
neuro
dev

LESSON 5:
NEURAL NETWORKS

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Today's agenda

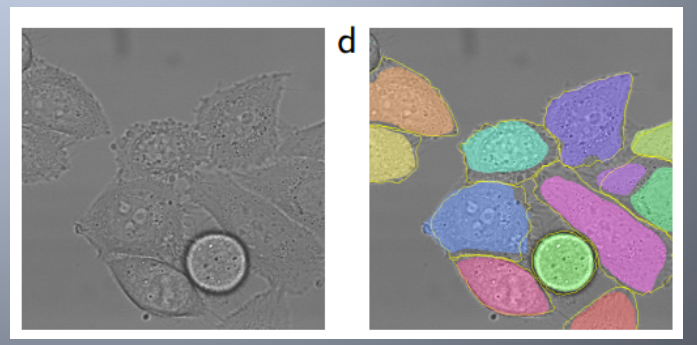
- Intro to Neural Networks: motivation, and basics
- Training and using of a neural network with Keras (TensorFlow) to read handwritten digits (MNIST)

Why neural networks?

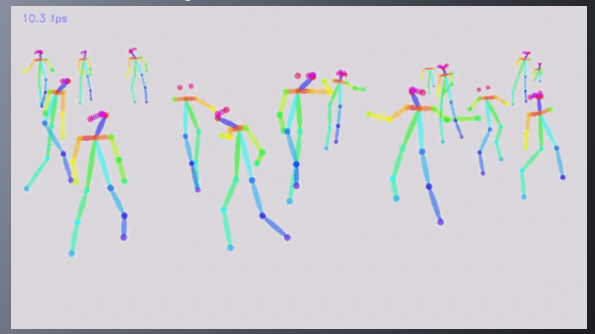
- State-of-the art performance for many challenging tasks….

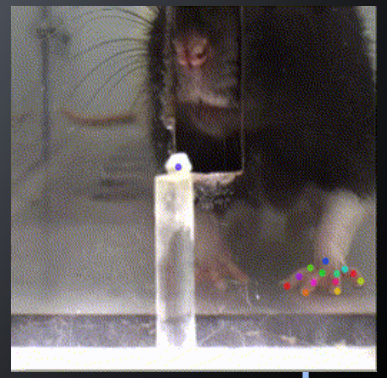
Object recognition,
Alexnet 2012

Cell tracking, U-Net



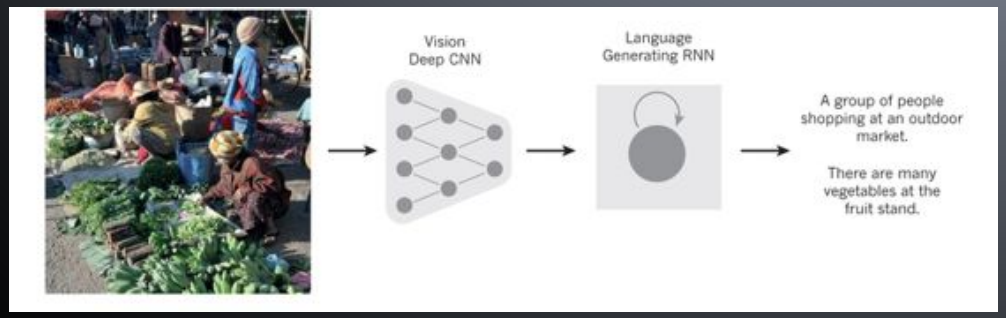
OpenPose





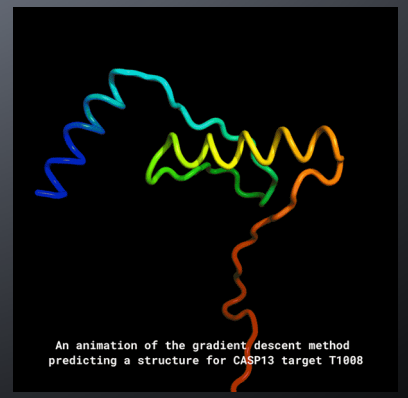
DeepLabCut

Speech recognition,
Image >>> text,



Deep Learning,
LeCun et al.
Nature 2015

Protein folding…
https://deepmind.com/blog/alphafold/

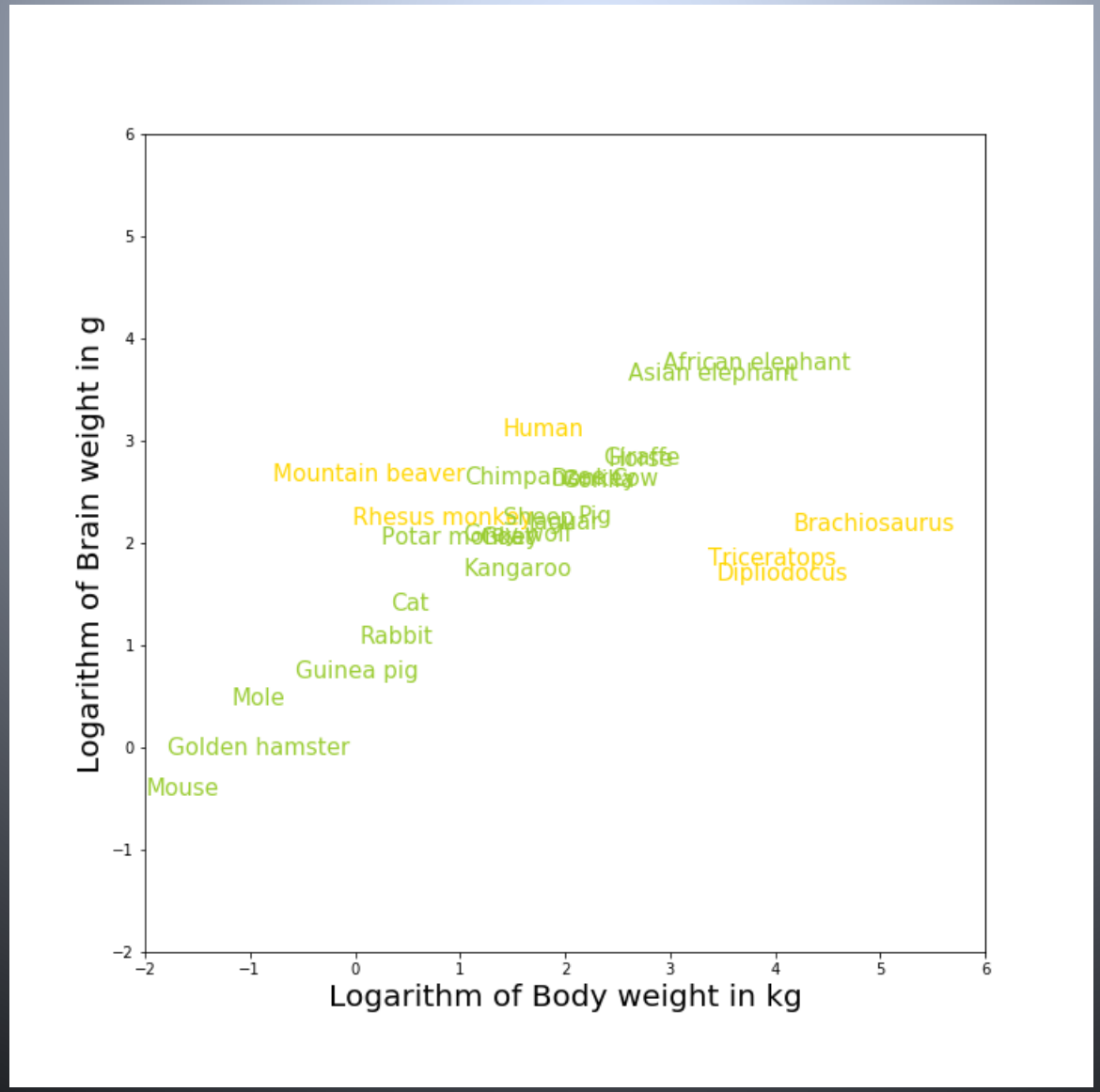


What is learning?

Learning is the process of acquiring new, or
modifying existing, knowledge, behaviors, skills, values, or preferences.
(wikipedia)

For today… learning is curve fitting!

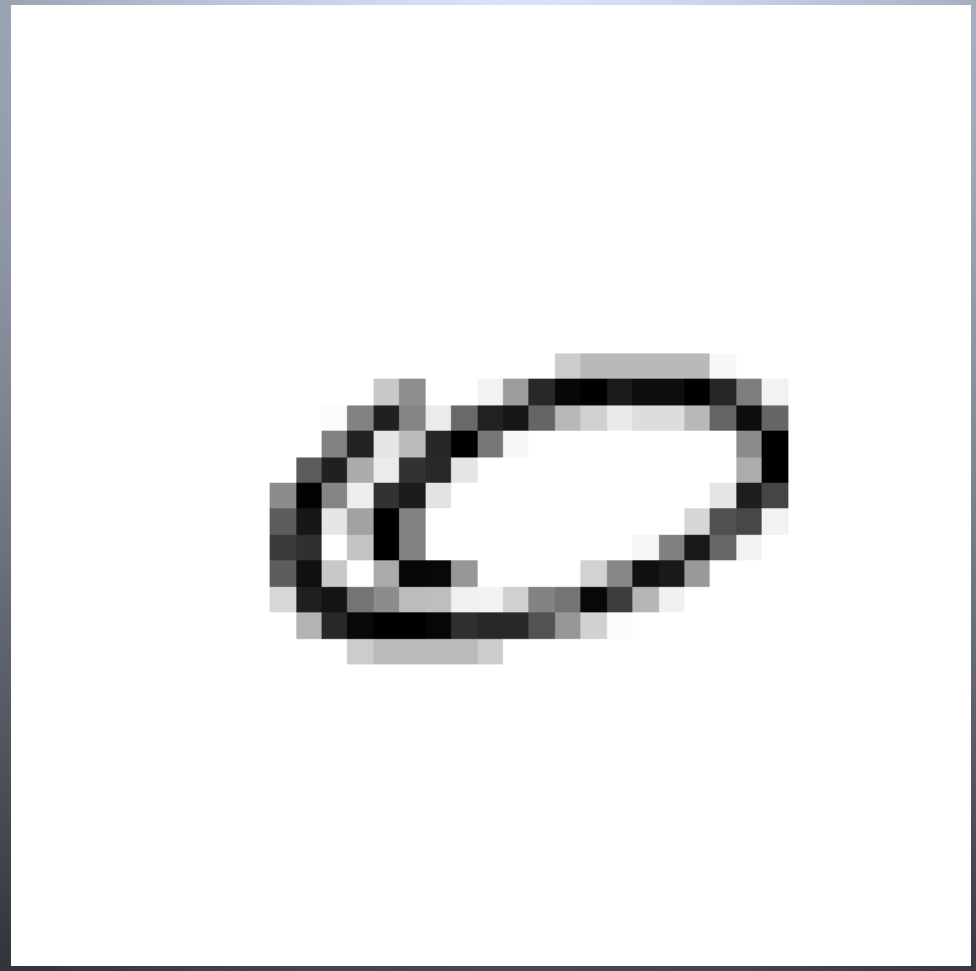
Example 1 – scientific data



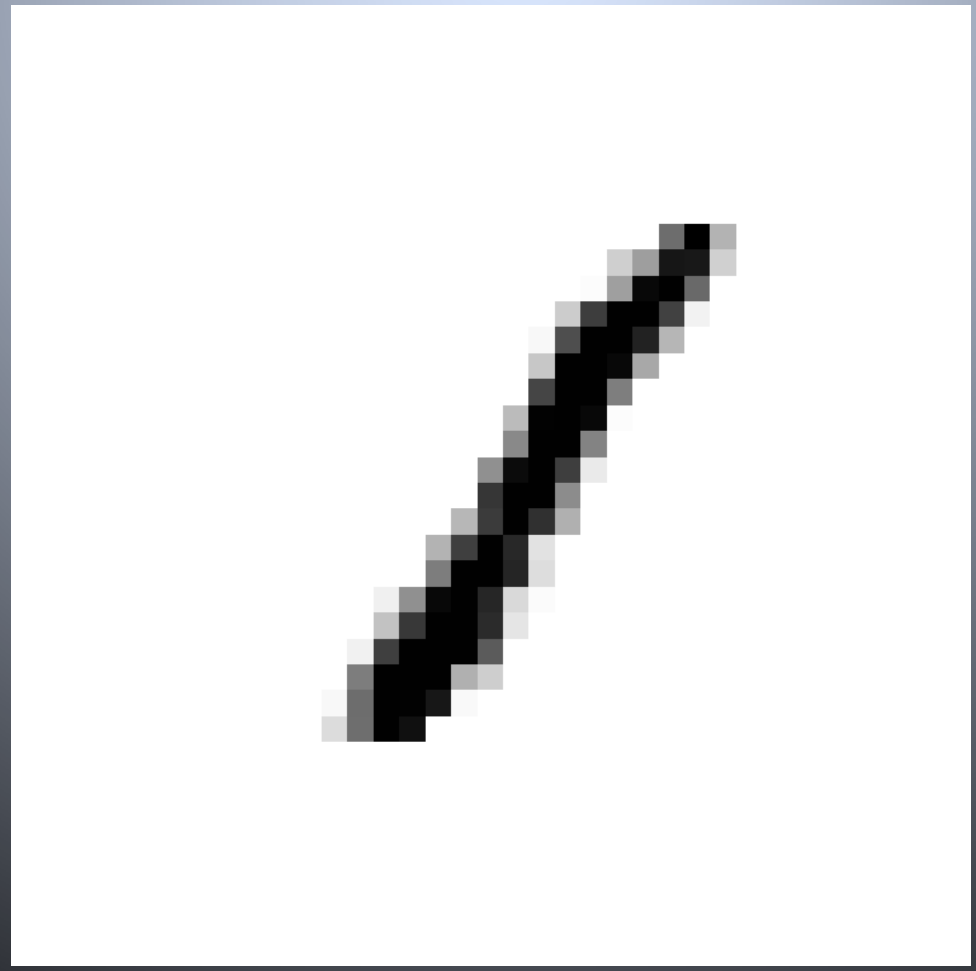
Average brain and body weights for 27 species of land animals.
Source: http://mste.illinois.edu/malcz/DATA/BIOLOGY/Animals.html

Example 1 – scientific data

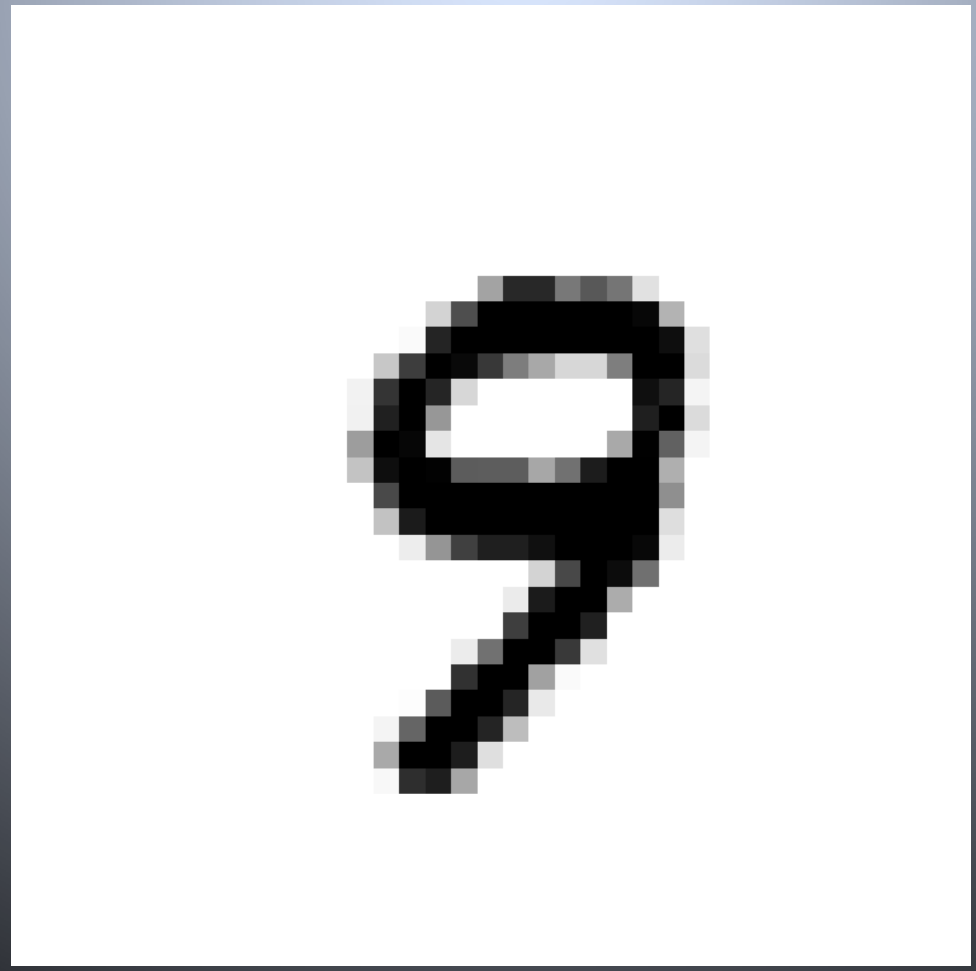
Example 2 – perception



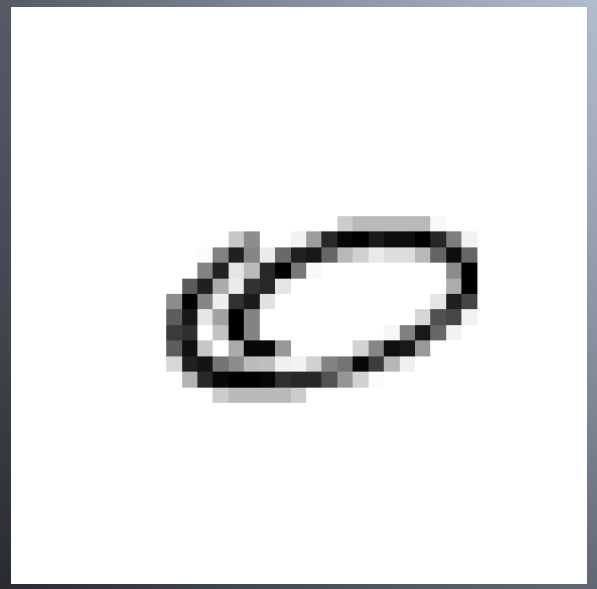
Example 2 – perception

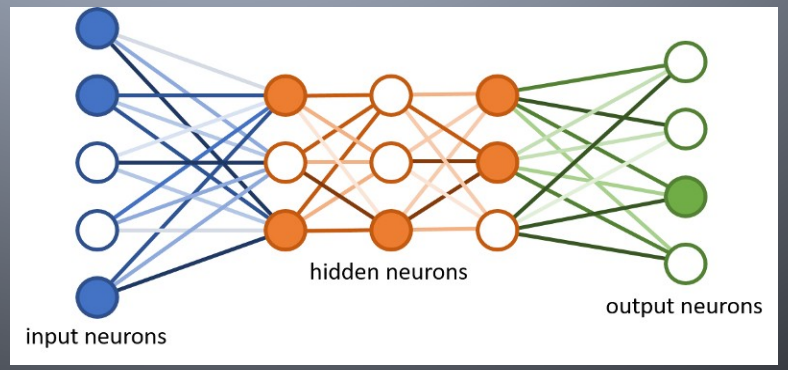


Example 2 – perception



Example 2 – perception





0?
1?
2?
..

The MNIST database of handwritten digits – classical problem for reading handwritten digits
http://yann.lecun.com/exdb/mnist/

Further resources….

The following slides are from
Prof. Russ Salakhutdinov (Carnegie Mellon)

His full lecture slides can be found on the MLSS website!

- Machine Learning Summer School http://mlss.tuebingen.mpg.de/2017/index.html
- Deep Learning Summer School Materials
  https://sites.google.com/site/deeplearningsummerschool2016/

ARTIFICIAL NEURON

- Neuron pre-activation (or input activation):

$$a(\mathbf{x}) = b + \sum_i w_i x_i = b + \mathbf{w}^\top \mathbf{x}$$

- Neuron output activation:

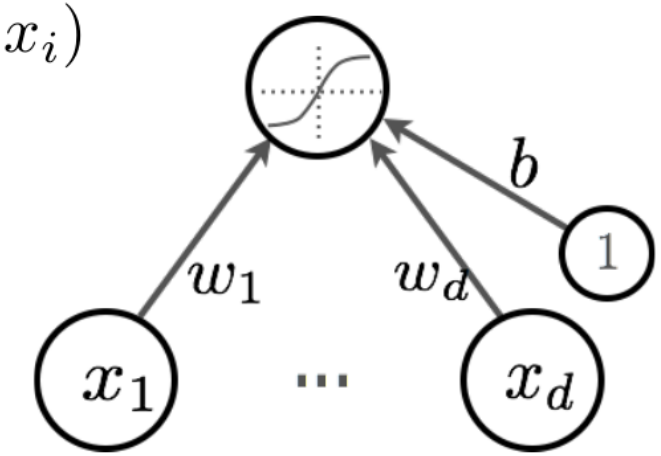
$$h(\mathbf{x}) = g(a(\mathbf{x})) = g(b + \sum_i w_i x_i)$$

where

$\mathbf{w}$ are the weights (parameters)

b is the bias term

$g(\cdot)$ is called the activation function



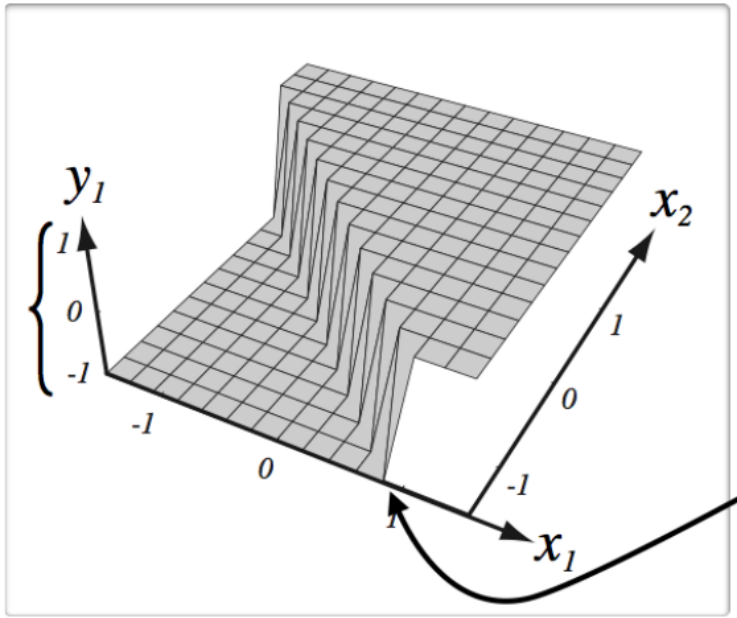
From Prof. Salakhutdinov

ARTIFICIAL NEURON

- Output activation of the neuron:

$$h(\mathbf{x}) = g(a(\mathbf{x})) = g(b + \sum_i w_i x_i)$$

Range is determined by $g(\cdot)$



(from Pascal Vincent's slides)

Bias only changes the position of the riff

From Prof. Salakhutdinov

SINGLE HIDDEN LAYER NET

- Hidden layer pre-activation:

$$\mathbf{a}(\mathbf{x}) = \mathbf{b}^{(1)} + \mathbf{W}^{(1)}\mathbf{x}$$

$$\left(a(\mathbf{x})_i = b_i^{(1)} + \sum_j W_{i,j}^{(1)} x_j\right)$$

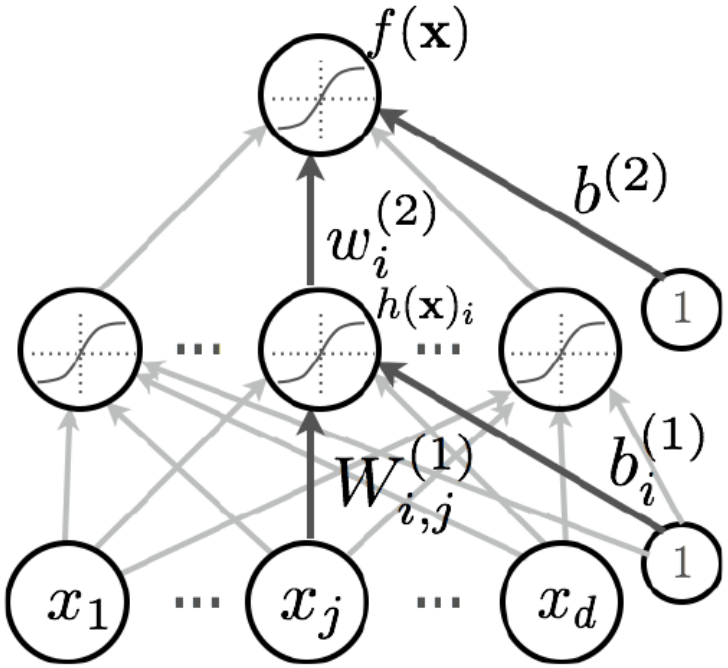
- Hidden layer activation:

$$\mathbf{h}(\mathbf{x}) = \mathbf{g}(\mathbf{a}(\mathbf{x}))$$

- Output layer activation:

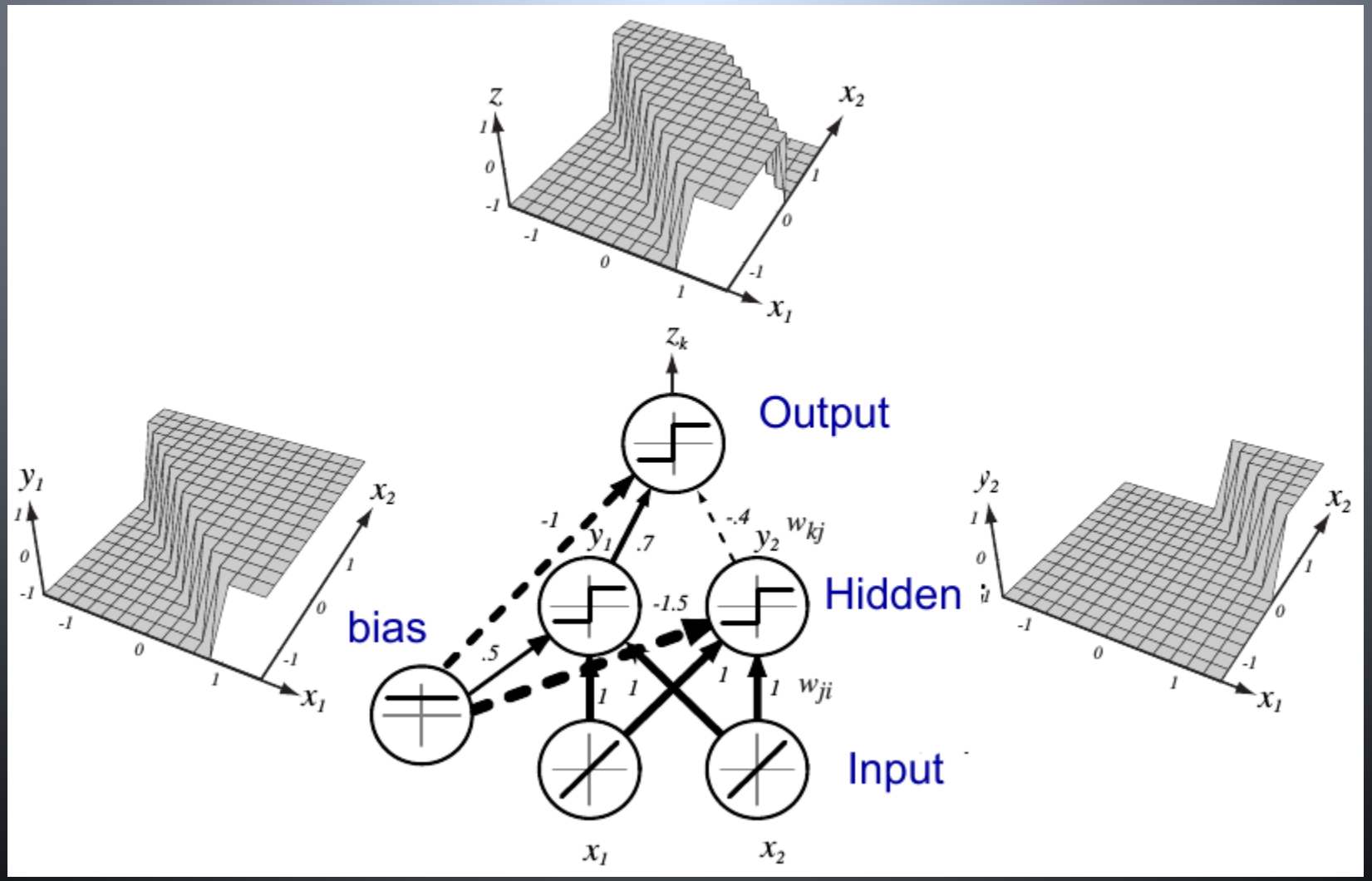
$$f(\mathbf{x}) = o\left(b^{(2)} + \mathbf{w}^{(2)\top}\mathbf{h}^{(1)}\mathbf{x}\right)$$

Output activation function



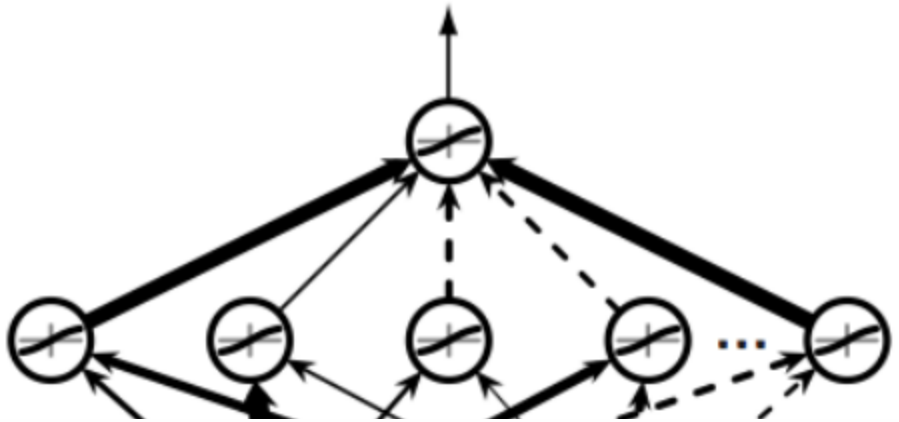
From Prof. Salakhutdinov

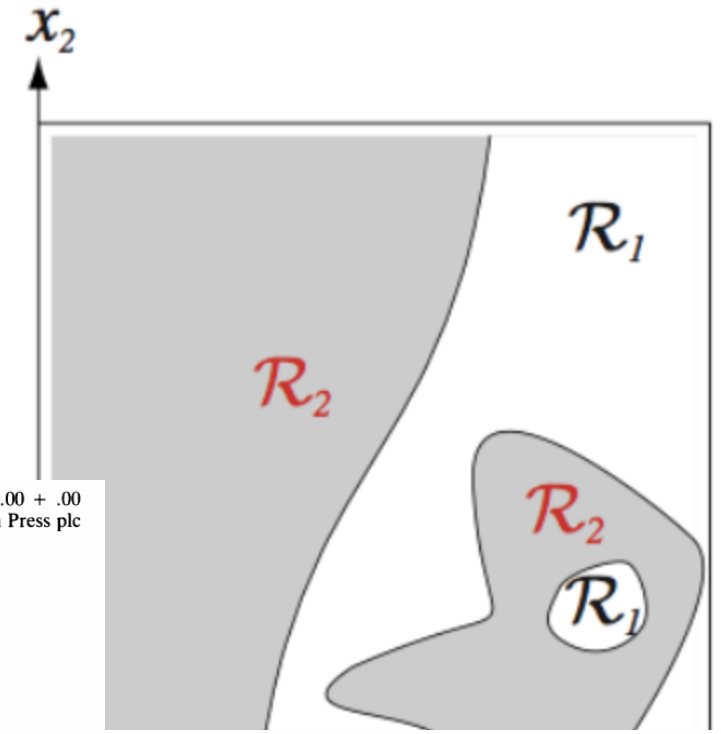
CAPACITY



From Prof. Salakhutdinov

CAPACITY





Neural Networks, Vol. 4, pp. 251–257, 1991
Printed in the USA.

0893-6080/91 $3.00 + .00

ORIGINAL CONTRIBUTION

Approximation Capabilities of Multilayer Feedforward Networks

KURT HORNIK

$$\mathfrak{N}_k^{(n)}(\psi) = \left\{ h: R^k \to R \middle| h(x) = \sum_{j=1}^{n} \beta_j \psi(a_j' x - \theta_j) \right\}$$

Theorem 1: *If ψ is unbounded and nonconstant, then $\mathfrak{N}_k(\psi)$ is dense in $L^p(\mu)$ for all finite measures μ on R^k.*

MULTILAYER NEURAL NET

- Consider a network with L hidden layers.
  - layer pre-activation for k>0

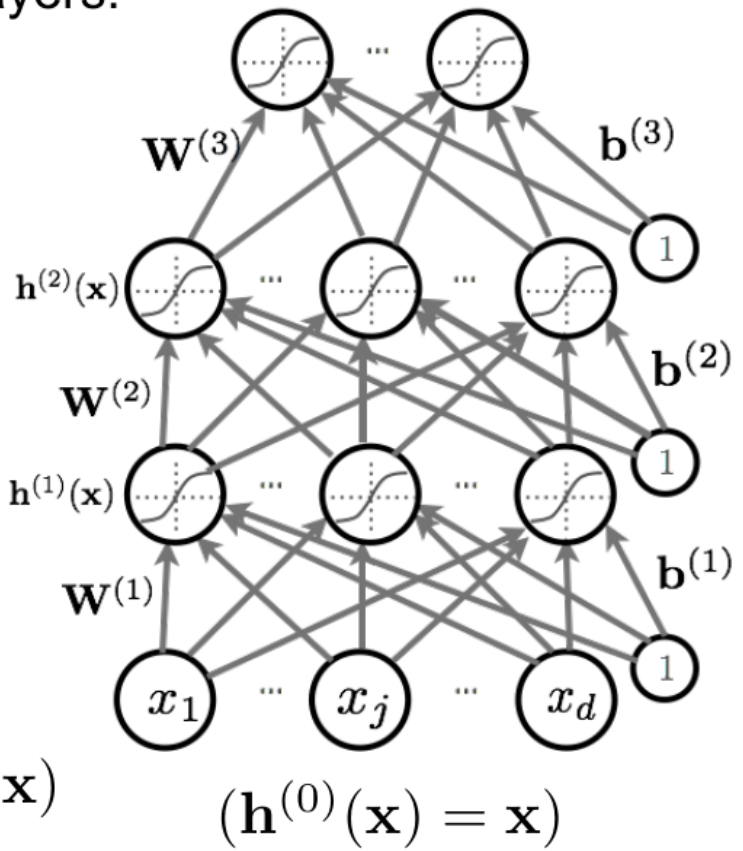
$$\mathbf{a}^{(k)}(\mathbf{x}) = \mathbf{b}^{(k)} + \mathbf{W}^{(k)}\mathbf{h}^{(k-1)}(\mathbf{x})$$

  - hidden layer activation from 1 to L:

$$\mathbf{h}^{(k)}(\mathbf{x}) = \mathbf{g}(\mathbf{a}^{(k)}(\mathbf{x}))$$

  - output layer activation (k=L+1):

$$\mathbf{h}^{(L+1)}(\mathbf{x}) = \mathbf{o}(\mathbf{a}^{(L+1)}(\mathbf{x})) = \mathbf{f}(\mathbf{x})$$



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WELL BUT HOW DO WE LEARN?

- Empirical Risk Minimization:

$$\arg\min_{\boldsymbol{\theta}} \frac{1}{T} \sum_{t} \underbrace{l(f(\mathbf{x}^{(t)}; \boldsymbol{\theta}), y^{(t)})}_{\text{Loss function}} + \underbrace{\lambda \Omega(\boldsymbol{\theta})}_{\text{Regularizer}}$$

- To train a neural net, we need:
  - Loss function: $l(\mathbf{f}(\mathbf{x}^{(t)}; \boldsymbol{\theta}), y^{(t)})$
  - A procedure to compute gradients: $\nabla_{\boldsymbol{\theta}} l(\mathbf{f}(\mathbf{x}^{(t)}; \boldsymbol{\theta}), y^{(t)})$
  - Regularizer and its gradient: $\Omega(\boldsymbol{\theta}), \nabla_{\boldsymbol{\theta}} \Omega(\boldsymbol{\theta})$

From Prof. Salakhutdinov

WELL BUT HOW DO WE LEARN?

- Perform updates after seeing each example:
  - Initialize: $\boldsymbol{\theta} \equiv \{\mathbf{W}^{(1)}, \mathbf{b}^{(1)}, \ldots, \mathbf{W}^{(L+1)}, \mathbf{b}^{(L+1)}\}$
  - For t=1:T
    - for each training example $(\mathbf{x}^{(t)}, y^{(t)})$

$$\Delta = -\nabla_{\boldsymbol{\theta}} l(f(\mathbf{x}^{(t)}; \boldsymbol{\theta}), y^{(t)}) - \lambda \nabla_{\boldsymbol{\theta}} \Omega(\boldsymbol{\theta})$$
$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha \, \Delta$$

Training epoch = Iteration of all examples

- To train a neural net, we need:
  - Loss function: $l(\mathbf{f}(\mathbf{x}^{(t)}; \boldsymbol{\theta}), y^{(t)})$
  - A procedure to compute gradients: $\nabla_{\boldsymbol{\theta}} l(\mathbf{f}(\mathbf{x}^{(t)}; \boldsymbol{\theta}), y^{(t)})$
  - Regularizer and its gradient: $\Omega(\boldsymbol{\theta}), \nabla_{\boldsymbol{\theta}} \Omega(\boldsymbol{\theta})$

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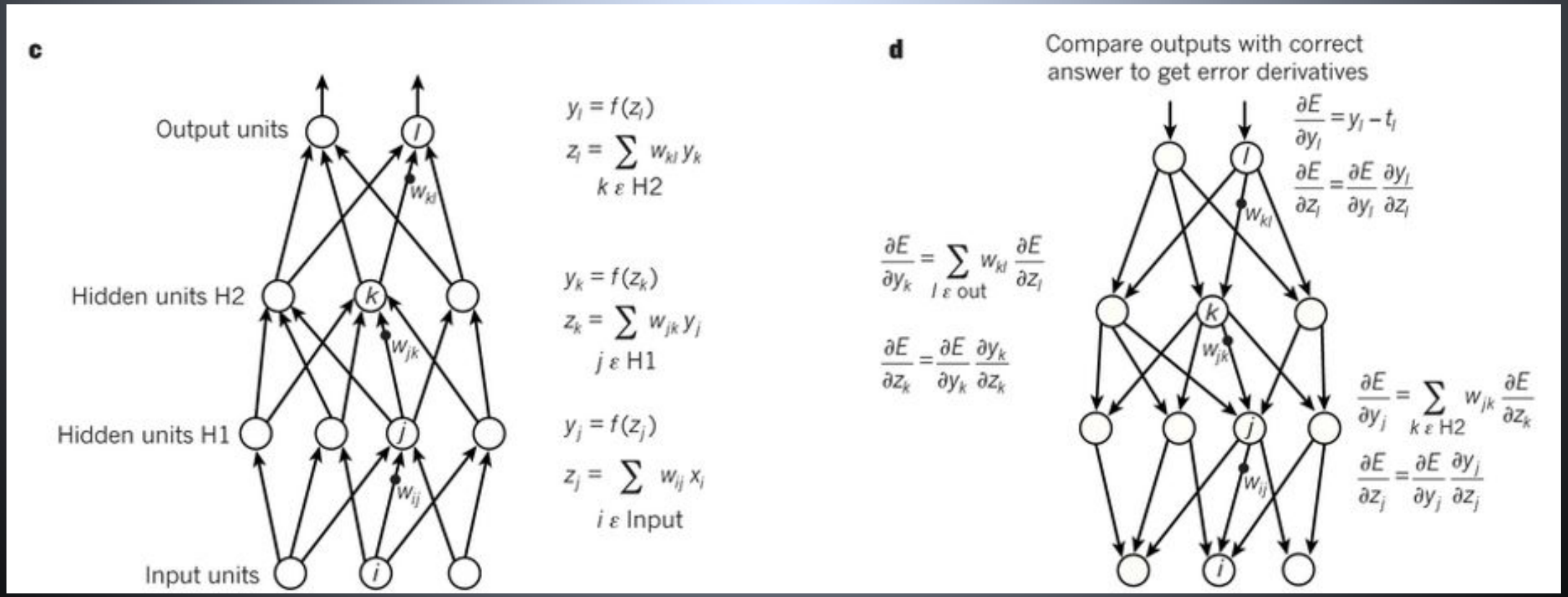
BACKPROPAGATION (OF ERRORS) ALGORITHM



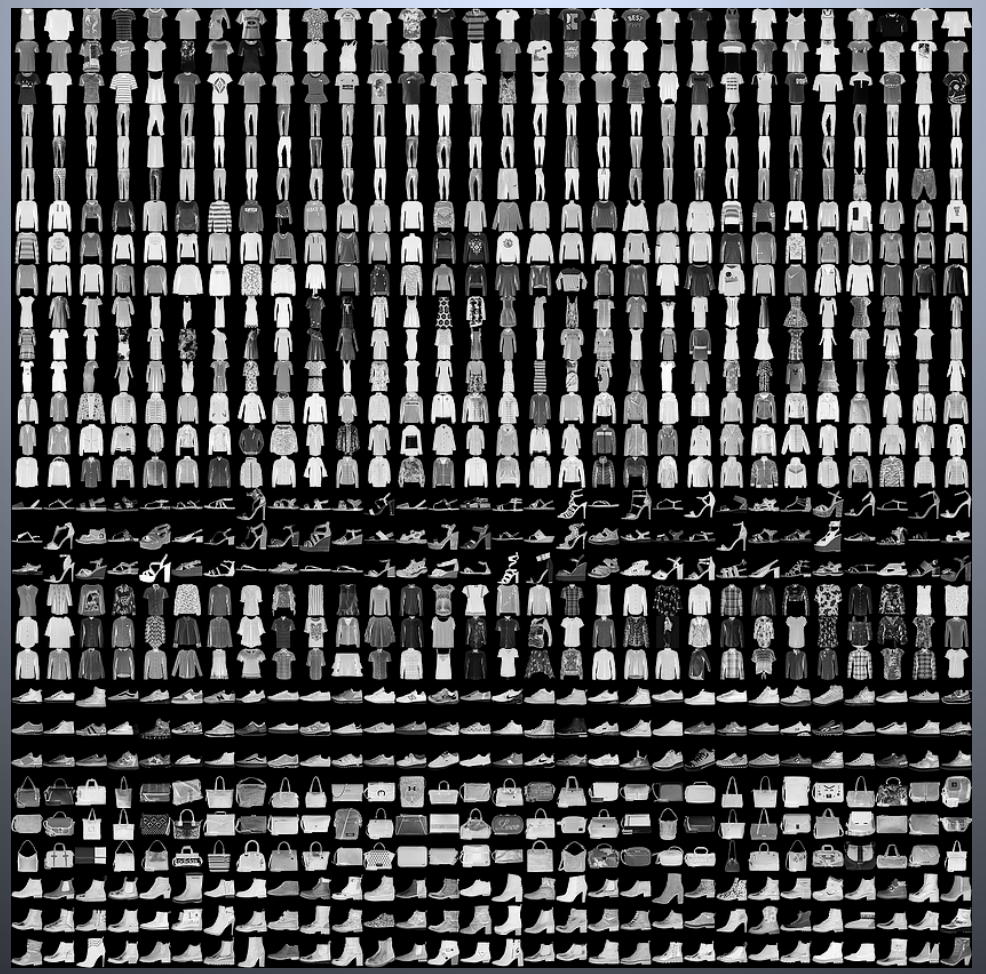
Deep Learning,
LeCun et al.
Nature 2015

Fortunately,

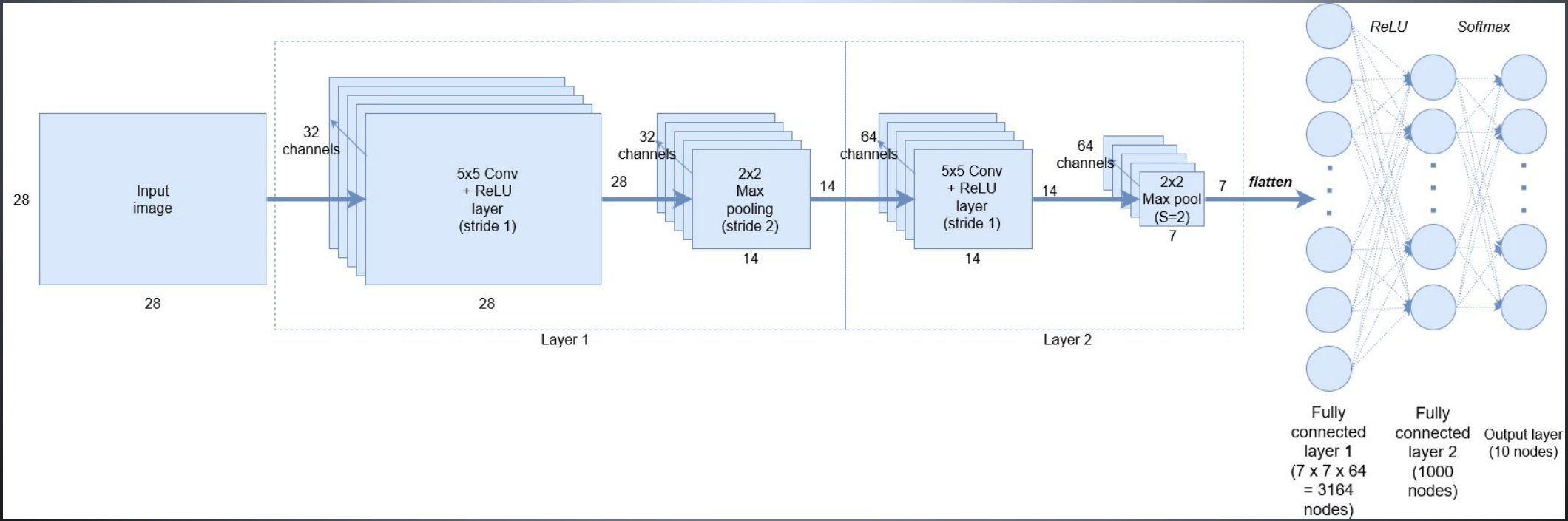
TensorFlow, Keras, Theano, PyTorch…

minimize the loss for us!

Keras demo with MNIST and fashion MNIST….
https://github.com/AlexEMG/Tutorials/blob/master/MNIST-Keras.ipynb



Convolutional Network architecture for Keras model with MNIST performance > 99%

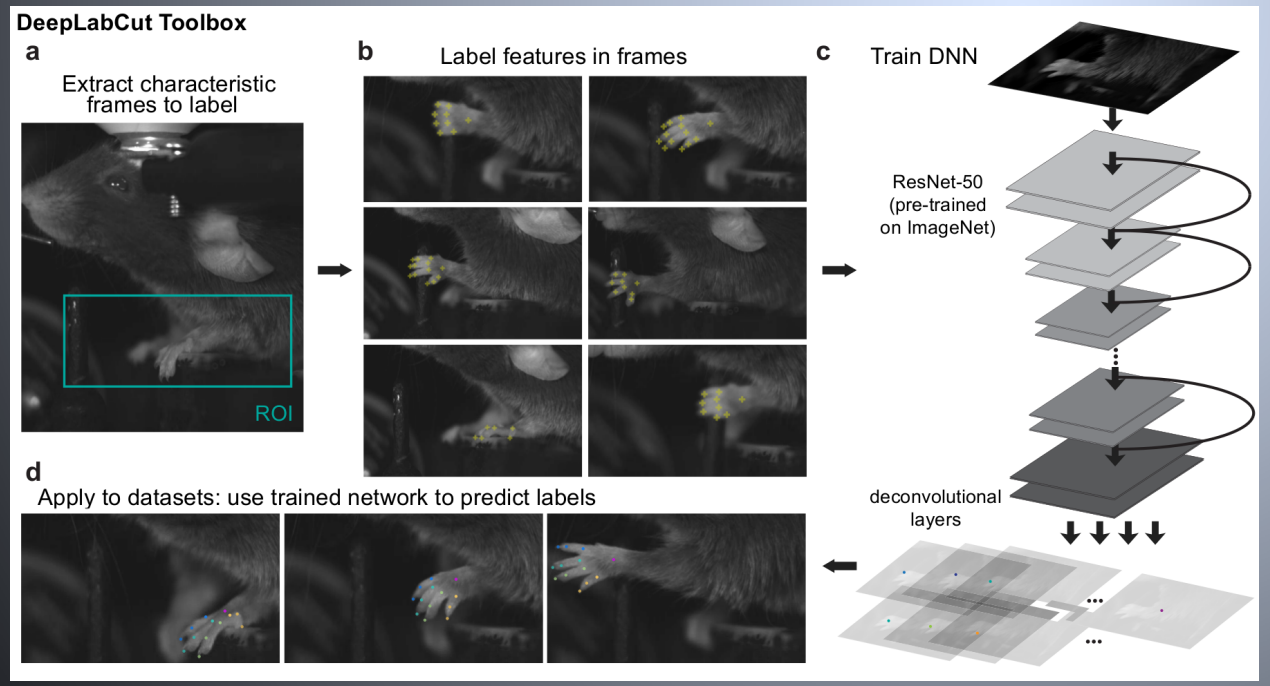


In Keras this is as easy as:
(see notebook for training etc.)

```
model = tf.keras.models.Sequential()
model.add(tf.keras.layers.Conv2D(32, kernel_size=(5, 5), strides=(1, 1),
                 activation='relu'))
model.add(tf.keras.layers.MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
model.add(tf.keras.layers.Conv2D(64, (5, 5), activation='relu'))
model.add(tf.keras.layers.MaxPooling2D(pool_size=(2, 2)))
model.add(tf.keras.layers.Flatten())
model.add(tf.keras.layers.Dense(1000, activation='relu'))
model.add(tf.keras.layers.Dense(10, activation='softmax'))
```

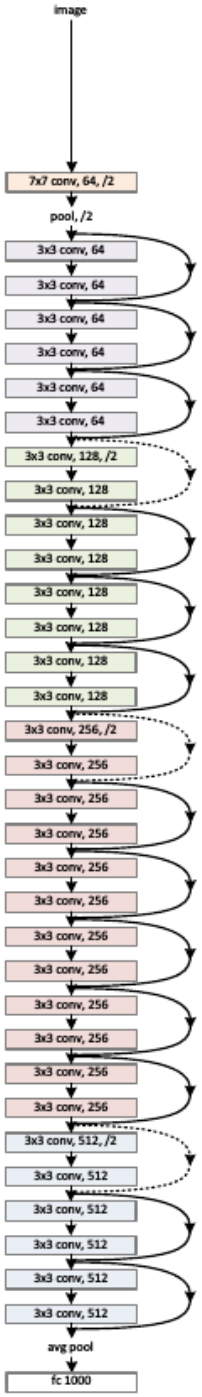
Source: http://adventuresinmachinelearning.com/keras-tutorial-cnn-11-lines/

Transfer learning…



ImageNet (>1Mio images
With 1,000 classes)

ResNet
He et al. 2016



nature neuroscience
TECHNICAL REPORT
https://doi.org/10.1038/s41593-018-0209-y

DeepLabCut: markerless pose estimation of user-defined body parts with deep learning

Alexander Mathis[1,2], Pranav Mamidanna[1], Kevin M. Cury[3], Taiga Abe[3], Venkatesh N. Murthy[2], Mackenzie Weygandt Mathis[1,4,8*] and Matthias Bethge[1,5,6,7,8]

A few links:

- Deep Learning textbook by Goodfellow, Bengio, Courville
- TensorFlow tutorial: https://github.com/chiphuyen/stanford-tensorflow-tutorials
- Awesome interpretability techniques for DeepNets
https://distill.pub/2018/building-blocks/
- Linking neural nets to topology
http://colah.github.io/posts/2014-03-NN-Manifolds-Topology/
https://cs.stanford.edu/people/karpathy/convnetjs//demo/classify2d.html
- Machine Learning Summer School
http://mlss.tuebingen.mpg.de/2017/index.html
- Deep Learning Summer School Materials
https://sites.google.com/site/deeplearningsummerschool2016

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