"Deep Learning Lecture"

Lecture 1 : Introduction

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Outline

1. Course Information
2. What is Deep Learning
3. Applications of Deep Learning
4. Future Directions

Course Goals

- Give you an opportunity for you to explore an interesting multivariate analysis problem of your choice in the context of a real-world data set
- How deep learning works
- How to frame tasks into learning problems
- How to use toolkits to implement designed models
- When and why specific deep learning techniques work for specific problems

Course Prerequisites

- Calculus and Linear Algebra
- Probability and Statistics
- Machine Learning
- Advanced programming language (like Python and C)
- Time and patience

Course Overview

1. Introduction
2. Mathematical Basics
3. Feedforward Network
4. Convolutional Neural Network
5. Recurrent Neural Network
6. Regularization and Optimization
7. Deep Generative Models
8. Reinforcement Learning
9. Attention and Memory
10. RBM, DBN and DBM
11. Graphical Model
12. DL Application
13. Project Presentation

Course Logistics

- Course: Theory (3 hours per week) + Course project
- The location of course room: 教1-101
- Final grade = 50% from the group project + 50% from the final exam
- The group project contains a technical report and project presentation
- The project presentation is decided by random sampling due to time limit
- Each team is composed of 5-10 members

Course Logistics

- We strongly encourage students to form study groups. Students may discuss and work on project problems in groups.

- However, each student must write down the solutions independently, and without referring to written notes from the joint session. In other words, each student must understand the solution well enough in order to reconstruct it by him/herself.

- In addition, each student should write on the problem set the bunch of people with whom s/he collaborated.

Course Logistics

Projects will be evaluated based on:

1. The technical quality of the work. (I.e., Does the technical material make sense? Are the things tried reasonable? Are the proposed algorithms or applications clever and interesting? Do the authors convey novel insight about the problem and/or algorithms?)

2. The completeness and novelty of the work, and the clarity of the write-up. (Spare enough time for the write-up since it may be harder than you imagine)

Course Logistics

Your final report is expected to be a 4~8 page report. You should submit both an electronic and a hardcopy version for your final report. It should roughly have the following format:

- Introduction - Motivation
- Problem definition
- Proposed method
  - Intuition - why should it be better than other methods?
  - Description of its algorithms
- Experiments
  - Description of your testbed; list of questions your experiments are designed to answer
  - Details of the experiments; observations
- Conclusions

Course Logistics

- Write final reports in the form of CVPR papers: http://cvpr2017.thecvf.com/submission/main_conference/author_guidelines (using Latex, which is very useful for your writing papers in later research life)
- Provide corresponding codes, and a “readme.txt” file to illustrate how to run the codes

People

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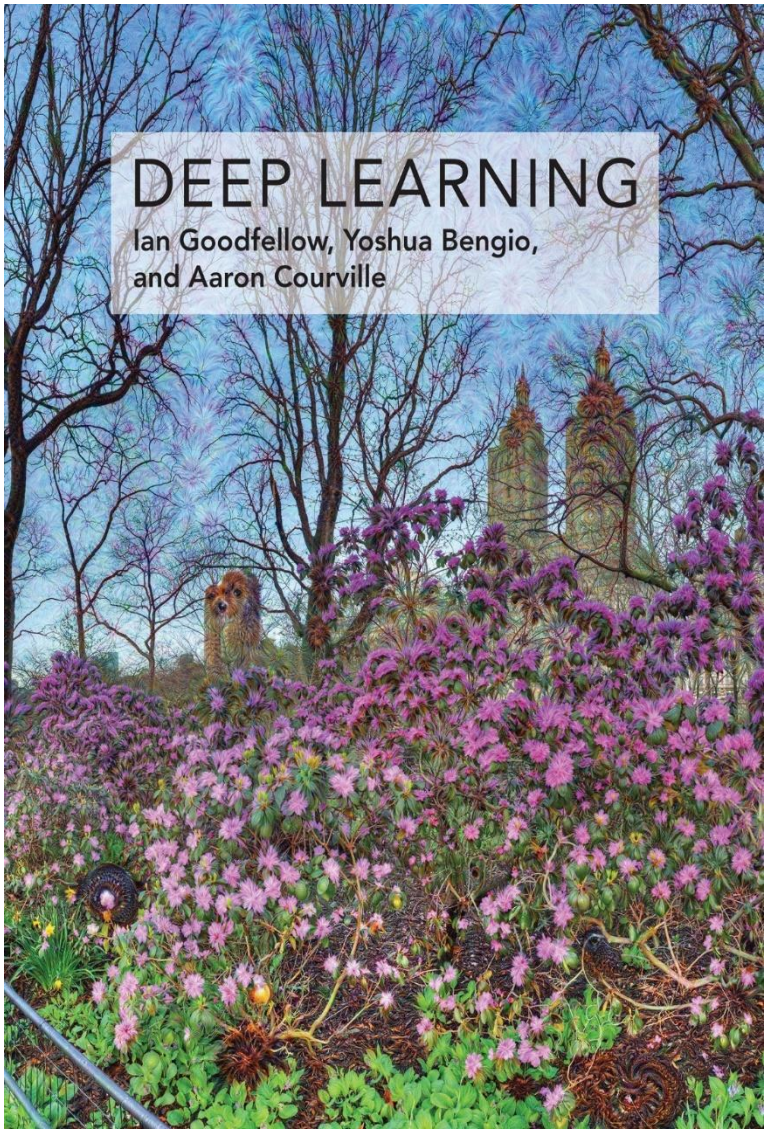
Homepage: http://www.cripac.ia.ac.cn/CN/column/column149.shtml

Our Group

Email： multimodal_comp@126.com

Reference book

- http://www.deeplearningbook.org/lecture_slides.html
- https://github.com/goodfeli/dlbook_exercises



Some Resources: Programming

- http://scikit-learn.org/stable/ (Scikit Learn: a Python library for machine learning)
- http://ubcmatlabguide.github.io/ (YAGTOM： Yet Another Guide TO Matlab)
- https://github.com/saitjr/C-Toturials (Learning C)

Some Resources: Deep Learning Tools

Name	Language	Link	Note
Pylearn2	Python	http://deeplearning.net/software/pylearn2/	A machine learning library built on Theano
Theano	Python	http://deeplearning.net/software/theano/	A python deep learning library
Caffe	C++	http://caffe.berkeleyvision.org/	A deep learning framework by Berkeley
Torch	Lua	http://torch.ch/	An open source machine learning framework
Overfeat	Lua	http://cilvr.nyu.edu/doku.php?id=code:start	A convolutional network image processor
Deeplearning4j	Java	http://deeplearning4j.org/	A commercial grade deep learning library
Word2vec	**C**	**https://code.google.com/p/word2vec/**	**Word embedding framework**
GloVe	C	http://nlp.stanford.edu/projects/glove/	Word embedding framework
Doc2vec	C	https://radimrehurek.com/gensim/models/doc2vec.html	Language model for paragraphs and documents
StanfordNLP	**Java**	**http://nlp.stanford.edu/**	**A deep learning-based NLP package**
TensorFlow	**Python**	**http://www.tensorflow.org**	**A deep learning based python library**

Some Resources: Conferences

A very good project will comprise a publishable or nearly-publishable piece of work. So, for inspiration, you might also look at some recent machine learning and artificial intelligence research papers.

Main machine learning and artificial intelligence conferences are ICML, NIPS, CVPR, AAAI and IJCAI. You can find papers from the following websites:

https://icml.cc/Conferences/2017/Schedule (ICML17)
https://nips.cc/Conferences/2017/Schedule (NIPS17)
http://openaccess.thecvf.com/CVPR2017.py (CVPR17)
https://www.aaai.org/Library/AAAI/aaai17contents.php (AAAI17)
https://ijcai-17.org/accepted-papers.html (IJCAI17)

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Deep Learning

Artificial Intelligence

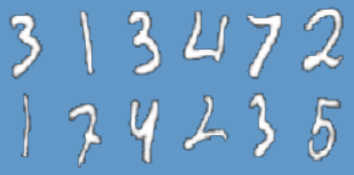
Any technique that enables computers to mimic human behavior

Machine Learning

Ability to learn without explicitly being programmed

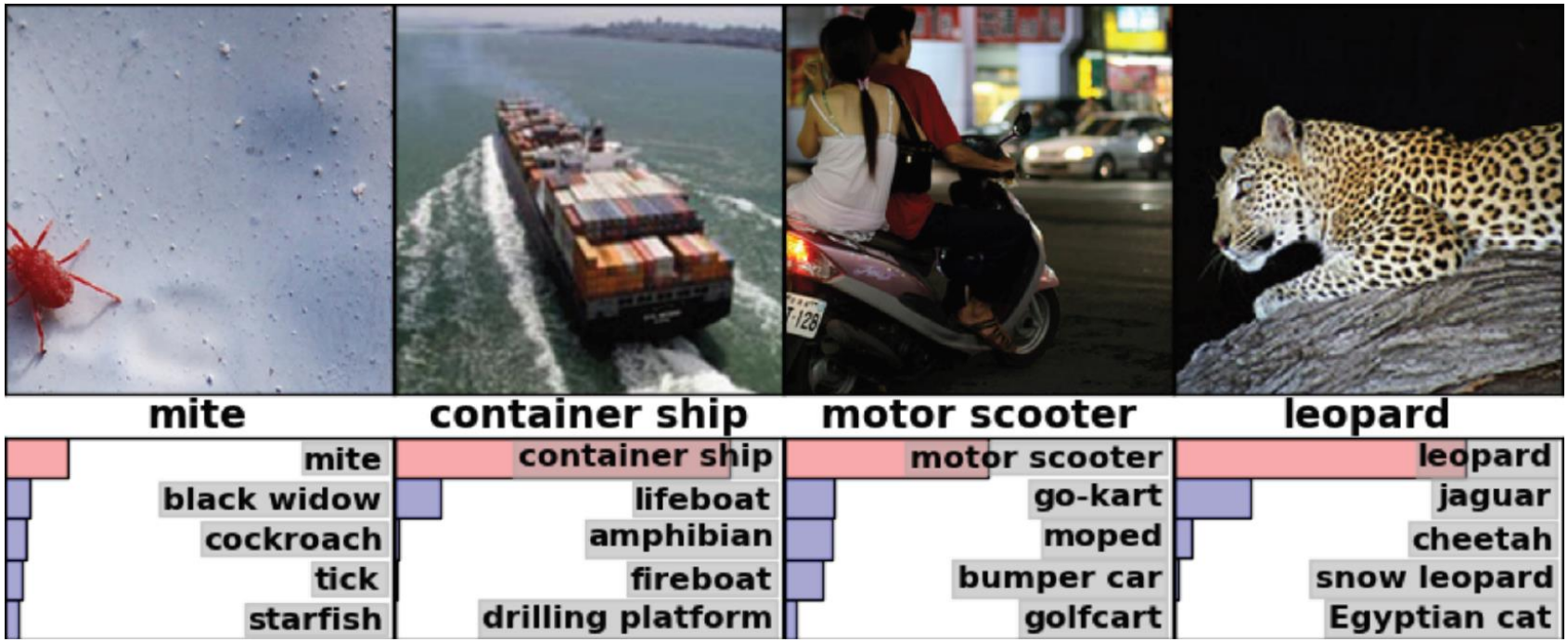
Deep Learning

Learn underlying features in data using neural networks



Deep Learning Success for Vision

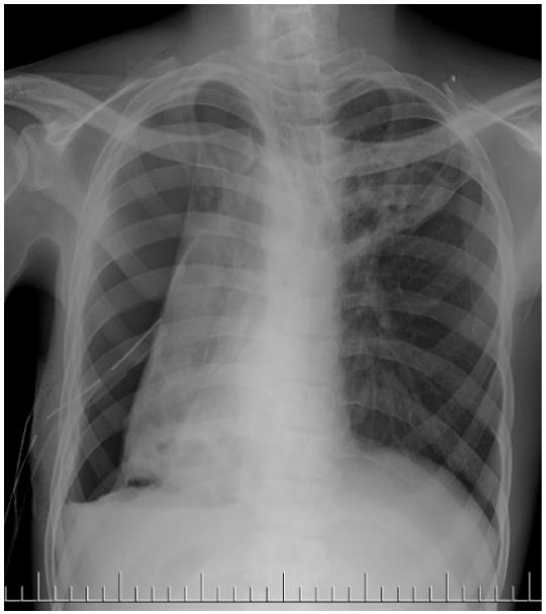
Image Recognition

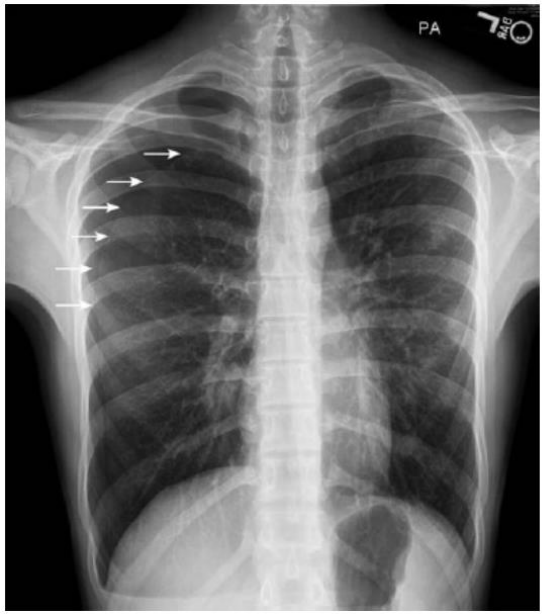


Deep Learning Success for Vision

Detect pneumothorax in real X-Ray scans

检测病灶





Deep Learning Success for Audio

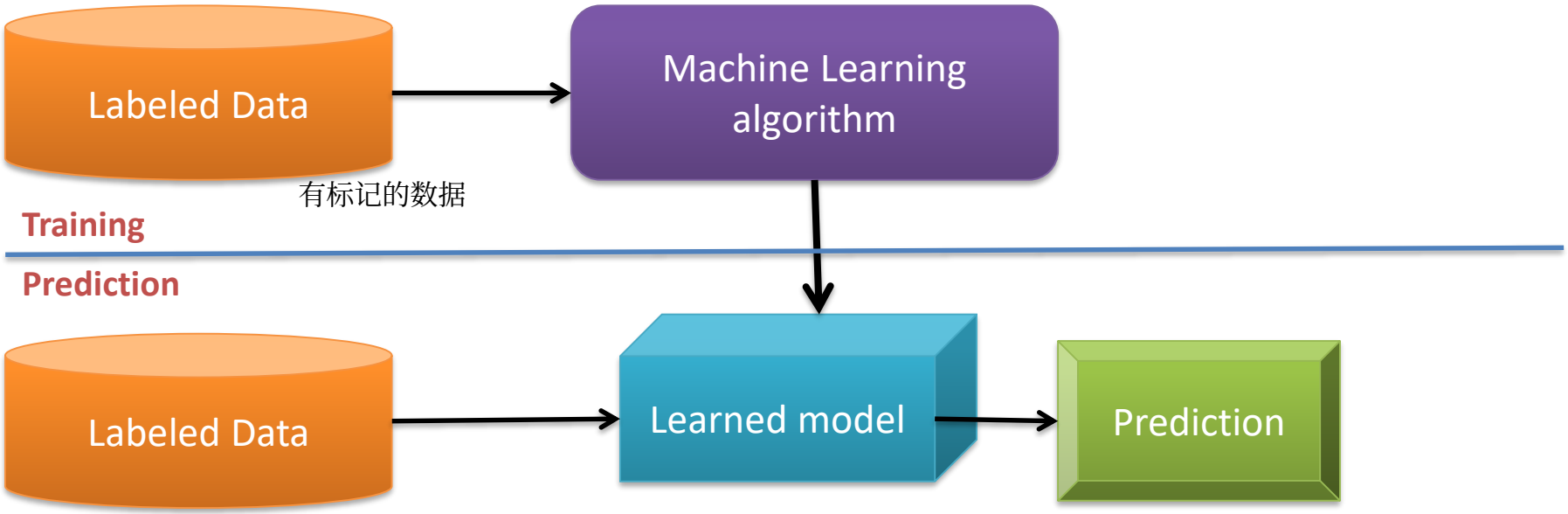
Music Generation

Deep Learning Success

So many more …

Machine Learning Basics

Machine learning is a field of computer science that gives computers the ability to **learn without being explicitly programmed**



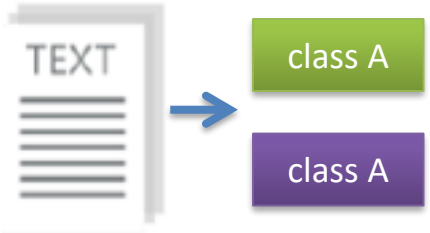
Methods that can learn from and make predictions on data

Types of Learning

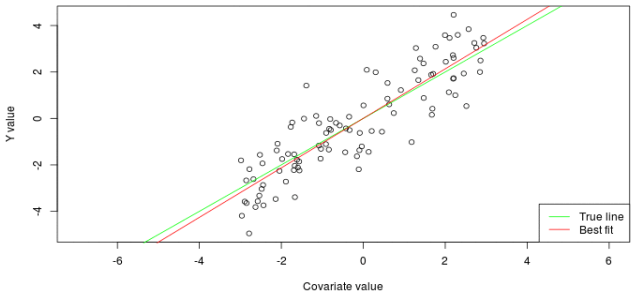
Supervised: Learning with a **labeled training** set
Example: email *classification* with already labeled emails

Unsupervised: Discover **patterns** in **unlabeled** data
Example: *cluster* similar documents based on text

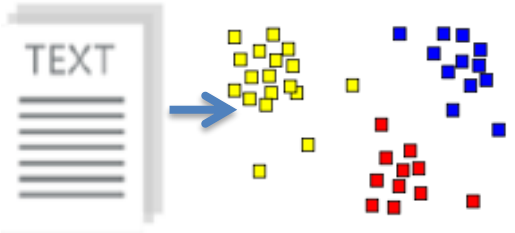
Reinforcement learning: learn to **act** based on **feedback/reward**
Example: learn to play Go, reward: *win or lose*



Classification



Regression

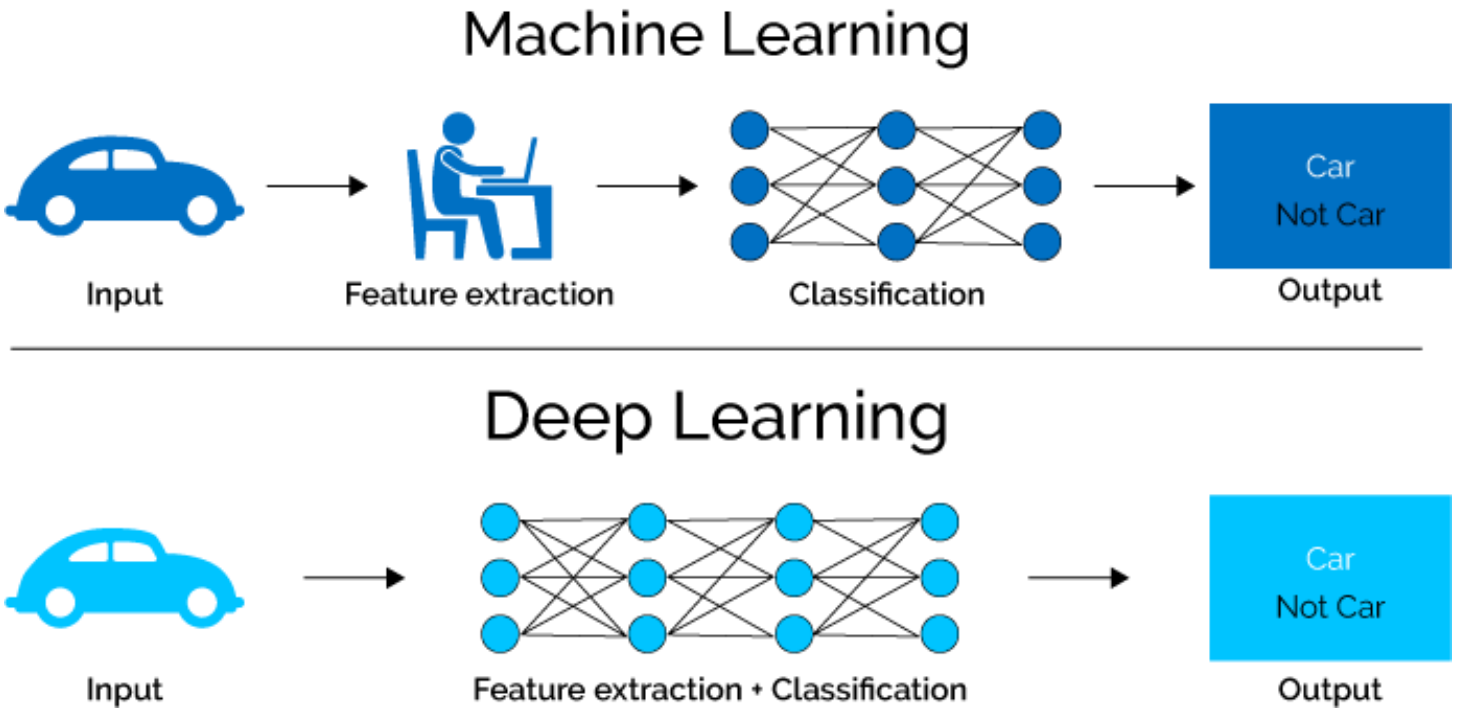


Clustering

Anomaly Detection 异常检测
Sequence labeling
…

ML vs. Deep Learning

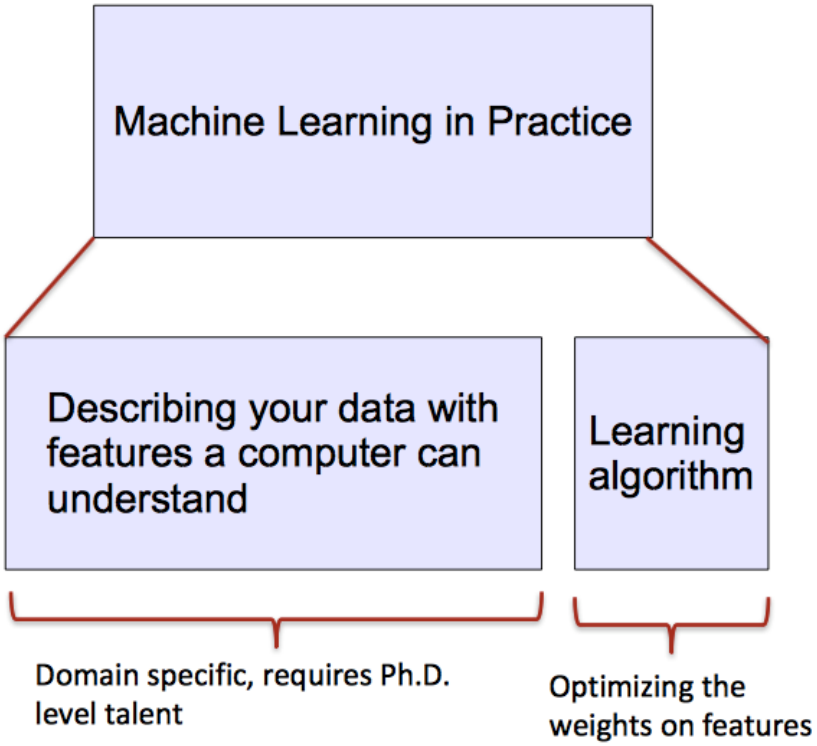
A machine learning subfield of learning **representations** of data.
Exceptional effective at **learning patterns**.
Deep learning algorithms attempt to learn (multiple levels of) representation by using a **hierarchy of multiple layers**
If you provide the system **tons of information**, it begins to understand it and respond in useful ways.



ML vs. Deep Learning

Most machine learning methods work well because of **human-designed representations** and **input features**

ML becomes just **optimizing weights** to best make a final prediction



Feature	NER
Current Word	✓
Previous Word	✓
Next Word	✓
Current Word Character n-gram	all
Current POS Tag	✓
Surrounding POS Tag Sequence	✓
Current Word Shape	✓
Surrounding Word Shape Sequence	✓
Presence of Word in Left Window	size 4
Presence of Word in Right Window	size 4

Deep Learning Today

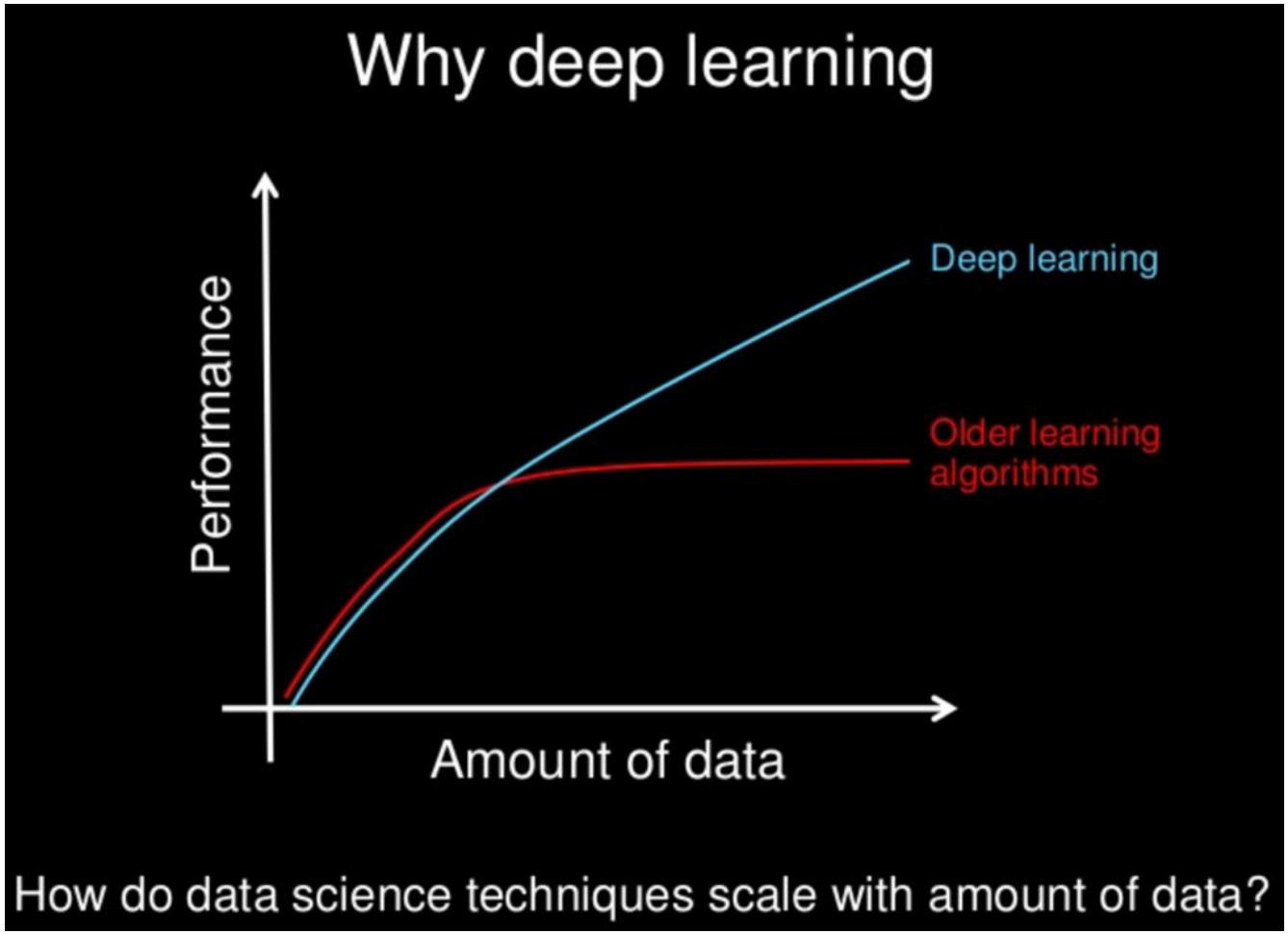
- Advancement in speech recognition in the last 2 years
  - A few long-standing performance records were broken with deep learning methods
  - Microsoft and Google have both deployed DL-based speech recognition systems in their products
- Advancement in Computer Vision
  - Feature engineering is the bread-and-butter of a large portion of the CV community, which creates some resistance to feature learning
  - But the record holders on ImageNet and Semantic Segmentation are convolutional nets
- Advancement in Natural Language Processing
  - Fine-grained sentiment analysis, syntactic parsing
  - Language model, machine translation, question answering

Deep Learning Today

In "Nature" 27 January 2016:

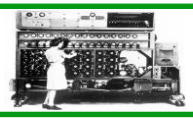
- "DeepMind's program AlphaGo beat Fan Hui, the European Go champion, five times out of five in tournament conditions..."
- "AlphaGo was not preprogrammed to play Go: rather, it learned using a general-purpose algorithm that allowed it to interpret the game's patterns."
- "...AlphaGo program applied **deep learning** in neural networks (convolutional NN) — brain-inspired programs in which connections between layers of simulated neurons are strengthened through examples and experience."

Why is Deep Learning Important



Deep Learning is finally enabling us to cross that line in places we weren't able to before.

Big Year for AI

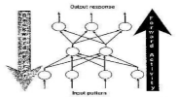


1936:**Turing Machine from Alan Turing**

1946: **Birth of ENIAC**

1956: Birth of AI

1966: **Turing Award**

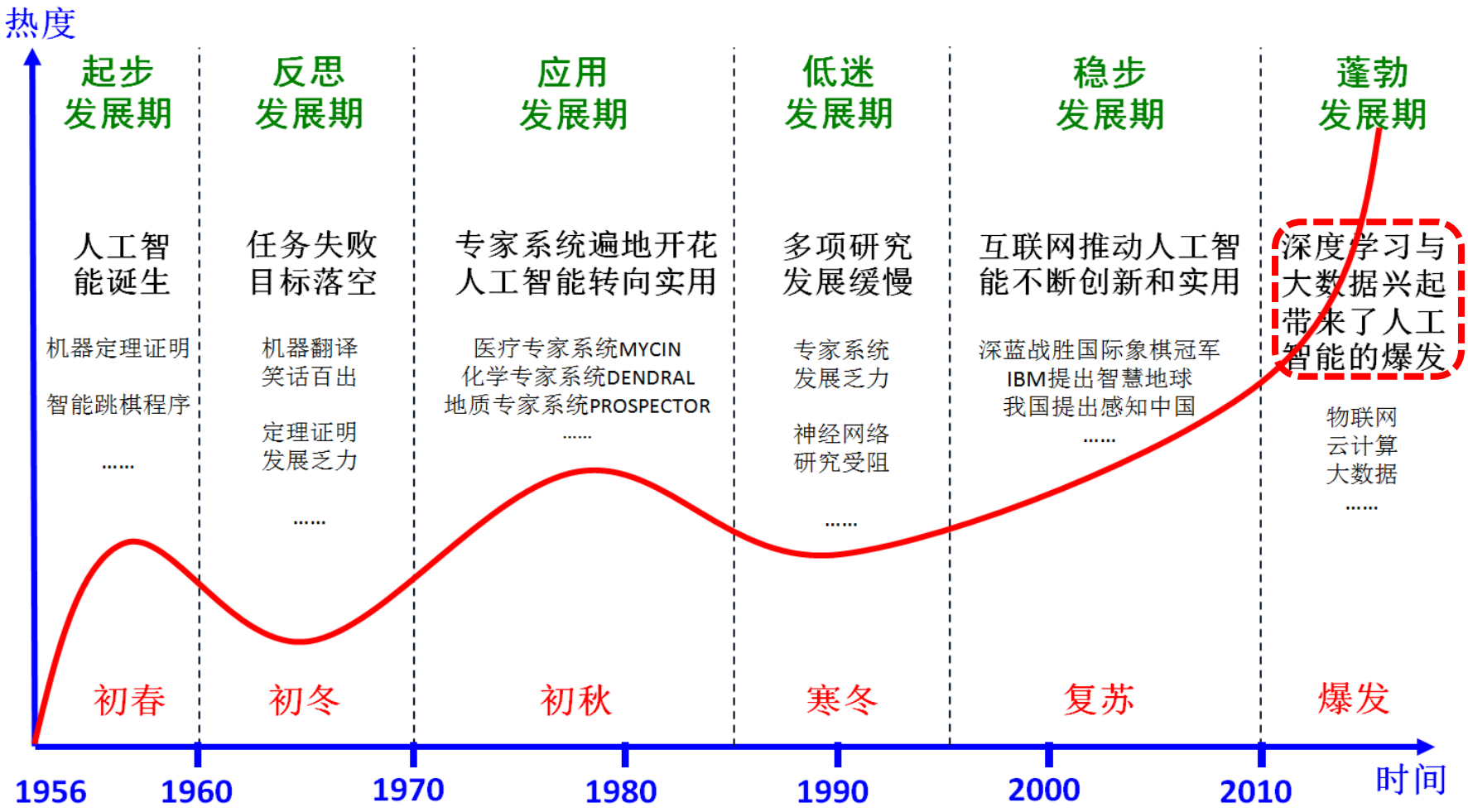


1986: **The BP Algorithm**

2006: **DNN, Deep Learning**

AlphaGo **2016: AlphaGo**

The History of AI



Deep Neural Networks (DNN)

- **Originate from**:
  - 1962 – simple/complex cell, *Hubel and Wiesel*
  - 1970 – efficient error backpropagation, *Linnainmaa*
  - 1979 – deep neocognitron, convolution, *Fukushima*
  - 1987 – autoencoder, *Ballard*
  - 1989 – convolutional neural networks (CNN), *Lecun*
  - 1991 – deep recurrent neural networks (RNN), *Schmidhuber*
  - 1997 – long short-term memory (LSTM), *Schmidhuber*
- **Two drawbacks:**

Large numbers of parameters → High computational cost

Small training set → Over-fitting problem

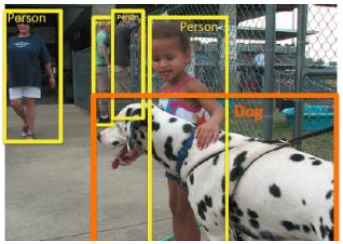
Two Recent Developments

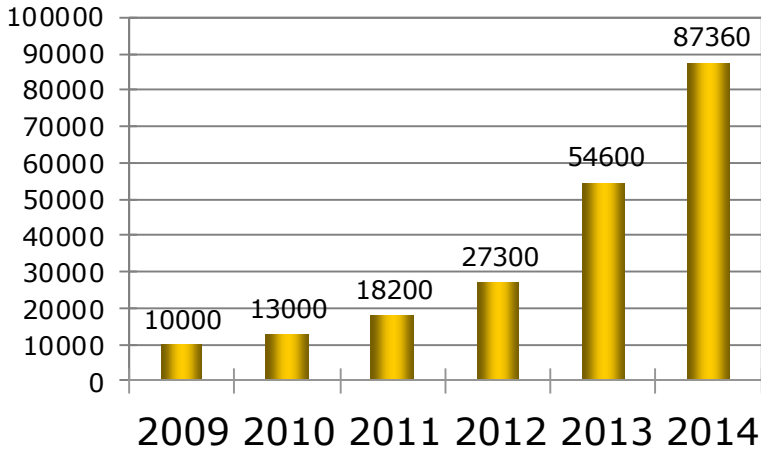
Big Data

IMAGENET Large Scale Visual Recognition Challenge (ILSVRC) 2010-2013

~~20 object classes~~ ~~22,591 images~~

200 object classes	456,191 images	DET (NEW)
1000 object classes	1,431,167 images	CLS-LOC





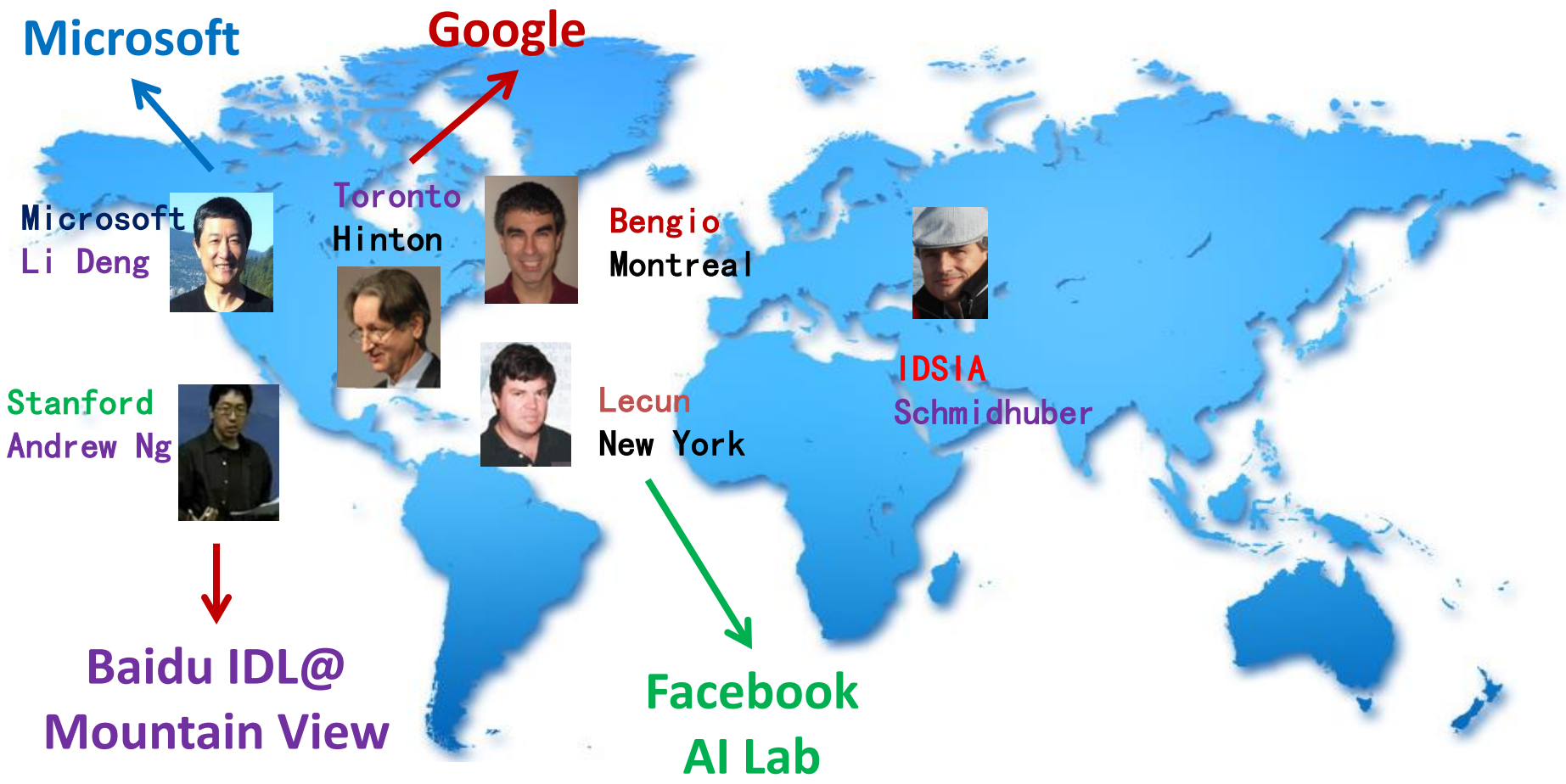
Video surveillance data size (PB)

Cheap Computation

Features	Tesla K40	Tesla K20X	Tesla K20
Number and Type of GPU	1 Kepler GK110B	1 Kepler GK110	
Peak double precision floating point performance	1.43 Tflops	1.31 Tflops	1.17 Tflops
Peak single precision floating point performance	4.29 Tflops	3.95 Tflops	3.52 Tflops
Memory bandwidth (ECC off)	288 GB/sec	250 GB/sec	208 GB/sec
Memory size (GDDR5)	12 GB	6 GB	5 GB
CUDA cores	2880	2688	2496

DNN can thus be fitted efficiently

Deep Learning Pioneers (2006-)



They lead deep learning through three major stages!

Deep Learning： The Resurgence of DNN

Breakthrough in 2006

Reducing the Dimensionality of Data with Neural Networks

G. E. Hinton* and R. R. Salakhutdinov

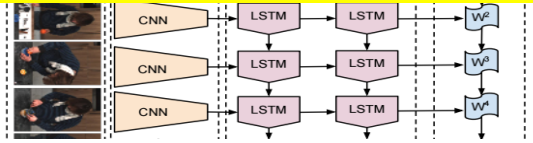
High-dimensional data can be converted to low-dimensional codes by training a multilayer neural network with a small central layer to reconstruct high-dimensional input vectors. Gradient descent can be used for fine-tuning the weights in such "autoencoder" networks, but this works well only if the initial weights are close to a good solution. We describe an effective way of initializing the weights that allows deep autoencoder networks to learn low-dimensional codes that work much better than principal components analysis as a tool to reduce the dimensionality of data.

Dimensionality reduction facilitates the classification, visualization, communication, and storage of high-dimensional data. A simple and widely used method is principal components analysis (PCA), which finds the directions of greatest variance in the data set and represents each data point by its coordinates along each of these directions. We describe a nonlinear generalization of PCA that uses an adaptive, multilayer "encoder" network

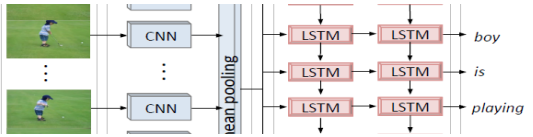
2006 VOL 313 SCIENCE www.sciencemag.org

ImageNet: 74% vs. 85%

RNN for sequence analysis



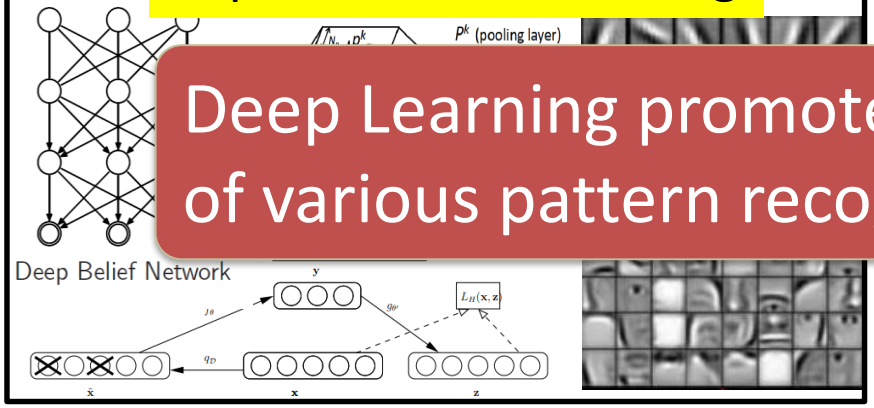
Activity recognition, CVPR2015



Video caption, CVPR2015

2006 2012 2015

Representation learning

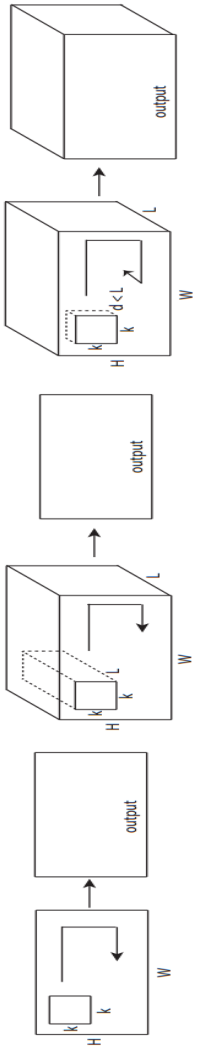


CNN for visual tasks

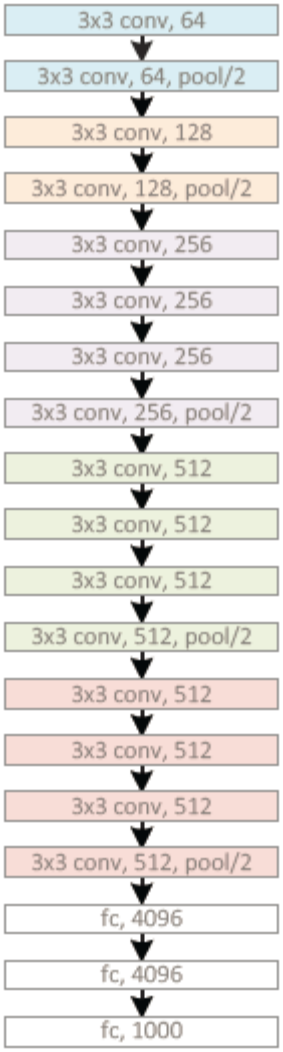
RCNN for detection, CVPR2014

Deep Learning promotes the fast development of various pattern recognition areas

Deep Neural Networks

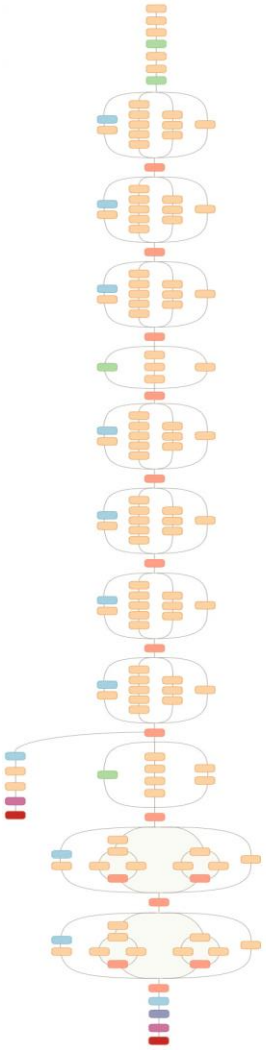


C3D

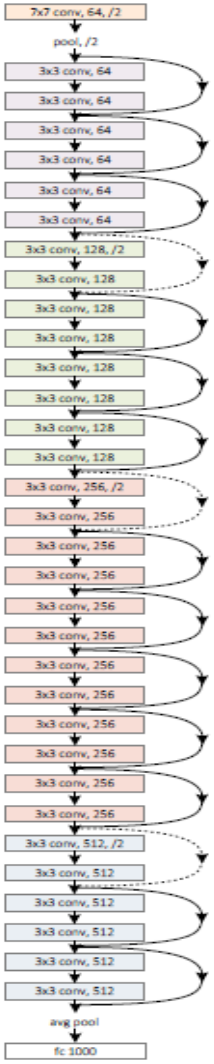


VGG-19

GoogleNet



Inception-3



Residual

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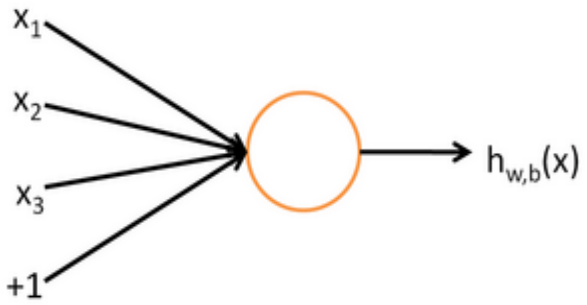
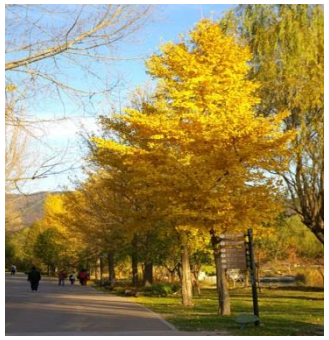
DNN: Full Connection

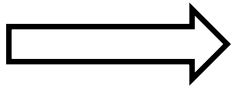
- **Each unit fully connects to all previous units**

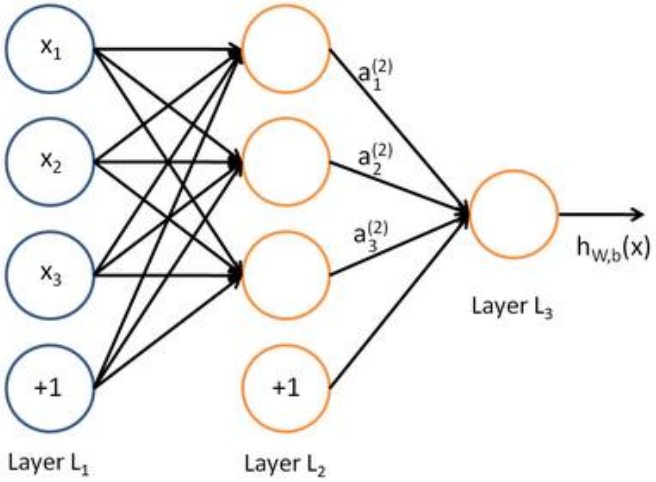


$$h_{W,b}(x) = f(W^T x) = f(\sum_{i=1}^{3} W_i x_i + b)$$



High-dimensional input



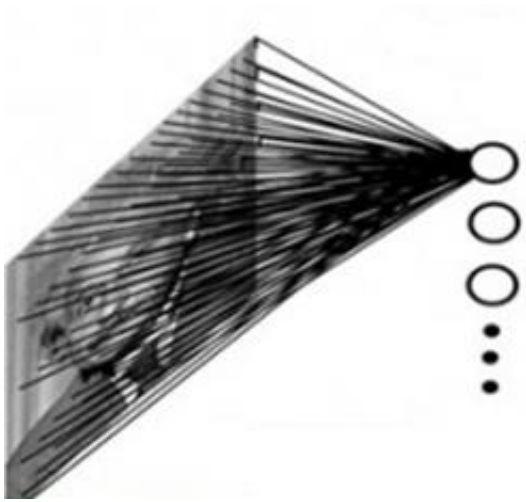


Large numbers of network parameters

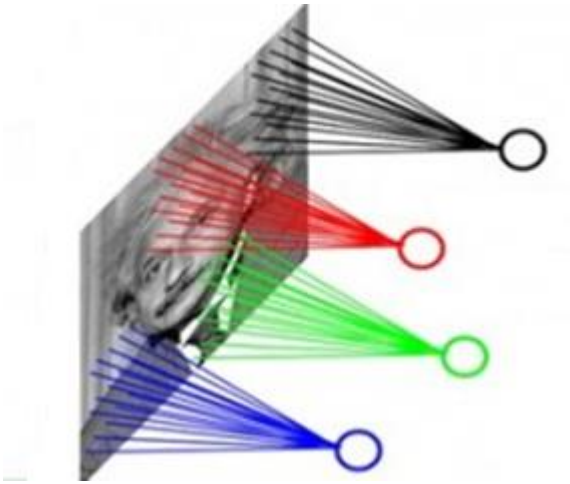
CNN: Local Connection

http://blog.csdn.net/stdcoutzyx/article/details/41596663

- **Local receptive field, biologically-plausible**



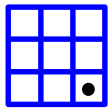
Full connection



Local connection

- **Image filtering**

$*$

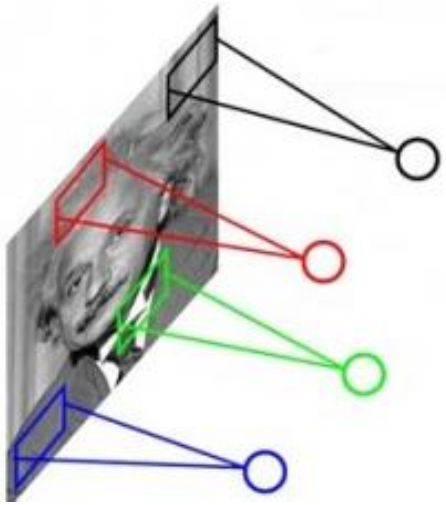


w_9

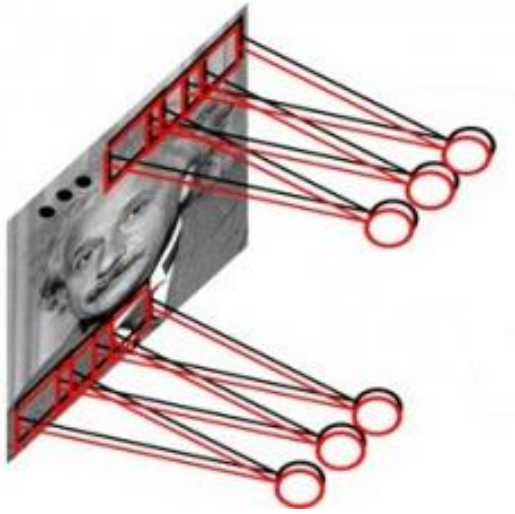
$$\Longrightarrow \quad y = p_1 w_1 + \cdots + p_9 w_9$$

CNN: Weight Sharing

- **All local regions share the same filter weights**

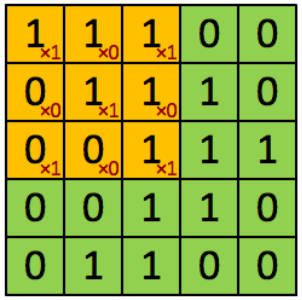


Local connection

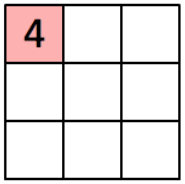


Weight sharing

- **Image convolution**



Image

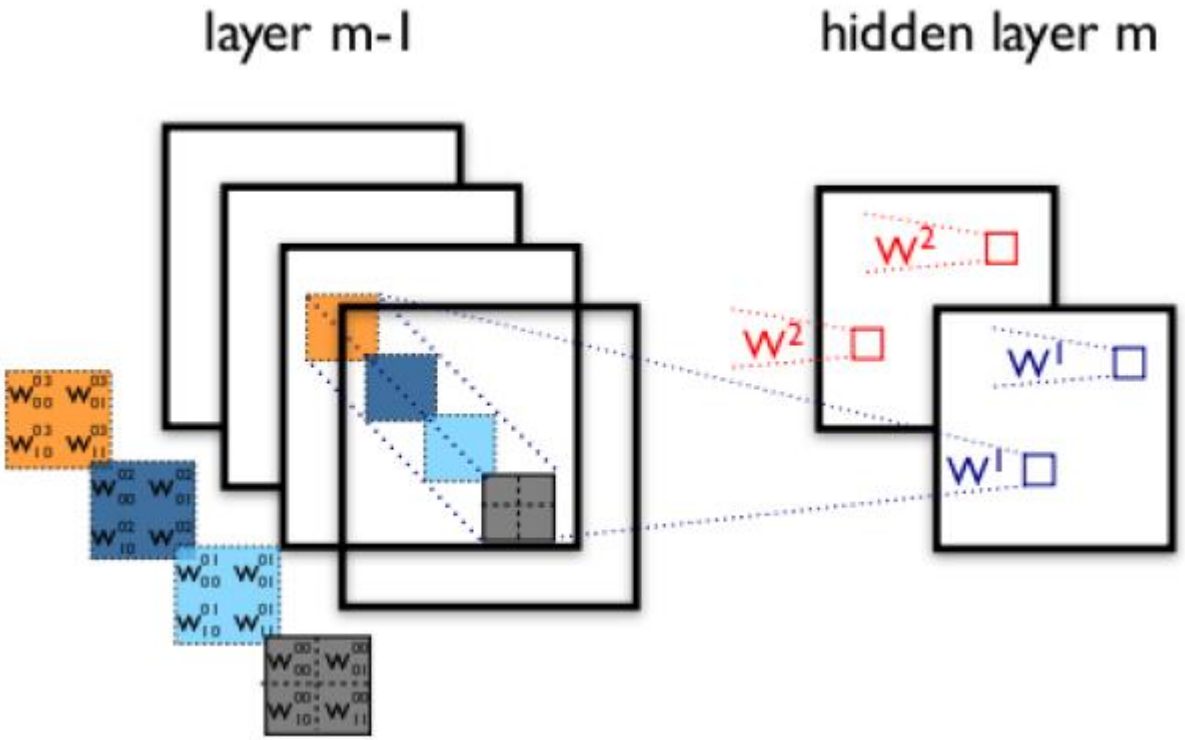


Convolved Feature

$$h_{ij}^{k} = \tanh((W^{k} * x)_{ij} + b_k)$$

CNN: Multiple Filters

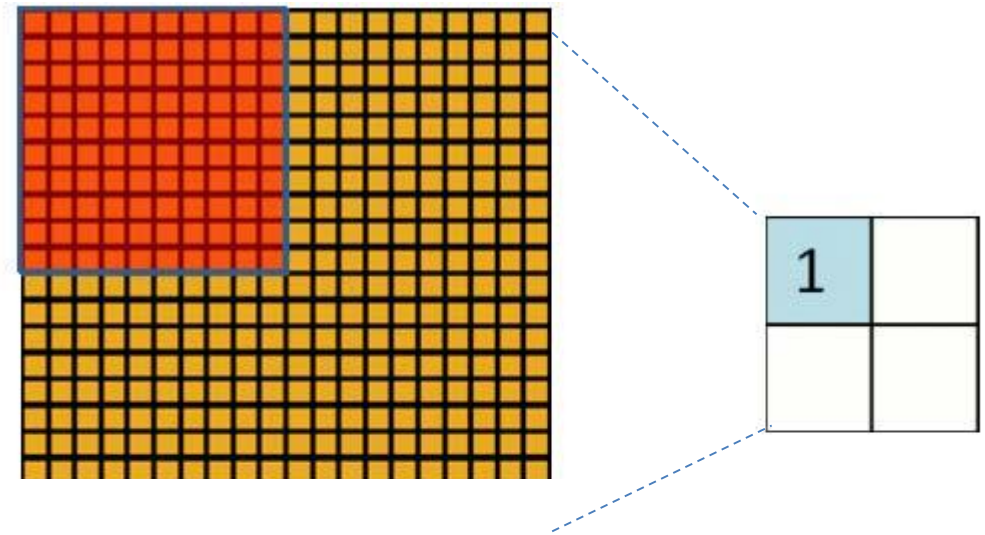
- **Use N different filters obtain N feature maps**



w_1: weights of the 1^{st} filter, w_2: weights of the 2^{nd} filter

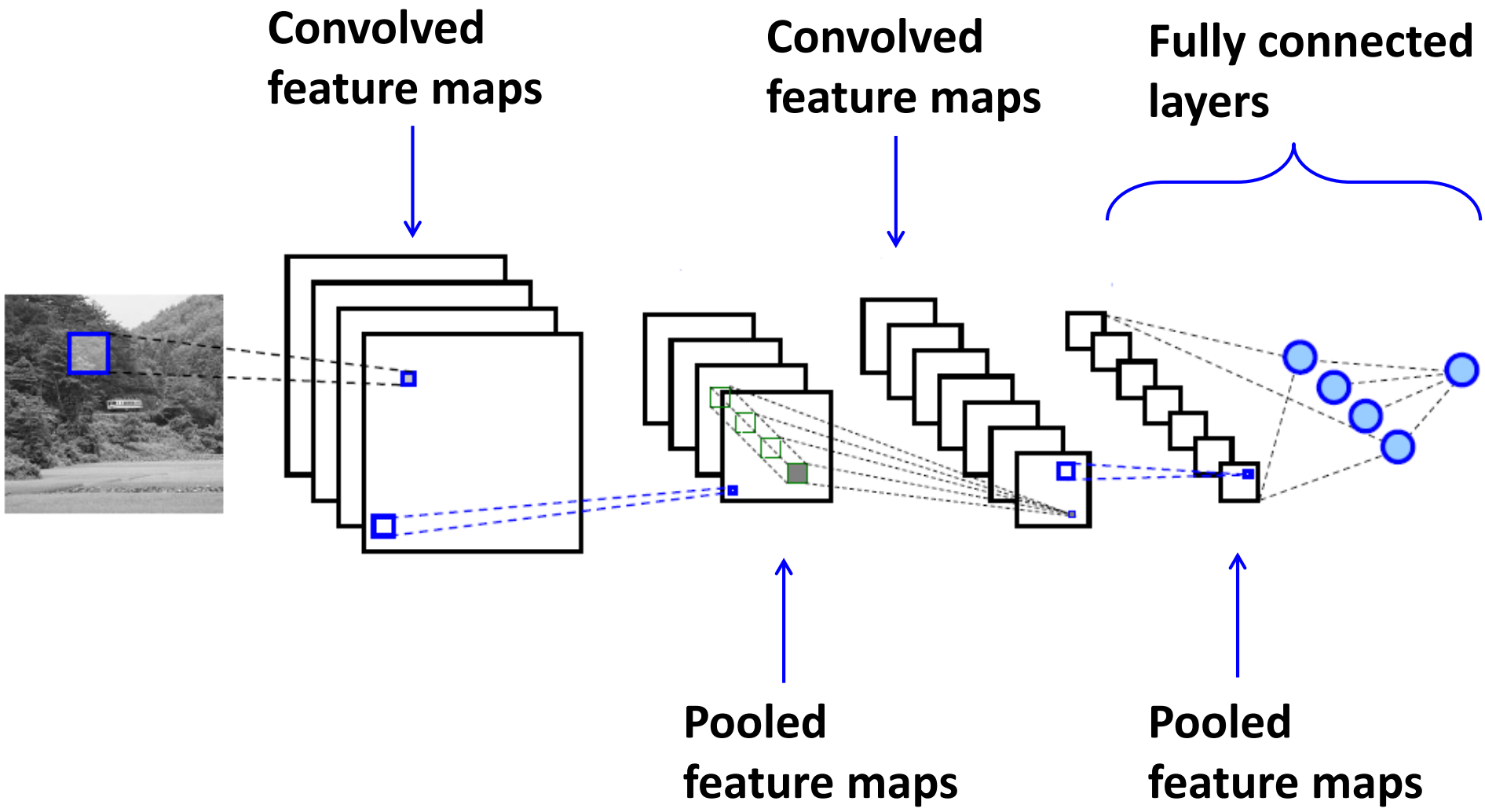
CNN: Pooling

- **Be invariant to image shifting using max (or average) pooling**

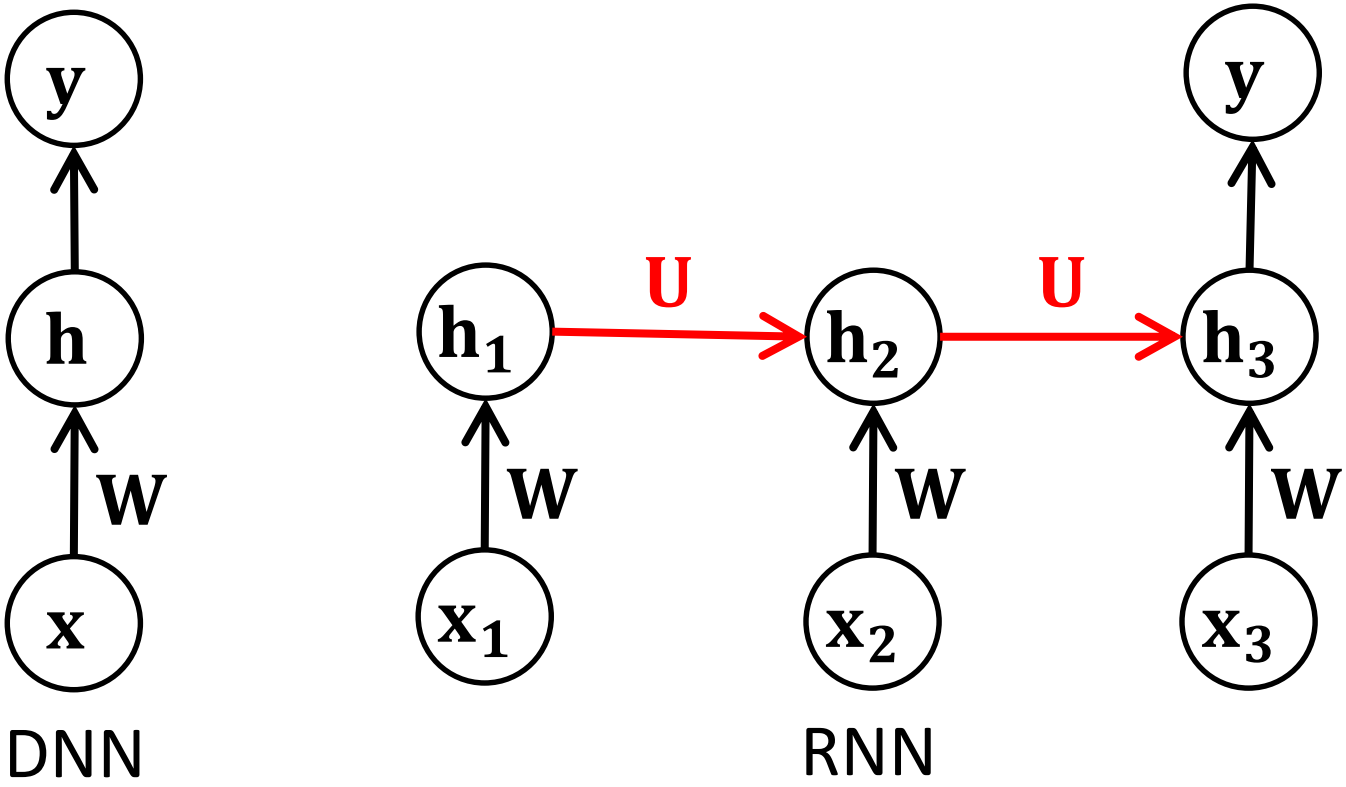


Convolved feature Pooled feature

The Whole Architecture



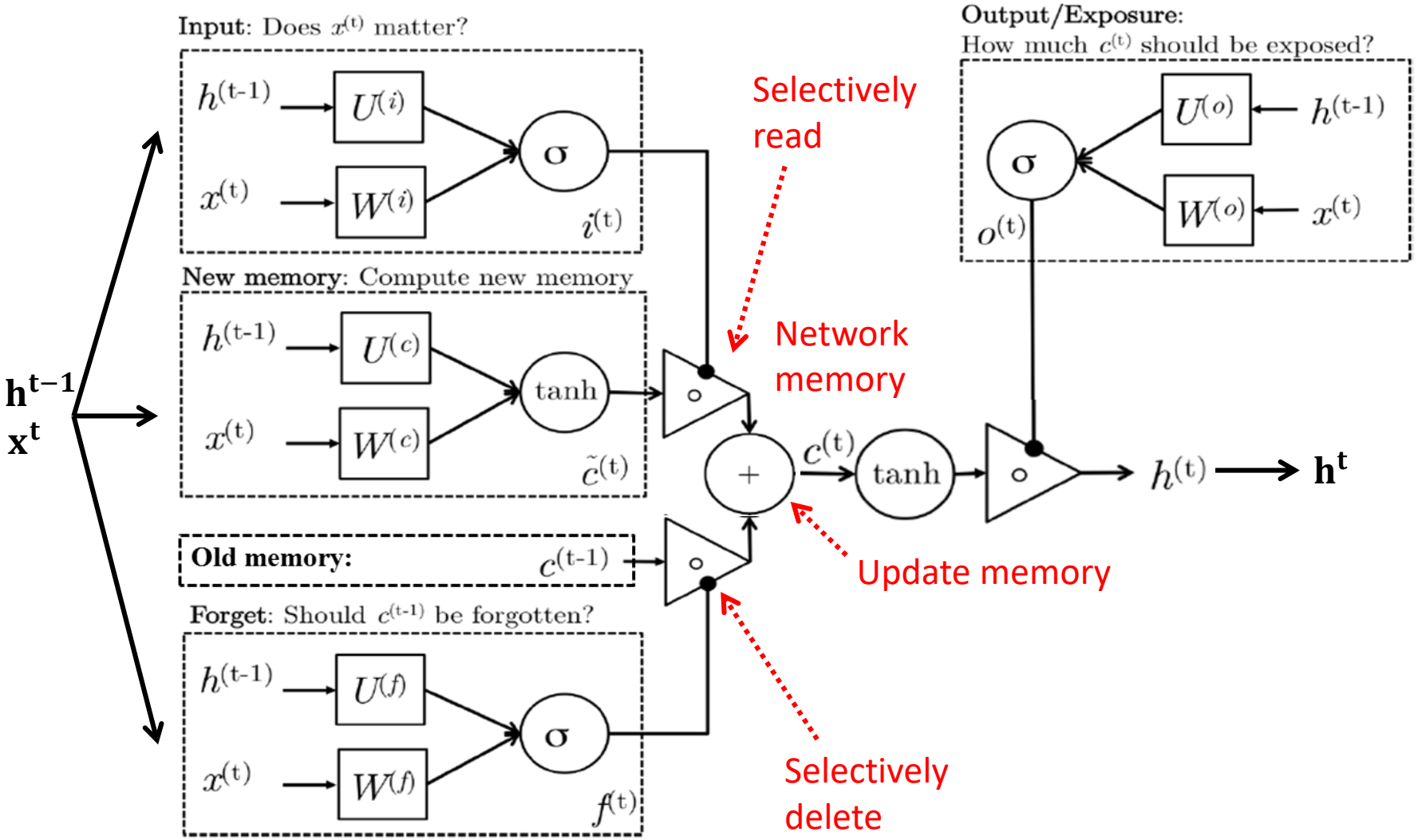
RNN



- $\mathbf{x_t} \in \mathbb{R}^d, \mathbf{h_t} \in \mathbb{R}^n, \mathbf{W} \in \mathbb{R}^{d \times n}, \mathbf{U} \in \mathbb{R}^{n \times n}$
- $\mathbf{h}_t$

RNN aim to model long-range contextual information in forward direction

LSTM



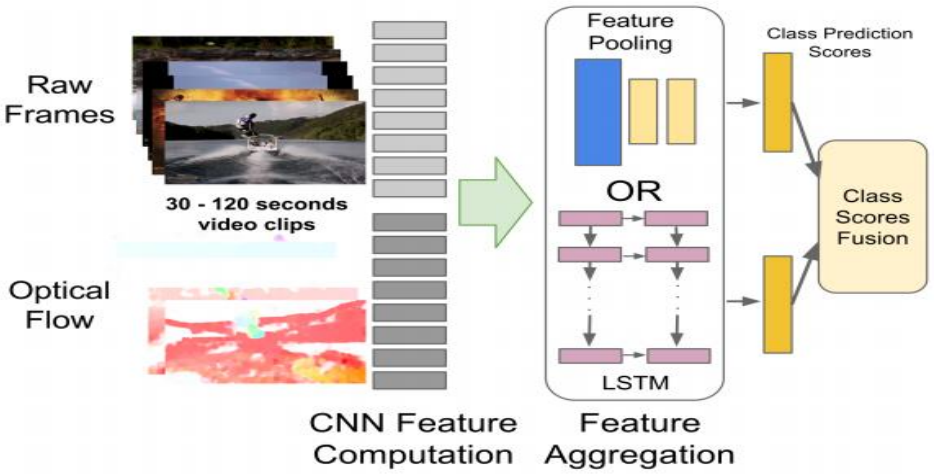
[Hochreiter and Schmidhuber, Neural computation1997]

Outline

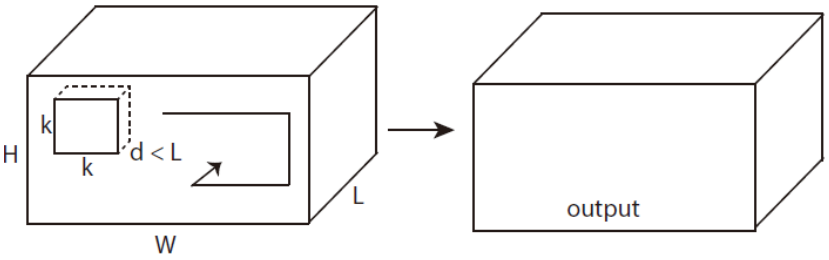
1. Course Information
2. What is Deep Learning
3. Applications of Deep Learning
4. Future Directions

Application for Video Classification

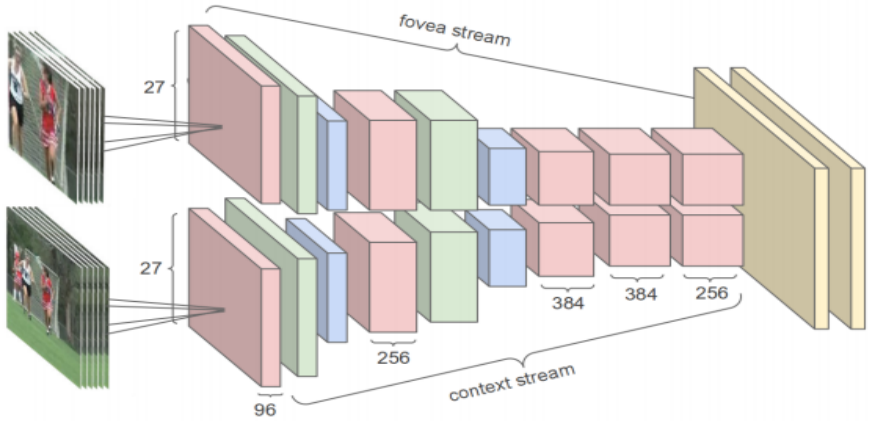
CNN: convolutional neural networks; RNN: recurrent neural networks



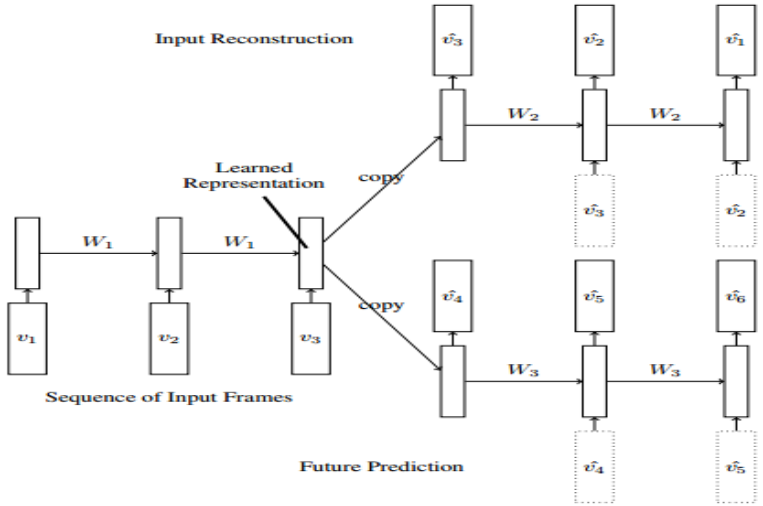
Long-range Videos Modelling, CVPR2015



3D Convolution, ICCV2015



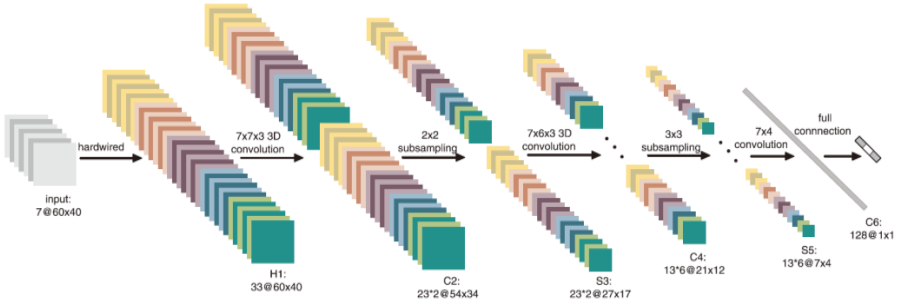
Multi-resolution CNN, CVPR2014



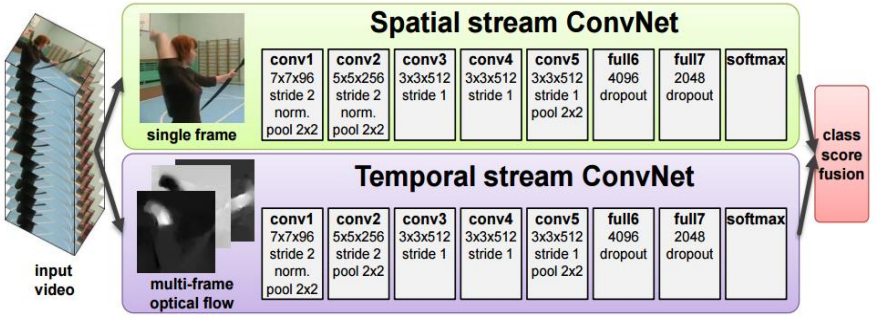
Autoencoder-RNN, ICML2015

Application for Action Recognition

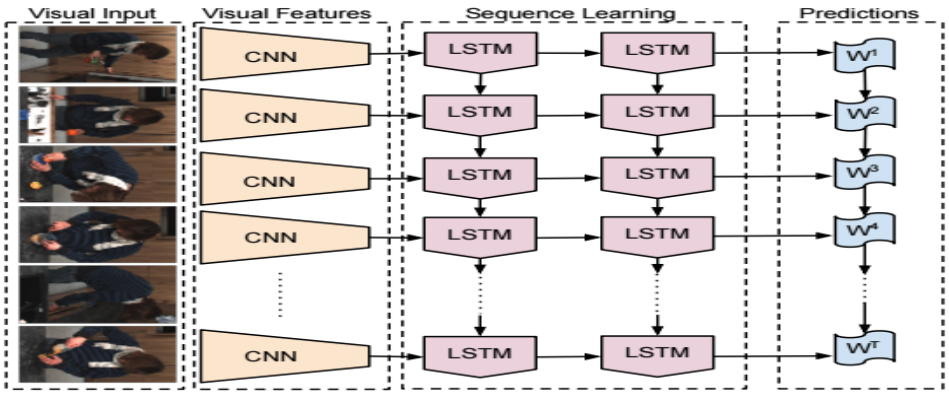
CNN: convolutional neural networks; LSTM: long short term memory; RNN: recurrent neural networks



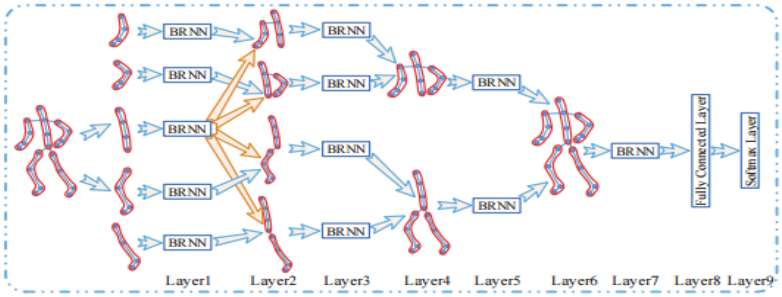
3D CNN, ICML2010



Two-stream CNN, NIPS2014



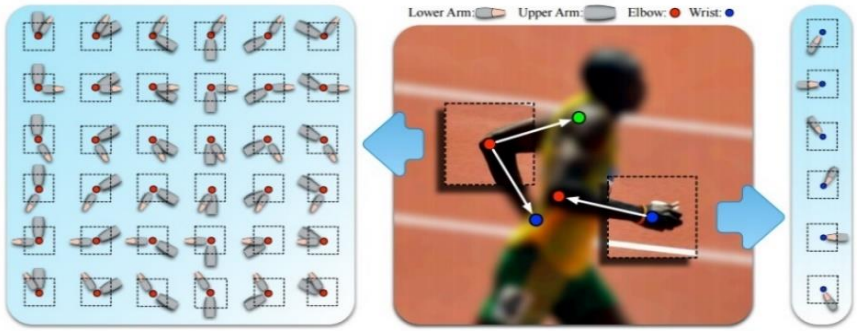
CNN + LSTM-RNN, CVPR2015



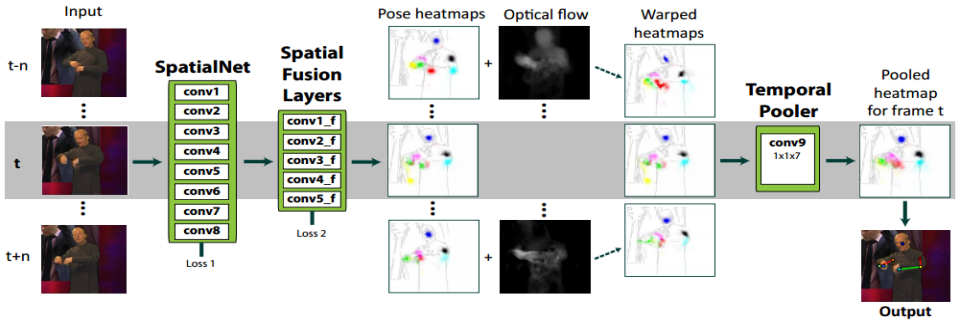
Skeleton + LSTM-RNN, CVPR2015

Application for Pose Estimation

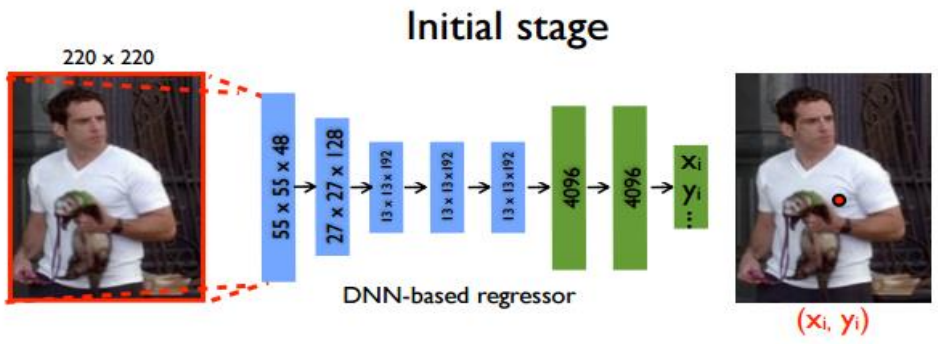
CNN: convolutional neural networks; DNN: deep neural networks

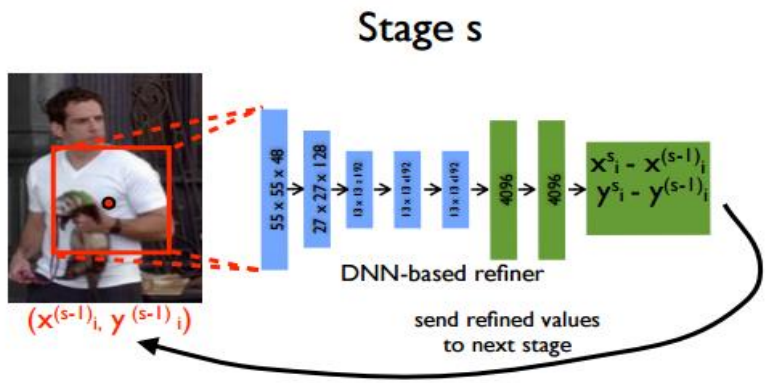


CNN + Graphical Model, NIPS2014



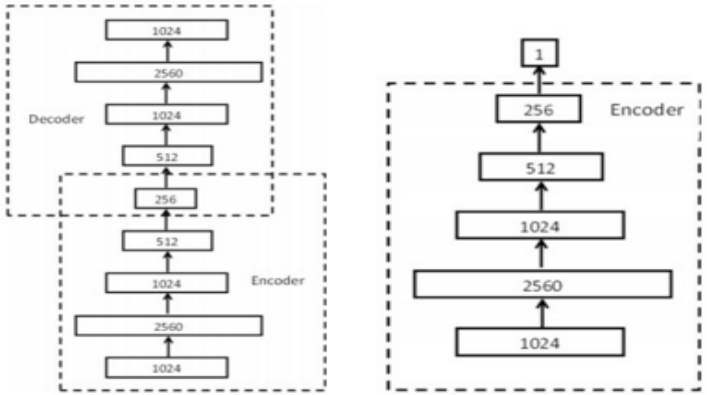
Flowing ConvNets, ICCV2015



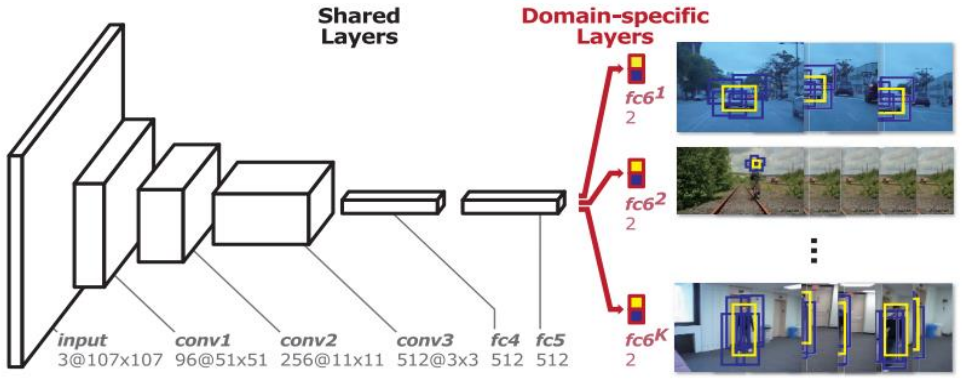


DNN-based Regression, CVPR2014

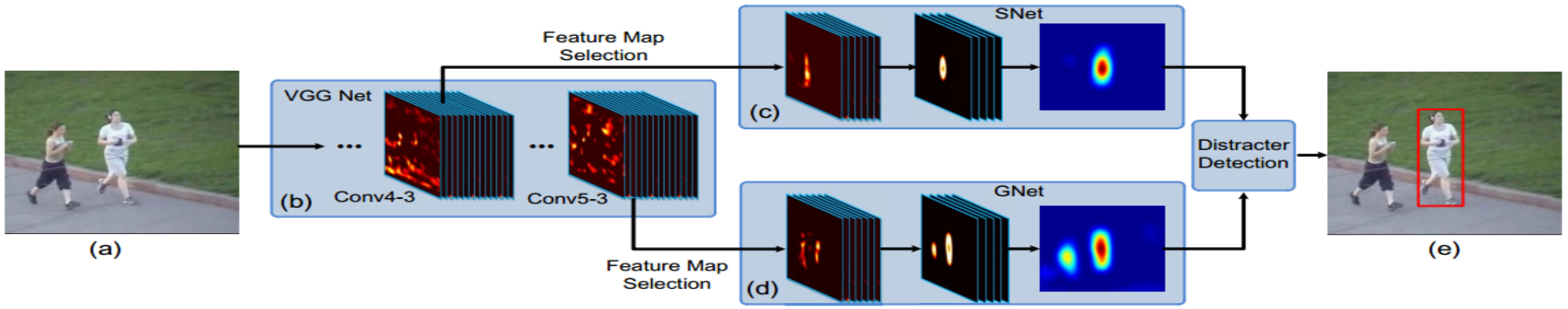
Application for Video Tracking



Stacked Denoising Auto-encoder, NIPS2013



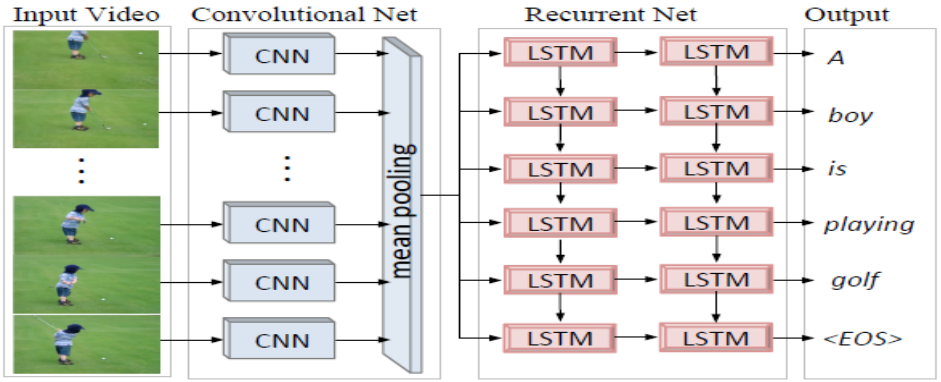
Multi-domain Networks, CVPR2016



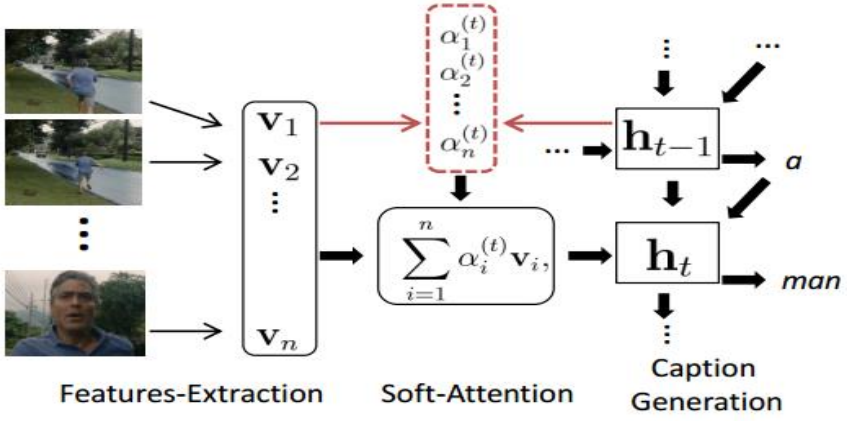
Fully Convolutional Networks, ICCV2015

Application for Video Caption

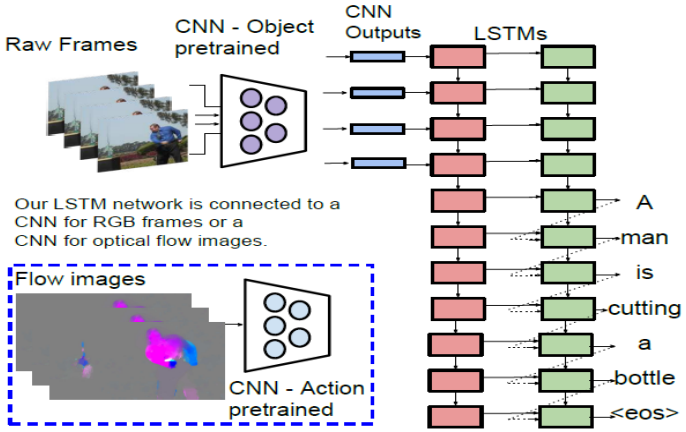
CNN: convolutional neural networks; LSTM: long short term memory; RNN: recurrent neural networks



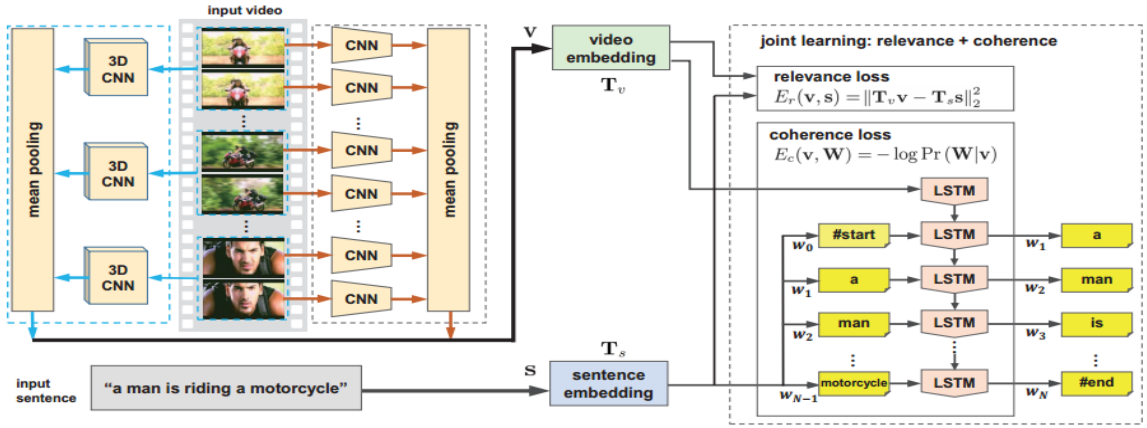
CNN + LSTM-RNN, CVPR2015



Attention-based LSTM-RNN, ICCV2015

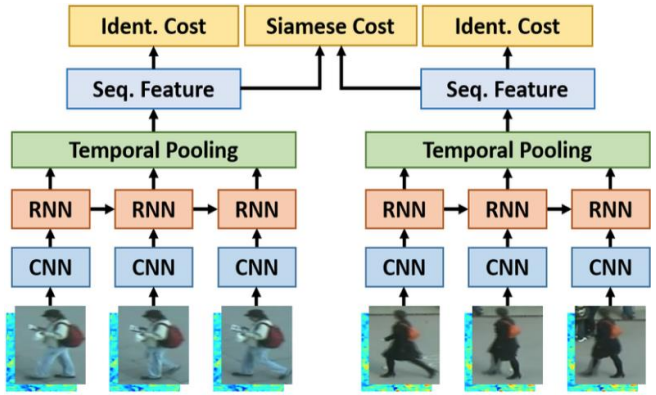


Video2Text, ICCV2015

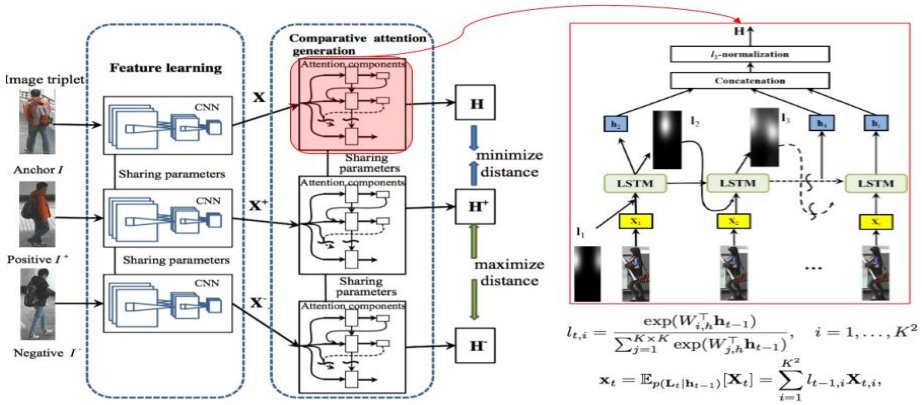


Visual-semantic Embedding + LSTM-RNN, CVPR2016

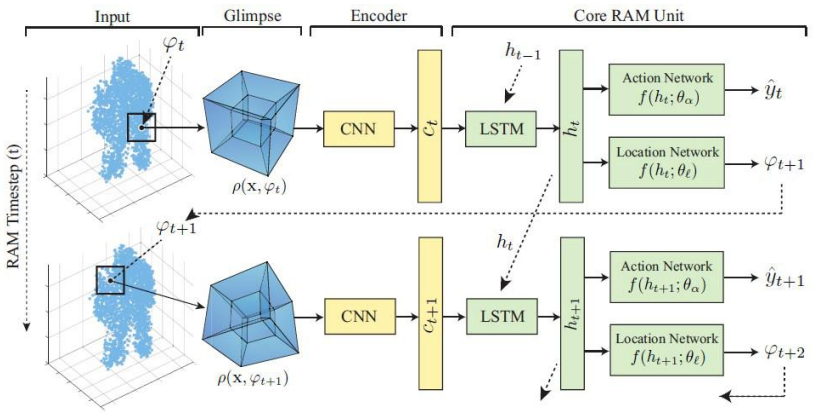
Application for Person Re-identification



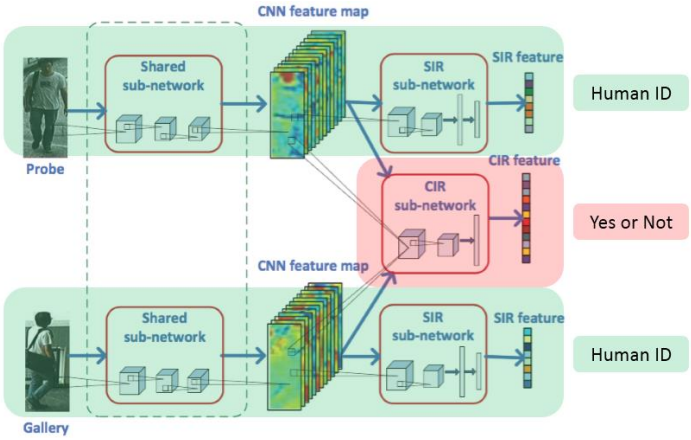
Recurrent CNN, **CVPR2016**



End-to-end Attention, **TIP2016**

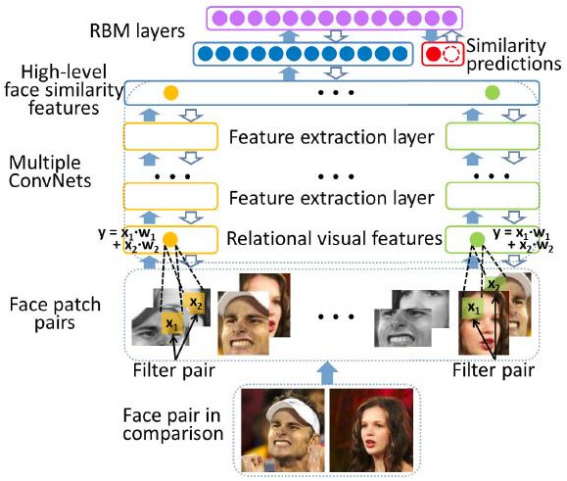


Sequential Local Attention, **CVPR2016**

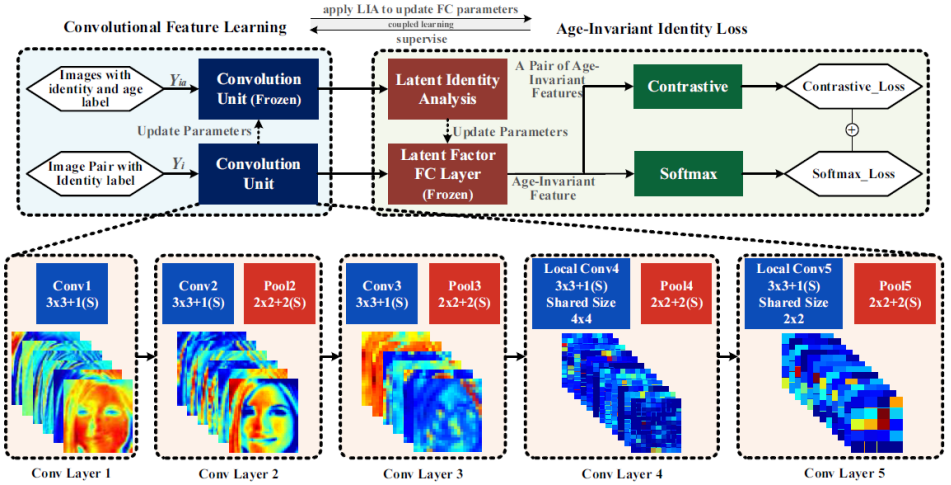


Single-/Cross-image Representations, **CVPR2016**

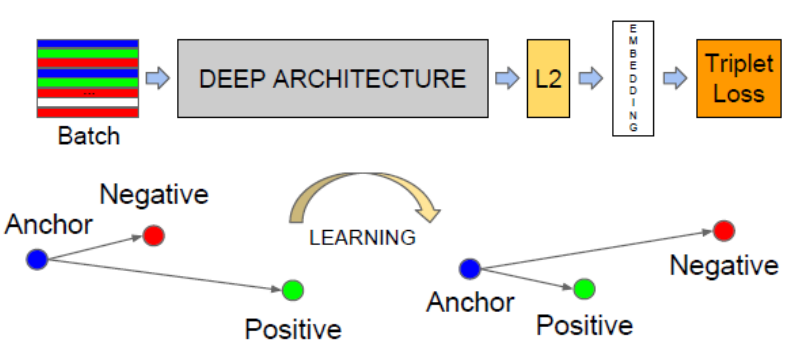
Application for Face Recognition



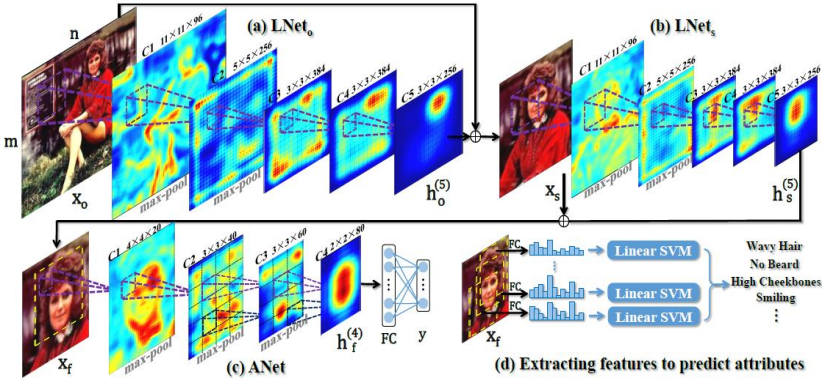
Hybrid ConvNet-RBM, **ICCV13**



LF-CNNs Model, **CVPR16**

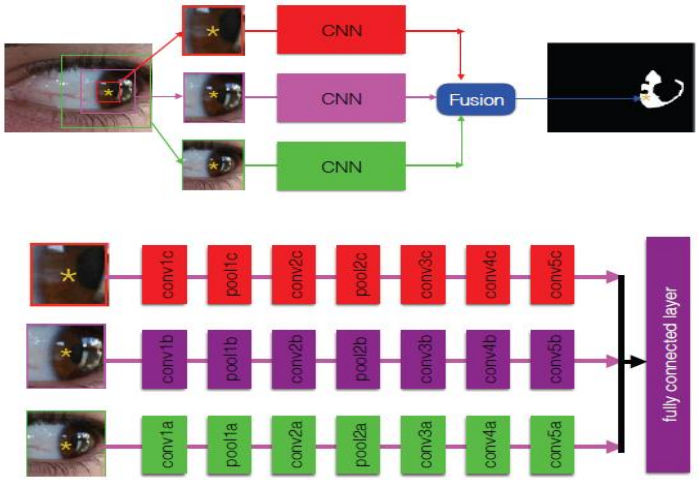


FaceNet, **CVPR15**

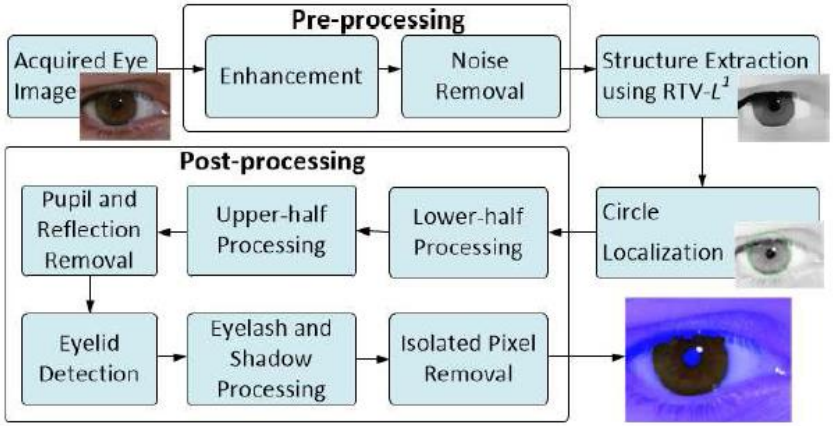


Face LNet and ANet, **ICCV15**

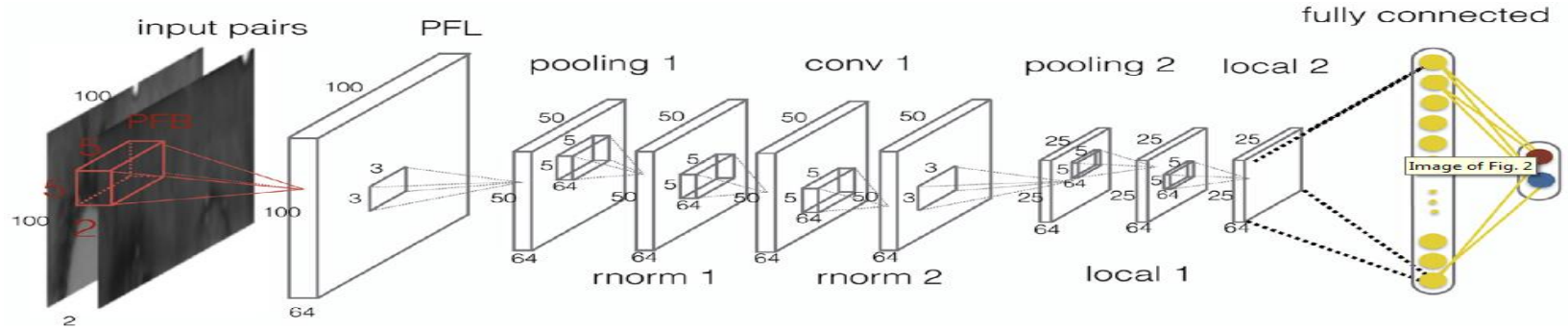
Application for Iris Recognition



HCNNs, **ICB16**

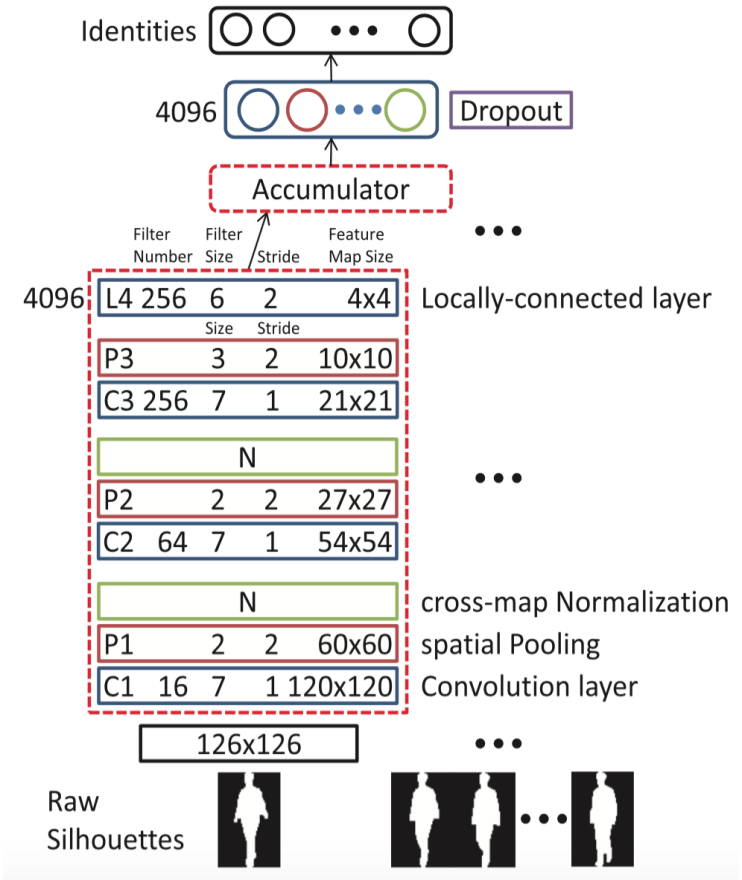


Iris Segmentation, **ICCV15**

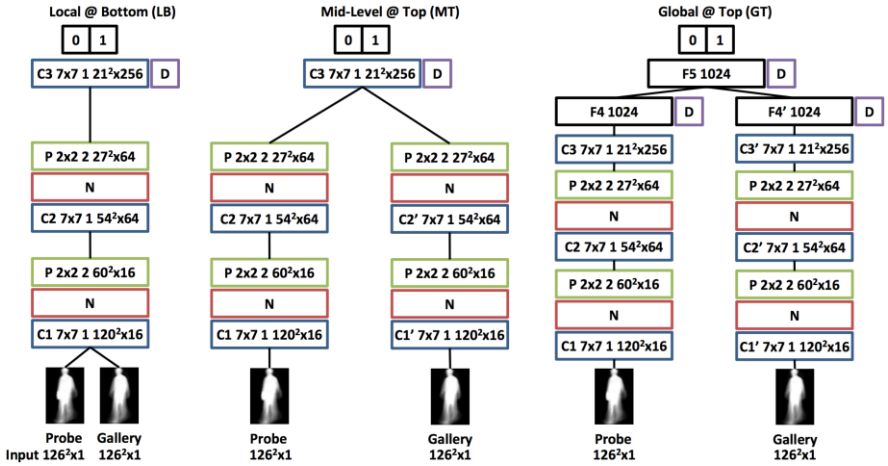


DeepIris, **PRL15**

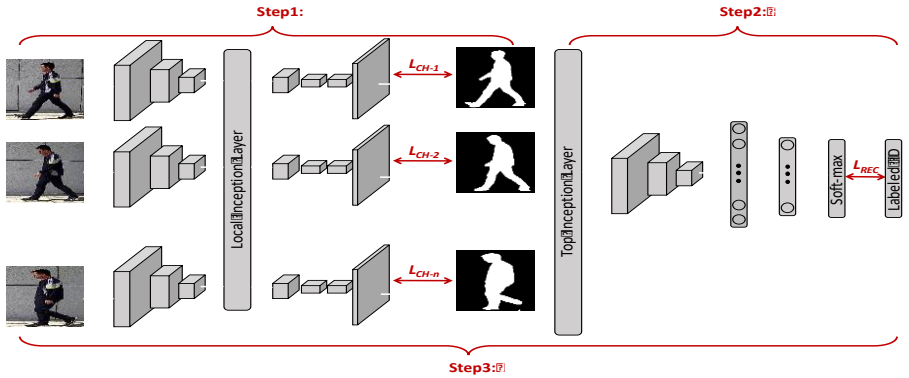
Application for Gait Recognition



Deep Gait Feature Learning by Image Set, **submitted to TIP 2017**

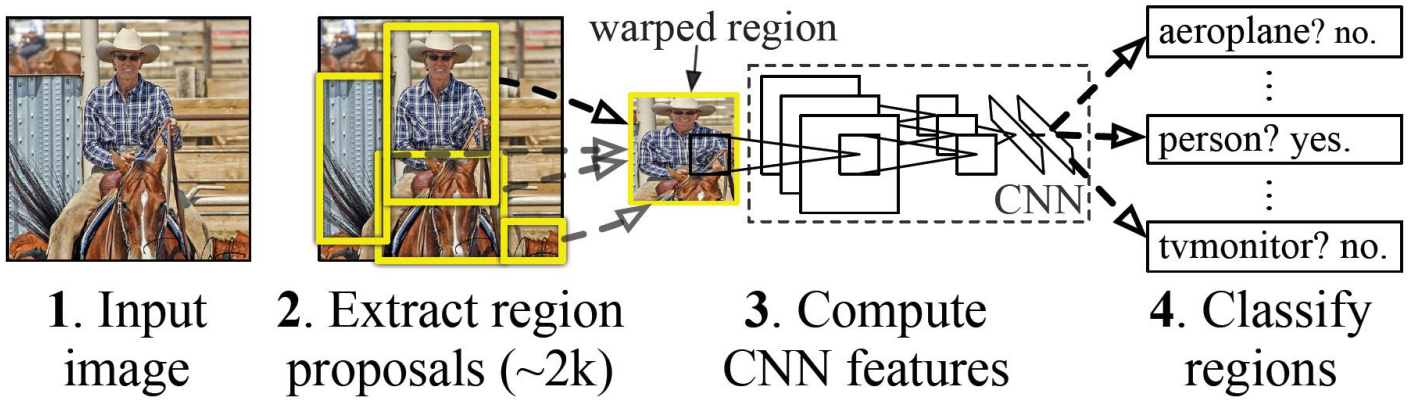


Cross-view Gait Identification, **TPAMI 2016**

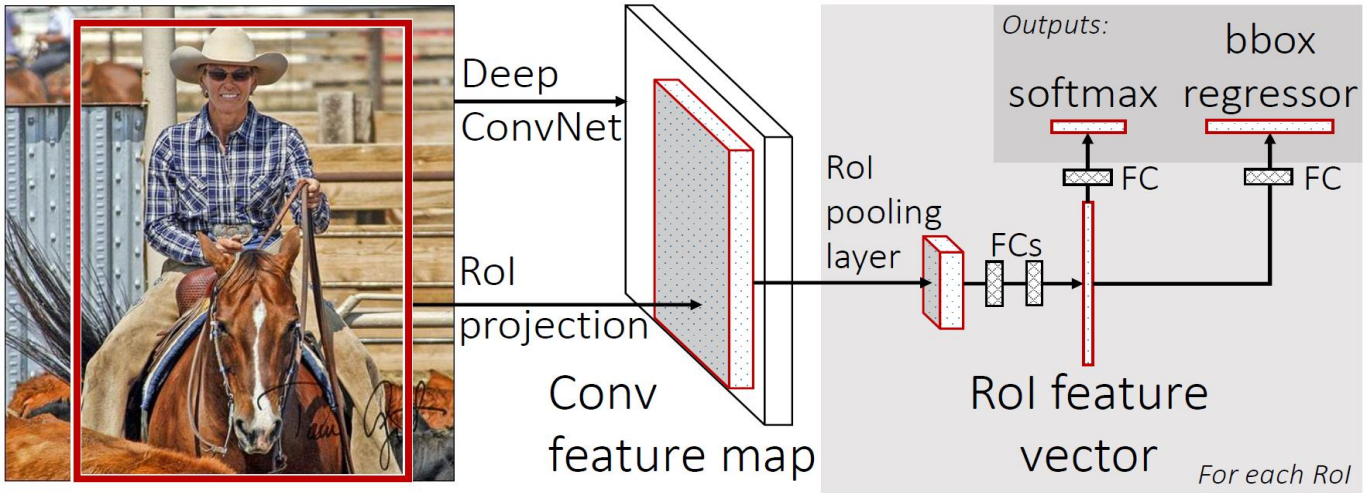


Joint Gait Segmentation and Recognition, **submitted to CVPR 2017**

Application for Object Detection

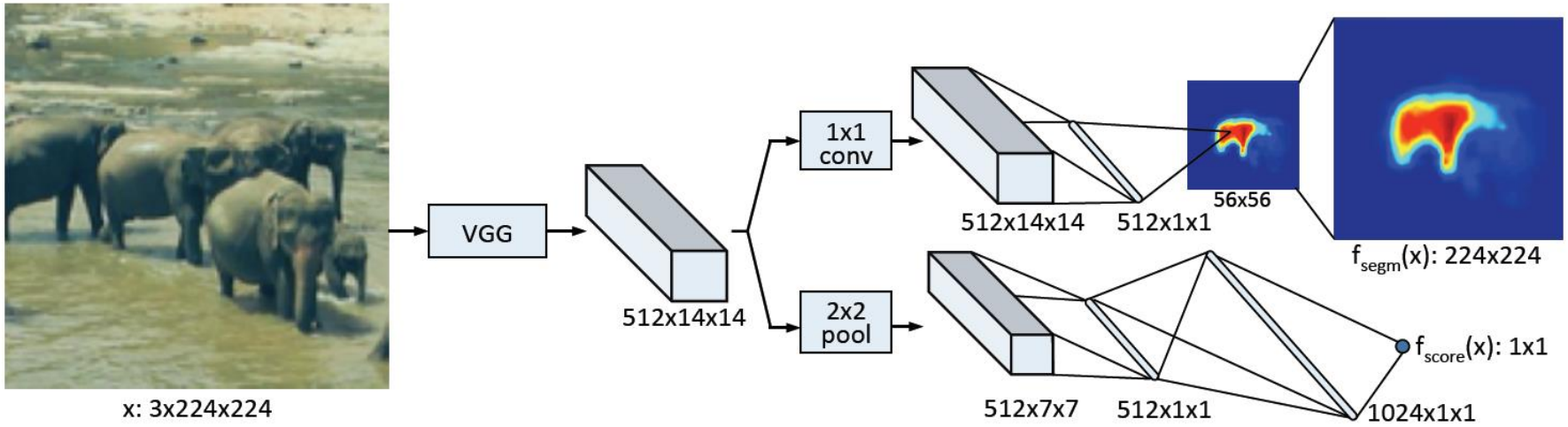


RCNN, **CVPR14**

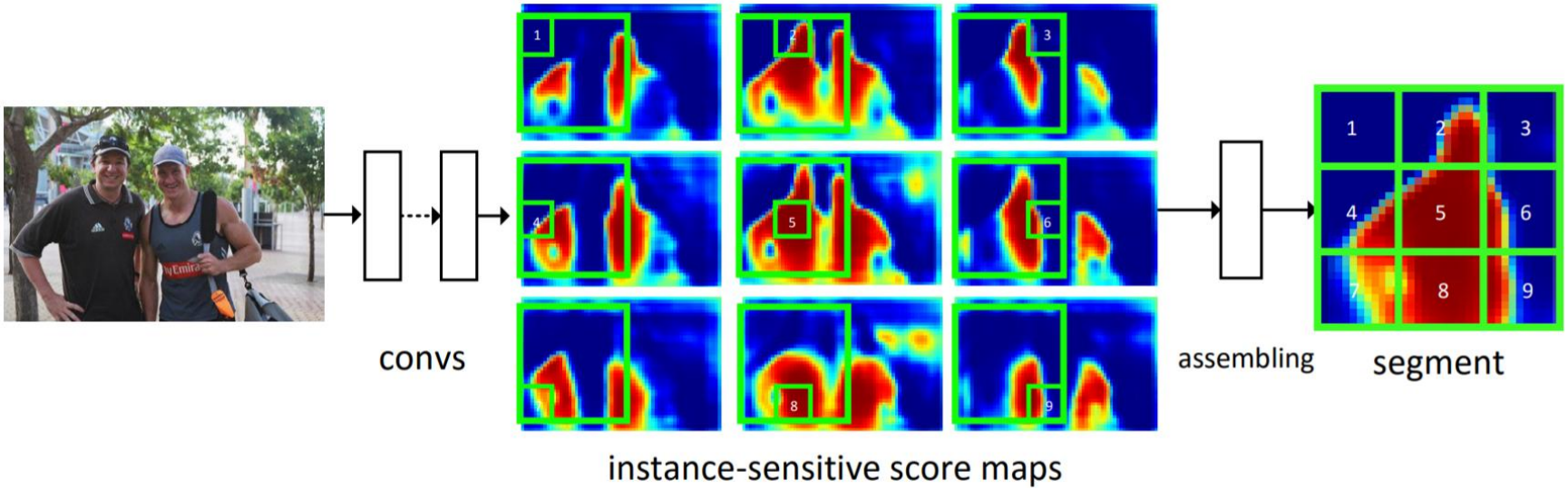


Fast R-CNN, **ICCV15**

Application for Semantic Segmentation

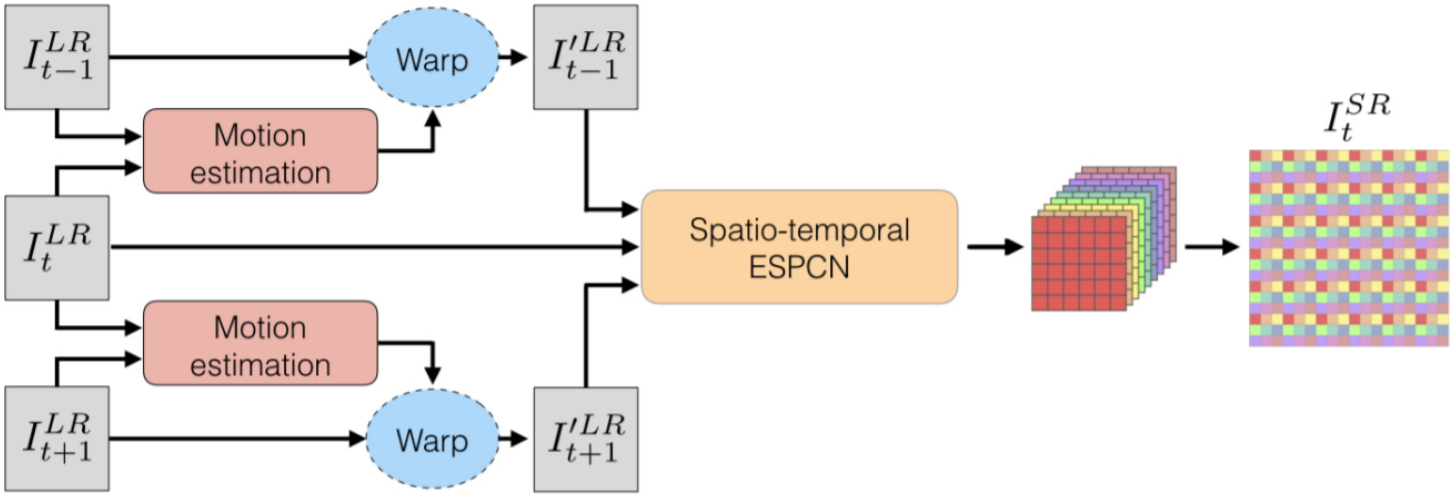


Instance-aware semantic segmentation, **CVPR16**

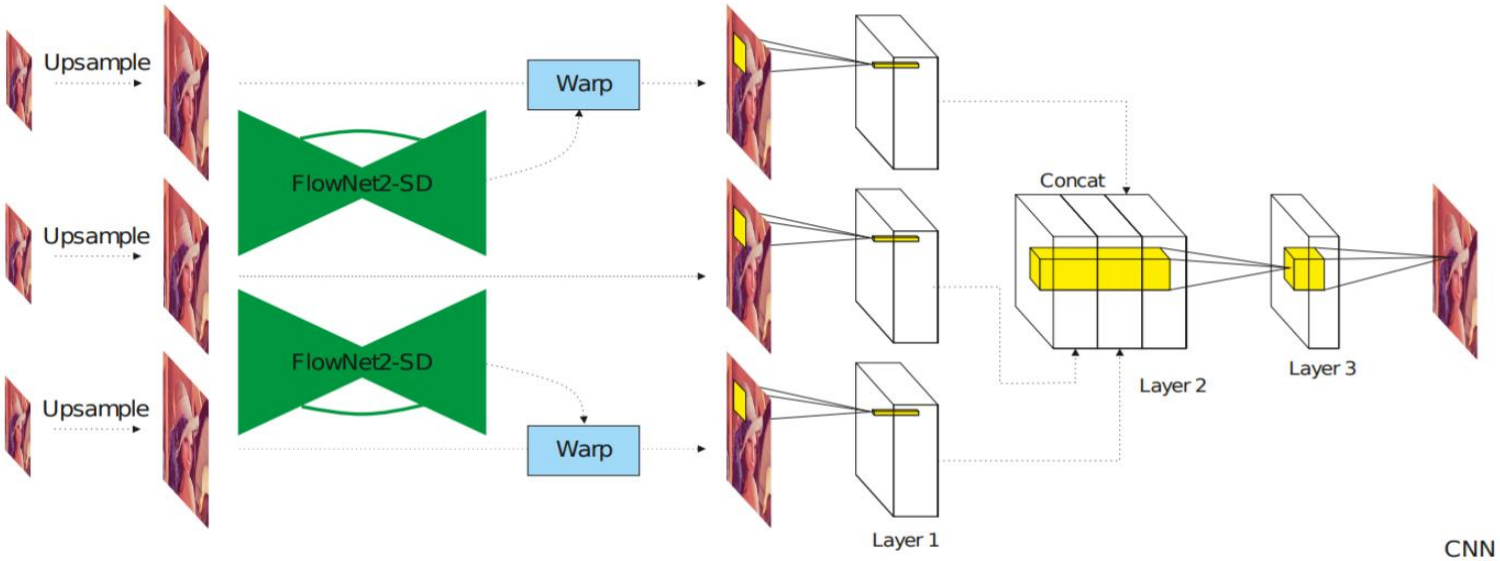


Learning to segment object candidates, **NIPS15**

Application for Video Super-resolution

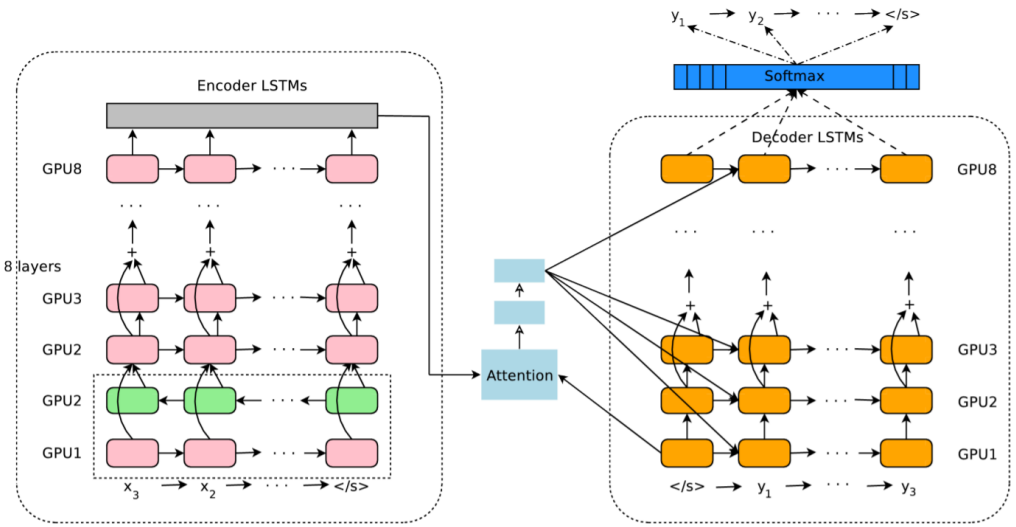


Real-Time Video Super-Resolution, **CVPR17**

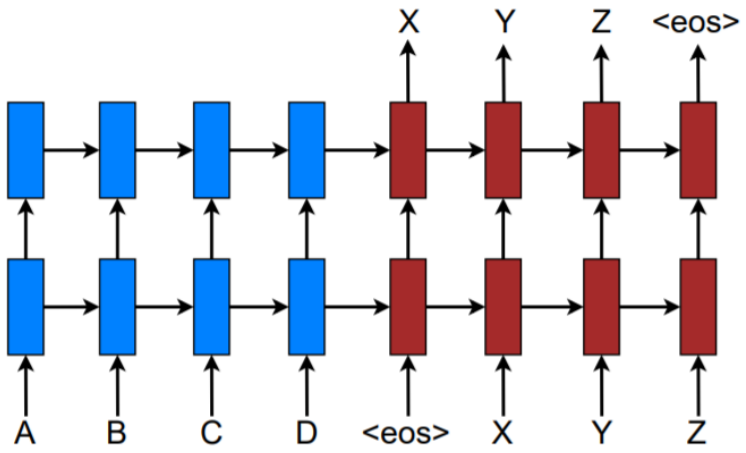


Video Super-Resolution with Motion Compensation, **GCPR2017**

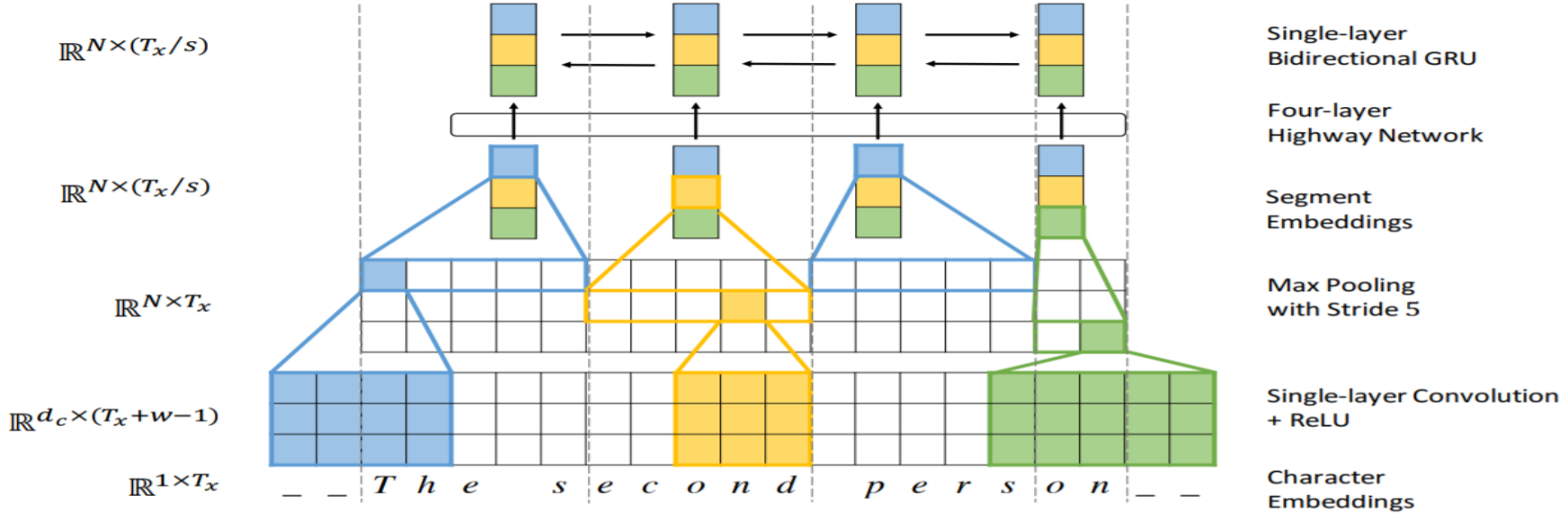
Application for Machine Translation



GNMT, **Arxiv16**

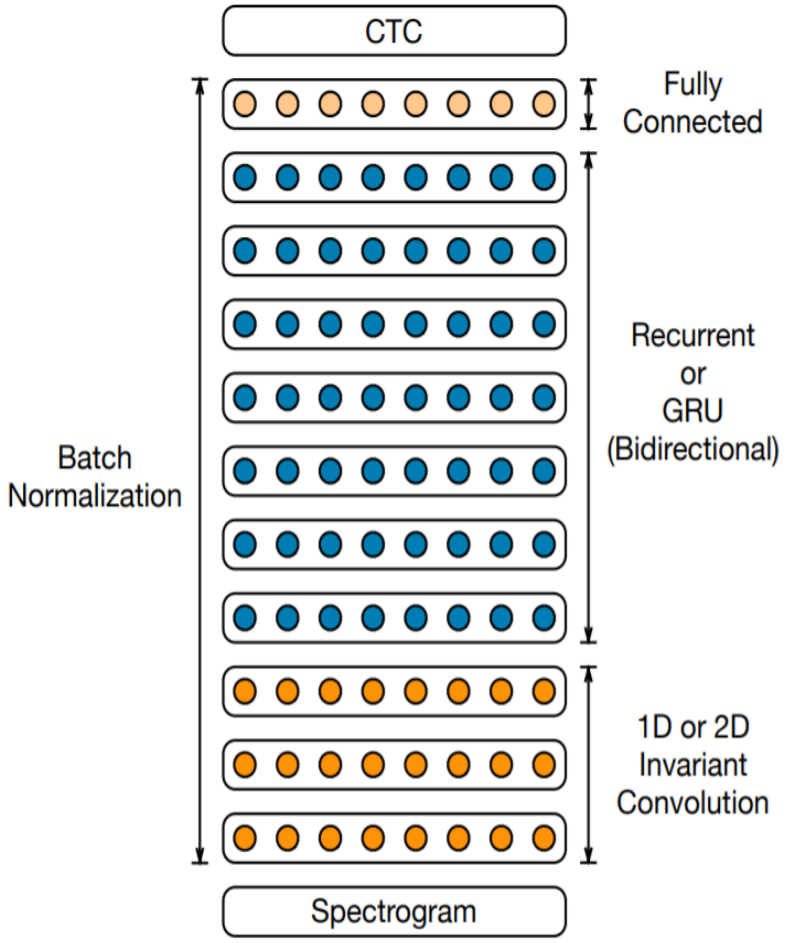


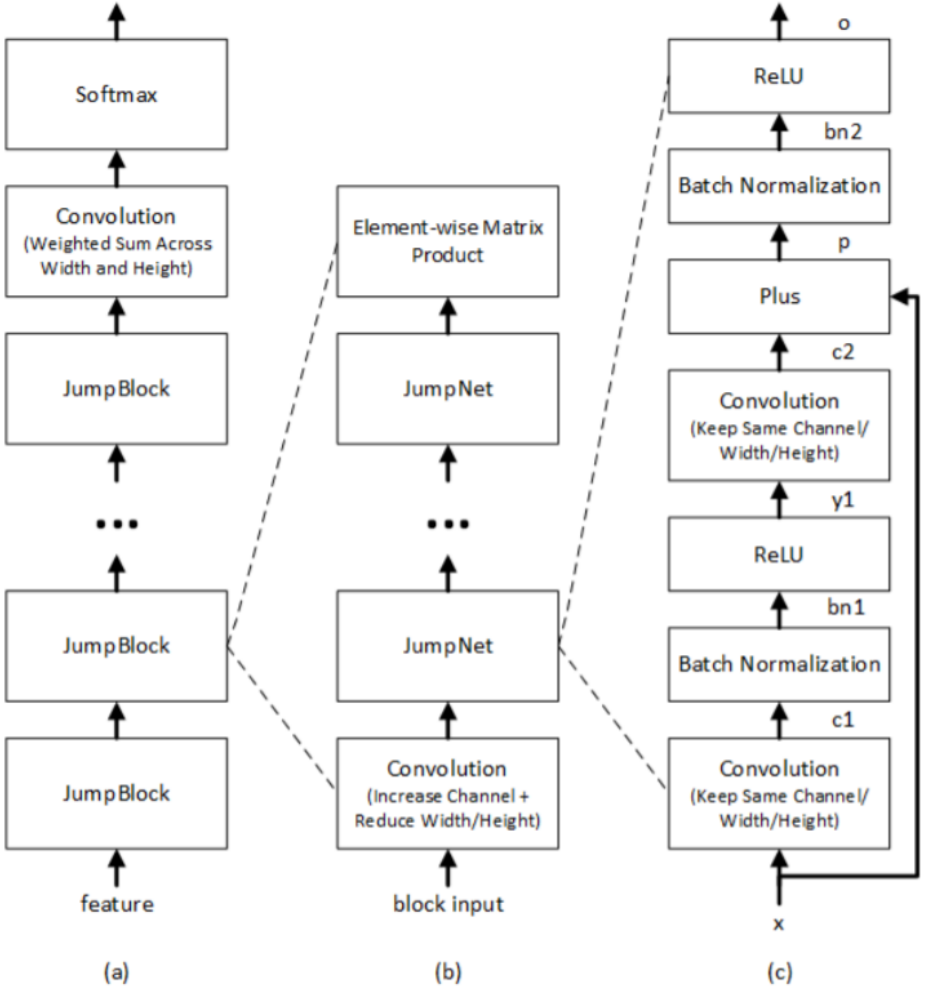
Attention-based NMT, **EMNLP 2015**



Fully Character-Level NMT, **TACL17**

Application for Speech Recognition

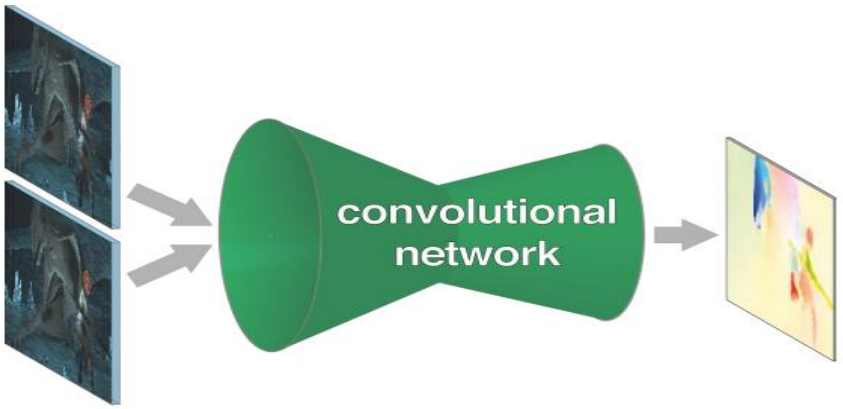




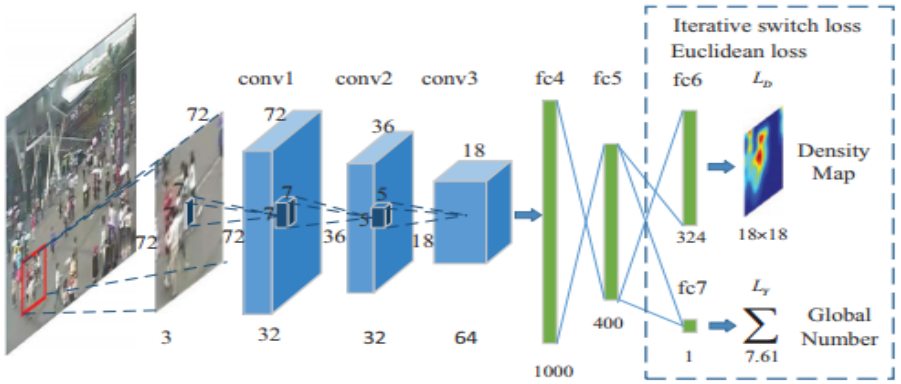
Speech Recognition in English and Mandarin, **TASLP16**

Conversational Speech Recognition, **TASLP17**

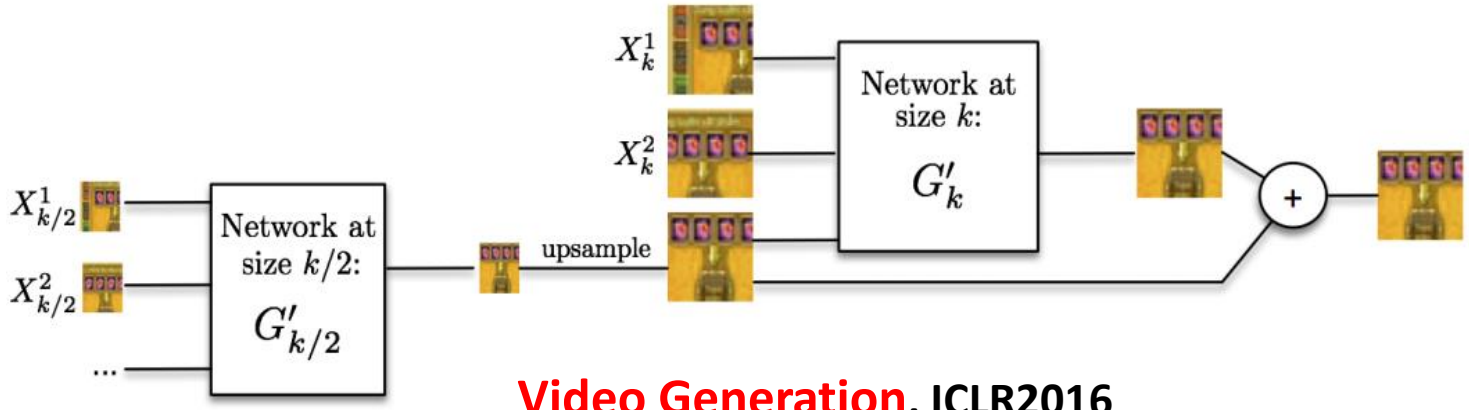
Applications for Others



Optical Flow Prediction, ICCV2015



Cross-scene Crowd Counting, CVPR2015



Video Generation, ICLR2016

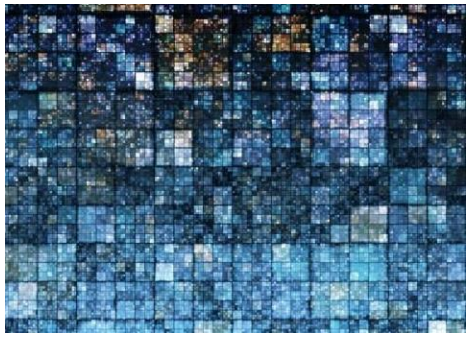
Achieve state-of-the-art results in various applications

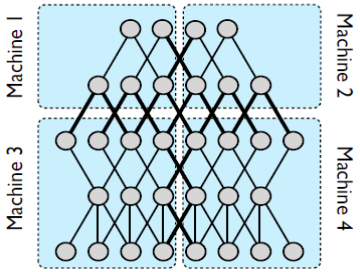
Outline

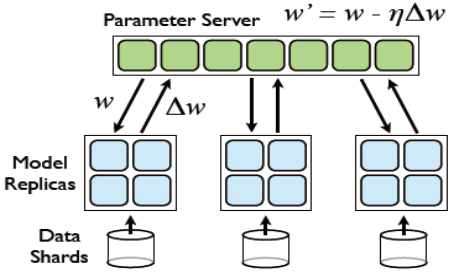
1. Course Information
2. What is Deep Learning
3. Applications of Deep Learning
4. Future Directions

Direction 1

- Large scale deep learning
  - multiple GPUs
  - distributed system

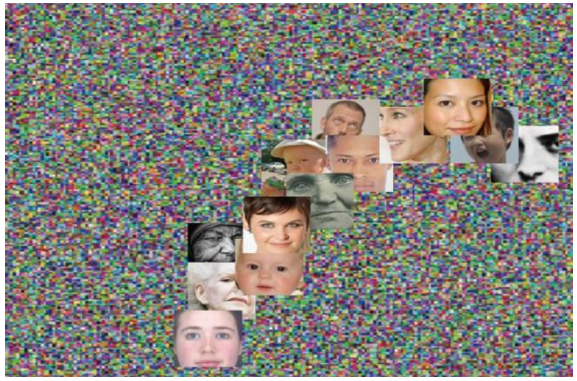




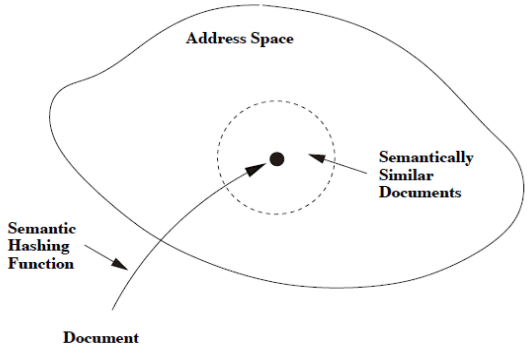


Direction 2

- Unsupervised (semi-supervised) video feature Learning
  - lack of supervised information in real applications



Unsupervised learned features



Manifold assumption

Direction 3

- Multimodal learning
  - videos are closely related to other data modalities, e.g., text, audio

Image classification

man woman street building
people kiss walk

Image captioning

Man kissing woman on a street

Visual QA

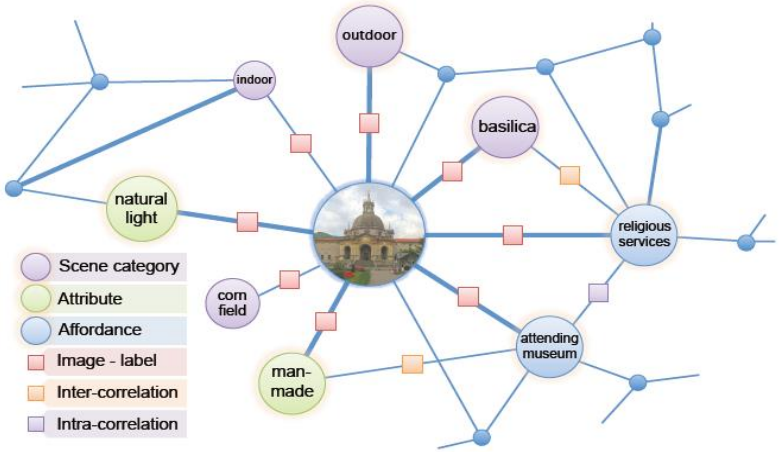
Q: What is the sailor doing?

A: He is kissing a nurse in a white dress.

Q: Why are they kissing?

A: To celebrate V-J Day in Times Square.

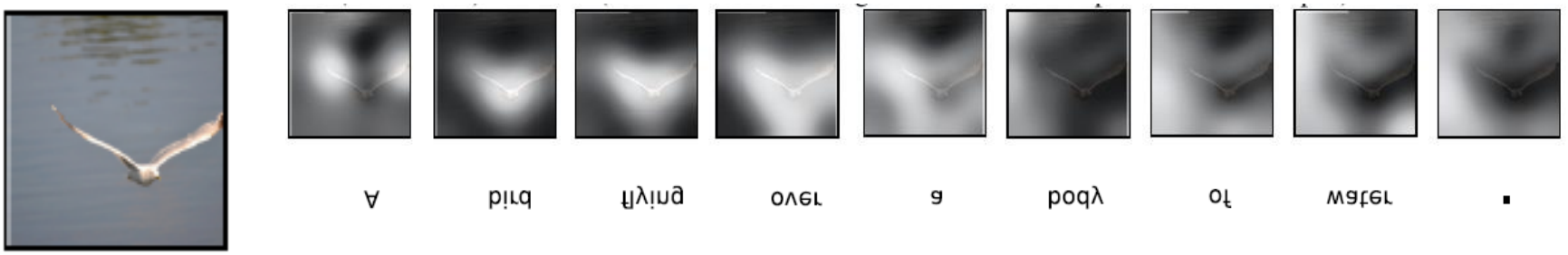
Question answering



Multimodal Knowledge Base [Zhu et al., arXiv16]

Direction 4

- Brain-inspired deep models
  - conventional neural networks are inspired by ***human cognitive mechanism***
  - refer to advanced achievements in the fields of neuroscience and brain science



Attention-based image caption [Xu et al., ICML15]

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1. **(Image Recognition) AlexNet** : Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton, ImageNet Classification with Deep Convolutional Neural Networks, NIPS, 2012
2. **(Action Recognition)**: Shuiwang Ji, Wei Xu, Ming Yang, Kai Yu, 3D Convolutional Neural Networks for Human Action Recognition, ICML, 2010
3. **(Detection) R-CNN**: Ross Girshick, Jeff Donahue, Trevor Darrell, Jitendra Malik, Rich feature hierarchies for accurate object detection and semantic segmentation, CVPR, 2014
4. **(Detection) Faster R-CNN**: Shaoqing Ren, Kaiming He, Ross Girshick, Jian Sun, Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks, arXiv:1506.01497
5. **(Segmentation) F-CNN**: Jonathan Long, Evan Shelhamer, Trevor Darrell, Fully Convolutional Networks for Semantic Segmentation, CVPR, 2015
6. **(Tracking)** Chao Ma, Jia-Bin Huang, Xiaokang Yang and Ming-Hsuan Yang, Hierarchical Convolutional Features for Visual Tracking, ICCV, 2015
7. **(Super-resolution)** Chao Dong, Chen Change Loy, Kaiming He, Xiaoou Tang, Learning a Deep Convolutional Network for Image Super-Resolution, ECCV, 2014

References

8. **(Edge Detection)**: Gedas Bertasius, Jianbo Shi, Lorenzo Torresani, DeepEdge: A Multi-Scale Bifurcated Deep Network for Top-Down Contour Detection, CVPR, 2015

9. **(Face Recognition)**: Yaniv Taigman, Ming Yang, Marc'Aurelio Ranzato, Lior Wolf, DeepFace: Closing the Gap to Human-Level Performance in Face Verification, CVPR, 2014

10. **(Question Answering)**: Hyeonwoo Noh, Paul Hongsuck Seo, and Bohyung Han, Image Question Answering using Convolutional Neural Network with Dynamic Parameter Prediction, arXiv:1511.05765

11. **(Video Caption)**: Jeff Donahue, Lisa Anne Hendricks, Sergio Guadarrama, Marcus Rohrbach, Subhashini Venugopalan, Kate Saenko, Trevor Darrell, Long-term Recurrent Convolutional Networks for Visual Recognition and Description, CVPR, 2015

12. **(Text Classification)**: Xiang Zhang, Junbo Zhao, Yann LeCun, Character-level Convolutional Networks for Text Classification, NIPS, 2015

13. **(Retrieval)**: Fang Zhao, Yongzhen Huang, Liang Wang, Tieniu Tan, Deep Semantic Ranking Based Hashing for Multi-Label Image Retrieval, CVPR, 2015

1.Human Action Recognition

Project idea: Suppose that we are given a few video clips. Can we classify whether these videos contain humans ? If yes, can we track the humans in the videos, detect the pose of human body parts, and eventually infer what activity the human make? In this project, you are encouraged **to implement your own human action recognition system.** Since this area of research is so vast, we do not recommend you to try a general problem. More specified is better. Here are some references as a starting point.

Following is a list of data sets you could use.

[1] KTH:http://www.nada.kth.se/cvap/actions/
[2] Weizmann:http://www.wisdom.weizmann.ac.il/~vision/SpaceTimeActions.html
[3] Hollywood Human Actions dataset:http://www.irisa.fr/vista/Equipe/People/Laptev/download.html
[4] VIRAT Video Dataset:http://www.viratdata.org/
(http://groups.inf.ed.ac.uk/calvin/articulated_human_pose_estimation_code/)

1.Human Action Recognition

Here are some references as a starting point.

[1] CVPR 2011 Tutorial on Human Activity Recognition
(http://cvrc.ece.utexas.edu/mryoo/cvpr2011tutorial/)
[2] Human Activity Recognition Summer course
(http://www.cs.sfu.ca/~mori/courses/cmpt888/summer10/)
[2] Stanford Vision lab (http://vision.stanford.edu/discrim_rf/)
(http://ai.stanford.edu/~bangpeng/ppmi.html)
[3] Poselet (http://www.cs.berkeley.edu/~lbourdev/poselets/)
[4] 2D articulated human pose estimation

You could use any code from the web for computing spatial-temporal features. One good example is the spatial-temporal interest point proposed by Piotr Dollar. Source code available at http://vision.ucsd.edu/~pdollar/research/research.html.

2.Image Categorization

Project idea: Image categorization/object recognition has been one of the most important research problems in the computer vision community. Researchers have developed a wide spectrum of different local descriptors, feature coding schemes, and classification methods.

In this project, **you will implement your own object recognition system**. You could use any code from the web for computing image features, such as SIFT, HoG, etc.
For computing SIFT features, you could use http://www.vlfeat.org/~vedaldi/code/sift.html.
You're also encouraged to try the state-of-the-art deep learning methods:
http://deeplearning.net/

Following is a list of data sets you could use.

[1]Caltech101/256:
http://www.vision.caltech.edu/Image_Datasets/Caltech101/Caltech101.html
[2] The PASCAL Object Recognition Database Collection:
http://pascallin.ecs.soton.ac.uk/challenges/VOC/databases.html
[3] LabelMe:http://labelme.csail.mit.edu/
[4] Face in the wild:http://vis-www.cs.umass.edu/lfw/
[5] ImageNet:http://www.image-net.org/index
[6] TinyImage:http://groups.csail.mit.edu/vision/TinyImages/

3.Multi-modal Social Media

Project idea: In this project, we encourage students to infer the underlying relations between different modalities of information on the Web. Here are some examples.

(1) Given a photo of movie poster (image), can we retrieve related trailers (video) or latest news articles (documents) of the movie?

To make project simpler, we recommend focusing on less than five movies (eg. 'Rise of the planet of the apes' and 'The smurfs'). You first download posters and trailers from some well-organized sites such as imdb.com or itunes.com. They will be used as training data to learn your classifiers. Now your job is to gather raw data from youtube.com or Flickr, and classify them. In this project, we encourage you to explore the possibility to build classifiers to be learned from one information modality (eg. images), and to be applicable to other modalities (eg. trailer videos).

3.Multi-modal Social Media

(2) Given a beer label (image), can we search for which frames of a given video clip the logo or bottle appears?
Suppose that you are a big fan of Guinness beer. You can easily download the clean Guinness logo or cup images by Google image search. These images can be used to learn your detector, which can discover the frames that the logo appears in the video clips. For testing, you can download some video clips from youtube.com.

The above examples are just two possible candidates, and any new ideas or problem definitions are welcome.

For this purpose, one may take advantage of some source codes available on the Web as unit modules (e.g., near-duplicated image detection, object recognition, action recognition in video).

Another interesting direction is to improve the current state-of-the-arts methods by considering more practical scenarios.

3.Multi-modal Social Media

Related Papers and Software::

- A good example of how a machine learning technique is successfully applied to real systems (ex. Google news recommendation).

[1] Das, Datar, Garg, Rajaram. Google news personalization: scalable online collaborative filtering. WWW 2007.

- One of most popular approaches to near duplicated image detection is LSH families.

[2] http://www.mit.edu/~andoni/LSH/ (This webpage links several introductory articles and source codes).

- Various hashing techniques in computer vision (papers and source codes).

[3] Spectral Hashing (http://www.cs.huji.ac.il/~yweiss/SpectralHashing/)

[4] Kernelized LSH (http://www.eecs.berkeley.edu/~kulis/klsh/klsh.htm)

- Recognition in video

[5] Naming of Characters in Video (http://www.robots.ox.ac.uk/~vgg/data/nface/index.html)

[6] Action recognition in Video (http://www.robots.ox.ac.uk/~vgg/data/stickmen/index.html)

- Recognition in images

[7] Human pose detection (Poselet) (http://www.eecs.berkeley.edu/~lbourdev/poselets/)

[8] General object detection (http://people.cs.uchicago.edu/~pff/latent/)

Other Projects

4. Image Segmentation
5. Face Recognition
6. Text Classification
7. Question Answering
8. Image Denosing/Super-resolution
9. Image Retrieval
10. Tracking
11. ……

Note that not all topics are equally difficult. But we'll take this into consideration when evaluating each team's performance and make the assessment as fair as possible.

Acknowledgement

Some of the materials in these slides are drawn inspiration from:

- Alexander Amini, MIT University, Introduction to Deep Learning course
- Hung-yi Lee, National Taiwan University, Machine Learning and having it Deep and Structured course
- Chenglin Liu, CASIA, Pattern Recognition course
- Fei-Fei Li, Standord University, CS231n Convolutional Neural Networks for Visual Recognition course

Questions?

Thank You !

WeChat Group for Deep Learning