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 Text

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, lightly 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 reading materials may also be assigned periodically to supplement the main text.

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
Aug 26	**1**	Course Introduction, Fundamentals of Supervised Learning & Risk Minimization	ESL Ch. 1–2 (ISL Ch. 1-2, Bach Ch. 2)
Aug 28	**2**	Model Evaluation: Bias-Variance Tradeoff, Model Assessment & Selection	ESL Ch. 2 & Ch. 7 (ISL Ch. 2 & Ch. 5, Bach Ch. 2)
Aug 29*	**3**	Tutorial	ESL + ISL + Bach
Sep 2	**4**	Linear Methods for Regression	ESL Ch. 3 (ISL Ch. 3, Bach Ch. 3)
Sep 4	**5**	Linear Methods for Classification, Regularization	ESL Ch. 4-5 (ISL Ch. 4 & Ch. 6)

Sep 5	6	Tutorial	ESL + ISL + Bach
Sep 9	7	Support Vector Machines, Kernel Methods	ESL Ch. 6 & Ch. 12 (ISL Ch. 9, Bach Ch. 7)
Sep 11	8	Generalization Theory: VC Dimension, Rademacher Complexity & Bounds	ESL Ch. 7 (Bach Ch. 4)
Sep 12	9	Tutorial, **Assignment 1 Due**	ESL + ISL + Bach
Sep 16	10	Tree-Based Methods, Ensemble Methods I: Bagging	ESL Ch. 9-10 (ISL Ch. 8, Bach Ch. 10)
Sep 18	11	Ensemble Methods II: Boosting & Random Forests	ESL Ch. 10 & Ch. 15 (ISL Ch. 8, Bach Ch. 10)
Sep 19*	12	Tutorial	ESL + ISL + Bach
Sep 23	13	Neural Networks I: Perceptrons, MLPs, Backpropagation & Optimization	ESL Ch. 11 (ISL Ch. 10, Bach Ch. 5)
Sep 25	14	Neural Networks II: Universal Approximation & Deep Architectures (CNNs, RNNs, Transformers)	ISL Ch. 10, Bach Ch. 9 (additional materials)
Sep 26	15	Tutorial, **Assignment 2 Due**	ESL + ISL + Bach
Sep 30	16	Neural Networks III: Theory for Overparameterized Models	Bach Ch. 12 (ISL Ch. 10, additional materials)
Oct 2	17	Unsupervised Learning: Dimensionality Reduction & Clustering	ESL Ch. 14 (ISL Ch. 12)
Oct 3	18	Tutorial	ESL + ISL + Bach
Oct 7	19	Probabilistic Methods: Bayesian Inference & Variational Methods	ESL Ch. 8 (Bach Ch. 14)
Oct 9	20	Generative Models Intro: VAEs, GANs & Diffusion Models	Additional materials
Oct 10	21	Tutorial, **Assignment 3 Due**	Additional materials
Oct 17	-	**Final Project Report Due**	-
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:

- *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)

- *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