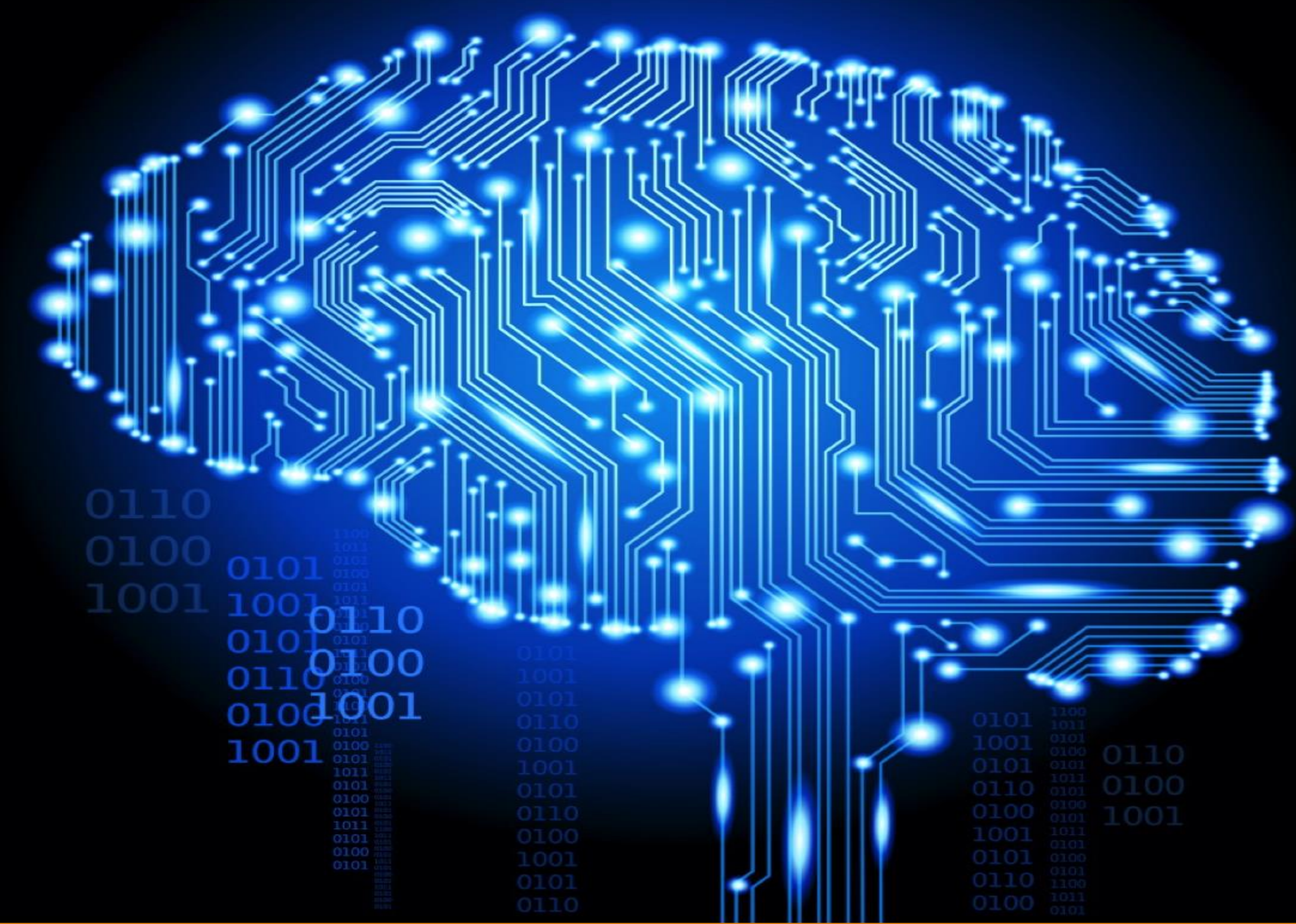


Lecture 5: Modern ConvNets

Efstratios Gavves

Lecture overview

- Popular Convolutional Neural Networks architectures
- Go deeper on what makes them tick
  - what makes them different

VGGnet

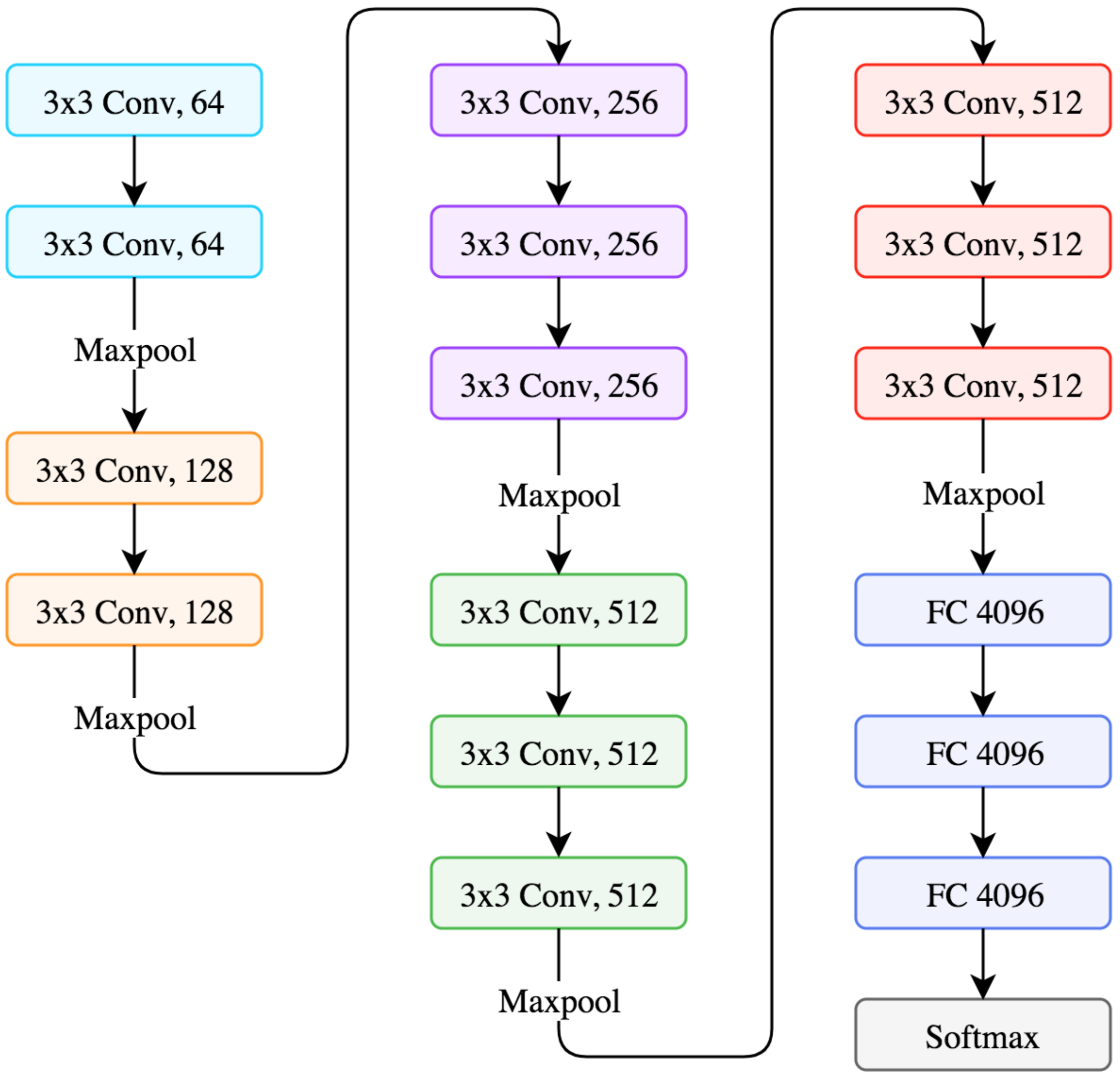
ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	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					

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

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

VGG16

- 7.3% error rate in ImageNet
- Compared to 18.2% of AlexNet



Picture credit: [Arden Dertat]

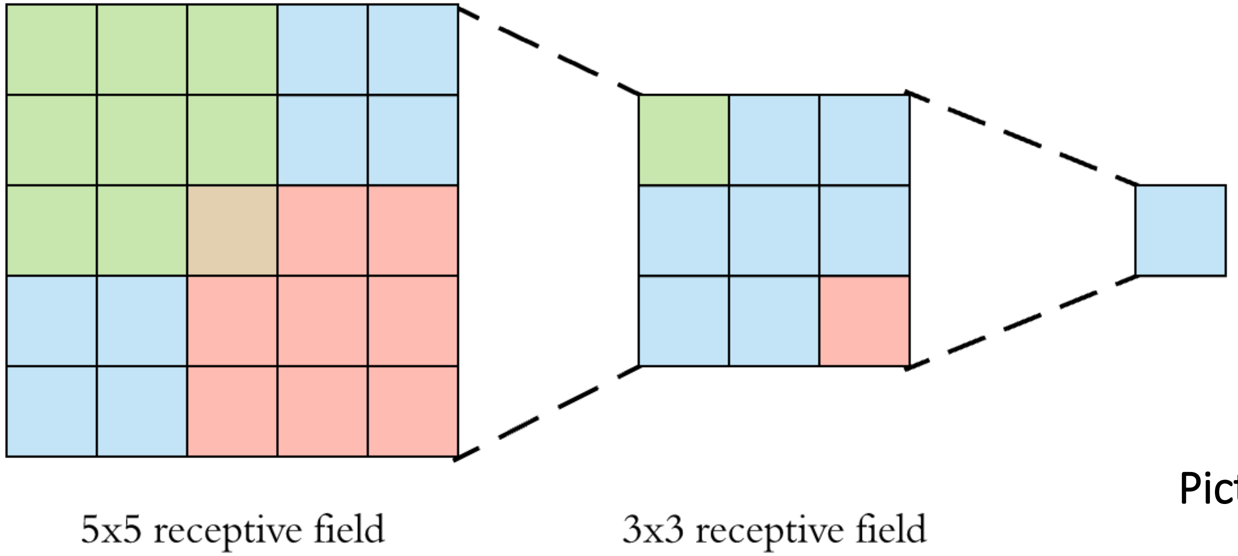
Characteristics

- Input size: 224×224
- Filter sizes: 3×3
- Convolution stride: 1
  - Spatial resolution preserved
- Padding: 1
- Max pooling: 2×2 with a stride of 2
- ReLU activations
- No fancy input normalizations
  - No Local Response Normalizations
- Although deeper, number of weights is not exploding

Why 3×3 filters?

Why 3×3 filters?

- The smallest possible filter to captures the “up”, “down”, “left”, “right”
- Two 3×3 filters have the receptive field of one 5×5
- Three 3×3 filters have the receptive field of …



Picture credit: Arden Dertat

Why 3×3 filters?

- The smallest possible filter to captures the “up”, “down”, “left”, “right”
- Two 3×3 filters have the receptive field of one 5×5
- Three 3×3 filters have the receptive field of one 7×7
- 1 large filter can be replaced by a deeper stack of successive smaller filters
- Benefit?

Why 3×3 filters?

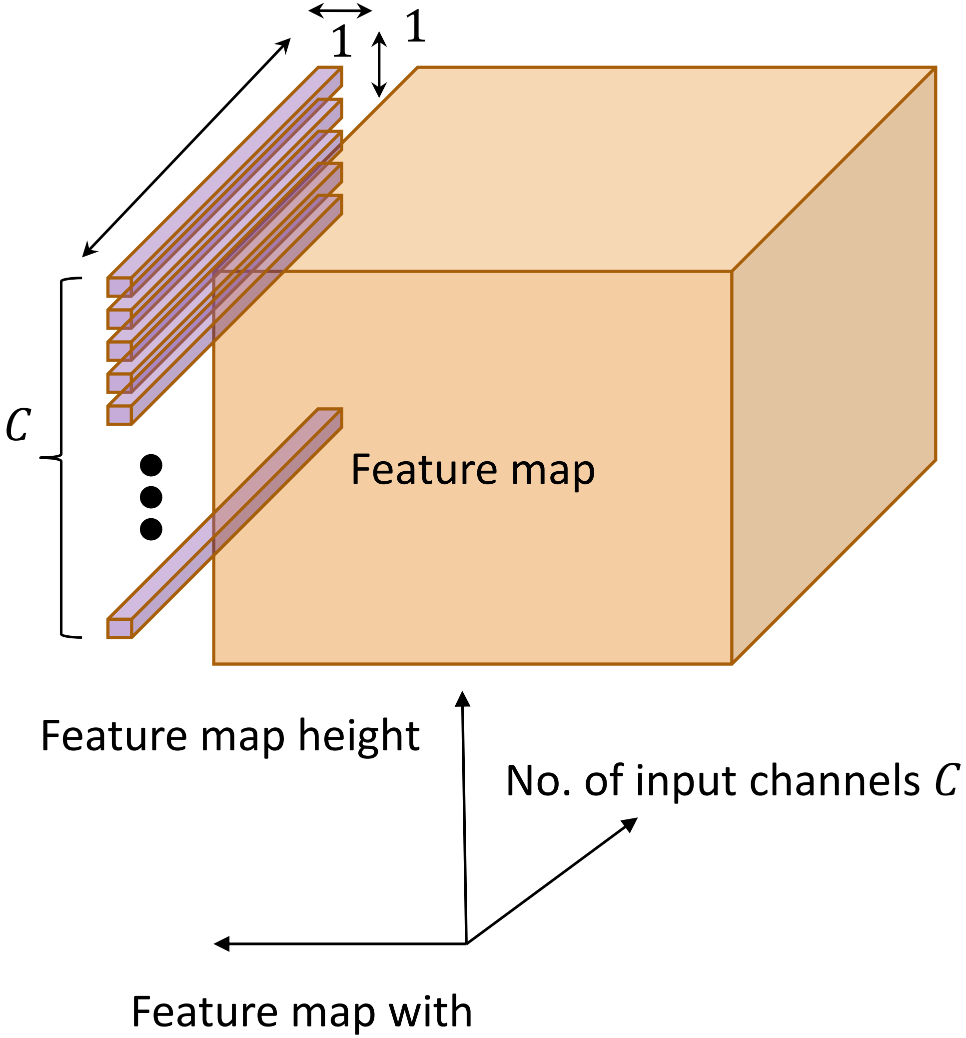
- The smallest possible filter to captures the "up", "down", "left", "right"
- Two 3×3 filters have the receptive field of one 5×5
- Three 3×3 filters have the receptive field of one 7×7
- 1 large filter can be replaced by a deeper stack of successive smaller filters
- Benefit?
- Three more nonlinearities for the same "size" of pattern learning
- Also fewer parameters and regularization

$$(3 \times 3 \times C) \times 3 = 27 \cdot C, 7 \times 7 \times C \times 1 = 49 \cdot C$$

- **Conclusion: 1 large filter can be replaced by a deeper, potentially more powerful, stack of successive smaller filters**

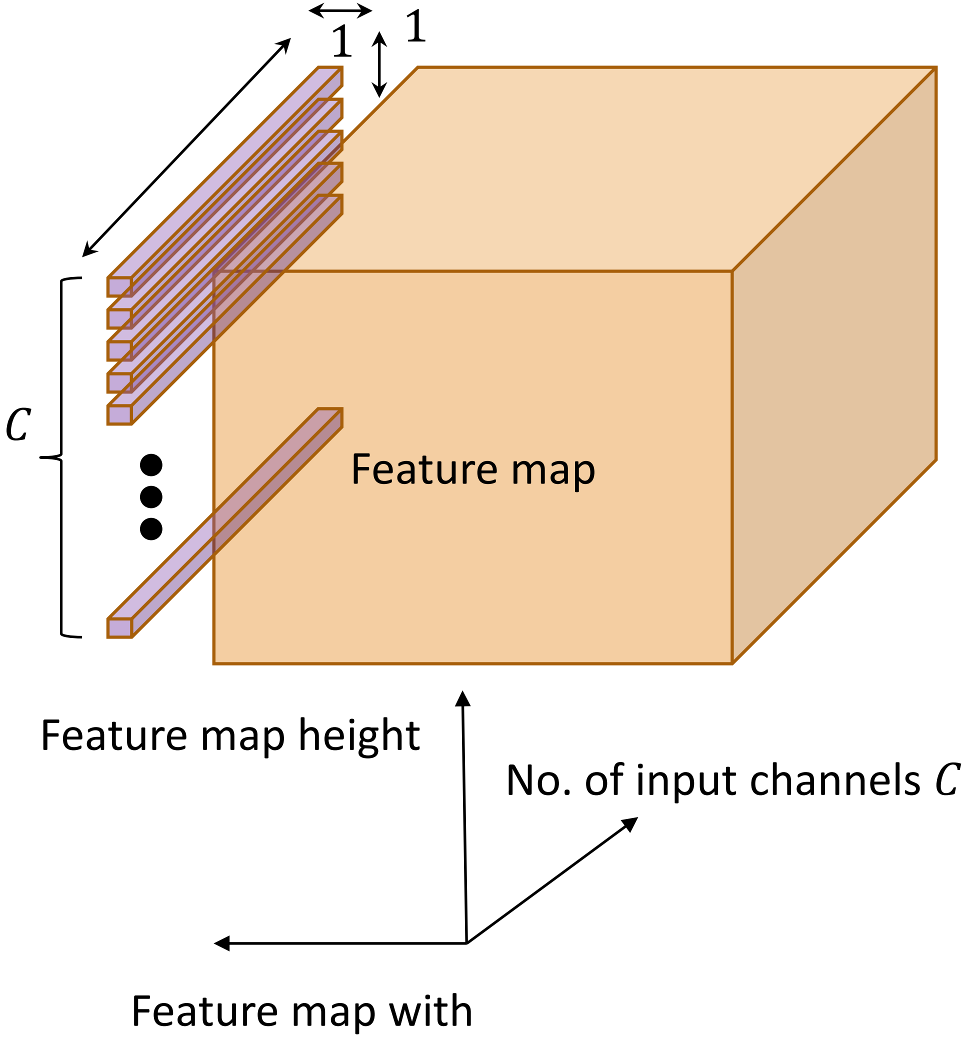
Even smaller filters?

- Also $1x1$ filters are used
- Followed by a nonlinearity
- Why?



Even smaller filters?

- Also $1x1$ filters are used
- Followed by a nonlinearity
- Why?
- Increasing nonlinearities without affecting receptive field sizes
  - Linear transformation of the input channels



Training

- Batch size: 256
- SGD with momentum=0.9
- Weight decay $\lambda = 5 \cdot 10^{-4}$
- Dropout on first two fully connected layers
- Learning rate $\eta_0 = 10^{-2}$, then decreased by factor of 10 when validation accuracy stopped improving
  - Three times this learning rate decrease
- Faster training
  - Smaller filters →
  - Depth also serves as regularization

Inception

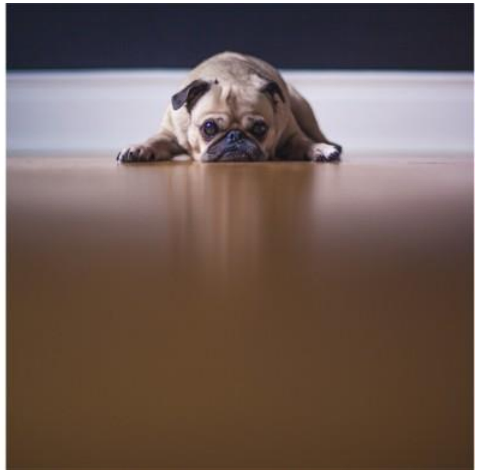
type	patch size/ stride	output size	depth	#1×1	#3×3 reduce	#3×3	#5×5 reduce	#5×5	pool proj	params	ops
convolution	7×7/2	112×112×64	1							2.7K	34M
max pool	3×3/2	56×56×64	0								
convolution	3×3/1	56×56×192	2		64	192				112K	360M
max pool	3×3/2	28×28×192	0								
inception (3a)		28×28×256	2	64	96	128	16	32	32	159K	128M
inception (3b)		28×28×480	2	128	128	192	32	96	64	380K	304M
max pool	3×3/2	14×14×480	0								
inception (4a)		14×14×512	2	192	96	208	16	48	64	364K	73M
inception (4b)		14×14×512	2	160	112	224	24	64	64	437K	88M
inception (4c)		14×14×512	2	128	128	256	24	64	64	463K	100M
inception (4d)		14×14×528	2	112	144	288	32	64	64	580K	119M
inception (4e)		14×14×832	2	256	160	320	32	128	128	840K	170M
max pool	3×3/2	7×7×832	0								
inception (5a)		7×7×832	2	256	160	320	32	128	128	1072K	54M
inception (5b)		7×7×1024	2	384	192	384	48	128	128	1388K	71M
avg pool	7×7/1	1×1×1024	0								
dropout (40%)		1×1×1024	0								
linear		1×1×1000	1							1000K	1M
softmax		1×1×1000	0								

Table 1: GoogLeNet incarnation of the Inception architecture

Basic idea

- Problem?





Picture credit: [Bharath Raj]

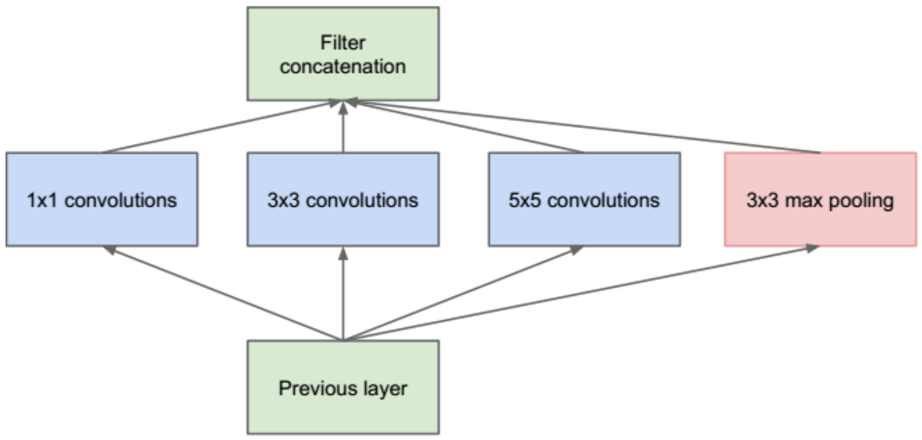
Basic idea

- Salient parts have great variation in sizes
- Hence, the receptive fields should vary in size accordingly
- Naively stacking convolutional operations is expensive
- Very deep nets are prone to overfitting

Picture credit: Bharath Raj

Inception module

- Multiple kernel filters of different sizes $(1 \times 1, 3 \times 3, 5 \times 5)$
  - Naïve version
- Problem?

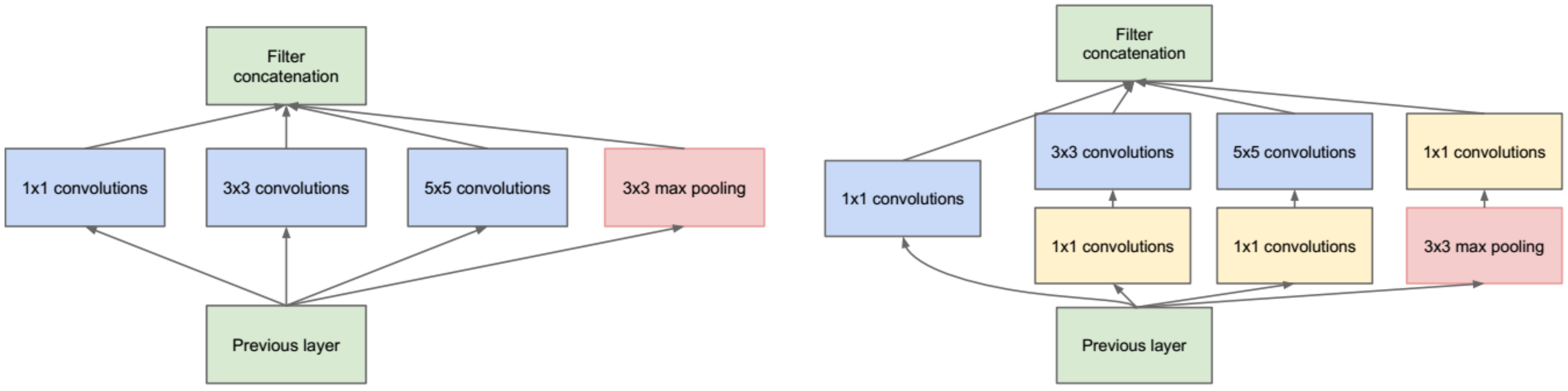


(a) Inception module, naïve version

Picture credit: [Bharath Raj]

Inception module

- Multiple kernel filters of different sizes $(1 \times 1, 3 \times 3, 5 \times 5)$
  - Naïve version
- Problem?
  - Very expensive!
- Add intermediate 1×1 convolutions

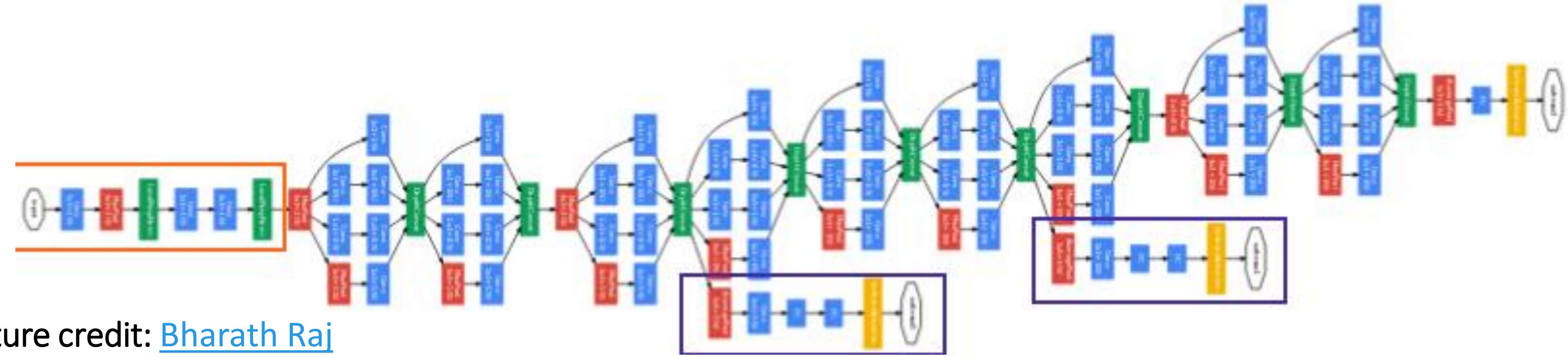


(a) Inception module, naïve version (b) Inception module with dimension reductions

Picture credit: [Bharath Raj]

Architecture

- 9 Inception Modules
- 22 layers deep (27 with the pooling layers)
- Global average pooling at the end of last Inception Module
- 6.67% Imagenet error, compared to 18.2% of Alexnet



Picture credit: [Bharath Raj]

Houston, we have a problem

Problem: Vanishing gradients

- The network was too deep (at the time)
- Roughly speaking, backprop is lots of matrix multiplications

$$\frac{\partial \mathcal{L}}{\partial w^l} = \frac{\partial \mathcal{L}}{\partial a^L} \cdot \frac{\partial a^L}{\partial a^{L-1}} \cdot \frac{\partial a^{L-1}}{\partial a^{L-2}} \cdot \ldots \cdot \frac{\partial a^l}{\partial w^l}$$

- Many of intermediate terms < 1 → the final $\frac{\partial \mathcal{L}}{\partial w^l}$ gets extremely small
- Extremely small gradient → ?

Picture credit: [Anish Singh Walia]

Problem: Vanishing gradients (more details later)

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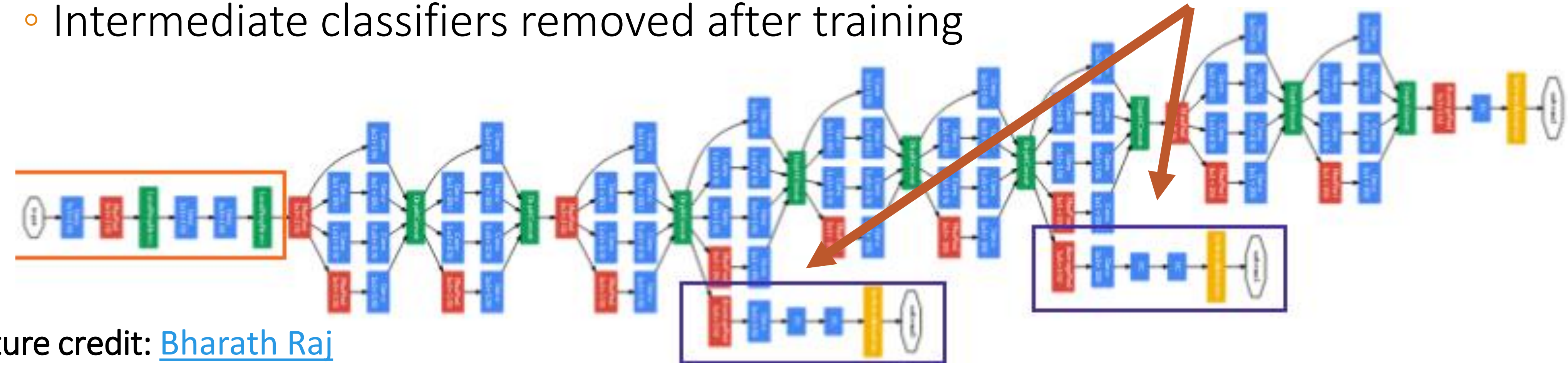
$$\frac{\partial \mathcal{L}}{\partial w^l} = \frac{\partial \mathcal{L}}{\partial a^L} \cdot \frac{\partial a^L}{\partial a^{L-1}} \cdot \frac{\partial a^{L-1}}{\partial a^{L-2}} \cdot \ \dots \cdot \frac{\partial a^l}{\partial w^l}$$

- Many of intermediate terms < 1 → the final $\frac{\partial \mathcal{L}}{\partial w^l}$ gets extremely small
- Extremely small gradient → Extremely slow learning

Picture credit: [Anish Singh Walia]

Architecture

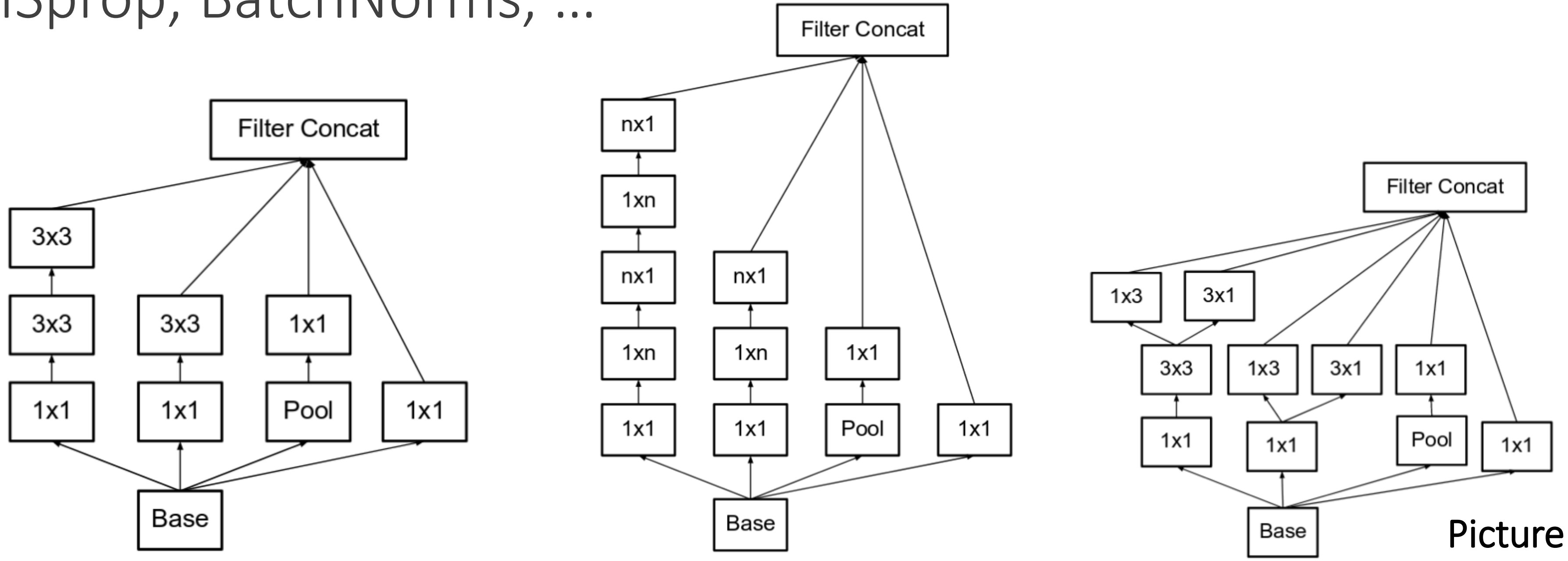
- 9 Inception Modules
- 22 layers deep (27 with the pooling layers)
- Global average pooling at the end of last Inception Module
- Because of the increased depth → **Vanishing gradients**
- Inception solution to vanishing gradients: **intermediate classifiers**
  - Intermediate classifiers removed after training



Picture credit: [Bharath Raj]

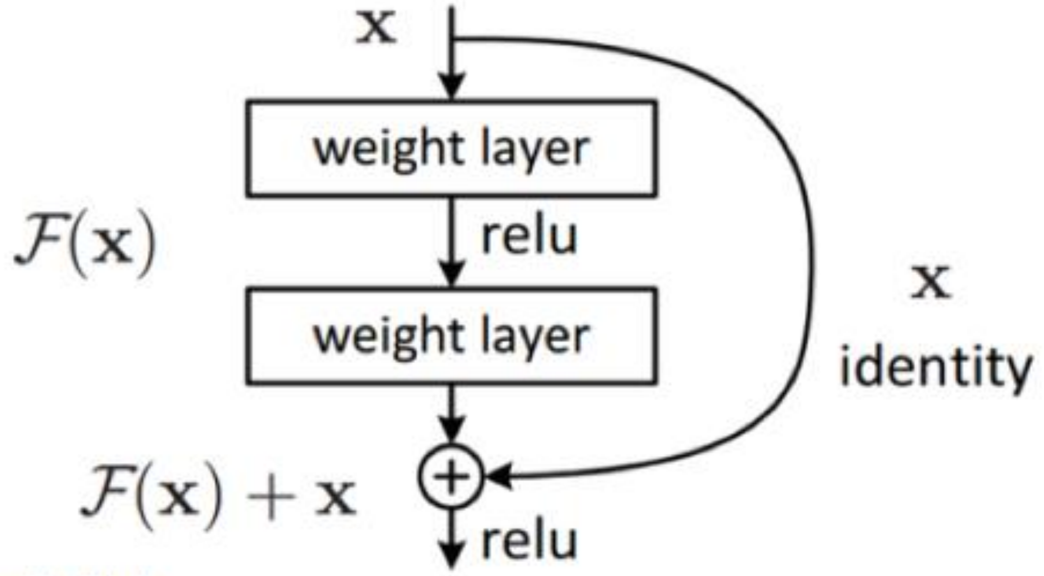
Inceptions v2, v3, v4, ….

- Factorize 5×5 in two 3×3 filters
- Factorize $n \times n$ in two $n \times 1$ and $1 \times n$ filters (quite a lot cheaper)
- Make nets wider
- RMSprop, BatchNorms, …



Picture credit: [Bharath Raj]

ResNets
DenseNets
HighwayNets



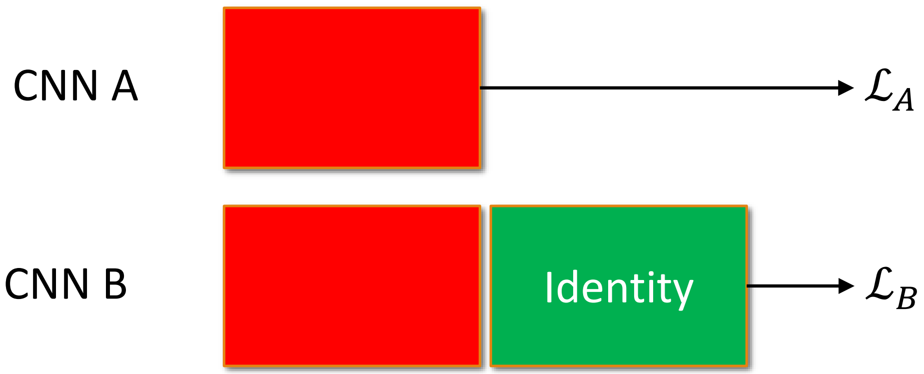
A residual block

Some facts

- The first truly Deep Network, going deeper than 1,000 layers
- More importantly, the first Deep Architecture that proposed a novel concept on how to gracefully go deeper than a few dozen layers
  - Not simply getting more GPUs, more training time, etc
- Smashed Imagenet, with a 3.57% error (in ensembles)
- Won all object classification, detection, segmentation, etc. challenges

Hypothesis

- **Hypothesis:** Is it possible to have a very deep network at least as accurate as averagely deep networks?
- **Thought experiment:** Let's assume two Convnets A, B. They are almost identical, in that B is the same as A, with extra "identity" layers. Since identity layers pass the information unchanged, the errors of the two networks should …



Hypothesis

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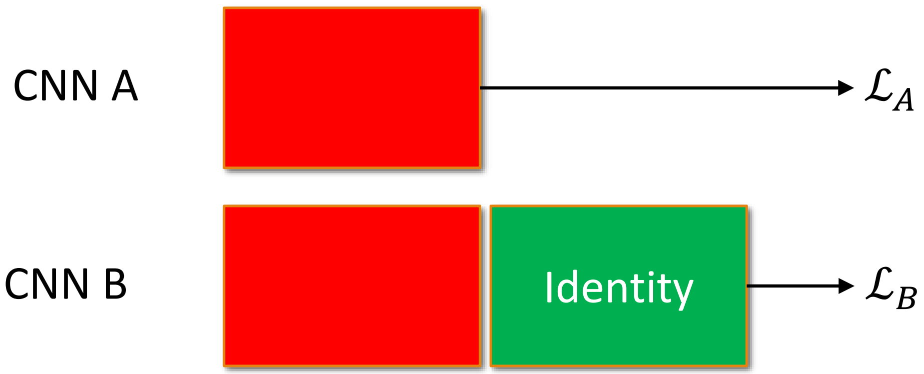
- **Thought experiment:** Let's assume two Convnets A, B. They are almost identical, in that B is the same as A, with extra "identity" layers. Since identity layers pass the information unchanged, the errors of the two networks should be similar. Thus, there is a Convnet B, which is at least as good as Convnet A w.r.t. training error



Quiz: What looks weird?

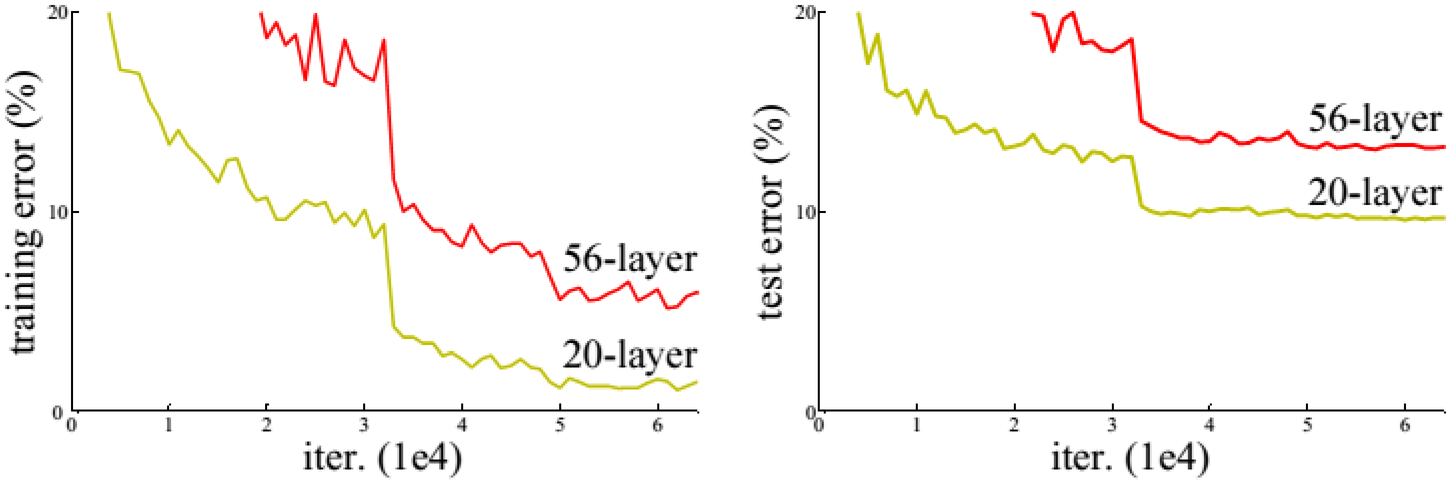
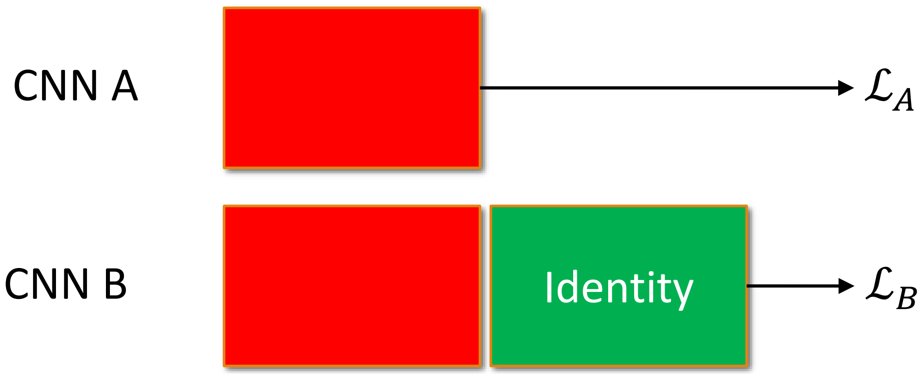


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

Testing hypothesis

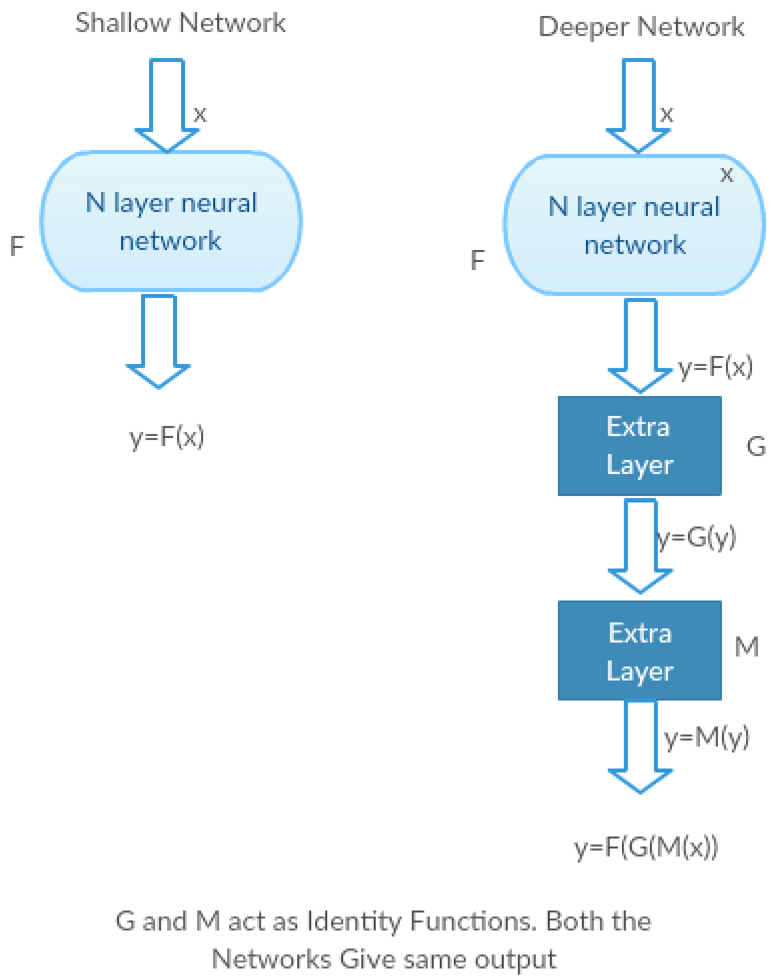
- Adding identity layers increases **training error**!!
  - Training error, not testing error
- **Performance degradation** not caused by overfitting
  - Just the optimization task is harder
- Assuming optimizers are doing their job fine, it appears that not all networks are the same as easy to optimize



$\mathcal{L}_A^{train} < \mathcal{L}_B^{train}$!!!

What is the problem?

- Very deep networks stop learning after a bit
  - An accuracy is reached, then the network saturates and starts unlearning
- Signal gets lost through so many layers
- Thought experiment: take a trained shallow network and just stack a few identity layers
  - $a = I(x) \rightarrow a \equiv x$
- What should happen?



Picture credit: [Prakash Jay]

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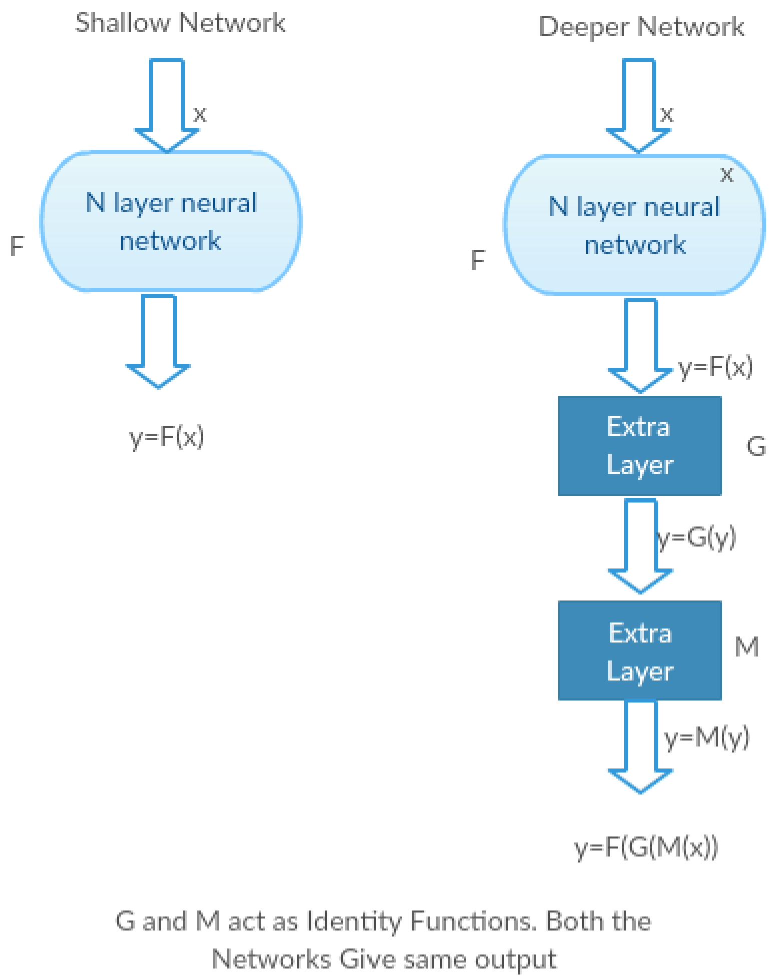
- Signal gets lost through so many layers
- Thought experiment: take a trained shallow network and just stack a few identity layers
  - $a = I(x) \rightarrow a \equiv x$
- The network should in principle just keep its existing knowledge
- Surprisingly, they start failing



Picture credit: Prakash Jay

Basic idea

- Let's say we have the neural network nonlinearity $\mathbf{a} = F(x)$
- Easier to learn a function $\mathbf{a} = F(x)$ to model differences $\mathbf{a} \sim \delta\mathbf{y}$ than to model absolutes $\mathbf{a} \sim \mathbf{y}$
  - Think of it like in input normalization → you normalize around 0
  - Think of it like in regression → you model differences around the mean value
- So, ask the neural network to explicitly model difference mapping

$$F(x) = H(x) - x \Rightarrow H(x) = F(x) + x$$

- $F(x)$ are the stacked nonlinearities
- x is the input to the nonlinear layer

ResNet block

- $H(x) = F(x) + x$
- If dimensions don't match
  - Either zero padding
  - Or a projection layer to match dimensions

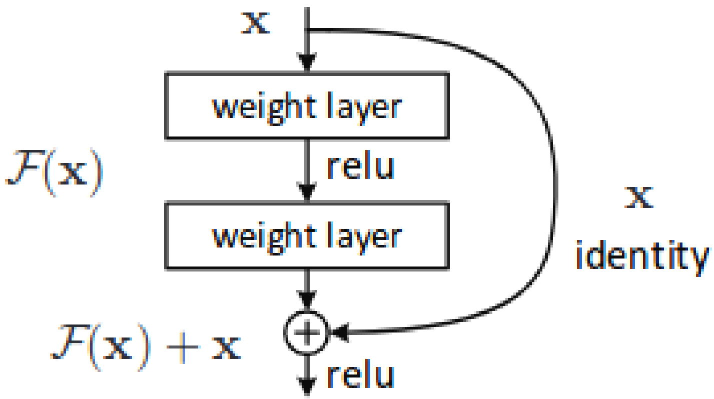
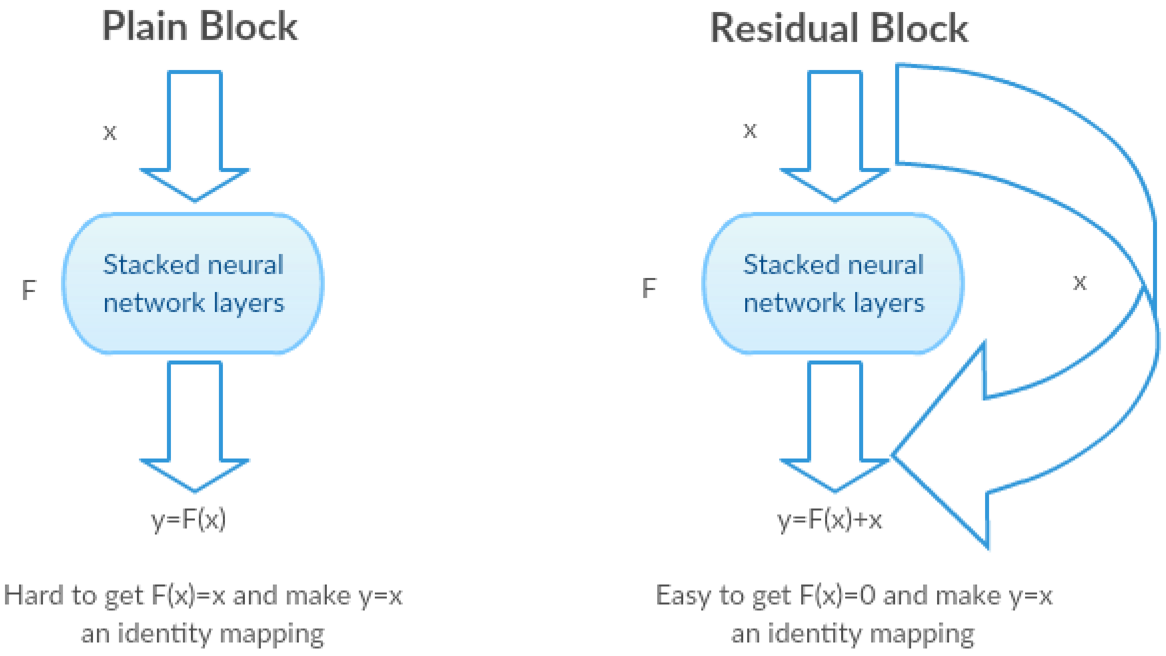


Figure 2. Residual learning: a building block.



No degradation anymore

- Without residual connections deeper networks are untrainable

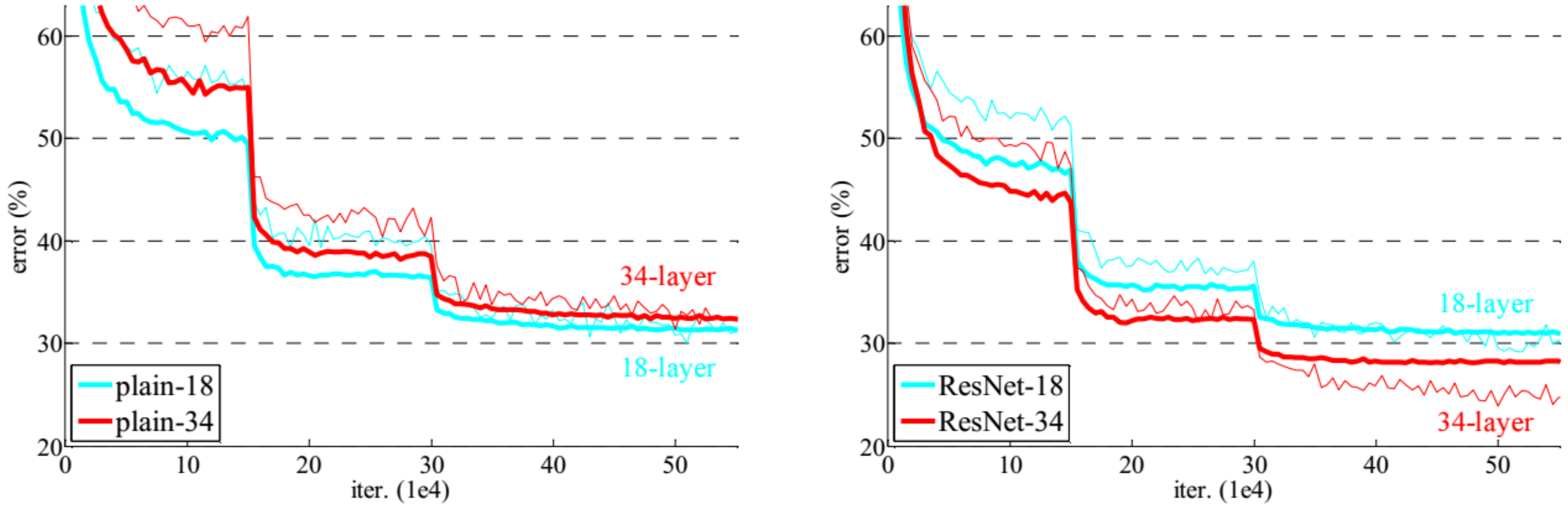


Figure 4. Training on **ImageNet**. Thin curves denote training error, and bold curves denote validation error of the center crops. Left: plain networks of 18 and 34 layers. Right: ResNets of 18 and 34 layers. In this plot, the residual networks have no extra parameter compared to their plain counterparts.

ResNet breaks records

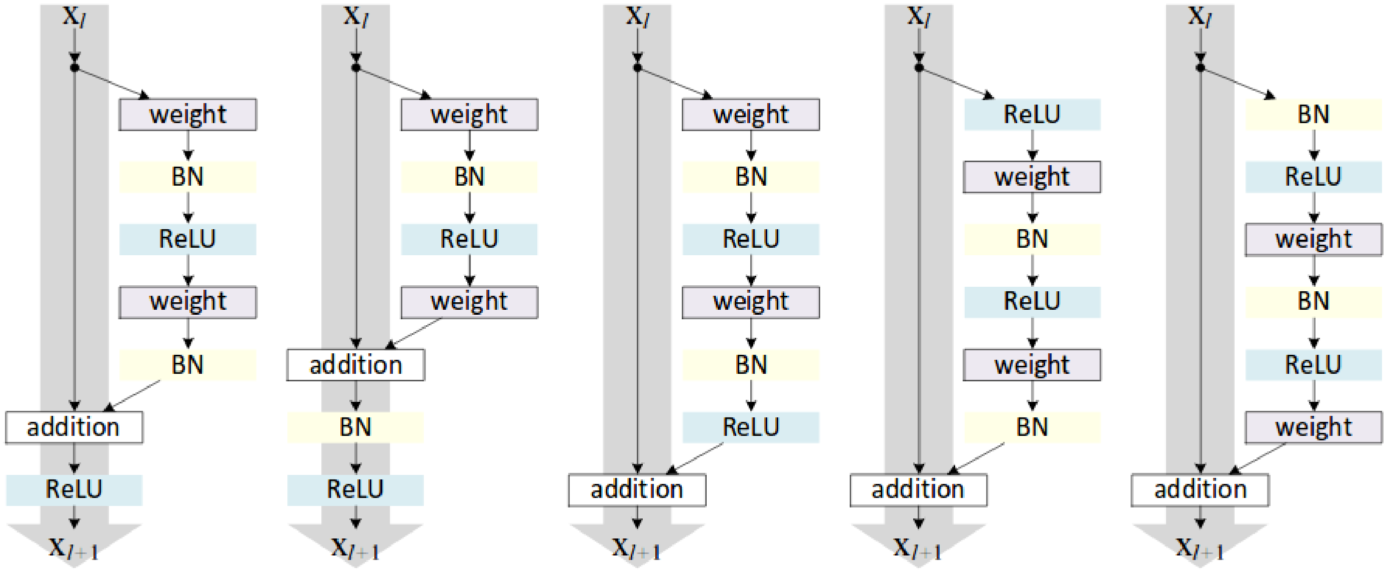
- Ridiculously low error in ImageNet

- Up to 1000 layers ResNets trained
  - Previous deepest network ~30-40 layers on simple datasets

method	top-5 err. (**test**)
VGG [41] (ILSVRC'14)	7.32
GoogLeNet [44] (ILSVRC'14)	6.66
VGG [41] (v5)	6.8
PReLU-net [13]	4.94
BN-inception [16]	4.82
ResNet (ILSVRC'15)	**3.57**

Table 5. Error rates (%) of **ensembles**. The top-5 error is on the test set of ImageNet and reported by the test server.

ResNet architectures & ResNeXt



(a) original (b) BN after addition (c) ReLU before addition (d) ReLU-only pre-activation (e) **full pre-activation**

case	Fig.	ResNet-110	ResNet-164
original Residual Unit [1]	Fig. 4(a)	6.61	5.93
BN after addition	Fig. 4(b)	8.17	6.50
ReLU before addition	Fig. 4(c)	7.84	6.14
ReLU-only pre-activation	Fig. 4(d)	6.71	5.91
full pre-activation	Fig. 4(e)	**6.37**	**5.46**

ResNeXt

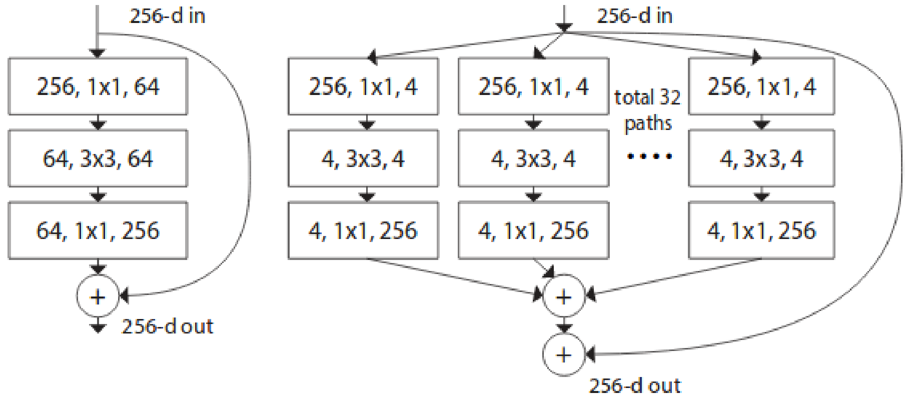


Figure 1. **Left**: A block of ResNet [14]. **Right**: A block of ResNeXt with cardinality = 32, with roughly the same complexity. A layer is shown as (# in channels, filter size, # out channels).

	setting	top-1 err (%)	top-5 err (%)
1× complexity references:			
ResNet-101	1×64d	22.0	6.0
ResNeXt-101	32×4d	21.2	5.6
2× complexity models follow:			
ResNet-**200** [15]	1×64d	21.7	5.8
ResNet-101, wider	$1 \times$ **100**d	21.3	5.7
ResNeXt-101	**2** $\times$ 64d	20.7	5.5
ResNeXt-101	**64** $\times$ 4d	**20.4**	**5.3**

Table 4. Comparisons on ImageNet-1K when the number of FLOPs is increased to 2× of ResNet-101's. The error rate is evaluated on the single crop of 224×224 pixels. The highlighted factors are the factors that increase complexity.

Some observations

- BatchNorms absolutely necessary because of vanishing gradients
- Networks with skip connections (like ResNets) converge faster than the same network without skip connections
- Identity shortcuts cheaper and almost equal to project shortcuts
- Hopefully, more on Neural Network dynamics later

HighwayNet

- Similar to ResNets, only introducing a gate with learnable parameters on the importance of each skip connection

$$y = H(x, W_H) \cdot T(x, W_T) + x \cdot (1 - T(x, W_T))$$

- Similar to …

HighwayNet

- Similar to ResNets, only introducing a gate with learnable parameters on the importance of each skip connection

$$y = H(x, W_H) \cdot T(x, W_T) + x \cdot (1 - T(x, W_T))$$

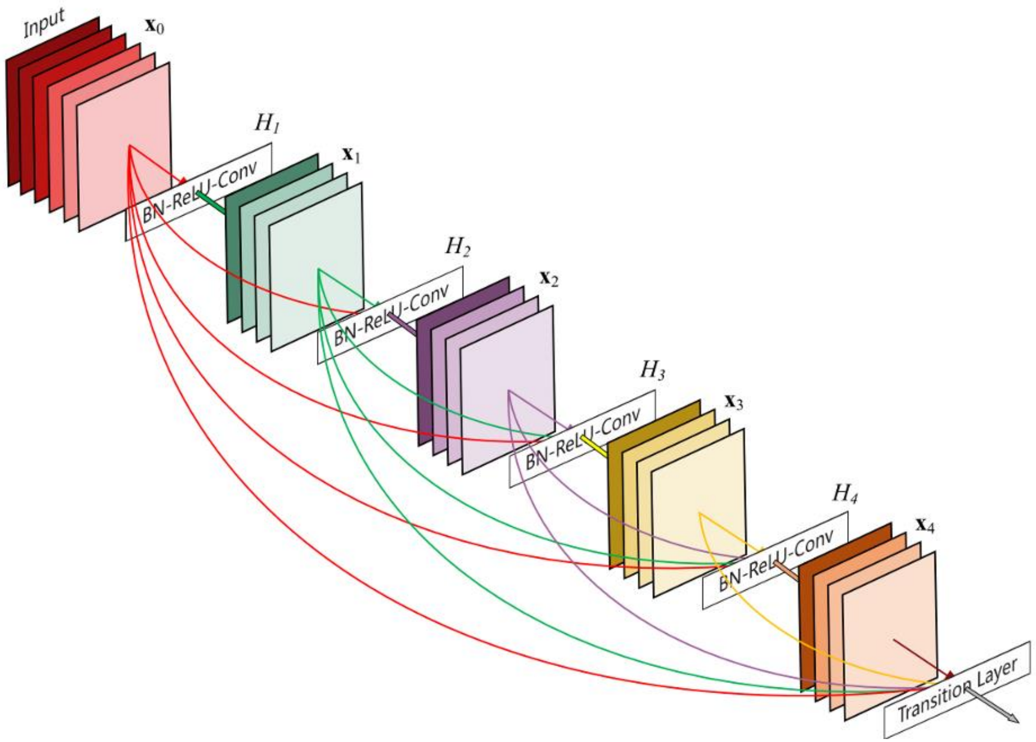
- Similar to … LSTMs as we will say later

DenseNet

- Add skip connections to multiple forward layers

$$y = h(x_l, x_{l-1}, \ldots, x_{l-n})$$

- Why?

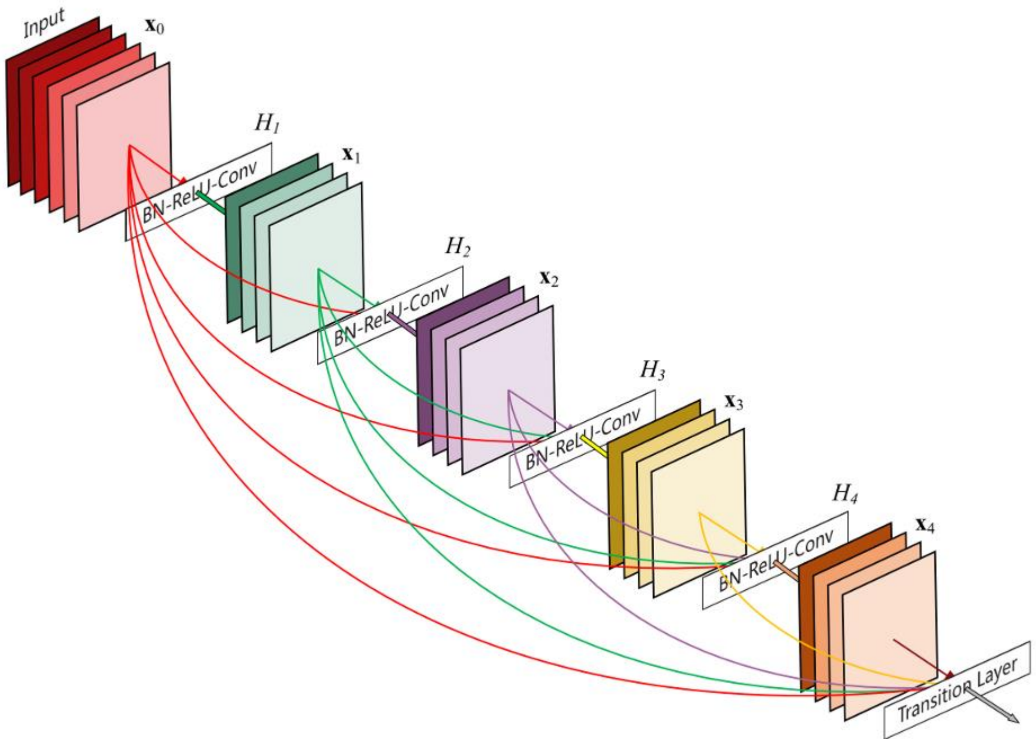


DenseNet

- Add skip connections to multiple forward layers

$$y = h(x_l, x_{l-1}, \dots, x_{l-n})$$

- Assume layer 1 captures edges, while layer 5 captures faces (and other stuff)
- Why not have a layer that combines both faces and edges (e.g. to model a scarred face)
- Standard ConvNets do not allow for this
  - Layer 6 combines only layer 5 patterns, not lower



Neural Architecture Search

- It is also possible to learn the neural architecture

- Problem?

Neural Architecture Search

- It is also possible to learn the neural architecture

- Problem?
- Architectures/graphs are discrete structures → Backprop?

- Still, some very interesting workarounds have been proposed in practice

- Will it work for you? If you are Facebook or Google, yes!

Evolutionary Search for NAS

- DARTS: Differentiable Architecture Search, Liu et al., 2018
- Efficient Neural Architecture Search via Parameter Sharing, Pham et al., 2018
- Evolving Space-Time Neural Architectures for Videos, Piergiovanni et al. 2018
- Regularized Evolution for Image Classifier Architecture Search, Real et al., 2019

Algorithm 1 Evolutionary search algorithm

function SEARCH
  Randomly initialize the population, P
  Evaluate each individual in P
  for $i <$ number of evolutionary rounds **do**
    $S =$ random sample of 25 individuals
    $parent =$ the most fit individual in S
    $child = parent$
    for $\max(\lceil d - \frac{i}{r} \rceil, 1)$ **do**
      $child = mutate(child)$
    end for
    evaluate $child$ and add to population
    remove least fit individual from population
  end for
end function

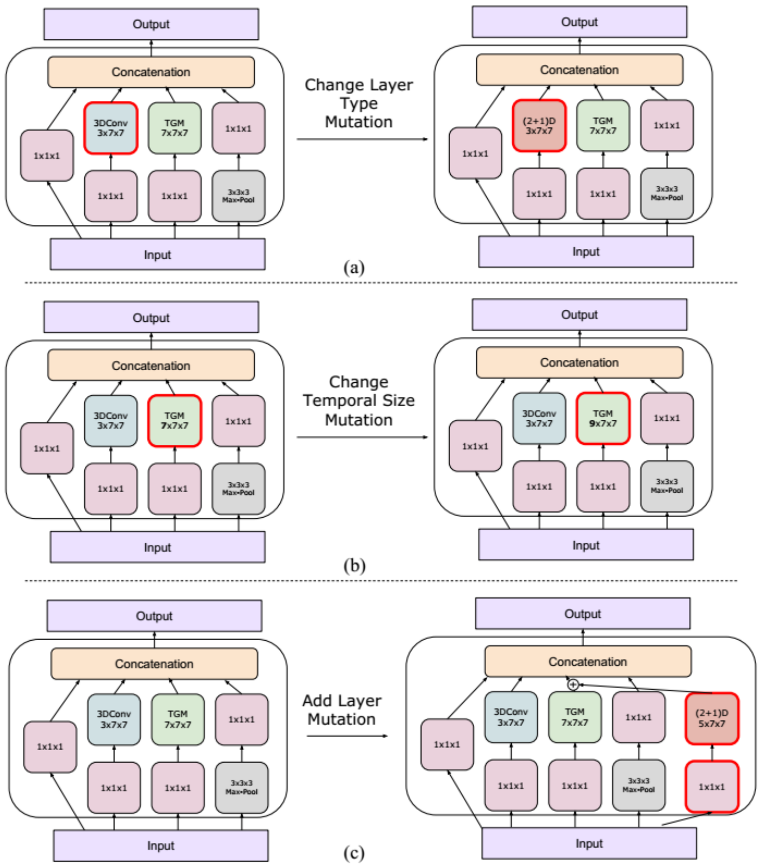
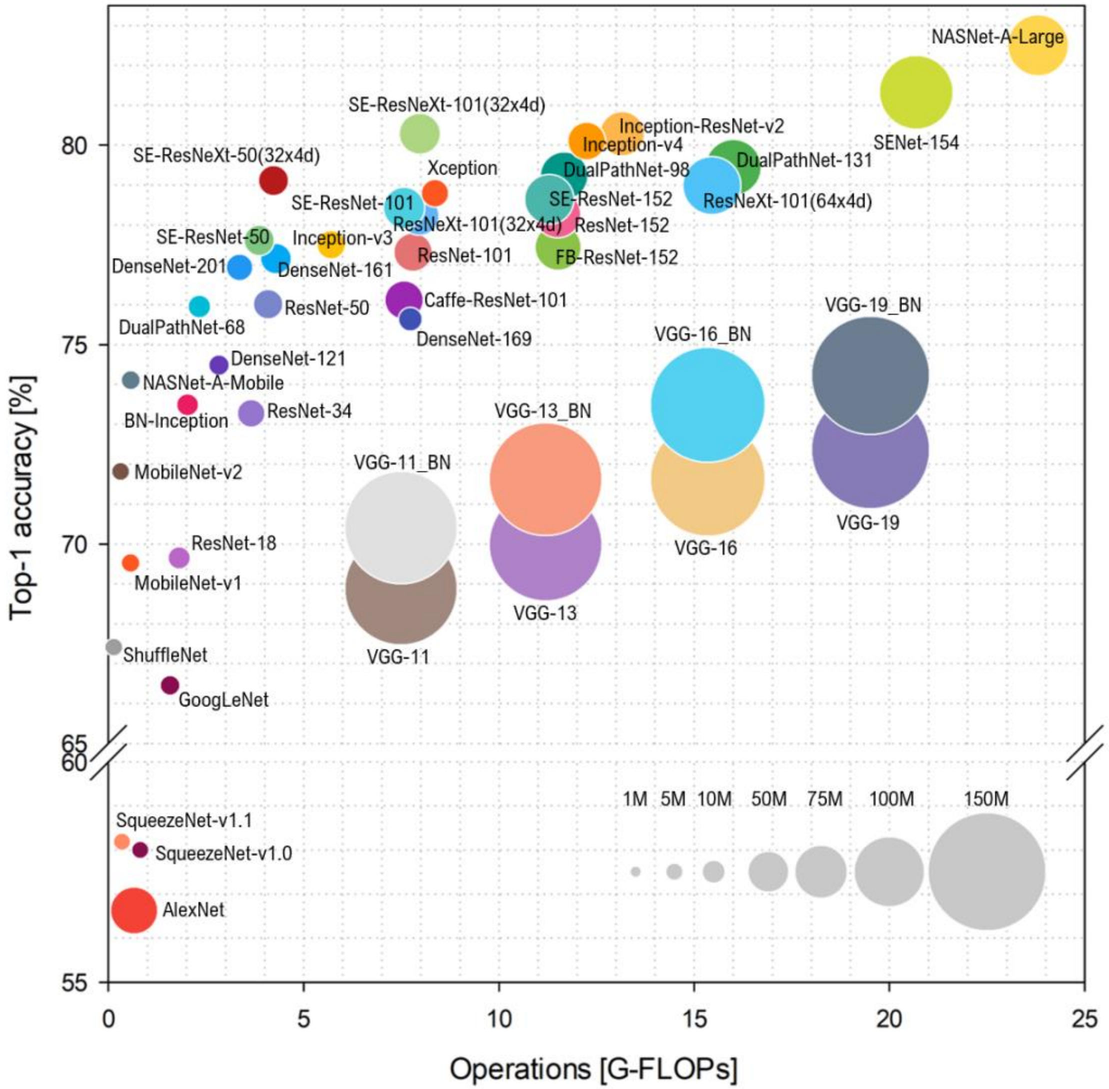
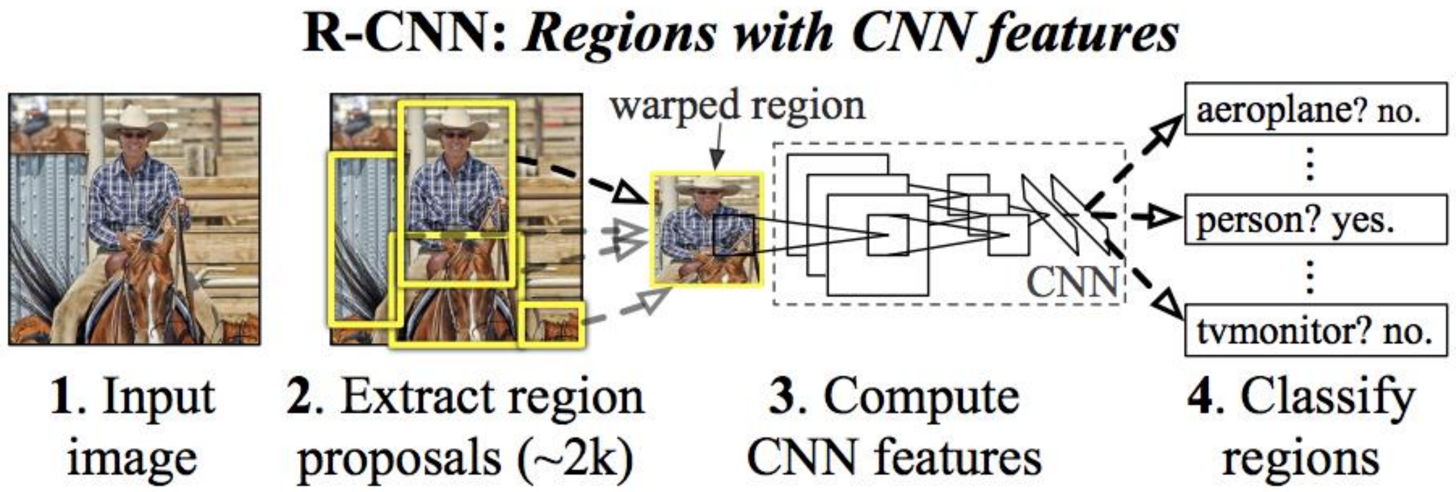


Figure 5. Example mutations applied to a module, including (a) layer type change, (b) filter length change, and (c) layer addition.

State-of-the-Art

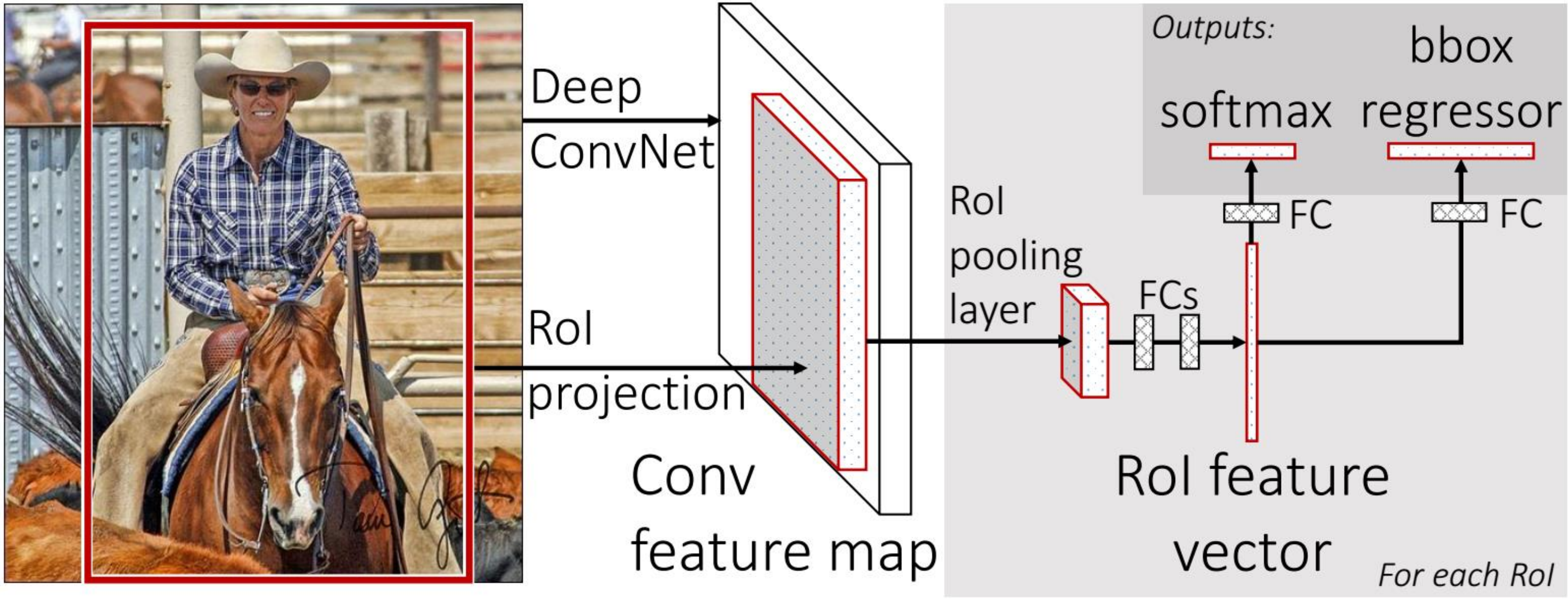


R-CNNs
Fully Convolutional Siamese Nets for Tracking



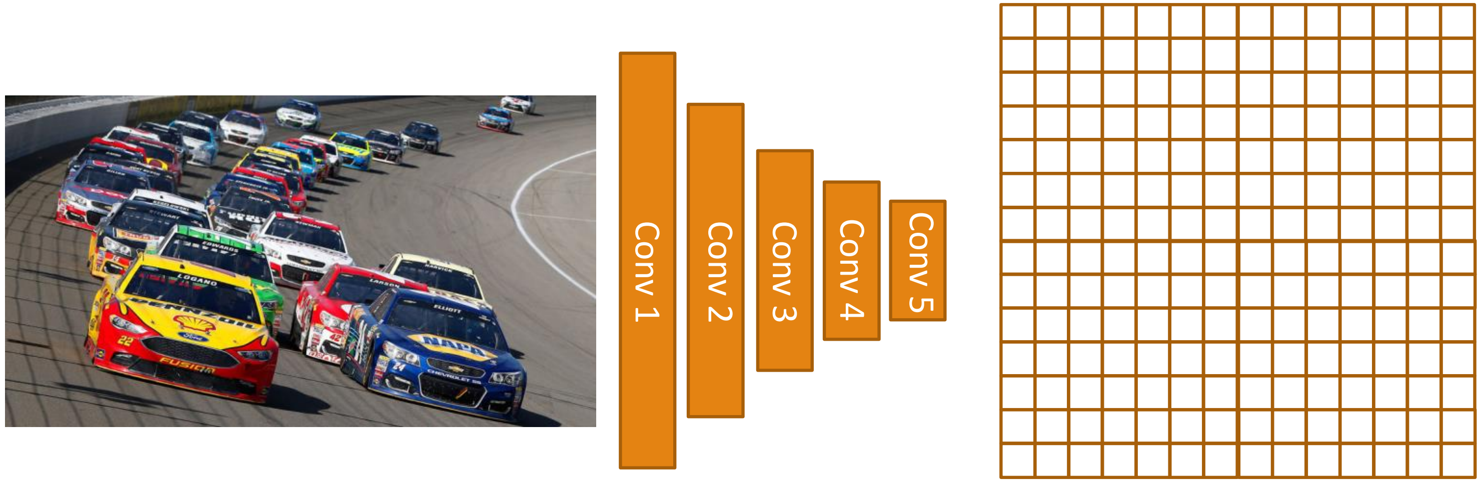
Sliding window on feature maps

- SPPnet [He2014]
- Fast R-CNN [Girshick2015]



Fast R-CNN: Steps

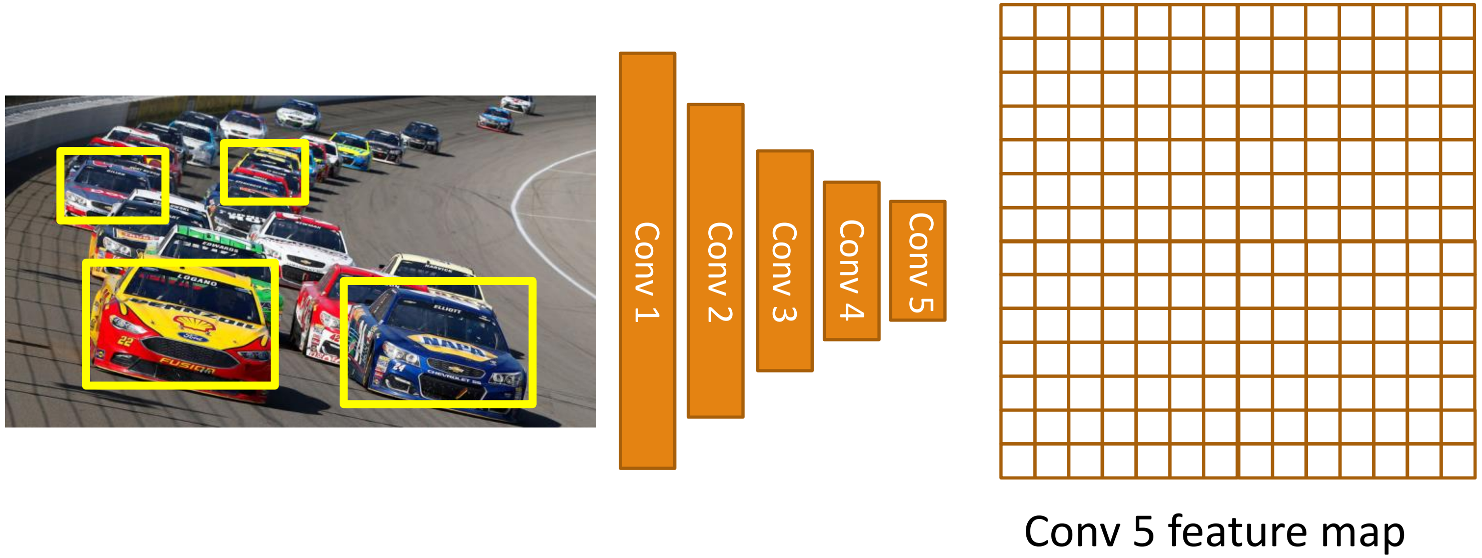
- Process the whole image up to conv5



Conv 5 feature map

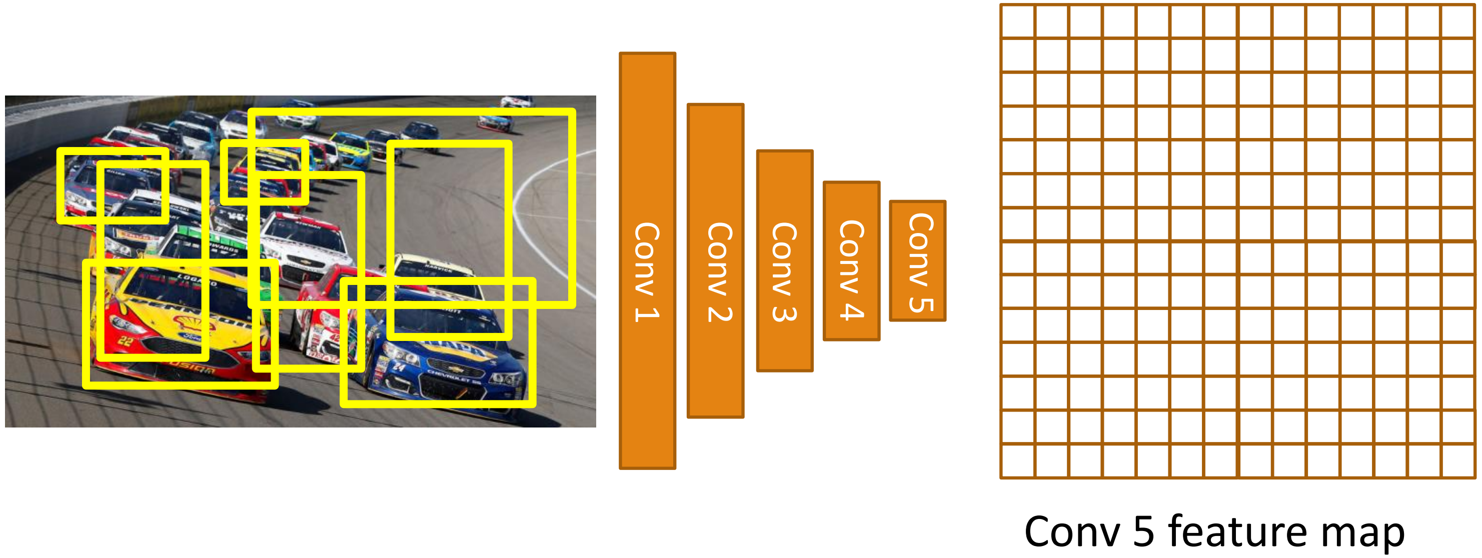
Fast R-CNN: Steps

- Process the whole image up to conv5
- Compute possible locations for objects



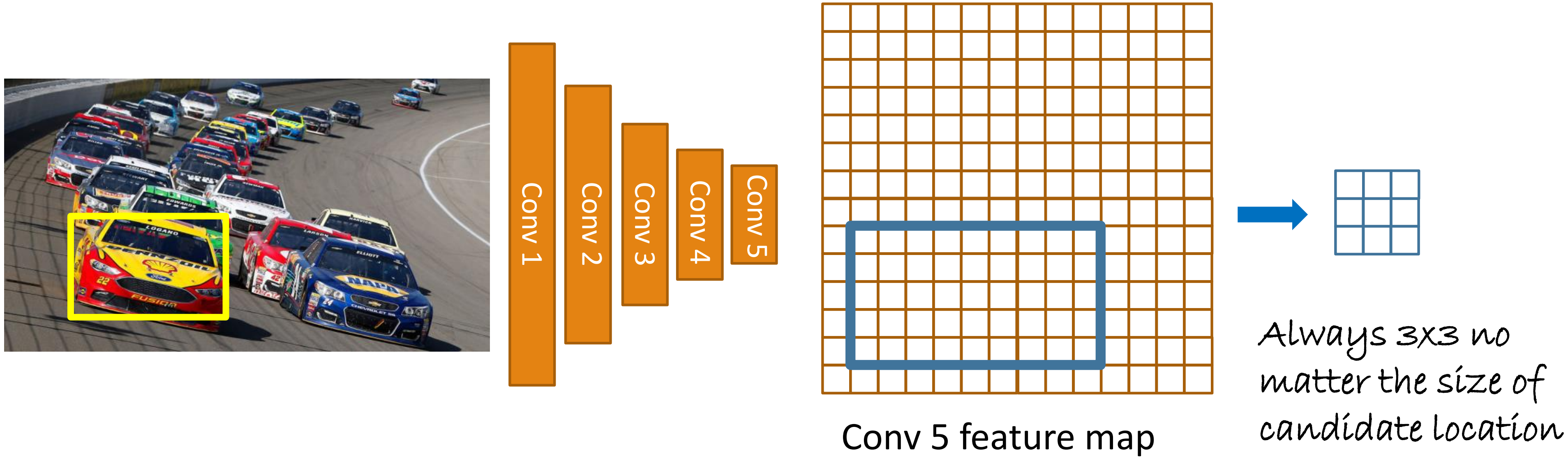
Fast R-CNN: Steps

- Process the whole image up to conv5
- Compute possible locations for objects (some correct, most wrong)



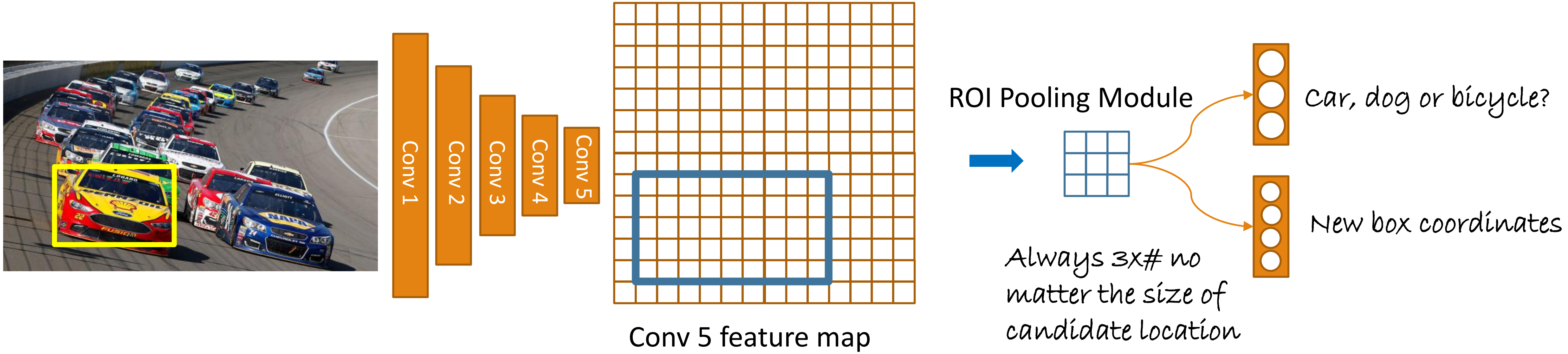
Fast R-CNN: Steps

- Process the whole image up to conv5
- Compute possible locations for objects
- Given single location → ROI pooling module extracts fixed length feature



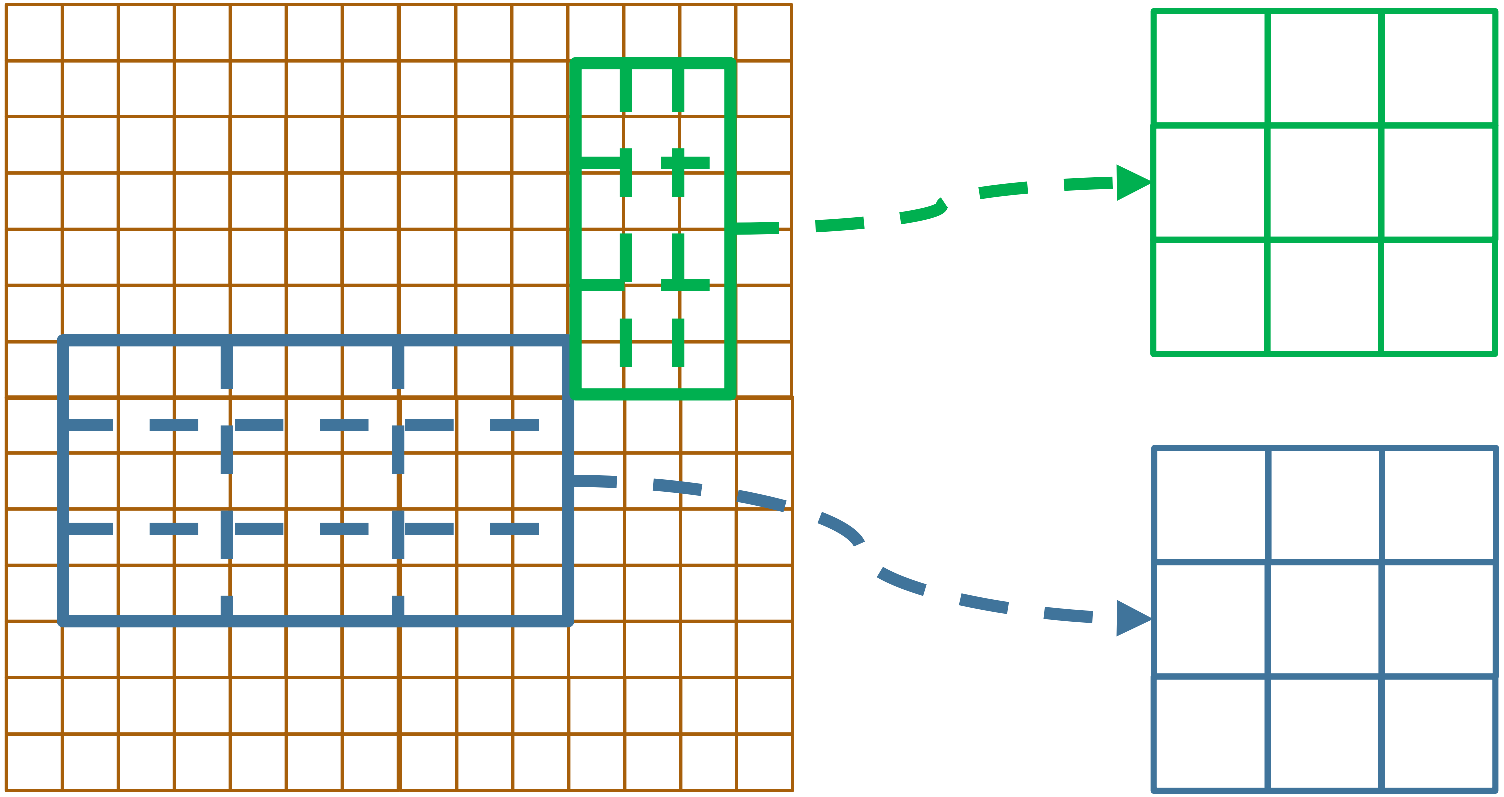
Fast R-CNN: Steps

- Process the whole image up to conv5
- Compute possible locations for objects
- Given single location → ROI pooling module extracts fixed length feature
- Connect to two final layers, 1 for classification, 1 for box refinement



Region-of-Interest (ROI) Pooling Module

- Divide feature map in TxT cells
  - The cell size will change depending on the size of the candidate location

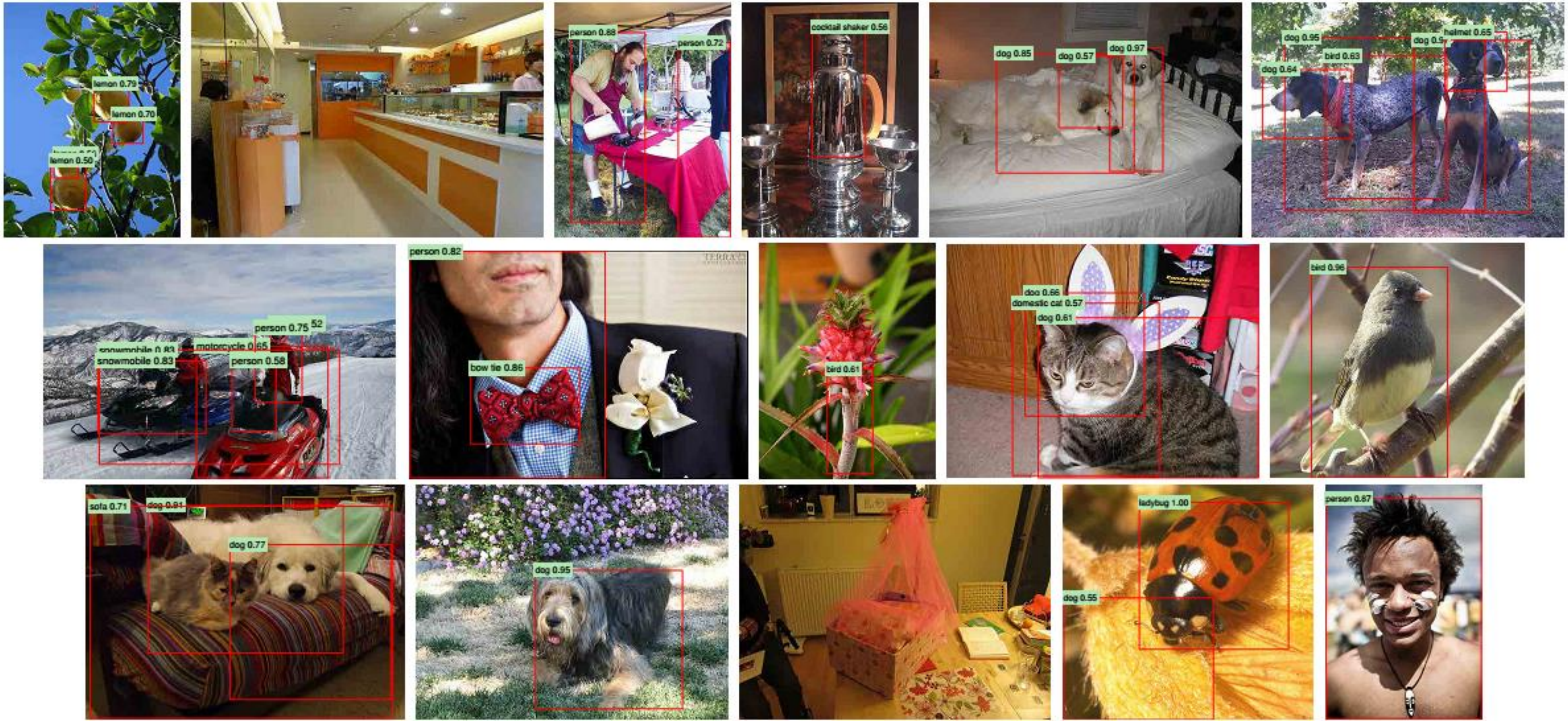


Always 3x3 no matter the size of candidate location

Smart fine-tuning

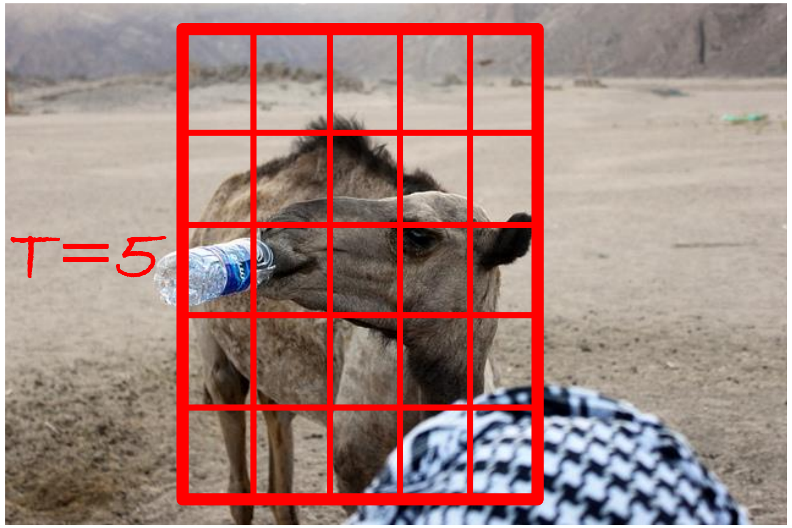
- Normally samples in a mini-batch completely random
- Instead, organize mini-batches by ROIs
- 1 mini-batch = N (images) $\times \frac{R}{N}$ (candidate locations)
- Feature maps shared → training speed-up by a factor of $\frac{R}{N}$
- Mini-batch samples might be correlated
  - In Fast R-CNN that was not observed

Some results



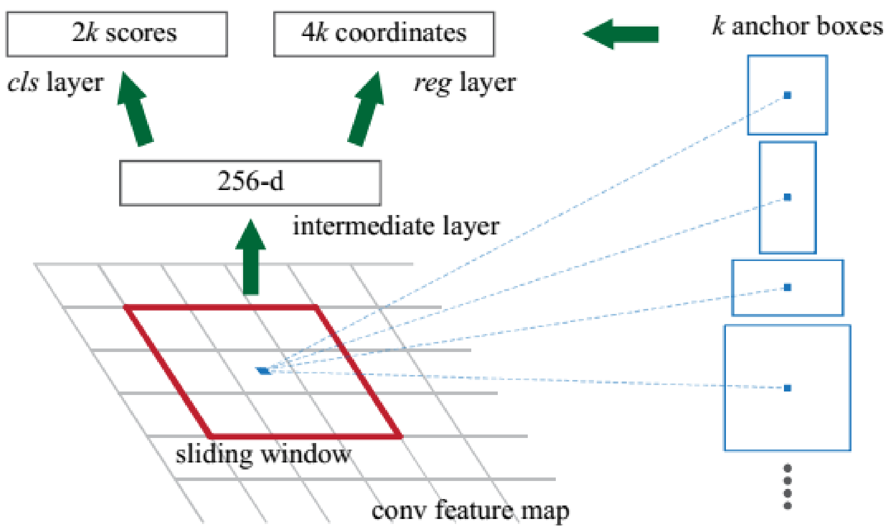
Fast-RCNN

- Reuse convolutions for different candidate boxes
  - Compute feature maps only once
- Region-of-Interest pooling
  - Define stride relatively → box width divided by predefined number of “poolings” T
  - Fixed length vector
- End-to-end training!
- (Very) Accurate object detection
- (Very) Faster
  - Less than a second per image
- External box proposals needed



Faster R-CNN [Girshick2016]

- Fast R-CNN → external candidate locations
- Faster R-CNN → deep network proposes candidate locations
- Slide the feature map → k anchor boxes per slide



Region Proposal Network

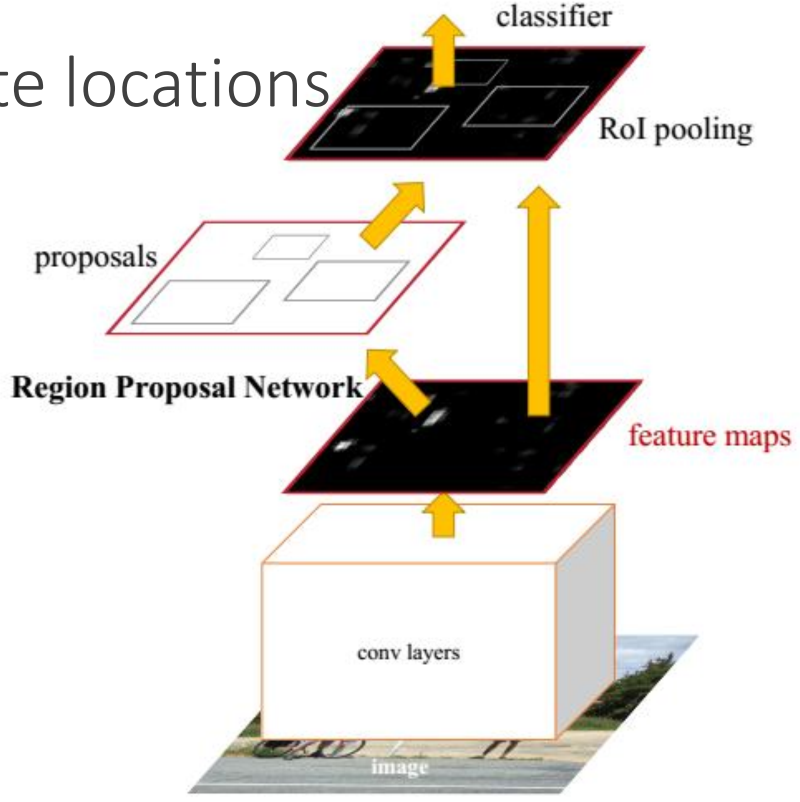
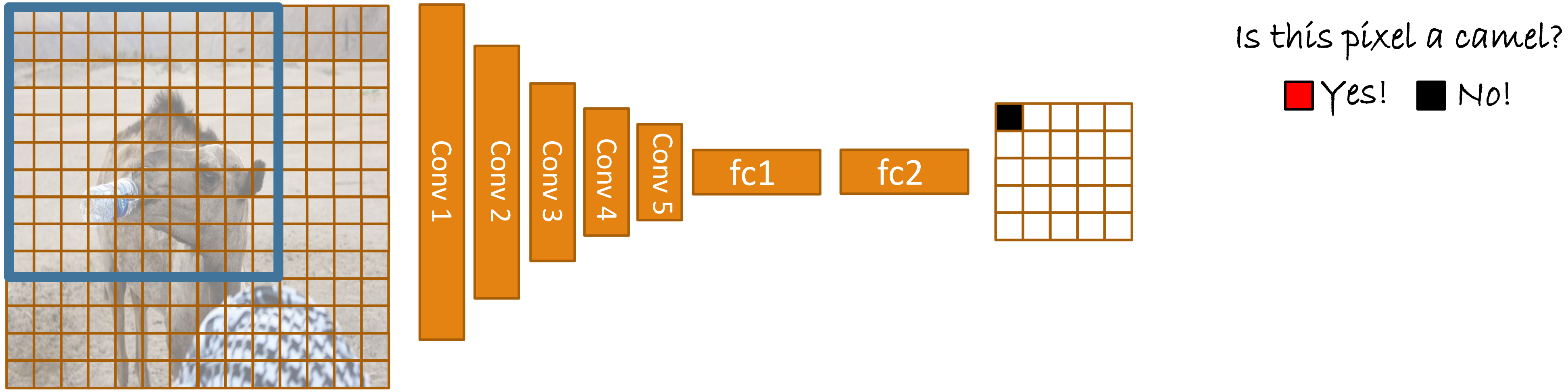


Figure 2: Faster R-CNN is a single, unified network for object detection. The RPN module serves as the 'attention' of this unified network.

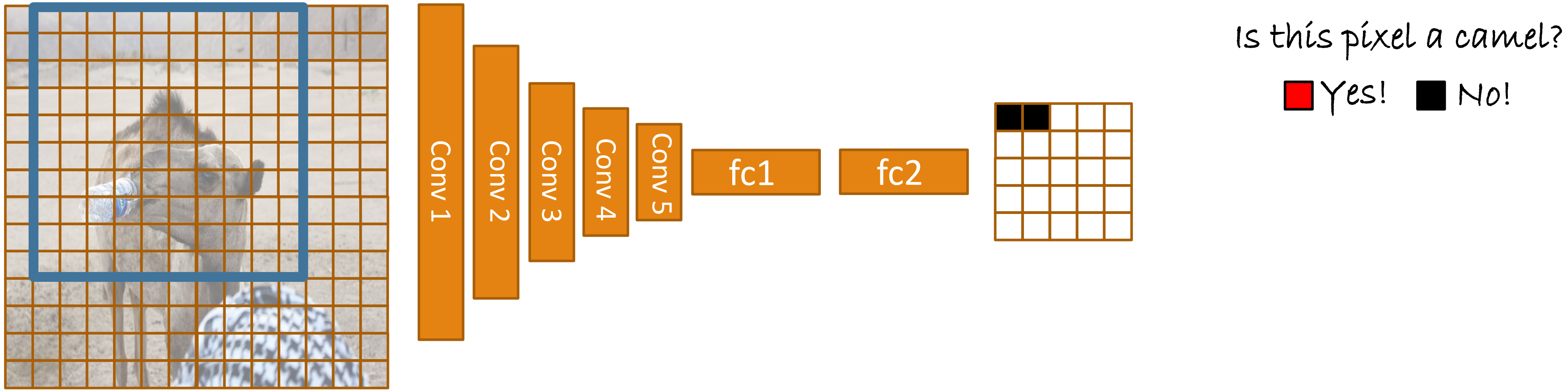
Going Fully Convolutional [LongCVPR2014]

- Image larger than network input → slide the network



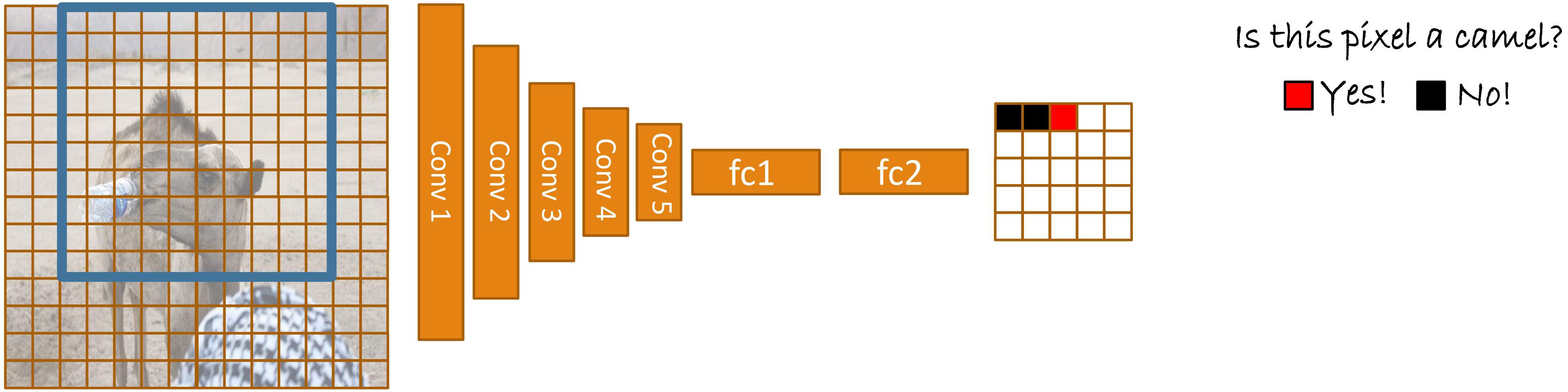
Going Fully Convolutional [LongCVPR2014]

- Image larger than network input → slide the network



Going Fully Convolutional [LongCVPR2014]

- Image larger than network input → slide the network



Going Fully Convolutional [LongCVPR2014]

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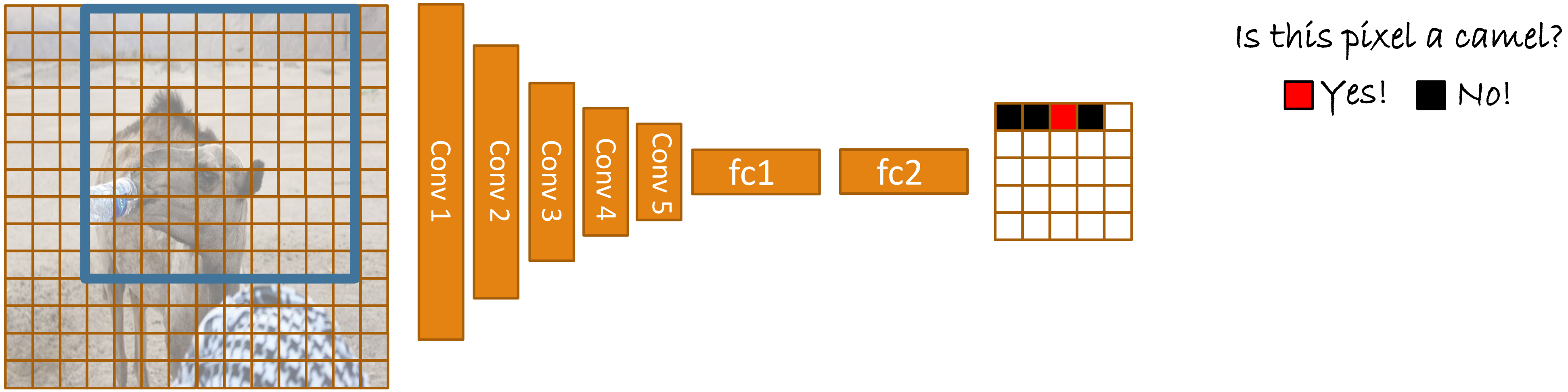
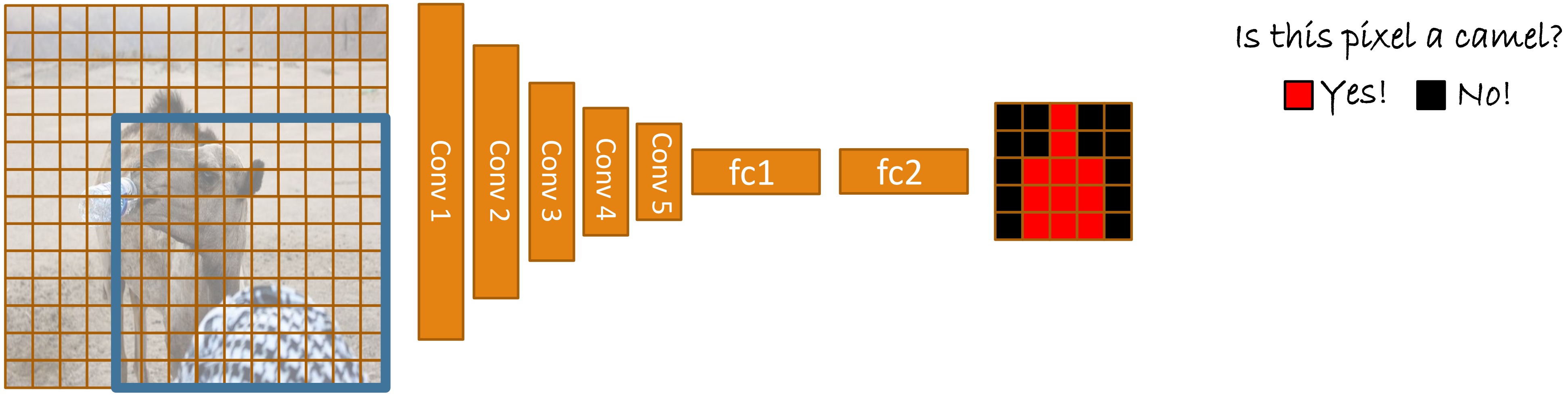
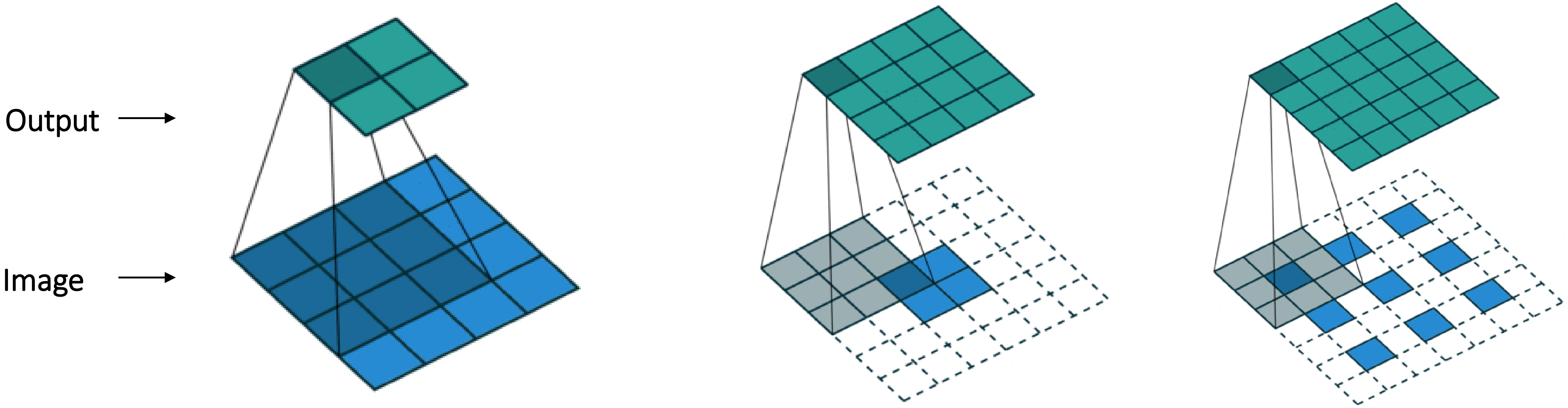


Going Fully Convolutional [LongCVPR2014]

- Image larger than network input → slide the network



Deconvolutional modules



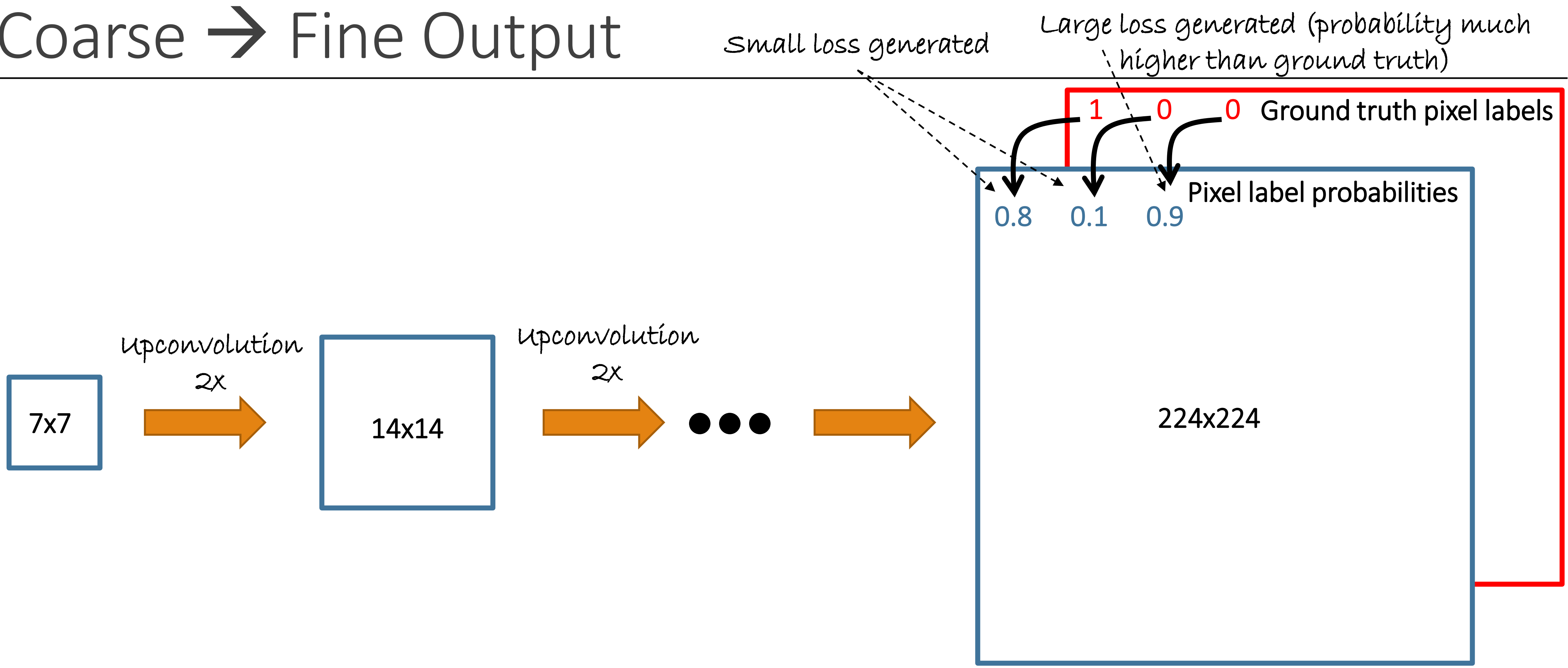
Convolution
No padding, no strides

Upconvolution
Padding, no strides

Upconvolution
Padding, strides

More visualizations: https://github.com/vdumoulin/conv_arithmetic

Coarse → Fine Output



Siamese Networks for Tracking

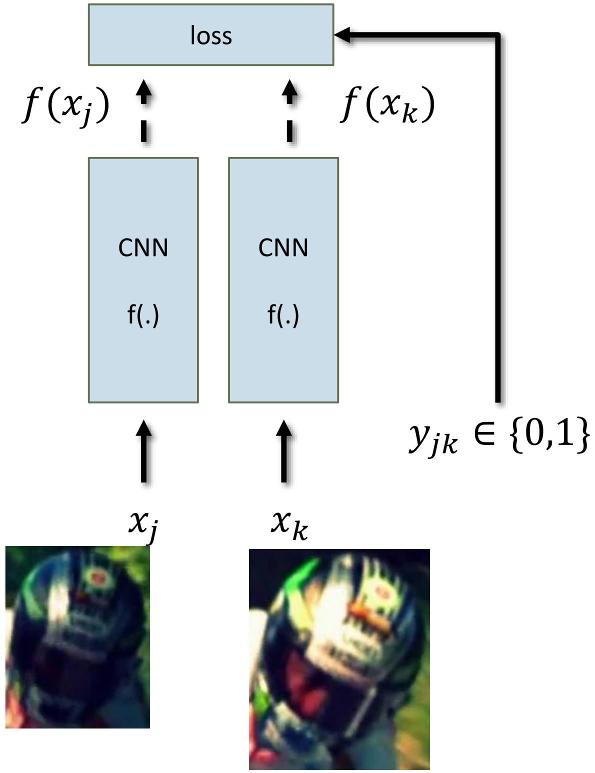
- While tracking, the only definitely correct training example is the first frame
  - All others are inferred by the algorithm
- If the “inferred positives” are correct, then the model is already good enough and no update is needed
- If the “inferred positives” are incorrect, updating the model using wrong positive examples will eventually destroy the model

- Siamese Instance Search for Tracking, R. Tao, E. Gavves, A. Smeulders, CVPR 2016

Basic idea

- No model updates through time to avoid model contamination
- Instead, learn invariance model $f(\boldsymbol{dx})$
  - invariances shared between objects
  - reliable, external, rich, category-independent, data
- Assumption
  - The appearance variances are shared amongst object and categories
  - Learning can accurate enough to identify common appearance variances
- Solution: Use a Siamese Network to compare patches between images
  - Then “tracking” equals finding the most similar patch at each frame (no temporal modelling)

Training



Marginal Contrastive Loss:

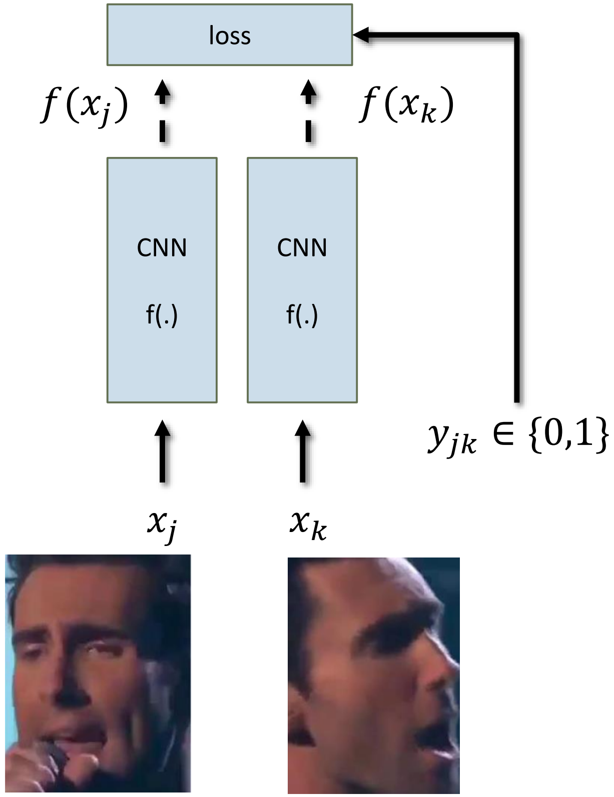
$$L(x_j, x_k, y_{jk}) = \frac{1}{2} y_{jk} D^2 + \frac{1}{2}(1 - y_{jk}) \max(0, \sigma - D^2)$$

$$D = \left\| f(x_j) - f(x_k) \right\|_2$$

Matching function (after learning):

$$m(x_j, x_k) = f(x_j) \cdot f(x_k)$$

Training



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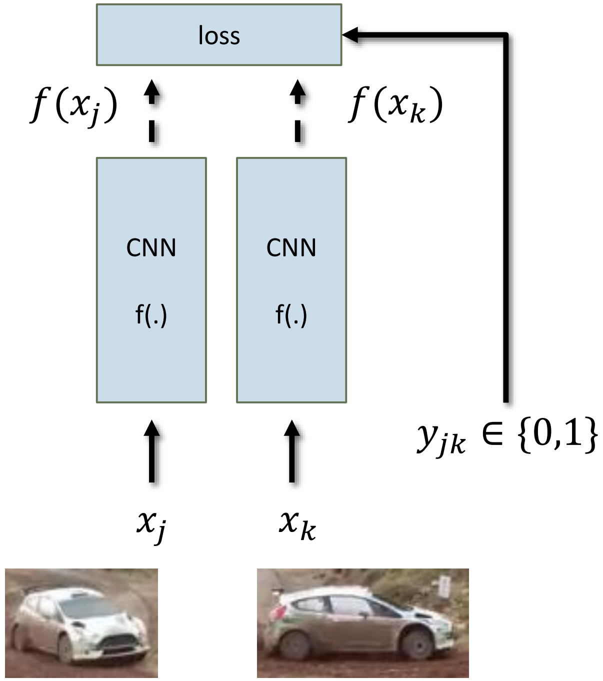
Training



Marginal Contrastive Loss:

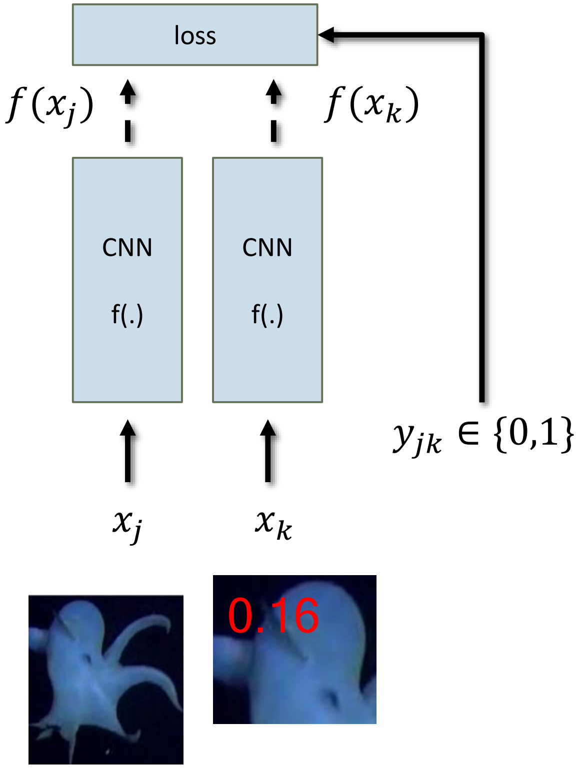
$$L(x_j, x_k, y_{jk}) = \frac{1}{2} y_{jk} D^2 + \frac{1}{2}(1 - y_{jk}) \max(0, \sigma - D^2)$$

$$D = \|f(x_j) - f(x_k)\|_2$$

Matching function (after learning):

$$m(x_j, x_k) = f(x_j) \cdot f(x_k)$$

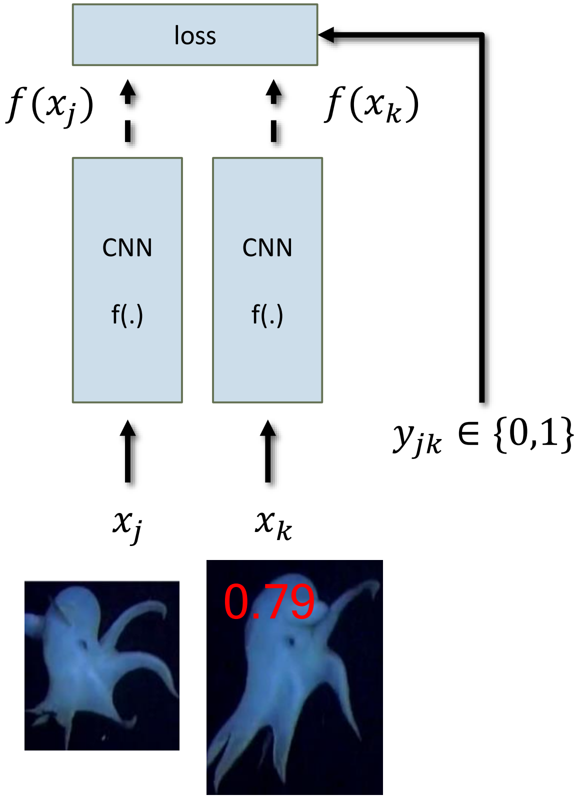
Testing



<u>Predicting the next location</u>

1. Define query x_0 at $t = 0$
2. Set current target location x_t
3. Measure similarity $\mathrm{s}_{\mathrm{t}+1}^{k} = s(x_0, x_{t+1}^{k})$ of x_0 with multiple boxes x'_{t+1} sampled around x_t
4. Select next target location with maximum similarity $\mathrm{s}_{\mathrm{t}+1}^{k}$
5. Go to 2

Testing



<u>Predicting the next location</u>

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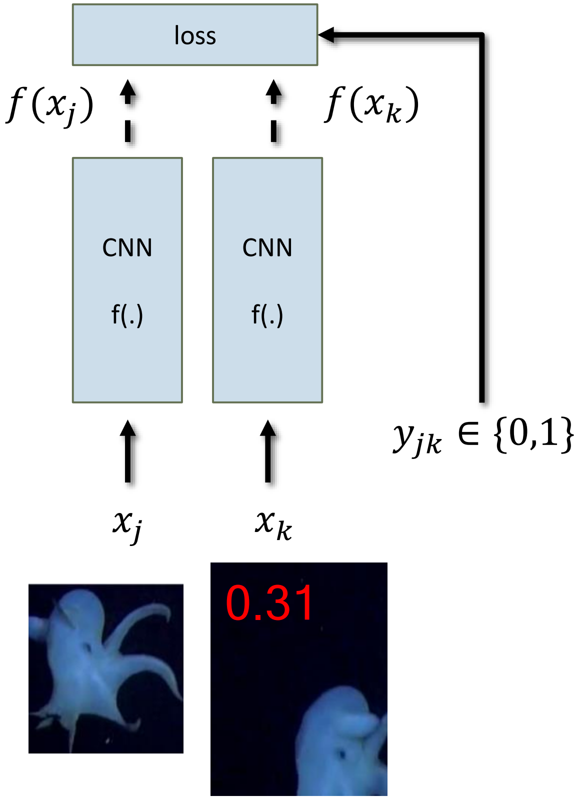
5. Go to 2

Testing

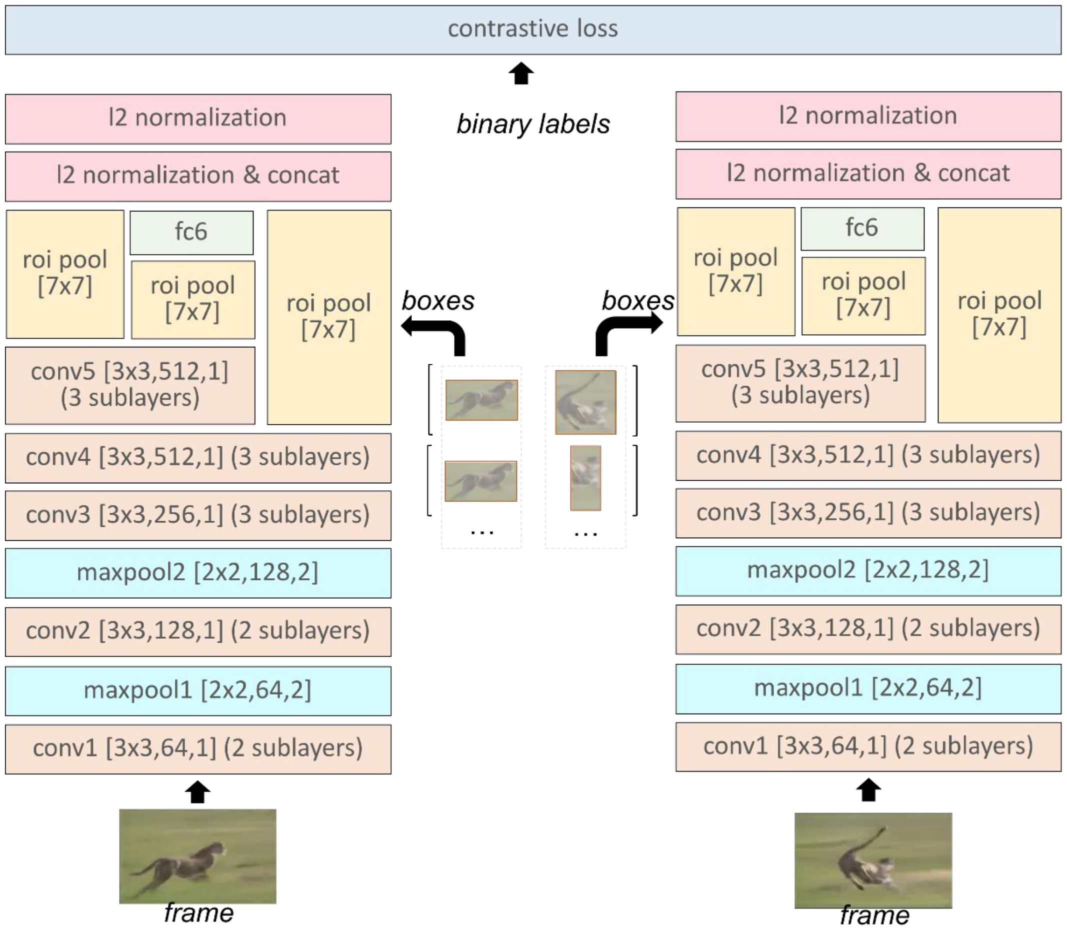


<u>**Predicting the next location**</u>

1. Define query x_0 at $t = 0$
2. Set current target location x_t
3. Measure similarity $\mathrm{s}_{\mathrm{t}+1}^{k} = s(x_0, x_{t+1}^{k})$ of x_0 with multiple boxes x'_{t+1} sampled around x_t
4. Select next target location with maximum similarity $\mathrm{s}_{\mathrm{t}+1}^{k}$
5. Go to 2

Network Architecture

- Very few max pooling layers → improve localization accuracy
- Region-of-interest (ROI) pooling→ process all boxes in a frame in one single pass through the network
- Use outputs of multiple layers (conv4_3, conv5_3, fc6) → robust in various situations



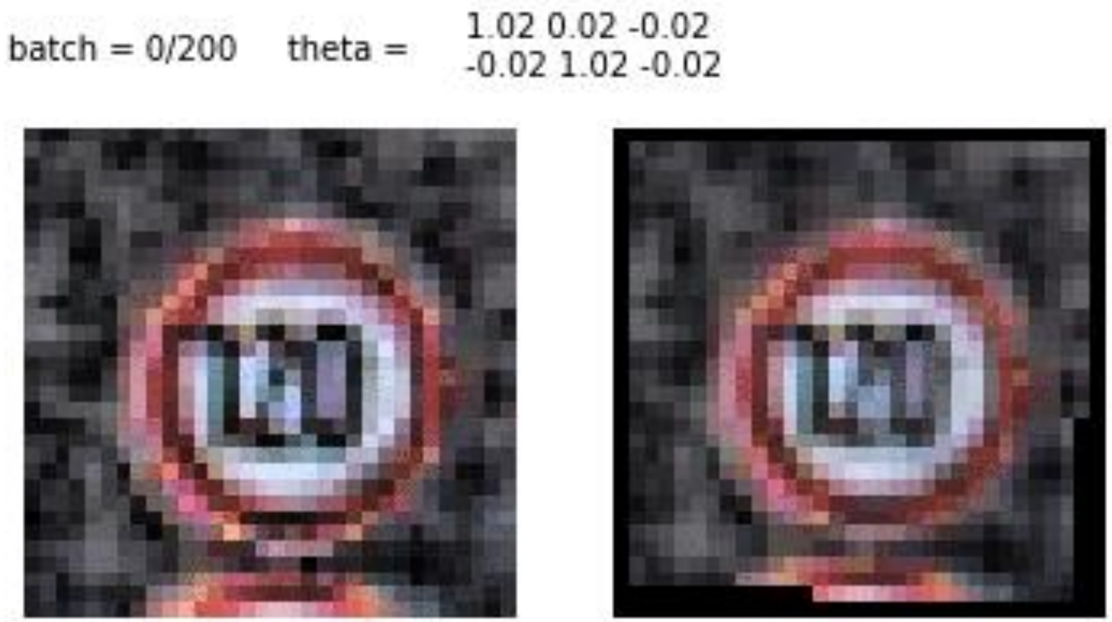
The two branches share the parameters.

Things to remember

- Operate on pairs
  - Two patches as input
  - Compute similarity
- Function learnt once
  - external, rich video dataset
  - object box annotations
- Once learned externally applied as is
  - to videos of previously unseen targets
  - to videos of previously unseen categories

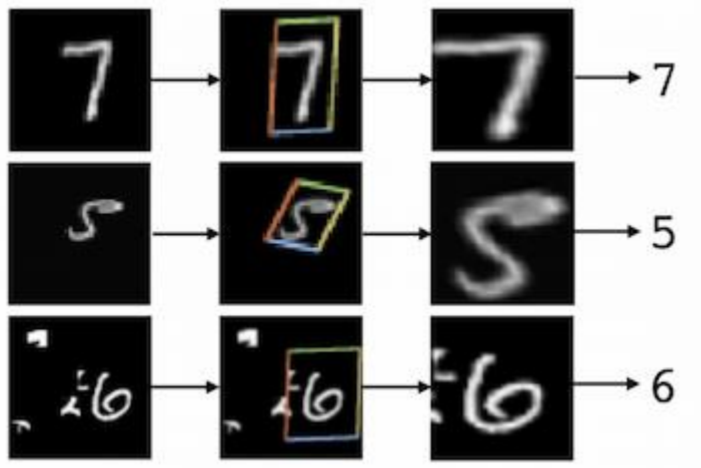
VISUAL OBJECT TRACKING BY NATURAL LANGUAGE SPECIFICATION, *TO APPEAR IN IEEE CVPR 2017*

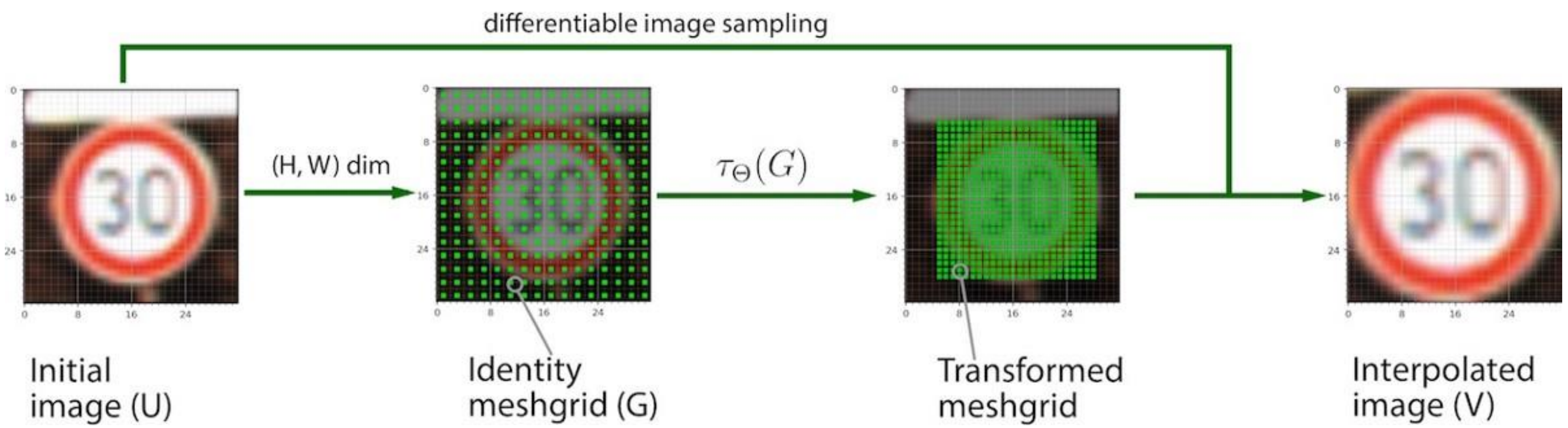
Spatial Transformer Network



Problem

- ConvNets sometimes are robust enough to input changes
  - While pooling gives some invariance, only in deeper layers the pooling receptive field is large enough for this invariance to be noteworthy
  - One way to improve robustness: Data augmentation
- Smarter way: Spatial Transformer Networks





Basic idea

- Define a geometric transformation matrix

$$\Theta = \begin{bmatrix} \theta_{11} & \theta_{12} & \theta_{13} \\ \theta_{21} & \theta_{22} & \theta_{23} \end{bmatrix}$$

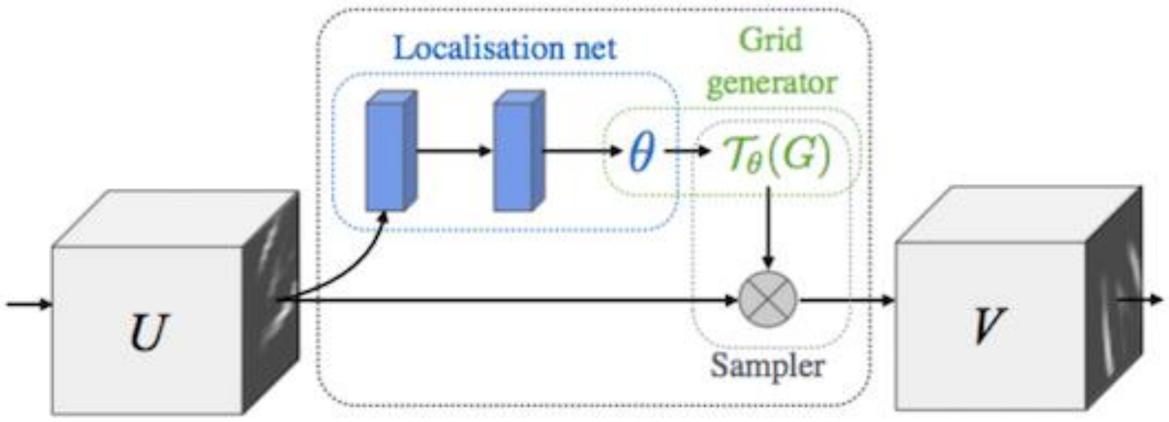
- Four interesting transformations
  - Identity, i.e. $\Theta = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$
  - Rotation, e.g., $\Theta \approx \begin{bmatrix} 0.7 & -0.7 & 0 \\ 0.7 & 0.7 & 0 \end{bmatrix}$ for 45^o, as $\cos(\frac{\pi}{4}) \approx 0.7$
  - Zooming in, e.g. $\Theta \approx \begin{bmatrix} 0.5 & 0 & 0 \\ 0 & 0.5 & 0 \end{bmatrix}$ for 2X zooming in
  - Zooming in, e.g. $\Theta \approx \begin{bmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \end{bmatrix}$ for 2X zooming out

Basic idea

- Then, define a mesh grid (x_i^t, y_i^t) on the original image and apply the geometric transformations

$$\begin{bmatrix} x_i^s \\ y_i^s \end{bmatrix} = \Theta \cdot \begin{bmatrix} x_i^t \\ y_i^t \\ 1 \end{bmatrix}$$

- Produce the new image using the transformation above and an interpolation method
- Learn the parameters Θ and the meshgrid from the data
- A localization network learns to predict Θ given a new image



C3D
i3D

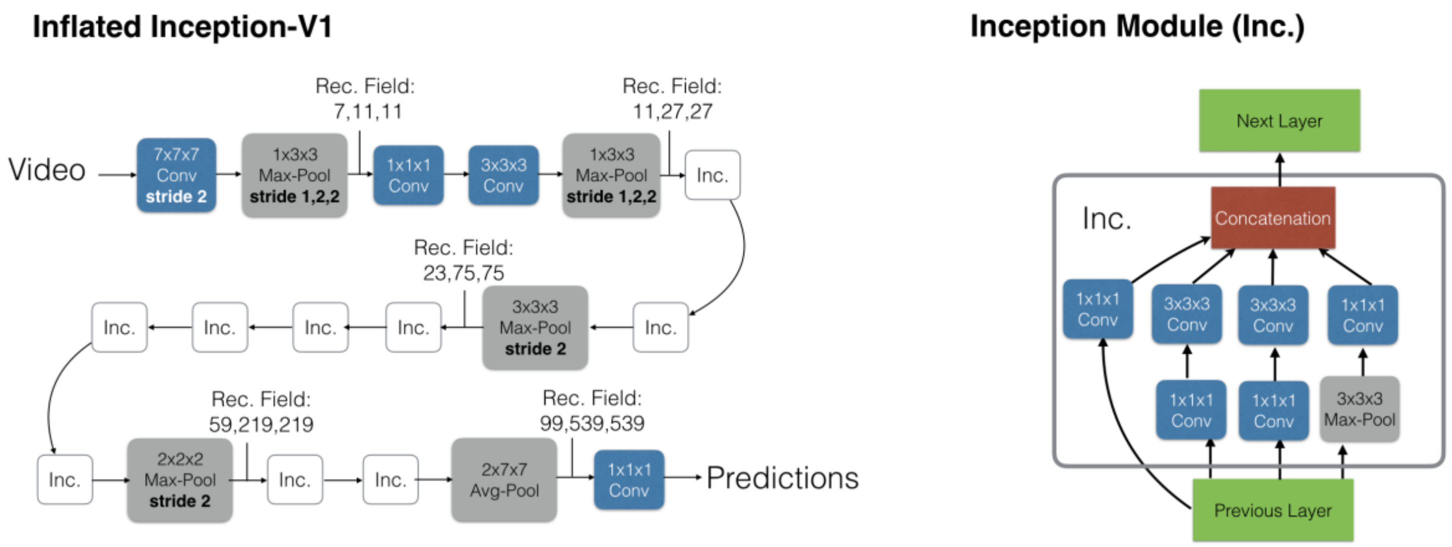


Figure 3. The Inflated Inception-V1 architecture (left) and its detailed inception submodule (right). The strides of convolution and pooling operators are 1 where not specified, and batch normalization layers, ReLu's and the softmax at the end are not shown. The theoretical sizes of receptive field sizes for a few layers in the network are provided in the format "time,x,y" – the units are frames and pixels. The predictions are obtained convolutionally in time and averaged.

Basic idea

- Replace 2D convolutions with 3D convolutions
- Train on same domain data
  - Videos

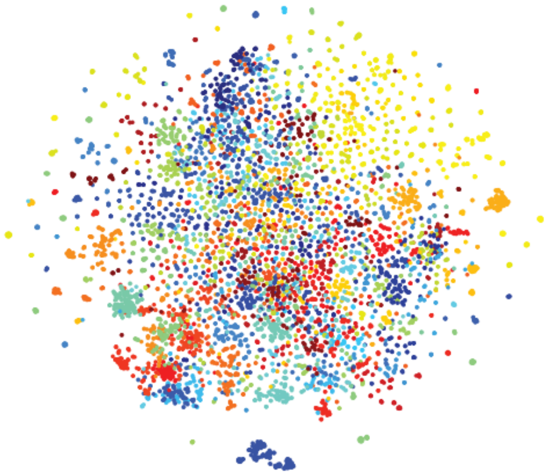
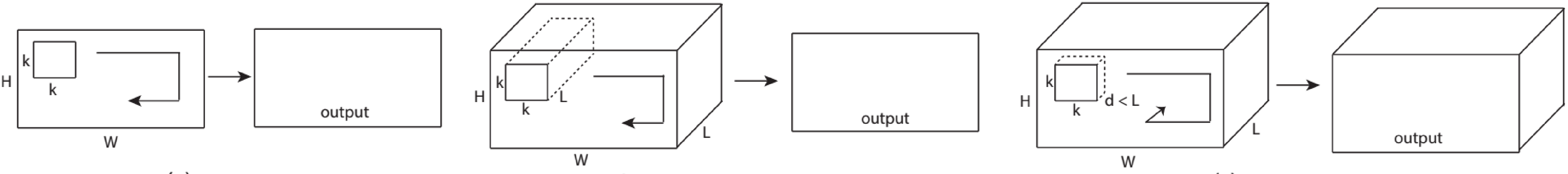


Figure 6. **Feature embedding**. Feature embedding visualizations of Imagenet and C3D on UCF101 dataset using t-SNE [43]. C3D features are semantically separable compared to Imagenet suggesting that it is a better feature for videos. Each clip is visualized as a point and clips belonging to the same action have the same color. Best viewed in color.



(a) 2D convolution (b) 2D convolution on multiple frames (c) 3D convolution

Some results

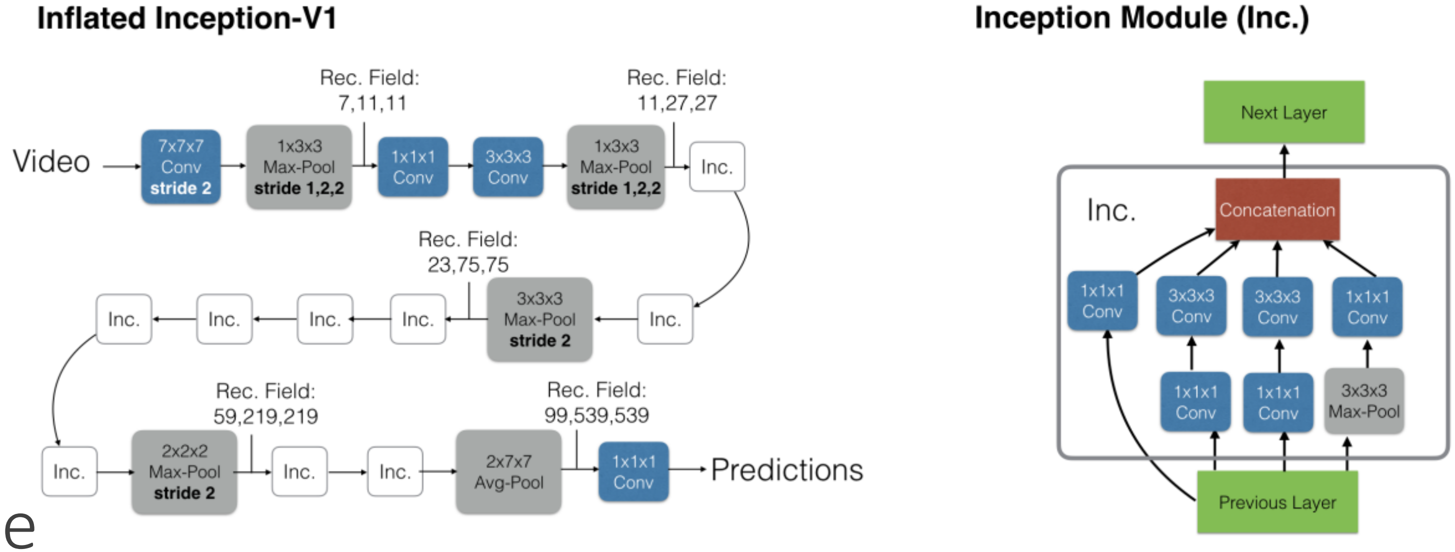
- Generally, it works pretty nicely
- Not for all temporal tasks though, as we will see later on in the course

Method	Accuracy (%)
Imagenet + linear SVM	68.8
iDT w/ BoW + linear SVM	76.2
Deep networks [18]	65.4
Spatial stream network [36]	72.6
LRCN [6]	71.1
LSTM composite model [39]	75.8
C3D (1 net) + linear SVM	82.3
C3D (3 nets) + linear SVM	**85.2**
iDT w/ Fisher vector [31]	87.9
Temporal stream network [36]	83.7
Two-stream networks [36]	88.0
LRCN [6]	82.9
LSTM composite model [39]	84.3
Conv. pooling on long clips [29]	88.2
LSTM on long clips [29]	88.6
Multi-skip feature stacking [25]	89.1
C3D (3 nets) + iDT + linear SVM	**90.4**

Table 3. **Action recognition results on UCF101**. C3D compared with baselines and current state-of-the-art methods. Top: simple features with linear SVM; Middle: methods taking only RGB frames as inputs; Bottom: methods using multiple feature combinations.

i3D

- i3D = C3D + Inception
  - Plus some neat tricks
- Take 2D filters and inflate them so that they become 3D filters
- Then, use them as initialization



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Architecture	UCF-101 RGB	UCF-101 Flow	UCF-101 RGB + Flow	HMDB-51 RGB	HMDB-51 Flow	HMDB-51 RGB + Flow	Kinetics RGB	Kinetics Flow	Kinetics RGB + Flow
(a) LSTM	81.0	–	–	36.0	–	–	63.3	–	–
(b) 3D-ConvNet	51.6	–	–	24.3	–	–	56.1	–	–
(c) Two-Stream	83.6	85.6	91.2	43.2	56.3	58.3	62.2	52.4	65.6
(d) 3D-Fused	83.2	85.8	89.3	49.2	55.5	56.8	–	–	67.2
(e) Two-Stream I3D	**84.5**	**90.6**	**93.4**	**49.8**	**61.9**	**66.4**	**71.1**	**63.4**	**74.2**

Table 2. Architecture comparison: (left) training and testing on split 1 of UCF-101; (middle) training and testing on split 1 of HMDB-51; (right) training and testing on Kinetics. All models are based on ImageNet pre-trained Inception-v1, except 3D-ConvNet, a C3D-like [31] model which has a custom architecture and was trained here from scratch. Note that the Two-Stream architecture numbers on individual RGB and Flow streams can be interpreted as a simple baseline which applies a ConvNet independently on 25 uniformly sampled frames then averages the predictions.

Summary

- Popular Convolutional Neural Networks architectures
- Go deeper on what makes them tick & what makes them different

Reading material

- All the papers from the models presented