KI Labor - Wintersemester 2021

Computer Vision 1

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Schedule

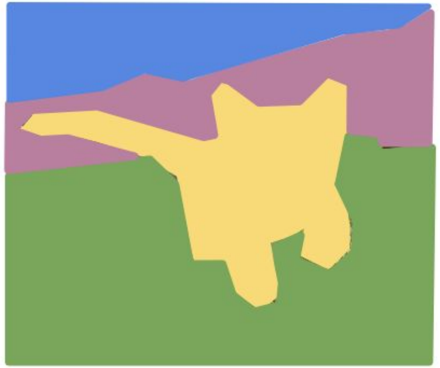
Datum	Thema	Inhalt	Präsenz
01.10.21	**Allg.**	**Organisation, Teamfindung**	Nein
08.10.21	**CV**	**Vorstellung CV**	**Nein**
15.10.21	CV	Q&A Sessions	Nein
22.10.21	CV	Sprintwechsel, Vorstellung Assignment	Ja
29.10.21	CV	Q&A Sessions	Nein
05.11.21	**CV / NLP**	**Abgabe CV, Vorstellung NLP**	**Ja**
12.11.21	NLP	Q&A Sessions	Nein
19.11.21	NLP	Sprintwechsel, Vorstellung Assignment	Ja
26.11.21	NLP	Q&A Sessions	Nein
03.12.21	NLP	Q&A Sessions	Nein
10.12.21	**NLP / RL**	**Abgabe NLP, Vorstellung RL**	**Ja**
17.12.21	RL	Q&A Sessions	Nein
14.01.22	RL	Sprintwechsel, Vorstellung Assignment	Ja
21.01.22	RL	Q&A Sessions	Nein
28.01.22	**RL**	**Abgabe RL, Abschluss KI Labor**	**Ja**

Agenda for today

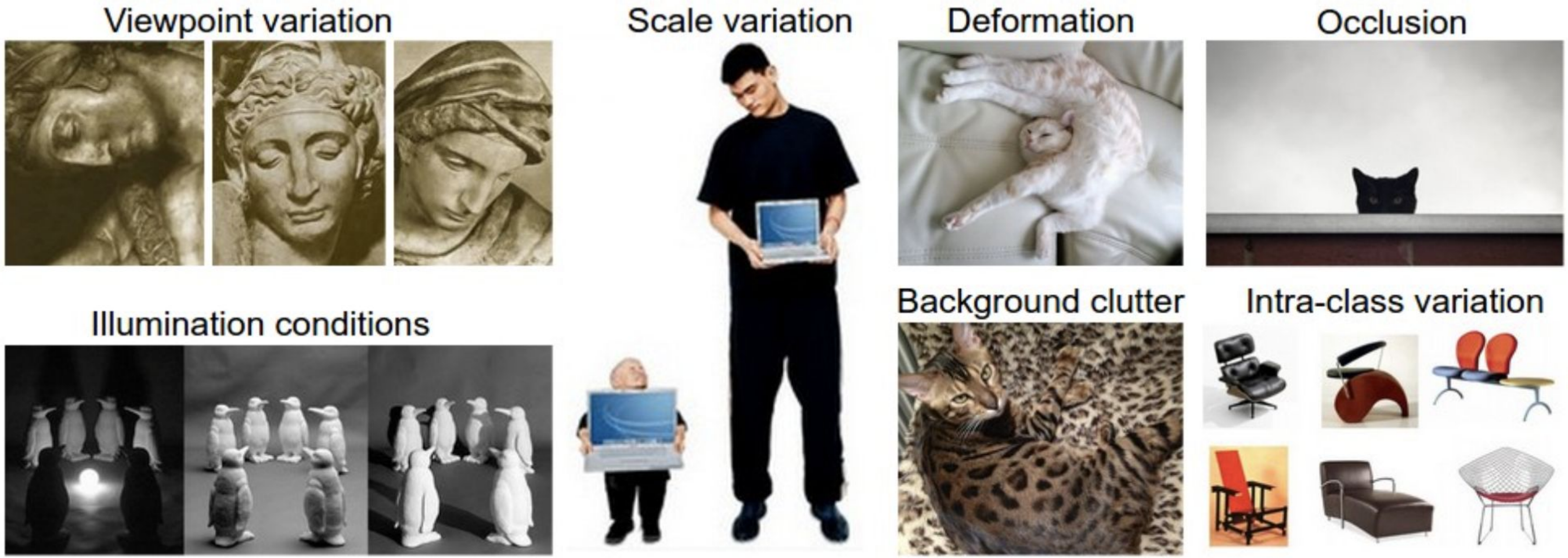
1. Introduction
2. Deep Learning
3. Overfitting
4. Exercise Notebooks

Introduction

What is Computer Vision (CV)?




CV has a number of challenges to overcome



Can we trust machines to make fair decisions?

Research shows AI is often biased. Here's how to make algorithms work for all of us

RETAIL   OCTOBER 11, 2018 / 1:04 AM / UPDATED 3 YEARS AGO

Amazon scraps secret AI recruiting tool that showed bias against women

Artificial intelligence

Predictive policing algorithms are racist. They need to be dismantled.

Lack of transparency and biased training data mean these tools are not fit for purpose. If we can't fix them, we should ditch them.

by **Will Douglas Heaven**   July 17, 2020

Battling bias and other toxicities in natural language generation

Despite numerous and concerted efforts to train NLG systems to generate content without offensive elements, success is still elusive.

Your favorite A.I. language tool is toxic

BY **JONATHAN VANIAN**
September 29, 2020 5:25 PM GMT+2

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The SOTA algorithms for solving CV problems are based on deep learning

Deep Learning

What is deep learning?

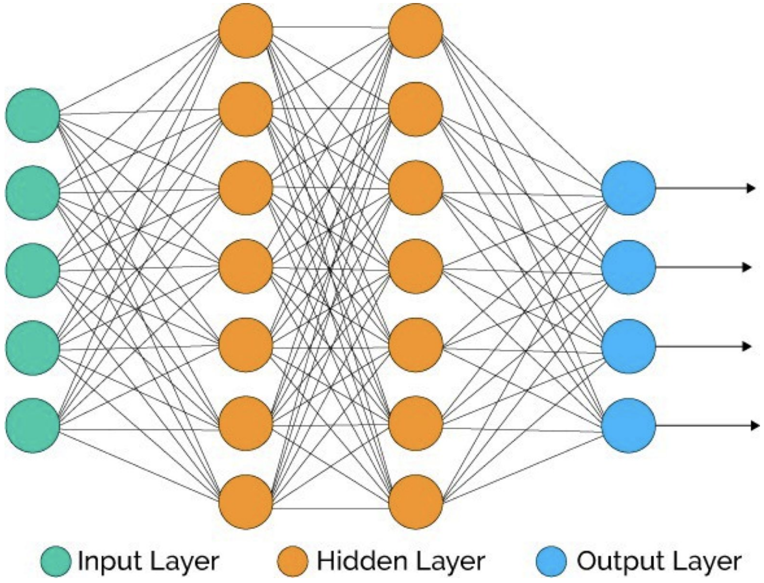
“[...] very large neural networks we can now have and …
huge amounts of data that we have access to [...]” - Andrew Ng (2015)

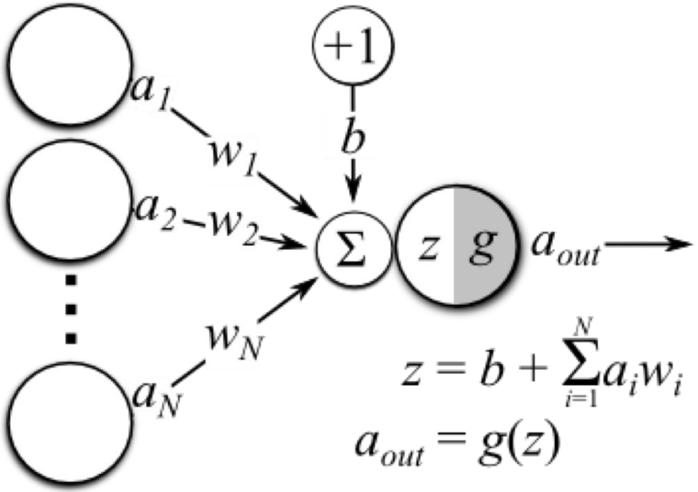
“Deep learning methods aim at learning feature hierarchies [...] at multiple levels of abstraction allow[ing] a system to learn complex functions mapping the input to the output directly from data, without depending completely on human-crafted features.” - Yoshua Bengio (2009)

“It has been obvious since the 1980s that backpropagation through deep autoencoders would be very effective for nonlinear dimensionality reduction, provided that computers were fast enough, data sets were big enough, and the initial weights were close enough to a good solution. All three conditions are now satisfied.” - Geoffrey Hinton (2006)

Let's start with building a simple Neural Network

Multi-Layer Perceptron

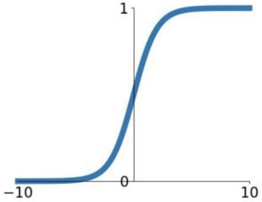




We can learn complex functions by applying non-linear activation functions

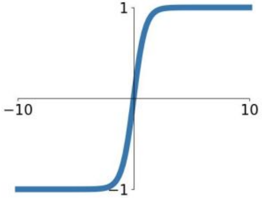
Sigmoid

$\sigma(x) = \frac{1}{1+e^{-x}}$



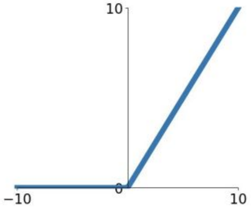
tanh

$\tanh(x)$



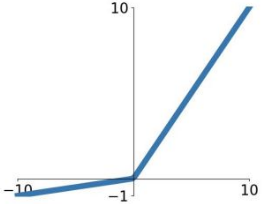
ReLU

$\max(0, x)$



Leaky ReLU

$\max(0.1x, x)$

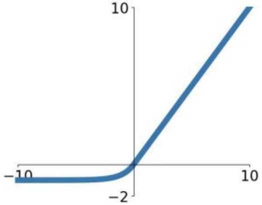


Maxout

$\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



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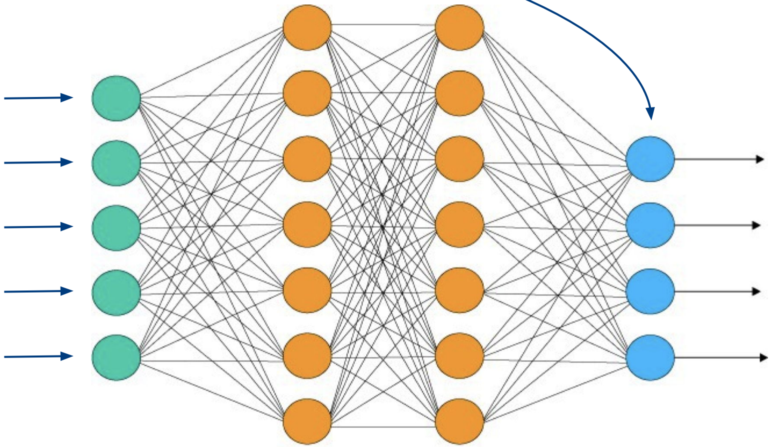
But how do we actually learn?

Forward Pass



Common loss function

$$-\frac{1}{N}\sum_{i=0}^{N}\sum_{c=1}^{M} y_c log(\hat{y}_c)$$

OR

$$\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

$$w_i \leftarrow w_i - \alpha \frac{\partial L(w)}{\partial w_i}$$

Backward Pass

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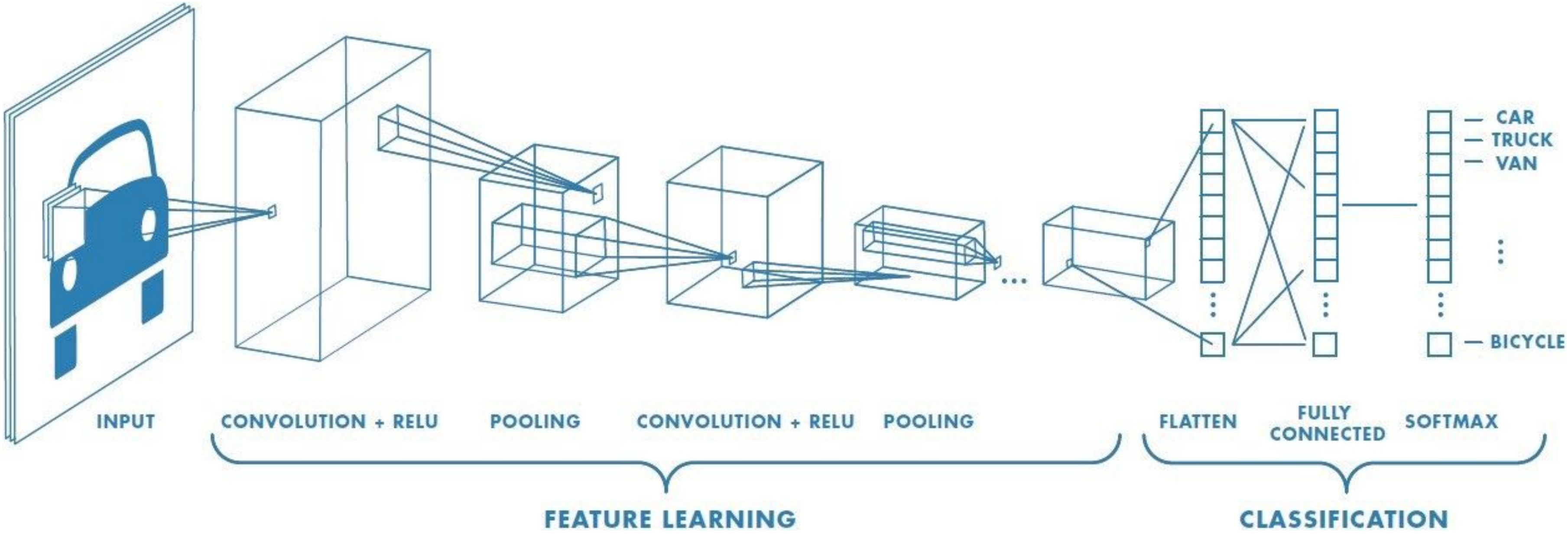
Let’s advance to more complex Neural Networks

Convolutional Neural Network



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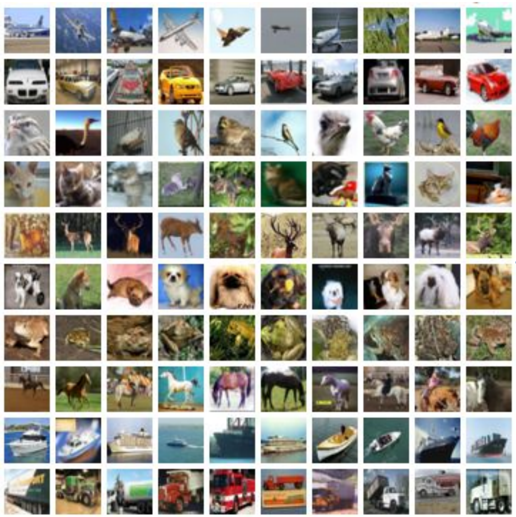
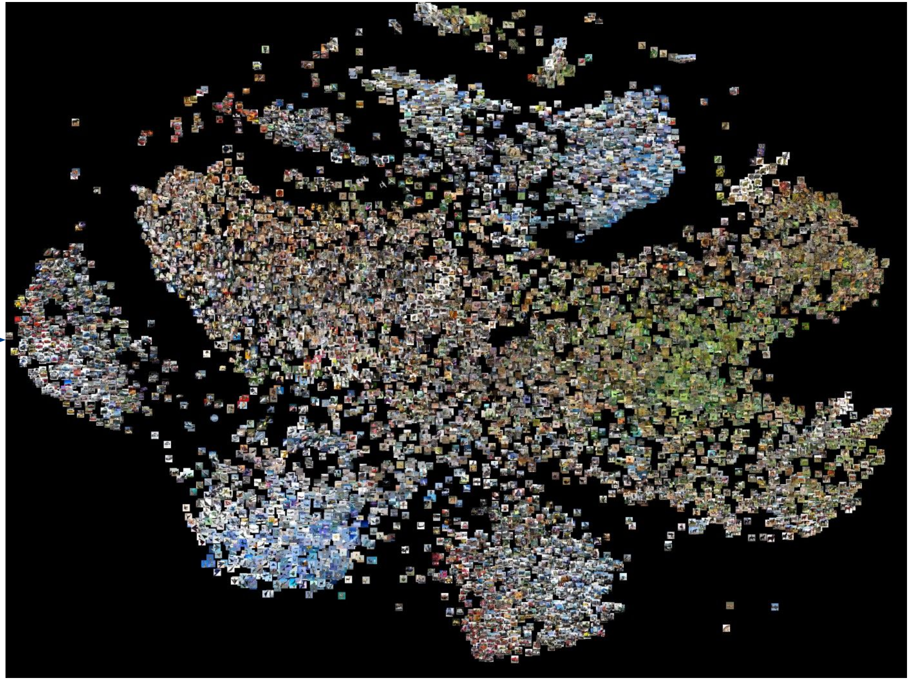
Can we show the discriminative power of NNs?

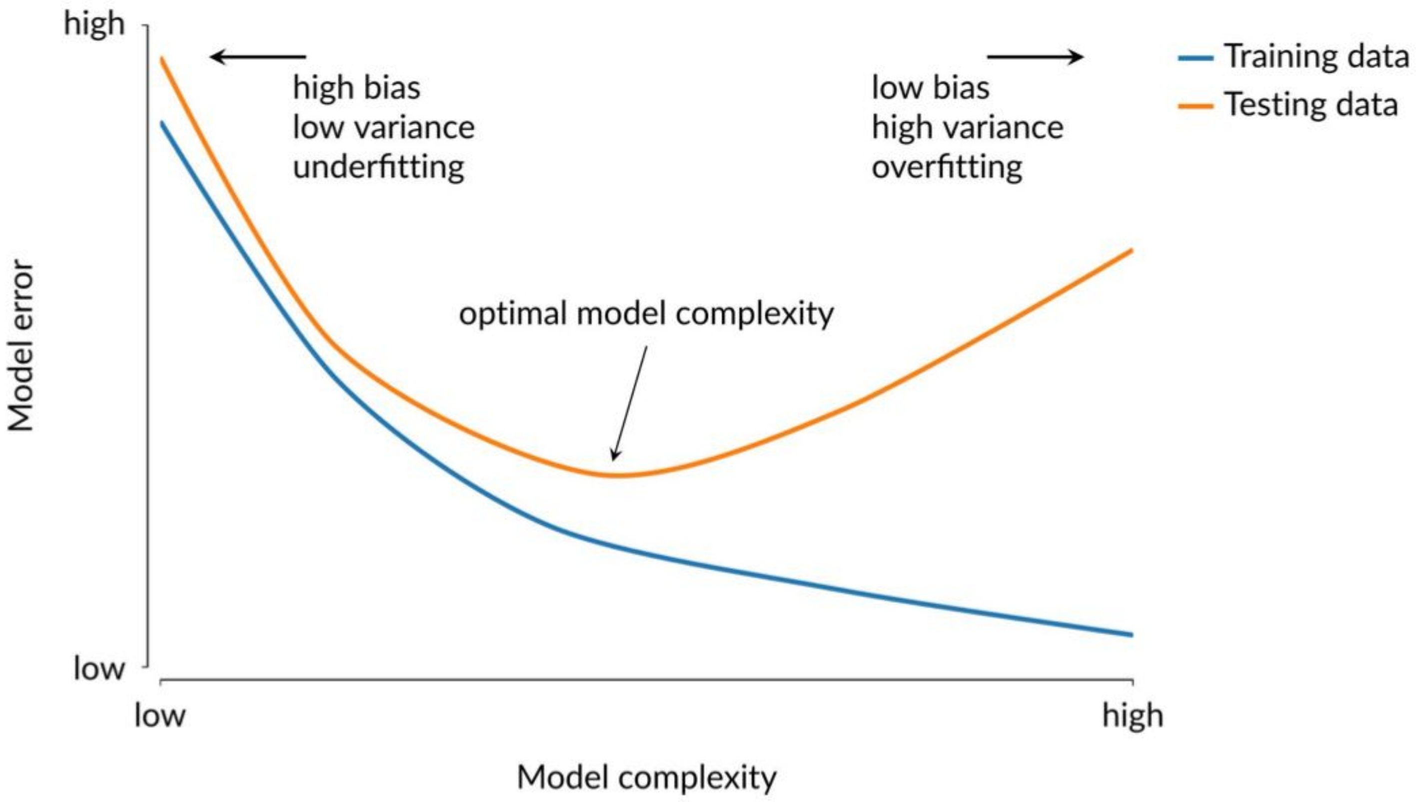
t-Distributed Stochastic Neighbor Embedding (t-SNE)





Overfitting

Bias-Variance-Tradeoff



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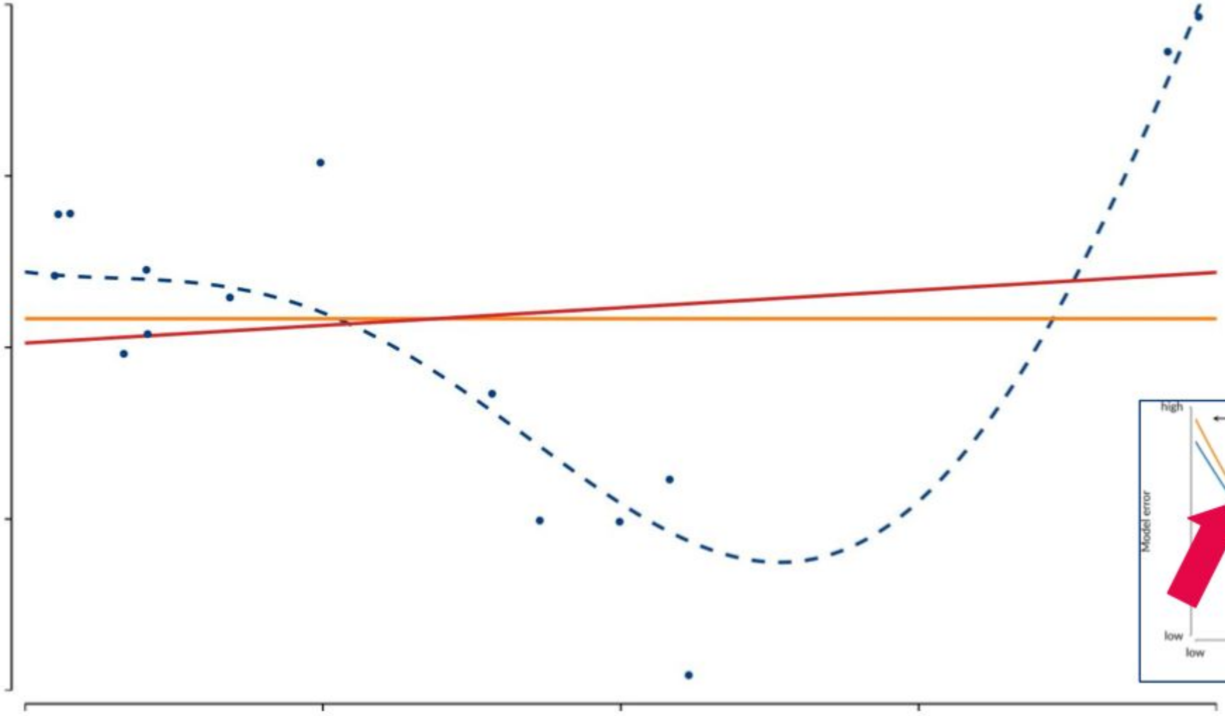
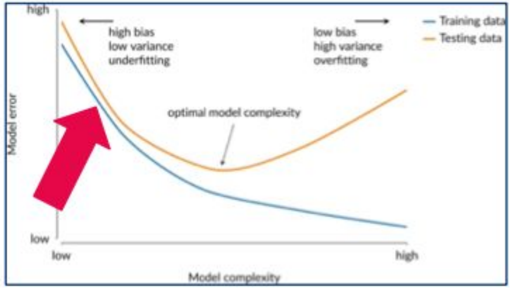
Bias-Variance-Tradeoff

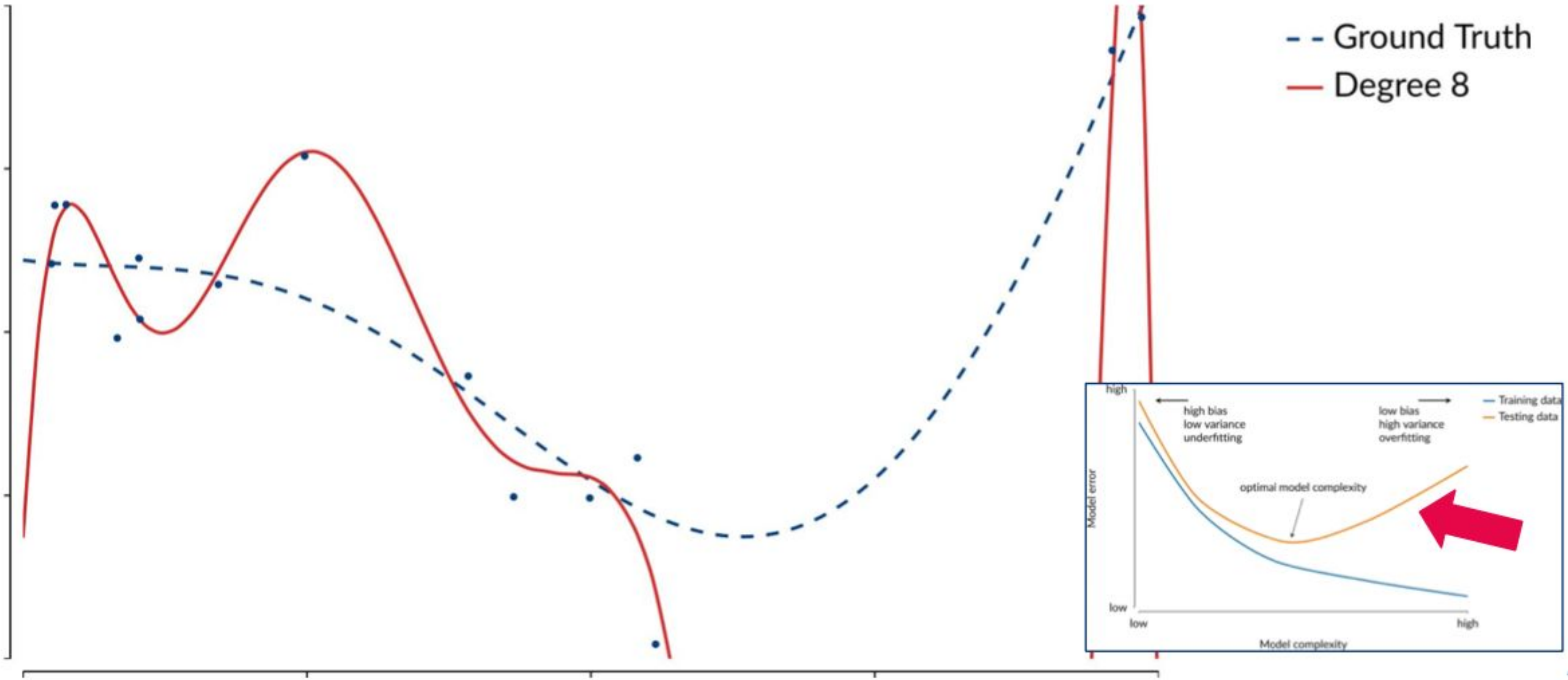
Underfitting: Model is too simple





Bias-Variance-Tradeoff

Overfitting: Model is too complex



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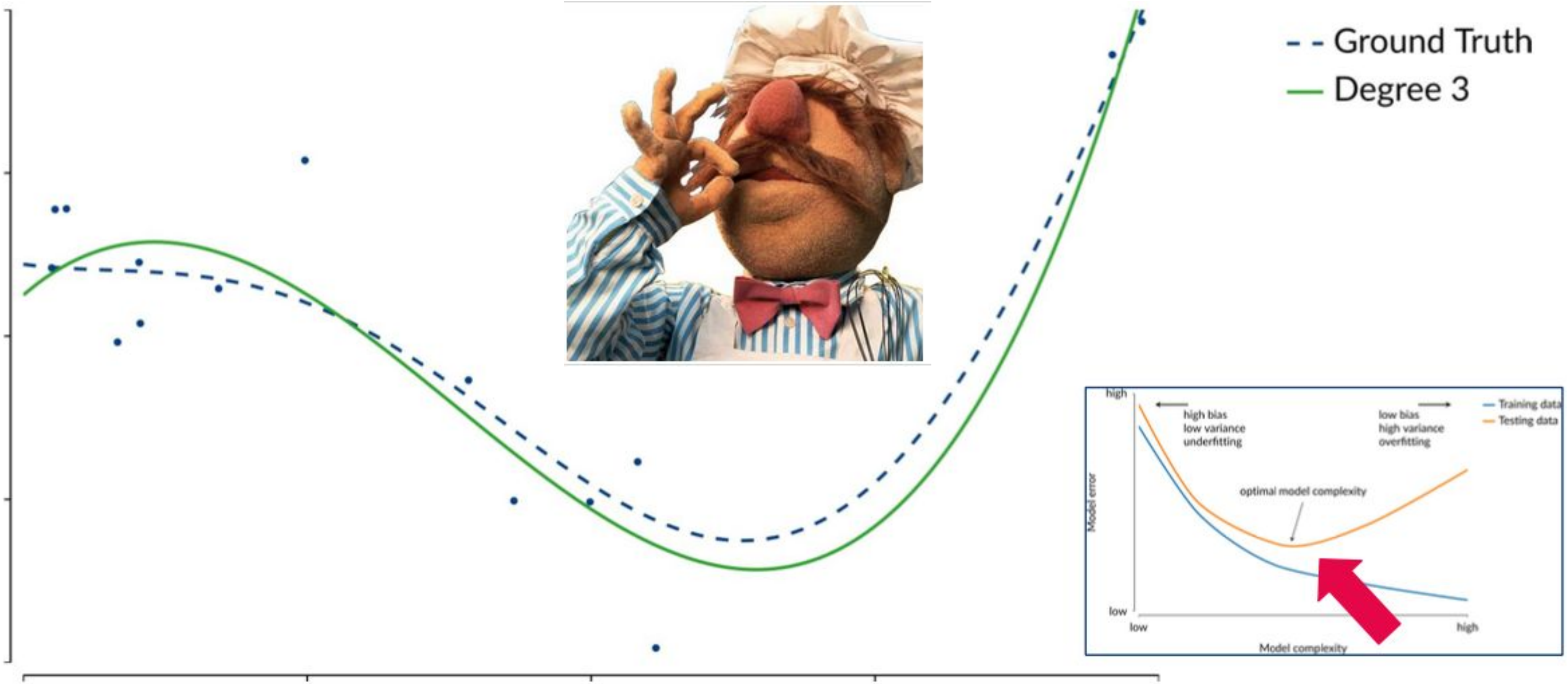
Bias-Variance-Tradeoff

Optimal model complexity



What about neural networks?

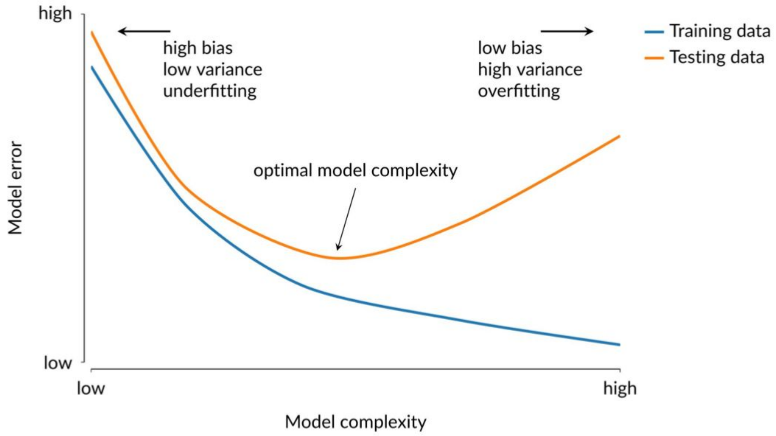
- Compared to polynomials, the complexity / variance of neural networks is extremely high

- Universal Approximation Theorem

- The tasks / targets are also very complex

Preventing overfitting in neural networks

- Using Validation set
  - Network size fine-tuning
  - Early stopping
- Regularization methods
  - Weight regularization
  - Dropout
- Data based methods
  - Data Augmentation
  - Noise
  - Extending the dataset



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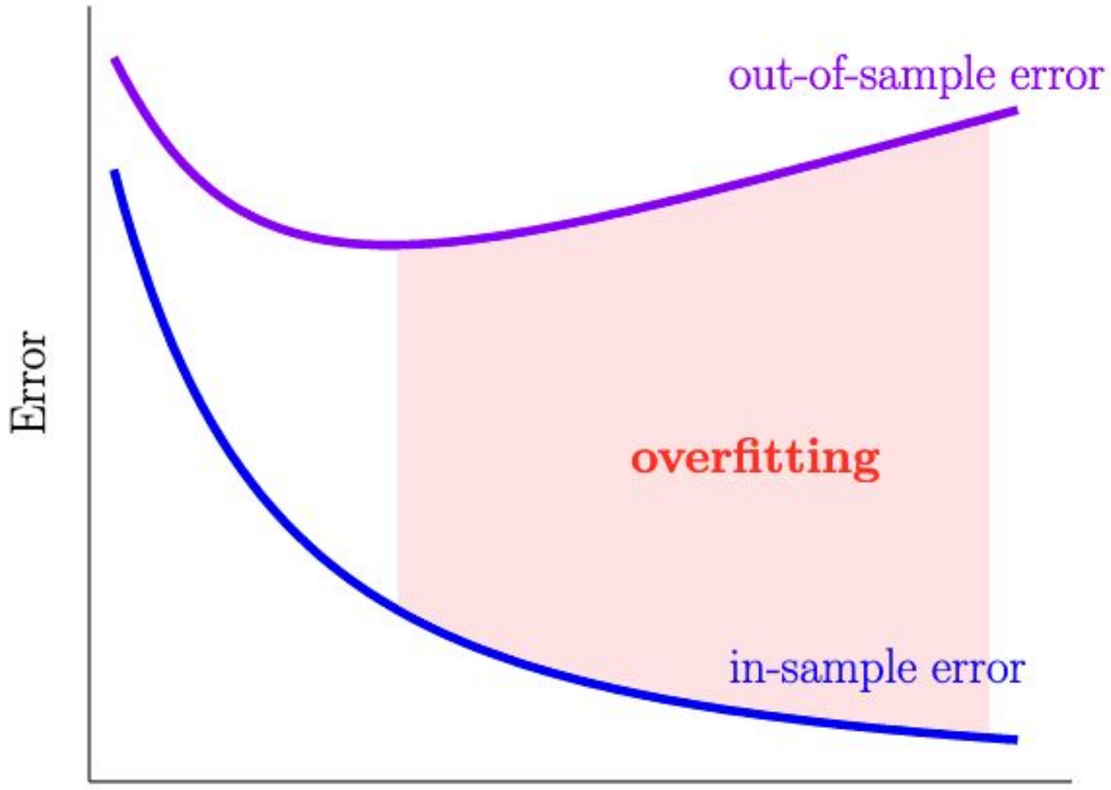
Early Stopping



Training iterations

Weight regularization

- Large weights in a NNs are a sign of a more complex network that has overfit the training data
- Penalizing a NN based on the size of the weights during training can reduce overfitting
- An L1 or L2 vector norm penalty can be added to the optimization of the network to encourage smaller weights

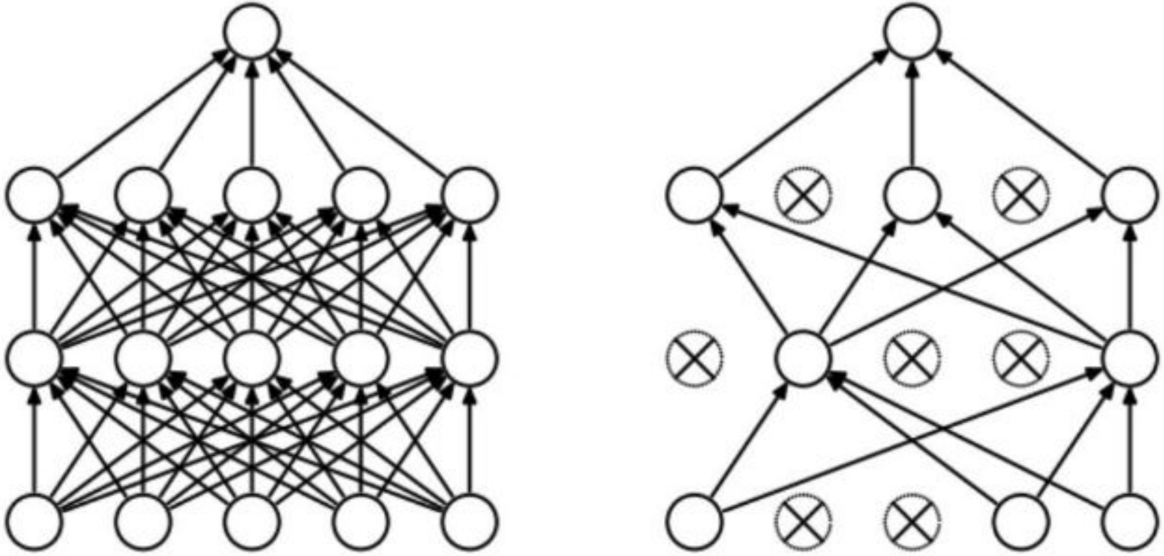
$$weight\ decay\ L1 = \sum_i |\theta_i|$$

$$weight\ decay\ L2 = \sum_i \theta_i^2$$

- Variation of scales of input variables causes the scale of the weights of the network to vary accordingly
  - Problematic for weight regularization
  - Solution: normalization, standardization

Dropout

- "Ephemeral sparsity"
- applied only during the training phase



(a) Standard Neural Net (b) After applying dropout.

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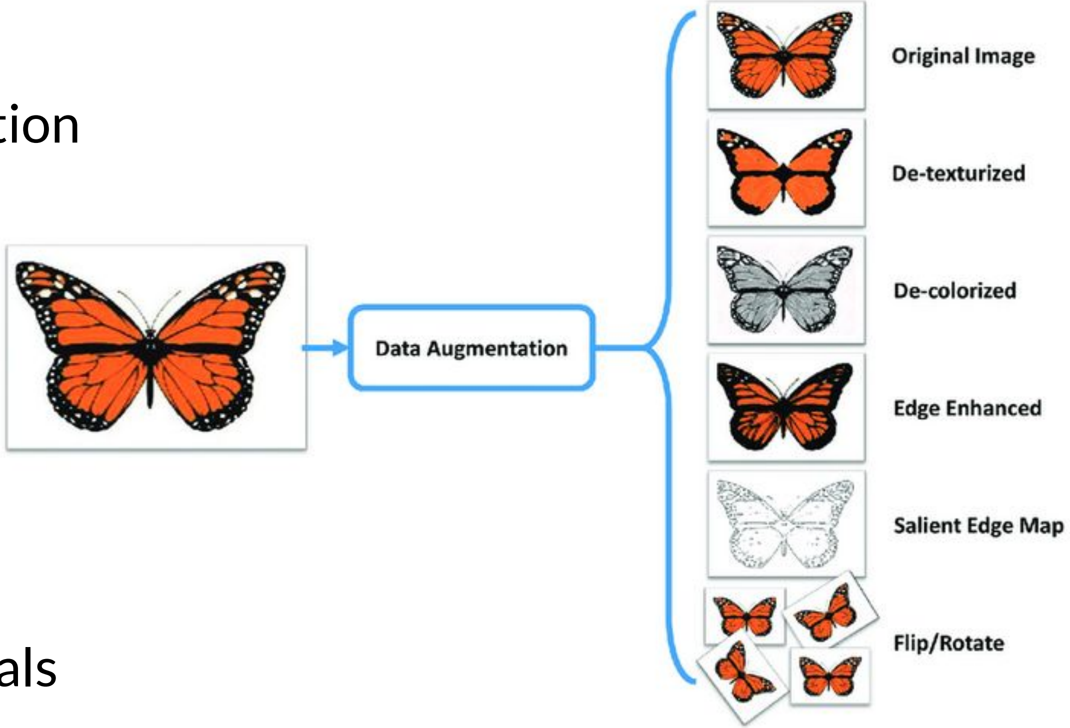
Data based methods

- Data Augmentation
  - Synthetic data generation
  - Data modification



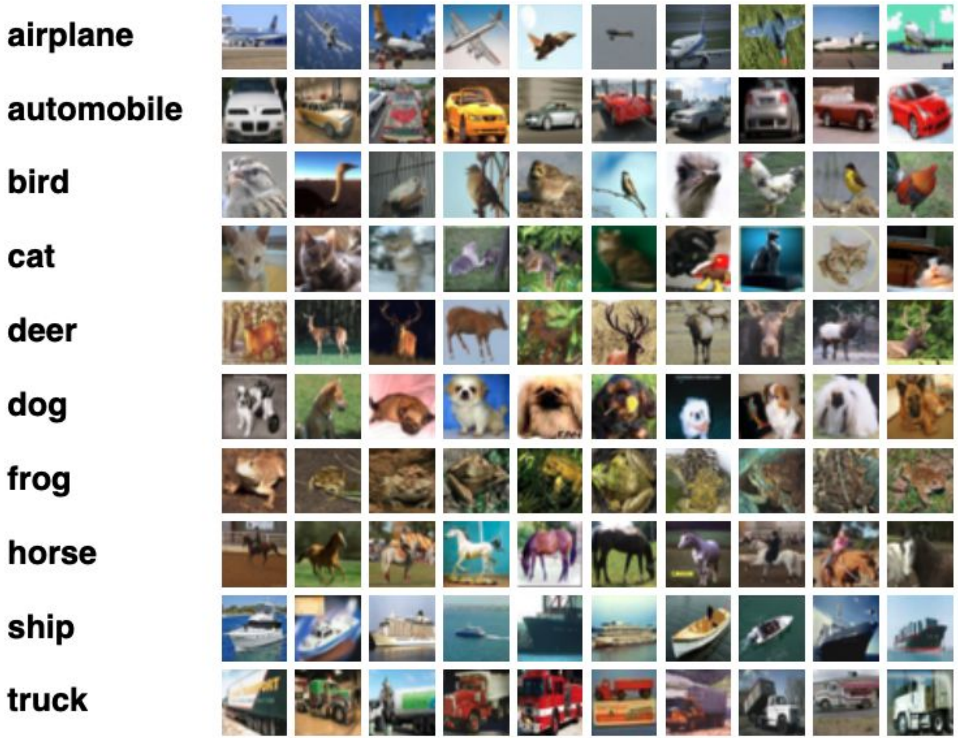
- Noise
  - Useful for natural signals
- Extending the dataset
  - Used in real world & kaggle competitions

Figure from “[Data augmentation-assisted deep learning of hand-drawn partially colored sketches for visual search](#)” DOI:[10.1371/journal.pone.0183838](#)

CIFAR-10 dataset

Canadian Institute for Advanced Research

- 60k RGB images
- 32x32 pixel
- 10 classes



Vielen Dank

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