Entreposage et fouille de données (STA211)
Neural Networks and Deep Learning

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le cnam

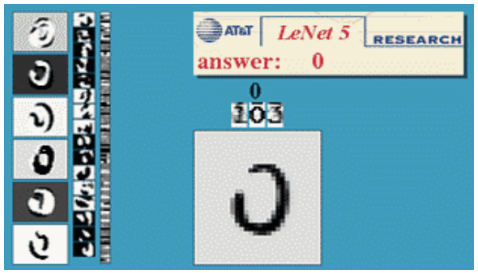
Cédric

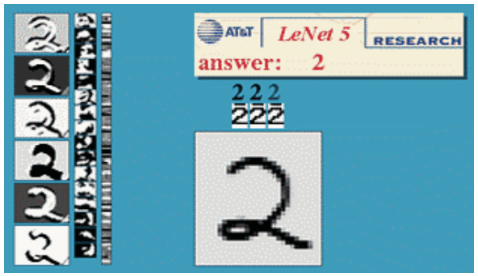
Outline

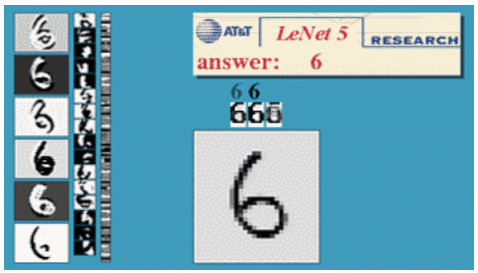
80's: LeNet 5 Model

- Evaluation on MNIST
- Total # parameters ~ 60000
  - 60,000 original datasets: test error: 0.95%
  - 540,000 artificial distortions + 60,000 original: Test error: 0.8%

- **Successful deployment for postal code reading in the US**



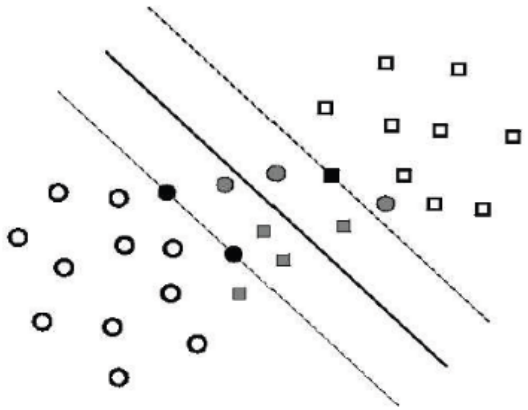


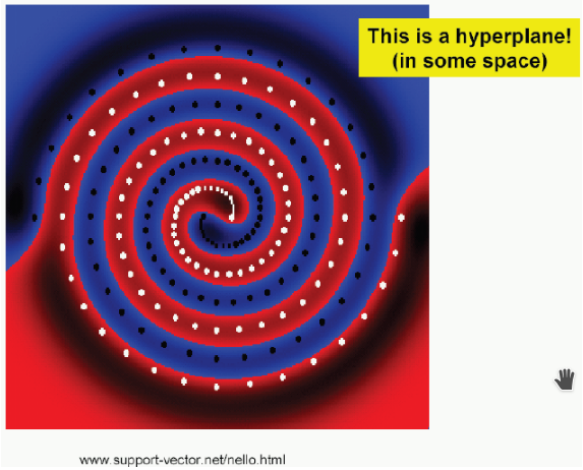


Deep Learning: Trends and methods in the last four decades

90's: start of winter for deep learning

- Deep neural nets =' black magic', black boxes
  - Lack of interpretability
  - Optimization issues for highly non-convex objective function
- **Golden age of kernel methods**
  - Generalization theory with Support Vector Machines
  - Extension to non-linear modes: kernel trick
    - Kernel encode prior knowledge (structure) on data
  - Convex optimization problem

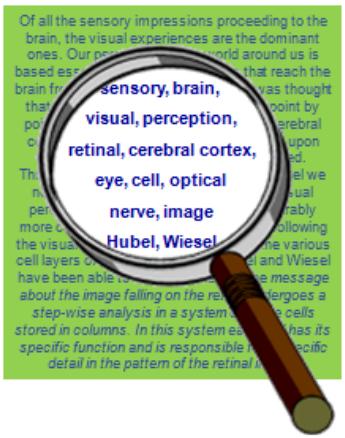


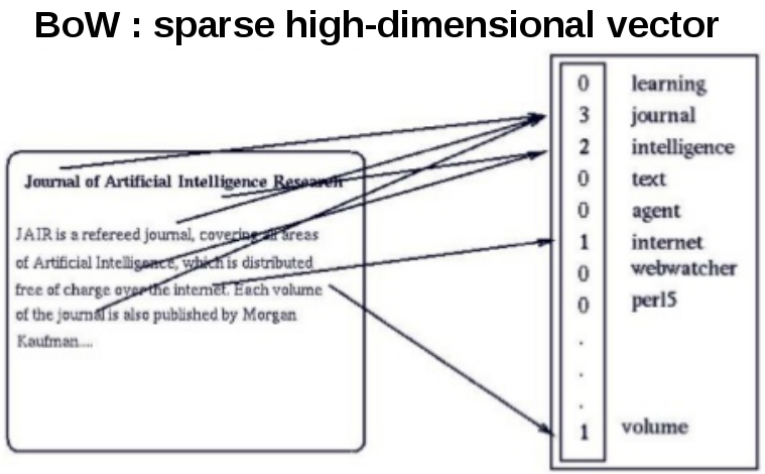


Deep Learning: Trends and methods in the last four decades

2000's: Bag of Words Model (BoW)

- Started from the Information Retrieval (IR) community
- Text classification : document as a histogram of word occurrences



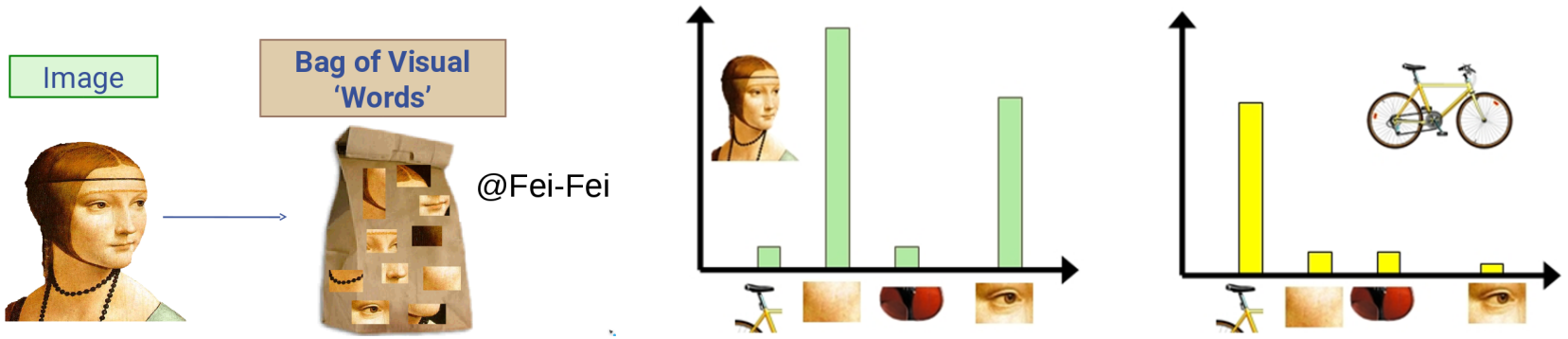


- Bow representation as input for powerful classifiers, *e.g.* SVM

Deep Learning: Trends and methods in the last four decades

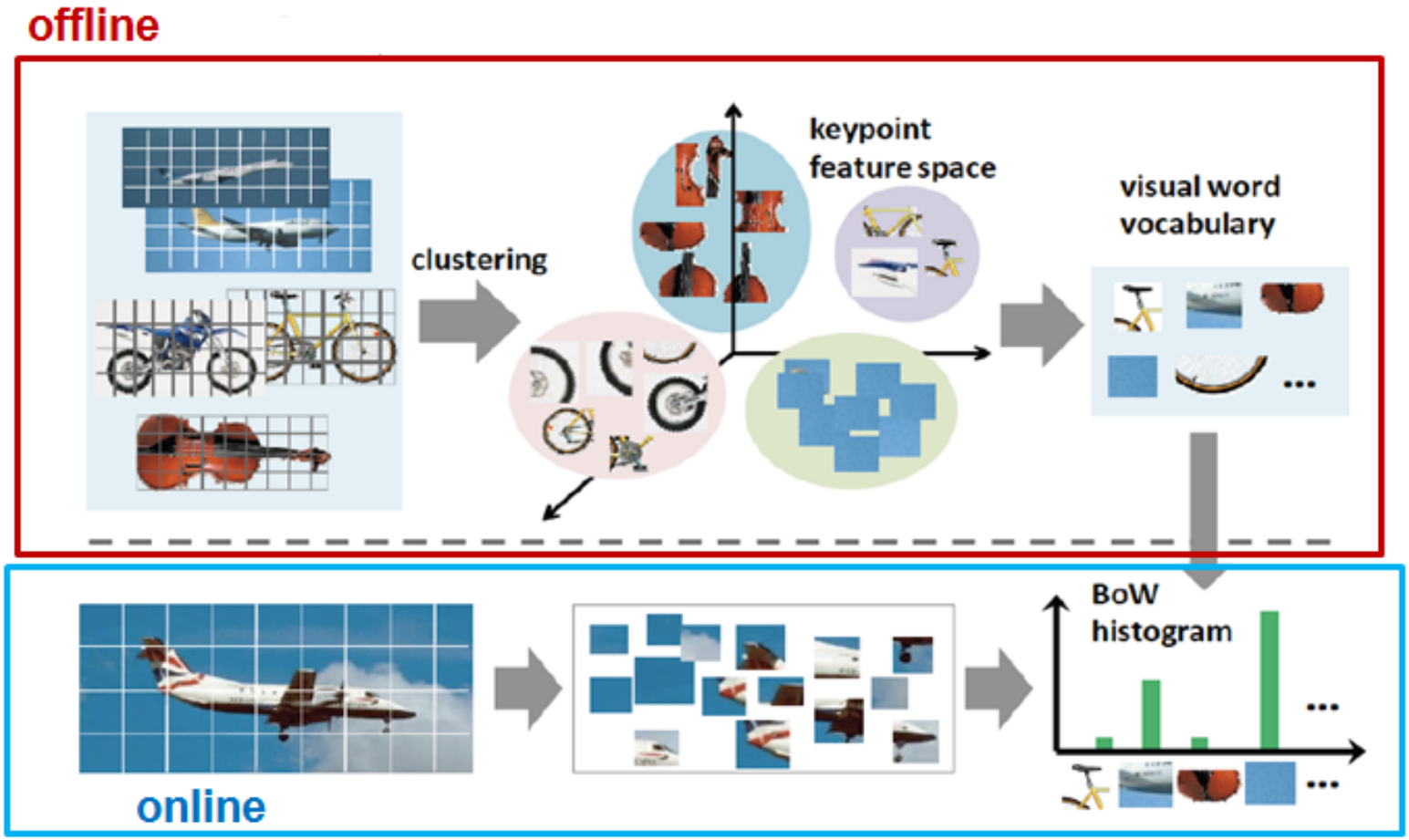
2000's: Bag of Words Model

- Adapting the BoW model for visual recognition ?
  ⇒ Bag of Visual Word (BoV)
- Main challenge: definition of visual words unclear!



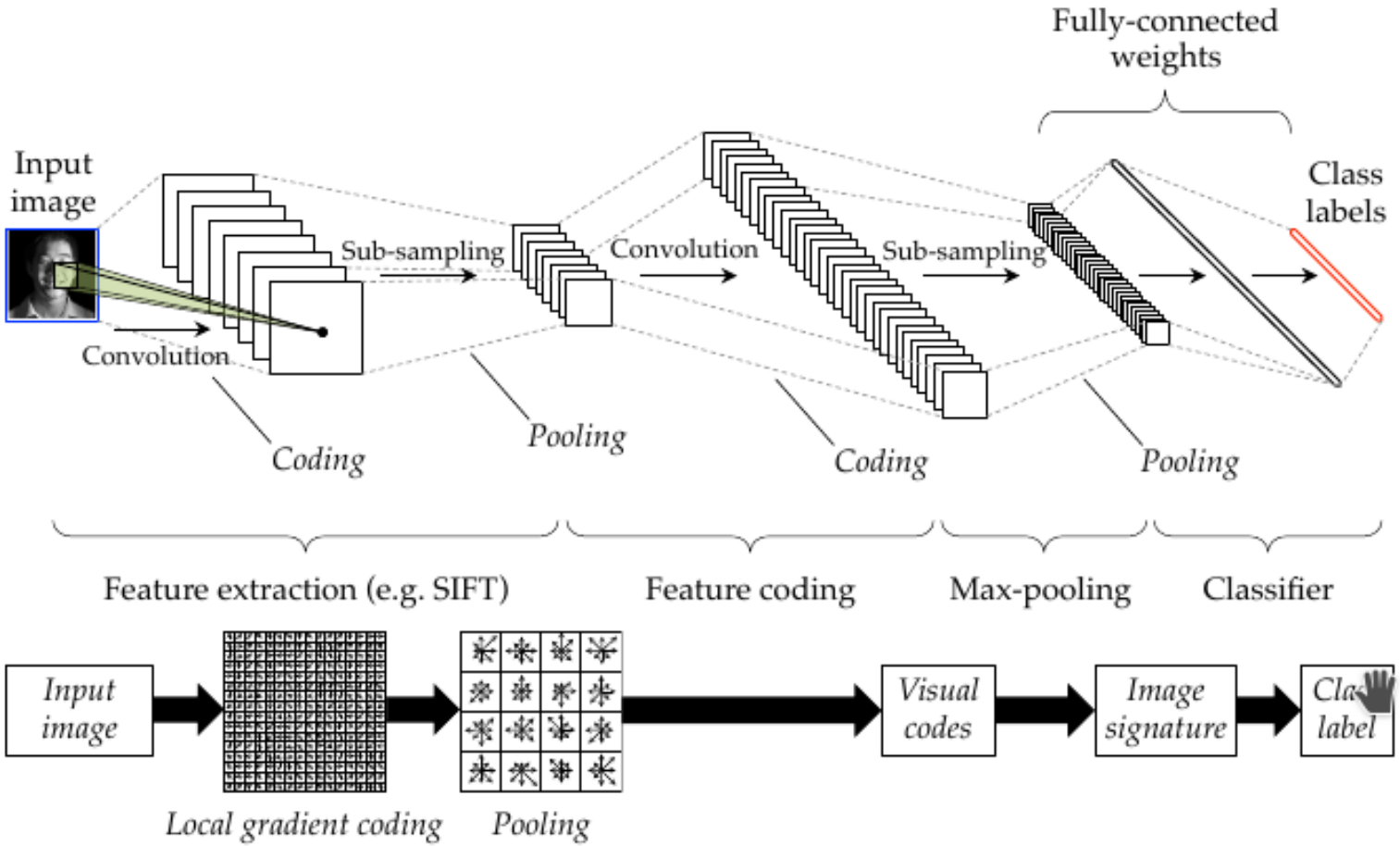
- Solution: compute a dictionary on local image regions (clustering)
  - Local regions represented by handcrafted descriptors, *e.g.* SIFT

2000's: Bag of Visual Words Model



- 2000's: BoW + SVM state-of-the-art
- Many works on kernel on BoW, coding & pooling → 2012

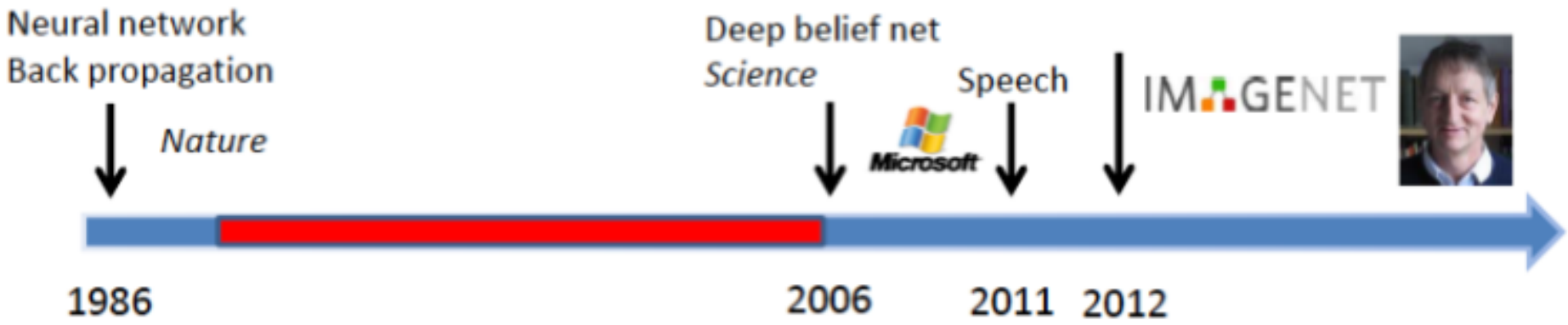
BoW *vs* ConvNet



- BoW architecture: ~ 2 block [Convolution+Pooling] ConvNet !
- ConvNet : learned features, more semantics with larger hierarchies
- **BUT:** not enough training data to learn such models in the 2000's !

Deep Learning: Trends and methods in the last four decades

Deep Learning renewal since 2006

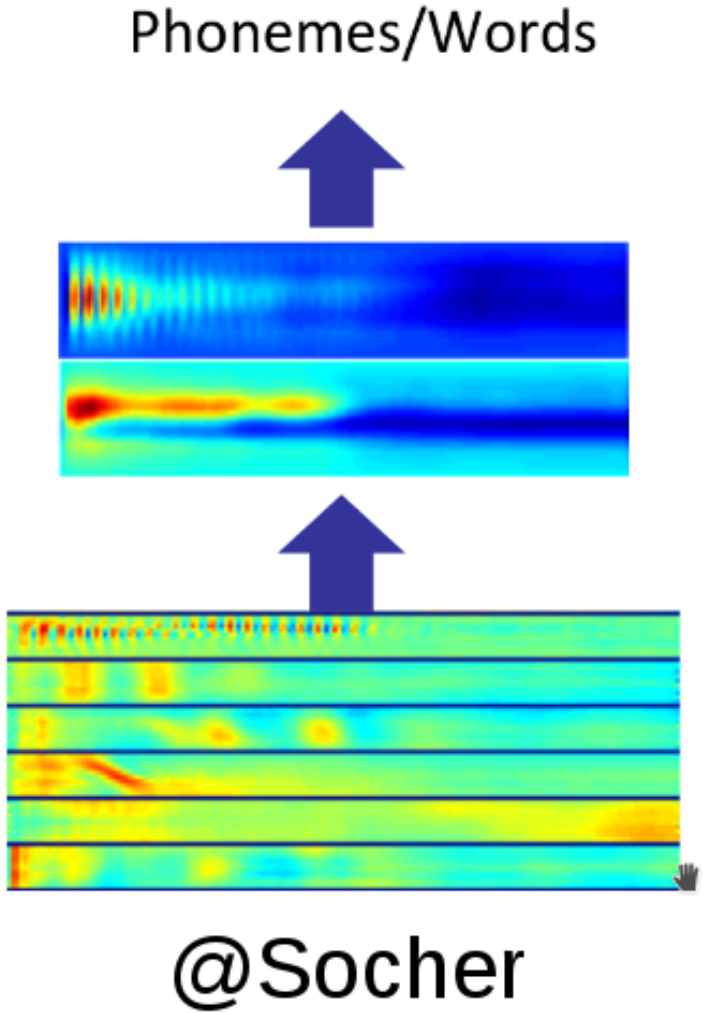


- 2006: new unsupervised learning for Deep Belief Nets (DBN) [HOT06]
- Theoretical results for improving model quality with depth
- Unsupervised training used as init for supervised learning with back-prop

Deep Learning and ConvNet for Speech Recognition

- First DL breakthrough on large datasets: speech recognition
- Context-Dependent Pre-trained Deep Neural Networks for Large Vocabulary Speech Recognition, Dahl et al. (2010)

Acoustic model	Recog \ WER	RT03S FSH	Hub5 SWB
Traditional features	1-pass –adapt	**27.4**	**23.6**
Deep Learning	1-pass –adapt	**18.5** (–33%)	**16.1** (–32%)



Deep Learning and ConvNet for Image Classification

- ImageNet ILSVRC Challenge (Stanford):
  - $1,200,000$ training images, $1,000$ classes, mono-label
  - Based on WordNet hierarchy (ontology)
  - Evaluation: top-5 error
- Up to 2012, leading approaches: BoW + SVM
- ILSVRC'12: the deep revolution $\Rightarrow$ outstanding success of ConvNets [KSH12]

Rank	Name	Error rate	Description
1	**U. Toronto**	0.15315	Deep learning
2	U. Tokyo	0.26172	Hand-crafted features and learning models. Bottleneck.
3	U. Oxford	0.26979	
4	Xerox/INRIA	0.27058	

2012: the deep revolution

Deep ConvNet success at ILSVRC'12

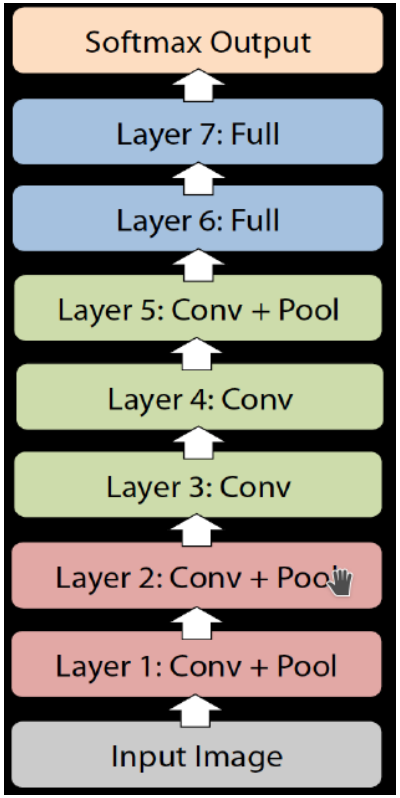
Two main practical reasons:

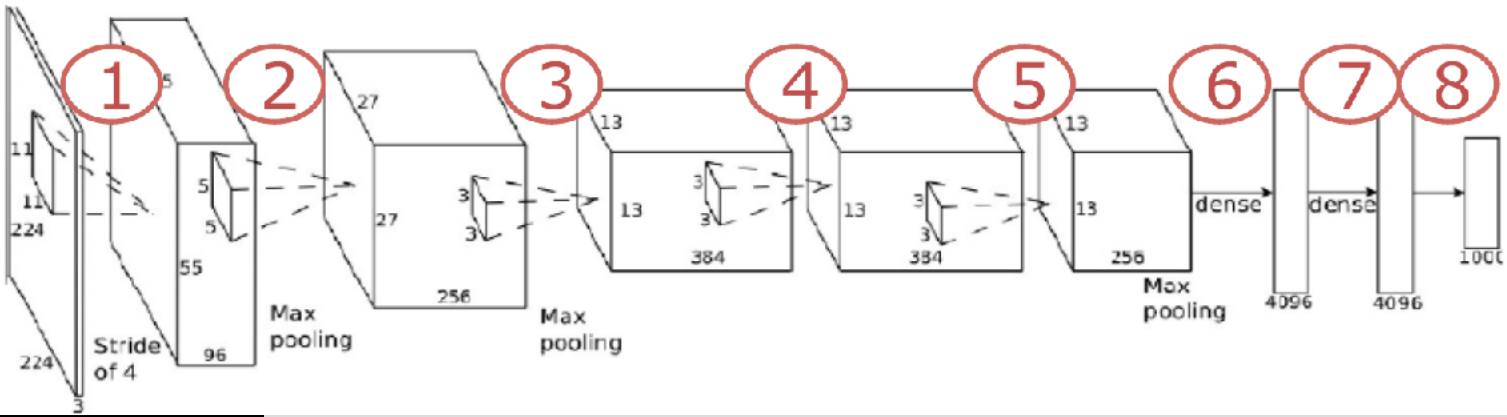
1. Huge number of labeled images (10^6 images)
   - Possible to train very large models without over-fitting
   - Larger models enables to learn rich (semantic) features hierarchies
2. GPU implementation for training
   - Relatively cheap and fast GPU
   - Training time reduced to 1-2 weeks (up to 50x speed up)

IMAGENET

AlexNet [KSH12] in ILSVRC'12

- 60,000,000 parameters
- 650,000 neurons - 630,000,000 connections
- 5 convolutional layers, 3 Fully Connected (FC)
  - Convolution layer: Convolution + non linearity (ReLU) + pooling
  - Full= FC + non linearity - Final FC: 4096-dim
- Trained on 2 GPUs for a week

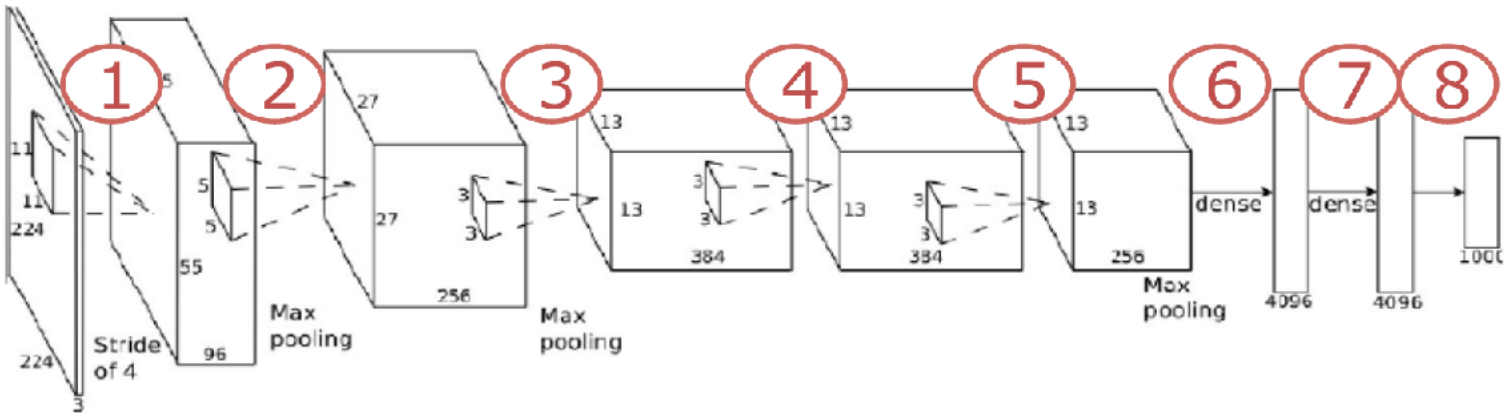




AlexNet [KSH12] in ILSVRC'12

First Convolutionnal Layer

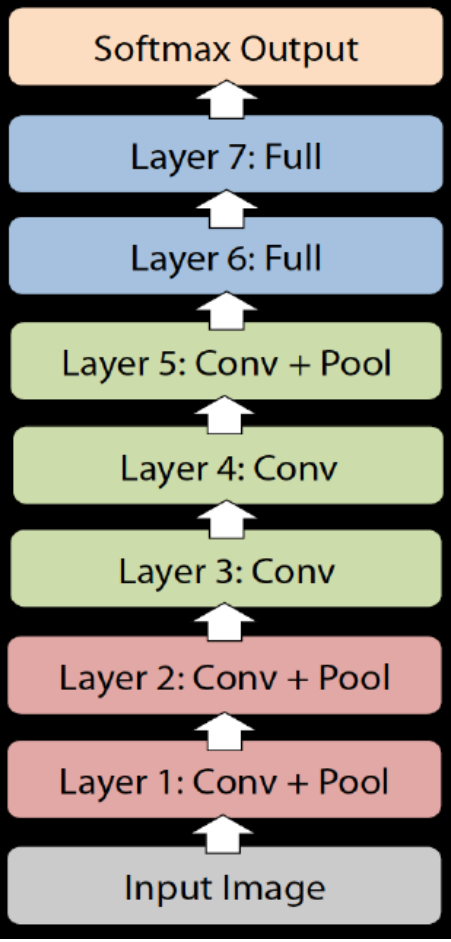
- Input: Images: 227x227x3
- Filter (receptive field) size F: 11, S (stride) = 4
- 96 filters ⇒ output size 55*55*96 = 290,400 neurons
- Each Filter: 11*11*3 = 363 weights + 1 bias = 364 params
  - N.B.: Convolution in whole feature map depth (*cf* LeNet 5 discussion)
- # parms: 96 * 364 = 34, 944



AlexNet [KSH12] in ILSVRC'12

Architecture of Krizhevsky et al.

- 8 layers total
- Trained on Imagenet dataset [Deng et al. CVPR'09]
- 18.2% top-5 error
- Our reimplementation: 18.1% top-5 error

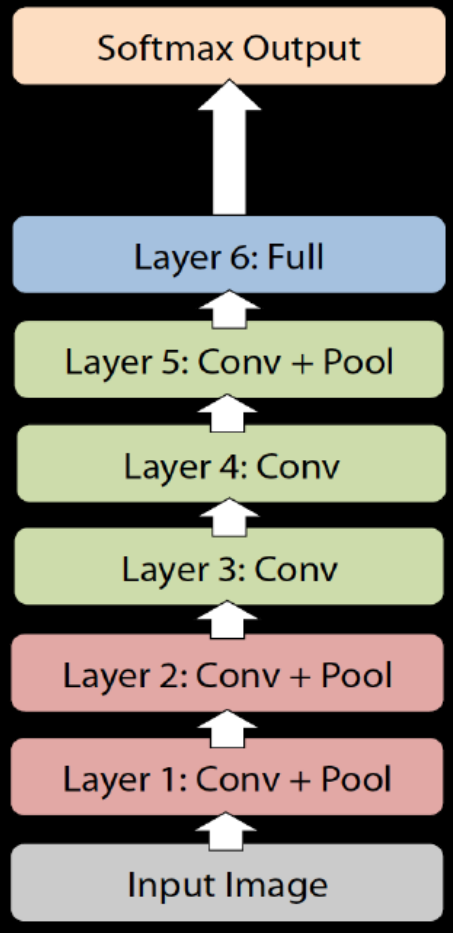


Credit: R. Fergus

AlexNet [KSH12] in ILSVRC'12

Architecture of Krizhevsky et al.

- Remove top fully connected layer
  – Layer 7
- Drop 16 million parameters
- Only 1.1% drop in performance!

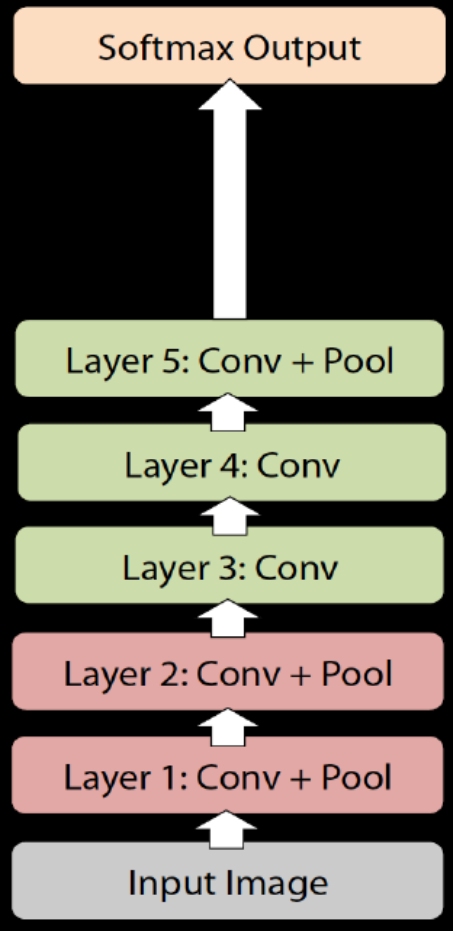


Credit: R. Fergus

AlexNet [KSH12] in ILSVRC'12

Architecture of Krizhevsky et al.

- Remove both fully connected layers
  - Layer 6 & 7
- Drop ~50 million parameters
- 5.7% drop in performance



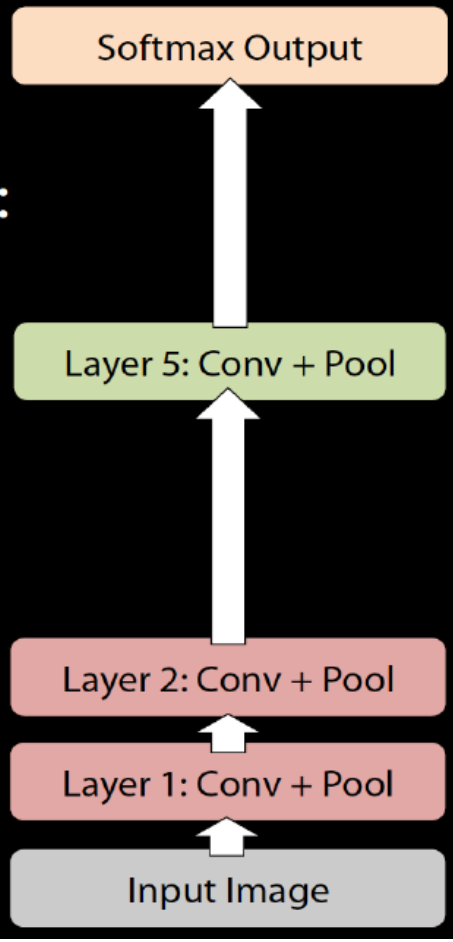
Credit: R. Fergus

AlexNet [KSH12] in ILSVRC'12

Architecture of Krizhevsky et al.

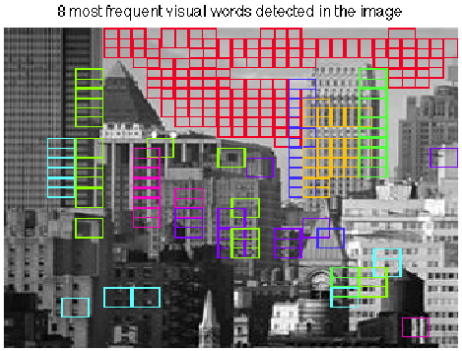
- Now try removing upper feature extractor layers & fully connected:
  - Layers 3, 4, 6 ,7
- Now only 4 layers
- 33.5% drop in performance

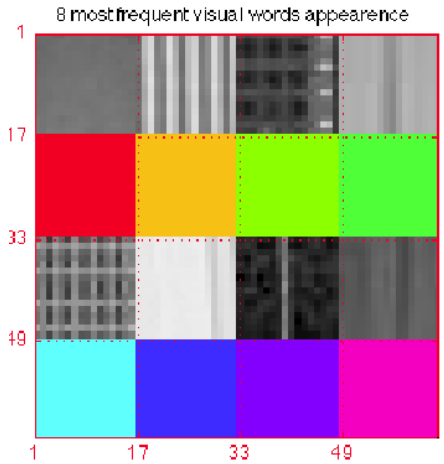
→Depth of network is key



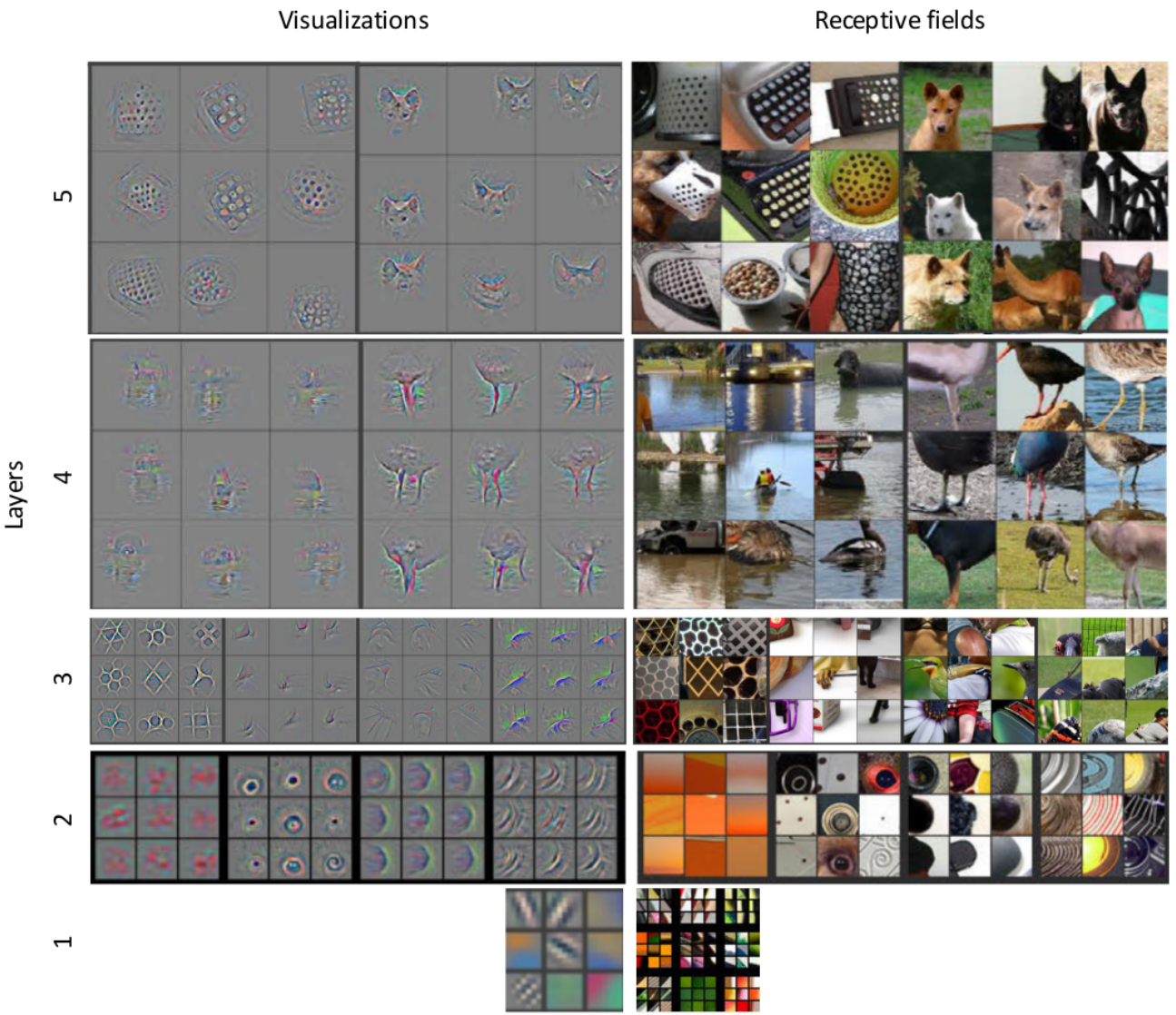
Credit: R. Fergus

Deep Learning in 2012: Representation Learning



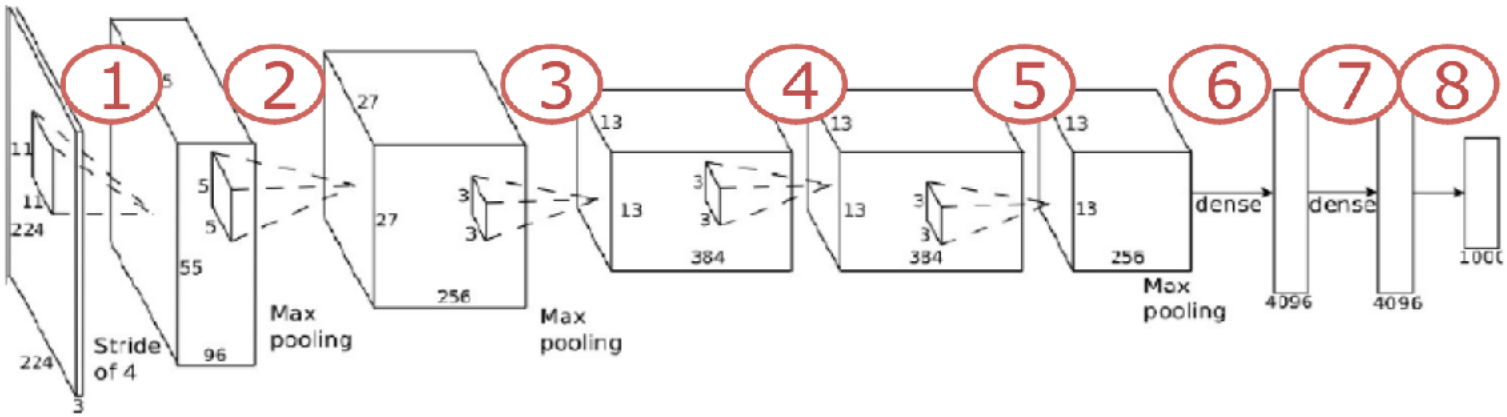


Deep: more semantic features



AlexNet [KSH12] in ILSVRC'12

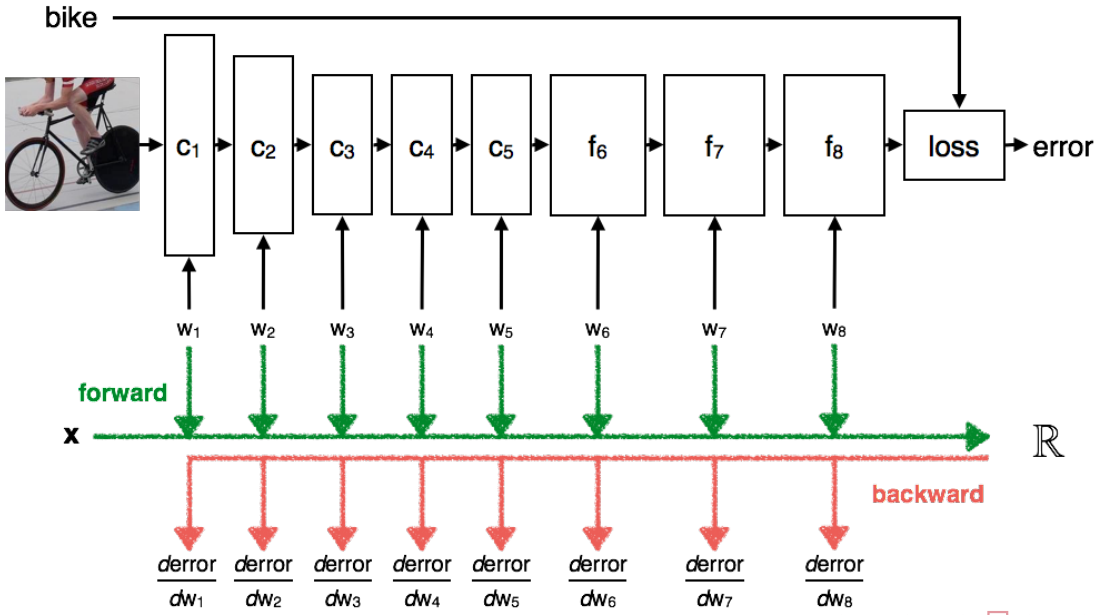
- Same global architecture as older nets, *e.g.* LeNet
  - Trained with back-prop and stochastic gradient descent
- But bigger (deeper and wider): 60 10^6 parameters *vs* 60 10^3
  - Needs more data (10^6 *vs* 10^4)
  - GPU implementation for fast training
- Also some architectural and optim improvements (see next course):
  - Non-linearity: ReLU *vs* sigmoid
  - Overlapping pooling (Local Response Normalisation, LRN)
  - Regularization: data augmentation, dropout



Outline

Deep Learning: resources for the community

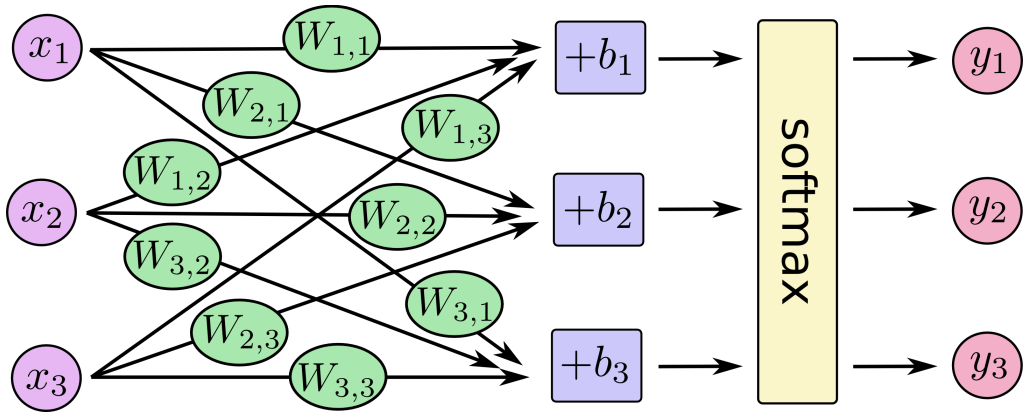
- Formal training of deep CNNs straightforward (backprop)
- Efficient CNN implementation far from trivial, especially convolution
- Libraries made available in the community:
  - Caffe / Decaf : script, non modular
  - MatConvNet (matlab): easy, Torch (Lua): efficiency, modularity
  - TensorFlow / Theano / PyTorch (python): auto-differentiation
  - Keras: wrapper on top of TensorFlow / Theano



Keras: simple example

Logistic Regression

$$p(\hat{y_{c,i}}|\mathbf{x}_i)) = \frac{e^{\langle \mathbf{x}_i; \mathbf{w_c} \rangle + b_c}}{\sum_{c'=1}^{K} e^{\langle \mathbf{x}_i; \mathbf{w_{c'}} \rangle + b_{c'}}}$$



- Example in MNSIT: $K = 10$ classes
- # parameters: $784 * 10 + 10 = 7850$

Keras: simple example

Logistic Regression

- Define an (empty) feedfoward network

```
from keras.models import Sequential
model = Sequential()
```

- Add fully connected layer (size 10) + softmax activation

```
from keras.layers import Dense, Activation
model.add(Dense(10, input_dim=784, name='fc1'))
model.add(Activation('softmax'))
```

Keras: simple example

Logistic Regression

- Compile model with cross-entropy loss

```
from keras.optimizers import SGD
learning_rate = 0.5
sgd = SGD(learning_rate)
model.compile(loss='categorical_crossentropy',optimizer=sgd,metrics=['accuracy'])
```

- Optimize model parameters to fit training data (*e.g.* MNIST)

```
from keras.datasets import mnist
# MNIST data, shuffled and split between train and test sets
(X_train, y_train), (X_test, y_test) = mnist.load_data()
# + some pre-processing ... and fit model to data
model.fit(X_train, y_train,batch_size=128, epochs=20,verbose=1)
```

Keras: more complex examples

- Design more complex model by adding layers : fully connected, convolution, non-linearity, pooling, *etc*
- Code for training remains unchanged (back-prop does the job)

```
s=(5,5)
ish=(28,28,1)
model = Sequential()
model.add(Conv2D(32,kernel_size=s,activation='sigmoid',input_shape=ish,padding='same'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(64, (5, 5), activation='sigmoid', padding='same'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Flatten())
model.add(Dense(100, activation='sigmoid'))
model.add(Dense(nb_classes, activation='softmax'))
```

Deep Learning Modules

Non-linearities

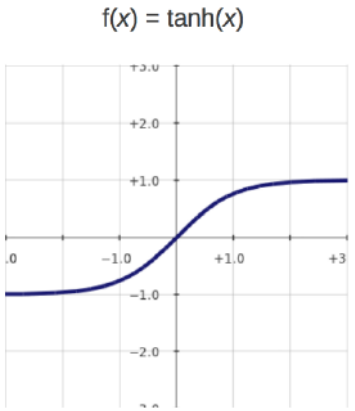
- Rectified Linear Unit (ReLU): $y = 0$ if $x < 0$, $y = x$ otherwise
- Solving vanishing gradients problems $\Rightarrow$ faster learning / convergence

RELU Nonlinearity

- Standard way to model a neuron

$f(x) = tanh(x)$ or $f(x) = (1 + e^{-x})^{-1}$

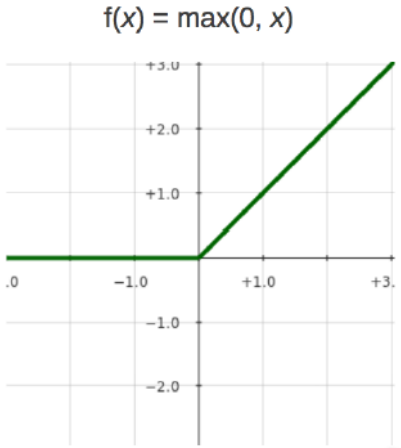
Very slow to train



- Non-saturating nonlinearity (RELU)

$f(x) = max(0, x)$

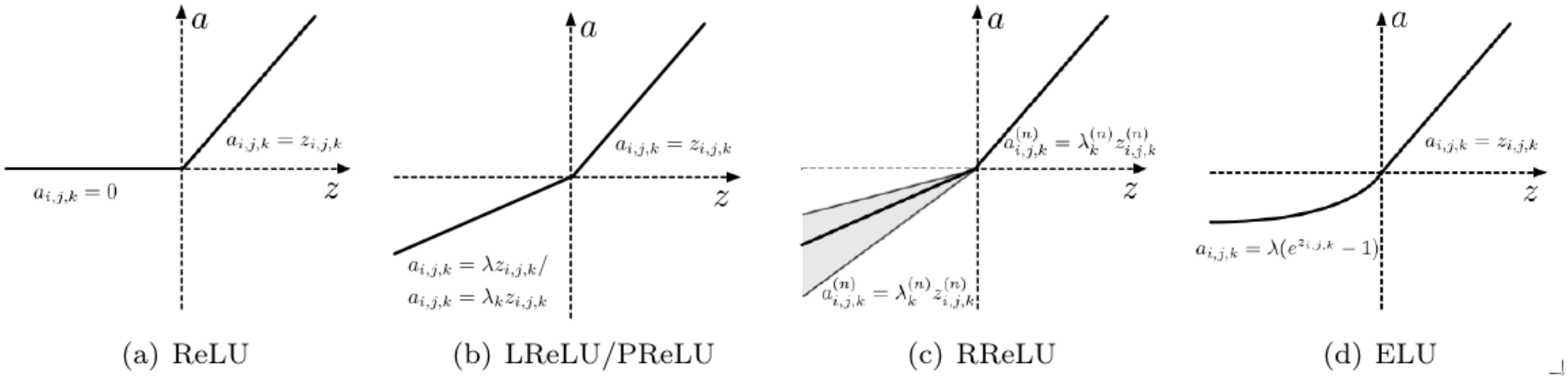
Quick to train



Deep Learning Modules

Non-linearities, ReLU variants

- Leaky ReLU (LReLU): λ is empirically predefined
- Parametric ReLU (PReLU) : λ_k is learned from training data
- Randomized ReLU (RReLU): λ_k^n is a random variable which is sampled from a given uniform distribution in training and keeps fixed in testing
- Exponential Linear Unit (ELU): λ fixed



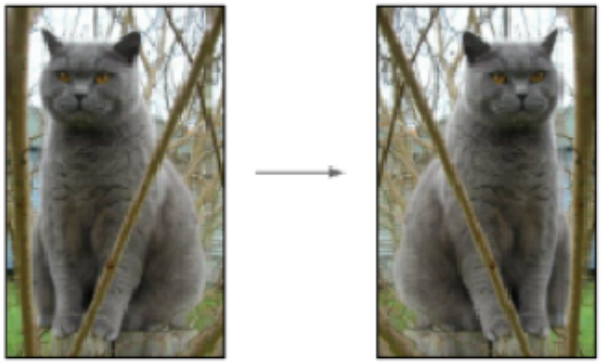
(a) ReLU (b) LReLU/PReLU (c) RReLU (d) ELU

From Gu *et. al.* [GWK+15]

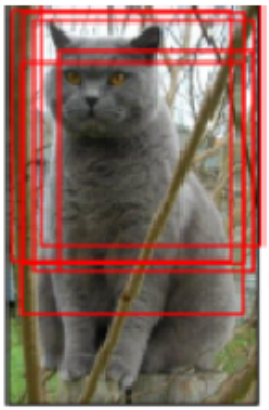
Deep Learning Modules

Training: data-augmentation

- Jittering, mirroring, color perturbation, rotation, stretching, shearing, lens distortions, *etc* of the original images
- Increases # training samples, adds robustness to irrelevant variations
- **Done in train AND in test**



Flip horizontally



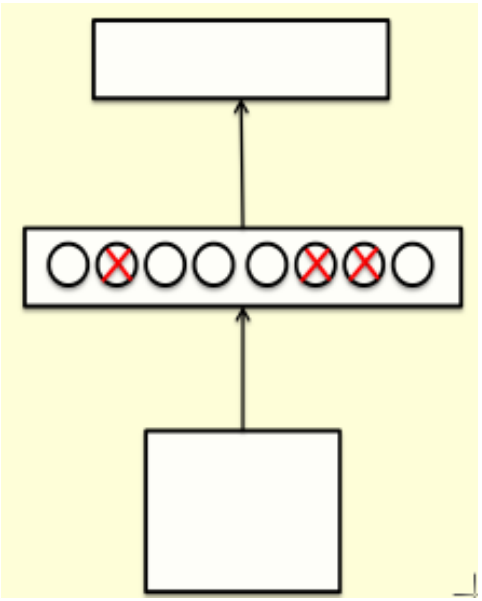
Random crops/scales

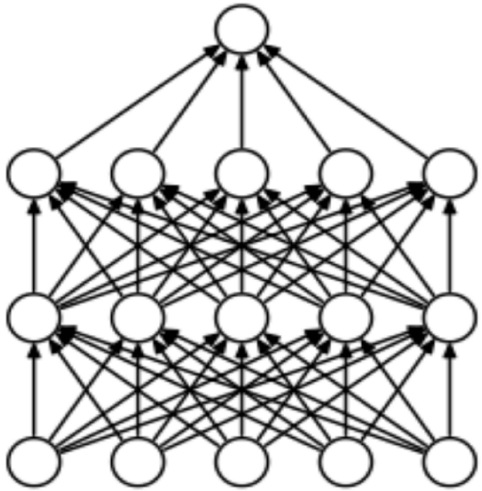
Color jittering

Deep Learning Modules

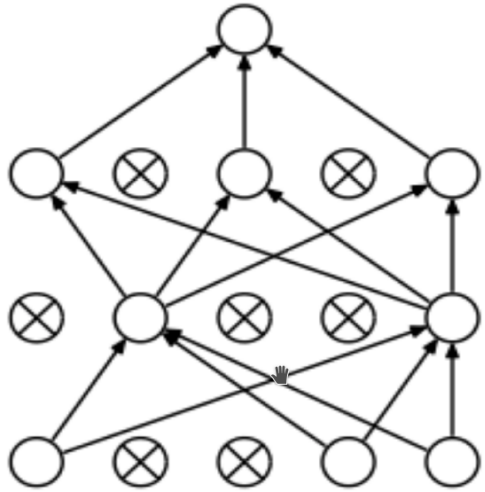
Training: droupout

- Randomly omit each hidden unit with probability 0.5
- **Regularization technique**, limits over-fitting (better generalization)
  - Pulls the weights towards what other models want, useful to prevent co-adaptation (feature only helpful when other specific features present)
  - May be viewed as averaging over many NN
  - Slower convergence





Standard Neural Net



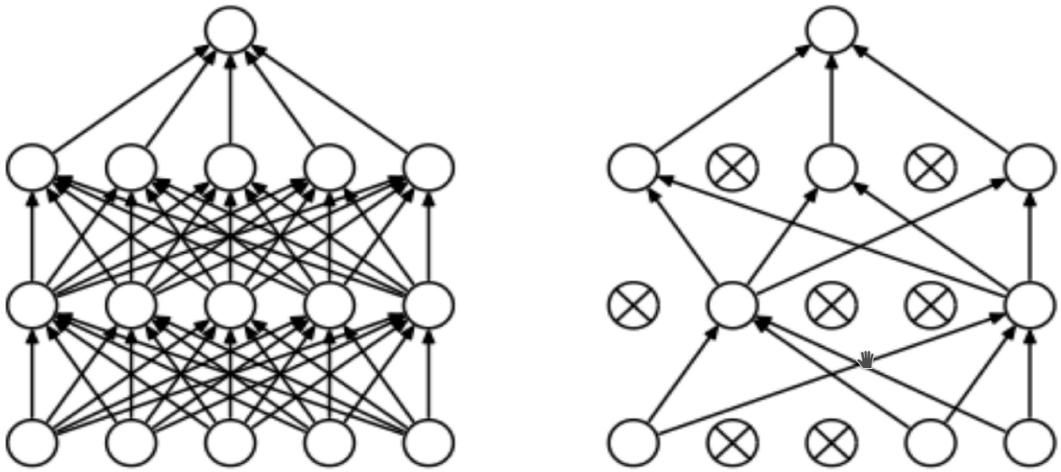
After applying dropout.

Credits: Geoffrey E. Hinton, NIPS 2012

Deep Learning Modules

Training: droupout

- What to do at test time ?
  - Sample many different architectures and take the geometric mean of their output distributions
  - Faster alternative: use all hidden units (but after halving their outgoing weights)
  - Equivalent to the geometric mean in case of single hidden layer
  - Pretty good approximation for multiple layers



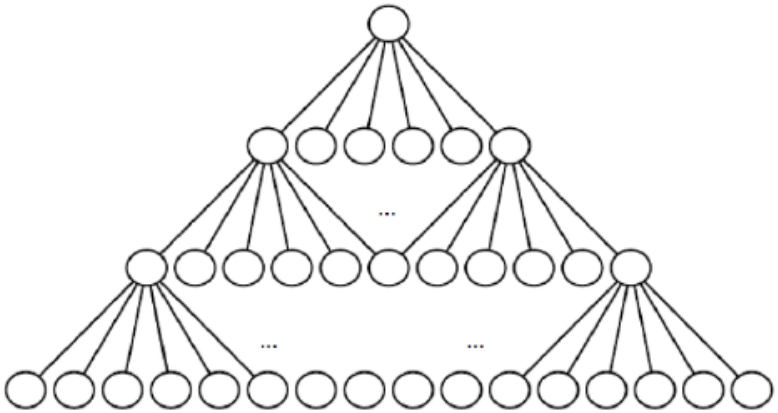
Standard Neural Net | After applying dropout.

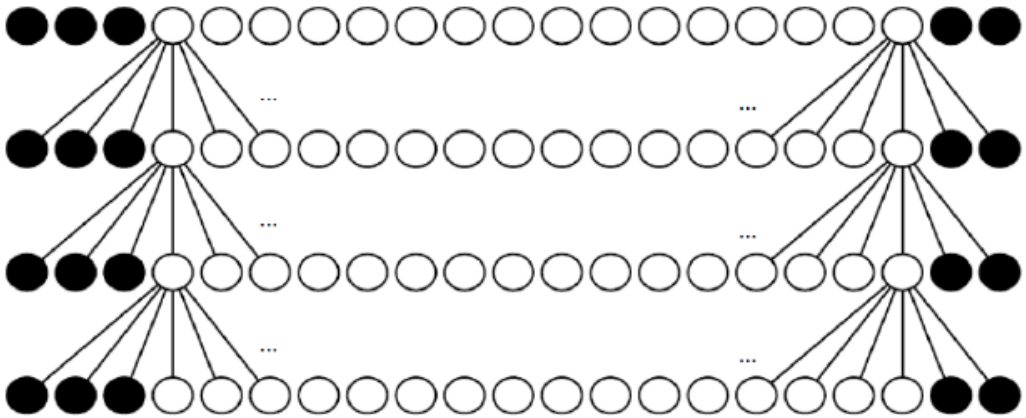
Credits: Geoffrey E. Hinton, NIPS 2012

Deep Learning Modules

Padding, *e.g.* zero-padding

- To avoid shrinking the spatial extent of the network rapidly

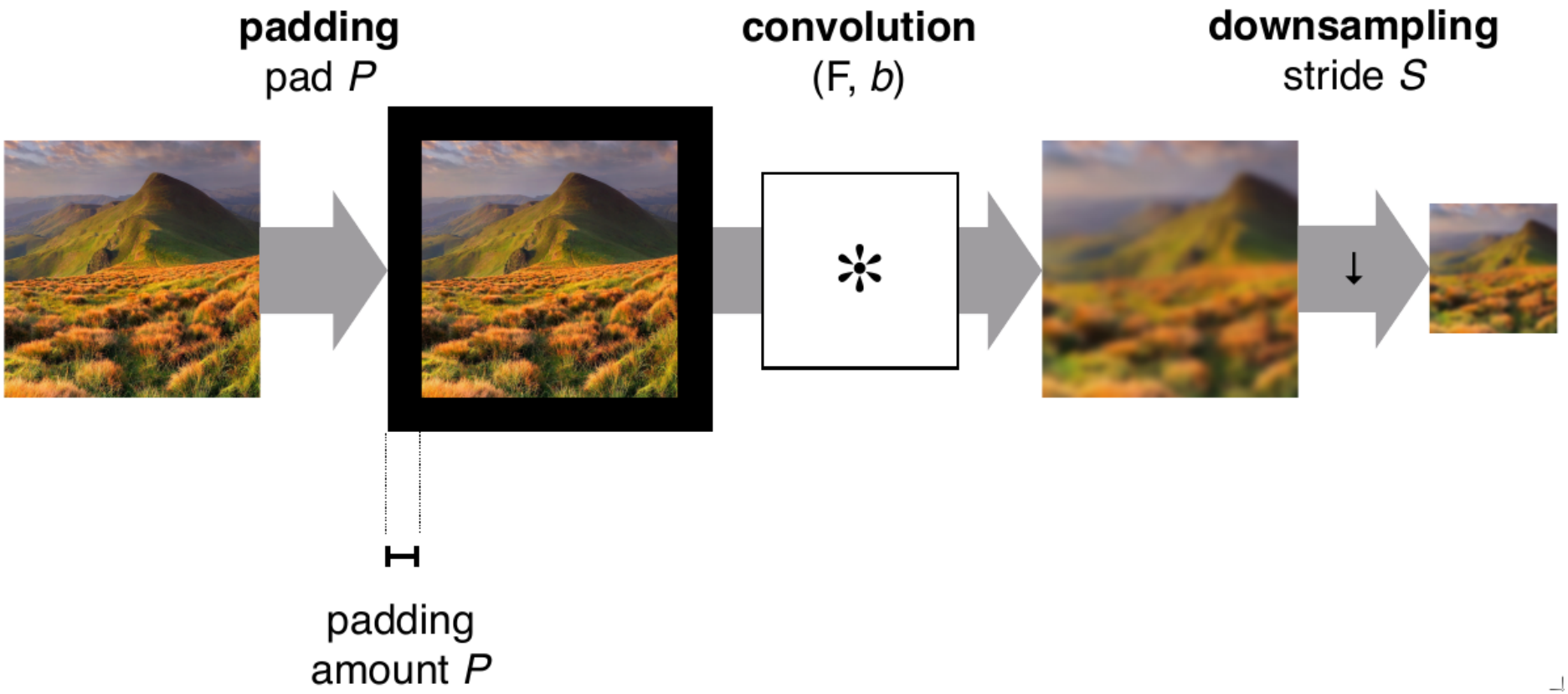




Deep Learning Modules

Padding, *e.g.* zero-padding

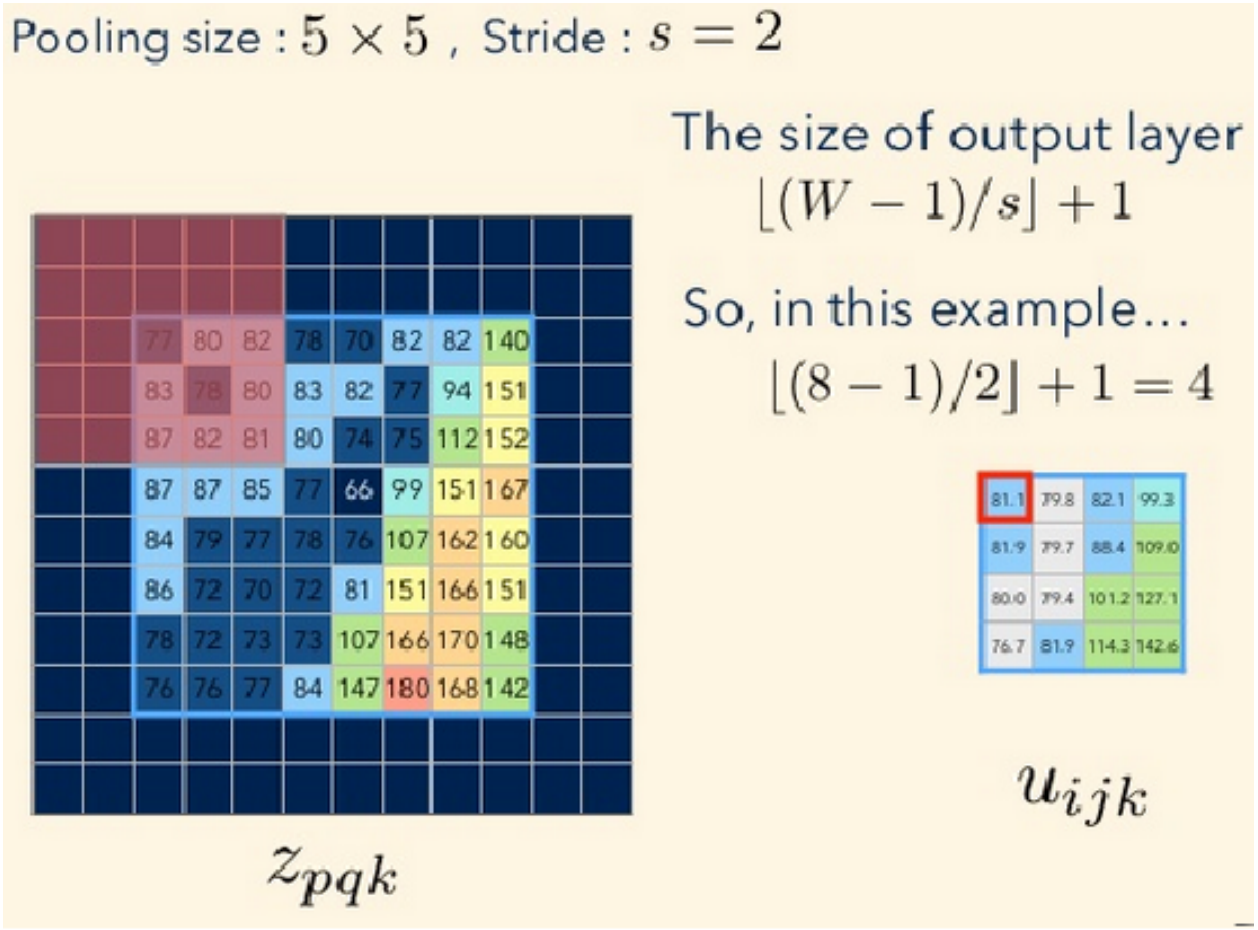
- Ex for images:



Credit: A. Vedaldi

Deep Learning Modules

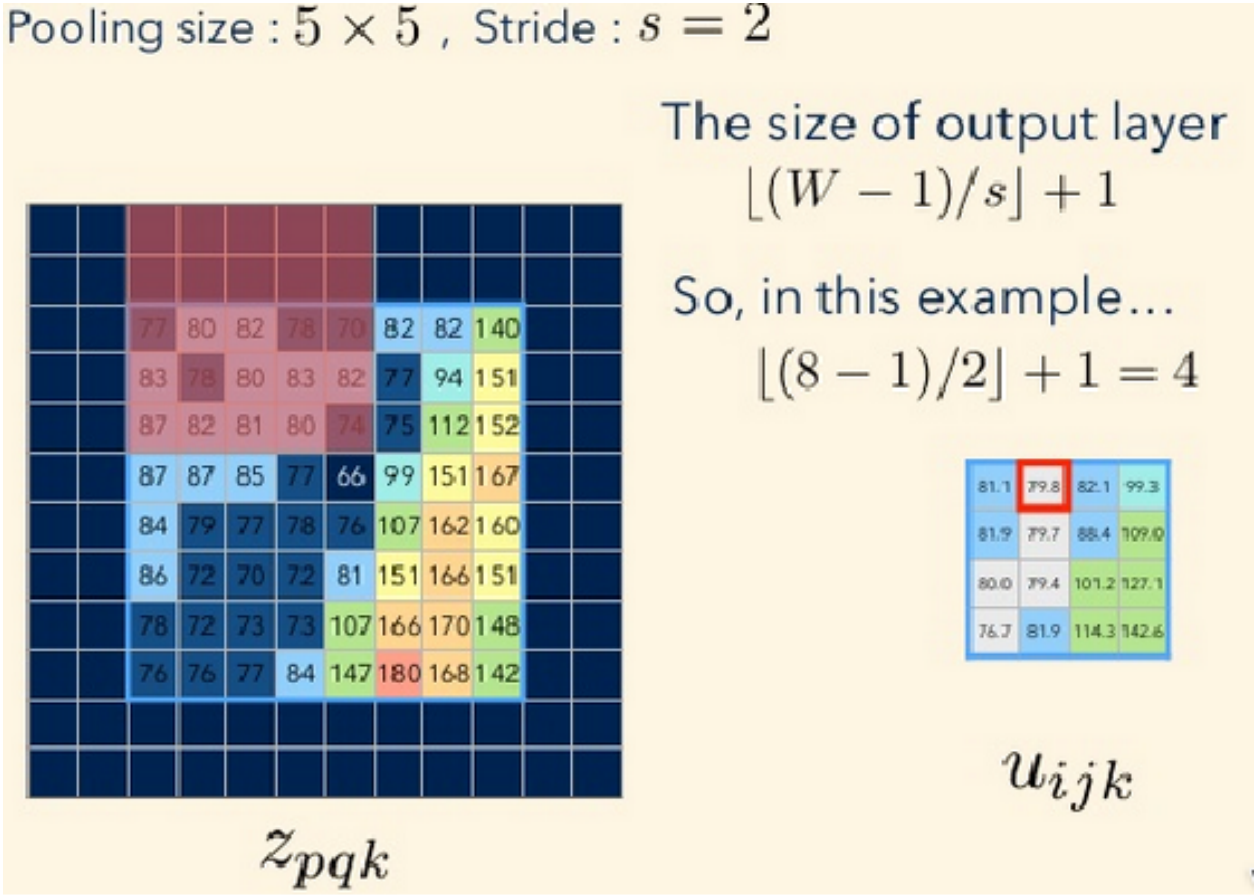
Overlapping Pooling



@Ken'ichi

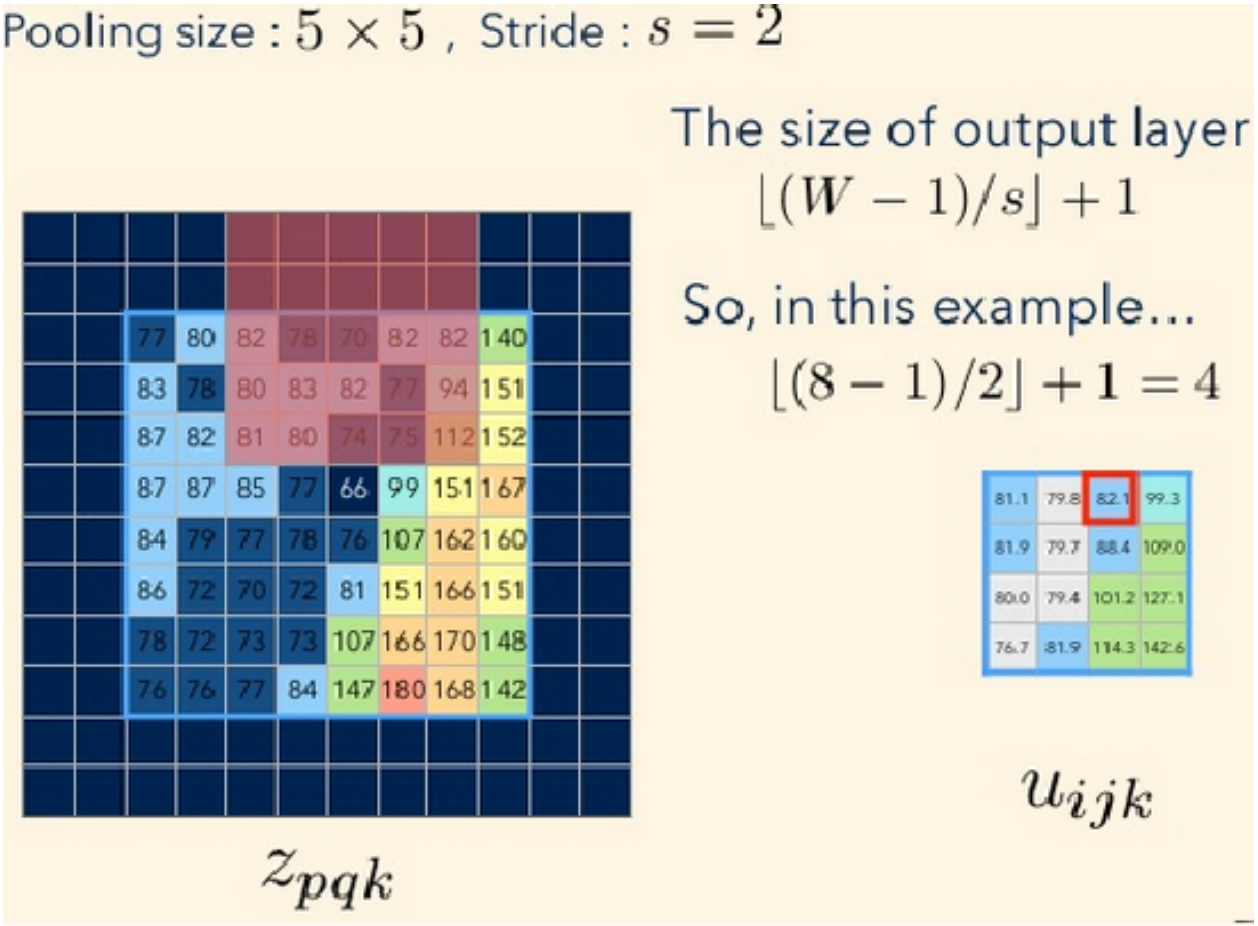
Deep Learning Modules

Overlapping Pooling



Deep Learning Modules

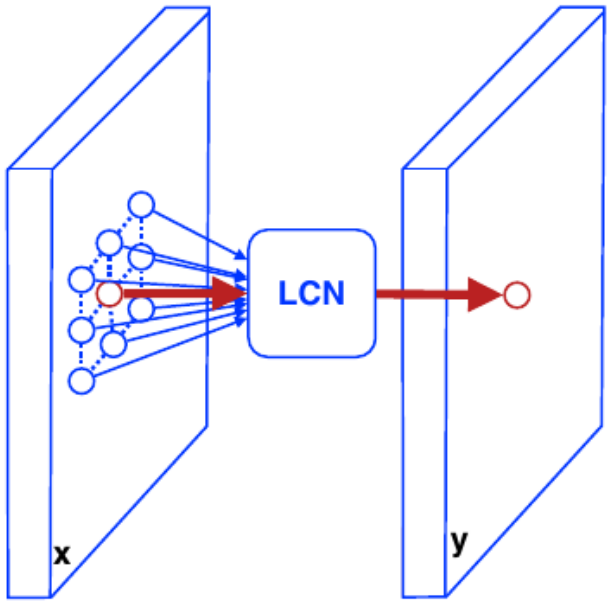
Overlapping Pooling



Deep Learning Modules

Local Response Normalization

Normalise image/feature patches



$$y_{ijq} = \frac{x_{ijq} - \mu_{ijq}}{\sigma_{ijq}}$$

$$\mu_{ijq} = \frac{1}{|\mathcal{N}(i,j)|} \sum_{(u,v)\in\mathcal{N}(i,j)} y_{uvq}$$

$$\sigma^2_{ijq} = \frac{1}{|\mathcal{N}(i,j)|} \sum_{(u,v)\in\mathcal{N}(i,j)} (y_{uvq} - \mu_{ijq})^2$$

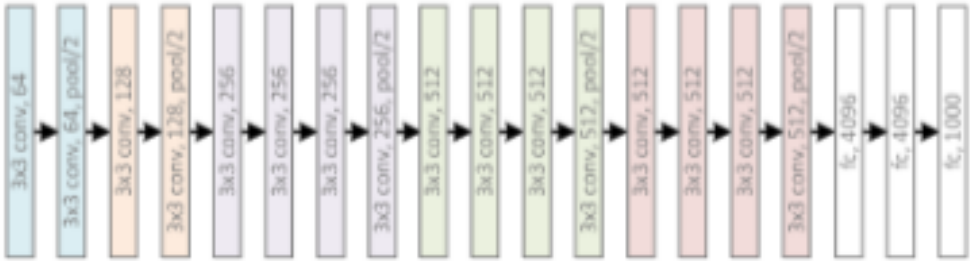
Credit: A. Vedaldi

Outline

Deep Learning since 2012

More & more data (Facebook 10^9 images / day), larger & larger networks

VGG, 16/19 layers, 2014



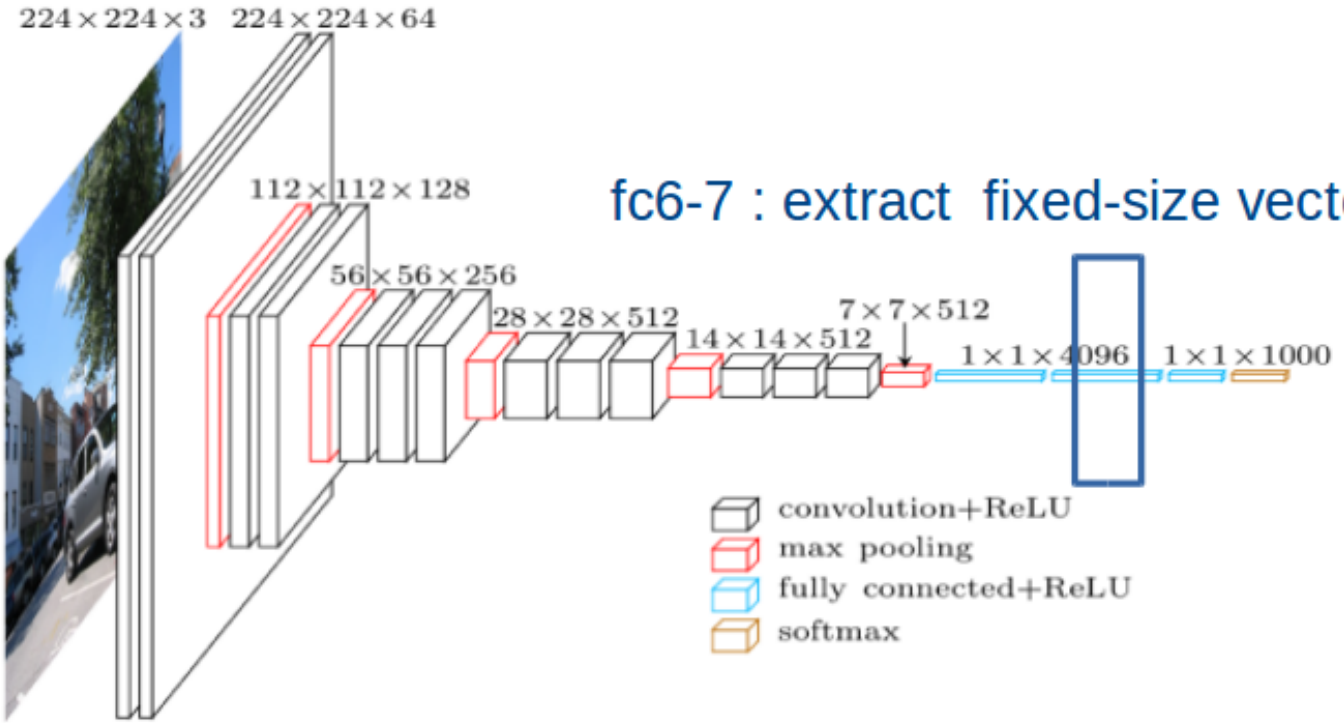
GoogleNet, 22 layers, 2014

ResNet, 152 layers, 2015

Deep Learning since 2012

Transferring Representations learned from ImageNet

- Deep ConvNets require large-scale annotated datasets
  - Huge # params ⇒ difficult to train from scratch on "small datasets"
- **BUT:** Extract layer ⇒ fixed-size vector: **"Deep Features" (DF)**



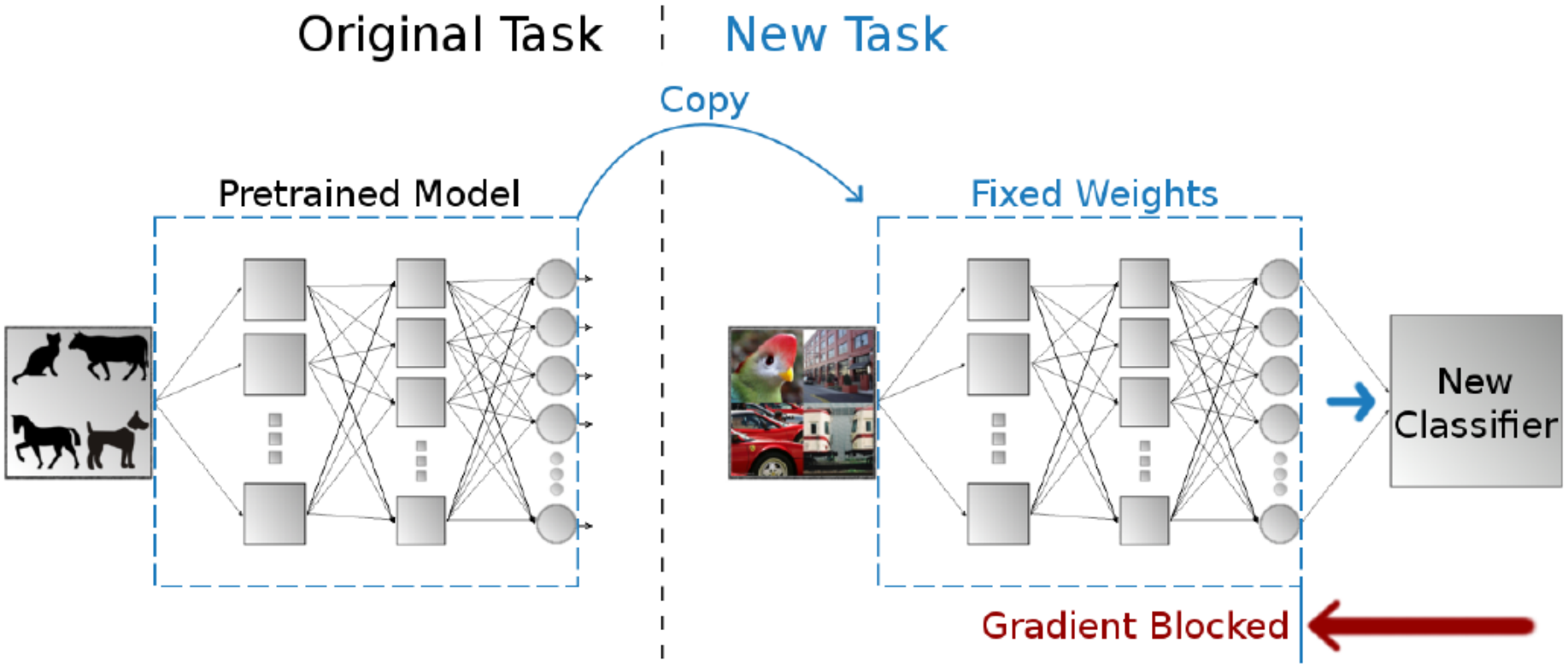
- **Now state-of-the-art for any visual recognition task**

Deep Features (DF) and Domain Adaptation

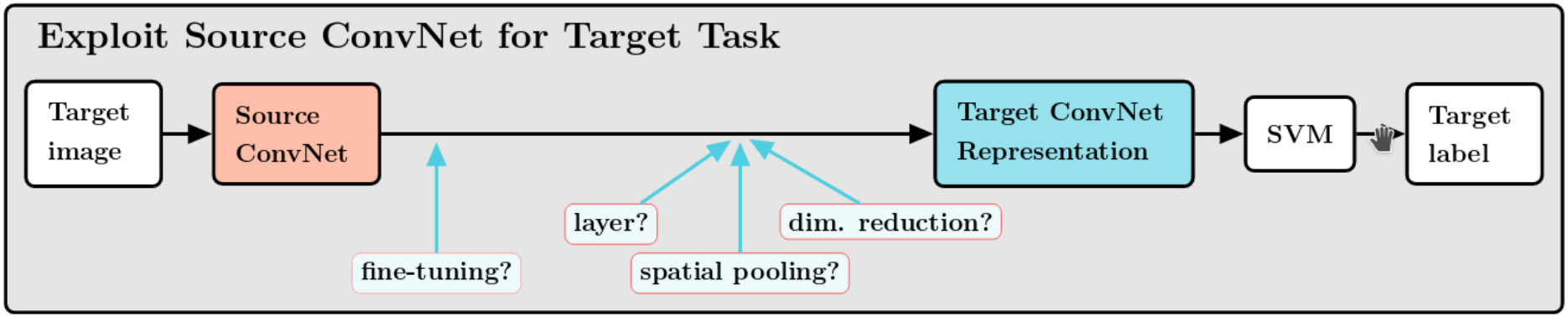
- DF $\Leftarrow$ Deep ConvNet trained on a large-scale dataset (ImageNet, Places, *etc*)
- DF: off-the-shelf features for any visual recognition task
- DF: Generic features, very robust to :
  - Dataset change $\Rightarrow$ apply DF for classification with different images, different classes
  - Domain change $\Rightarrow$ apply DF for other visual tasks, *e.g.* localization, segmentation, pose estimation, retrieval *etc*
- Since 2012: all performance re-benchmarked with DF
- Need to adapt the final layer to match the target domain goal

Deep Features (DF) and Domain Adaptation

DF: off-the-shelf descriptors



Deep Features (DF) and Domain Adaptation

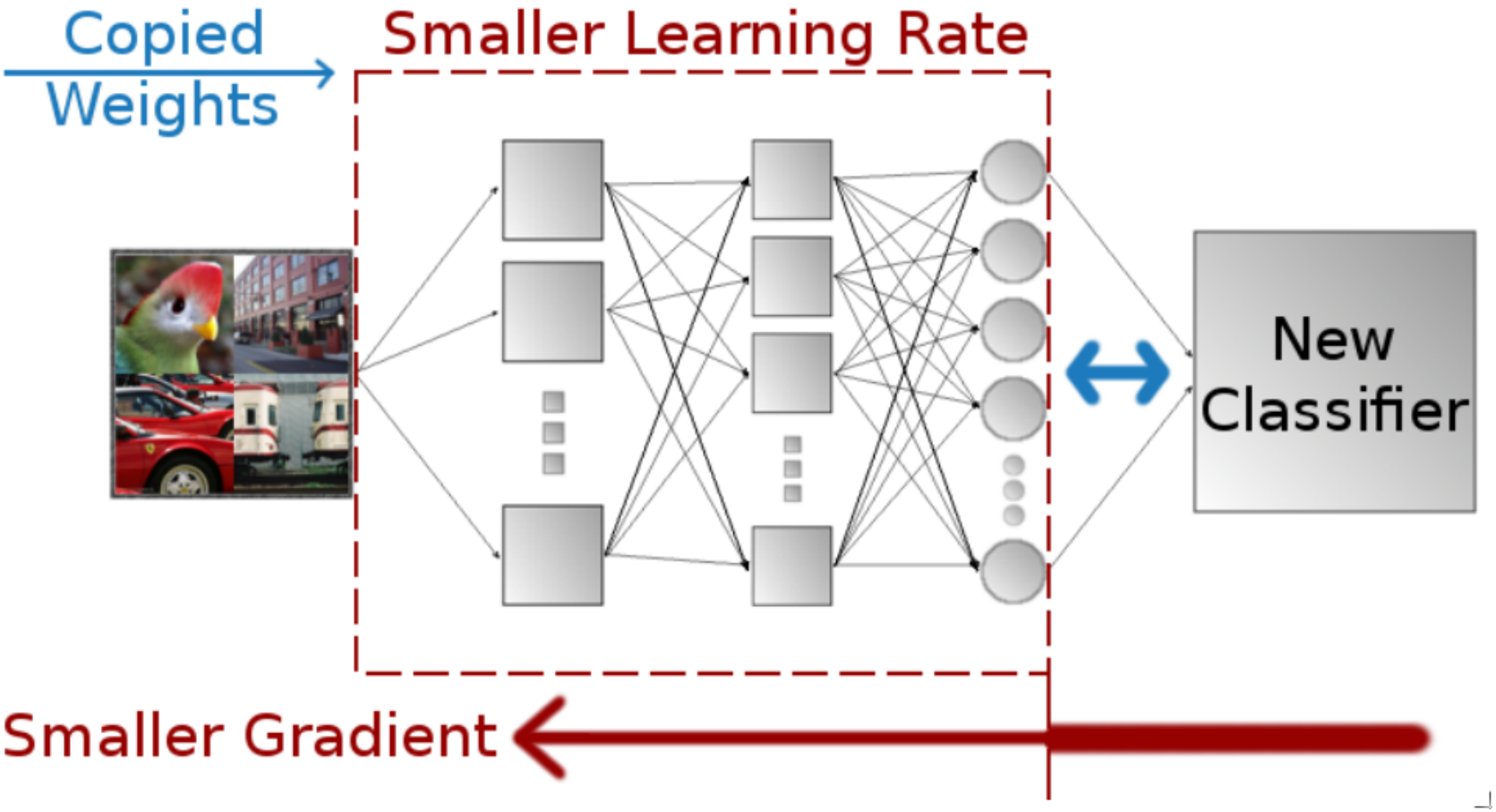


Credit: Razavian *et. al.* [ARS+16]

- Dataset change: fine-tuning ConvNet parameters on the target domain
  - Different learning for fined-tuned & from scratch parameters
- Domain (task) change: adapt archi to the target task (*e.g.* pooling)

Deep Features (DF) and Domain Adaptation

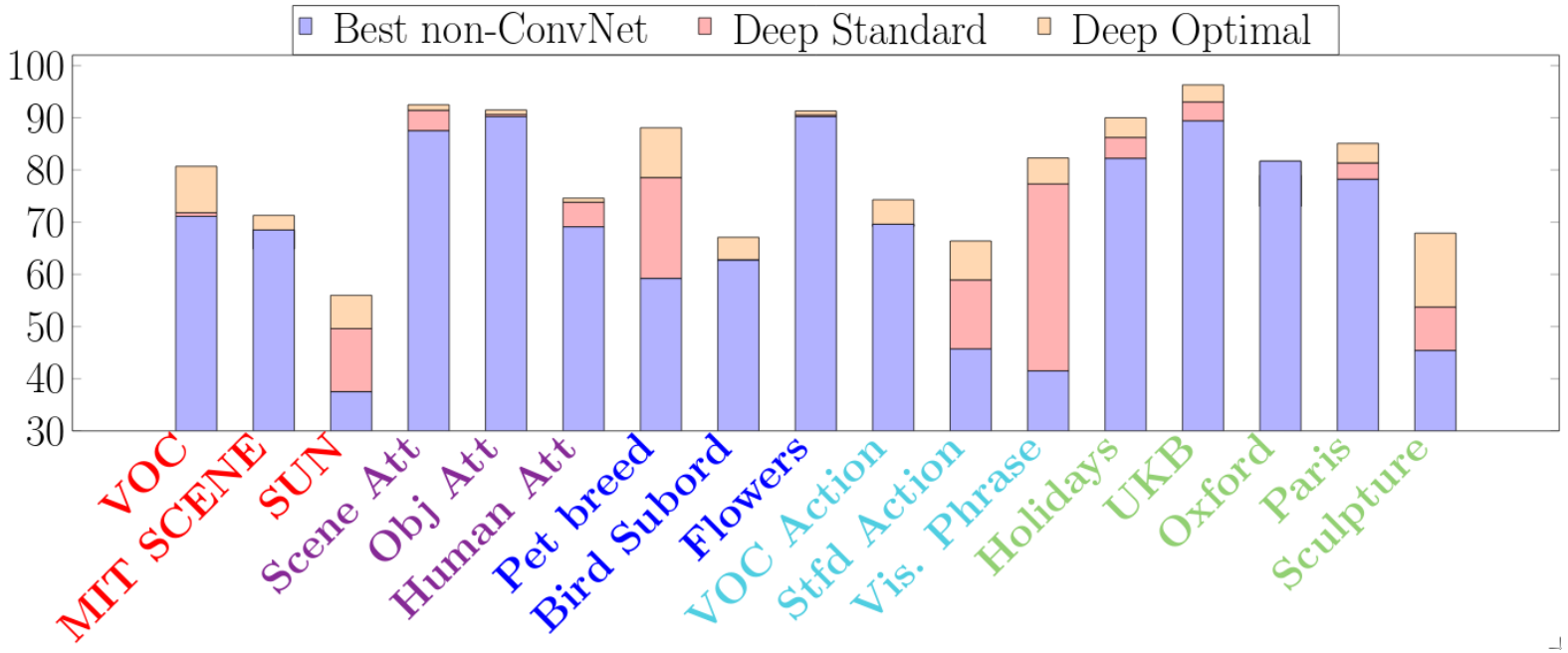
DF: fine-tuning



Deep Features (DF) and Domain Adaptation

Increasing distance from ImageNet →

Image Classification	Attribute Detection	Fine-grained Recognition	Compositional	Instance Retrieval
PASCAL VOC Object [9]	H3D human attributes [6]	Cat&Dog breeds [29]	VOC Human Action [9]	Holiday scenes [17]
MIT 67 Indoor Scenes [33]	Object attributes [10]	Bird subordinate [43]	Stanford 40 Actions [46]	Paris buildings [31]
SUN 397 Scene [45]	SUN scene attributes [30]	102 Flowers [27]	Visual Phrases [34]	Sculptures [4]

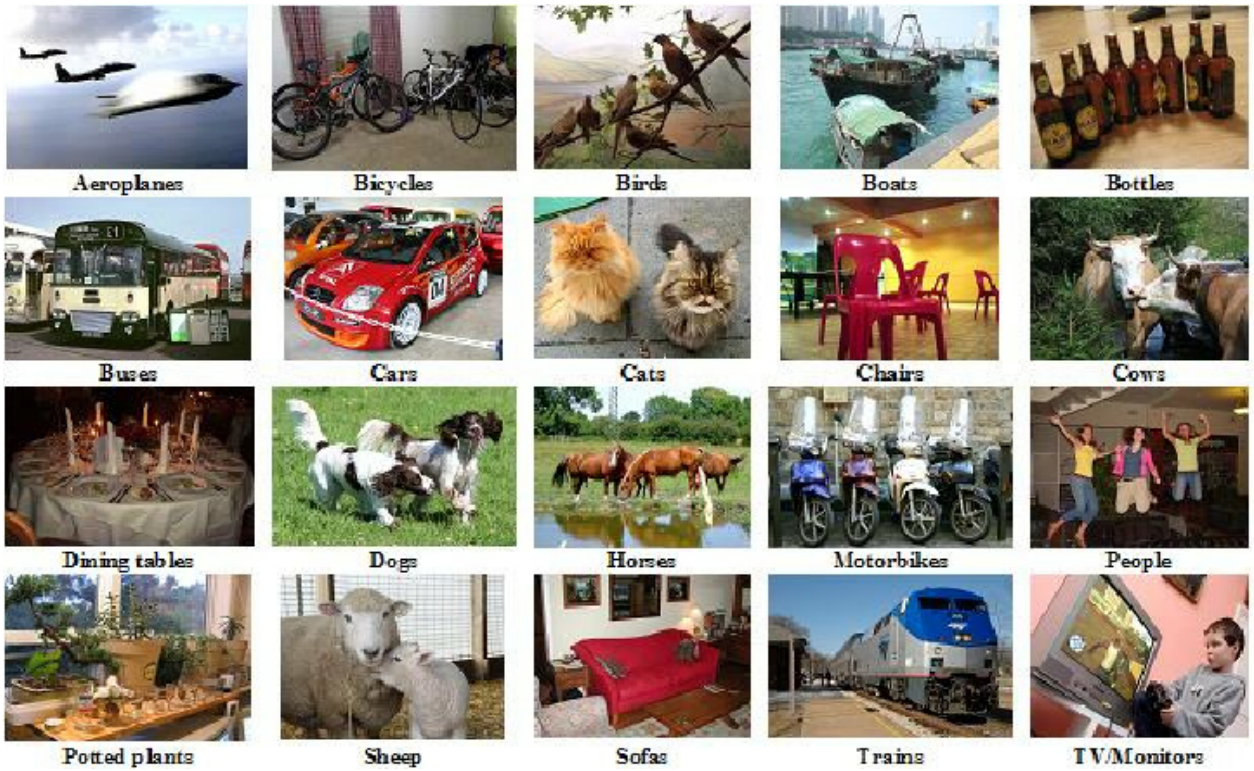


Credit: Razavian *et. al.* [ARS+16]

Deep Features (DF) and Domain Adaptation

DF for Image classification on other datasets

- **Small size datasets**: $\sim 10^3 - 10^4$ ex, *e.g.* VOC'07 (20 classes, 5000 ex)



Model type	Test mAP
From Scratch	39.79
BoW [ATC+13]	61.6
Transfer	83.22
Fine Tuning	**85.70**

Table : Mean Average Precision.

- Fine Tuning > Transfer >> Handcrafted (BoW)
- From scratch does not work (not enough training data)

Deep Features (DF) and Domain Adaptation

DF for Image classification on other datasets

- **Medium size datasets**, *e.g.* Food (LIP6) : 101 classes, 10^5 ex

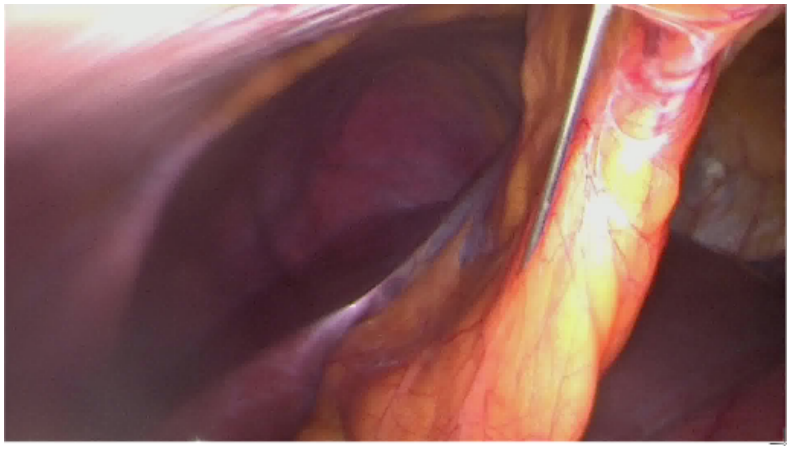
Modèle	Test top 1 (%)
(a) Bag of visual Words	23.96
Overfeat & Extraction	33.91
Overfeat & From Scratch	47.46
Overfeat & Fine Tuning	57.98
(b) Vgg16 & Extraction	40.21
Vgg16 & From Scratch	53.62
Vgg16 & Fine Tuning	**65.71**

- From scratch DOES work (well !)
- Fine Tuning >> From scratch >> Transfer >> Handcrafted (BoW)

Deep Features (DF) and Domain Adaptation

DF for Image classification on other datasets

- Another ex: M2CAI'16 challenge - large domain shift (medical images)
  - Medium-size: 22 videos, $\sim 60 \cdot 10^4$ images, 8 classes

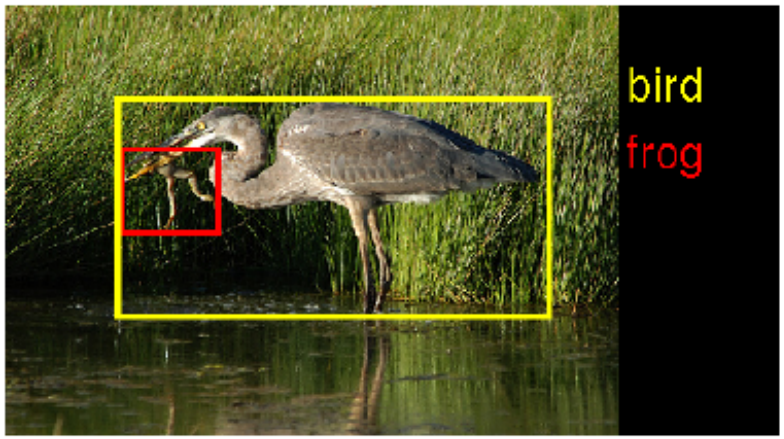


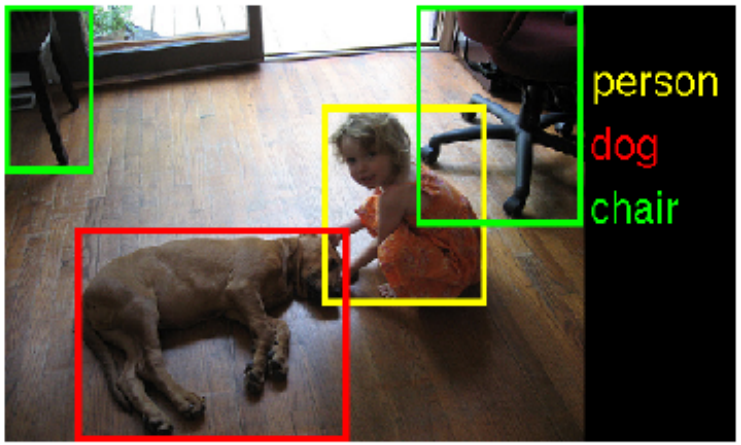
Model	Acc Top1(%)
Transfer	59.27
From Scratch	69.13
Fine Tuning	79.06

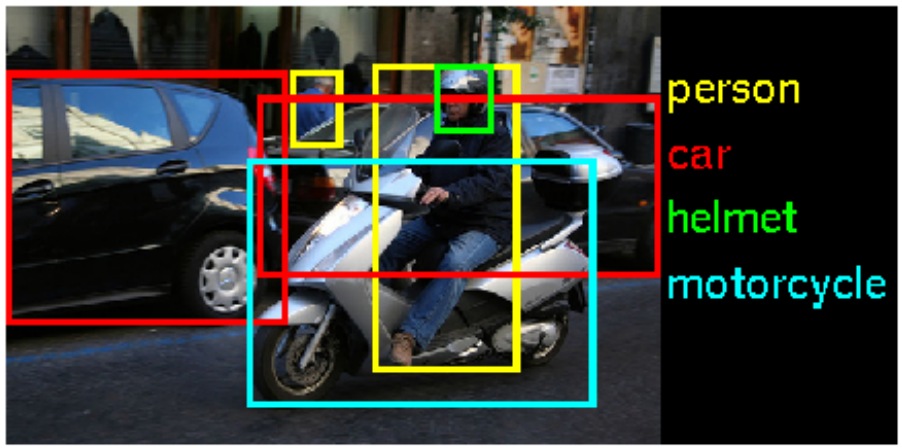
- Fine Tuning >> From scratch >> Transfer
- Transfer already good baseline despite big visual content shift

Deep Features (DF) and Domain Adaptation

Task Adaptation: Localization



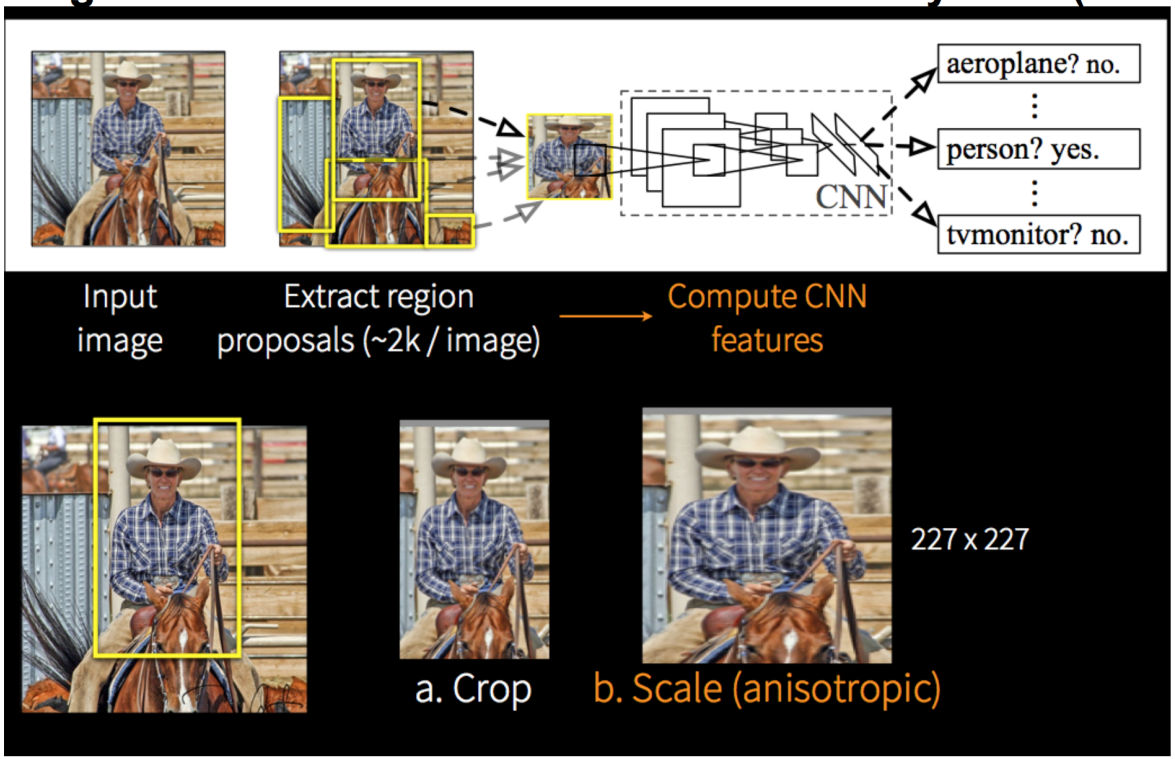




Deep Features (DF) and Domain Adaptation

Task Adaptation: Localization

Regions with Convolutional Neural Net.s system (RCNN)



R. Girshick, J. Donahue, T. Darrell, and J. Malik. Rich feature hierarchies for accurate object detection and semantic segmentation. *CVPR* 14

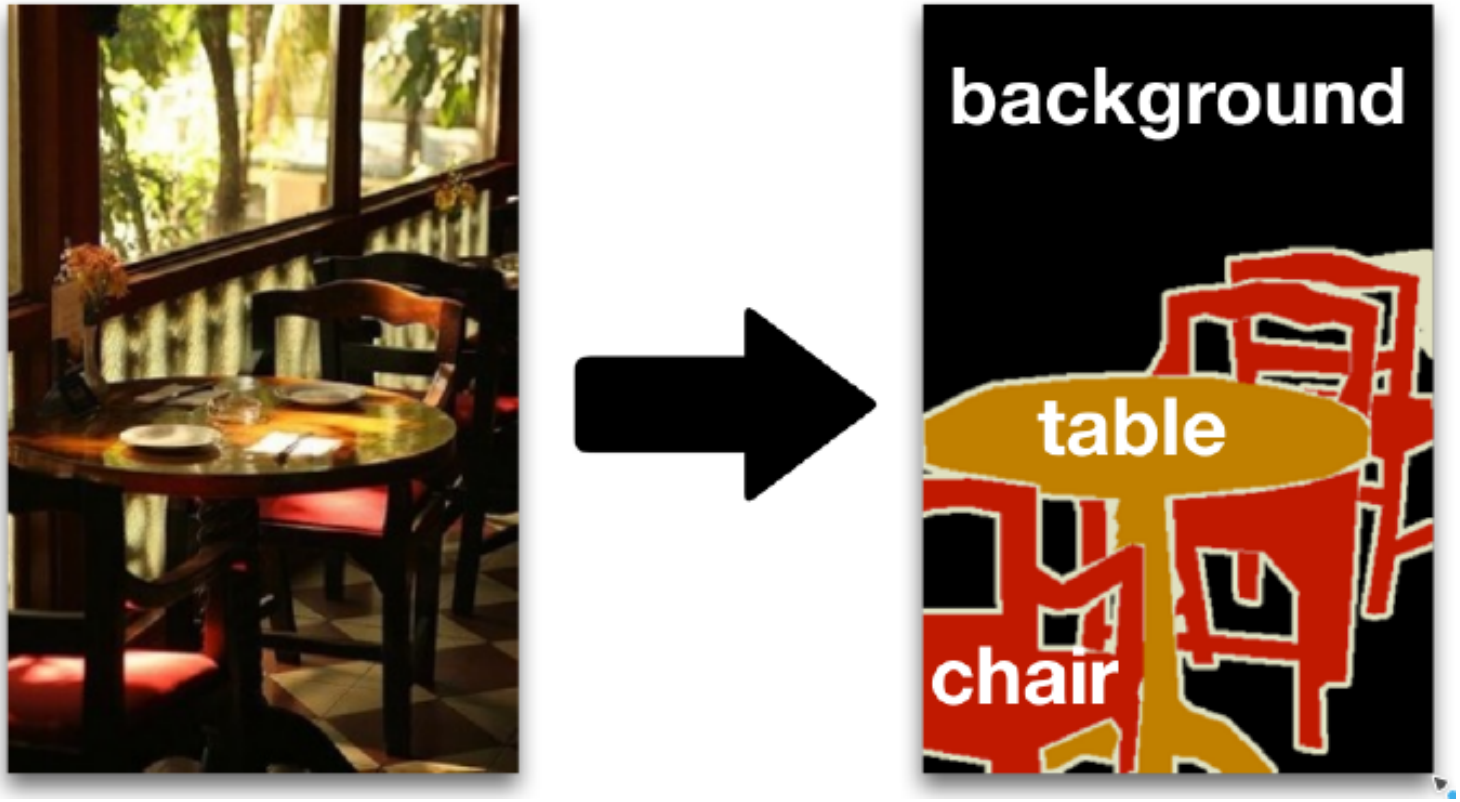
Eval on VOC'07:

R-CNN	**58.5**
DPM HoG	34.3

- R-CNN ⇒ region proposals ⇒ Deep Features ⇒ classify
- Significantly outperformed previous models (DPM on HoG features)

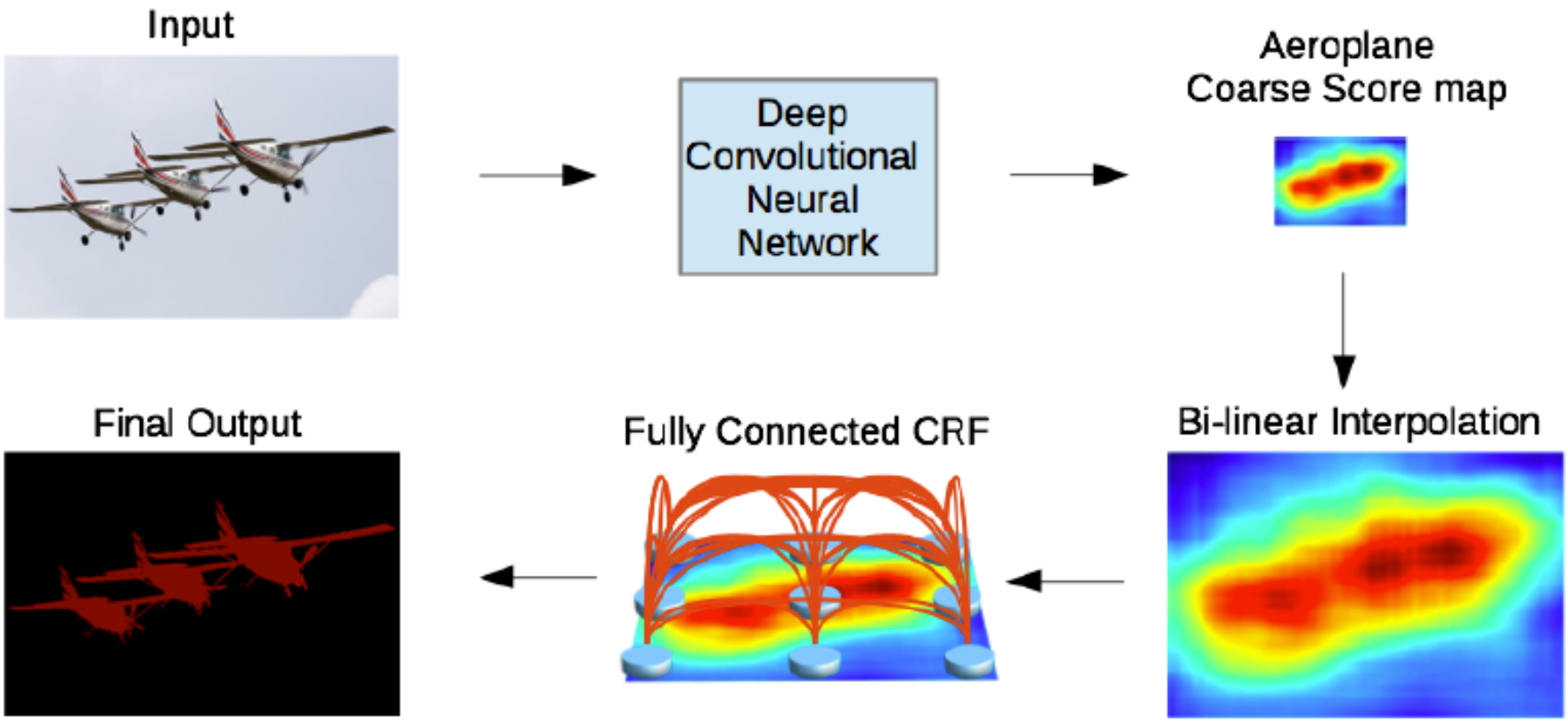
Deep Features (DF) and Domain Adaptation

Task Adaptation: Semantic Segmentation



Deep Features (DF) and Domain Adaptation

Task Adaptation: Semantic Segmentation

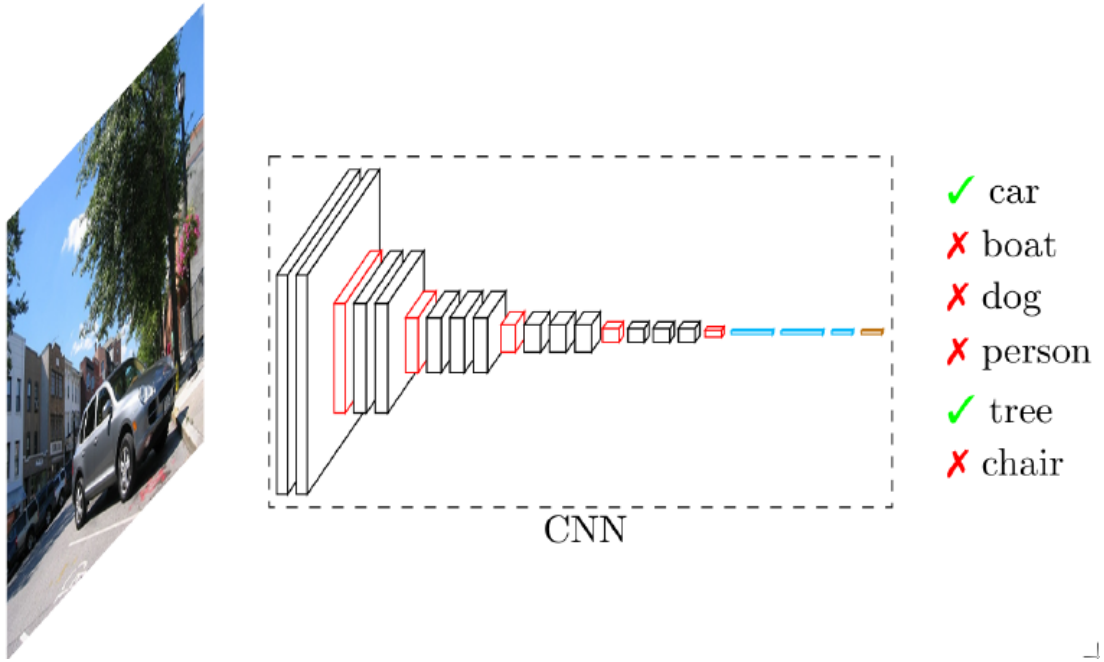


Chen *et.al.* ICLR'15

Deep Features (DF) and Domain Adaptation

Conclusion

- Deep Feature in transfer mode
  - Very good baseline
  - Ofter > descriptors based on expert knowledge
  - The solution for small databases
- From medium-size: from scratch possible and very competitive
- Fine-tuning always improves performances (small → large datasets)



Outline

Ongoing Issues in Deep Learning

CNN and invariance

- Standard ConvNets: limited invariance capacity (small shifts)
- ImageNet: single centered object ≠ other datasets (VOC, MS COCO)

⇒ **Learn shift invariance: region alignment !**

ImageNet

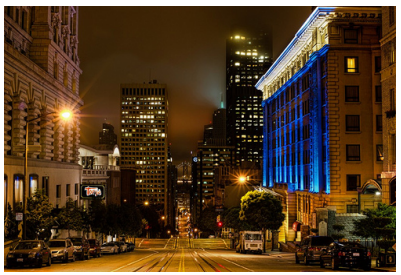



VOC 2007




MS COCO

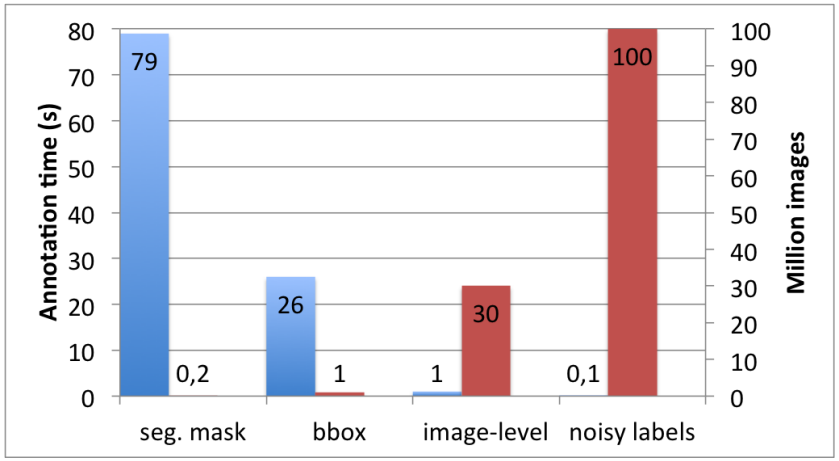


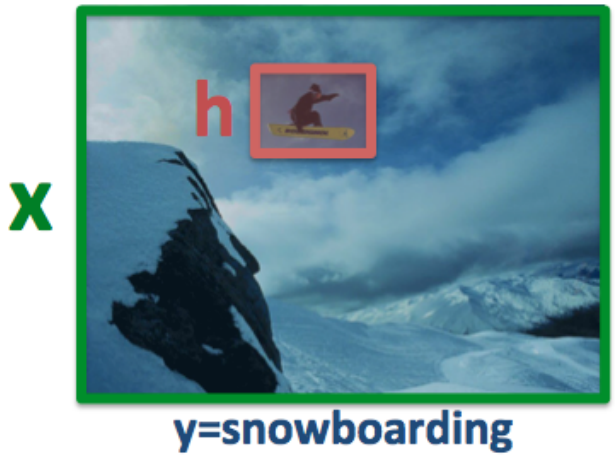



Ongoing Issues in Deep Learning

CNN and invariance: Weakly Supervised Learning

- Full annotations expensive ⇒ training with weak supervision [BRFFF16]



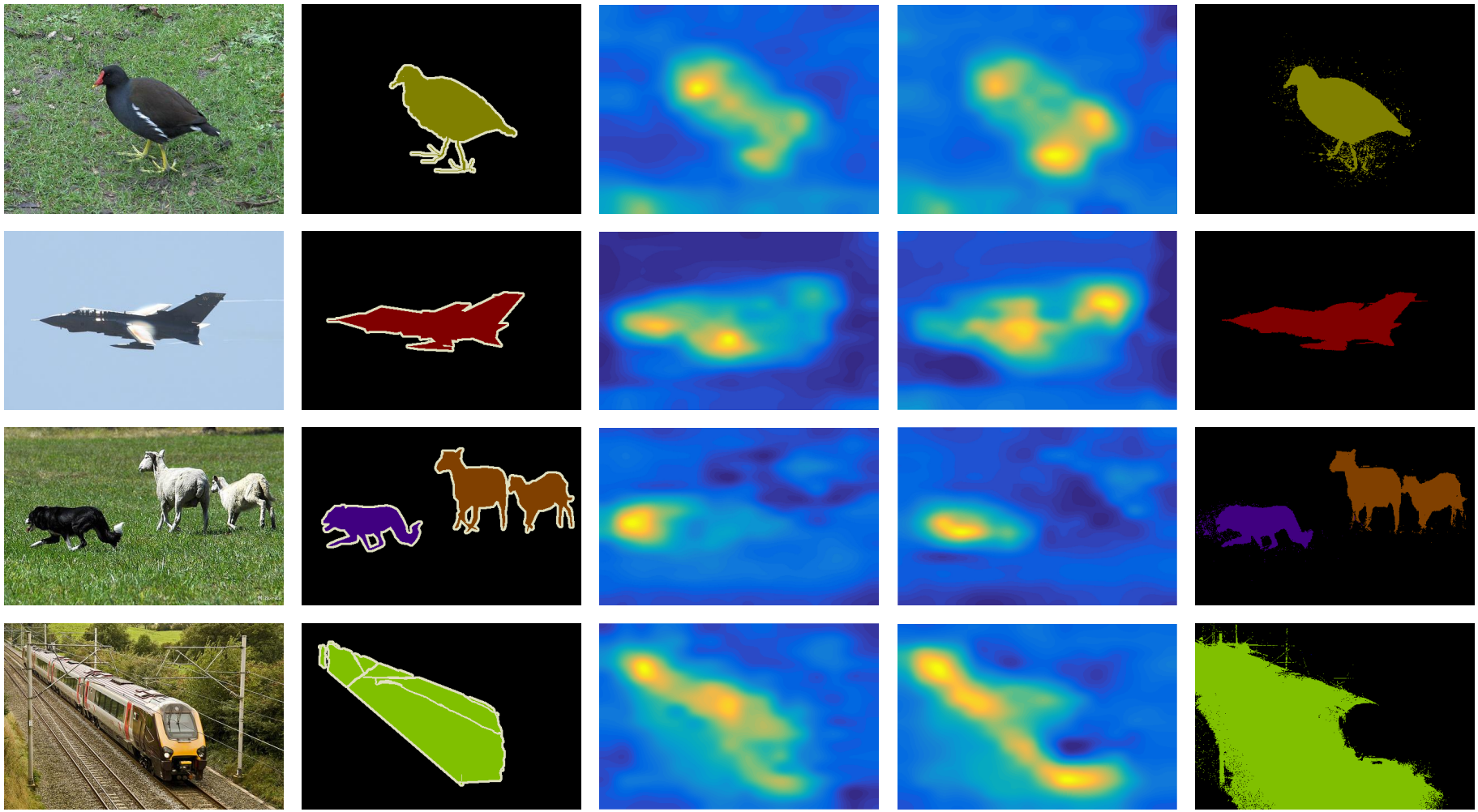


- **Incorporating latent variables $\mathbf{h} \in \mathcal{H}$, *e.g.* training object / part detector / segmenter from global image labels**

Variable	Notation	Space	Train	Test
Input	$\mathbf{x}$	$\mathcal{X}$	observed	observed
Output	$\mathbf{y}$	$\mathcal{Y}$	observed	unobserved
Latent	$\mathbf{h}$	$\mathcal{H}$	unobserved	unobserved

CNN and invariance: Weakly Supervised Learning

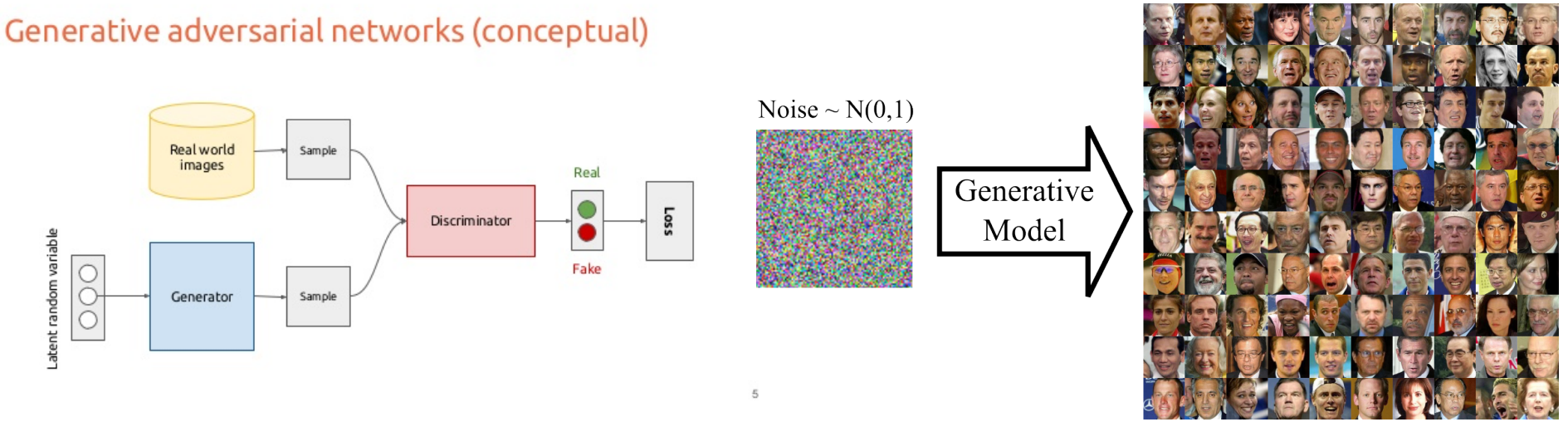
Training detector / segmenter from global image labels [DTC16]



Ongoing Issues in Deep Learning

Unsupervised Training

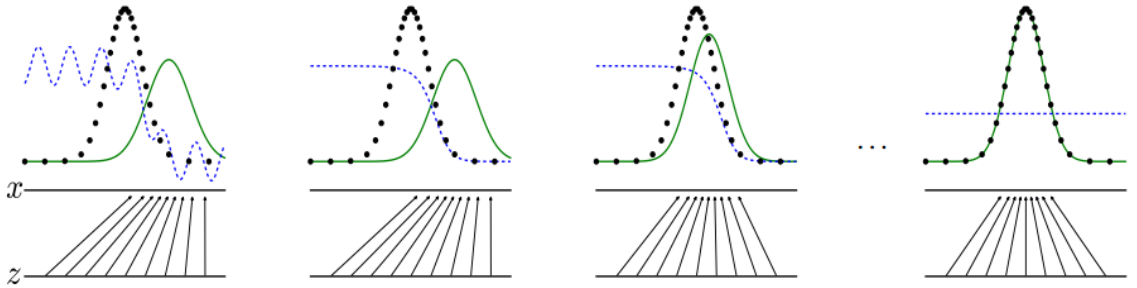
- Standard ways to perform unsupervised: learning representations fitting data well, *e.g.* Maximum likelihood, reconstruction error, *etc*
- Success of deep learning essentially for supervised problem
- Solution: cast unsupervised problem as a supervised one
  ⇒ **auto-supervision**
  - Trendy example: Generative Adversarial Networks (GAN) [GPAM+14]



Ongoing Issues in Deep Learning

Unsupervised Training: GAN

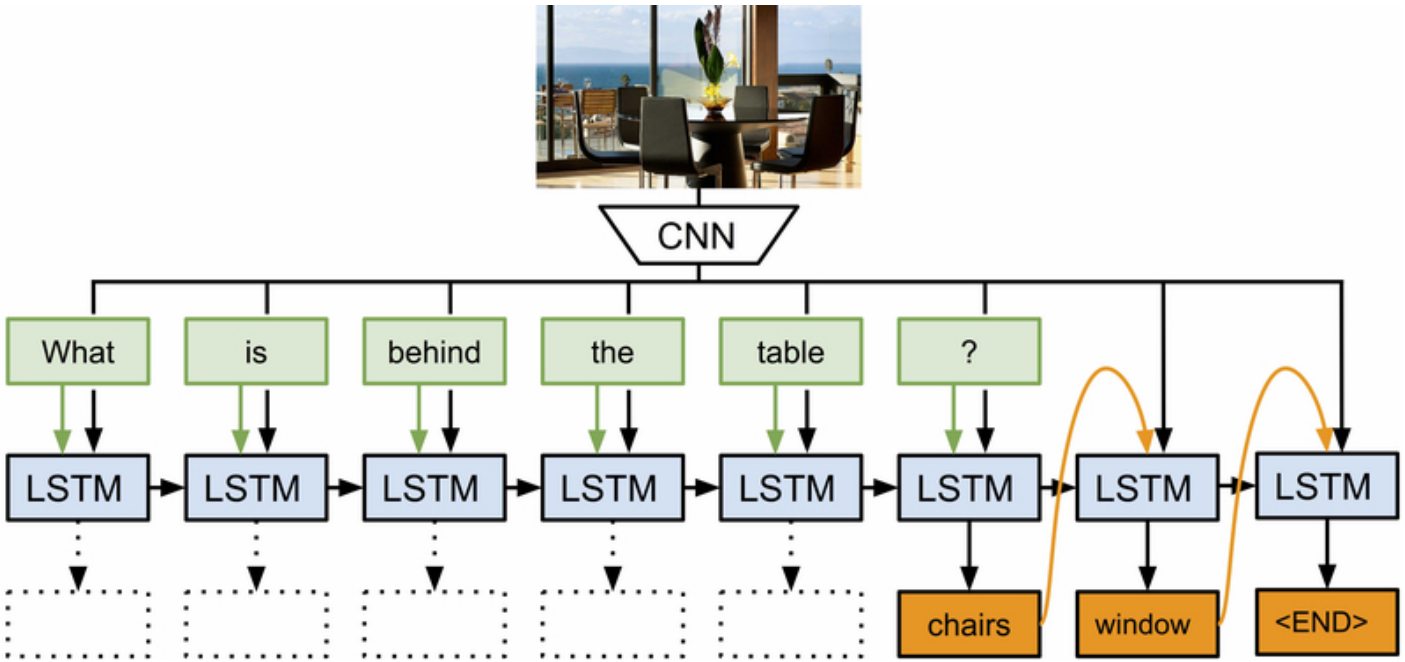
- Unsupervised problem ⇒ 2-player game theory problem
- Interesting results: optimal generator learns data distribution



Ongoing Issues in Deep Learning

New Tasks in Artificial Intelligence

- Vision and language, Visual Question Answering (VQA)

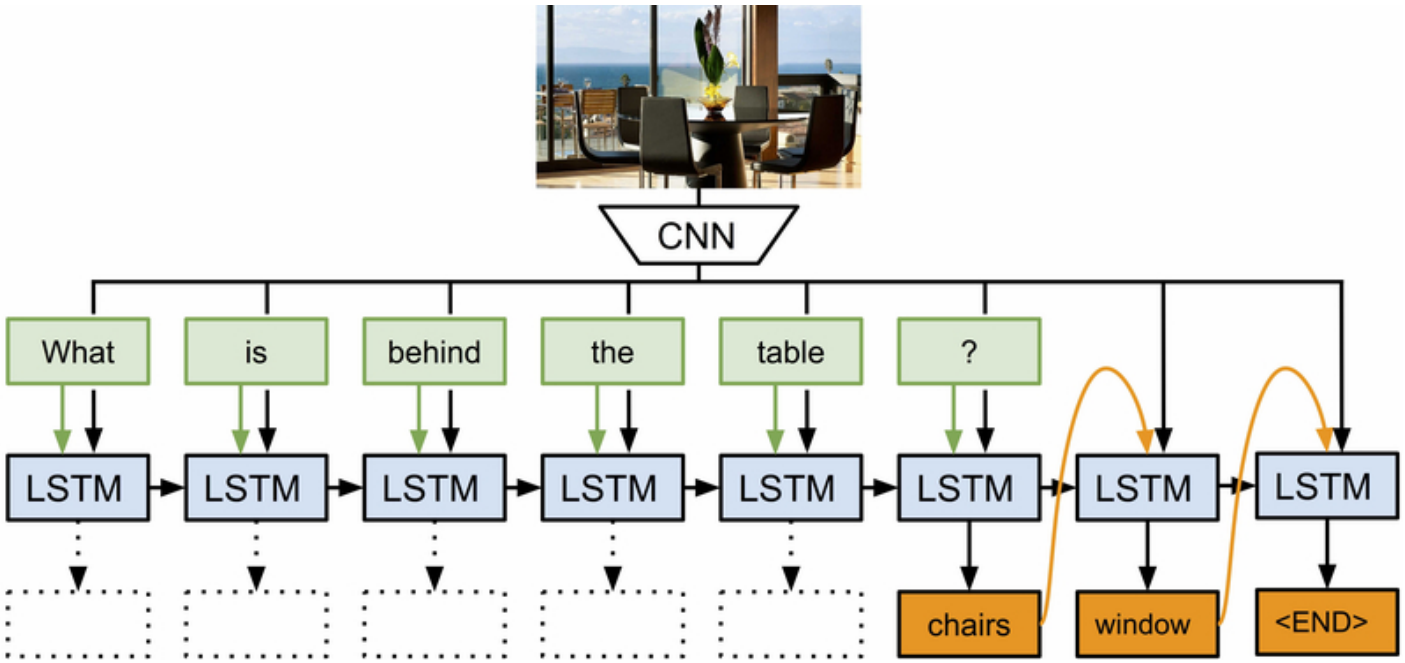


Credit: M. Malinowski [MRF15]

Ongoing Issues in Deep Learning

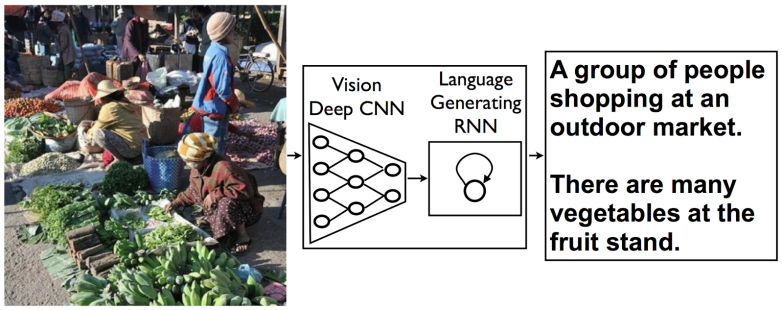
New Tasks in Artificial Intelligence

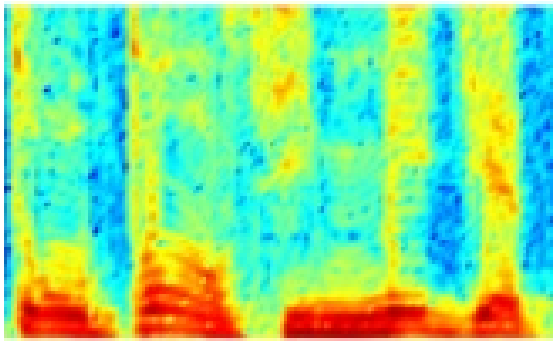
- But still a long way to go toward real AI ...

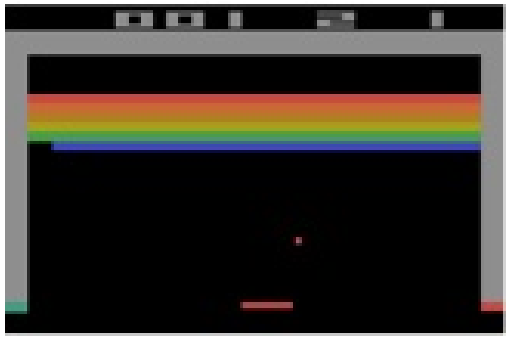


Credit: M. Malinowski [MRF15]

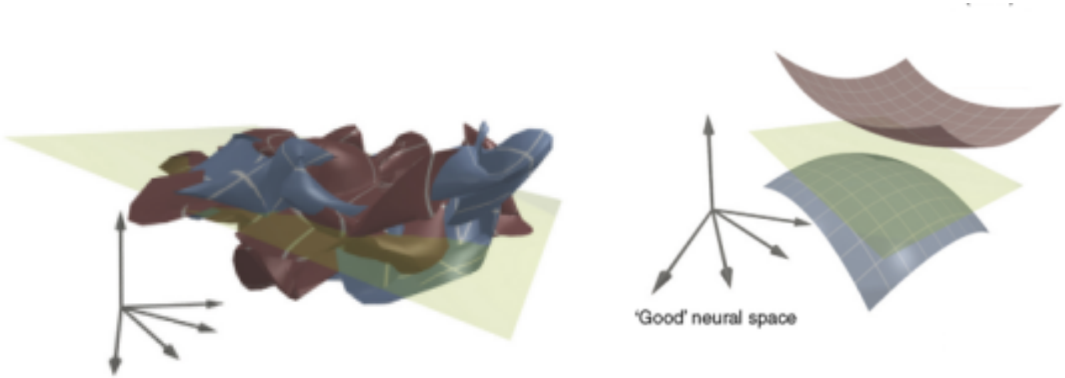
Conclusion







- Deep Learning: huge impact in terms of experimental results
- BUT: formal understanding still limited,
  - Optimization: non-convex problem
  - Model: ability to untangle manifold
  - Robustness to over-fitting & generalization



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