DECOMPOSING NEURAL NETWORKS

An applicant's guide to artificial learning 29.11.2022

LEUPHANA UNIVERSITÄT LÜNEBURG

ightarrow JENNIFER MATTHIESEN & TINO PAULSEN | WINTERSEMESTER 2022 |

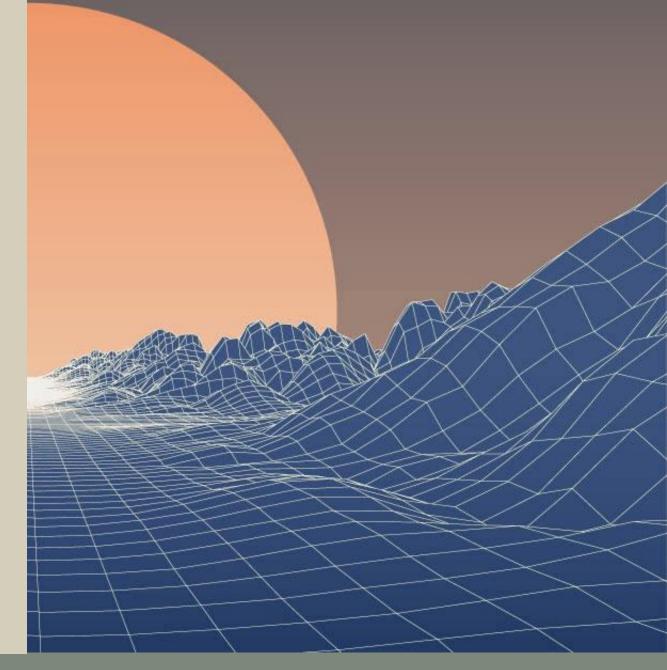
RECAP About data, cats & dogs

- Vectors, Matrix, Tensor
- Classification & bias
- -BIAS from data
- How NN's understand images
 Convolutions & pooling
- Train your own network in a supervised manner

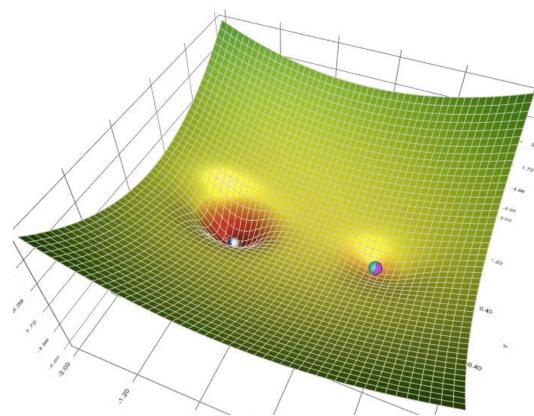


TODAY: OPTIMISATION

- Objective functions
- Numerical optimization
- How to train your network
- Optimizers?



What are we doing today? Marbles!





https://towardsdatascience.com/a-visual-explanation-of-gradient-descent-methods-momentum-adagrad-rmsprop-adam-f898b102325c

How does a neural network understand what to learn?

—A neural network is trained on data, but how?

— The "goal" must be understandable for the machine



— Operationalizing "goals" into objective functions

How can an **Objective function** look like?

Objective functions How do they need to be?

Imagine we have the telemetry data of a smartphone...



Objective functions Properties

—An objective function is typically like a distance metric:

— Symmetric: dist(a, b) = dist(b, a)



Objective functions Properties

— An objective function is typically like a distance metric:

— Positive: $dist(a, b) \ge 0$

A B

Objective functions Properties

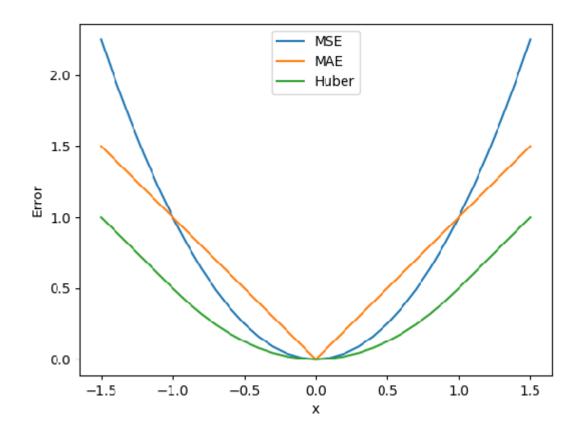
—An objective function is typically like a distance metric:

- Symmetric: dist(a, b) = dist(b, a)
- Positive: $dist(a, b) \ge 0$



— Beware! This is in no way exhaustive!

Objective functions Examples





https://www.researchgate.net/profile/Thibaut-Theate/publication/340644261/figure/fig3/AS:880423299186688@1586920680062/Comparison-of-the-MSE-MAE-and-Huber-losses.png

Objective functions Examples

— Mean squared error

$$mse = \sum_{i=1}^{N} (x - \bar{x})^2$$

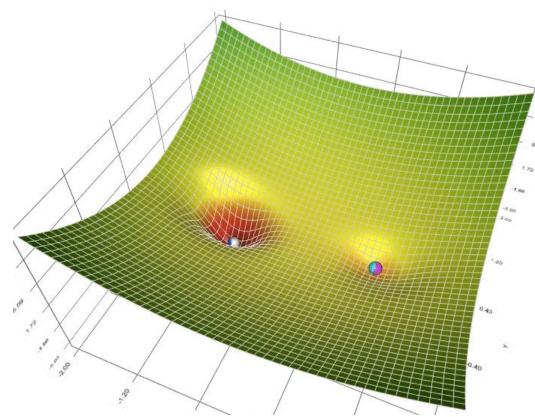
— Mean absolute error

$$mae = \sum_{i=1}^{N} |x - \bar{x}|$$

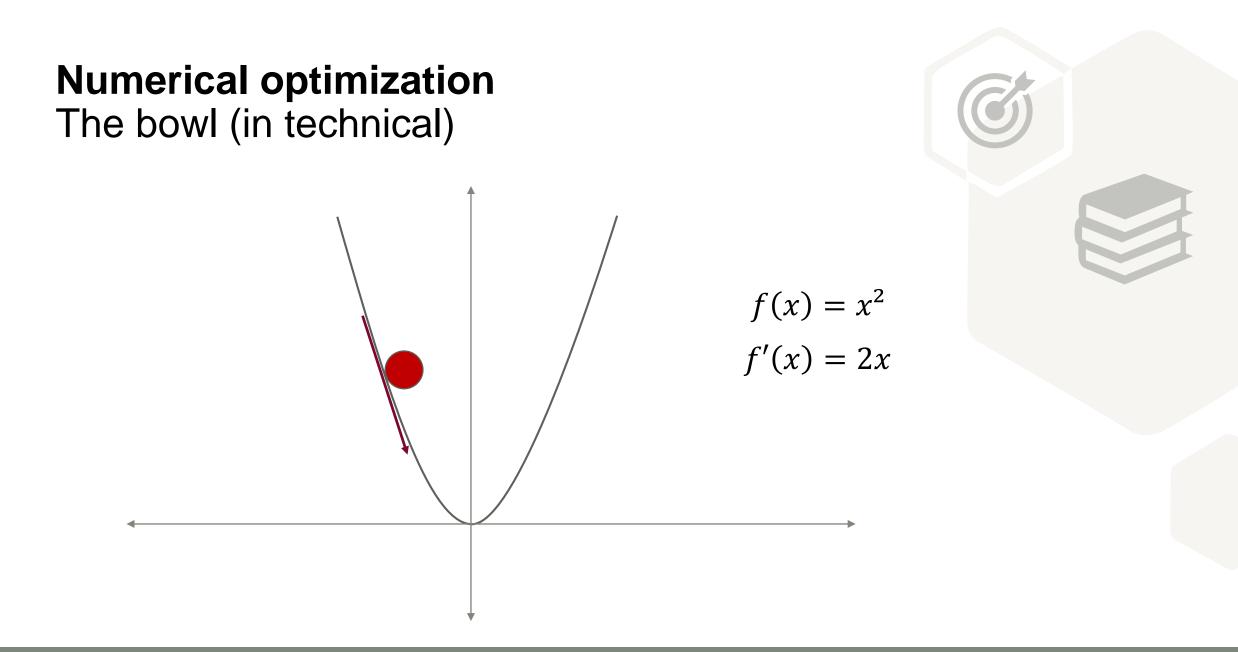
How can a function for **Classification** look like?

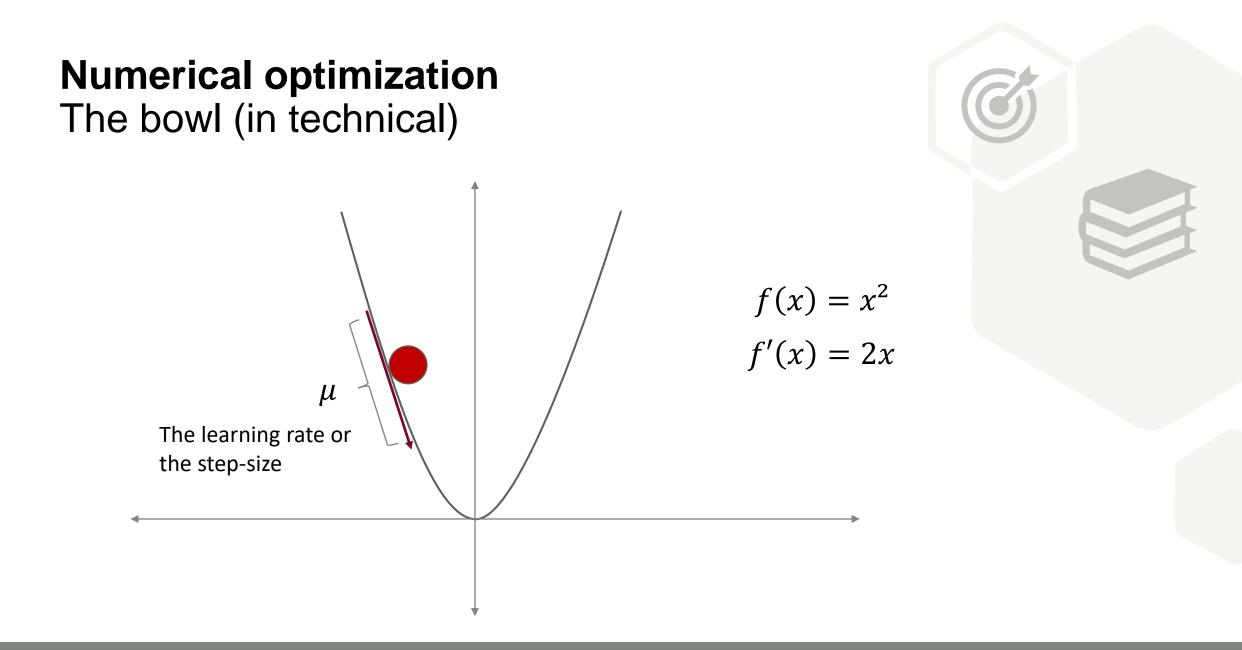
Create your own Objective function! Desmos

What are we doing today? Marbles!



https://towardsdatascience.com/a-visual-explanation-of-gradient-descent-methods-momentum-adagrad-rmsprop-adam-f898b102325c



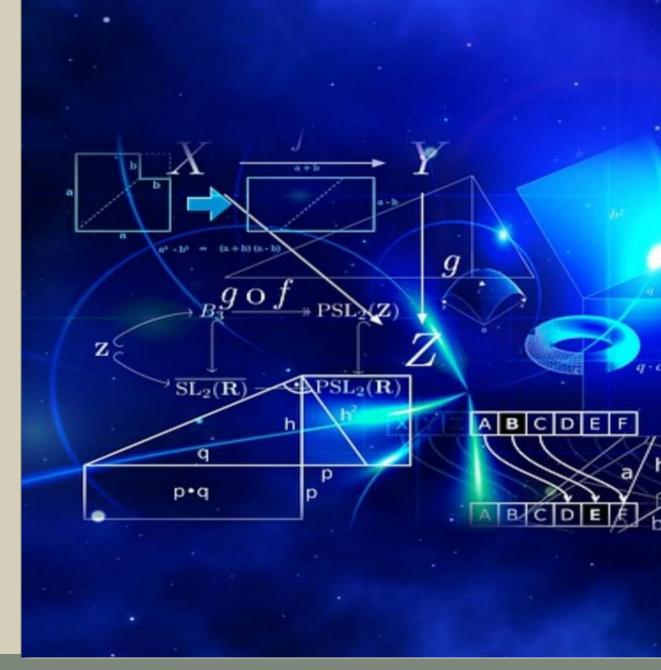


 \bigotimes

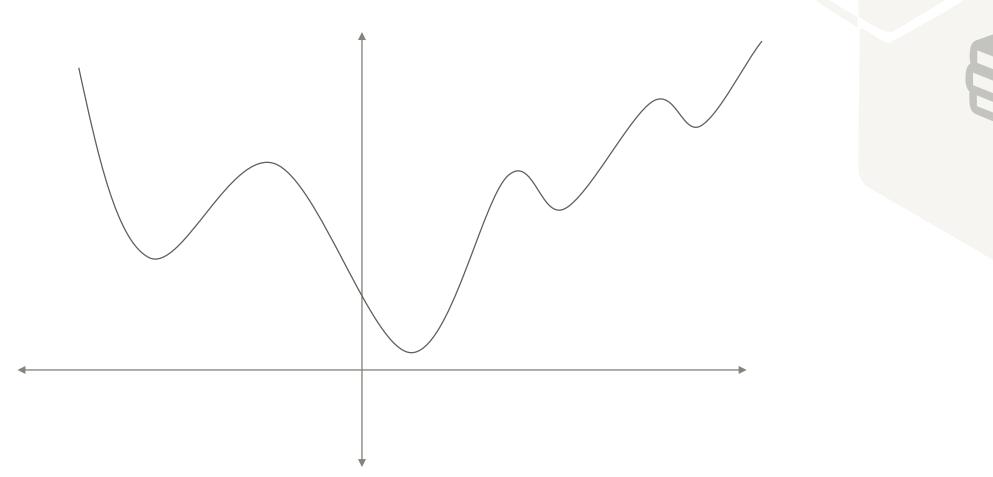
TIME FOR TRYING IT OUT!



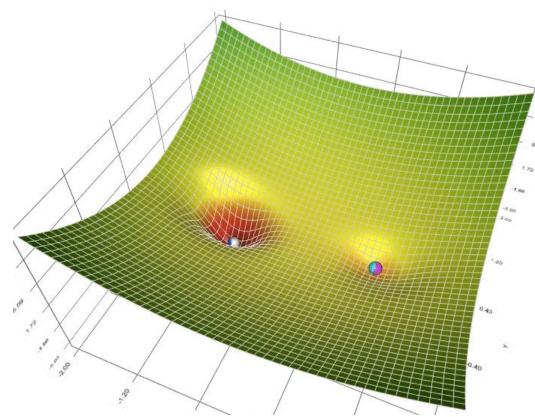
https://www.benfrederickson.com/numericaloptimization/







What are we doing today? Marbles!



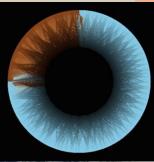
https://towardsdatascience.com/a-visual-explanation-of-gradient-descent-methods-momentum-adagrad-rmsprop-adam-f898b102325c

How to train your network Combining knowledge

- Our objective function defines our measure of "goodness", the resulting mathematical landscape is called the loss surface
- This loss surface is the "bowl" we optimize then, as it can be very complex, there can be many local minima

C.t.	

Backpropagation

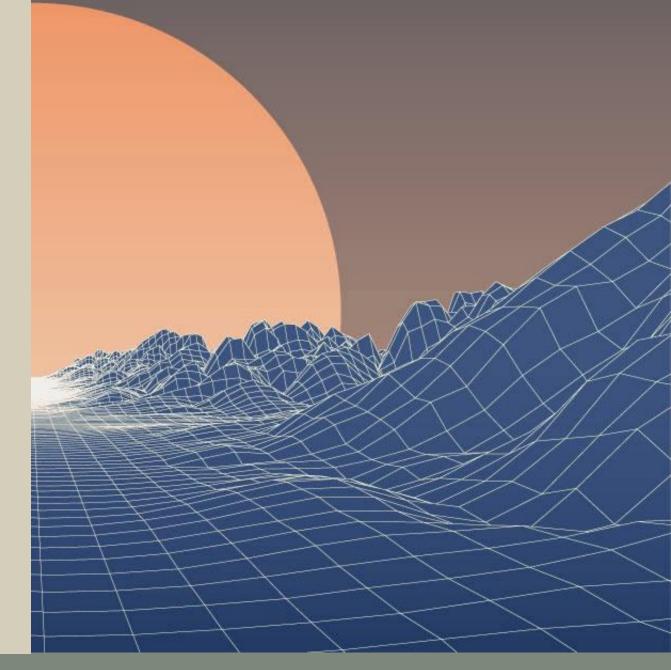


 \bigotimes

Blue1Brown Backpropagation

Practice: Plotting

- Train your network (again)
- Keep track of the losses
- Plot them (you can use the provided function, if you want)
- Try out different optimizers



SUMMARY OF TODAY OPTIMISATION

— Objective functions

 $-\!\!-\!\!$ What they look like, what they do and why they limit a network

---- Numerical optimization and local vs globa minima

— How to train your network — And plot it!

— Optimizers and a rough idea why they are powerful

If you want to repeat todays content in a guided manner



 \bigotimes

Blue1Brown Intuitive Fraining of NN