Intelligent Prompting Systems for People with Cognitive Disabilities

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Background

- ✦ Age-specific cognitive disabilities
  - ✦ Among the population of the elderly
  - ✦ Dementia (or Alzheimer's)
- ✦ Other forms of cognitive Disabilities
  - ✦ Traumatic Brain Injury (***TBI***)
  - ✦ Developmental disabilities, mental retardation, etc.

	Population (millions), aged ≥60 years (2001)	Number of people (millions) with dementia, aged ≥60 years			Proportionate increase (%) in number of people with dementia	
		2001	2020	2040	2001–2020	2001–2040
Western Europe (EURO A)	89·6	4·9	6·9	9·9	43	102
Eastern Europe low adult mortality (EURO B)	27·4	1·0	1·6	2·8	51	169
Eastern Europe high adult mortality (EURO C)	44·6	1·8	2·3	3·2	31	84
North America (AMRO A)	53·1	3·4	5·1	9·2	49	172
Latin America (AMRO B/D)	40·1	1·8	4·1	9·1	120	393
North Africa and Middle Eastern Crescent (EMRO B/D)	27·5	1·0	1·9	4·7	95	385
Developed western Pacific (WPRO A)	34·5	1·5	2·9	4·3	99	189
China and developing western Pacific (WPRO B)	151·1	6·0	11·7	26·1	96	336
Indonesia, Thailand, and Sri Lanka (SEARO B)	23·7	0·6	1·3	2·7	100	325
India and south Asia (SEARO D)	93·1	1·8	3·6	7·5	98	314
Africa (AFRO D/E)	31·5	0·5	0·9	1·6	82	235
TOTAL	616·2	24·3	42·3	81·1	74	234

Figure 1: Number of people with dementia world-wide (Ferri et al., 2005)

Challenges with Cognitive Disabilities

- **Executive function deficiency**
  - prospective memory; planning and problem solving; task sequencing and switching; self-monitoring, and self-initiation
  - failing to initiate, sustain, or terminate an action, forgetting an unfinished task after interruptions, performing task incorrectly, and so on
- **Cognitive Support**
  - People: cost, burden
  - Technology
    - Timers, electronic calenders
    - **Assisted Cognition** (Kautz 2002)
      - Artificial Intelligence
      - Ubiquitous computing
        - Sense aspects of the context

Intelligent Prompting

- Context-Aware: take context into account and adapt accordingly
  - State estimator
    - interpret behaviors
  - Controller
    - integrate heterogeneous sources of information
    - autonomous decision making
  - User interface
    - Various forms of prompts

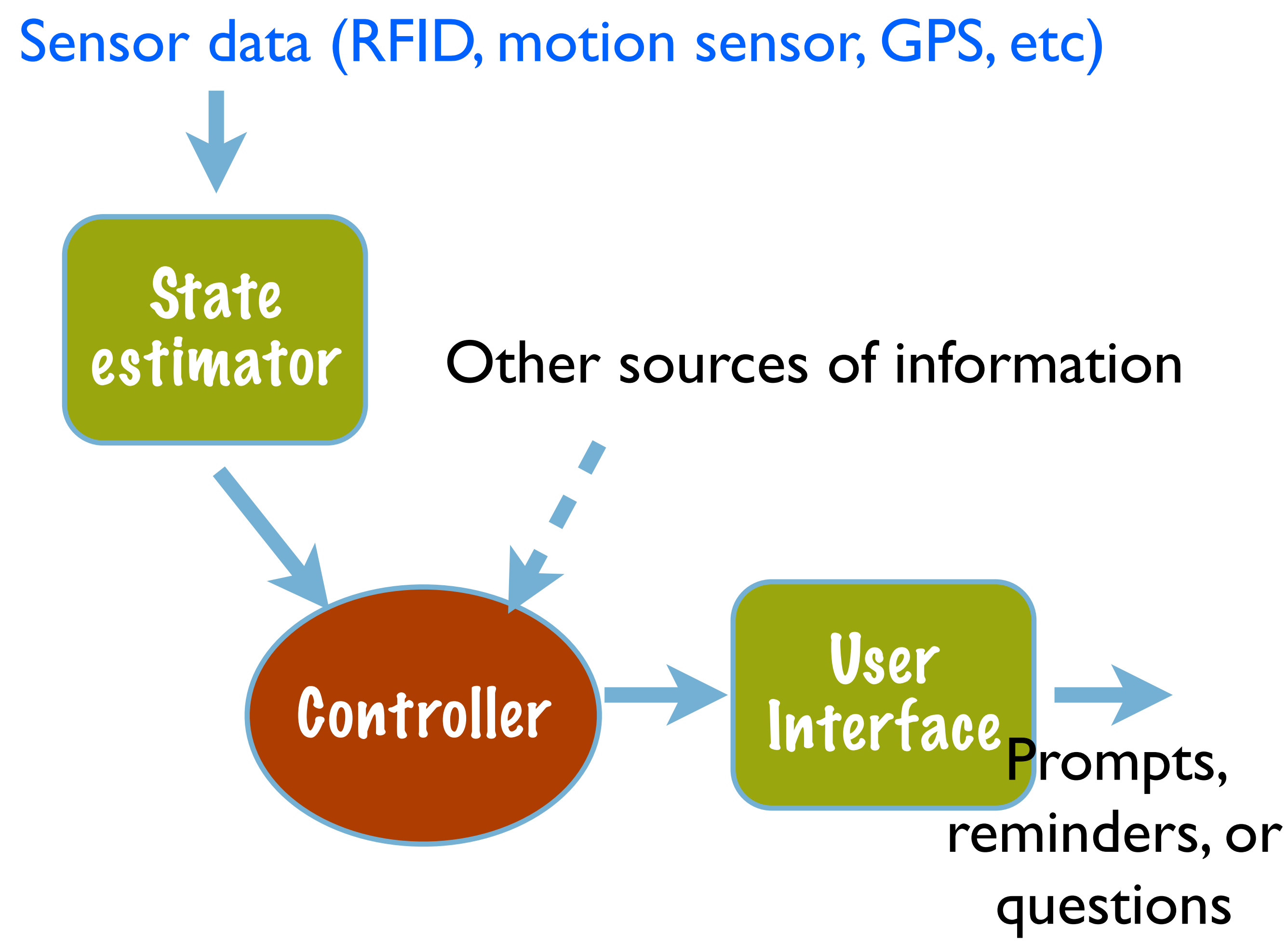
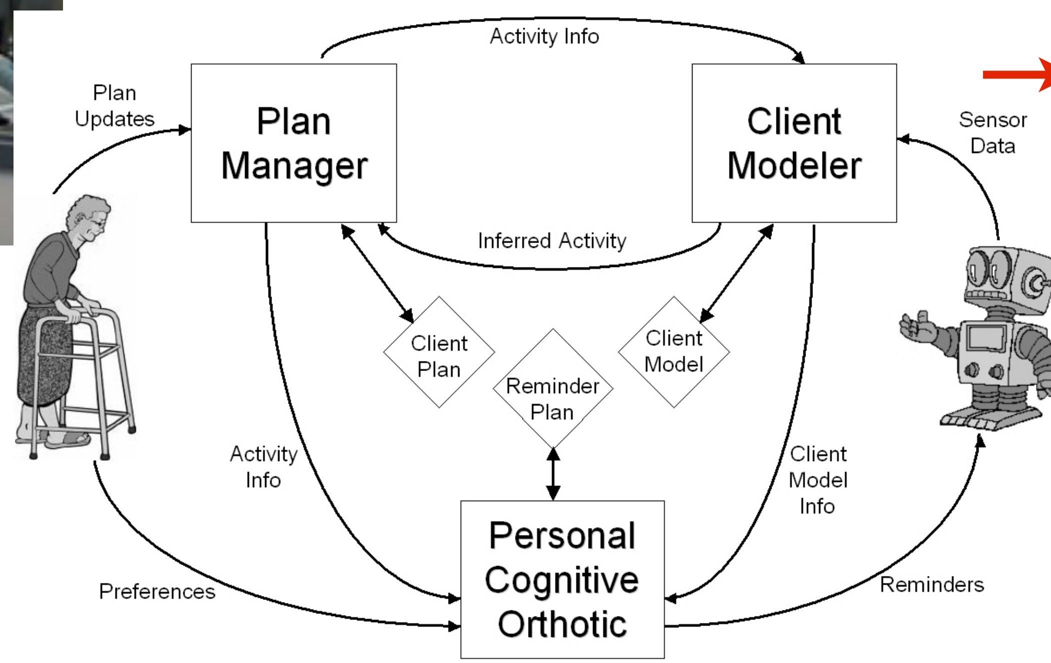


Figure 2. Typical Structure of Prompting System

Prompting Systems for Cognitive Disabilities

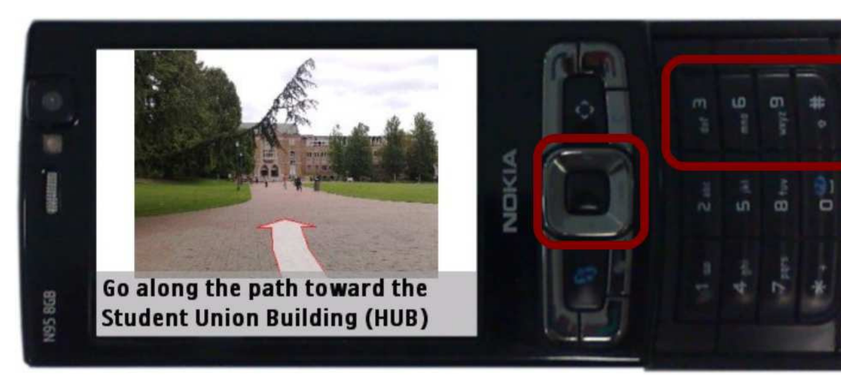
COACH automated hand-washing assistance (Mihailidis, 2008)



Autominder: introduce unified framework of a context-aware prompting system (Pollack, 2002)

PEAT planning and execution assistant (Levinson, 1997)

Others: way-finding (Liu, 2009)



Outline

- **Challenges**
  - Avoiding unnecessary prompts (e.g., *system of least prompts (SLS)*)
  - Decision making under uncertainty
  - Adapting and customizing prompts
  - Identifying the state reliably

Solution: Partially observable Markov Decision Process (POMDP) $\longrightarrow$ Computational Cost (Intractable)

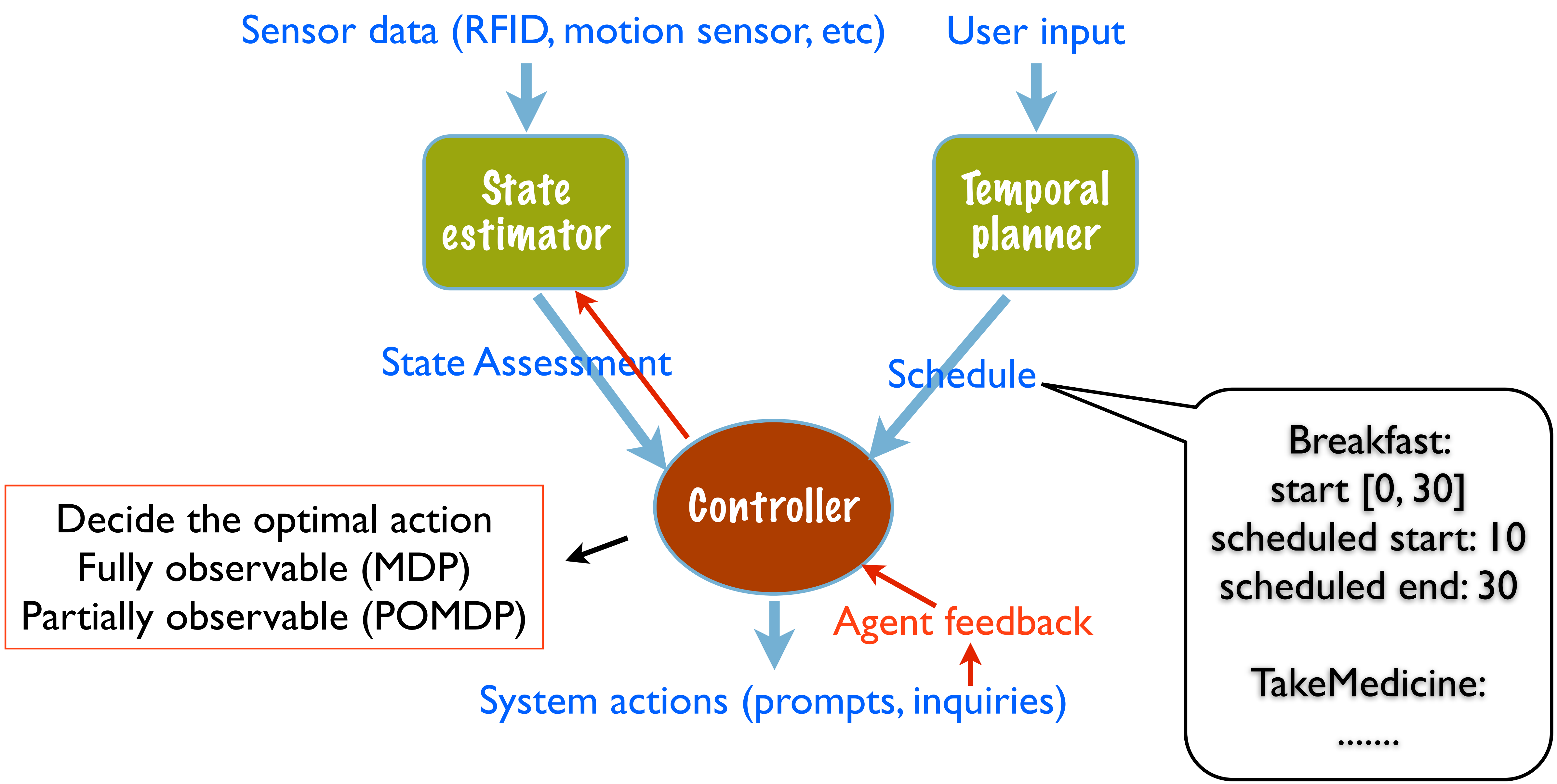
- **Key contributions**
  - Hierarchical Control
  - Adaptive Prompting
  - Selective-inquiry based dual control
    - Robust state estimation
    - Unified model
- **Focus group study**

Model Architecture

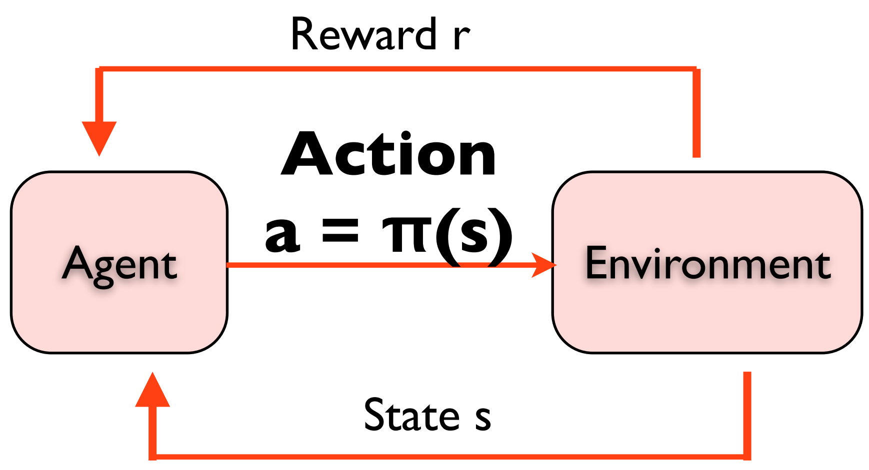
: Hierarchical Control

System Overview

- Main Goal: support schedule adherence and time management

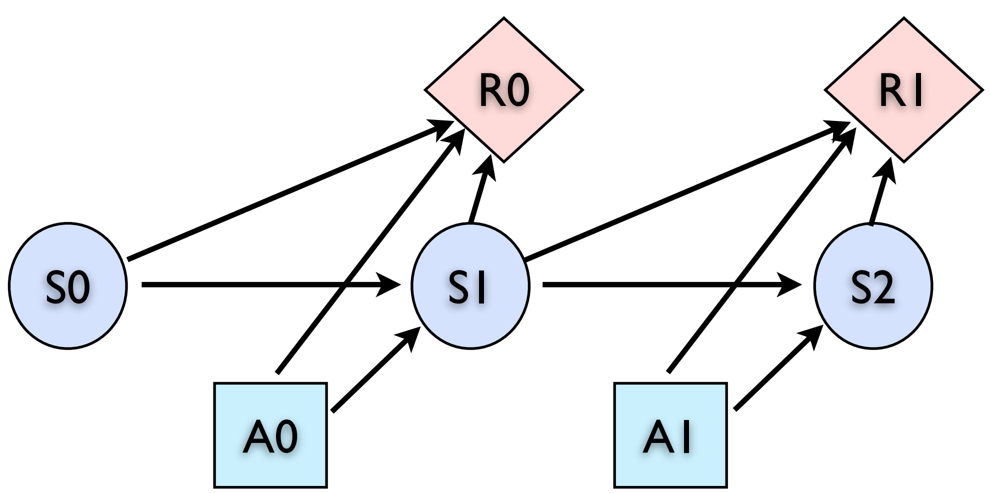


Markov Decision Process



Intelligent agent interacting with the world

- state $s \in S$
- action $a \in A$
- policy $\pi(s)$: ***S*** → ***A***
- reward $r(s, a)$
- dynamics $\mathbf{p(s' \mid s, a)}$



Part of an MDP

Goal:
find the optimal policy $\boldsymbol{\pi}^*$ that will maximize

$\gamma \in [0,1]$: discount factor

$$\mathbf{E}[\underbrace{r_0+\gamma^1 r_1+\cdots+\gamma^t r_t+\cdots}_{\text{Cumulative Discounted Reward}}]$$

Solving MDPs

- Dynamic programming
- $p(s'|\ s, a)$ & $r(s, a)$ are known
- Solve Bellman equation - **Value Iteration**
  - Value function ***V*(s)*** : expected cumulated reward starting from ***s*** by following **π***
    - $\mathbf{V^*(s)} = \max E[\underbrace{\mathbf{r_t}}+\underbrace{\boldsymbol{\gamma^1 r_{t+1}} + \cdots + \boldsymbol{\gamma^T r_{t+T}} + \cdots}|\ s, t, \pi^*]$

      $= \max_a [\boxed{r(s, a)} + \boxed{\gamma\sum_{s'}P(s'|s, a)\mathbf{V^*(s')}}]$
    - $\boldsymbol{\pi^*} = \text{argmax}_a \sum_{s'}P(s'|s, a)V(s')$

✓ **Reinforcement learning**

- $p(s'|\ s, a)$ & $r(s, a)$ are unknown
- Learn from actual experience $[s_1, a_1, r_1, s_2, a_2, r_2, \ldots]$
- Q-learning
  - Action value function ***Q(s, a)*** $= r(s, a) + \sum_{s'}\gamma P(s'|s, a)\max_{a'}Q(s', a')$
  - Value update
    - $\mathbf{Q_{k+1}(s, a_t) = (1-\alpha)\underbrace{Q_k(s, a_t)}_{\text{Old Value}} + \alpha(\underbrace{r_{t+1} + \gamma \max_a Q_k(s', a)}_{\text{Learned Value}})}$

Hierarchical Reinforcement Learning

Motivation

- "Flat" RL works well but on small problems.
- In the prompting domain:
  - Multiple task
  - Each task could be divided into sub-stages or subtasks.
  - Complex prompting behavior
  - Need to scale up? - curse of dimensionality

Solution - Temporal abstraction

- include temporal extended actions: persist over a variable period of time
- semi-MDP
  - Q update ***Q(s, a)***
    - System executes ***a*** in ***s***, takes τ steps, and transits to ***s'***
      - $Q_{t+1}(s_t, a_t) = (1-\alpha)Q_t(s_t, a_t) + \alpha(\underbrace{r_{t+1} + \gamma r_{t+2} + \cdots + \gamma^{\tau-1} r_{t+\tau}}_{\text{accumulated reward over temporal extended action } a} + \gamma^{\tau} \max\_{a} Q_t(S_{t+1}, a))$

accumulated reward over
temporal extended action ***a***

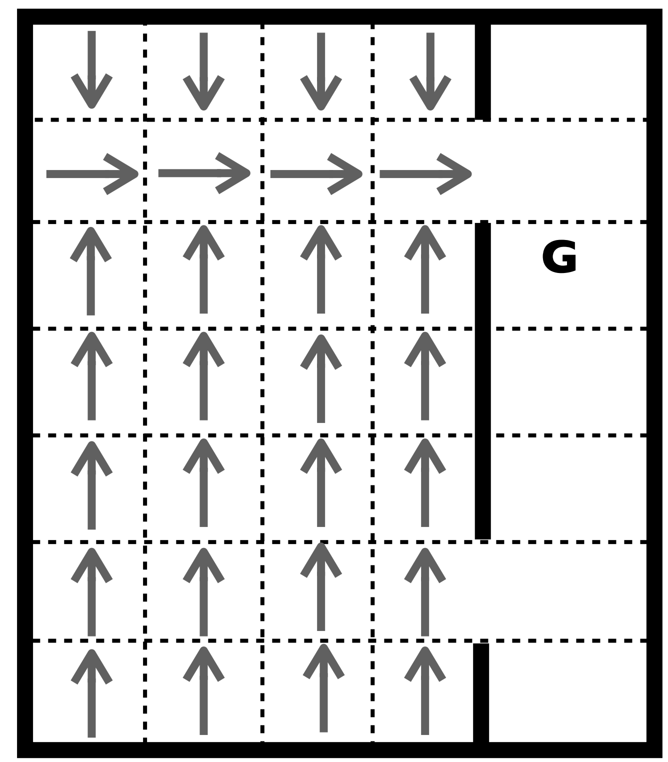
Options

- **An option is defined with:**
  - A region of the initiated state space
  - An internal policy π
  - A termination condition

- **Learning over options**
- Basic idea: treat each option as a primitive action
- Fundamental Observations: MDP + options = semi-MDP (Sutton 1999)
  - Q update **Q(s, o)**
    - $Q_{k+1}(s, o) = (1-\alpha)Q_k(s, o) + \alpha(\mathbf{r} + \gamma^{\tau}\max\_{o'}Q_k(S', o'))$

accumulated return over option

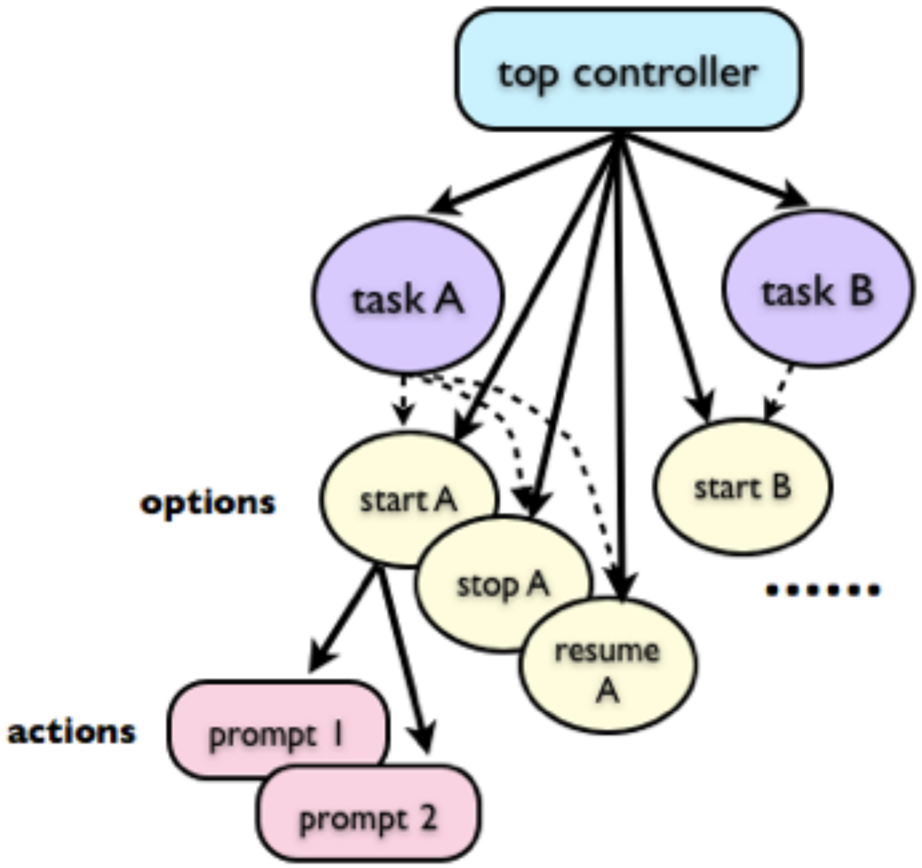
Room example (Sutton et al. 1999)



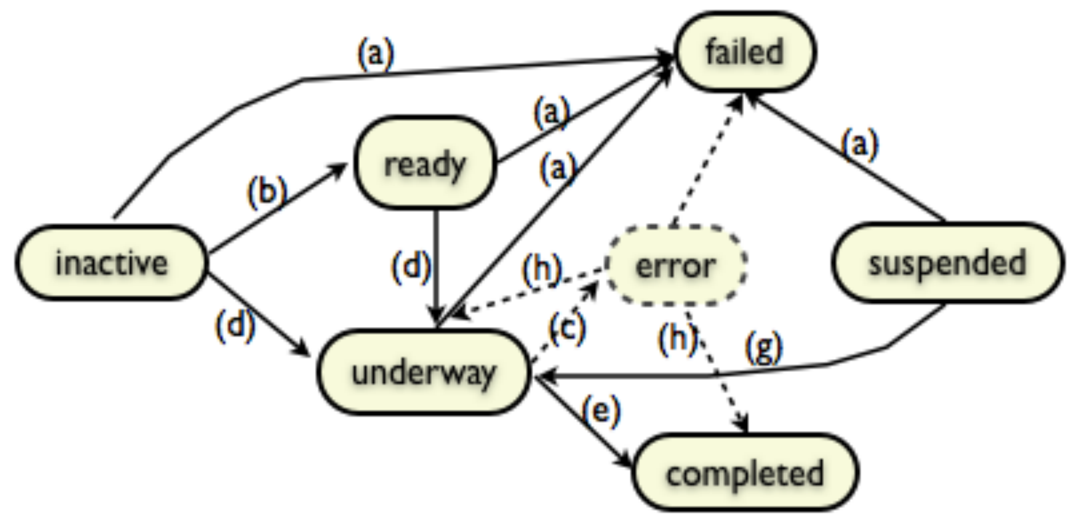
Policy under one of the exit options.

Example Option: *"Exit room by upper hallway"*

Control Hierarchy for Prompting



Options help progress a task through different **status**.



(a). pass deadline; (b). scheduled time arrives; (c). execute incorrectly; (d). get started;
(e). get finished; (f). get interrupted; (g). get resumed; (h). get recovered

- Task domain {$\mathbf{T_1, T_2, \ldots, T_N}$}
- Define an option-based $\mathbf{MDP_i}$ over each $\mathbf{T_i}$
- Each $\mathbf{MDP_i}$ has its own set of options $\mathbf{O_i}$.

Type: start,
Task id: breakfast
Initiation: task is *ready*
Termination: task is *failed*, *underway* or *completed*
Strategy: first prompt at t_p, ...

Example ***Start*** option in the prompting domain

The Complete Observable Control Algorithm

Procedure: **CO-Controller**

Input
S_t: the state vector at time t

Return
a: the primitive action to be generated

At each time step, the controller

1. check the termination condition of the running option (if there is any) against the current state S_t, and **terminate** it when the condition is met

2. form the set of available options O_t based on the policy of each MDP π_{MDPi}, and select the option with highest utility o_{max} for execution

3. Run o_{max} only when no other option is running, or **interrupt** the running option if o_{max} is of higher priority

4. Decide an action ***a*** (wait or prompt) based on the prompting strategy of the running option

Conclusion

- System structure: state estimator, temporal planner, and controller
- Controller : option-based MDPs
  - **Why options for prompting?**
    - support early deployment
    - exploit problem structure
    - specify complex prompting routine
    - improve interpretability and facilitate design
  - Completely observable control algorithm (CO-Controller)
    - distribute control among individual MDPs
  - Task independent assumption

Adaptive Prompting

: a decision-theoretic approach

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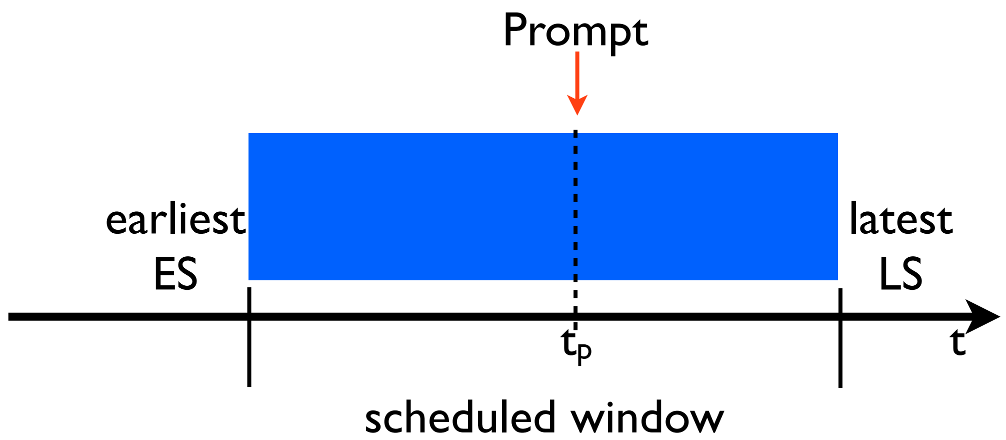
Learn Timing of Prompt



- Prompt too early - user being over reliant
- Prompt too late - jeopardize system performance
- User behaviors vary a lot
- How to adapt the timing to different needs?

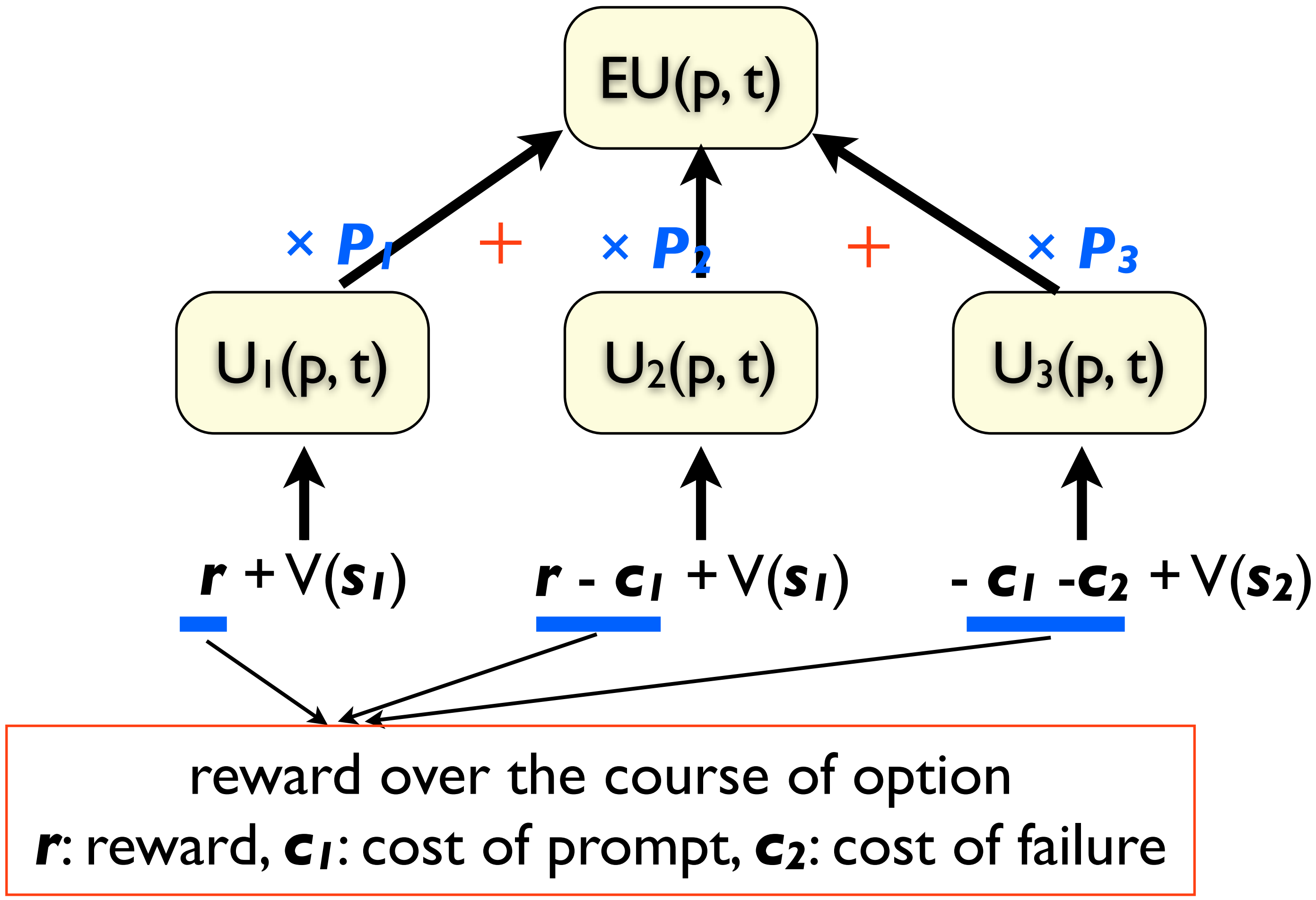
Approach

- timing as one of the features of state
  - RL (Rudary et al. 2004) -- exponentially increase state space
- timing as one of the parameters of prompting strategy of an option
  - learn a set of different options with fixed timings -- exponentially increase state-option pair
  - adaptive prompting strategy -- avoid long period policy exploration
    - user modeling: *initiative* and *responsiveness*
    - decision-theoretic analysis based on the expected utility

Adaptive Option

- ✦ Adaptive option adapts its strategy to different user models.

Example: expected utility of generating a prompt at time ***t***, ***EU(p, t)***



States: s_1 (action is ***started***), s_2 (action is ***failed***)

Considering three outcomes:

1. user initiates the action
2. user starts the action after a prompt
3. user failed to start the action

Objective: find the t that maximizes EU

P_1, P_2 and P_3 are computed based on user model

- F_1 probability of initiating an action
- F_2 probability of responding to a prompt
- Reliability model (Weibull) and censored data analysis

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Experiment I: Simulation

✦ **Method**: compare the learning result of adaptive options with that of different *fixed* options

Consider the ***start*** options of four different prompt strategies

I. no prompt

II. earliest prompt (t_p = ***ES***)

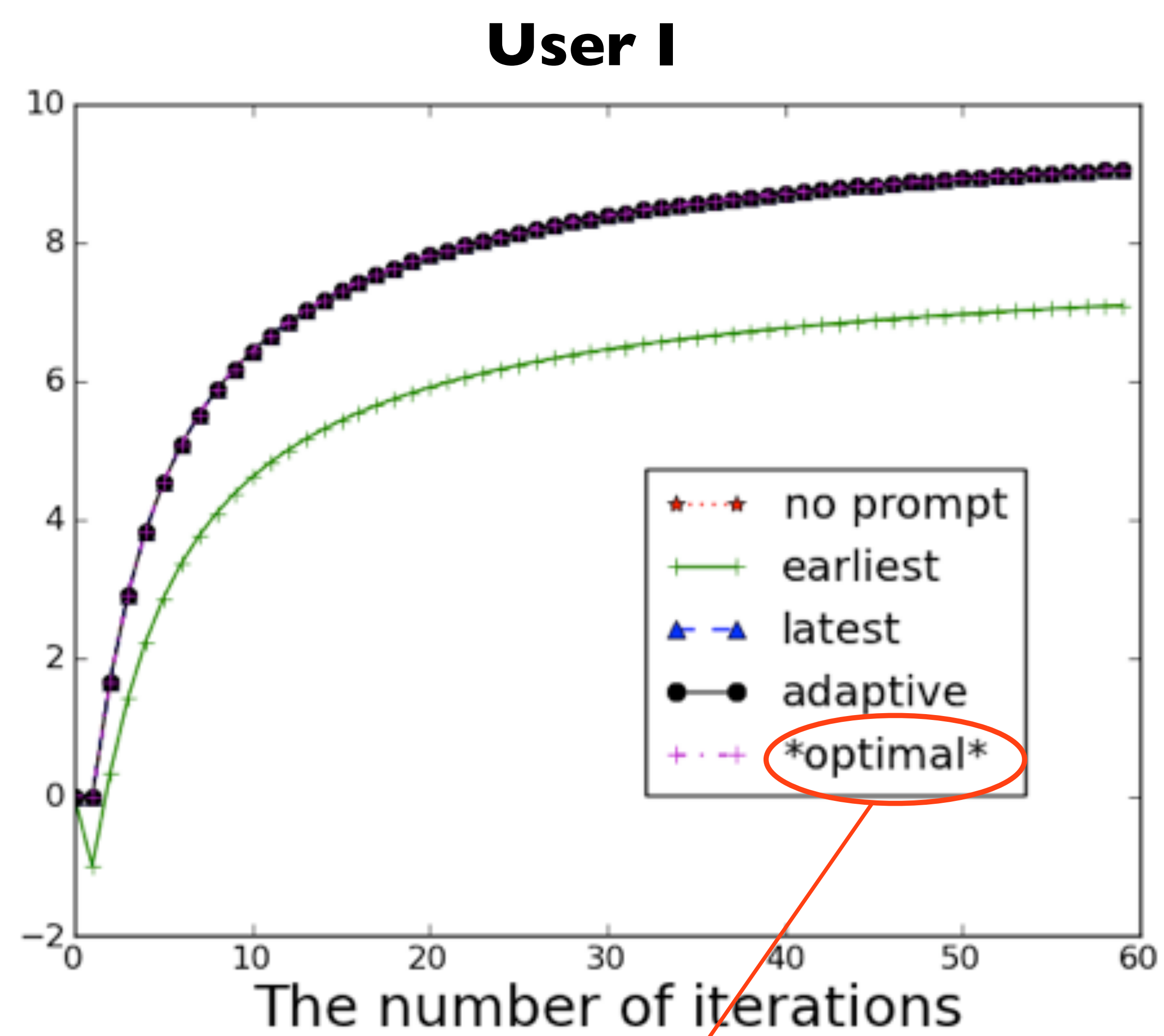
III. latest prompt (t_p = ***LS*** - 5)

IV. adaptive prompt

Simulated Users

- ***Type I***: high initiative, high responsiveness
- ***Type II***: low initiative, high responsiveness
- ***Type III***: low initiative, low responsiveness

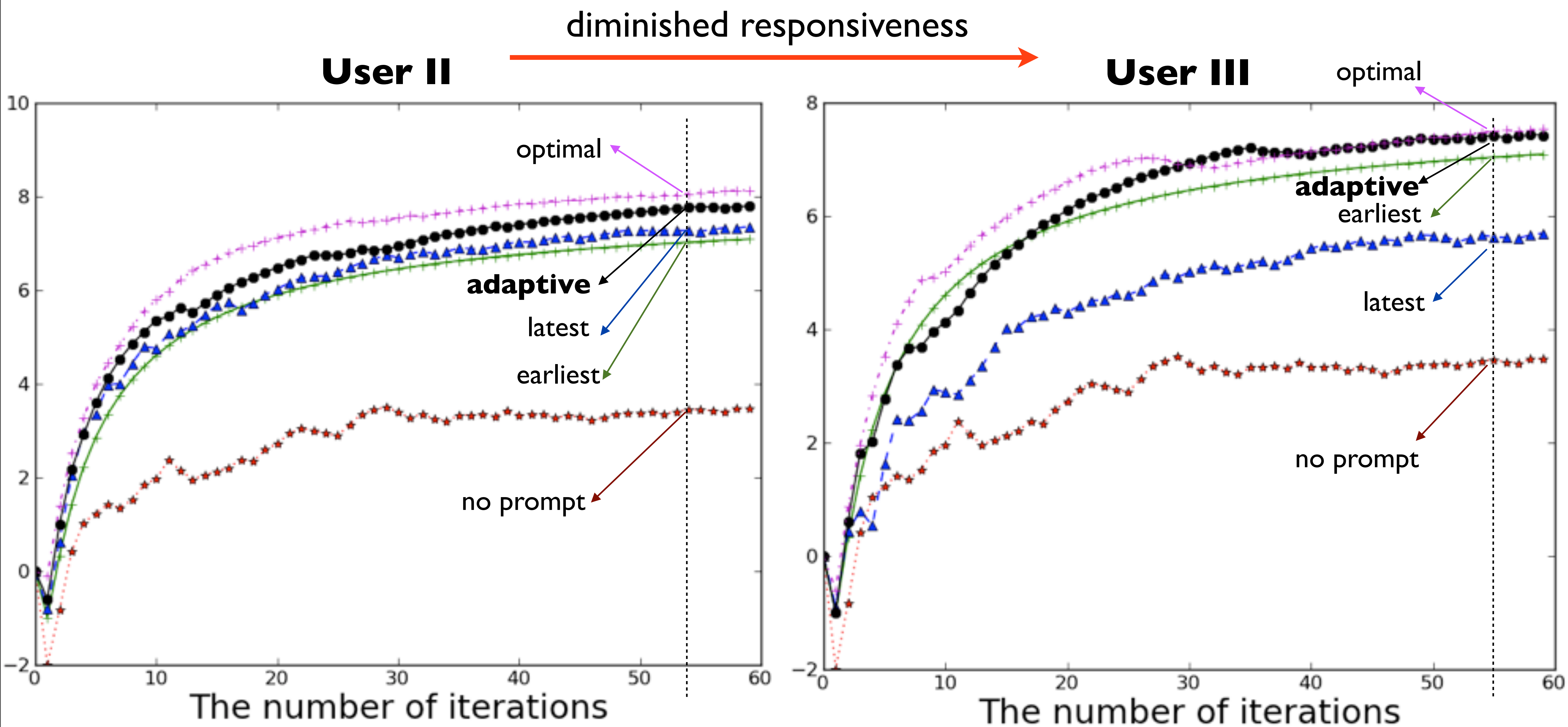
✦ *How well did the adaptive strategy adapt to different users?*



determine t_p using true values of user variables

Simulation Result

- *How well did the adaptive strategy adapt to different users?*



Simulation Result

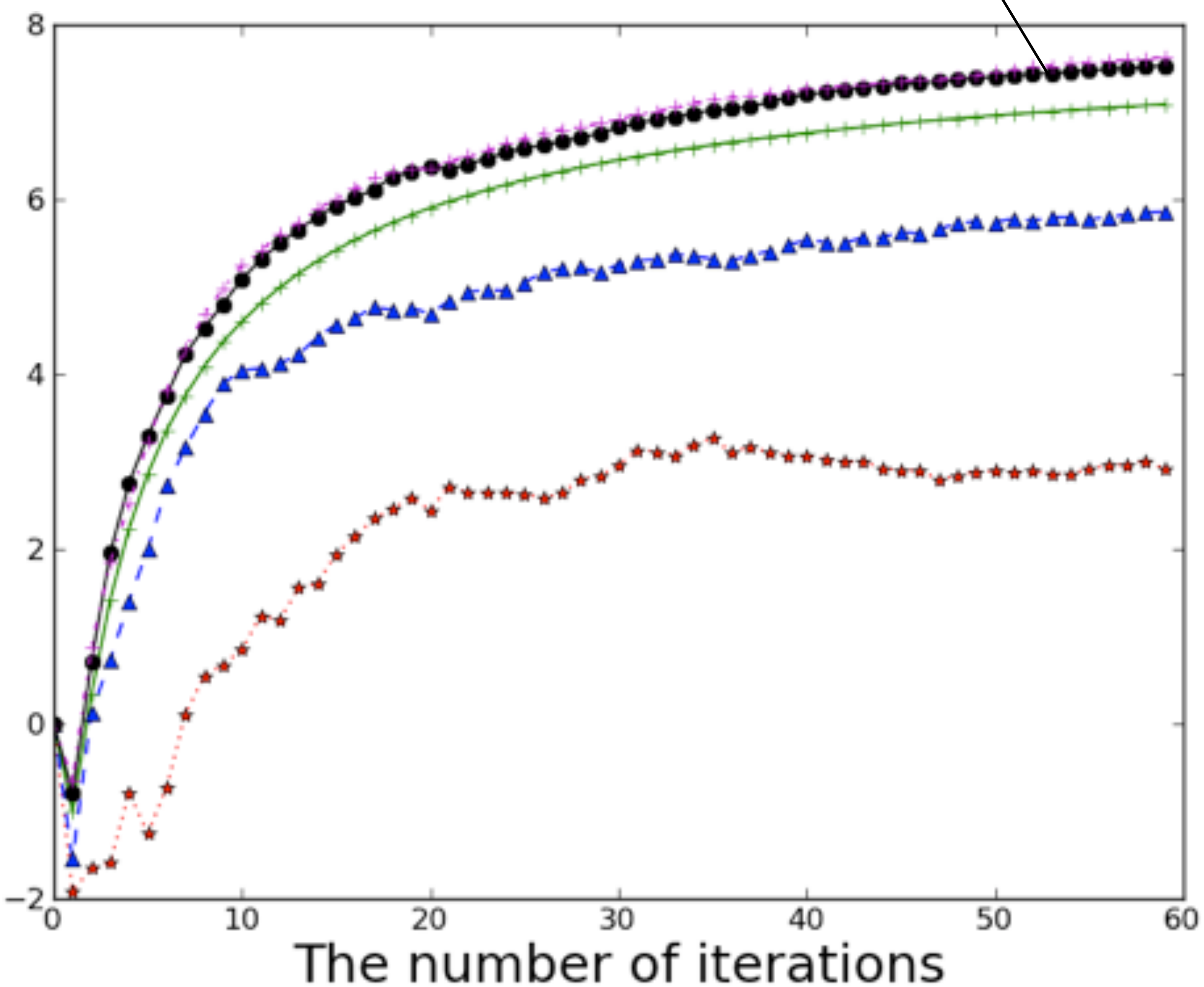
✦ ***How well did the adaptive strategy adapt to user preferences?***

Scheduled (preferred) execution time t_s;
Penalized when later than t_s

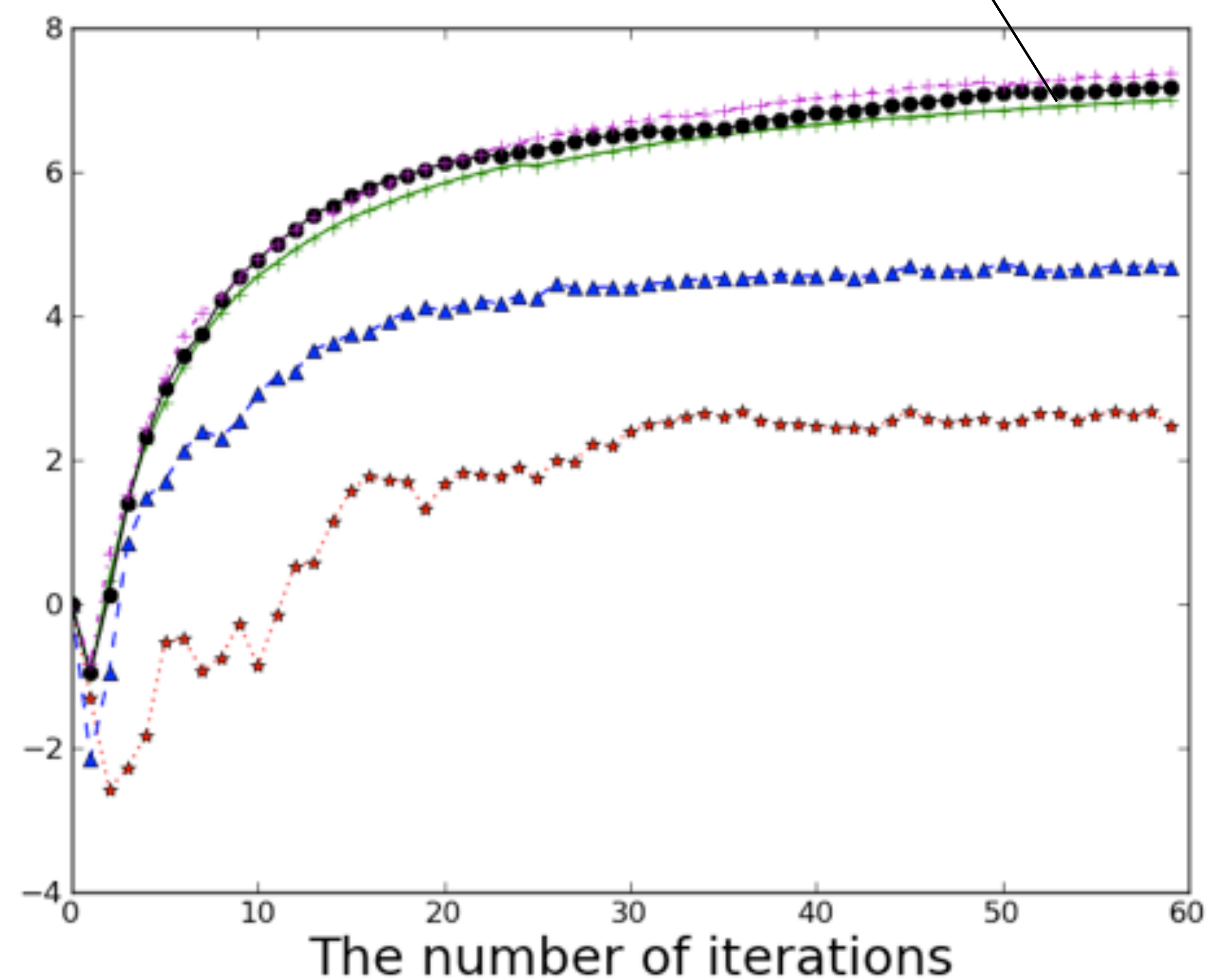
$$EU_d(p, t) = EU(p, t) - EDC(p, t)$$

Expected Delay Cost

User II

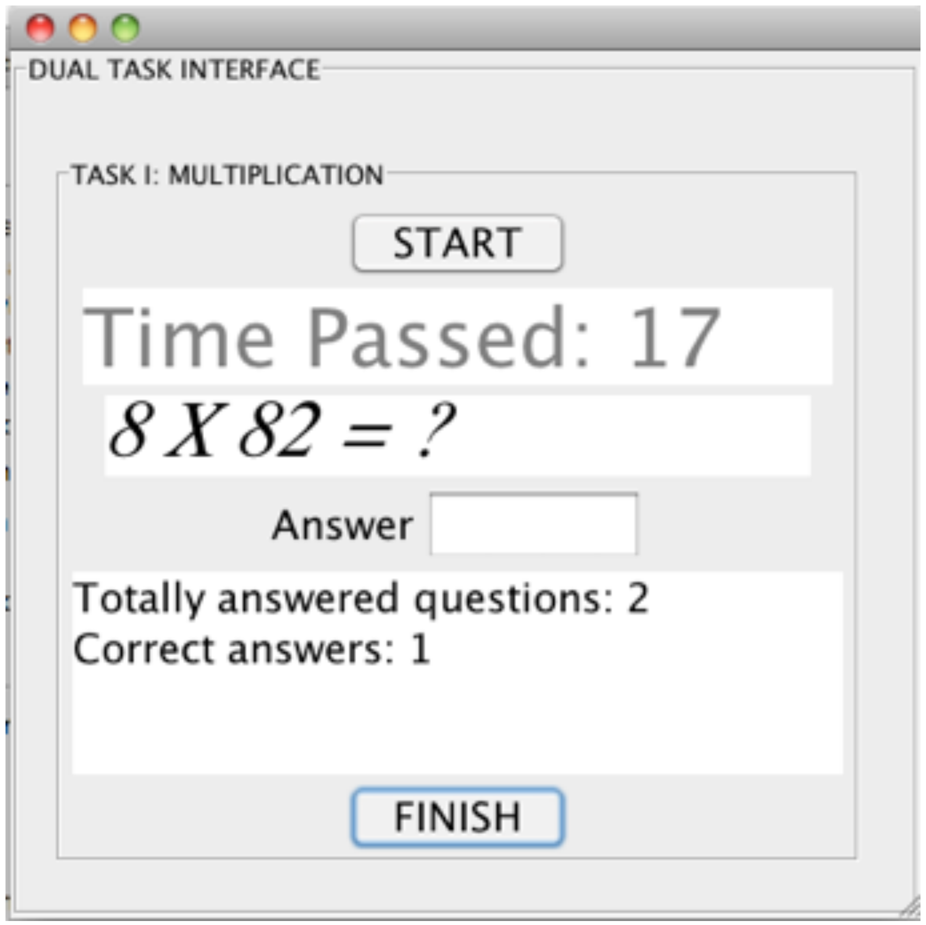


User III



Experiment II: Human Subjects

- **Experiment Design**
- Subjects: 9 (6 male, 3 female), ordinary unimpaired
- Primary Task : sequence of randomly ordered steps
- Dual Task : simulate cognitive impairment
  - mental arithmetic, i.e., multiplication



Example Task Script

1. **pour** sugar and water into blue cup
2. pour pepper into yellow cup
3. pour water into green cup
4. **stir** yellow cup
5. pour salt into red cup
6. **mix** yellow into blue cup

- **Procedure (individual session)**
  - Memory practice
    - listen to the script once
    - go through all steps once
  - Data collection
    - four runs (same script)

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Experimental Setup

- **Prompts**

  remind of the next step
  (text-to-speech API)

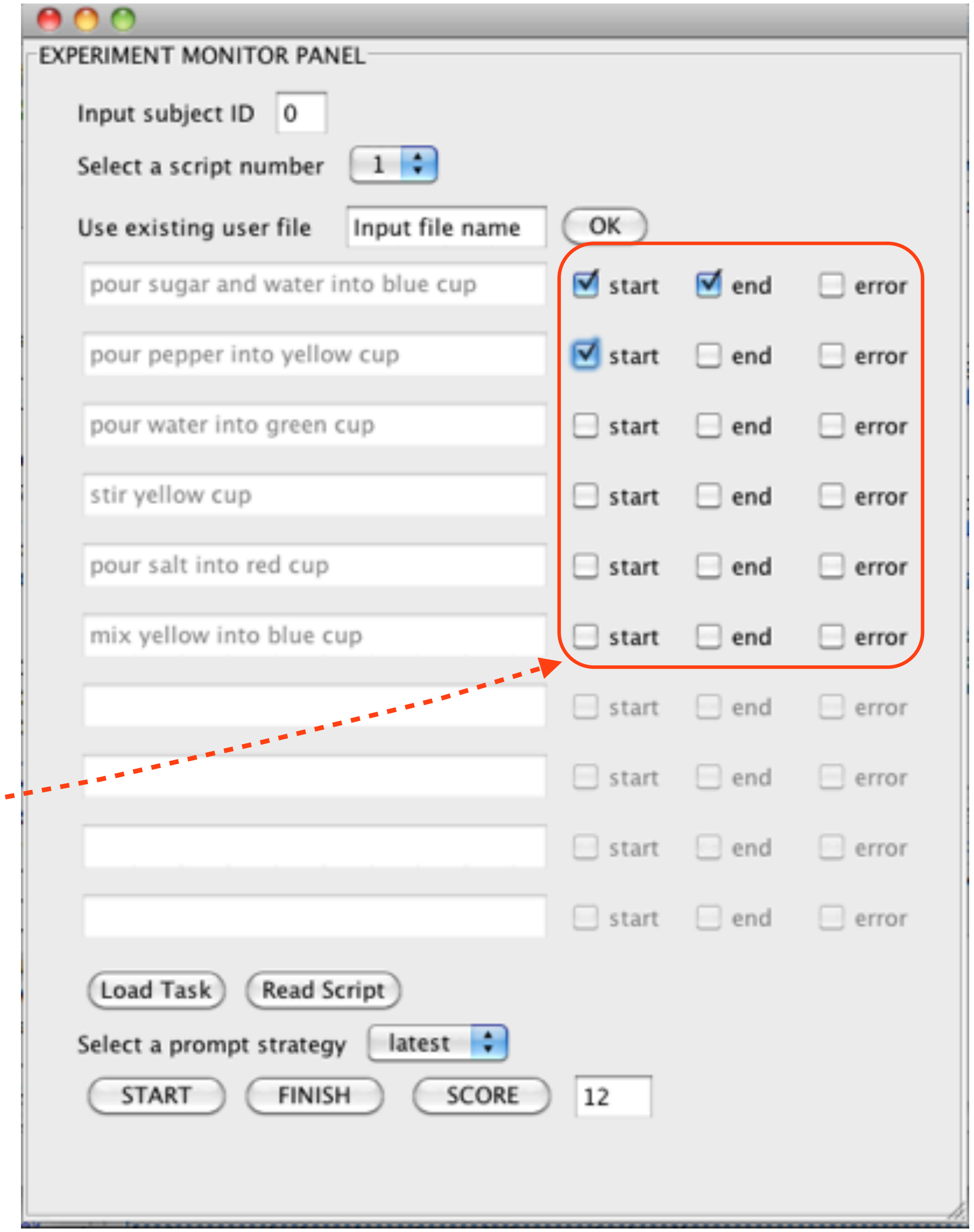
- **Sessions**

  (Four different task scripts)

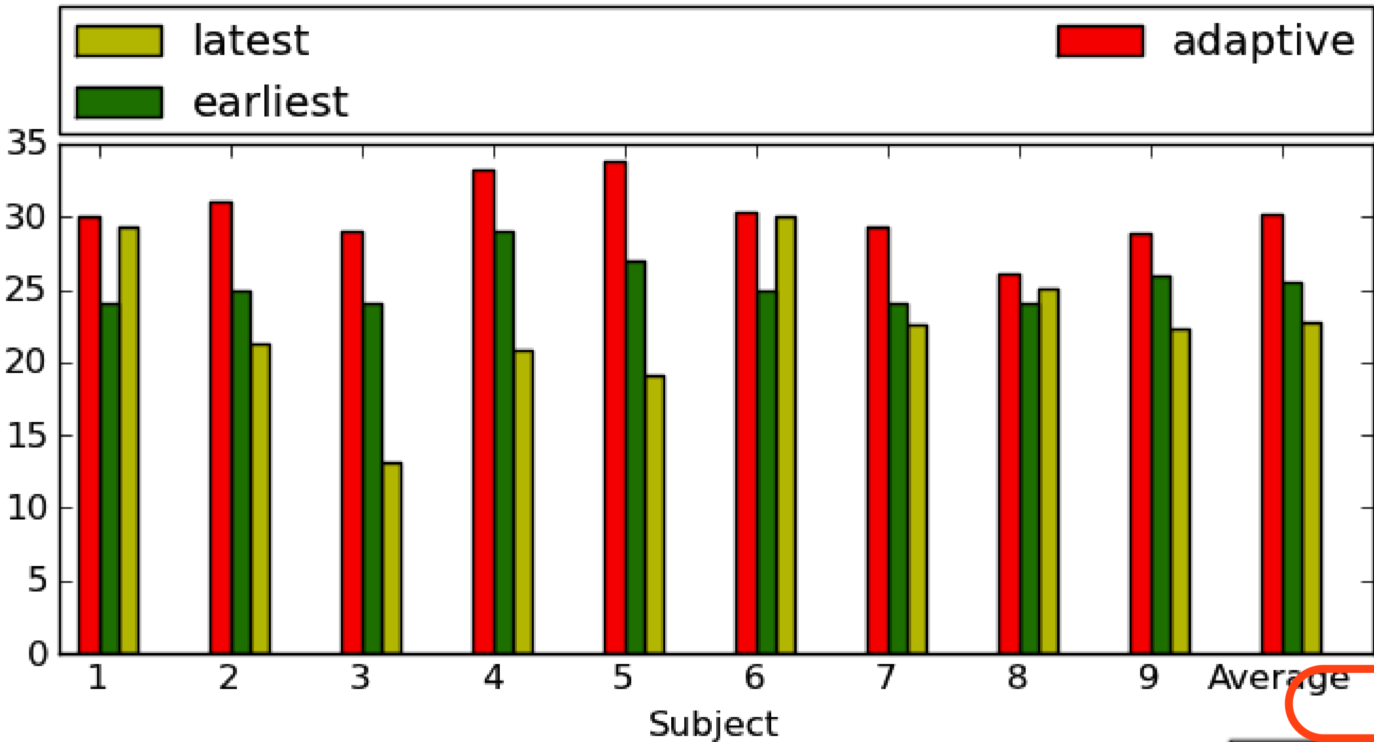
  I. earliest prompt
  II. latest prompt
  III. adaptive prompt
  IV. adaptive prompt (single task)

- **Experimenter**

  I. select a task script
  II. select a prompting strategy
  III. carefully mark the start and end of each step, record error



Experiment Results



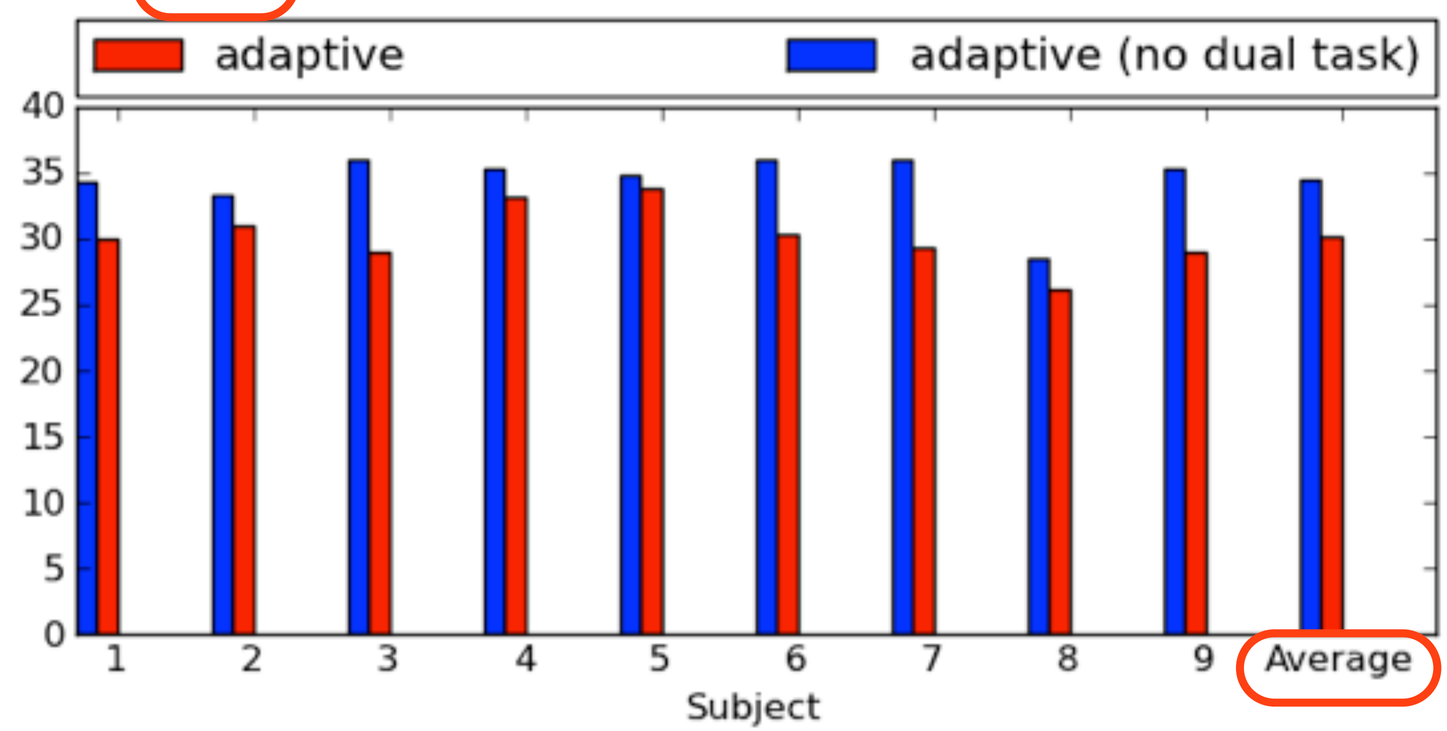
Significantly better

✦ *How did the adaptive prompting perform compared with other strategies?*

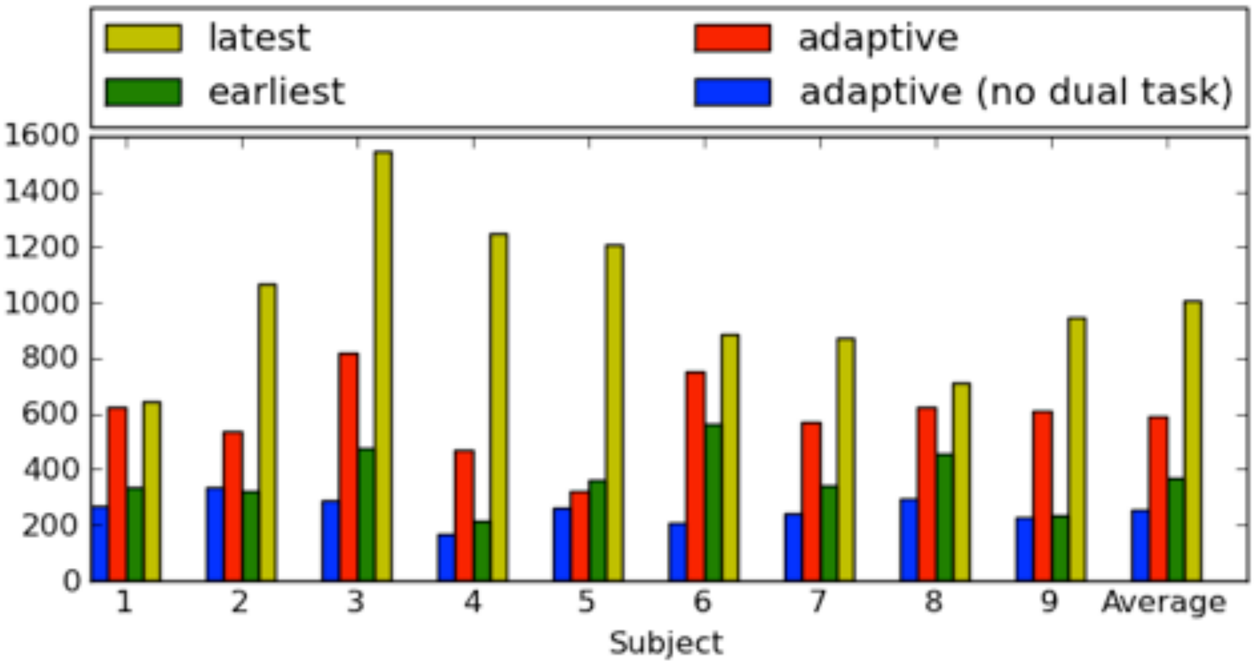
	p	result	confidence interval
Adaptive - Latest: $H_0 : A - L < 0$, vs. $H_1 : A - L > 0$			
Means Diff	$\ll 0.05$	reject H_0	[7.4-2.4, 7.4+2.4]
Paired Means Diff	$0.003 < 0.05$	reject H_0	[7.6-3.7, 7.6+3.7]
Adaptive - Earliest: $H_0 : A - E < 0$, vs. $H_1 : A - E > 0$			
Means Diff	$\ll 0.05$	reject H_0	[4.7-1.2, 4.7+1.2]
Paired Means Diff	$\ll 0.05$	reject H_0	[4.9-0.9, 4.9+0.9]

Significance Test

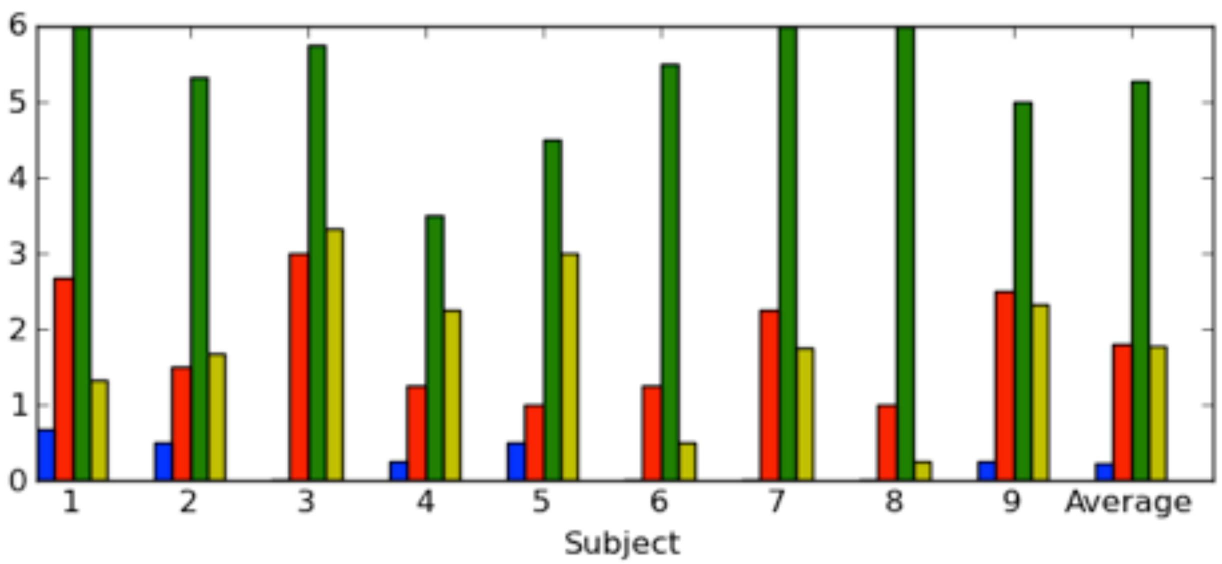
✦ *Did the multitasking successfully induce cognitive overload?* **Yes**



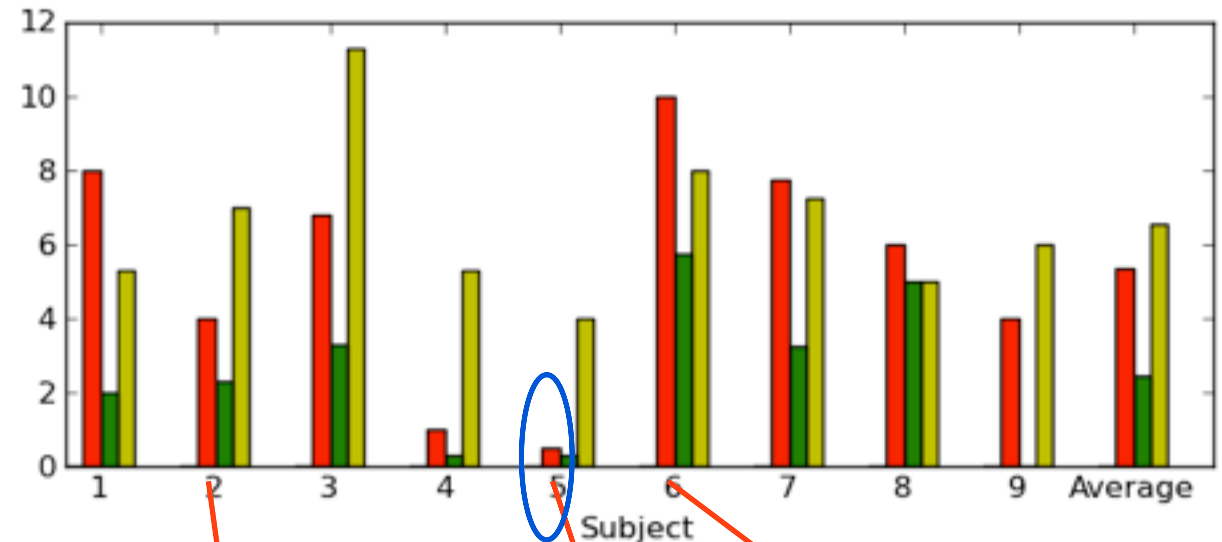
Experiment Results



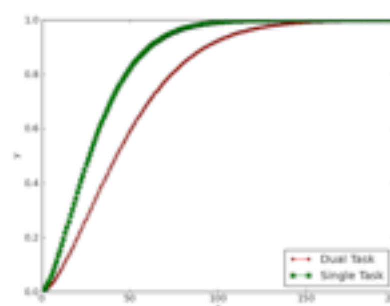
Averaged time per trial



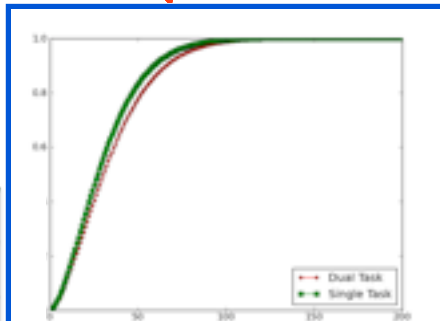
Averaged number of prompts per trial



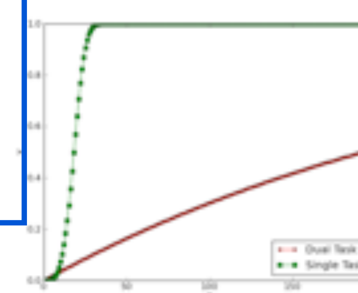
Averaged number of arithmetic questions



Subject 2



Subject 5



Subject 6

The learned *initiative* function

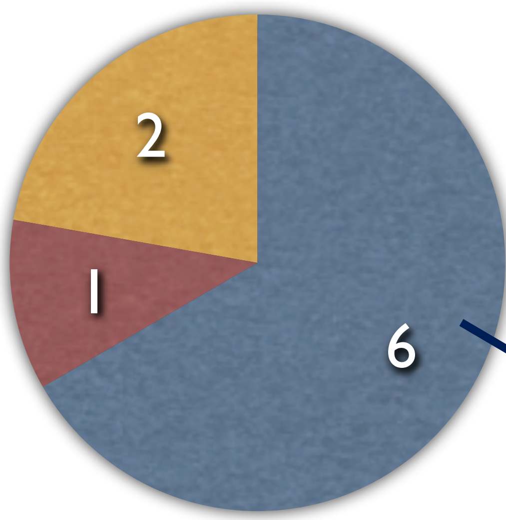
Was the system able to correctly learn user behavior? **Yes**

Experiment Results

✦ ***Did the participants find the prompts useful?***

dislike   like   indifferent   particularly like

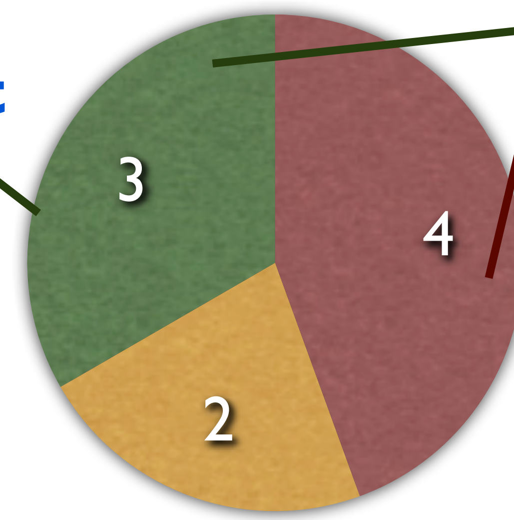
Immediate prompt



All agree "learning is the worst"

"annoying"
"overwhelmed"
"no chance using the memory"
"no time recalling the order of steps"

Later prompt



Adaptive works best

Get some time to think, but don't want to want too long

Illustration of Participants' Preferences

Summary

Simulation

- Adaptive prompting adapts to different user needs
- Adaptive prompting scores best
- User modeling is done correctly

Human Subjects

- Adaptive prompting scores best across all subjects
- User modeling is done correctly
- Overall, participants responded positively to the use of prompts
  - Immediate prompts compromise learning, and could be annoying
    - People are easily driven by prompts
  - A relatively "later" prompt is most desirable : **key to improve usability**

Partial Observability

: Dual control approach and unified model

Partially Observable Markov Decision Process

System state can not always be determined ➡ ***Partial Observability***

- ✦ Action outcomes are not fully observable
- ✦ Add a set of observations ***O*** to the ***MDP*** model
- ✦ Add an observation distribution ***O(s, o)*** to the model
- ✦ Add an initial state distribution ***I***

Key notion: belief state ***b***, a distribution over all possible system states

"where I think I am"

Belief update: $b'(s') = \alpha O(s', o) \sum_s P(s, a, s') b(s)$

normalizing constant

⇒ optimal action depends on b, $a = \pi^*(b)$

Solving POMDP

- Equivalent Belief-State MDP
  - Each MDP state is continuous belief state b
  - Hugely intractable to solve optimally!
  - Approximately solved offline ➡ computationally expensive
  - Learning is difficult ➡ require extensive training instances
- Heuristic (Greedy) Approaches
  - Solve underlying MDP
    - $\pi_{MDP}: S \rightarrow A,\ Q_{MDP}$
  - Choose action based on current belief state
    - "most likely" $\pi_{MDP}(\operatorname{argmax}_s b(s))$
    - "Q-MDP" $\operatorname{argmax}_a(\Sigma_{s \in S}\ b(s)\ Q_{MDP}(s, a))$
  - Act optimally as if the world were to become observable after the next action

Dual-Mode Control

- Extension to greedy approaches to allow information seeking actions
  - Compute entropy ***H(b)*** of belief state
  - If entropy is below a threshold, use a heuristic for choosing action
  - If entropy is above a threshold, choose the action that reduces the uncertainty most
    - In our case, choose to inquiry the user
    - User reply is used to help reset the internal state model

- Selective-inquiry based dual mode control
  - Ask only when necessary
    - Different states lead to different actions (at least one is "prompt")
    - The value of inquiry action is highest among all possible actions
  - Adaptive option supports selective-inquiry
    - Time of prompt action is optimal ➡ critical decision point

Selective-Inquiry based Dual Control Algorithm

- Run on top of the completely observable control algorithm (***Controller-CO***)
- Recall ***Controller-CO (S)*** returns action ***a***

Input
b, the belief state of internal state model

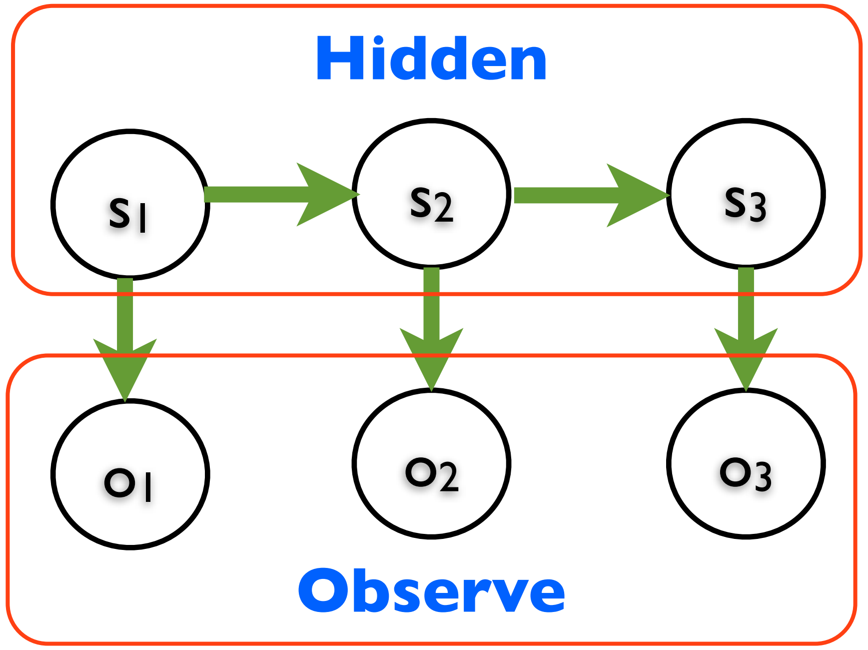
Return
a′: the system action

At each time step, the controller

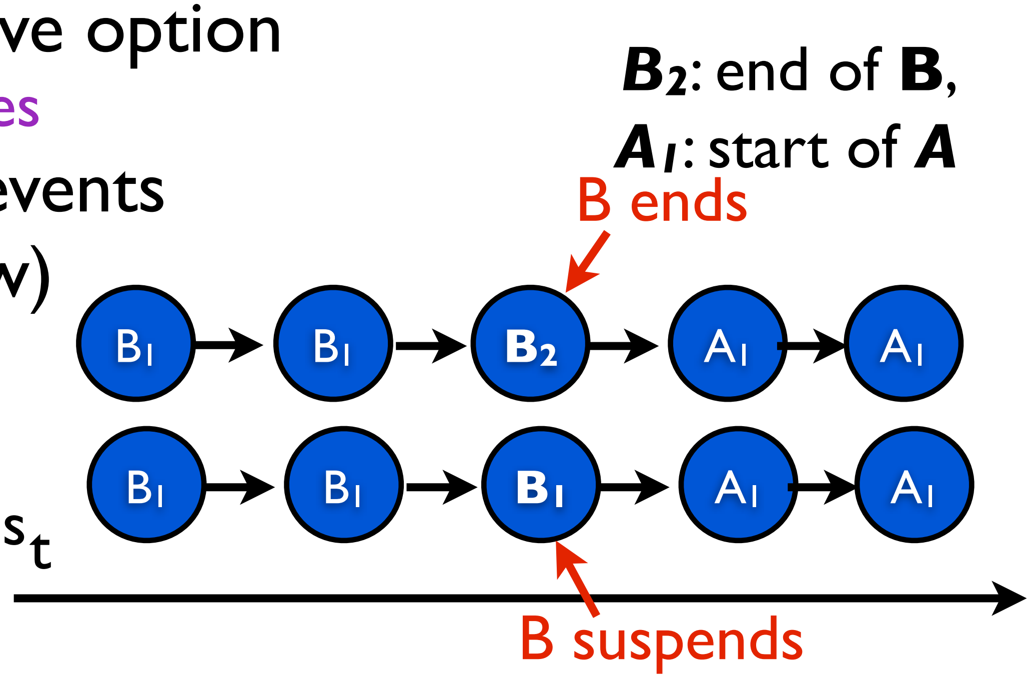
1. If get confirmed reply after an inquiry, reset internal state model and set ***H(b)*** to 0.
2. If ***H(b)*** is less than threshold, select $s \leftarrow \mathrm{argmax}_s b(s)$, update system state vector ***S***, and return $a' \leftarrow$ ***Controller-CO(S).***
3. Otherwise, iterate through n most likely states S_n, and for each $s \in S_n$
   - construct the pseudo state vector ***S′*** based on ***s***
   - add $action \leftarrow$ ***Controller-CO(S′)*** into the set of permissible actions ***A***
4. If A contains different actions, return $a' \leftarrow$ ***inquiry***, otherwise return $a' \leftarrow$ ***any*** $a \in A$.

Robust State Estimation

- Key to dual control : estimate the belief state of the world, ***b***
- State model to recognize the user activity
  - Hidden Markov model (***HMM***)
  - Filtering
    - Compute the belief state of current state given all evidence to date
    - Estimate the current activity given a sequence of sensor readings, e.g., cup, cup, cup, none, spoon, ...,



- Key to selective-inquiry : implementation of adaptive option
  - know when an activity starts, ends, suspends, and resumes
- Extend the model to recover the exact timing of events
  - The current state s_t is unambiguous ($H(b)$ is low)
  - Viterbi (Most Likely State Sequence)
    - Retrieve the state sequence that ends at s_t
    - Determine the time point when activity status changes



Example state sequence

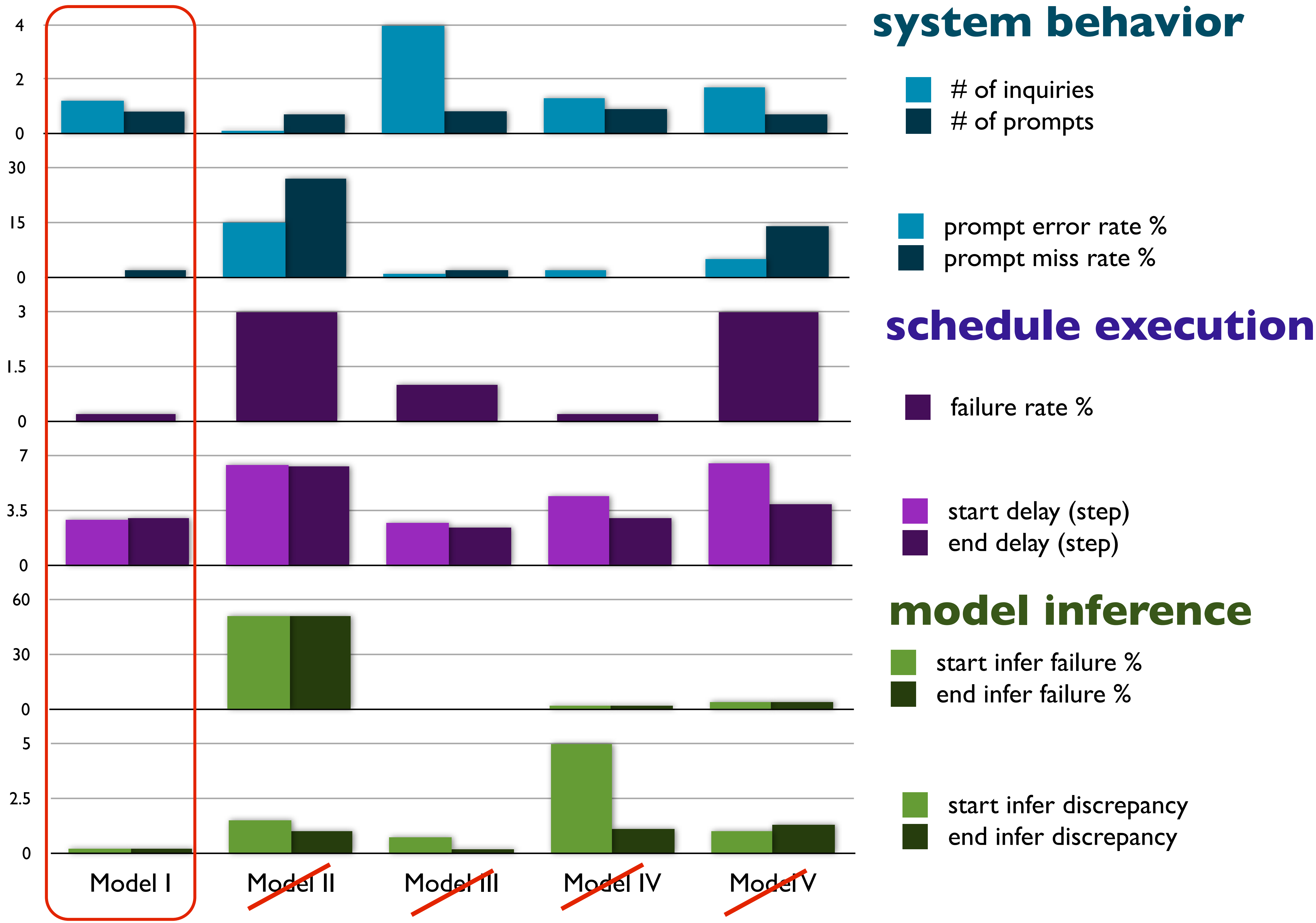
Evaluation

- Proposed unified model (**I**)
  - ✓ Selective-inquiry based dual control with adaptive option and robust state estimation
- Experiment Method
  - Simulate partially observable environment (uncertainty 61%)
- Compare with alternative models
  - **II** never inquiry
  - **III** always inquiry
  - **IV** only estimate the current state
  - **V** run with a set of fixed options

Breakfast : {cupboard, cup, spoon, cereal}
Medicine : {cupboard, cup, spoon, medicine}

- Evaluation Metrics
  - System action : minimize interruptions
  - Execution of schedule : improve adherence
  - Inference : accurately log events

Result



The smaller number is better!

Demonstrative Experiments

- Test the system's performance in identifying states, generating prompts, asking questions and handling interruptions

- Two volunteer actors walk through three scenarios.
  - Breakfast is sequenced by taking medicine
  - Breakfast is interleaved with taking medicine
  - Breakfast is interleaved with watching TV

task	start window	scheduled start	scheduled end
BF	[0, 30]	15	115
TM	[120, 150]	135	175

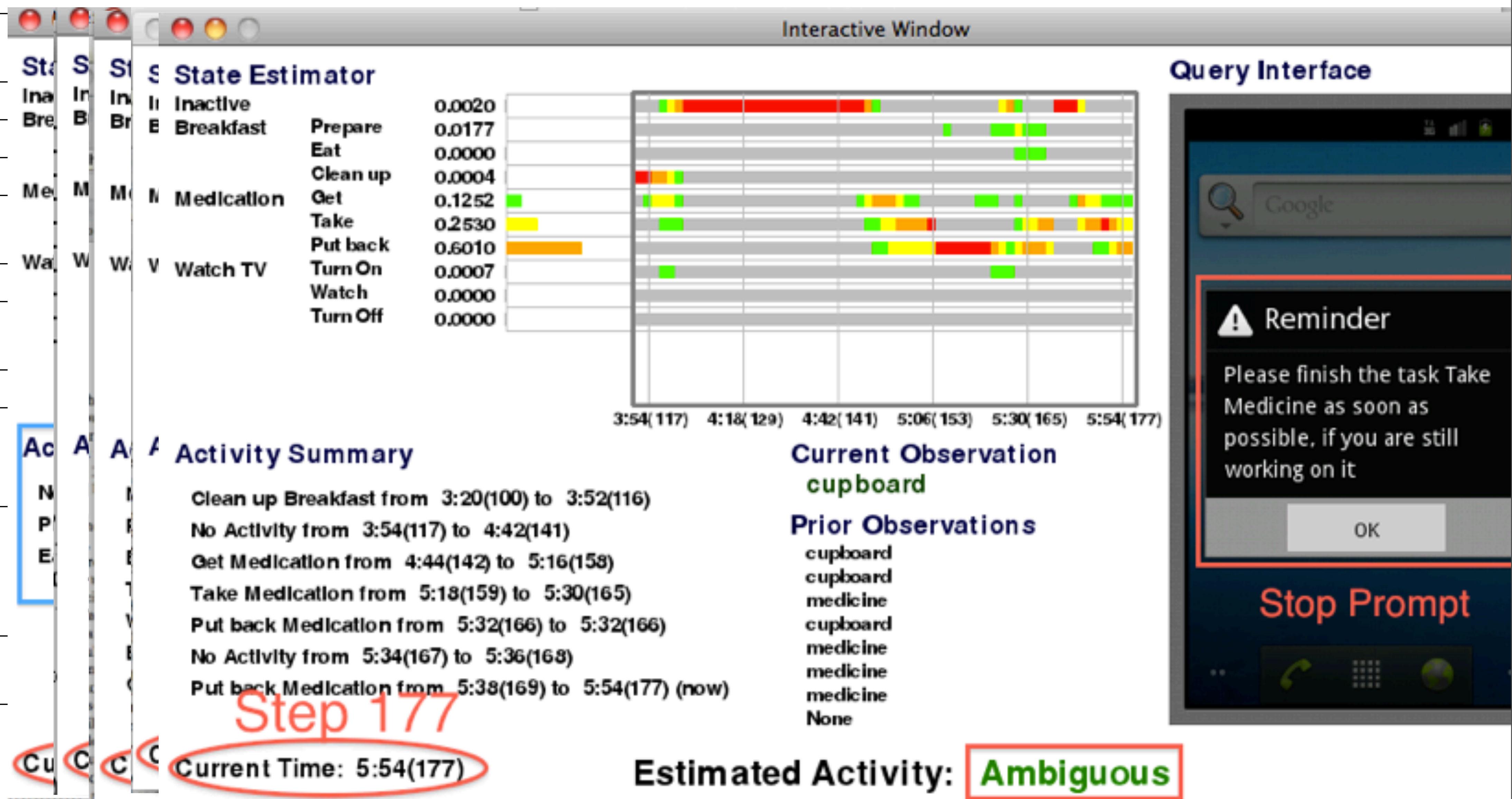
BF : BF_B (preparing), BF_M (eating), BF_E (cleaning up)
TM : TM_B (getting), TM_M (taking medicine), TM_E (putting away)

Example

- Scenario III, Breakfast ⇨ watch TV ⇨ Breakfast ⇨ Take medicine

Step	Real Situation
10	Start preparing BF;
57	Suspend eating BF;
59	Start watching TV
73	Watching TV; BF: suspended, TM: not ready;
80	Resume eating BF;
116	BF: resumed, TM: not ready
137	BF: completed, TM: ready
142	Start getting medicine; BF: completed, TM: started
162	BF: completed, TM:started
176	(same as above)
184	Finish putting away medicine; BF: completed, TM: completed

Example Transcript



Summary

Simulation

- Selective inquiry based dual control (Unified model) shows consistently sound performance across all measures

Human Subjects

- System performs generally well in recognizing states, generating proper prompts, handling interruptions, and dealing with ambiguity
  - 20 prompts from a total of 6 scenarios (one error)
  - Avoid unnecessary prompts by being aware of contexts
  - Selective-inquiry limited the number of questions
    - 7 inquires out of 172 ambiguous steps
  - Dual control works well in presence of partial observability (average uncertainty rate 27%)

Focus Group Study: Traumatic Brain Injury

Study Methods

Sample

Group	TBI	Caregiver
I	4	2
II	3	2

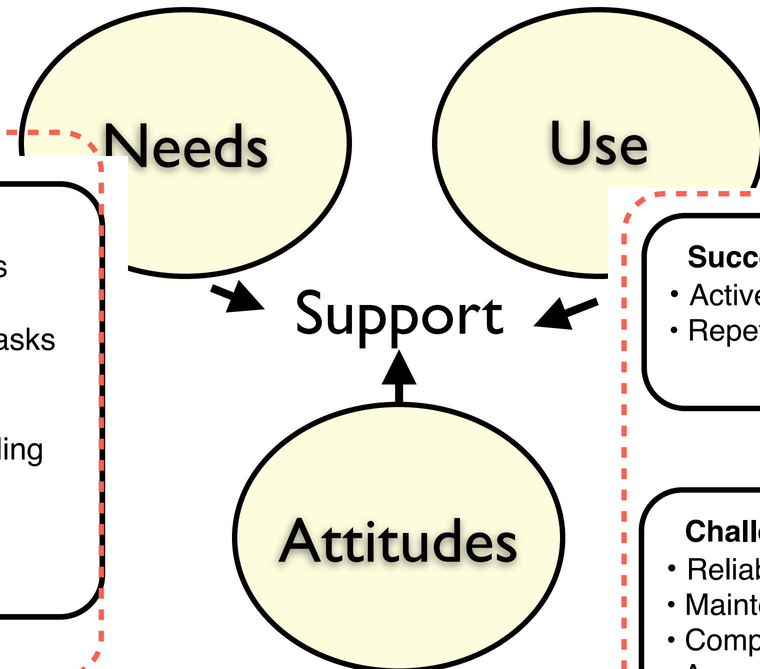
Analysis

- Standard qualitative methods
  - identify categories
  - identify themes across categories

Data Collection

1. What types of support, if any, do you need to perform everyday tasks (including at home and work)?
2. What is it about a task you need help with?
3. How do you accomplish these tasks now? What works well, what doesnt?
4. What additional types of support or accommodations would be helpful, if available?
5. Current use, comfort and familiarity with technology.
6. What technology was tried and failed and why?
7. What concerns do you have about the reliability of technology? What if software or services stop working?
8. Where do you fall on the spectrum of wanting technology for independence versus wanting assistance from a caregiver?

Results



Psychosocial Support Needs
- Information overload
- Social miscues
- Distractibility
- Environmental stimuli
- Isolation

Memory Support Needs
- Early reminders
- Immediate prompts

Task Support Needs
- Adhering to schedules
- Initiating activities
- Performing complex tasks
- Social interactions
- Learning new tasks
- Navigation & path finding
- Attention Control

Successful Strategies
- Active engagement
- Repetition

Challenges
- Reliability of technology
- Maintenance of technology
- Complexity of technology
- Accessibility

Technology as Support
- Cell phones
- Computers
- Cameras
- Textual reminder
- Assistive Technology
- Video games

People as Support
- Emotional support
- Memory support
- Organizational & scheduling support

Users and Caregivers
- Users want technology for independence but do not want to do away with caregiver support
- Caregivers report that human support is integral; need for emotional support; people promote personal relationship

Interest in New Technology

Positive as long as:
- it is easy to use
- helps to connect user and caregiver
- includes training in use

Needs of Support

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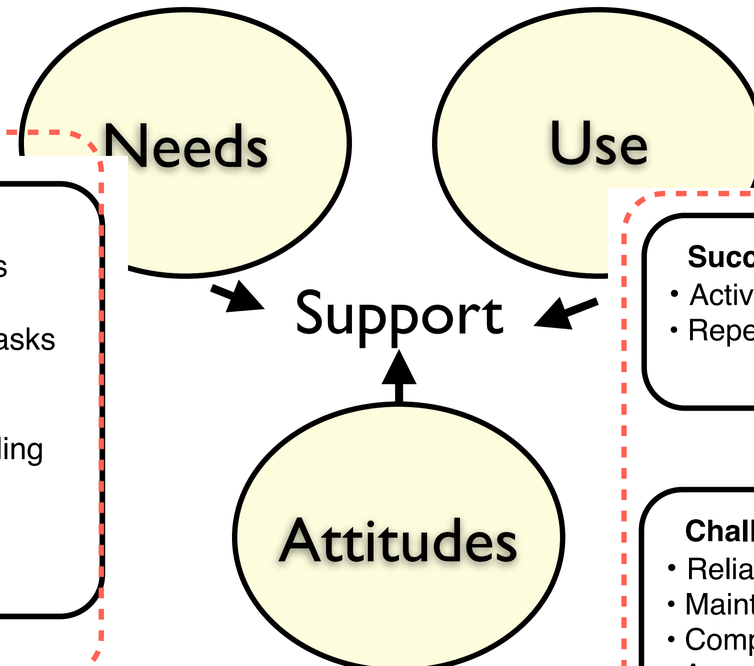

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Use of Support

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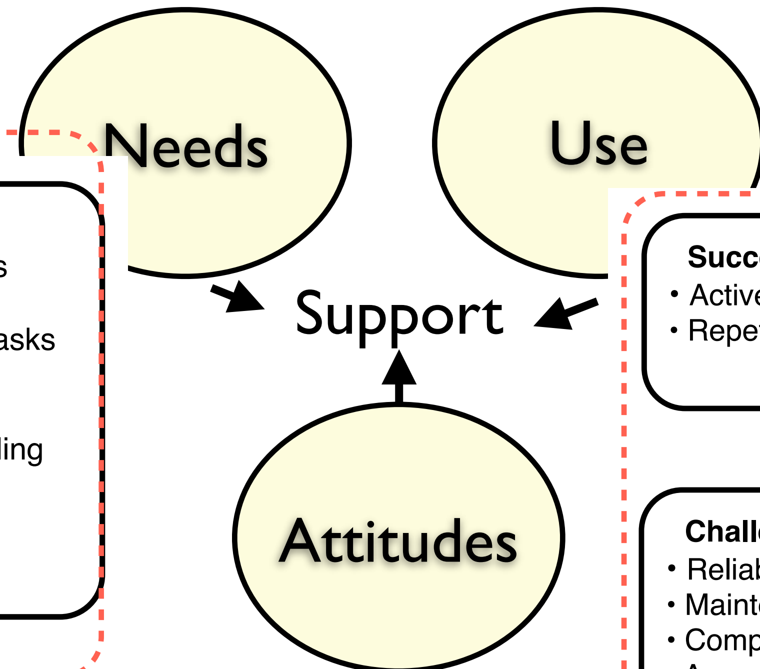

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Attitudes Towards Support

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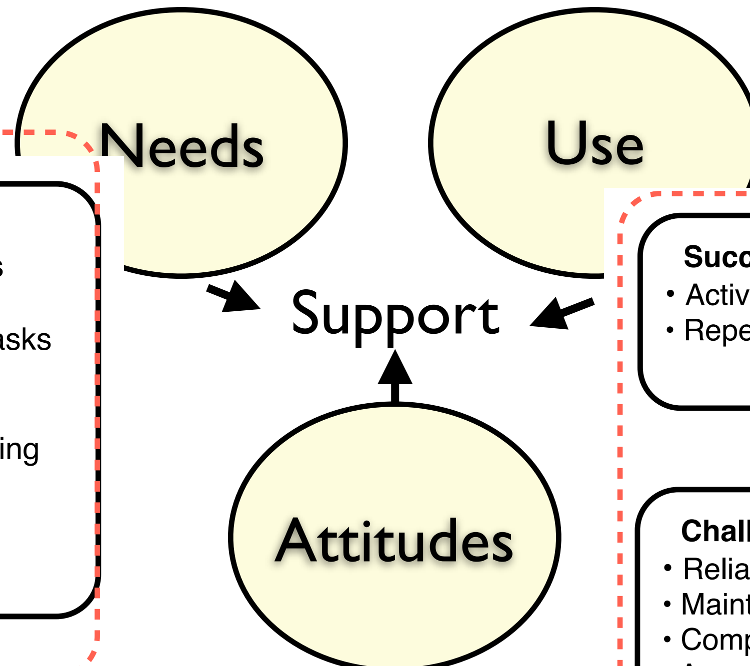

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Implications for Technology Design

- **Verbal prompts are more effective than written ones.**
  - Textual reminder fails
  - Difficulty in initiation
  - ***Immediate*** prompt helps with short-term memory

*"Because, when I give him **cues**, everybody says he does so well with **cues**. He's hearing my voice. Not only that I'm his wife, and I'm pretty strong. But I think the cues are really important. The cues of **"You need to do this.'"***

*"I think people with brain injuries need **verbal** commands, **verbal** memory, **verbal** whatever it is. You speak into it." -- caregiver*

*I "I said don't put the seats down in the car. He's going to pack the car. ......But the first thing he did is put the seats down....... So it's those kinds of things that the **short term memory** is oh, she said not to put the seats down. It's something that could come back at you **right away** and say okay, I was supposed to this. Now don't put the seats down......**Talks back at you right away,** that it could be you know that's more **interactive**." -- caregiver.*

- **Earlier**, **repeated** prompting helps to avoid surprises and allow for preparation time.

*I don't like to find out today that I have to go to a doctor today. It has to be **two or three days** so that I can **prepare** myself, ... Now tomorrow I have to go to the doctor, but to wake up and then have my phone say 'doctor at 12:00,' I'm **panicked**. I'm really **disturbed** with that. So if everything comes to me slowly, then I'm **prepared** for it"*

Implications for Technology Design

- Technology is not only designed for patients.

- People are an important part of the broader support network.
  - Emotion feedback
  - Promote personal relations

" a thing on my phone because I'm always worried (Ben) is going to get lost and I track his phone. So I know where he is all the time. And it's a safety it makes if me ***feel better to know that he's okay."*** -- *caregiver*

"I think that some way to ***connect you with your partner****, if technology-wise would be great. Because then I have a calendar -- like I have a lot of things that go on in Seattle, and we live in Maple Valley, and so he isn't always aware of where I'm going to be going." -- caregiver*

"I Because I think a telephone can't go and say, yay, you did it! You need that ***positive input*** *I think every once in a while. And phones can't* ***give a hug****, so you got to have that. You got to have it." -- caregiver.*

"But interaction with -- having another individual is more in promotion of developing --than using a piece of technology. That's different. The technology is in promotion of relying upon it, where the person, it ends up being in ***promotion of****, you know, that's -- developing further or, you know --* ***Personal relations****." -- caregiver.*

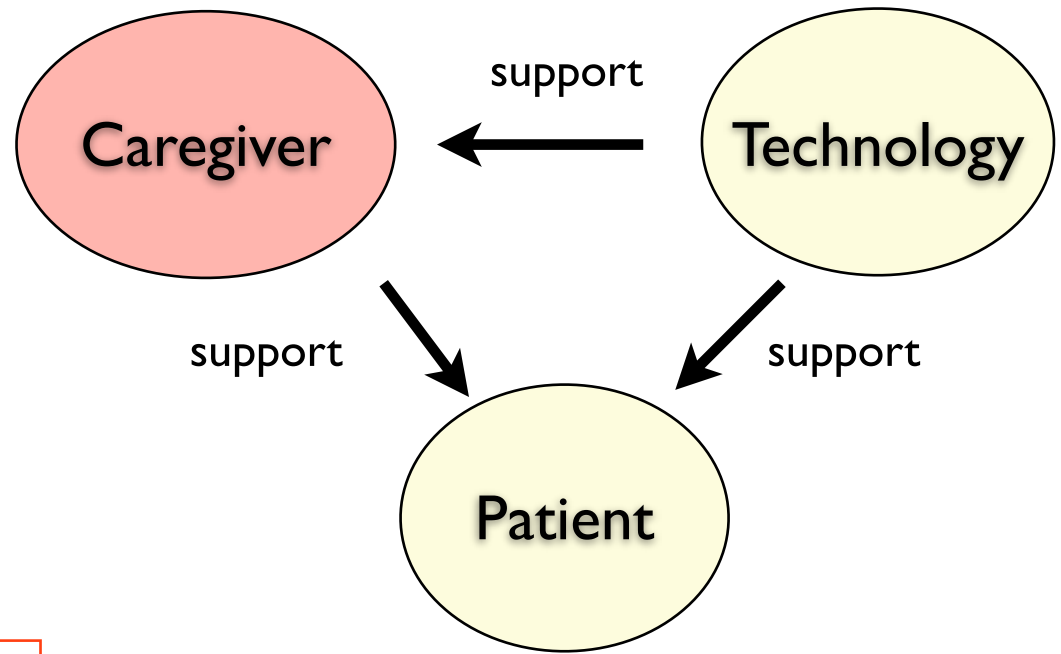
But isolate, you ***isolate*** *or you spend too much time farming on Facebook or you know, these virtual I caught myself ...... It's usually but* ***it's very isolating****." -- patient*

Conclusion

"Sometimes people are there and sometimes they're not. So if I was able to have something with me all the time, I would -- it would be more reliable, and then I would be more independent..." -- patient

- Technology
  - increase independence
  - Availability of training
  - Design challenge
- Human
  - **Essential role**
  - Not always available
  - Expensive, time intense

diminished quality of life, increased level of anxiety, poor self-esteem, and social isolation (Burns and Rabins, 2000)



Broader Support Network

Technology should be viewed as an opportunity to increase independence while providing a way to communicate support needs on an as-needed basis

Conclusions

- A unified model that integrates the sensing, planning, prompting and user
- Scale to large of set of tasks that are divided into subtasks
- Explored the following issues :
  - Hierarchical control
    - Set of option-based MDPs, on-line learning and planning
  - Adaptive prompting
    - Adaptive option implements decision-theoretic analysis
  - Partial Observability
    - Selective-inquiry based dual control algorithm
    - Robust state estimation
    - Unified model
- Focus group study
  - broader support network that includes people as essential element

- **Future work**
  - **Test wit clinical populations**

Thanks

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UNIVERSITY *of* ROCHESTER

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