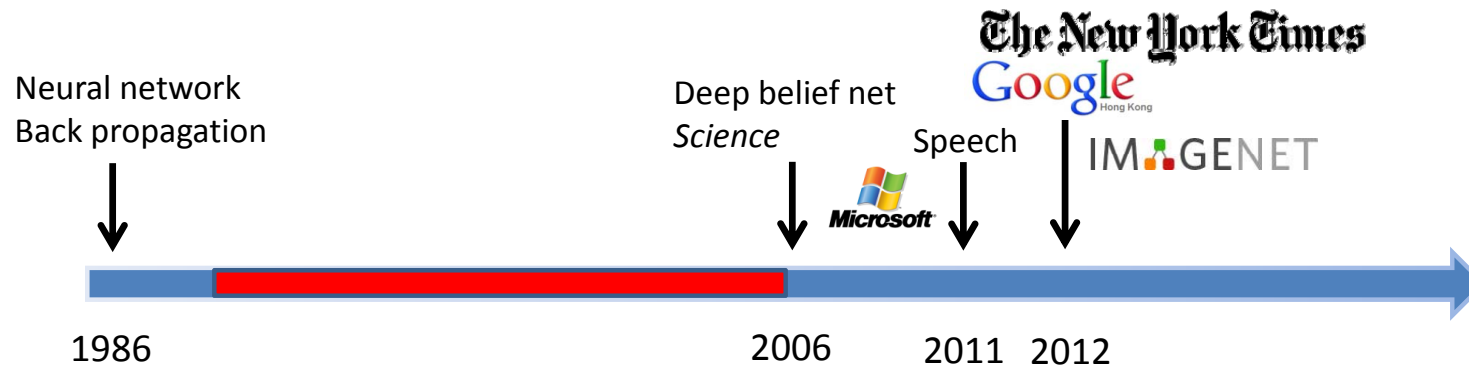


Lecture 18: Learning 7

http://cs.nju.edu.cn/yuy/course_ai17.ashx

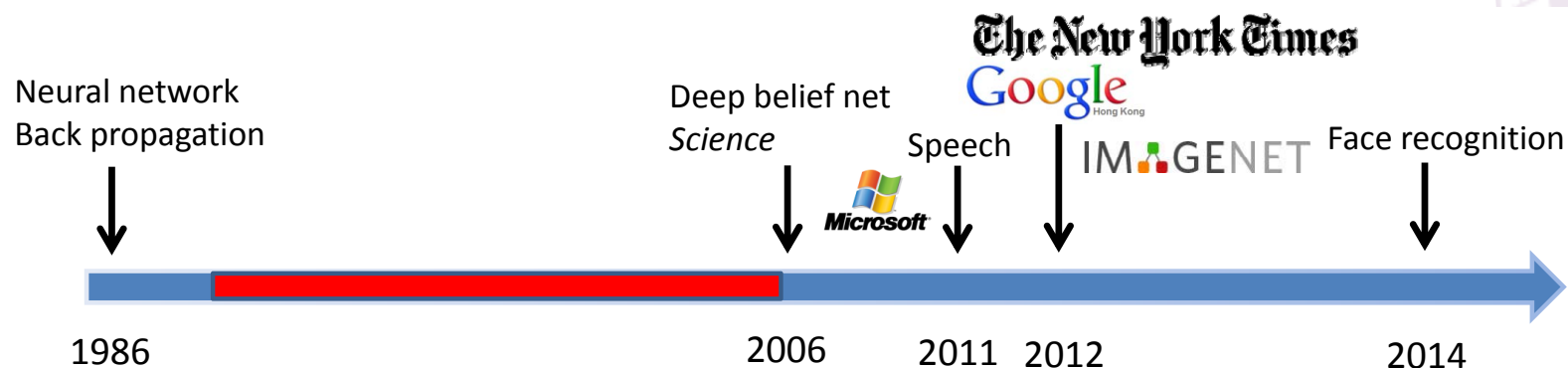


Historical review of deep learning



- Google and Baidu announced their deep learning based visual search engines (2013)
 - [Google](#)
 - “on our test set we saw **double the average precision** when compared to other approaches we had tried. We acquired the rights to the technology and went full speed ahead adapting it to run at large scale on Google’s computers. We took cutting edge research straight out of an academic research lab and launched it, in just a little over six months.”
 - [Baidu](#)

Historical review of DL (con't)



- Deep learning achieves 99.47% face verification accuracy on Labeled Faces in the Wild (LFW), higher than human performance

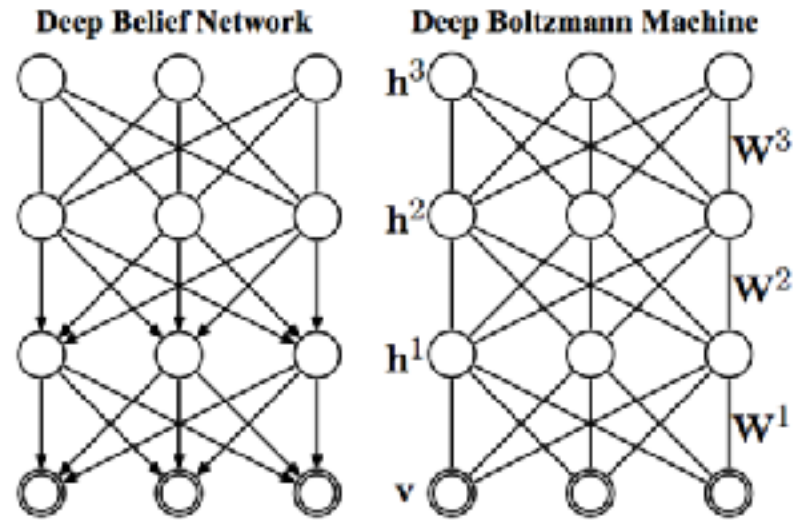
Y. Sun, X. Wang, and X. Tang. Deep Learning Face Representation by Joint Identification-Verification. NIPS, 2014.

Y. Sun, X. Wang, and X. Tang. Deeply learned face representations are sparse, selective, and robust. CVPR, 2015.

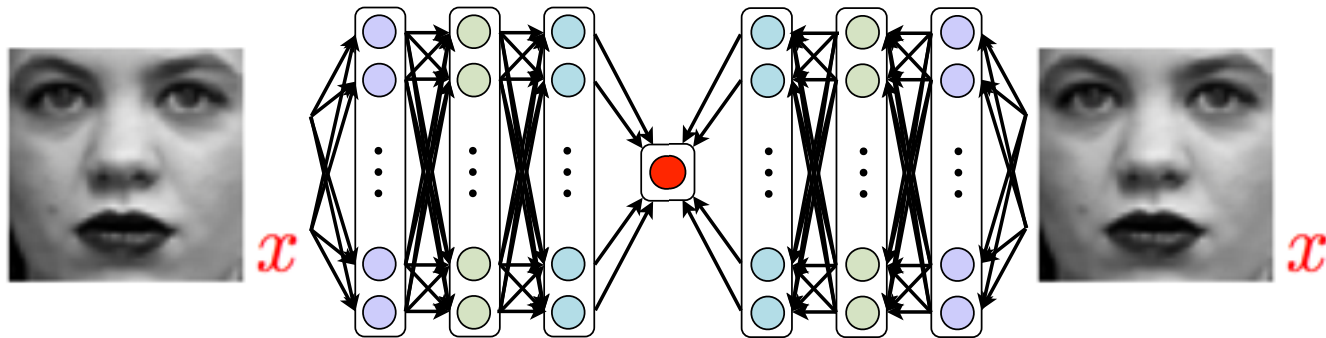
Major types



Deep Boltzmann machine:



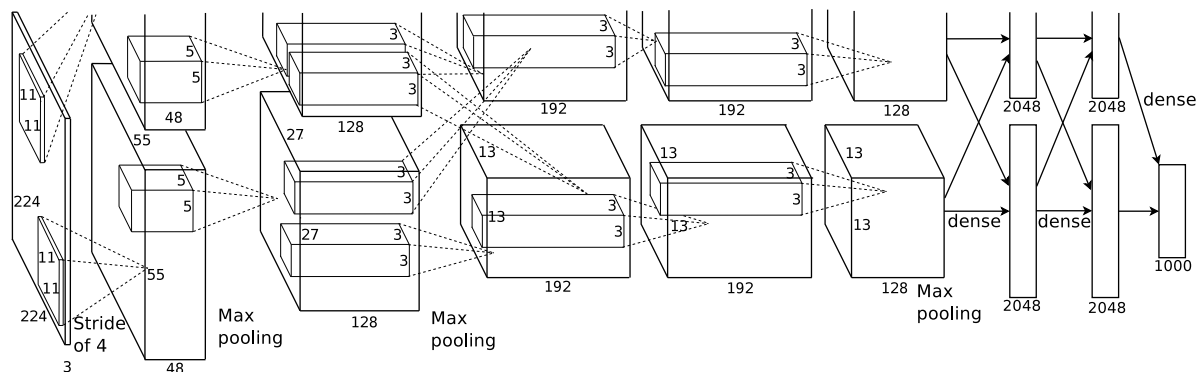
Auto-encoder:



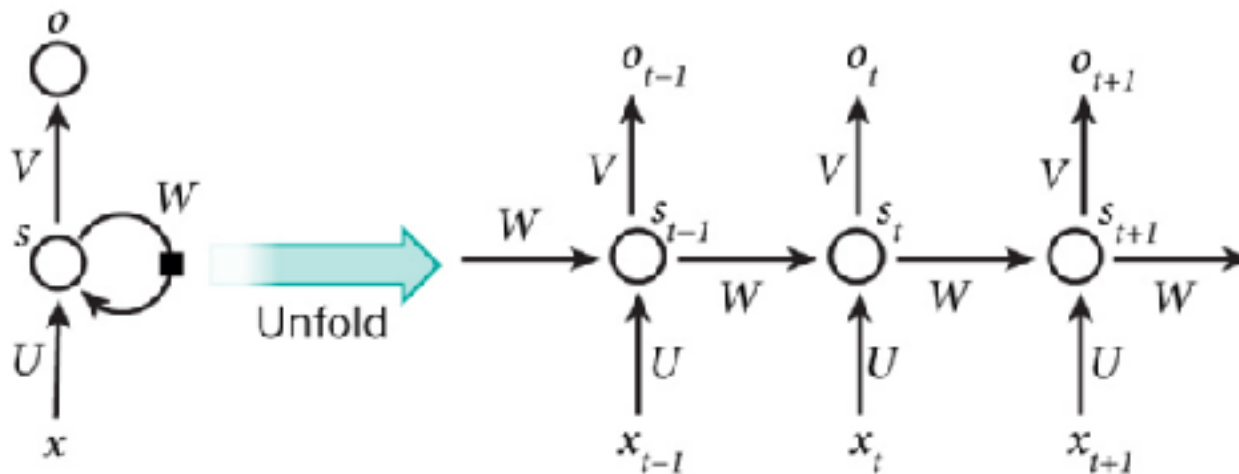
Major types



Convolutional neural networks:



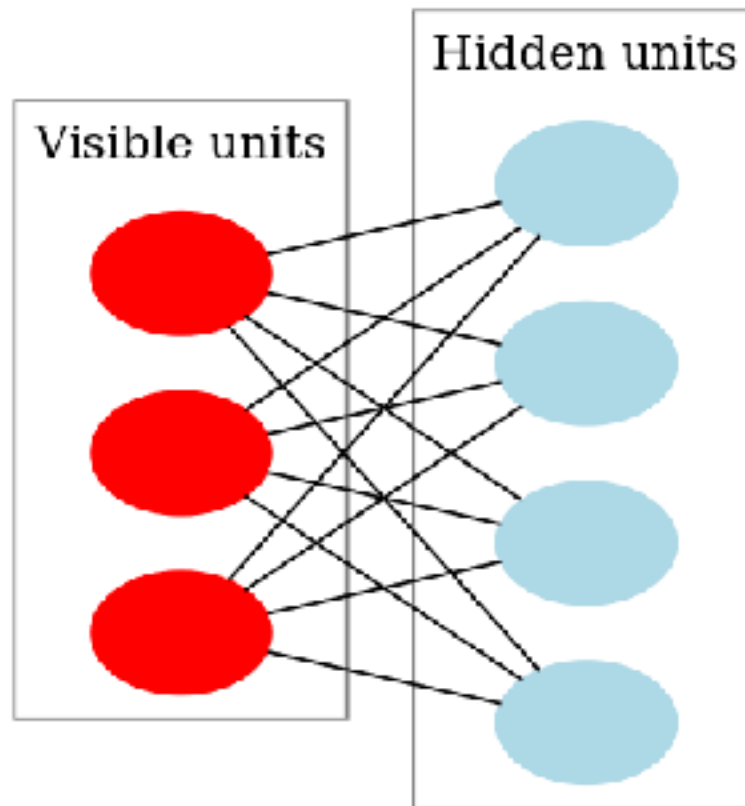
Recurrent neural networks:



Autoencoder

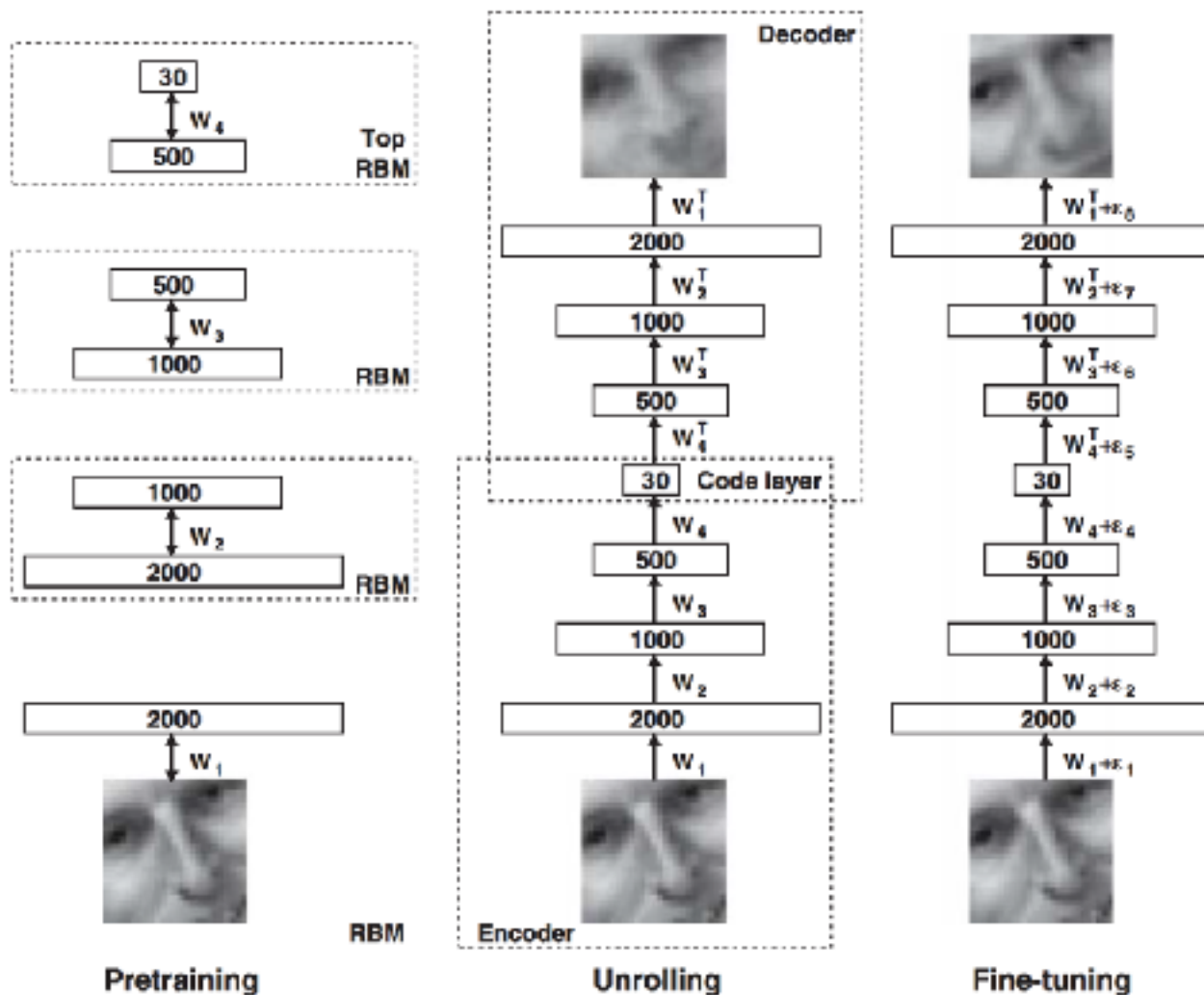
autoencoder

restricted Boltzmann machine
a type of associative memory network



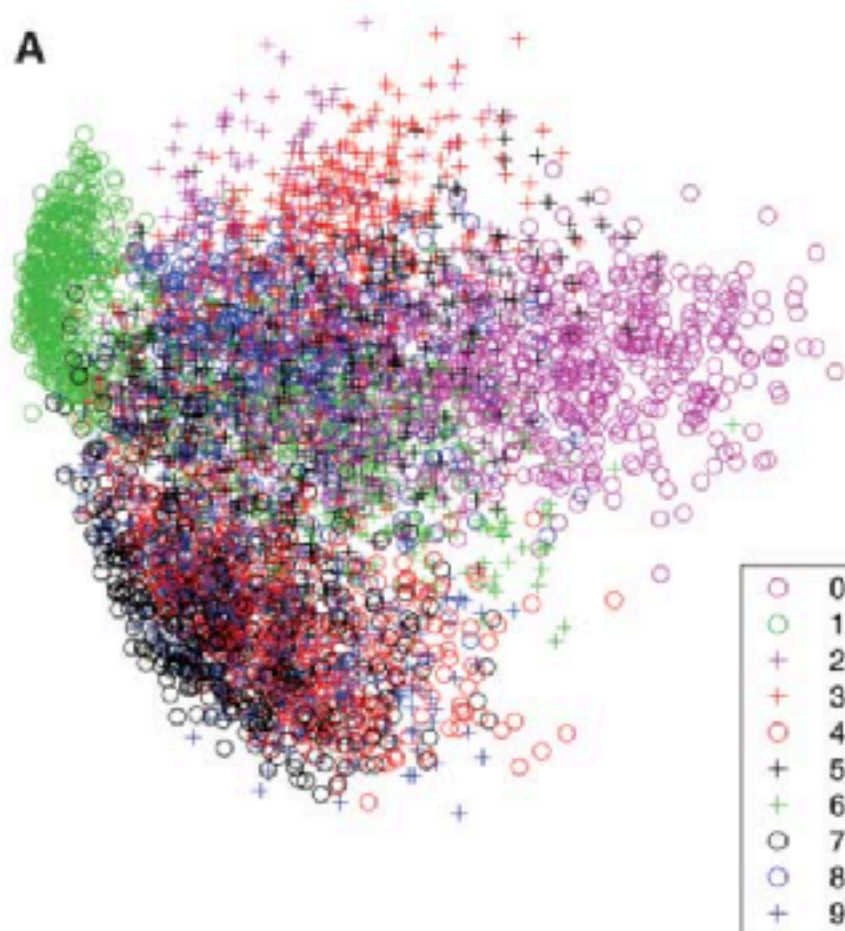
Autoencoder

autoencoder

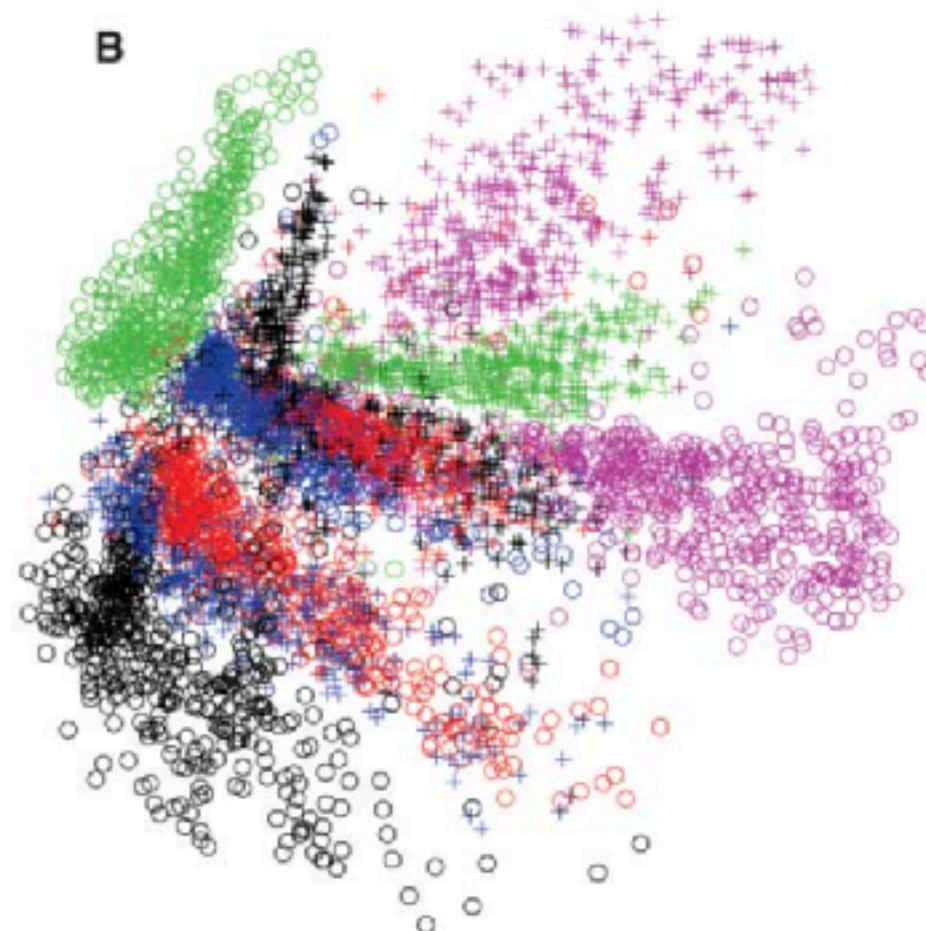


Autoencoder

autoencoder



PCA

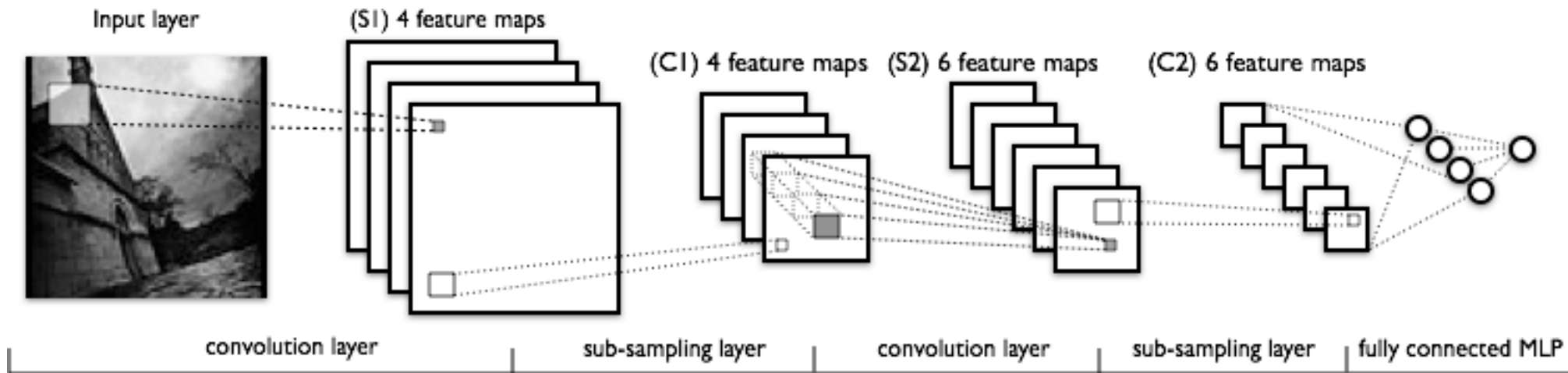


autoencoder

CNN



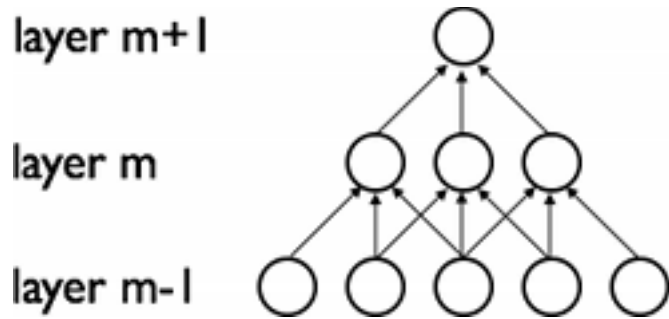
Convolutional Neural Networks (CNN/LeNet) for general image feature extraction



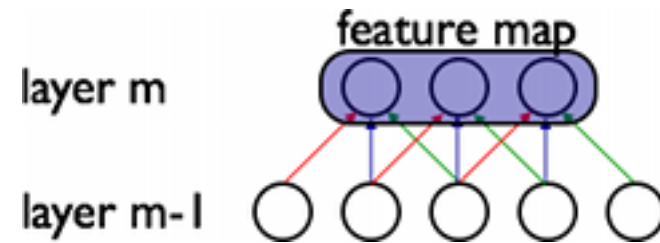
CNN



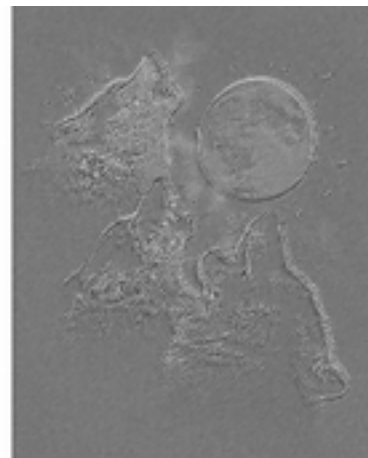
Convolution layer



sparse connectivity

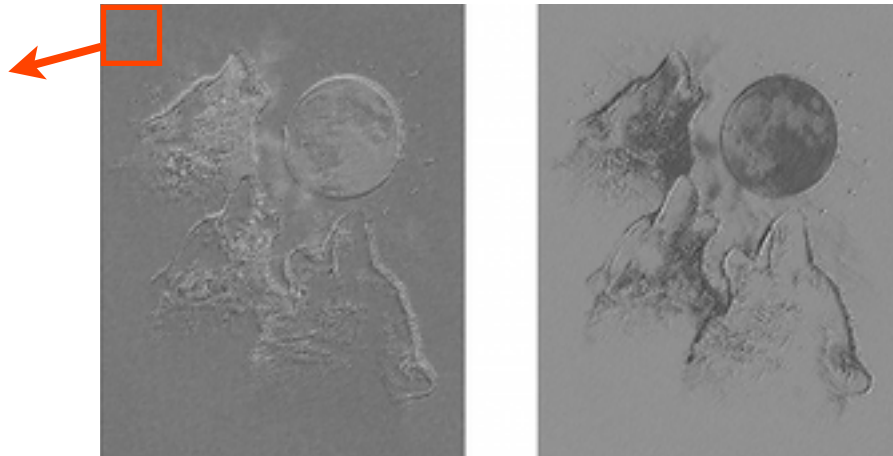


shared weights



CNN

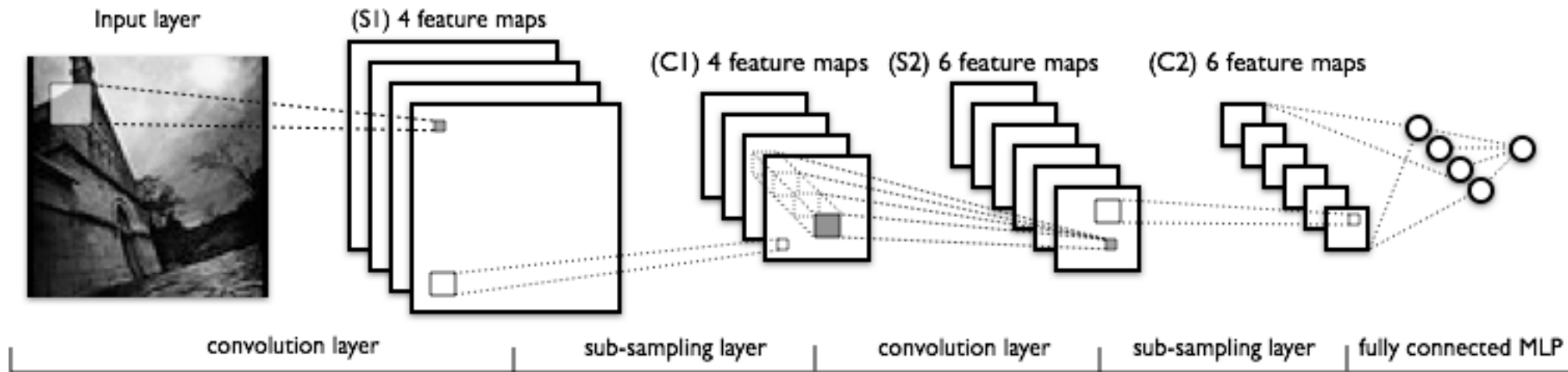
Subsampling layer



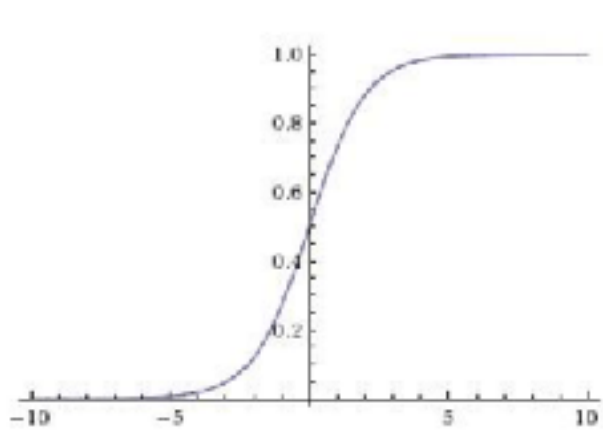
CNN



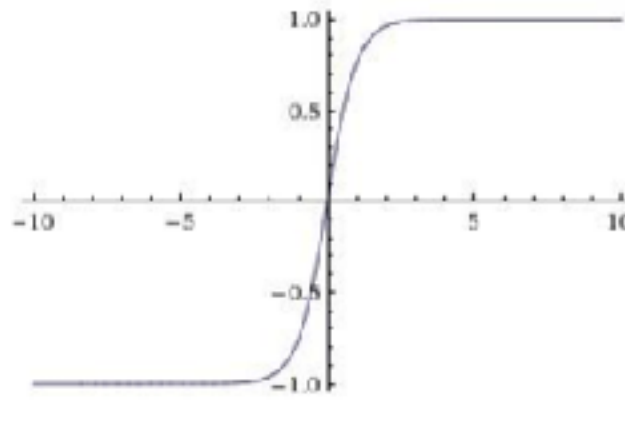
Convolutional Neural Networks (CNN/LeNet) for general image feature extraction



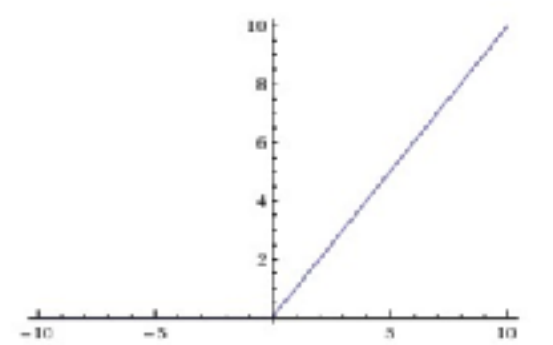
Activation functions (con't)



Sigmoid



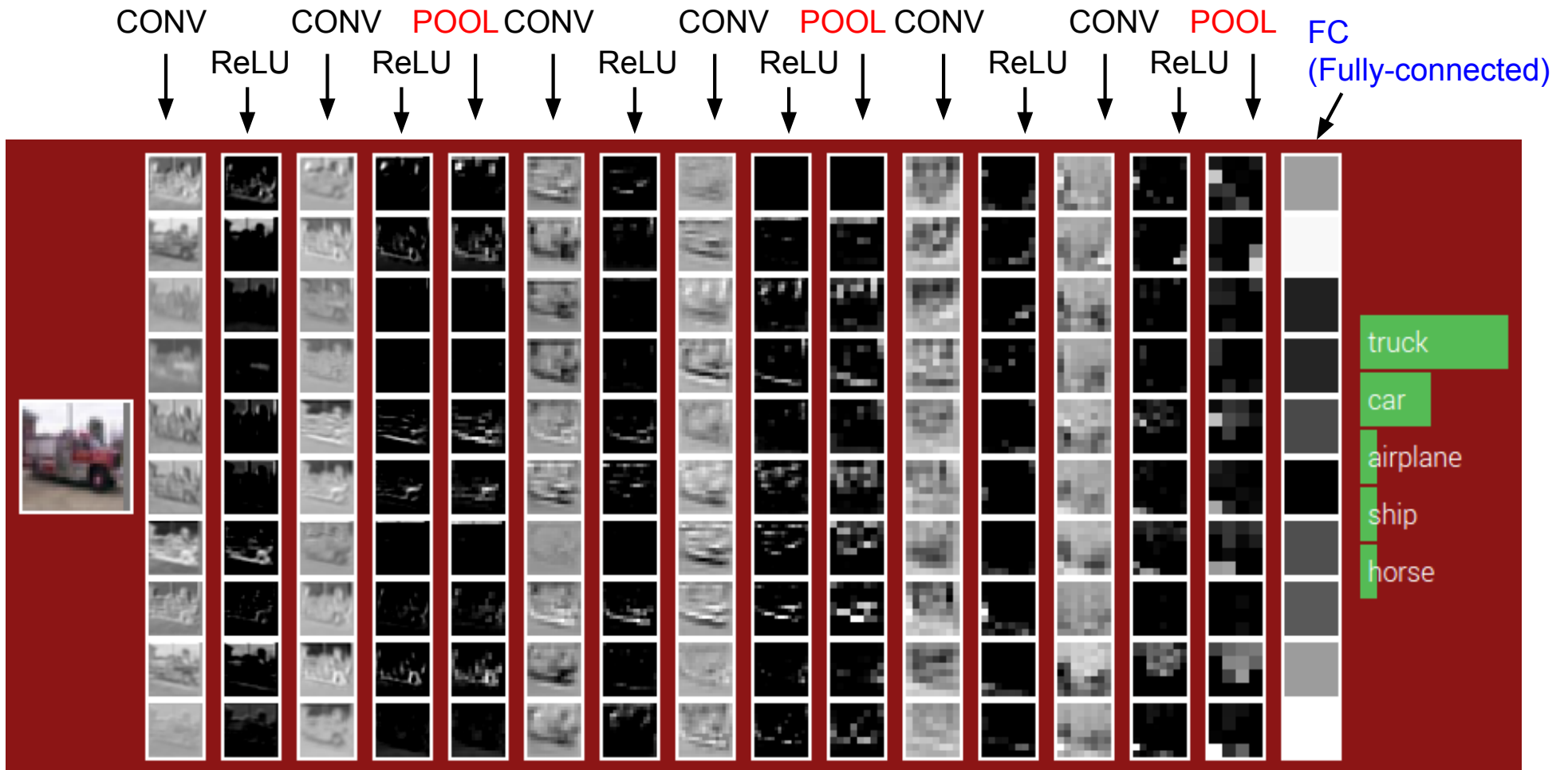
$\tanh(x)$



ReLU
(Rectified Linear Unit)

And many more ...

CNN



CNN Tricks



Must Know Tips/Tricks in Deep Neural Networks (by Xiu-Shen Wei)

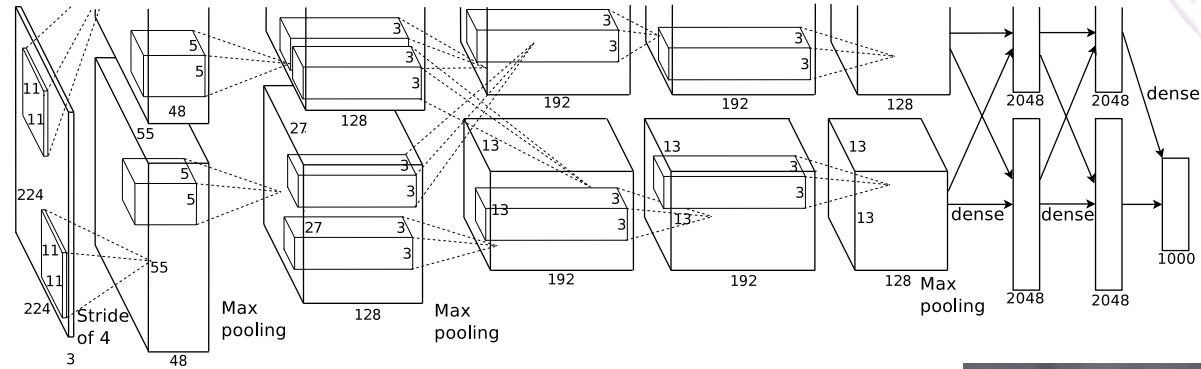


Deep Neural Networks, especially *Convolutional Neural Networks* (CNN), allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction. These methods have dramatically improved the state-of-the-arts in visual object recognition, object detection, text recognition and many other domains such as drug discovery and genomics.

In addition, many solid papers have been published in this topic, and some high quality open source CNN software packages have been made available. There are also well-written CNN tutorials or CNN software manuals. However, it might lack a recent and comprehensive summary about the details of how to implement an excellent deep convolutional neural networks from scratch. Thus, we collected and concluded many implementation details for DCNNs. **Here we will introduce these extensive implementation details, i.e., *tricks or tips*, for building and training your own deep networks.**

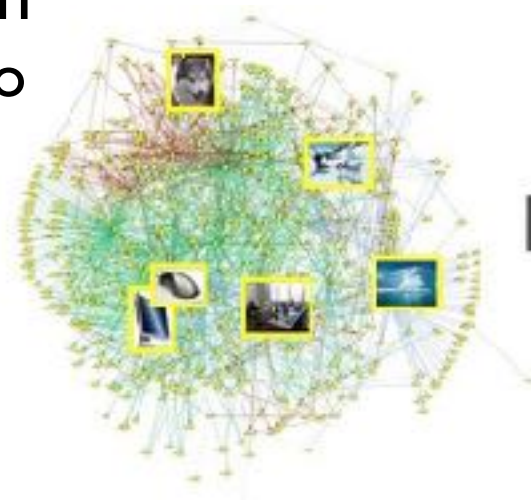
- Data augmentation
- Pre-processing
- Initializations
- During training
- Activation functions
- Regularizations
- Insights from figures
- Ensemble

CNN



4.94% (DL) vs 5.1% (human)

Geoffrey E. Hinton
University of Toronto



IMAGENET



Fei-Fei Li
Stanford University

CNN toolbox

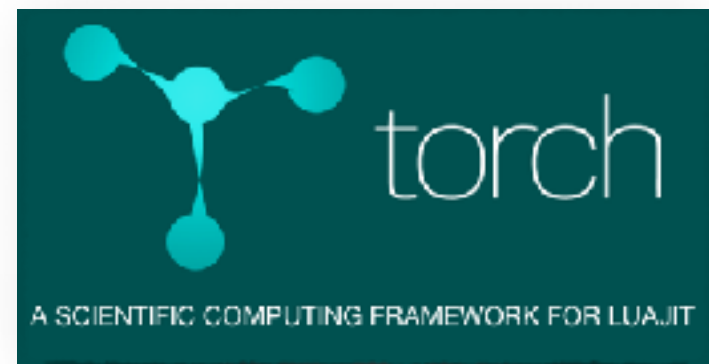


- ★ MatConvNet (Oxford University)
- ★ Caffe (UC Berkeley)
- ★ Torch (Facebook & NYU)
- ★ ...

Caffe

Deep learning framework
by the **BVLC**

Created by
Yangqing Jia



NVIDIA-GPUs

DEEP LEARNING

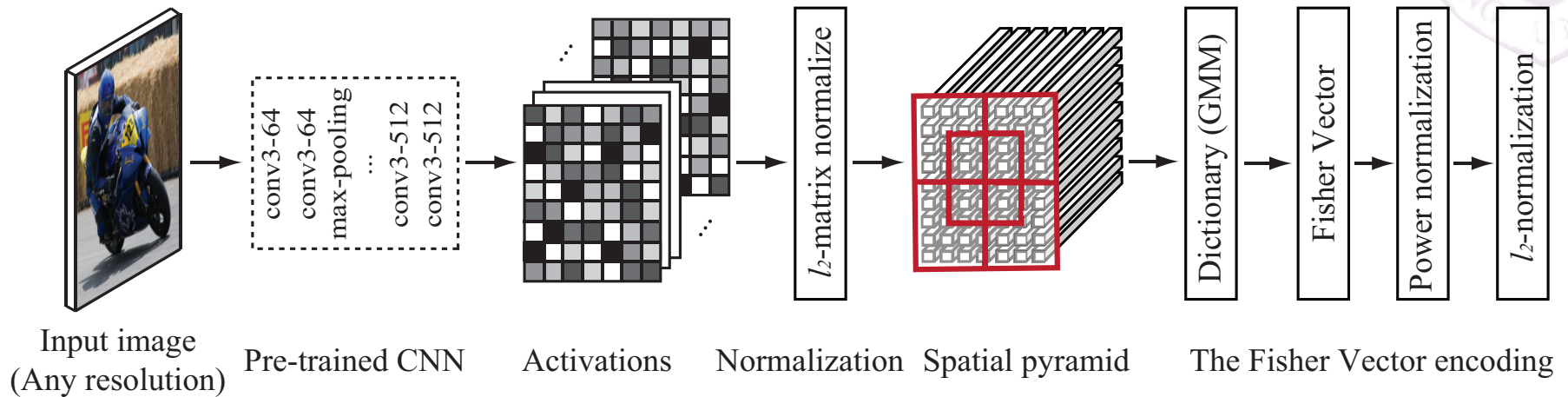
NVIDIA Home > Products > NVIDIA DGX-1

 [Subscribe](#)

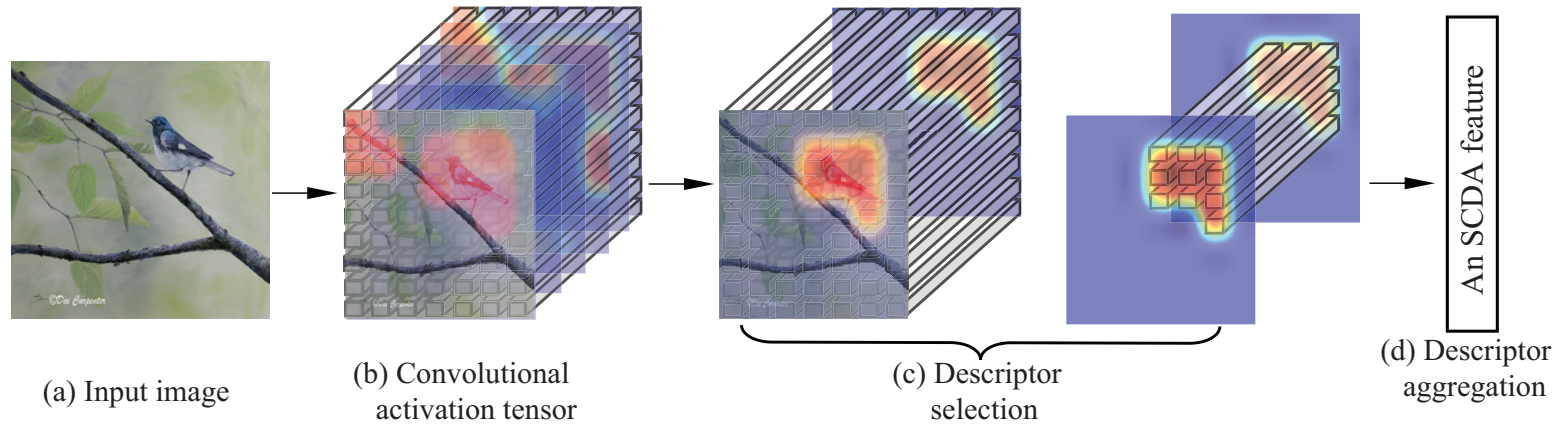


THE WORLD'S FIRST DEEP LEARNING
SUPERCOMPUTER IN A BOX

Some Applications



Pre-trained model as feature extractor

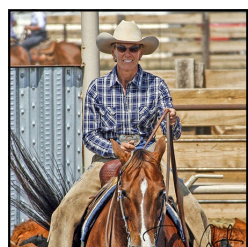


Fine-grained image retrieval

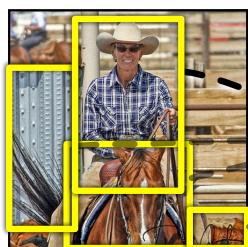
Some Applications



R-CNN: *Regions with CNN features*

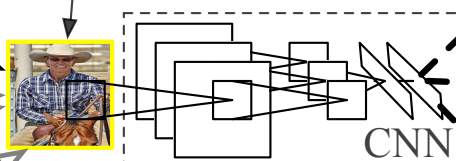


1. Input image



2. Extract region proposals (~2k)

warped region



3. Compute CNN features

aeroplane? no.

⋮

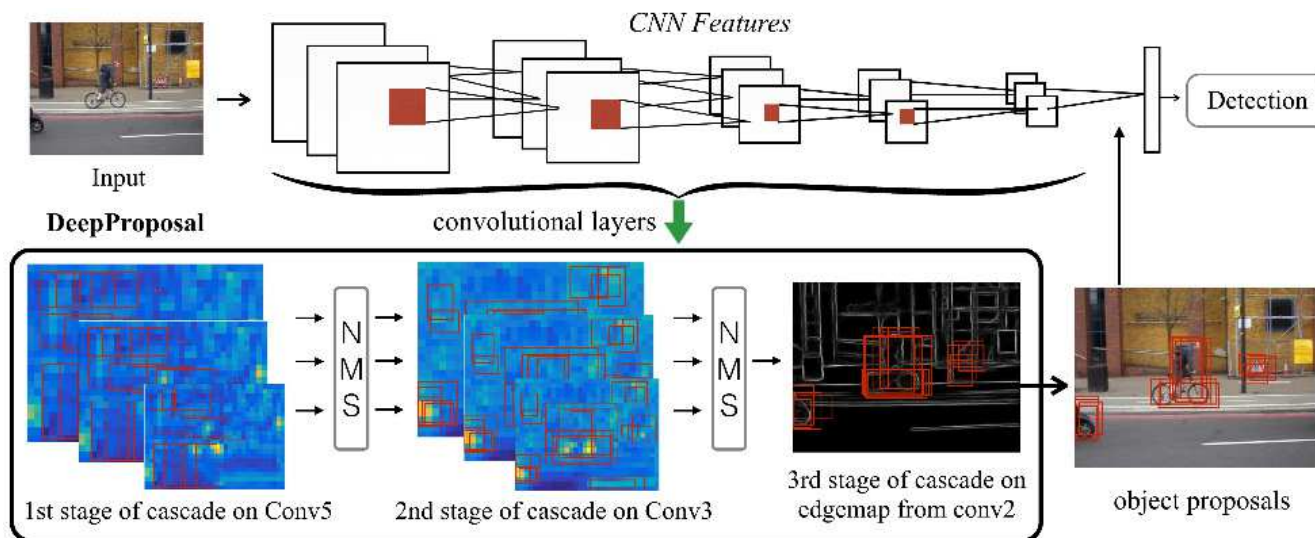
person? yes.

⋮

tvmonitor? no.

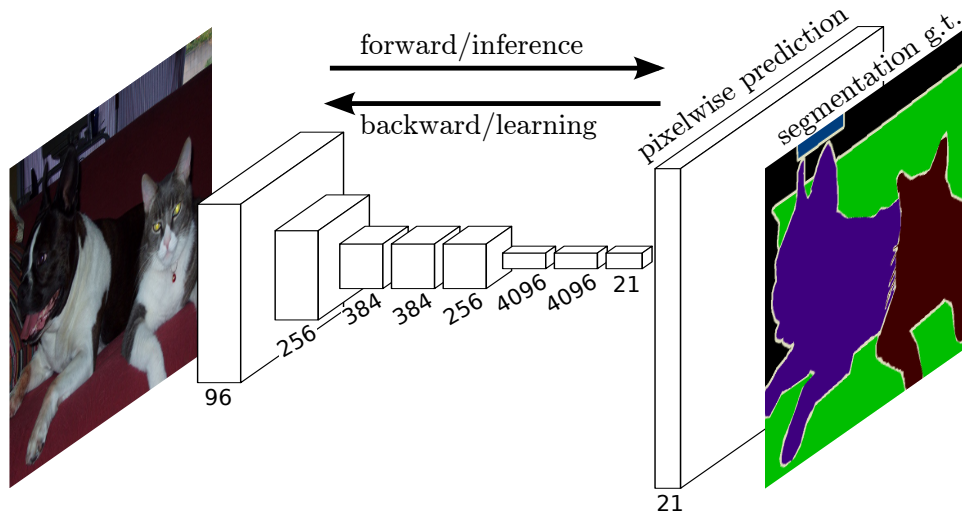
4. Classify regions

Object detection

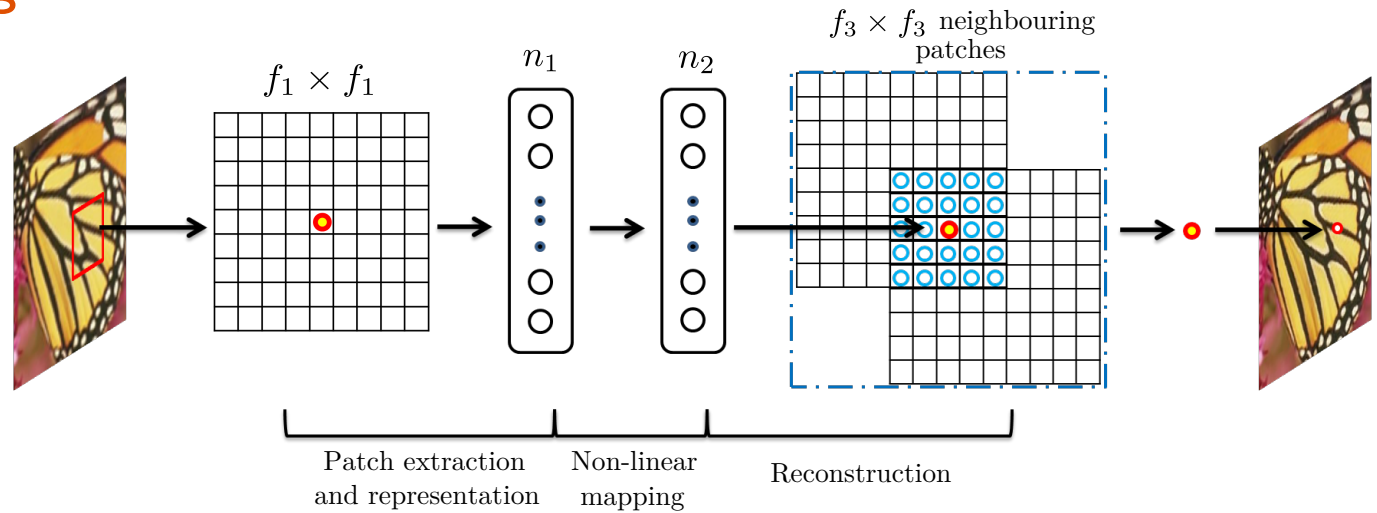


DeepProposal

Some Applications



Semantic segmentation



Super-resolution

Some Applications

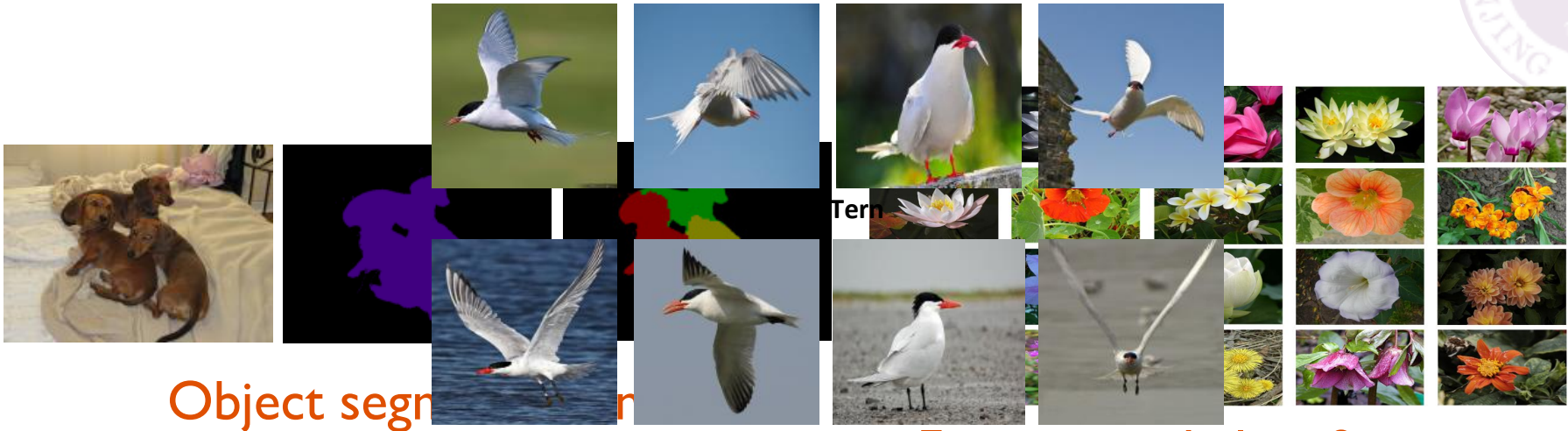


Object segmentation



Fine-grained classification

Some Applications

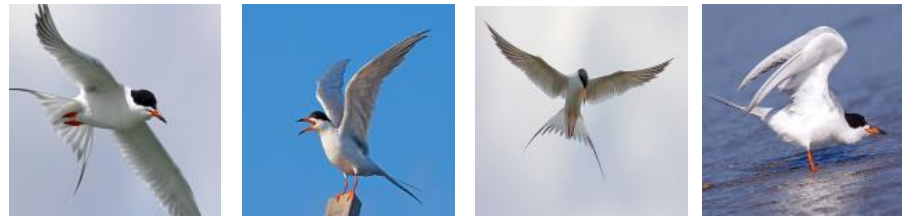


Object segmentation

Caspian_Tern Fine-grained classification



Common_Tern



Fosters_Tern

Some Applications



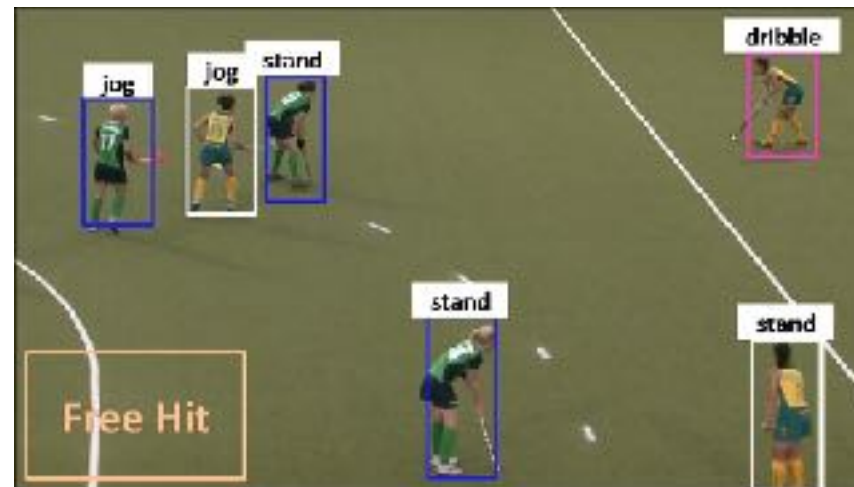
Object segmentation



Fine-grained classification

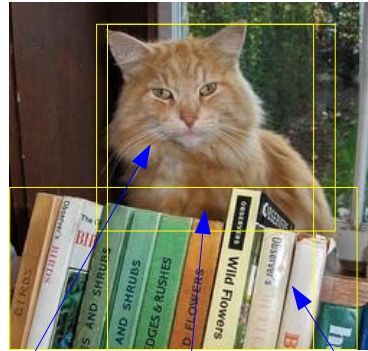


Face recognition



Action recognition

Some Applications



A cat is sitting behind some books

Image caption



Automatic driving



Ballon_Fiesta



Australia_day



Heiva



Chinese_New_Year



Keene_Pumpkin



Sapporo_Snow_Festival

Cultural event recognition

Some Applications



Multimodal Linguistic Regularities

Nearest images



- blue + red =



- blue + yellow =



- yellow + red =



- white + red =



Some Applications



Multimodal Linguistic Regularities

Nearest images



- day + night =



- flying + sailing =



- bowl + box =



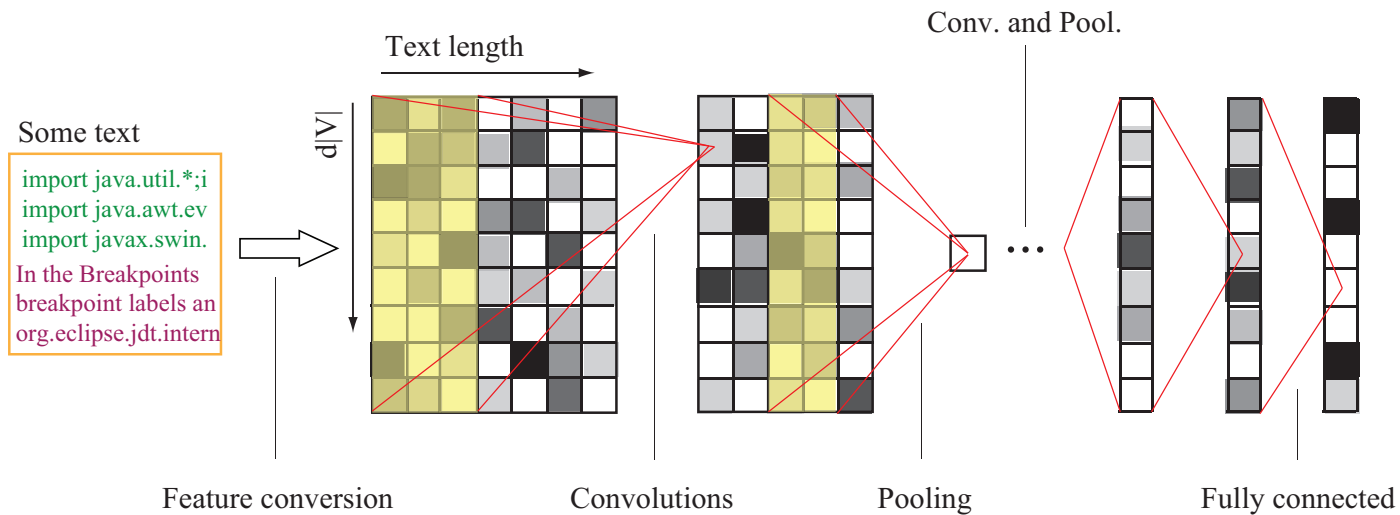
- box + bowl =



Some Applications: NLP



How does CNN apply to NLP?



Effective Use of Word Order for Text Categorization with Convolutional Neural Networks

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RJ Research Consulting
Tarrytown, NY, USA
riejohnson@gmail.com

Tong Zhang
Baidu Inc., Beijing, China
Rutgers University, Piscataway, NJ, USA
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Character-level Convolutional Networks for Text Classification*

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719 Broadway, 12th Floor, New York, NY 10003
{xiang, junbo.zhao, yann}@cs.nyu.edu

Transformation for text



One-hot encoding

“I love it.” \longrightarrow $\mathbf{x} = [00100 | 00001 | 00010]^T$

$V = \{\text{“don’t”, “hate”, “I”, “it”, “love”}\}$

Transformation for text



Seq-CNN for text

“I love it.” \longrightarrow $\mathbf{r}_0(\mathbf{x}) =$

0	don't
0	hate
1	I
0	it
0	love

$\mathbf{r}_1(\mathbf{x}) =$

0	don't
0	hate
0	I
0	it
1	love

$\begin{matrix} 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{matrix} \begin{matrix} \text{don't} \\ \text{hate} \\ \text{I} \\ \text{it} \\ \text{love} \end{matrix}$

$\begin{matrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{matrix} \begin{matrix} \text{don't} \\ \text{hate} \\ \text{I} \\ \text{it} \\ \text{love} \end{matrix}$

$$V = \{\text{“don't”, “hate”, “I”, “it”, “love”}\}$$

Transformation for text



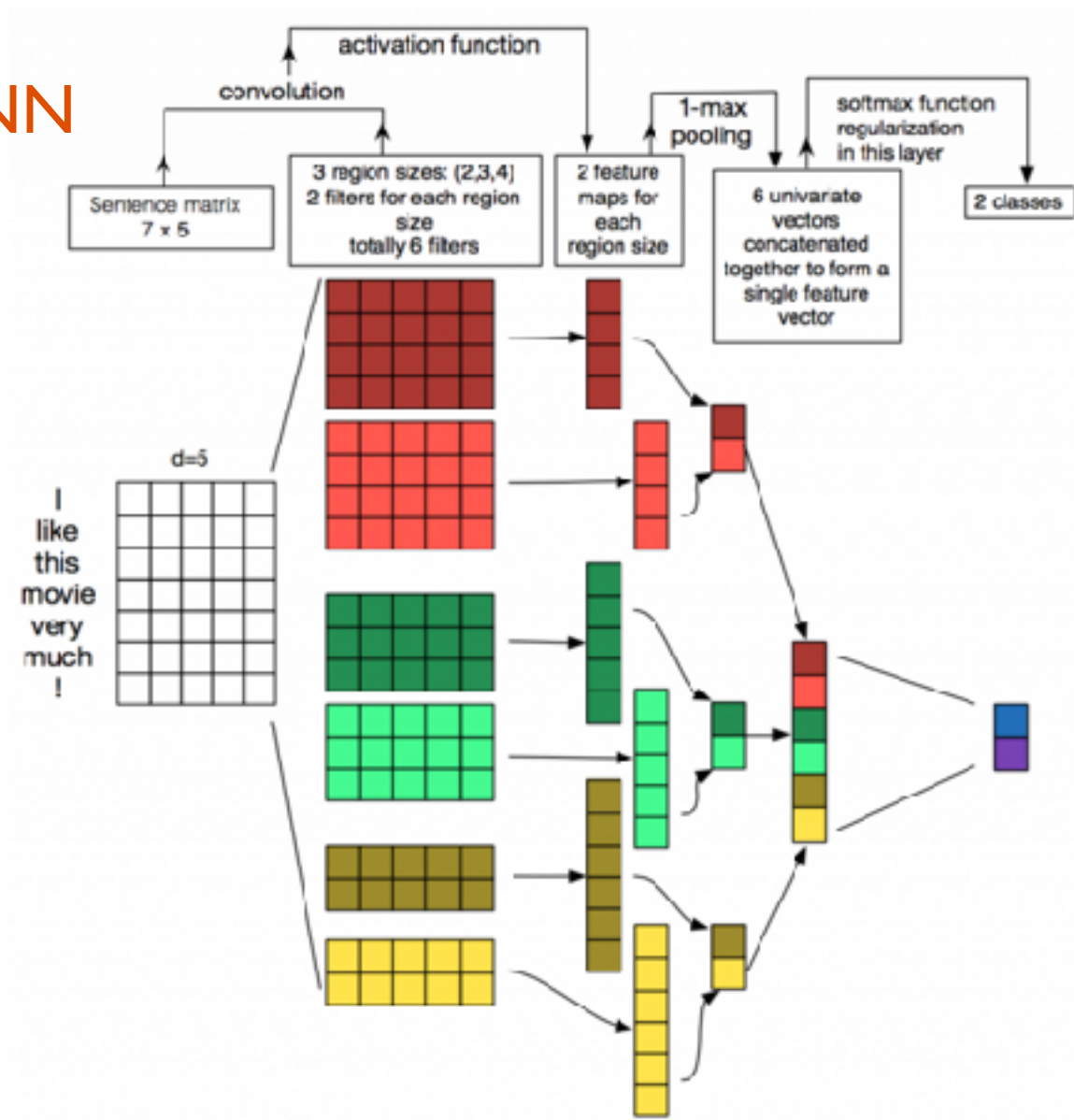
bow-CNN for text

“I love it.” \longrightarrow $\mathbf{r}_0(\mathbf{x}) = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 1 \end{bmatrix} \begin{matrix} \text{don't} \\ \text{hate} \\ \mathbf{I} \\ \text{it} \\ \text{love} \end{matrix}$ $\mathbf{r}_1(\mathbf{x}) = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 1 \end{bmatrix} \begin{matrix} \text{don't} \\ \text{hate} \\ \mathbf{I} \\ \text{it} \\ \text{love} \end{matrix}$

$$V = \{\text{“don't”, “hate”, “I”, “it”, “love”}\}$$

More for text

Shallow-CNN



More for text



Deep-CNN

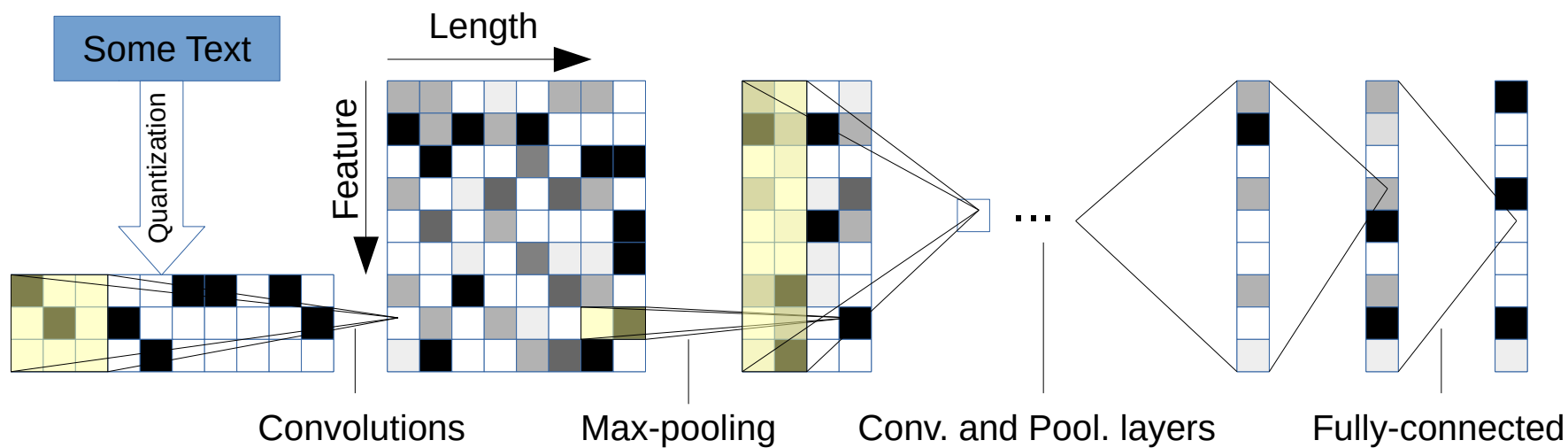


Figure courtesy of [Xiang Zhang et. al, NIPS' 15]