A Methodological Framework for Decision-Theoretic Software Customization Assistance

PhD Thesis

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Need for Software Customization

- One-size-fits-all:
  - Cluttered interfaces, *bloat*-ware
  - *Dis*satisfied users
  - Most affected users
    - People with cognitive, sensory, motor impairments
    - Elderly/Children
    - Novices

- Recognize varying user needs and preferences

Interface Customization

- Objectives
  - Minimize user effort
  - Maximize interaction experience

Commercial Apps	Research Apps
Windows “Start” menu	Auto meeting scheduler
Mini toolbar in Office 2007	Folder prediction
Auto text completions	Adaptive menus

- Different benefits and costs involved

Where do I start?

– Which existing research results can I draw upon?
– What are components in such a system?
– What steps are involved?

Thesis Contributions

- Decision-theoretic framework and guidelines
  - Techniques from interdisciplinary fields
  - Data collection, simulation testing, user evaluation
- Formal model of user types, characteristics, goals
  - Probabilistic models
  - Fast, online inference
  - Explains individual preferences
- Formal model of interaction cost
  - Models of interaction factors
  - Account for objective and subjective utility
  - Characteristics parameters to capture evolving preferences
  - New method for eliciting experienced utility

What aspects of the system should I make adaptive?

- Which tasks do users need help with?
- How do I model individual differences?
- What does the system need to know?

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How do I know if it works?

– For different user groups?
– Can I anticipate “impact” before adapting the interface?
– What if user preferences change over time?

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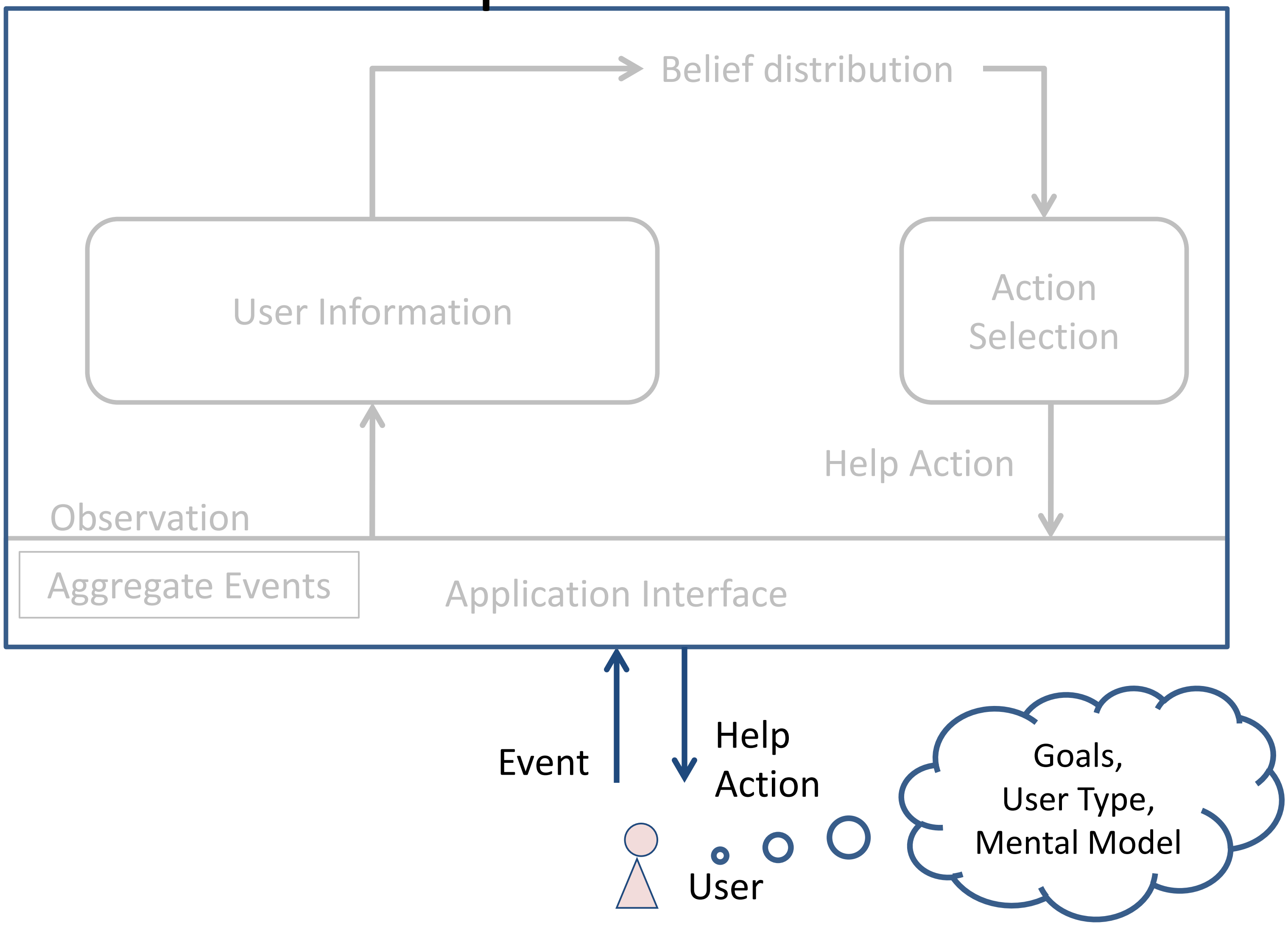
  - New method for eliciting *experienced* utility
  - Characteristics parameters to capture evolving preferences

Software Customization Assistance (SCA) Development Architecture



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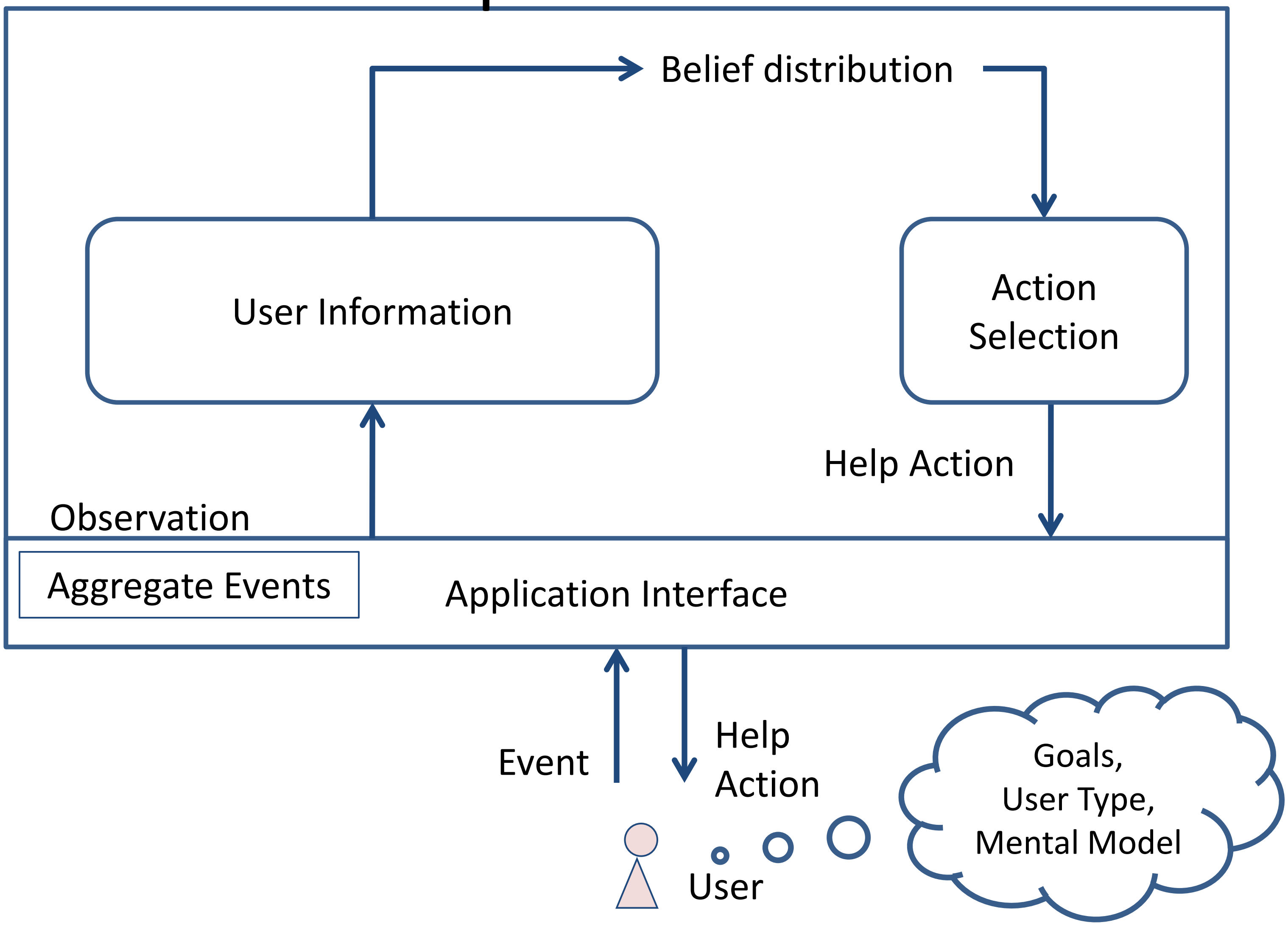

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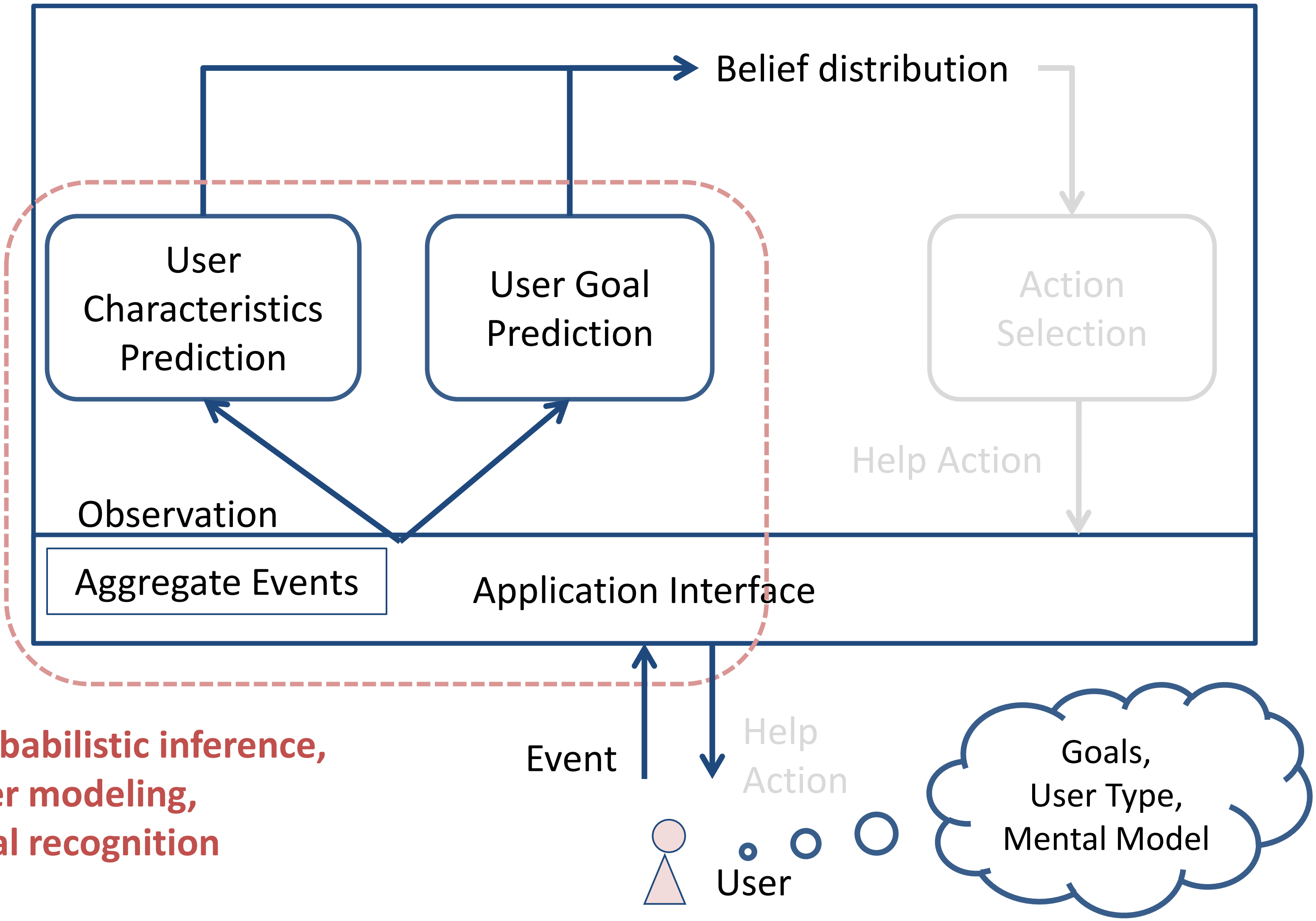
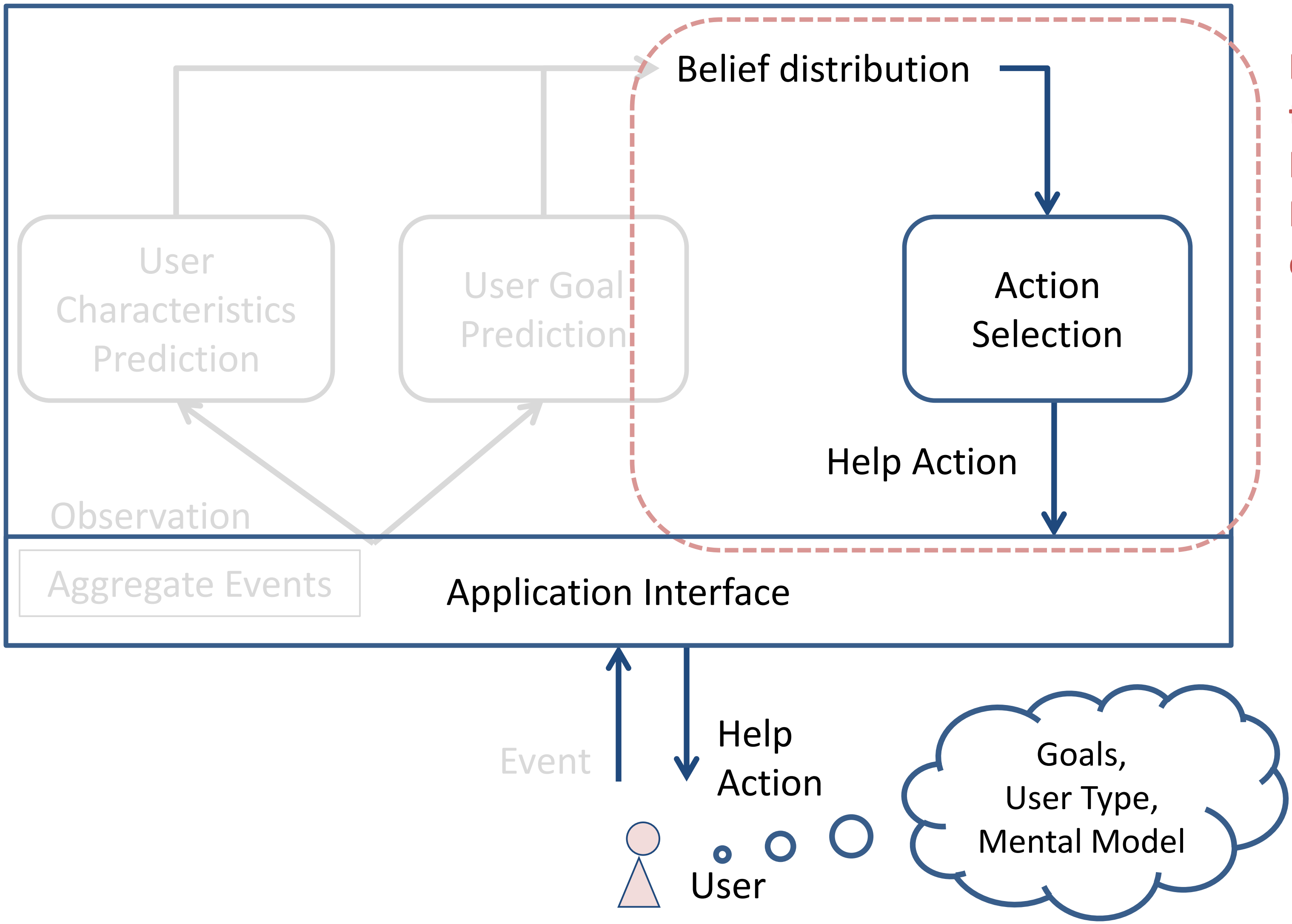


Probabilistic inference,
User modeling,
Goal recognition

SCA Development Architecture

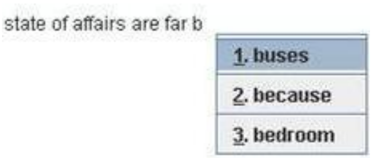


Decision theory, HCI, Preference elicitation

Case Studies

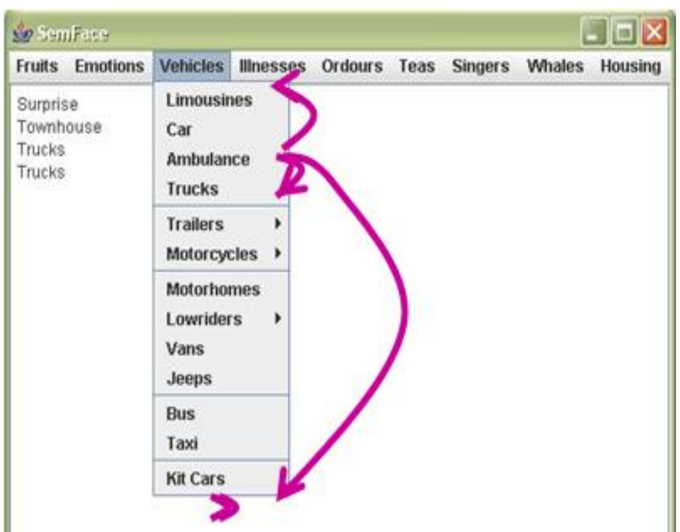
Word completion [Hui & Boutilier 06; ACM Finals 07]

Bayesian user characteristics model



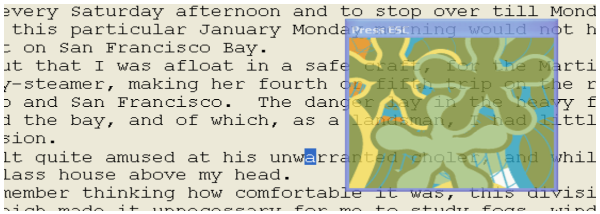
Adaptive menu [Hui et al. 09]

Probabilistic mental model



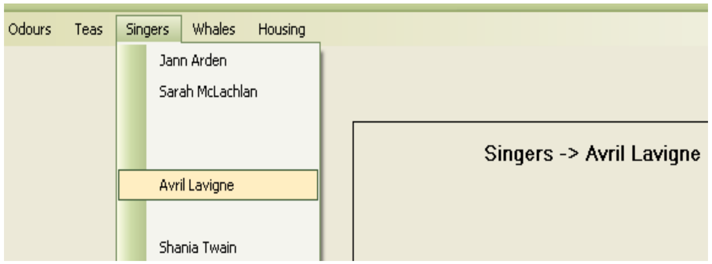
Typing [Hui et al. 08]

Occlusion model



Menu selection [Hui et al. 08]

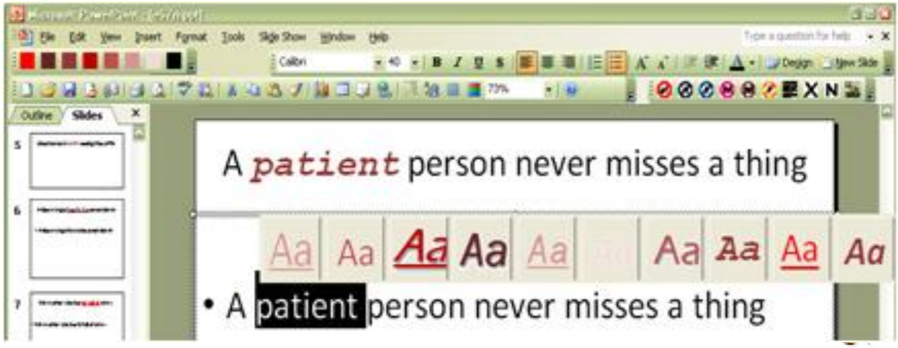
Bloat model



Highlighting toolbar [Hui & Boutilier 08]

Goal model

Experiential elicitation



Case Studies

Word completion [Hui & Boutilier 06; ACM Finals 07]

Bayesian user characteristics model

- Data collection: 45 users
- Simulation: Always, Never, MEU, Thresh
- Usability: 4 users
- Analysis: standard error, EM, KL-divergence, factor analysis

Adaptive menu [Hui et al. 09]

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- Data collection: 48 users
- Simulation: Best-Static, Split-4, JES, WER(.1), WER(.5), WER(.9)
- Usability: 8 users
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Typing [Hui et al. 08]

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- Data collection: *online-adaptation*
- Simulation: Static, Freq-Char, Freq-only, Goal-Char, Goal-only
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Experienced utility elicitation

- Data collection: 38 users
- Analysis: t-test, Hotelling's T2 test

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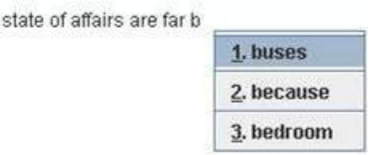
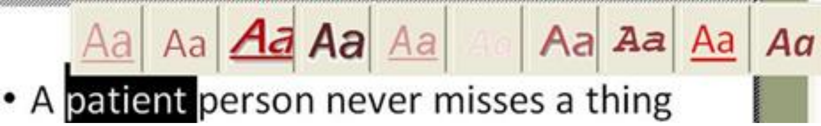


Findings – Char. Model

- **Inference is feasible**
  - 36 user types
  - Convergence between 20-150 words
  - System behaviour adapts to user characteristics

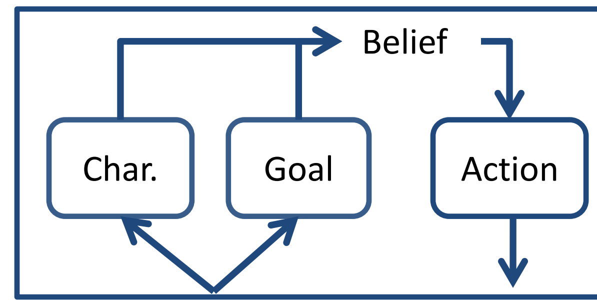
- **Users perceive help utility**
  - Joint expected savings vs. bigrams (ML)
    - ~2% more exact word matches
    - ~11% more character savings
    - *Greedy*: ~6.4% more character savings
  - Users accept 20% *inexact* matches

E.g., “the nu”:
- number
- nuclear
- nurses



Findings – Goal Model

- **Adaptive help saves user effort**
  - Average event reduction
    Freq: 13%
    Goal: 22%
    Goal-Char: 21% (w.r.t. NeverHelp)
  - % Suggestions accepted
    Goal: 3.5x
    Goal-Char: 3.3x (w.r.t. Freq)



- **Users like Goal/Goal-Char better than baseline**
  - Personalization and Helpfulness:
    Goal >> Freq ($p < 0.05$)
    Goal-Char >> Freq ($p < 0.05$)
  - Incremental inference more suited for sequential task

Summary

- **Intelligent assistance as decision-theoretic planning problem**
  - Propose POMDP-SCA framework
  - Model both user characteristics and user goals
- **Formal user models and parameter acquisition experiments**
  - Incorporate user behaviour and feedback
  - Explain interaction preferences
  - Monitor changes in characteristics over time
  - Recognize personalized goals
- **Learning interaction preferences**
  - Learn interaction cost models
  - Trade off adaptation benefits with interaction costs
  - Elicit experiential preferences
  - Use joint action selection for wider coverage of true goal