Detailed Syllabus for SF2935: Modern Methods of Statistical Learning, 7.5 Credits (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 mathematical principles, the material will be reinforced through empirical demonstrations using a variety of datasets.

The basic 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 Main Texts

The main texts for this course are:

- ***The Elements of Statistical Learning: Data Mining, Inference, and Prediction***, by Trevor Hastie, Robert Tibshirani, and Jerome Friedman (2nd edition, corrected 12th printing, 2017). Available at: `https://hastie.su.domains/ElemStatLearn/` (ESL)
- ***Learning Theory From First Principles***, by Francis Bach (final version, 2025). Available at: `https://www.di.ens.fr/~fbach/ltfp_book.pdf` (Bach)

These texts provide both theoretical and practical foundations for the methods covered in the course. We aim to cover about 70% of the materials in ESL and Bach. Additional reading materials may also be assigned periodically to supplement the main texts.

2 Tentative Schedule

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

Date	**Session**	Topic	References (ESL / Bach)
Aug 26	**1**	Course Introduction, Fundamentals of Supervised Learning & Risk Minimization	ESL Ch. 1–2 / Bach Ch. 1–2
Aug 28	**2**	Model Evaluation: Bias-Variance Tradeoff, Selection & Cross-Validation	ESL Ch. 2, 7.1–7.3 / Bach Ch. 2
Aug 29*	**3**	Tutorial	ESL + Bach
Sep 2	**4**	Linear Models: Regression, Classification & Regularization (Ridge, Lasso)	ESL Ch. 3–4, 18.1 / Bach Ch. 4–5
Sep 4	**5**	Instance-Based Learning: Nearest Neighbors & Support Vector Machines (SVMs)	ESL Ch. 12–13 / Bach Ch. 6.1–6.3
Sep 5	**6**	Tutorial	ESL + Bach
Sep 9	**7**	Kernel Methods: Kernel Trick, Duality, Reproducing Kernel Hilbert Spaces (RKHS)	ESL Ch. 12 / Bach Ch. 6.2–6.3
Sep 11	**8**	Generalization Theory: VC Dimension, Rademacher Complexity & Bounds	ESL Ch. 7 / Bach Ch. 7–8
Sep 12	**9**	Tutorial	ESL + Bach

Sep 16	**10**	Decision Trees: CART, Splitting Criteria, Overfitting & Pruning Strategies	ESL Ch. 9 / Notes
Sep 18	**11**	Ensemble Methods: Bagging, Boosting, Random Forests & Model Averaging	ESL Ch. 8, 10, 15 / Notes
Sep 19*	**12**	Tutorial	ESL + Bach
Sep 23	**13**	Neural Networks I: Perceptrons, MLPs, Backpropagation & Optimization	ESL Ch. 11 / Bach Ch. 8.3
Sep 25	**14**	Neural Networks II: Deep Architectures (CNNs, RNNs, Transformers) & Universal Approximation	Additional materials
Sep 26	**15**	Tutorial	ESL + Bach
Sep 30	**16**	Neural Networks III: Deep Learning Theory (SGD, Overparameterization, Double Descent)	ESL Ch. 11 / Bach Ch. 8 + additional materials
Oct 2	**17**	Unsupervised Learning: Dimensionality Reduction (PCA, Kernel PCA), Clustering (k-Means) & Representation Learning (Autoencoders)	ESL Ch. 14 / Bach Ch. 10
Oct 3	**18**	Tutorial	ESL + Bach
Oct 7	**19**	Probabilistic Methods: Bayesian Inference & Variational Methods	Bach Ch. 14
Oct 9	**20**	Generative Models Intro: VAEs, GANs & Diffusion Models	Additional materials
Oct 10	**21**	Tutorial	Additional materials
Oct 17	**-**	**Final Project Submission Deadline**	-
Oct 23	**-**	**Final Exam**	-

3 Assessments and Grading

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

- Biweekly assignments (3 in total): 30%
- Final project: 30%
- Final exam: 40%

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

4 Additional Resources

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

- *An Introduction to Statistical Learning*, by Gareth James, Daniela Witten, Trevor Hastie, and Robert Tibshirani (2nd edition, 2021)
- *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)
- *Neural Networks and Deep Learning*, by Michael Nielsen (2015)
- *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