Machine Learning at DIKU

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Machine learning

Machine learning is a branch of computer science and applied statistics covering software that improves its performance at a given task based on sample data or experience.
Why machine learning?

• Computer systems are required for tasks for which solutions cannot be specified in the traditional way, e.g., because
  • the designer’s knowledge is limited, and/or
  • the sheer complexity and variability precludes an accurate description.
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Machine learning turns data into knowledge
Machine learning research at DIKU

We are concerned with the design and analysis of adaptive systems for pattern recognition (data mining, time series prediction), data modeling, and behaviour generation (decision making).

Our fields of expertise include

- state-of-the-art classification, regression, and density estimation techniques,
- efficient and robust learning algorithms for large scale problems, and
- computational intelligence methods for non-linear optimisation including vector optimisation and multi-criteria decision making.
DIKU researchers in learning systems

Machine Learning Lab
http://image.diku.dk/MLLab

Image Group
http://www.diku.dk/forskning/Billedgruppen

DIKU faculty doing machine learning, information retrieval, and pattern recognition: Corinna Cortes (head of Google Research New York, adjunct), Marleen De Bruijne, Sune Darkner, Aasa Feragen, Christian Igel (head of ML Lab), Francois Lauze, Christina Lioma, Mads Nielsen (head of Image Group), Marco Loog (TU Delft, adjunct) Søren Olsen, Jon Sporring, Kim Steenstrup Pedersen, ...
Important themes in our work

**Autonomous learning**

Technical systems should **learn robustly and autonomously**, e.g., not requiring an expert to select

- learning algorithm and hyperparameters,
- appropriate data representation, etc.
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### Autonomous learning

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- learning algorithm and hyperparameters,
- appropriate data representation, etc.

### Scalability of adaptive systems

We need learning algorithms able to
- handle large amounts of data as well as to
- generalise from few training examples.
Exemplary method:
Support Vector Machines (SVMs)
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Scaling up SVMs

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We address this issue by

1. new optimization algorithms,
   Dogan, Glasmachers, Igel: Fast Training of Multi-class Support Vector Machines, submitted

2. new (e.g., cascaded) learning architectures,
   Prasoon et al.: Cascaded classifier for large-scale data applied to automatic segmentation of articular cartilage. SPIE Medical Imaging, 2012

3. parallelization.
Example: Cartilage segmentation
Business example: Credit scoring

A credit score measures the creditworthiness of a client.

figures in this section provided by Kasper Nybo Hansen
Results from MSc thesis

Accuracy

LDA    LOG    K-NN    RF    CART    C4.5    SVM    Mod. RF

0.76  0.78  0.80  0.82  0.84  0.86  0.88

0.846 0.835 0.833

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When theory and practice meet...

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Roth, Igel, Handmann: *IJCIA* 4, 2004

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Suttorp, Igel: *Multi-objective Machine Learning* Ch. 9, Springer, 2006

Igel et al.: *IEEE/ACM TCBB* 4, 2007
Mersch et al.: *IJNS* 17, 2007

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