SF2935: Modern Methods of Statistical Learning (Autumn 2025)

This advanced course in statistical learning dives into modern methods and their theoretical foundations. While the core focus is on conceptual understanding and statistical principles, the material will be reinforced through empirical demonstrations using data.

The basic course syllabus is available at `https://www.kth.se/student/kurser/kurs/SF2935/?l=en`. This document provides a detailed course plan, including information on the main texts, tentative schedule, assessment structure, and recommended supplementary resources.

1 Prerequisites

Students are expected to have a strong[1] background in linear algebra, calculus, probability and statistics, and proficiency in a programming language suitable for scientific computing. A prior introductory course in machine learning or statistical modeling is highly recommended.

2 Course Materials

The main text for this course is:

- ***The Elements of Statistical Learning: Data Mining, Inference, and Prediction*** (ESL), by Trevor Hastie, Robert Tibshirani, and Jerome Friedman (2nd edition, corrected 12th printing, 2017).
  Available at: `https://hastie.su.domains/ElemStatLearn/`

ESL is widely regarded as the gold standard reference for statistical learning, offering comprehensive coverage of both theory and methodology. We aim to cover approximately 70% of the materials in ESL, supplemented with:

- ***An Introduction to Statistical Learning: With Applications in Python*** (ISL), by Gareth James, Daniela Witten, Trevor Hastie, and Robert Tibshirani (2023).
  Available at: `https://www.statlearning.com/`
- ***Learning Theory From First Principles*** (Bach), by Francis Bach (final version, 2025).
  Available at: `https://www.di.ens.fr/~fbach/ltfp_book.pdf`

ISL emphasizes a conceptual and application-oriented understanding of statistical learning methods, while Bach provides a rigorous treatment of the underlying mathematical principles. Additional materials may also be used to supplement the main text.

Lecture slides and the associated code will be made available after each class.

3 Tentative Schedule

We have 14 lecture sessions and 7 tutorial sessions. All the sessions are held from 13:00-15:00 except the sessions on Aug 29 and Sep 19 (15:00-17:00).

[1] At a minimum, you should be familiar with most of the material in Part I of: `https://mml-book.github.io/`.

Date	Session	Topic	References
Aug 26	**L1**	Introduction to Supervised Learning	ESL (Ch. 1–2), ISL (Ch. 1–2), Bach (Ch. 2)
Aug 28	**L2**	Linear Methods for Regression	ESL (Ch. 3), ISL (Ch. 3, 6), Bach (Ch. 3)
Aug 29*	**T1**	Tutorial	-
Sep 2	**L3**	Linear Methods for Classification	ESL (Ch. 4, 12.1-12.2), ISL (Ch. 4)
Sep 4	**L4**	Basis Expansions, Local Averaging, Kernel Smoothing	ESL (Ch. 5.1-5.7, 6), ISL (Ch. 7), Bach (Ch. 6)
Sep 5	**T2**	Tutorial	-
Sep 9	**L5**	Support Vector Machines, Kernel Methods	ESL (Ch. 5.8-5.9, 12.1-12.3), ISL (Ch. 9), Bach (Ch. 7)
Sep 11	**L6**	Generalization Theory, Model Assessment and Selection	ESL (Ch. 7), ISL (Ch. 5), Bach (Ch. 4)
Sep 12	**T3**	Tutorial, **Project Proposal Due**	-
Sep 16	**L7**	Tree-Based Methods, Ensemble Methods	ESL (Ch. 9-10), ISL (Ch. 8), Bach (Ch. 10)
Sep 18	**L8**	Optimization for Machine Learning	Bach (Ch. 5), additional materials
Sep 19*	**T4**	Tutorial	-
Sep 23	**L9**	Neural Networks I: Methods	ESL (Ch. 11), ISL (Ch. 10), Bach (Ch. 9)
Sep 25	**L10**	Neural Networks II: Theory	ISL (Ch. 10), Bach (Ch. 9), additional materials
Sep 26	**15**	Tutorial	-
Sep 30	**L11**	Neural Networks III: Special Topics	ISL (Ch. 10), Bach (Ch. 12), additional materials
Oct 2	**L12**	Unsupervised Learning: Dimensionality Reduction & Clustering	ESL (Ch. 14), ISL (Ch. 12)
Oct 3	**T6**	Tutorial	-
Oct 7	**L13**	Probabilistic Methods: Bayesian Inference & Variational Methods	ESL (Ch. 8), Bach (Ch. 14)
Oct 9	**L14**	Generative Models: VAEs & Diffusion Models	Additional materials
Oct 10	**T7**	Tutorial	-

Oct 17	**-**	**Project Report Due**	-
Oct 23	**-**	**Final Exam**	-

4 Assessments and Grading

The final grade for the course will be based on the following two components:

- A **course project**: 50%
- A **final exam**: 50%

Further details regarding the format, expectations, and evaluation criteria for each component will be provided during the course.

5 Additional Resources

The following additional references may also be useful for deepening your understanding of the topics covered:

- *Pattern Recognition and Machine Learning*, by Christopher M. Bishop (2006)
- *Deep Learning: Foundations and Concepts*, by Christopher M. Bishop and Hugh Bishop (2024)
- *Probabilistic Machine Learning: An Introduction*, by Kevin P. Murphy (2022)
- *Patterns, Predictions, and Actions*, by Moritz Hardt, Benjamin Recht (2022)
- *Understanding Machine Learning: From Theory to Algorithms*, by Shai Shalev-Shwartz and Shai Ben-David (2014)
- *Foundations of Machine Learning*, by Mehryar Mohri, Afshin Rostamizadeh, and Ameet Talwalkar (2nd edition, 2018)
- *Learning from Data*, by Yaser S. Abu-Mostafa, Malik Magdon-Ismail, and Hsuan-Tien Lin (2012)
- *Deep Learning*, by Ian Goodfellow, Yoshua Bengio, and Aaron Courville (2016)
- *Mathematics for Machine Learning*, by Marc Peter Deisenroth, A. Aldo Faisal, and Cheng Soon Ong (2020)
- *Scikit-learn: Machine Learning in Python** (available at `https://scikit-learn.org/stable/`)
- *Dive into Deep Learning (D2L)**, by Aston Zhang, Zachary C. Lipton, Mu Li, and Alexander J. Smola (available at `https://d2l.ai/`)
- *Practical Deep Learning for Coders**, by Jeremy Howard (available at `https://course.fast.ai/`)
- *PyTorch in One Hour: From Tensors to Training Neural Networks on Multiple GPUs**, by Sebastian Raschka (available at `https://sebastianraschka.com/teaching/pytorch-1h/`)

*: useful references for coding and implementation in Python and PyTorch