



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.

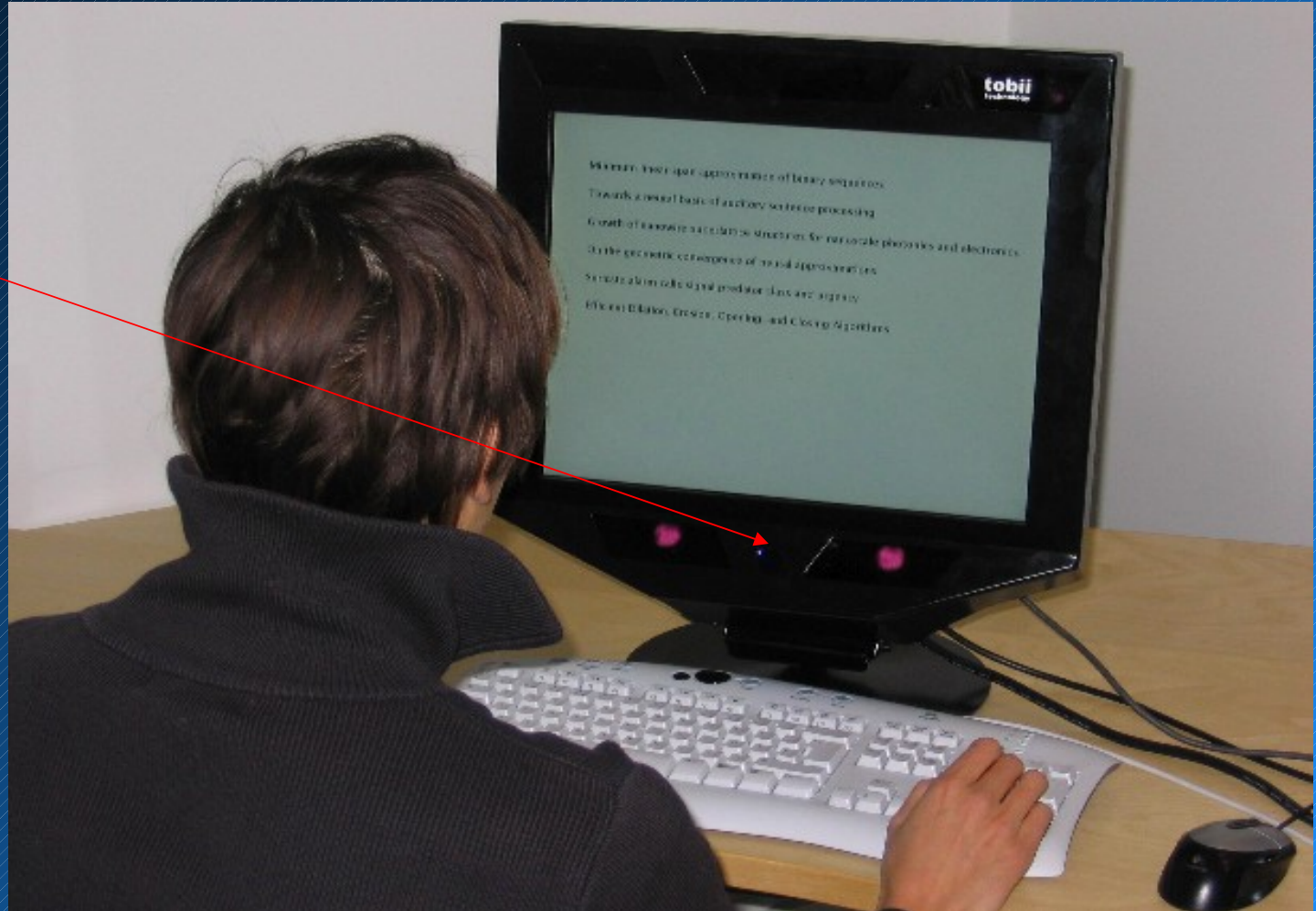
We need: a way of inferring the mental state of the user (from implicit feedback).

Mental state from eye movements?



Gaze direction and target can be measured

Eye tracker





Grab File Edit Capture Window Help

Google-haku: information search eye movements

http://www.google.fi/search?hl=fi&q=information+search+eye+movements&btnG=Hae&meta=

Google Mail Uutiset Fun Work Kirjasto Musiikki

Web Kuvat Keskusteluryhmät Hakemisto

information search eye movements Hae Tarkennettu haku Asetukset

Haku: Web-sivuilta suomenkielisiä sivuja sivuja Suomi:sta

Web Tulokset 1 - 10 noin 846 000 osuman joukosta haulle information search eye movements. (0,35 sekuntia)

Vihje: Säästä aikaa painamalla enter-näppäintä Hae-painikkeen sijasta.

Research - Eye Movements

FINDINGS ON EYE MOVEMENTS DURING SEARCH The information limits of saccadic targeting: How much guidance is there in eye movements during search? ...
www.psych.ucsb.edu/~eckstein/lab/vp_EMdet.html - 7k - Välimuistissa - Samankaltaisia sivuja

Research - Eye Movements

What are the processes that guide eye-movements during search? What is the information available to the 1st saccade during search and how does it compare to ...
www.psych.ucsb.edu/~eckstein/lab/vp_EM.html - 6k - Välimuistissa - Samankaltaisia sivuja
[Lisää tuloksia kohteesta www.psych.ucsb.edu]

Eye Movements and Visual Search in Dentistry

Eye Movements and Visual Search in Dentistry. ... interpretation and the behavior of radiologists; the necessity of using other information for diagnosis ...
www.underwijs.acta.nl/ radiologieweb/research/farwest.htm - 12k - Välimuistissa - Samankaltaisia sivuja

Eye movements - uncontrollable

... Search: Dr.Koop, Web, MEDLINE, ... oculography: An electrical method of measuring eye movements using tiny ... The information provided herein should not be used during ...
www.drkoop.com/ency/article/003037.htm - 40k - Välimuistissa - Samankaltaisia sivuja

Eye movements - uncontrollable

... Search: Dr.Koop, Web, MEDLINE, ... Rapid eye movements from side to side; Uncontrolled eye movements. ... The information provided herein should not be used during any ...
www.drkoop.com/ency/article/003037trt.htm - 38k - Välimuistissa - Samankaltaisia sivuja
[Lisää tuloksia kohteesta www.drkoop.com]

An Introduction to Eye Movements and Visual Search

... Often visual search studies finds that what the observer ... then ask the driver to recall information from it ... Alternatively, if we record the eye movements of the ...
ibs.derby.ac.uk/avru/em/intro/vissearch.shtml - 5k - 23 marraskuu 2004 - Välimuistissa - Samankaltaisia sivuja

- Reading

- Visual Search

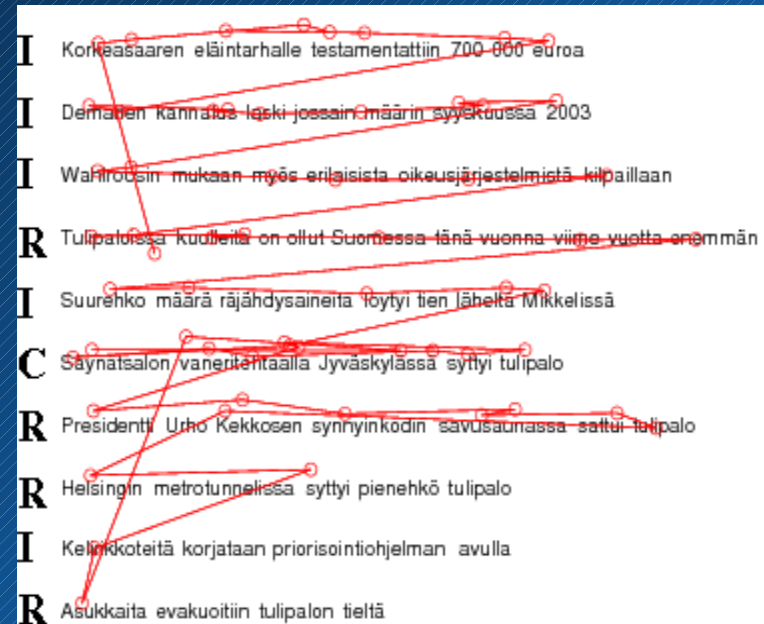


Pilot study: Inferring relevance from eye movements



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!



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:

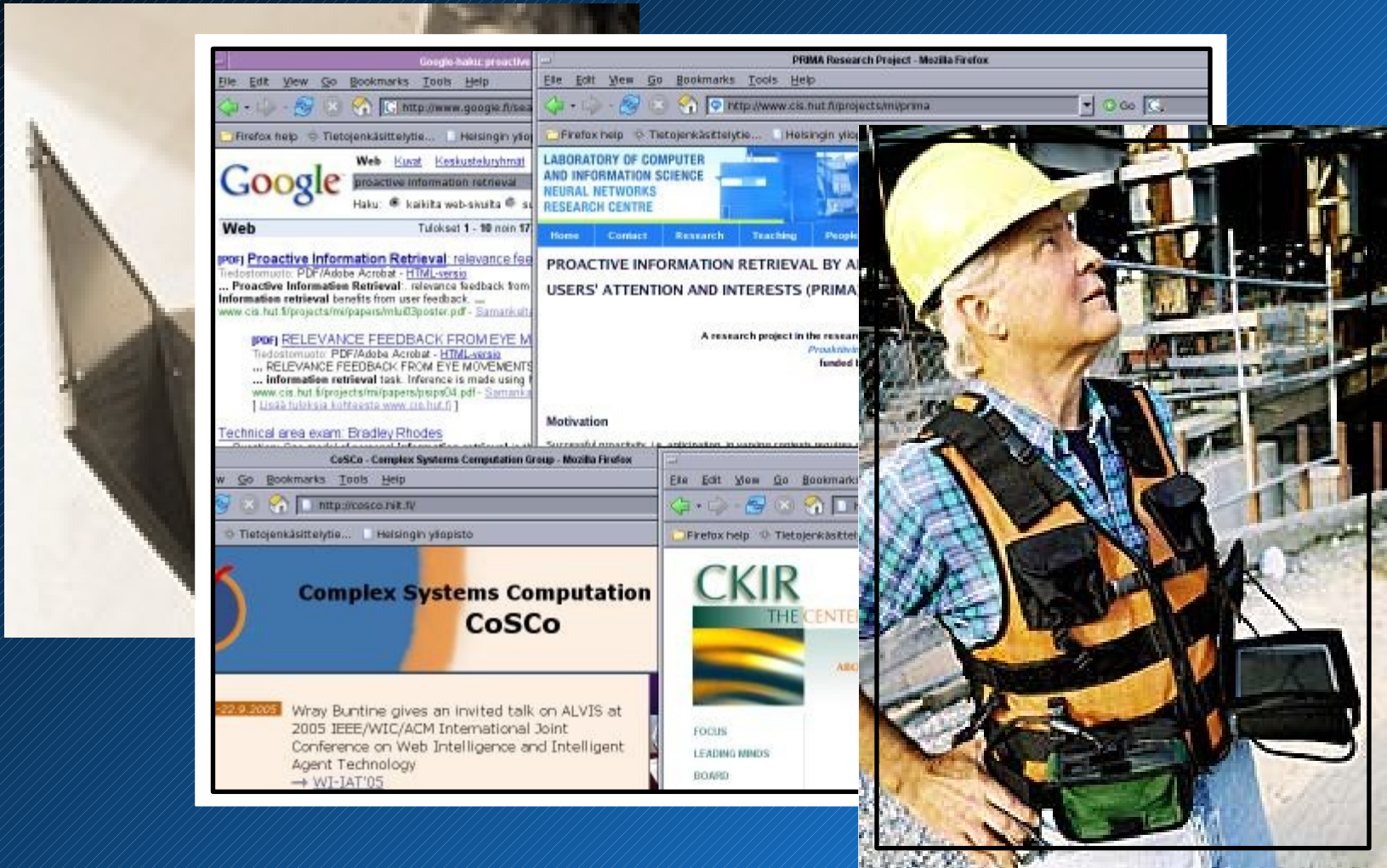
<http://www.cis.hut.fi/eyechallenge2005/>

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

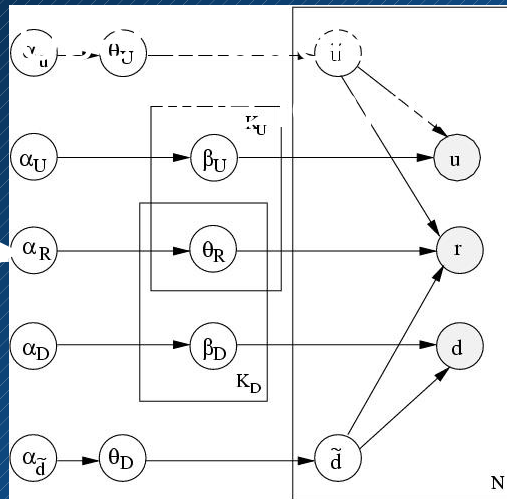
Proceedings of the NIPS Workshop on Machine Learning for Implicit Feedback and User Modeling. Puolamäki and Kaski (eds.) Otaniemi, Finland. May 2006.



There are other sources of implicit feedback as well



Model



Implicit feedback

Other data:

- history
- collaborative filtering
- text content

Inferred relevance or interestingness

Usable in a variety of applications, including proactive IR



HELSINKI UNIVERSITY OF TECHNOLOGY
LABORATORY OF COMPUTER AND INFORMATION SCIENCE

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.

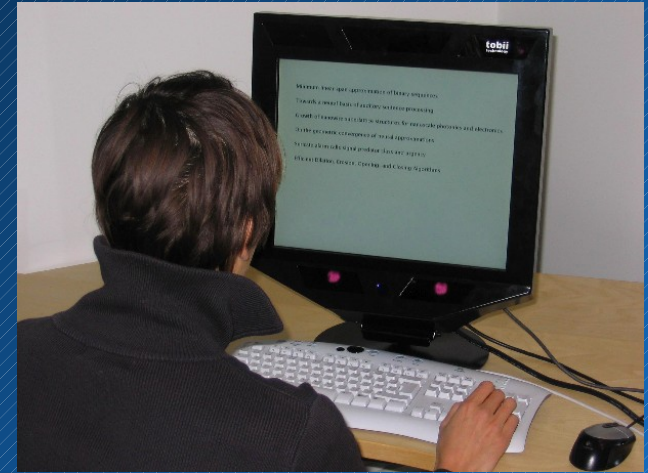
Task: predict relevance for new titles, given the eye movement trajectory.

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

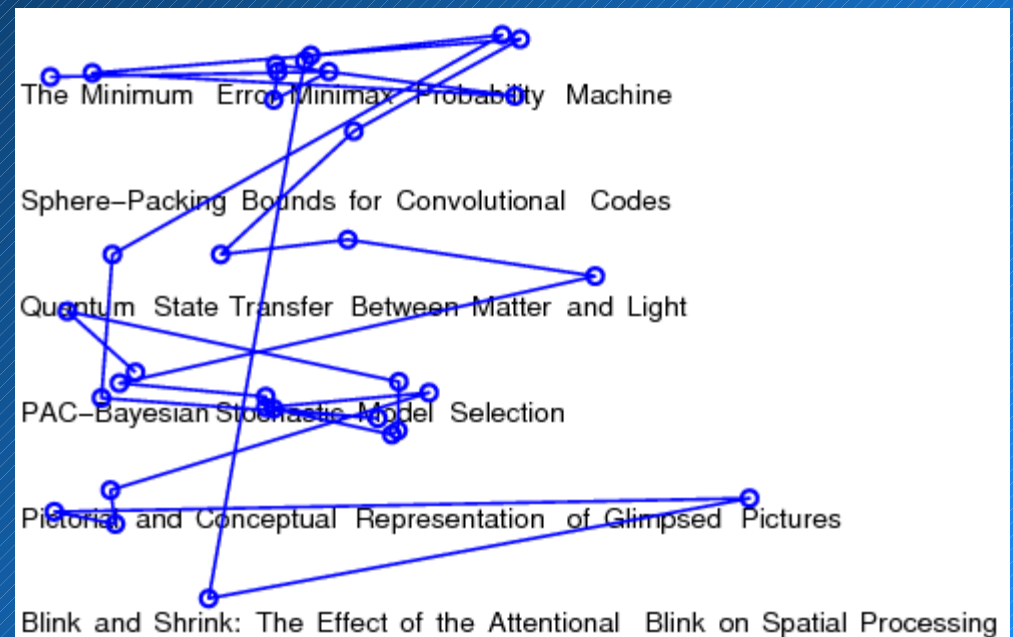


Eye movements

- Goal: estimate $p(\text{"title relevant"} \mid \text{eye movements})$



Jaana Simola and Tobii 1750 Eye Tracker

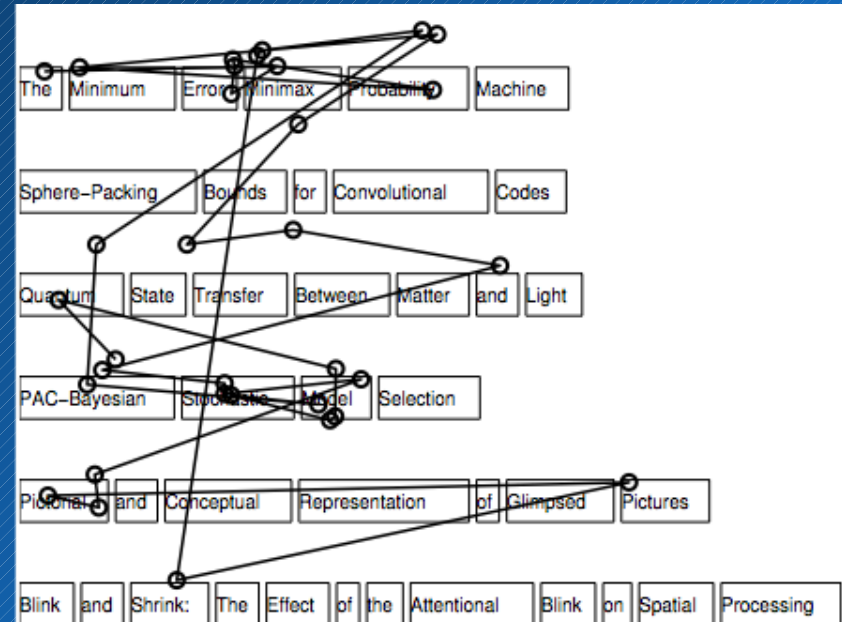


Eye movements of 3 subjects
were measured



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

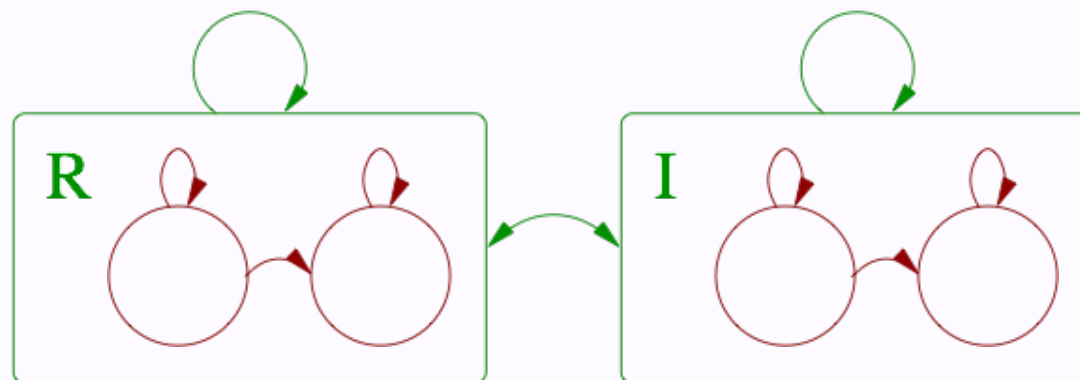




Predicting relevance with *Discriminative* Hidden Markov Models (HMM)

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)



Performance measures

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



		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...
Researchers							
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”



Trial_1

http://www. /experiment/37.php? Google

Apple .Mac Amazon eBay Yahoo!

1 2

- ☐ ☐ A Unifying View of the Basis of Social Cognition
- ☐ ☐ Quantum-to-Classical Transition with Single-Photon-Added Coherent States of Light
- ☐ ☒ Support Vector Machine Soft Margin Classifiers: Error Analysis
- ☐ ☐ Cognitive Neural Prosthetics
- ☐ ☐ Representing and Aggregating Conflicting Beliefs
- ☒ ☐ A Differential Semantics for Jointree Algorithms

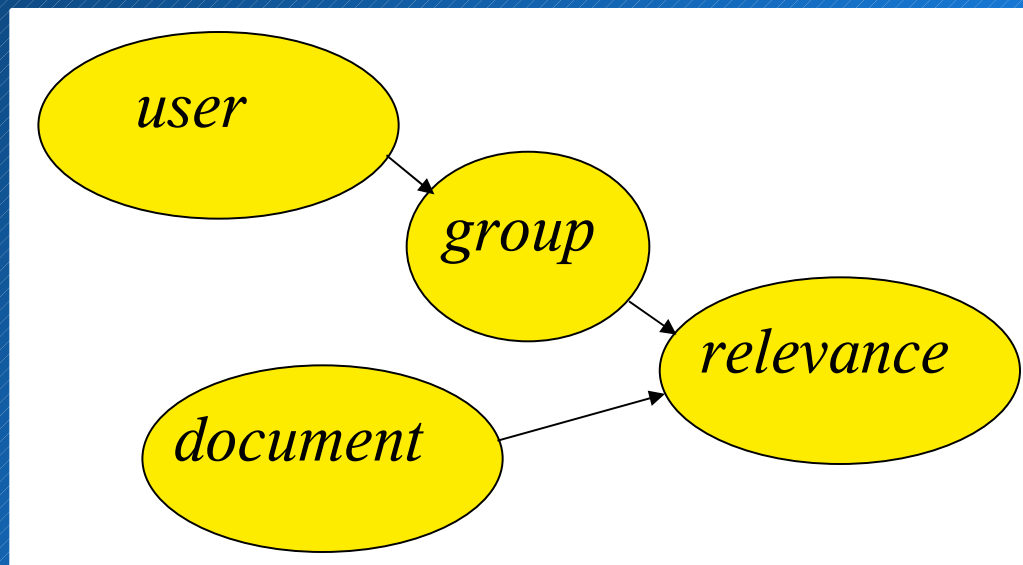
Submit

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
- $p(relevance \mid user, document)$ evaluated with Markov Chain Monte Carlo

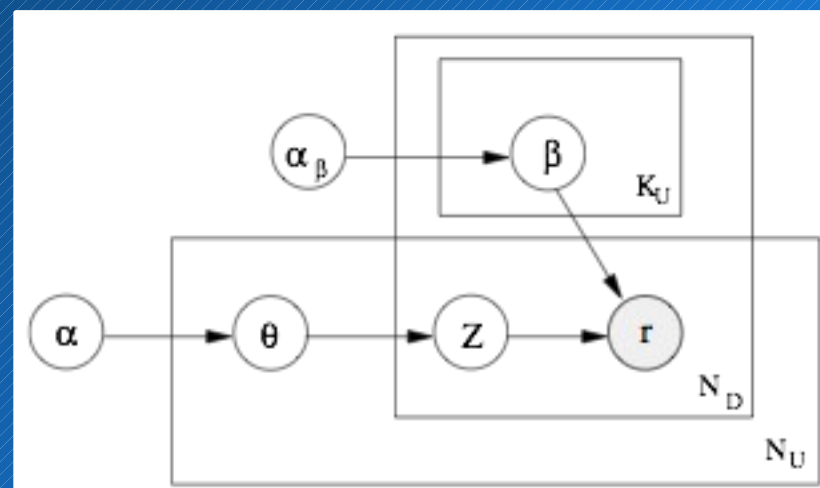




User Rating Profile (URP) Model

- URP (Marlin 2004) is a generative model which generates binary ratings $relevance=\{I,R\}$ for *(user, document)* pairs
- $p(relevance \mid user, document)$ evaluated with MCMC

Graphical model representation of URP





Results

Small perplexity and large accuracy are better.

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

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



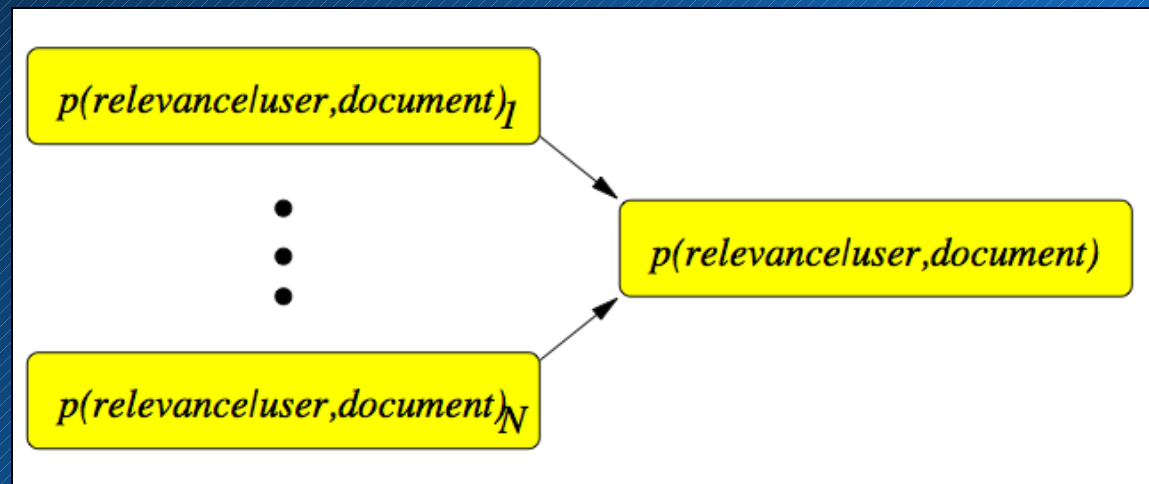
Combining predictions

- Our models produce probabilities
 $p(\text{relevance} \mid \text{user}, \text{document})$
- How to combine the probabilistic predictions into one probability -
 $p(\text{relevance} \mid \text{user}, \text{document})$?



Dirichlet Mixture Model

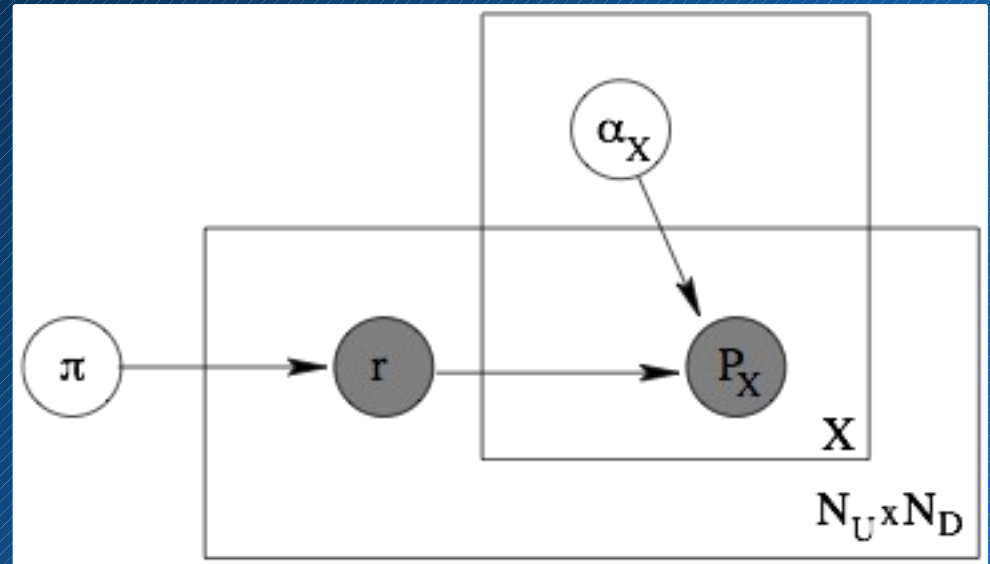
- Combines predictions by taking their uncertainty into account
- Modular approach: arbitrary probabilistic models can be combined





Dirichlet Mixture Model

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



Graphical
model
representation
of Dirichlet
Mixture Model



Results

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

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

Model	Perplexity	Accuracy
Dirichlet mixture	1.48	85.2 %

Small perplexity and large accuracy are better.

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/xhnp/30/3> - Cached - Similar pages



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

**Laboratory of Computer and Information Science, Helsinki
University of Technology**

Samuel Kaski, Kai Puolamäki, Jarkko Salojärvi, Eerika Savia

**Complex systems computation group CoSCo, Helsinki
Institute of Information Technology HIIT and Department
of Computer Science, University of Helsinki**

Petri Myllymäki, Miikka Miettinen, Ville Tuulos

**Center for Knowledge and Innovation Research CKIR,
Helsinki School of Economics and Business
Administration**

Ilpo Kojo, Jaana Simola

More information:

<http://www.cis.hut.fi/projects/mi/proact>