Toward Brain Computer Interfacing

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Outline

Some remarks on learning machines

- scope of my group
- Machine Learning in a nutshell

Machine Learning applications

- lots of throughout all our daily life
- Brain Computer Interfacing
Intelligent Data Analysis Group

**Group profile**: 1 professor, 18 post-doctoral researchers, 23 researchers, 3 guests = > 40+- researchers @ TU & 30+ master students

**Memberships**: Collaborative Research Center for Theoretical Biology (SFB 618), Bernstein Center for Computational Neuroscience Berlin, Bernstein Center for Neurotechnology Berlin, PASCAL 2 NoE, IP TOBI, Excellence School etc.

**Collaborations**: MPIs Tübingen & Berlin, WIAS, U & ETH Zürich, EPFL, NAIST, RIKEN, TIT, U Tokyo & Kyoto, Charité Berlin, ANU Australia, U Montreal, CNNY US, Columbia University, UC Santa Cruz, U TÜ, EPFL, Wadsworth, U Glasgow, HU Berlin, FU Berlin, UCLA, UCI, UT, Korea University

**Industrial partners**: Bayer-Schering, Boehringer, Daimler AG, Audi, Siemens AG, Deutsche Bank, MIC, Brain Products, ITSO, Nikon, Objectivity, Sony, Nokia, Alcatel-Lucent, 14 spinoffs (idalab, pyrexx, picoimaging …)
IDA: scientific profile

Machine learning:
- supervised learning: non-linear classification, regression and prediction
  - Support Vector Machines (SVM)
  - Kernel Fisher Discriminant (KFD)
- unsupervised learning:
  - Support Vector Data Description (SVDD), anomaly/outlier detection
  - clustering
  - non-linear feature extraction, de-noising, explorative data analysis

Signal processing:
- Denoising
- Blind Source Separation (BSS, ICA)

Time series analysis
- Nonstationarity, coherence
- Synchronization, causality, localization

Data analysis from theory to application and back
IDA applications

- brain computer interfacing (BCI) and computational neuroscience (EEG, EMG)
- protein/DNA analysis, computational/quantum chemistry
- security: hacker intrusion detection
- text, semantic annotation, trends
- wind turbine control

Cooperation with Siemens
Typical scenario: learning from data

- given data set $X$ and labels $Y$ (generated by some joint probability distribution $p(x,y)$)
- LEARN/INFER underlying unknown mapping

\[ Y = f(X) \]

Example: speech recognition, value tweet importance, distinguish brain states ...

BUT: how to do this optimally with good performance on unseen data?
ALICE – Autonomous Learning in Complex Environments

External Influences
- External influences hidden in sensor data
  - non-stationary
  - state estimation
  - change detection (SSACD)

Classical
- Reinforcement Learning (no stability guarantee)
- Adaptive/Robust Control (inflexible, model based)

Kernel methods, online-learning
Histopathology: Cancer prediction on pixel-level from patch-level information

Goal: Find cancer cells in histopathological images

H & E stained image of breast tissue

Pixel-wise cancer prediction

Highlighting of cancer cells

Challenge:
- Varying morphologies of cancer cells
- Multiple normal cell types
- Staining & Lighting variations
- Artifacts (distorted cell kernels)
- Segmentation/pixel-wise classification unreliable

Solution:
- Classify on patch level
- Pixel-wise superresolution from patch level features
- Specificity & Sensitivity > 93% on breastcancer database

Training Set Annotation (binary):
- Cancer present in patch (Yes/No)?
- No manual boundaries/segmentation
- Very fast to obtain by experts

EPA patent applied
Noninvasive Brain-Computer Interface

**BCI:** Translation of human intentions into a technical control signal without using activity of muscles or peripheral nerves
The cerebral cocktail party problem

- use ICA/NGCA projections for artifact and noise removal
- feature extraction and selection

Towards imaginations: Modulation of Brain Rhythms

Most rhythms are idle rhythms, i.e., they are attenuated during activation.

- $\alpha$-rhythm (around 10 Hz) in visual cortex:

  eyes closed
  ![Waveform](image1)
  eyes open
  ![Waveform](image2)

  Single channel

- $\mu$-rhythm (around 10 Hz) in motor and sensory cortex:

  arm at rest
  ![Waveform](image3)
  arm moves
  ![Waveform](image4)

  IMAGINATION of left arm

C4
Variance I: Single-trial vs. Averaging

Time Courses at Electrode C4

- left avg
- foot avg
- left singles
- foot singles

micro volt

-500 0 500 1000 1500 2000 2500 3000
time in ms

Single channel
Variance II: Session to Session Variability

- Experiment: **One subject** imagined **left** vs. **right** hand movements on different days.
- Even though each ERD map represents an **average** across 140 trials, they exhibit an apparent diversity.

**Maps**

![Left hand ERD maps](image1)

![Right hand ERD maps](image2)
Variance III: inter subject variability [l vs r]
BBCI paradigms

Leitmotiv: *let the machines learn*

- healthy subjects *untrained* for BCI

A: training <10min: right/left hand *imagined* movements
   → infer the respective brain activities (ML & SP)

B: online feedback session
Playing with BCI: training session (20 min)
Machine learning approach to BCI: infer prototypical pattern

Imagine left hand movements

Inference by CSP Algorithm

Imagine right hand movements
BBCI Set-up

multi-channel EEG → FFT based low-pass filter → band-pass 4-40 Hz → AR coeffs. → Artifact removal
subject-specific band-pass filter, e.g. 7-14Hz, -> multi-class CSP

multiple feature extraction → $x_{\text{MRF}}$, $x_{\text{AR}}$, $x_{\text{CSP}}$

classifier → feature combiner 'PROB'

continuous feedback

$\min_{w,b,\xi} \frac{1}{2} \|w\|^2 + \frac{C}{K} \|\xi\|^2$

subject to $y_k(w^T x_k + b) = 1 - \xi_k$ for $k = 1, \ldots, K$

Spelling with BBCI: a communication for the disabled
Change of distributions within experiment
Real Man Machine Interaction
Future issues: sensors

Popescu et al 2007
Conclusion

• BBCI: non-invasive with high Information transfer rates
• BBCI: Untrained, Calibration <<10min
• 5-8 letters/min mental typewriter on
  Brain2Robot@Medica 07, INdW 09
• Applications:
  Rehabilitation:  TOBI EU IP
  Computational Neuroscience:  Bernstein
  Man Machine Interaction:  brain@work
• Machine Learning and modern data

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Machine Learning open source software initiative: MLOSS see www.jmlr.org