A Shallow Introduction into the Deep Machine Learning

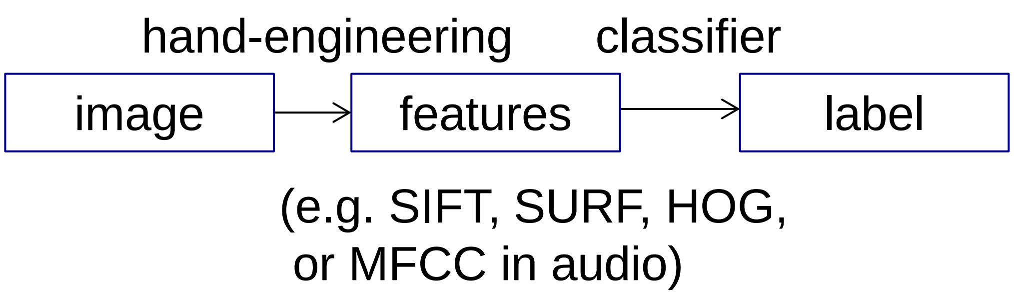
Jan Čech

What is the “Deep Learning” ?

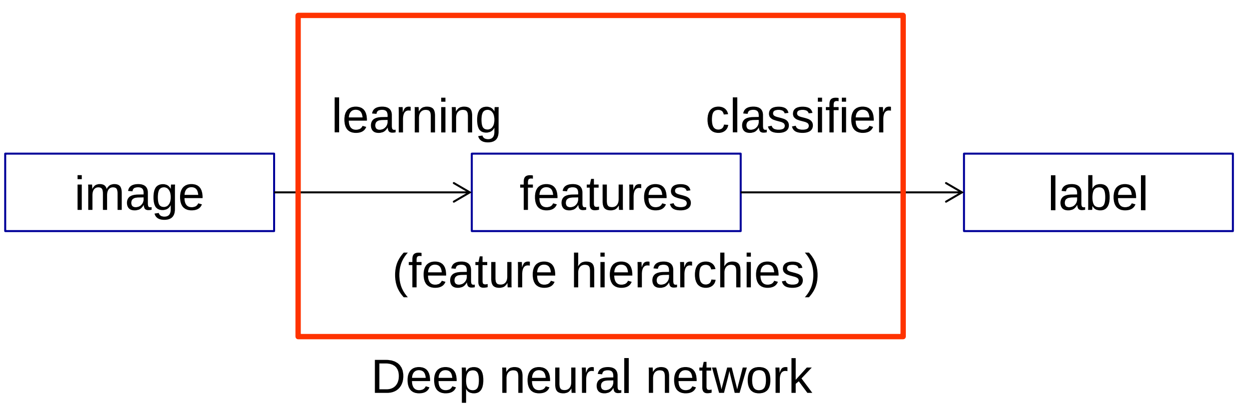
- Deep learning

  = both the classifiers and the features are learned automatically

- Typically not feasible, due to high dimensionality



- Suboptimal, requires expert knowledge, works in specific domain only



Deep learning successes

- Deep learning methods have been extremely successful recently
  - Consistently beating state-of-the-art results in many fields, winning many challenges by a significant margin

nowadays everywhere

Computer vision:

- Hand writing recognition, Action/activity recognition, Face recognition
- Large-scale image category recognition (ILSVRC' 2012 challenge)

INRIA/Xerox	33%,
Uni Amsterdam	30%,
Uni Oxford	27%,
Uni Tokyo	26%,
Uni Toronto	**16% (deep neural network)** [Krizhevsky-NIPS-2012]

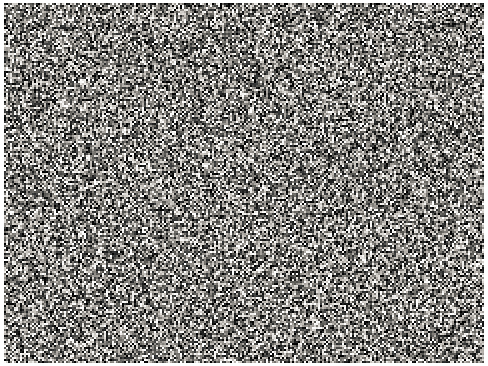
Automatic speech recognition:

- TIMIT Phoneme recognition, speaker recognition, lip reading

Natural Language Processing, Text Analysis:

- IBM Watson, Google translate

Learning the representation – Sparse coding



- Natural image statistics
  - Luckily, there is a redundancy in natural images
  - Pixel intensities are not i.i.d. (but highly correlated)

- Sparse coding [Olshausen-1996, Ng-NIPS-2006]

Input images: $x^{(1)}, x^{(2)}, \ldots, x^{(m)}; (x^{(i)} \in R^{n \times n})$

Learn dictionary of basis functions $\phi_1, \phi_2, \ldots, \phi_k; (\phi_j \in R^{n \times n})$ that

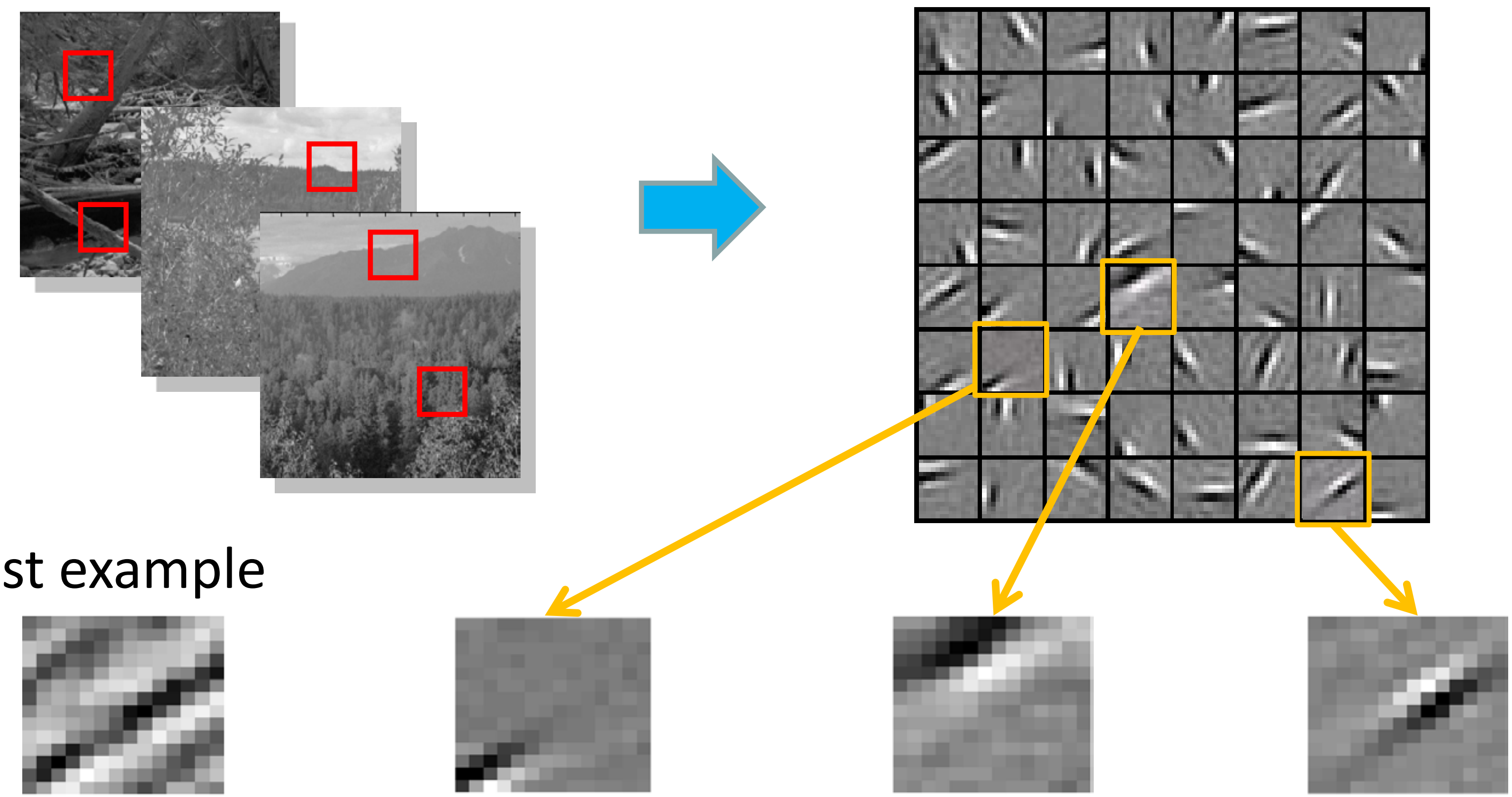
$$x \approx \sum_{j=1}^{k} a_j \phi_j \text{ ; s.t. } a_j \text{ are mostly zero, “sparse”}$$

$$\min_{a,\phi} \sum_{i=1}^{m} \left(\left\| x^{(i)} - \sum_{j=1}^{k} a_j^{(i)} \phi_j \right\|^2 + \lambda \sum_{j=1}^{k} |a_j^{(i)}| \right)$$

Sparse coding

Natural Images

Learned bases ($\phi_1, \ldots, \phi_{64}$): "Edges"



$$x \approx 0.8 * \phi_{36} + 0.3 * \phi_{42} + 0.5 * \phi_{63}$$

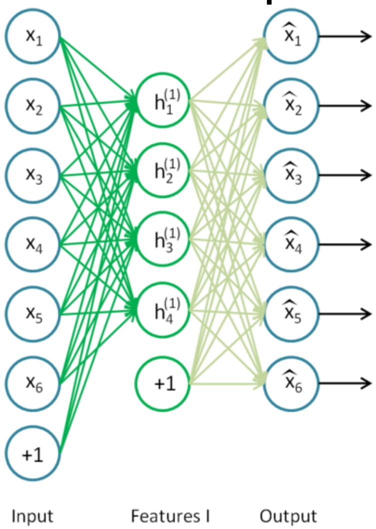
[0, 0, …, 0, **0.8**, 0, …, 0, **0.3**, 0, …, 0, **0.5**, …]

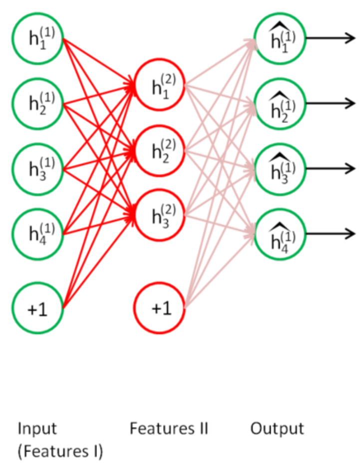
= [a_1, …, a_{64}] (feature representation)

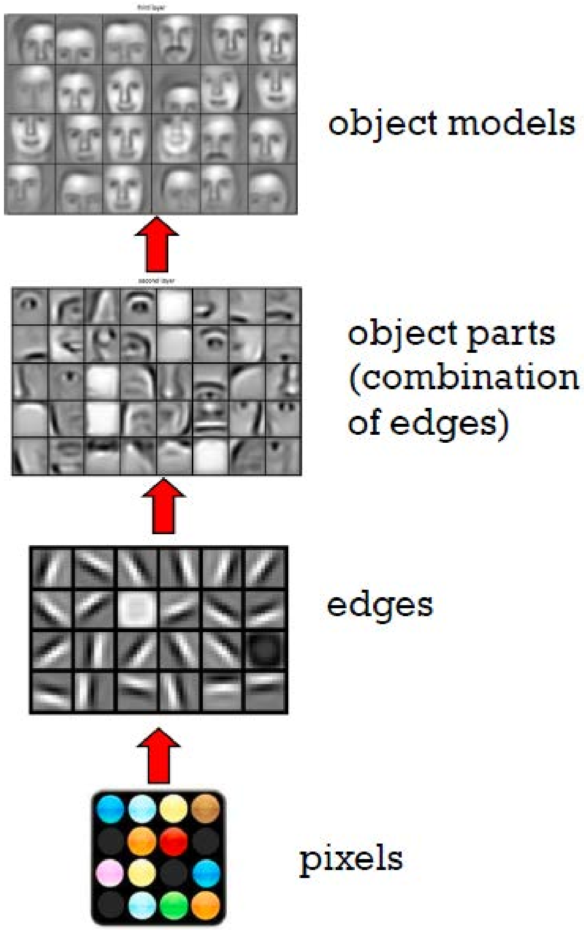
Compact & easily interpretable

Unsupervised Learning Hierarchies of features

- Many approaches to unsupervised learning of feature hierarchies
  – Sparse Auto-encoders [Bengio-2007]
  – Restricted Boltzmann Machines [Hinton-2006]
- These model can be stacked: lower hidden layer is used as the input for subsequent layers





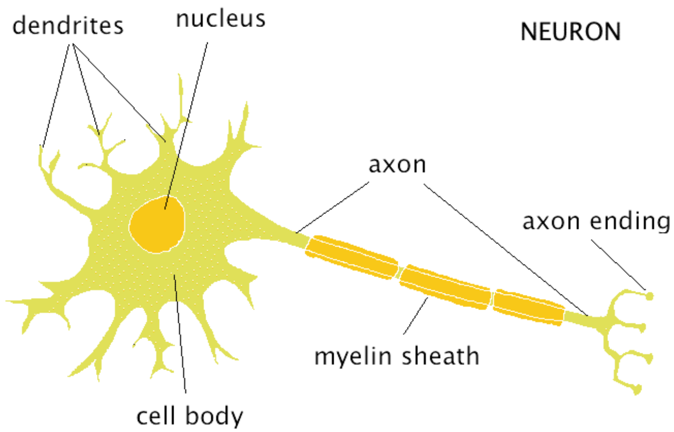


[Lee-ICML-2009]

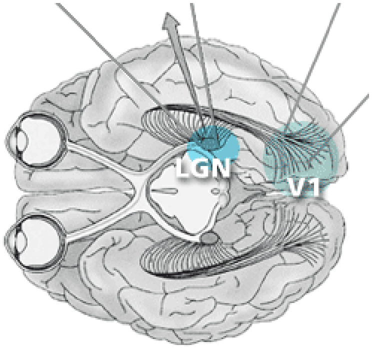
- **The hidden layers are trained to capture higher-order data correlations.**
- Learning the hierarchies and classification can be implemented by a (Deep) Neural Network

Resemblance to sensory processing in the brain

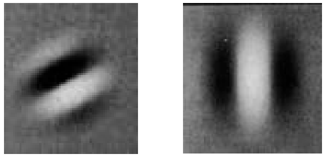
- Needless to say that the brain is a neural network



~ 2e-11 neurons
~ 1e-14 synapses



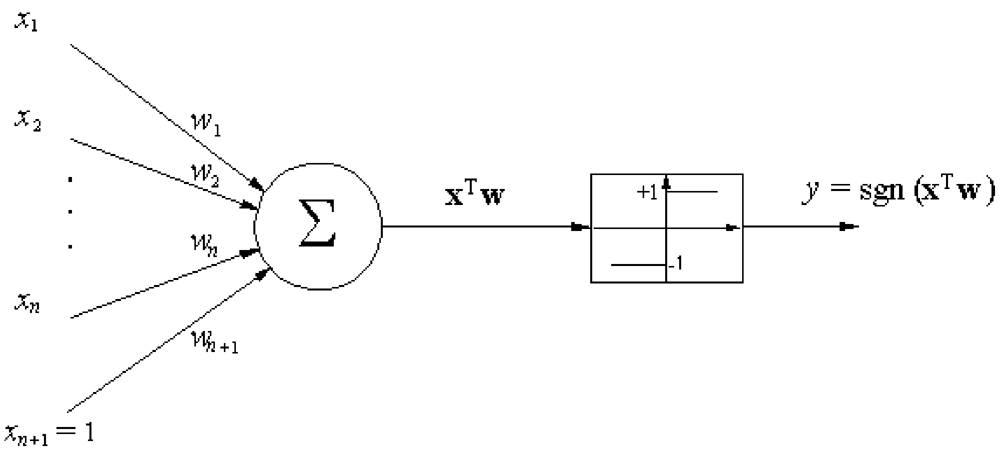
- Primary visual cortex V1
  - Neurophysiological evidences that primary visual cells are sensitive to the orientation and frequency (Gabor filter like impulse responses)
  - [Hubel-Wiesel-1959] (Nobel Price winners)
    - Experiments on cats with electrodes in the brain



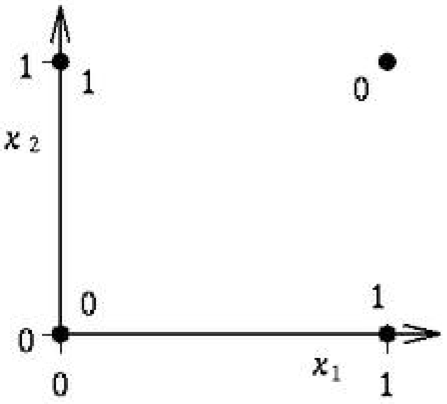
- A single learning algorithm hypothesis ?
  - “Rewiring” the brain experiment [Sharma-Nature-2000]
    - Connecting optical nerve into A1 cortex (a subject was able to solve visual tasks by using the processing in A1)

(Artificial) Neural Networks

- Neural networks are here for more than 50 years
  - Rosenblatt-1956 (perceptron)



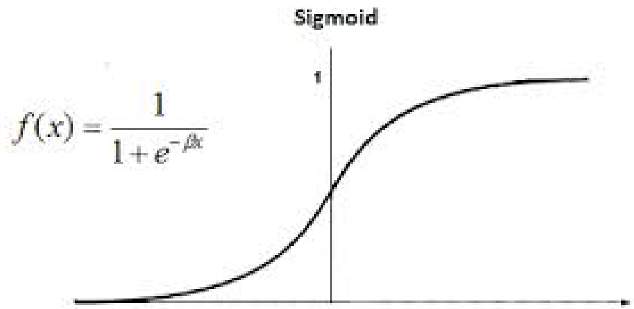
  - Minsky-1969 (xor issue, => skepticism)



Neural Networks

Rumelhart and McClelland – 1986:

- Multi-layer perceptron,
- Back-propagation (supervised training)
  - Differentiable activation function
  - Stochastic gradient descent

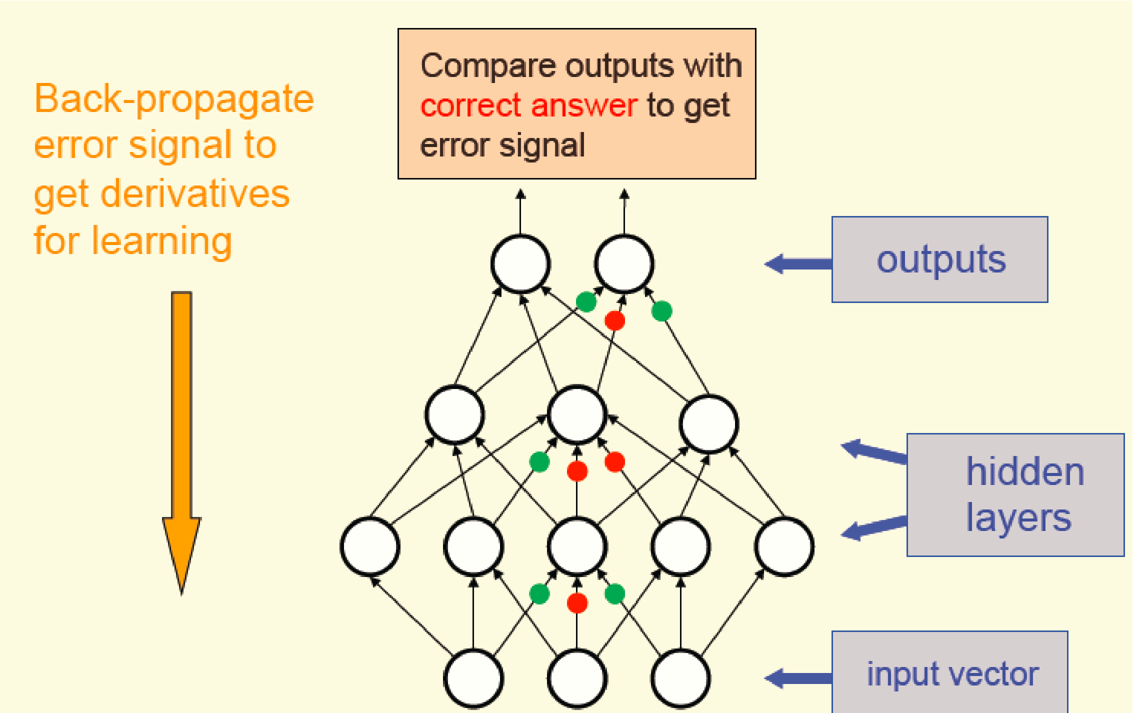


Empirical risk

$$Q(w) = \sum_{i=1}^{n} Q_i(w),$$

Update weights:

$$w := w - \alpha \nabla Q_i(w).$$



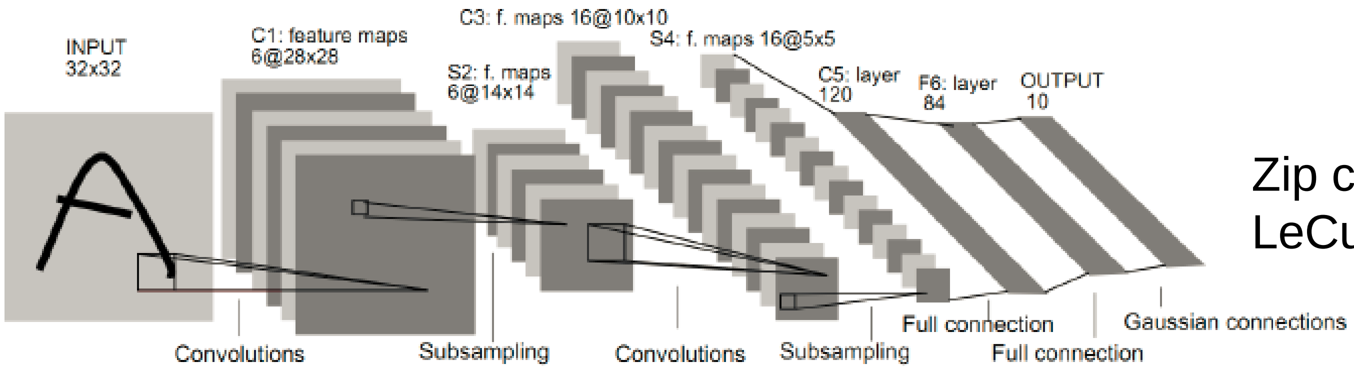
What happens if a network is deep?
(it has many layers)

What was wrong with back propagation?

- Local optimization only (needs a good initialization, or re-initialization)
- Prone to over-fitting
  - too many parameters to estimate
  - too few labeled examples
- Computationally intensive

=> Skepticism: A deep network often performed worse than a shallow one

What was wrong with backpropagation?



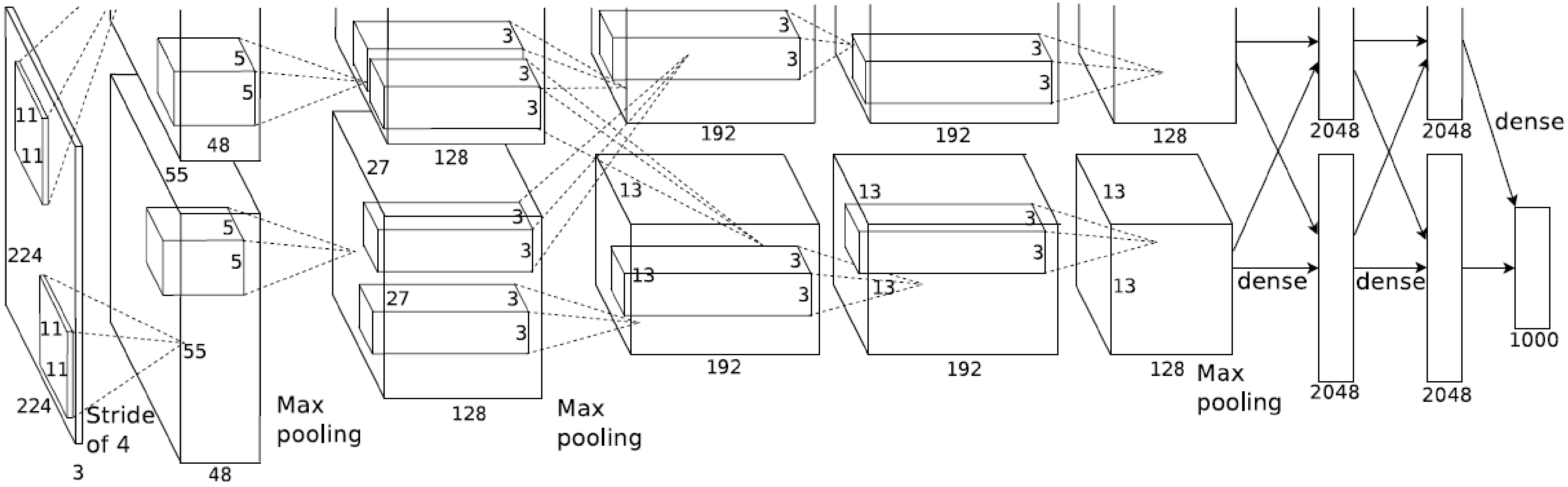
Zip codes recognition, LeCun 1989

- However nowadays:
  - Weights can be initialized better (Use of unlabeled data)
  - Large collections of labeled data available
    - ImageNet (14M images, 21k classes, hand-labeled)
  - Reducing the number of parameters by weight sharing
    - **Convolutional** layers – [LeCun-1989]
  - Novel tricks to prevent overfitting of deep nets
  - Fast enough computers (parallel hardware, GPU)

=> Optimism: It works!

Deep convolutional neural networks

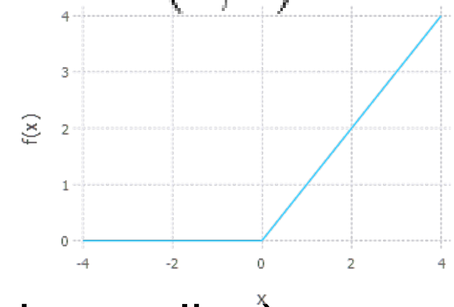
- An example for Large Scale Classification Problem:
  - Krizhevsky, Sutskever, Hinton: ImageNet classification with deep convolutional neural networks. NIPS, 2012.
    - Recognizes 1000 categories from ImageNet
    - Outperforms state-of-the-art by significant margin (ILSVRC 2012)



- 5 convolutional layers, 3 fully connected layers
- 60M parameters, trained on 1.2M images (~1000 examples for each category)

Deep convolutional neural networks

$$f(x) = \max(0, x)$$



- Additional tricks: "Devil is in the details"
  - Rectified linear units instead of standard sigmoid

    => Mitigate vanishing gradient problem
  - Convolutional layers followed by max-pooling
    - Local maxima selection in overlapping windows (subsampling)

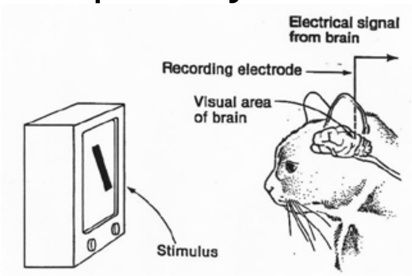
    => dimensionality reduction, shift insensitivity
  - Dropout
    - Averaging results of many independent models (similar idea as in Random forests)
    - 50% of hidden units are randomly omitted during the training, but weights are shared in testing time

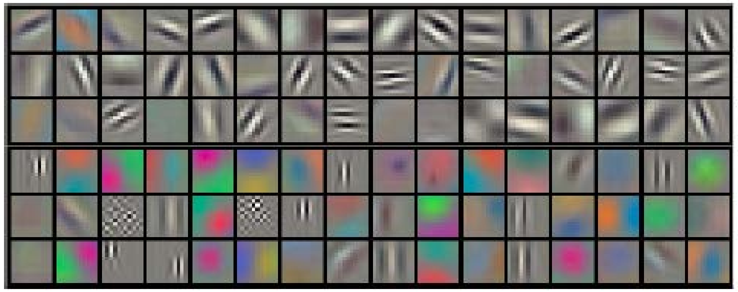
    => Probably very significant to reduce overfitting
  - Data augmentation
    - Images are artificially shifted and mirrored (10 times more images)

    => transformation invariance, reduce overfitting

Deep convolutional neural networks

- No unsupervised pre-initialization!
  - The training is supervised by standard back-propagation
  - enough labeled data: 1.2M labeled training images for 1k categories
  - Learned filters in the first layer
    - Resemble cells in primary visual cortex

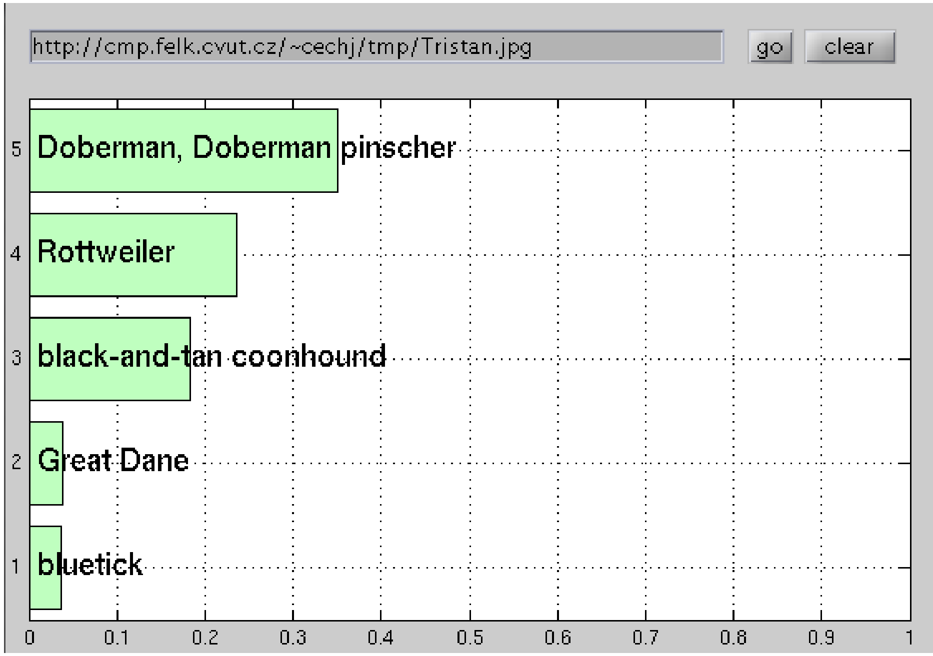




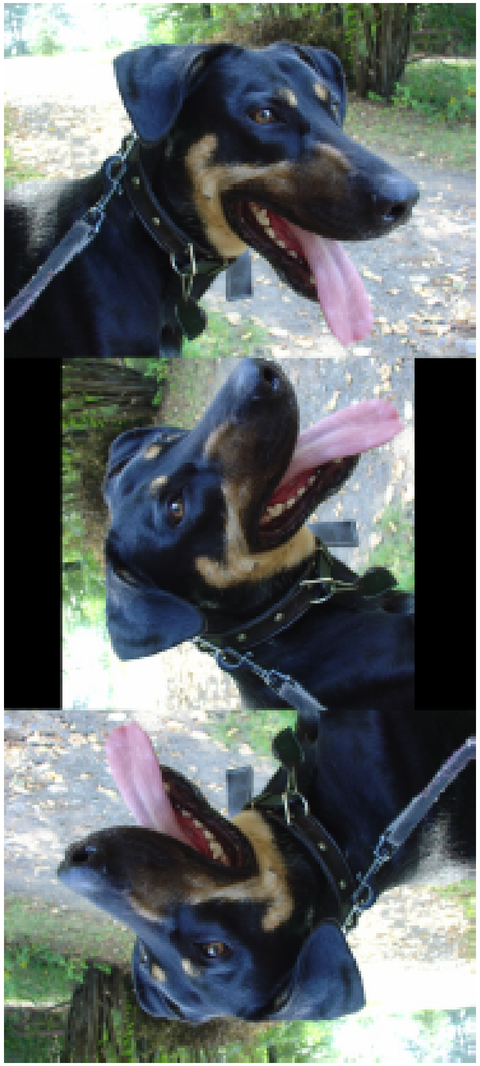
- Training time:
  - 5 days on NVIDIA GTX 580, 3GB memory (Krizhevsky, today faster)
  - 90 cycles through the training set
- Test time (forward step) on GPU
  - Implementation by Yangqing Jia, http://caffe.berkeleyvision.org/
  - 5 ms/image in a batch mode
  - (my experience: 100 ms/image in Matlab, including image decompression and normalization)

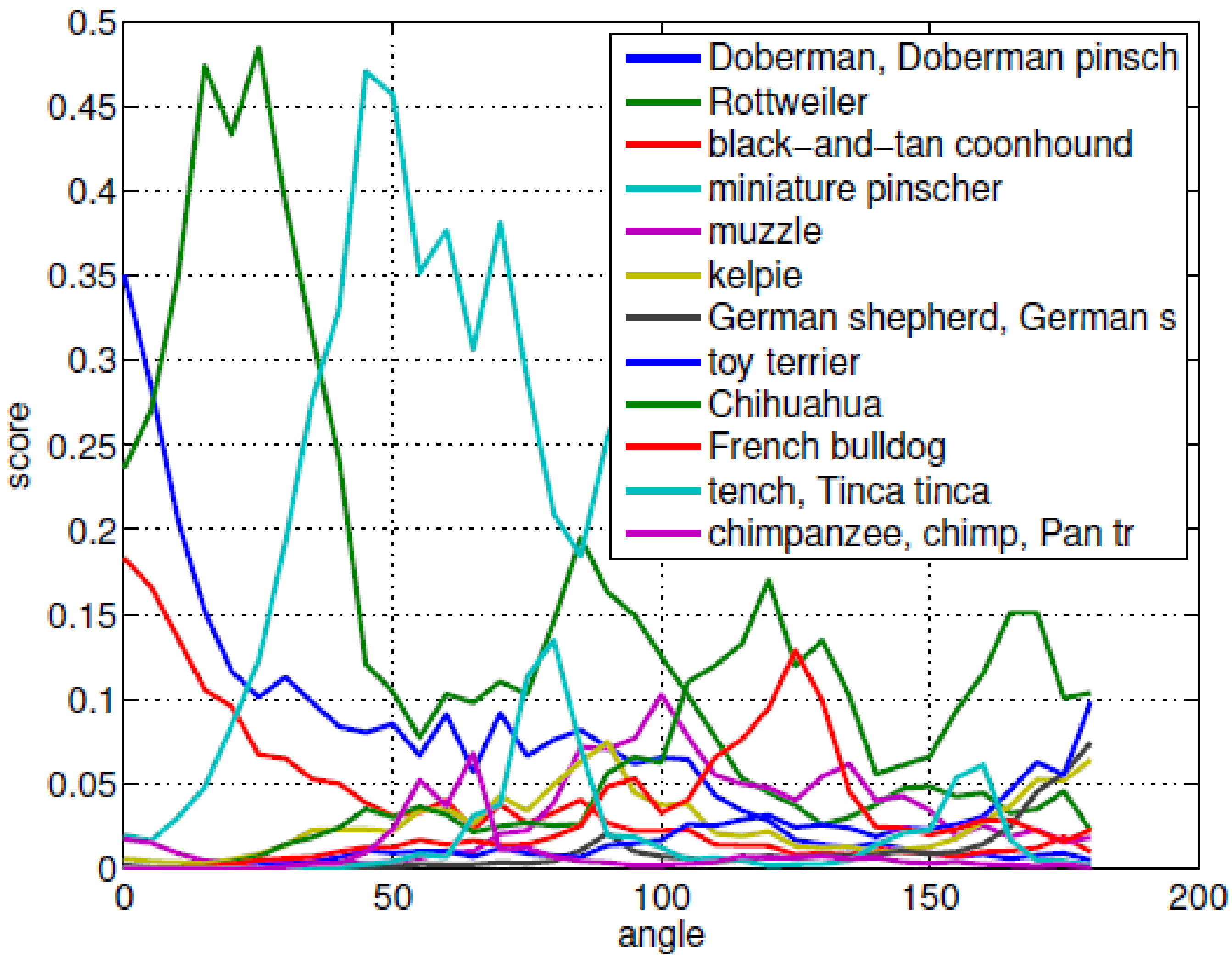
Preliminary experiments 1: Category recognition

- Implementation by Yangqing Jia, http://caffe.berkeleyvision.org/
  – network pre-trained for 1000 categories provided
- Which categories are pre-trained?
  – 1000 "most popular" (probably mostly populated)
  – Typically very fine categories (dog breeds, plants, vehicles…)
  – Category "person" (or derived) is missing
  – Recognition subjectively surprisingly good…

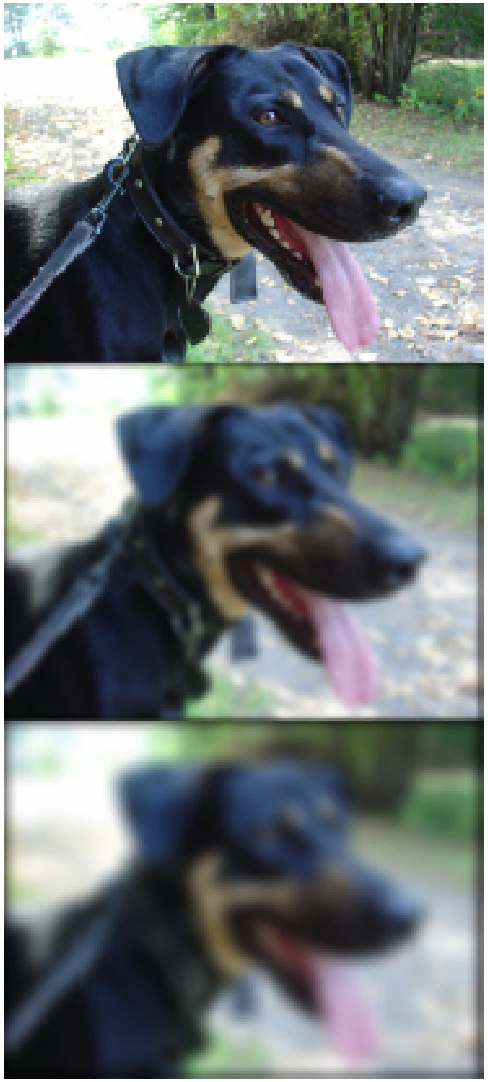


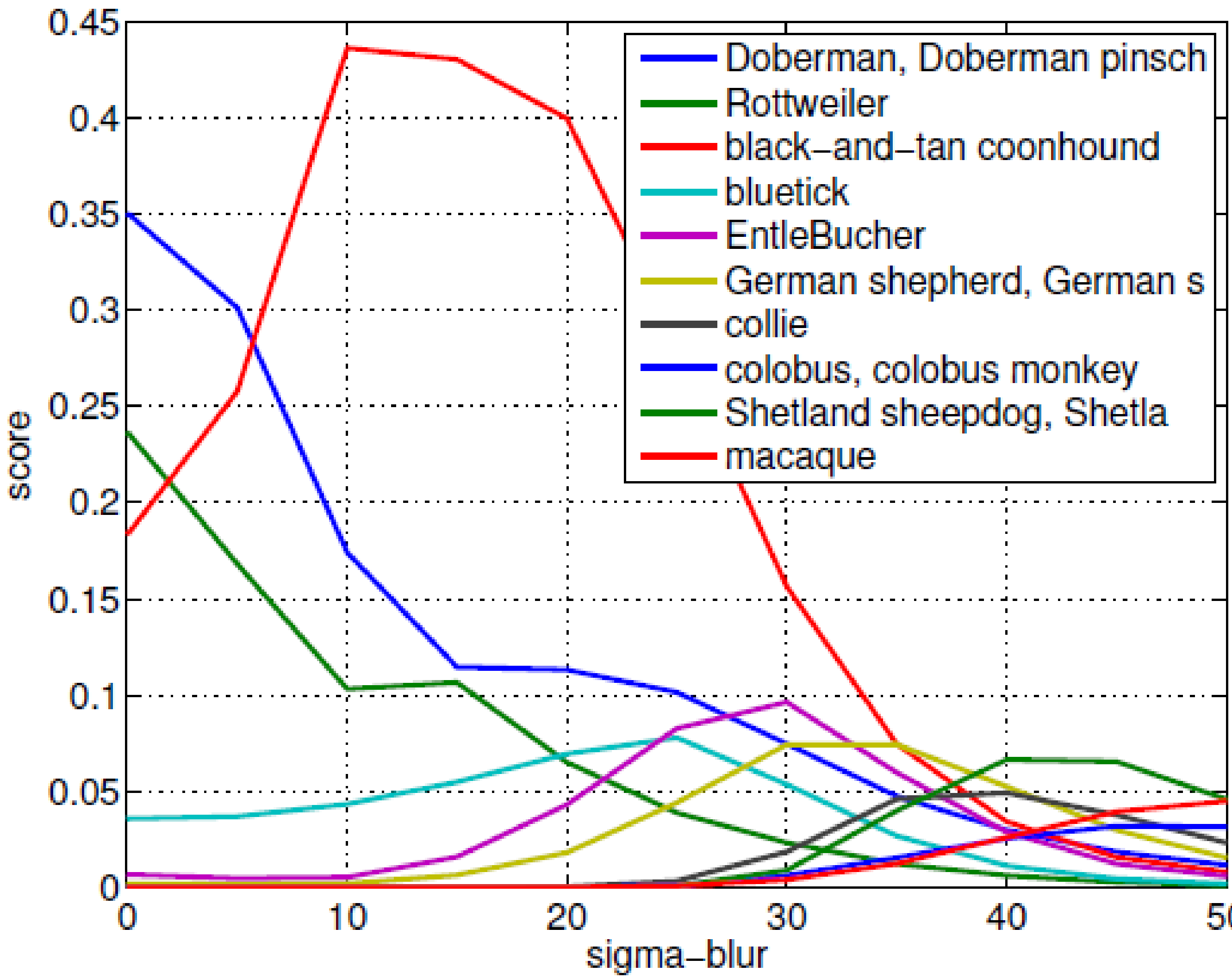
Sensitivity to image rotation



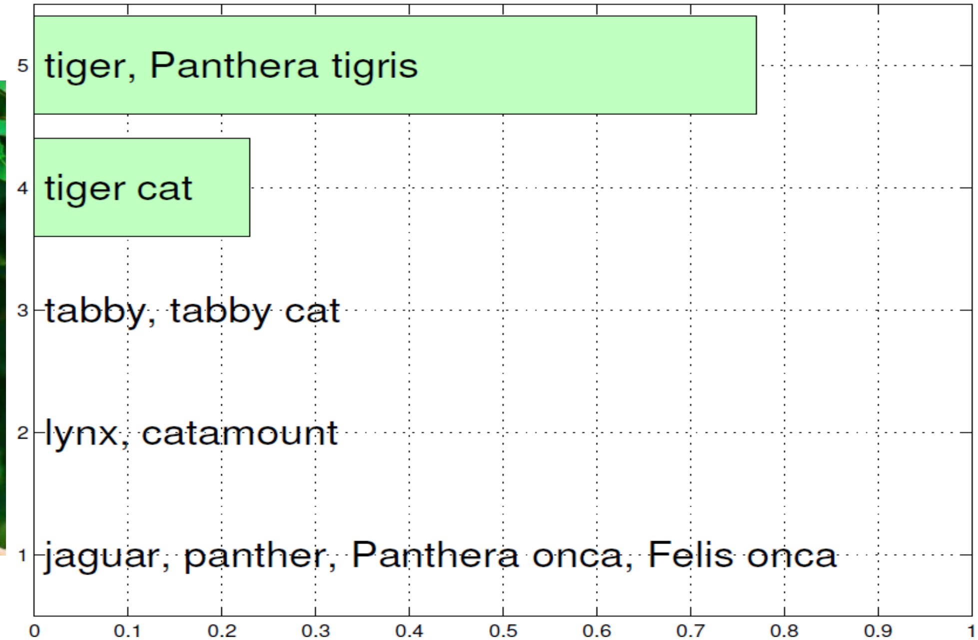


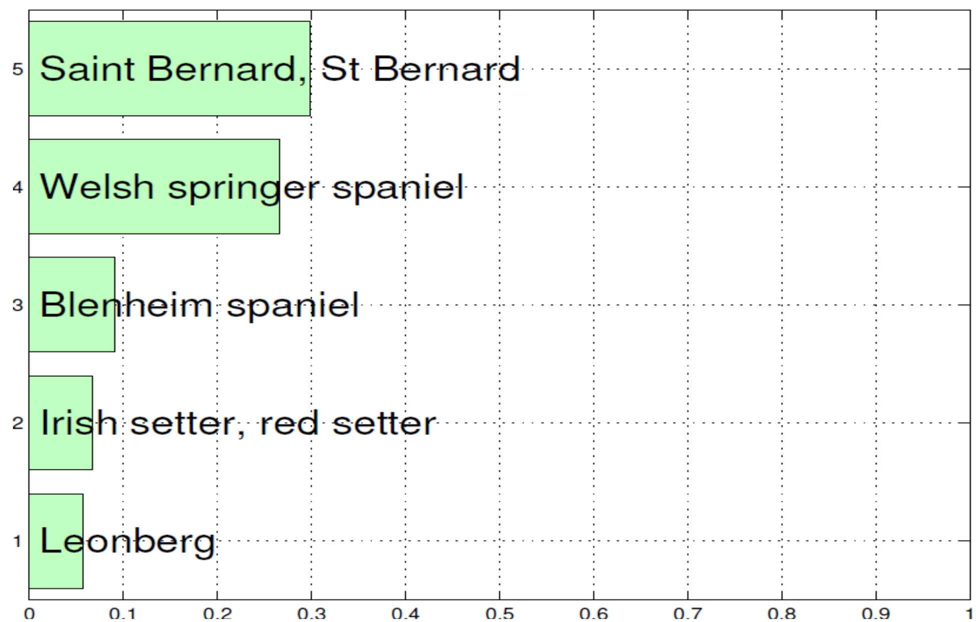
Sensitivity to image blur





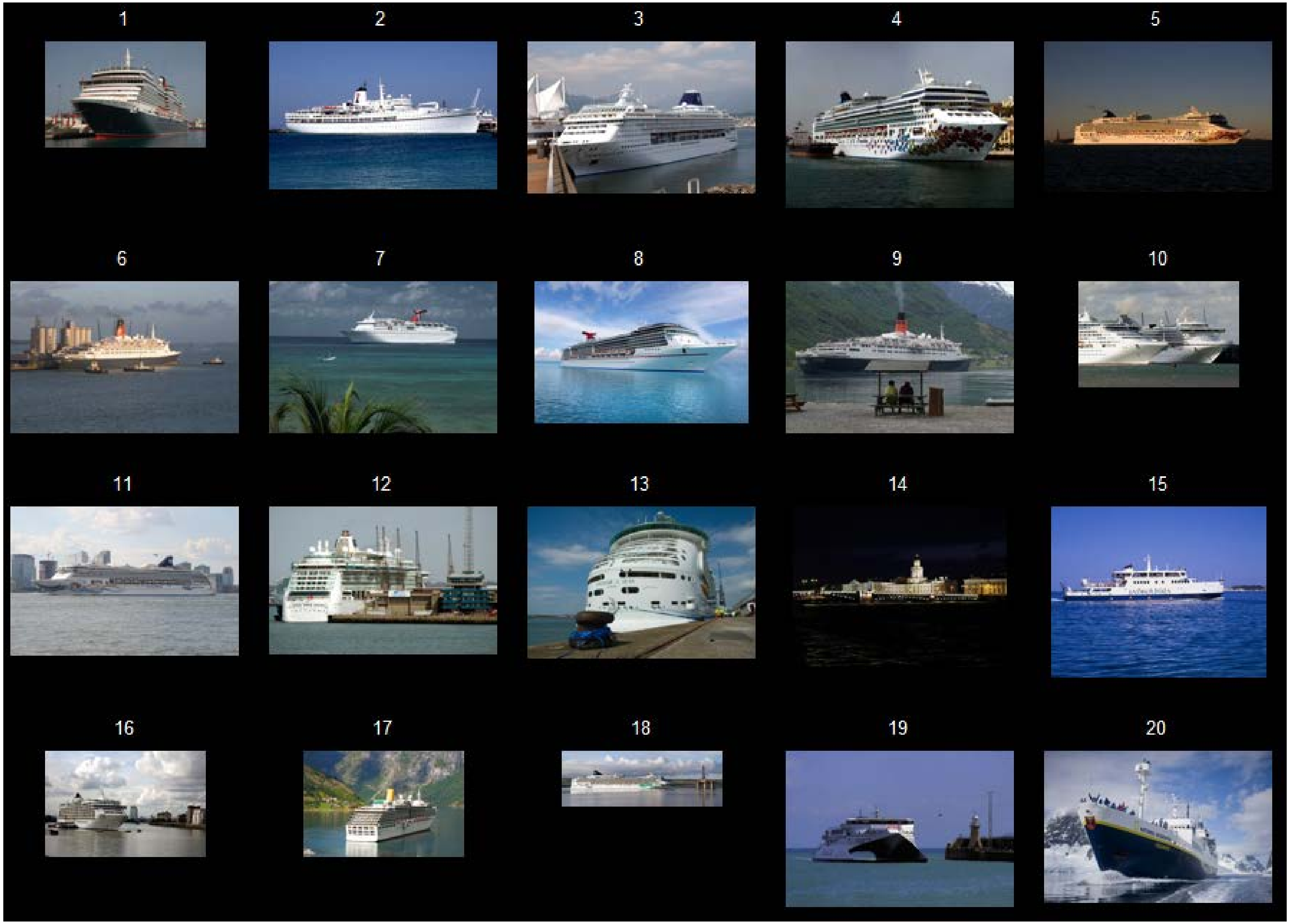
It is not a texture only...





Preliminary experiments 2: Category retrieval

- 50k randomly selected images from Profimedia dataset
- Category: Ocean liner



Preliminary experiments 2: Category retrieval

- Category: Restaurant (results out of 50k-random-Profiset)

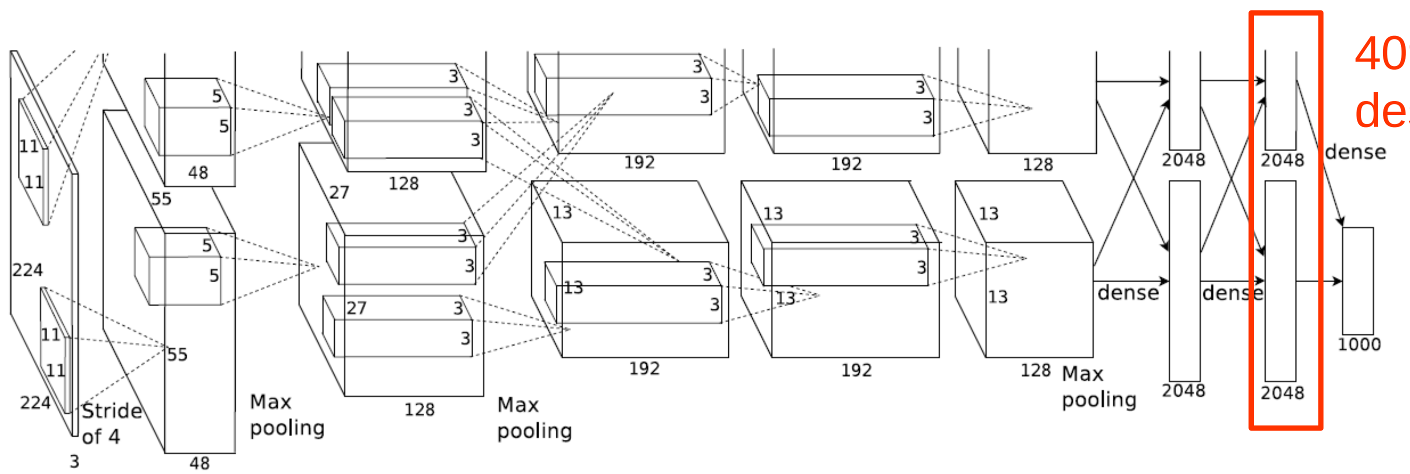
Preliminary experiments 2: Category retrieval

- Category: stethoscope (results out of 50k-random-Profiset)

Preliminary experiments 3: Similarity search

- Indications in the literature that the last hidden layer carry semantics
  - Last hidden layer (4096-dim vector), final layer category responses (1000-dim vector)
  - New (unseen) categories can be learned by training (a linear) classifier on top of the last hidden layer
    - Oquab, Bottou, Laptev, Sivic, CVPR, 2014
    - Girshick, Dphanue, Darell, Malik, CVPR, 2014
  - **Responses of the last hidden layer can be used as a compact global image descriptor**
    - Semantically similar images should have small Euclidean distance

image



4096-dim descriptor

Preliminary experiments 3: Similarity search

- Qualitative comparison: (20 most similar images to a query image)
  1. MUFIN annotation (web demo), http://mufin.fi.muni.cz/annotation/, [Zezula et al., *Similarity Search: The Metric Space Approach.* 2005.]
     - Nearest neighbour search in **20M** images of Profimedia
     - Standard global image statistics (e.g. color histograms, gradient histograms, etc.)
  2. Caffe NN (last hidden layer response + Euclidean distance),
     - Nearest neighbour search in **50k** images of Profimedia

MUFIN results

Preliminary experiments 3: Similarity search

Caffe NN results

Preliminary experiments 3: Similarity search

MUFIN results

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Caffe NN results

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MUFIN results

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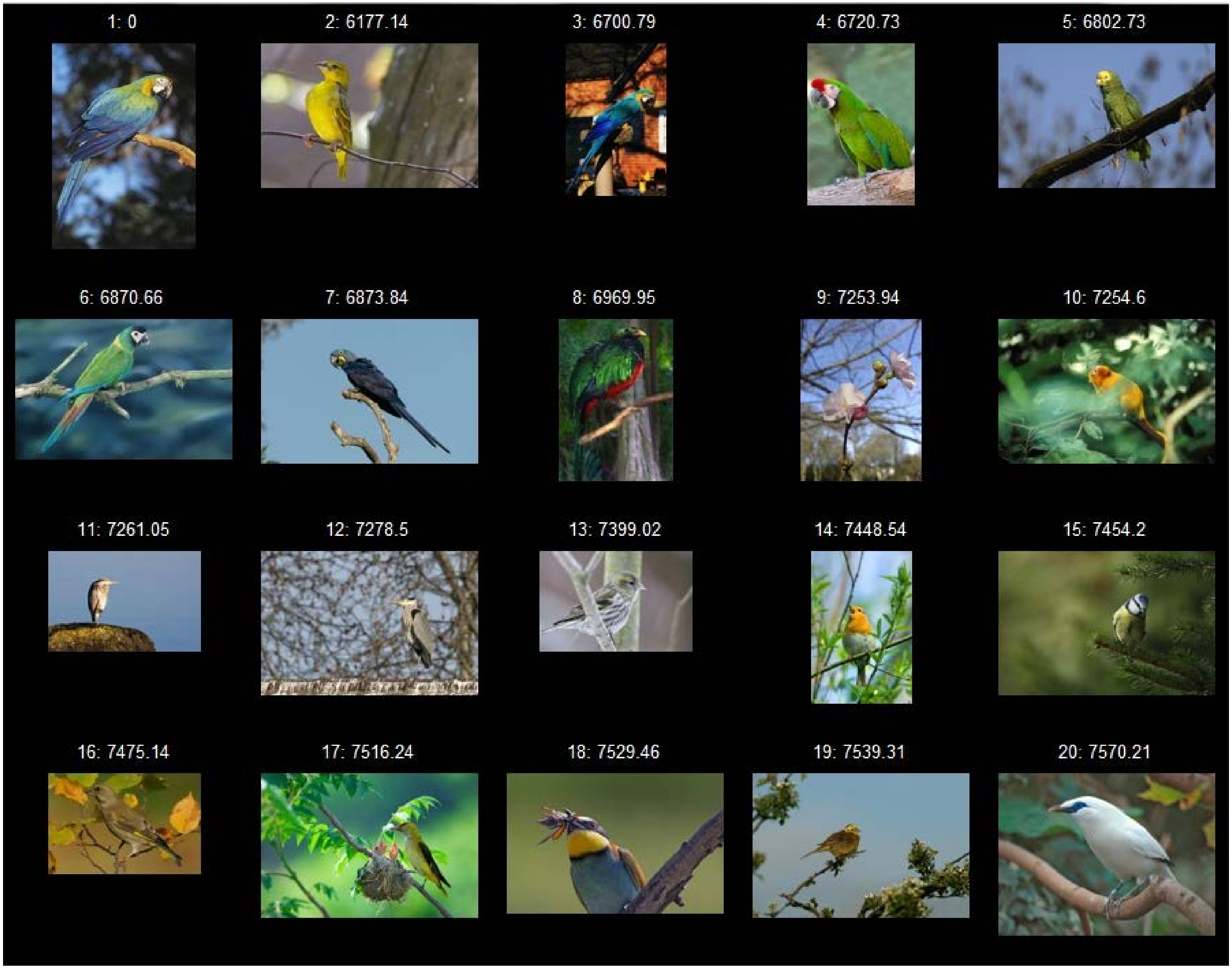
Caffe NN results



Preliminary experiments 3: Similarity search

MUFIN results

Preliminary experiments 3: Similarity search

Caffe NN results

Preliminary experiments 3: Similarity search

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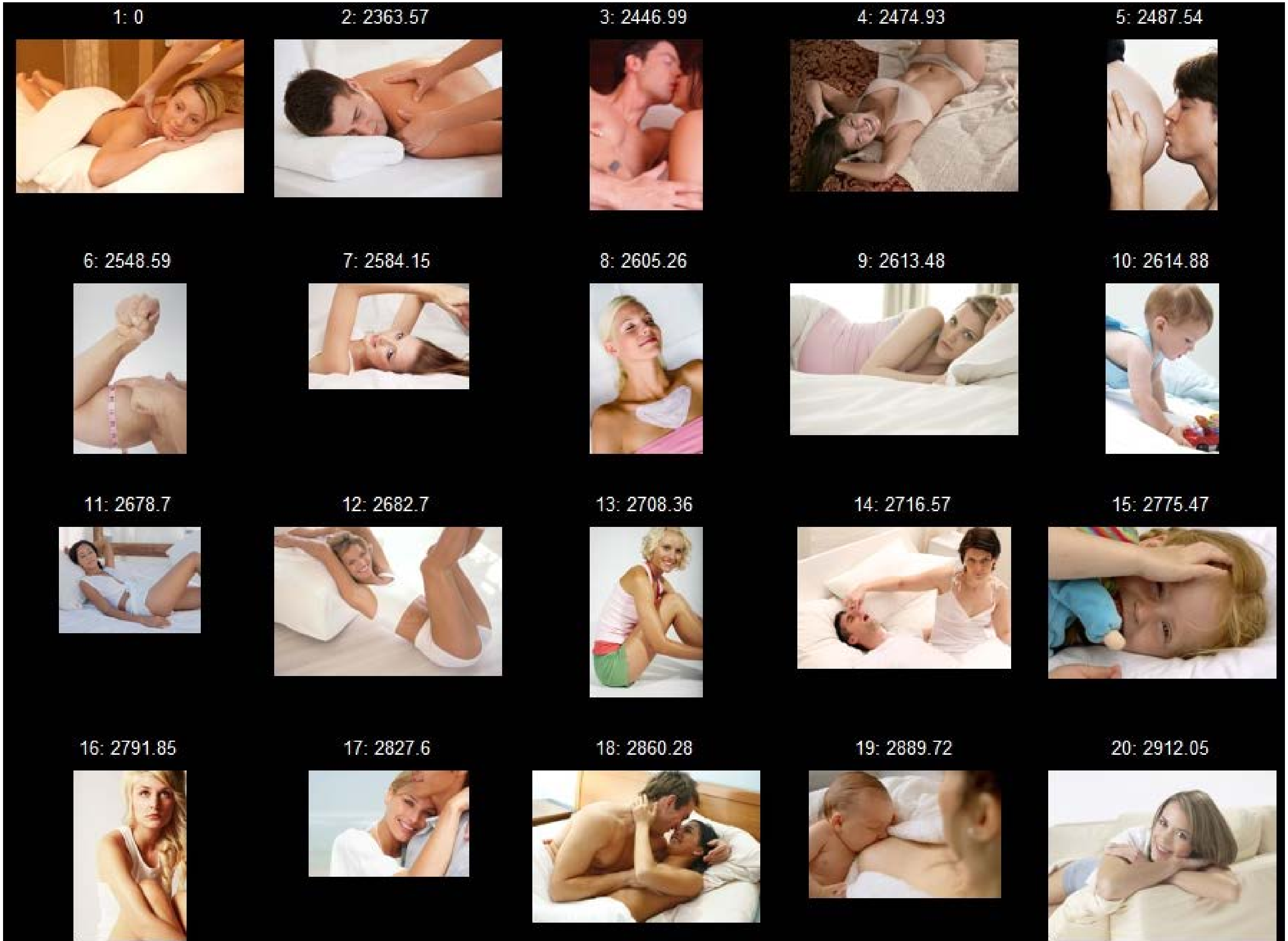
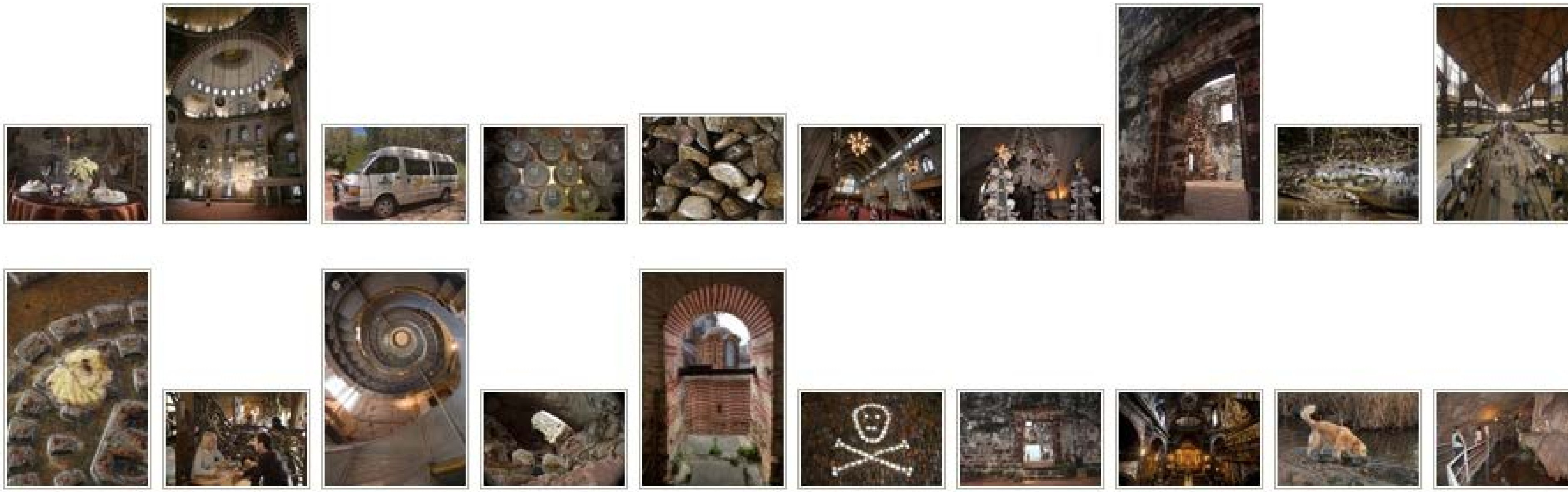
Caffe NN results



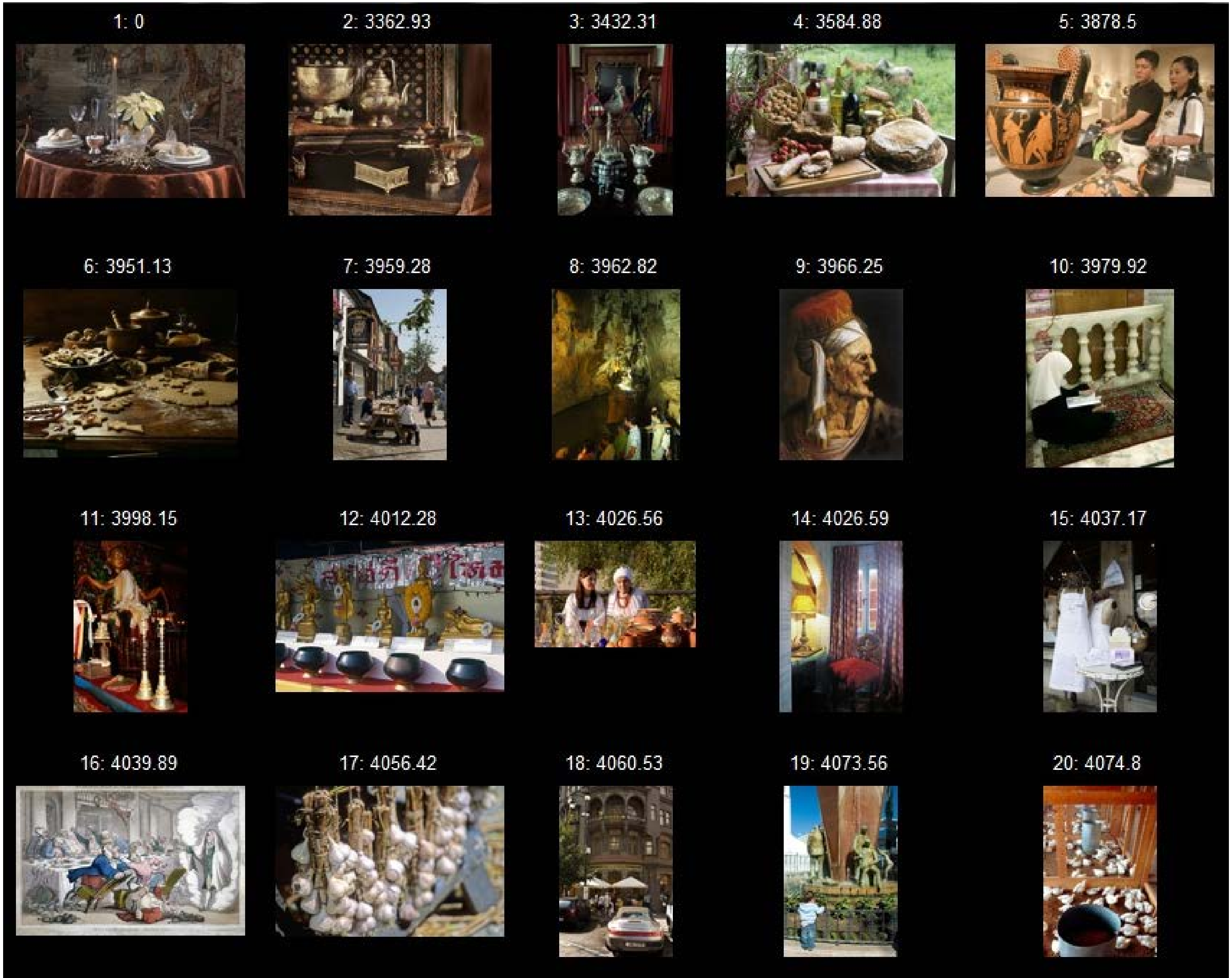
Preliminary experiments 3: Similarity search

MUFIN results

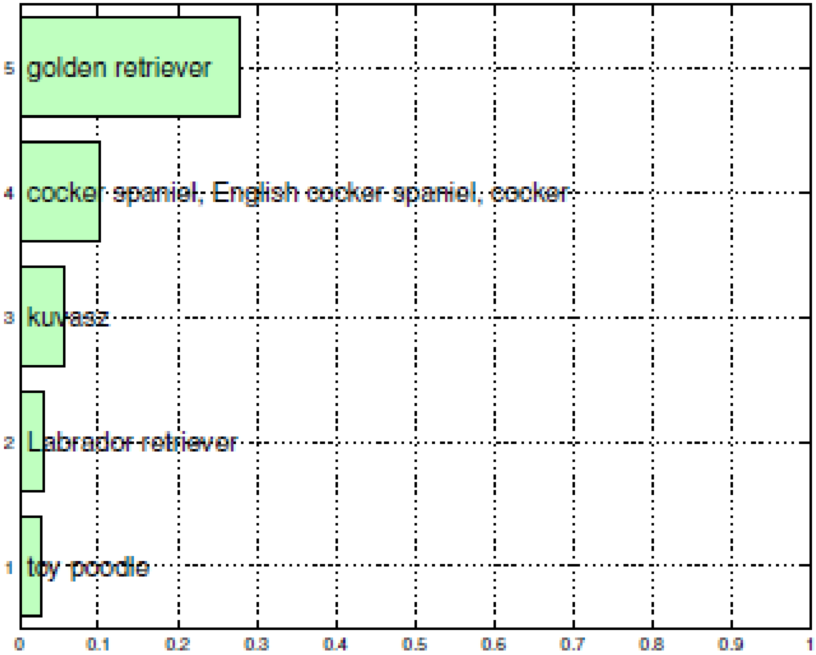


Preliminary experiments 3: Similarity search

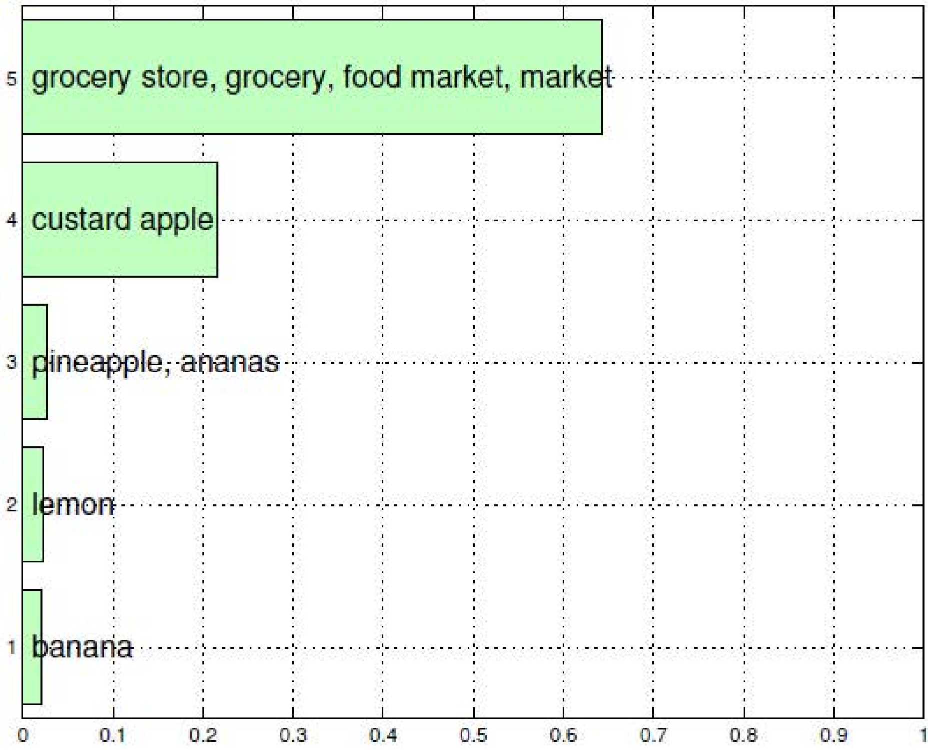
Caffe NN results



Multiple object classes



Multiple object classes



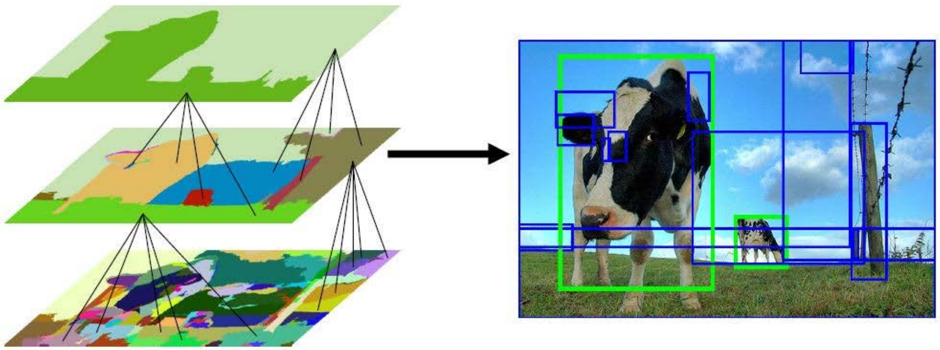
Object detection: Deep Nets and Sliding Windows

- An image of a scene contains multiple objects
- Exhaustive sliding window detector is prohibitively slow

=> Category independent region proposals:

  – Objectness [Alexe-TPAMI-2012]
  – Selective search [Uijlings-IJCV-2013]

More recent approches, see next lecture



  – Edgeboxes [Zitnick-ECCV-2014]

Novel tricks

- Network initialization
  - Mishkin, Matas. *All you need is a good init*. ICLR 2016
  - Weights initialization: zero mean, unit variance, orthogonality

- Batch normalization
  - Iosse, Szegedy. *Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift.* NIPS 2015
  - Zero mean and unit variance weights are “supported” during training to avoid vanishing gradient

⇒ Small sensitivity to learning rate setting (can be higher, faster training – 10 times fewer epochs needed)

⇒ Regularizer (dropout can be excluded/smaller) (better optimum found)

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1 \ldots m}\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m} \sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m} \sum_{i=1}^{m} (x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \qquad \text{// normalize}$$

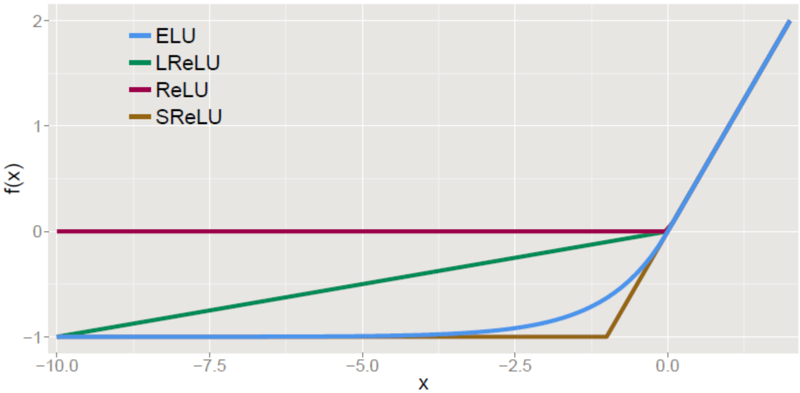
$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Algorithm 1: Batch Normalizing Transform, applied to activation x over a mini-batch.

Novel tricks II.

- Exponential Linear Units (ELU) [Clevert et al., ICLR 2016]

$$f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha\,(\exp(x) - 1) & \text{if } x \le 0 \end{cases}$$



  – Self normalizing properties, batch normalization unnecessary
  – Faster training reported

- ADAM optimizer [Kingma and Ba, ICLR 2015]
  = (ADAptive moments)
  – Often improves over SGD (with momentum),
  – Low sensitivity on learning rate setting

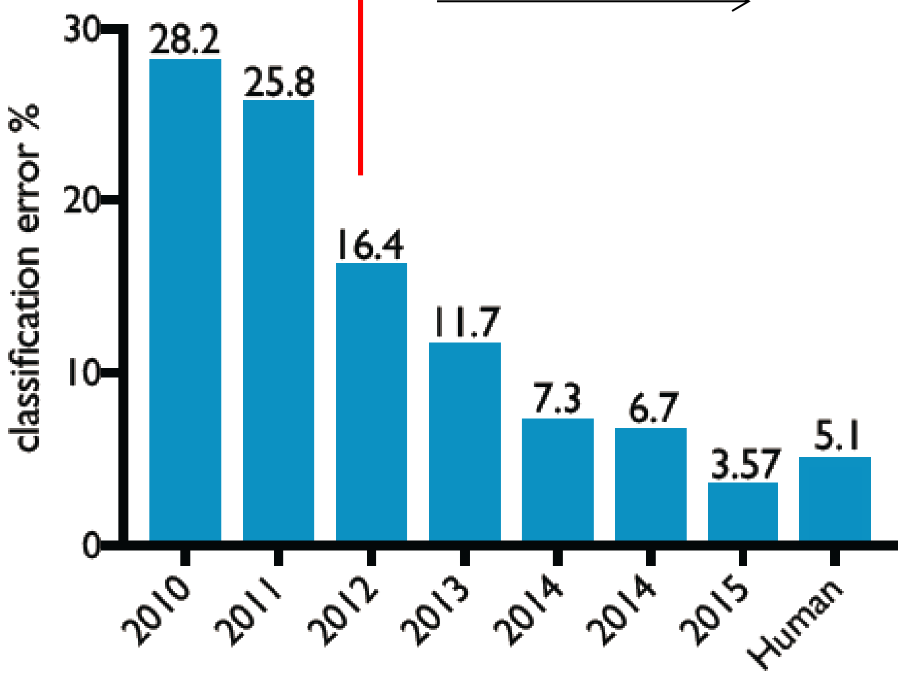
Novel architectures

- ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

IMAGENET

HoG + DPM

CNN

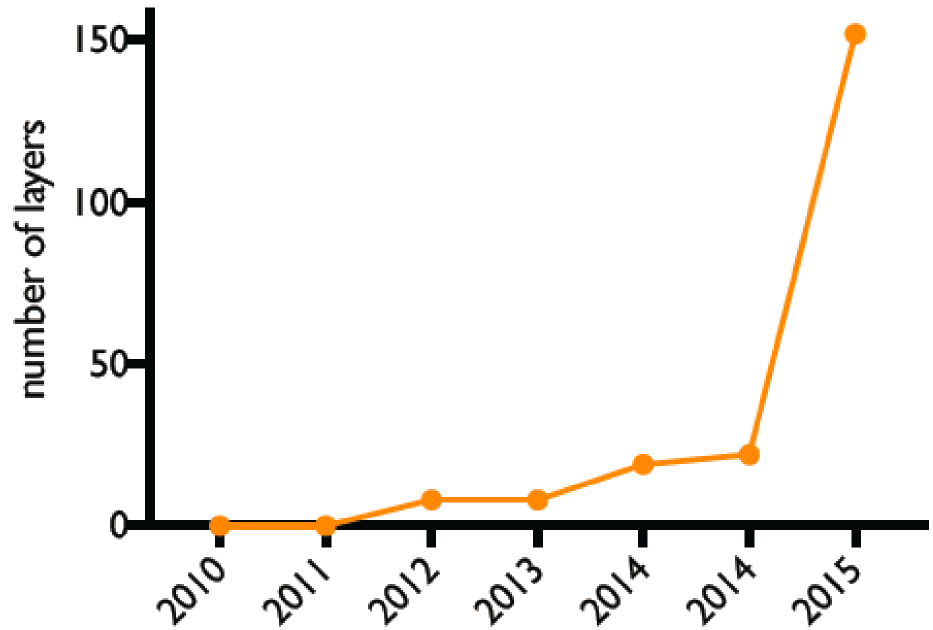


AlexNet

VGG Net

GoogLeNet

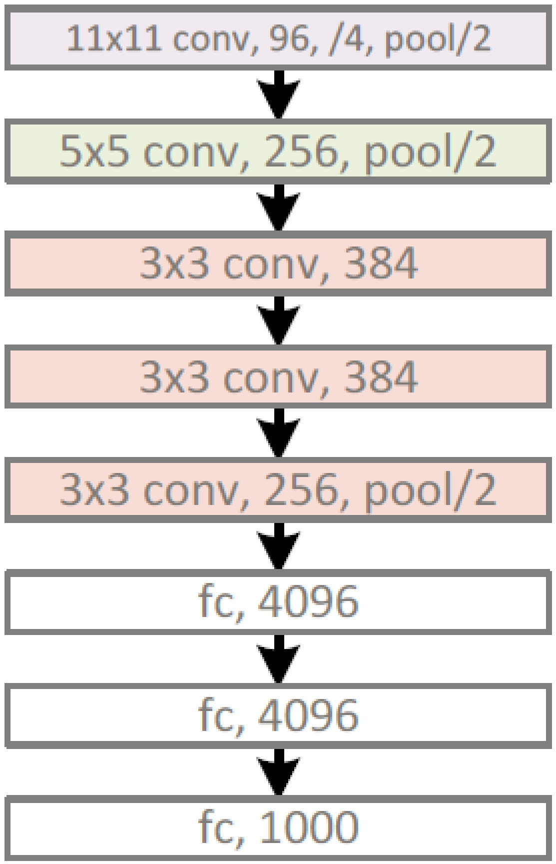
ResNet

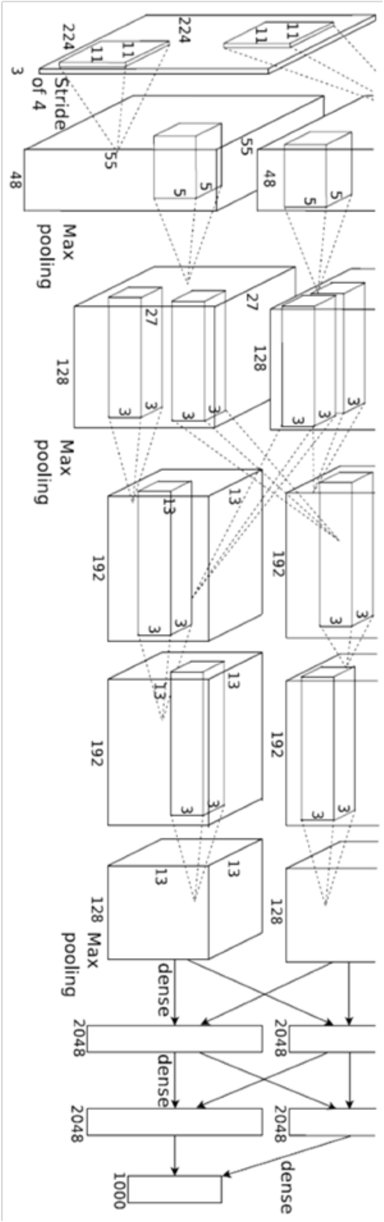


=> “Go deeper”

CNN architectures

- AlexNet
  - [Krishevsky et al., NIPS 2012]



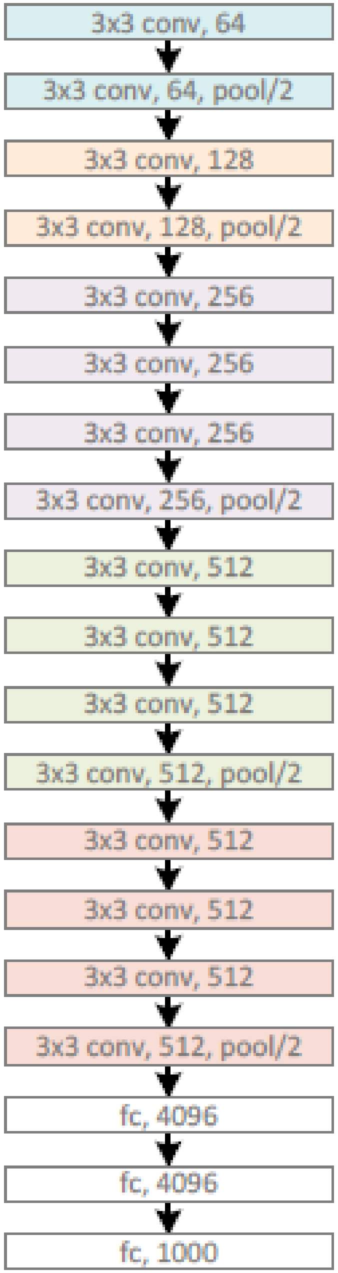


CNN architectures

- VGG Net: VGG-16, VGG-19
  - [Simonyan and Zisserman, ICLR 2015]
  - Deeper than AlexNet
  - Smaller filters (3x3 convolutions), more layers

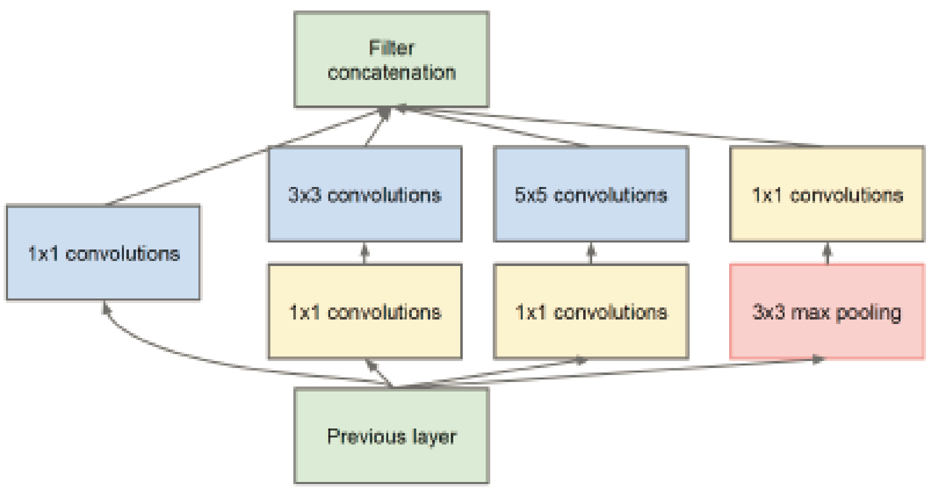
    => Same effective receptive field,

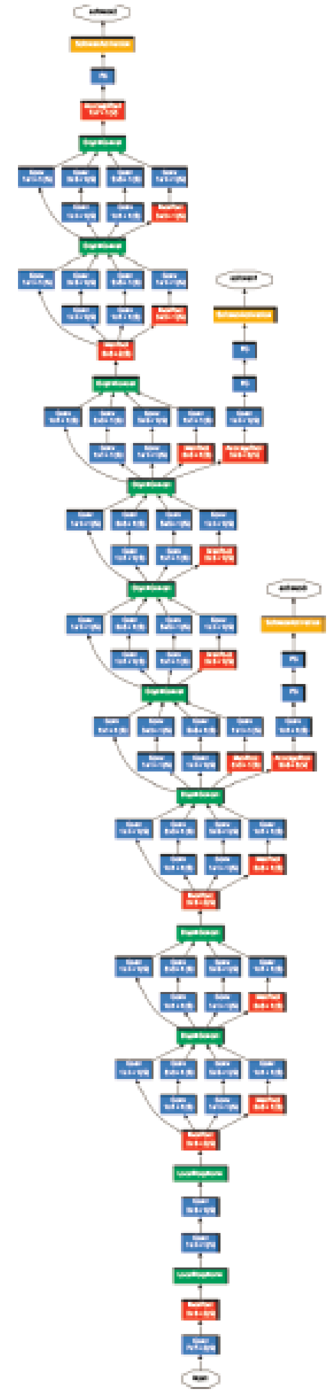
    but more “non-linearity



CNN architectures

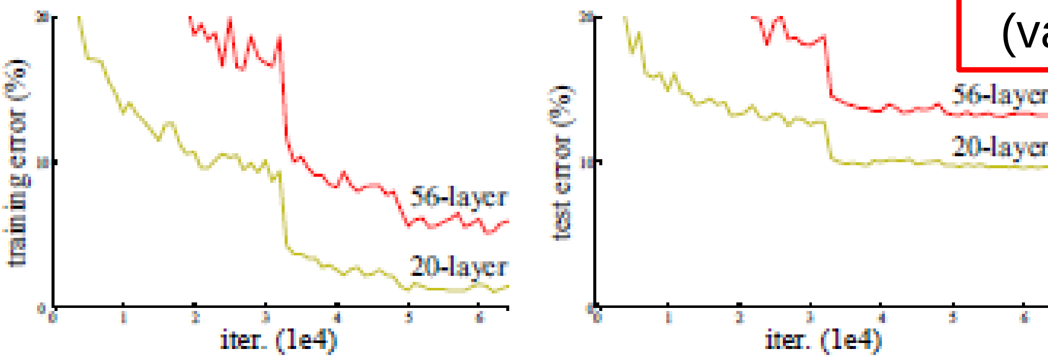
- GoogLeNet
  - [Szegedy et al., CVPR 2015]
  - 22 layers, No Fully-Connected layers
  - Accurate, much less parameters
  - “Inception” module (Net in net)





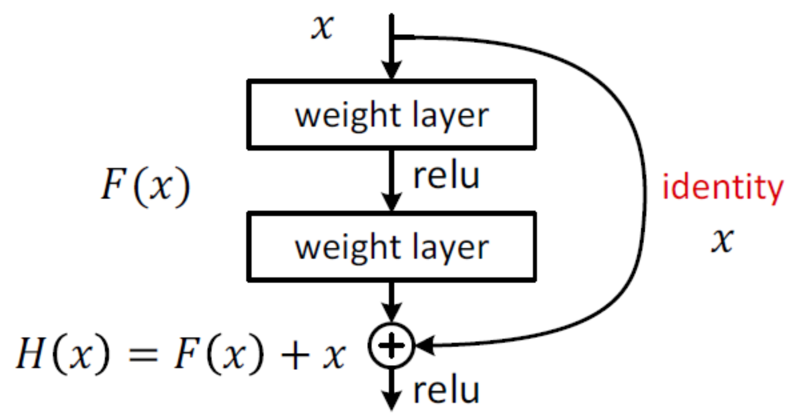
CNN architectures

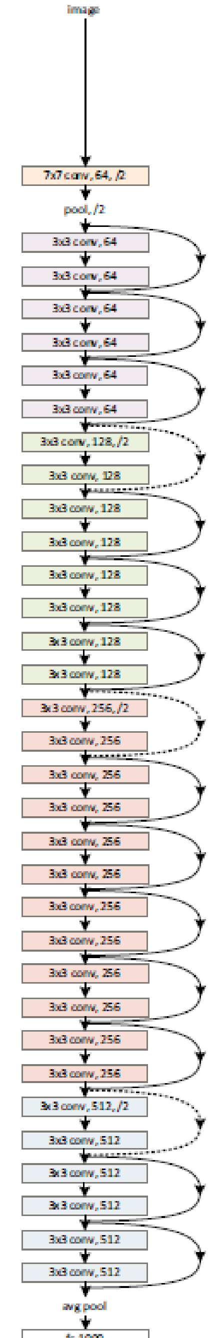
- ResNet
  - [He et al., CVPR 2016]



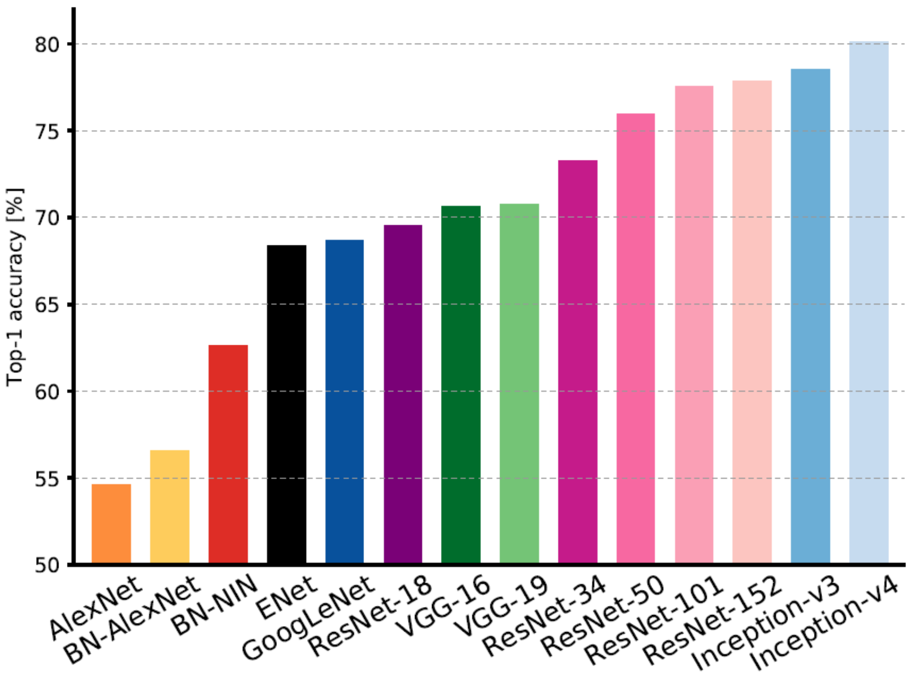
=> Plain deeper models are not better (vanishing gradient)

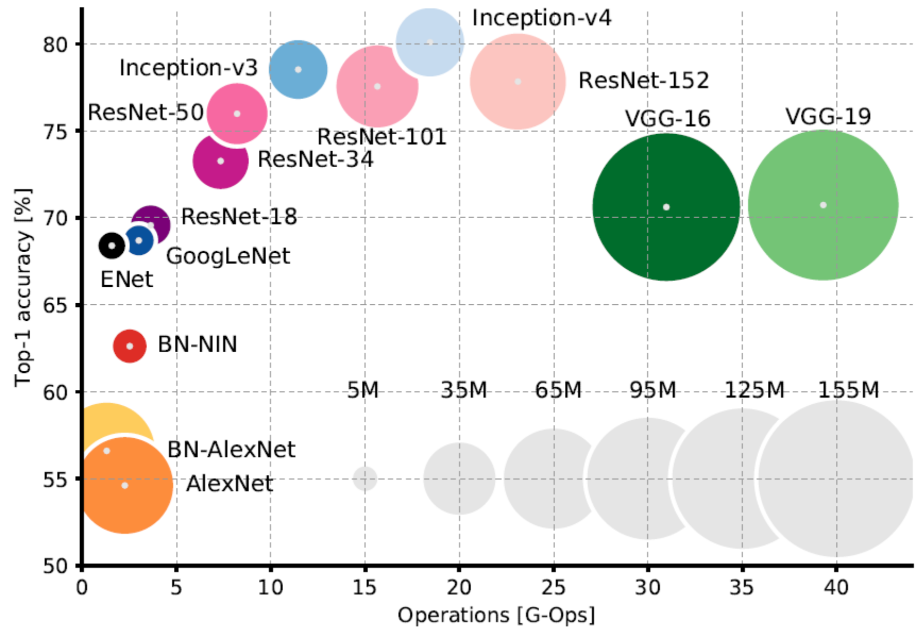
  - Residual modules, 152 layers





CNN models (comparison)





- [Canziani et al., An Analysis of Deep Neural Network Models for Practical Applications, 2017. arXiv:1605.07678v4]

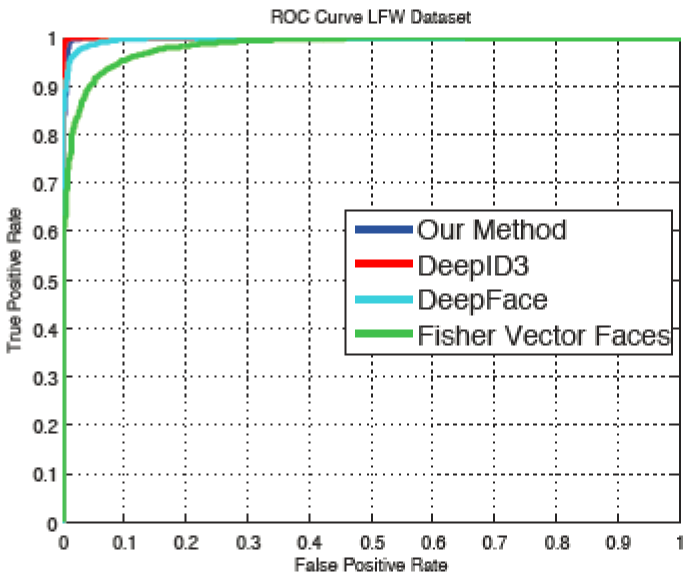
Face interpretation tasks

- Face recognition, face verification
  - Architecture similar to AlexNet - very deep CNN (softmax at the last layer)

  [Taigman-ECVV-2014] DeepFace: Closing the Gap to Human-Level Performance in Face Verification (authors from Facebook)

  [Parkhi-BMVC-2015] Deep Face recognition (authors from Oxford Uni)

  - 2.6M images of 2.6k celebrities, trained net available

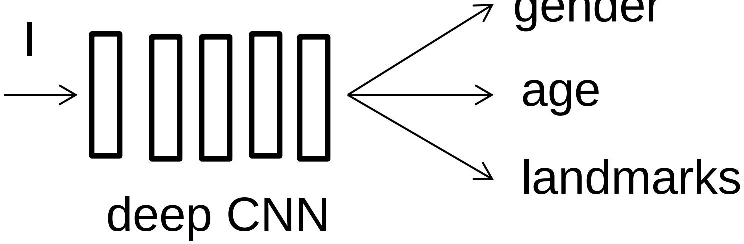


No.	Method	# Training Images	# Networks	Accuracy
1	Fisher Vector Faces	-	-	93.10
2	DeepFace (Facebook)	4 M	3	97.35
3	DeepFace Fusion (Facebook)	500 M	5	98.37
4	DeepID-2,3	Full	200	99.47
5	FaceNet (Google)	200 M	1	98.87
6	FaceNet+ Alignment (Google)	200 M	1	99.63
7	(VGG Face)	2.6 M	1	98.78

- Face represented by penultimate layer response, similarity search, large scale indexing

Face interpretation tasks

- Facial landmarks, Age / Gender estimation
  - Multitask network
    - Shared representation
    - Combination of both classification and regression problems



Age estimation – How good the network is?

- Our survey

  ~20 human subjects , ~100 images of 2 datasets

MORPH dataset

True: 22, MAE: 18.8

True: 36, MAE: 17.8

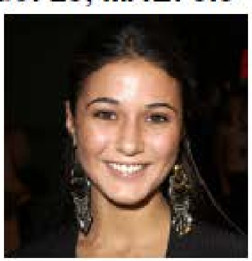
True: 33, MAE: 16.3

True: 22, MAE: 16.1

True: 25, MAE: 16.0

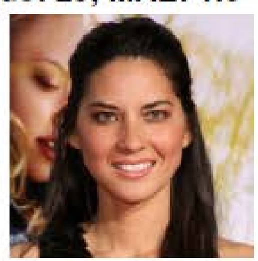
IMDB dataset

True: 25, MAE: 0.5



True: 66, MAE: 1.0

True: 29, MAE: 1.0

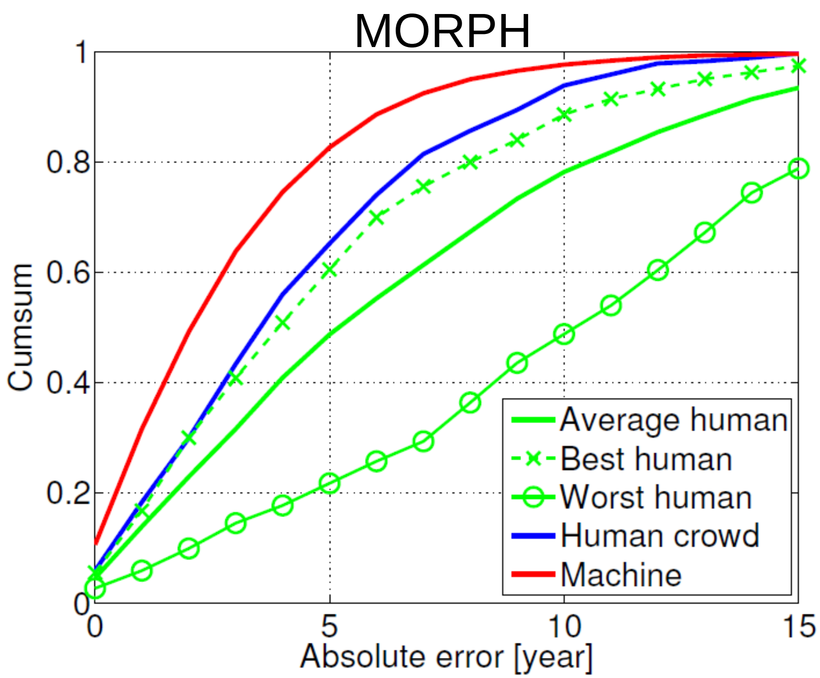


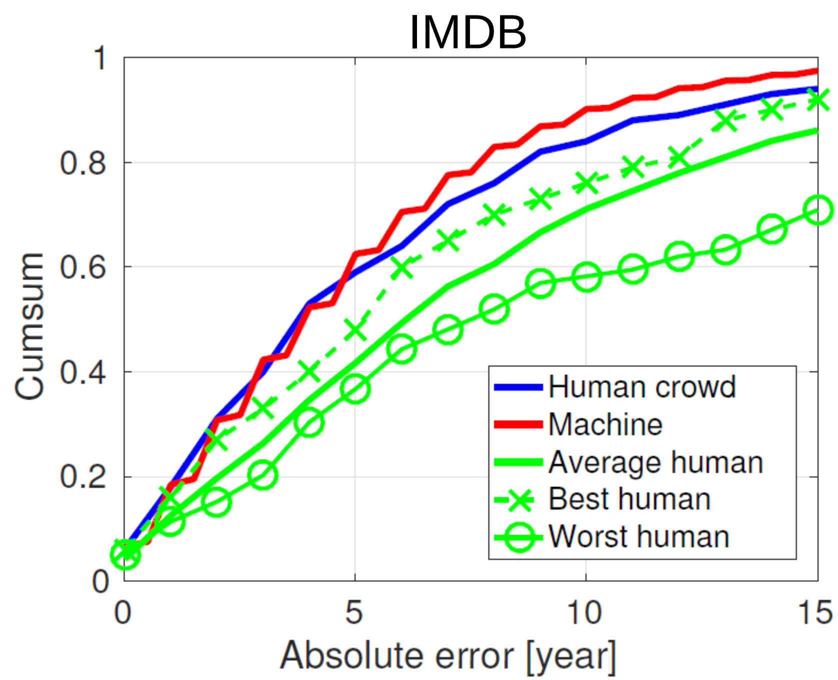
True: 19, MAE: 1.0

True: 43, MAE: 1.0

Age estimation – How good the network is?

- Better than average human…





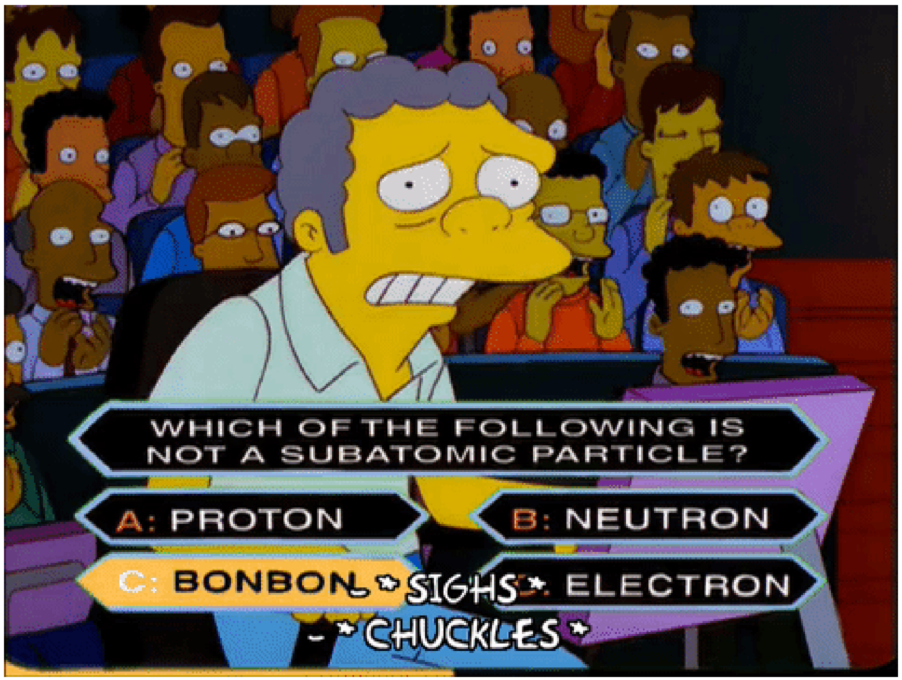
	MAE	CS5	MaxAE
Average human :	6.8	48.6	24.1
Human crowd :	4.7	65.1	19.0
Machine :	3.2	82.6	26.0

	MAE	CS5	MaxAE
Average human :	8.2	41.7	31.5
Human crowd :	5.7	59.0	21.0
Machine :	5.1	62.5	42.7

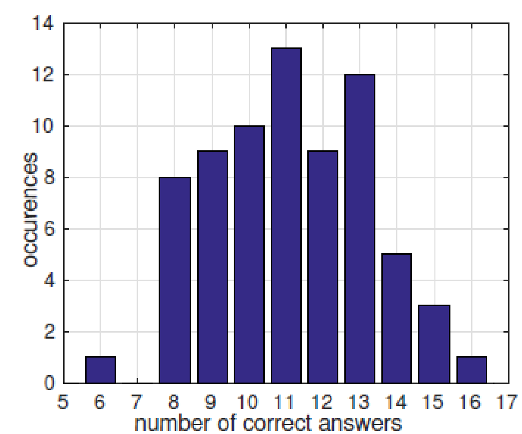
- [Franc-Cech-BwildW-2017]
- Network runs real-time on CPU

Predicting Decision Uncertainty from Faces

- [Jahoda, Vobecky, Cech, Matas. *Detecting Decision Ambiguity from Facial Images*. In Face and Gestures, 2018]
- Can we train a classifier to detect uncertainty?



Training set: 1,628 sequences
Test set: 90 sequences

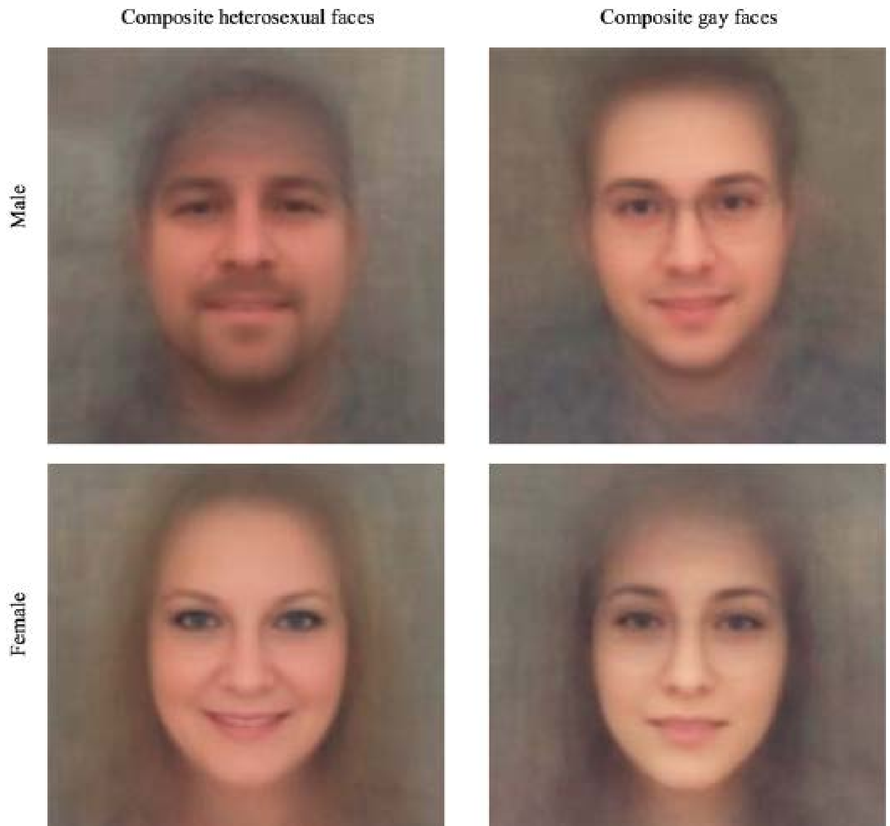


=> YES, we can…

- CNN 25% error rate, while human volunteers 45%

Sexual Orientation from Face Images

- [Wang and Kosinki. *Deep Neural Networks can detect sexual orientation from faces*. Journal of Personality and Social Psychology, 2017]
- Better accuracy than human in (gay vs. heterosexual)
  - 81% accuracy (for men), average human accuracy (61%)
  - 71% accuracy (for women) average human accuracy (54%)
  - Accuracy further improved if 5 images provided (91%, 83%)



General recipe to use deep neural networks

- Recipe to use deep neural network to “solve any problem” (G. Hinton 2013)
  - Have a deep net
  - If you do not have enough labeled data, pre-train it by unlabeled data; otherwise do not bother with pre-initialization
  - Use rectified linear units instead of standard neurons (sigmoid)
  - Use dropout to regularize it (you can have many more parameters than training data)
  - If there is a spatial structure in your data, use convolutional layers

- Novel:
  - Use Batch Normalization [Ioffe-Szegedy-NIPS-2015]
  - ReLU => ELU
  - Adaptive Optimizers (ADAM)
  - Various architectures (AlexNet, VGG, GoogLeNet, ResNet)

- Experience:
  - Data matters (the more data the better), data augmentation helps

Conclusions

- CNNs efficiently learns the abstract representation (shared among classes)
- Low computational demands for running, Training needs GPU
- Many “deep” toolboxes: Caffe (Berkeley), MatconvNet (Oxford), TensorFlow (Google), Theano (Montreal), Torch, …
- NNs are (again) in the “Golden Age” (or witnessing a bubble), as many practical problems seem solvable in near future
- Explosion of interest of DNN in literature, graduates get incredible offers, start-ups appear all the time

- Do we understand enough what is going on?

http://www.youtube.com/watch?v=LVLoc6FrLi0

Human_Abducted_by_UFO.mp4

Acknowledgement: I borrowed some images from slides of G. Hinton, A. Ng, Y. Le Cun, Fei-Fei Li, K. He.

Further Resources

- Deep Learning Textbook
  - Ian Goodfellow and Yoshua Bengio and Aaron Courville, Deep Learning, MIT Press, 2016
  - Available on-line for free.

- Lectures / video-lectures
  - Stanford University course on Deep Learning (cs231n)
  - MIT lectures on Introduction in Deep Learning (MIT 6.S191)

- Various blogs and on-line journals
  - Andrej Karpathy (blog)
  - Distill (distill.pub)