HELSINKI UNIVERSITY OF TECHNOLOGY
LABORATORY OF COMPUTER AND INFORMATION SCIENCE

Proactive Information Retrieval by User Modeling from Eye Tracking

Jarkko Salojärvi

People can infer a lot from gaze

So far, machines cannot, which makes them clumsy.

Proactive user interface

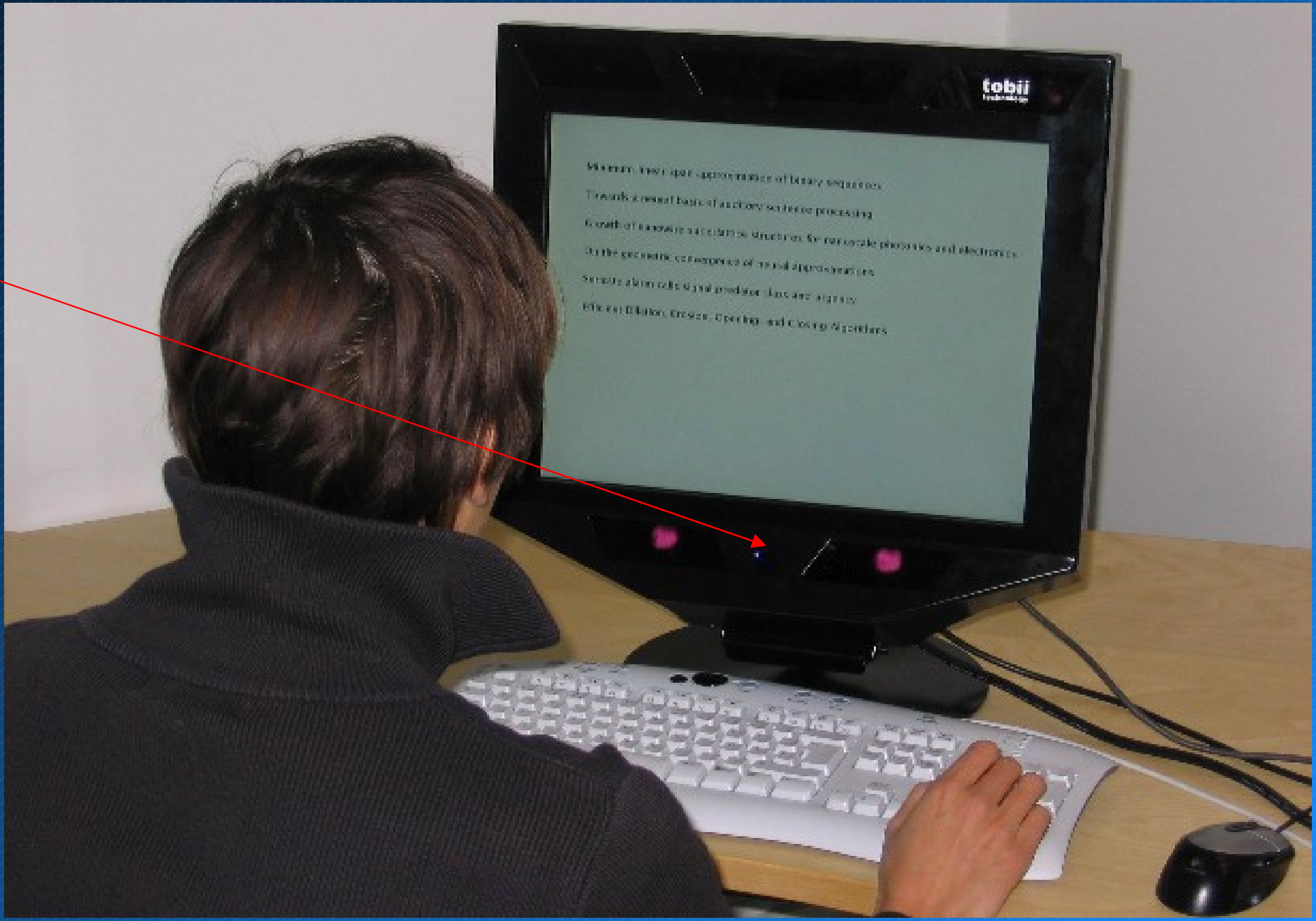
- An interface that can anticipate the user's needs?
- Computers need to understand incomplete and inaccurate messages of humans.
- The user can concentrate on the essential things if her intentions can be modelled.

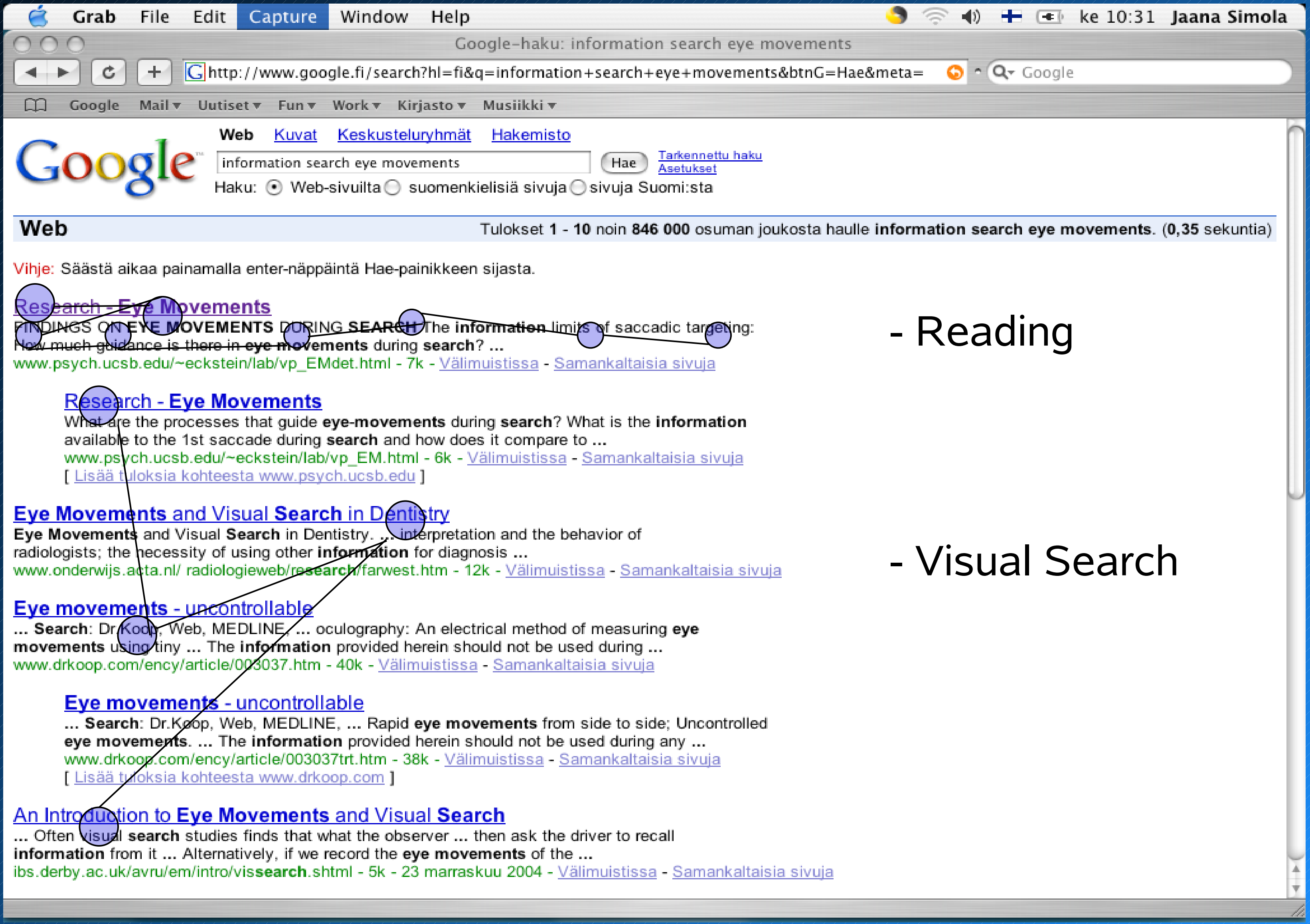
We need: a way of inferring the mental state of the user (from implicit feedback).

Mental state from eye movements?

Gaze direction and target can be measured

Eye tracker





- Reading

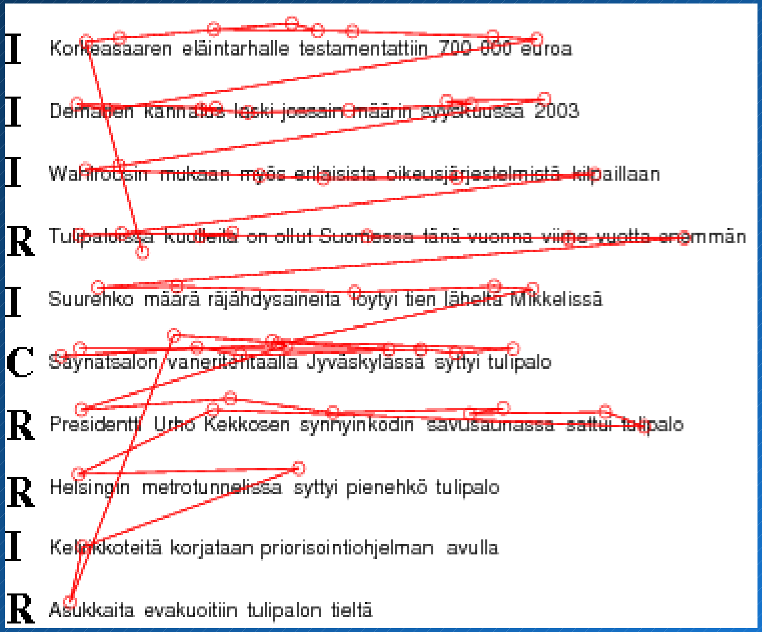
- Visual Search

Pilot study: Inferring relevance from eye movements

Experimental setup

- First, a question was shown.
- Task: read the titles and give the number of the title containing the answer.

- Predict the class of the title, given eye movements.



Accuracy: LDA: 59.8 %, HMM 65.8 %, dumb 50 %

Relevance can be predicted!

Implicit Relevance Feedback from Eye Movements. Salojärvi, Puolamäki and Kaski. ICANN'05.

Pascal NoE Challenge (2005)

Title: “Inferring relevance from eye movements”

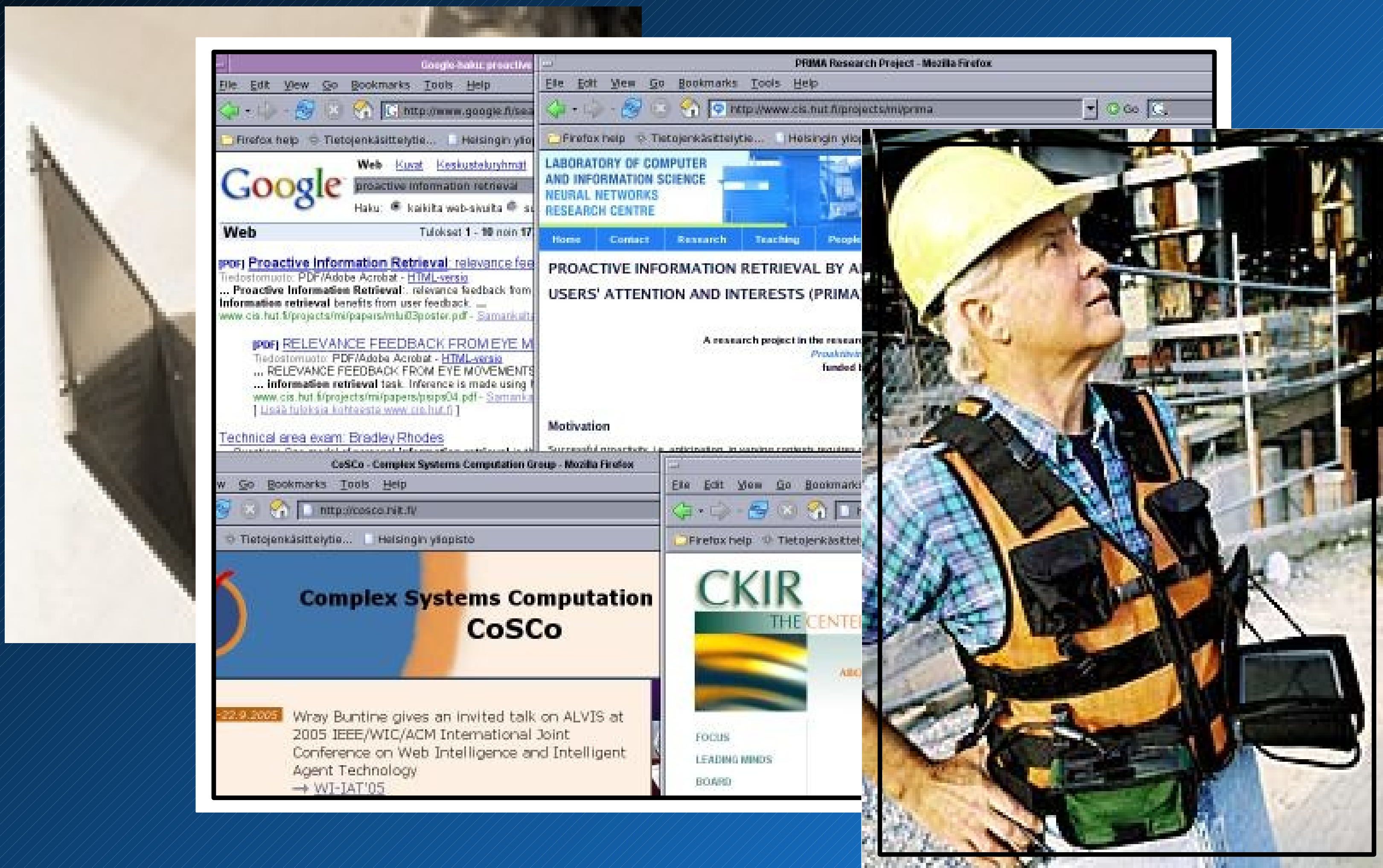
- A machine learning competition.
- Task: Predict relevance of titles, given the eye movements.
- 11 participants, best accuracy 72.3% (TU Graz)
- Data available at:

http://www.cis.hut.fi/eyechallenge2005/

Workshop on Machine Learning for Implicit Feedback and User Modeling at NIPS'05

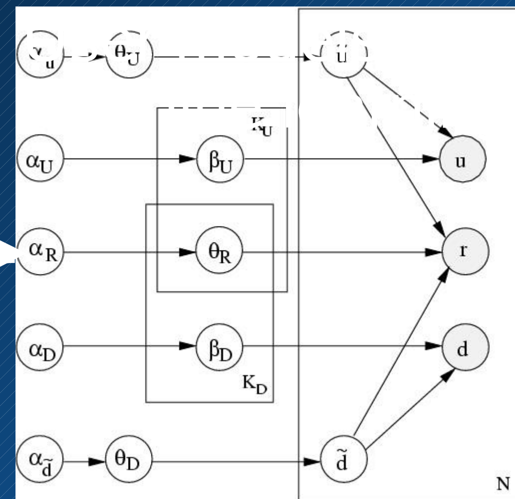
Proceedings of the NIPS Workshop on Machine Learning for Implicit Feedback and User Modeling. Puolamäki and Kaski (eds.) Otaniemi, Finland. May 2006.

There are other sources of implicit feedback as well



Implicit feedback

Model



Other data:
- history
- collaborative filtering
- text content

Inferred relevance or interestingness

Usable in a variety of applications, including proactive IR

Case study: Infer the relevance of titles of scientific articles

Setting

Gather a learning data set where relevance is known:
- Show a set of titles of scientific papers
- Measure eye movement trajectory
- Ask about the relevance of the titles afterwards.

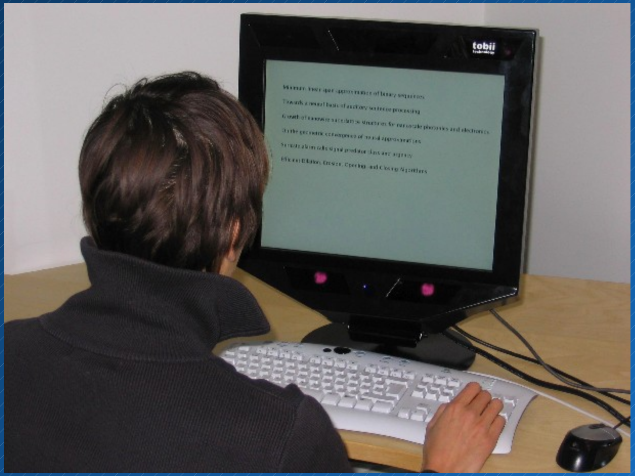
Task: predict relevance for new titles, given the eye movement trajectory.

Combining Eye Movements and Collaborative Filtering for Proactive Information Retrieval. Puolamäki, Salojärvi, Savia, Simola and Kaski **.** SIGIR'05.

Eye movements

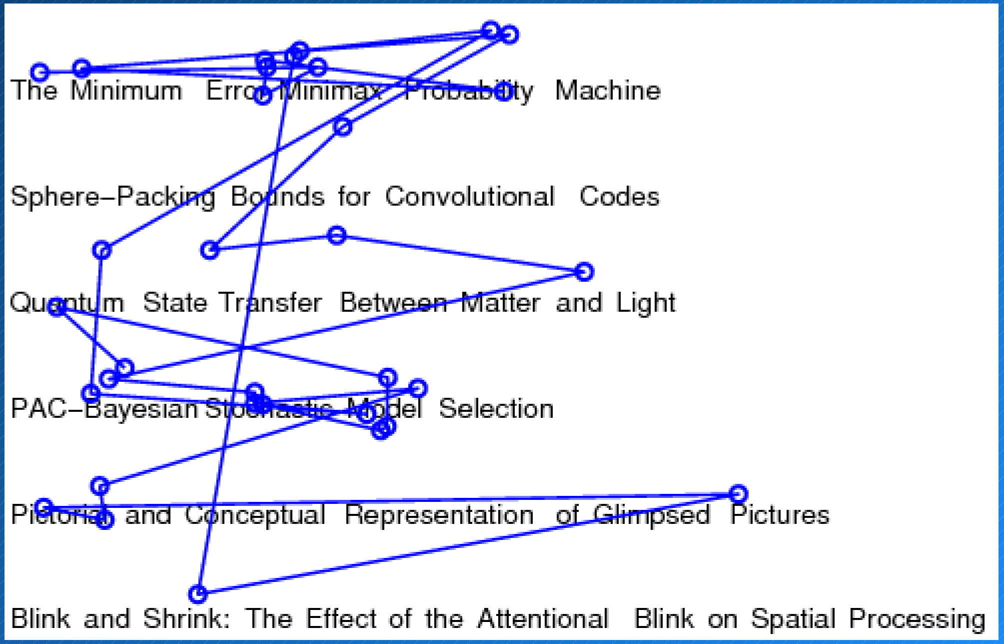
- Goal: estimate

p(“title relevant” | eye movements)



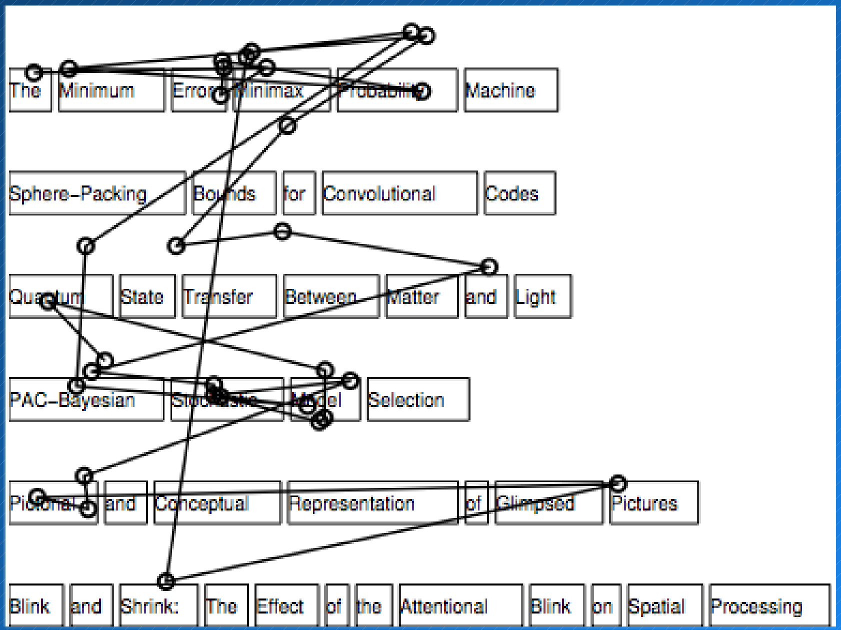
Jaana Simola and Tobii 1750 Eye Tracker

Eye movements of 3 subjects were measured



Feature extraction

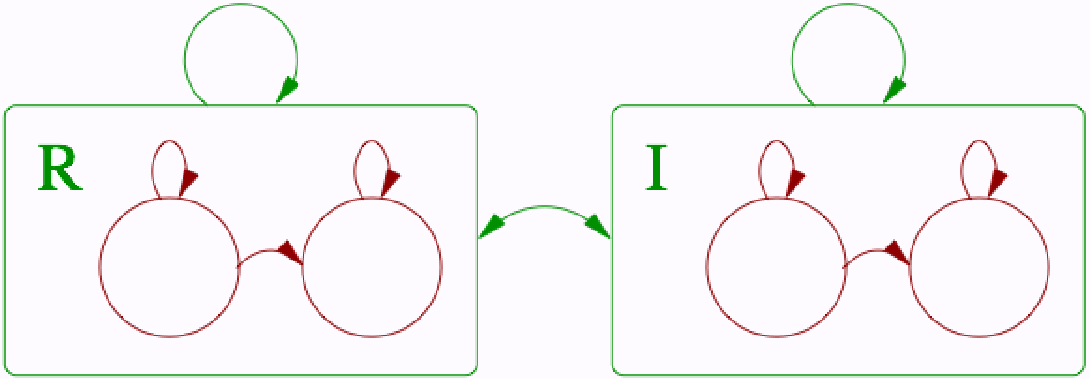
- Separate fixations and saccades
- Assign fixations to the closest words.
- Compute features:
  - one or many fixations
  - total fixation duration
  - reading behaviour
- Result: Each title is encoded into a sequence of word-specific feature vectors



Predicting relevance with *Discriminative* Hidden Markov Models (HMM)

First level: transitions between sentences

Second level: transitions between words



relevance={R,I}

- Optimized with *Discriminative* Expectation Maximization (EM) algorithm(described in our ICML'05 paper)

Expectation-Maximization Algorithms for Conditional Likelihoods. Salojärvi, Puolamäki and Kaski. ICML'05.

Performance measures

- *Accuracy.* Fraction of titles in the test set for which the prediction was correct.
- *Perplexity=(likelihood)*$^{-1/N}$, inverse of geometric mean of the *N* test set item likelihoods.

Results

Small perplexity and large accuracy are better.

Model	Perplexity	Accuracy
Dumb Model	-	66.6 %
HMM (eye movements)	1.78	73.3 %

Clearly better than by chance but not very high because eye movements are a very noisy and indirect indicator of relevance

=> How about other sources of information?

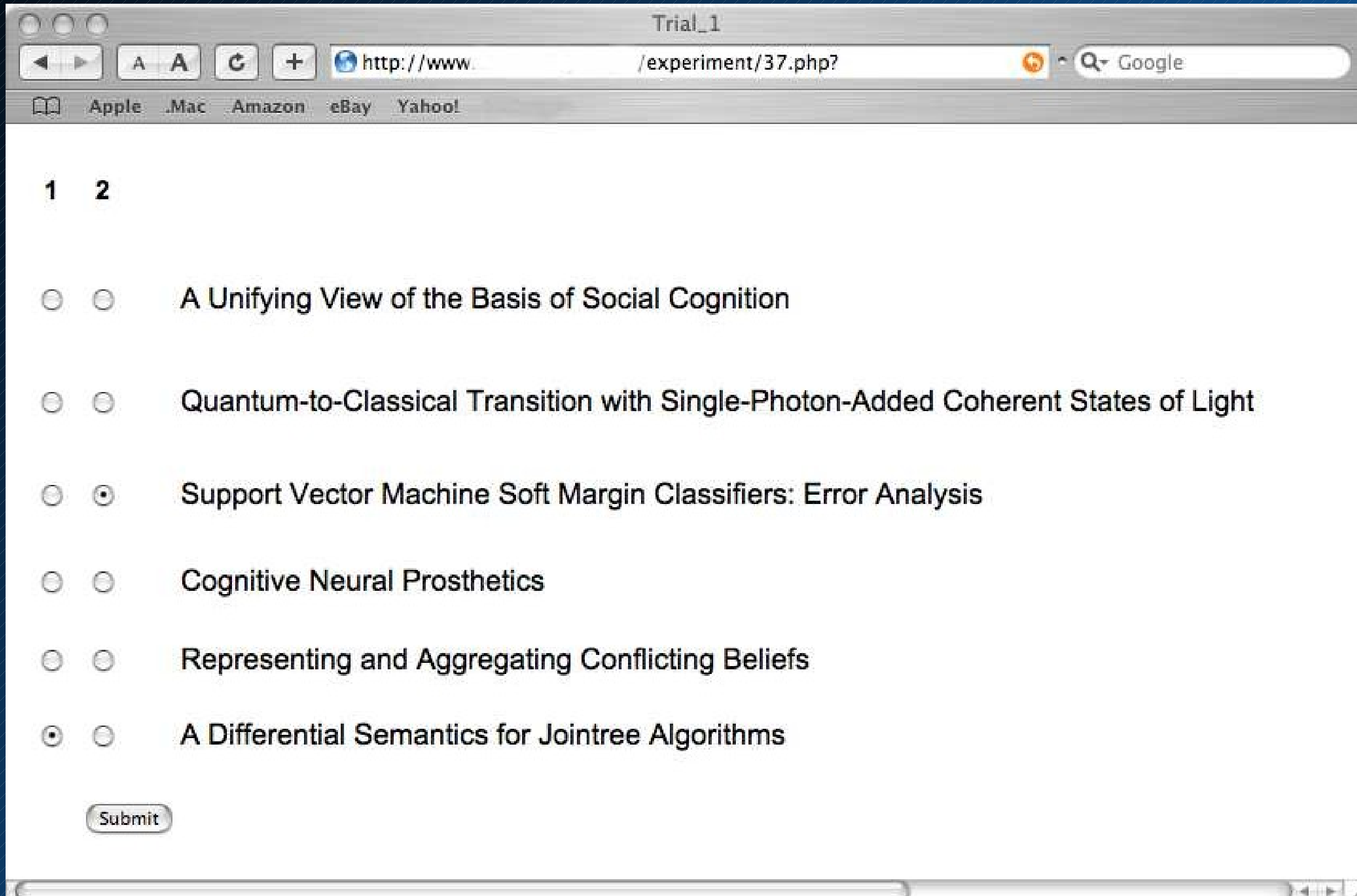
Collaborative Filtering =
Relevance out of others’ interests

Researchers		The minimum error minimax…	Sphere–packing bounds for co…	Quantum state transfer betw…	PAC–Bayesian stochastic m…	Pictorial and conceptual rep…	Blink and shrink the effect of th…
Samuel Kaski		?	☹	☺	?	☺	☺
Kai Puolamäki		☹	?	☹	☺	?	?
Jarkko Salojärvi		☺	☺	?	?	☹	?
Eerika Savia		☺	☹	☺	☺	?	?
Lauri Kovanen		☹	?	?	☺	?	☺

Experimental setup

25 test subjects were shown 80 pages, each containing titles of 6 scientific articles

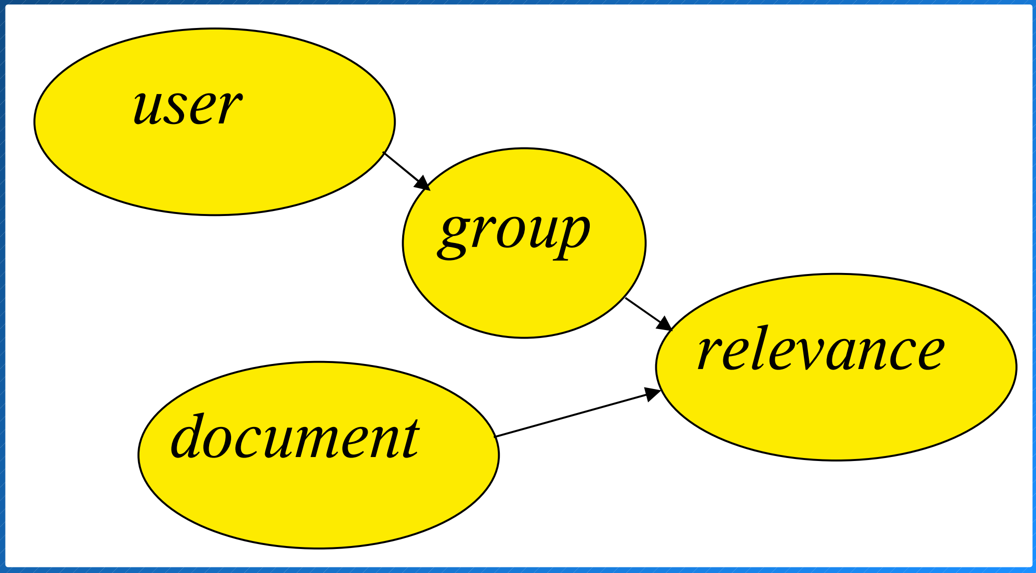
Asked to “pick 2 most interesting titles”



22 subjects gave the feedback with a web form.

User Rating Profile (URP) Model

- URP (Marlin 2004) is a generative model which generates binary ratings *relevance={I,R}* for *(user, document)* pairs
- *p(relevance | user,document)* evaluated with Markov Chain Monte Carlo



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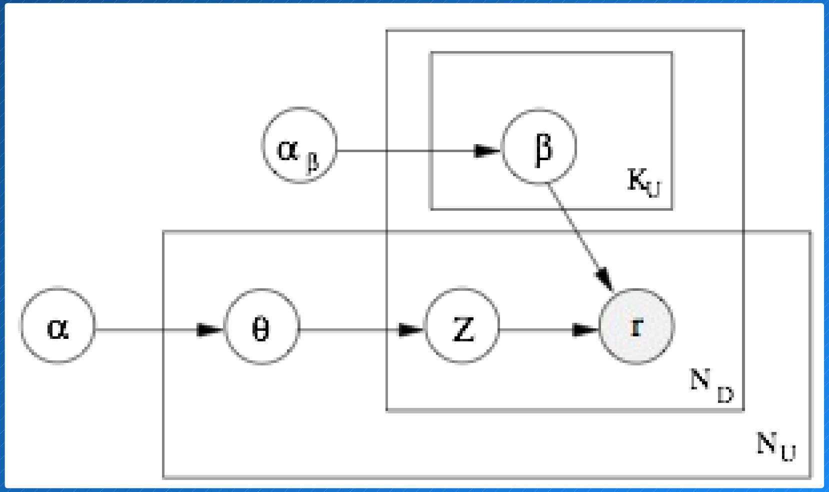
Graphical model representation of URP



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Model	Perplexity	Accuracy
URP (collab. filtering)	1.50	83.0 %

Very good!

But are eye movements needed at all?

Combining collaborative filtering and eye movements

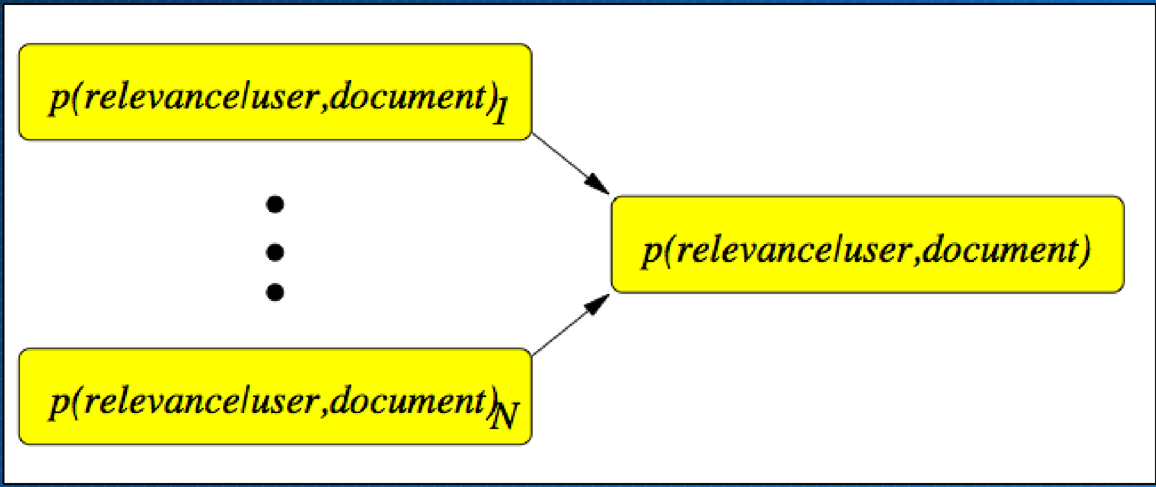
Combining predictions

- Our models produce probabilities
  p(relevance | *user,document)*

- How to combine the probabilistic predictions into one probability -
  p(relevance |*user,document)* ?

Dirichlet Mixture Model

- Combines predictions by taking their uncertainty into account
- Modular approach: arbitrary probabilistic models can be combined



On Discriminative Joint Density Modeling. Salojärvi, Puolamäki and Kaski. ECML'05.

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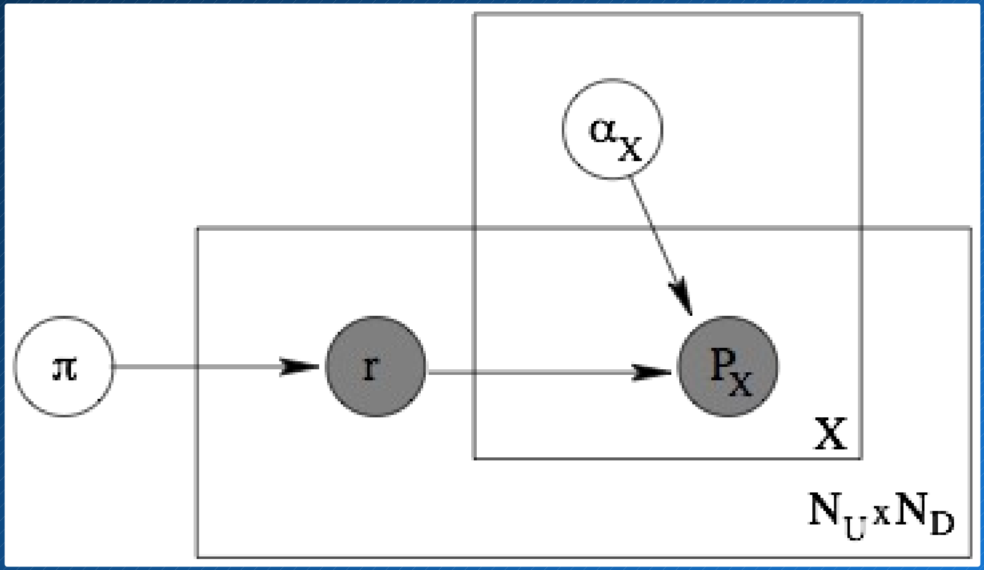

Graphical model representation of Dirichlet Mixture Model

On Discriminative Joint Density Modeling. Salojärvi, Puolamäki and Kaski. ECML'05.

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Model	Perplexity	Accuracy
Dirichlet mixture	**1.48**	**85.2 %**

Small perplexity and large accuracy are better.


Eyeogle
Results 1–6
The Minimum Error Minimax Probability Machine
by Kaizhu Huang, Haiqin Yang, Irwin King, Michael R. Lyu, Laiwan Chan
Journal of Machine Learning Research vol. 5, pp. 1253–1286, 2004
http://jmlr.csail.mit.edu/papers/v5/huang04a.html – Cached – Similar pages
Sphere–Packing Bounds for Convolutional Codes
by E.Rosnes and O.Ytrehus
IEEE Transactions on Information Theory Vol.50(11), pp. 2801–2809, 2004.
ccc.ustc.edu.cn/abstract/rosnes.ps – Cached – Similar pages
Quantum State Transfer Between Matter and Light
by D. N. Matsukevich and A. Kuzmich
Science vol. 306(5696), 2004.
http://arxiv.org/abs/quant-ph/0410092 – Cached – Similar pages
PAC–Bayesian Stochastic Model Selection
by David A. McAllester
Machine Learning Vol. 51(1), pp. 5–21, 2003.
ttic.uchicago.edu/~dmcallester/posterior01.ps – Cached – Similar pages
Pictorial and Conceptual Representation of Glimpsed Pictures
by Mary C. Potter, Adrian Staub, and Daniel H. O'Connor
Journal of Experimental Psychology, Human Perception and Performance Vol. 30(3), 2004.
cvcl.mit.edu/IAP05/potterstauboconnor2004.pdf – Cached – Similar pages
Blink and Shrink: The Effect of the Attentional Blink on Spatial Processing
by Christian and N. L. Olivers
Journal of Experimental Psychology, Human Perception and Performance Vol. 30(3), 2004.
http://content.apa.org/journals/xhp/30/3 – Cached – Similar pages
Eyeoooooooogle
Result page: 1 2 3 4 5 6 7 8 9 10 Next

Conclusions

- Our goal: Develop machine learning models which computers need in order to adapt to different users and situations
- The computer needs to model the user in the same way as people model each other
- Implicit feedback is gathered from eye movements and by following the users' actions
- Pilot application: Proactive information retrieval
- Status: First promising results achieved.

- This is a very promising new research area - welcome to join us in studying it!

The research consortium

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Petri Myllymäki, Miikka Miettinen, Ville Tuulos

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Ilpo Kojo, Jaana Simola

More information:
http://www.cis.hut.fi/projects/mi/proact