Detailed Syllabus for SF2935: Modern Methods of Statistical Learning, 7.5 Credits (Autumn 2025)

The basic syllabus is available at `https://www.kth.se/student/kurser/kurs/SF2935/?l=en`.
This document aims to provide a detailed course plan that includes information on the main texts, the tentative schedule, and the course assessments.

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 about 30% of the materials in 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 (2023)
- *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