Predicting Term-Relevance from Brain Signals

Accepted to SIGIR'14 / WP3

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MindSee Meeting
Helsinki, May 6-7, 2014

Aalto University

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Motivation

HIIT SCINET machine learning Ignite!

Articles [show bookmarked (0)]

A REVIEW OF MACHINE LEARNING IN SCHEDULING

H AYTUG, S BHATTACHARYYA, G J KOEHLER, J L SNOWDON (IEEE TRANSACTIONS ON ENGINEERING MANAGEMENT, 1994-01-01)

machine learning(0.85) | learning(1.00) | scheduling

This paper has two primary purposes: to motivate the need for machine learning in scheduling systems and to survey work on machine learning in scheduling. In order to motivate the need for machine learning in scheduling, we briefly motivate the need for systems employing artificial intelligence methods for scheduling. This leads to a need for incorporating adaptive methods-learning.

Quantum Learning Machine

Jeongho Bang, James Lim, M. S. Kim, Jinhyoung Lee (arXiv.org, 2008-01-01)

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We propose a novel notion of a quantum learning machine for automatically controlling quantum coherence and for developing quantum algorithms. A quantum learning machine can be trained to learn a certain task with no a priori knowledge on its algorithm. As an example, it is demonstrated that the quantum learning machine learns Deutsch's task and finds itself a quantum algorithm, that is different from but equivalent to the original one.

LEARNING CONTROL FOR AUTONOMOUS MACHINES

R SHOURESHI, D SWEDES, R EVANS (ROBOTICA, 1991-01-01)

autonomous machines | learning control | human learning | adaptive scheme | robots | learning(1.00)

Today's industrial machines and manipulators have no capability to learn by experience. Performance and productivity could be greatly enhanced if a machine could modify its operation based on previous actions. This paper presents a learning control scheme that provides the

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Relevant, because one of your psychophysiological signals said so.

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Articles [show bookmarked (0)]

↑43 **Approximate Learning Algorithm in Boltzmann Machines**

M Yasuda, K Tanaka (NEURAL COMPUTATION, 2009-01-01)

generality(0.23) learning algorithms(0.22) learning(1.00)

Boltzmann machines can be regarded as Markov random fields. For binary cases, they are equivalent to the Ising spin model in statistical mechanics. Learning systems in Boltzmann machines are one of the NP-hard problems. Thus, in general we have to use approximate methods to construct practical learning algorithms in this context. In this letter, we propose new and practical learning algorithms for Boltzmann machines by using the belief propagation algorithm and the linear response approximation, which are often referred as advanced mean field methods. Finally, we show the validity of our algorithm using numerical experiments.

↑26 **A simple algorithm for learning stable machines**

S Andonova, A Elisseeff, T Evgeniou, M Pontil (ECAI 2002: 15TH EUROPEAN CONFERENCE ON ARTIFICIAL INTELLIGENCE, PROCEEDINGS, 2002-01-01)

machine learning(0.66) statistical learning theory bagging statistical learning support vector machine learning(1.00)

We present an algorithm for learning stable machines which is motivated byrecent results in statistical learning theory. The algorithm is similar toBreiman's bagging despite some important differences in that it computes an ensemble combination of machines trained on small random sub-samples of an initial training set. A remarkable property is that it is often possible to just use the empirical error of these combinations of machines for modelselection. We report experiments using support vector machines and neural networks validating the theory.

new **Approximate Learning Algorithm for Restricted Boltzmann Machines**

M Yasuda, K Tanaka (2008 INTERNATIONAL CONFERENCE ON COMPUTATIONAL INTELLIGENCE FOR MODELLINGCONTROL & AUTOMATION, VOLS 1 AND 2, 2008-01-01)

algorithms(1.00)

A restricted Boltzmann machine consists of a layer of visible units and a layer of hidden units with no visible-visible or hidden-hidden connections.The restricted Boltzmann machine is the main component used in building upthe deep belief network and has been studied by many researchers. However,the learning algorithm for the

“Big vision”

MindSee Kickoff Meeting, Berlin

Three conditions (five tasks) in increasing complexity:

1. Highly controlled task with (T1) keywords and (T2) abstracts
2. Partially controlled task with (T3) keywords and (T4) abstracts
3. Free task with (T5) articles

Physiological measurements:

1. Electroencephalography (EEG)
2. Facial Electromyography (fEMG)
3. Electrodermal activity (EDA)
4. Pupillometry and gaze
5. Electrocardiography (ECG)

Predicting Term-Relevance from Brain Signals

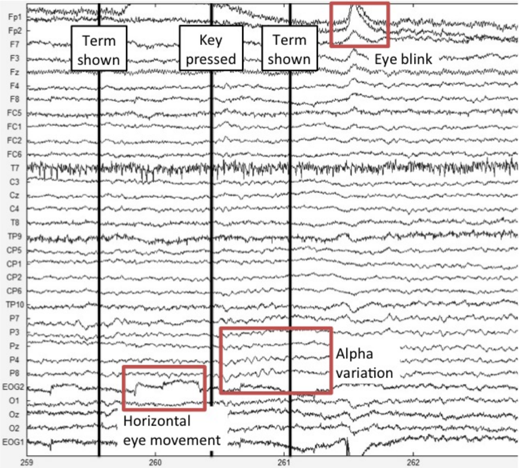
$\rightarrow$ predefined and highly controlled task with keywords and EEG

Research questions:

1. How well can we predict relevance judgements on terms from the brain signals of unseen participants?
2. Which parts of the EEG signals are important for the prediction?

Data:
38 participants, each one judged six terms (three relevant and three irrelevant) in six topics.

EEG signal



"Simple" processing to reduce DC interference and to eliminate noise and potential confounds of common artifacts such as eye movements and blinks (see Eugster et al., 2014).

EEG views

Views	$\mathbf{v}_k$	Features
Relevance judgement view:		
Relevance		A binary relevance judgement provided by a participant for a term for a given topic
Frequency-band-based views:		
Theta	1	40 features for each frequency band:
Alpha	2	20 features of average power over
Beta	3	1 second epochs before the relevance
Gamma1	4	judgement; 20 features of average
Gamma2	5	power over entire period, minus power
Engage	6	of the second before term onset
Event-related-potential-based view:		
ERPs	7	80 features of average amplitude: 20 features for 80–150 ms, P1; 20 features for 150–250 ms, N1/P2; 20 features for 250–450 ms, N2 or P3a; 20 features for 450–800 ms: N4 or P3b

Classification setup

- Bayesian MKL (Gönen, 2012):

$$y = f(\mathbf{v}_1, \ldots, \mathbf{v}_K) = \sum_{k=1}^{K} \beta_k \langle \mathbf{w}_k, \Phi_k(\mathbf{v}_k) \rangle + b$$

  with y the binary relevance judgment and $\mathbf{v}_k$ the views.

- Leave-one-participant-out strategy to estimate the classification accuracy.

- Use only observations that conformed to the ground truth, balance between relevant and irrelevant observations, five repetitions.

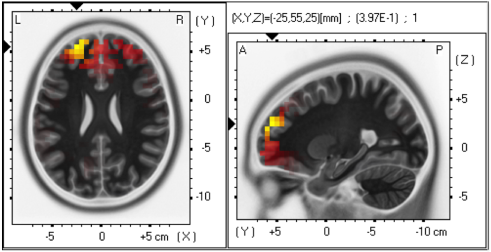
Results: Classification accuracy

Views	Mean accuracy	p-value	Mean improvement
All	0.5415	**0.0003**	8.30%
Selected combined views:			
Al+Ga1	0.5429	0.0014	8.59%
Al+E	0.5475	**0.0007**	9.50%
Ga1+E	0.5528	**0.0002**	10.55%
Al+Ga1+Be	0.5369	0.0022	7.37%
Al+Ga1+E	0.5586	<**0.0001**	11.72%
Individual views:			
Alpha (Al)	0.5242	0.0265	4.83%
Gamma1 (Ga1)	0.5143	0.1445	2.86%
Beta (Be)	0.5005	0.4838	0.10%
Gamma2	0.5101	0.2003	2.02%
Theta	0.5000	0.4984	0.01%
ERPs (E)	0.5312	0.0092	6.24%
Engage	0.4773	0.9673	−4.55%

Bold entries denote that iprovements are statistically significant at a level $\alpha = 0.01$, p-value $< \alpha$ with correction for multiple testing.

Results: Physiological findings

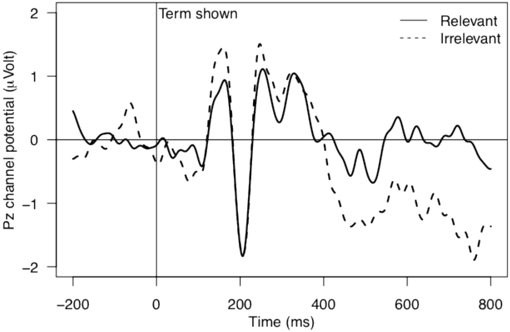
Localization of **Alpha** change assoziated with relevance mapped to a normalized brain:

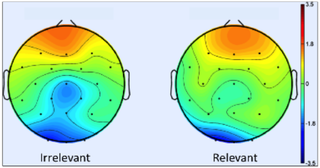


Brodmann Area 10: associated with a range of cognitive functions that are important for relevance judgments, such as recognition, semantic processing, memory recall, and intentional planning.

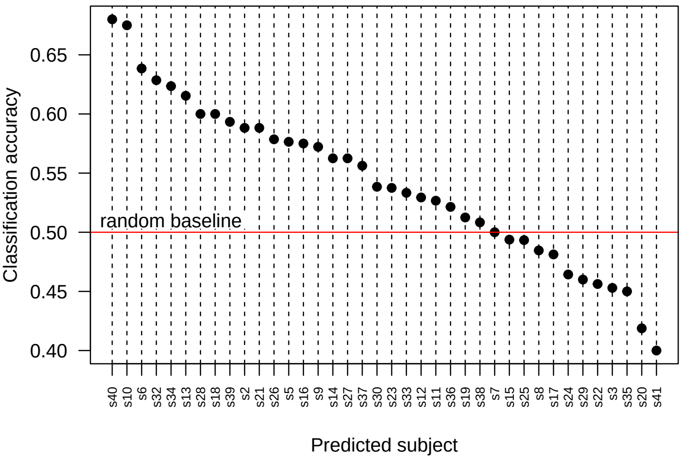
Results: Physiological findings

ERP in the Pz channel:





Results: “BCI illiteracy” analogy



Results: "BCI illiteracy" analogy

Views	#	Mean accuracy	p-value	Mean improvement
All	26	0.5750	$<$**0.0001**	15.00%
Al+Ga1	28	0.5641	$<$**0.0001**	12.82%
Al+E	25	0.5853	$<$**0.0001**	17.06%
Ga1+E	26	0.5792	$<$**0.0001**	15.83%
Al+Ga1+Be	25	0.5490	0.0019	9.81%
Al+Ga1+E	28	0.5545	**0.0005**	10.89%

No result about generalization—just to demonstrate that there might be an analogy to the well-known "BCI illiteracy" (Vidaurre and Blankertz, 2010) effect.

Results: High-Precision classifier

In IR the target is to detect true positives (i.e., relevant with very high probability, here > 0.99; see, e.g., SciNet, Ruotsalo et al., 2013):

Topic	Count		Precision	Recall	Top 5 relevant terms
	all	relevant			
Climate change and global warming	209	111	0.5238	0.0991	Snowmelt, Elevated CO2, Climate change, *hardware synchronization*, *sightseeing*
Entrepreneurship	199	110	0.6897	0.1818	business risk, startup company, business creation, *shopping*, *virtual relationships*
Immigration integration	204	105	0.5238	0.1048	citizenship, ethnic diversity, xenophobia, *arsonist*, *morse code*
Intelligent Vehicles	185	109	0.8000	0.1101	pedestrian tracking, collision sensing, remote driving, radar vision, *arsonist*
Iraq war	208	111	0.6296	0.1532	Saddam Hussein, US army, Tony Blair, *morse code*, *rock n roll*
Precarious employment	204	106	0.5714	0.1132	minimum wage, employment regulation, job instability, *virtual relationships*, *video-games*
Mean	202	109	0.6231	0.1270	

Summary

1. Term-relevance prediction using only brain signals seems to be possible.
2. We can support the classification results with physiological findings.
3. Interesting for IR because (i) it requires no explicit feedback, and (ii) signals can be captured with high throughput.
4. But of course lots of future challenges in order to make it a real system...

$\rightarrow$ Sami Kaski will talk about the plans in WP3 and T5.1 tomorrow.

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