Image Classification

Convolutional networks - Why

- Convolutions
  - Reduce parameters
  - Capture shift-invariance: location of patch in image should not matter
- Subsampling
  - Allows greater invariance to deformations
  - Allows the capture of large patterns with small filters

How to do machine learning

- Create training / validation sets
- Identify loss functions
- Choose hypothesis class
- Find best hypothesis by minimizing training loss

How to do machine learning

- Create training / validation sets
- Identify loss functions
- Choose hypothesis class
- Find best hypothesis by minimizing training loss

Multiclass classification !!

$$h(x) = \mathbf{s} \qquad \hat{p}(y = k|x) \propto e^{s_k} \qquad \hat{p}(y = k|x) = \frac{e^{s_k}}{\sum_j e^{s_j}}$$

$$L(h(x), y) = -\log \hat{p}(y|x)$$

Negative log likelihood for multiclass classification

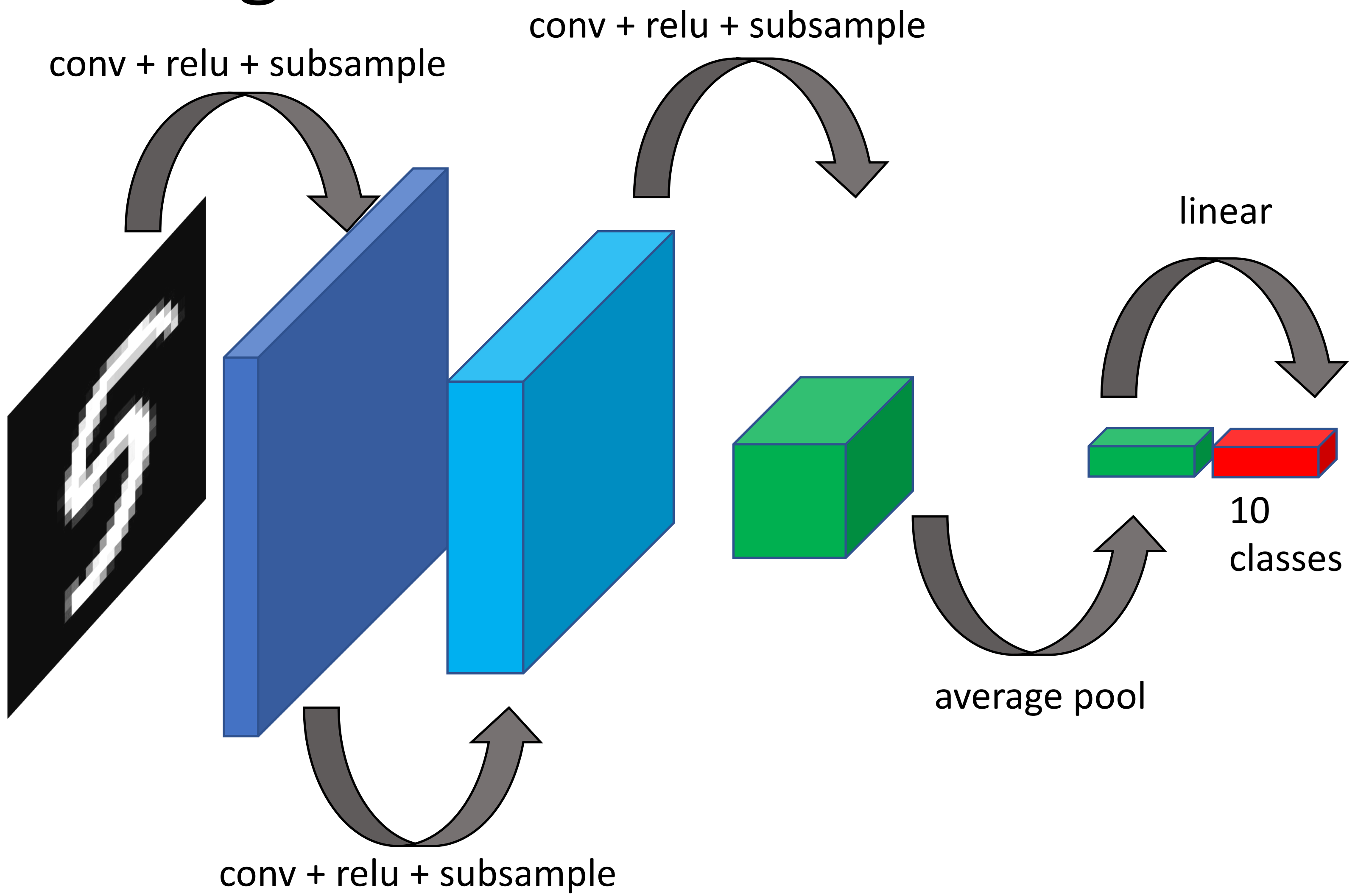
Negative log likelihood for multiclass classification

$$L(h(x), y) = -\log \hat{p}(y|x)$$

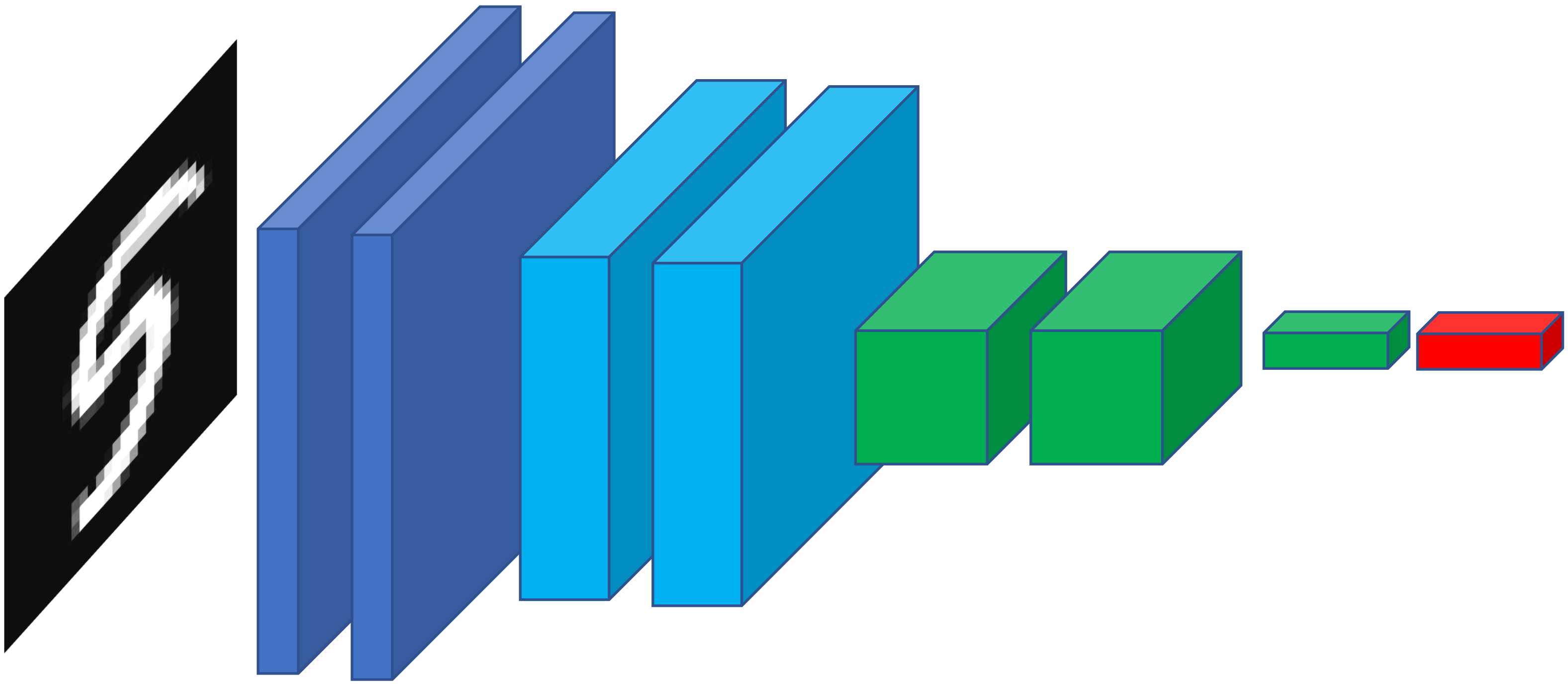
- Often represent label as a ``one-hot'' vector **y**
  - **y** = [0, 0, …, 1,… 0]
  - y_k = 1 if label is k, 0 otherwise

$$L(h(x), \mathbf{y}) = -\sum_k y_k \log \hat{p}(y = k|x)$$

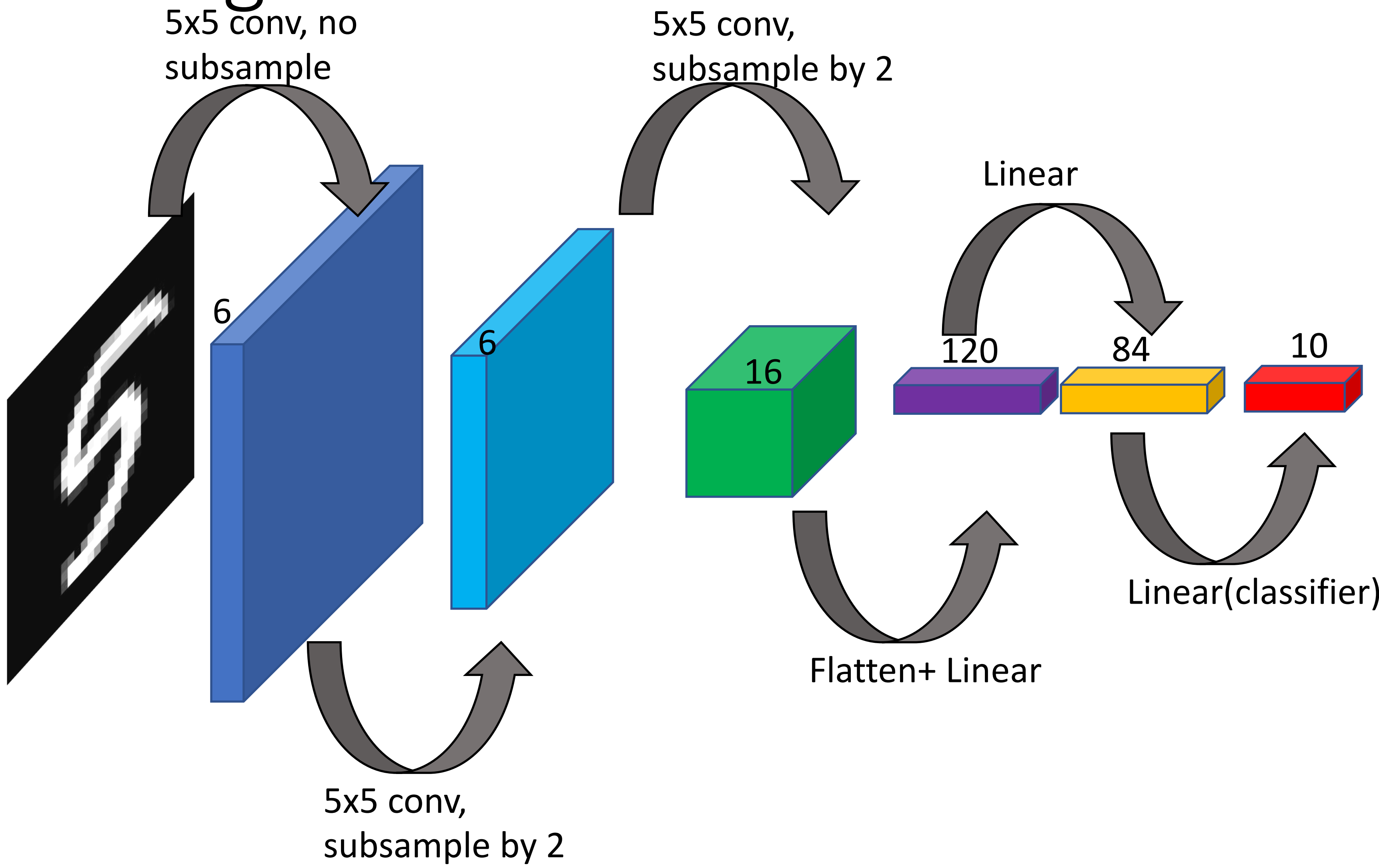
Building a convolutional network



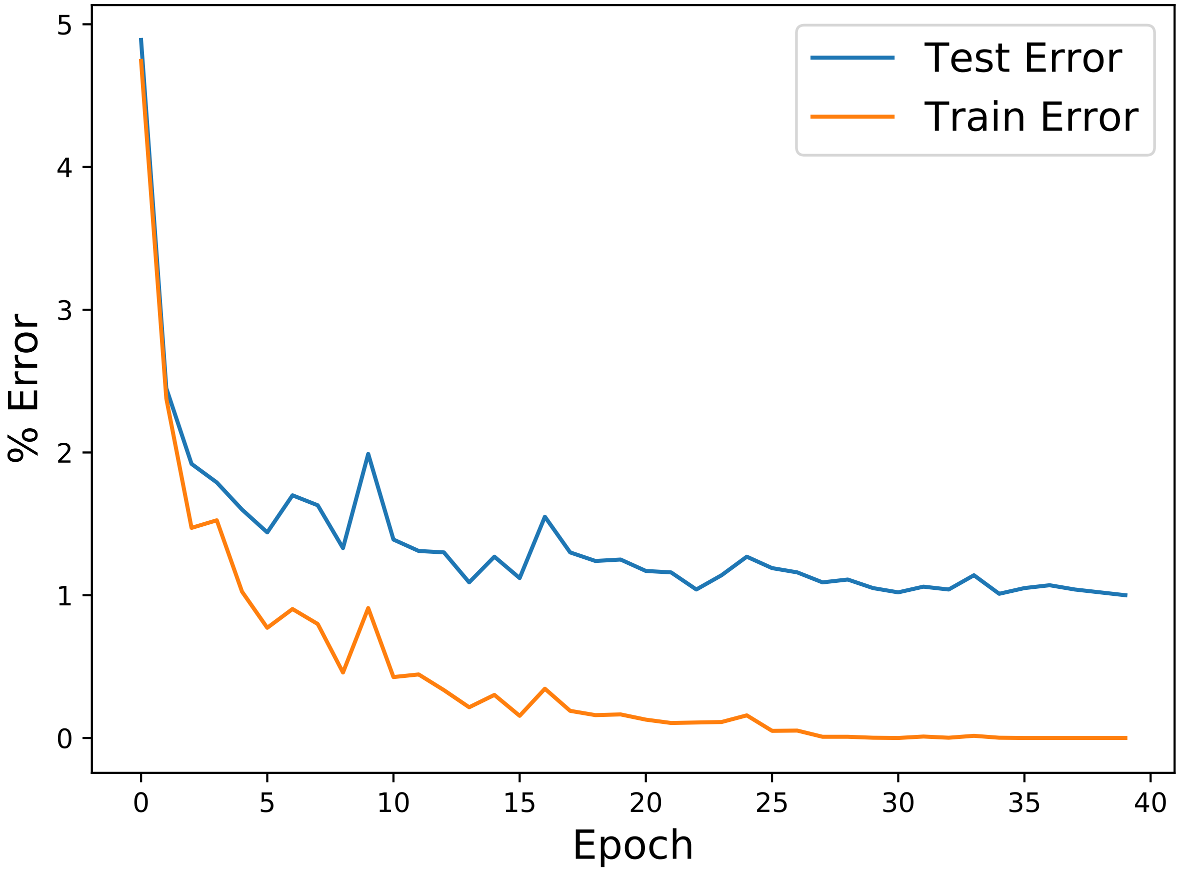
Building a convolutional network



Building a convolutional network



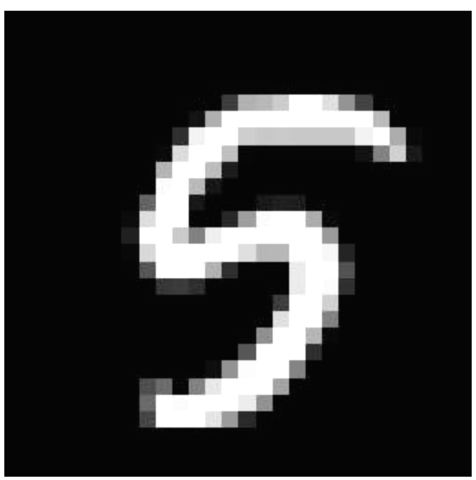
Training the network

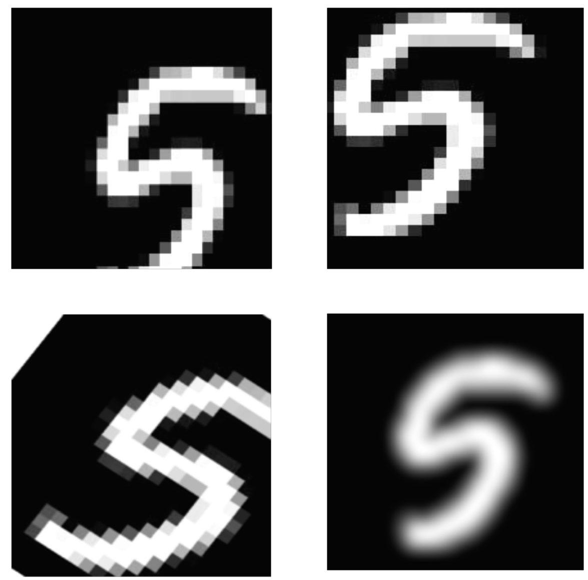


Overfitting

Controlling overfitting in convolutional networks

- Reduce parameters?
- Increase dataset size?
  - Automatically by jittering examples - “Data augmentation”

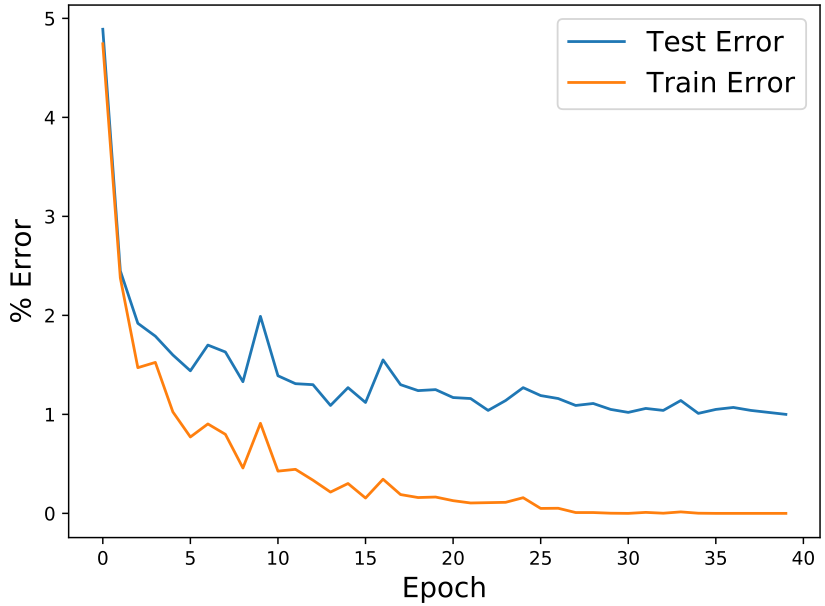




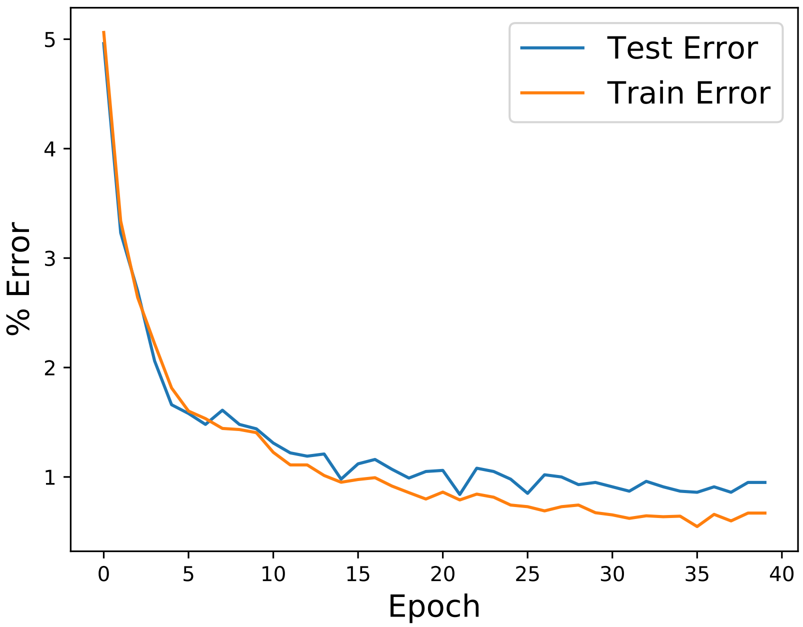
Controlling overfitting in convolutional networks

- Dropout: Internally create data augmentations
  - Randomly zero out some fraction of values before a layer
  - Can be thought of as per-layer data augmentation
  - Typically applied on inputs to linear layers (since linear layers have tons of parameters)

Dropout



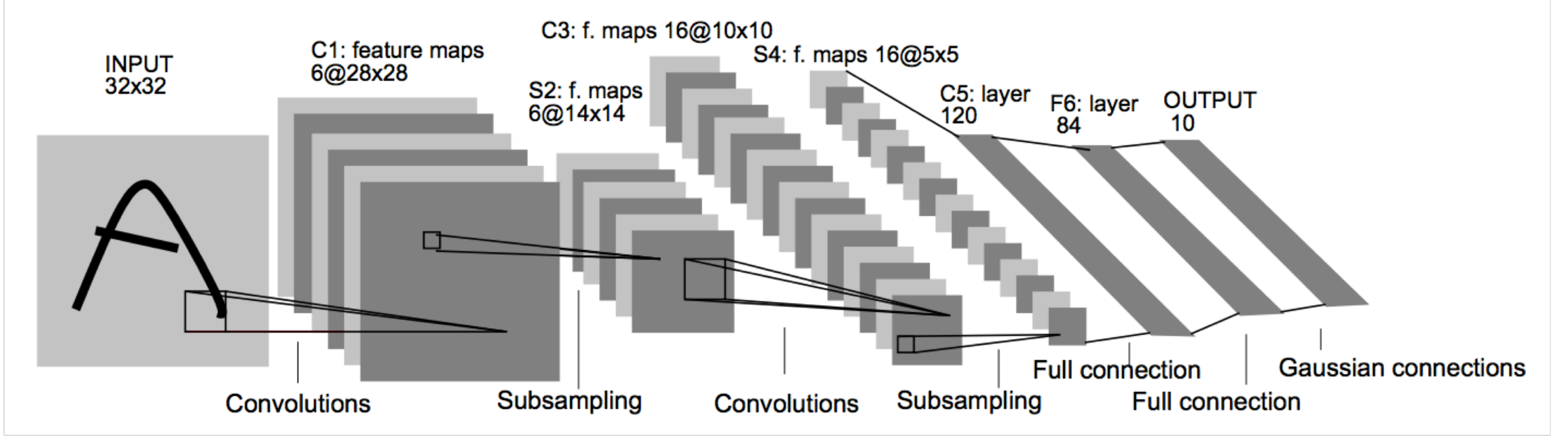
Without dropout
Train error: 0%
Test error: 1%



With dropout
Train error: 0.7%
Test error: 0.85%

MNIST Classification

Method	Error rate (%)
Linear classifier over pixels	12
Non-linear classifier over pixels	1.41
Linear classifier over HOG	1.44
Kernel SVM over HOG	0.79
Convolutional Network	0.95



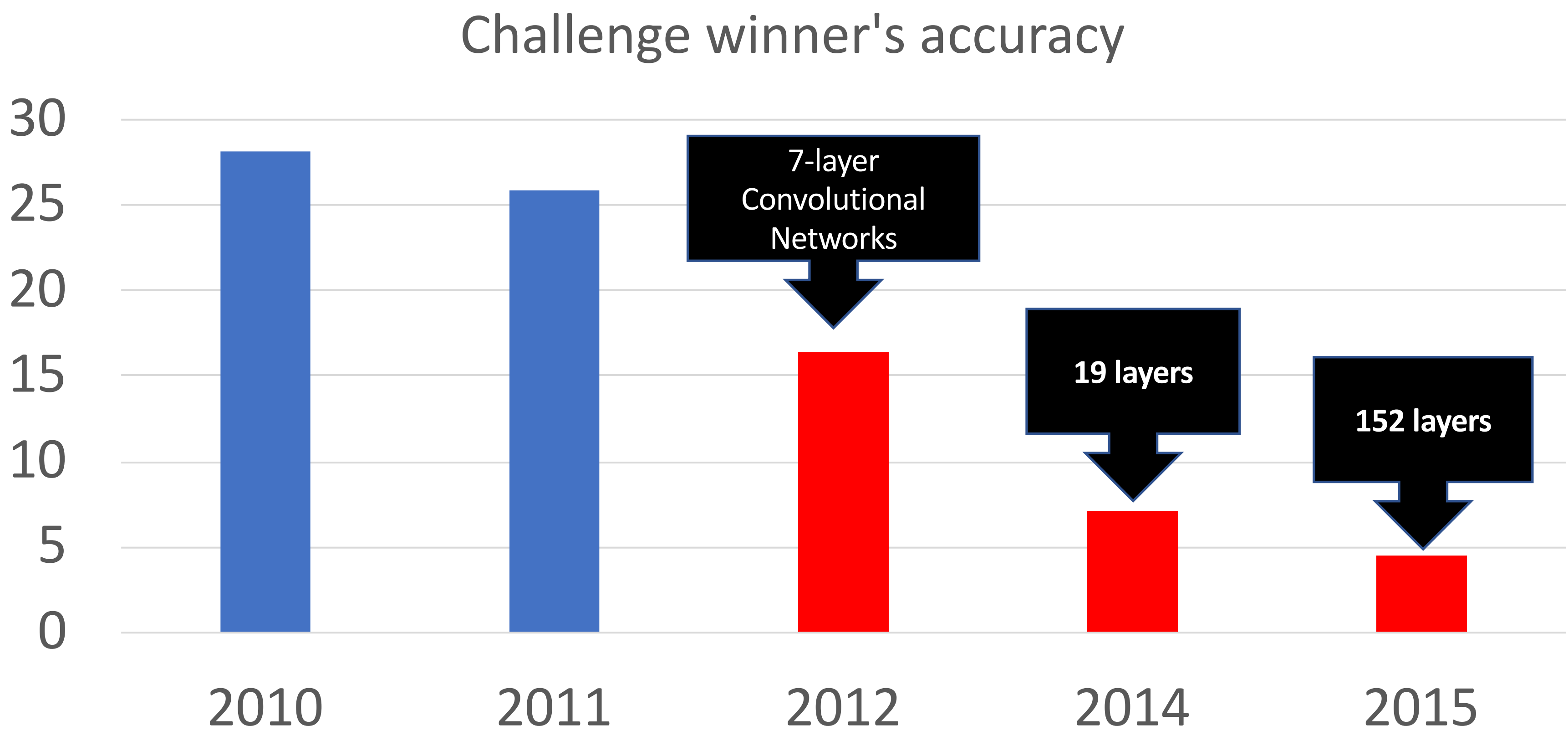
ImageNet

- 1000 categories
- ~1000 instances per category

Olga Russakovsky*, Jia Deng*, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg and Li Fei-Fei. (* = equal contribution) **ImageNet Large Scale Visual Recognition Challenge**. *International Journal of Computer Vision*, 2015.

ImageNet

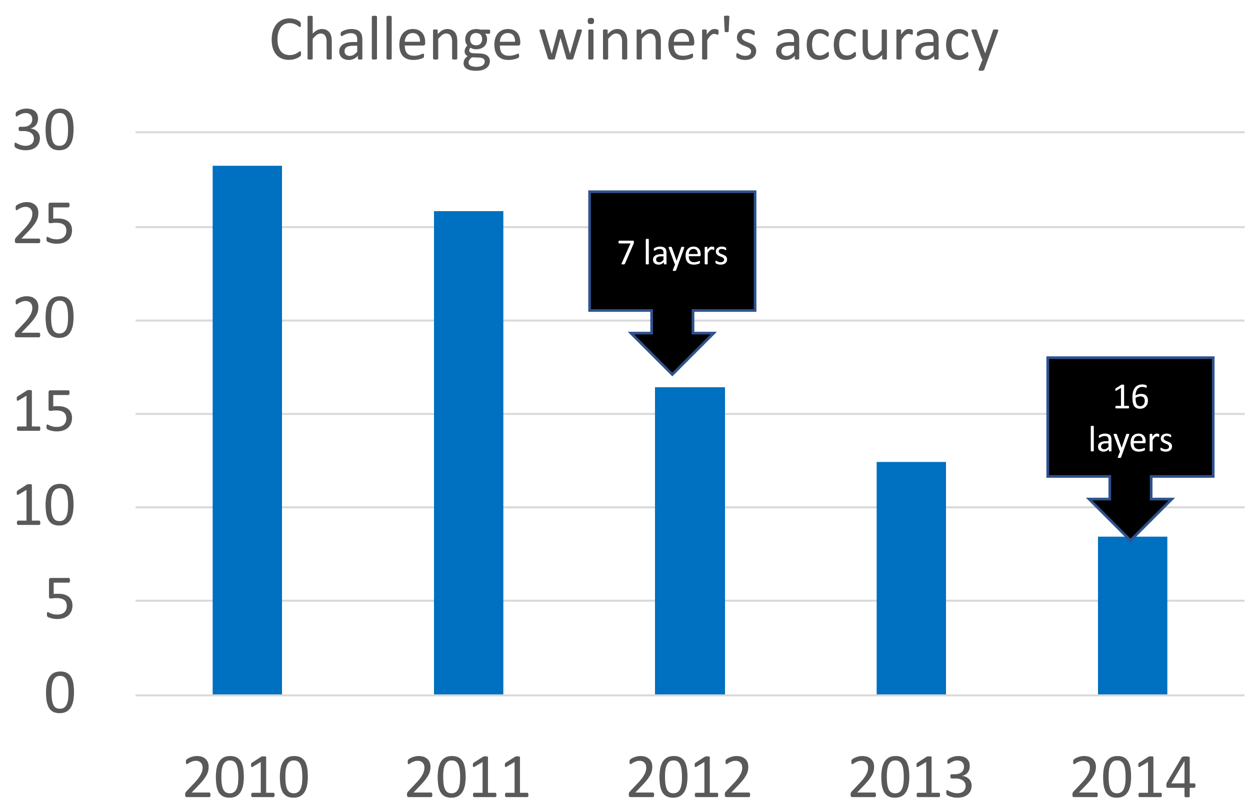
- Top-5 error: algorithm makes 5 predictions, true label must be in top 5
- Useful for incomplete labelings



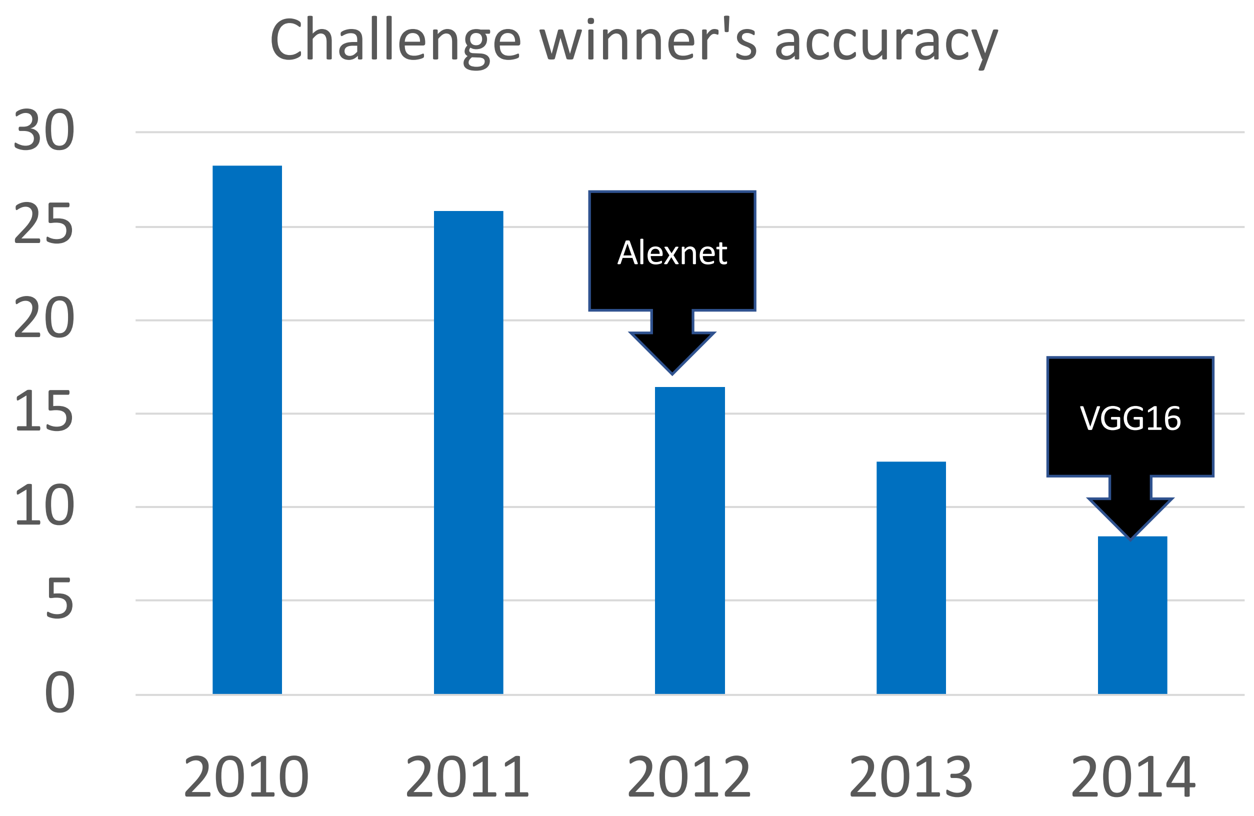
Challenge winner's accuracy
30
25
20
15
10
5
0
7-layer Convolutional Networks
19 layers
152 layers
2010
2011
2012
2014
2015

Exploring convnet architectures

Deeper is better



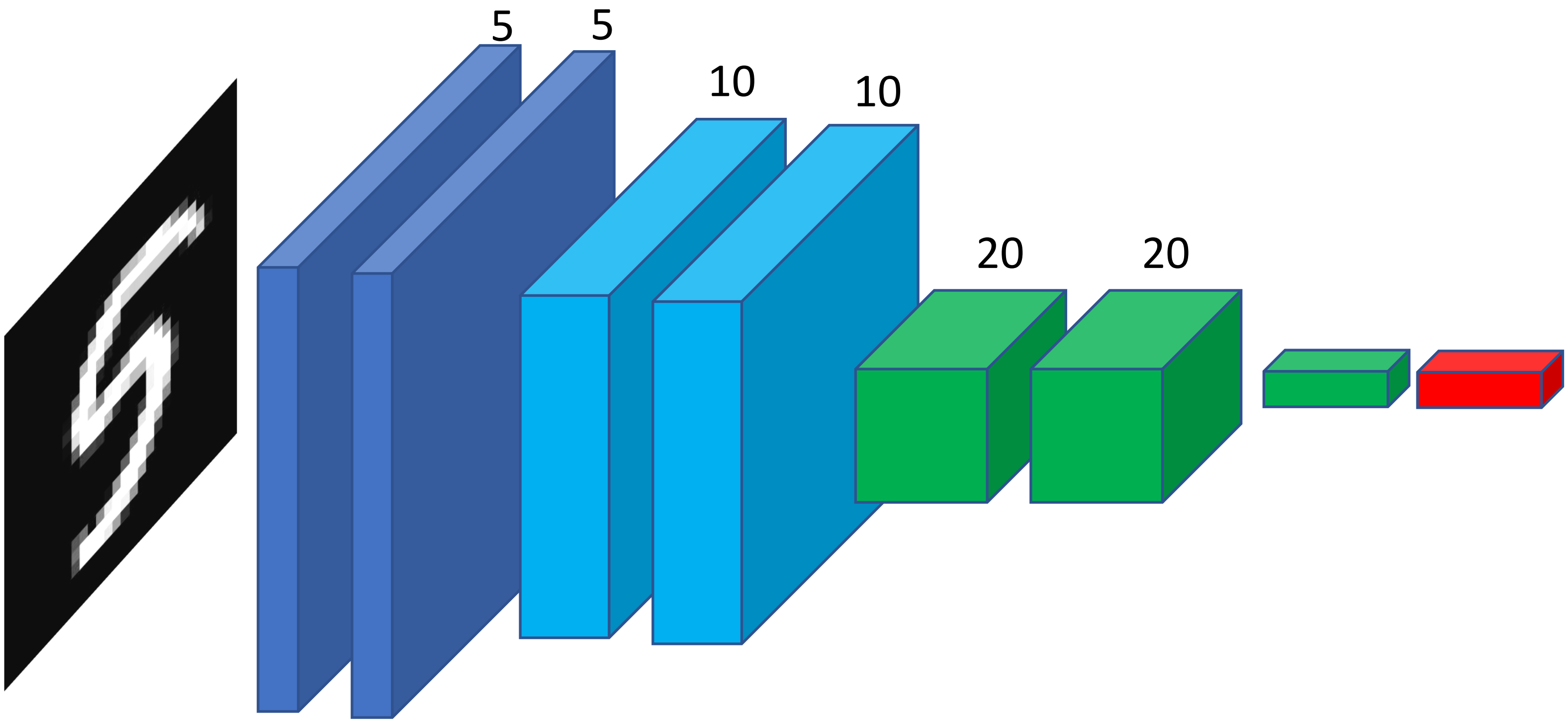
Deeper is better



The VGG pattern

- Every convolution is 3x3, padded by 1
- Every convolution followed by ReLU
- ConvNet is divided into "stages"
  - Layers within a stage: no subsampling
  - Subsampling by 2 at the end of each stage
- Layers within stage have same number of channels
- Every subsampling → double the number of channels

Example network



Challenges in training: exploding / vanishing gradients

- Vanishing / exploding gradients

$$\frac{\partial z}{\partial z_i} = \frac{\partial z}{\partial z_{n-1}} \frac{\partial z_{n-1}}{\partial z_{n-2}} \cdots \frac{\partial z_{i+1}}{\partial z_i}$$

  - If each term is (much) greater than 1 → *explosion of gradients*
  - If each term is (much) less than 1 → *vanishing gradients*

Residual connections

- In general, gradients tend to vanish
- Key idea: allow gradients to flow unimpeded

$$z_{i+1} = f_{i+1}(z_i, w_{i+1}) \qquad \frac{\partial z_{i+1}}{\partial z_i} = \frac{\partial f_{i+1}(z_i, w_{i+1})}{\partial z_i}$$

$$\frac{\partial z}{\partial z_i} = \frac{\partial z}{\partial z_{n-1}} \frac{\partial z_{n-1}}{\partial z_{n-2}} \dots \frac{\partial z_{i+1}}{\partial z_i}$$

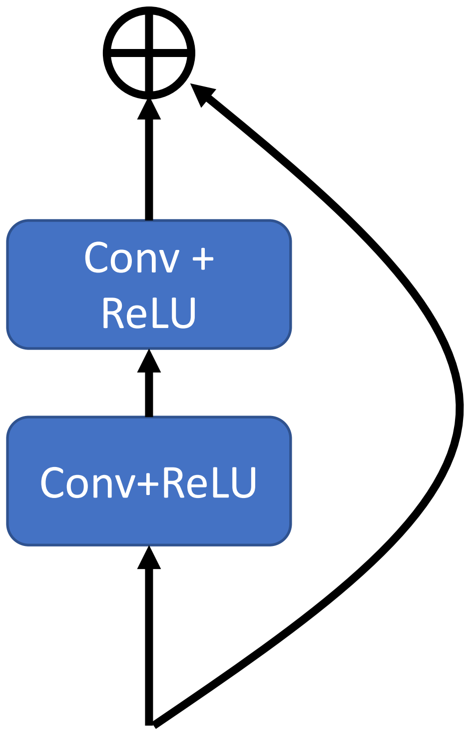
Residual connections

- In general, gradients tend to vanish
- Key idea: allow gradients to flow unimpeded

$$z_{i+1} = g_{i+1}(z_i, w_{i+1}) + z_i \qquad \frac{\partial z_{i+1}}{\partial z_i} = \frac{\partial g_{i+1}(z_i, w_{i+1})}{\partial z_i} + I$$

$$\frac{\partial z}{\partial z_i} = \frac{\partial z}{\partial z_{n-1}} \frac{\partial z_{n-1}}{\partial z_{n-2}} \dots \frac{\partial z_{i+1}}{\partial z_i}$$

Residual block



Residual connections

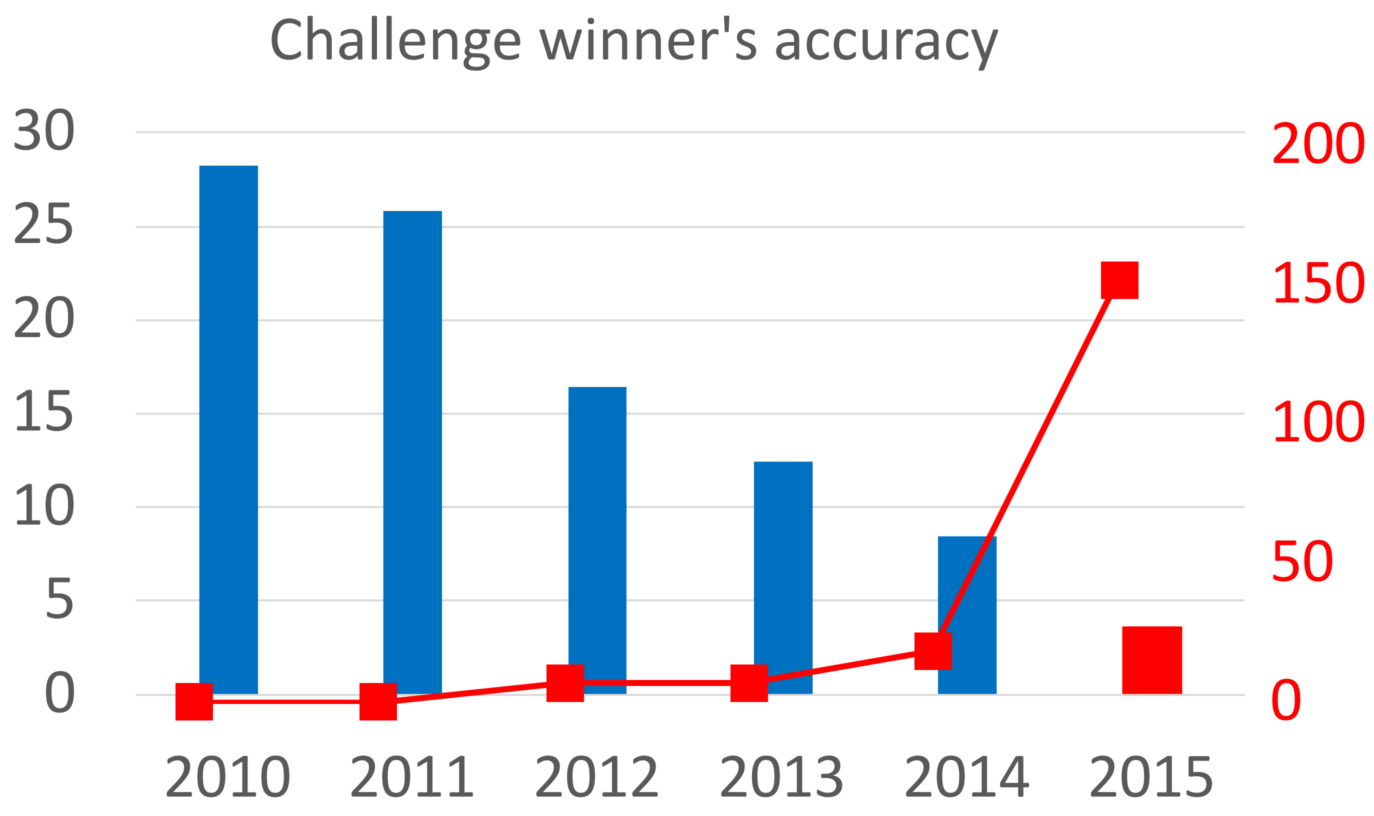
- Assumes all z_i have the same size
- True within a stage
- Across stages?
  - Doubling of feature channels
  - Subsampling
- Increase channels by 1x1 convolution
- Decrease spatial resolution by subsampling

$$z_{i+1} = g_{i+1}(z_i, w_{i+1}) + \text{subsample}(W z_i)$$

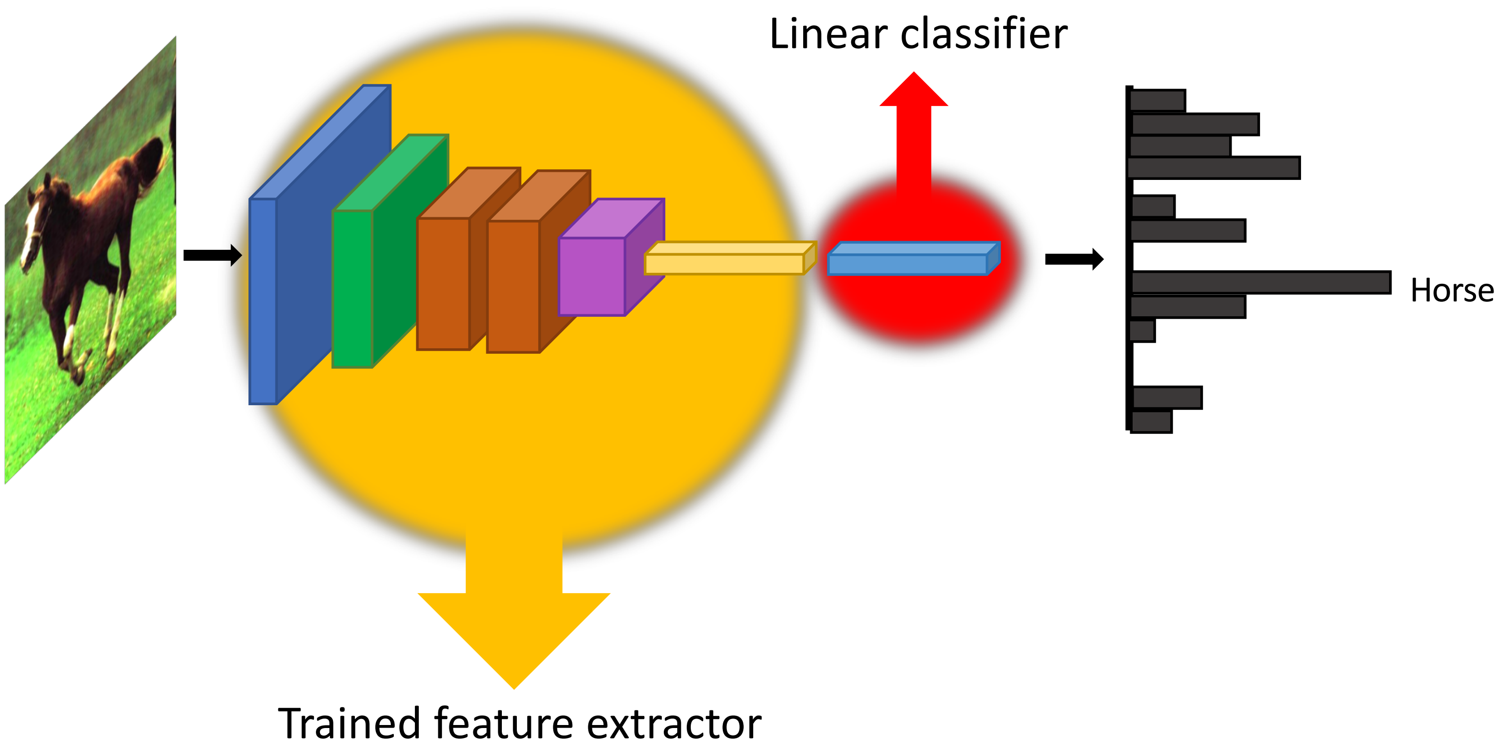
The ResNet pattern

- Decrease resolution substantially in first layer
  - Reduces memory consumption due to intermediate outputs
- Divide into stages
  - maintain resolution, channels in each stage
  - halve resolution, double channels between stages
- Divide each stage into residual blocks
- At the end, compute average value of each channel to feed linear classifier

Putting it all together - Residual networks

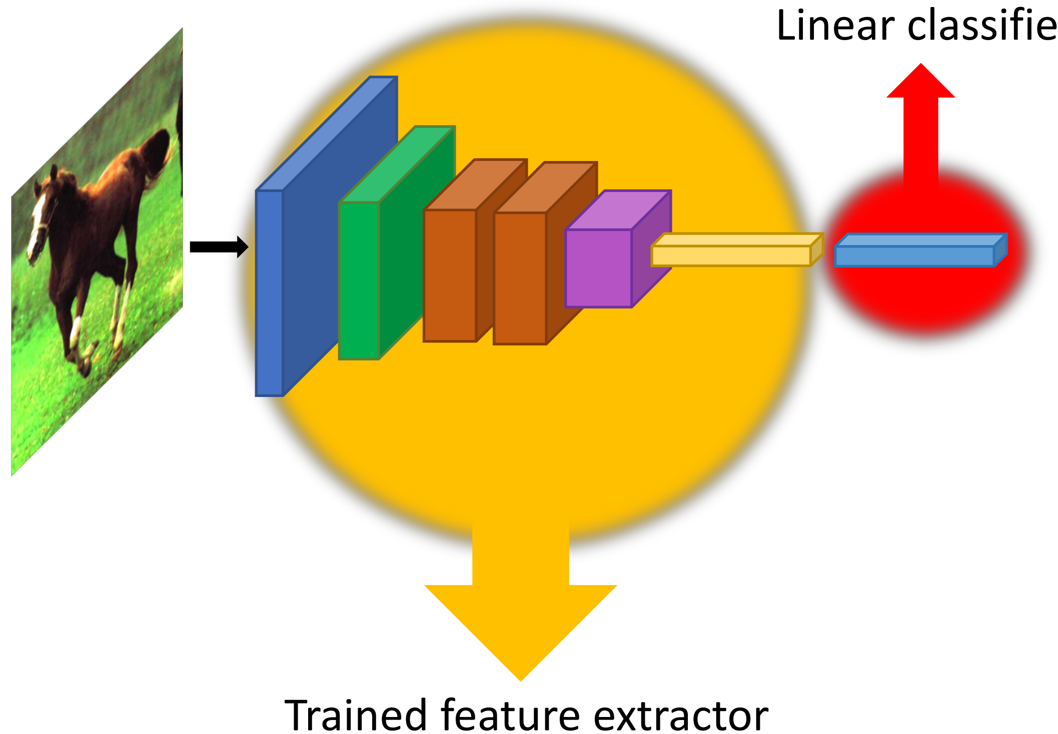


Transfer learning with convolutional networks



Transfer learning with convolutional networks

- What do we do for a new image classification problem?
- Key idea:
  - *Freeze* parameters in feature extractor
  - *Retrain* classifier



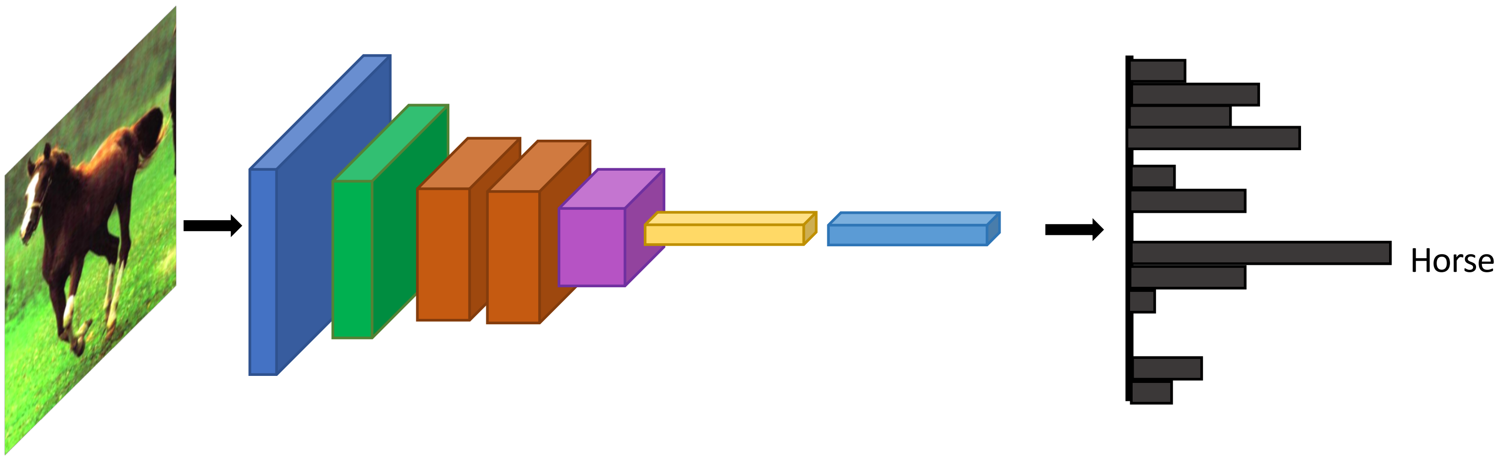
Transfer learning with convolutional networks

Dataset	Best Non-Convnet perf	Pretrained convnet + classifier	Improvement
Caltech 101	84.3	87.7	+3.4
VOC 2007	61.7	79.7	+18
CUB 200	18.8	61.0	+42.2
Aircraft	61.0	45.0	-16
Cars	59.2	36.5	-22.7

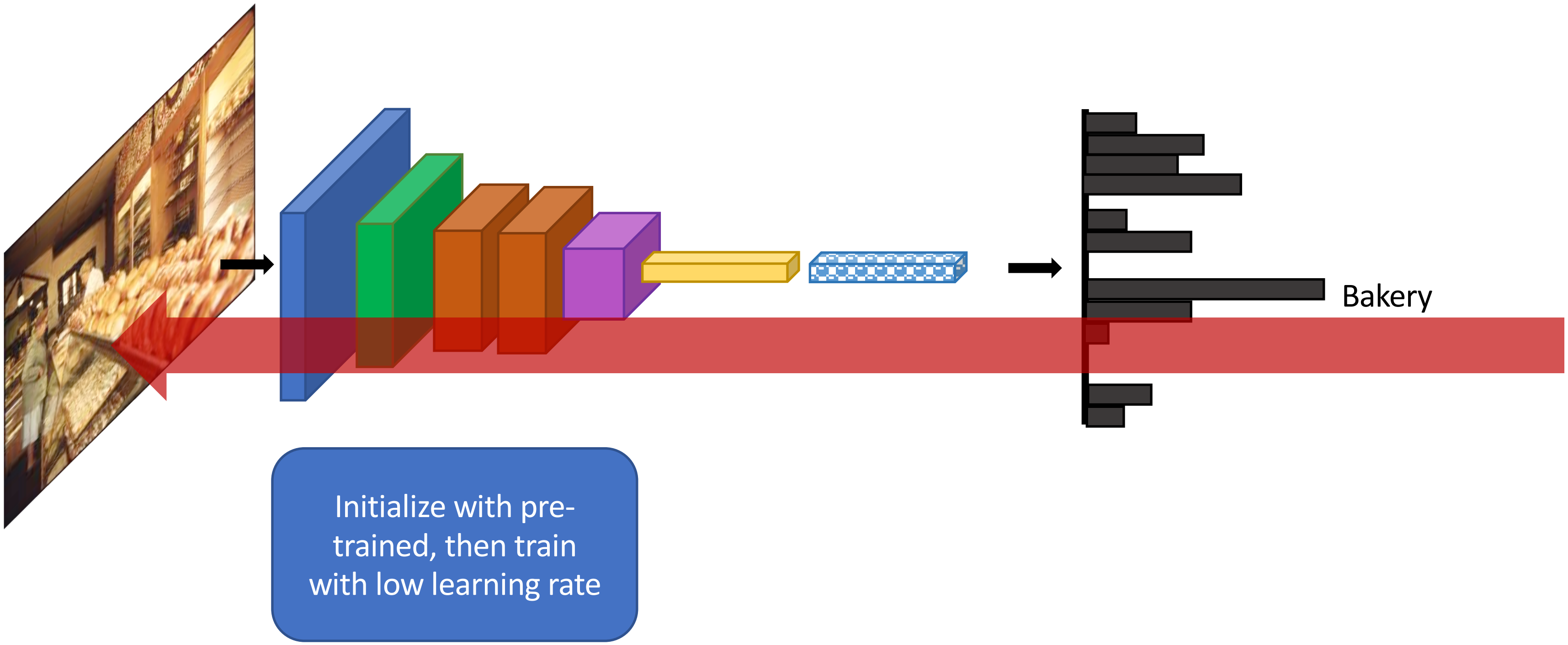
Why transfer learning?

- Availability of training data
- Computational cost
- Ability to pre-compute feature vectors and use for multiple tasks
- *Con: NO end-to-end learning*

Finetuning



Finetuning


Bakery
Initialize with pre-trained, then train with low learning rate

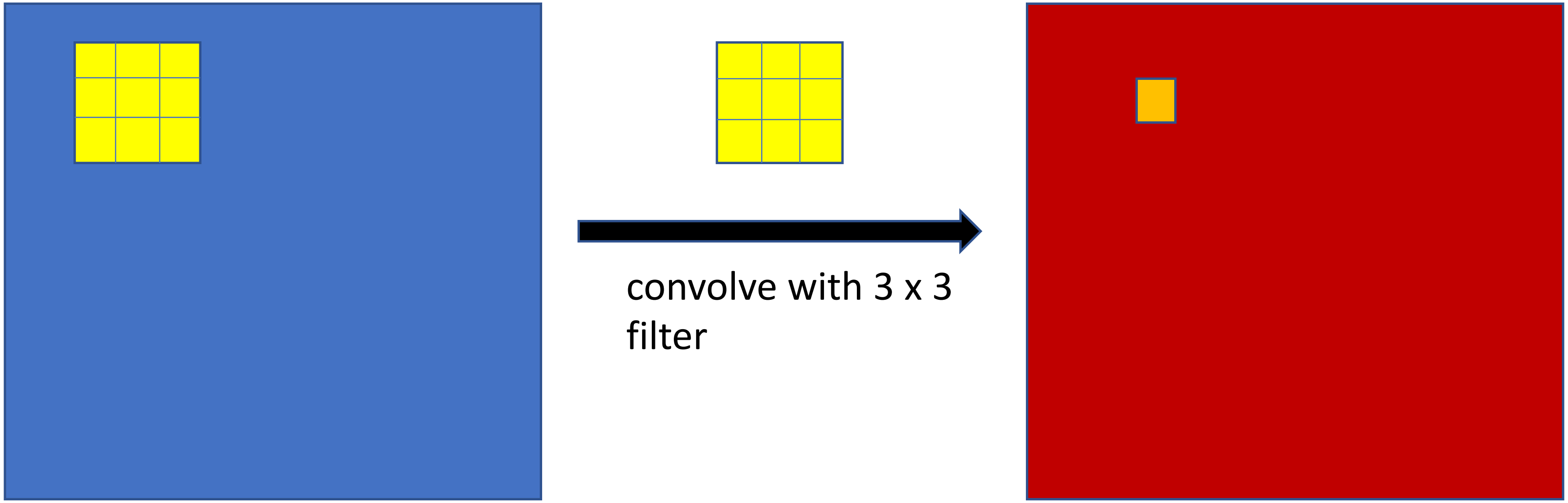
Finetuning

Dataset	Best Non-Convnet perf	Pretrained convnet + classifier	Finetuned convnet	Improvement
Caltech 101	84.3	87.7	88.4	+4.1
VOC 2007	61.7	79.7	82.4	+20.7
CUB 200	18.8	61.0	70.4	+51.6
Aircraft	61.0	45.0	74.1	+13.1
Cars	59.2	36.5	79.8	+20.6

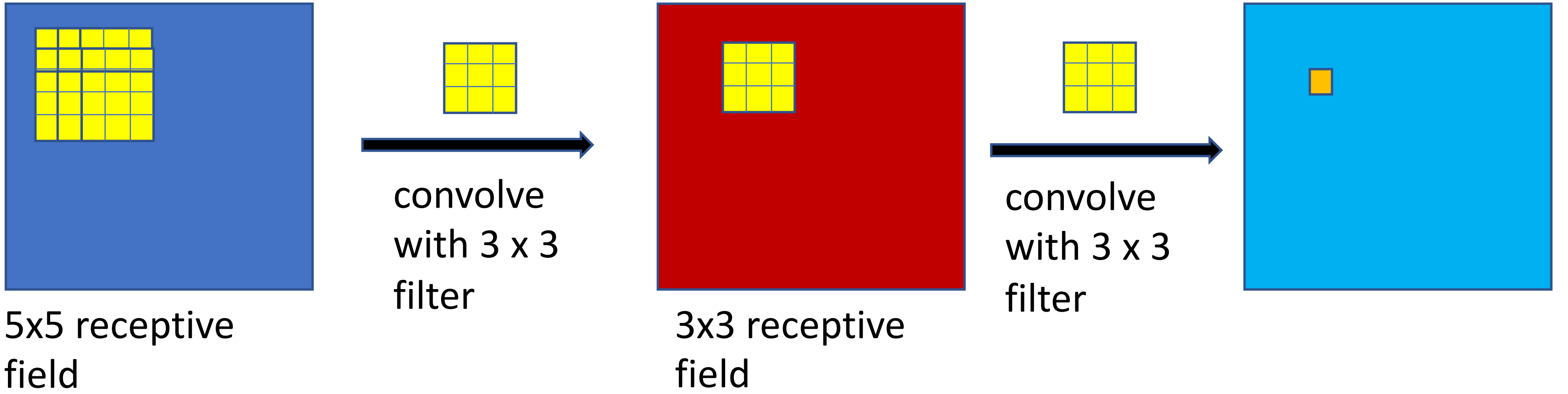
Visualizing convolutional networks

Receptive field

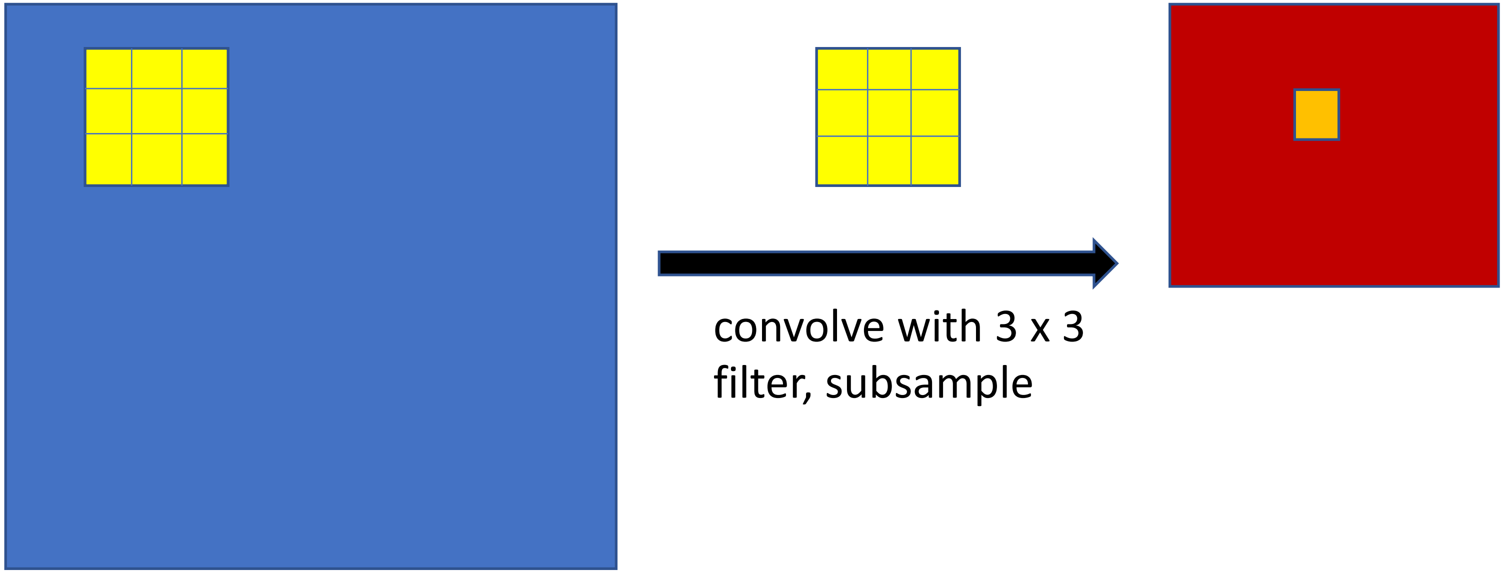
- Which input pixels does a particular unit in a feature map depends on



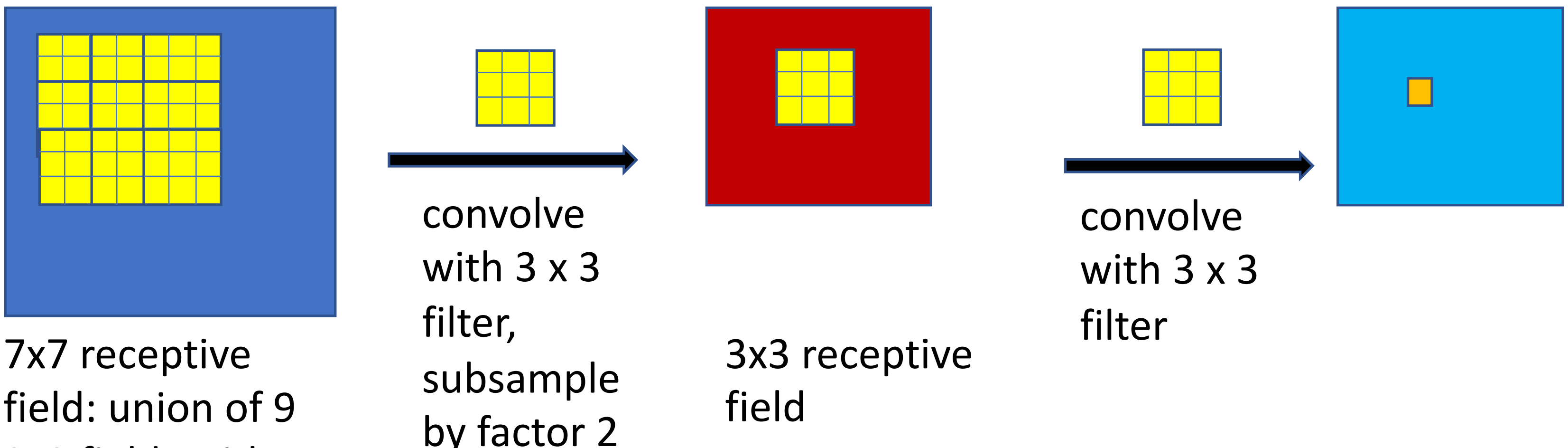
Receptive field



Receptive field



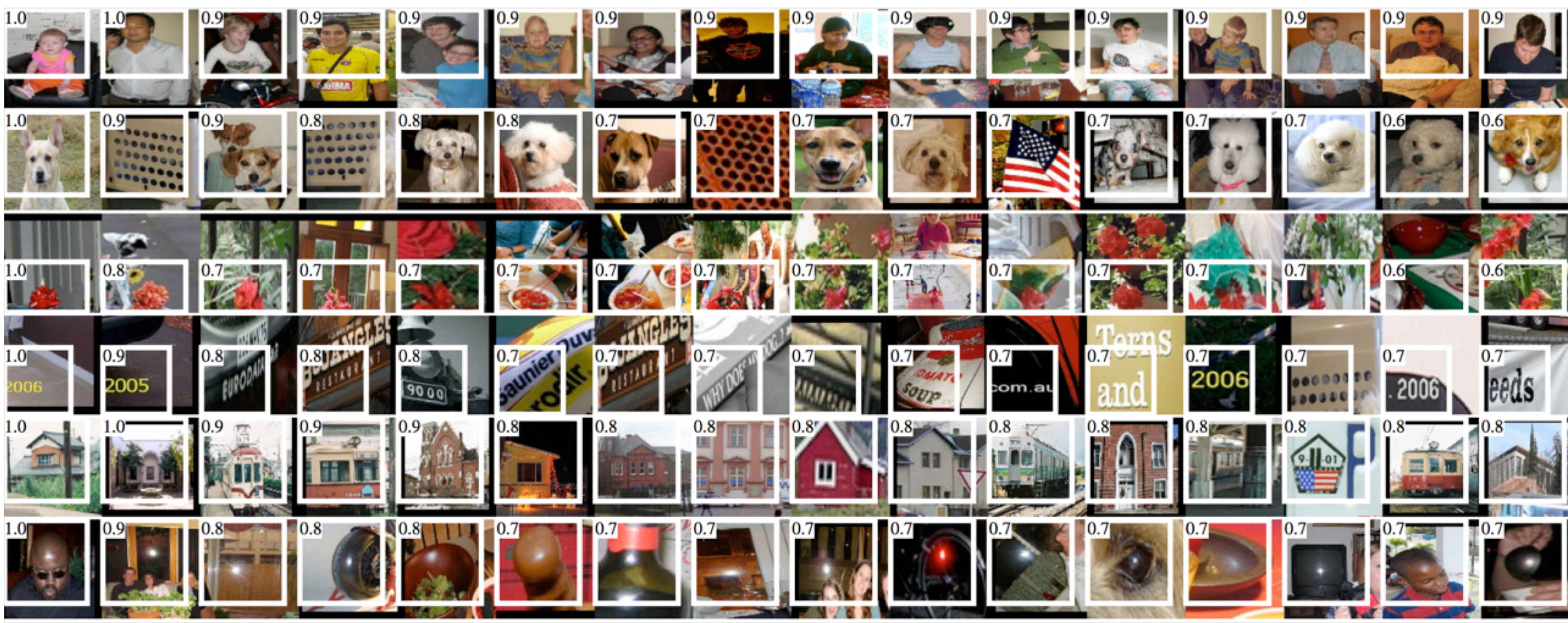
Receptive field



7x7 receptive field: union of 9 3x3 fields with stride of 2

Visualizing convolutional networks

- Take images for which a given unit in a feature map scores high
- Identify the receptive field for each.



Rich feature hierarchies for accurate object detection and semantic segmentation. R. Girshick, J. Donahue, T. Darrell, J. Malik. In *CVPR,* 2014.

Visualizing convolutional networks II

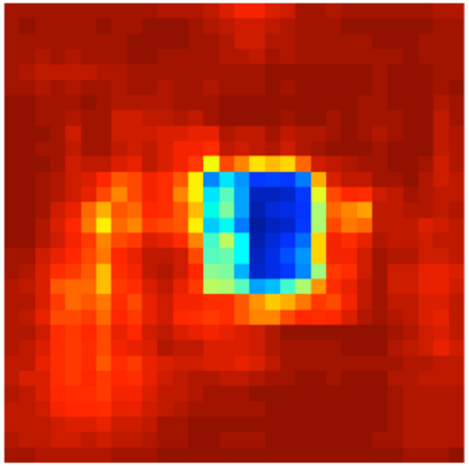
- Block regions of the image and classify

Visualizing and Understanding Convolutional Networks. M. Zeiler and R. Fergus. In *ECCV 2014.*

Visualizing convolutional networks II

- Image pixels important for classification = pixels when blocked cause misclassification

(d) Classifier, probability of correct class



Visualizing and Understanding Convolutional Networks. M. Zeiler and R. Fergus. In *ECCV 2014.*