Deep-Learning:

general principles
+ Convolutional Neural Networks

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Acknowledgements

During preparation of these slides, I got inspiration and borrowed some slide content from several sources, in particular:

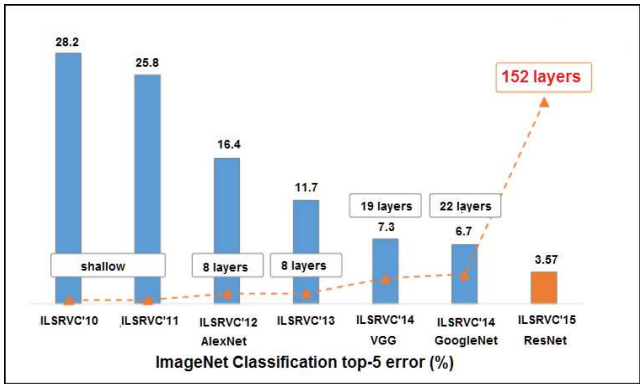
- Yann LeCun + MA Ranzato: slides on « *Deep Learning* » from the corresponding course at NYU
  http://cilvr.cs.nyu.edu/doku.php?id=deeplearning:slides:start
- Hinton+Bengio+LeCun: slides of the *NIPS'2015 tutorial on Deep Learning*
  http://www.iro.umontreal.ca/~bengioy/talks/DL-Tutorial-NIPS2015.pdf
- Fei-Fei Li + A.Karpathy + J.Johnson: Stanford course lecture slides on *« Convolutional Neural Networks »*
  http://cs231n.stanford.edu/slides/winter1516_lecture7.pdf

Outline

- Introduction to Deep Learning
- Convolutional Neural Networks (CNN or ConvNets)
  - Intro + Short reminder on Neural Nets
  - Convolution layers & Pooling layers + global architecture
  - Training algorithm + Dropout Regularization
- Useful pre-trained convNets
- Coding frameworks
- Transfer Learning
- Object localization and Semantic segmentation
- Deep-Learning on 1D signal and 3D data
- Recent other image-based applications

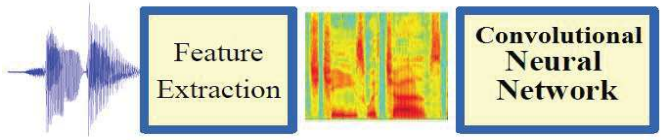
Deep-Learning recent breakthroughs

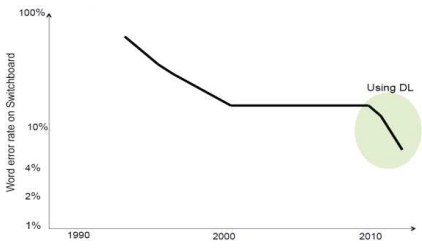
Very significant improvement over State-of-the-Art in Pattern Recognition / Image Semantic Analysis:



- won many vision pattern recognition competitions (OCR, TSR, object categorization, facial expression,…)
- deployed in photo-tagging by Facebook, Google,Baidu,…

Similar dramatic progress in Speech recognition + Natural Language Processing (NLP)

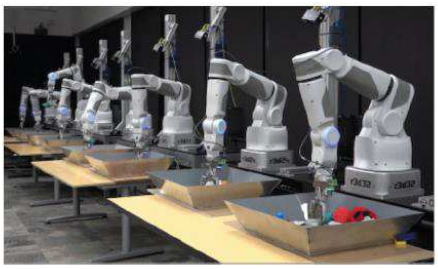




Main application domains of Deep-Learning

Object recognition

Scene analysis

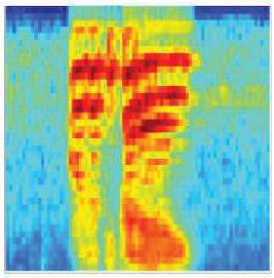


Robotics

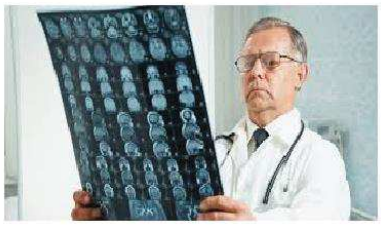
Все счастливые семьи похожи друг на друга, каждая несчастливая семья несчастлива по-своему.

Happy families are all alike. Every unhappy family is unhappy in its own way.

Language processing



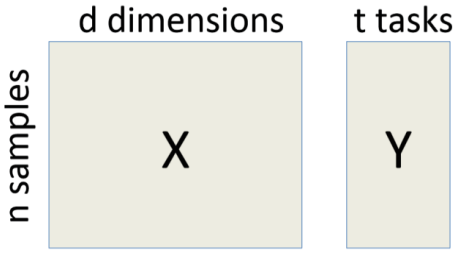
Speech recognition



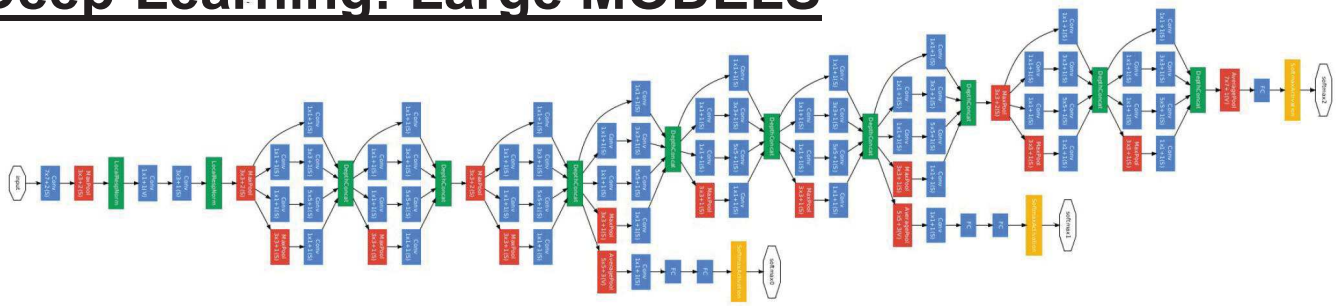
Medical diagnosis & Bio-informatics

Is Deep-Learning « Large-Scale »?

Big and/or « Fat » data



Deep-Learning: Large MODELS



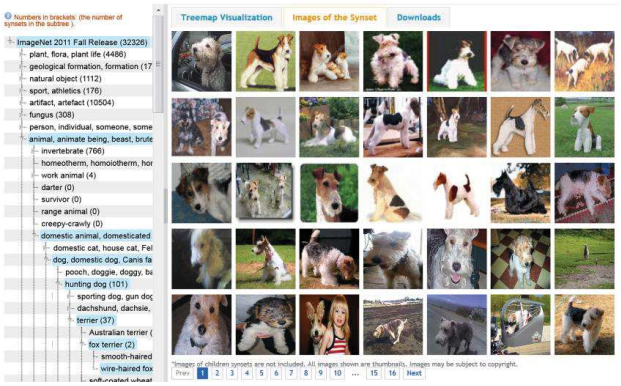
State-of-the-Art Convolutional Neural Networks contain > 100 layers, millions of parameters

Importance of training data!

Dramatic recent progresses in image classification and visual object categorization not only due to Deep-Learning and convNets:

it was made possible largely thanks to ImageNet dataset, which is a HUGE collection of labelled general-purpose images (1000 categories, > 1 million examples)

IMAGENET



Most powerful convNets have been trained on this huge dataset!

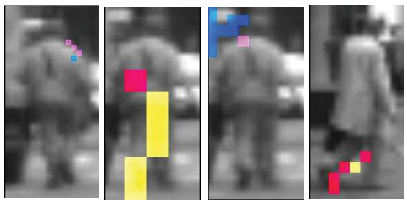
Importance of « features » in classical Machine-Learning

Traditional Machine Learning Flow

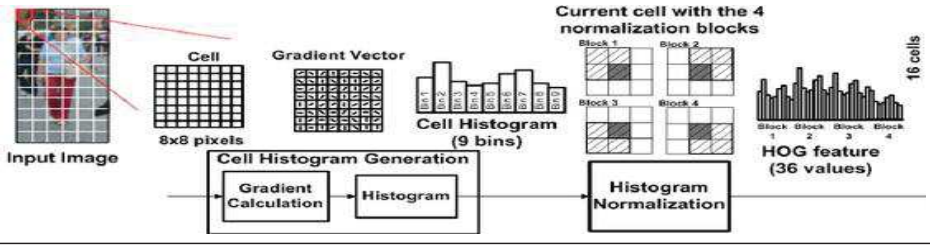
Examples of *hand-crafted* features

Haar features

Control-points features

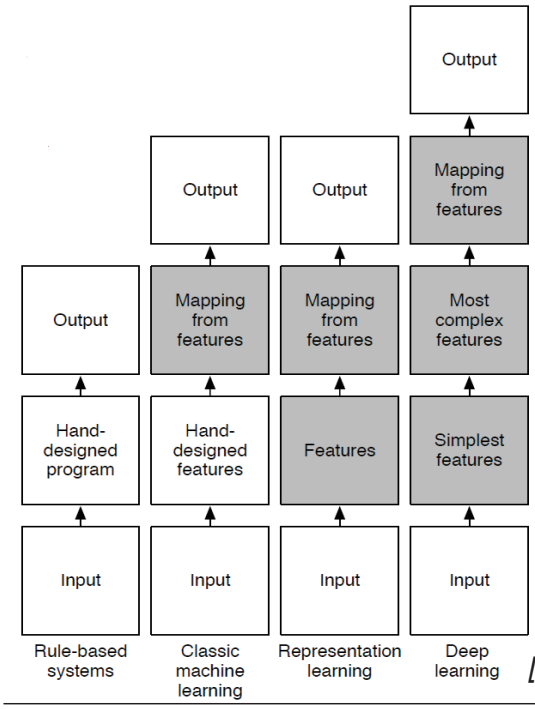


HoG (Histogram of Gradients)



What is Deep-Learning?

Learning a *hierarchy* of increasingly abstract *representations*



[Figure from Goodfellow]

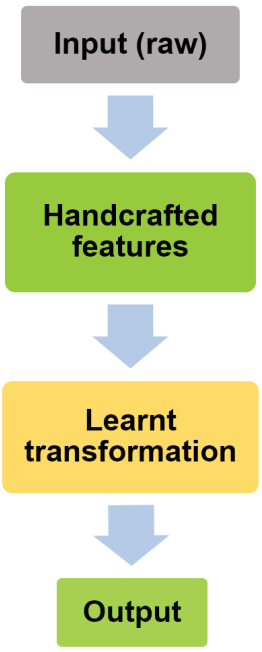
Increasing level of abstraction
Each stage ~ trainable feature transform

Image recognition
Pixel → edge → texton → motif → part → object

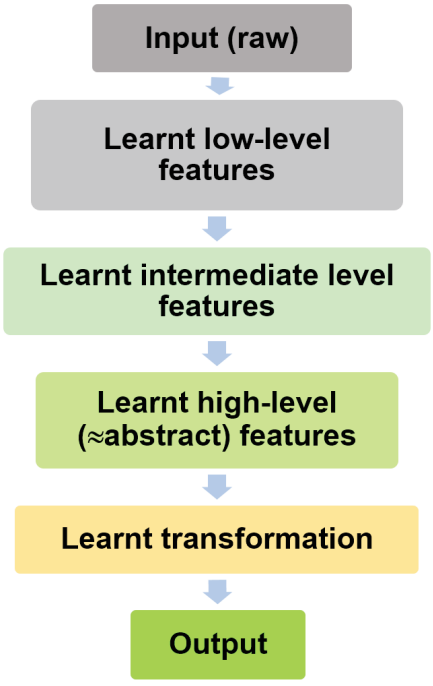
Speech
Sample → spectral band → … → phoneme → word

Text
Character → word → word group → clause → sentence → story

Deep-Learning vs. shallow Machine-Learning



Shallow ML using *handcrafted* features



DL: *jointly* learn classification *and features*

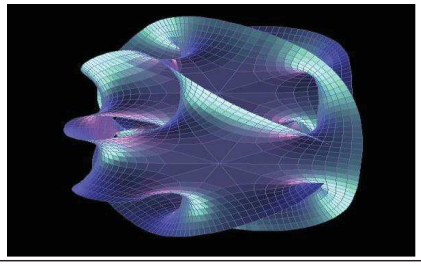
Why features should be learnt?

Real data examples for a given task are usually not spreaded everywhere in input space, but rather clustered on a low-dimension « manifold »

Example: Face images of 1000x1000 pixels
➔ « raw » examples are vectors in $R^{1000000}$!!

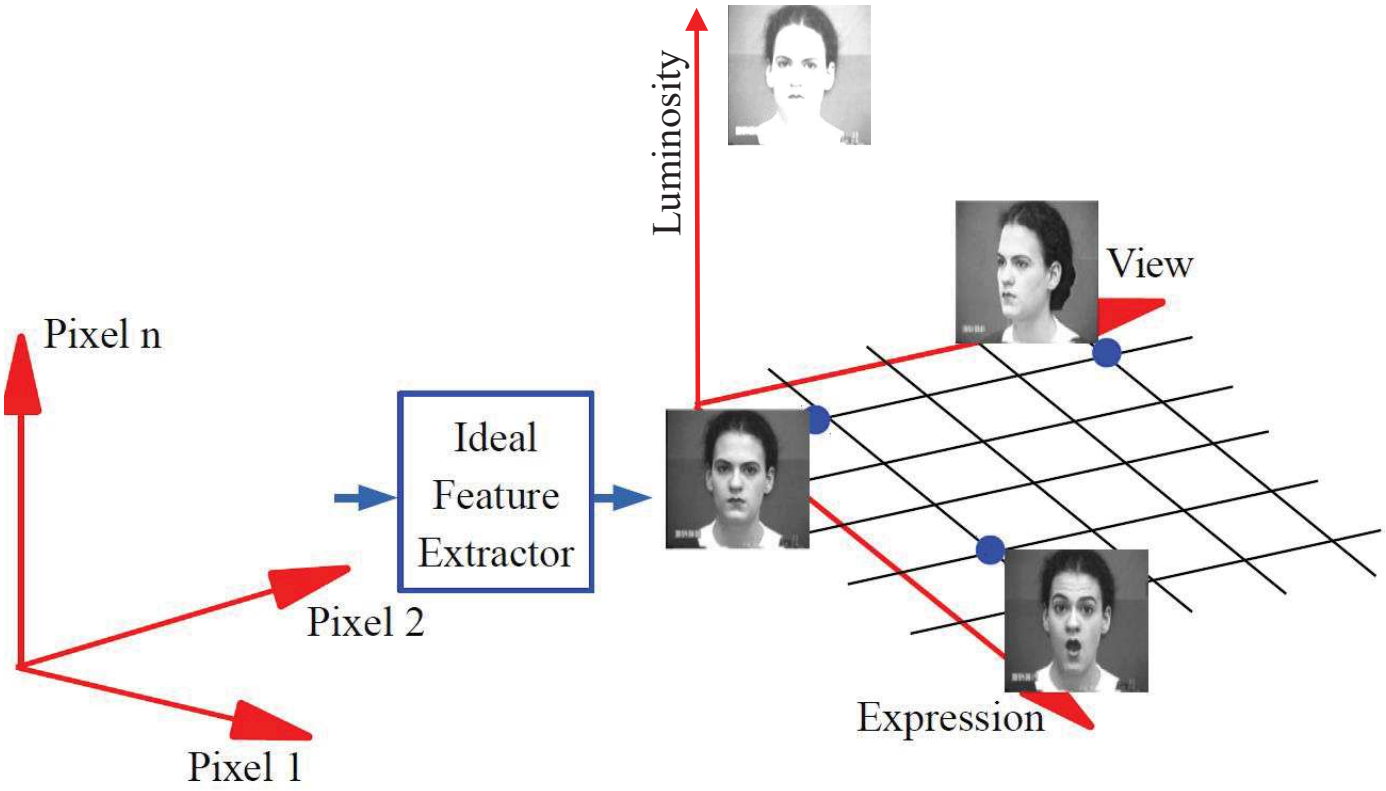
- **BUT:**
  - **position = 3 cartesian coord**
  - **orientation 3 Euler angles**
  - **50 muscles in face**
  - **Luminosity, color**

➔ Set of all images of ONE person has ≤ 69 dim



➔ Examples of face images *of 1 person* *are all in a LOW-dim manifold* *inside a HUGE-dim space*

Good features ~ « mapping » on manifold



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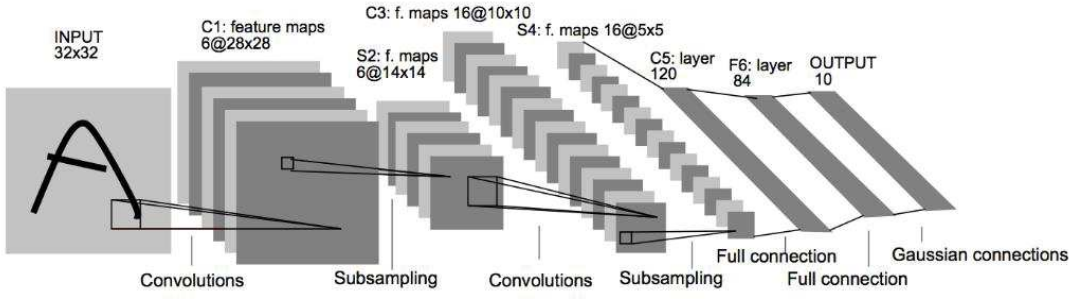
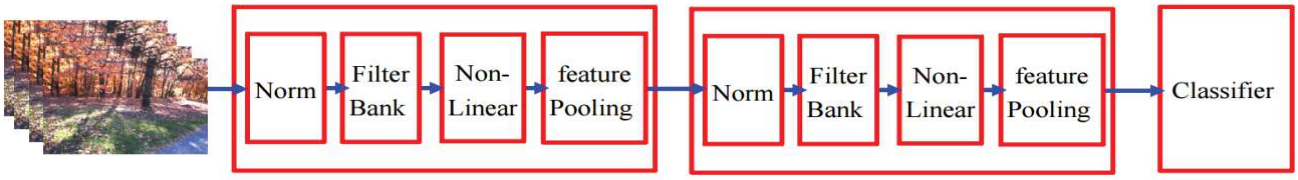
Convolutional Neural Networks (CNN, or ConvNet)

- Proposed in 1998 by Yann LeCun (french prof.@ NYU, now also AI research director of Facebook)

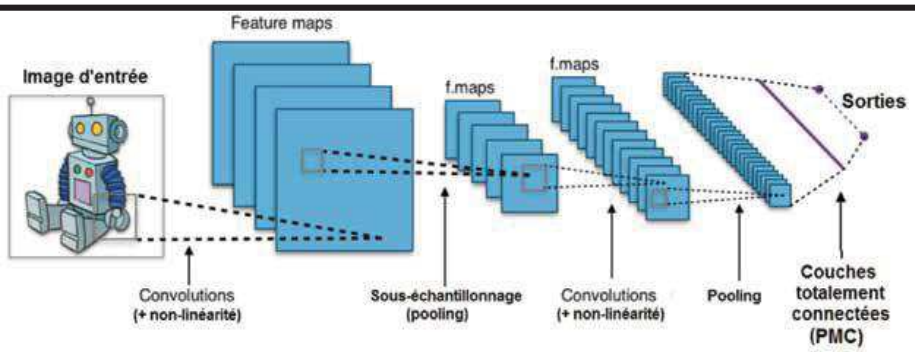


CNN called LeNet by Yann LeCun (1998)

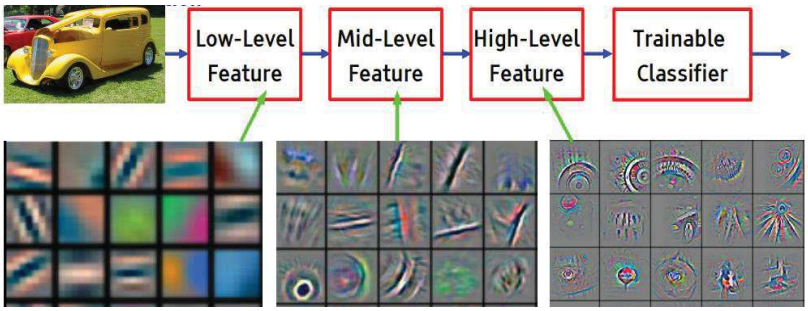


- For inputs with correlated dims (2D *image*, 1D signal,…)
- Supervised learning

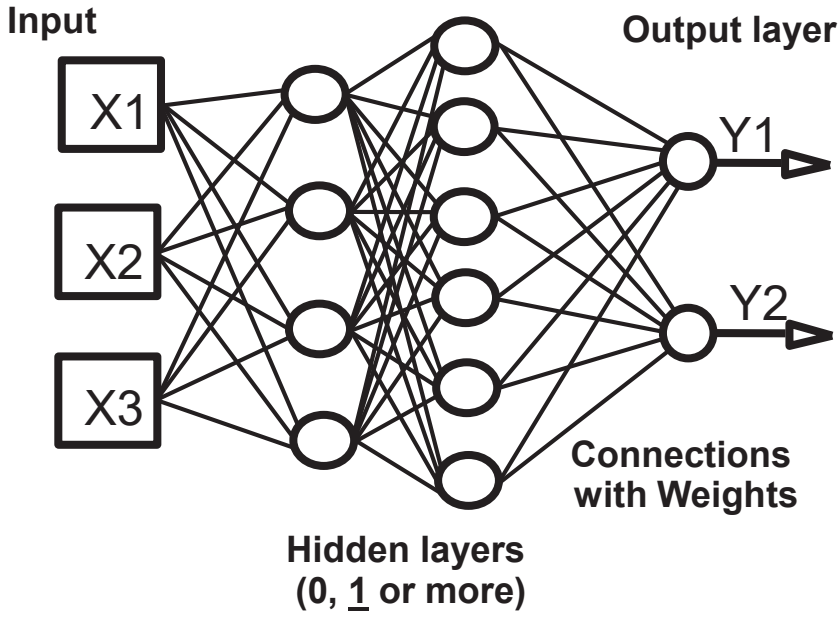
ConvNets (2)



- **Wins most vision pattern recognition competitions (OCR, TSR, object categorization, facial expression,…)**
- **Deployed in photo-tagging by Facebook, Google, Baidu,…**
- **Also used in real-time video analysis for self-driving cars**



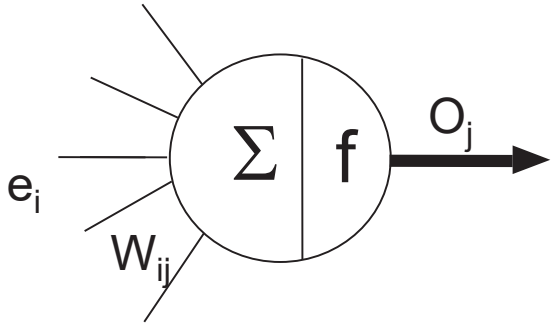
Short reminder on what is a (multi-layer) Neural Network



For "Multi-Layer Perceptron" (MLP), neurons type generally "summating with sigmoid activation"

Reminder on artificial "neurons"

PRINCIPLE

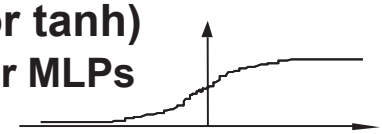


$$O_j = f\left(W_{0j} + \sum_{i=1}^{n_j} W_{ij} e_i\right)$$

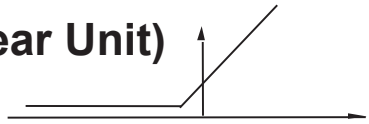
W_{0j} = "bias"

ACTIVATION FUNCTIONS

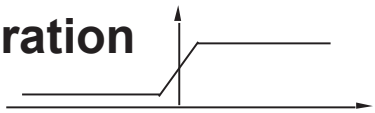
- **Threshold** (Heaviside or sign)
  → ***binary*** neurons
- **Sigmoïd** (logistic or tanh)
  → most common for MLPs



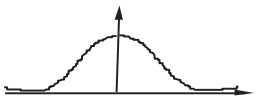
- **Identity** → ***linear*** neurons
- **ReLU** (Rectified Linear Unit)



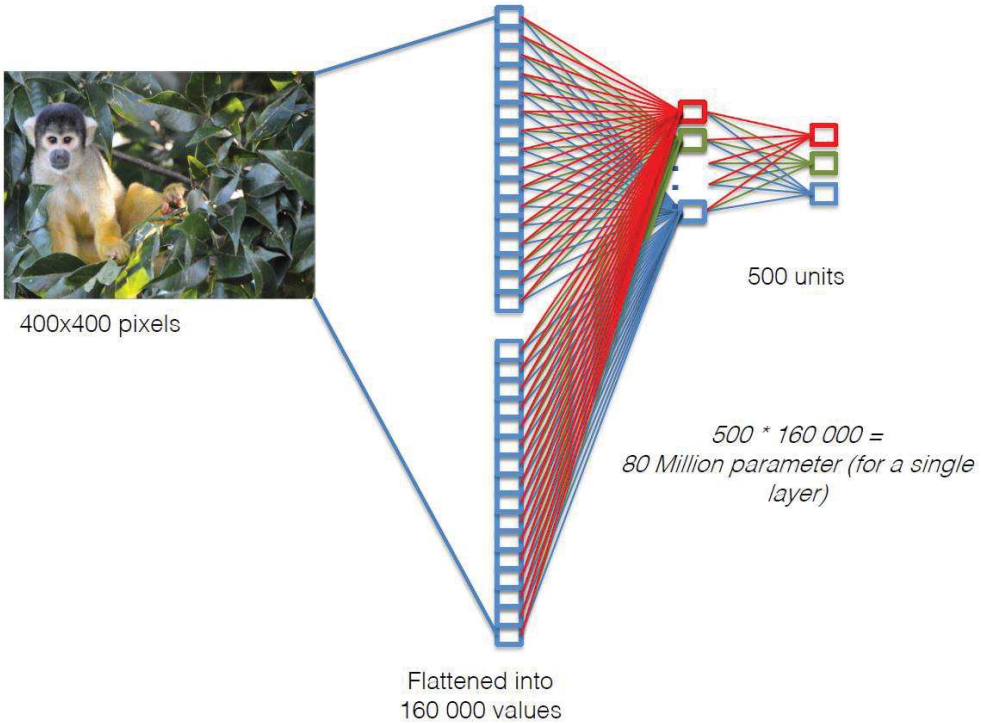
- **Saturation**



- **Gaussian**



Why MLP directly on pixels is generally a BAD idea?



Huge # of parameters, NO invariance at all

Why convolutions?

For image "semantic" classification, shift-invariance of features is useful

And ANY shift-invariant & linear system can always be expressed as a *CONVOLUTION*:

$$y[n] = \sum x[m]\, h[n-m]$$

(where *h*[*n*] is the impulse response).

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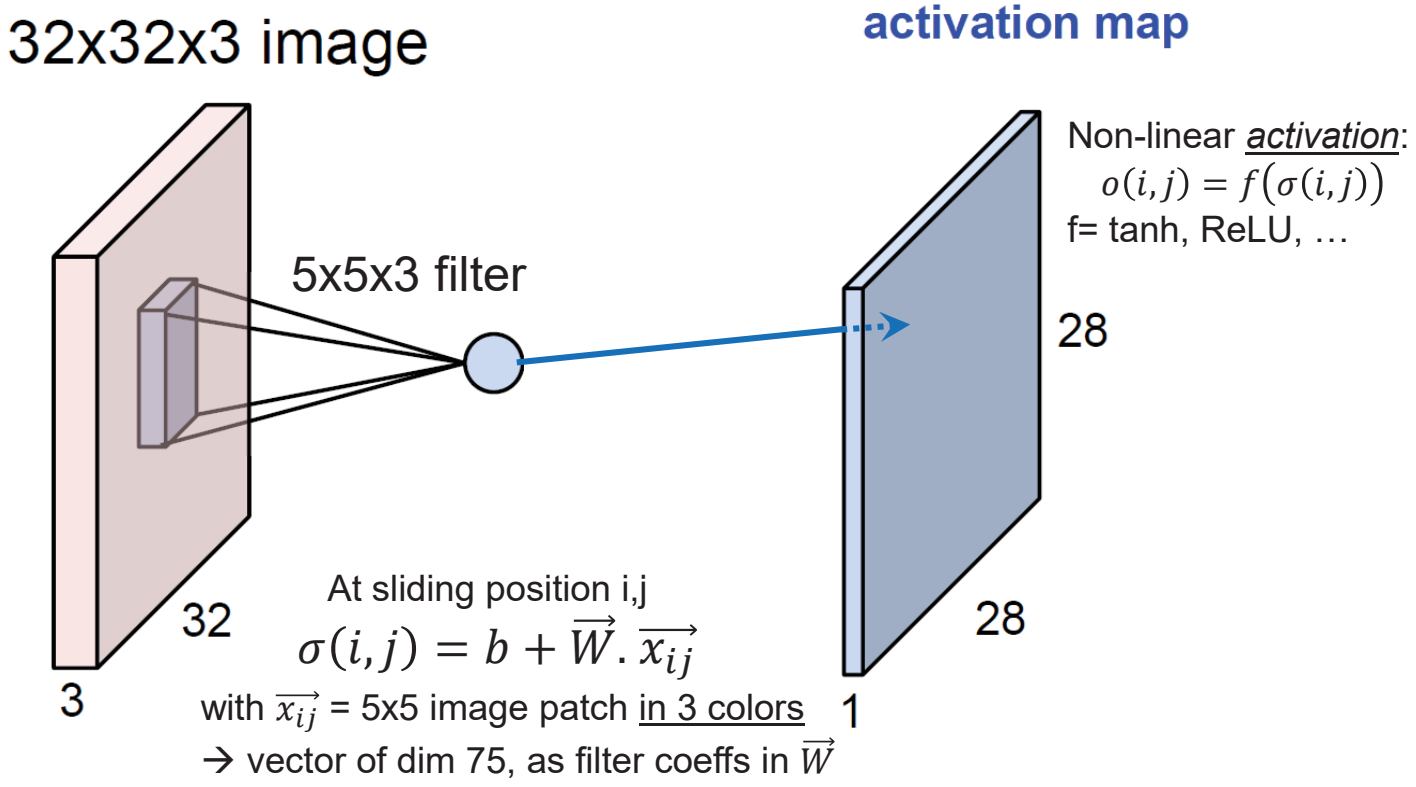
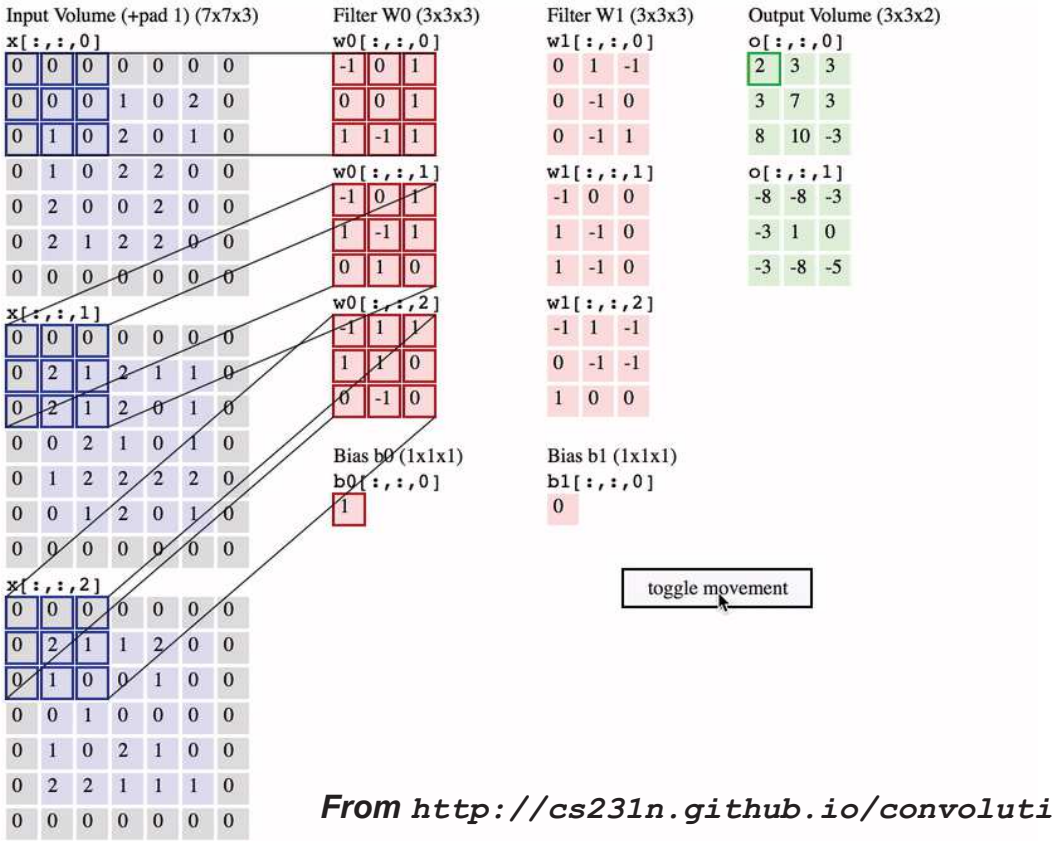
Convolution: sliding a 3D filter over image

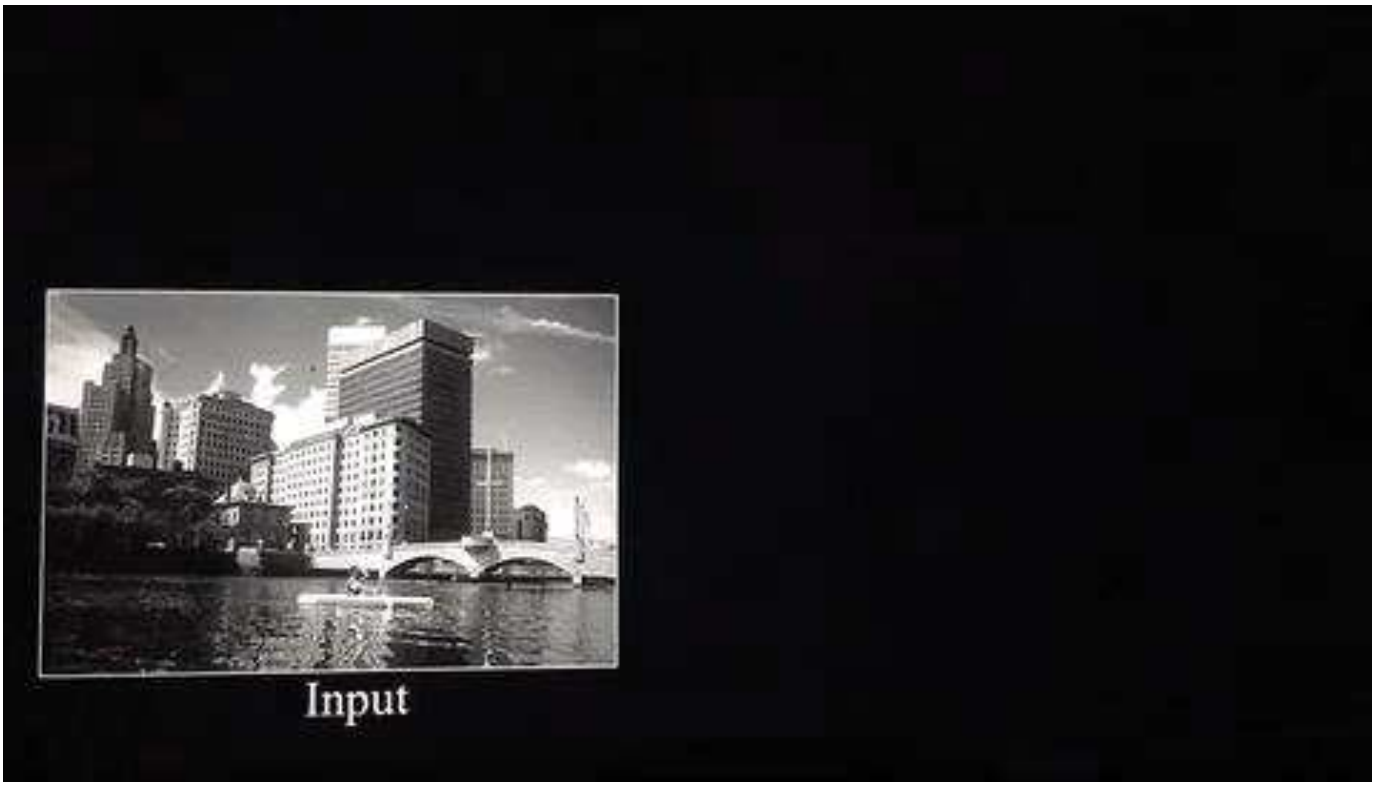


Convolution in action

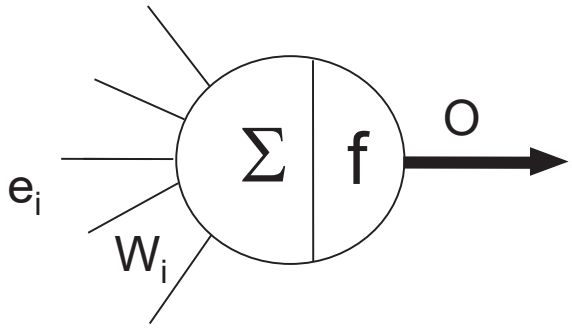


From `http://cs231n.github.io/convolutional-networks/`

Example of typical results of convolution



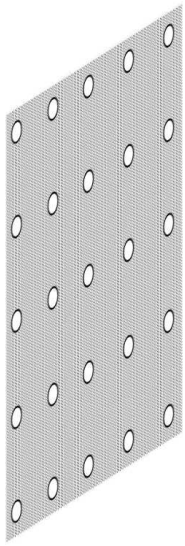
« Neural » view of convolution filters and layers



$$O = f\left(W_0 + \sum_{i=1}^{n} W_i e_i\right)$$

W_0 = "bias"
f = activation function

Each convolution FILTER is one set of neuron parameters



Each convolution LAYER is a set of `~imageSize` neurons, but they all have <u>same SHARED weights</u> <u>(perform SAME convolution)</u>

Convolutional v.s. Fully-connected

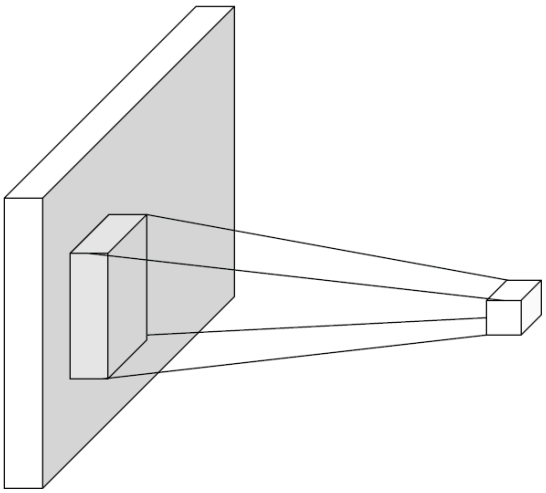
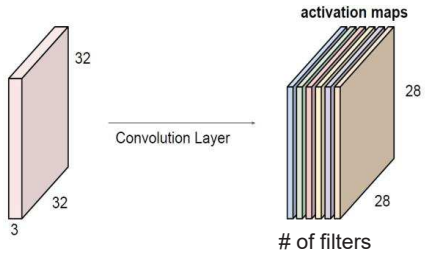


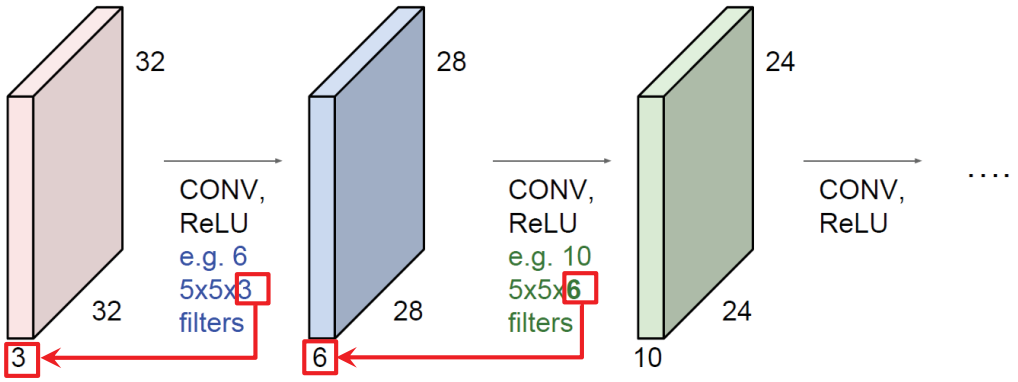
image Convolutional layer

Convolutional layers



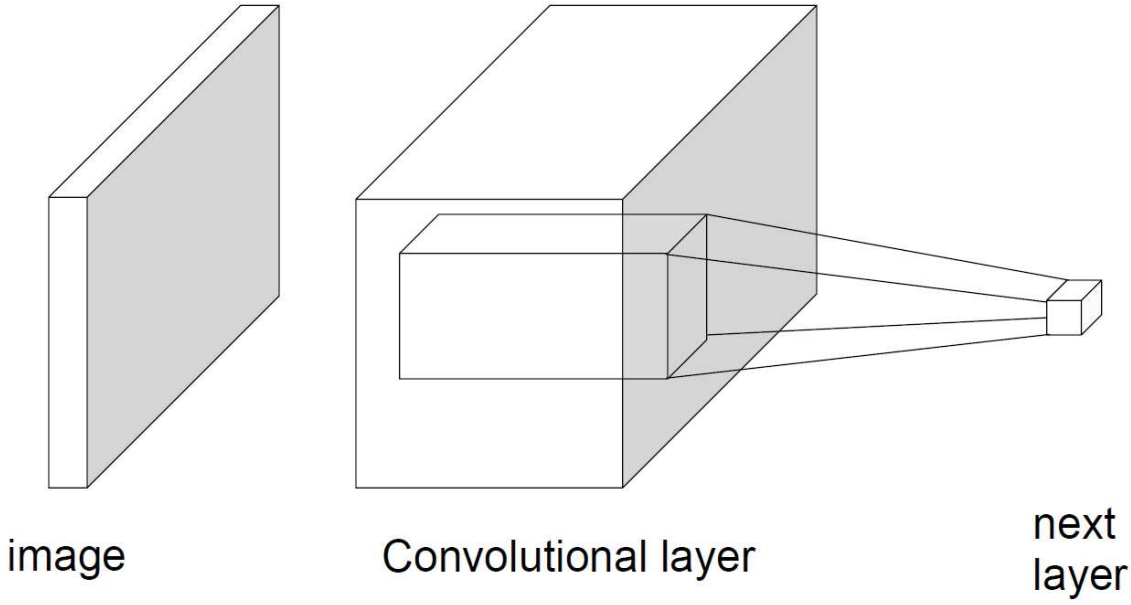
One "activation map" for each convolution filter

A convNet: succession of Convolution+activation Layers



NB: each convolution layer processes *FULL DEPTH* of previous activation map

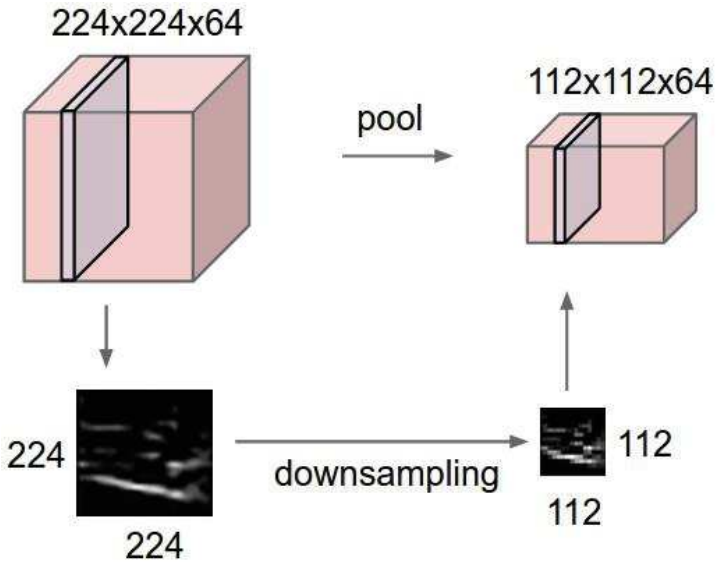
Convolution of convolutions!



Pooling layers

Goal:

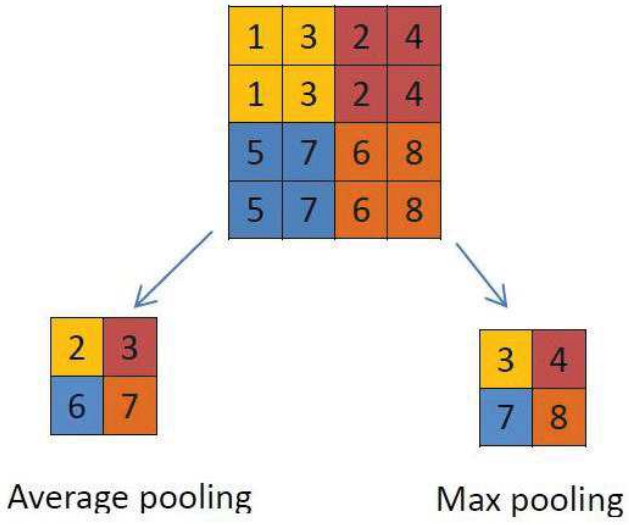
- **aggregation over space**
- **noise reduction,**
- **small-translation invariance,**
- **small-scaling invariance**



Pooling layers algorithm details

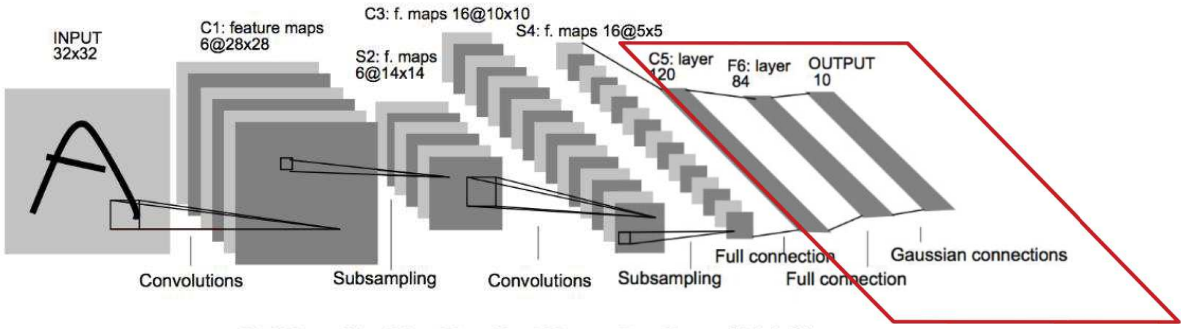
Parameters:

- pooling size (often 2x2)
- pooling stride (usually = pooling_size)
- Pooling operation: ***max***, average, Lp,…



Example: 2x2 pooling, stride 2

Final classification layer: just a classical MLP



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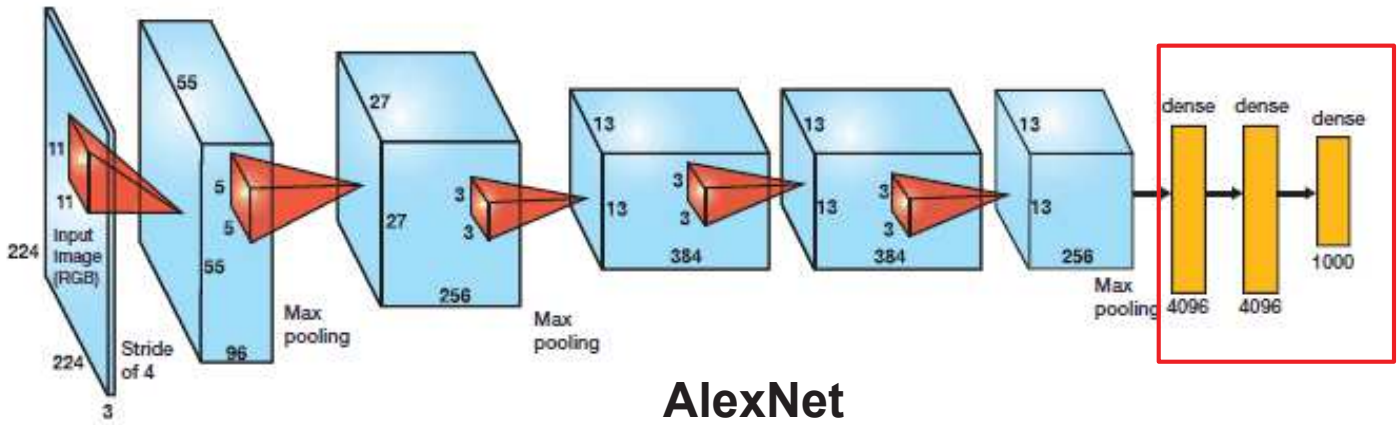
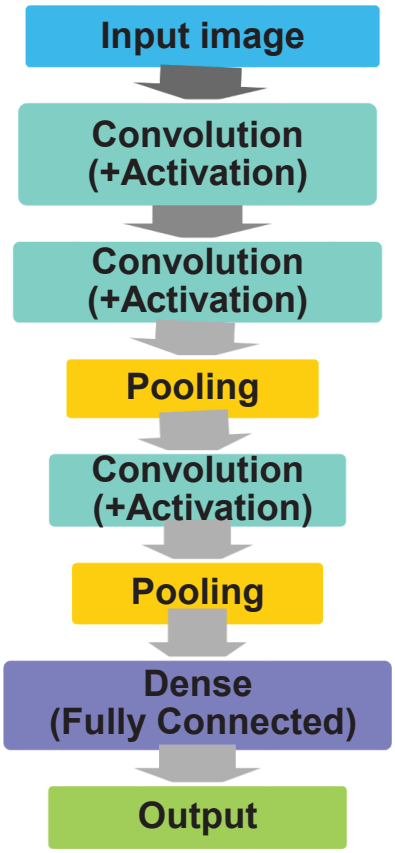


AlexNet

Global architecture of convNets

Succession of Convolution (+ optional activation) layers and Pooling layers, which extract the hierarchy of features, followed by dense (fully connected) layer(s) for final classification



Typical convolutional filters after training

Architecture with a deep succession of layers processing coarser and coarser "images"

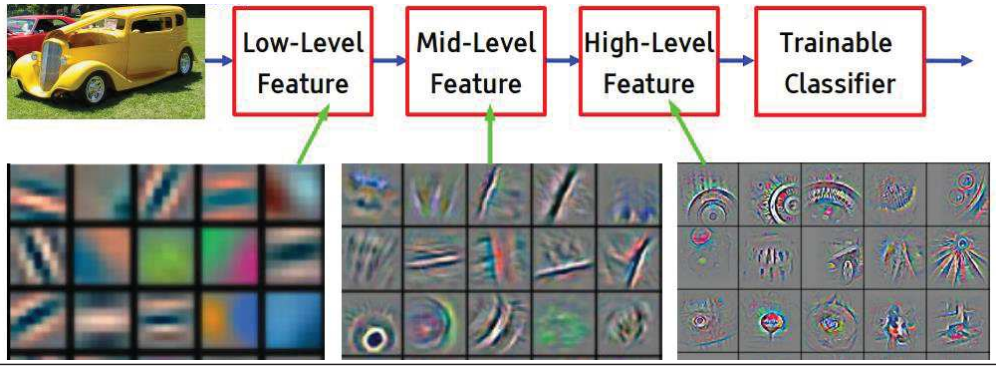
➔ Lower layer learns optimized low-level filters

(detection of ~edges in L1, ~corners/arcs in L2)

➔ Higher level layers learn more "abstract" filters

(~"texture types" in L3, ~object parts in L4)

➔ Last layer output a representation on which it is easy to discriminate between classes



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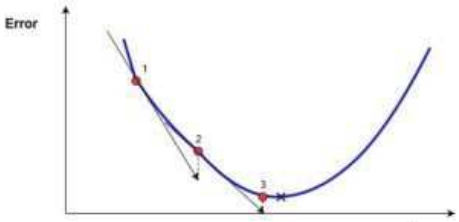
ConvNet training

All successive layers of a convNet forms a Deep neural network (with weigh-sharing inside each conv. Layer, and specific pooling layers).

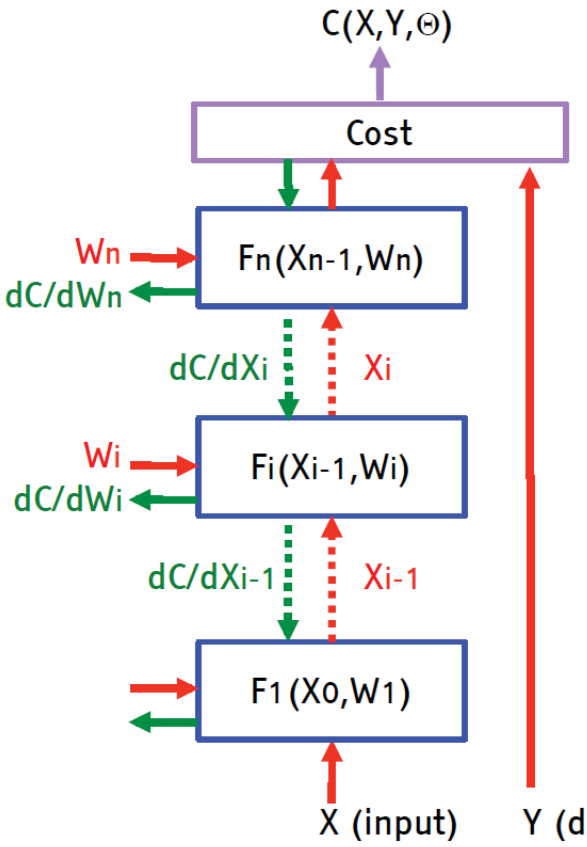
Training = optimizing values of weights&biases
Method used = gradient descent



➔ Stochastic Gradient Descent (SGD), using *back-propagation*:

- Input 1 (or a few) random training sample(s)
- Propagate
- Calculate error (loss)
- Back-propagate through all layers from end to input, to compute gradient
- Update convolution filter weights

Computing gradient through cascade of modules



- A practical Application of Chain Rule
- Backprop for the state gradients:
- $dC/dX_{i-1} = dC/dX_i \cdot dX_i/dX_{i-1}$
- $dC/dX_{i-1} = dC/dX_i \cdot dF_i(X_{i-1},W_i)/dX_{i-1}$
- Backprop for the weight gradients:
- $dC/dW_i = dC/dX_i \cdot dX_i/dW_i$
- $dC/dW_i = dC/dX_i \cdot dF_i(X_{i-1},W_i)/dW_i$

Recall of back-prop principle

Smart method for efficient computing of gradient (w.r.t. weights) of a Neural Network cost function, based on chain rule for derivation.

Cost function is $Q(t) = \sum_m loss(Y_m,D_m)$, where m runs over training set examples

Usually, $loss(Y_m,D_m) = ||Y_m-D_m||^2$ [quadratic error]

Total gradient:

$$W(t+1) = W(t) - \lambda(t)\, grad_W(Q(t)) + \mu(t)(W(t)-W(t-1))$$

Stochastic gradient:

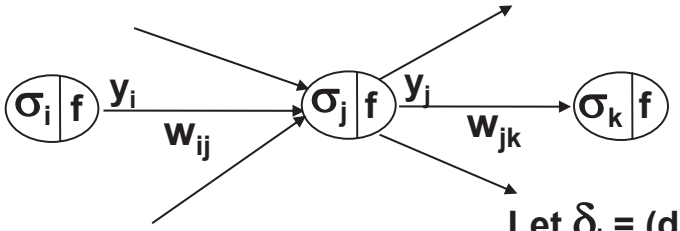
$$W(t+1) = W(t) - \lambda(t)\, grad_W(Q_m(t)) + \mu(t)(W(t)-W(t-1))$$

where $Q_m = loss(Y_m,D_m)$, is error computed on only ONE example randomly drawn from training set at every iteration and

$\lambda(t)$ = learning rate (fixed, decreasing or adaptive), $\mu(t)$ = momentum

Now, how to compute dQ_m/dW_{ij}?

Backprop through layers: chain rule derivative computation



$dE_m/dW_{ij} = (dE_m/d\sigma_j)(d\sigma_j/dW_{ij}) = (dE_m/d\sigma_j)\, y_i$

Let $\delta_j = (dE_m/d\sigma_j)$. Then $\boxed{W_{ij}(t+1) = W_{ij}(t) - \lambda(t)\, y_i\, \delta_j}$

(and $W_{0j}(t+1) = W_{0j}(t) - \lambda(t)\delta_j$)

If neuron j is output, $\delta_j = (dE_m/d\sigma_j) = (dE_m/dy_j)(dy_j/d\sigma_j)$ with $E_m = ||Y_m - D_m||^2$

so $\boxed{\delta_j = 2(y_j - D_j)f'(\sigma_j)}$ if neuron j is an output

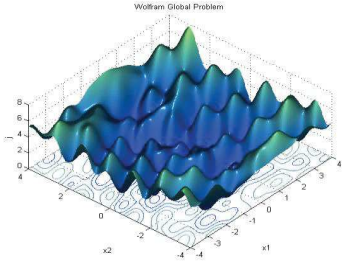
Otherwise, $\delta_j = (dE_m/d\sigma_j) = \Sigma_k (dE_m/d\sigma_k)(d\sigma_k/d\sigma_j) = \Sigma_k \delta_k (d\sigma_k/d\sigma_j) = \Sigma_k \delta_k W_{jk}(dy_j/d\sigma_j)$

so $\boxed{\delta_j = (\Sigma_k\ W_{jk}\delta_k)f'(\sigma_j)}$ if neuron j is "hidden"

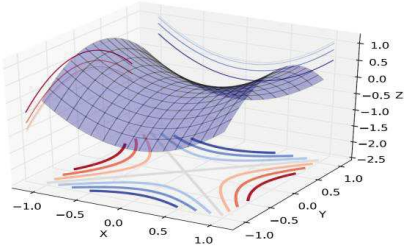
➔ all the δ_j can be computed successively from last layer to upstream layers by "error backpropagation" from output

Why gradient descent works *despites non-convexity*?

Error surface for neural net are NOT CONVEX !

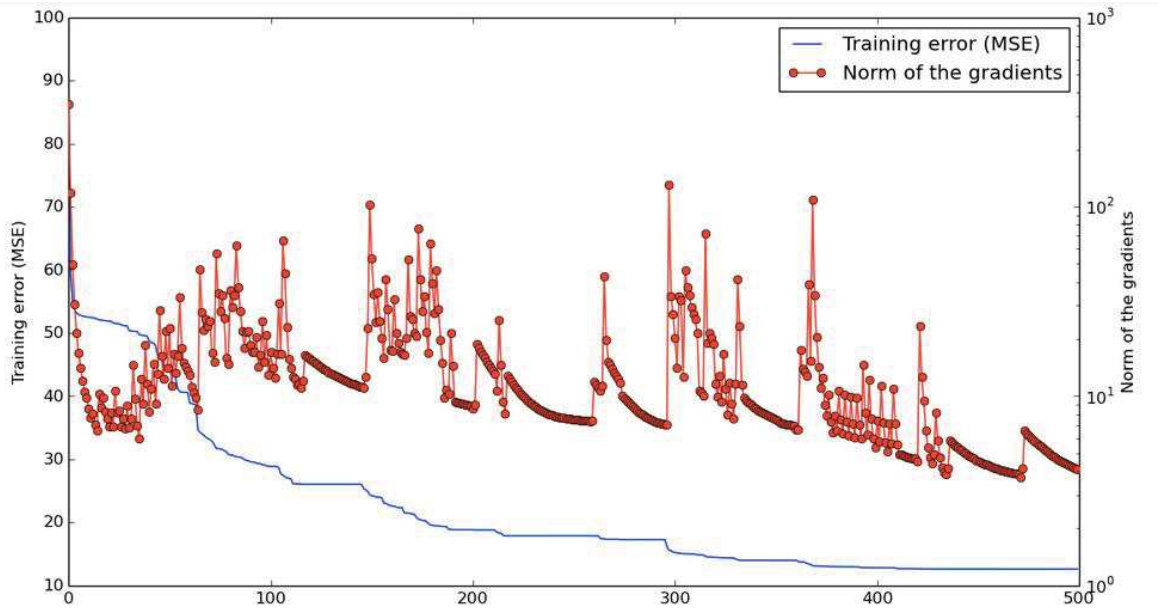


- Local minima dominate in low-Dim…
- …but recent work has shown that ***saddle points*** dominate in high-Dim



- Furthermore, most local minima are close to the global minimum

Saddle points in training curves

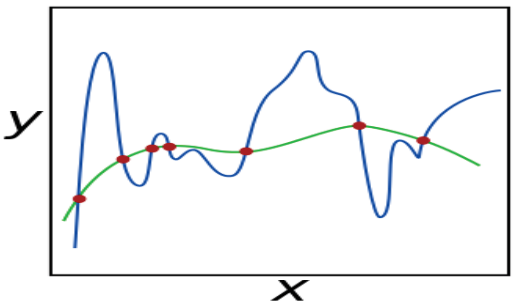


- **Oscillating between two behaviors:**
  - **Slowly approaching a saddle point**
  - **Escaping it**

Some ConvNet training « tricks »

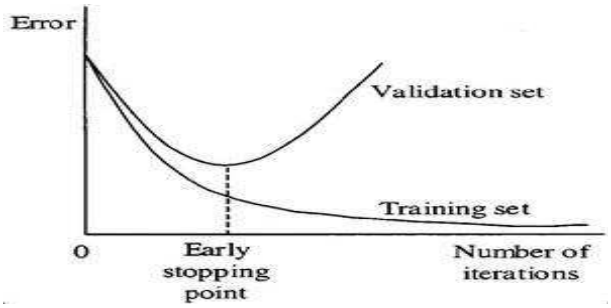
- **Importance of input normalization**
  (zero mean, unit variance)
- **Importance of weights initialization**
  random but SMALL and prop. to 1/sqrt(nbInputs)
- **Decreasing (or adaptive) learning rate**
- **Importance of training set size**
  ConvNets often have a LARGE number of free parameters
  ➔ train them with a sufficiently large training-set !
- ***Avoid overfitting* by:**
  - **Early Stopping of learning iterations**
  - **Use of L1 or L2 regularization (after some epochs)**
  - **Use « *Dropout* » regularization (esp. on large FC layers)**

What is Overfitting?



Trying to fit too many free parameters with not enough information can lead to *overfitting*

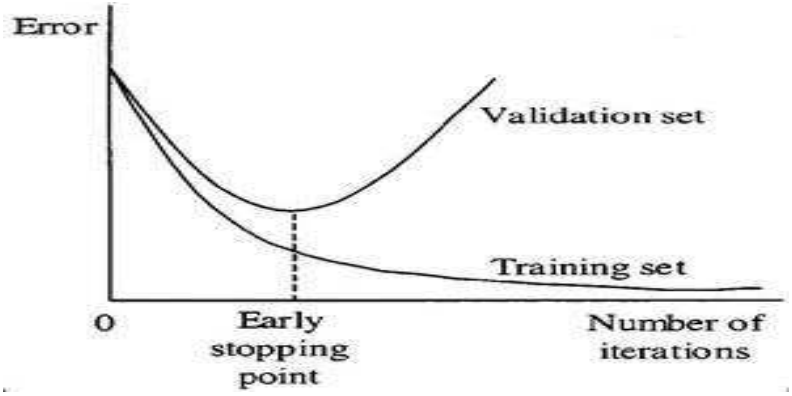
How to detect overfitting for iterative training?



Better = AVOID overfitting by REGULARIZATION

Avoid overfitting by EARLY STOPPING

- For Neural Networks, a first method to avoid overfitting is to STOP LEARNING iterations as soon as the *validation*_error stops decreasing
- Generally, not a good idea to decide the number of iterations beforehand. Better to ALWAYS USE EARLY STOPPING



Avoid overfitting using L1/L2 regularization

Regularization = penalizing too complex models

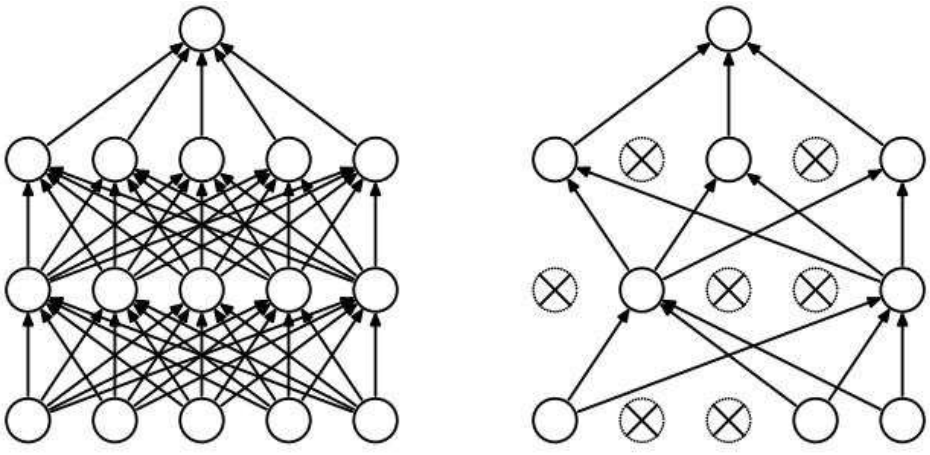
Often done by adding a special term to cost function

For neural network, the regularization term is just the L2- or L1- norm of the vector of all weights:

$$K = \sum_m(\text{loss}(Y_m,D_m)) + \beta \sum_{ij} |W_{ij}|^p \quad \text{with p=2 (L2) or p=1 (L1)}$$

→ name "Weight decay"

DropOut regularization for convNet training



(a) Standard Neural Net (b) After applying dropout.

At each training stage, individual nodes can be temporarily "dropped out" of the net with probability p (usually ~0.5), or re-installed with last values of weights

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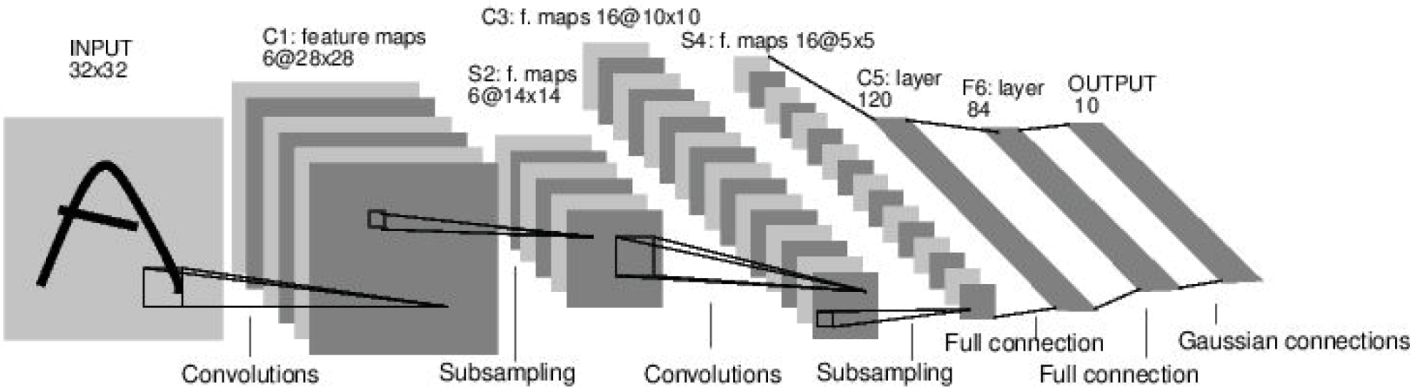
Examples of very successful ConvNets

- **LeNet:** 1st successful applications of ConvNets, by Yann LeCun in 1990's. Used to read zip codes, digits, etc.
- **AlexNet:** Beginning of ConvNet "buzz": largely outperformed competitors in ImageNet_ILSVRC2012 challenge. Developped by Alex Krizhevsky et al., architecture similar to LeNet (but deeper+larger, and some chained ConvLayers before Pooling). 60 M parameters !
- **ZF Net:** ILSVRC 2013 winner. Developped by Zeiler&Fergus, by modif of AlexNet on some architecture hyperparameters.
- **GoogLeNet:** ILSVRC 2014 winner, developed by Google. Introduced an *Inception Module*, + AveragePooling instead of FullyConnected layer at output. Dramatic reduction of number of parameters (4M, compared to AlexNet with 60M).
- **VGGNet:** Runner-up in ILSVRC 2014. Very deep (16 CONV/FC layers) → 140M parameters !!
- **ResNet:** ILSVRC 2015, "Residual Network" introducing "skip" connections. Currently ~ SoA in convNet. Very long training but fast execution.

LeNet, for digits/letters recognition *[LeCun et al., 1998]*

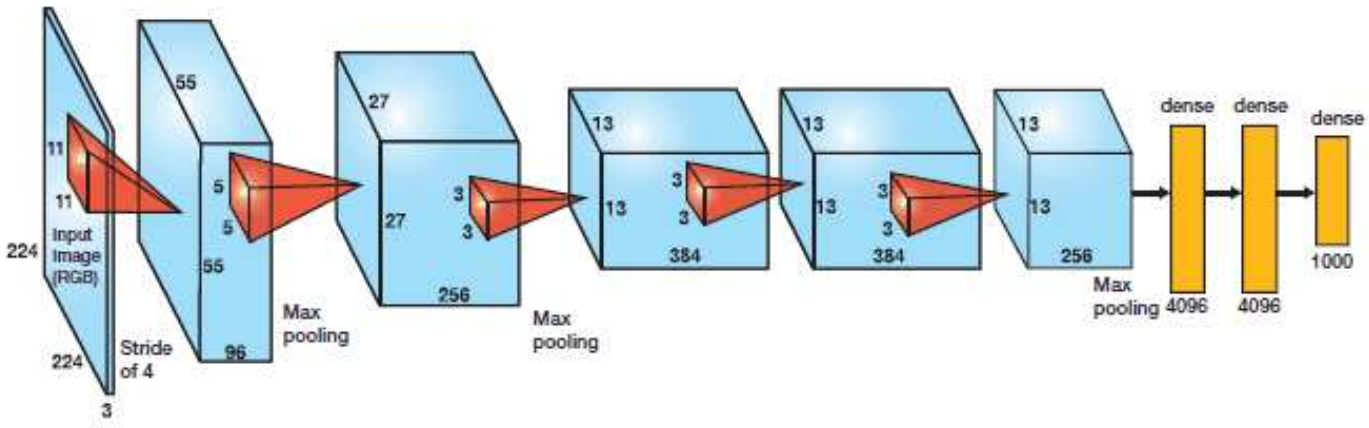
Input: 32x32 image



Conv filters were 5x5, applied at stride 1
Subsampling (Pooling) layers were 2x2 applied at stride 2
i.e. architecture is [CONV-POOL-CONV-POOL-CONV-FC]

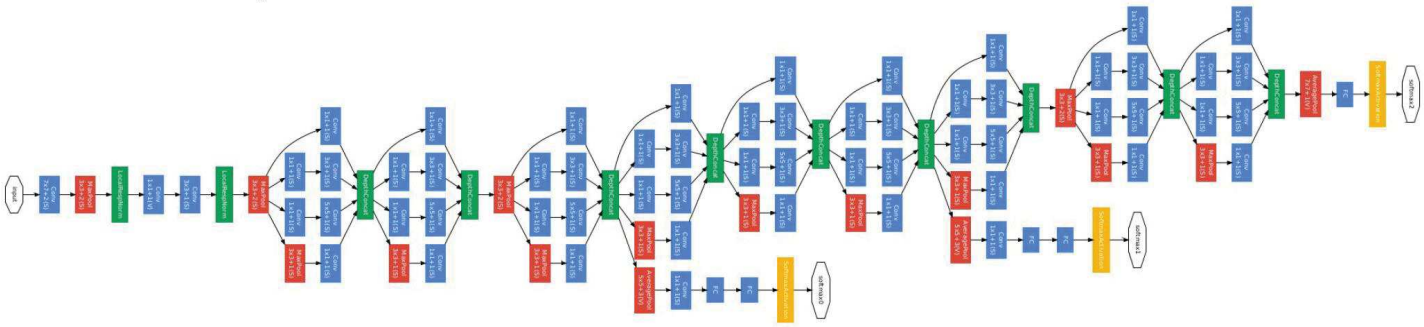
AlexNet, for image categorisation *[Krizhevsky et al. 2012]*

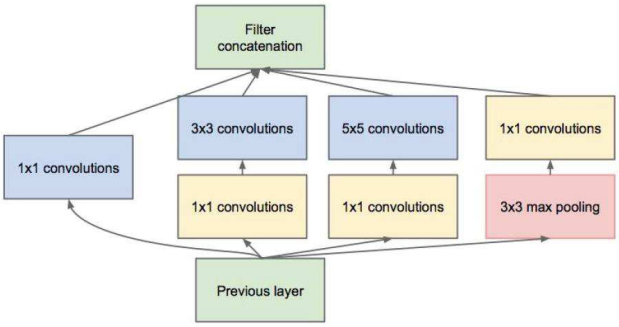
Input: 224x224x3 image



60 million parameters !...

GoogleNet
[Szegedy et al., 2014]



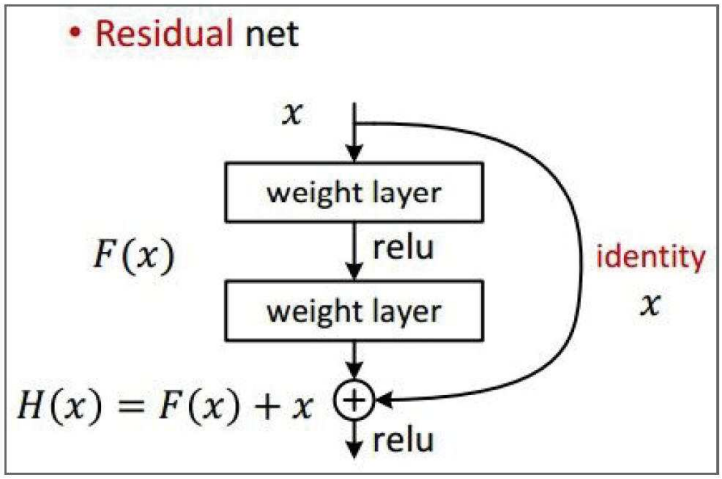


Inception module

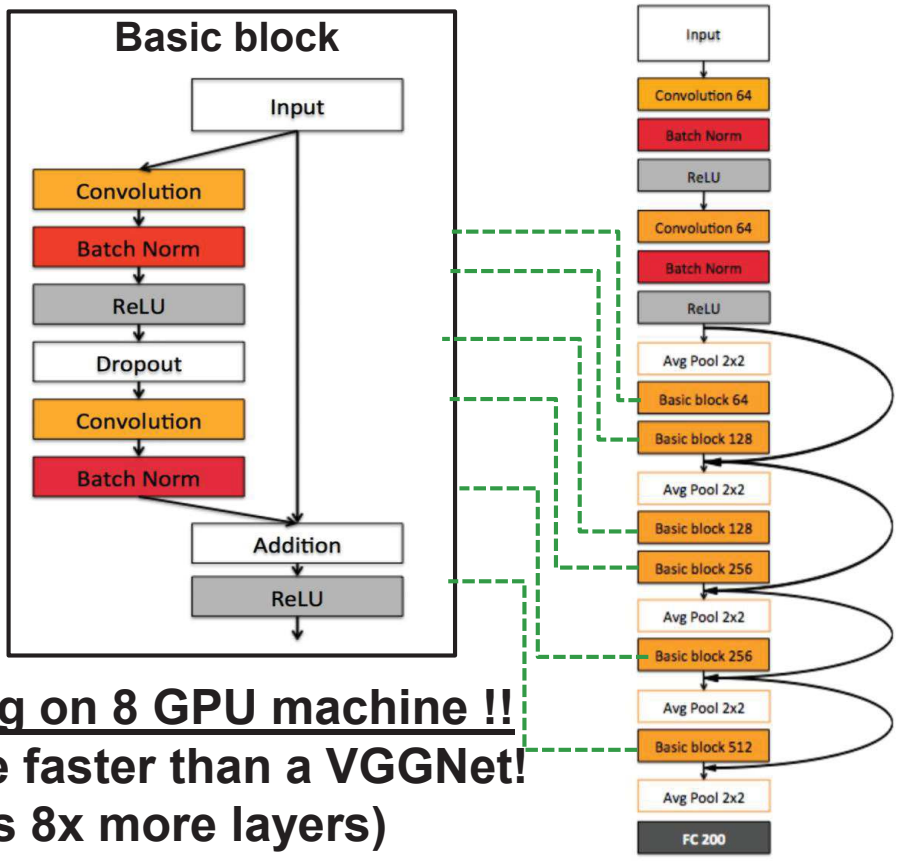
ILSVRC 2014 winner (6.7% top 5 error)

ResNet (Residual Net), by Microsoft *[He et al., 2015]*

- **ILSVRC 2015 *large* winner in 5 main tracks (3.6% top 5 error)**
- **152 layers!!!**
- **But novelty = *"skip" connections***

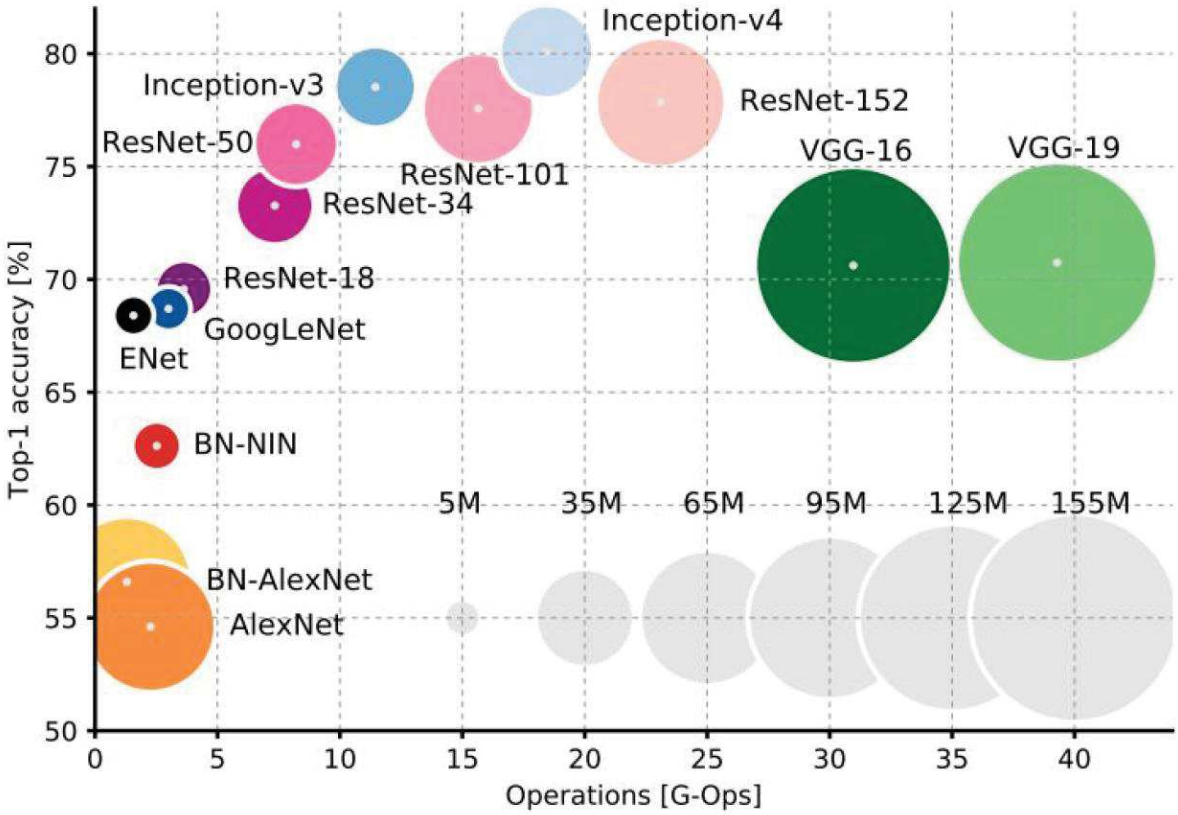


ResNet global architecture

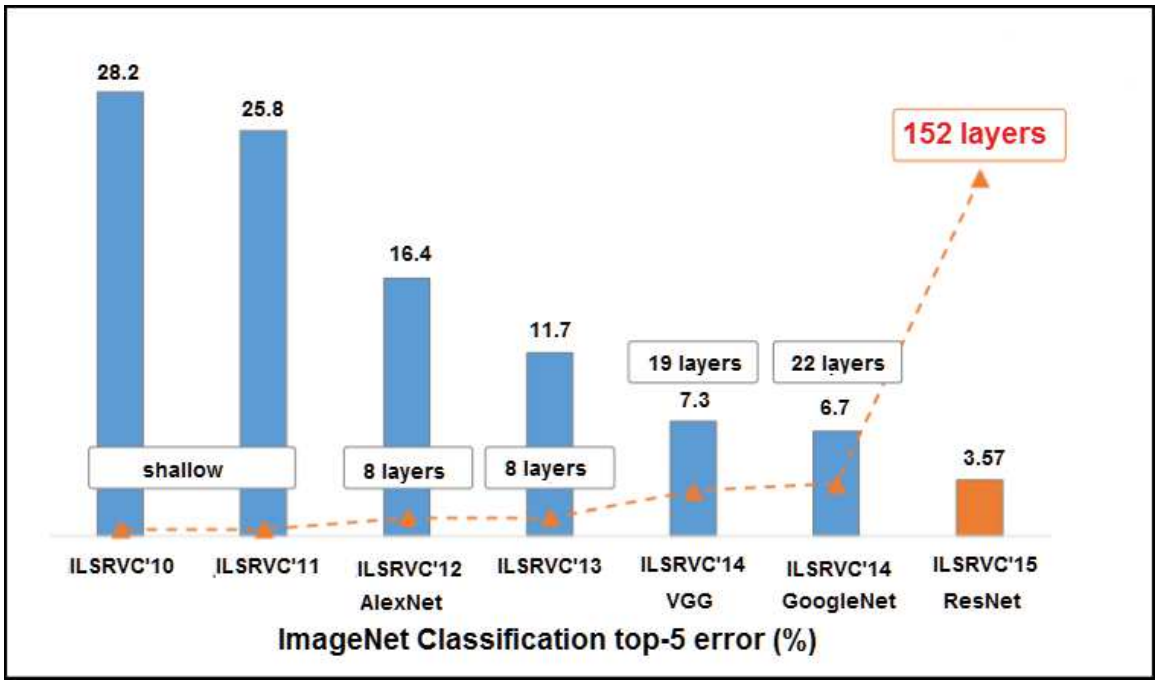


- **2-3 weeks of training on 8 GPU machine !!**
- **However, at runtime faster than a VGGNet! (even though it has 8x more layers)**

Performance comparison of usual convNet architectures



Summary of recent ConvNet history



But most important is the choice of *ARCHITECTURAL STRUCTURE*

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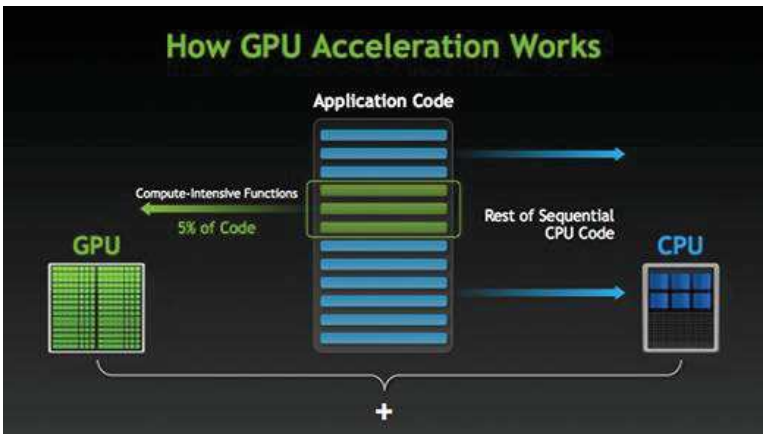
convNets and GPU

Good convNets are very big (millions of parameters!)

Training generally performed on BIG datasets

➔ Training time more manageable using GPU acceleration for ultra-parallel processing



Programming environments for Deep-Learning

- **TensorFlow** https://www.tensorflow.org
- **KERAS** https://keras.io
  Python front-end APIs mapped either on Tensor-Flow or Theano back-end
- **PyTorch** https://pytorch.org/
- ***Caffe*** http://caffe.berkeleyvision.org/
  C++ library, hooks from Python → notebooks
- ***Theano*** http://www.deeplearning.net/software/theano/
- ***Lasagne*** http://lasagne.readthedocs.io
  lightweight library to build+train neural nets in Theano

All of them handle transparent use of GPU, and most of them are used in Python code/notebook

Example of convNet code in Keras

```
model = Sequential()

# 1 set of (Convolution+Pooling) layers, with Dropout
model.add(Convolution2D(conv_depth_1, kernel_size, kernel_size,
            border_mode='valid', input_shape=(depth, height, width)))
model.add( MaxPooling2D(pool_size=(pooling_size, pooling_size)) )
model.add(Activation('relu'))
model.add(Dropout(drop_prob))

# Now flatten to 1D, and apply 1 Fully_Connected layer
model.add(Flatten())
model.add(Dense(hidden_size1, init='lecun_uniform'))
model.add(Activation('sigmoid'))

# Finally add a Softmax output layer, with 1 neuron per class
model.add(Dense(num_classes, init='lecun_uniform'))
model.add(Activation('softmax'))

# Training "session
sgd = SGD(lr=learning_rate, momentum=0.8) # Optimizer
model.compile(loss='categorical_crossentropy', optimizer=sgd)
model.fit(X_train, Y_train, batch_size=32, nb_epoch=2, verbose=1,
                                    validation_split=valid_proportion)

# Evaluate the trained model on the test set
model.evaluate(X_test, Y_test, verbose=1)
```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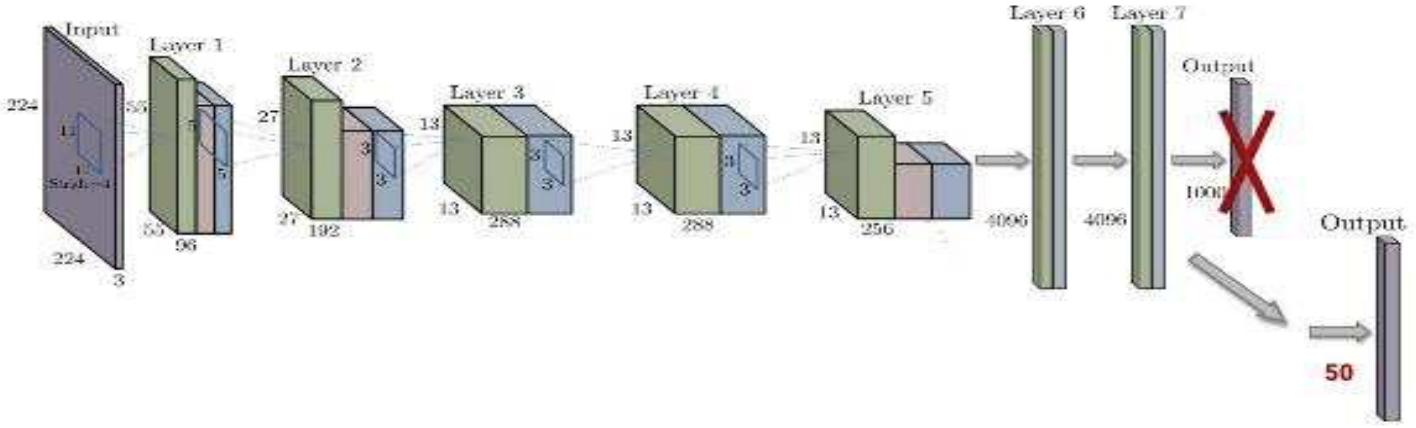
Power and Generality of learnt representation



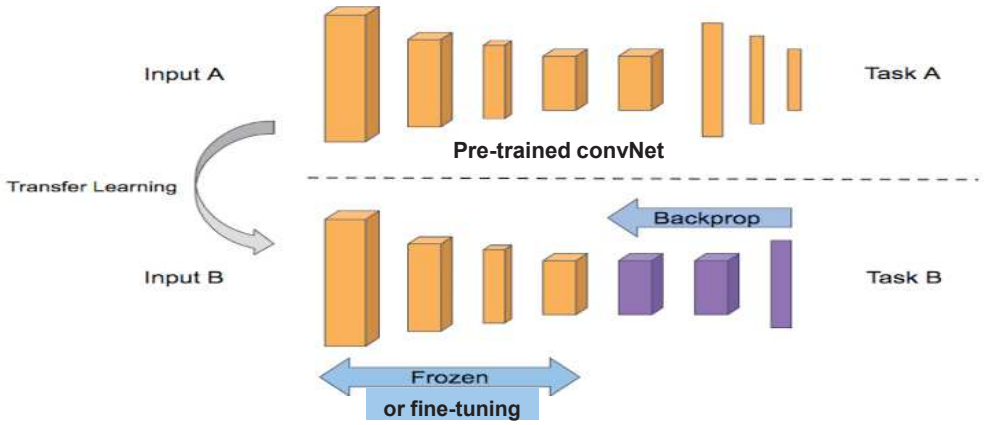
By removing *last layer(s)* (those for classification) of a convNet trained on ImageNet, one obtains a *transformation of any input image into a semi-abstract representation,* which can be used for learning SOMETHING ELSE (« transfer learning »):

- **either by just using learnt representation as features**
- **or by creating new convNet output and perform learning of new output layers + fine-tuning of re-used layers**

Transfer learning and fine-tuning

- **SoA convNets trained on ImageNet are image CLASSIFIERS for one object per image**
- **Many object categories can be irrelevant (e.g. boat in a office)**

➔ **For each application, models are usually obtained from state-of-the-art ConvNets pre-trained on ImageNet (winners of yearly challenge, eg: AlexNet, VGG, Inception, ResNet, etc…)**



➔ **Adaptation is performed by *Transfer Learning*, ie modification+training of last layers and/or fine-tuning of pre-trained weights of lower layers**

Transfer Learning with few training examples

- **Using a CNN pre-trained on a large dataset, possible to adapt it to another task, *using only a SMALL training set*!**

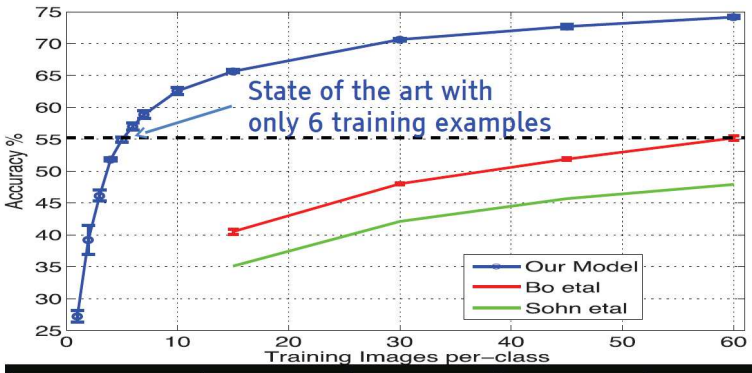
Network first trained on ImageNet.

Last layer chopped off

Last layer trained on Caltech 256,

first layers N-1 kept fixed.

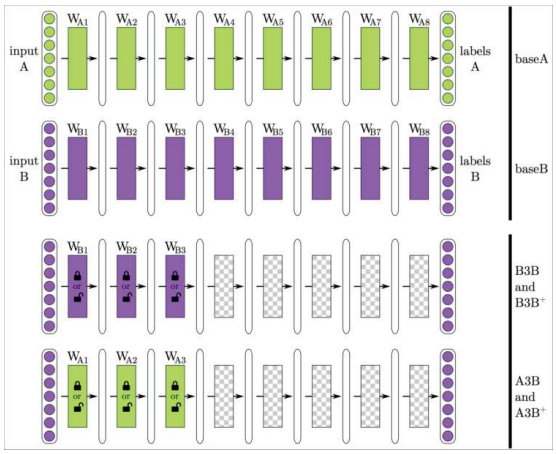
State of the art accuracy with only 6 training samples/class



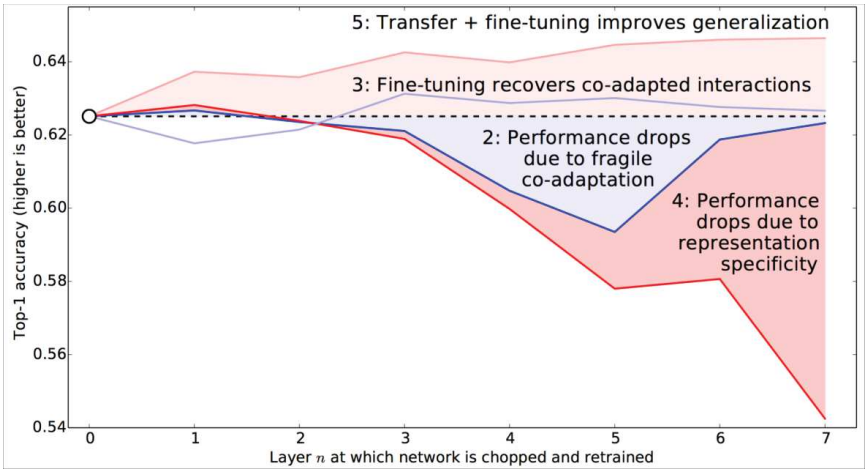
# Train	Acc % 15/class	Acc % 30/class	Acc % 45/class	Acc % 60/class
Sohn *et al.* [16]	35.1	42.1	45.7	47.9
Bo *et al.* [3]	40.5 ± 0.4	48.0 ± 0.2	51.9 ± 0.2	55.2 ± 0.3
Non-pretr.	9.0 ± 1.4	22.5 ± 0.7	31.2 ± 0.5	38.8 ± 1.4
ImageNet-pretr.	$\mathbf{65.7 \pm 0.2}$	$\mathbf{70.6 \pm 0.2}$	$\mathbf{72.7 \pm 0.4}$	$\mathbf{74.2 \pm 0.3}$

3: [Bo, Ren, Fox. CVPR, 2013] 16: [Sohn, Jung, Lee, Hero ICCV 2011]

Transfer-Learning even improves permormances!



[Yosinski, Clune, Bengio, Lipson, "How transferable are features in deep neural networks?", ICML'2014]



Some transfer-learning applications

- Learning on simulated synthetic images
  + fine-tuning on real-world images
- Recognition/classification for OTHER categories or classes
- Training an objects detector (or a semantic segmenter)

- Precise localization (position+bearing) = PoseNet
- Human posture estimation = openPose
- End-to-end driving (imitation Learning)
- 3D informations (depth map) from monovision!

Transfer Learning code example in Keras

```
from keras.applications.inception_v3 import InceptionV3
from keras.preprocessing import image
from keras.models import Model
from keras.layers import Dense, GlobalAveragePooling2D
from keras import backend as K
# create the base pre-trained model base_model = InceptionV3(weights='imagenet',
                                                             include_top=False)
# add a global spatial average pooling layer
x = base_model.output x = GlobalAveragePooling2D()(x)
# let's add a fully-connected layer
x = Dense(1024, activation='relu')(x)
# and a logistic layer -- let's say we have 200 classes
predictions = Dense(200, activation='softmax')(x)
# this is the model we will train
model = Model(input=base_model.input, output=predictions)
# first: train only the top layers (which were randomly initialized)
# i.e. freeze all convolutional InceptionV3 layers
for layer in base_model.layers:
  layer.trainable = False
# compile the model (should be done *after* setting layers to non-trainable)
model.compile(optimizer='rmsprop', loss='categorical_crossentropy')
# train the model on the new data for a few epochs
model.fit_generator(...)
```

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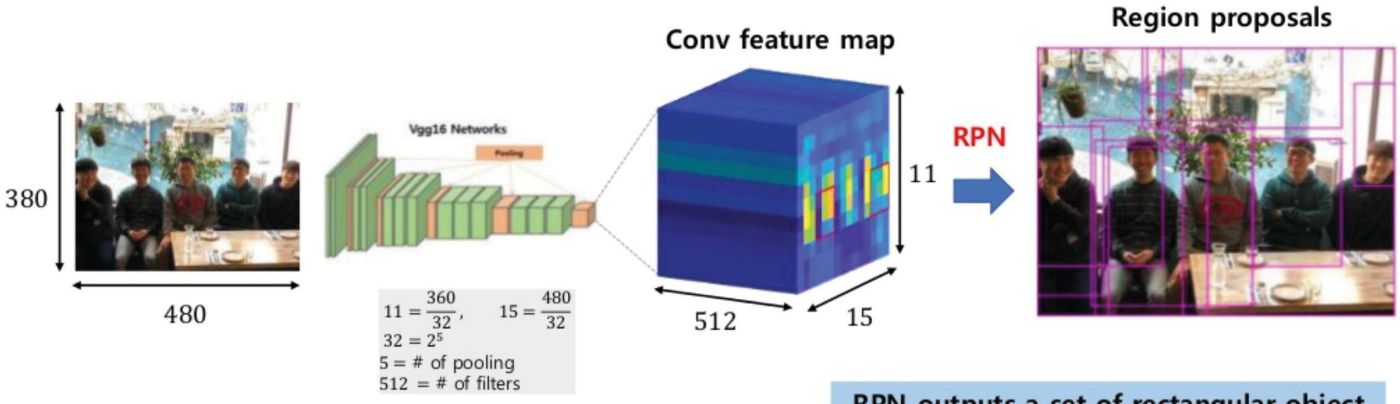
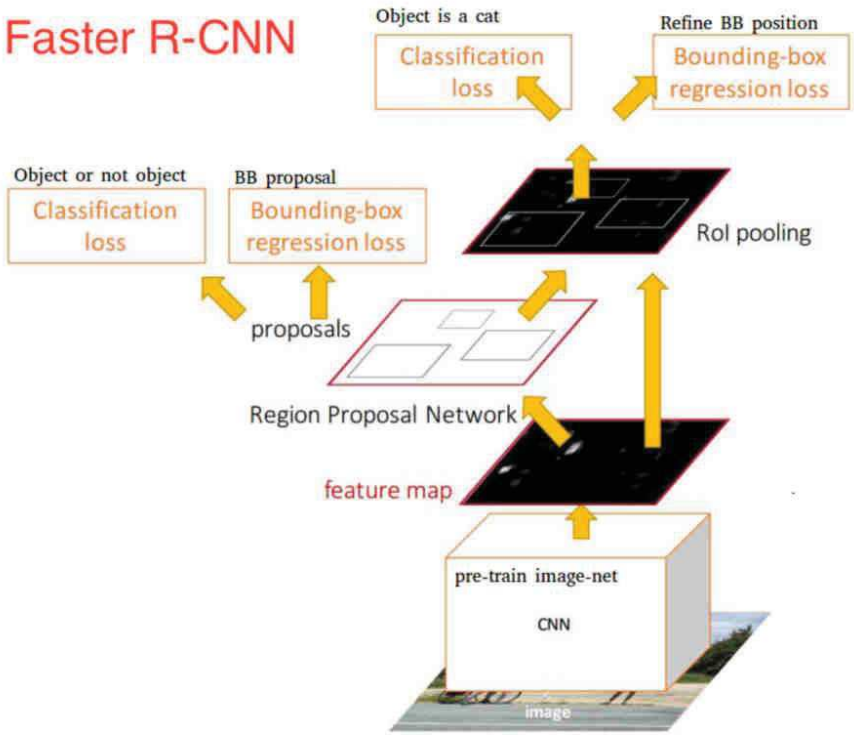
- Deep-Learning on 1D signal and 3D data
- Recent other image-based applications

Deep-Learning for visual object DETECTION



The high-level representation computed by last convolution layer can be analyzed for detection and localization (bounding-boxes) of all objects of interesting categories

Visual objects Detection and Categorization: Faster_RCNN



Region Proposal Network (RPN) on top of standard convNet.
End-to-end training with combination of 4 losses

Example of visual DETECTION & categorization with Faster_R-CNN

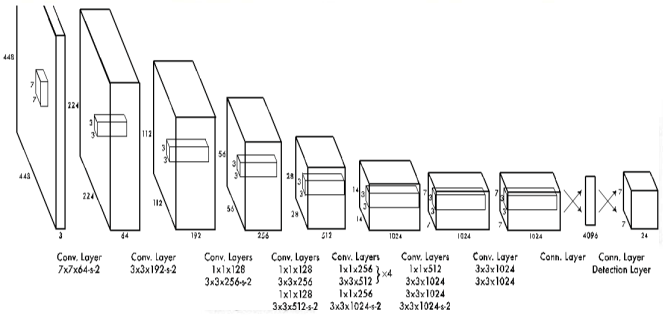
ConvNets are currently state-of-the-art ALSO for visual objects detection

Object visual detection *without proposal*

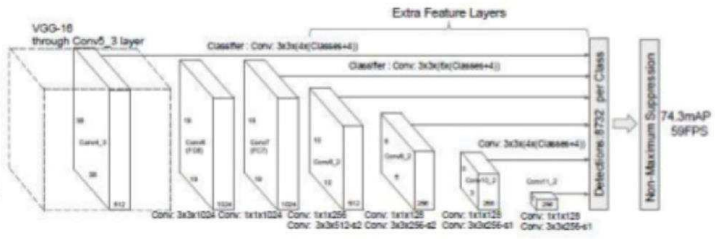
Solve detection as a regression problem ("single-shot" detection)

YOLO and SSD

YOU ONLY LOOK ONCE(YOLO)



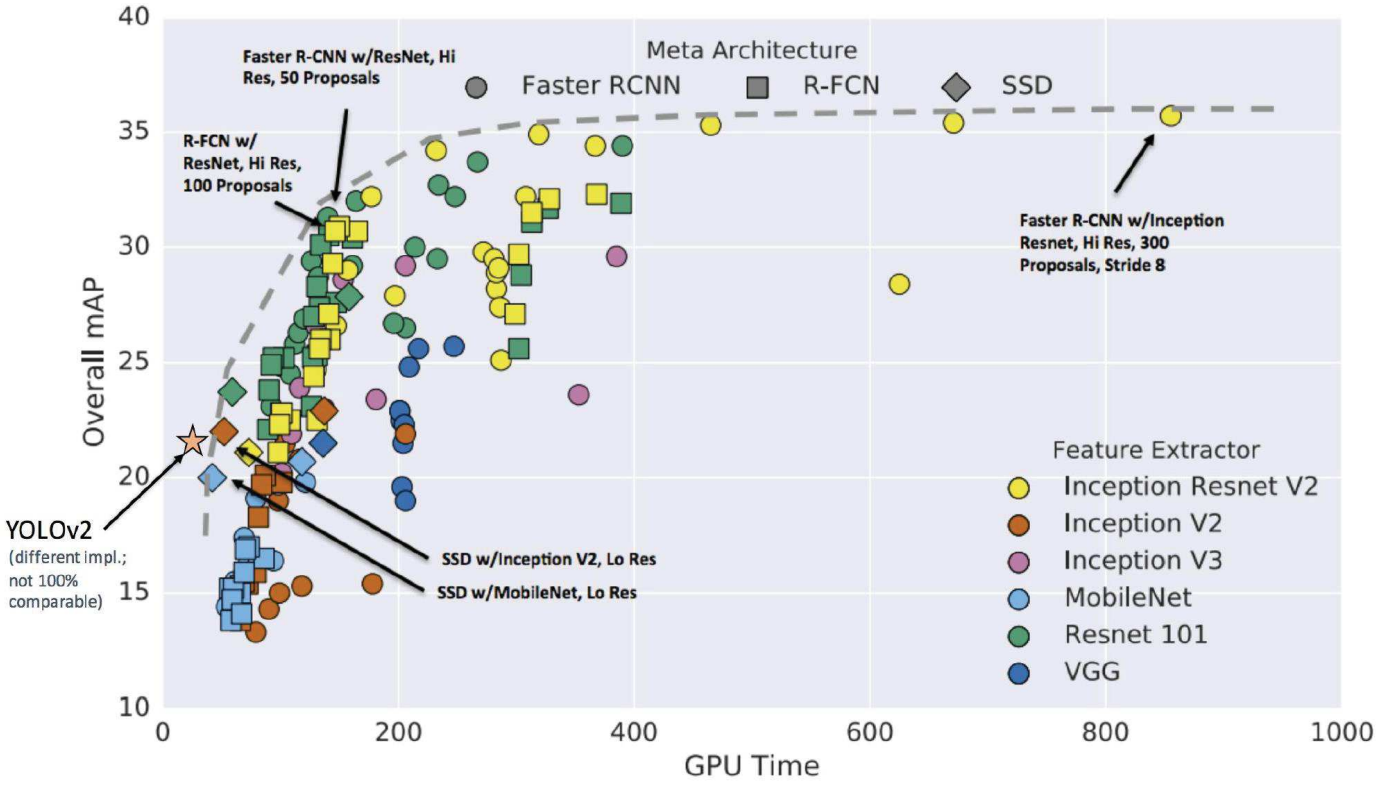
SINGLE SHOT MULTIBOX DETECTOR(SSD)



Images from: https://www.slideshare.net/TaegyunJeon1/pr12-you-only-look-once-yolo-unified-realtime-object-detection

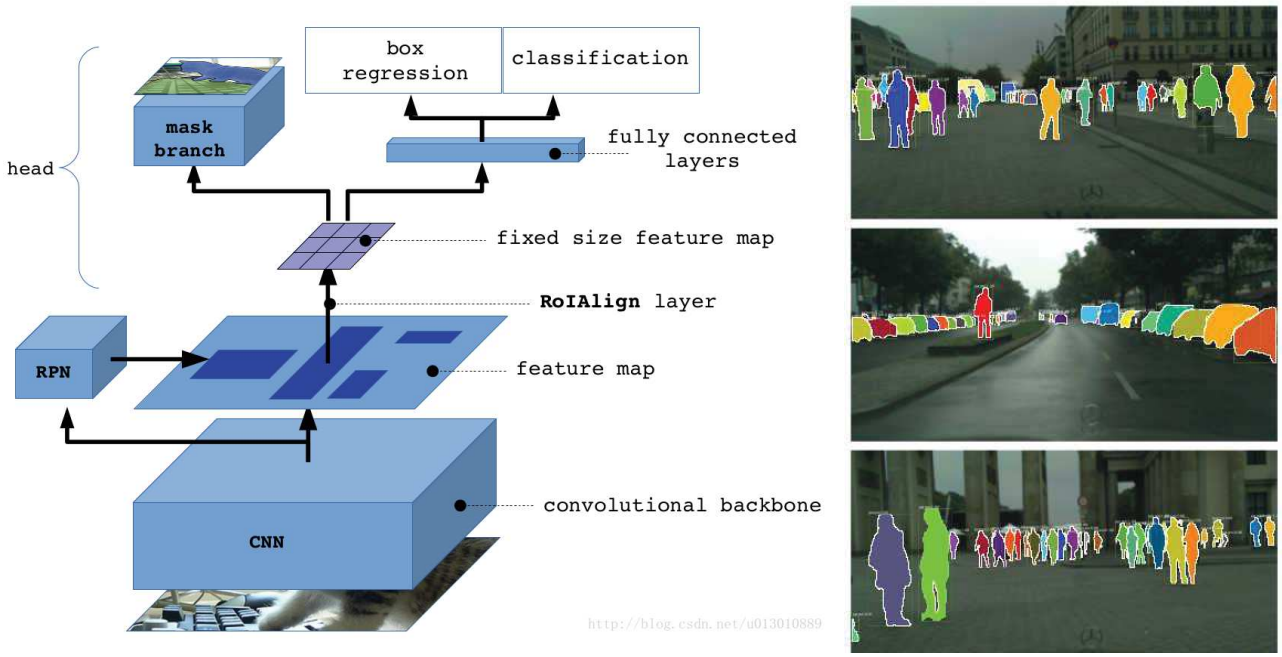
Both are faster, but less accurate, than Faster_R-CNN

Recent comparison of object detection convNets



Slide from Ross Girshick's CVPR 2017 Tutorial, Original Figure from Huang et al

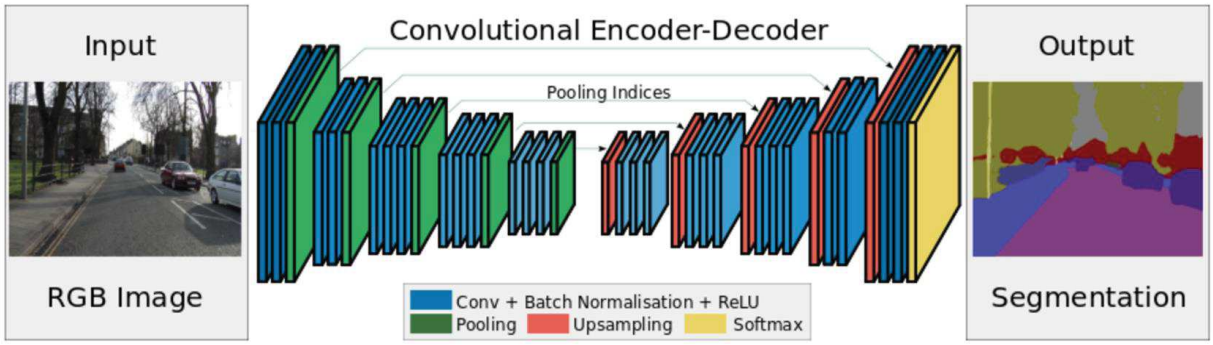
Mask_RCNN: categorization and localization with shape/*contours*

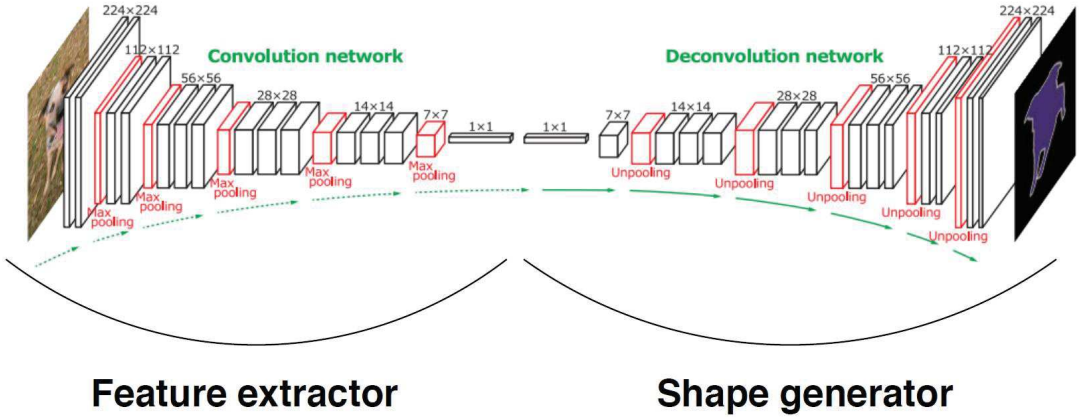


Mask R-CNN architecture (left) extracts detailed contours and shape of objects instead of just bounding-boxes

Semantic segmentation

Convolutional Encoder-Decoder





Many competitors for DL of semantic segmentation

Many competitors for semantic segmentation by deep-learning:

- **SegNet (2015)**
- **U-Net (2015)**
- **RefineNet (2016)**
- **ICnet (2017)**
- **DeepLab**
- **…**

VERY HOT TOPIC !!!

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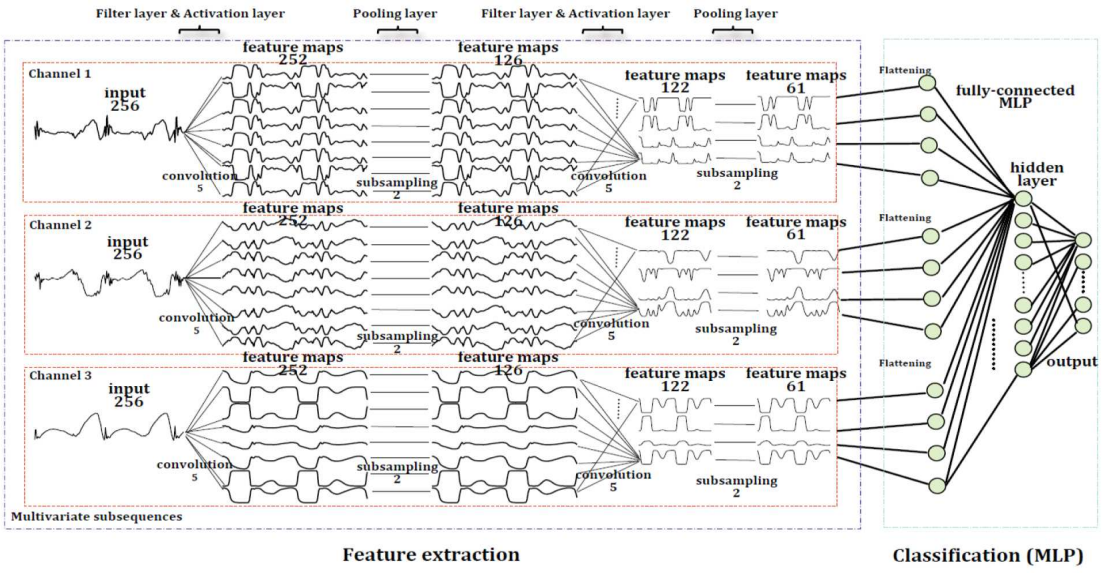
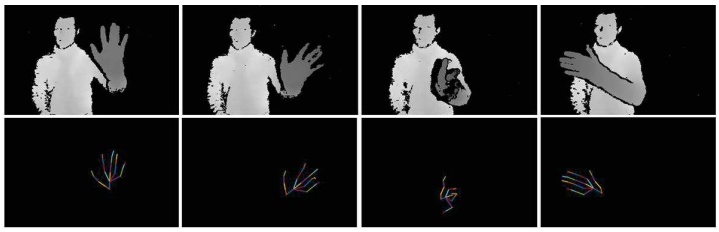
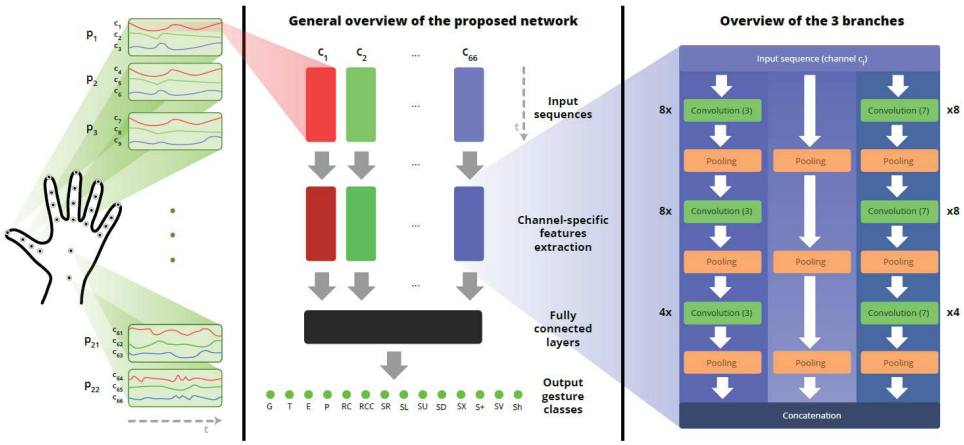
Deep-TEMPORAL Convolution for multivariate *time-series*



MC-DCNN model
(separate 1D temporal convolution of each time-serie)

Deep Gesture Recognition





Hand gesture recognition: 90% acuracy (vs 83% baseline)

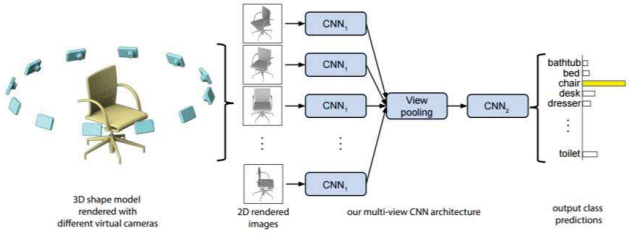
Work in progress at center for Robotics of MINES ParisTech (PhD thesis of Guillaume Devineau)

Potential applicability to other kinds of time-series!

Deep-Learning on 3D data

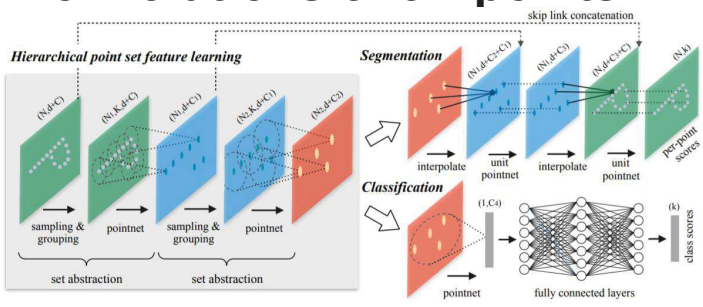
Possible to use:

- **ConvNets on 2D images of multiple views**

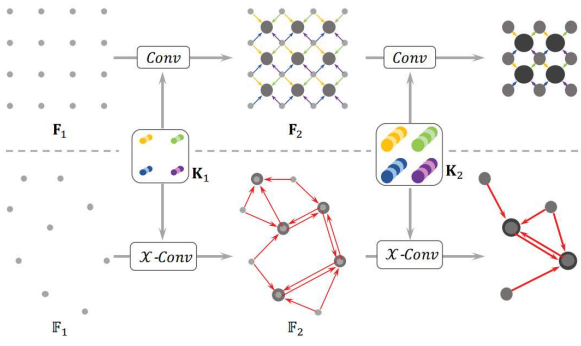


Multiview (Su et al., 2015)

- **ConvNet on 2D DEPTH image(s)**
- **Convolutions of 3D points**



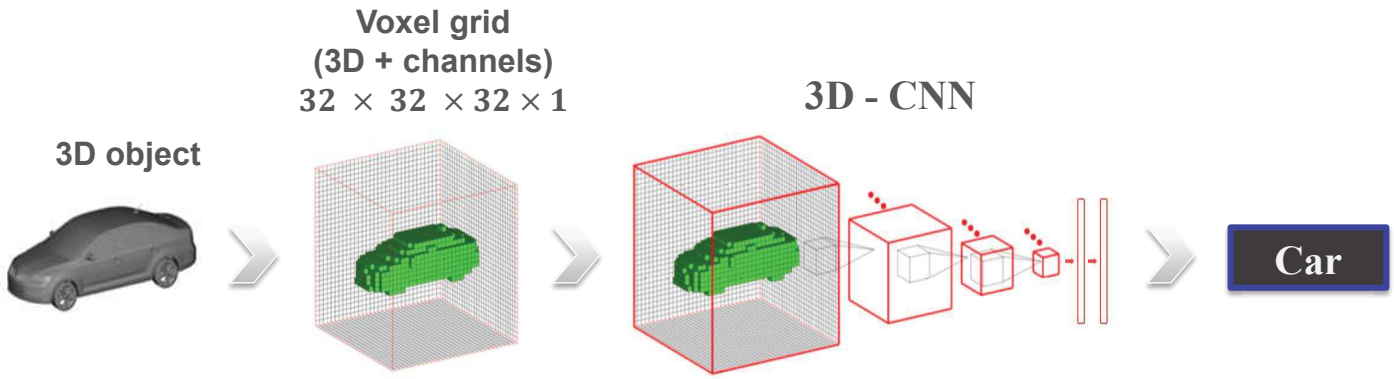
PointNet++ (Qi et al., 2017)



PointCNN (Li et al., 2018)

- **3D convolutions on voxels (see next slide)**

Deep-Learning with 3D convolutions on voxels



VoxNet
(Maturana et al., 2015)

3D ShapeNets
(Wu et al., 2015)

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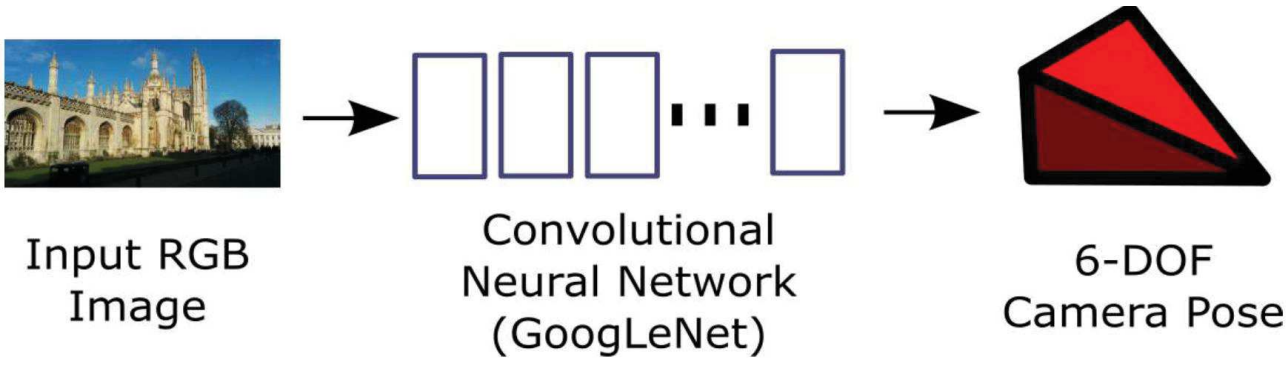
What can Deep Convolutional Networks perform?

- Image classification
- Visual object detection and categorization
- Semantic segmentation of images
- …

AND ALSO:

- Image-based localization
- Estimation of Human pose
- Inference of 3D (depth) from monocular vision
- Learning image-based behaviors
  - End-to-end driving from front camera
  - Learning robot behavior from demonstration/imitation

PoseNet: 6-DoF camera-pose regression with Deep-Learning

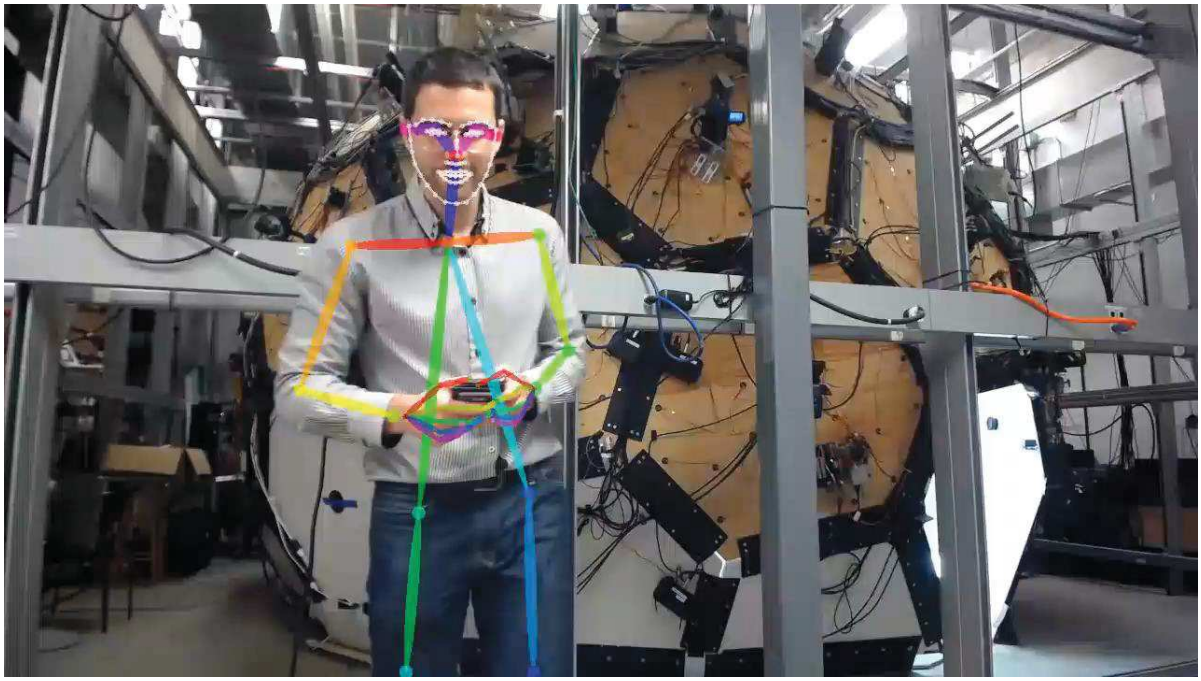


King's College *Street* *Old Hospital* *Shop Façade* *St Mary's Church*

Figure 4: **Map of dataset** showing training frames (green), testing frames (blue) and their predicted camera pose (red). The testing sequences are distinct trajectories from the training sequences and each scene covers a very large spatial extent.

[A. Kendall, M. Grimes & R. Cipolla, "PoseNet: A Convolutional Network for Real-Time 6-DOF Camera Relocalization" , ICCV'2015, pp. 2938-2946]

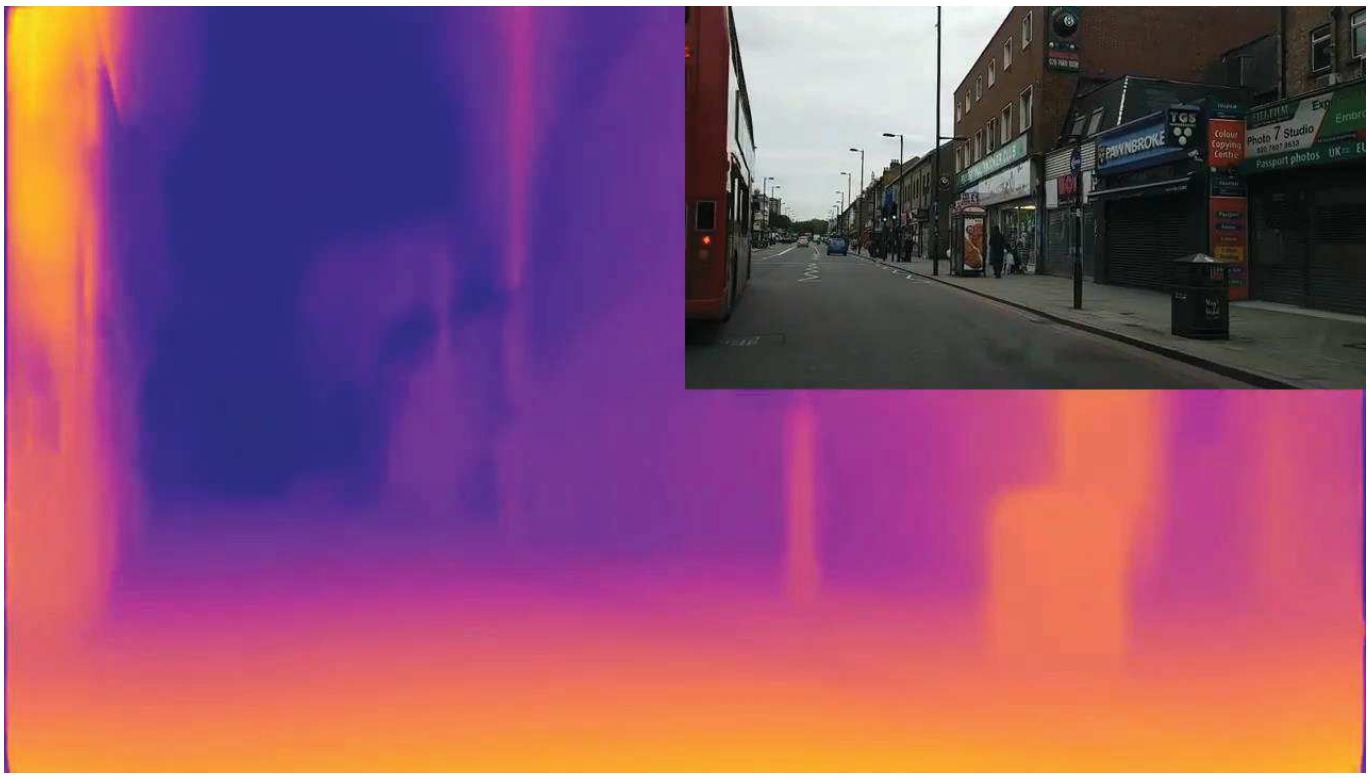
Human posture estimation by Deep-Learning



Real-time estimation of Human poses on *RGB* video

OpenPose ***[Realtime Multi-Person 2D Pose Estimation using Part Affinity Field, Cao et al., CVPR'2017 [CMU]***

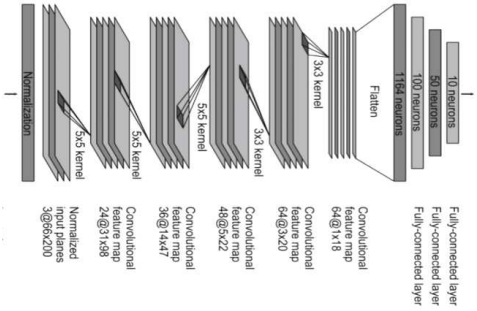
Inference of 3D (depth) from monocular vision



Unsupervised monocular depth estimation with left-right consistency C Godard, O Mac Aodha, GJ Brostow - CVPR'2017 [UCL]

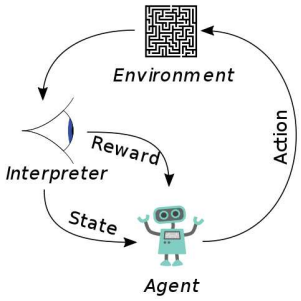
End-to-end driving from camera by Deep-Learning

ConvNet input:
Cylindrical projection of fisheye camera



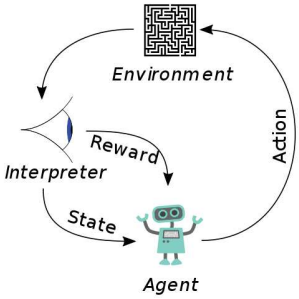
ConvNet output:
steering angle

Imitation Learning from Human driving on real data

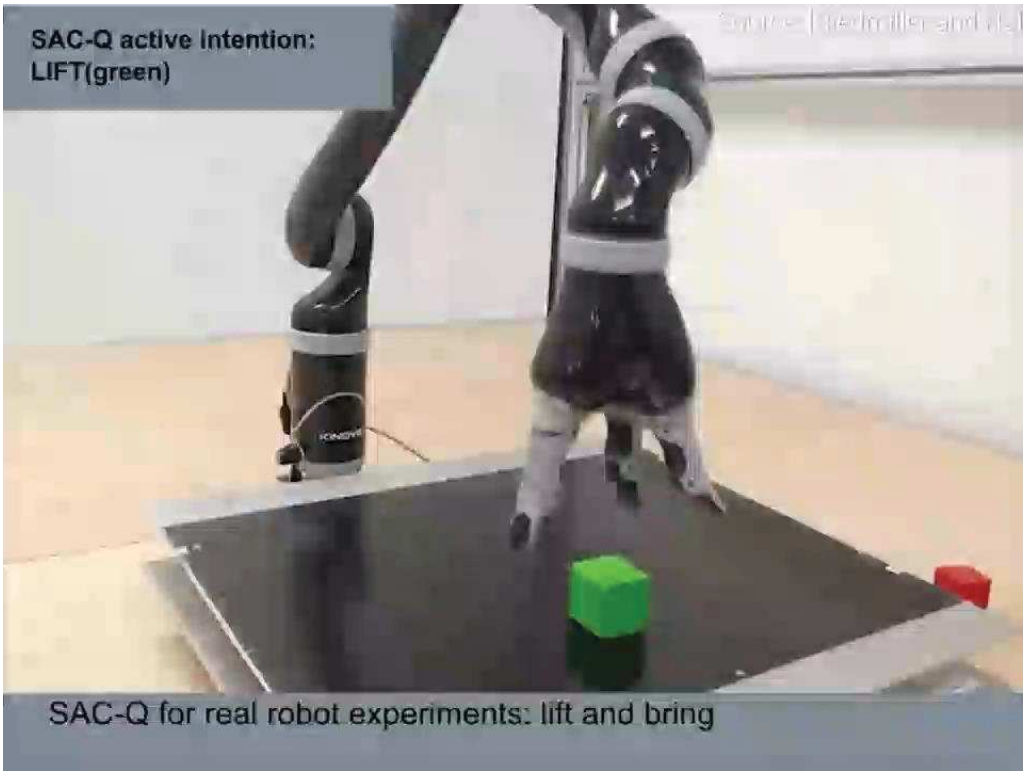


End-to-end driving via Deep *Reinforcement* Learning
[thèse CIFRE Valeo/MINES-ParisTech en cours]

Robot task learning using *Reinforcement* Learning



Learning complex behavior with Deep Reinforcement Learning



Work by Google DeepMind

[Learning by Playing Solving Sparse Reward Tasks from Scratch, Riedmiller et al. (ICML'2018)]

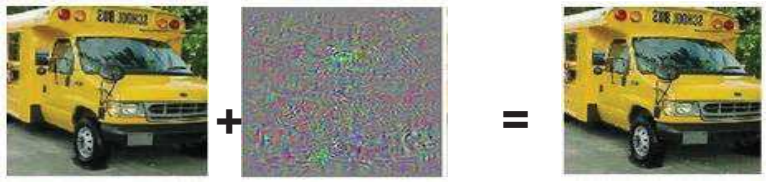
Summary on ConvNets & Deep-Learning

- **Proven advantage of learning features empirically from data**
- **Large ConvNets require huge amounts of labelled examples data for training**
- **Current research/progresses = finding efficient global architecture of ConvNets**
- **Enormous potential of TRANSFER-LEARNING on small datasets for restricted/specialized problems**
- **ConvNets also for multivariate time-series (1D temporal convolutions) and for 3D data (3D conv on voxels, etc…)**
- **ConvNets can potentially infer from image ANYTHING for which information is in the image (3D, movement, planning, …)**

Perspectives on Deep-Learning

Next frontiers:

- **Theoretical aspects**
- **Robustness issues (cf. adversarial examples)**



Van diff Ostrich!!

- ***UNsupervised*** **deep-learning on unlabelled data**
- **Deep *Reinforcement* Learning (DRL)**
- **Deep *Recurrent* Neural Networks (LSTM, GRU, etc…) for sequence processing (NLP!) or modeling behavior & dynamics**

Any QUESTIONS ?