≡ HOME

[Convolutional Neural Networks] week2. Deep convolutional models: case studies

2017-11-22 / VIEWS: 3

[TOC]

I-Case studies

Why look at case studies?

Good way to get intuition of different component of CNN: case study & reading paper.

Outline

- classic networks:
  - LeNet-5
  - AlexNet
  - VGG
- ResNet (152-layer NN)
- Inception

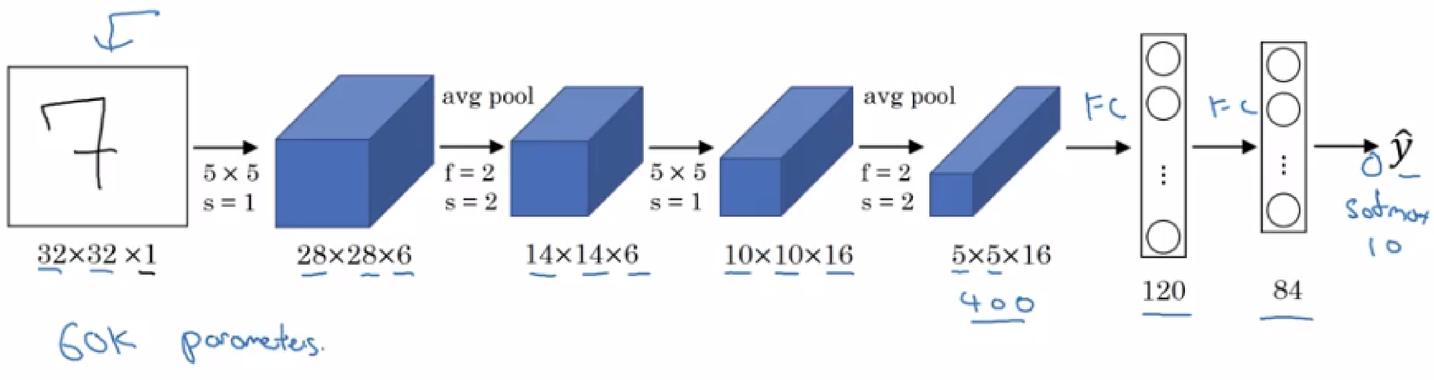
Classic Networks

LeNet-5(1998)

[LeCun et al., 1998. Gradient-based learning applied to document recognition]

Goal: recognize hand-written digits.

image → 2 CONV-MEANPOOL layers, all CONV are valid (without padding) → 2 FC → softmax



takeaway (patterns still used today):

- as go deeper, n_H, n_W goes down, n_C goes up
- conv-pool repeated some times, then FC-FC-output

sidenote:

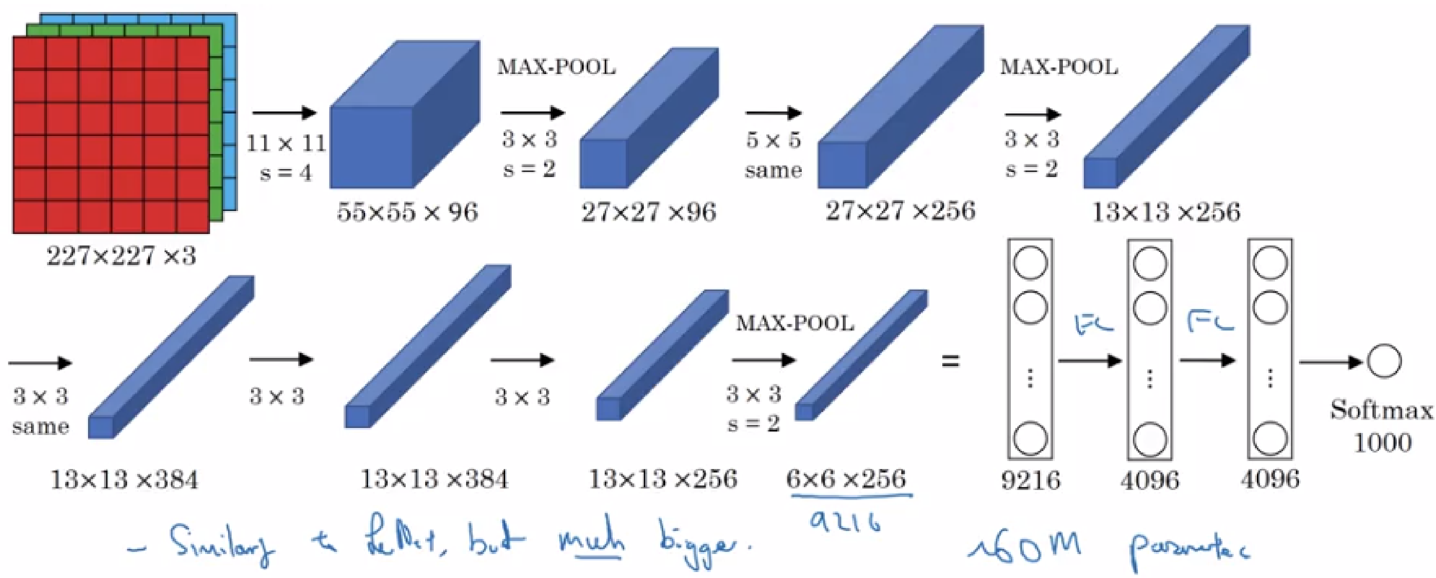
- used sigmoid/tanh as activation, instead of ReLU.
- has non-linearity after pooling
- orignial paper hard to read

AlexNet

[Krizhevsky et al., 2012. ImageNet classification with deep convolutional neural networks]

Same pattern: conv-maxpool layers → FC layers → softmax

but much more params.



sidenote:

- use ReLU as activation

- multi-GPU training
- "local response normalization" (LRN): normalize across all channels (not widely used today).
- a lot hparams to pick

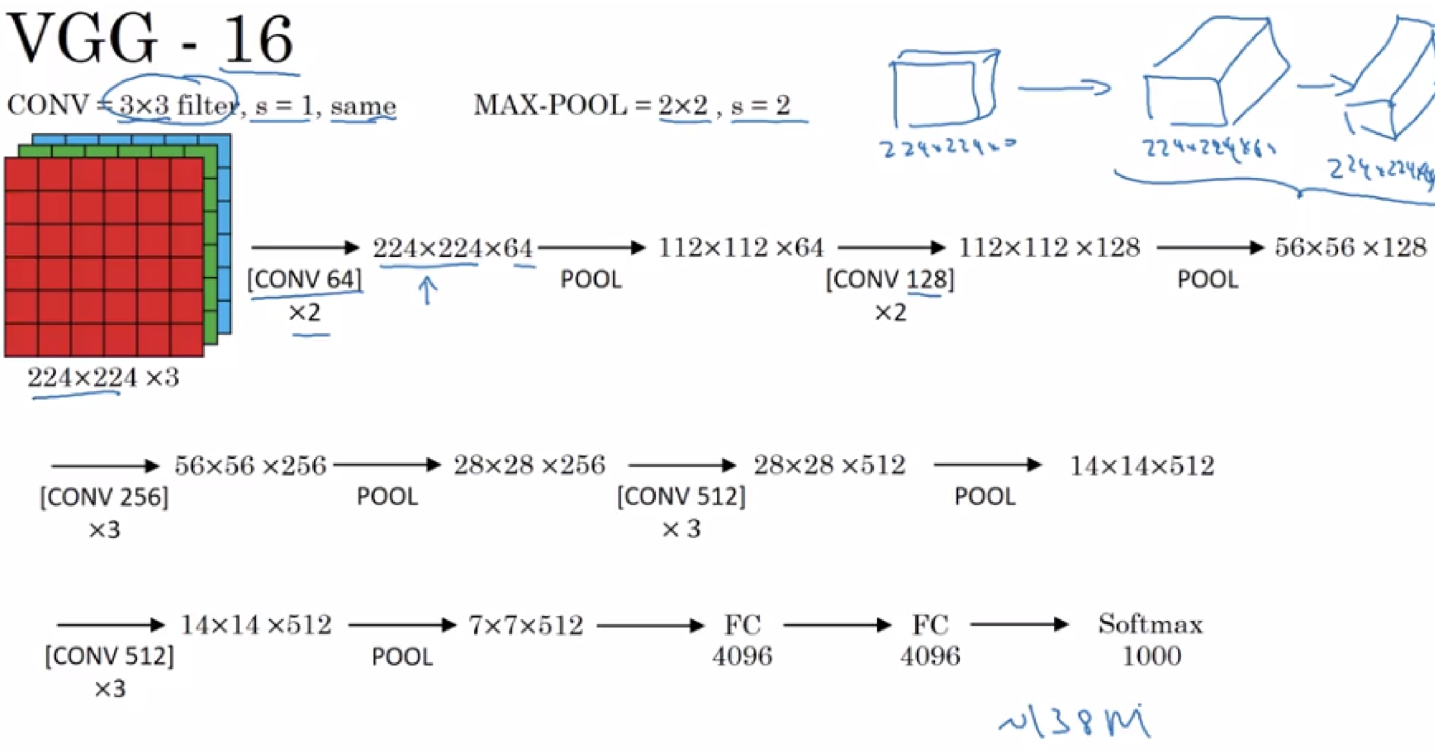
VGG-16

Simonyan & Zisserman 2015. Very deep convolutional networks for large-scale image recognition]

Much less hparams:

All **CONV: 3 *3,s=1,padding=same, MAXPOOL: 2* 2,s=2**

→ e.g. "(CONV 64) * 2" meaning 2 conv layers (3*3,s=1,padding=same) of 64 channels.



note:

- pretty large even by modern standard: 138M params
- simplicity in architecture: POOL reduce n_H/n_W by 2 each time; CONV n_C=64->128->256->512 (increase by 2), very systematic.

ResNets

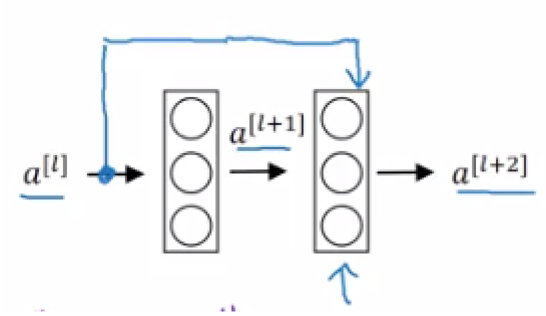
Very deep NN are hard to train → ResNet: *skip connections* , to be able to train ~100 layers NN.

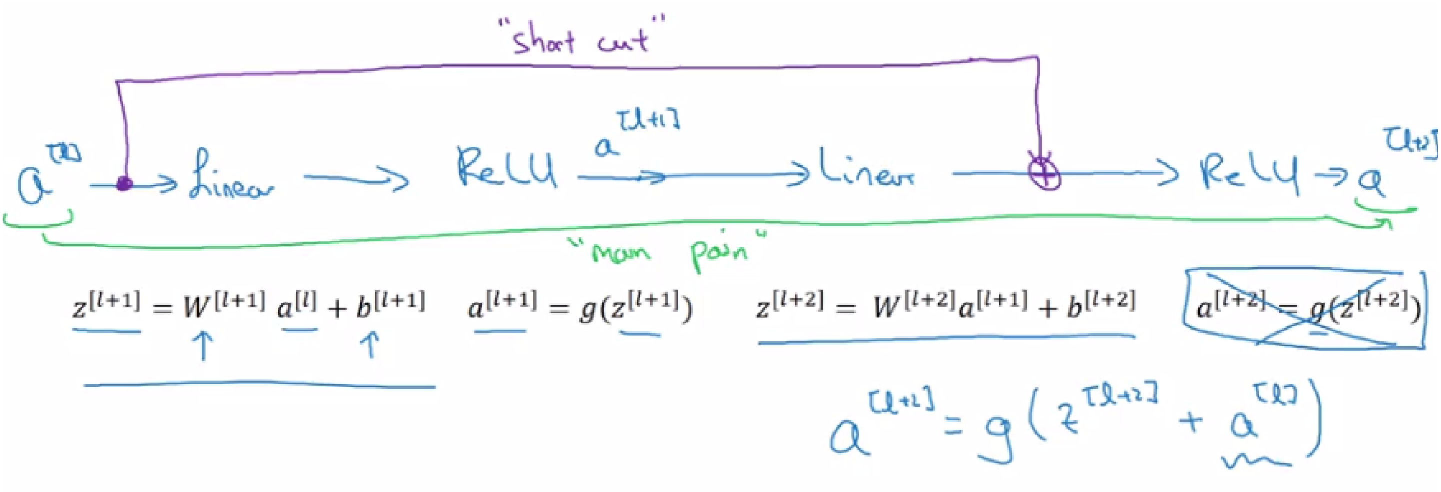
Residual block

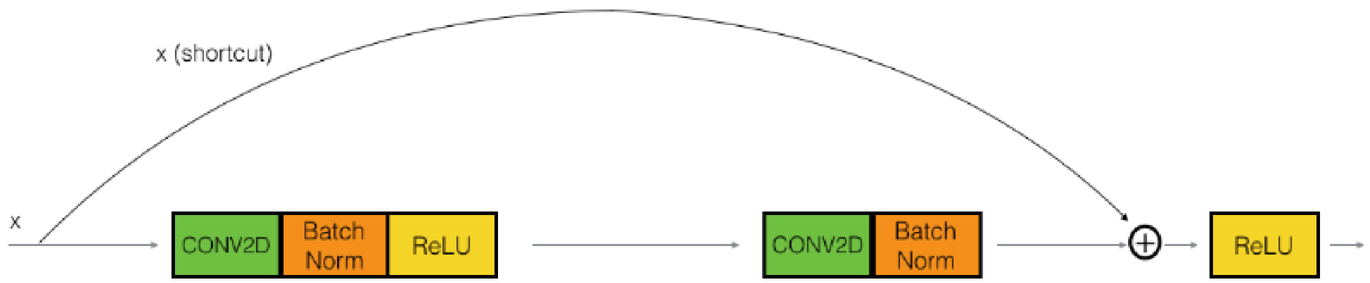
[He et al., 2015. Deep residual networks for image recognition]

Normal NN: from a[l] to a[l+2], two linear & ReLU operations. *"main path"* .

ResNet: a[l] taks shortcut and *goes directly to a[l+2]'s non-linearity* . " *shortcut* " / " *skip connection* ".

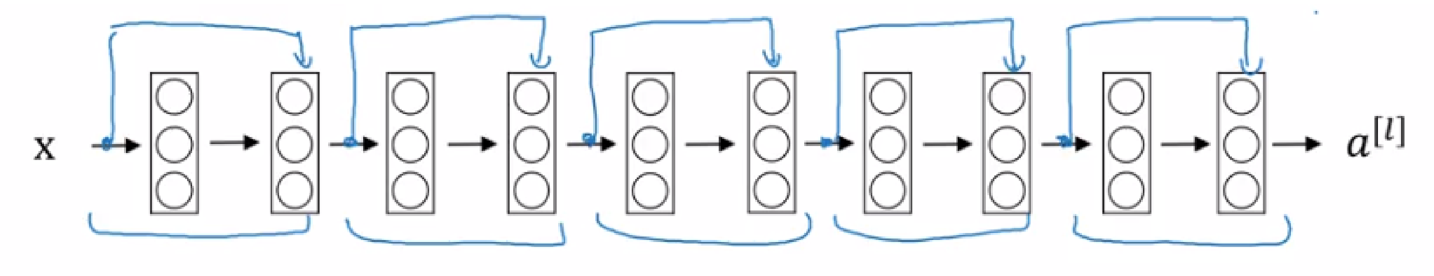






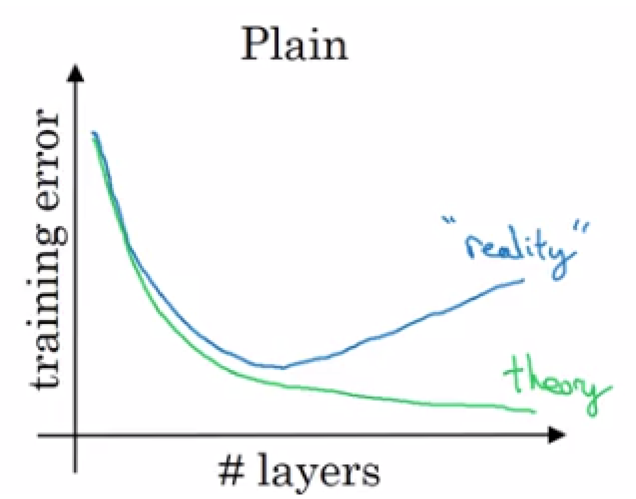
Using residual block allows training *very deep* NN:

stack them to get ResNet (i.e. add shortcuts to "plain" NN).

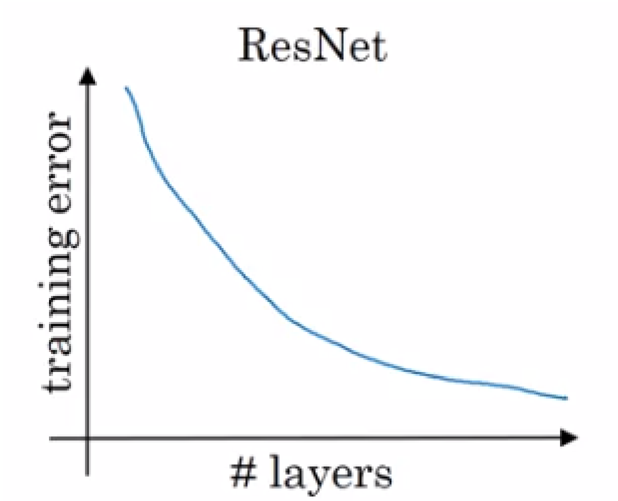


Problem of training plain NN: *training error goes up (in practice) when having deeper NN* .

Because deeper NN are harder to train (vanishing/exploding gradients, etc.)



With ResNet: training error goes down even with deeper layers.



Why ResNets Work

```
a[l+2] = g(z[l+2] + a[l])
   = g(w[l+1] * a[l+1] + b[l+1] + a[l])
```

→ note: when applying weight decay, w can be small (w~=0, b~=0)

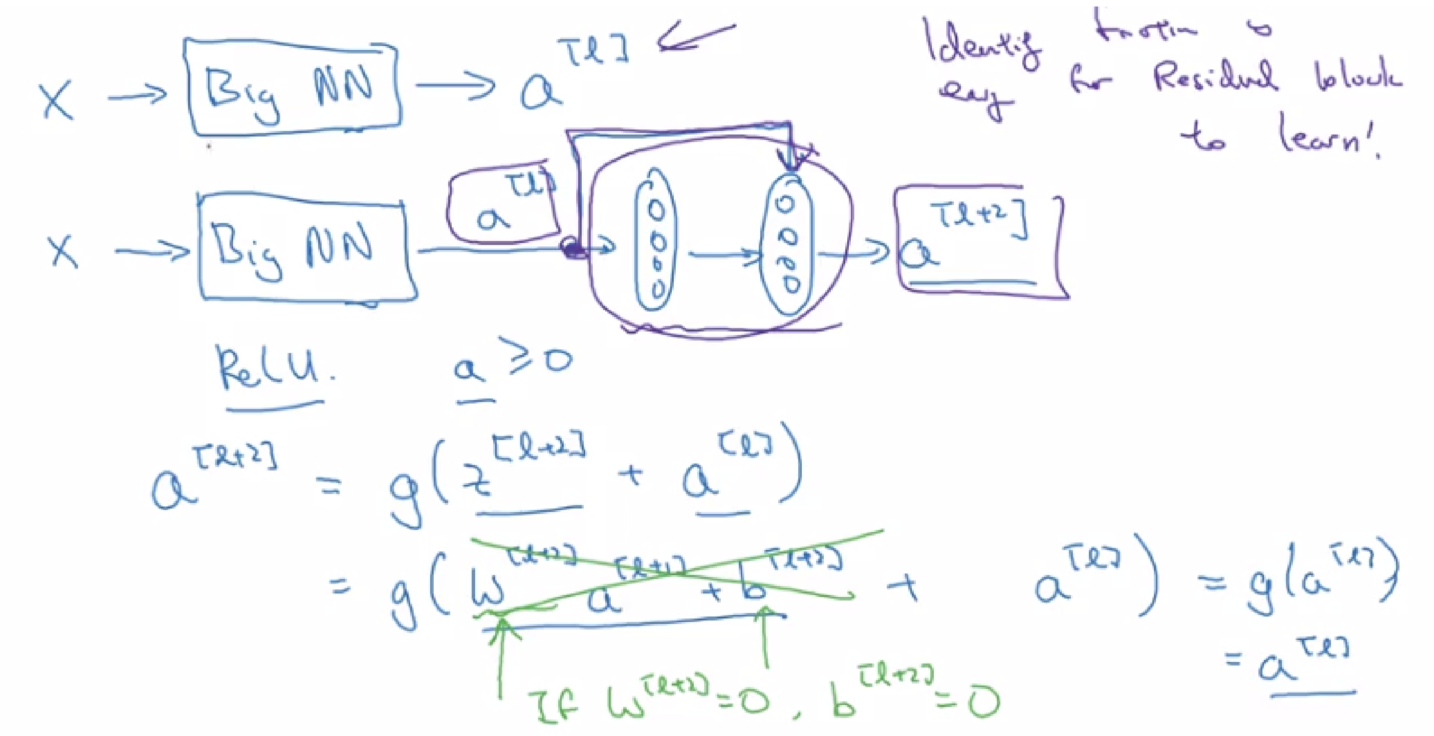
⇒ a[l+2] ~= g(a[l]) = a[l] (assume g=ReLU)

⇒ it's easy to get a[l+2]=a[l], i.e. *identity function from a[l] to a[l+2] is easily learned*

→ whereas in plain NN, it's difficult to learn an identity function between layers, thus more layers make result *worse*

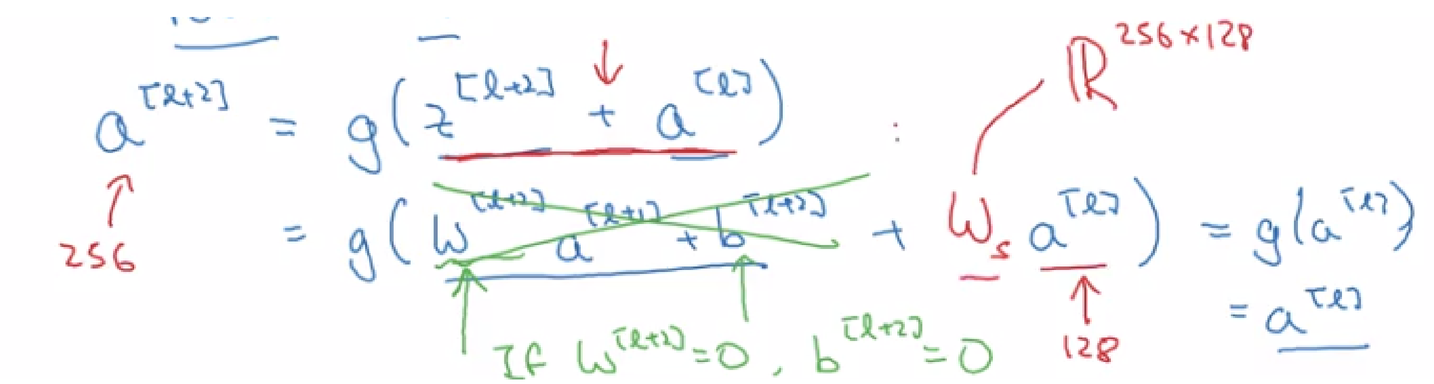
→ adding 2 layers doesn't hurt the network to learn a shallower NN's function, i.e. performance is not hurt when increasing #layers.

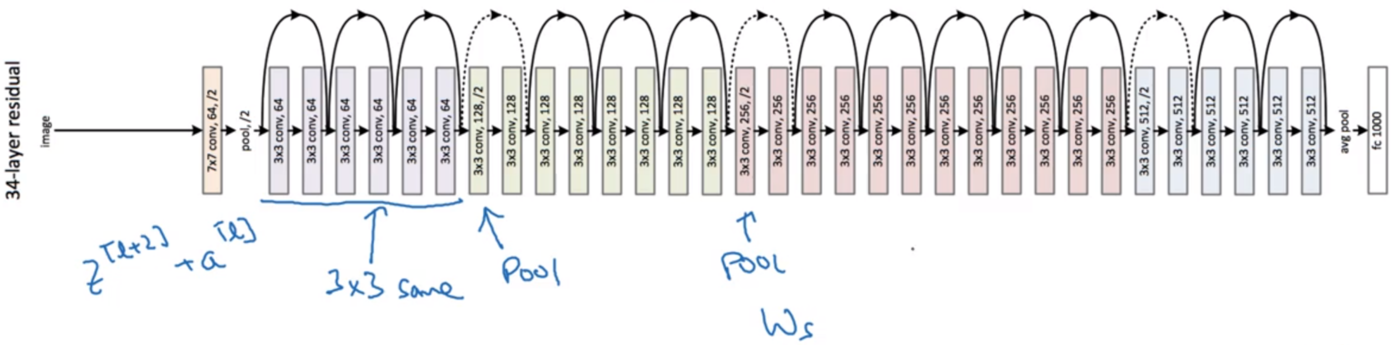
→ when necessary can do even better than learning identity function



Side note:

- `z[l+2]` and `a[l]` have the same dimension (so that they can be added in g) → i.e. many "same" padding are used to preserve dimension.
- If their dimensions are not matched (e.g. for pooling layers) → add extra `w_s` to be applied on `a[l]` .



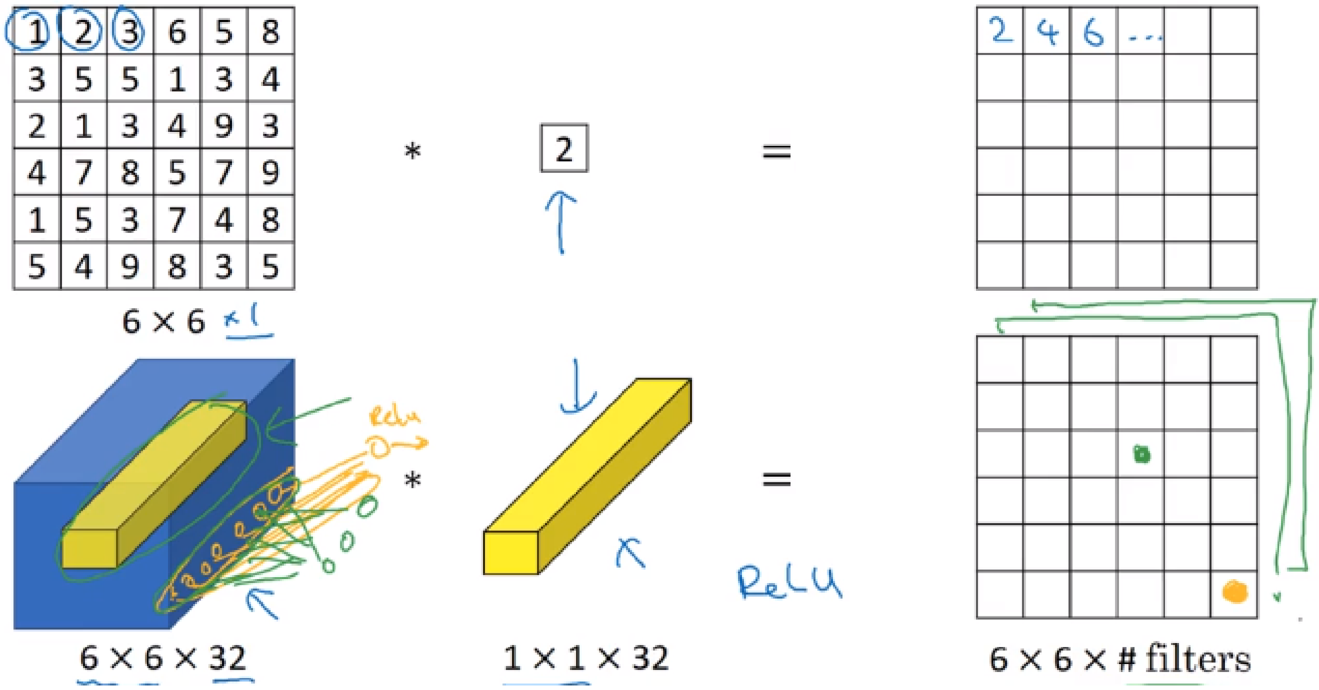


Networks in Networks and 1x1 Convolutions

[Lin et al., 2013. Network in network]

Using 1*1 conv: for one single channel, just multiply the input image(slice) by a constant...

But for >1 channels: each output number is inner prod of input channel "slice" and conv filter.

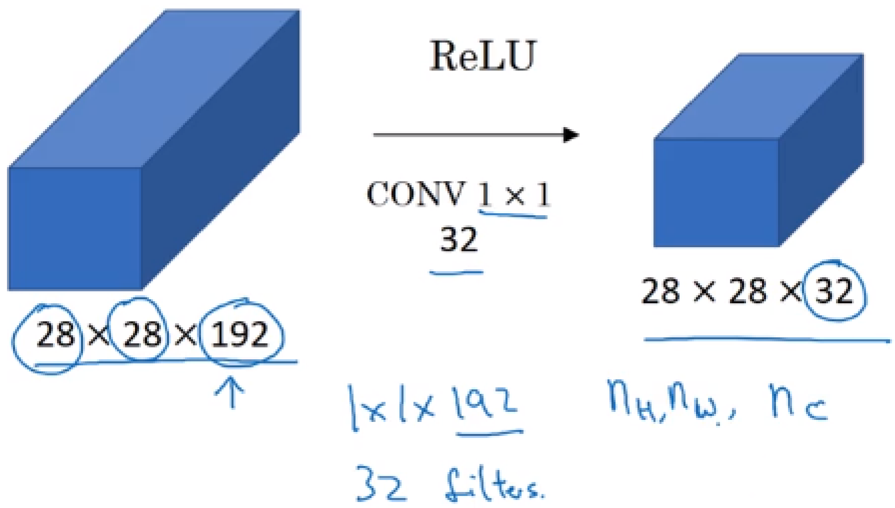


1 *1 conv: ~= fully-connected layer applied to each of n_H* n_W slices, adds non-linearity to NN.

→ 1 *1 conv also called "* network in network*"

example:

To *shrink* #channels via 1*1 conv.

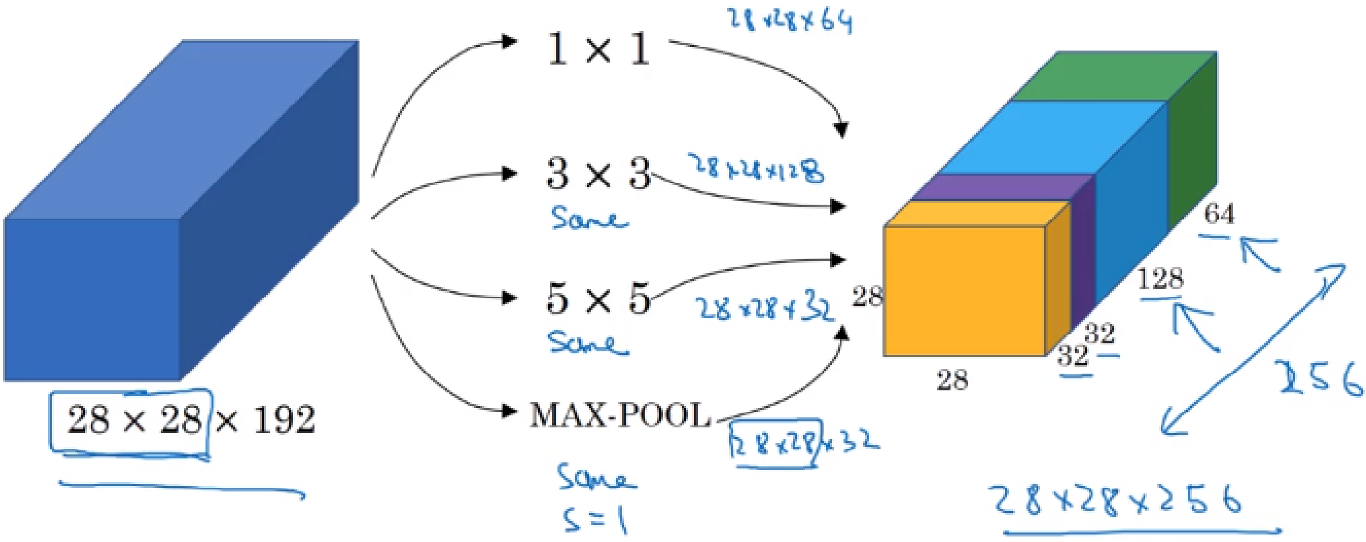


Inception Network Motivation

[Szegedy et al. 2014. Going deeper with convolutions]

Instead of choosing filter size, *do them all in parallel.*

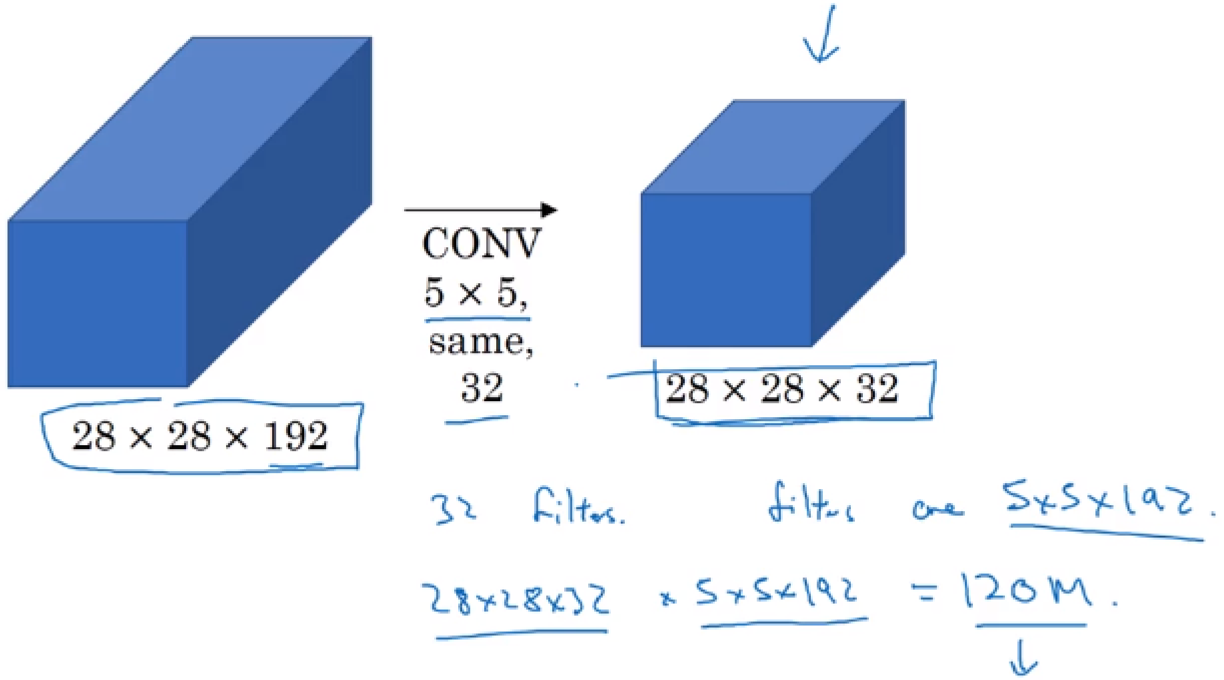
note: use SAME padding & stride=1 to have the same n_H, n_W



Problem: computation cost.

example: input shape = 28 *28* 192, filter 5 *5* 192, 32 filters, output shape = 28 *28* 32

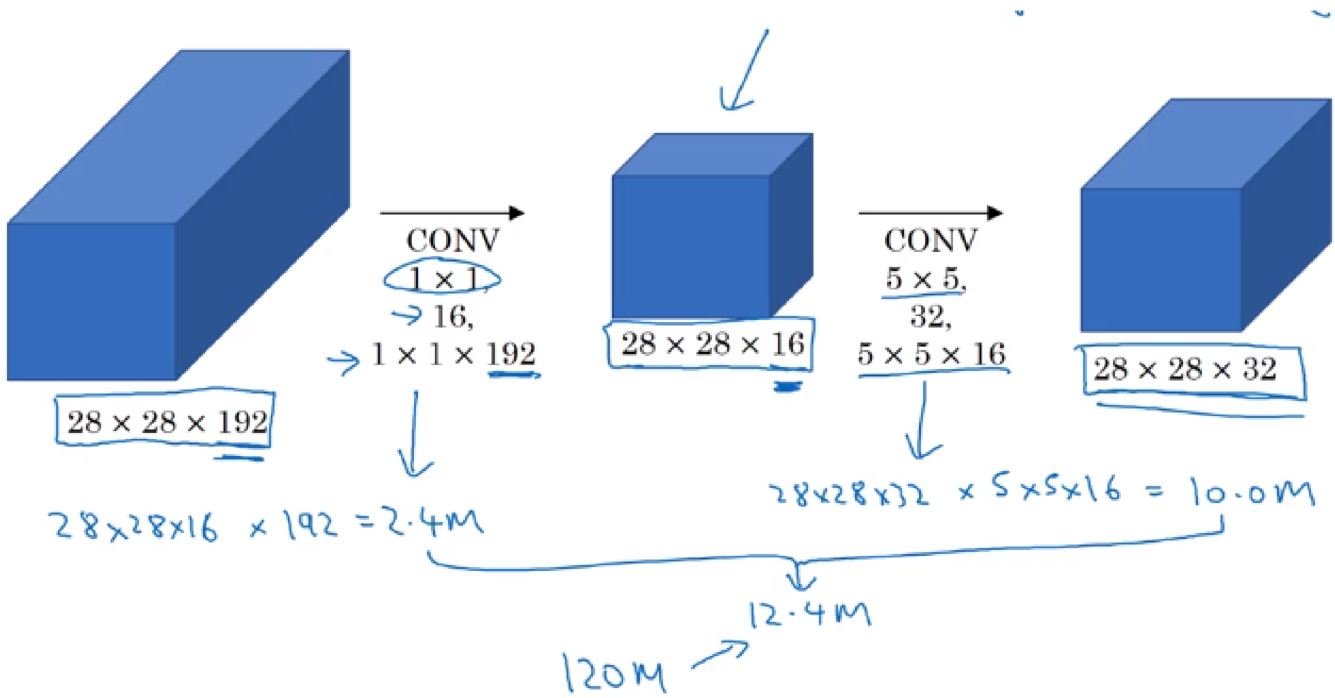
totoal #multiplication = 28 * 28 * 32 * 5 * 5 * 192 = 120M



→ reduce #computation with 1*1 conv

Reduce n_C of input by 1 *1 conv ("bottleneck-layer") before doing the 5* 5 conv.

computation = 1 *1* 192 * 28 *28* 16 + 5 *5* 16 * 28 *28* 32 = 12.4M

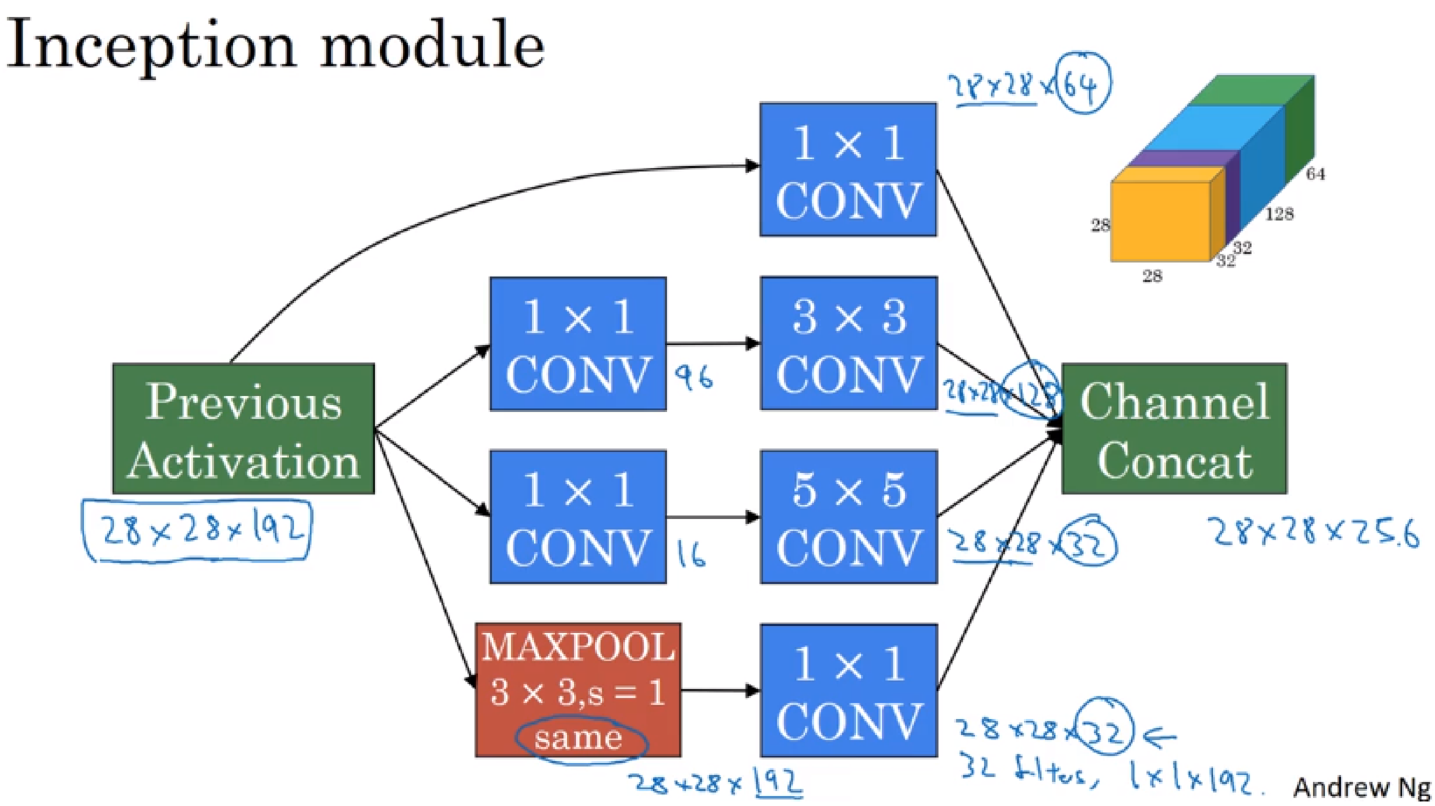


Does bottleneck layer hurt model performance ? → no.

Inception Network

Inception module:

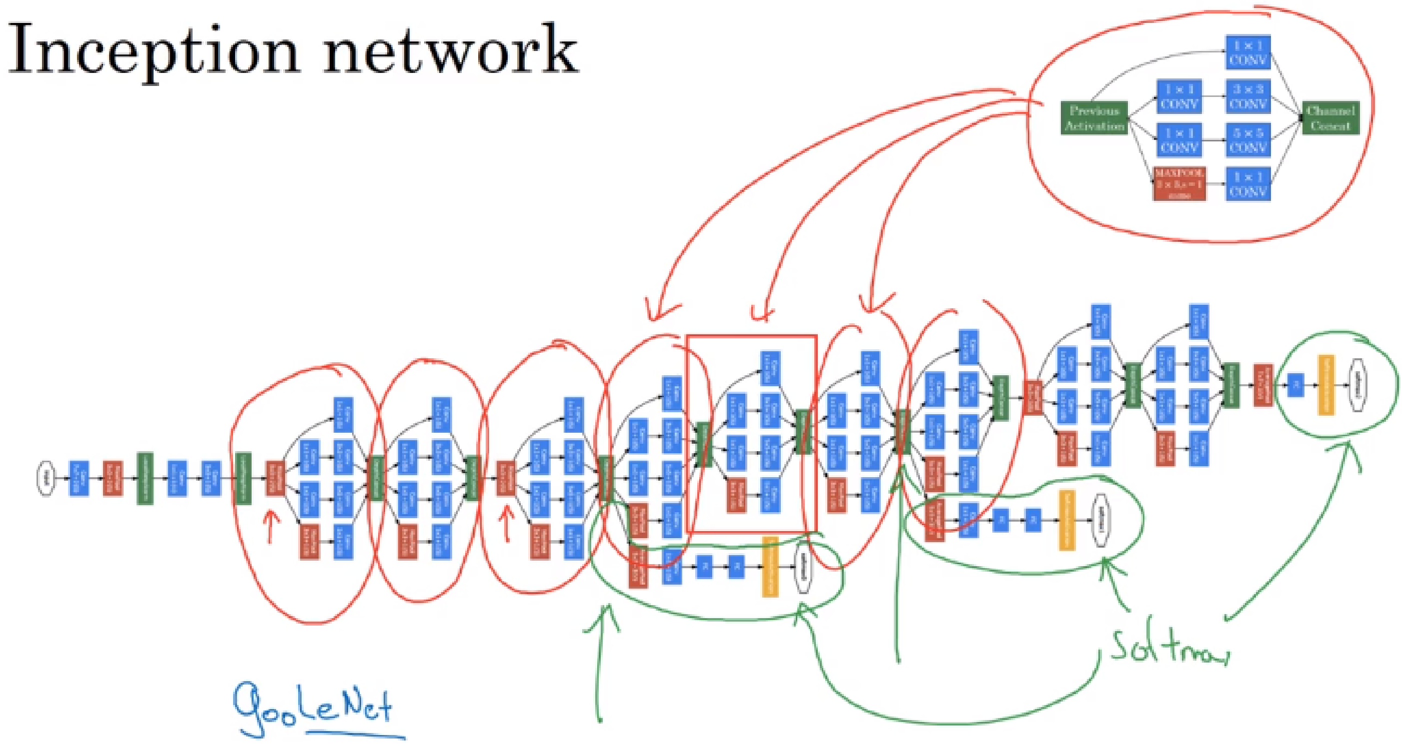
For max pooling layer, out n_C equals input n_C → *use a 1* 1 conv to shrink n_C*.



Inception network:

- Putting inception modules together.
- Have *side branches* : taking hidden layer and feed to FC for output.

— ensure features from hidden units at intermediate layers are not too bad for prediction — kind of regularization



The name "inception" come from: a meme...

II-Practical advice for using ConvNets

Advices on how to use these classical CNN models.

Using Open-Source Implementation

Difficult to replicate the work just from paper: a lot of details&hparams

→ use open-sourced version.

Transfer Learning

Download weights of other's NN as pretrained params.

→ pretrained params are trained on huge datasets, and takes weeks to train on multiple GPUs.

example: cat detector

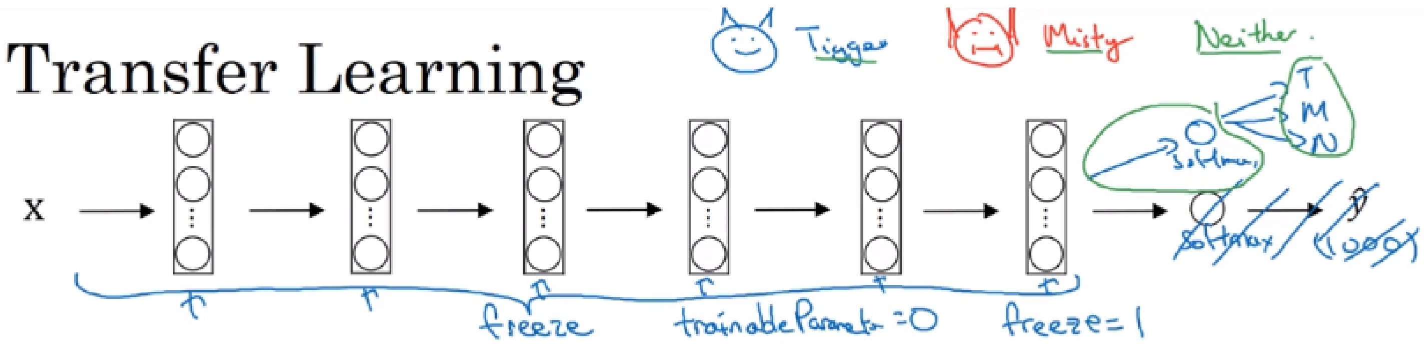
- 3 class: tigger/misty/neither
- training set at hand is small
- → download both code and weights online

e.g. ImageNet NN

→ change last layer's softmax

→ all Conv/Pool layers set *frozen* (not trainable)

→ only training softmax layer's weight with training set.

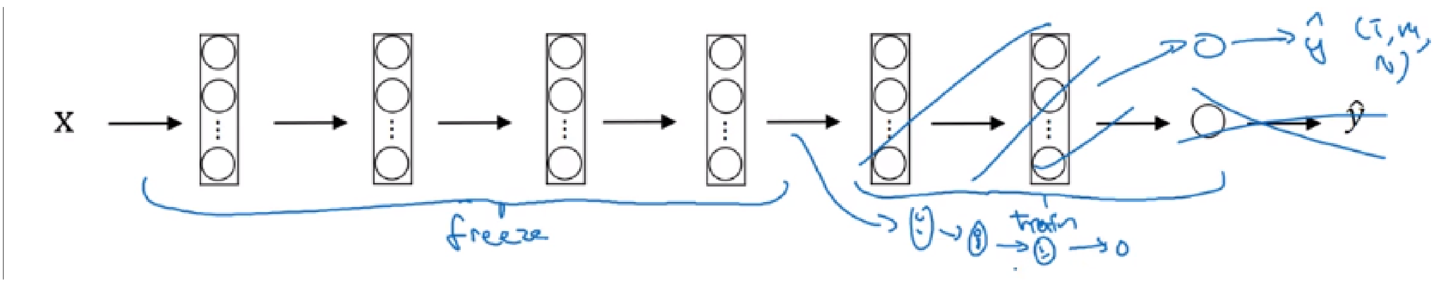


OR:

Precompute the hidden layer (fixed function mapping from x to feature vector) and save to disk.

→ train a shallow model on top. → save computation.

If have a large training set at hand ⇒ freeze a few layers and train the rest.



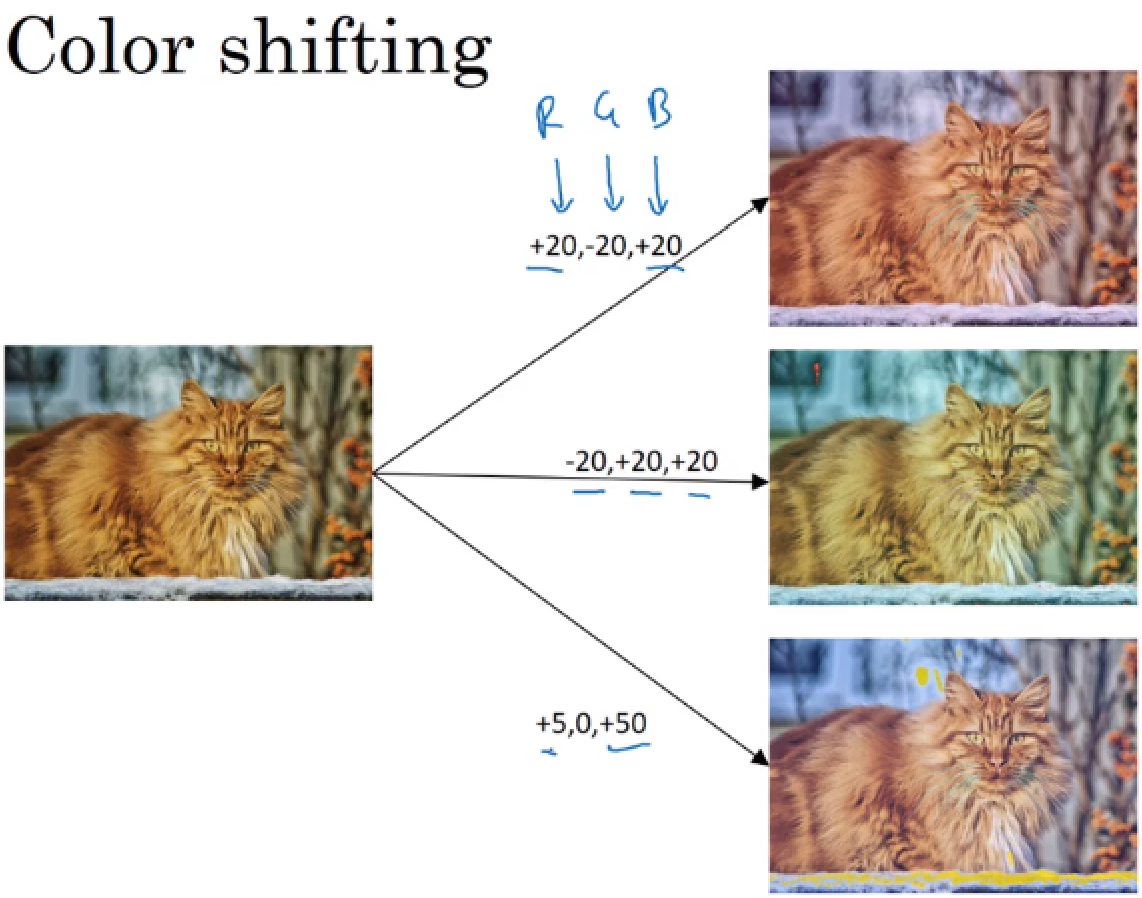
If have a *huge* dataset: train the whole NN.

Data Augmentation

More data are alway welcome.

Common augmentation method:

- Mirroring
- Randome cropping
- Rotation/Shearing/Local warping: used a bit less in practice
- Color shifting

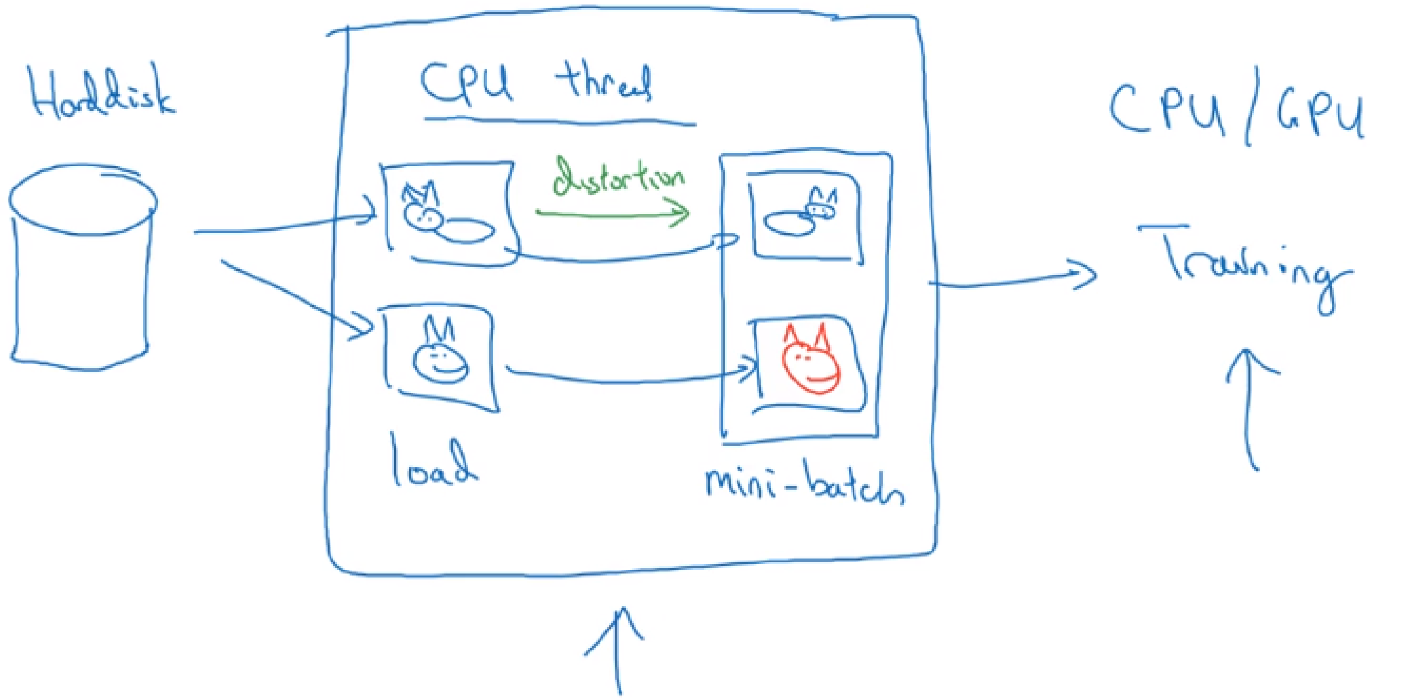


In practice: shifts drawn from some random distribution.

e.g. PCA-color-augmentation (details in AlexNet paper): ~keep overall color the same.

Implementaing distortions during training

If data is huge → CPU thread to get *stream* of images → add distortion for each image → form minibatch of data → pass to training.

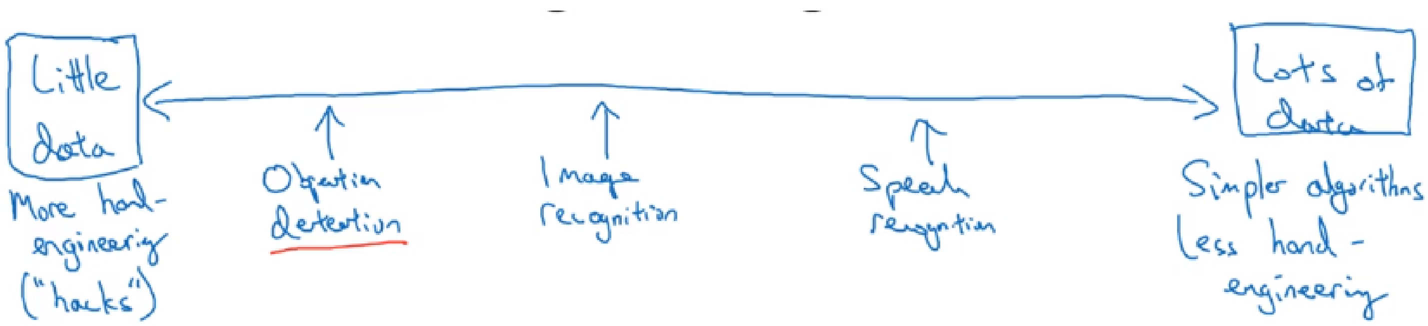


State of Computer Vision

Observations for DL for CV.

Data VS. hand-engineering

As more data are available → simpler algo, less hand-engineering.



Learing algo has 2 sources of knowledge:

- labeled data
- hand engineered features / network architecture / specialized components

Transfer learning can help when dataset is small.

Tips for doing well on benchmarks/winning competitions

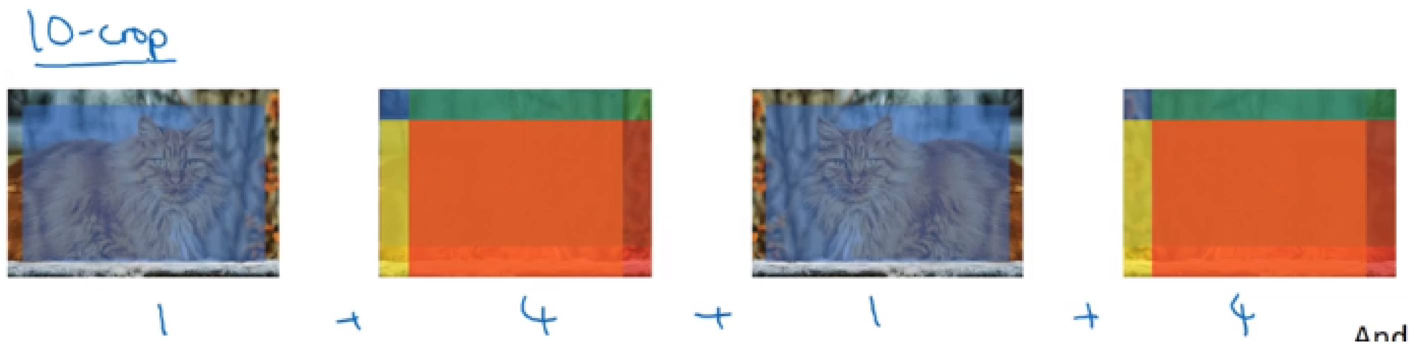
- Ensembling:

Train several(3~15) NN independently, then *average their outputs* .

- *Multi-crop at test time*

Predict on multiple versions of test images and average results.

e.g. 10-crop at test time



關鍵詞：神經網絡 AlexNet

相關推薦：

Carvana Image Masking Challenge–1st Place Winner's Interview

DL05: Convolutional Neural Networks

Image classification with Keras and deep learning

Custom Layers in CoreML

Text Classification – Classifying product titles using Convolutional Neural Network and Wor...

[Convolutional Neural Networks] week3. Object detection

Art: Neural Style Transfer

Read more posts by this author.

China /source/site/x-wei_github_io

Share this post