# Predicting Term-Relevance from Brain Signals

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Helsinki Institute for Information Technology HIIT
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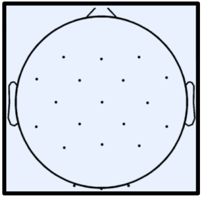
ACM SIGIR 2014

# Vision and Motivation

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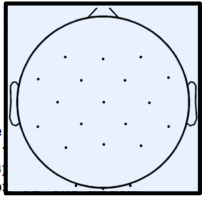
**HIIT SCINET** | Robotics



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*V Wigotsky* (PLASTICS ENGINEERING, 1998-01-01)

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Traces the development of artificial intelligence and mobile service robots and predicts that intelligent robots will emerge by 2020.

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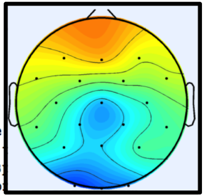

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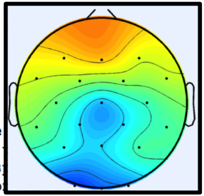

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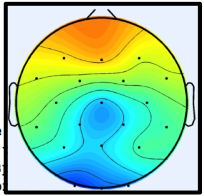

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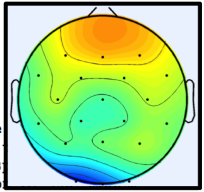

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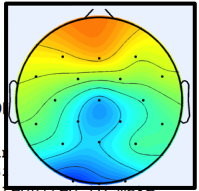


### Turning Segways into soccer robots

*B Browning, E Searock, P E Rybski, M Veloso* (INDUSTRIAL RO
INTERNATIONAL JOURNAL, 2005-01-01)

`Purpose - To adapt the segway RMP, a dynamically balanci build robots capable of playing soccer autonomously. Des approach - Focuses on the electro-mechanical mechanisms required to make the Segway RMP autonomous, sensitive, and able to controla football. Findings - Finds that turning a Segway RMP into a soccer-playing [...]`

### Multi-robot-systems in entertainment - Robot soccer

*M W Han, G Novak* (MULTI-AGENT-SYSTEMS IN PRODUCTION, 2000-01-01)

`The robot soccer was introduced with the purpose to develop the intelligent cooperative multi-robot (agents) systems (MAS). From the scientific viewpoint the soccer robot is an intelligent autonomous agent, which carries outtasks with other agents in cooperative, coordinated and communicative way. The robot soccer provides a good opportunity to [...]`

### Modelling and control of a soccer robot

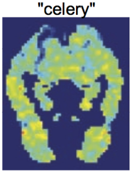
*F Solc, B Honzik* (7TH INTERNATIONAL WORKSHOP ON ADVANCED MOTION CONTROL, PROCEEDINGS, 2002-01-01)

`The paper describes some results of development of robot soccer team RoBohemia fi-oin Brno University of Technology. The robot soccer team belongs toMIROSOT (Micro RObut SOccer Tournament) robot soccer category. The paper introduces mathematical model and simulation scheme of the robot player simultaneously with sonic construction details. [...]`

### Robot soccer: A multi-robot challenge

## "In contrast to, for example, ..."

**Mind-reading Computer** [2]: "computational model that makes directly testable predictions of the fMRI activity associated with thinking about arbitrary concrete nouns".




**BCI-Pinball** [9]: "system was calibrated individually for each of the subjects to discriminate two classes of motor imagery (left hand and right hand)."

... we aim to detect and learn brain patterns that are naturally associated with (subliminal) relevance judgments rather than to detect artificial, memorized patterns or pre-seen objects.

# First steps toward our vision

**Predicting term-relevance from brain signals:**

1. A given topic $T$ is relevant to a user
2. A term $w$ is shown to the user
3. Brain signals are recorded using electroencephalography (EEG)
4. Classifier predicts the user's relevance of term $w$ for topic $T$

# Predicting term-relevance from brain signals

**Research questions:**

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

## Experiment

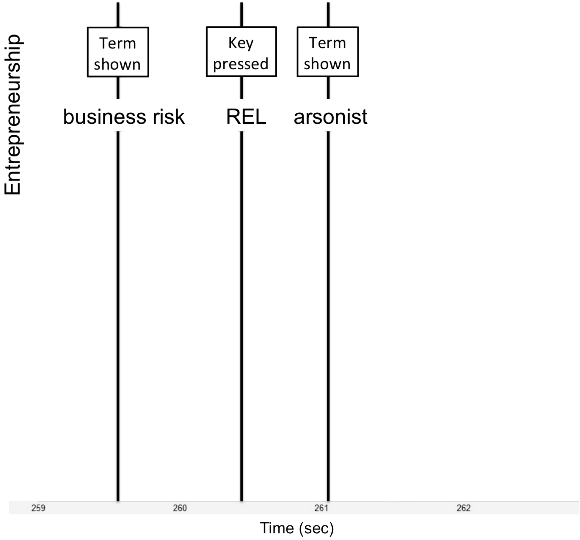
**Scenario:**
Each participant read and judged six terms (three relevant and three irrelevant) in six topics.

**Examples:**

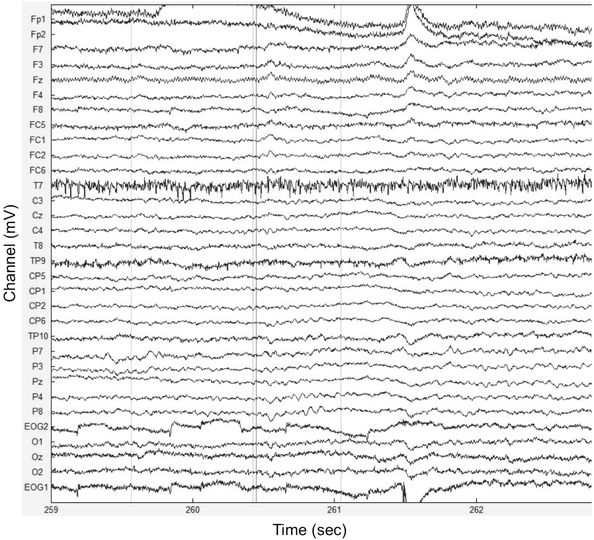
| | |
|---|---|
| Entrepreneurship: | business risk, startup company, ... |
| Iraq war: | US army, Saddam Hussein, ... |
| *Irrelevant words*: | shopping, video-games, ... |

**Data:**
38 participants, balanced ground-truth

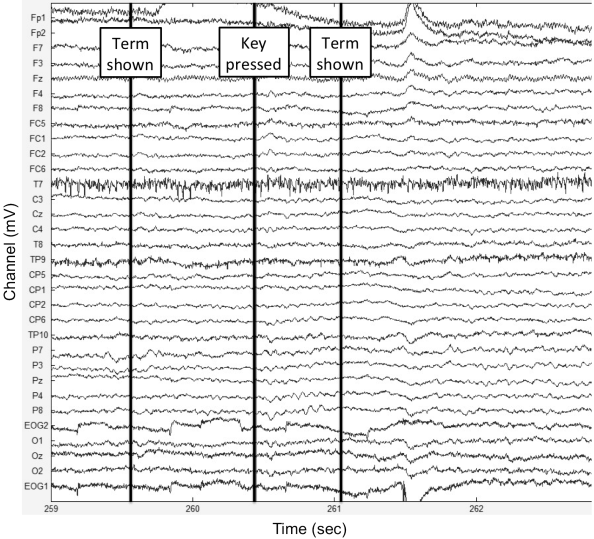
# Experiment


Entrepreneurship
Term shown
Key pressed
Term shown
business risk
REL
arsonist
259
260
261
262
Time (sec)

# EEG signals


Fp1
Fp2
F7
F3
Fz
F4
F8
FC5
FC1
FC2
FC6
T7
C3
Cz
C4
T8
TP9
CP5
CP1
CP2
CP6
TP10
P7
P3
Pz
P4
P8
EOG2
O1
Oz
O2
EOG1
Channel (mV)
259
260
261
262
Time (sec)

# EEG signals


Term shown
Key pressed
Term shown
Fp1
Fp2
F7
F3
Fz
F4
F8
FC5
FC1
FC2
FC6
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C3
Cz
C4
T8
TP9
CP5
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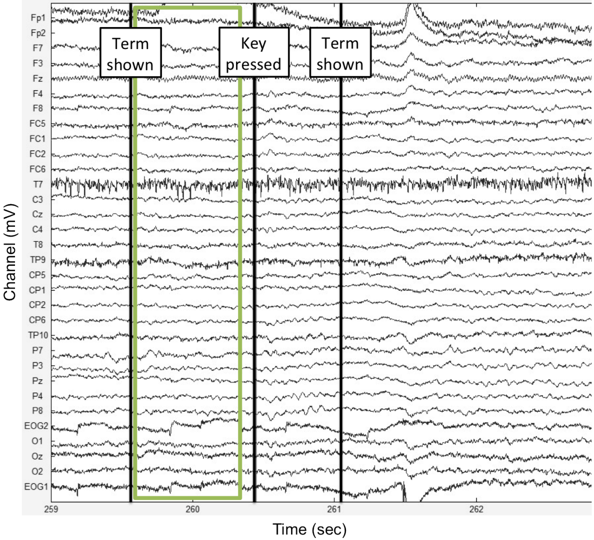

Term shown
Key pressed
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Fp1
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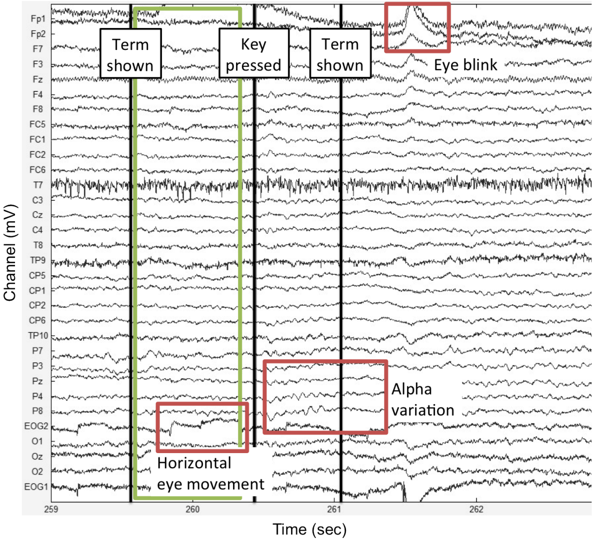



"Simple" processing to reduce DC interference and to eliminate noise and potential confounds of common artifacts such as eye movements and blinks.

# 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 |

Feature engineering in the *frequency domain* (i.e., frequency-band based) and in the *time domain* (i.e., event-related-potential based).

## Classification setup

- Bayesian Efficient Multiple Kernel Learning [1],

$$y(\mathbf{x}_*) = \mathbf{a}^T \left( \sum_{k=1}^{K} e_k \mathbf{v}_{k,*} \right) + b$$

  with $\mathbf{y}$ the binary relevance judgements, $\mathbf{v}_k$ the views, and $e_k$ the kernel weights (RQ2).

- Leave-one-participant-out strategy to estimate the classification accuracy (RQ1).

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

- Simple automatic feature selection procedure based on the $t$-statistic [8].

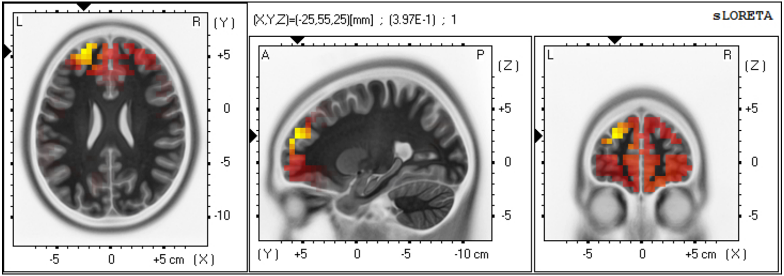
# Classification accuracy

| 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 improvements are statistically significant at a level $\alpha = 0.01$, $p$-value $< \alpha$ with correction for multiple testing.

## Physiological findings

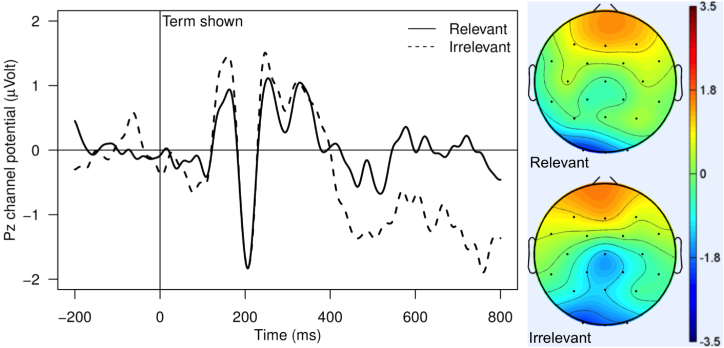
**Localization of Alpha change** assoziated with relevance mapped to a normalized brain:




*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 [6, 5, 3].

# Physiological findings

**Grand average of the ERP** in the Pz channel:




*ERP* after irrelevant and relevant term onset with significance difference after 450ms, maximizing at 747ms. The latency and topography of the potential suggest the involvement of a P3-like potential [4].

## Why interesting for IR?

- In certain IR applications the target is to detect true positive terms (i.e., relevant with very high probability) that represent a user's search intent [7].
- In such applications, a classifier that trades recall for the benefit of precision can be used to maximize user experience.
- We can take advantage of the fact that brain signals can be captured continuously and with high throughput—compared to signals that require explicit user interaction.
- As a result, a large number of relevance judgments can be observed in a relatively short time.

# Application: Topic representation

Topic-wise prediction using a **high-precision classifier** with $p > 0.99$ as threshold for a term being classifed as relevant:

| Topic | Count all | Count relevant | Precision | Recall | Top 5 relevant terms |
|---|---|---|---|---|---|
| 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 | |

Normal font indicats a relevant term according to the ground truth, italics indicates an irrelevant term according to the ground truth.

## Summary

- Relevance judgments happen in the brain and therefore the most intriguing way to predict relevance is to directly use the brain signals.

- We showed that term-relevance prediction using only brain signals captured via EEG is possible. The classification results showed significantly better performances than the random baseline.

- As a practical application of TRPB, we demonstrated a high-precision relevance predictor, which can construct meaningful sets of terms for unknown topics and new users.

For future developments and all our other research related to IR, visit `http://augmentedresearch.hiit.fi/`.

# Appendix

# Acknowledgments

This work has been partly supported by the Academy of Finland (Multivire, 255725; and the Finnish Centre of Excellence in Computational Inference Research COIN, 251170), Re:Know funded by TEKES, and MindSee (FP7 – ICT; Grant Agreement # 611570).

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