

Machine Learning

DD2421, 7.5 credits

Atsuto Maki, Bob Sturm, Jörg Conradt

Autumn, 2020

1 About the course

- Course Contents
- Textbooks
- Who are teaching?

2 Logistics

- Lectures
- Labs
- Examinations
- Miscellaneous

3 A very brief overview of Machine Learning

- Applications
- Types of Learning
- Supervised and Unsupervised

The aim of the course is to provide:

- basic knowledge of the most important algorithms and theory that form the foundation of machine learning
- a practical knowledge of machine learning algorithms and methods

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Course contents:

- Lectures 1–11
- Lecture 12, mini lectures
- Labs 1–3 (NB. there is a deadline for each)
- Programming challenge
- Written exam

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DD2421 is:

- Compulsory for the Masters Programme in Machine Learning
- Prerequisite for DD2434 Machine Learning, Advanced Course

Intended outcomes – students will be able to:

- describe the most important algorithms and the theory that constitutes the basis for machine learning and artificial intelligence
- explain the principle for machine learning and how the algorithms and the methods can be used
- discuss advantages with and limitations of machine learning for different applications

in order to be able to identify and apply appropriate machine learning technique for classification, pattern recognition, regression and decision problems.

Recommended reading

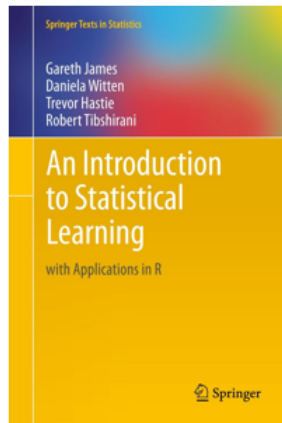
Gareth James, Daniela Witten,
Trevor Hastie and Robert Tibshirani

An Introduction to Statistical Learning

Springer, 2013

Available online:

<https://faculty.marshall.usc.edu/gareth-james/ISL/>



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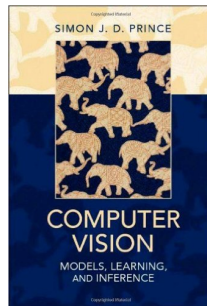
Simon Prince

Computer Vision: Models, Learning,
and Inference

Cambridge University Press, 2012

Available online:

web4.cs.ucl.ac.uk/staff/s.prince/book/book.pdf



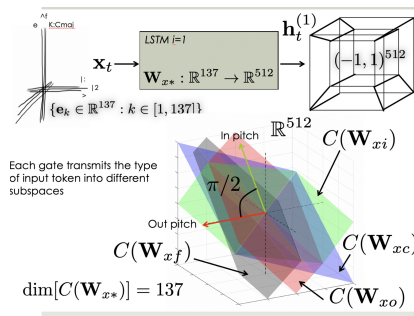
NB. Pointers to other reference materials under Lectures page.

Who are teaching?

- **Atsuto Maki**
Div. Robotics, Perception, and Learning
- **Bob L. T. Sturm**
Div. Speech, Music, and Hearing
- **Jörg Conradt**
Div. Computational Science and Technology
- Course Assistant: **Alexander Kozlov**
Div. Computational Science and Technology
- 10+ teaching assistants (mostly PhD students)

Bob Sturm

Research topics: Machine Music Listening, AI for Music Creation, Machine Learning Evaluation

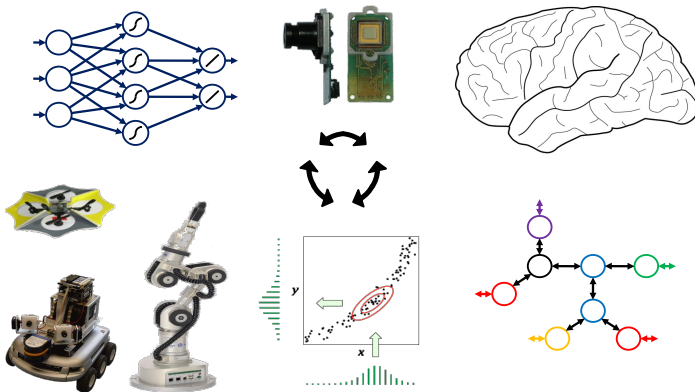


<https://youtu.be/EC1TrQzBVSE>

DT2470 "Music Informatics"

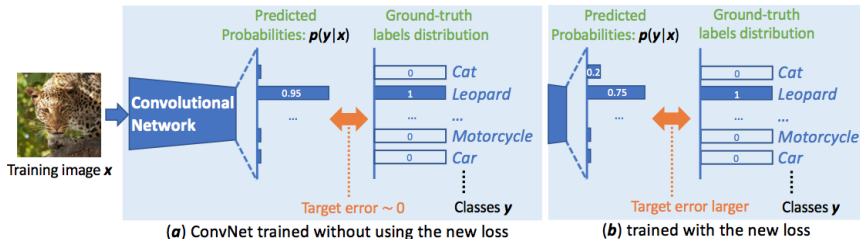
Jörg Conradt

Research Topic: Neural Computation for Real-Time System Engineering



Atsuto Maki

Research topics: Computer Vision, Machine/Deep Learning



<https://robotics.sciencemag.org/content/4/30/eaaw1329.full>

<https://www.kth.se/profile/atsuto>

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Course Information on Canvas

<https://kth.instructure.com/courses/20445>

Course Information on KTH Social

<https://www.kth.se/social/course/DD2421/>
<https://www.kth.se/social/course/DD2421/calendar/>
<https://www.kth.se/social/course/DD3431/>

Course registration needed!

Any inquiries to student office / service center
(Email: service@eecs.kth.se).

For administrative questions please consult this page:
www.kth.se/en/eecs/studentsupport

Lectures

- ➊ Nearest Neighbour Classifier (Memory-based)
- ➋ Decision Trees (Logical inference)
- ➌ Challenges in Machine Learning
- ➍ Regression
- ➎ Probabilistic Methods
- ➏ Learning as Inference
- ➐ Learning with Latent Variables
- ➑ Support Vector Machines
- ➒ Artificial Neural Networks
- ➓ Ensemble Methods
- ➑ Dimensionality Reduction
- ➒ Mini lectures (beyond the scope of DD2421), exam Q&A

Labs (3.5 credits)

- ① Decision Trees
 - ② Support Vector Machines
 - ③ Bayes Classifier & Boosting
- labs are carried out by students and examined by TAs
 - use Canvas to book time slots for examination

Labs (3.5 credits)

- 1 Decision Trees
- 2 Support Vector Machines
- 3 Bayes Classifier & Boosting

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Examination:

- It is **your** task to convince the examiner that you have done the assignment and understood the results.
- Strongly encouraged to work+report by pairs of two students.
- 10 minutes
- No programming code to be shown
- Bring your ID (tell the TA if you are yet to be registered)

Examination (4 credits)

A written “take-home” examination, not an in-class exam.

Date: Friday 23 October 14:00-17:00 (time to be finalised)

Chance for re-exam (in December).

Examination (4 credits) cont'd: a programming challenge.

Build and train a classifier given a labeled dataset.

Use it to infer the labels of a given unlabeled evaluation dataset.

Submit the inferred labels - will be compared to the ground truth.

Planned schedule (one week): 16-22 October

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The accuracy is proportional to the point you receive.

Logistics found on Canvas:

<https://kth.instructure.com/courses/20445/assignments/127950>

FAQ

Q. Are course slides available?

A. Will be uploaded on the "Lectures" page on Canvas.

Q. Could we make a group of 3 students for the lab?

A. No – the slot is too short to examine three students.

Q. Can you register me to the course, please?

A. Please consult student office/service center: service@eecs.kth.se

Miscellaneous

Message board available on “Discussion” on KTH Canvas (but bear with us – teachers cannot promise to respond :-)).

A form to get a KTH-account available at the reception of EECS (for PhD-students from other universities). See instructions:
<https://intra.kth.se/en/eecs/forskarutbildning/courses>

Kursnämnd: It will be a great pleasure to have students' course committee (a.k.a. kursnämnd). Anyone volunteers, please?

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Sample Applications

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- Speech recognition and synthesis
- Natural language processing
- Autonomous robots
- Spam-filter for e-mail
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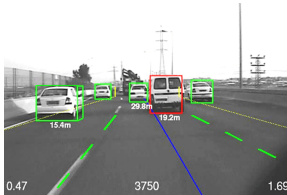
Where is machine learning useful?

A pattern exists

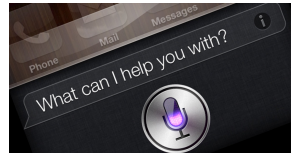
Data available for training

Hard/impossible to define rules mathematically

Driving assistants
(Google, Toyota, Volvo, ...)



Personal assistants
(Apple Siri, Amazon Eco, ...)



Board games
(DeepMind AlphaGo)



Types of Learning

- **Supervised Learning** (covered)
- **Unsupervised Learning** (briefly covered)
- **Reinforcement Learning** (not covered)
- **Evolutionary Learning** (not covered)

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 - Consider how a baby learns to walk for instance.
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 - General Purpose Optimization

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Conflates two different distinctions:

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 - Learning mappings from A to B.
(Neutral mathematics.)
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- **Unsupervised Learning**, a.k.a. descriptive
 - Analyzing unstructured raw data. There is no B, only A.
 - Learning without human supervision.
(Scalable and biologically plausible.)