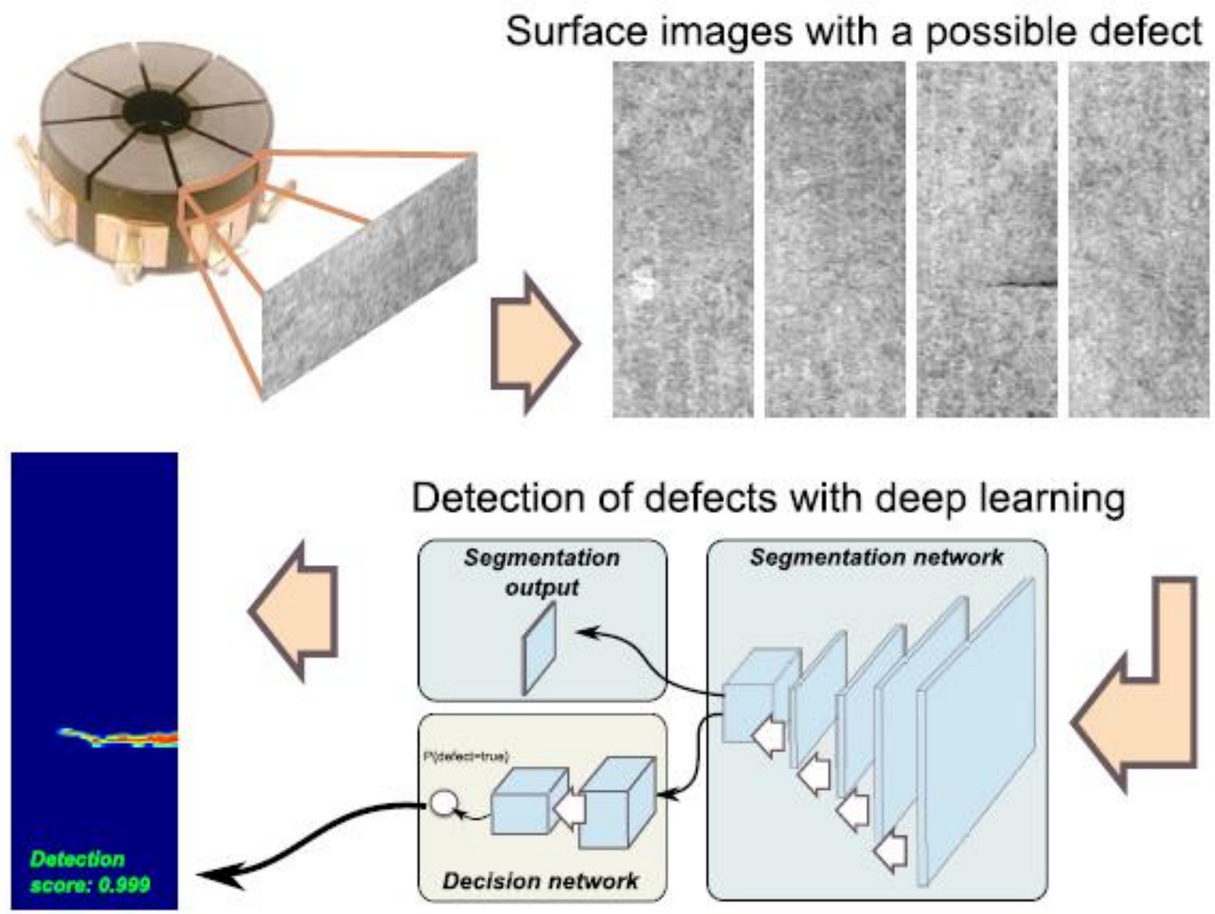


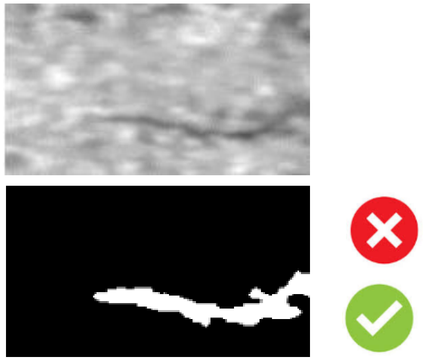
Image Captioning

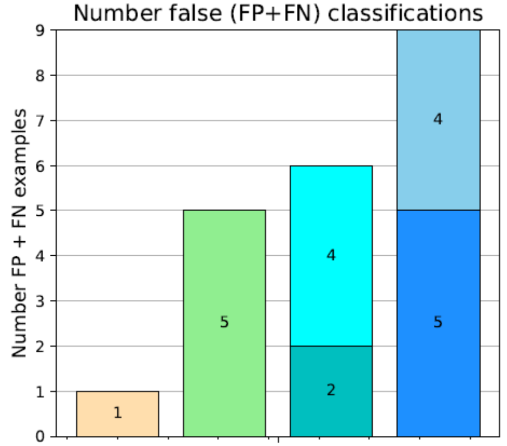
[Vinyals et al., 2015]

Slide credit: Fei-Fei Li, Andrej Karpathy, Justin Johnson

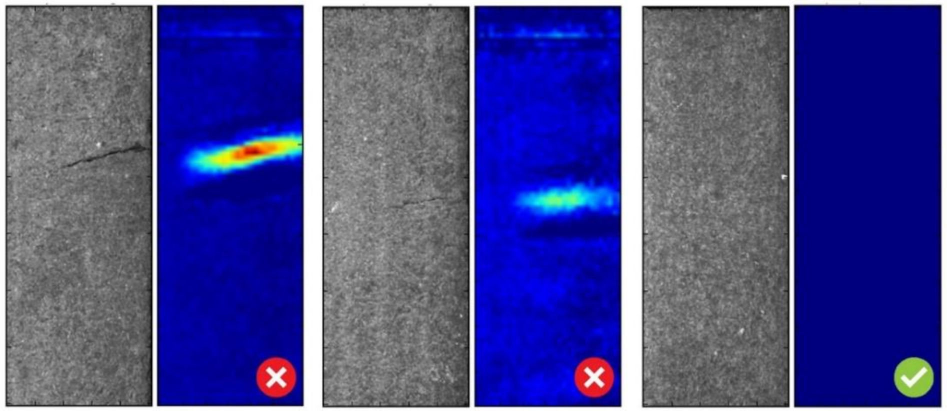
Surface-defect detection



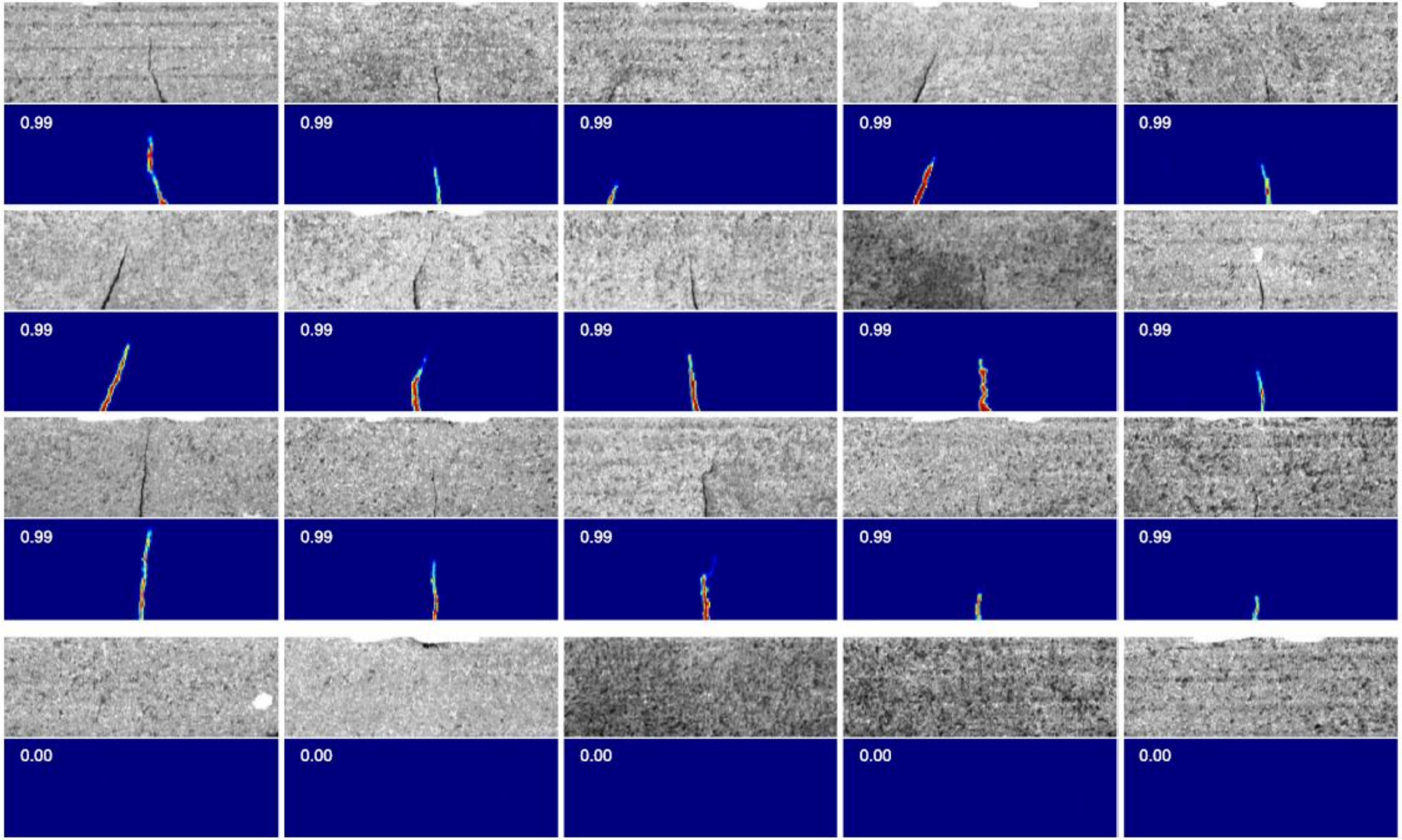




Segmantation-based data-driven surface-defect detection

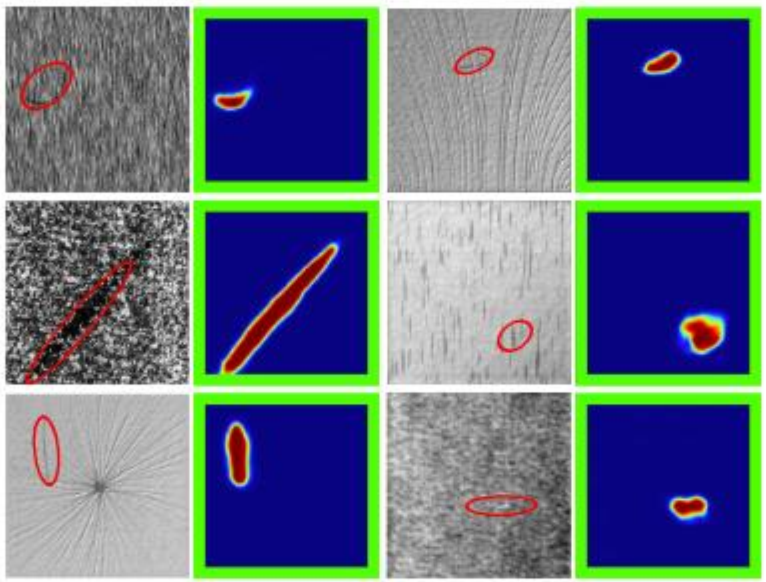


Surface-defect detection



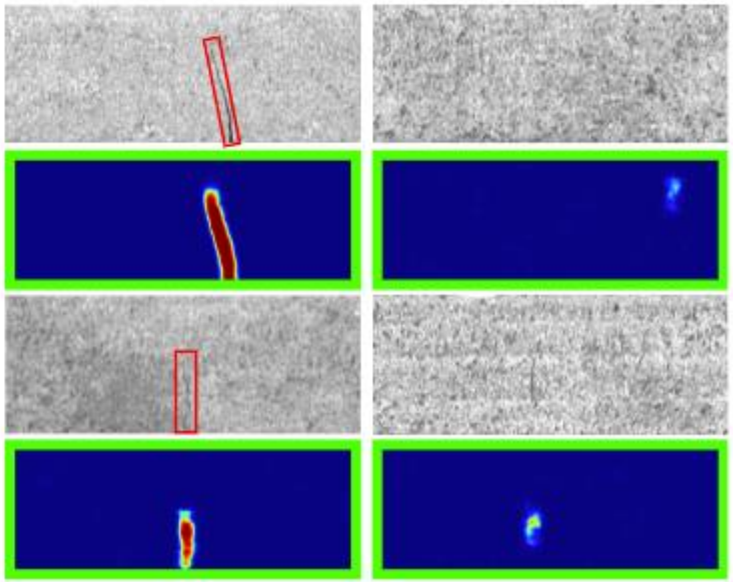
Surface-defect detection

DAGM



True positives

Kolektor SDD

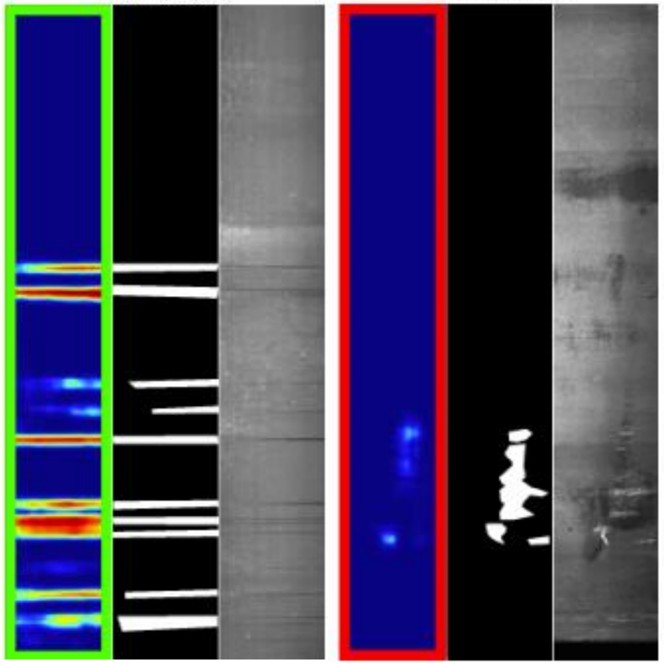


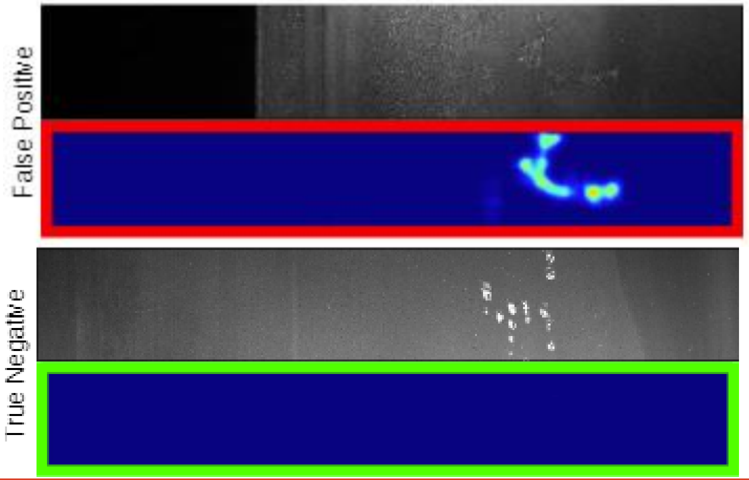
True positives

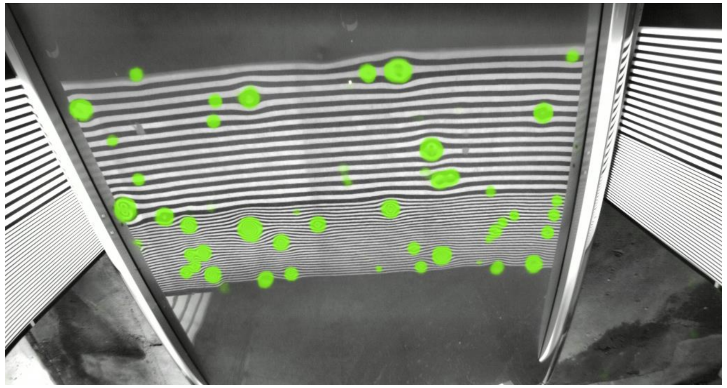
True negatives

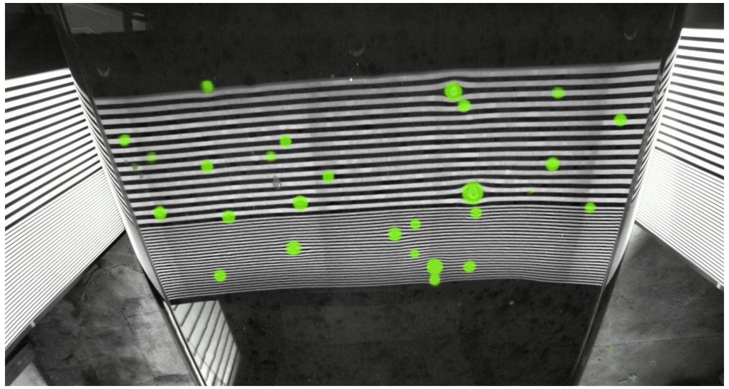
True Positive

False Negative

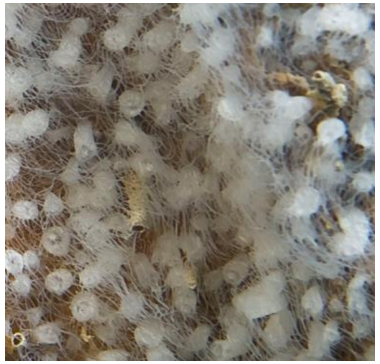


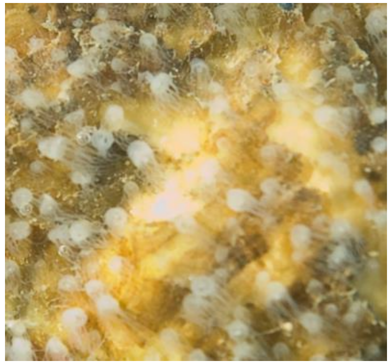


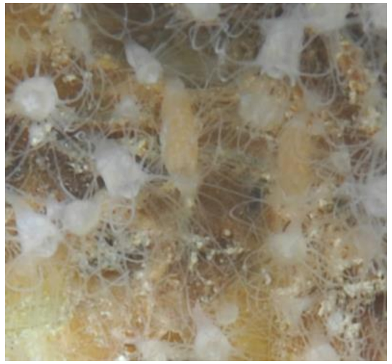


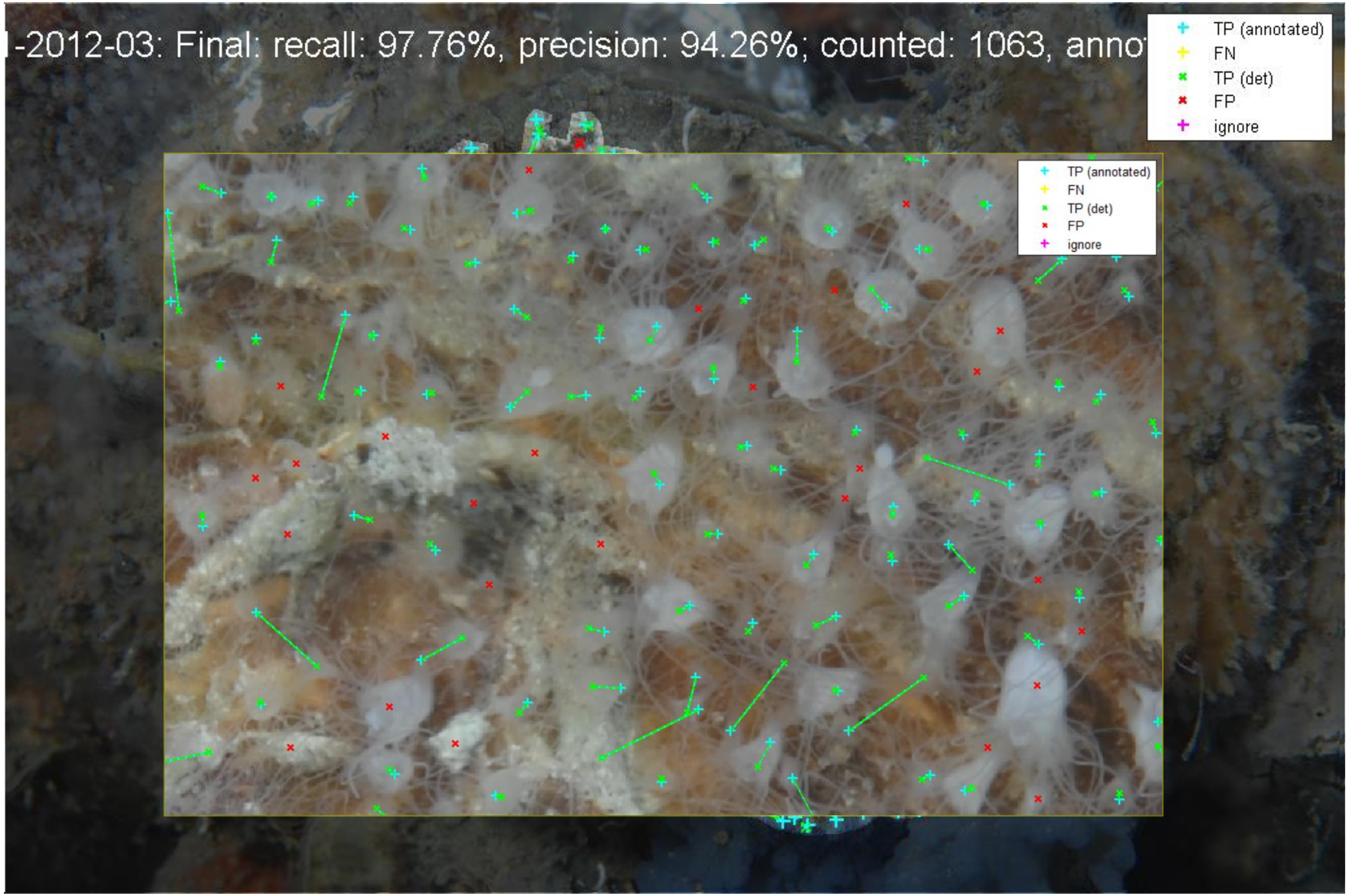


Polyp counting

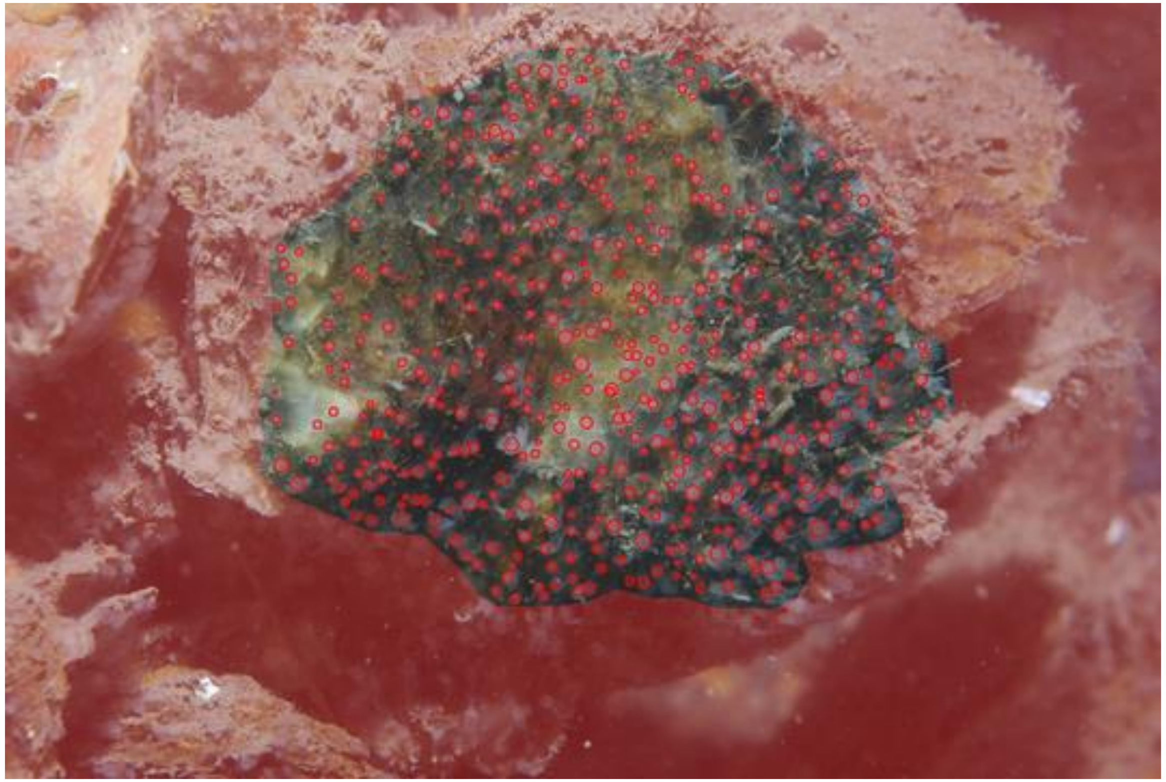


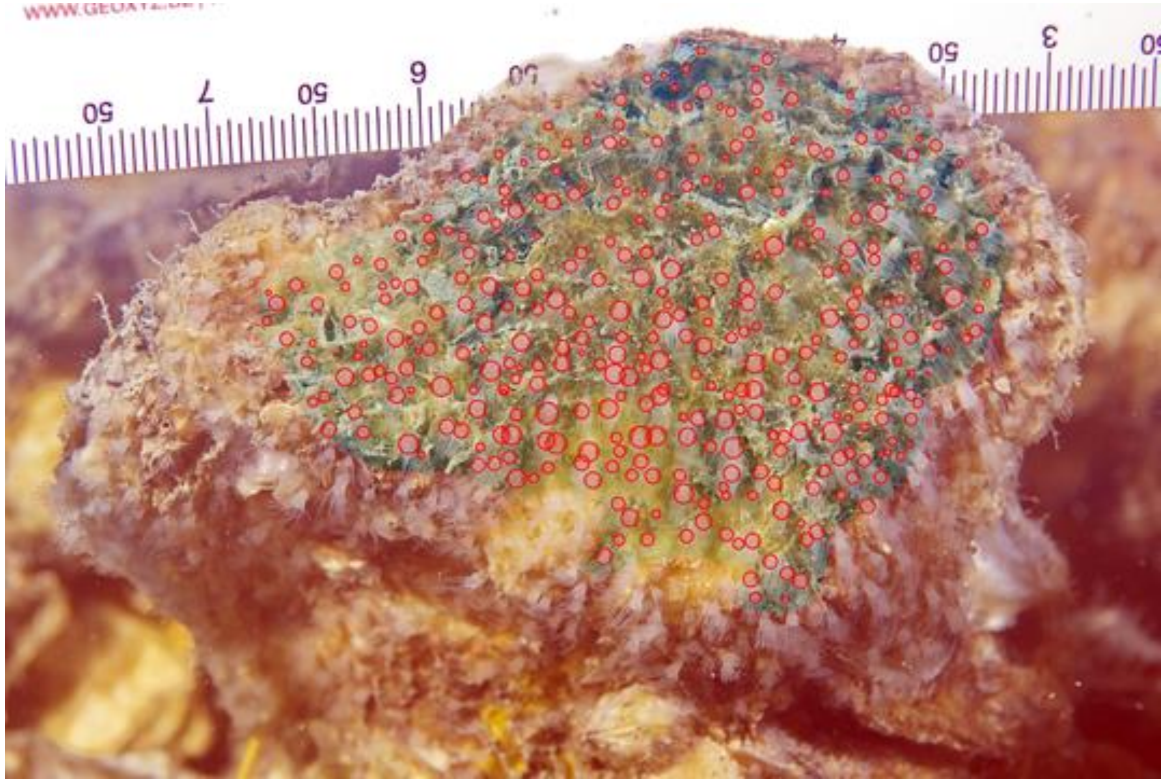




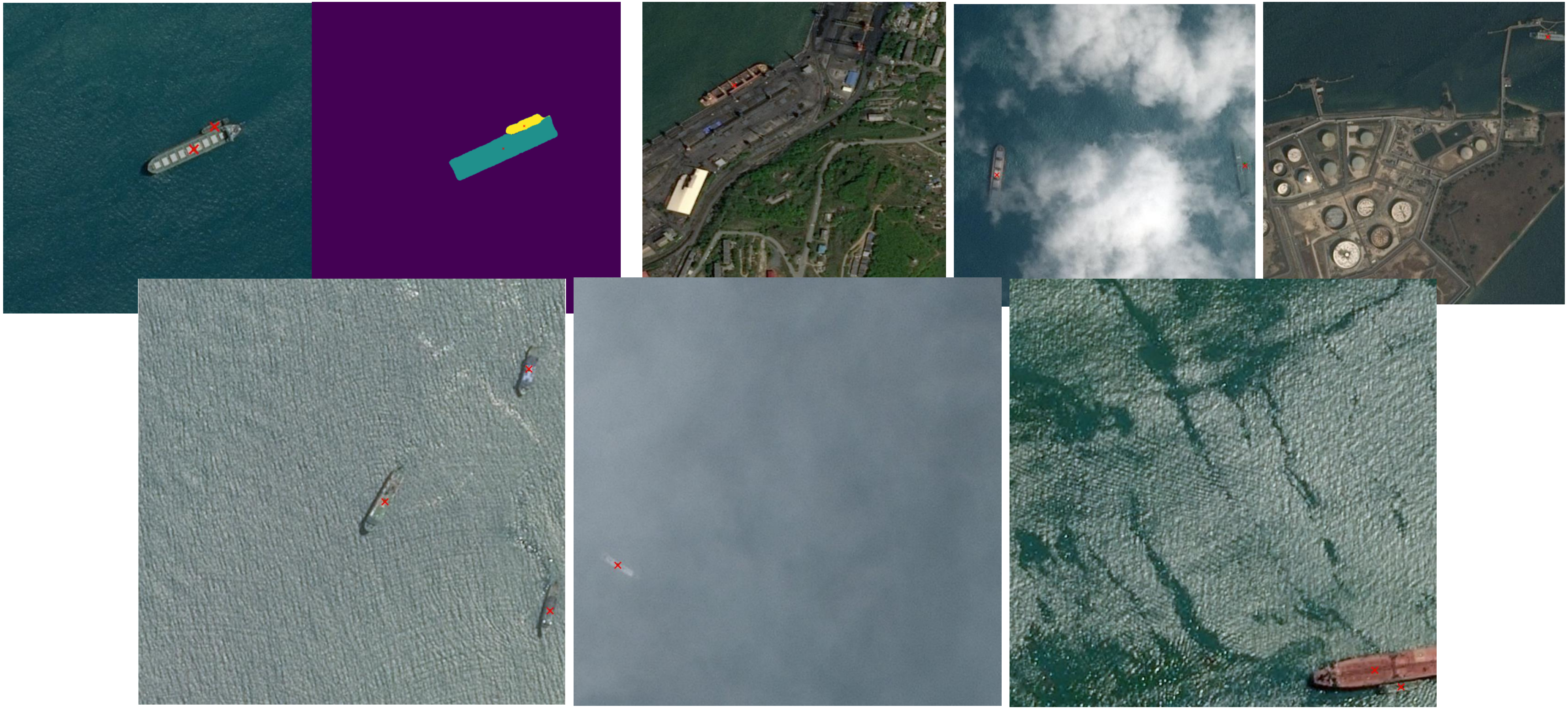


Polyp counting



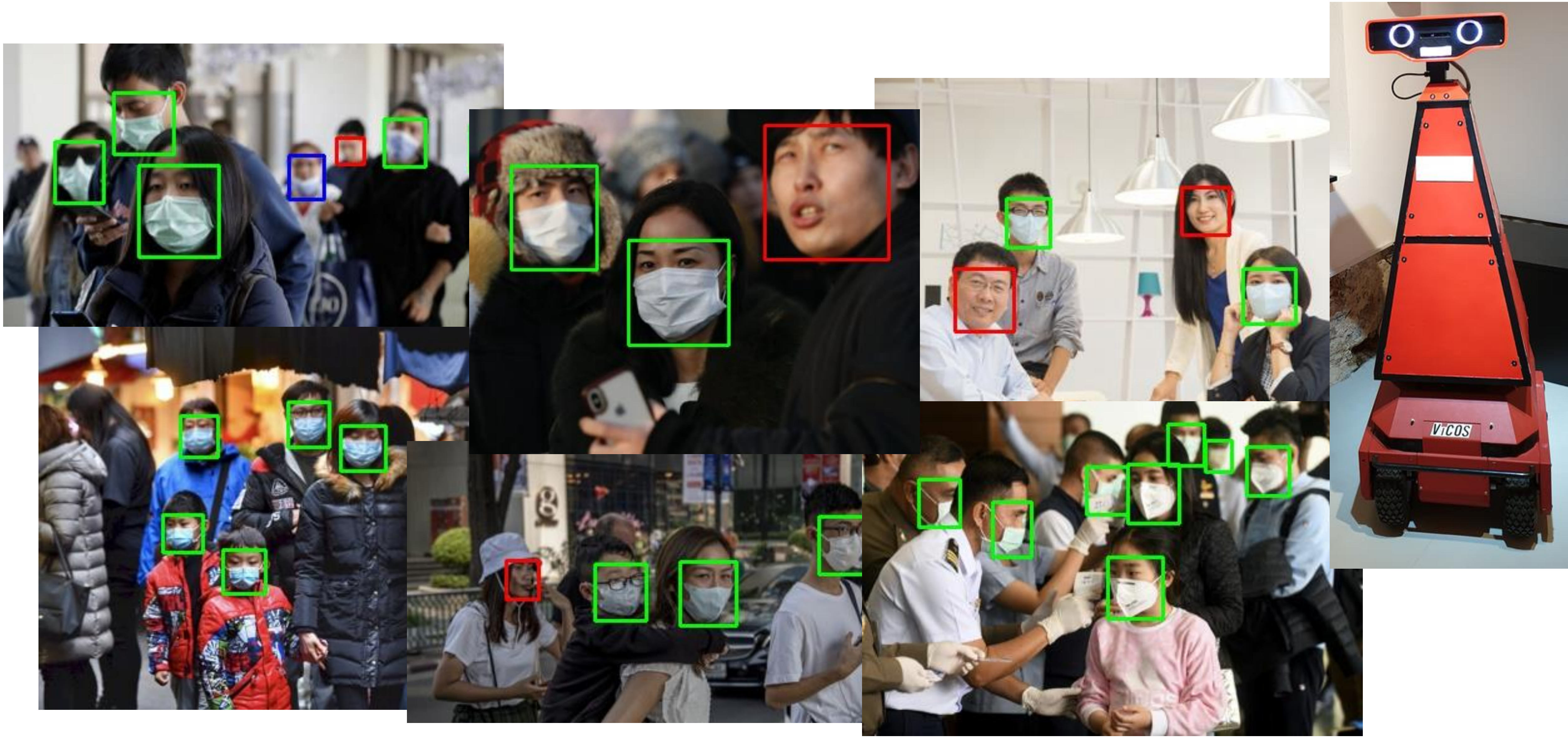


Ship detection



Face detection

Mask-wearing detection

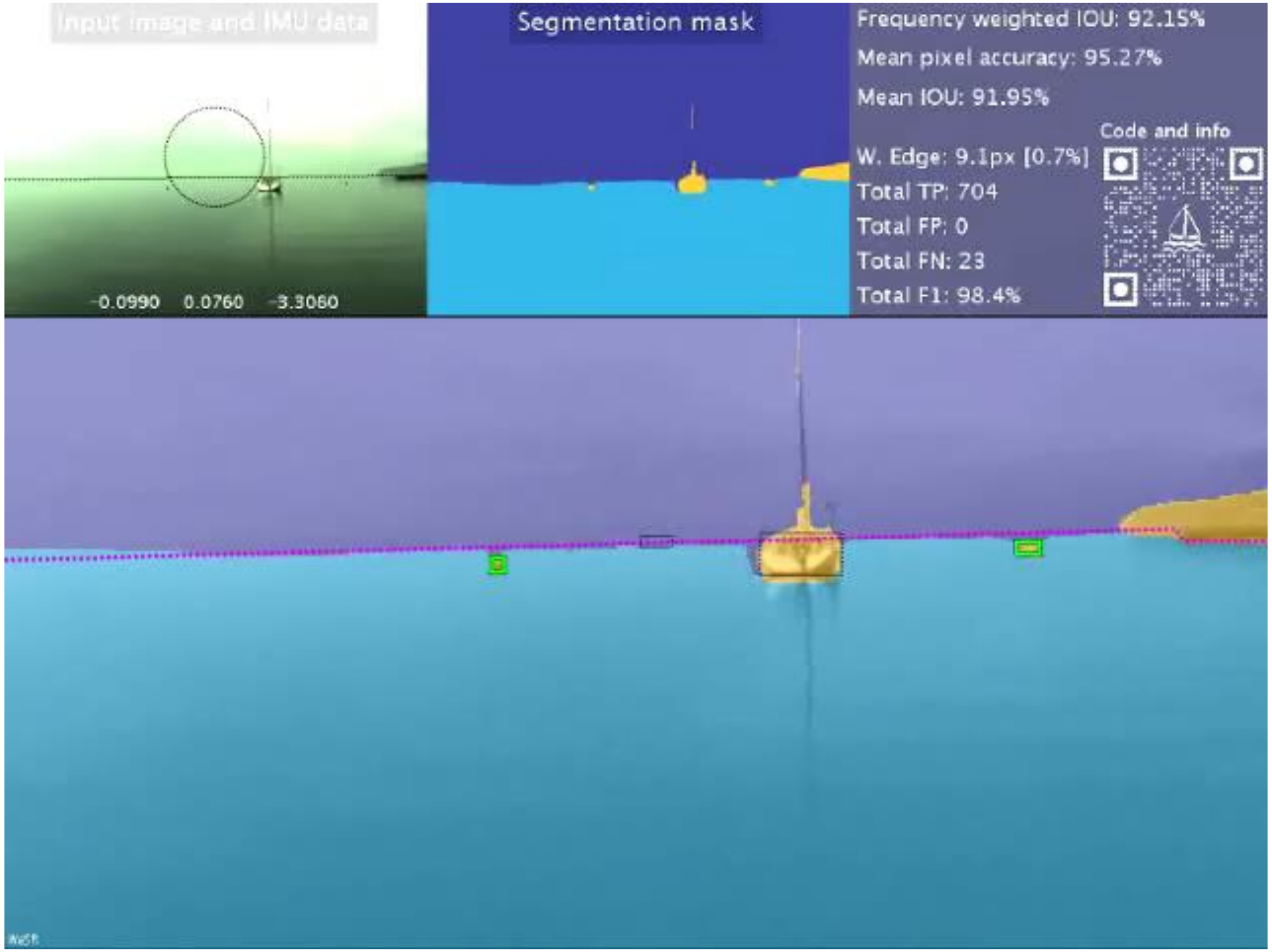


Obstacle detection on autonomous boat

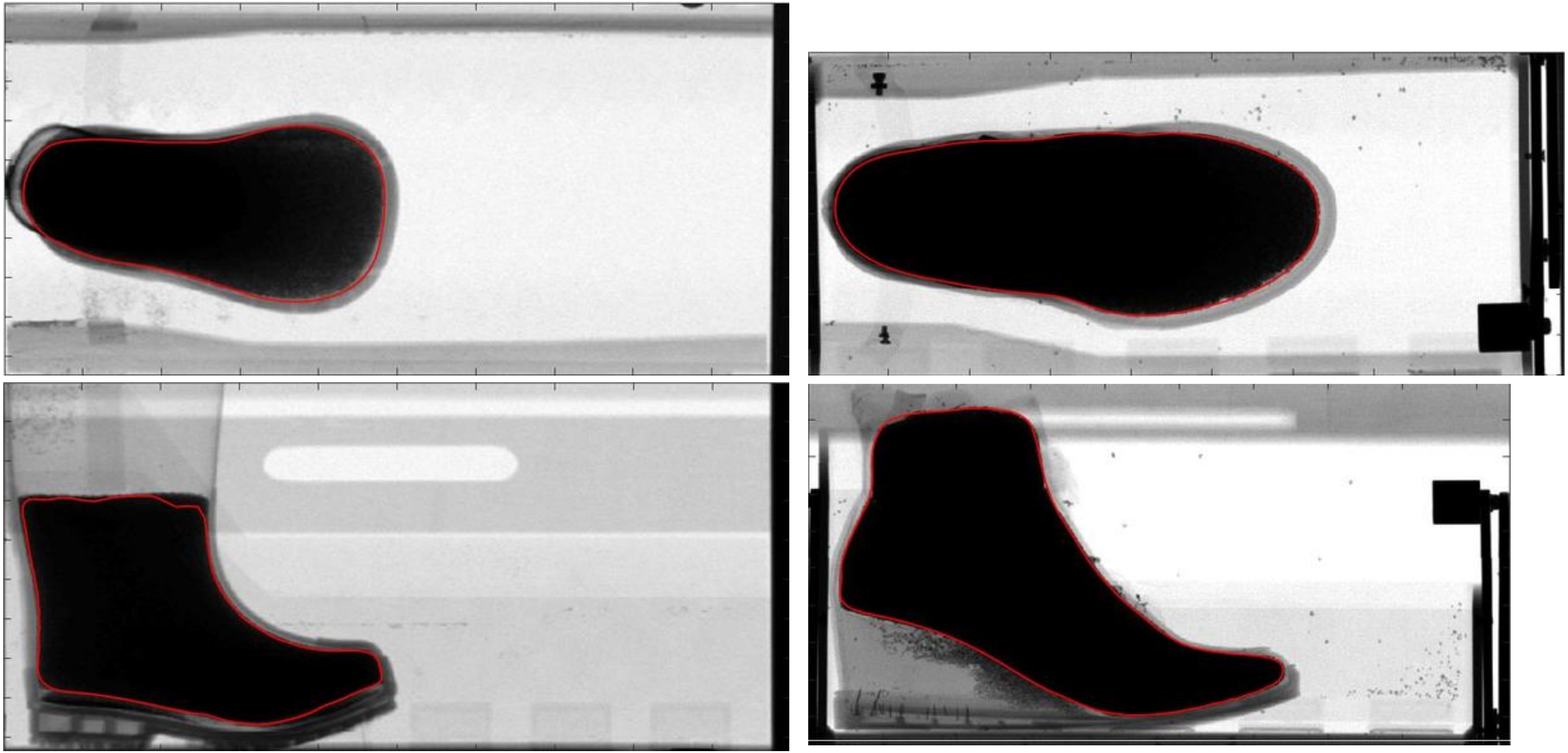
USV equipped with different sensors:

- stereo camera
- IMU
- GPS
- compass

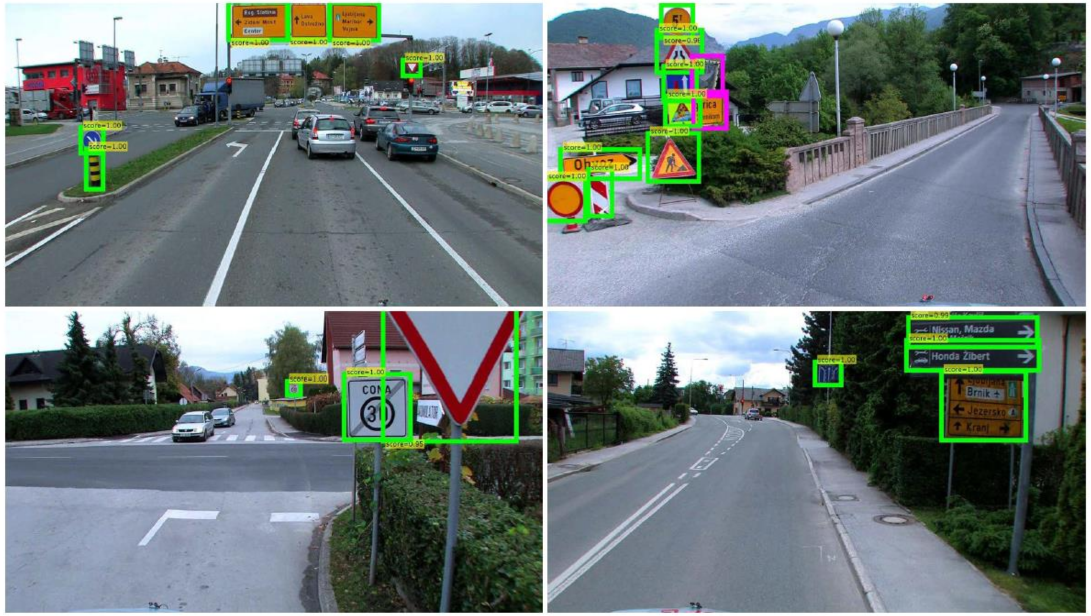
Segmentation based on RGB + IMU

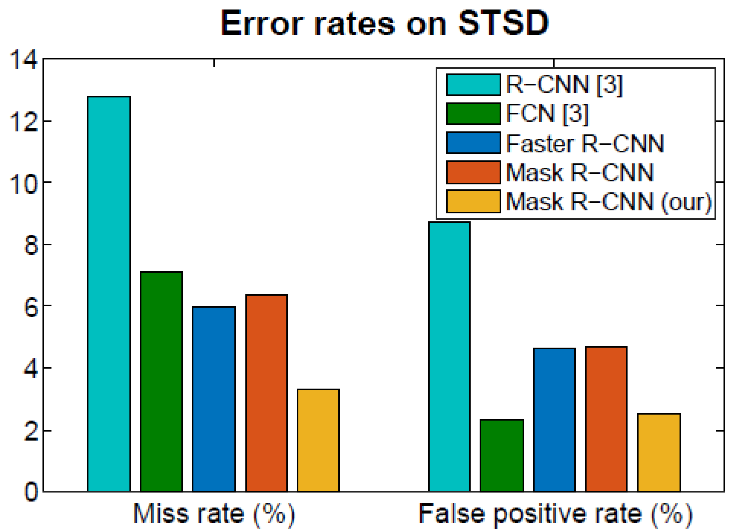


Semantic edge detection



Object (traffic sign) detection

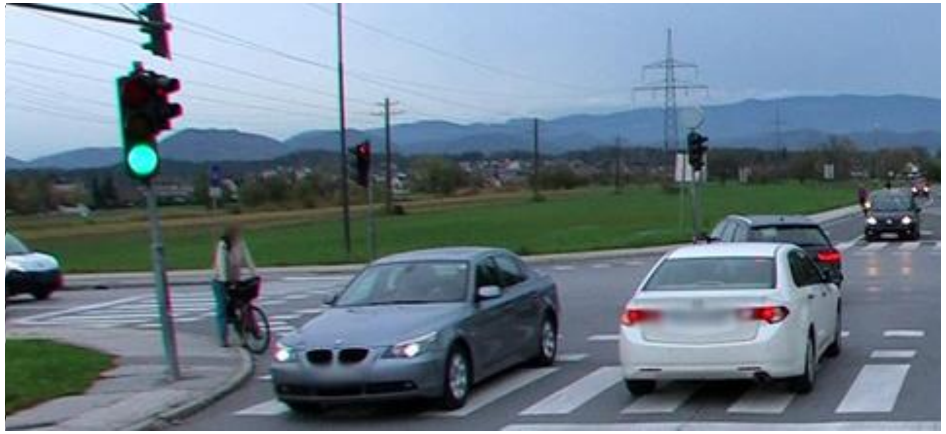




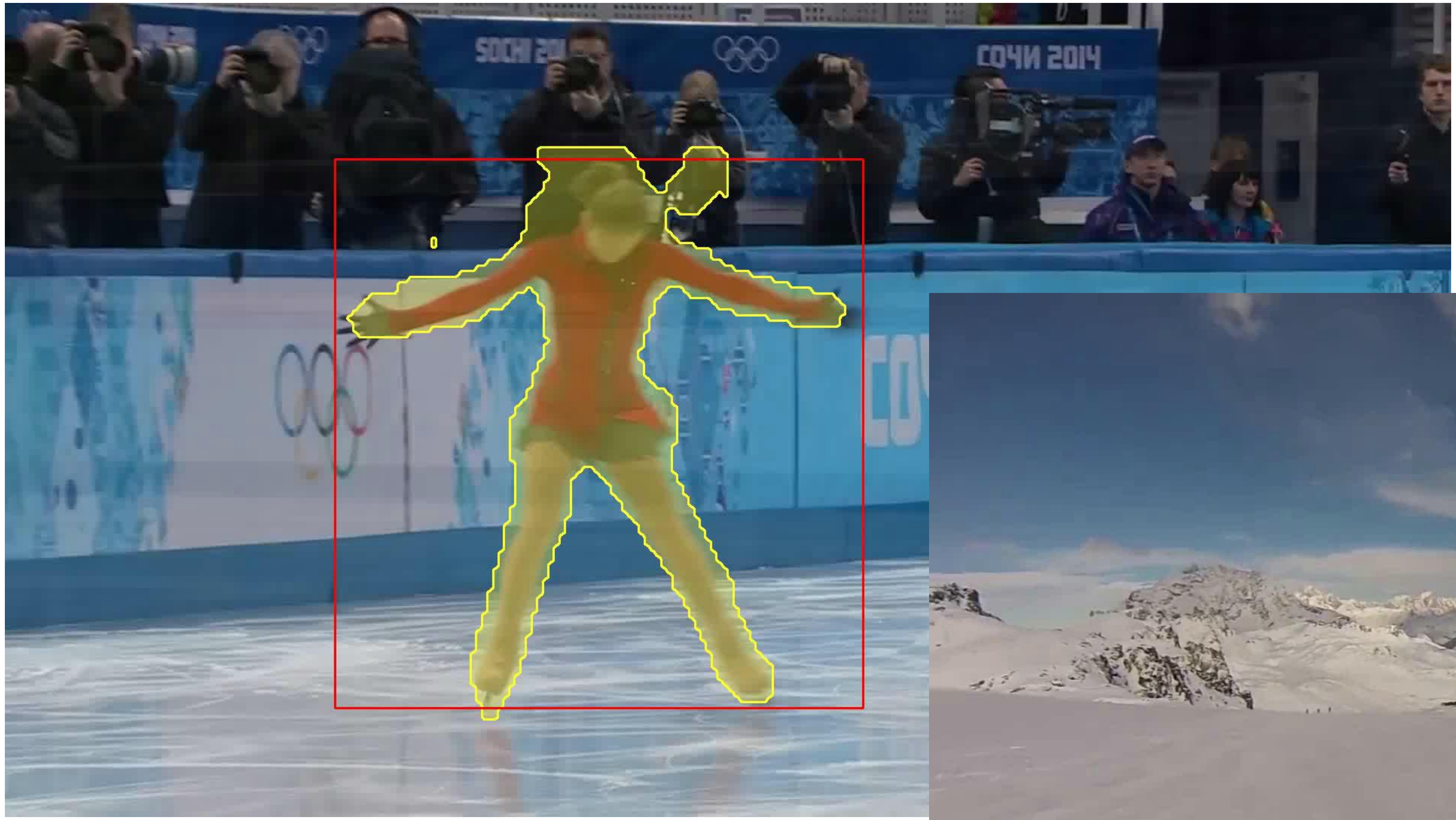
Object (traffic sign) detection

Image anonymisation

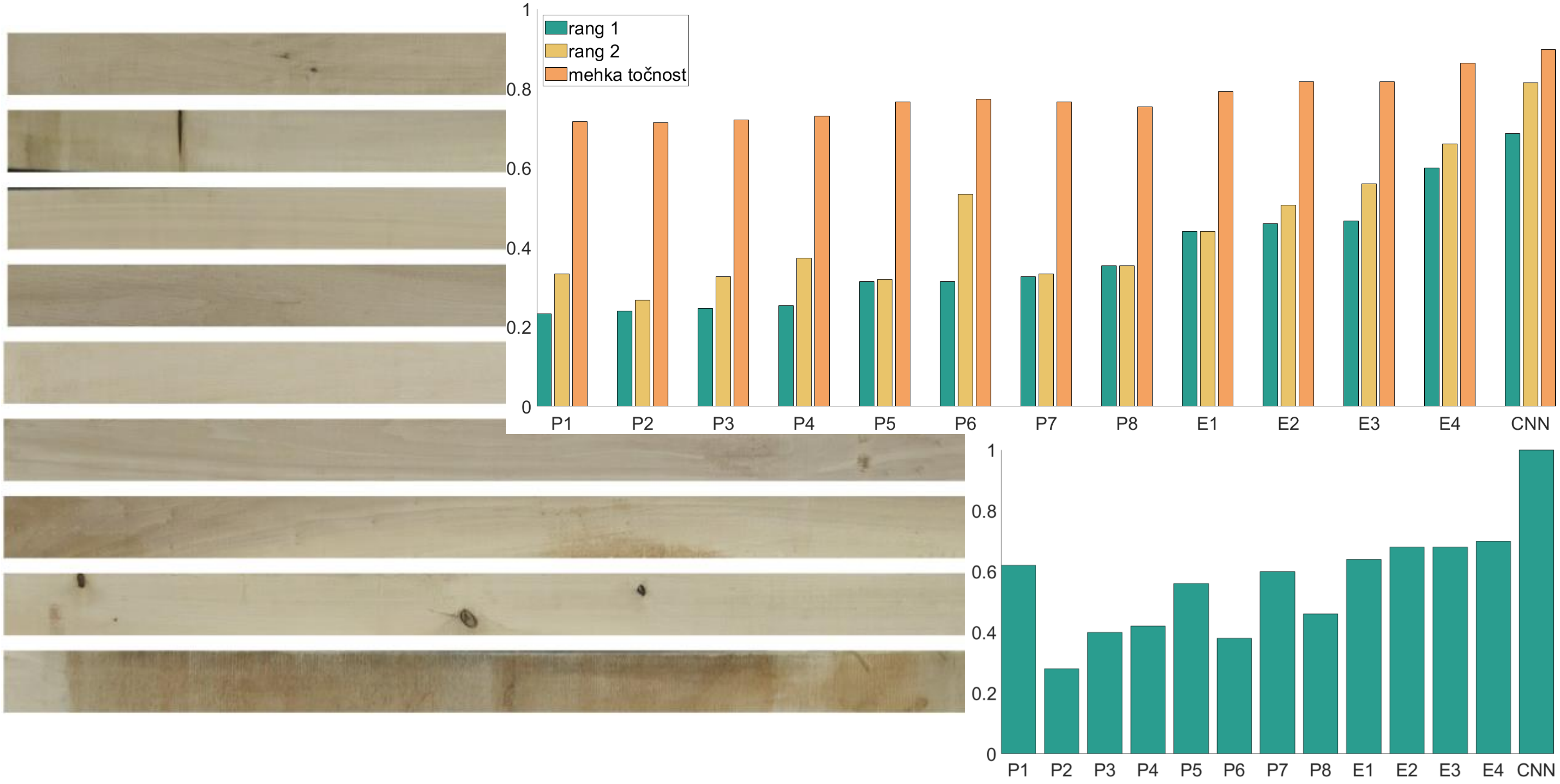
- Detection and anonimysation of car plates and faces



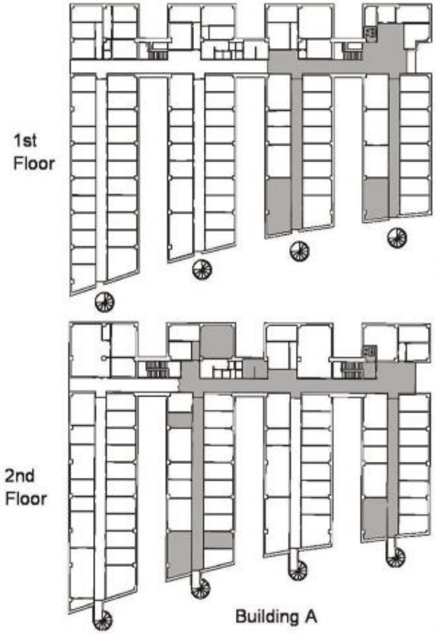
Visual tracking



Plank classification



Place recognition



Semantic segmentation

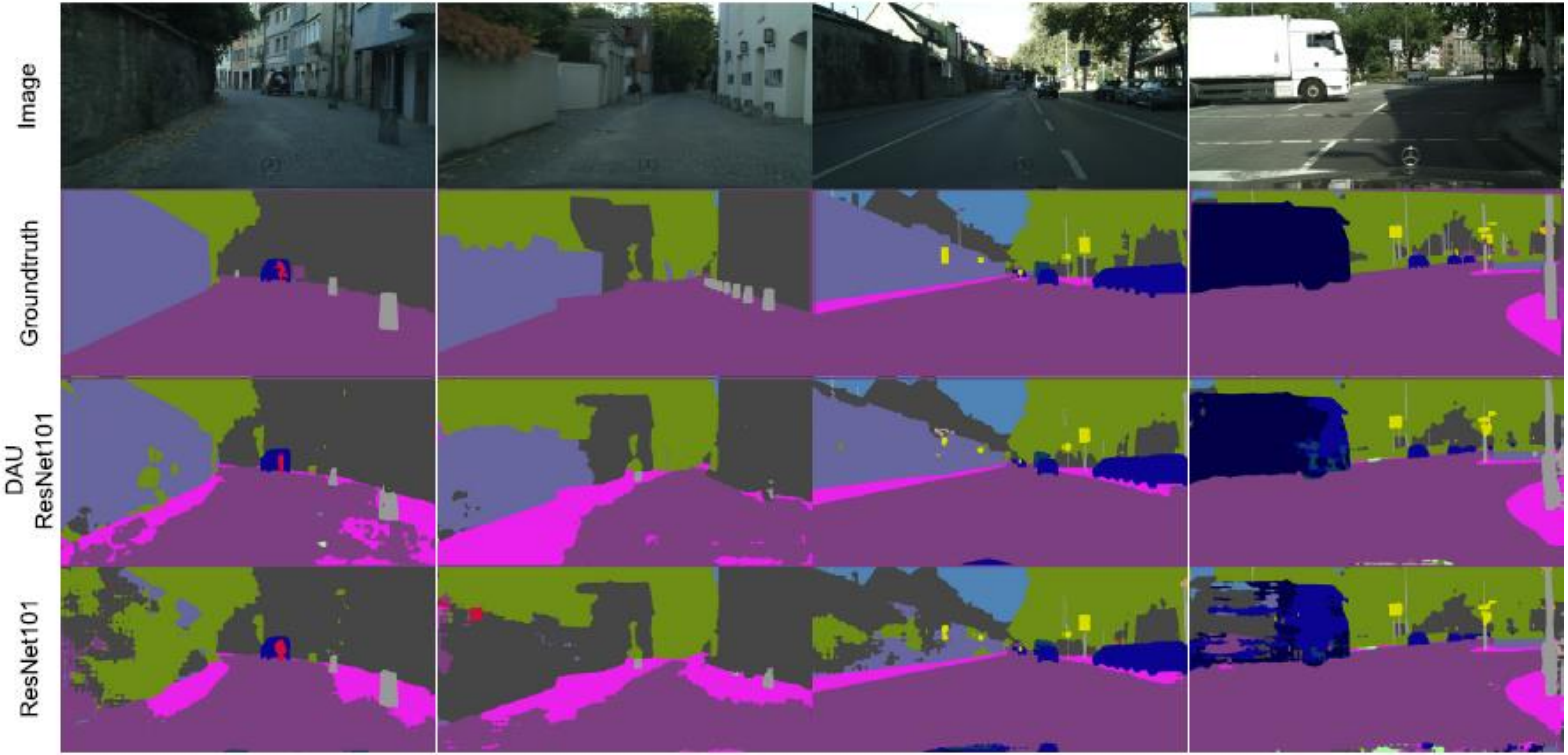


Image enhancement

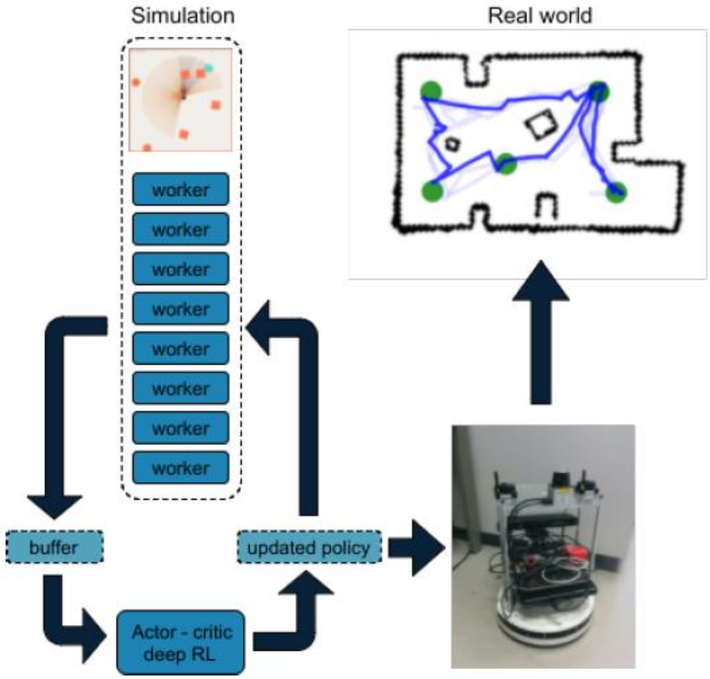
- Deblurring, super-resolution

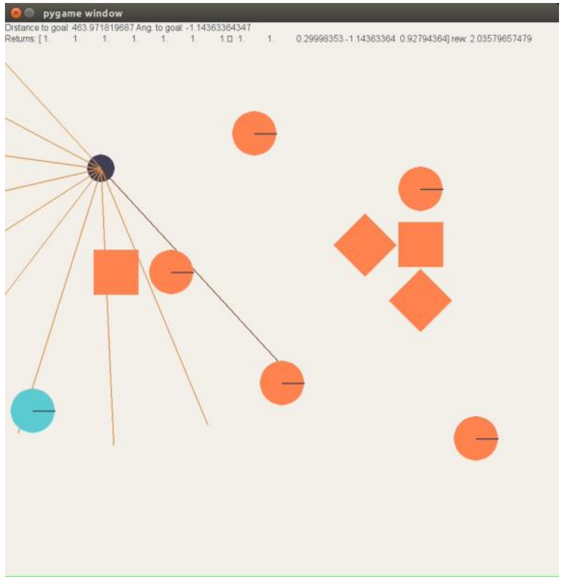

Original
Original
DAU-SNR-Deblur (our)
DAU-SNR-Deblur (our)

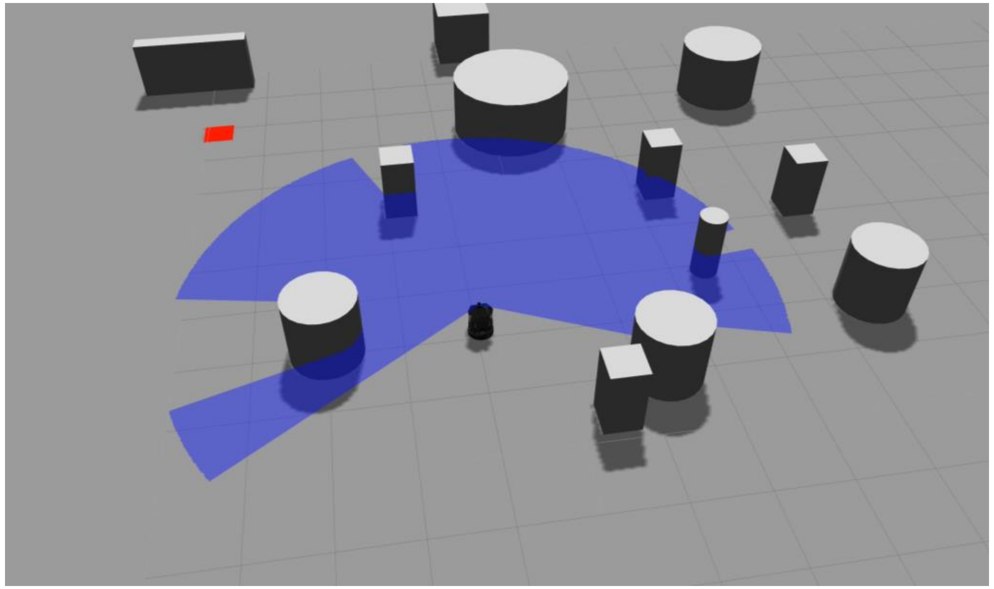

Original
Original
DAU-SNR-Deblur (our)
DAU-SNR-Deblur (our)

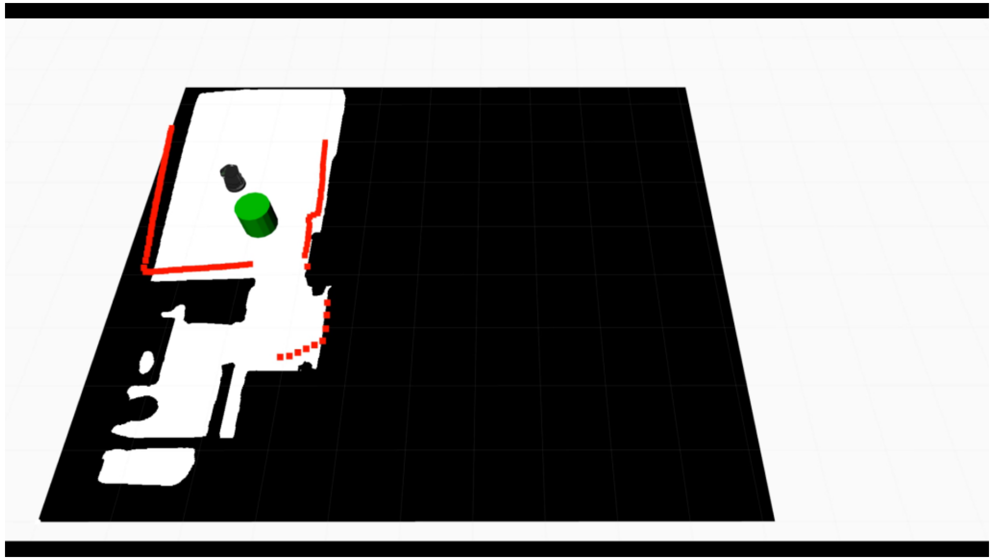
Deep reinforcement learning

- Automatic generation of learning examples
- Goal-driven map-less mobile robot navigation



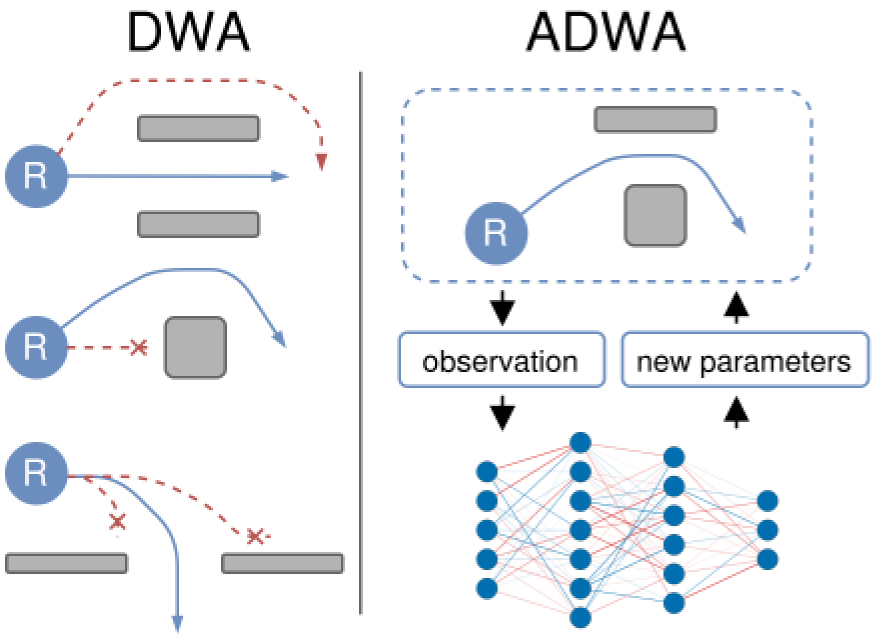


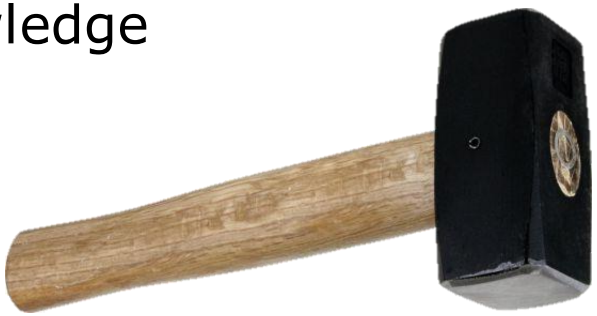


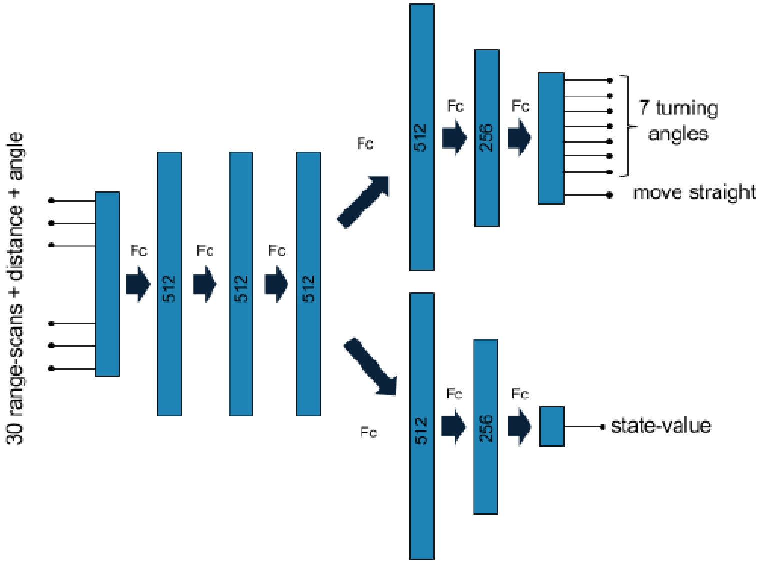


Innate and learned

- Goal-driven map-less mobile robot navigation
- Constraining the problem using a priory knowledge







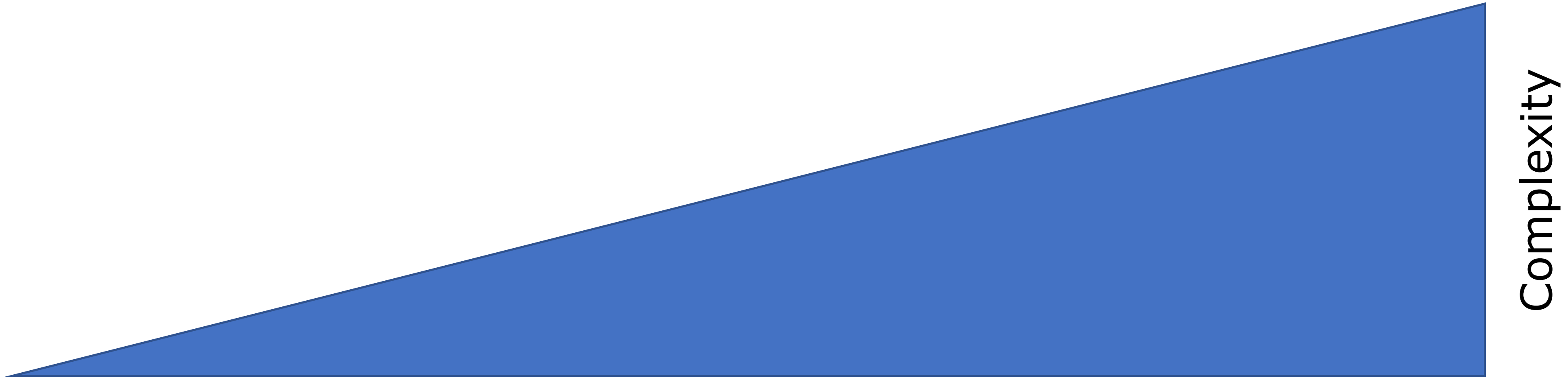
Engineering approach

Engineering approach + deep learning

Pure learning

Problem solving

- Different problem complexities



Simple,
well defined problems

Complex, vaguely
defined problems

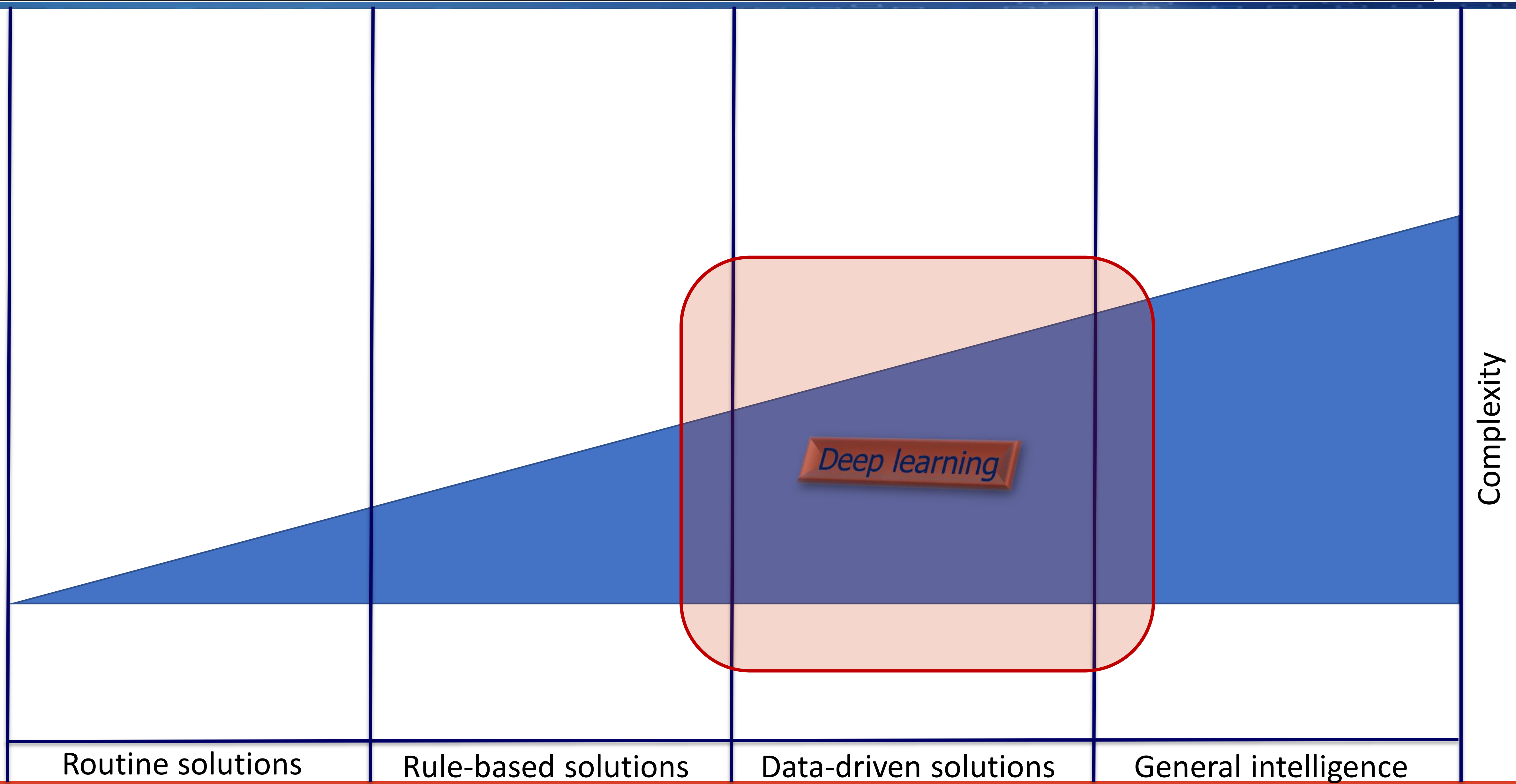
Rule-based
decision making

Data-driven
decision making

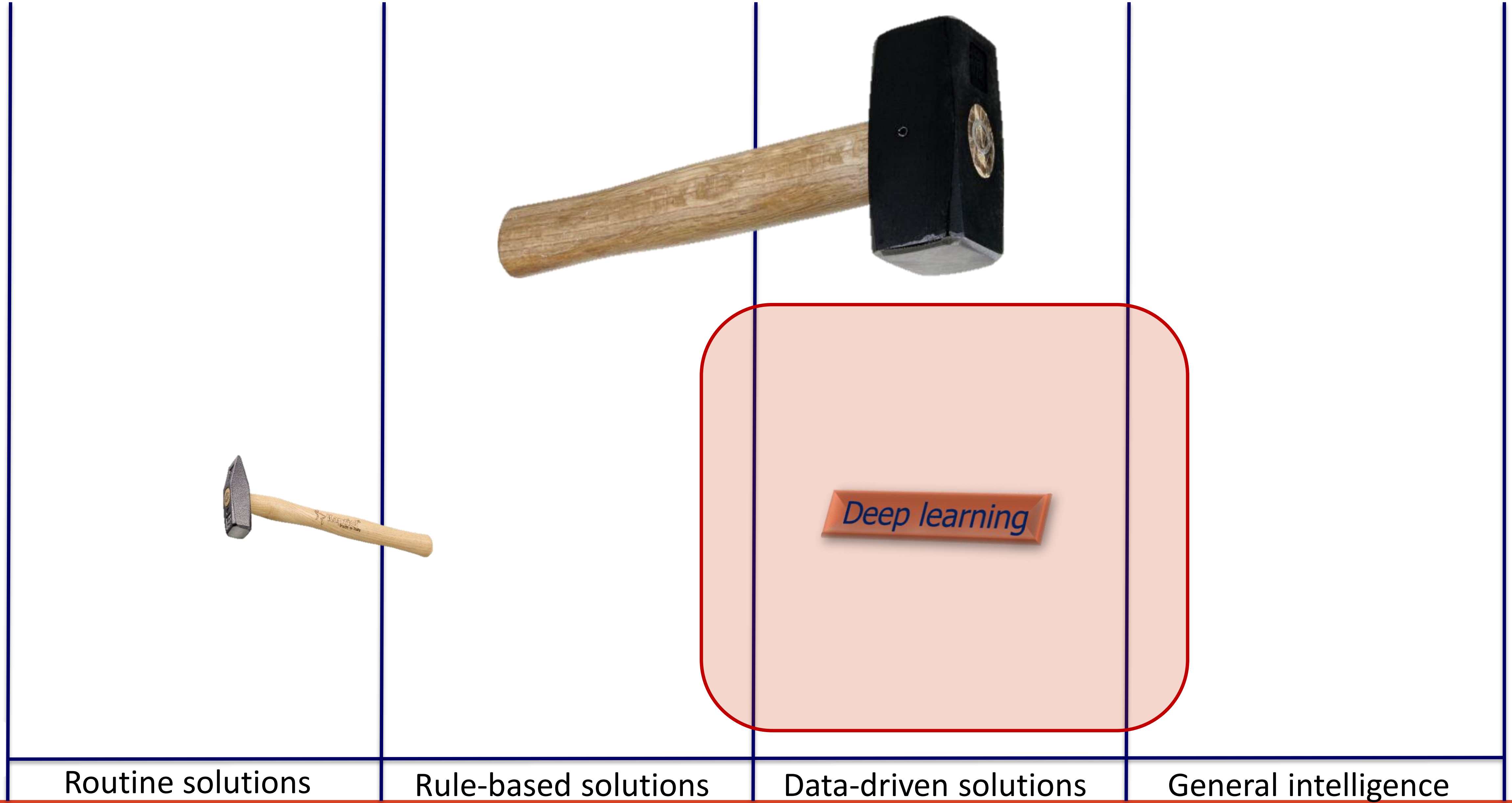
Programming

Machine learning

Problem solving



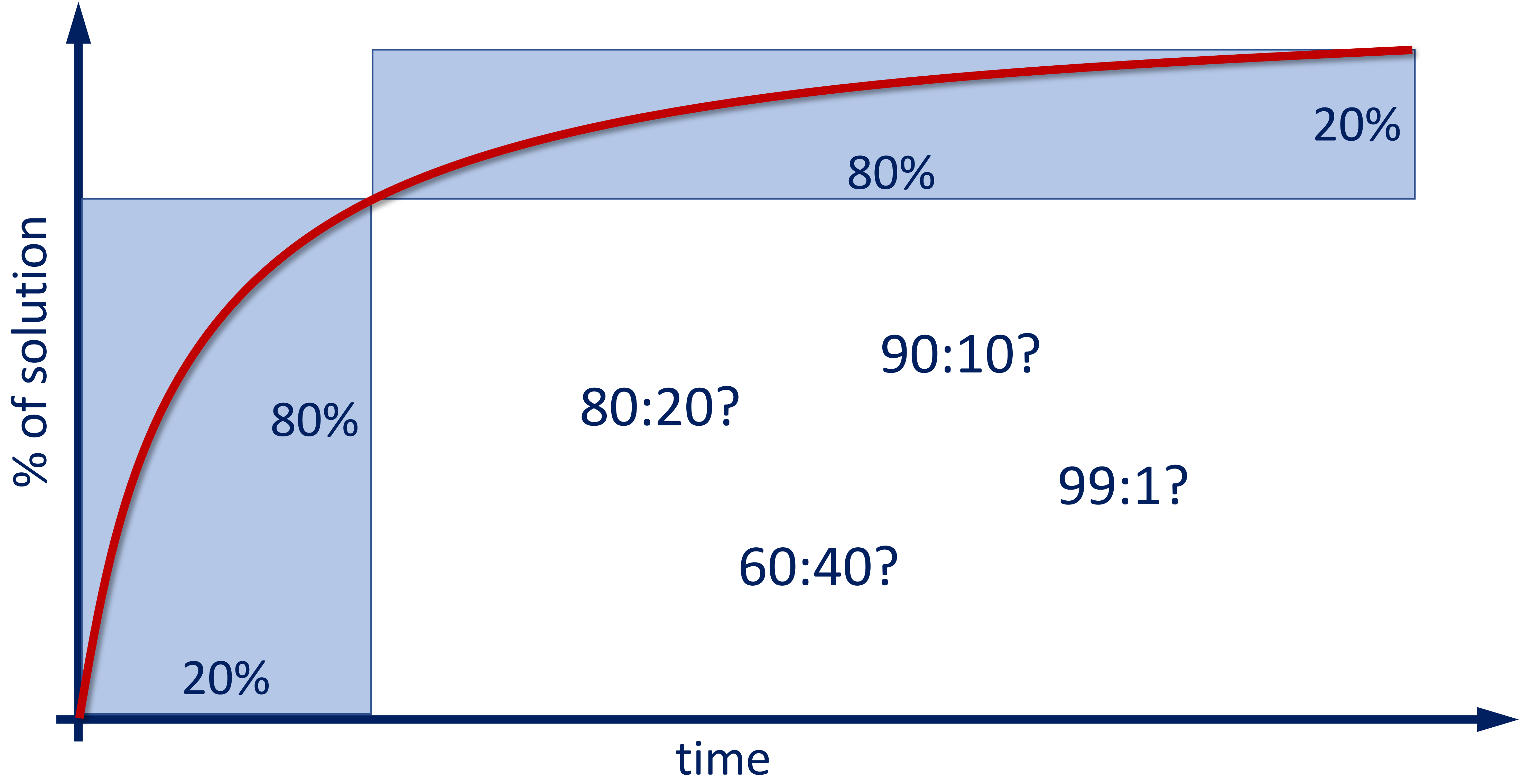
Adequate tools



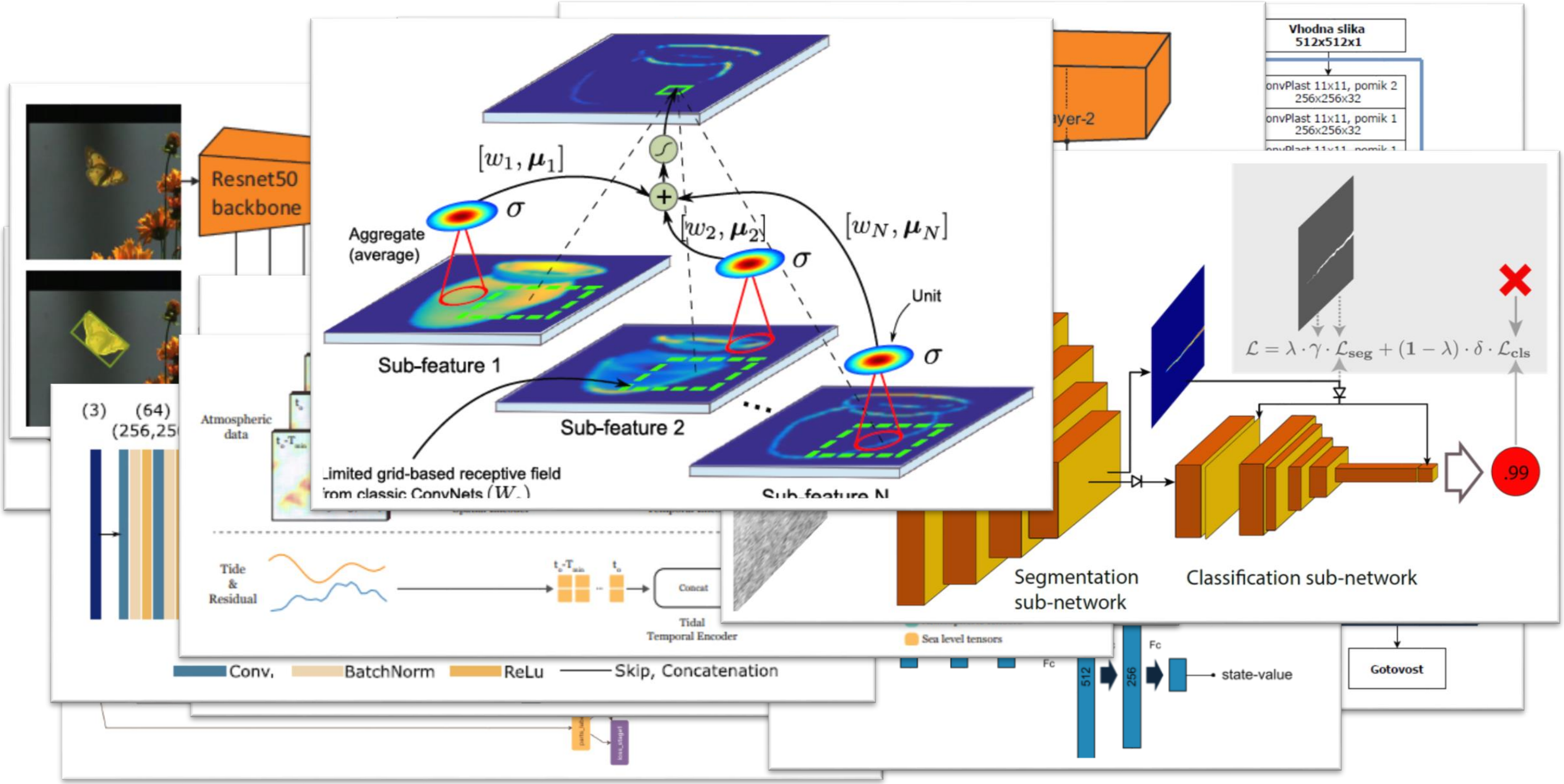
Development, deployement and maintainance

- Data, data, data!
  - Enough data, representative data
  - Correctly annotated data
- Appropriate deep architecture design
  - Proper backbone, architecture, loss function, …
  - Learning, parameter optimisation
- Efficient implementation
  - Execution speed
  - Integration
- Maintenance
  - Incremental improvement of the learned model
  - Reflecting to changes in the environment

Development of deep learning solutions



Knowledge and experience count



Software

- Neural networks in Python
- Convolutional neural networks using PyTorch or TensorFlow
- or other deep learning frameworks
- Optionally use Google Colab

Literature

- Michael A. Nielsen, Neural Networks and Deep learning, Determination Press, 2015
  http://neuralnetworksanddeeplearning.com/index.html

- Ian Goodfellow and Yoshua Bengio and Aaron Courville, Deep Learning, MIT Press, 2016
  http://www.deeplearningbook.org/

- Fei-Fei Li, Andrej Karpathy, Justin Johnson, CS231n: Convolutional Neural Networks for Visual Recognition, Stanford University, 2016
  http://cs231n.stanford.edu/

- Papers