DM1590 Machine Learning for Media Technology 7.5 credits

Maskininlärning för medieteknik

This is a translation of the Swedish, legally binding, course syllabus.

If the course is discontinued, students may request to be examined during the following two academic years

Establishment

Course syllabus for DM1590 valid from Autumn 2019

Grading scale

A, B, C, D, E, FX, F

Education cycle

First cycle

Main field of study

Technology

Specific prerequisites

Completed courses

SF1624 Algebra and Geometry, SF1625 Calculus in One Variable, DD1318 Programming and Scientific Computing as well as at least two of SF1626 Calculus in Several Variables, SF1919 Probability Theory and Statistics or DD1320 Applied Computer Science or the equivalent.

Language of instruction

The language of instruction is specified in the course offering information in the course catalogue.

Intended learning outcomes

After passing the course, the students should be able to:

- develop and modify media technology applicationsthat use machine learning and evaluate them in an appropriate manner,
- recommend methods for machine learning for particular media technology applications,
- describe and explain the machine learning pipeline,
- explain and contrast supervised and unsupervised learning methods,
- explain and contrast parametric and non-parametric methods,
- explain training validation and testing of machine learning models,
- summarise best practice and pitfalls in applied machine learning for media technology.

in order to

• being able to apply and evaluate machine learning modelsand methods in media technology.

Course contents

Course starts with an overview of what machine learning is and why it is important. This is illustrated with several real applications in various media, e g text summarisation, sound and music recommendation and image retrieval. The course then presents the workflow of machine learning development that serves as an overview of the remainder of the course. The course presents the two general classes of machine learning methods: supervised learning (for example closest neighbour, decision tree) and unsupervised learning (e g k-means clustering, principal component analysis). For these, the course presents different types of modelling: parametric (e.g. Bayes, least squares) and non-parametric (for example closest neighbours, decision trees). The course reviews common methods for evaluation of machine learning models (e g holdout, bootstrap). Finally, best practices are presented (e.g. partition) together with common pitfalls (e g over fitting).

Course literature

nformation about the course literature will be announced in the course memo.

Examination

- LAB1 - Laboratory work, 4.5 credits, grading scale: P, F
- PRO1 - Project, 3.0 credits, grading scale: A, B, C, D, E, FX, F

Based on recommendation from KTH’s coordinator for disabilities, the examiner will decide how to adapt an examination for students with documented disability.

The examiner may apply another examination format when re-examining individual students.

The examiner decides, in consultation with KTH's coordinator for disabilities (Funka), about possible adapted examination for students with documented, permanent disabilities. The examiner may permit other examination format for re-examination of individual students.

Ethical approach

- All members of a group are responsible for the group's work.
- In any assessment, every student shall honestly disclose any help received and sources used.
- In an oral assessment, every student shall be able to present and answer questions about the entire assignment and solution.