

# Hot Topics in Machine Learning

Summer Term 2016

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Prof. Marius Kloft, Florian Wenzel

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# Organization

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The seminar is organized by Prof. Marius Kloft and Florian Wenzel (PhD student). For questions regarding the seminar please contact me:

## Contact

Florian Wenzel

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[www.florian-wenzel.de](http://www.florian-wenzel.de)

## Course Website

[http://www2.informatik.hu-berlin.de/~wenzelfl/teaching/2016\\_hot\\_topics.html](http://www2.informatik.hu-berlin.de/~wenzelfl/teaching/2016_hot_topics.html)

## Doodle: Pick a slot please!

<http://doodle.com/poll/67ffvtdnmec4qcsb>

# Organization

- each participant should choose (at least) one topic which she/he wants to present
- topics can be everything regarding ML (as long as it's hot)
  - interesting paper
  - interesting ML method or algorithm
  - Bachelor's or Master's thesis (work in progress is totally fine)
  - own ML project
  - choose a topic from our list of potential topics

# Organization

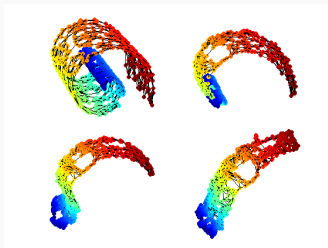
- doodle for open slots
- presentation should be around 45min + Q&A
- **2 weeks before presentation meet with Marius and discuss / rehearse presentation (~10min meeting)**
- we will meet each week (exceptions will be announced: email list)
- credit points for successful presentation and active participation

## Possible Topics: Dimensionality Reduction

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# ISO-MAP

- nonlinear dimensionality reduction method
- estimate of the intrinsic geometry of a data manifold based on a rough estimate of each data point's neighbors



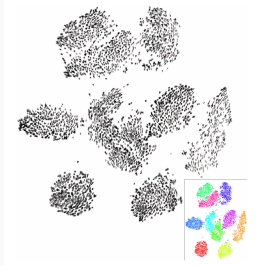
Sources:

<http://isomap.stanford.edu/>



# t-SNE

- nonlinear dimensionality reduction method
- t-SNE constructs a probability distribution over pairs of high-dimensional objects in such a way that similar objects have a high probability
- very popular and used in a wide range of applications

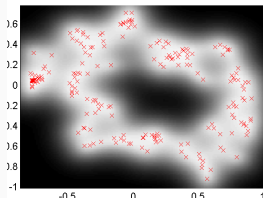


Sources:

<http://jmlr.org/papers/volume9/vandermaaten08a/vandermaaten08a.pdf>

# GP-LVM

- really cool nonlinear dimensionality reduction method based on Gaussian Processes
- embeds data points in a latent variable space (equipped with a probability measure)
- gives simultaneously probabilities for data points on the learned manifold for belonging to the true (unknown) latent space



Sources:

<https://www.youtube.com/watch?v=198Lw9KHzfC>

Paper: *gaussian process latent variable models for visualisation of high dimensional data*

## Other Dim Reduction Related Topics

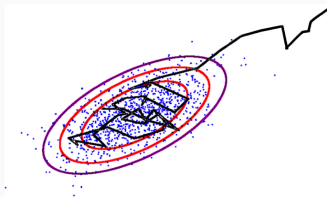
- NMF (Nonnegative Matrix Factorization)
- LLE (Locally Linear Embedding)

## Possible Topics: Inference

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# Markov Chain Monte Carlo (MCMC)

- aim: sample from a (intractable) posterior
- construct Markov chain that converges to the target distribution (as equilibrium distribution)
- for the seminar you can focus on the popular Metropolis-Hastings algorithm
- other (more advanced) MCMC algorithms: Hamiltonian Monte Carlo (HMC), SGD-based MC (next slide)

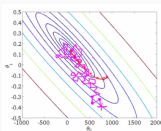


Sources:

Paper: *An Introduction to MCMC for Machine Learning*

# Scalable Bayesian Inference

- most MCMC algorithms need swap through the whole dataset per sample
- SGD-based Sampling uses only a little fraction (so called mini batch) of the dataset for each sample
- based on Stochastic Gradient Descent (SGD)
- for seminar suitable: **SGLD (Langevin Dynamics)** or SGFS (improved version of SGLD)



Sources:

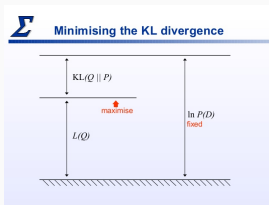
<https://www.youtube.com/watch?v=qBf5EBdEw7Q>

Paper: *Bayesian Learning via Stochastic Gradient Langevin Dynamics*

Paper: *Bayesian Posterior Sampling via Stochastic Gradient Fisher Scoring*

# Variational Inference

- approximate the posterior with another (easier) distribution
- aim: Minimize the Kullback-Leibler divergence
- this is equivalent to maximizing the ELBO (evidence lower bound)
- different Assumptions lead to different algorithms, for the seminar the mean field VI algorithm is suitable
- scalable version: Stochastic Variational Inference



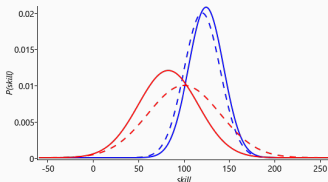
Sources:

Books: Bishop, Murphy

Paper: Blei et al: *Variational Inference: A Review for Statisticians*

# Expectation Propagation

- similar idea to Variational Inference, but now minimize the reverse KL divergence
- but leads to completely different algorithm
- find approximative distribution by moment matching



Sources:

Books: Bishop, Murphy

Paper: *Minka: Expectation Propagation for Approximate Bayesian Inference*

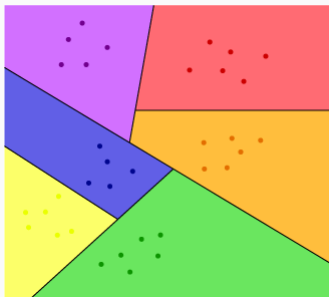


## Possible Topics: Multi Stuff

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# Multi Class Learning

- present different generalizations of binary class to multi class models
- compare different strategies (one-vs-rest, one-vs-one)
- focus on Multi Class SVM (present different formulations)
- extreme classification (thousands of classes)



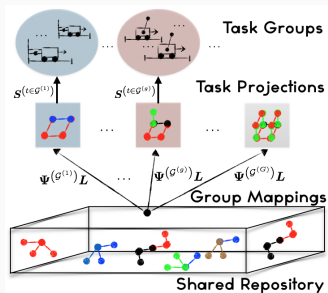
Sources:

Papers by Marius Kloft

Book: Bishop

# Multi Task Learning

- transfer knowledge from mastering one task to the other
- idea: solve related problems at the same time, using a shared representation
- present an MTL framework (e.g. Multi Task SVM)



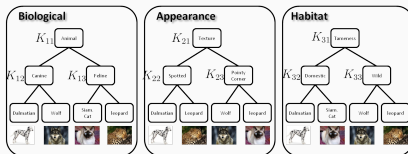
Sources:

Papers by Marius Kloft

*Paper: Caruana: Multitask Learning*

# Multiple Kernel Learning

- we have a (large) set of predefined kernels and want to combine them to one
- aim: find the best weights of linear combination
- present an MKL framework (e.g. Multi Kernel SVM)
- $\ell_p$ -norm kernel learning (Kloft)



Sources:

PhD thesis and papers by Marius Kloft

*Paper: Caruana: Multitask Learning*

## **Possible Topics: Other Cool Possibilities**

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- CRF (Conditional Random Fields)
- Gradient Boosting
- RNNs (Recurrent Neural Networks)
- NLP Topics: Topic Models, Word Embeddings, Sentiment Analysis
- Bandits
- Online Learning Theory

**Possible Topics: Your Own Ideas**

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# Your Own Ideas

- please feel free to come up with your own topics
- explicitly welcome
- you can meet or contact me via mail if you have questions