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Personalization of Search Results using Interactive Intent Modeling

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Interactive Intent Modeling

Problem

- In exploratory search, user is uncertain of precise search intent
- User needs to learn while searching
- How to allow the user to learn quickly and to find relevant results?

User perspective

- Need easy and meaningful ways to modify query
- Need to get approximate understanding of information space quickly
- Easier to recognize relevant search features than to generate them

Interactive intent modeling [1, 2]

- After user initiates search session, a search intent model is constructed
- The intent model is visualized to the user, along with the search results
- User can modify her query by making changes to the intent model
- Dynamic approach to personalization

Extensions

Controllability [3]

“How to enable the user to achieve the kind of changes in the search model that the users wants to happen?”

Solution: Choose the weight for the most recent user feedback adaptively, so that the resulting user model agrees well enough with it.

Predictability [3]

“How to allow the user to predict what essential changes will happen in the user model as a consequence of different actions?”

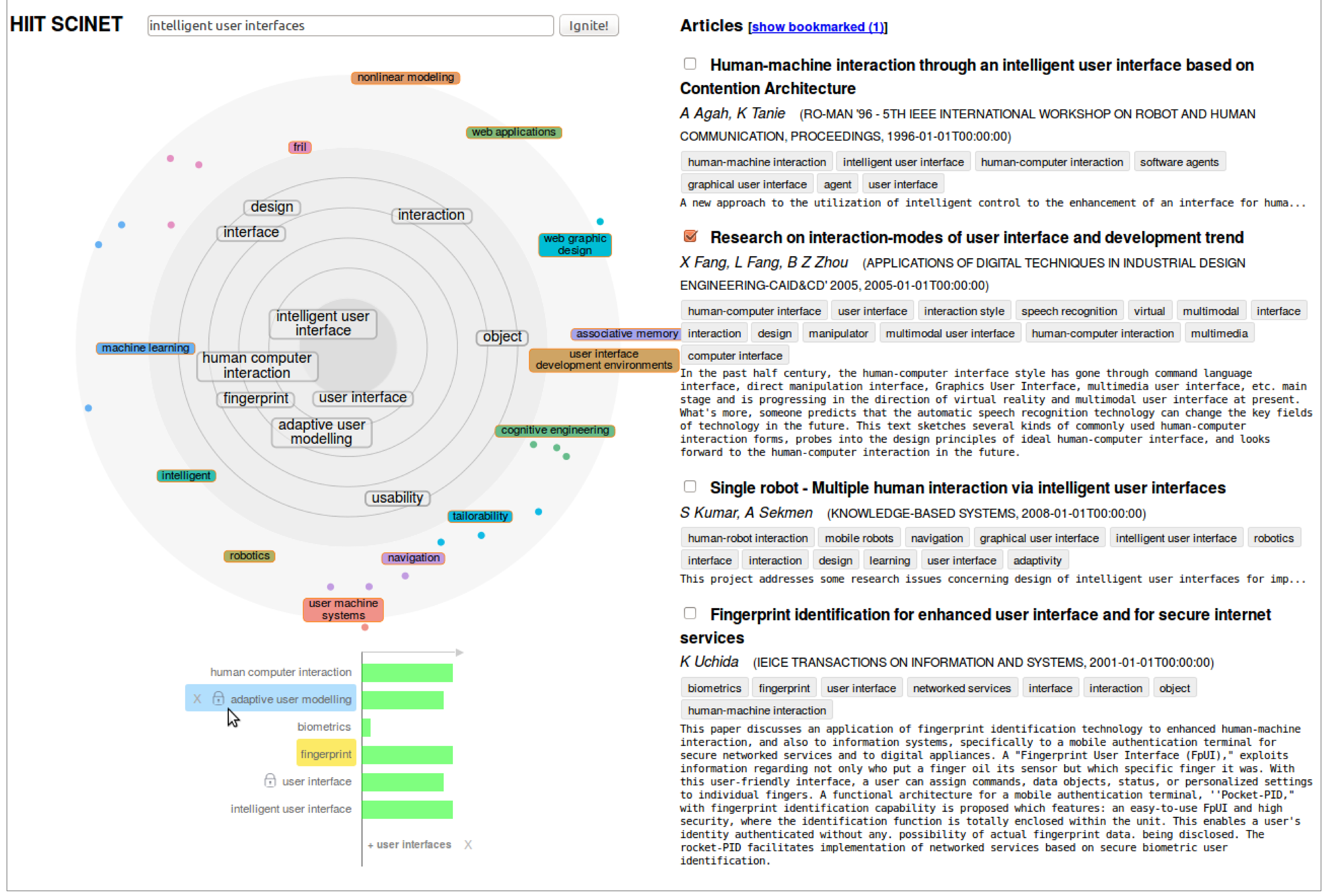
Solution: Simulate 'possible future models' when user is choosing what feedback to give, visualize approximate resulting model on-line to the user.

Drift Detection [4]

“How to detect what user feedback is still relevant to modeling the current user interest?”

Solution: Estimate accuracy of each user feedback (simultaneously with the current user model), highlight feedbacks with low accuracy to the user so that she can either correct the feedback or indicate that the feedback was accurate.

User Interface



User Models

LinRel exploration/exploitation model [Auer 2002]

- A linear regression model with error bounds.
- Balances between exploration and exploitation by using Upper Confidence Bound estimates for the relevance of keywords.

$$a_i = x_i(X^T X + \mu)^{-1} X^T$$
$$ucb_i = a_i(Y + \frac{C}{2} a_i a_i^T)$$

Automatic Relevance Determination model

- Linear Bayesian regression model that also estimates the accuracy of keyword feedback.
- Can incorporate feedback on the accuracy by changing the prior of w_i according to feedback

$$y_i \sim Normal(x_i \phi, \frac{\sigma^2}{w_i})$$
$$\phi_i \sim Normal(\mu_\phi, \lambda_\phi)$$
$$\sigma^2 \sim InverseGamma(\alpha_{\sigma^2}, \beta_{\sigma^2})$$
$$w_i \sim Gamma(\alpha_w, \beta_w)$$
$$w_i^{fix} \sim Delta(1.0)$$

Experimental Results

When offered the option to use interactive intent modeling, users tended to use it as their primary interaction mode (instead of performing keyword query modifications) [1,2]

Compared to a baseline with only keyword query modification possibility, interactive intent modeling resulted in better quality of results (Figure 1) and also improved the task performance. [1,2]

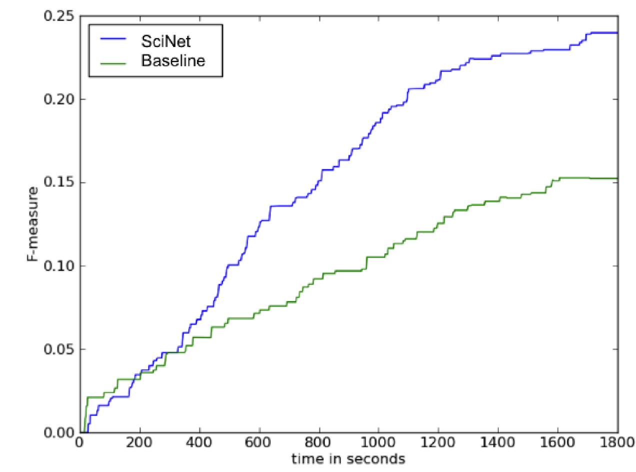


Fig 1: Avg F1-score / time

Improving controllability seemed to improve user performance in focused search tasks but reduce it in broader tasks. [3]

Improving predictability was found useful by the users: 70% of the users reported that helped them in their search tasks. This was both because the feature helped them predict the effects of actions and showed them which keywords were related to each other. [3]

In a simulation experiment where a simulated user is giving noisy feedback, the ARD model is able to perform asymptotically as well as an oracle (Figure 2), given a small amount of additional user feedback. [4]

Users rated the quality of recommendations given by the ARD model higher than a linear baseline model. [4]

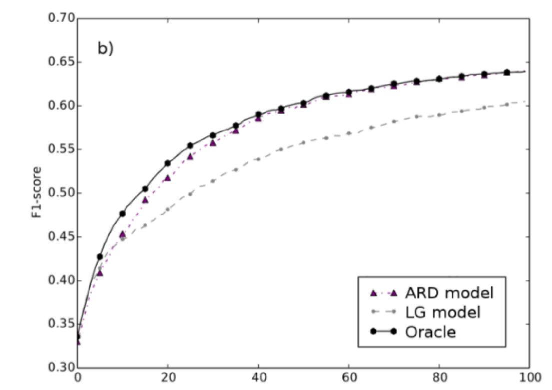


Fig 2: Avg F1-score / iterations

Users interacted more with the interface when the timeline was present: they gave more feedback with the radar (and timeline) and issued less keyword queries, while retaining similar task performance. [4]

References

[1] D. Glowacka, T. Ruotsalo, K. Konyushkova, K. Athukorala, S. Kaski, G. Jacucci. **Directing exploratory search: Reinforcement learning from user interactions with keywords.** Proc. of the International Conference on Intelligent User Interfaces, 2013. Best paper award.

[2] T. Ruotsalo, K. Athukorala, D. Glowacka, K. Konyushkova, A. Oulasvirta, S. Kaipiainen, S. Kaski, G. Jacucci. **Supporting exploratory search tasks with interactive user modelling.** Proc. of the American Society for Information Science and Technology, 2013.

[3] A. Kangasrääsiö, D. Glowacka, S. Kaski. **Improving controllability and predictability of interactive recommendation interfaces for exploratory search.** Proc. of the International Conference on Intelligent User Interfaces, 2015.

[4] A. Kangasrääsiö, Y. Chen, D. Glowacka, S. Kaski. **Interactive modeling of concept drift and errors in relevance feedback.** Proc. of the Conference on User Modeling, Adaptation and Personalization, 2016. To appear. (Preprint in arXiv)