Machine Learning – Lecture 17

Convolutional Neural Networks III

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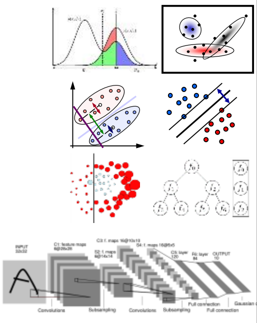
Course Outline

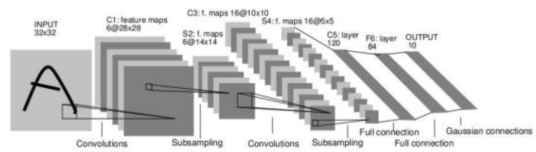
- Fundamentals
  - Bayes Decision Theory
  - Probability Density Estimation
- Classification Approaches
  - Linear Discriminants
  - Support Vector Machines
  - Ensemble Methods & Boosting
  - Random Forests
- Deep Learning
  - Foundations
  - Convolutional Neural Networks
  - Recurrent Neural Networks



Topics of This Lecture

- Recap: CNN Architectures
- Residual Networks
  - Detailed analysis
  - ResNets as ensembles of shallow networks
- Applications of CNNs
  - Object detection
  - Semantic segmentation
  - Face identification

Recap: Convolutional Neural Networks

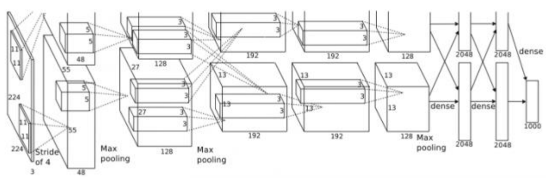


- Neural network with specialized connectivity structure
  - Stack multiple stages of feature extractors
  - Higher stages compute more global, more invariant features
  - Classification layer at the end

Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, Gradient-based learning applied to document recognition, Proceedings of the IEEE 86(11): 2278–2324, 1998.

Slide credit: Svetlana Lazebnik

Recap: AlexNet (2012)



- Similar framework as LeNet, but
  - Bigger model (7 hidden layers, 650k units, 60M parameters)
  - More data (10^6 images instead of 10^3)
  - GPU implementation
  - Better regularization and up-to-date tricks for training (Dropout)

A. Krizhevsky, I. Sutskever, and G. Hinton, ImageNet Classification with Deep Convolutional Neural Networks, NIPS 2012.

Image source: A. Krizhevsky, I. Sutskever and G.E. Hinton, NIPS 2012

Recap: VGGNet (2014/15)

- Main ideas
  - Deeper network
  - Stacked convolutional layers with smaller filters (+ nonlinearity)
  - Detailed evaluation of all components
- Results
  - Improved ILSVRC top-5 error rate to 6.7%.

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Mainly used

Image source: Simonyan & Zisserman

Recap: GoogLeNet (2014)

- Ideas:
  - Learn features at multiple scales
  - Modular structure

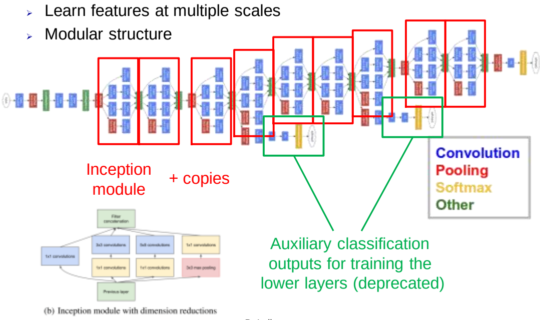
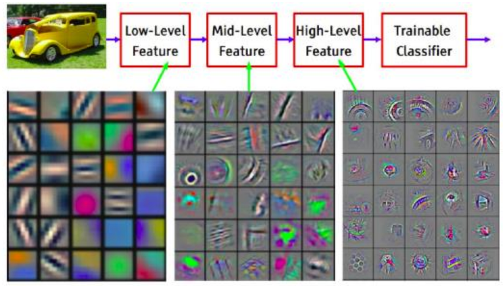


Image source: Szegedy et al.

Recap: Visualizing CNNs



Slide credit: Yann LeCun

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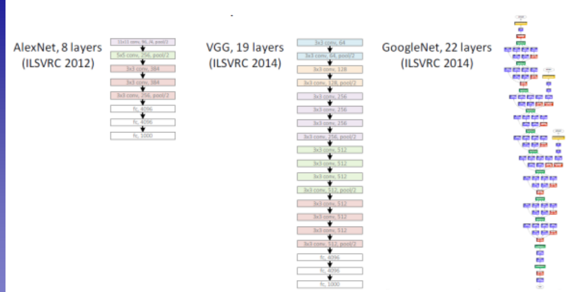
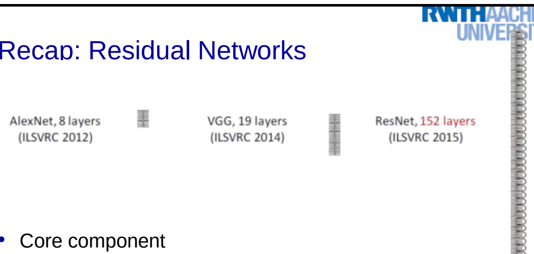
Recap: Residual Networks

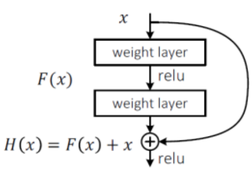


Slide credit: Kaiming He

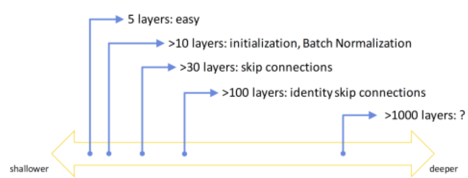
Recap: Residual Networks



- Core component
  - Skip connections bypassing each layer
  - Better propagation of gradients to the deeper layers



Spectrum of Depth



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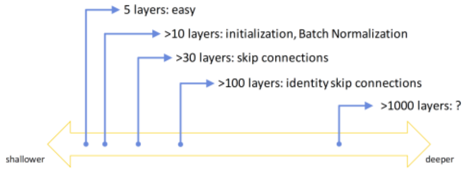
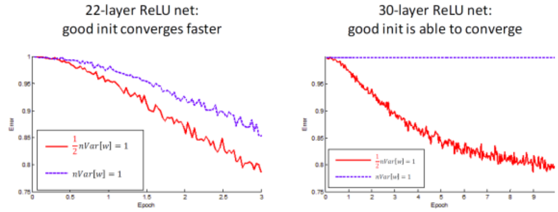
Spectrum of Depth



- Deeper models are more powerful
  - But training them is harder.
  - Main problem: getting the gradients back to the early layers
  - The deeper the network, the more effort is required for this.

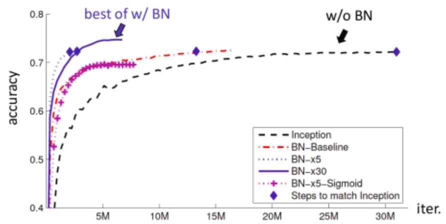
Initialization



- Importance of proper initialization (Recall Lecture 14)
  - Glorot initialization for tanh nonlinearities
  - He initialization for ReLU nonlinearities

  ⇒ For deep networks, this really makes a difference!

Batch Normalization



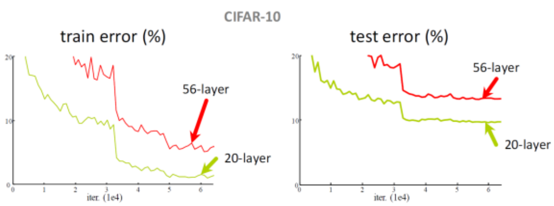
- Effect of batch normalization
  - Greatly improved speed of convergence

Going Deeper

- Checklist
  - Initialization ok
  - Batch normalization ok

  - Are we now set?
    - Is learning better networks now as simple as stacking more layers?

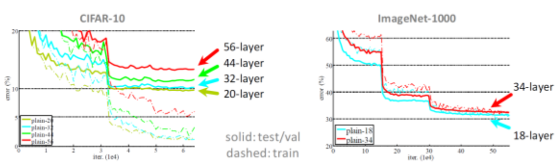
Simply Stacking Layers?



- Experiment going deeper
  - Plain nets: stacking 3×3 convolution layers

  ⇒ 56-layer net has higher training error than 20-layer net

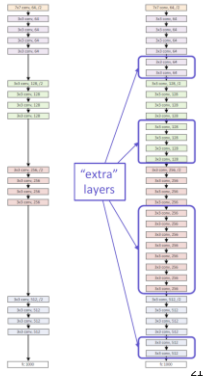
Simply Stacking Layers?



- General observation
  - Overly deep networks have higher training error
  - A general phenomenon, observed in many training sets

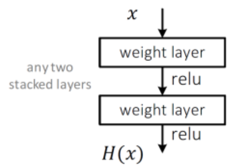
Why Is That???

- A deeper model should not have higher training error!
  - Richer solution space should allow it to find better solutions
- Solution by construction
  - Copy the original layers from a learned shallower model
  - Set the extra layers as identity
  - Such a network should achieve at least the same low training error.
- Reason: Optimization difficulties
  - Solvers cannot find the solution when going deeper…



Deep Residual Learning

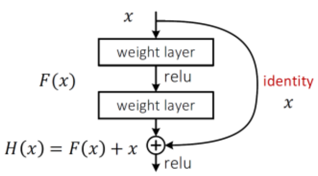
- Plain net



  - $H(x)$ is any desired mapping
  - Hope the 2 weight layers fit $H(x)$

Deep Residual Learning

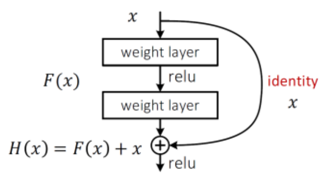
- Residual net



  - $H(x)$ is any desired mapping
  - ~~Hope the 2 weight layers fit $H(x)$~~
  - Hope the 2 weight layers fit $F(x)$
    Let $H(x) = F(x) + x$

Deep Residual Learning

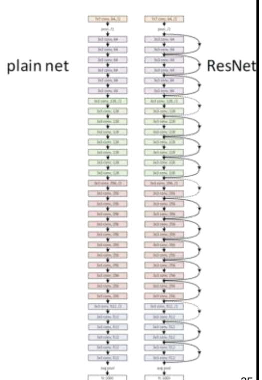
- $F(x)$ is a residual mapping w.r.t. identity



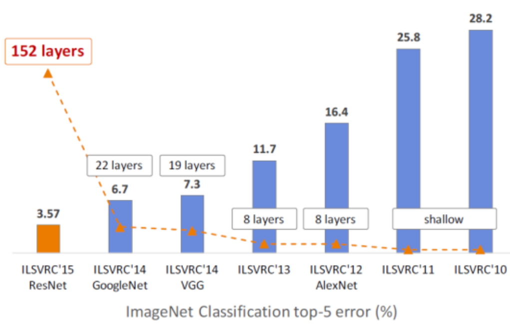
  - If identity were optimal, it is easy to set weights as 0
  - If optimal mapping is closer to identity, it is easier to find small fluctuations
  - Further advantage: direct path for the gradient to flow to the previous stages

Network Design

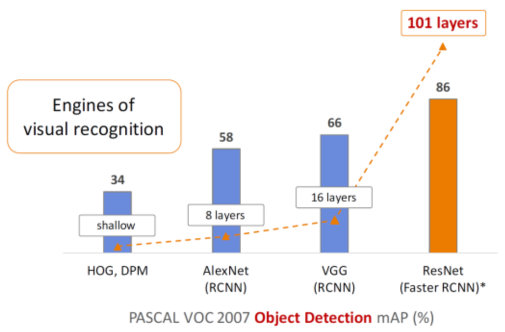
- Simple, VGG-style design
  - (Almost) all 3×3 convolutions
  - Spatial size /2 ⇒ #filters · 2 (same complexity per layer)
  - Batch normalization
  - ⇒ Simple design, just deep.



ImageNet Performance



PASCAL VOC Object Detection Performance



Slide credit: Kaiming He

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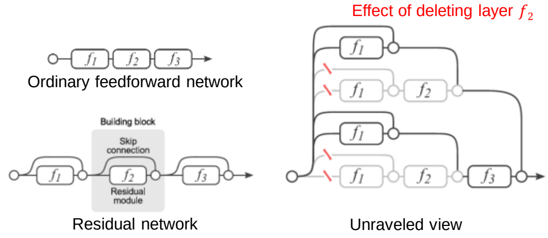
What Is The Secret Behind ResNets?

- Empirically, they perform very well, but why is that?
- He's original explanation [He, 2016]
  - ResNets allow gradients to pass through the skip connections in unchanged form.
  - This makes it possible to effectively train deeper networks.
  - ⇒ Secret of success: depth is good
- More recent explanation [Veit, 2016]
  - ResNets actually do not use deep network paths.
  - Instead, they effectively implement an ensemble of shallow network paths.
  - ⇒ Secret of success: ensembles are good

A, Veit, M. Wilber, S. Belongie, Residual Networks Behave Like Ensembles of Relatively Shallow Networks, NIPS 2016

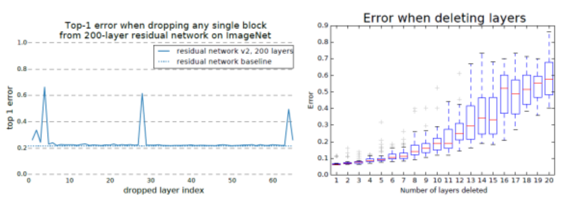
Idea of the Analysis



- Unraveling ResNets
  - ResNets can be viewed as a collection of shorter paths through different subsets of the layers.
  - Deleting a layer corresponds to removing only some of those paths

Image source: Veit et al., 2016

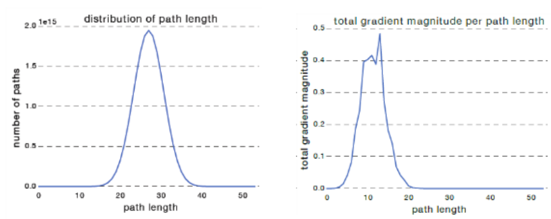
Effect of Deleting Layers at Test Time



- Experiments on ImageNet classification
  - When deleting a layer in VGG-Net, it breaks down completely.
  - In ResNets, deleting a single layer has almost no effect (except for the pooling layers)
  - Deleting an increasing number of layers increases the error smoothly
  - ⇒ *Paths in a ResNet do not strongly depend on each other.*

Image source: Veit et al., 2016

Which Paths Are Important?

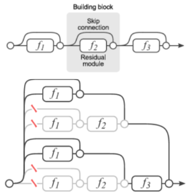


- How much does each of the paths contribute?
  - Distribution of path lengths follows a Binomial distribution
  - Sample individual paths and measure their gradient magnitude
  - ⇒ Effectively, only shallow paths with 5-17 modules are used!
  - ⇒ This corresponds to only 0.45% of the available paths here.

Image source: Veit et al., 2016

Summary

- The effective paths in ResNets are relatively shallow
  - Effectively only 5-17 active modules
- This explains the resilience to deletion
  - Deleting any single layer only affects a subset of paths (and the shorter ones less than the longer ones).
- New interpretation of ResNets
  - ResNets work by creating an ensemble of relatively shallow paths
  - Making ResNets deeper increases the size of this ensemble
  - Excluding longer paths from training does not negatively affect the results.



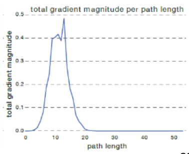


Image source: Veit et al., 2016

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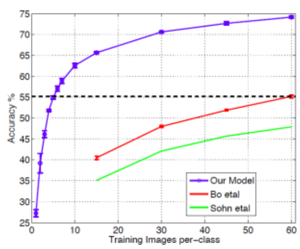
The Learned Features are Generic



state of the art level (pre-CNN)

- Experiment: feature transfer
  - Train AlexNet-like network on ImageNet
  - Chop off last layer and train classification layer on CalTech256

⇒ State of the art accuracy already with only 6 training images!

Image source: M. Zeiler, R. Fergus

Transfer Learning with CNNs

1. Train on ImageNet

2. If small dataset: fix all weights (treat CNN as fixed feature extractor), retrain only the classifier

I.e., swap the Softmax layer at the end

Slide credit: Andrej Karpathy

Transfer Learning with CNNs

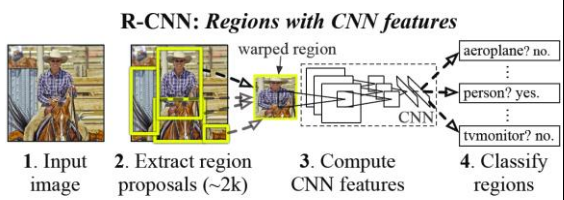
1. Train on ImageNet

3. If you have medium sized dataset, "finetune" instead: use the old weights as initialization, train the full network or only some of the higher layers.

Retrain bigger portion of the network

Slide credit: Andrej Karpathy

Other Tasks: Detection

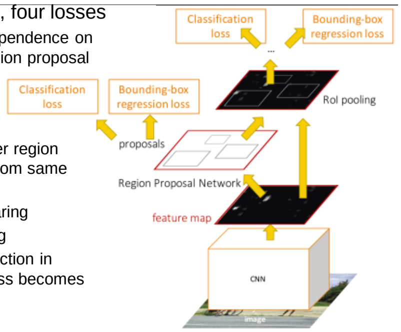


- Results on PASCAL VOC Detection benchmark
  - Pre-CNN state of the art: 35.1% mAP [Uijlings et al., 2013]
    33.4% mAP DPM
  - R-CNN: 53.7% mAP

R. Girshick, J. Donahue, T. Darrell, and J. Malik, Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation, CVPR 2014

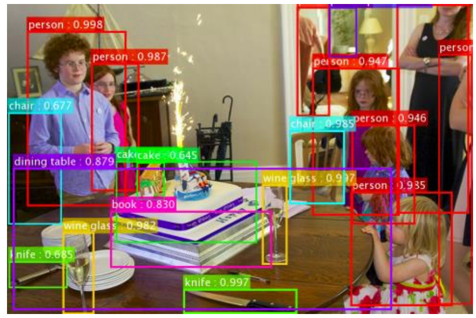
More Recent Version: Faster R-CNN

- One network, four losses
  - Remove dependence on external region proposal algorithm.
  - Instead, infer region proposals from same CNN.
  - Feature sharing
  - Joint training
  - ⇒ Object detection in a single pass becomes possible.



Slide credit: Ross Girshick

Faster R-CNN (based on ResNets)



K. He, X. Zhang, S. Ren, J. Sun, Deep Residual Learning for Image Recognition, CVPR 2016.

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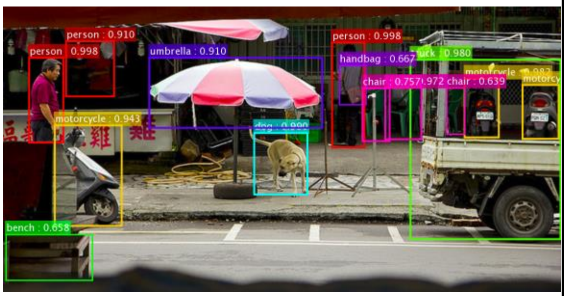
Faster R-CNN (based on ResNets)



K. He, X. Zhang, S. Ren, J. Sun, Deep Residual Learning for Image Recognition, CVPR 2016.

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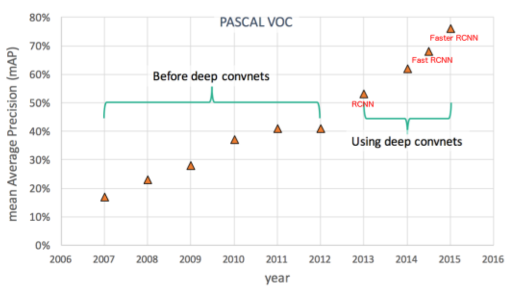
YOLO

J. Redmon, S. Divvala, R. Girshick, A. Farhadi, You Only Look Once: Unified, Real-Time Object Detection, CVPR 2016.

Object Detection Performance



Slide credit: Ross Girshick

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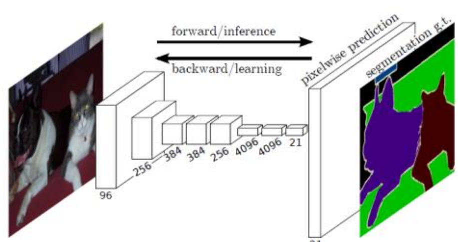
Semantic Image Segmentation

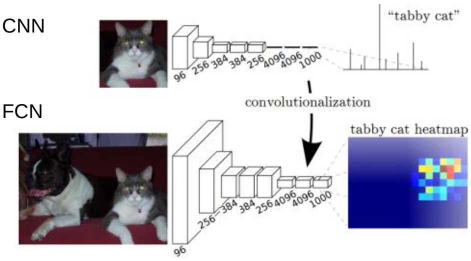


- Perform pixel-wise prediction task
  - Usually done using Fully Convolutional Networks (FCNs)
    - All operations formulated as convolutions
    - Advantage: can process arbitrarily sized images

Image source: Long, Shelhamer, Darrell

CNNs vs. FCNs

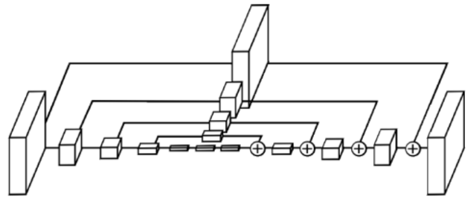
- CNN
- FCN



- Intuition
  - Think of FCNs as performing a sliding-window classification, producing a heatmap of output scores for each class

Image source: Long, Shelhamer, Darrell

Semantic Image Segmentation



- Encoder-Decoder Architecture
  - Problem: FCN output has low resolution
  - Solution: perform upsampling to get back to desired resolution
  - Use skip connections to preserve higher-resolution information

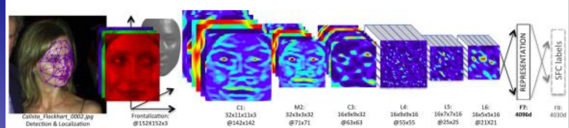
Image source: Newell et al.

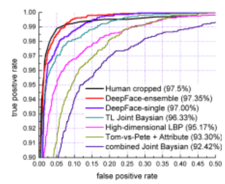
Semantic Segmentation

- Current state-of-the-art
  - Based on an extension of ResNets

[Pohlen, Hermans, Mathias, Leibe, CVPR 2017]

Other Tasks: Face Identification



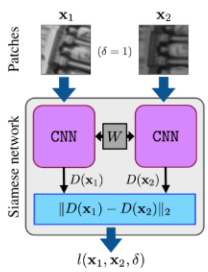


Y. Taigman, M. Yang, M. Ranzato, L. Wolf, DeepFace: Closing the Gap to Human-Level Performance in Face Verification, CVPR 2014

Slide credit: Svetlana Lazebnik

Learning Similarity Functions

- Siamese Network
  - Present the two stimuli to two identical copies of a network (with shared parameters)
  - Train them to output similar values if the inputs are (semantically) similar.
- Used for many matching tasks
  - Face identification
  - Stereo estimation
  - Optical flow
  - …



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Extension: Triplet Loss Networks

- Learning a discriminative embedding
  - Present the network with triplets of examples

Negative Anchor Positive

  - Apply triplet loss to learn an embedding $f(\cdot)$ that groups the positive example closer to the anchor than the negative one.

$$\|f(x_i^a) - f(x_i^p)\|_2^2 < \|f(x_i^a) - f(x_i^n)\|_2^2$$

⇒ Used with great success in Google's FaceNet face identification

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References and Further Reading

- ResNets

  - K. He, X. Zhang, S. Ren, J. Sun, Deep Residual Learning for Image Recognition, CVPR 2016.
  - A, Veit, M. Wilber, S. Belongie, Residual Networks Behave Like Ensembles of Relatively Shallow Networks, NIPS 2016.

References: Computer Vision Tasks

- Object Detection

  - R. Girshick, J. Donahue, T. Darrell, J. Malik, Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation, CVPR 2014.
  - S. Ren, K. He, R. Girshick, J. Sun, Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks, NIPS 2015.
  - J. Redmon, S. Divvala, R. Girshick, A. Farhadi, You Only Look Once: Unified Real-Time Object Detection, CVPR 2016.
  - W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C-Y. Fu, A.C. Berg, SSD: Single Shot Multi Box Detector, ECCV 2016.

References: Computer Vision Tasks

- Semantic Segmentation

  - J. Long, E. Shelhamer, T. Darrell, Fully Convolutional Networks for Semantic Segmentation, CVPR 2015.
  - H. Zhao, J. Shi, X. Qi, X. Wang, J. Jia, Pyramid Scene Parsing Network, arXiv 1612.01105, 2016.