# Seminar: Theoretical Advances in Deep Learning

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TU Munich, Department of Informatics

Winter Semester 2024

# Course information

- Master seminar (IN2107, IN4409)
    - 5 ECTS, 2 SWS

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  - 5 ECTS, 2 SWS
- Organisers:
  - Alexandru Crăciun a.craciun@tum.de (main coordinator of course)
  - Maedeh Zarvandi maedeh.zarvandi@tum.de
  - Prof. Debarghya Ghoshdastidar ghoshdas@cit.tum.de

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- New algorithms with some experiments showing their properties
  - Provides some understanding (less common in ML than DL)

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- Dedicated theory papers
  - Mathematically explain why DL / ML methods work (rare in DL)

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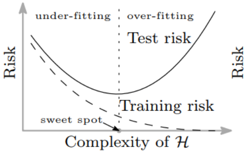
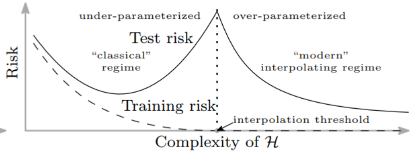
# Why do we need mathematical analysis of DL?

- Deep learning contradicts conventional wisdom

  Complex models generalise well



(a) U-shaped "bias-variance" risk curve



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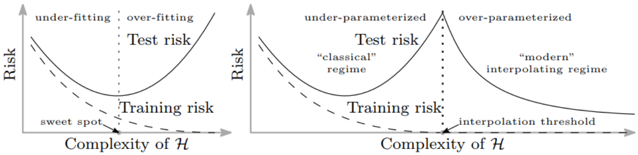


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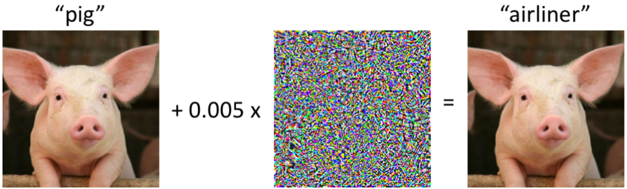

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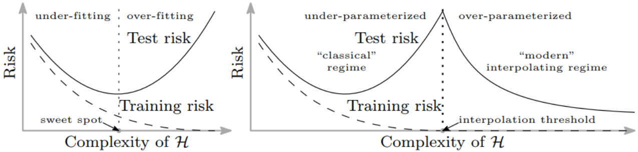
- The output of deep networks lack explainability

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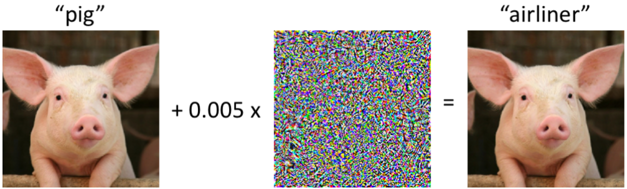

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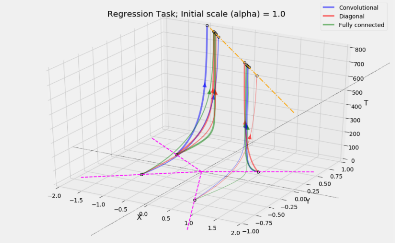
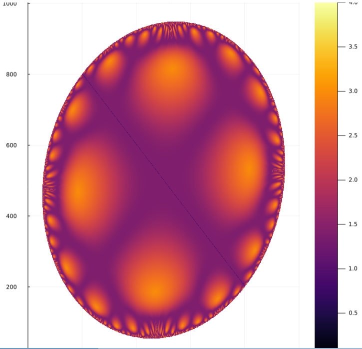
- Familiarise with publication and review process in ML

# Focus of this seminar
# Possible Topics

# Training Dynamics, Stability and Implicit Bias

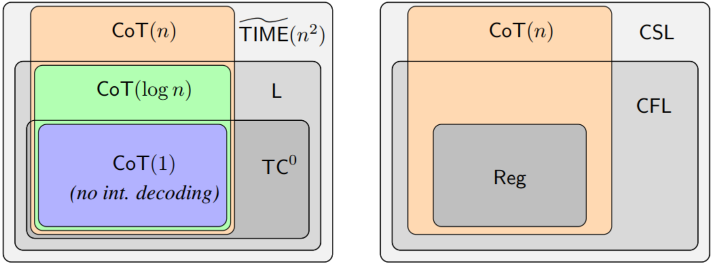
- When is gradient flow a good approximation of gradient descent?
- How much can one change the hyper-parameters and still expect the same results?
- Why does gradient descent find solutions that generalize well?



# Theory of LLMs - Expressivity

Transformer's reasoning can be improved by allowing them to use a "chain of thought" (i.e. using intermediate tokens before answering). Does such intermediate generation fundamentally extend the computational power of a transformer?



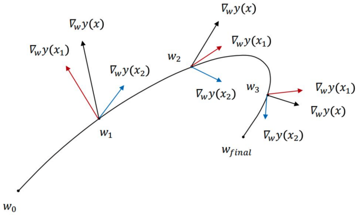
# Over-parameterised NN (infinite width)

Analyse Over-parametrised NNs asymptotically as width goes to infinity

- Under small learning rate, (S)GD training ≡ Neural Tangent Kernel (NTK), a dot product kernel in gradient space of the NN parameters.

- Finite width networks can deviate from the kernel regime.

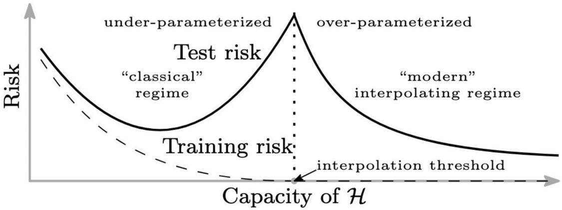
$$NTK(x_i, x_j) = \nabla_w y(x_i) \, . \, \nabla_w y(x_j)$$



# Double-descent in bias-variance curve

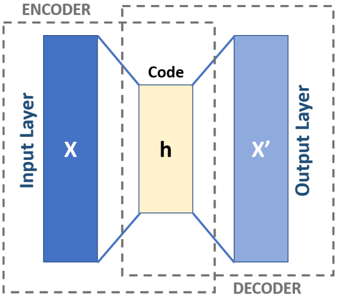
- Over-parameterised NNs deviate from bias-variance trade-off - NNs may perform best in zero training loss / interpolating regime.

- Currently, this behaviour has been analytically derived in simpler settings.



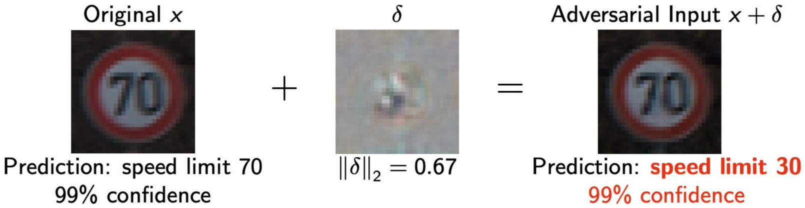
# Kernel Unsupervised/Self-Supervised Learning

What guarantees can we give in a self-supervised setting?
Kernel methods provide a principled way to perform non-linear learning, relying on solid foundations. We aim to look at neural networks from the theoretical point of view, in order to analyse the equivalent kernel based algorithms in self-supervised approaches.



# Adversarial ML / Robustness

- Performance of NNs significantly affected if data is slightly perturbed.
- Why? How can we build robust ML models / guarantee robustness?



# For a more in-depth look...

join the *recent advances in ML / DL* reading group as part of the *statistical foundations of deep learning* course

on 03.07.2023 (Wednesday) 10:30 - 12:00 (seminar room 03.19.014)

# Administration

# Seminar details

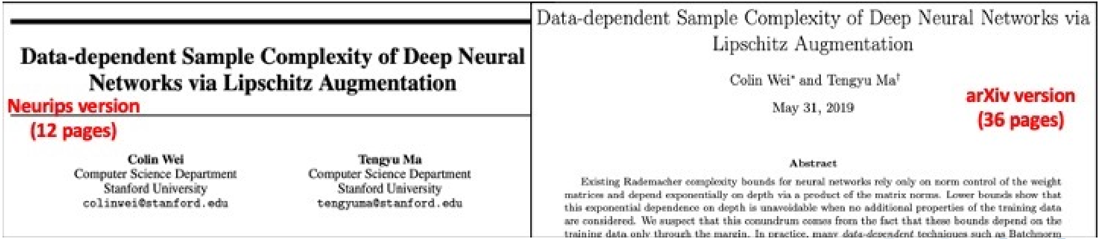
- We will use Moodle for coordination
- Desired number of participants = 20
- Pre-requisites: Machine Learning (IN2064), Deep learning (IN2346)
- **Must be comfortable with mathematical techniques / proving results**
  - Taking Statistical foundations of learning (CIT4230004) would help

# Assessment

- Everyone assigned one paper
- Submit a report. Details will be provided in the introduction lecture.
  - summary of paper, explaining main results and their implications
  - review (we will discuss how to write reviews)
  - summary of proofs (main techniques, key lemmas and ideas)
- Present paper and your report
  - Block seminar; everyone needs to attend all talks
- Grading: Report (40%) + Presentation (60%) (both are needed)

# Report + Presentation of papers

- Mostly publications from recent ML conferences (ICML, ICLR, Neurips, COLT)
    - Conference papers are short (8 page, no proofs)
- **Report has to follow longer version on arXiv** (link will be provided)
    - Considerable focus on understanding mathematical results



**Data-dependent Sample Complexity of Deep Neural Networks via Lipschitz Augmentation**



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Data-dependent Sample Complexity of Deep Neural Networks via Lipschitz Augmentation

Colin Wei* and Tengyu Ma†

May 31, 2019



Abstract

Existing Rademacher complexity bounds for neural networks rely only on norm control of the weight matrices and depend exponentially on depth via a product of the matrix norms. Lower bounds show that this exponential dependence on depth is unavoidable when no additional properties of the training data are considered. We suspect that this conundrum comes from the fact that these bounds depend on the training data only through the margin. In practice, many data-dependent techniques such as Batchnorm

# Timeline (tentative)

- August: Provide preference for papers
- Start of lecture period: First meeting (assignments, reports and organisation)
- November 01: Deadline for de-registration
- Mid January : Submit report and first version of slides (both as PDF)
- Mid February: Final presentation (block seminar, date to be finalised)
- Office hours: weekly 2h

# Most important thing to do now...

Fill out the form to help us match you in the system
https://forms.gle/bb5HyZHSMLotijv88

The form will be uploaded to the web-page