Machine Intelligence:: Deep Learning
Week 1

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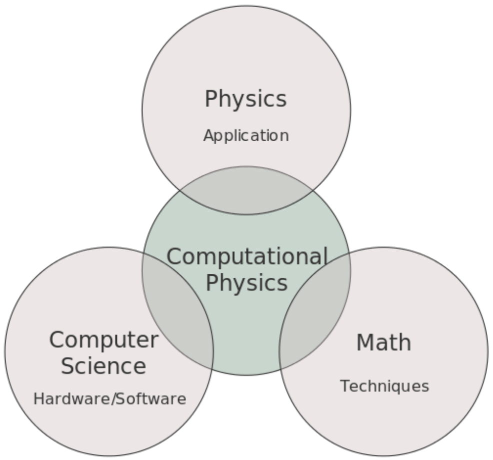
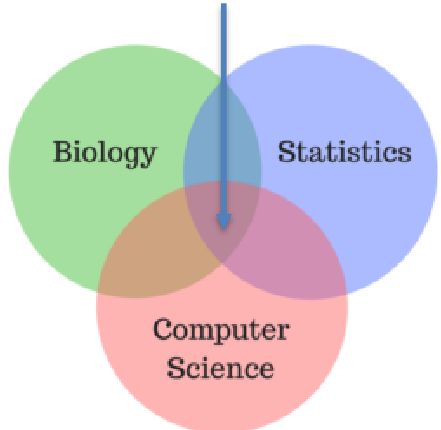
Oliver's Background

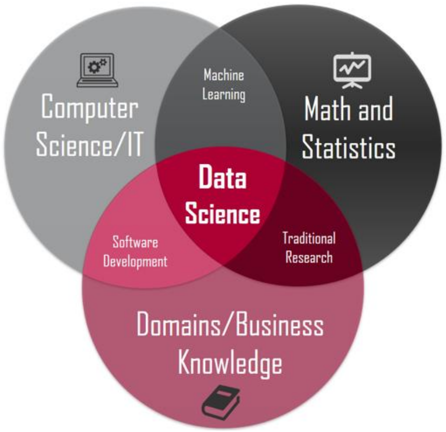
Computational Physics



Bioinformatics



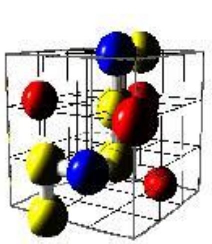
Data Science

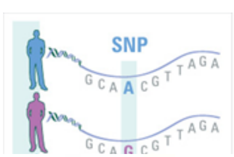


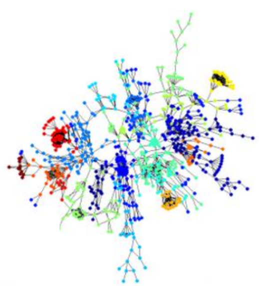
1990's
Uni-Konstanz

2000's
Genedata Basel

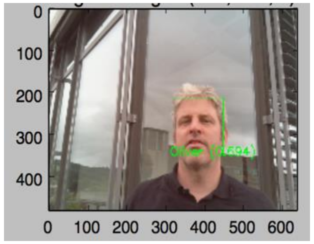
2010's
ZHAW Winterthur HTWG Konstanz







eclipse



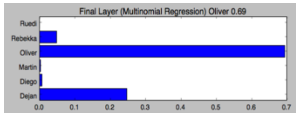


Image credits: Wikipedia, http://omgenomics.com/what-is-bioinformatics/ https://www.fox.temple.edu/institutes-and-centers/data-science/

Beate's Background

Head of bioinformatics

Focus: Gene expression

Researcher and Professor for applied statistics

Focus: deep learning

Researcher and lecturer

Focus: Biostatistics, DL

Tell us something about you

- Computer Science Background
  - Fluent in python?

- Statistics / Math
  - Who visited CAS StMo (statistisches Modellieren)?
  - What is a distribution?
  - Vector times Matrix?
    - Please make sure to check https://tensorchiefs.github.io/dl_course_2022/prerequistites.html

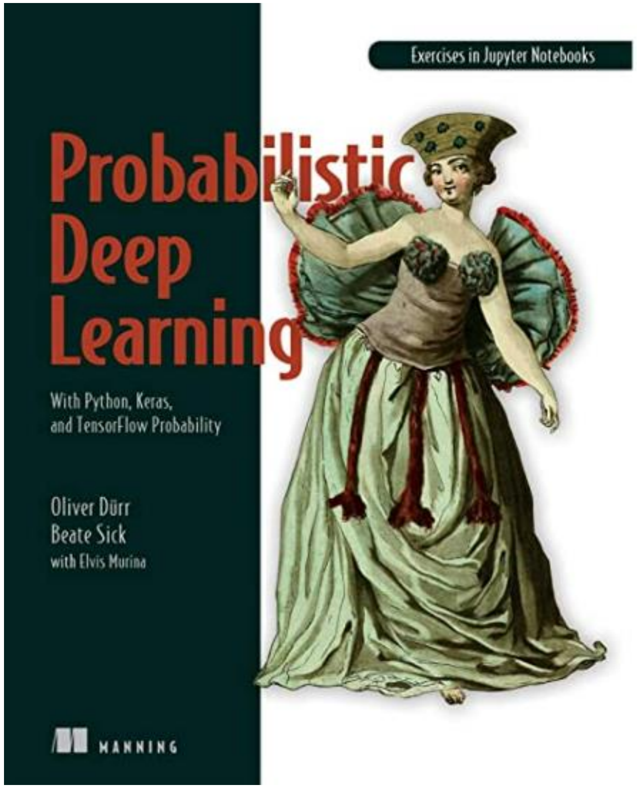
- Any contacts with deep learning yet?

Technical details for this course

- Running the code:
  - Colab Notebooks
    - needs no installation, only internet and google account
  - Anaconda
    - Installation by your own

Material for the course

- Website and Github repository
  - The CAS Deep Learning Course
    - https://tensorchiefs.github.io/dl_course_2022/
- Our Book "Probabilistic Deep Learning"
  - Can be used in addition to the course
  - https://www.manning.com/books/probabilistic-deep-learning-with-python?a_aid=probabilistic_deep_learning&a_bid=78e55885
  - https://github.com/tensorchiefs/dl_book



Organizational Issues: ~~Test~~ Projects

- Projects (2-3 People)

- Presented on the last day
  - Spotlight talk (5 Minutes)
  - Poster
- Topics
  - You can / should choose a topic of your own (please discuss your topic with us by week4 latest)

  - Possible Topics (see website)
    - Take part in a Kaggle Competition (e.g. Leaf Classification / Dogs vs. Cats)
    - Music classification
    - Polar bear detection
    - ...

- Computing: colab, laptop (or cloud computing)

Organizational Issues: Times

- Dates and times: see our webpage

- Afternoon sessions
  - 13:30-17:00

- Theory and exercises will be mixed
  - Could be 50 minutes theory 30 minutes exercises
  - Could be vice versa

- **Please interrupt us if something is unclear! The less we talk the better!**

Outline of the DL Module (tentative)

- Day 1: Jumpstart to DL
  - What is DL
  - Basic Building Blocks
  - Keras
- Day 2: CNN I
  - ImageData
- Day 3: CNN II and RNN
  - Tips and Tricks
  - Modern Architectures
  - 1-D Sequential Data
- Day 4: Looking at details
  - Linear Regression
  - Backpropagation
    - Resnet
  - Likelihood principle
- Day 5: Probabilistic Aspects
  - TensorFlow Probability (TFP)
  - Negative Loss Likelihood NLL
  - Count Data
- Day 6: Probabilistic models in the wild
  - Complex Distributions
  - Generative modes with normalizing flows
- Day 7: Uncertainty in DL
  - Bayesian Modeling
- Day 8: Uncertainty cont'd
  - Bayesian Neural Networks
  - Projects

Day 1-4 should get you ready for your project.

Learning Objectives for today

- Get a rough idea what the DL is about
- Get a first idea on patterns in NN / DL
  - Flow of tensors
    - Matrix and Tensor operations
  - Backpropagation
    - To fit the weights of a network efficiently
- Framework
  - Introduction to Keras

Introduction to Deep Learning
--what's the hype about?

Machine Perception

- Computers have been quite bad in things which are easy for humans (images, text, sound)
- A Kaggle contest 2012
- In the following we explain why

[Kaggle dog vs cat competition]

Deep Blue beat Kasparov at chess in 1997.
Watson beat the brightest trivia minds at Jeopardy in 2011.
Can you tell Fido from Mittens in 2013?

Deep Learning vs. Machine Learning

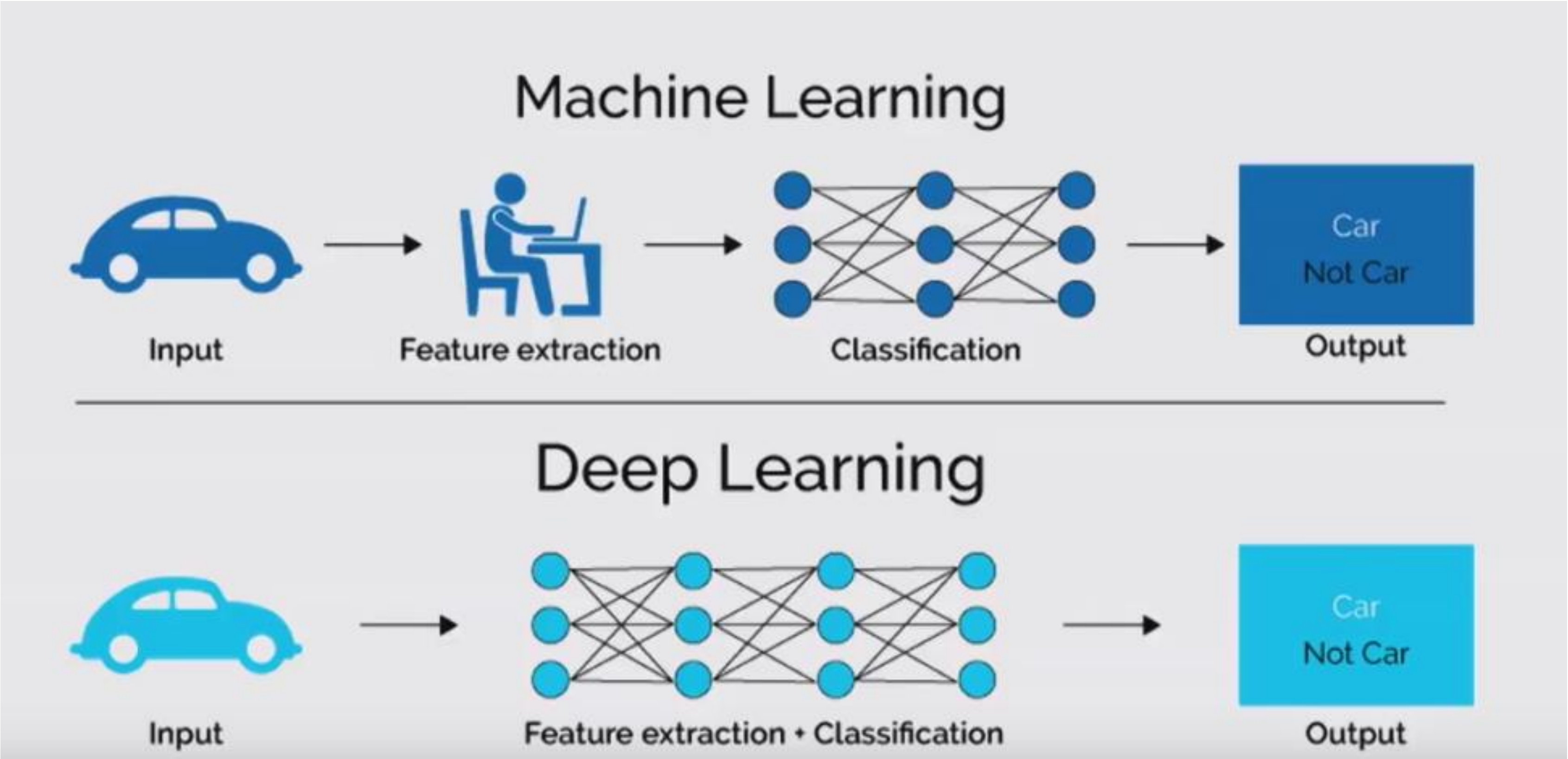
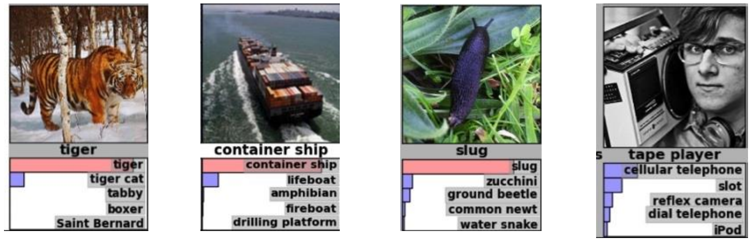


image credit: [Siraj Raval]

The most convincing case for DL (subjective view)

Why DL: Imagenet 2012, 2013, 2014, 2015

1000 classes
1 Mio samples



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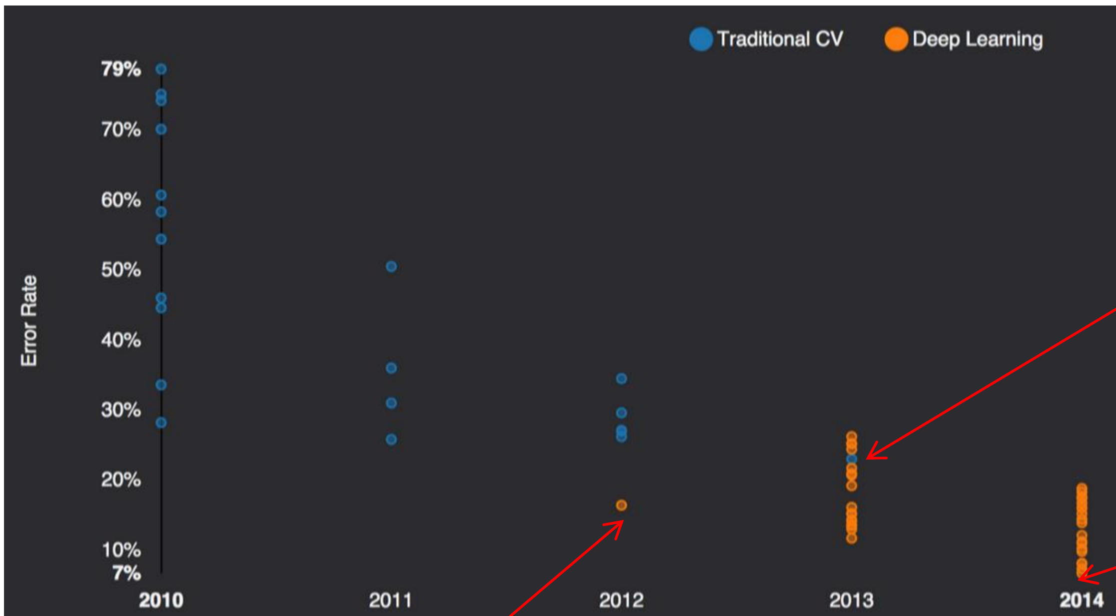


Human: 5% misclassification

Only one non-CNN approach in 2013

GoogLeNet 6.7%

A. Krizhevsky
first CNN in 2012
Und es hat zoom gemacht

2015: It gets tougher

4.95% Microsoft (Feb 6 surpassing human performance 5.1%)
4.8% Google (Feb 11) -> further improved to 3.6 (Dec)?
4.58% Baidu (May 11 banned due too many submissions)
3.57% Microsoft (Resnet winner 2015) → task solved!

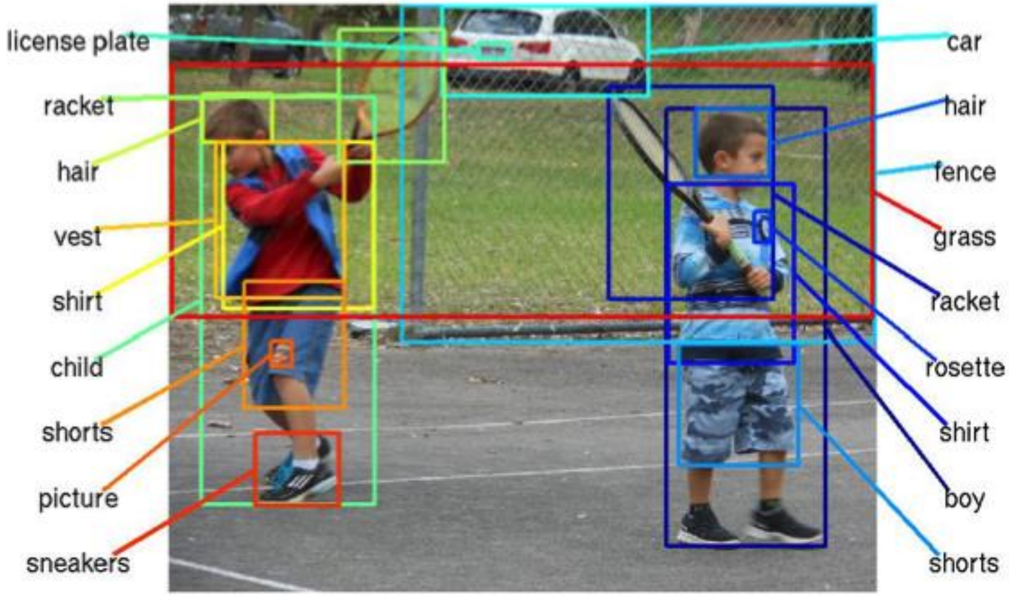
Figure: https://medium.com/global-silicon-valley/machine-learning-yesterday-today-tomorrow-3d3023c7b519

15

The computer vision success story

- With DL it took approx. 3 years to solve object detection and other computer vision task

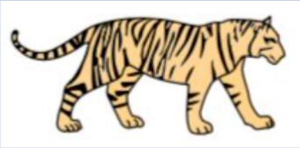
Deep Blue beat Kasparov at chess in 1997.
Watson beat the brightest trivia minds at Jeopardy in 2011.
Can you tell Fido from Mittens in 2013?



"man in black shirt is playing guitar."

Images form cs229n

Use cases of deep learning

Input x to DL model	Output y of DL model	Application
Images 	Label “Tiger”	Image classification
Audio 	Sequence / Text “see you tomorrow”	Voice Recognition
Sequence (prompt) An astronaut riding a horse in a photorealistic style		Image Generation
Sequences (prompt) “Hallo, wie?”	Next word “geht”	Language Models
Simple number (age) age=52	Simple number (SPB) sbp = 152	Simple Regression Educational

Deep Learning öffnet Tür zu hören, sehen und Texten.
Status Quo: kein Verstehen aber Erfassung statistische Zusammenhänge.

This is the new shit: ChatGPT

Die gefühlte Revolution

4. Dezember 2022, 18:51 Uhr | Lesezeit: 3 min

Das kommt heraus, wenn man der künstlichen Intelligenz Dall-E die Anweisung gibt: "Ein Roboter lässt beim Turing-Test einen Menschen glauben, dass sie ein Mensch ist, im Stil von Kehinde Wiley." (Foto: Dall-E-Bild: SZ)

Marilyn Manson - This Is The New Shit (Official Music Video)

GPT (short for "**Generative Pre-training Transformer**")

is a type of language processing AI model developed by OpenAI. It is a large, deep learning model that has been trained on a diverse range of texts and can generate human-like text when given a prompt.

https://www.slideshare.net/SilentShikari/what-is-chat-gpt

Deep learning
Artificial Intelligence?

All the impressive achievements of deep learning amount to just curve fitting

Juda Pearl, 2018

Pearl's ladder of causality

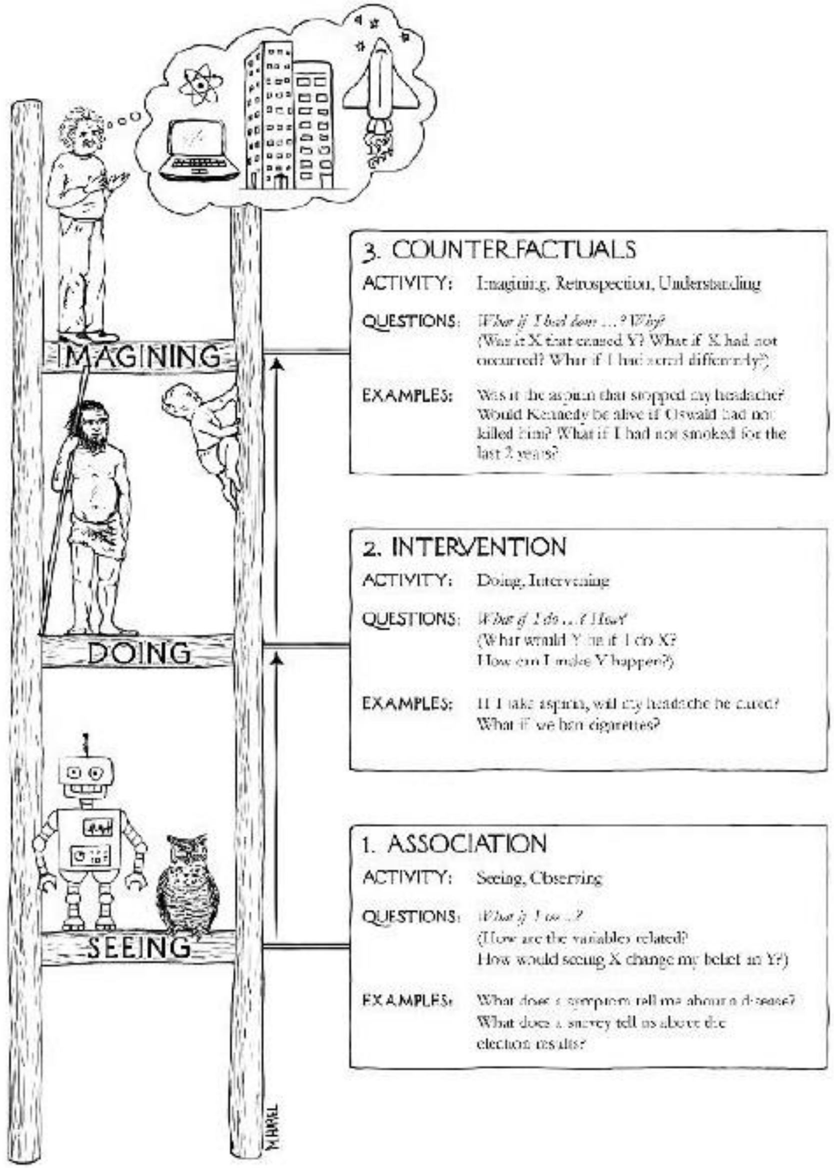
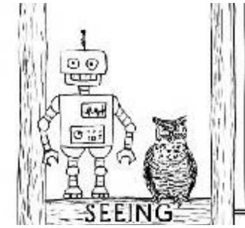


FIGURE 1.2. The Ladder of Causation, with representative organisms at each level. Most animals, as well as present-day learning machines, are on the first

Image credits: "The Book of Why"

On the first rung of the ladder
DL is currently as good as a ensemble of pigeons ;-)



https://www.youtube.com/watch?v=NsV6S8EsC0E

PLOS | ONE

RESEARCH ARTICLE

Pigeons (*Columba livia*) as Trainable Observers of Pathology and Radiology Breast Cancer Images

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OPEN ACCESS

Citation: Levenson RM, Krupinski EA, Navarro VM, Wasserman EA (2015) Pigeons (*Columba livia*) as Trainable Observers of Pathology and Radiology Breast Cancer Images. PLoS ONE 10(11): e0141357. doi:10.1371/journal.pone.0141357

Editor: Jonathan A Coles, Glasgow University, UNITED KINGDOM

Received: August 25, 2015

Accepted: October 7, 2015

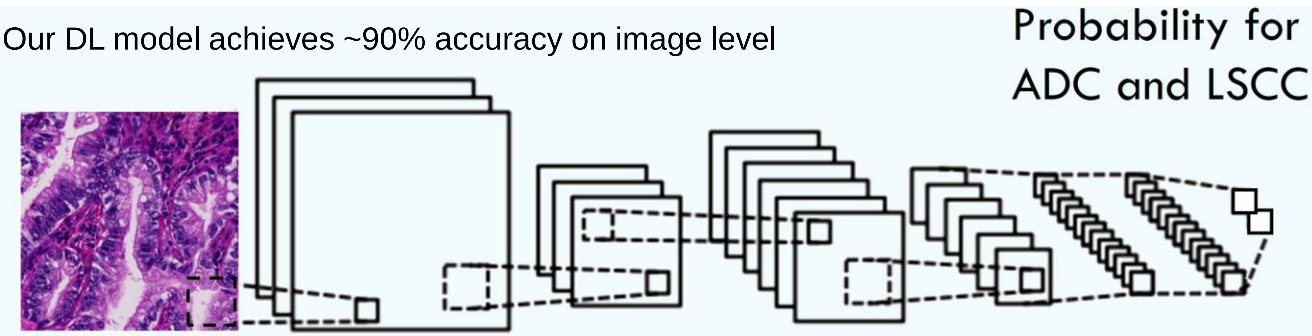
Published: November 18, 2015

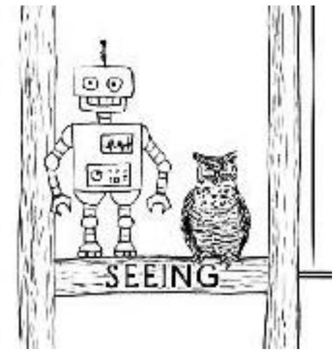
Abstract

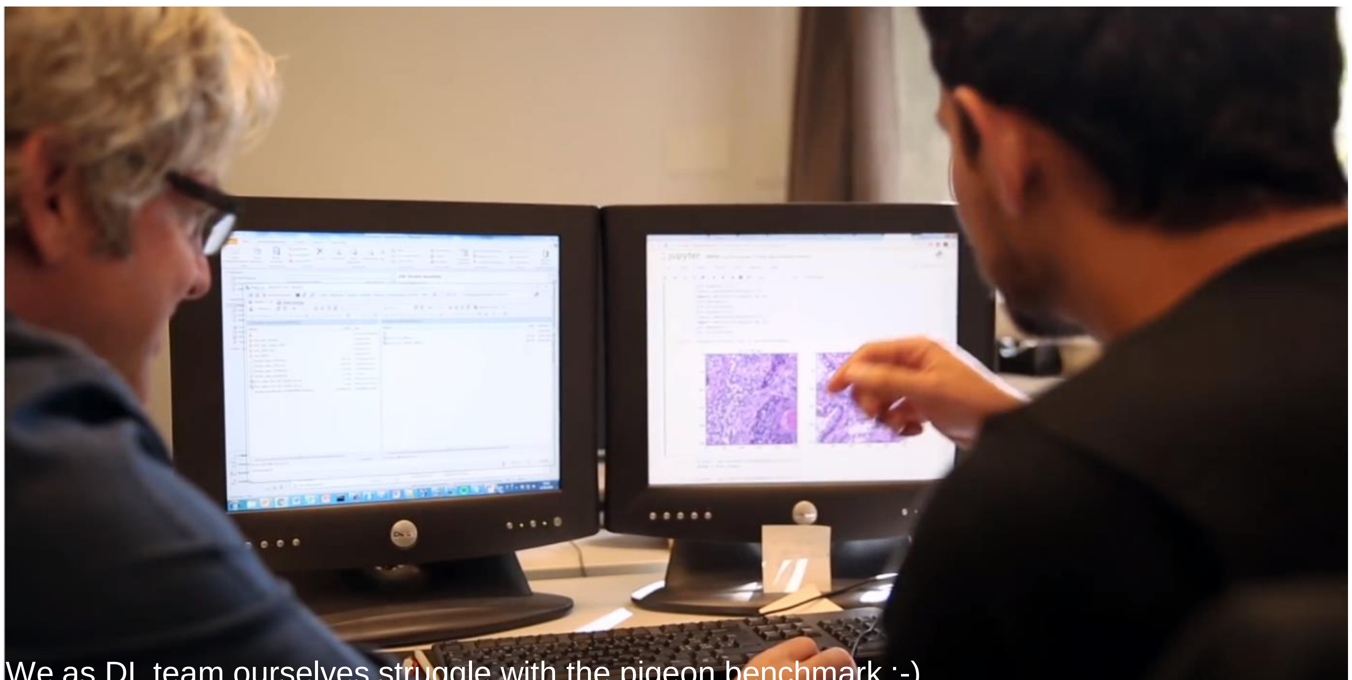
Pathologists and radiologists spend years acquiring and refining their medically essential visual skills, so it is of considerable interest to understand how this process actually unfolds and what image features and properties are critical for accurate diagnostic performance. Key insights into human behavioral tasks can often be obtained by using appropriate animal models. We report here that pigeons (*Columba livia*)—which share many visual system properties with humans—can serve as promising surrogate observers of medical images, a capability not previously documented. The birds proved to have a remarkable ability to distinguish benign from malignant human breast histopathology after training with differential food reinforcement; even more importantly, the pigeons were able to generalize what they had learned when confronted with novel image sets. The birds' histological accuracy, like that of humans, was modestly affected by the presence or absence of color as well as by degrees of image compression, but these impacts could be ameliorated with further training. Turning to radiology, the birds proved to be similarly capable of detecting cancer-relevant microcalcifications on mammogram images. However, when given a different (and for humans quite difficult) task—namely, classification of suspicious mammographic densities (masses)—the pigeons proved to be capable only of image memorization and were unable

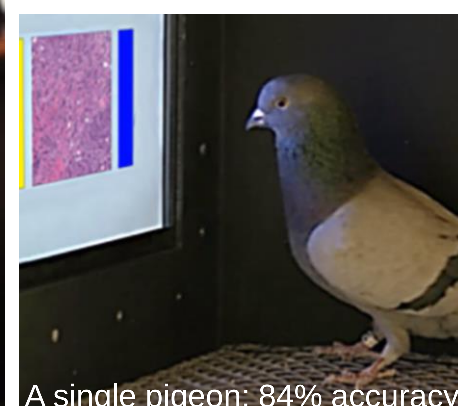
On the first rung of the ladder
DL is currently as good as an ensemble of pigeons

Our DL model achieves ~90% accuracy on image level






We as DL team ourselves struggle with the pigeon benchmark ;-)


A single pigeon: 84% accuracy

First Neural Network

The Single Cell: Biological Motivation

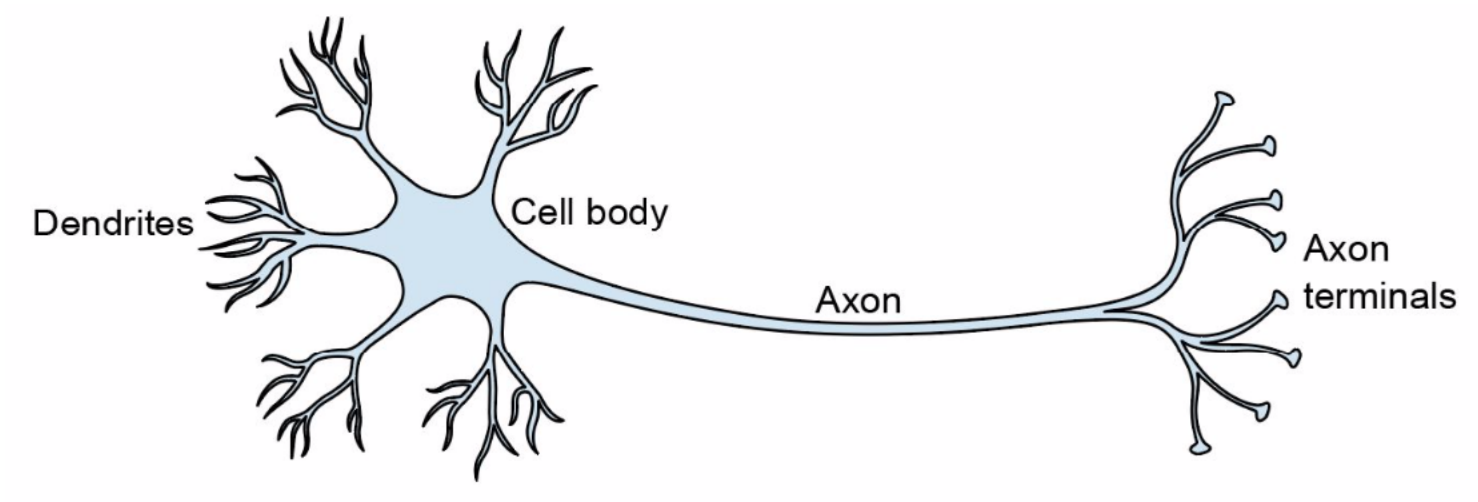
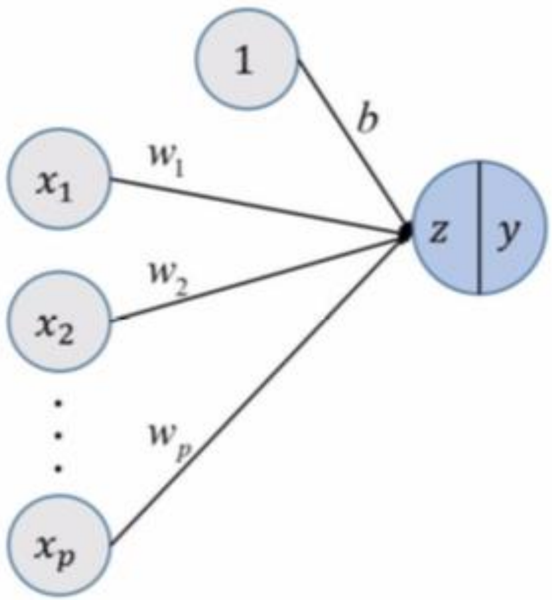


Figure 2.2 A single biological brain cell. The neuron receives the signal from other neurons via its dendrites shown on the left. If the cumulated signal exceeds a certain value, an impulse is sent via the axon to the axon terminals, which, in turn, couples to other neurons.

Neural networks are **loosely** inspired by how the brain works

The Single Cell: Mathematical Abstraction



$$z = b + x_1 \cdot w_1 + x_2 \cdot w_2 + \cdots x_p \cdot w_p$$

$$z = b + \sum x_i \cdot w_i = b + \boldsymbol{x} \cdot \boldsymbol{w}$$

Activation (many possibilities)

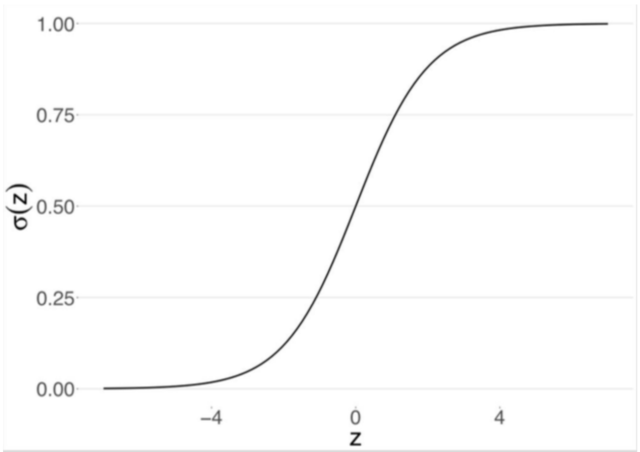


Figure 2.3 The mathematical abstraction of a brain cell (an artificial neuron). The value *z* is computed as the weighted sum of the *p* input values, *x*1 to *xp*, and a bias term *b* that shifts up or down the resulting weighted sum of the inputs. The value *y* is computed from *z* by applying an activation function.

```
# definition of the sigmoid function
def sigmoid(z):
    return (1 / (1 + np.exp(-z)))
```

Toy Task

- Task tell fake from real banknotes
- Banknotes described by two features

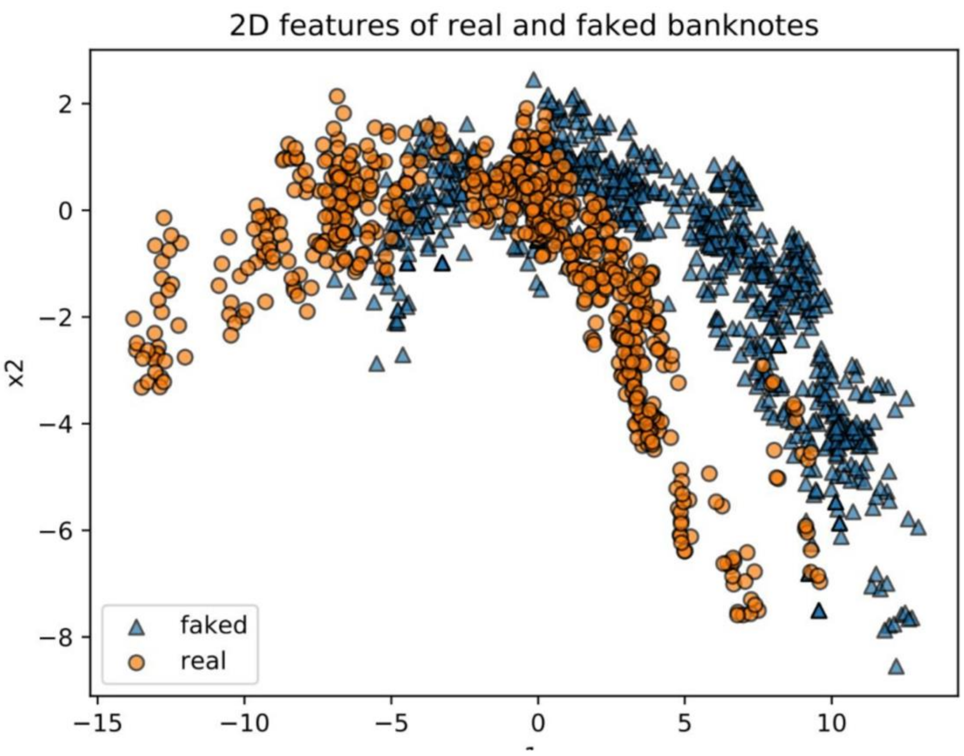
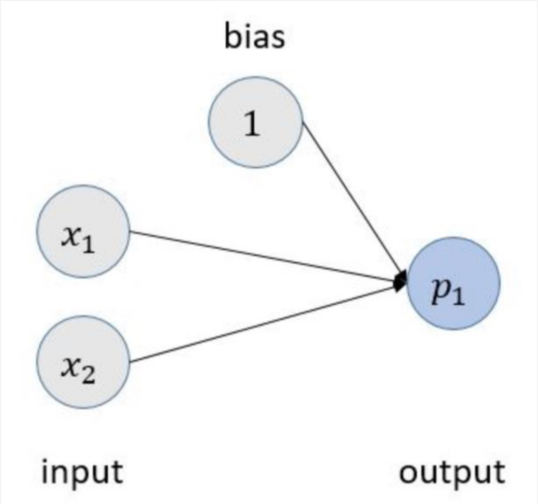
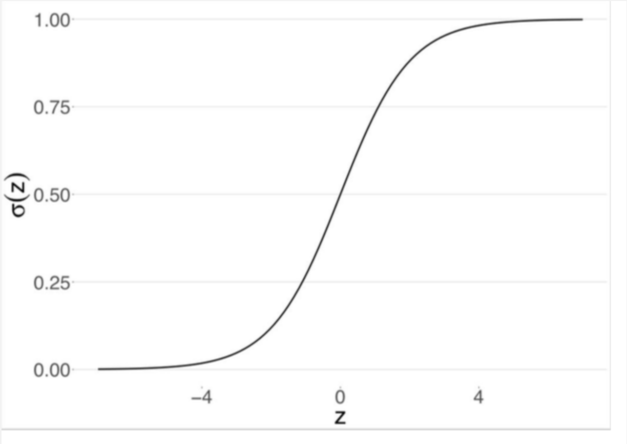


Figure 2.5 The (training) data points for the real and faked banknotes

https://github.com/tensorchiefs/dl_book/blob/master/chapter_02/nb_ch02_01.ipynb

Exercise: Part 1





Model: The above network models the **probability** p_1 that a given banknote is false.

TASK (with pen and paper)
The weights (determined by a training procedure later) are given by

$$w_1 = 0.3, w_2 = 0.1, \text{ and } b = 1.0$$

The probability can be calculated from z using the function sigmoid(z)

What is the probability that a banknote, that is characterized by x_1=1 and $x_2 = 2.2$, is a faked banknote?

GPUs love Vectors

$F^{\mu\nu}$

In Math:

$$p_1 = \text{sigmoid}\left(\begin{pmatrix} x_1 & x_2 \end{pmatrix} \cdot \begin{pmatrix} w_1 \\ w_2 \end{pmatrix} + b \right)$$

In code:

```
## function to return the probability output after the matrix multiplication
def predict_no_hidden(X):
    return sigmoid(np.matmul(X,W)+b)
```

Recap: Matrix Multiplication aka dot-product of matrices

We can only multiply matrices if their dimensions are compatible.

$$\mathbf{A} \times \mathbf{B} = \mathbf{C}$$
$$(m \times n) \times (n \times p) = (m \times p)$$

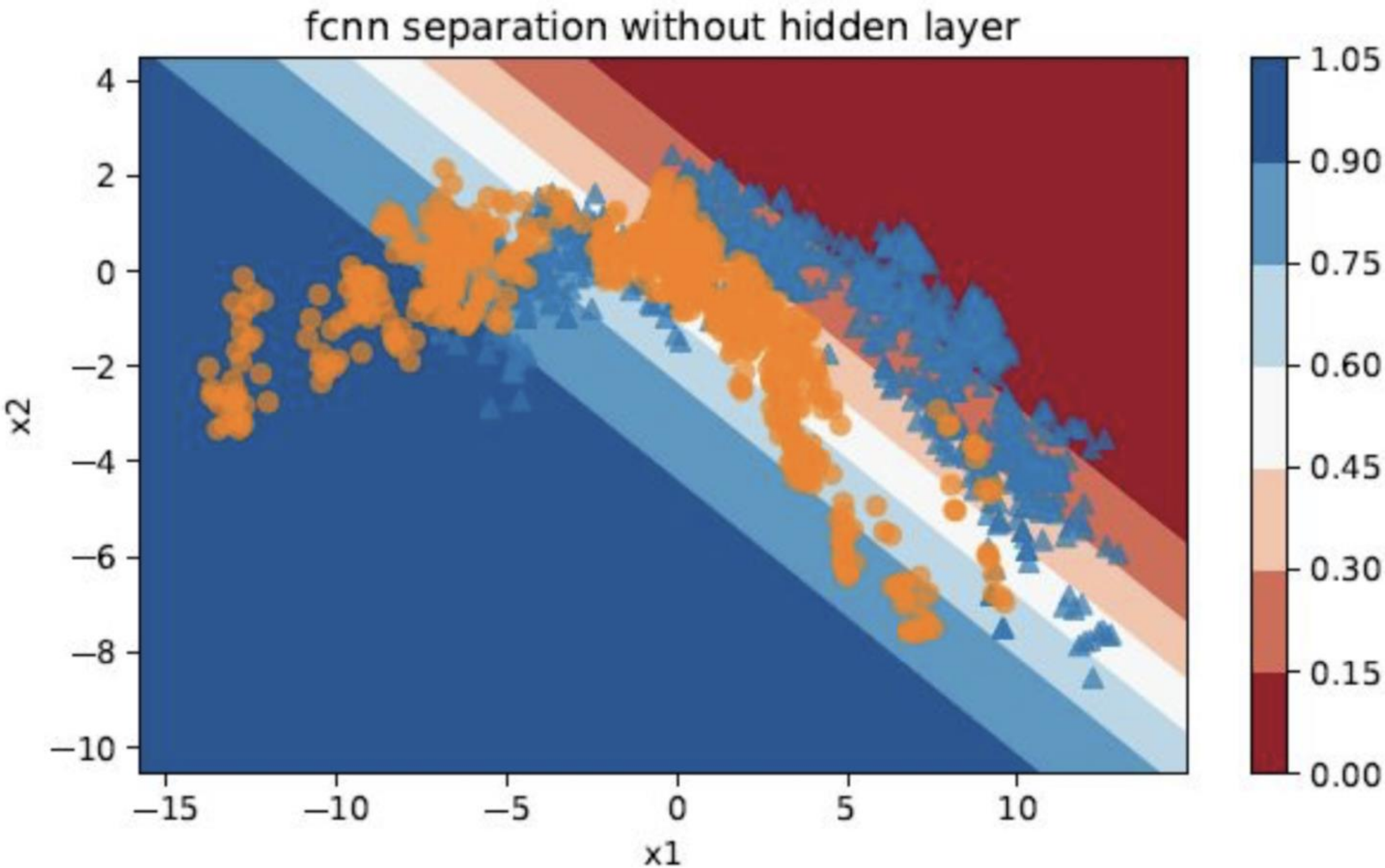
$$\underset{\mathbf{A}_{3x3}}{\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}} x \underset{\mathbf{B}_{3x2}}{\begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \\ b_{31} & b_{32} \end{bmatrix}} = \underset{\mathbf{C}_{3x2}}{\begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \\ \boxed{c_{31}} & c_{32} \end{bmatrix}}$$

$$c_{11} = a_{11}b_{11} + a_{12}b_{21} + a_{13}b_{31}$$
$$c_{12} = a_{11}b_{12} + a_{12}b_{22} + a_{13}b_{32}$$
$$c_{21} = a_{21}b_{11} + a_{22}b_{21} + a_{23}b_{31}$$
$$c_{22} = a_{21}b_{12} + a_{22}b_{22} + a_{23}b_{32}$$
$$\boxed{c_{31} = a_{31}b_{11} + a_{32}b_{21} + a_{33}b_{31}}$$
$$c_{32} = a_{31}b_{12} + a_{32}b_{22} + a_{33}b_{32}$$

Example:

$$\mathbf{A}_{2x2} = \begin{pmatrix} 2 & 1 \\ 0 & 3 \end{pmatrix} \qquad \mathbf{B}_{2x3} = \begin{pmatrix} 3 & 1 & 7 \\ 8 & 2 & 4 \end{pmatrix} \qquad \mathbf{C}_{2x3} = \mathbf{A}_{2x2} \cdot \mathbf{B}_{2x3} = \begin{pmatrix} 11 & 4 & 18 \\ 24 & 6 & 12 \end{pmatrix}$$

Result (see later in the notebook)



General rule: Networks without hidden layer have linear decision boundary.

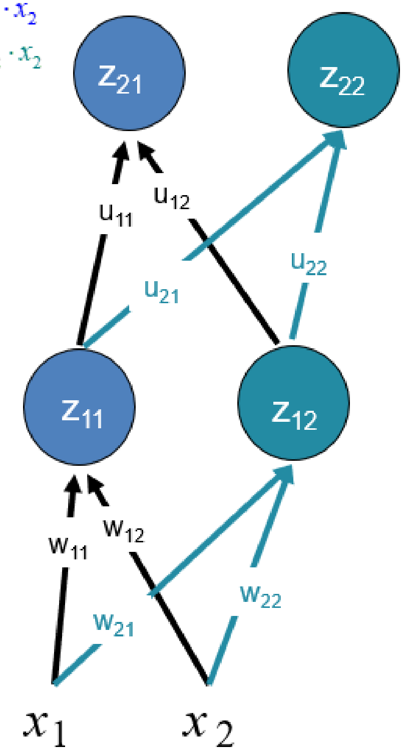
To go deep non-linear activation functions are needed

2 linear layers can be replaced by 1 linear layer -> can't go deep with linear layers!

$$z = (x \cdot W) \cdot U = x \cdot (W \cdot U) = x \cdot V$$

$$z_{21} = z_{11} \cdot u_{11} + z_{12} \cdot u_{12} = (w_{11} \cdot x_1 + w_{12} \cdot x_2) \cdot u_{11} + (w_{21} \cdot x_1 + w_{22} \cdot x_2) \cdot u_{12}$$
$$= x_1 \cdot (w_{11} \cdot u_{11} + w_{21} \cdot u_{12}) + x_2 \cdot (w_{12} \cdot u_{11} + w_{22} \cdot u_{12})$$

$$z_{11} = w_{11} \cdot x_1 + w_{12} \cdot x_2$$
$$z_{12} = w_{21} \cdot x_1 + w_{22} \cdot x_2$$



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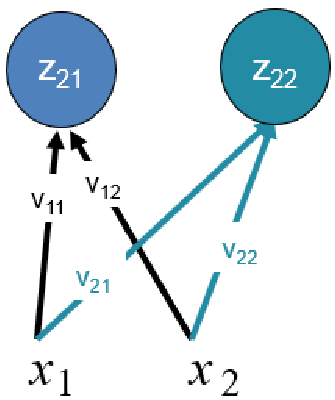
$$z_{21} = v_{11} \cdot x_1 + v_{12} \cdot x_2$$

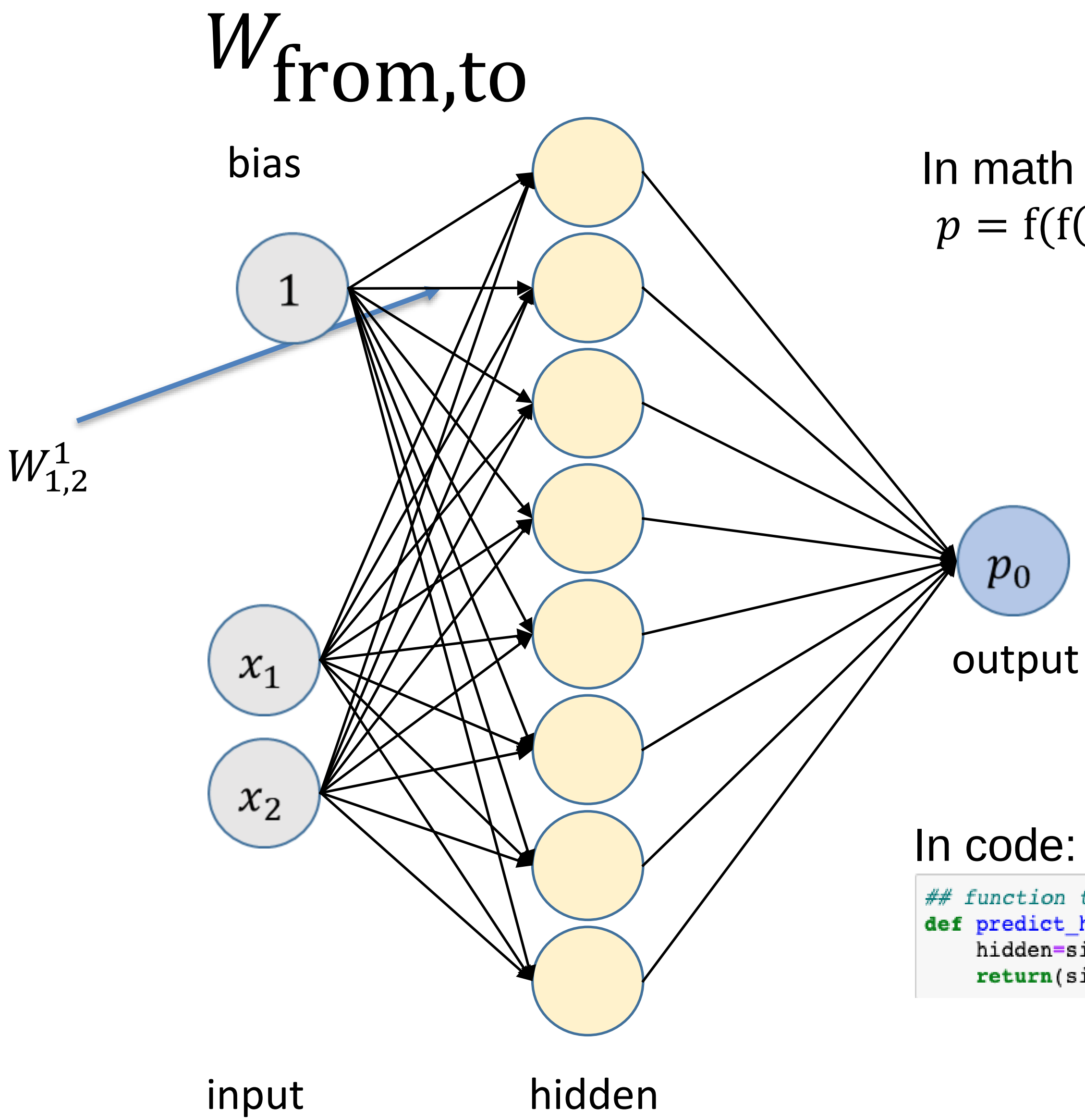


$$v_{11} = w_{11} \cdot u_{11} + w_{21} \cdot u_{12}$$
$$v_{12} = w_{12} \cdot u_{11} + w_{22} \cdot u_{12}$$
$$v_{21} = w_{11} \cdot u_{21} + w_{21} \cdot u_{22}$$
$$v_{22} = w_{12} \cdot u_{21} + w_{22} \cdot u_{22}$$

Remark: biases are ignored here, but do not change fact


WE NEED TO GO
DEEPER
memegene

A first deep network



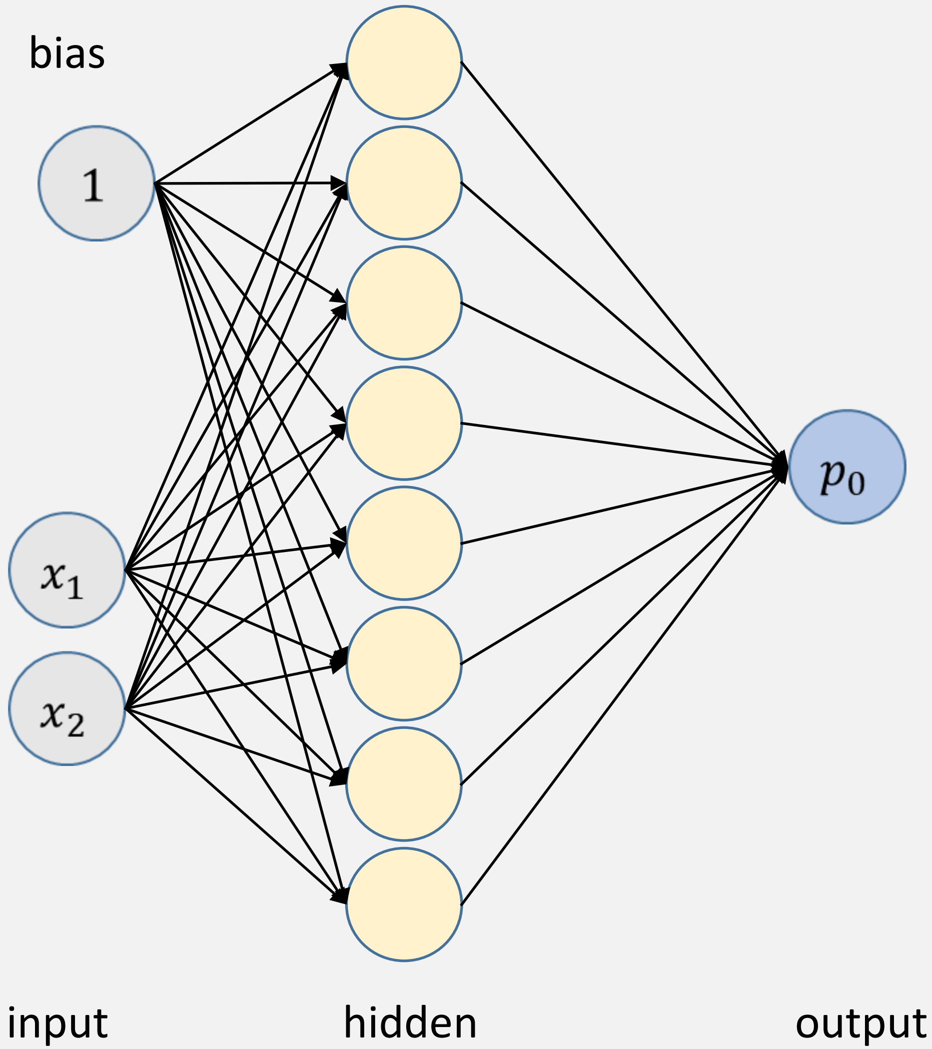
In math (f = sigmoid)

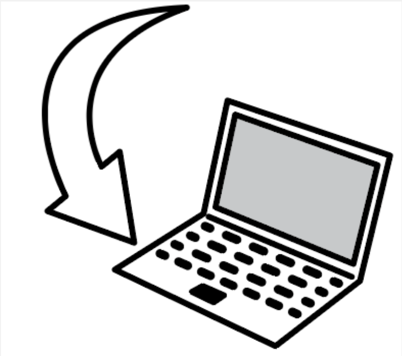
$p = \mathrm{f}(\mathrm{f}(X \cdot W_1 + b_1) \cdot W_2 + b_2)$

In code:

```python
## function to return the probability output after the hidden layer
def predict_hidden(X):
    hidden=sigmoid(np.matmul(X,W1)+b1)
    return(sigmoid(np.matmul(hidden,W2)+b2))
```

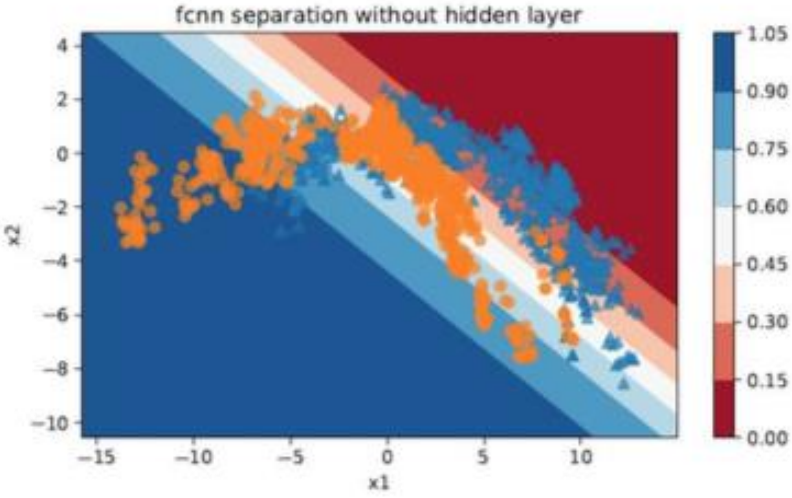
Exercise:

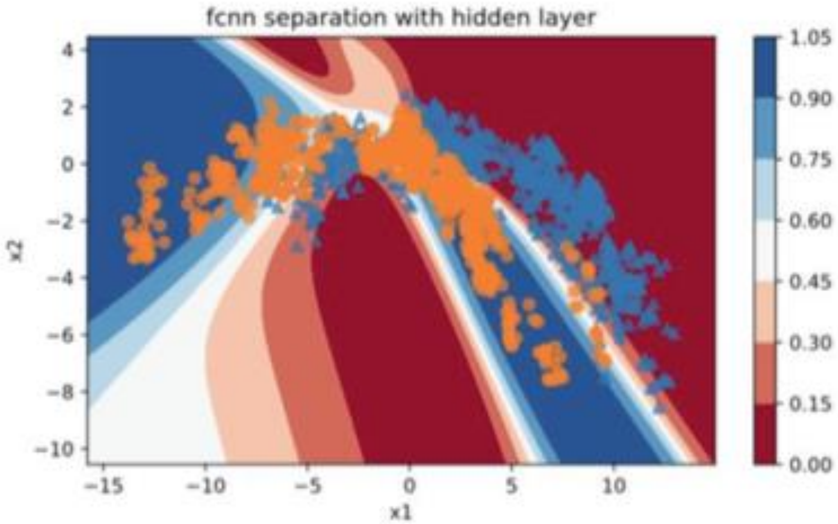




Open NB 01_simple_forward_pass.ipynb and do exercise stop before Keras

Observations from NB: The benefit of hidden layers

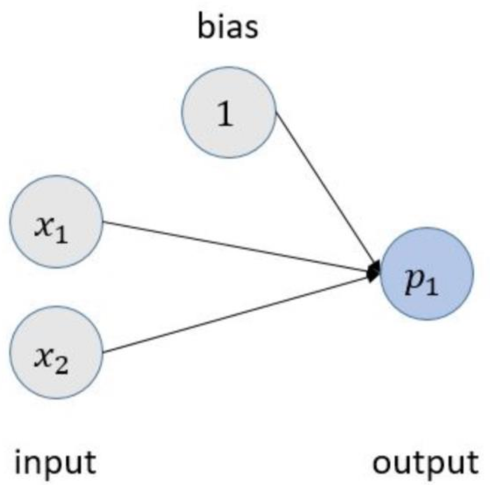


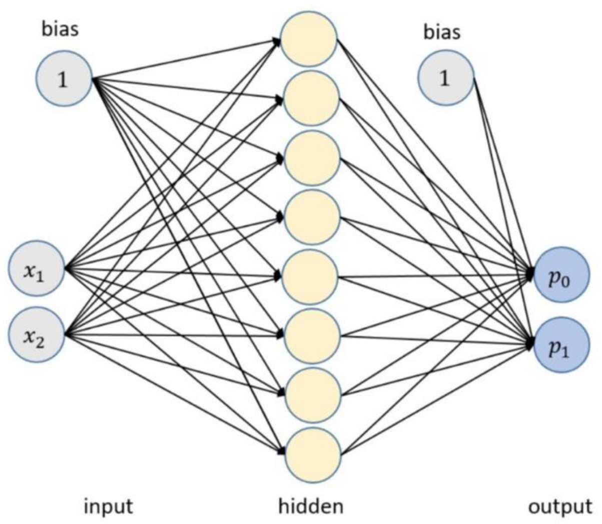


Training NN

How to determine the weights

- The output of a NN is defined by the weights and biases
- These weights and biases are tuned so that the NN bests fits the training data
- The goodness of fit to the training data is quantified by a loss





Loss Functions

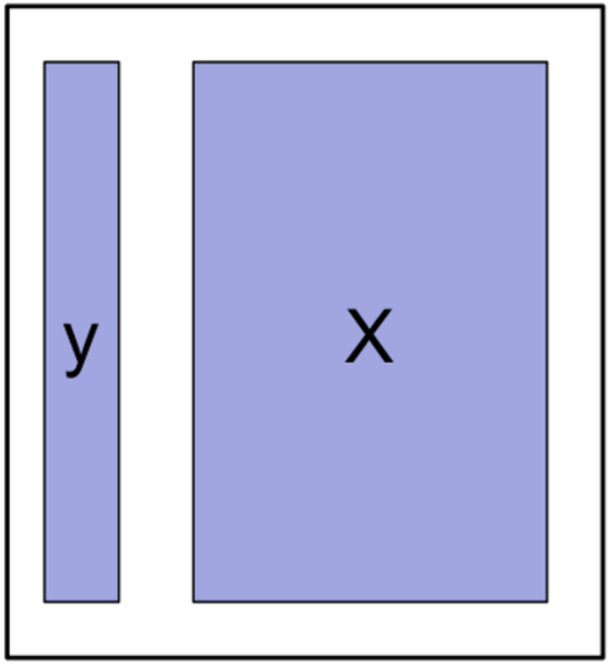
Tasks in DL

- The loss function depends on the task

- 2 Main tasks in DL predict y given x

  - Regression
    - Predict a number*

  - Classification
    - Predict a class*



Supervised Learning

*Later we refine this notion and predict probability distribution instead single numbers

Example Regression: Estimate Age From Picture

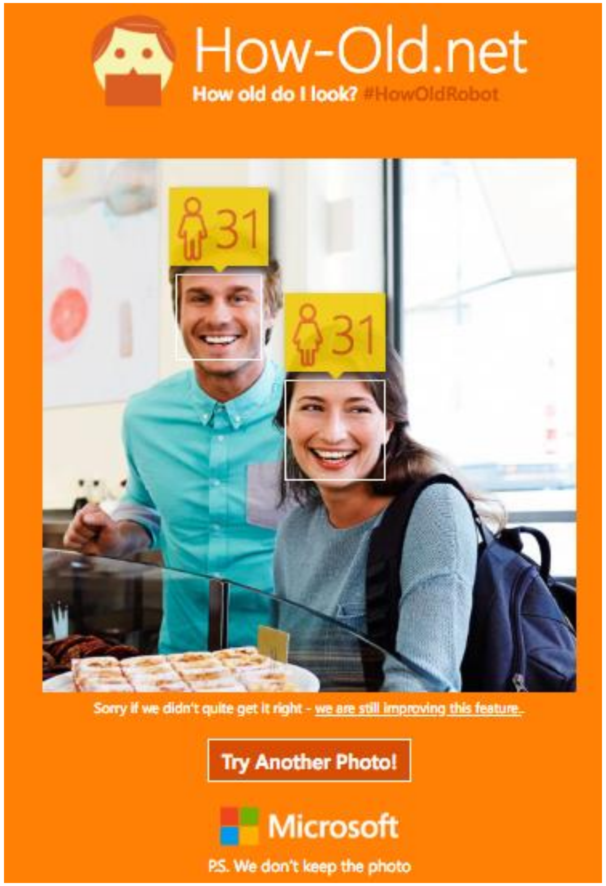
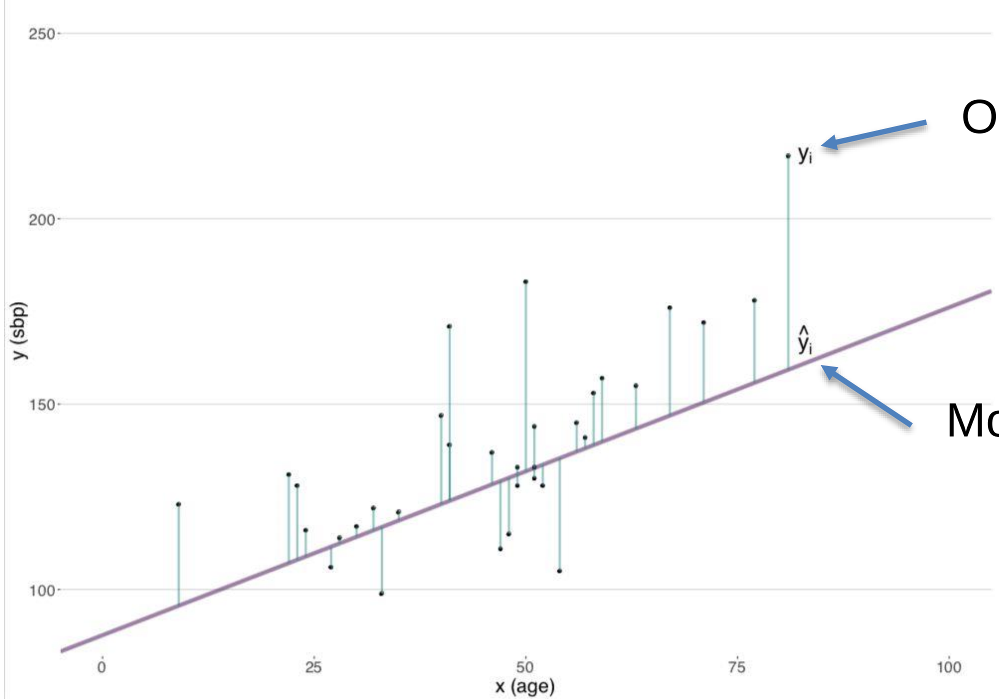


Image --> Age

https://www.how-old.net/

Loss Functions for Regression Problems

- Regression = Predict a number
- Example (Linear Regression)
  - Blood pressure of 31 women vs. age (training data)



Observed value

Model prediction

Loss: Mean Squared Error (MSE) $\frac{1}{N}\sum_i (y_i - \hat{y}_i)^2$ also for regression problems (not only linear regression)

Classification

- Predict class
- Usually in DL the model predicts a probability for a class
- Example:
  - Banknote from exercise
  - Typical example Number from hand-written digit

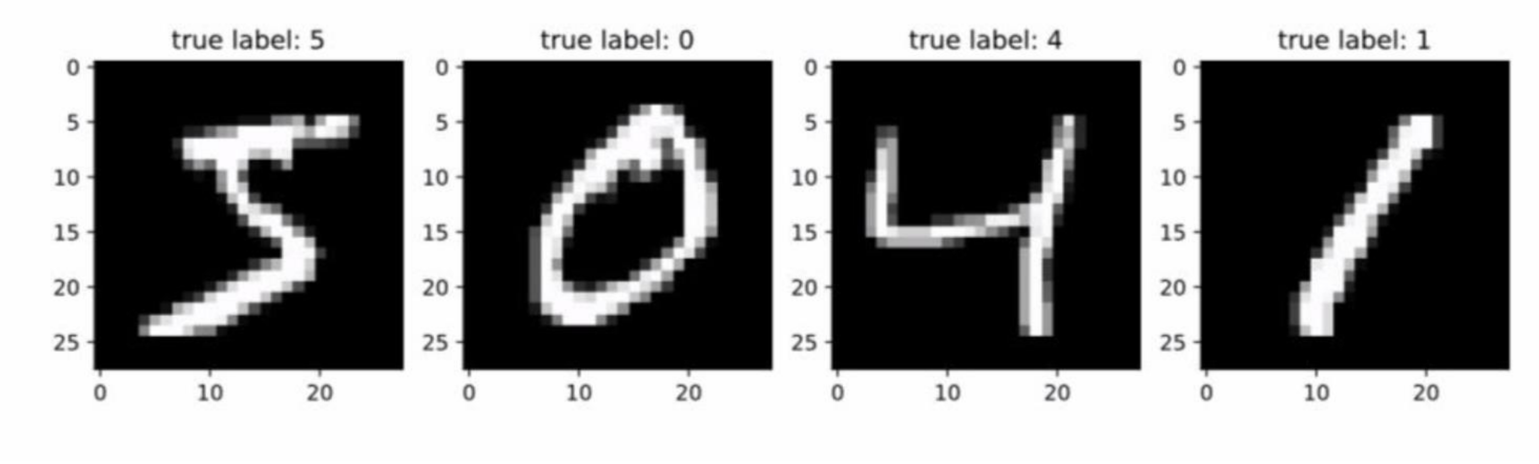


Figure 2.11 The first four digits of the MNIST data set—the standard data set used for benchmarking NN for images classification

Classification: Softmax Activation

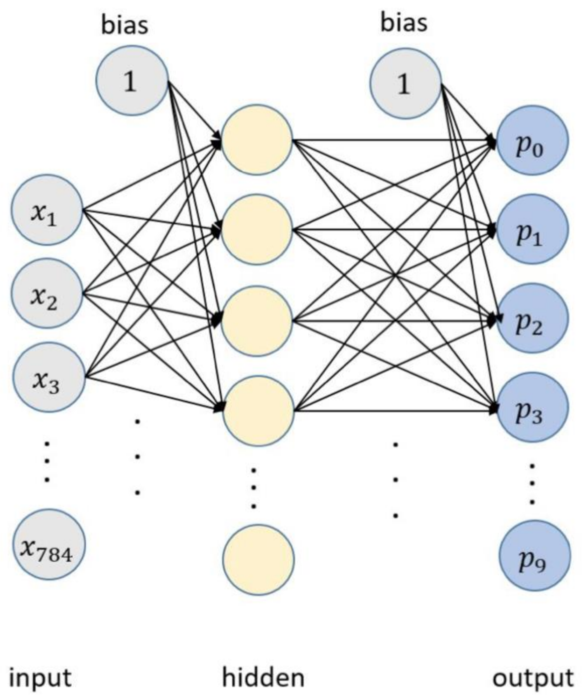


Figure 2.12: A fully connected NN with 2 hidden layers. For the MNIST example, the input layer has 784 values for the 28 x 28 pixels and the output layer out of 10 nodes for the 10 classes.

$p_o, p_1 \ldots p_9$ are probabilities for the classes 0 to 9.

Activation of last layer z_i incomming

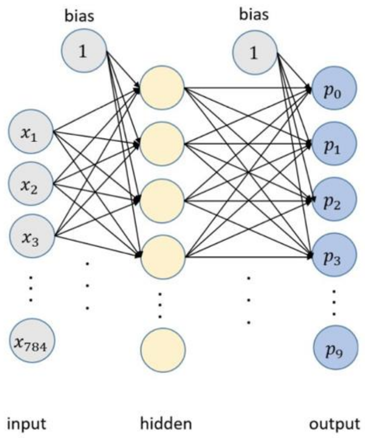
$$p_i = \frac{e^{z_i}}{\sum_{j=0}^{9} e^{z_j}}$$

Makes outcome positive

Ensures that pi's sum up to one

This activation is called softmax

Loss for classification ('categorical cross-entropy')



$p_o, p_1 \ldots p_9$ are probabilities for the classes 0 to 9.

- Loss is averaged of individual losses l_i of training data $\mathrm{i} = 1, \ldots N$
- Want l_i
  - 0 for perfect match, i.e. predicts class of training example $y^{(i)}$ with probability 1
  - ∞ for worst match, i.e. predicts class $y^{(i)}$ with probability 0

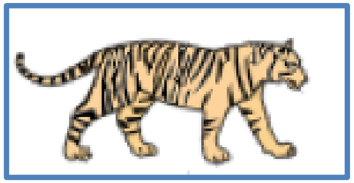
  - $l_i = -\log\left(p_{model}\left(y^{(i)} \middle| x^{(i)}\right)\right)$
  - loss = $\frac{1}{N}\sum l_i$

Training / Gradient Descent

Prinzipielle Funktionsweise: Training Bild Klassifikation

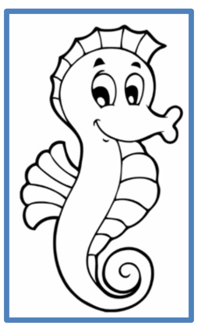
Wahre Klasse

Vorhergesagtes Label

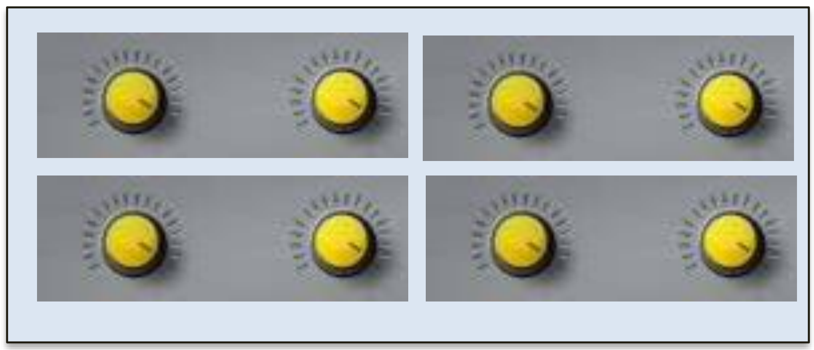


Tiger → Seehund

Tiger → Tiger



Seepferd → Seepferd



...

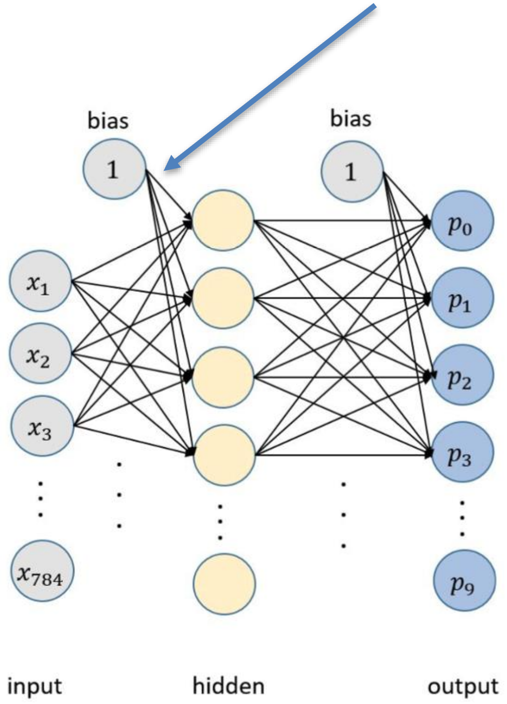
Typisch 1 Mio. Trainingsdaten

Trainingsprinzip:
Parameter werden so eingestellt, dass möglichst wenige Fehler in den Trainingsdaten gemacht werden.

Optimization in DL

- DL many parameters
  - Optimization by gradient descent
- Algorithm
  - Take a batch of training examples
  - Calculate the loss of that batch
  - Tune the parameters so that loss gets minimized

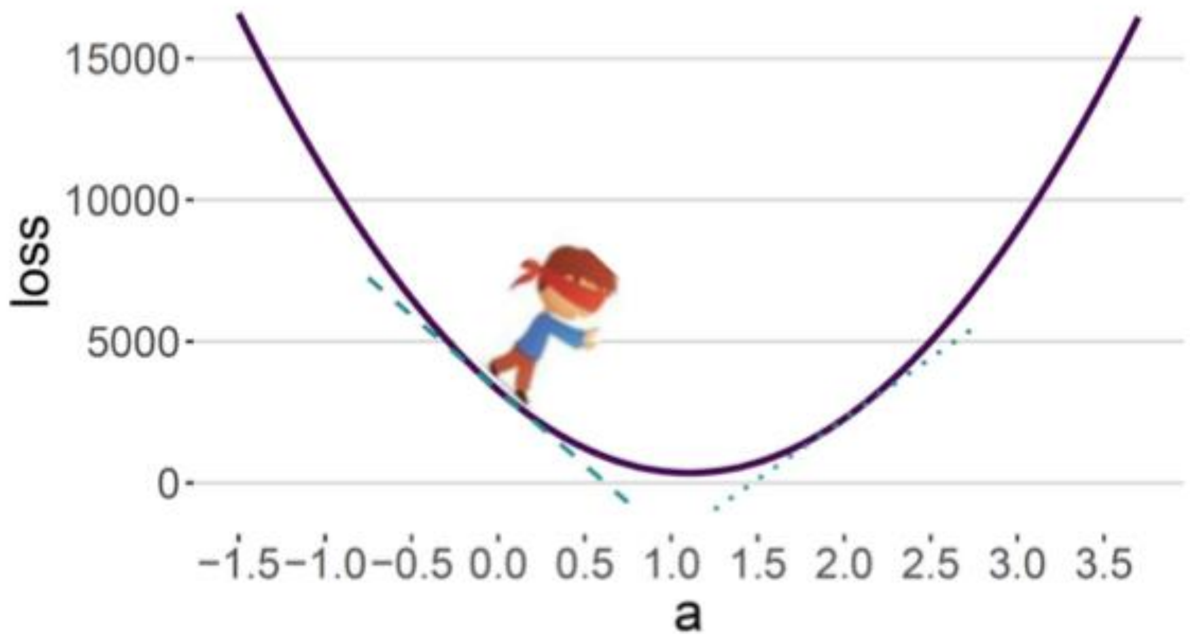
Parameters of the network are the weights.



Modern Networks have Billions (10^9) of weights. Record 2020 1.5E9 https://openai.com/blog/better-language-models/

Idea of gradient descent

- Shown loss function for a single parameter *a*



- Take a large step if slope is steep (you are away from minimum)
- Slope of loss function is given by gradient
- Iterative update of the parameters
  - $a_{t+1} = a_t - \eta \cdot \text{grad\_}a(\text{loss})$

Backpropagation

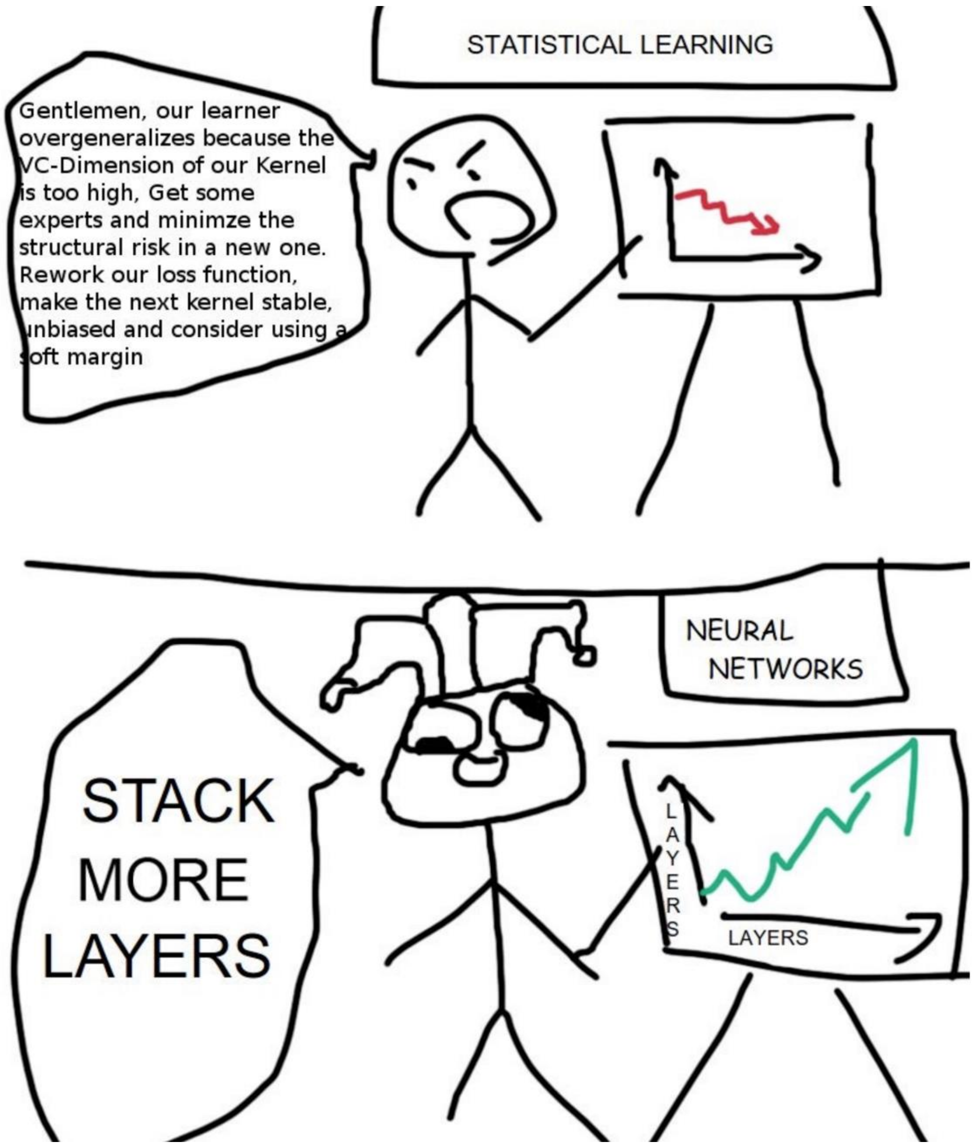
- There is an efficient way to update all parameters of the network
- This is called Backpropagation (see lecture 4)

- We need to calculate the derivative of the loss function w.r.t. all weights

- Doing this efficiently (on graphic cards GPU) by hand is tedious

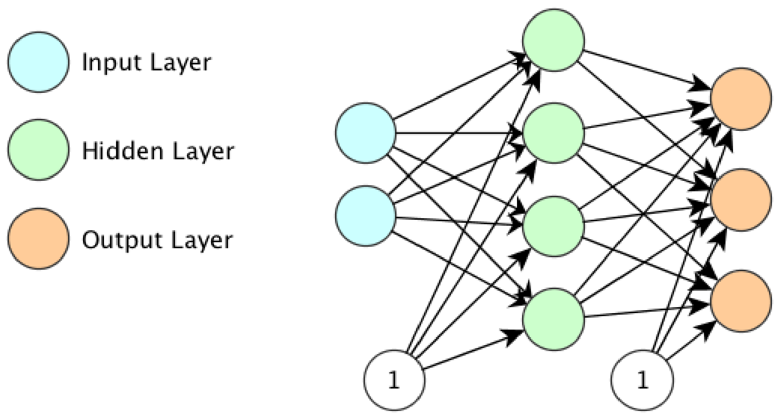
- Enter:
  - Deep Learning Frameworks

DL vs Machine Learning Meme

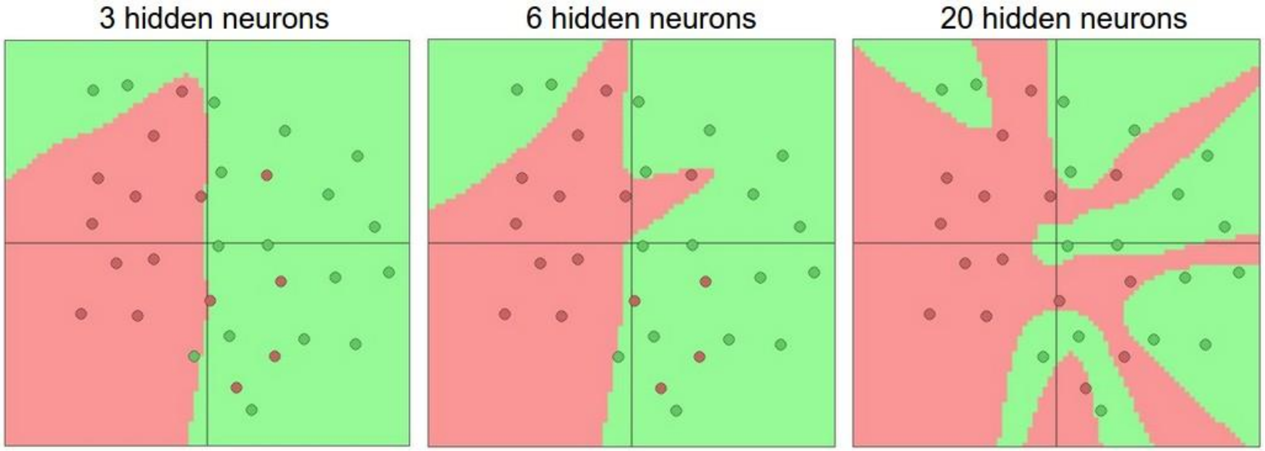


https://www.reddit.com/r/ProgrammerHumor/comments/8c1i45/stack_more_layers/

One hidden Layer

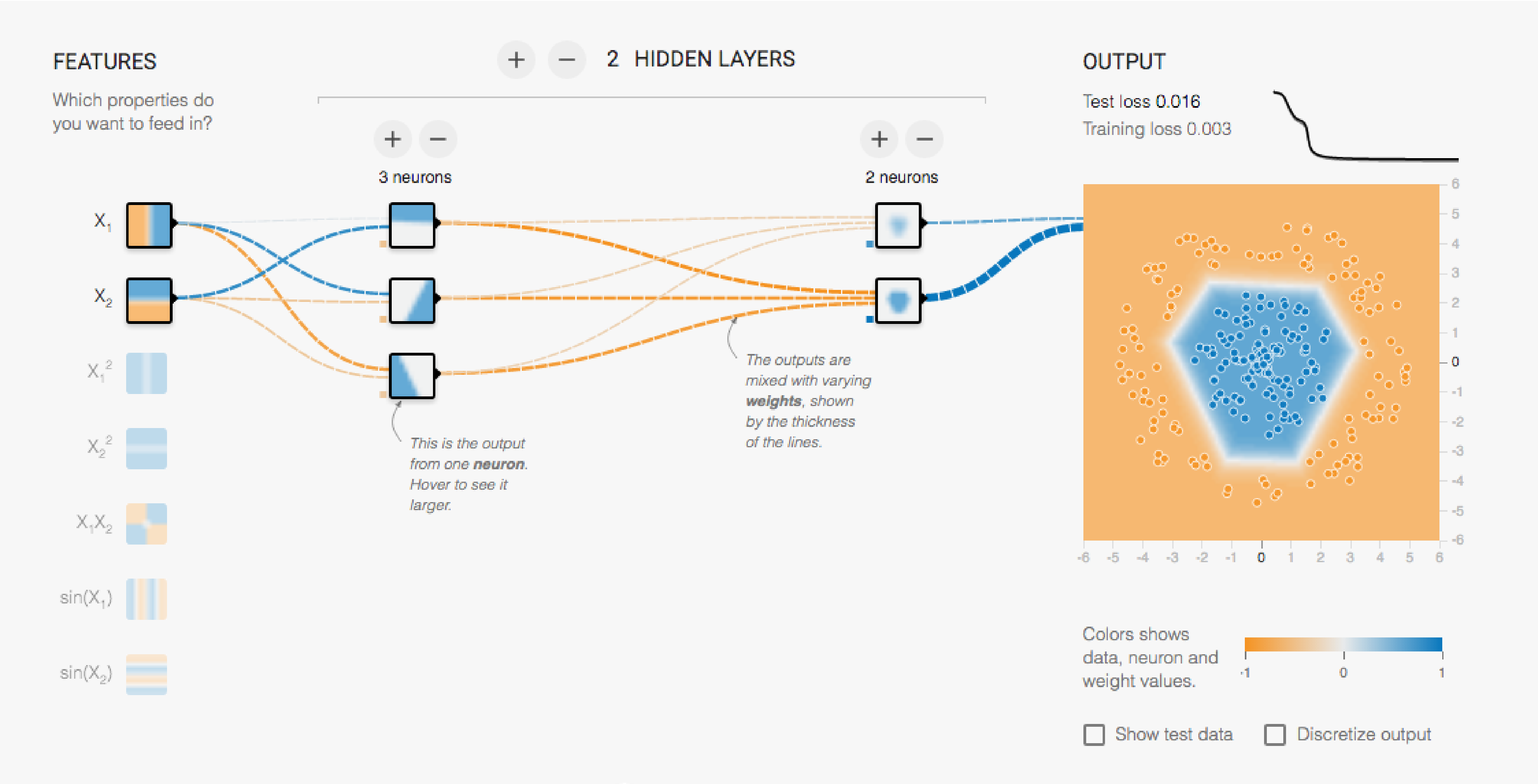


A network with one hidden layer is a universal function approximator!



http://cs231n.github.io/neural-networks-1/

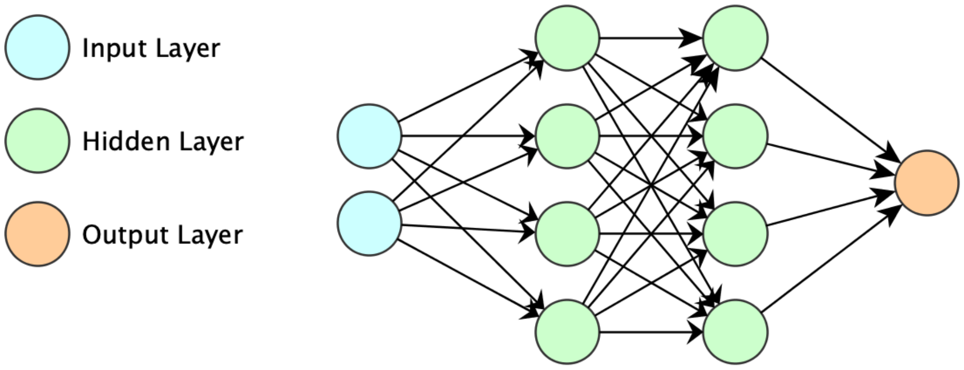
Experiment yourself (homework)



http://playground.tensorflow.org

Let’s you explore the effect of hidden layers

Structure of the network



In code:

```
## Solution 2 hidden layers
def predict_hidden_2(X):
    hidden_1=sigmoid(np.matmul(X,W1)+b1)
    hidden_2=sigmoid(np.matmul(hidden_1,W2)+b2)
    return(sigmoid(np.matmul(hidden_2,W3)+b3))
```

In math (f = sigmoid) and b1=b2=b3=0

$$p = f(f(f(\mathrm{x}\,\mathrm{W}^1)\mathrm{W}^2))$$

Looks a bit like onions, matryoshka (Russian Dolls) or lego bricks