Neural Networks and Learning Systems
TBMI26 / 732A55
2019

Lecture 1

Introduction

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Course information

- All information will be available on Lisam
- Lectures will be published during the course

- You must register for classes and labs on Lisam
  - Chose group A, B or C for classes – and follow your group!
  - Chose group 1, 2, 3 or 4 for the labs (not connected to class)

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Staff

- Examiner: Magnus Borga (magnus.borga@liu.se)
- Course admin: Anette Karlsson (anette.k.karlsson@liu.se)

- Lectures: Magnus Borga, Michael Felsberg
- Lessons: Anette Karlsson, Martin Hultman, Lasse Alfredsson
- Labs:
  - Annette Karlsson, Martin Hultman, David Abramiam
  - Abdelrahman Eldesokey , Mikael Persson, Hannes Ovrén

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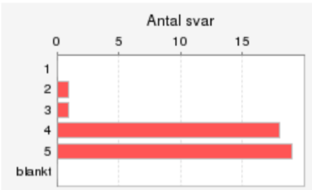
Course evaluation and development

På en femgradig skala ger jag kursen sammanfattningsbetyget / On a scale 1-5 (5 being the best) I give the overall credit to this course



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4	18	45%	
5	19	48%	
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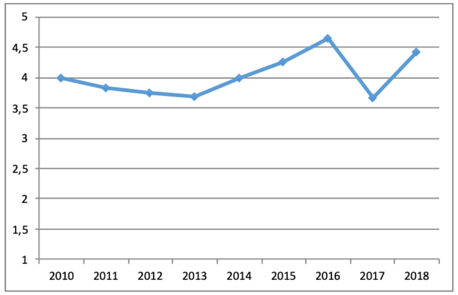
Overall credit over time



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The Course - Overview

- 9 lectures
- 9 lessons
- 4 assignments
- 1 written exam

Must be completed

- Course language is English.

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The Course - Lectures

PPT lectures, handouts on course page

1. Introduction
2. Supervised learning – Linear classification
3. Supervised learning – Neural networks
4. Supervised learning – Ensemble learning & Boosting methods
5. Supervised learning – Convolutional Networks *
6. Supervised learning – Deep Networks *
7. Reinforcement learning
8. Unsupervised learning – Dimensionality reduction, Clustering
9. Kernel methods

* Lectures 5 and 6 are given by Michael Felsberg

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The Course - Lessons

- One lesson after each lecture
- Pen & paper exercises
- Complementary presentations
- Preparations and help with assignments
- Choose group (A/B/C) on Lisam and follow that group

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The Course - Assignments

- 4 laboratory exercises/assignments:
  1. Pattern recognition using linear classifiers and neural networks
  2. Face recognition in images using Boosting techniques
  3. Deep learning
  4. Reinforcement learning
- Matlab (and Python in lab 3)
- Assignments are done in pairs. (Not more than 2 students together!)
- Supervision time scheduled ("Laboration" in schedule) –
  – Choose lab group (1 - 4) on Lisam and follow that group
- Deadlines for written reports.
- Late reports will not be corrected until the re-exam in June.

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Course literature

- Lecture notes
- Recommended reading on the Lectures-page
- Exercise collection
- Assignments

- Additional links in lecture notes (not required reading)

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Prerequisites

- Linear algebra
  – Vectors, scalar products, eigenvalues
- Multidimensional calculus
  – Gradients, partial derivatives
- Mathematical statistics
  – Mean, variance, covariance, correlation, Gaussian distribution,
- Programming
  – Some programming experience
  – Matlab knowledge helps a lot

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Challenges this year

- Number of students
  – Important to follow your group schedule (lessons and labs)

- New lab on deep learning.

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Machine Learning

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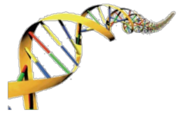
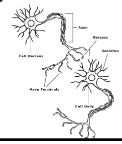
Applications of machine learning

- Pattern and speech recognition
- Robots & autonomous systems
- Games
- Big data
- Evolutionary systems
- Expert systems & decision support
- Models of the brain

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What is (machine) learning?

Encyclopaedia Britannica (1964):
"Any relatively permanent change in behaviour resulting from past experience."

Bishop (2006):
"The core objective of a learner is to generalize from its experience."

Wikipedia (2015):
"Machine learning is a scientific discipline that explores the construction and study of algorithms that can learn from data. Such algorithms operate by building a model based on inputs and using that to make predictions or decisions, rather than following only explicitly programmed instructions."

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How can a machine learn?

"Any relatively permanent change in behaviour resulting from past experience."

- The "behaviour" of the machine is determined by model parameters.
- "past experience" is previously observed data.

- Machine learning = changing parameter values (behaviour) as a result of observed data (experience).

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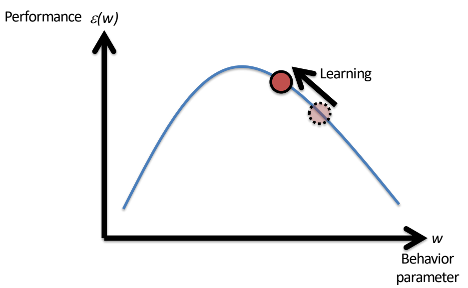
Learning = optimization



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Mathematical foundations of machine learning

Find parameters for optimal behaviour

Machine Learning

Optimization theory | Statistics

Multidimensional calculus

Linear algebra

Model uncertainty

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Why machine learning?

- Algorithm too complex for a human to implement, but we can easily generate examples of what the algorithm should do.
- Relationships in high-dimensional data too complex for a human to see, but a computer can find these.
- The computer should learn and adapt continuously to new situations.

Big companies are using it

- Apple https://machinelearning.apple.com
- Microsoft https://blogs.microsoft.com/ai/
- Google https://ai.google/research/
- IBM http://www.research.ibm.com/cognitive-computing/
- .... (long list)

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Three main categories of machine learning methods

- **Supervised learning (predictive)**
  Learn to generalize and classify new data based on labelled training data.
  - Pattern recognition
  - Classification
  - Regression
- **Unsupervised learning (descriptive)**
  Discover structure and relationships in complex high-dimensional data.
- **Reinforcement learning (active)**
  Generate policies/strategies that lead to a (possibly delayed) reward. Learning by doing.

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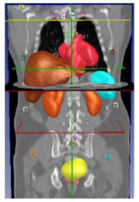
Pattern recognition examples

Face recognition

Organ segmentation



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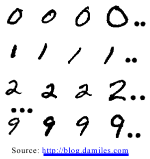
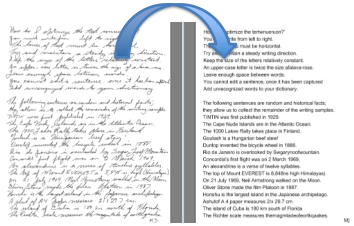
Pattern recognition examples

Optical Character Recognition (OCR)





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Pattern recognition examples

Xbox Kinect – Pose estimation

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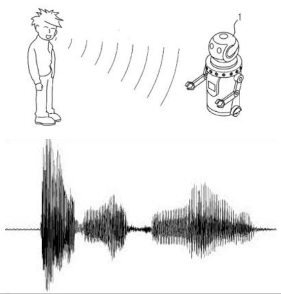
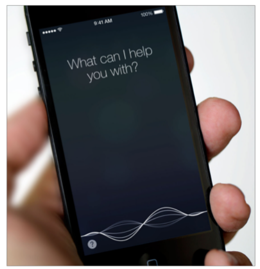
Pattern recognition examples

Speech recognition





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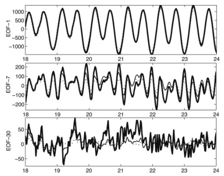
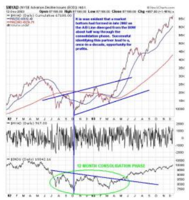
Pattern recognition examples

Prediction and forecasting

Weather and natural phenomena



Financial markets



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Pattern recognition examples

Game positions

Spam filters

#1
100% satisfied
4U
Accept credit cards
Act Now!
Additional Income
Affordable
All natural

Movie & music recommendation

Spotify

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Features

- A <u>feature</u> is a measurement or scalar number that describes some aspect of a phenomenon or object
  - Size, length, shape, velocity
  - Intensity and color (RGB)
  - Position (x,y)
  - Signal frequency
  - Sensor measurements (e.g., temperature)
  - Game piece present at certain location (yes/no)
  - Word present in an email (yes/no)
- <u>Feature extraction</u> is the process of measuring features from data.

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Features – Iris dataset

Iris setosa

Iris versicolor

Iris virginica

Fisher's Iris Data

Sepal Length	Sepal Width	Petal Length	Petal Width	Species
5.7	4.4	1.5	0.4	*I. setosa*
5.8	2.6	4.0	1.2	*I. versicolor*
5.8	2.7	5.1	1.9	*I. virginica*

From Wikipedia

Feature vectors: $\mathbf{x}_1 = \begin{bmatrix} 5.7 \\ 4.4 \\ 1.5 \\ 0.4 \end{bmatrix}$ $\mathbf{x}_2 = \begin{bmatrix} 5.8 \\ 2.6 \\ 4.0 \\ 1.2 \end{bmatrix}$ $\mathbf{x}_3 = \begin{bmatrix} 5.8 \\ 2.7 \\ 5.1 \\ 1.9 \end{bmatrix}$

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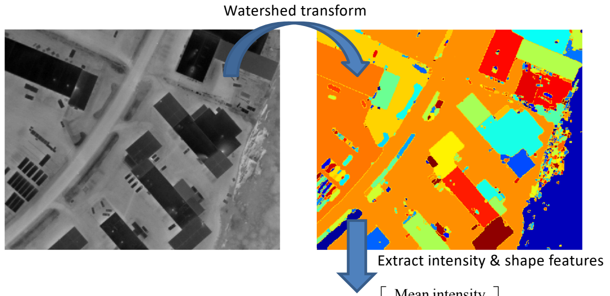
Features – Image classification



$$\mathbf{x} = \begin{bmatrix} \text{Mean intensity} \\ \text{Std intensity} \\ \text{Border regularity} \\ \text{Compactness} \end{bmatrix}$$

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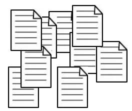
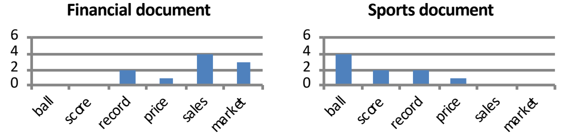
Features – Document analysis



Articles, mail, web pages, ...

Dictionary:
{'ball', 'score', 'record', 'price', 'sales', 'market'}



$$\mathbf{x} = \begin{bmatrix} \#\text{'ball'} \\ \#\text{'score'} \\ \#\text{'record'} \\ \#\text{'price'} \\ \#\text{'sales'} \\ \#\text{'market'} \end{bmatrix}$$

Bag-of-words model

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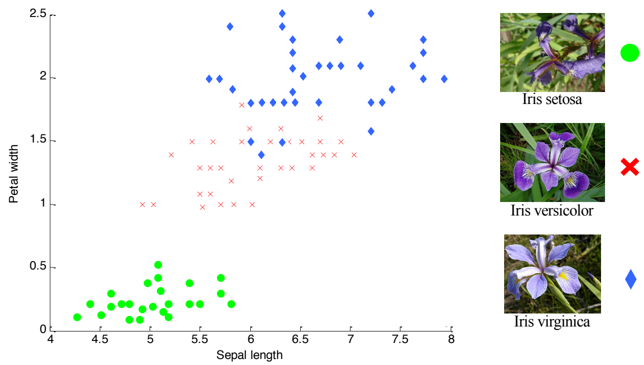
Feature space



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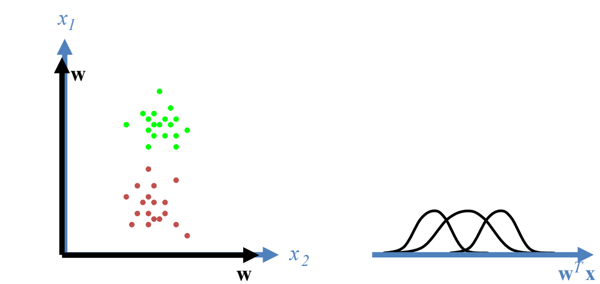
Representation



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Supervised learning

- **Task:** Learn to predict/classify new data from labeled examples.
- **Input:** Training data examples $\{\mathbf{x}_i, y_i\}$, i=1...N, where $\mathbf{x}_i$ is a feature vector and y_i is a class label in the set Ω.
- **Output:** A function $f(\mathbf{x}; w_1,\ldots,w_k) \rightarrow \Omega$

Find a function *f* and adjust the parameters $w_1,\ldots,w_k$ so that new feature vectors are classified correctly. ***Generalization!!***

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Classification vs. regression vs. ranking

- **Classification**: Select one of a discrete set of classes (the set Ω is discrete).
  - Which horse is going to win this race?
  - Which letter does this image depict?
  - Is this email spam (yes/no)?
- **Regression**: Learn to predict a continuous value ($\Omega = \mathbb{R}$).
  - Learn to predict the temperature tomorrow.
  - What is the *probability* that this image depicts the letter 'a'?
- **Ranking**: Learn to rank a set of items ($\Omega = \mathbb{R}$).
  - Rank webpages, movies, etc.

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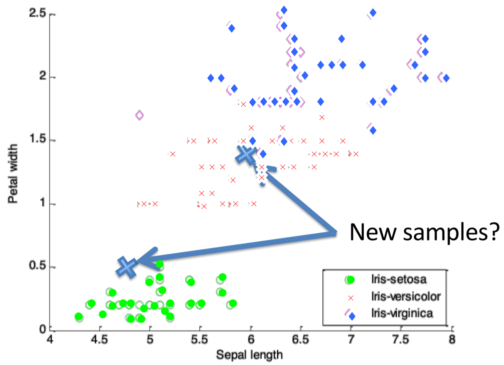
Example



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k-Nearest Neighbours (k-NN)

- Save all training data.
- For a new case, find similar examples among the training data.
- Requires a similarity measure (metric), for example the Euclidian distance

$$\|\mathbf{x}-\mathbf{y}\| = \sqrt{\sum_i (x_i - y_i)^2}$$

- A majority vote among the *k* nearest neighbours decides the class, where *k* can be 1,2,3,4...

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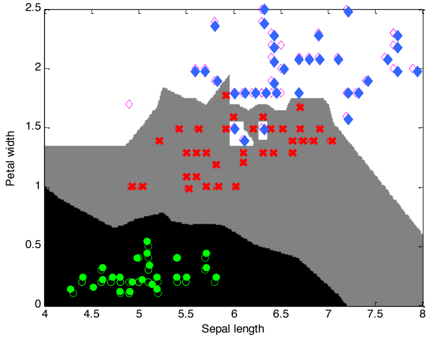
Classification areas

k = 1



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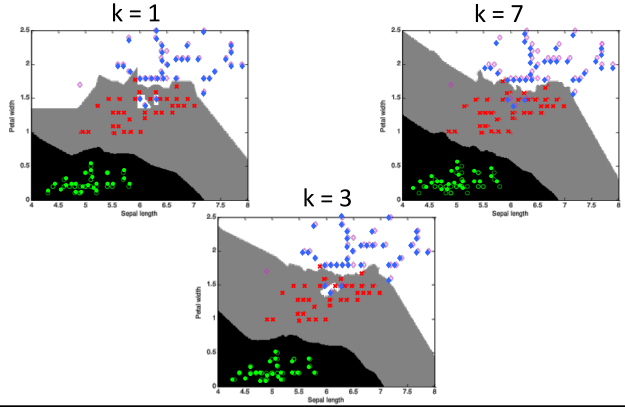
Classification areas



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Pros and cons of k-NN

- Very simple – no “training“ or modeling required
- Must store all training data – problem for large data sets:

$$f(\mathbf{x};\underbrace{w_1,\ldots,w_k}_{})\rightarrow \Omega$$

Parameters equal to training data $\mathbf{x}_i$

- Slow classification for large data sets – must compare new samples with all stored samples.

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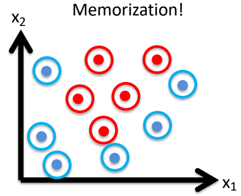
Generalization!

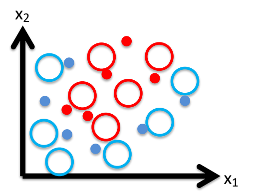
“The core objective of a learner is to generalize from its experience.”

Classifying training data is trivial. Memorization!



$f(\mathbf{x};w_1,\ldots,w_k)\rightarrow \Omega$

Classifying **new data** is the challenge!



Generalization error!

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Evaluating classifiers

- How can we compare the performance of different classifiers?
- What happens if we use the same data for training and evaluation?
- How can we train and test a classifier if we only have a finite amount of collected data?

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Confusion matrix

Iris setosa

Iris versicolor

Iris virginica

Predicted class

Actual class	Setosa	Versicol.	Virginica
Setosa	50	0	0
Versicol.	0	45	5
Virginica	0	7	43

Accuracy: $\frac{50+45+43}{150} = 92\%$

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Training data vs. test data

- A classifier must be able to <u>generalize</u>, i.e., it must be tested using <u>previously unseen</u> data.
- Evaluating using training data will give an overly optimistic accuracy.
- Three ways to perform the evaluation:
  - Hold out
  - Cross validation
  - Leave one out

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Hold out

- Simplest approach, hold out one part of the entire data set as test data.

Training data	Test data

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n-fold Cross-Validation

- Divide data set into n segments. Train using n-1 segments and evaluate using the n:th.
- Example of 3-fold Cross-Validation:

Training data	Training data	Test data
Training data	Test data	Training data
Test data	Training data	Training data

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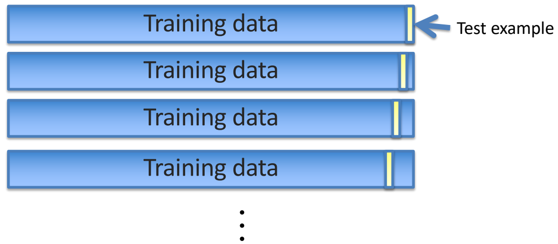
Leave-one-out

- Extreme case of Cross-Validation: Use all data but one example for training and use the last one to evaluate



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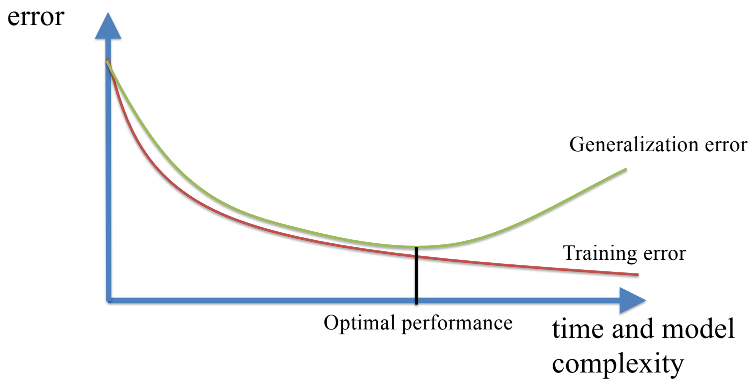
Overfitting



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How can we find the minimum generalization error?

- What happens if the generalization error is not low enough?
- Modify the classifier (change the model) and train again…
- But – then the validation data is used to select the model!
- How do we know how well the new model generalizes?
- Need new validation data to test the final model – this dataset is called test data.
- Test data must <u>never</u> be used more than once!

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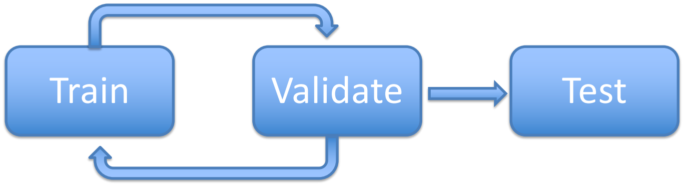
Training – Validation –Testing



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