MindSee

Symbiotic Mind Computer Interaction for Information Seeking

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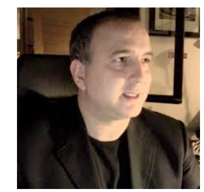
Graz BCI, EU BCI Day,16.09.2014

Consortium

- **Prof Giulio Jacucci,** University of Helsinki
  - HCI, surface computing, exploratory search, peripheral physiology
  - MindSee project coordinator

- **Prof Samuel Kaski**, Aalto University
  - Probabilistic modeling, machine learning, reinforcement learning



- **Prof Luciano Gamberini**, University of Padova
  - Cognitive ergonomics, user evaluation, eye tracking

- **Prof Benjamin Blankertz**, TU Berlin
  - Brain-Computer Interfaces, EEG, machine learning

- **Dr Jonathan Freeman**, i2 media
  - Digital consumer research, media and user experience

General objective

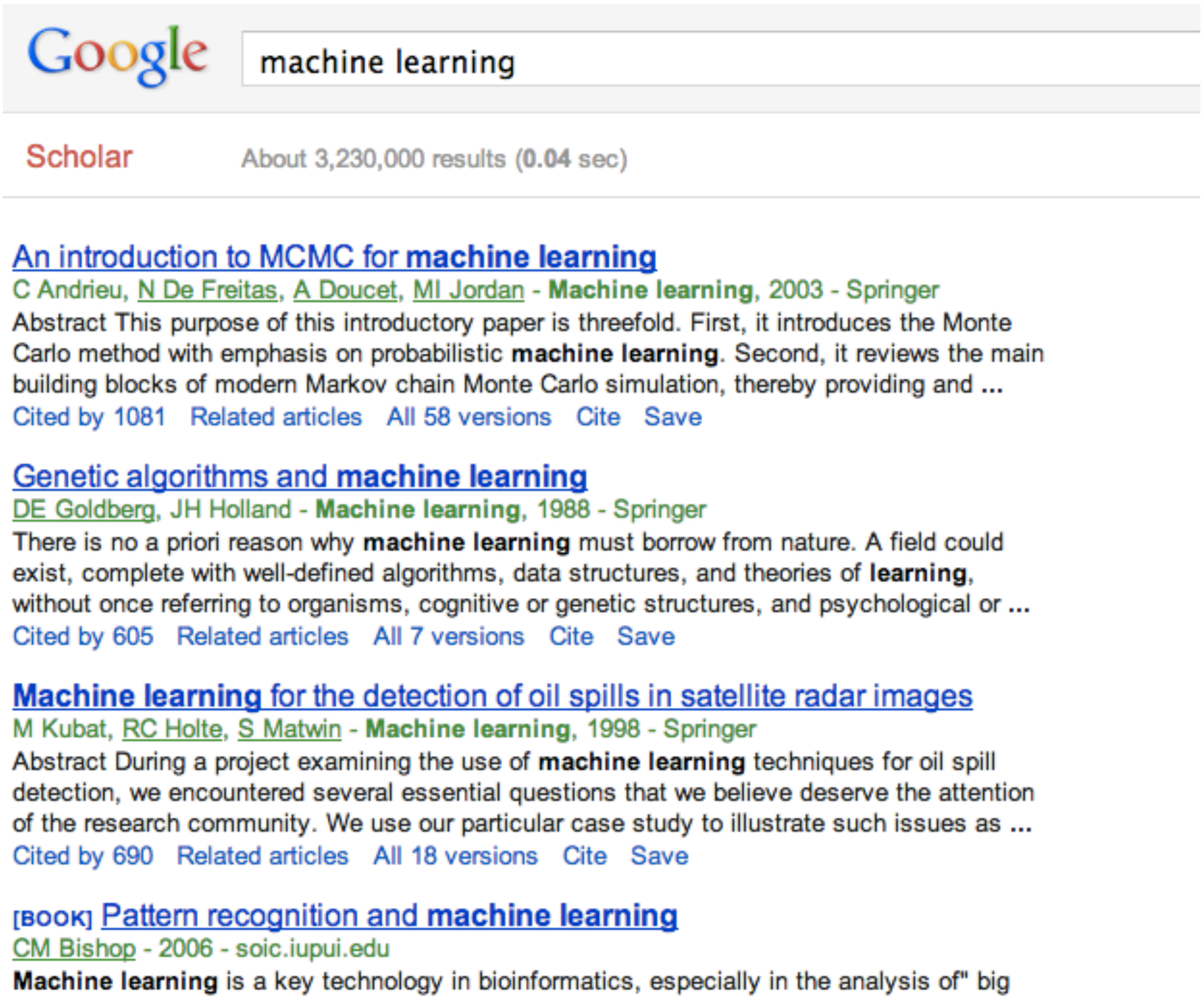
Exemplify the fruitful symbiosis of modern BCI technology with a recent real-world HCI application to obtain a cutting-edge information retrieval system that outperforms state-of-the-art tools by more than doubling the performance of information seeking in realistic tasks.

Information seeking

- Three types of search activities:
  “lookup”, “learning”, and “investigation”

- Task:
  Prepare materials to write an essay on “machine learning”

Information seeking


Google
machine learning

Scholar
About 3,230,000 results (**0.04** sec)

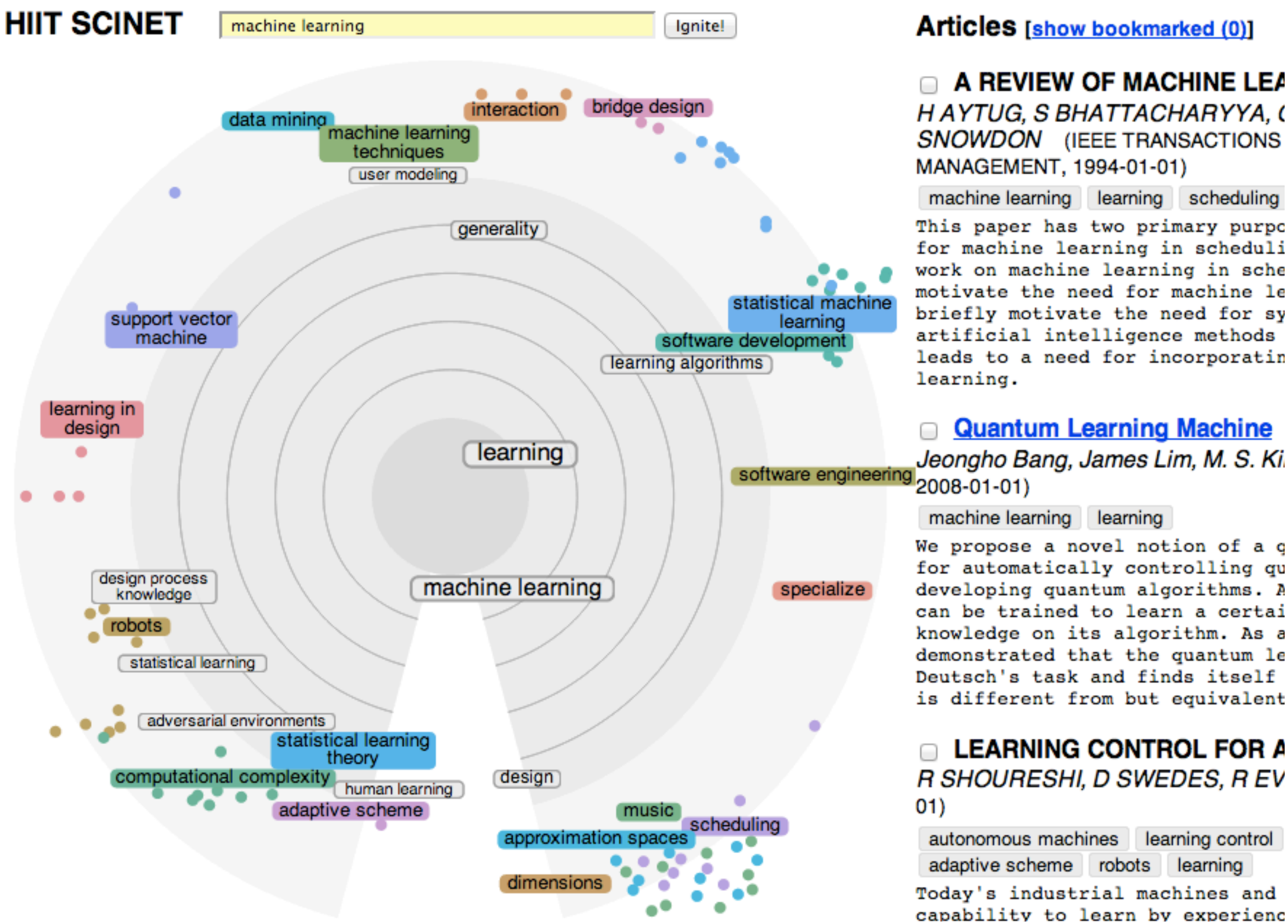
[An introduction to MCMC for **machine learning**]
C Andrieu, N De Freitas, A Doucet, MI Jordan - **Machine learning**, 2003 - Springer
Abstract This purpose of this introductory paper is threefold. First, it introduces the Monte Carlo method with emphasis on probabilistic **machine learning**. Second, it reviews the main building blocks of modern Markov chain Monte Carlo simulation, thereby providing and ...
Cited by 1081 Related articles All 58 versions Cite Save

[Genetic algorithms and **machine learning**]
DE Goldberg, JH Holland - **Machine learning**, 1988 - Springer
There is no a priori reason why **machine learning** must borrow from nature. A field could exist, complete with well-defined algorithms, data structures, and theories of **learning**, without once referring to organisms, cognitive or genetic structures, and psychological or ...
Cited by 605 Related articles All 7 versions Cite Save

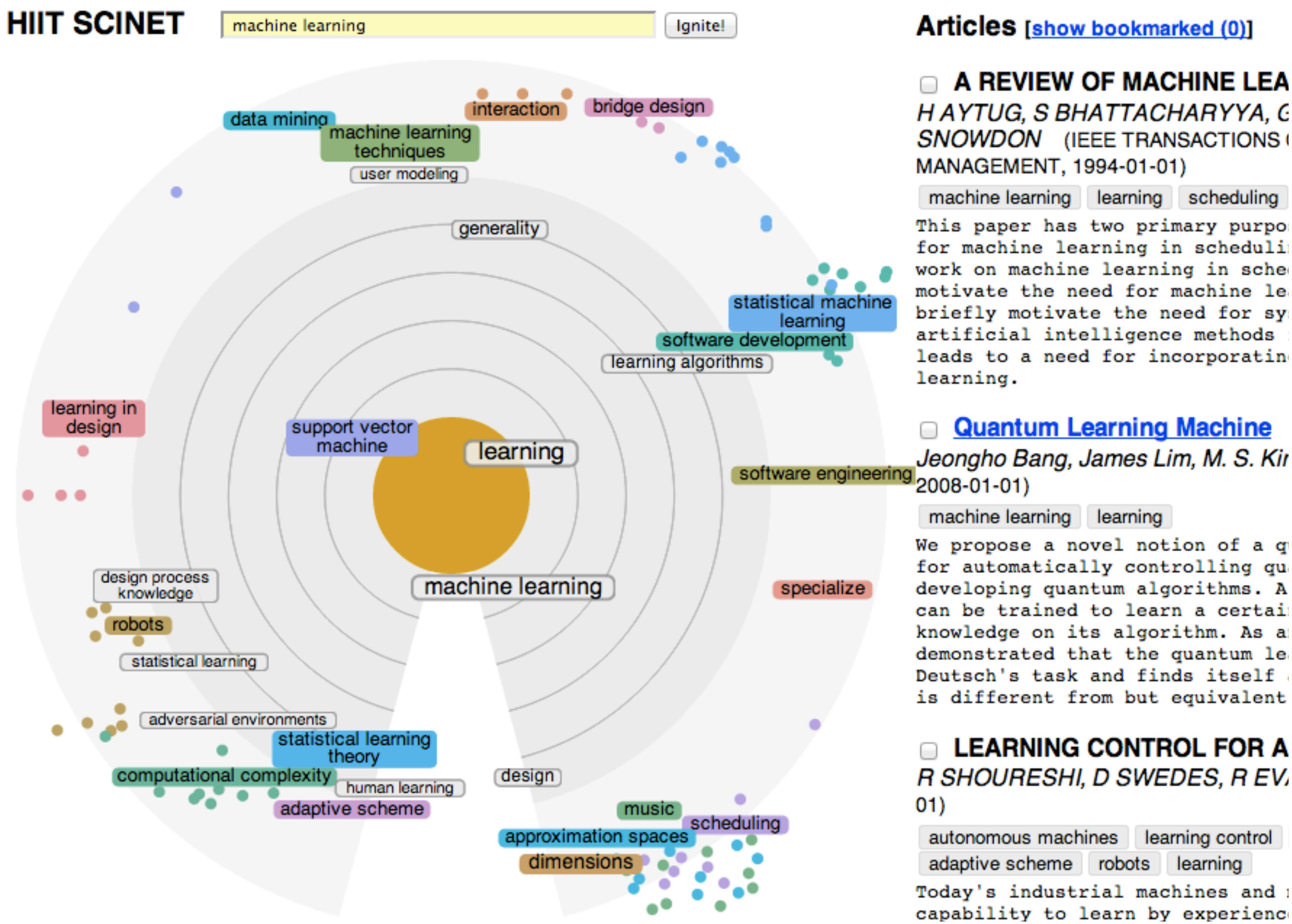
[**Machine learning** for the detection of oil spills in satellite radar images]
M Kubat, RC Holte, S Matwin - **Machine learning**, 1998 - Springer
Abstract During a project examining the use of **machine learning** techniques for oil spill detection, we encountered several essential questions that we believe deserve the attention of the research community. We use our particular case study to illustrate such issues as ...
Cited by 690 Related articles All 18 versions Cite Save

[BOOK] [Pattern recognition and **machine learning**]
CM Bishop - 2006 - soic.iupui.edu
Machine learning is a key technology in bioinformatics, especially in the analysis of" big

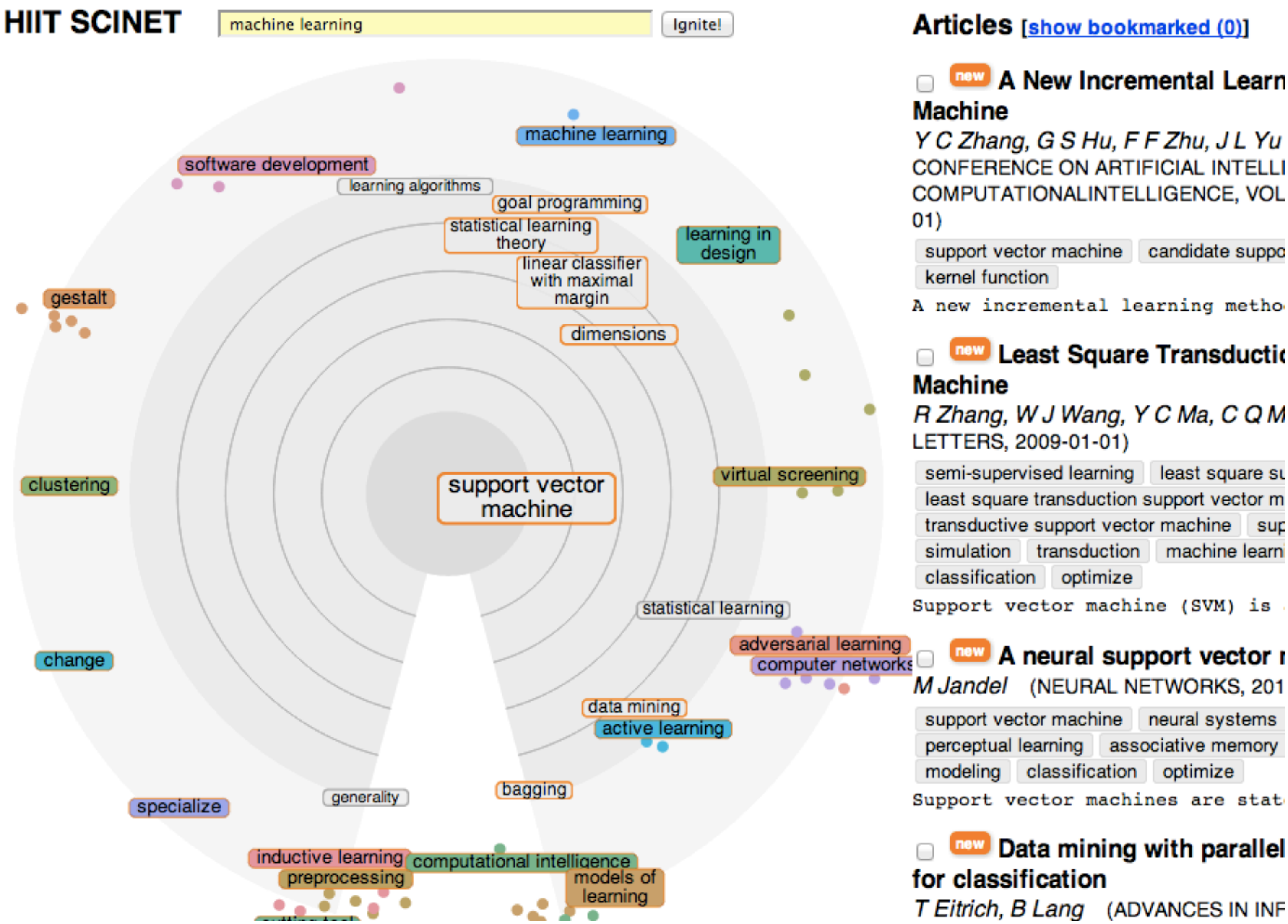
Information seeking



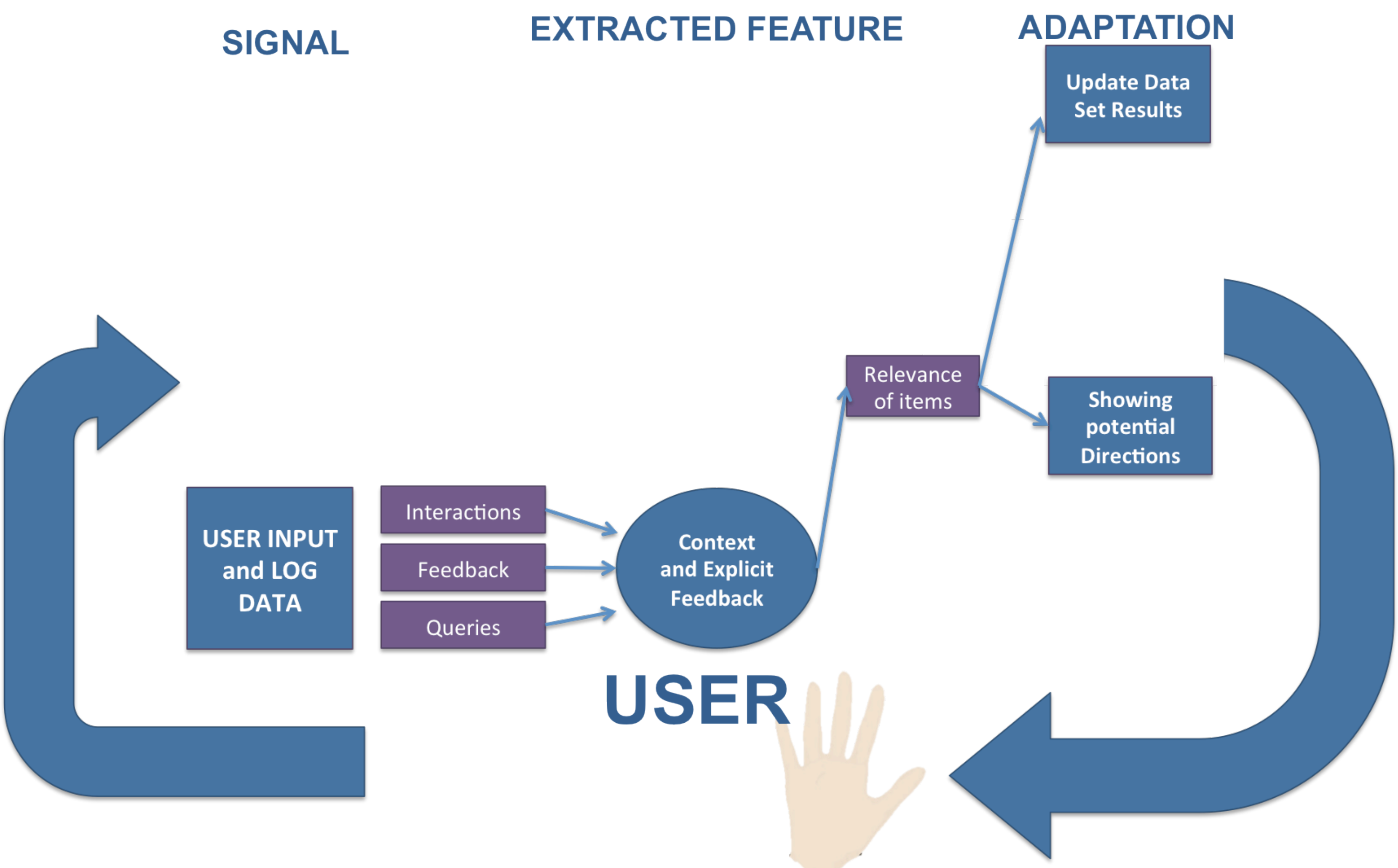
Information seeking



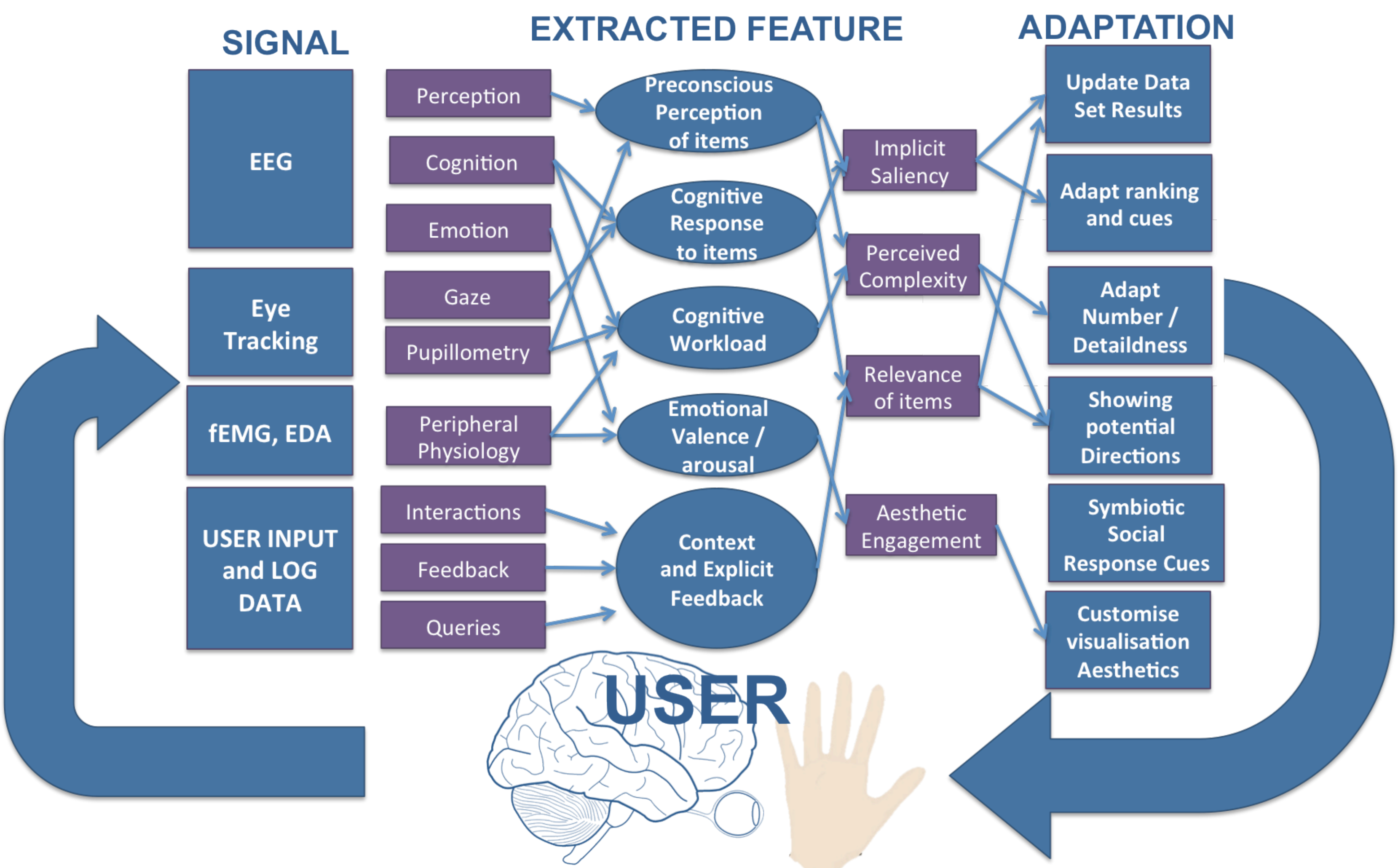
Information seeking



Concept


SIGNAL
EXTRACTED FEATURE
ADAPTATION
Update Data Set Results
Relevance of items
Showing potential Directions
USER INPUT and LOG DATA
Interactions
Feedback
Queries
Context and Explicit Feedback
USER

Concept



SIGNAL
EXTRACTED FEATURE
ADAPTATION
EEG
Eye Tracking
fEMG, EDA
USER INPUT and LOG DATA
Perception
Cognition
Emotion
Gaze
Pupillometry
Peripheral Physiology
Interactions
Feedback
Queries
Preconscious Perception of items
Cognitive Response to items
Cognitive Workload
Emotional Valence / arousal
Context and Explicit Feedback
Implicit Saliency
Perceived Complexity
Relevance of items
Aesthetic Engagement
Update Data Set Results
Adapt ranking and cues
Adapt Number / Detaildness
Showing potential Directions
Symbiotic Social Response Cues
Customise visualisation Aesthetics
USER

Key parts

- Brain-Computer Interfaces
  - EEG for real-time detection of perception, cognition and emotions
- Physiological data for user modeling in adaptive systems
  - Other sensors beyond EEG from physiology to model the user and adapt the system
- Probabilistic Machine Learning for Multisource Data
  - Modeling techniques that allow fusion of multi-source data for the different signals
- Interactive Retrieval, relevance feedback and visualization in information exploration
  - Application view of relevance feedback in information retrieval

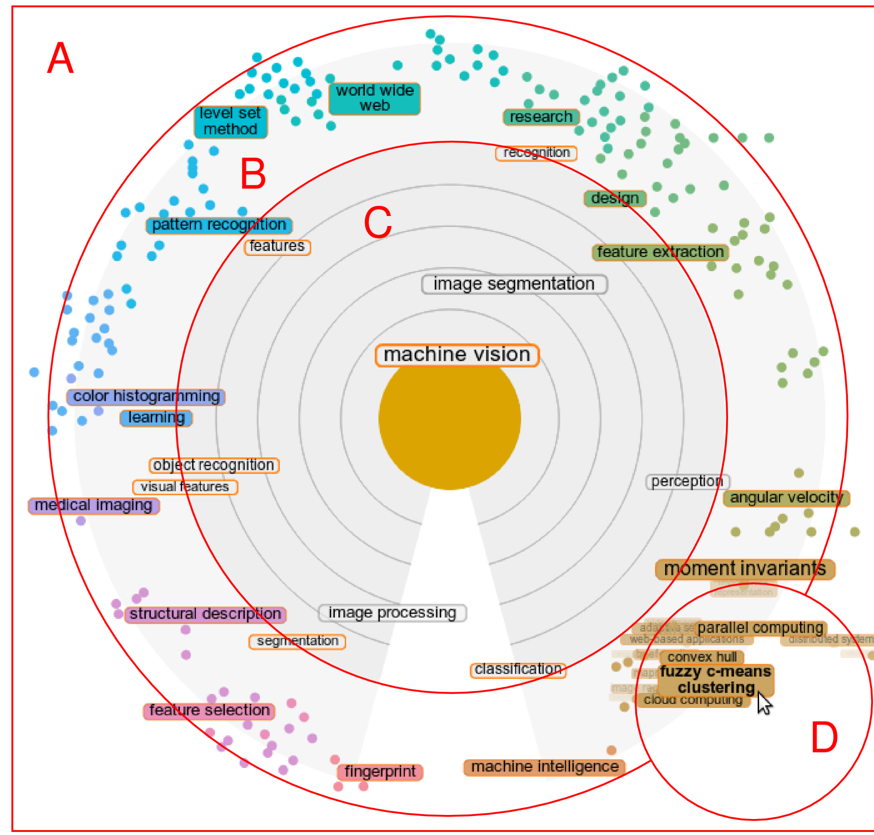
Two “Finland” projects

- **Directing exploratory search with interactive intent modeling.** Ruotsalo T, Peltonen J, Eugster MJA, et al., Conference on Information and Knowledge Management (CIKM), 2013.

- **Predicting term-relevance from brain signals.** Eugster MJA, Ruotsalo T, Spapé MM, et al., 37th international ACM SIGIR conference on Research & development in information retrieval (SIGIR), 2014.

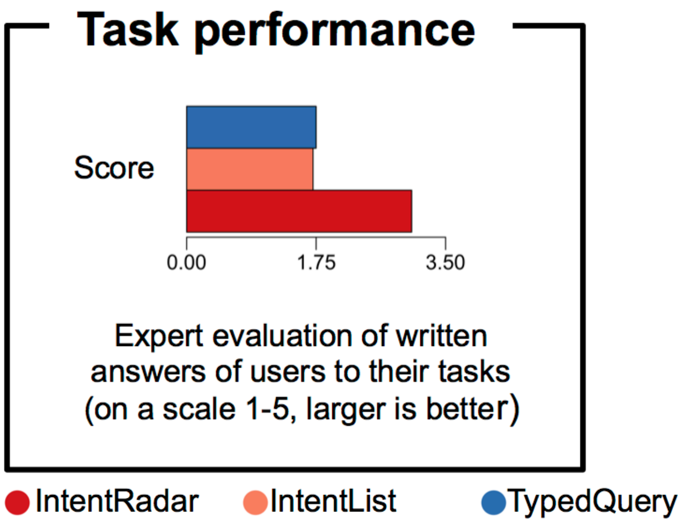
Interactive intent modeling

- User directs exploratory search by providing explicit relevance feedback
- Feedback is used for estimates of search intent
- Estimated intents are visualized
  - Relevant intents are close to the center
  - Similar intents have similar angles



Interactive intent modeling

- Task: Prepare materials to write an essay on a given topic
  1. Search for relevant articles that would be likely used as reference source in the essay
  2. Answer a set of predefined questions related to the task topic



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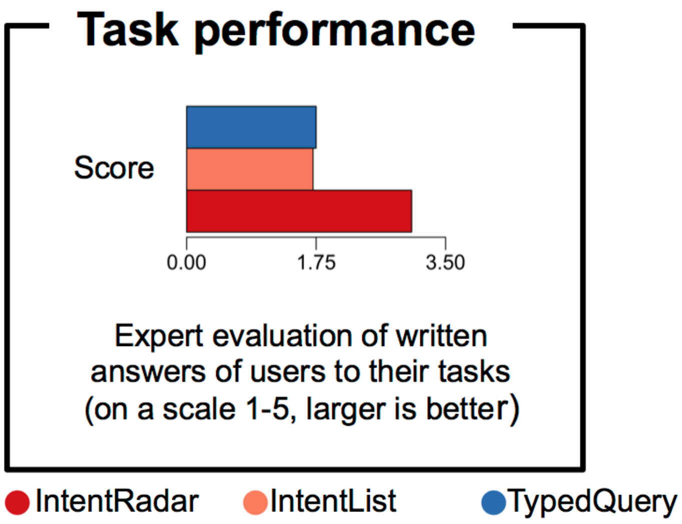


- **MindSee:**
  - What if we use other signals than explicit feedback? Can we predict the intent better? Can we improve the performance in an exploratory search task even more?

Term-relevance prediction from brain signals

- Predict a user's relevance of a term for a given topic (motivated by the keywords visualized in SciNet).

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

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

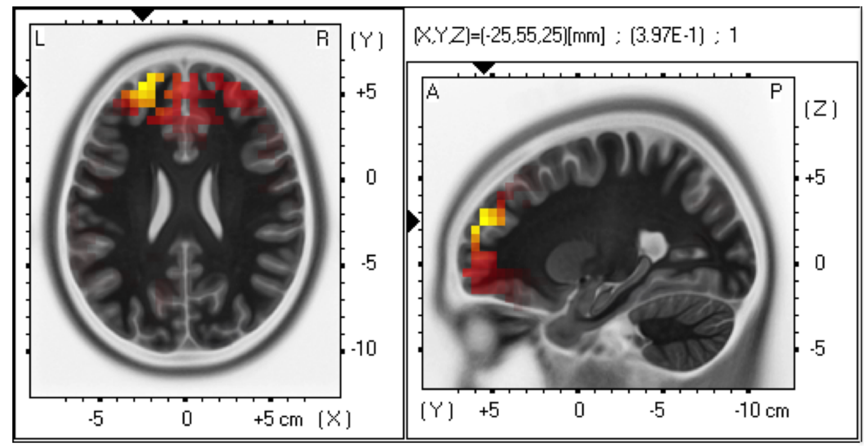
Term-relevance prediction from brain signals

- Prediction performance:

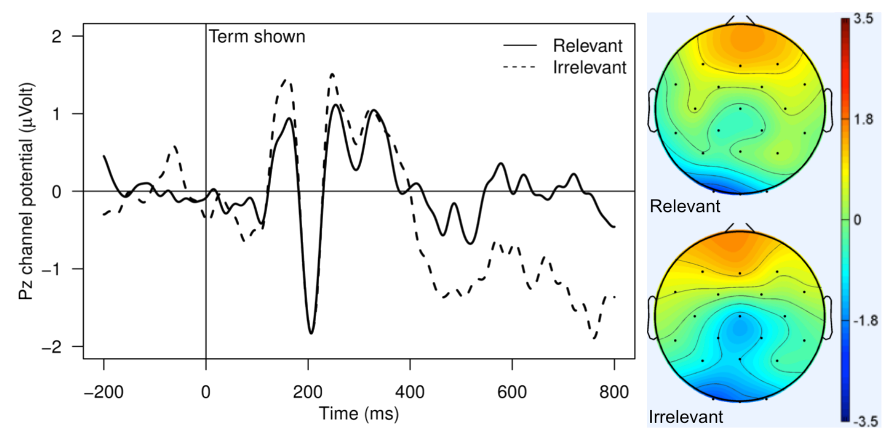
Views	Mean accuracy	p-value	Mean improvement
All	0.5415	**0.0003**	8.30%
Selected combined views:			
Al+Ga1	0.5429	0.0014	8.59%
Al+E	0.5475	**0.0007**	9.50%
Ga1+E	0.5528	**0.0002**	10.55%
Al+Ga1+Be	0.5369	0.0022	7.37%
Al+Ga1+E	0.5586	**<0.0001**	11.72%
Individual views:			
Alpha (Al)	0.5242	0.0265	4.83%
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%

Classification accuracy of different EEG views

- Physiological findings:



Localization of Alpha change



Grand average of the ERP in the Pz channel

Term-relevance prediction from brain signals

- High-precision classifier (p > 0.99):

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	

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- **MindSee:**
  - Can we use utilize this in reading real documents and in a real information retrieval system?

Summary

> ***"MindSee is Information retrieval, BCI, machine learning, neuroscience, affective computing and more..."***
>
> **—from the MindSee Blog**

- For future developments and all our research related to MindSee, visit http://www.mindsee.eu/!
- For general questions, contact Giulio Jacucci, giulio.jacucci@helsinki.fi.

References

- Tuukka Ruotsalo, Jaakko Peltonen, Manuel J. A. Eugster, Dorota Głowacka, Ksenia Konyushkova, Kumaripaba Athukorala, Ilkka Kosunen, Aki Reijonen, Petri Myllymäki, Giulio Jacucci, and Samuel Kaski. **Directing exploratory search with interactive intent modeling**. In *Proceedings of CIKM 2013, the ACM International Conference of Information and Knowledge Management*, pages 1759–1764, New York, NY, 2013. ACM. http://dx.doi.org/10.1145/2505515.2505644

- Manuel J. A. Eugster, Tuukka Ruotsalo, Michiel M. Spapé, Ilkka Kosunen, Oswald Barral, Niklas Ravaja, Giulio Jacucci, and Samuel Kaski. **Predicting term-relevance from brain signals**. In *Proceedings of the 37th International ACM SIGIR Conference on Research & Development in Information Retrieval*, pages 425–434, 2014. http://dx.doi.org/10.1145/2600428.2609594

- http://augmentedresearch.hiit.fi/

