Statistical Foundations of Learning

Debarghya Ghoshdastidar

School of Computation, Information and Technology Technical University of Munich Course Organisation and Overview

Statistical Foundations of Learning

- Module: CIT4230004 (replaces IN2378)
- \bullet ECTS: 8 credits (THEO) ; 4V+2Ü SWS
- Intended audience: Master
- Pre-requisites:
 - Machine learning (IN2064)
 - Probability (IN0018) or equivalent; Course in statistics is a bonus
 - Some knowledge of linear algebra (MA0901), analysis (MA0902)

Contact persons

- Lecturer:
 - Debarghya Ghoshdastidar
 - ghoshdas@cit.tum.de / Room: 03.11.043
- Teaching assistants
 - Maximilian Fleissner
 - maximilian.fleissner@tum.de
- Office hours: By appointment or Ask on Moodle Q&A forum

Course format

- Lectures (Debarghya Ghoshdastidar)
 - Tuesdays / 16:15–17:45 / 00.13.009A and TUMLive
 - \bullet Wednesdays / 8:15–9:45 / 00.08.038 and TUMLive
- Tutorials (Maximilian Fleissner)
 - Fridays / 14:15-15:45 / 00.13.009A (no streaming)
 - Participants encouraged to upload discussed solutions on Wiki (Moodle)
- Further Q&A and lecture materials on Moodle Weekly schedule also on Moodle (see changes in first 2 weeks of May)

Assessment

- Grades will be based on final examination
 - Written exam, 120 minutes on **01.08.2024** (oral only if too few registrations)
 - Must be registered in TUM to write exam / get grades (if not, then contact me)
 - There will be retake exam, possibly on 24.09.2024 (written/oral based on number of registrations)
- Bonus 0,3 or 0,4 note possible from assignments
 - Example: 2.3 + bonus = 2.0; 2.7 + bonus = 2.3
 - No bonus if final exam note is 1,0; 4,0; 4,3; 4,7; 5,0
- If you have obtained bonus in IN2378 / CIT423004 in a previous semester, then bonus from the previous course will be considered

Assignments

- There will be 6 written assignments, which will be graded (not mandatory)
 - Securing 70% of total points will lead to bonus in final note
- Submit assignments through Moodle as single PDF
 - You are welcome to discuss assignments in small groups
 - But submissions MUST be individually written / submitted
- Deadline specified on Moodle (typically 10-12 days after handed out)
 - NO late submissions

Purpose / expected outcomes of this course

- Understand supervised machine learning from a statistics perspective
 - Learn the fundamentals of the statistical learning problem
 - Learn how to theoretically analyse a ML algorithm (without experiments)
 - Glimpse of recent statistical theories in machine / deep learning
- This course is NOT about practical ML
 - No coding / Practical motivations / Examples on datasets
 - May not help in your other ML projects

What should you expect from this course?

- \bullet Good knowledge of ML (IN2064); Probability (IN0018 or equivalent) will be assumed
- Depending on your background, you may enjoy this course or find it too difficult
 - Master Informatik: Not an easy THEO course
 - Master Mathematics / Math in DS: Course partly aligned with MA4801
 - Others: Course is purely mathematical; Not ideal for learning ML
- To get idea of math level:
 - See sample lecture videos on Moodle
 - Try first sheet of sample problems (should be able to solve at least 50% by yourself)

What should you expect from this course?

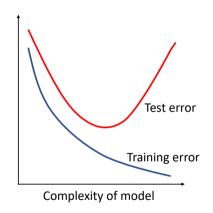
- Statistics from SoSe 2022 (IN2378)
 - 313 registered for course
 - 51 submitted 1st assignment / 33 submitted assignments till end
 - 115 registered for exams / only 36 appeared for exam / 28 passed (average note 2,3)
- ullet If first 2-3 weeks seem too difficult / time-consuming, consider dropping / contact us

Course content

- Part I: Classical theories (mostly for binary classification)
 - Statistical learning framework and Bayes error
 - Theories of generalisation Vapnik-Chervonenkis theory ; Statistical consistency ; Algorithmic stability
 - Applications of above to derive performance guarantees of k-nearest neighbour; support vector machines; 2-layer neural network; boosting
 - Probably approximately correct (PAC) learning and No Free Lunch theorem
- Part II: Recent theories
 - Regression: Double descent phenomena, Neural tangent kernel
 - Clustering: Worst-case approximation bounds, Cost of explainability

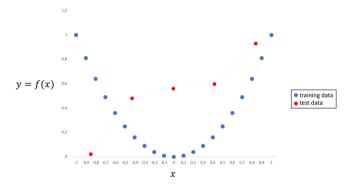
A Motivating Question

- Would you like your ML model to overfit on training data?
- Why do overfitted models show high test error?



Essence of Theory of Generalisation

• We cannot predict well if test data too different from training data

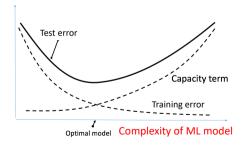


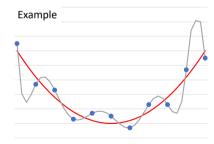
- Assume training and test data samples from same probability distribution $(x,y) \sim \mathcal{D}$
- Goal: Find model $h(\cdot)$ that minimises $\mathbb{E}_{(x,y)\sim\mathcal{D}}\left[(y-h(x))^2\right]$

Essence of Theory of Generalisation

• Theory of Generalisation:

$$\underbrace{\mathbb{E}_{(x,y)\sim\mathcal{D}}\left[(y-h(x))^2\right]}_{\text{expected test error}} \leq \underbrace{\frac{1}{n}\sum_{i=1}^n(y_i-h(x_i))^2}_{\text{training error}} + \sqrt{\frac{1}{n}} \cdot \text{complexity of ML model}$$





Are complex models (that can overfit) really bad?

Rank Model

Benchmarks on ImageNet



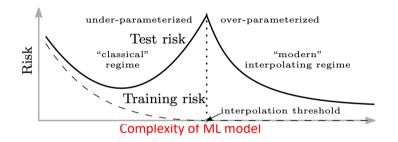
1.2M training images

1	Florence-CoSwin-H	90.05%	99.02%	893M
2	Meta Pseudo Labels (EfficientNet-L2)	90.2%	98.8%	480 M
3	Meta Pseudo Labels (EfficientNet-B6-Wide)	90%	98.7%	390M
4	FixEfficientNet-L2	88.5%	98.7%	480M
5	NoisyStudent (EfficientNet-L2)	88.4%	98.7%	480M

Number of

Accuracy Accuracy

Double descent phenomena



- In Part II, we may see some mathematical theories on why this happens
- Is above plot "at odds" with the notion "overfitting is bad"?

Reading material and references

- Part I:
 - Shai Shalev-Shwartz & Shai Ben David.

 Understanding Machine Learning: From theory to algorithms

(available online)

• Luc Devroye, László Györfi & Gábor Lugosi. A probabilistic theory of pattern recognition

(available online)

- Part II:
 - Lecture slides (additional references will be mentioned, but not necessary)

Feedback / emergency contacts

- For feedback / issues, talk to us or use anonymous feedback module on Moodle
- For further support:
 - If you experience / observe any discrimination or insensitive behaviour, including racism/sexism, contact
 - Fachschaft
 - TUM Compliance office
 - Gender equality officers at CIT School or CS Department