Deep learning hands-on
Lecture 1 Introduction

Ole Winther

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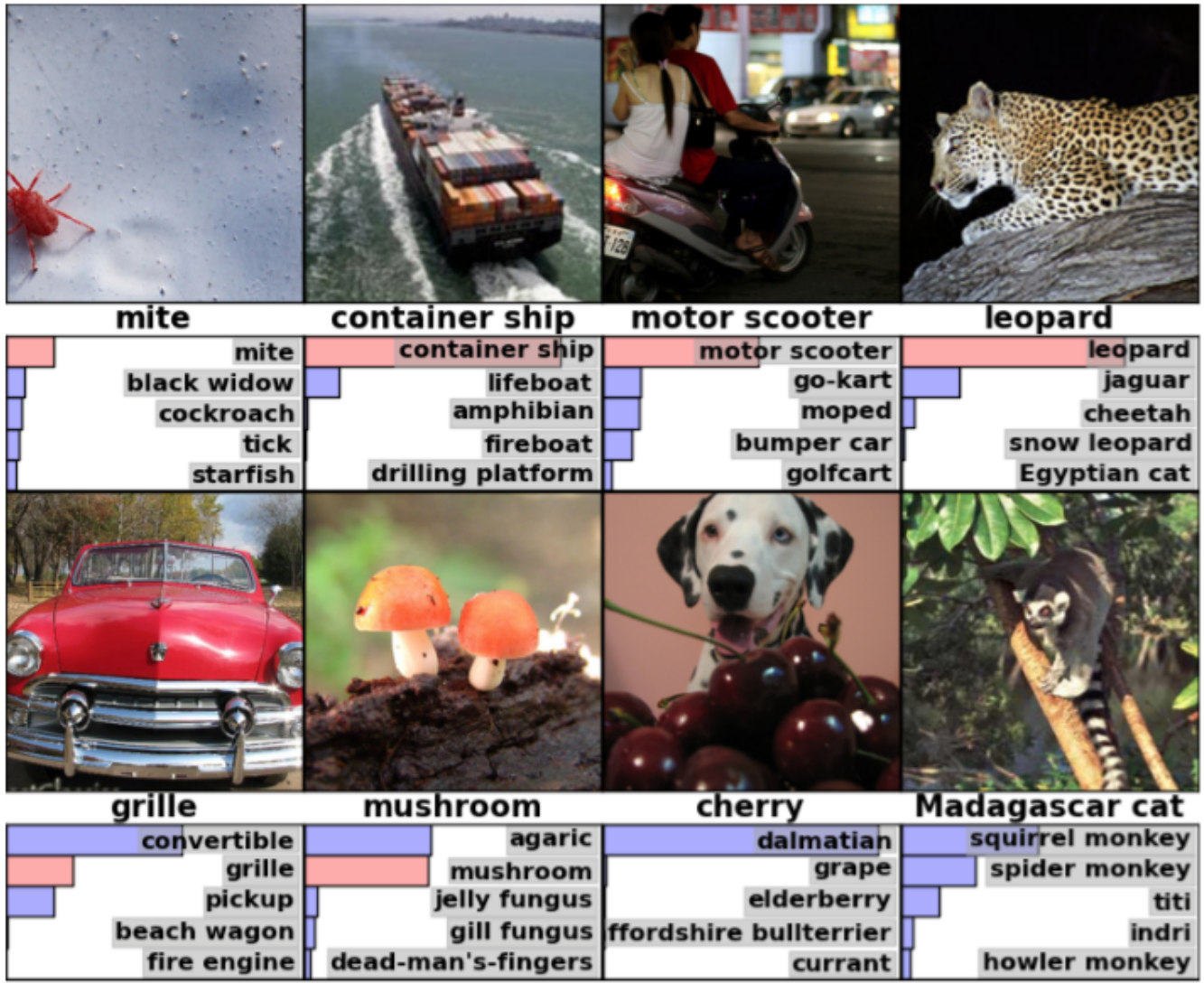
Technical University of Denmark (DTU)

August 17, 2018

ImageNet - image classification



Agenda

- Why the AI and deep learning hype
- Deep learning 101 - feed-forward neural networks
- Convolutional neural networks
- Biological applications of deep learning
- Hands-on labs!

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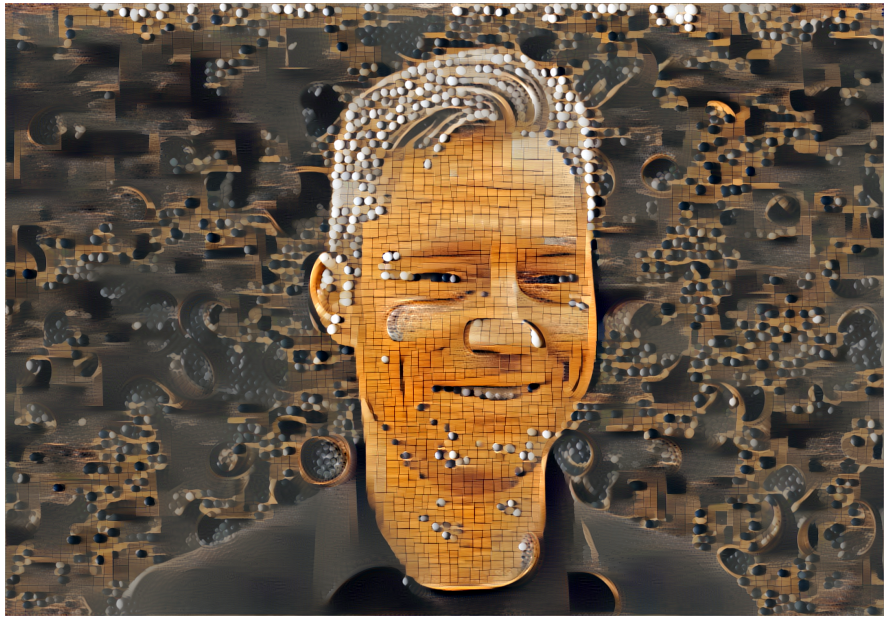
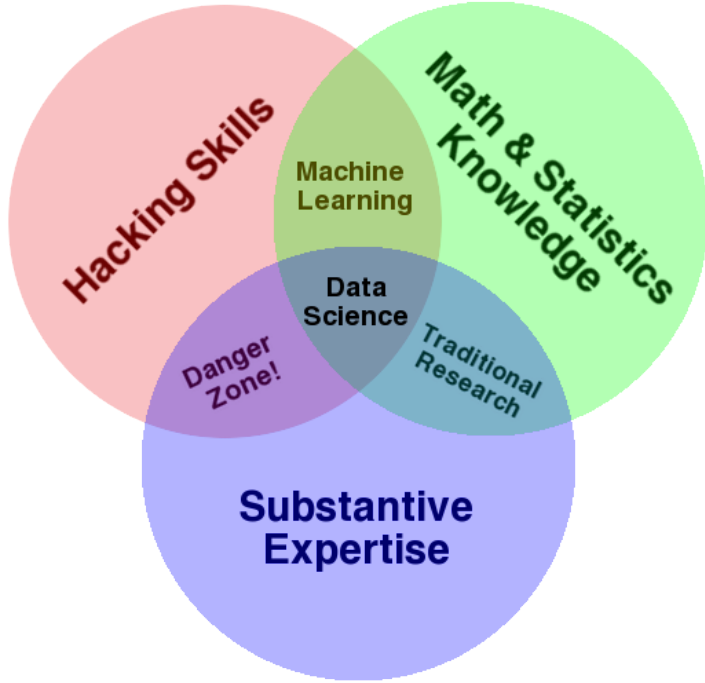
- Deep learning 101 - feed-forward neural networks
- Convolutional neural networks
- Biological applications of deep learning
- Hands-on labs!
- A bit about myself

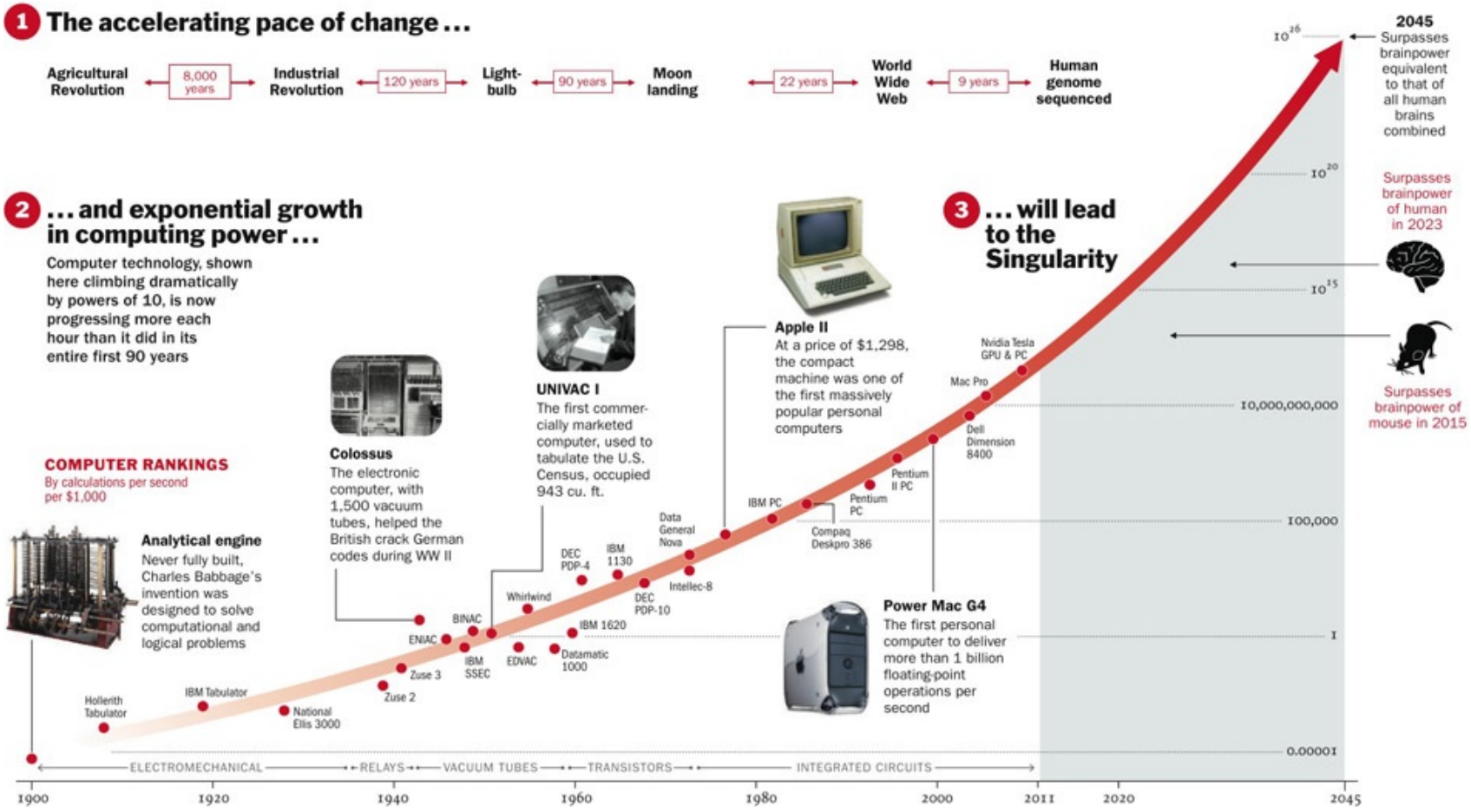




Agenda (approximate timing)

09:15 Deep learning lecture
10:00 Tensorflow playground + break
10:30 Back-propagation lecture
10:45 Hands-on lab 1
12:00 Lunch
13:00 Convolutional neural networks (CNN) lecture
13:30 Hands-on lab 2
15:00 Break
15:15 Deep learning tricks of the trade
15:50 Ole's closing comments and questions
16:00 Hands-on lab 3.

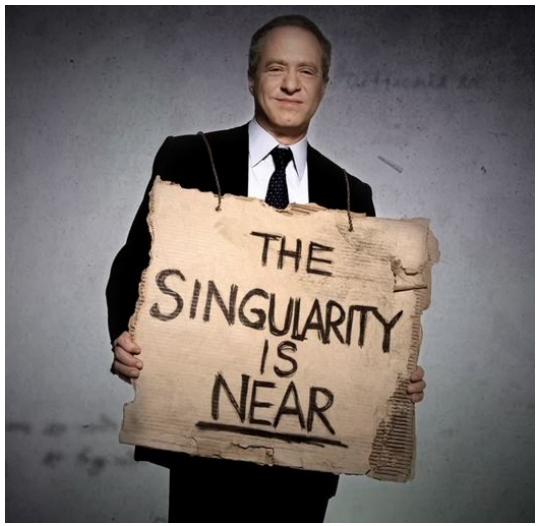
Computing - why we are here!



Data - why we will have self-driving cars

The Cityscapes dataset

Are we heading towards the singularity?



kurzweilai.net

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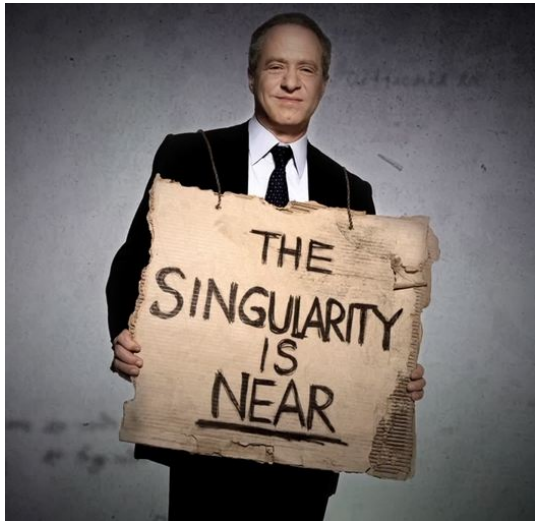

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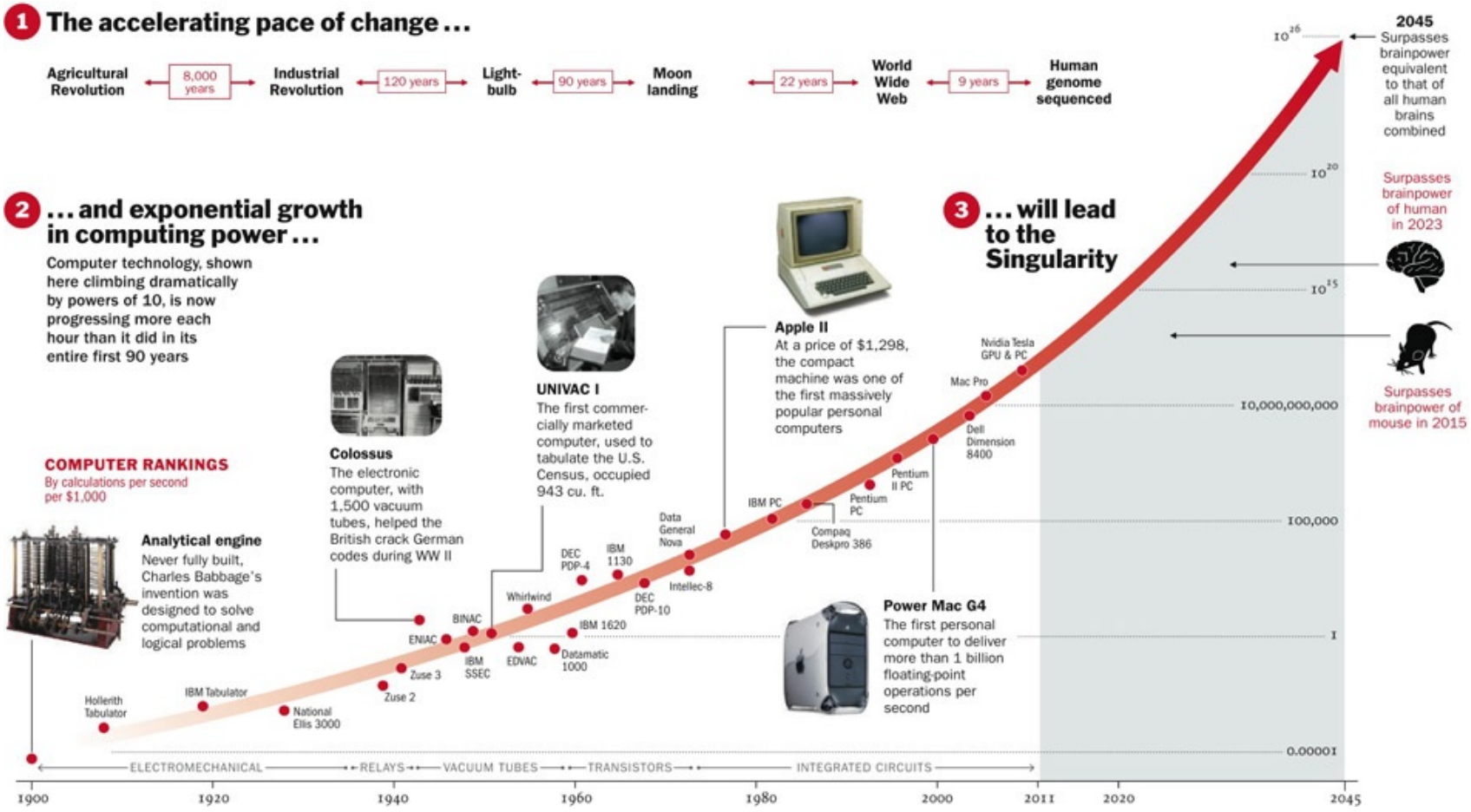
- Elon Musk at MIT AeroAstro Symp:
- If I were to guess at what our biggest existential threat is, it's probably that...
- With artificial intelligence, we are summoning the demon..
- Inofficial quotes (email to friend):
- The risk of something seriously dangerous happening is in the five year timeframe. 10 years at most,
- Unless you have direct exposure to groups like Deepmind, you have no idea how fast — it is growing at a pace close to exponential.

Computing - reaching the singularity



Part 2:

The deep learning revolution

Achilles' heel of traditional AI: Perception in natural environment

xkcd.com/1425

Major areas in Artificial intelligence (AI)

- Speech recognition
- Image classification
- Machine translation
- Question-answering
- Self-driving vehicles
- Dialogue systems
- General unsupervised learning

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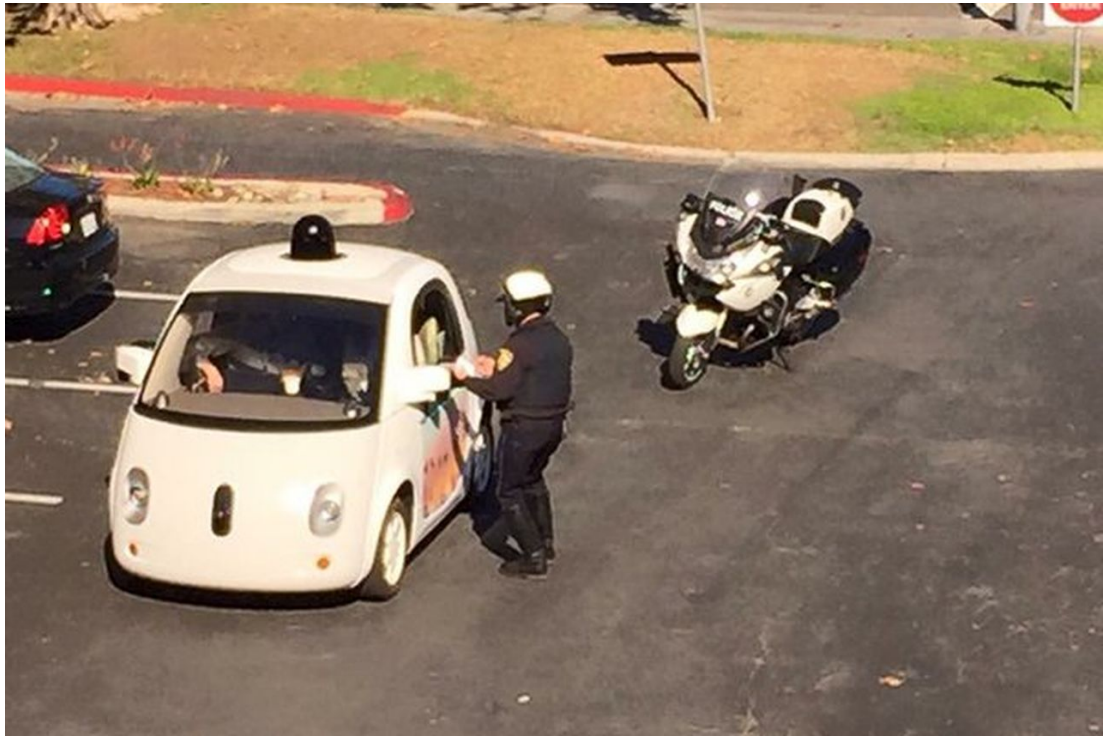
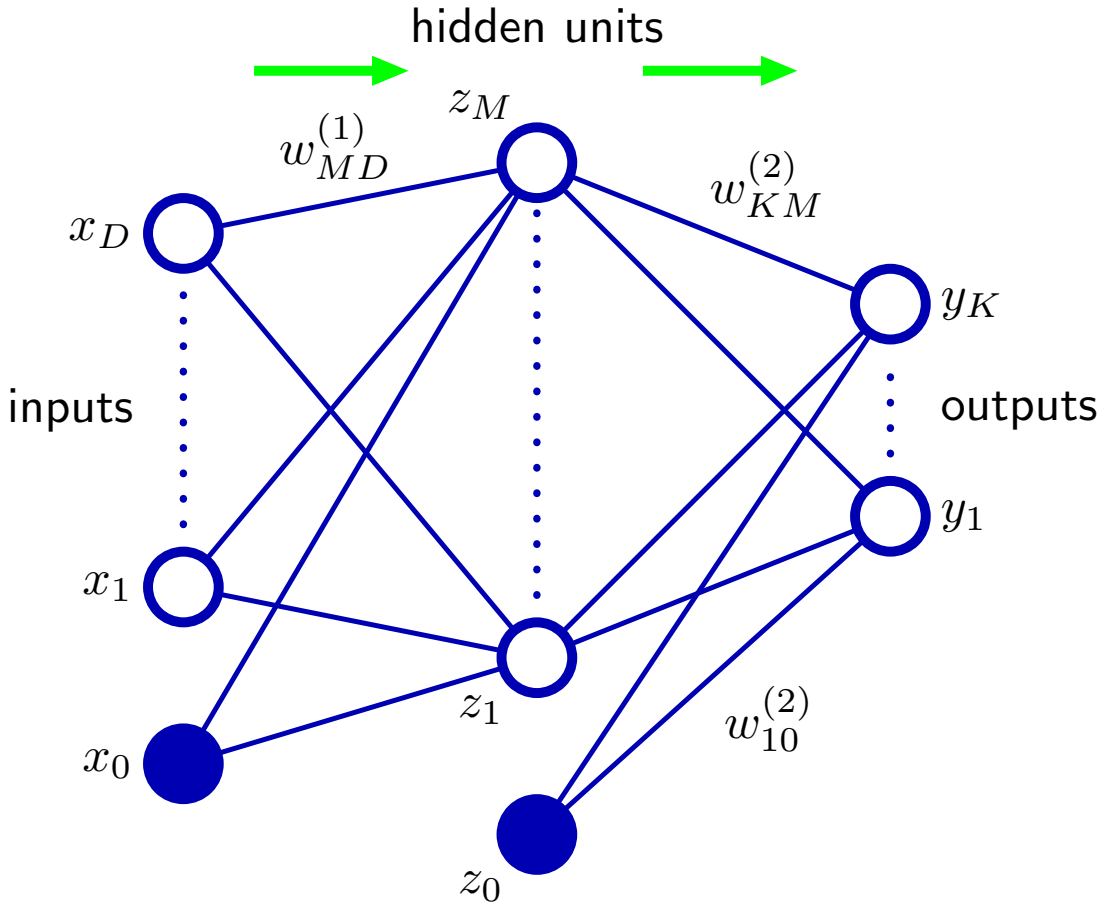
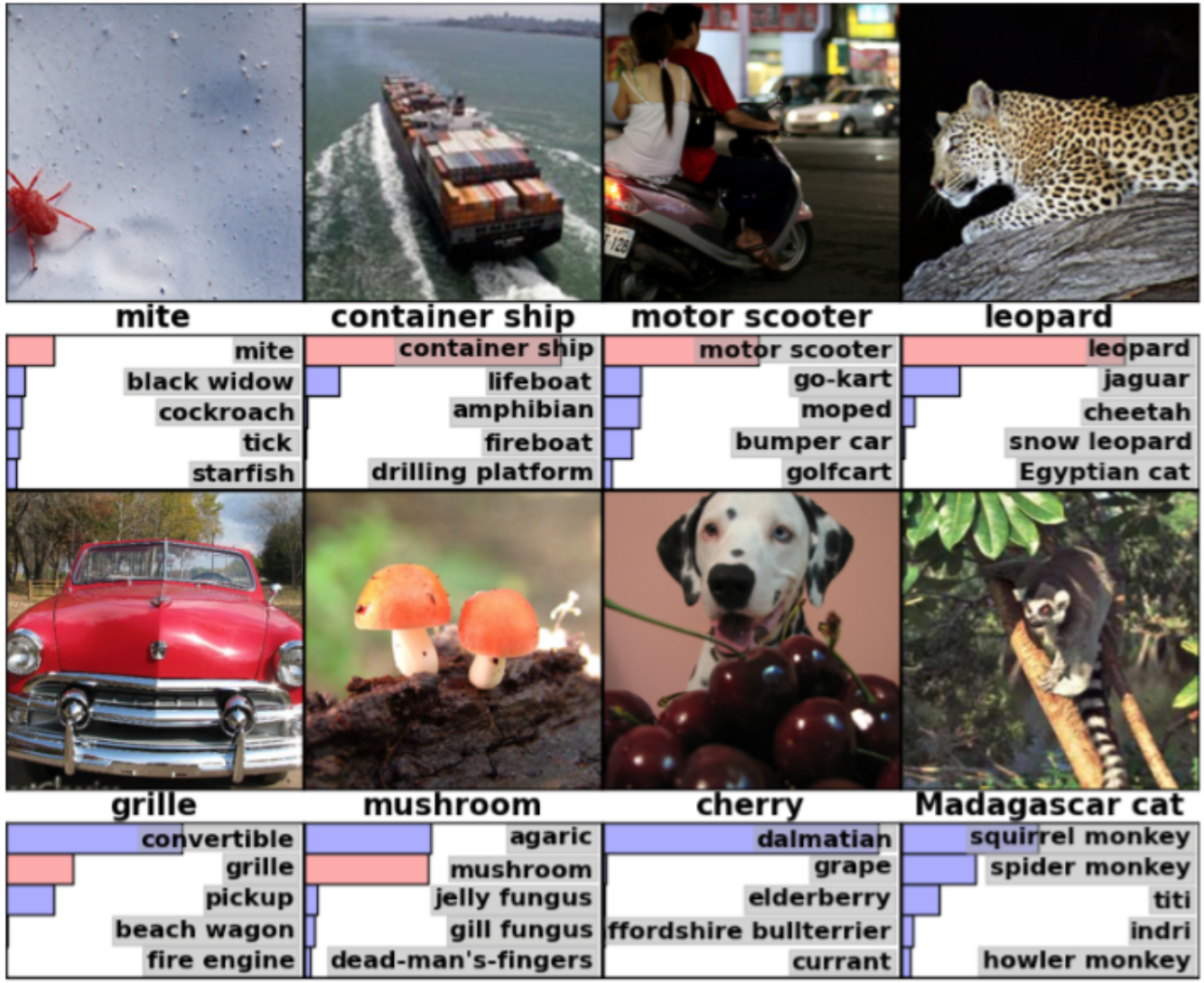


Feed forward neural networks



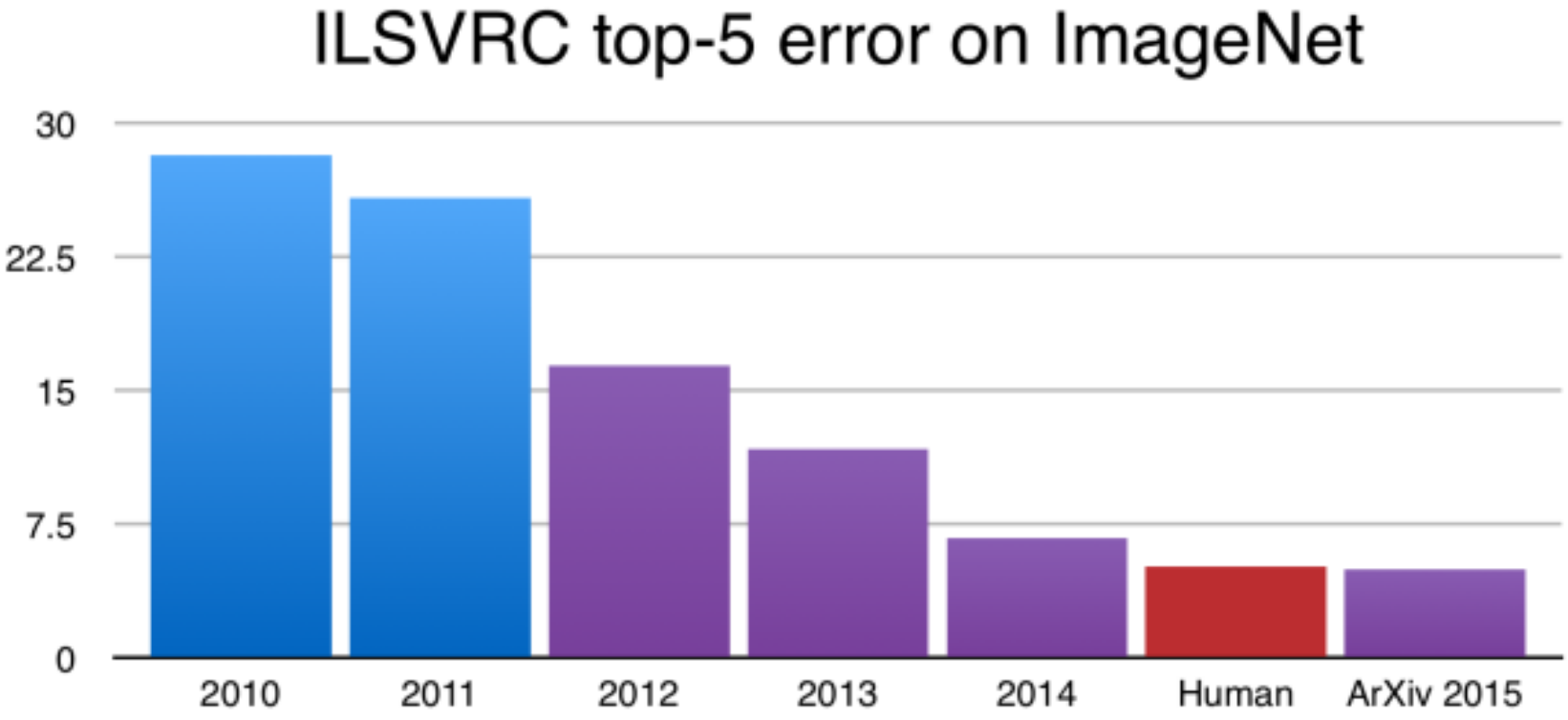
$$y_k(\mathbf{x}, \mathbf{w}) = \sigma\left(\sum_{j=0}^{M} w_{kj}^{(2)} \underbrace{f\left(\sum_{i=0}^{D} w_{ji}^{(1)} x_i\right)}_{z_j}\right)$$

ImageNet - image classification



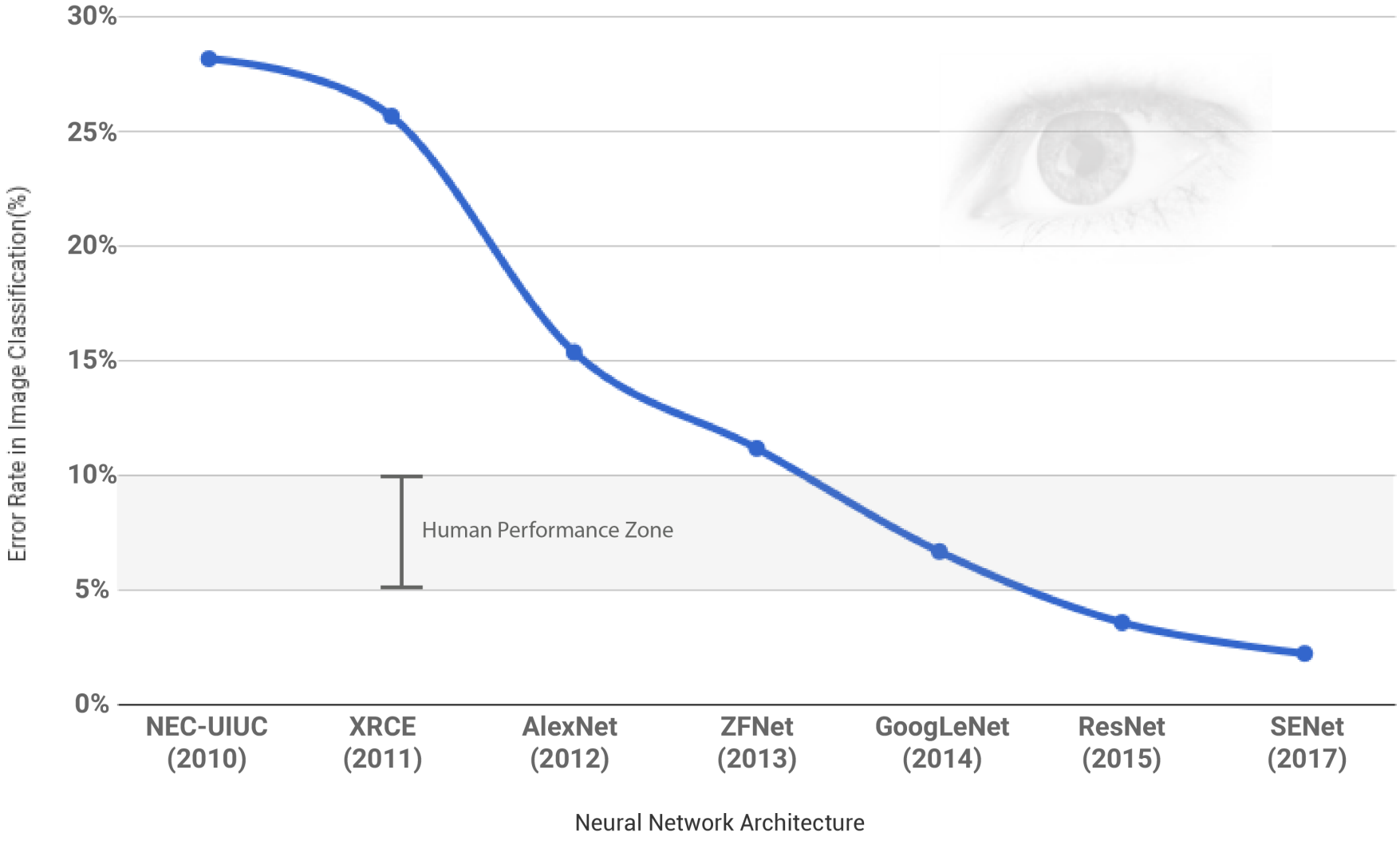
- 1.000 different classes - including many types of dogs!
- 1.000.000 training images

ImageNet classification challenge



- AlexNet - A Krizhevsky et al. (2012) won with huge margin!
- Soon everyone started using deep learning and GPUs.

ImageNet classification challenge 2017 update



Feature engineering vs engineered models

ImageNet Classification with Deep Convolutional Neural Networks

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Geoffrey E. Hinton
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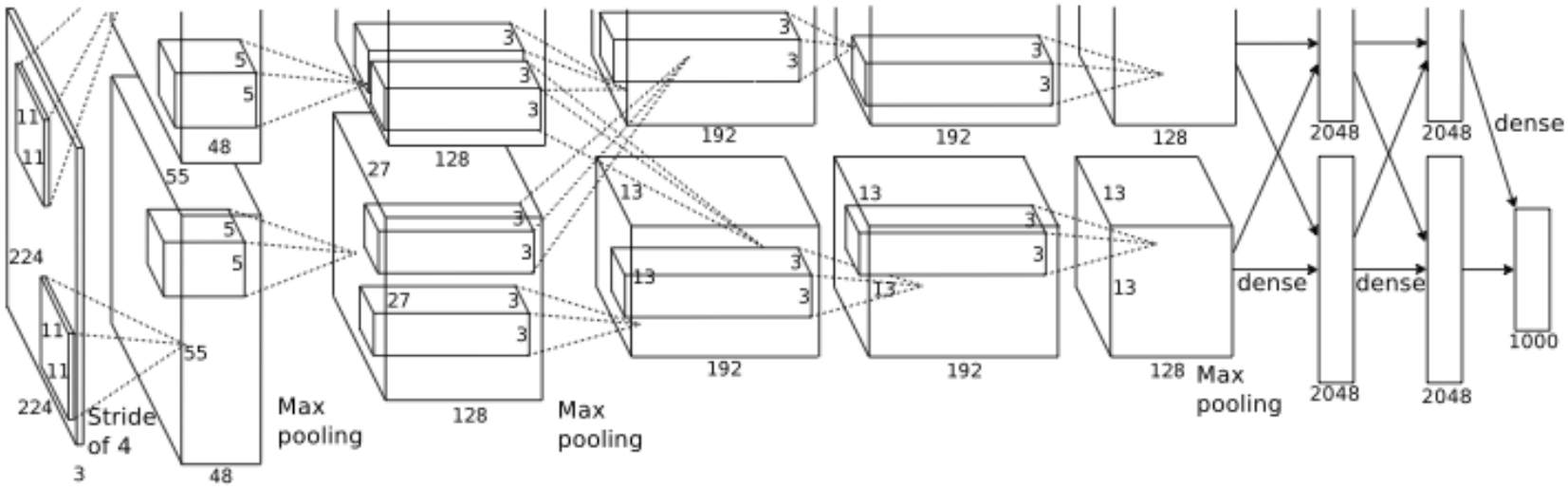
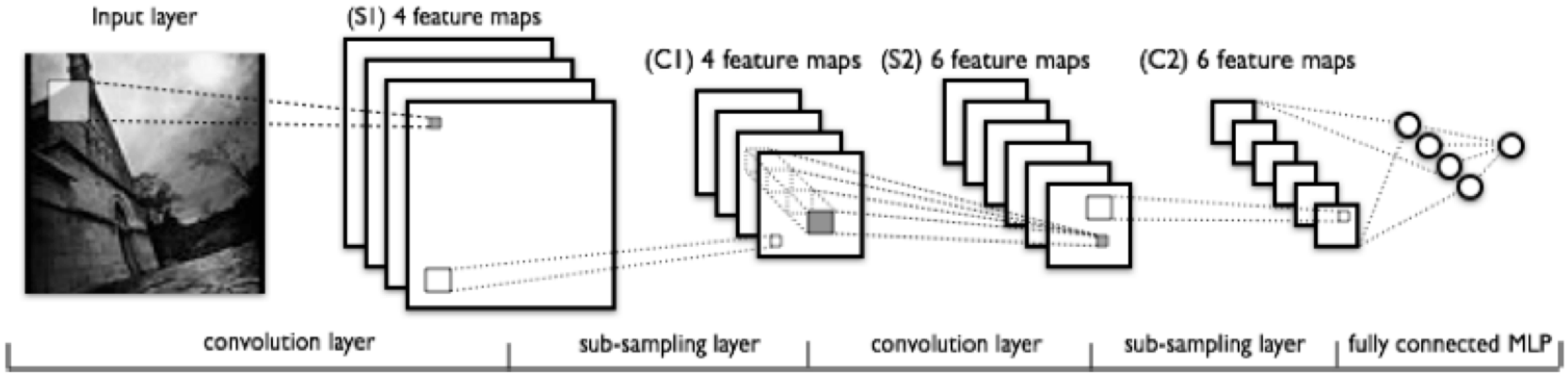
hinton@cs.utoronto.ca



www.cs.toronto.edu/~fritz/absps/imagenet.pdf

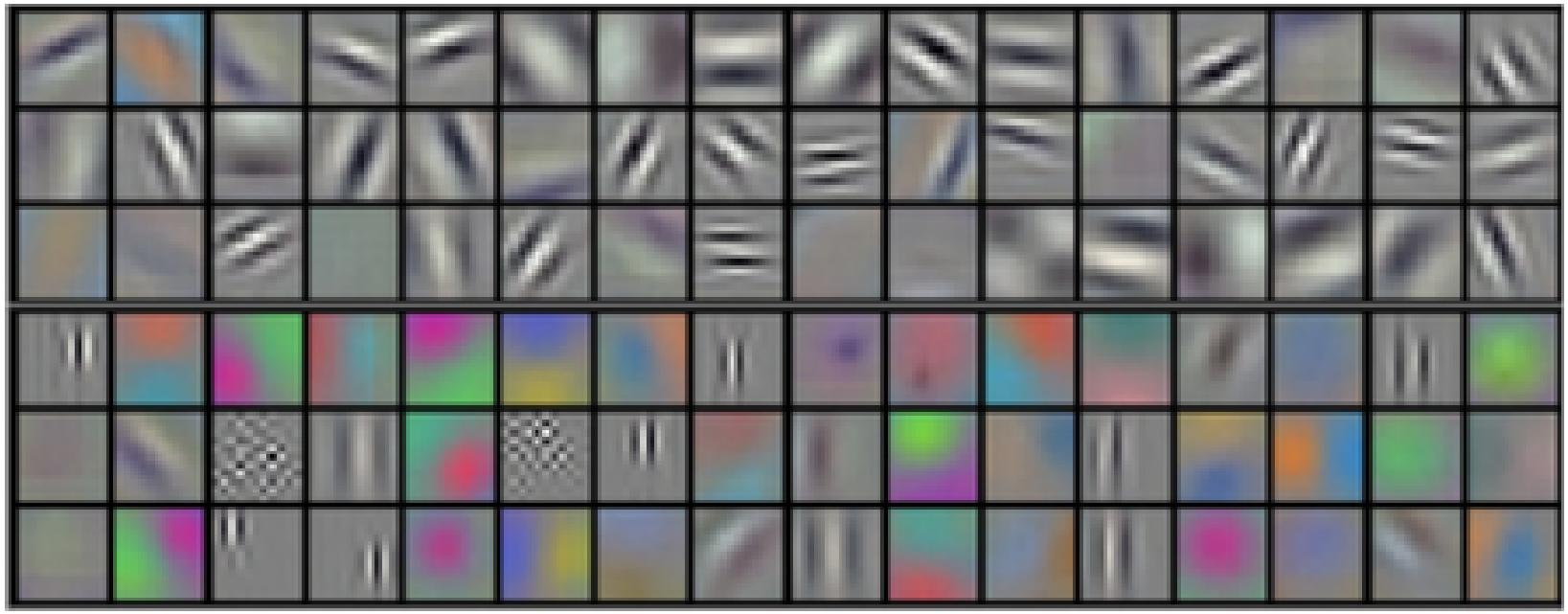
Convolutional neural networks



$$\begin{bmatrix} 10 & 0 & -10 \\ 0 & 0 & 0 \\ -10 & 0 & 10 \end{bmatrix}$$

All filters are learned from training data

- First layer filters



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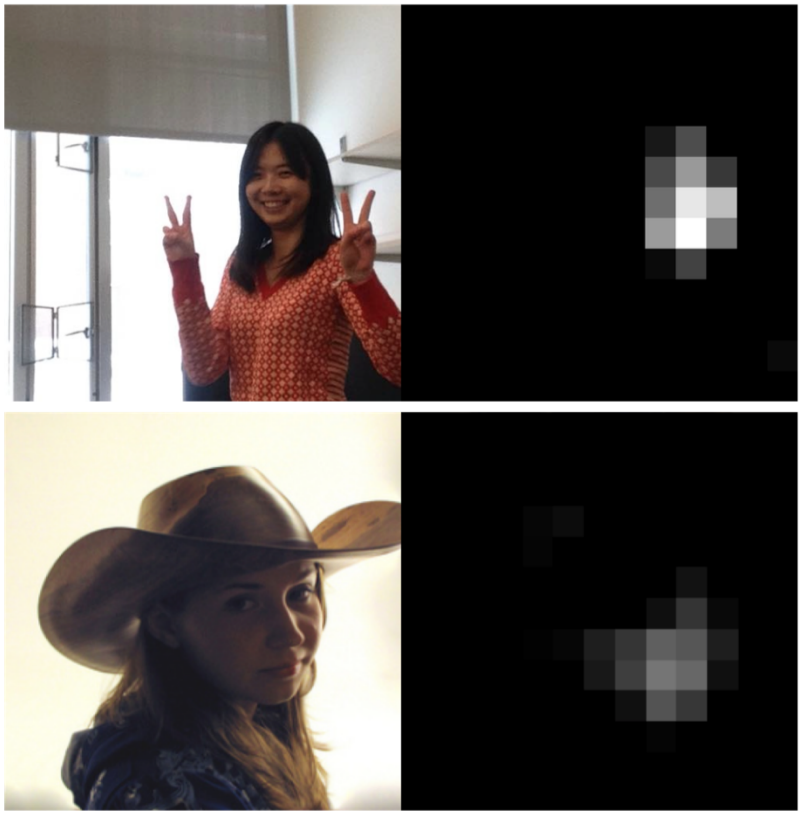
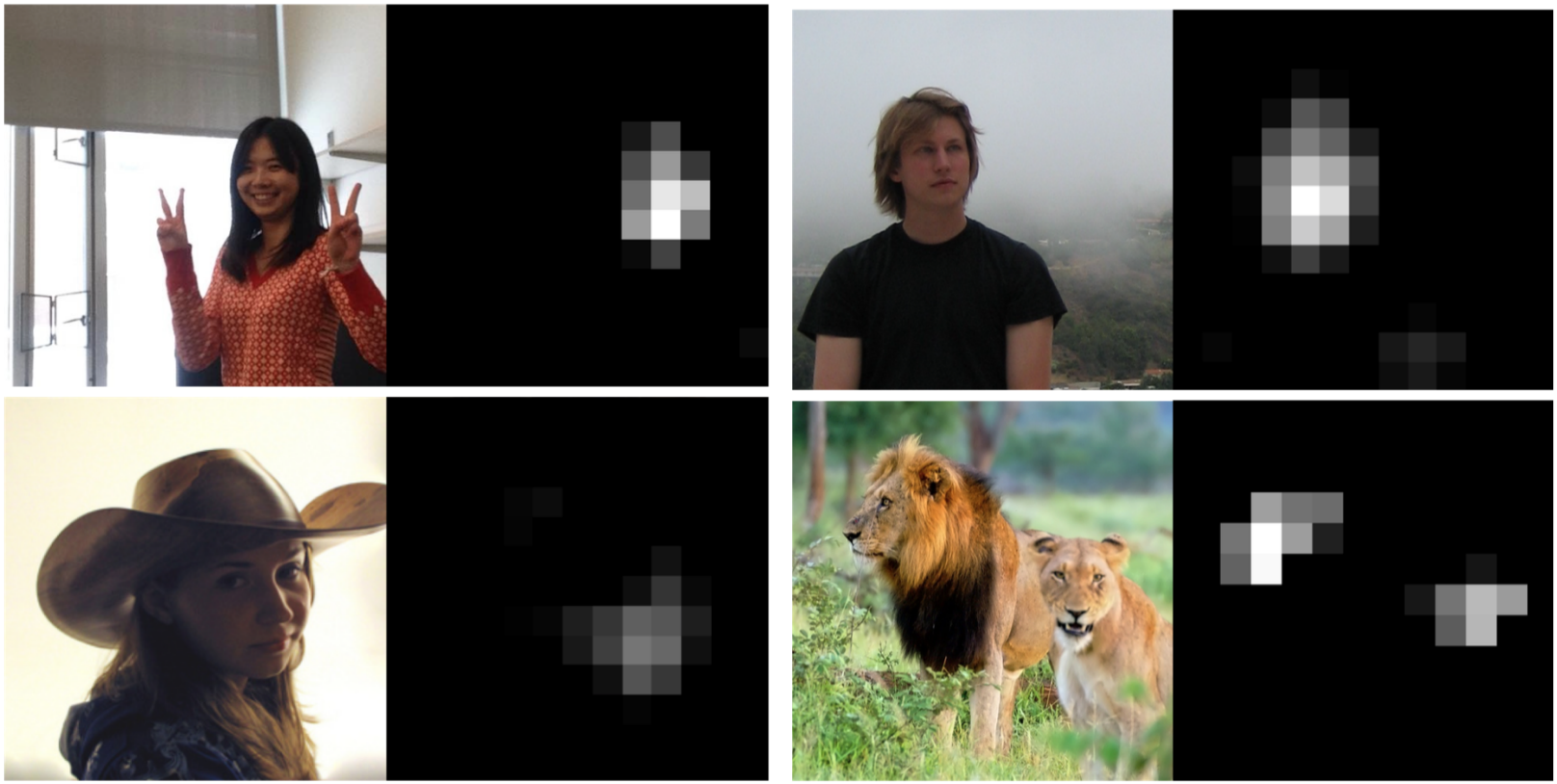
Emergent higher level abstractions

- Look at output of filter in 5th layer!



Emergent higher level abstractions

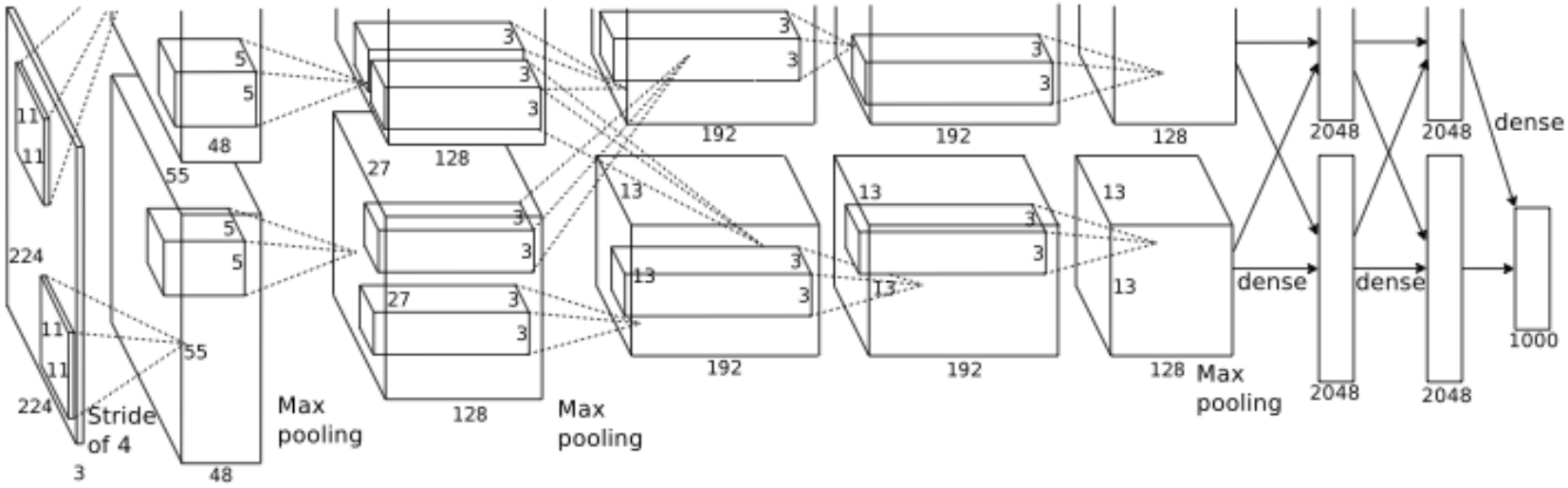
- Look at output of filter in 5th layer!



Yosinski et. al., ICML, google: deepvis

We need bigger brains

- AlexNet (2012): 16.4% error, 8 layers, 1.4 Gflop



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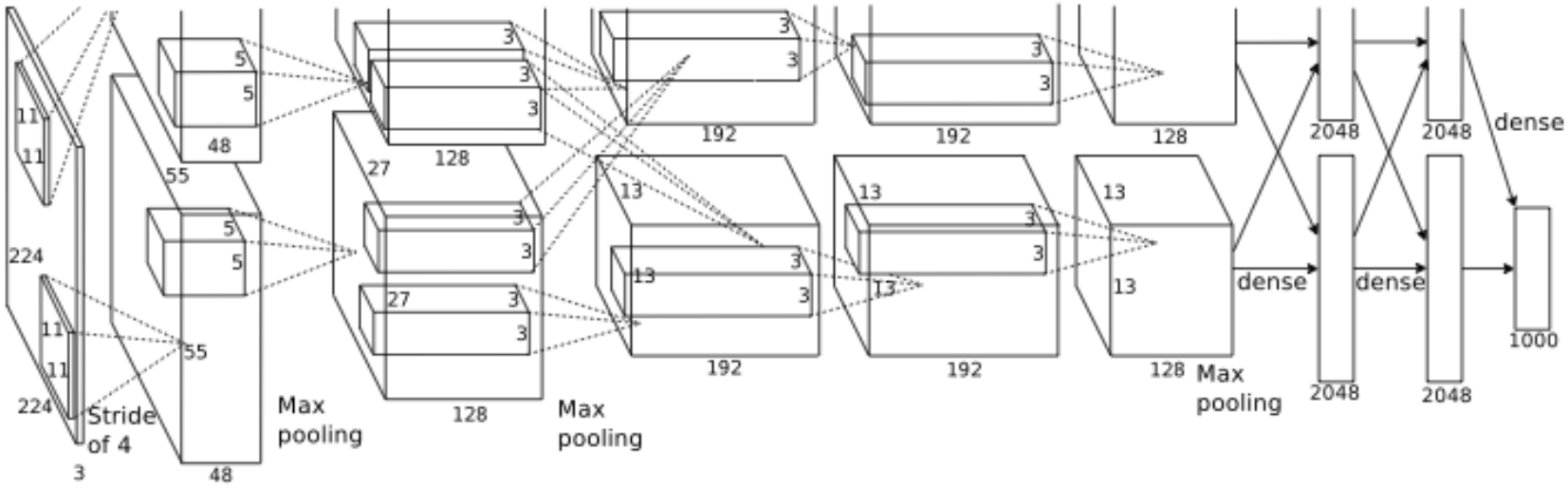
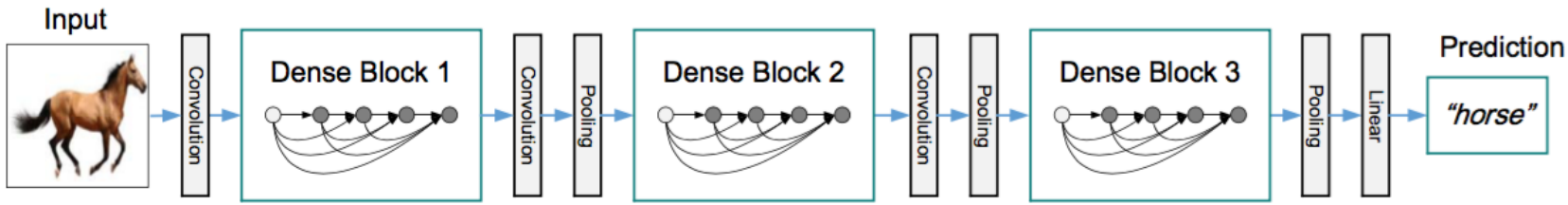
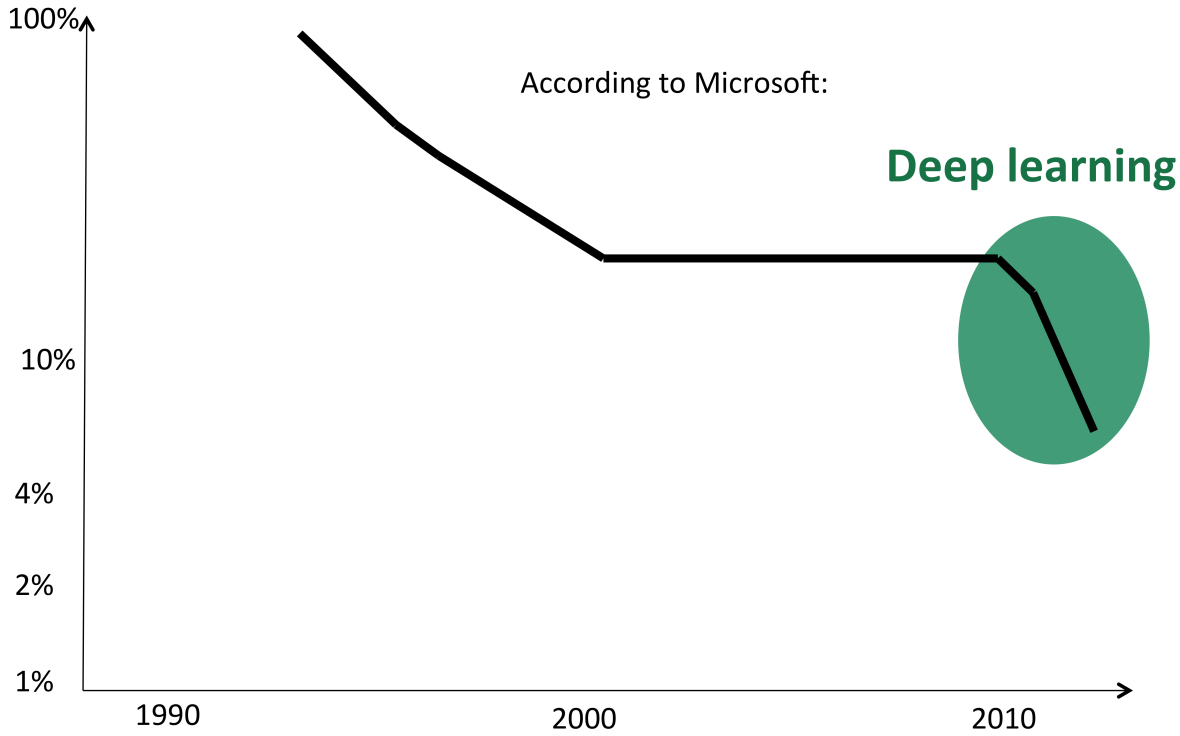


- ResNet (2016): 3.5% error, 152 layers, 22.6 Gflop.



- (This is a so-called DenseNet and not a ResNet.)
- Source: Source Jen-Hsun Huang, CEO NVIDIA, GTC Europe, 2016

Speech recognition breakthrough



Plot from Yoshua Bengio

Encoder-decoder - machine translation

Sequence to Sequence Learning with Neural Networks

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Quoc V. Le
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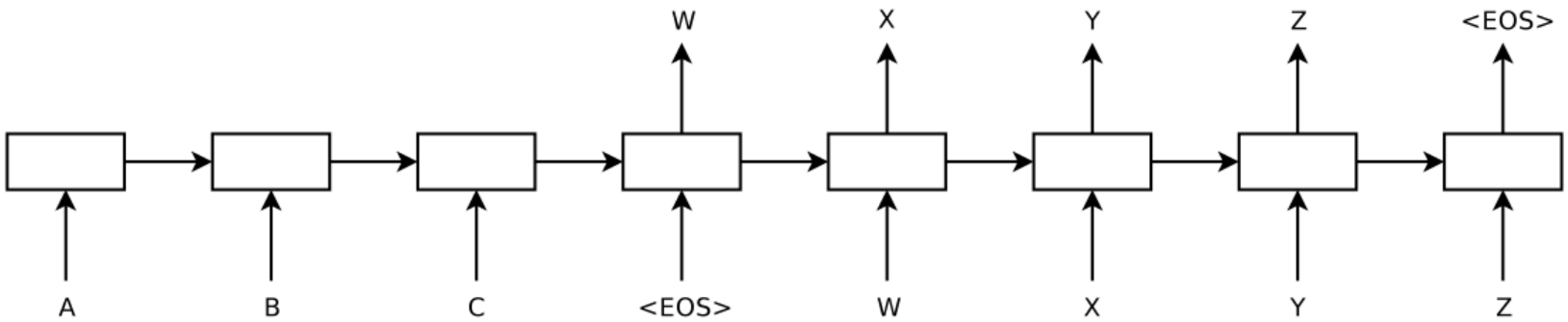
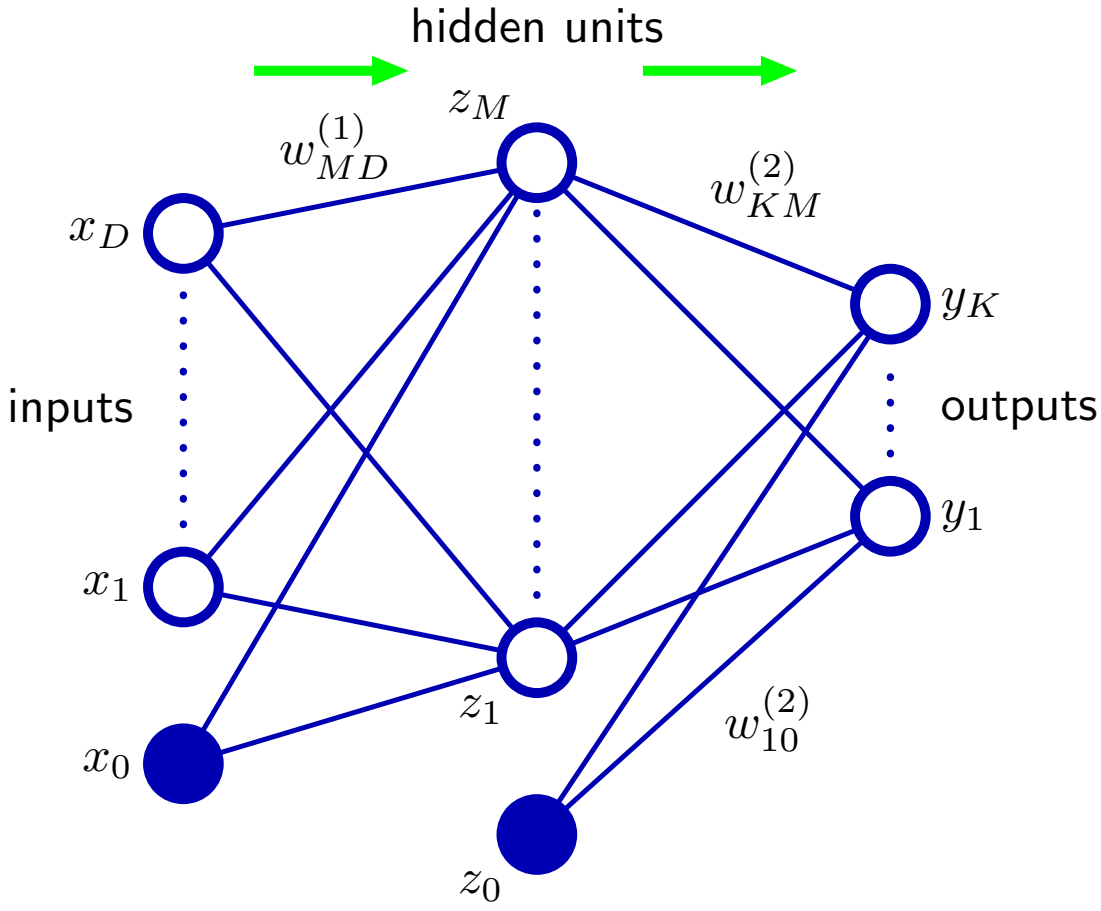


Part 3:

Feed-forward neural networks

Feed forward neural networks



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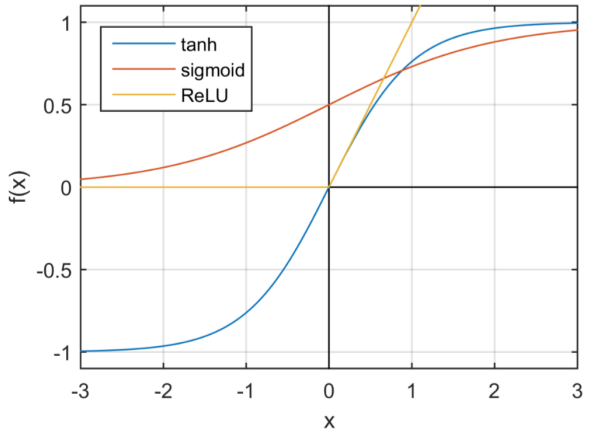
Non-linearity and training

- Linear activation functions will give a linear network.
- Logistic function $\sigma(a) = \frac{1}{1+e^{-a}}$
- Hyperbolic tangent $\tanh(a) = \frac{e^{a}-e^{-a}}{e^{a}+e^{-a}}$
- Rectified linear $\mathrm{relu}(a) = \max(0, a)$



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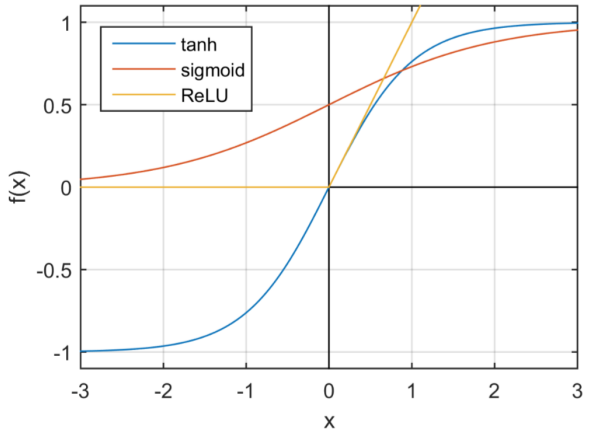

- Supervised learning
- Labeled training set

$$\mathcal{D} = \{(x_i, y_i) | i = 1, \ldots, n\} \ .$$

- Input x_i and output y_i.

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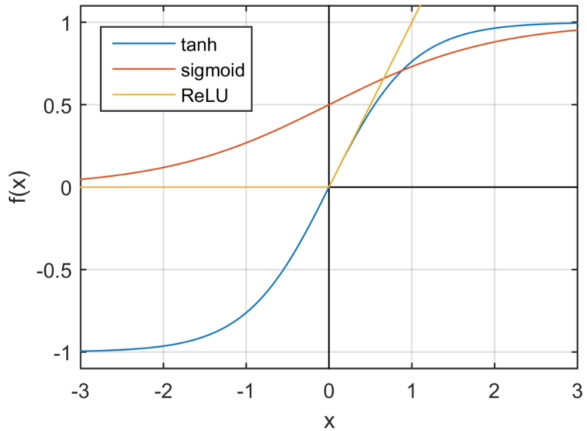

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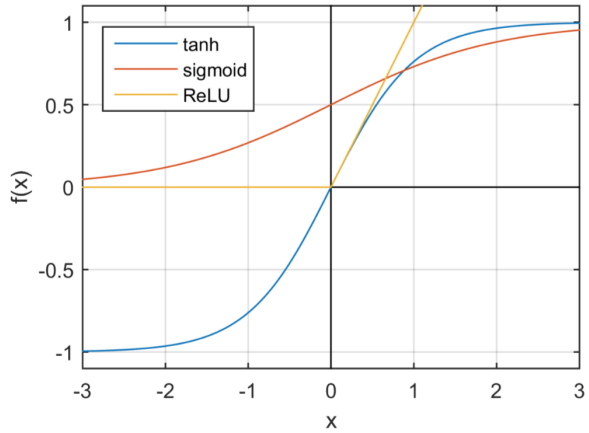

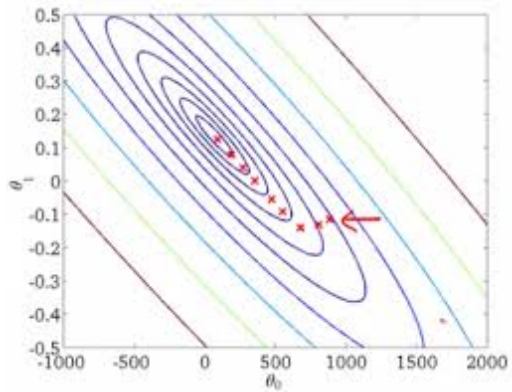

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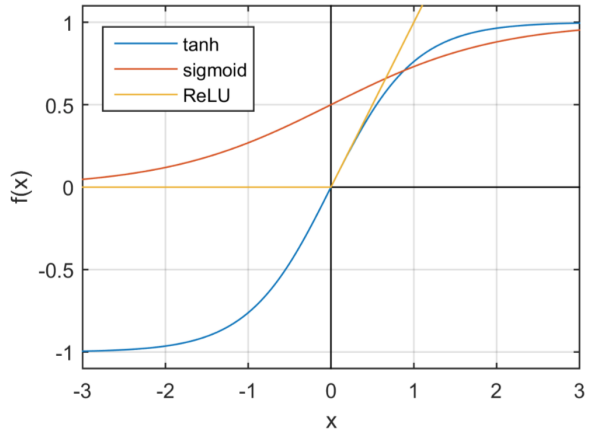

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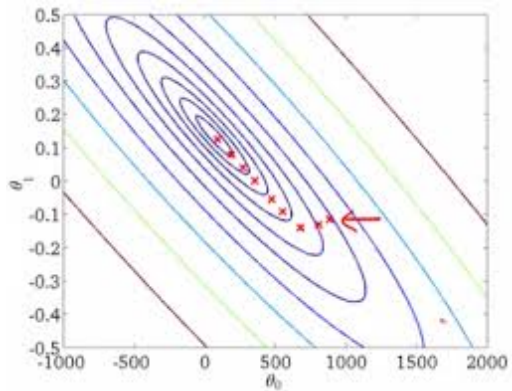
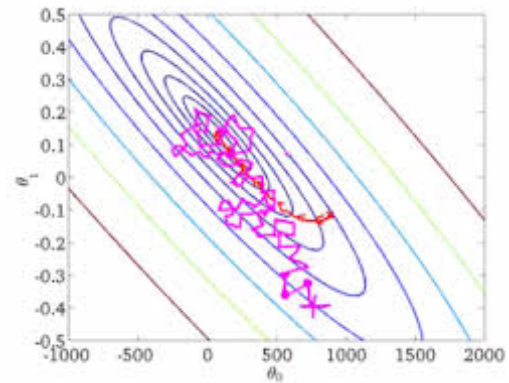
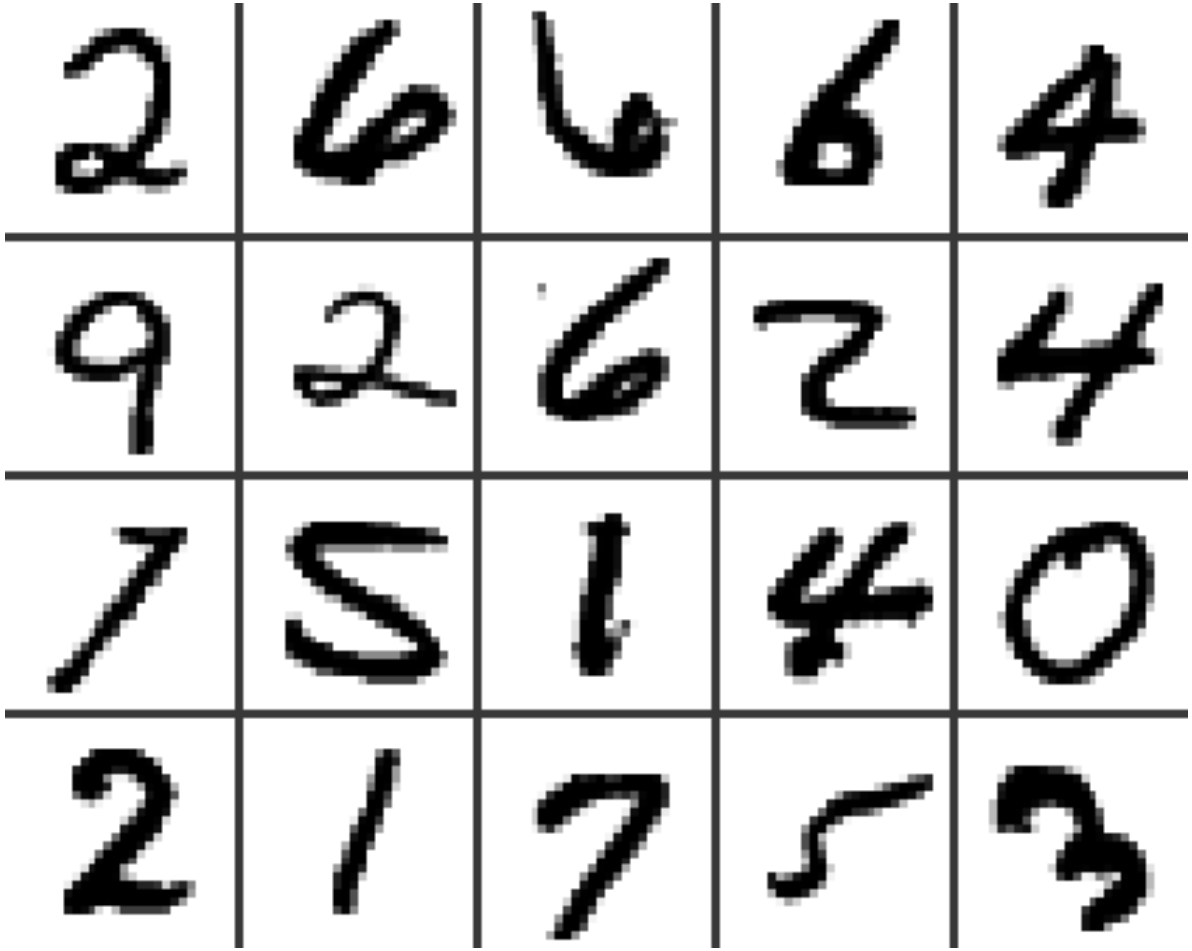




Overfitting!

Example: MNIST handwritten digits

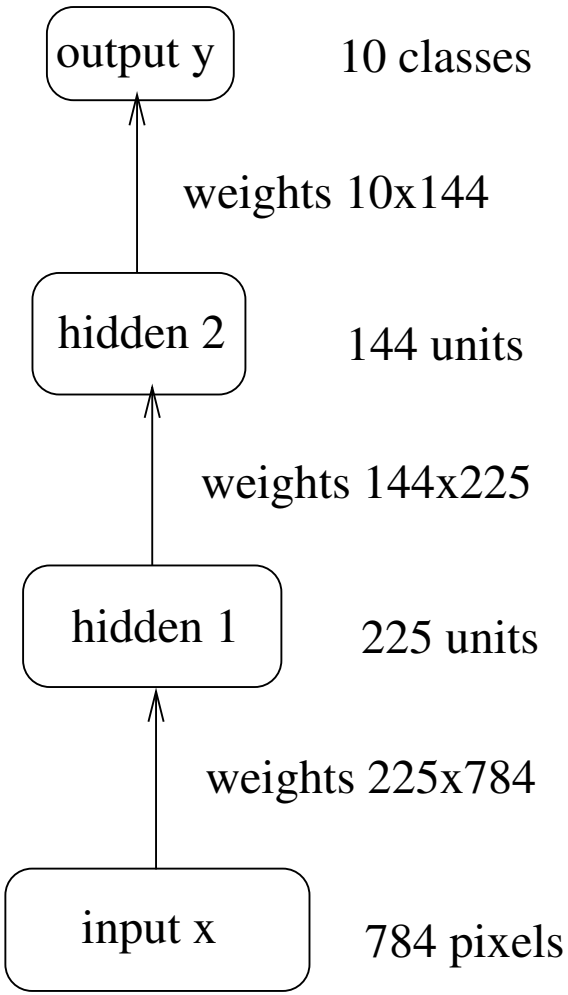


Train a network to classify 28×28 images.

Data: 60000 input images $\mathbf{x}(n)$ and labels $y(n)$.

Example model gives around 1.2% test error.

Example Network



$$\mathbf{h}^{(3)} = \text{softmax}(\mathbf{W}^{(3)}\mathbf{h}^{(2)} + \mathbf{b}^{(3)})$$

$$\mathbf{h}^{(2)} = \text{relu}(\mathbf{W}^{(2)}\mathbf{h}^{(1)} + \mathbf{b}^{(2)})$$

$$\mathbf{h}^{(1)} = \text{relu}(\mathbf{W}^{(1)}\mathbf{x} + \mathbf{b}^{(1)})$$

$$\text{softmax}(\mathbf{z})_i = \frac{\exp(z_i)}{\sum_j \exp(z_j)}$$

$$\text{relu}(z) = max(0, z)$$

Softmax

- Softmax function

$$\text{softmax}(\mathbf{z})_i = \frac{\exp(z_i)}{\sum_j \exp(z_j)}$$

has two nice properties:

- $\text{softmax}(\mathbf{z})_i \geq 0$
- $\sum_i \text{softmax}(\mathbf{z})_i = 1$

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  has two nice properties:

- $\text{softmax}(\mathbf{z})_i \geq 0$
- $\sum_i \text{softmax}(\mathbf{z})_i = 1$
- MNIST, output labels: $0, 1, \ldots, 9$.
- Output of network

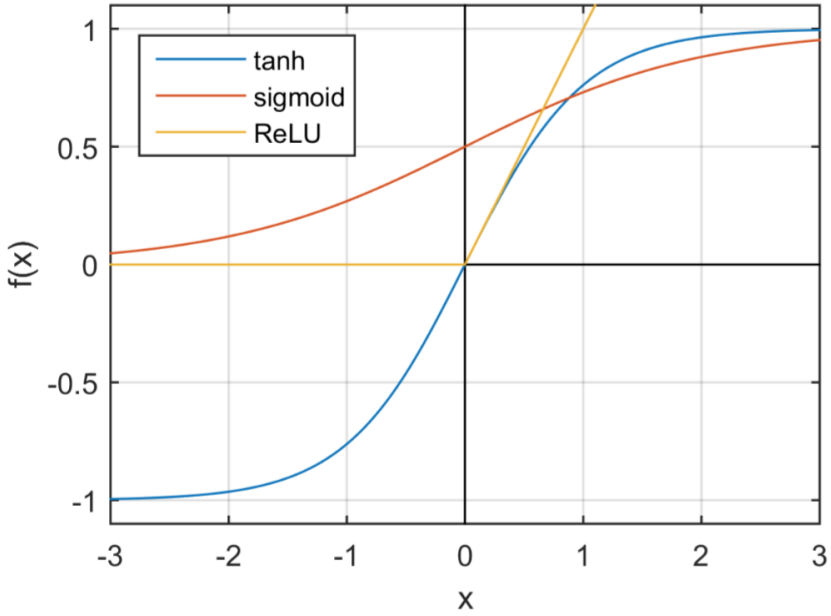
$$\mathbf{h}^{(3)} = \text{softmax}(\mathbf{W}^{(3)}\mathbf{h}^{(2)} + \mathbf{b}^{(3)})$$

  interpreted as class(-conditional) probabilities:

- For example:

$$p(\text{digit} = 5|\mathbf{x}) = \mathbf{h}_6^{(3)}$$

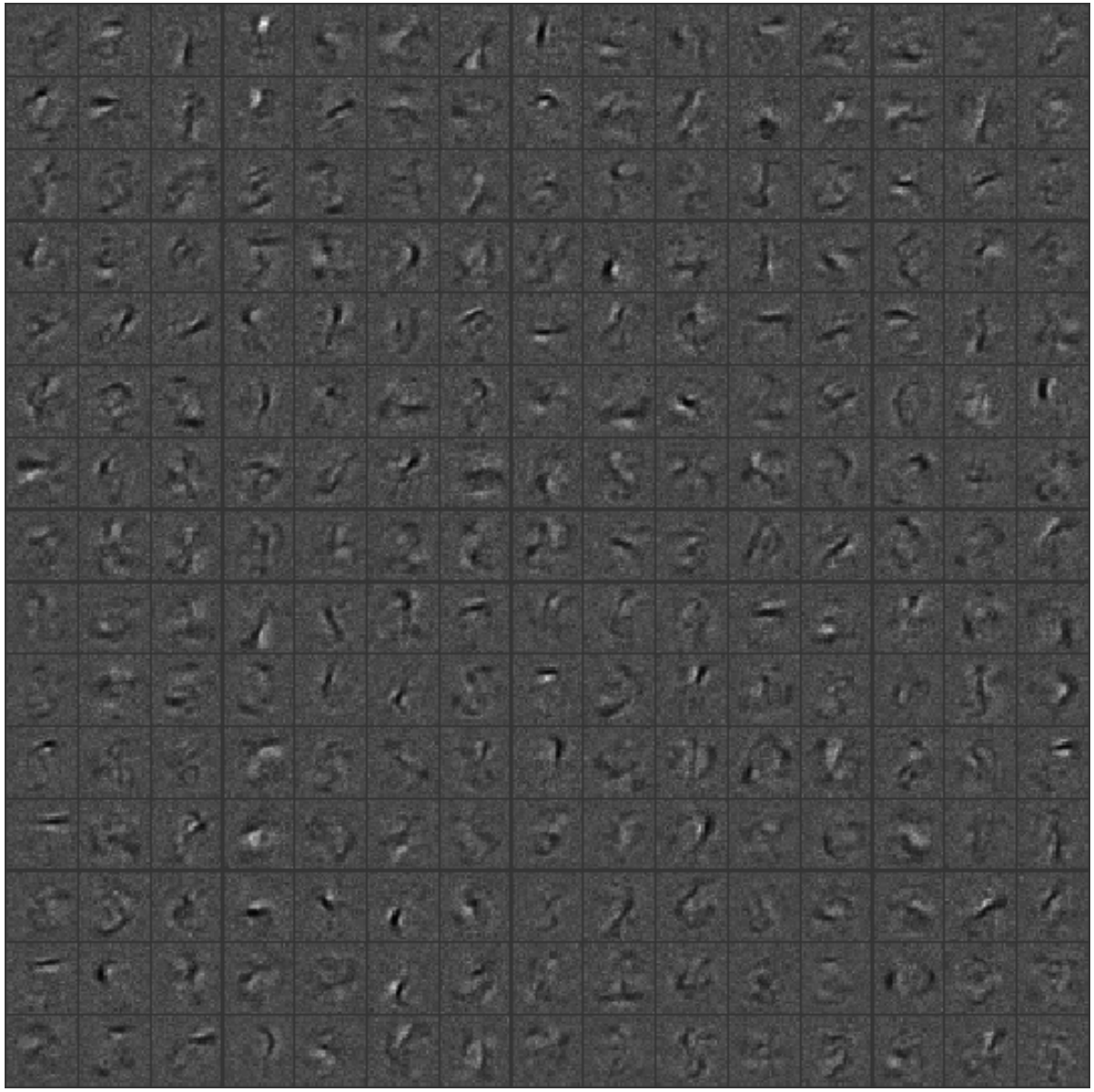
On activation functions



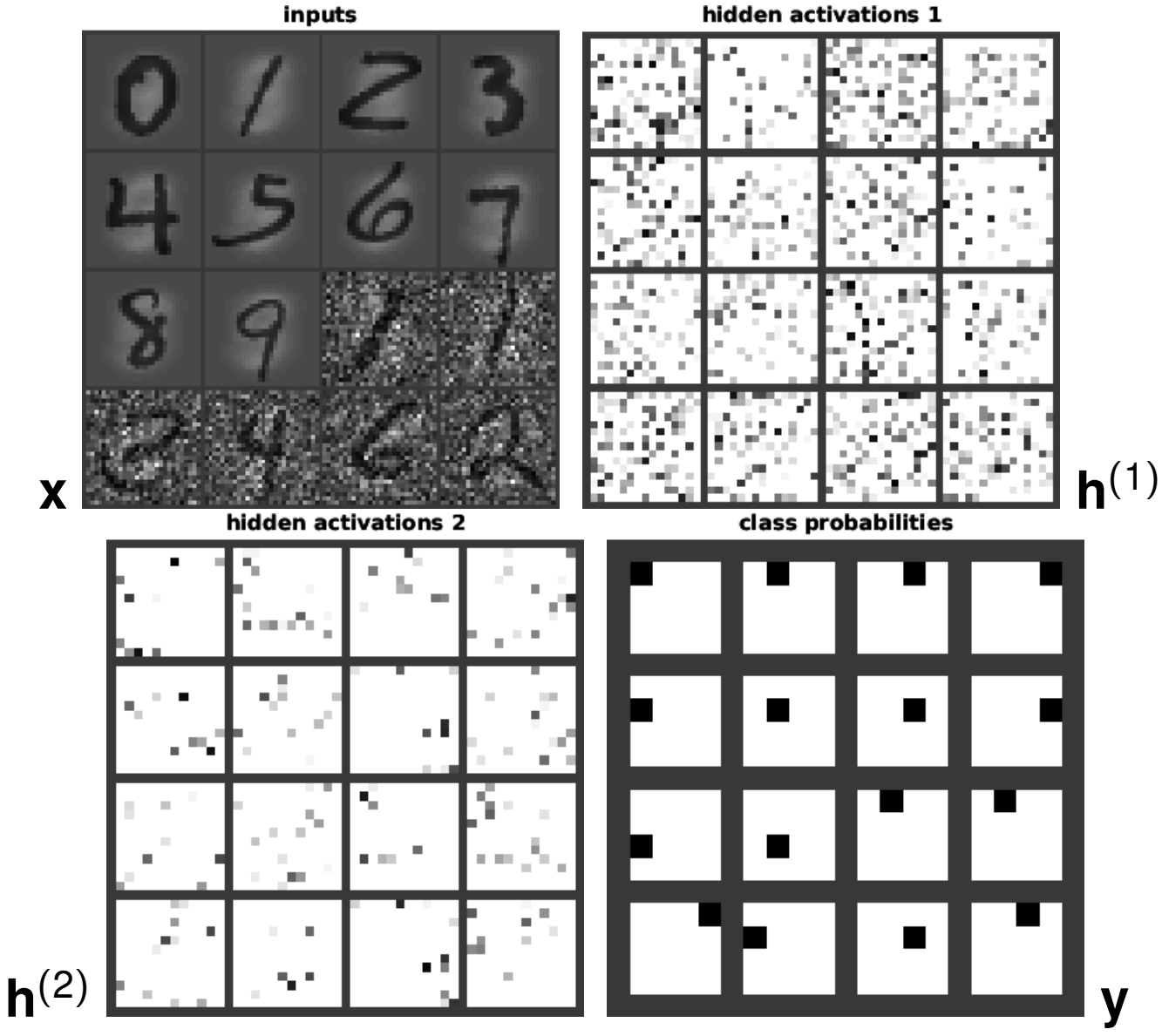
- $\text{relu}(z) = \max(0, z)$ is replacing old sigmoid and tanh.
- Note that identity function would lead into:

$$\begin{aligned}
\mathbf{h}^{(2)} &= \mathbf{W}^{(2)}\mathbf{h}^{(1)} + \mathbf{b}^{(2)} \\
&= \mathbf{W}^{(2)}(\mathbf{W}^{(1)}\mathbf{x} + \mathbf{b}^{(1)}) + \mathbf{b}^{(2)} \\
&= (\mathbf{W}^{(2)}\mathbf{W}^{(1)})\mathbf{x} + (\mathbf{W}^{(2)}\mathbf{b}^{(1)} + \mathbf{b}^{(2)}) \\
&= \mathbf{W}'\mathbf{x} + \mathbf{b}'
\end{aligned}$$

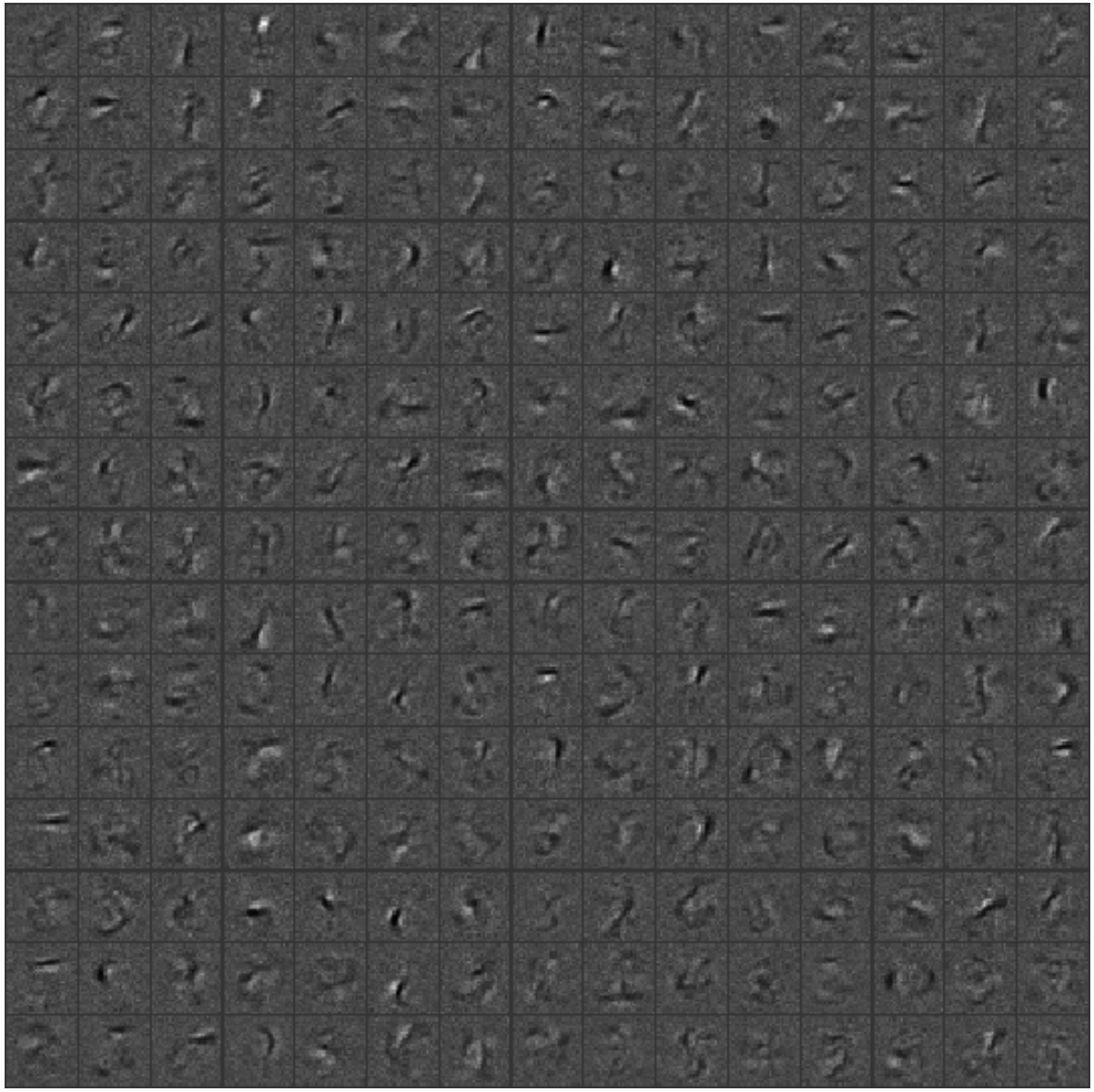
Weight matrix $\mathbf{W}^{(1)}$ size 225×784



Signals $\mathbf{x} \rightarrow \mathbf{h}^{(1)} \rightarrow \mathbf{h}^{(2)} \rightarrow \mathbf{h}^{(3)}$



Weight matrix $\mathbf{W}^{(1)}$ size 225×784



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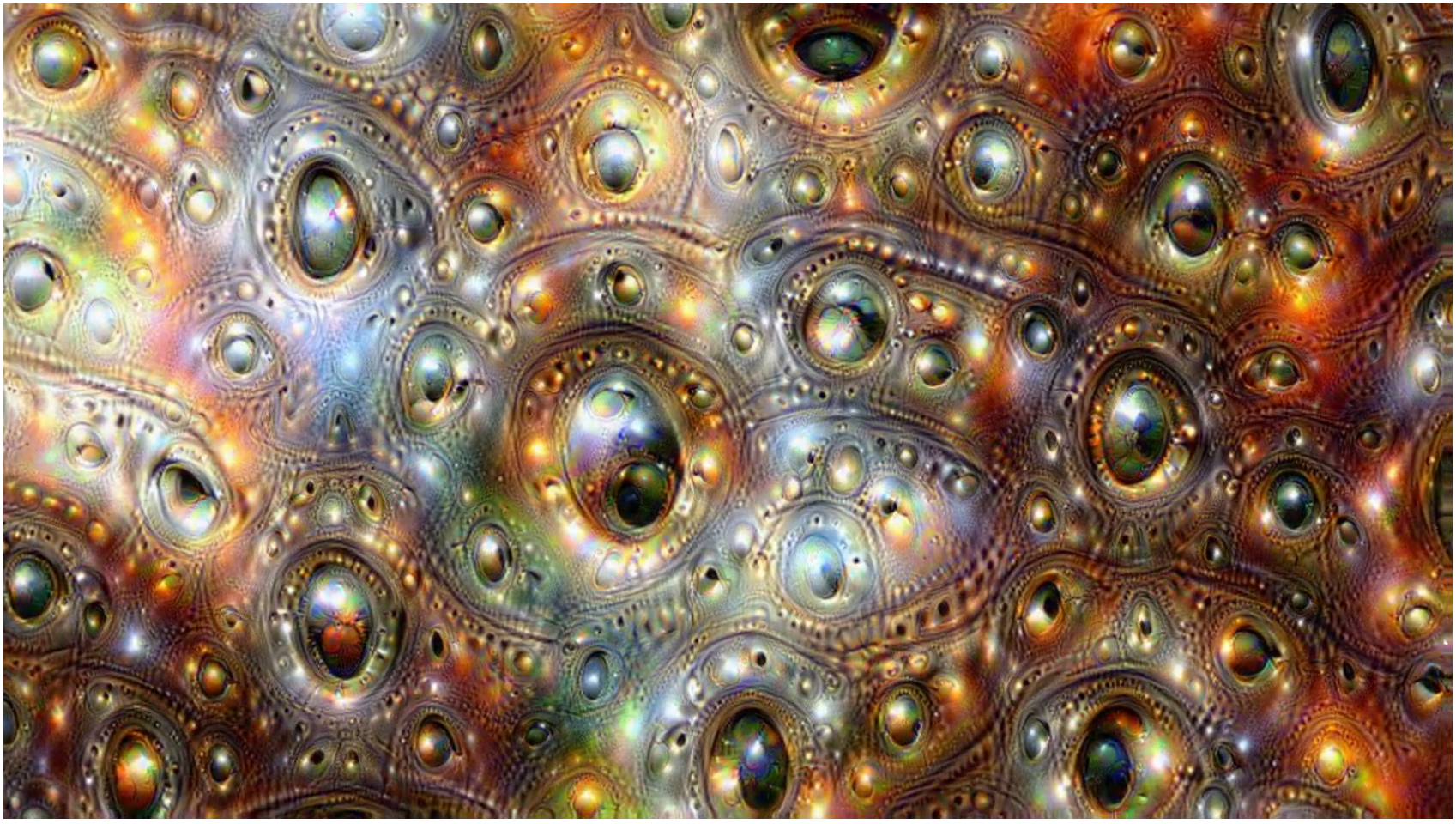

Thanks!
Ole Winther