https://arxiv.org/abs/1612.00653

INVERSE MODELING FOR BEHAVIORAL SCIENCES AND HCI

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userinterfaces.aalto.fi

A GRAND CHALLENGE

- It has become **easy to collect** data about users
- But: **hard to explain and predict** what, how, and why they are doing

advanced inference methods

TECHNICALLY…

- **How to estimate (theoretically plausible) model parameters** without intervention and from limited, noisy, naturalistic observational data?

- **Complicated by the strategic flexibility and idiosyncratic properties** of the human.

- **Any behavior can be produced by numerous architectures**

- **Absence of solutions to this challenge hampers theory-formation in this area**

WHY DID YOU CLICK 'EXCEL'?

MODELING AND INFERENCE

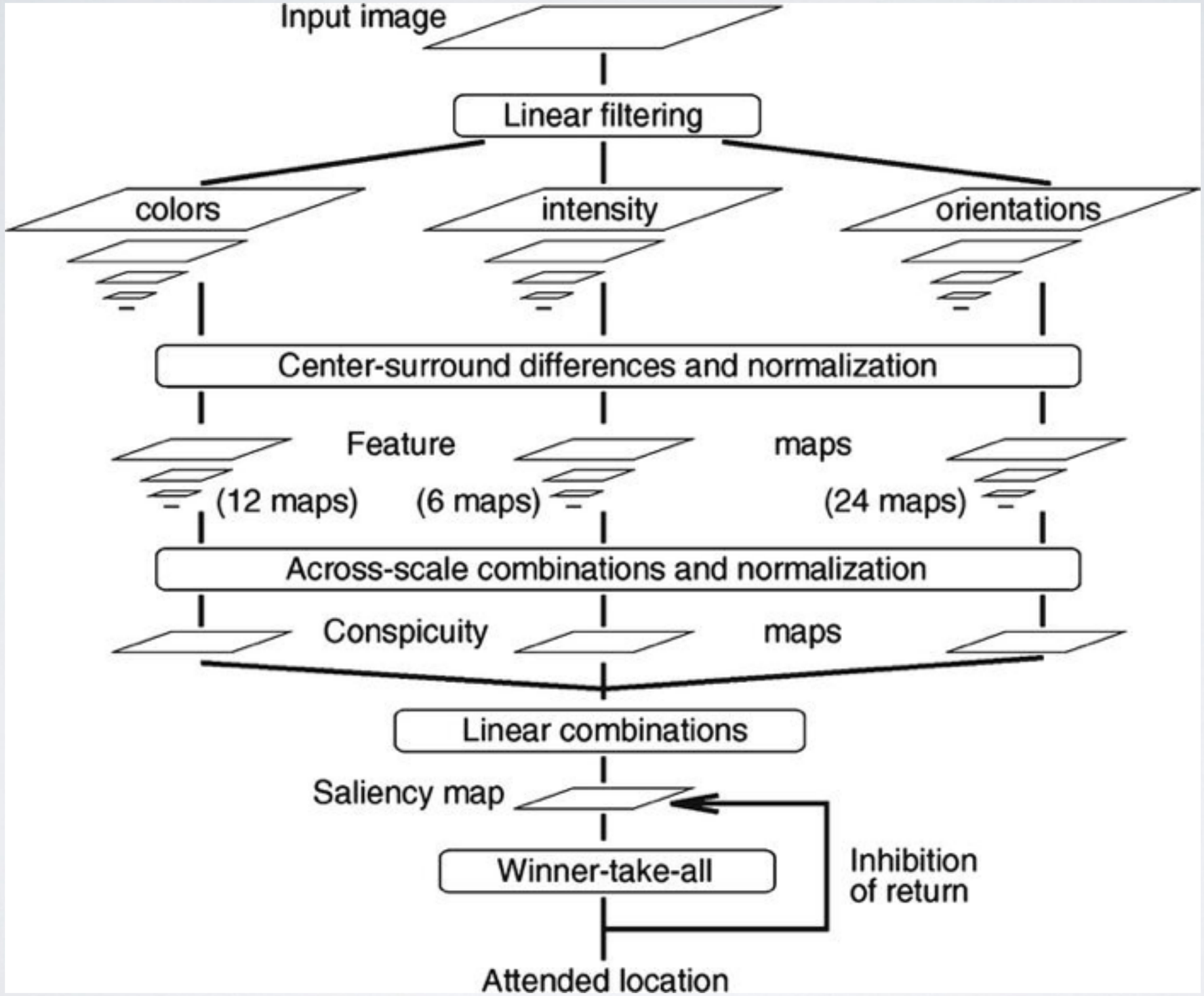
- **Problem 1: Modeling:** Build a model that is sufficiently flexible to capture a broad range of behaviors. Such models unavoidably get complex

- **Problem 2: Inference**: How to set parameter values of the model such that the values agree with literature and the resulting predictions match with our observations?

CLASSES OF MODELS IN HCI

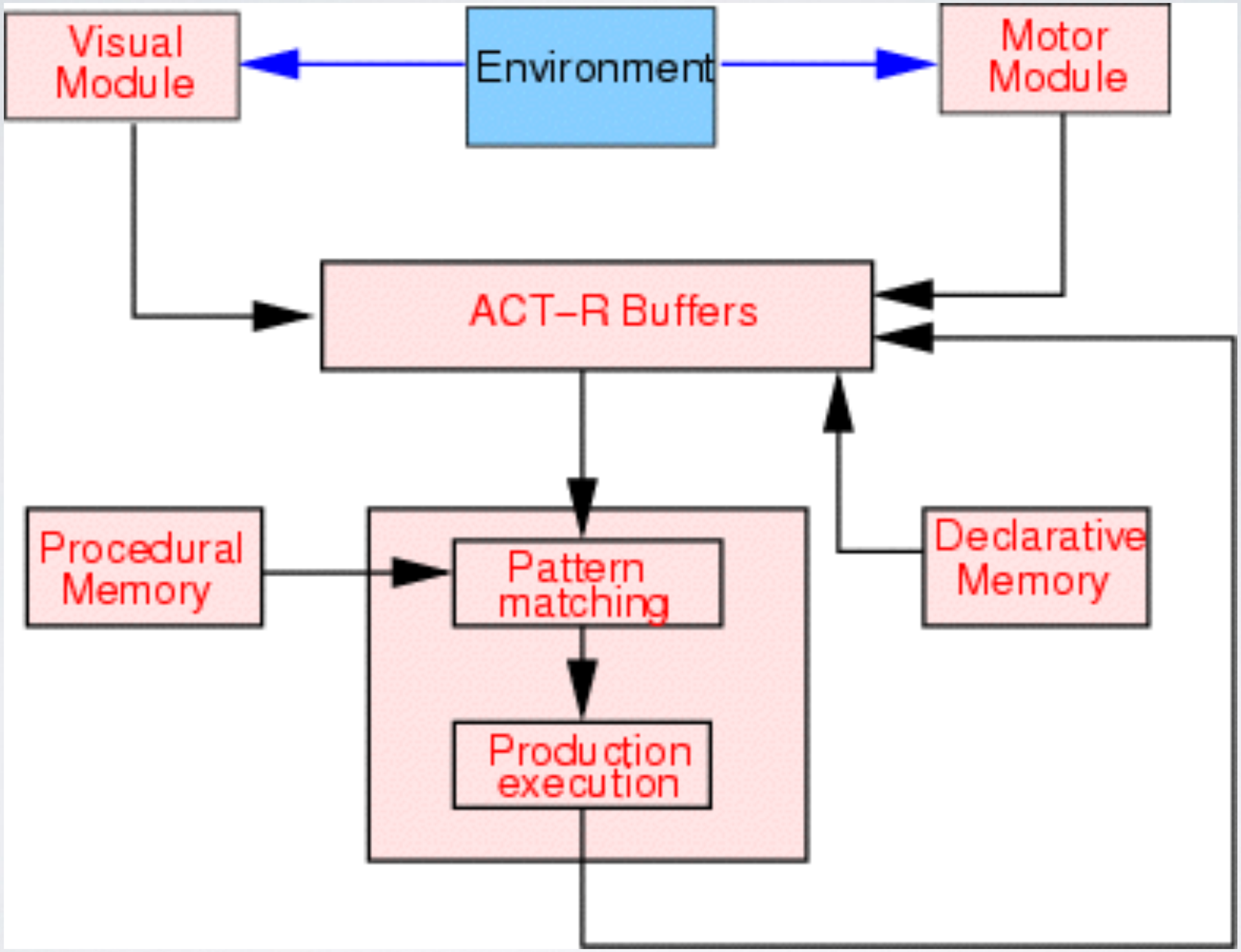
- **Rule-based**
- Models expressed in **logic**
- **Regression** models
  - E.g., Fitts' law $MT = a + b\log_2(D/W + 1)$
- **Simulation** models
  - Numerous examples…

EXAMPLE 1: A COMPLEX MODEL



Itti-Koch saliency map

EXAMPLE 2: A COGNITIVE SIMULATION



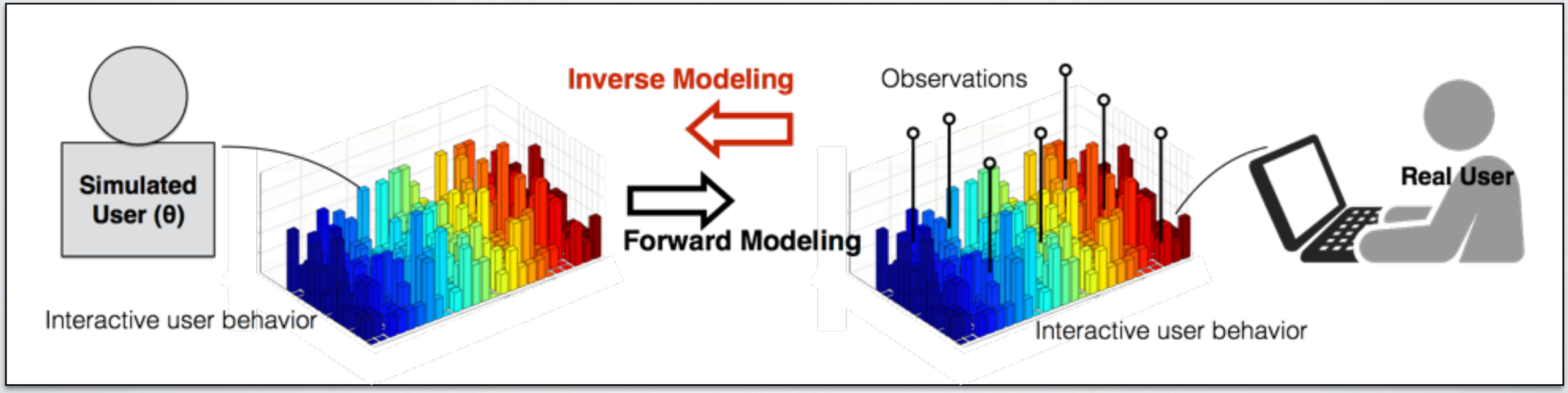
ACT-R

INVERSE MODELING

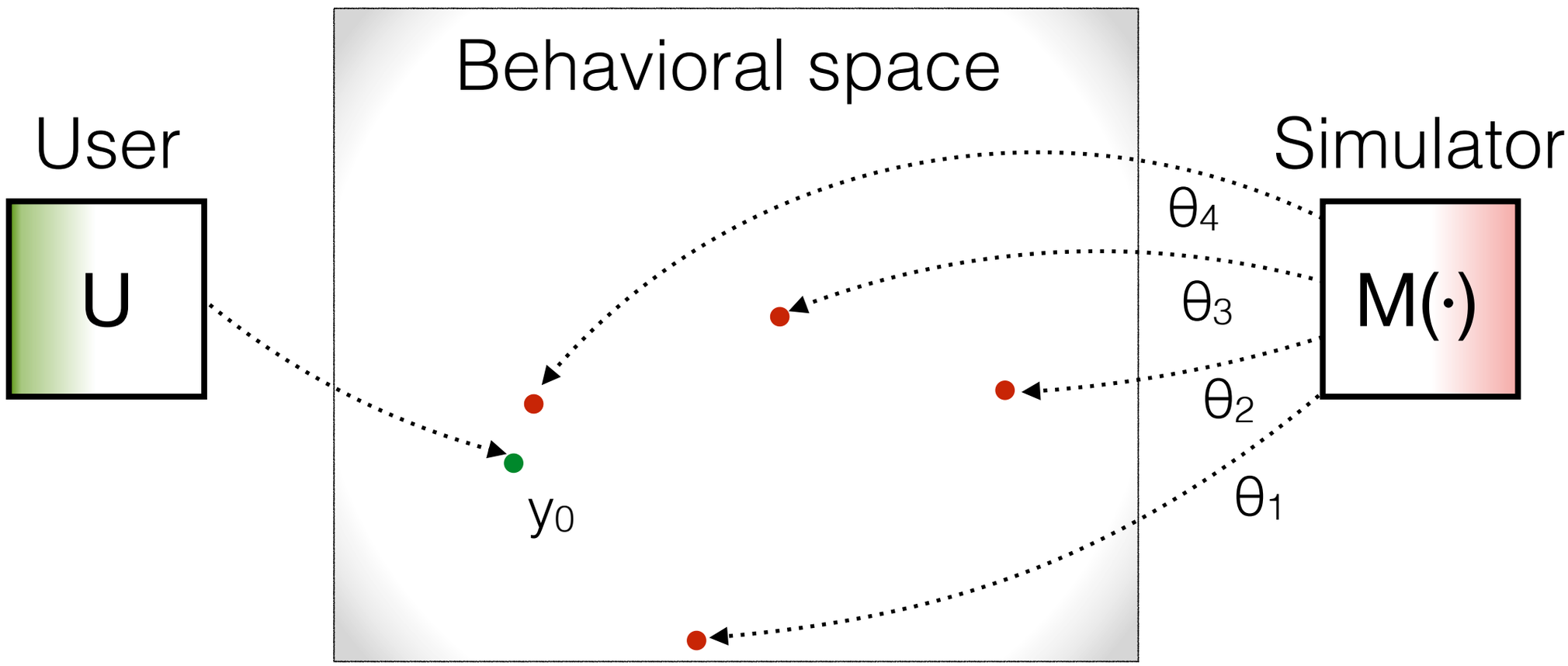
Given model $M(\theta)$ and observation data,

find the most likely parameter values θ and their distribution

such that the predictions made by the model agree with the observations (and literature)



INFERENCE PROBLEM OVERVIEW



PREVIOUS WORK: IM IN HCI

- **Models with simple algebraic form** that allow writing down a formula for the most likely parameter values

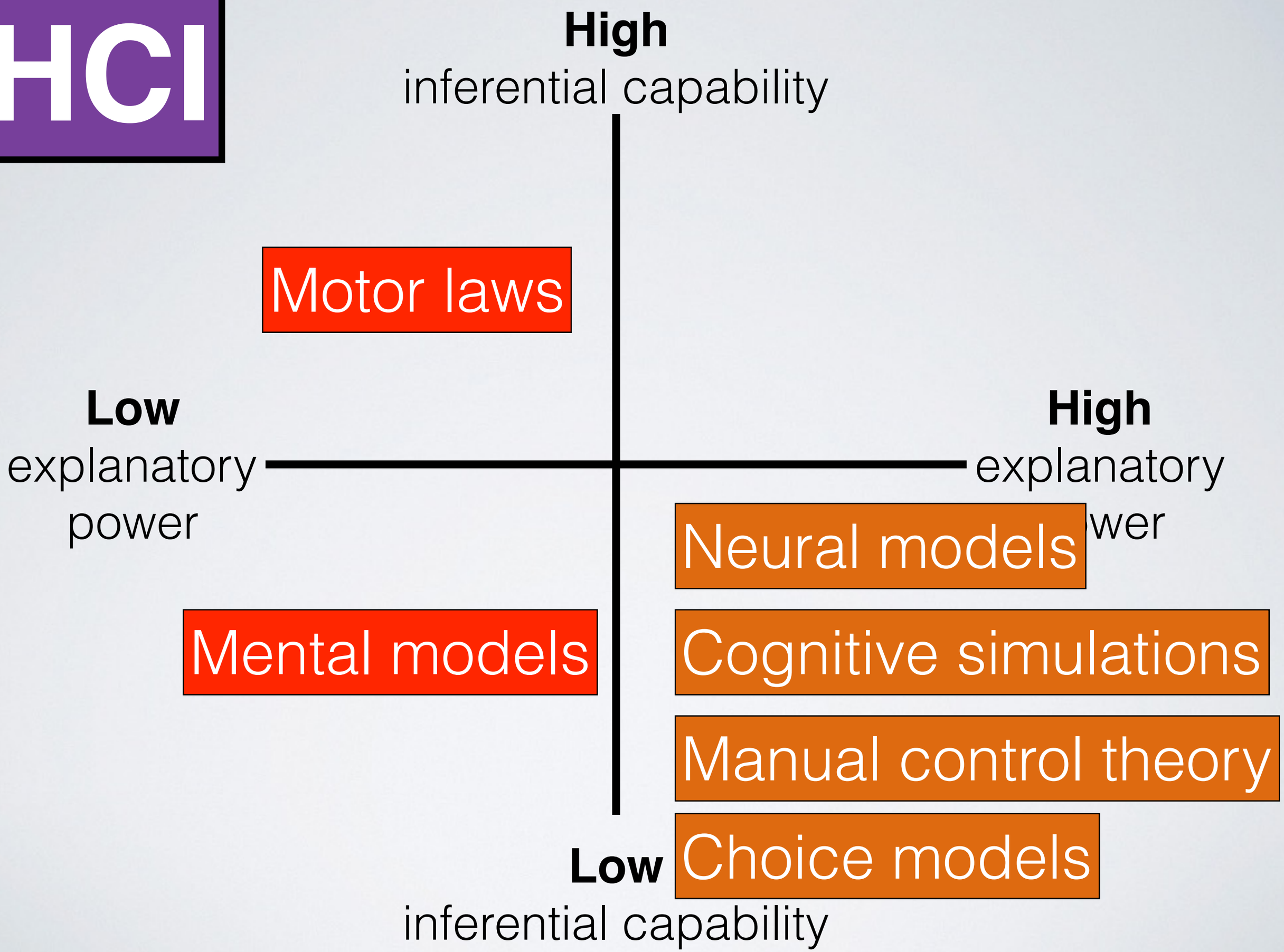
- **Complex models for which a likelihood function** can be written $L(\theta|Y_{obs})$

- **Complex models with no known likelihood function** require likelihood-free methods

SOME INVERSE MODELING PRACTICES IN HCI

laborious, ineffective, and high potential for bias and cheating

HCI


High
inferential capability
Motor laws
Low
explanatory
power
High
explanatory
wer
Neural models
Mental models
Cognitive simulations
Manual control theory
Choice models
Low
inferential capability

GOAL: A "MODELING ORACLE"

- *Given observational data of user behavior from known enviroment (UI, task, ..), the task is to infer any of these:*
  - **capacities and traits** like visual acuity, working memory capacity, personality types…
  - "**conations**", or goals, interests and preferences
  - **mental representations**: knowledge we have about a task
  - **behavioral strategies**: individual and task-specific ways of acting

SEVERAL RESEARCH AREAS WOULD TAKE A LEAP FORWARD…

- User modeling
- Adaptive user interfaces
- Recommendation systems
- Interactive search
- Visualization and graphics

- Data-driven interaction design
- Computational interface design

- Psychometrics
- Cognitive sciences
- Developmental psychology

OPPORTUNITY FOR ML

- **Could lift behavioral modeling and HCI from the rut where they now are …**

- ***But ML needs to seriously engage with the particular data, models, and modeling purposes…***

SCOPE AND ACKS

- **Based on one year of collaboration** with Samuel Kaski, Antti Kangasrääsiö, Kumaripaba Athukorala, Luana Micallef, Ulpu Remes, Jukka Corander, Jussi Jokinen, Aki Vehtari, Zhengzin Wang

- **A cognitive scientist's point of view**

Inferring Cognitive Models from Data using Approximate Bayesian Computation

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ABSTRACT
An important problem for HCI researchers is to estimate the parameter values of a cognitive model from behavioral data. This is a difficult problem, because of the substantial complexity and variety in human behavioral strategies. We report an investigation into a new approach using approximate Bayesian computation (ABC) to condition model parameters to data and prior knowledge. As the case study we examine menu interaction, where we have click time data only to infer a cognitive model that implements a search behaviour with parameters such as fixation duration and recall probability. Our results demonstrate that ABC (i) improves estimates of model parameter values, (ii) enables meaningful comparisons between model variants, and (iii) supports fitting models to individual users. ABC provides ample opportunities for theoretical HCI research by allowing principled inference of model parameter values and their uncertainty.

ACM Classification Keywords
H.1.2 User/Machine Systems: Human factors, Human information processing

Author Keywords
Approximate Bayesian computation; Cognitive models in HCI; Computational rationality; Inverse modeling

INTRODUCTION
It has become relatively easy to collect large amounts of data about complex user behaviour. This provides an exciting opportunity as the data has the potential to help HCI researchers understand and possibly predict such user behavior. Yet, unfortunately it has remained difficult to explain what users are doing and why in a given data set.

The difficulty lies in two problems: modeling and inference. The *modeling problem* consists of building models that are sufficiently general to capture a broad range of behaviors. Any model attempting to explain real-world observations must cover a complex interplay of factors, including what users are interested in, their individual capacities, and how they choose to process information (strategies). Recent research has shown progress in the direction of creating models for complex behavior [5, 13, 14, 16, 19, 21, 25, 27, 29, 36]. After constructing the model, we are then faced with the *inference problem*: how to set the parameter values of the model, such that the values agree with literature and prior knowledge, and that the resulting predictions match with the observations we have (Figure 1). Unfortunately, this problem has been less systematically studied in HCI. To this end, the goal of this paper is to report an investigation into a flexible and powerful method for inferring model parameter values, called *approximate Bayesian computation* (ABC) [42].

ABC has been applied to many scientific problems [7, 15, 42]. For example, in climatology the goal is to infer a model of climate from sensor readings, and in infectious disease epidemiology an epidemic model from reports of an infection spread. Inference is of great use both in applications and in theory-formation, in particular when testing models, identifying anomalies, and finding explanations to observations. However ABC, nor any other principled inference method, have, to our knowledge, been applied to complex cognitive models in HCI[1].

We are interested in principled methods for inferring parameter values, because they would be especially useful for process models of behaviour. This is because the models are usually defined as simulators, and thus the inference is very difficult to perform using direct analytical means[2]. Such process models in HCI have been created, for example, based on cognitive science [2, 9, 11, 16, 26, 41], control theory [23], biomechanics [4], game theory [10], foraging [38, 37], economic choice [3], and computational rationality [13]. In the absence of principled inference methods for such models, some approaches

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[Kangasrääsiö et al. Proc. CHI'17]

THIS TALK: STATUS REPORT + VISION

1. Cognitive models and inverse modeling in HCI

2. First attempts at using ABC in HCI

3. On-going work and emerging challenges

4. Future opportunities

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Fundamentals and Recent Developments in Approximate Bayesian Computation

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Abstract.—Bayesian inference plays an important role in phylogenetics, evolutionary biology, and in many other branches of science. It provides a principled framework for dealing with uncertainty and quantifying how it changes in the light of new evidence. For many complex models and inference problems, however, only approximate quantitative answers are obtainable. Approximate Bayesian computation (ABC) refers to a family of algorithms for approximate inference that makes a minimal set of assumptions by only requiring that sampling from a model is possible. We explain here the fundamentals of ABC, review the classical algorithms, and highlight recent developments. [ABC; approximate Bayesian computation; Bayesian inference; likelihood-free inference; phylogenetics; simulator-based models; stochastic simulation models; tree-based models.]

INTRODUCTION

Many recent models in biology describe nature to a high degree of accuracy but are not amenable to analytical treatment. The models can, however, be simulated on computers and we can thereby replicate many complex phenomena such as the evolution of genomes (Marttinen et al. 2015), the dynamics of gene regulation (Toni et al. 2009), or the demographic spread of a species (Currat and Excoffier 2004; Fagundes et al. 2007; Itan et al. 2009; Excoffier et al. 2013). Such simulator-based models are often stochastic and have multiple parameters. While it is usually relatively easy to generate data from the models for any configuration of the parameters, the real interest is often focused on the inverse problem: the identification of parameter configurations that would plausibly lead to data that are sufficiently similar to the observed data. Solving such a nonlinear inverse problem is generally a very difficult task.

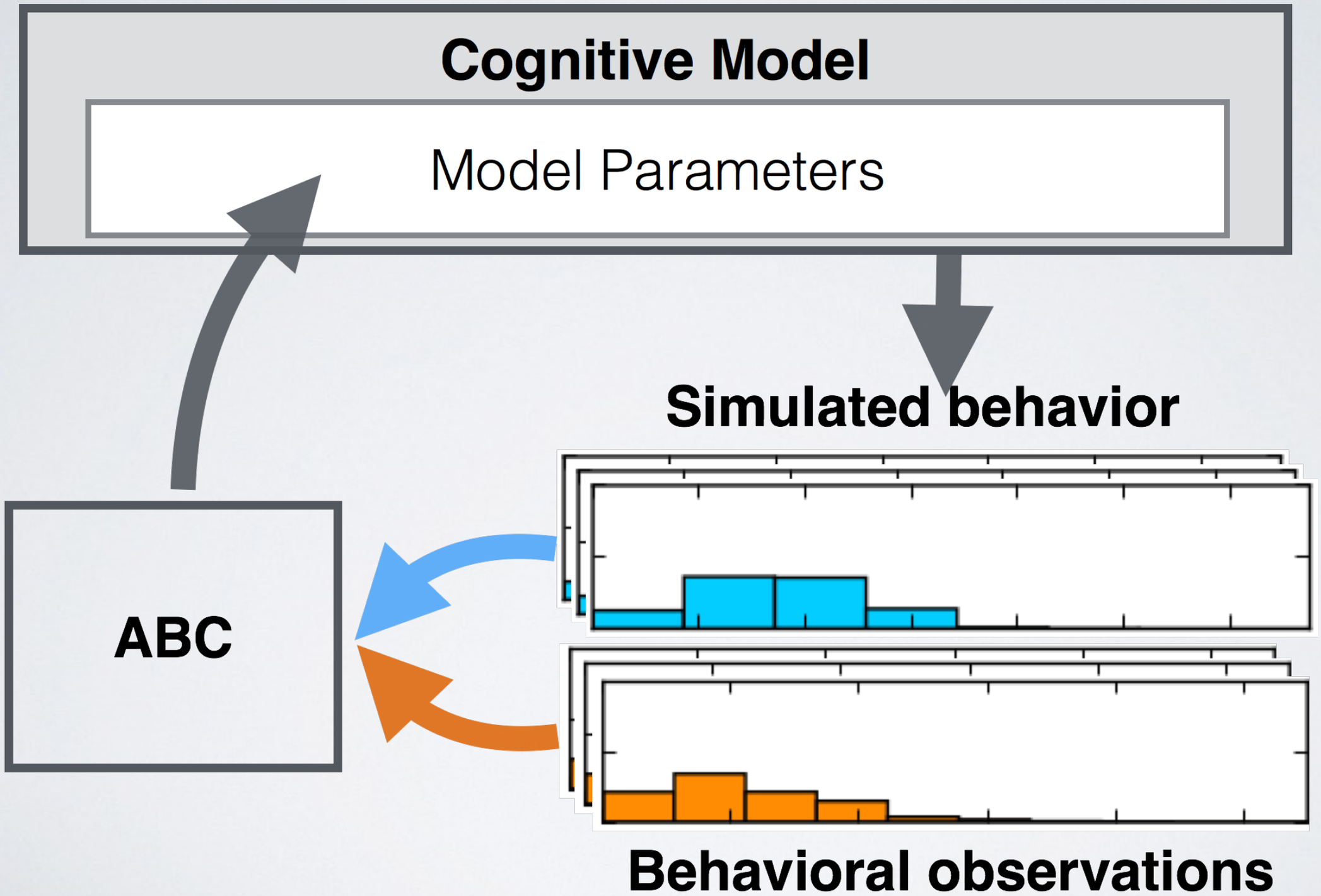
Bayesian inference provides a principled framework for solving the aforementioned inverse problem. A prior probability distribution on the model parameters is used to describe the initial beliefs about what values of the parameters could be plausible. The prior beliefs are updated in light of the observed data by means of the likelihood function. Computing the likelihood function, however, is mostly impossible for simulator-based models due to the unobservable (latent) random quantities that are present in the model. In some cases, Monte Carlo methods offer a way to handle the latent variables such that an approximate likelihood is obtained, but these methods have their limitations, and for large and complex models, they are "too inefficient by far" (Green et al. 2015, p. 848). To deal with models where likelihood calculations fail, other techniques have been developed that are collectively referred to as likelihood-free inference or approximate Bayesian computation (ABC).

In a nutshell, ABC algorithms sample from the posterior distribution of the parameters by finding values that yield simulated data sufficiently resembling the observed data. ABC is widely used in systematics. For instance, Hickerson et al. (2006) used ABC to test for simultaneous divergence between members of species pairs. Fan and Kubatko (2011) estimated the topology and speciation times of a species tree under the coalescent model using ABC. Their method does not require sequence data, but only gene tree topology information, and was found to perform favorably in terms of both accuracy and computation time. Slater et al. (2012) used ABC to simultaneously infer rates of diversification and trait evolution from incompletely sampled phylogenies and trait data. They found their ABC approach to be comparable to likelihood-based methods that use complete data sets. In addition, it can handle extremely sparsely sampled phylogenies and trees containing very large numbers of species. Ratmann et al. (2012) used ABC to fit two different mechanistic phylodynamic models for interpandemic influenza A(H3N2) using both surveillance data and sequence data simultaneously. The simultaneous consideration of these two types of data allowed them to drastically constrain the parameter space and expose model deficiencies using the ABC framework. Very recently, Baudet et al. (2015) used ABC to reconstruct the coevolutionary history of host–parasite systems. The ABC-based method was shown to handle large trees beyond the scope of other existing methods.

While widely applicable, ABC comes with its own set of difficulties, that are of both computational and statistical nature. The two main intrinsic difficulties are how to efficiently find plausible parameter values and how to define what is similar to the observed data and

ABC: A REVIEW

APPROACH STUDIED IN THIS WORK



MODELING ISSUE

- **Unlike traditional cognitive models,** a model should not require a predefined specification of the user's task

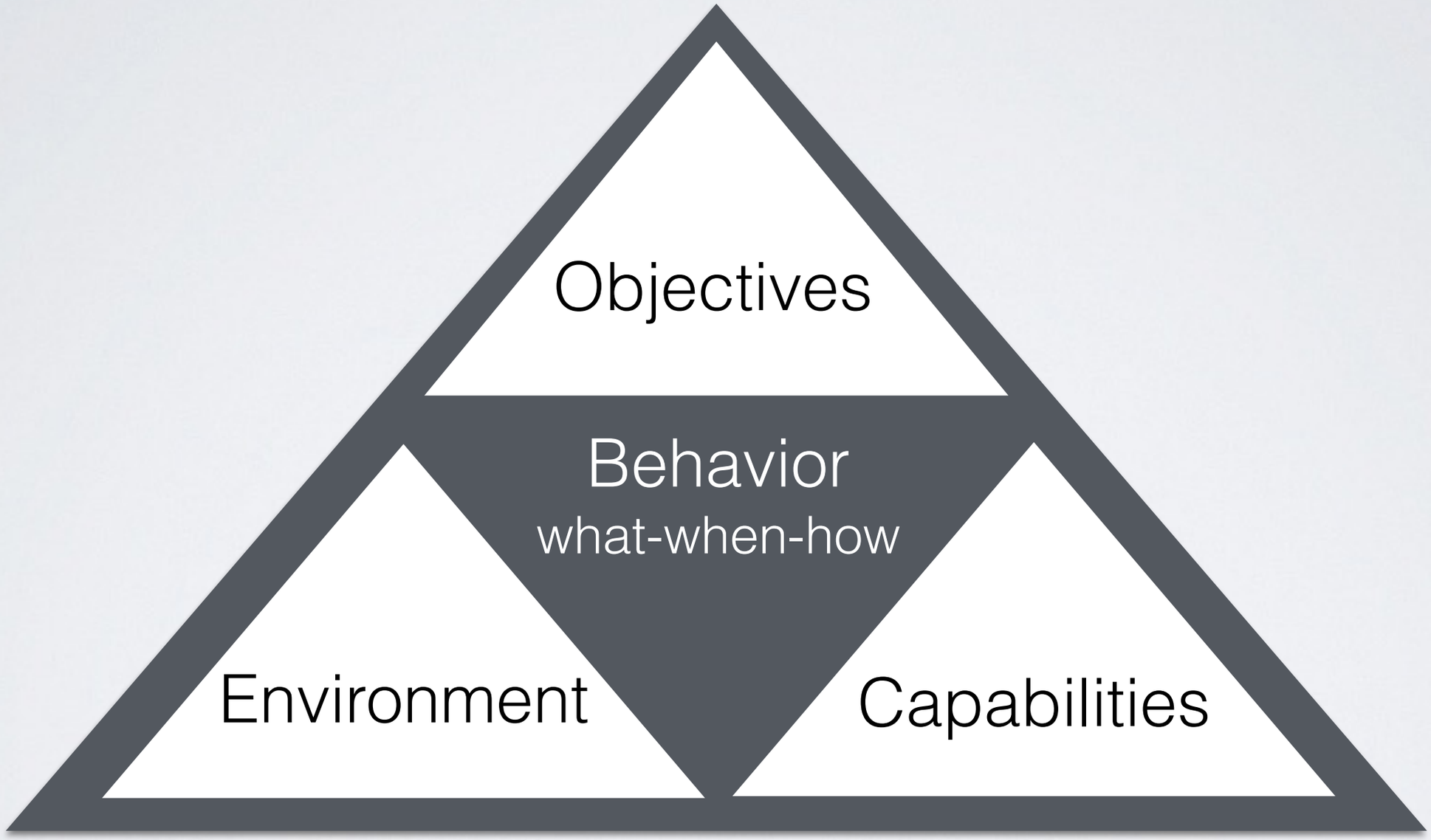
Example: manually created task specification in GOMS

```
GOAL: CLOSE-WINDOW
.   [select GOAL: USE-MENU-METHOD
            .   MOVE-MOUSE-TO-FILE-MENU
            .   PULL-DOWN-FILE-MENU
            .   CLICK-OVER-CLOSE-OPTION
           GOAL: USE-CTRL-W-METHOD
            .   PRESS-CONTROL-W-KEYS]

For a particular user:

   Rule 1: Select USE-MENU-METHOD unless another
           rule applies
   Rule 2: If the application is GAME,
           select CTRL-W-METHOD
```

APPROACH: COMPUTATIONAL RATIONALITY

- **Assume** that users behave (approximately) to maximize utility given limits on their own capacity.
- **Learn optimal behavioral strategies using RL**
- **Predict** how a user will behave in situations constrained by (1) the environment; (2) goals; and (3) the user's cognitive and perceptual capabilities

COMPUTATIONAL RATIONALITY



[Howes et al. *Psych Review* 2009]

APPROXIMATE BAYESIAN COMPUTATION

- **A principled method** for finding parameter values for complex HCI models, including simulators, based on observed data and prior knowledge

- **Repeatedly** simulates data using different parameter values, in order to find regions of the parameter space that lead to simulated data that is similar to the observed data.

- **The only assumption** needed is that the researcher is able to repeatedly simulate observations with different parameter values.

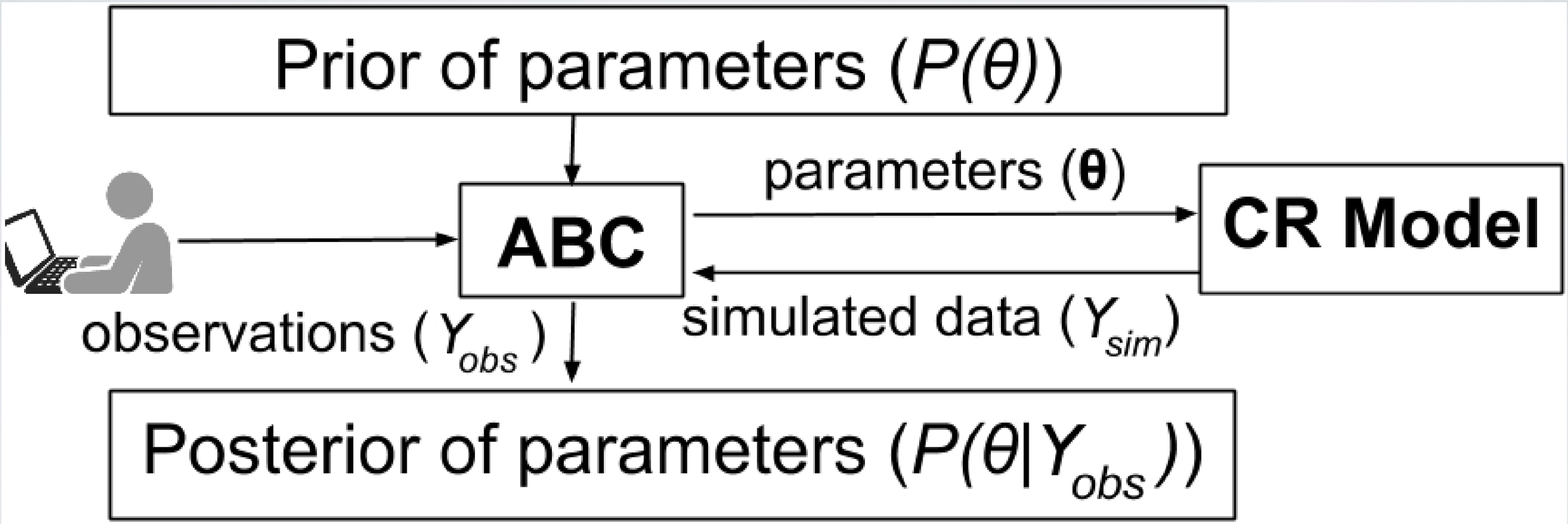
APPROXIMATE BAYESIAN COMPUTATION

- **Inputs:** Model M with unknown parameters θ , observations Y_{obs}

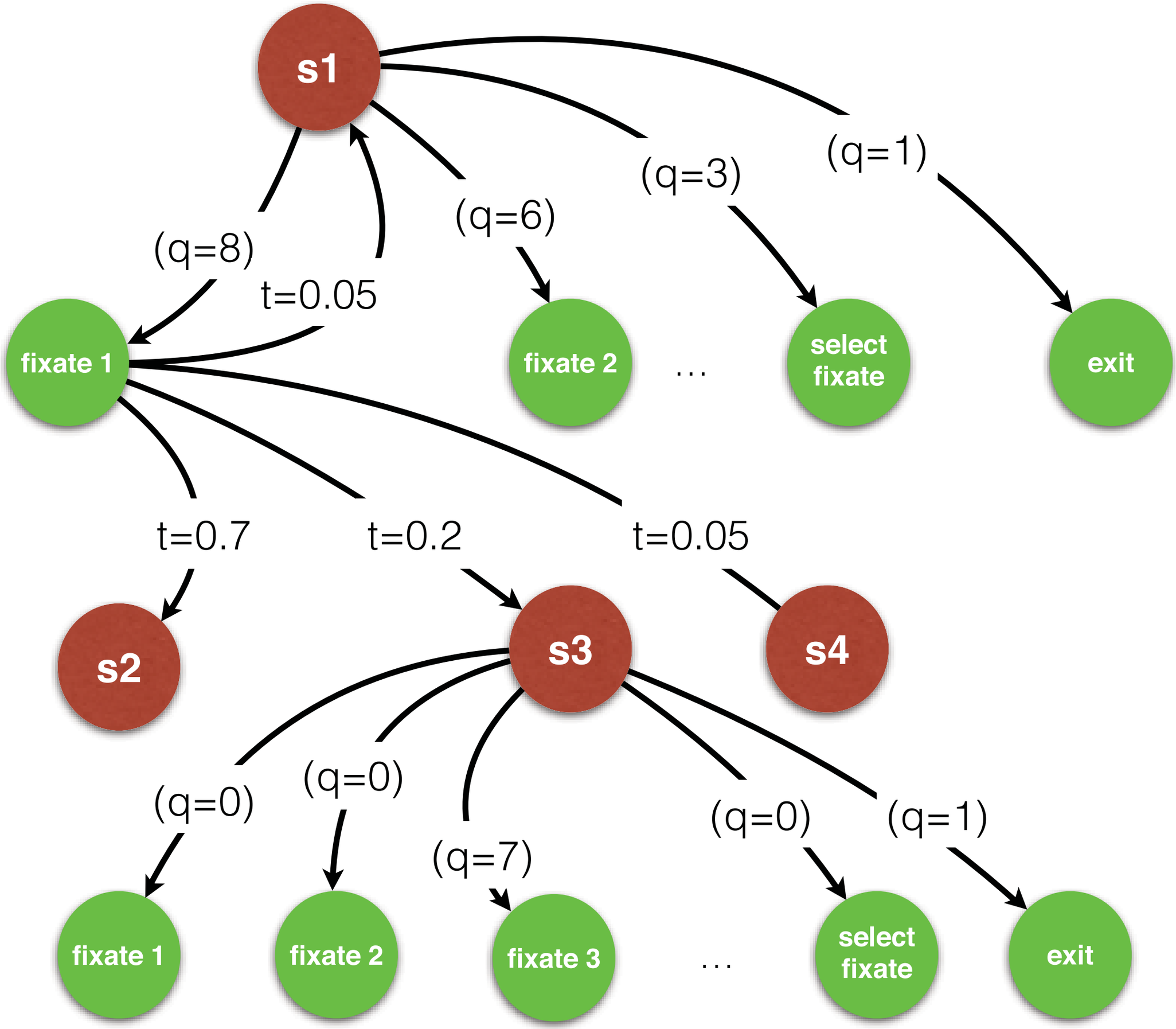
- **Outputs**: Estimates of likely values for parameters θ and their uncertainty.

- Should produce $M(\theta) \approx Y_{obs}$, while still being plausible given prior knowledge.

APPLICATION TO HCI



An ABC variant called **BOLFI** was used in this work


s1
(q=8)
t=0.05
(q=6)
(q=3)
(q=1)
fixate 1
fixate 2
...
select fixate
exit
t=0.7
t=0.2
t=0.05
s2
s3
s4
(q=0)
(q=0)
(q=7)
(q=0)
(q=1)
fixate 1
fixate 2
fixate 3
...
select fixate
exit

OVERVIEW OF PROBLEM

- Given realistic data (menu design and log of how long it took to select an item),
  - infer a model with plausible parameters of the human perceptual system and its deployment strategy
- Compare against ground truth measurements ("**baseline**")

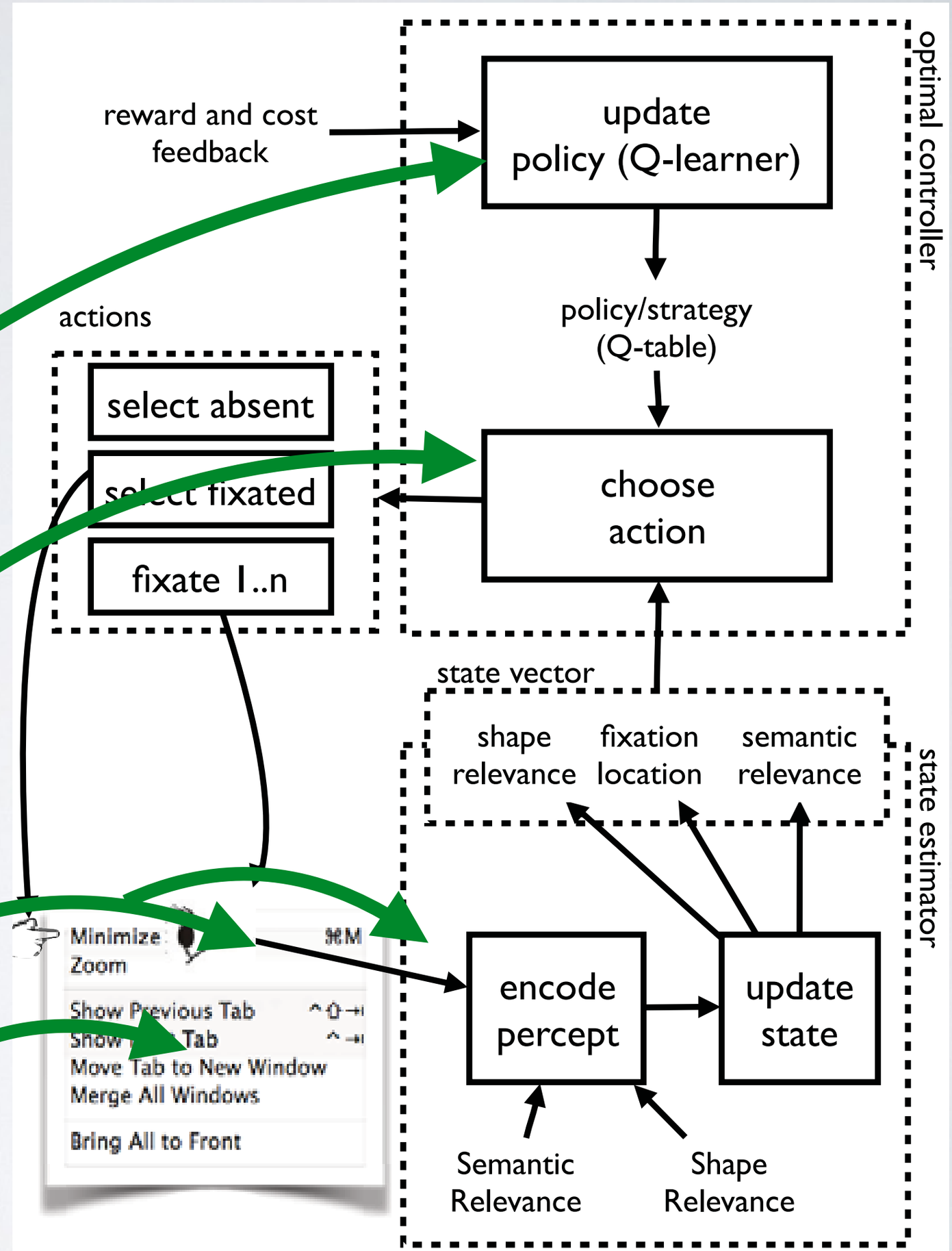
MODEL: MENU SEARCH

Q-learning

Markov Decision Process

Model of attention

Task environment

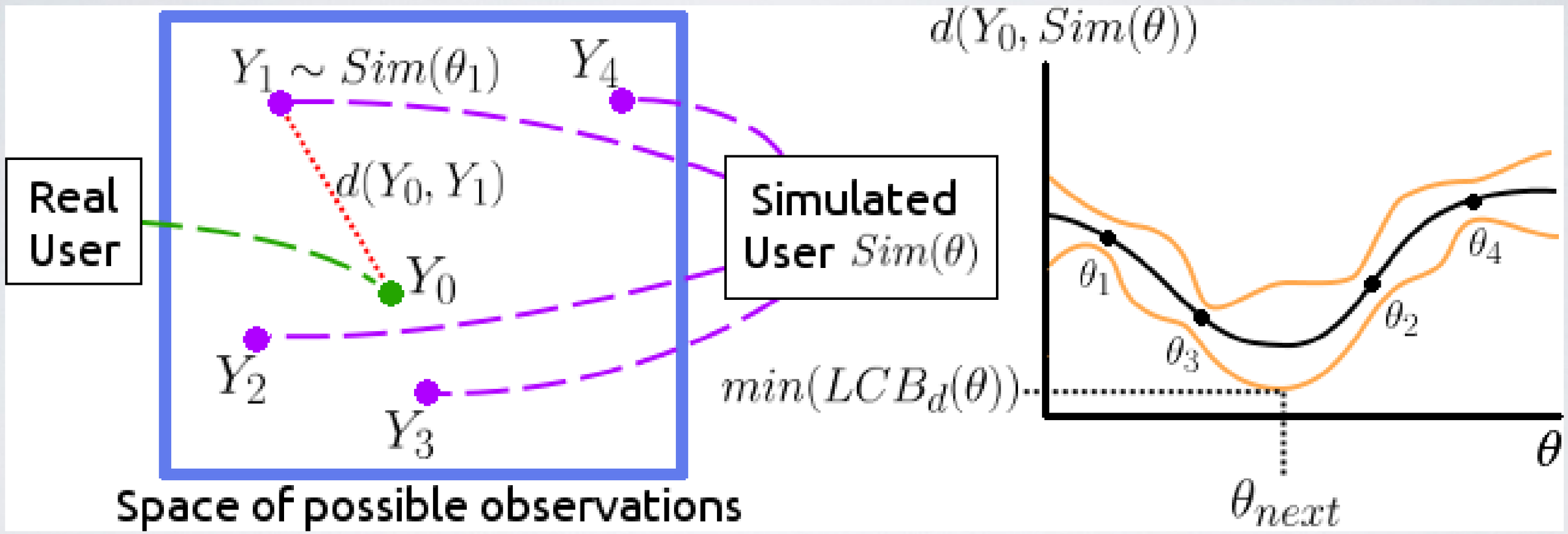


THREE STUDIES

- **Study 1.** ABC compared to manual tuning
- **Study 2.** ABC in model development
- **Study 3.** ABC in modeling individual differences

Parameter	Description
f_{dur}	Fixation duration
d_{sel}	Time cost for selecting an item (added to the duration of the last fixation of the episode if the user made a selection)
p_{rec}	Probability of recalling the semantic relevances of all of the menu items during the first fixation of the episode
p_{sem}	Probability of perceiving the semantic relevance of menu items above and below of the fixated item

HOW BOLFI WORKS

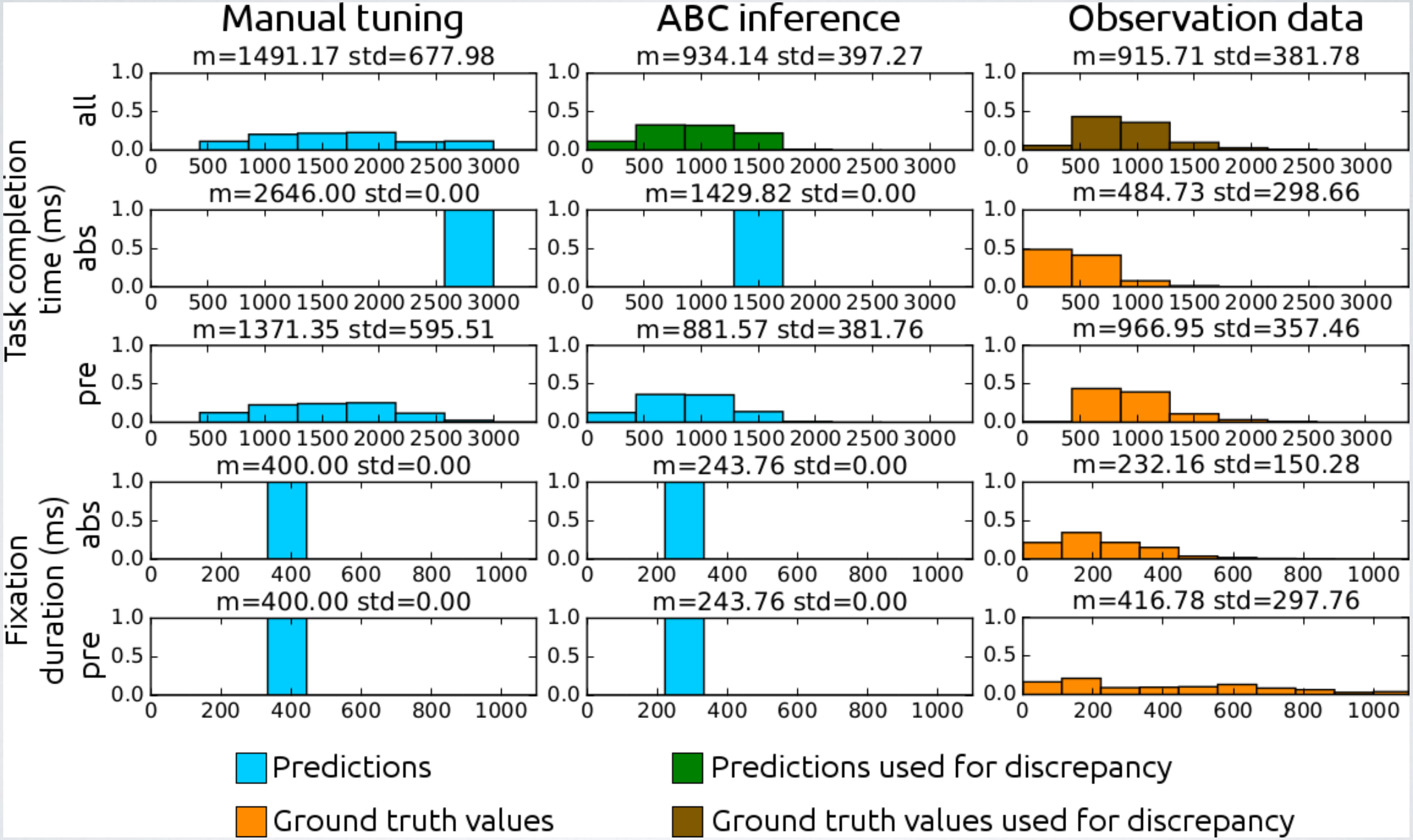


(ABC BOLFI IMPLEMENTATION)

APPENDIX: ABC BOLFI IMPLEMENTATION

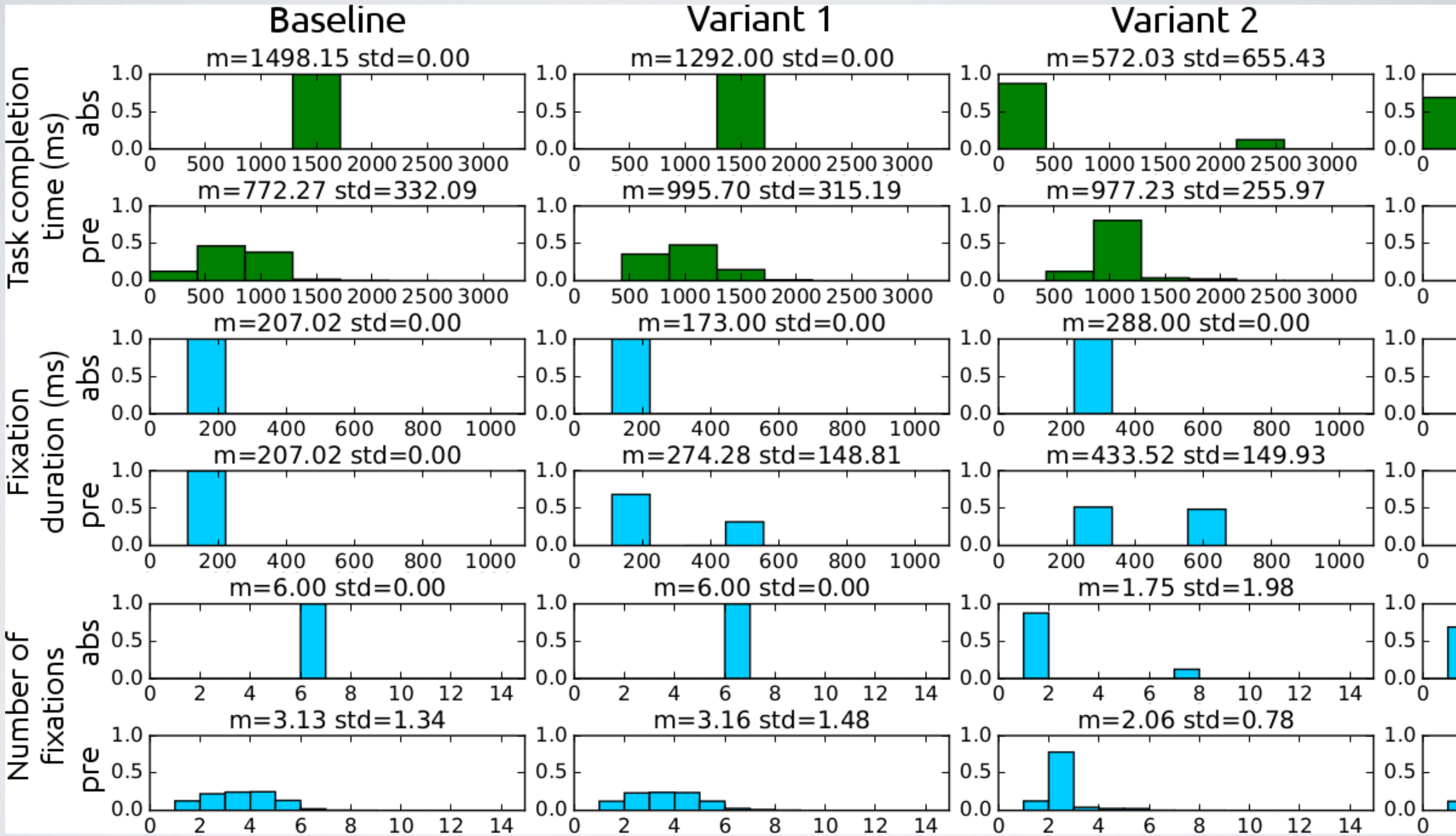
We implemented BOLFI in Python with the following details. We used a Gaussian process (GP) model from the GPy Python library to model the discrepancy. The kernel was Matern 3/2 with variance 0.01, scale 0.1, and noise variance 0.05. The first N_{init} sample locations were drawn from the quasi-random Sobol sequence (equal to the number of CPU cores allocated for the job). The remaining sample locations were decided as follows. We created a function that computed the lower confidence bound (LCB) for the GP: $LCB(x) = \mu_{GP}(x) - b\sigma_{GP}(x)$. We used $b = 1.0$. For asynchronous parallel sampling, we needed a way to acquire multiple locations that were reasonable, but also sufficiently well apart. For this purpose we created a function that calculated the sum of radial-basis function kernels that were centered at the locations P currently being sampled: $R(x) = \sum_{p \in P} a \exp((x-p)^2/l)$. We used $a = 0.04$, $l = 0.04$. The acquisition function for the next sample location was $A(x) = \min_x [LCB(x) + R(x)]$. Additionally, there was a 10 % chance of the location being drawn from the prior instead of the acquisition function.

STUDY 1: COMPARISON



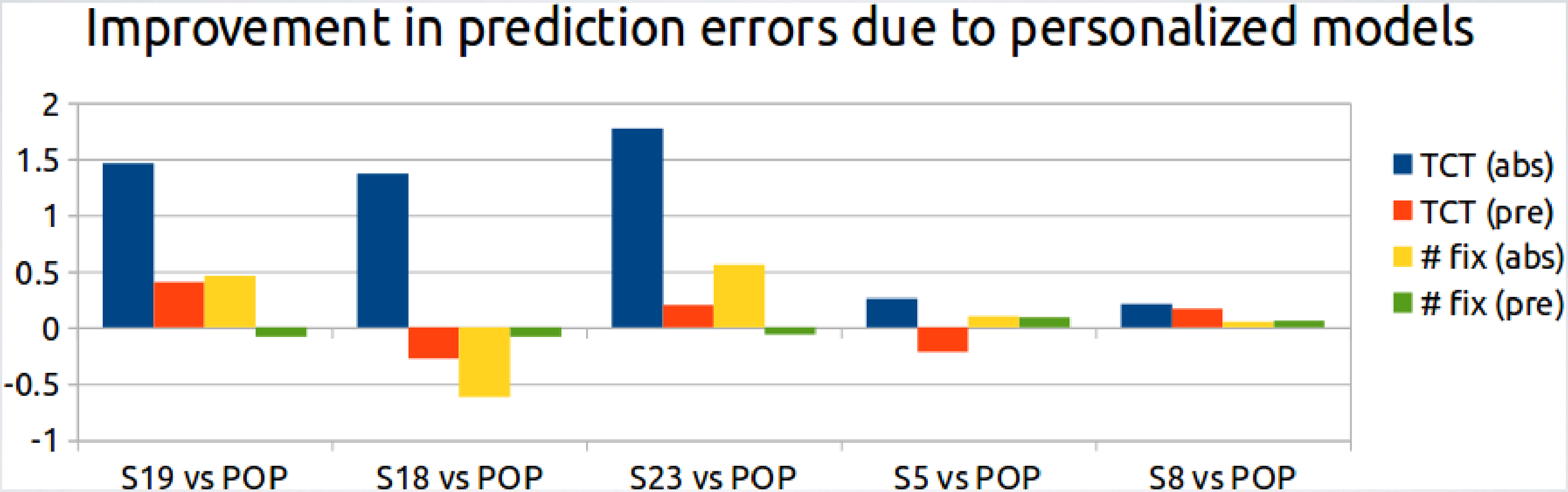
Improved predictions compared to manual tuning of parameters

STUDY 2: MODEL DEVELOPMENT



Theoretically plausible changes to model further improved predictions…

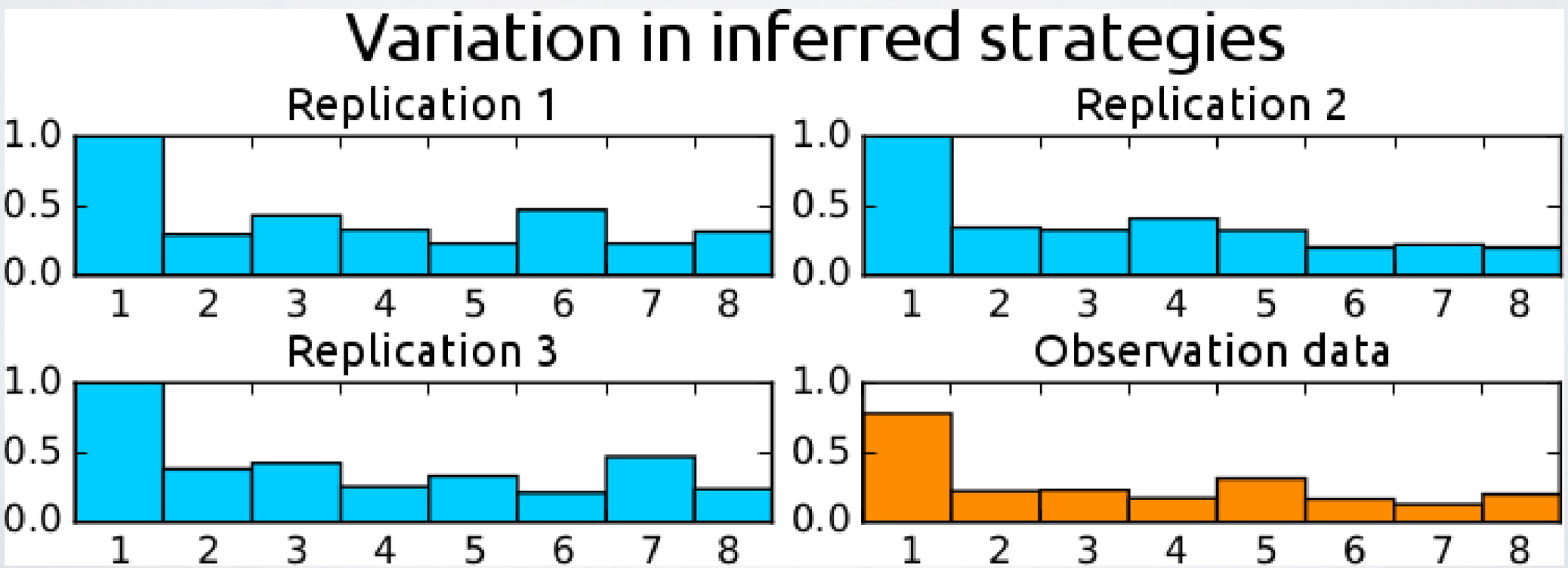
STUDY 3: IND. DIFFERENCES



Individual differences could be inferred despite decreasing amount data…

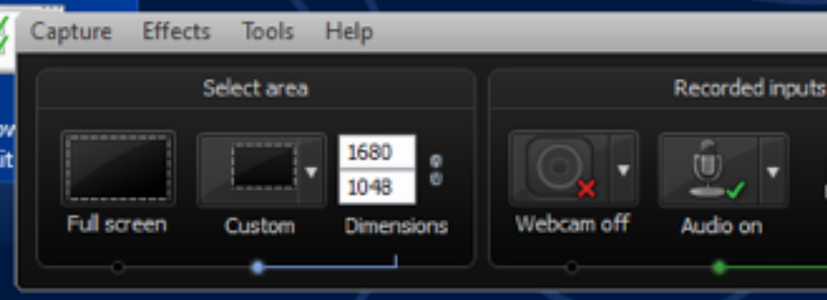
TECHNICAL CHALLENGES

- Discrepancy function designed by hand
- Not known: how many samples are needed
- BO sampling behavior
- GP kernel parameters?
- Inaccurate generative model
- Poor convergence of RL
- Slow RL



Start

Internet Explorer
Microsoft Word 2010
Microsoft PowerPoint 2010
Microsoft Mediagalerie
Notepad++
PictureViewer
Adobe Reader X
Windows Performance...
GPUView
Créat d'arc
Microsoft Office Picture Manager
Microsoft Project 2010
Microsoft Silverlight
Digitaal certificaat voor...
Microsoft Project Server 2010...
Microsoft SharePoint...
Windows Performance...
Global Flags (X86)
Visua logs
Microsoft Excel 2010
Microsoft Expression We...
Taalvoorkeuren voor Microsoft...
Microsoft Office 2010 Upload...
Microsoft Mouse and Keyboard...
kSign
WinDbg (X86)
Dossier d'installation d...
8
Microsoft Expression We...
Microsoft Expression...
7-Zip File Manager
Apple Software Update
Bug Radar
Opties
Outil de rapport de bugs
Editeur de fichiers langues
Microsoft Expression...
Microsoft Expression...
Skype
iTunes
Developer Command...
Microsoft Test Manager
Configurer des programmes
DreamShield IDE
Visual Studio 2012
Blend for Visual Studio 2012
QuickTime Player
Over QuickTime
Windows Software...
Window Cert Kit



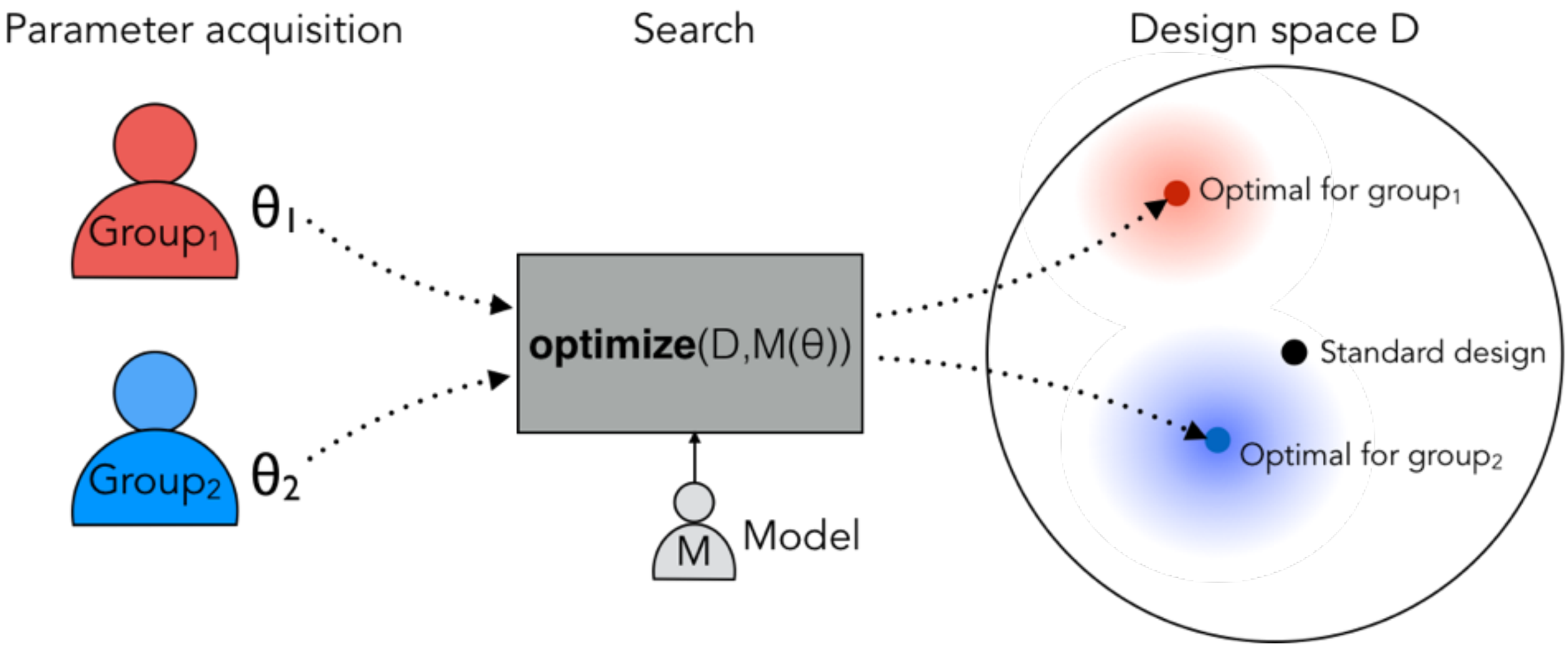
TOPICS FOR FUTURE WORK

- **Perceptual capabilities** due to low-level (physiological, retinal, cortical) issues
- **Cognitive capabilities** like working memory capacity
- **Mental representations** (e.g., associative memory structures)
- **Interests, goals, preferences** - all studied extensively in cognitive and social psychology
- **Personality** and other more stable traits
- **Cultural differences**
- …

POTENTIAL OF ABC FOR HCI

- **Better account** of variability of human behavior by disentangling idiosyncratic and task-specific factors
- **Advance theorizing and model-building** by more rigorous conditioning of models to data
- **Improve hit rates** in adaptive systems, recommendation engines etc
- **Foundations** of self-optimizing interactive technology

ABILITY-BASED OPTIMIZATION

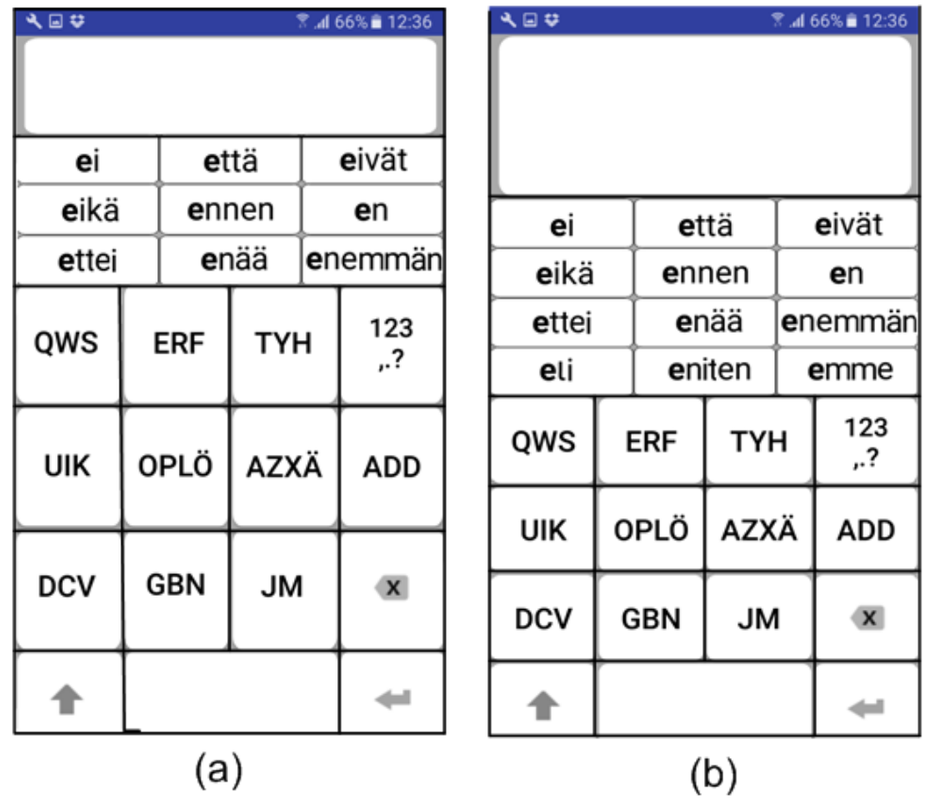


Given tapping data on a smartphone, the task is to infer psychometric properties like visual acuity, tremor, dyslexia…


T-Mobile
10:29
61%
Facebook
Twitter
Google+
LinkedIn
Pinterest
Instagram
Tumblr
Myspace
Flickr
Meetup
Vimeo
Viber
Messenger
Tumblr

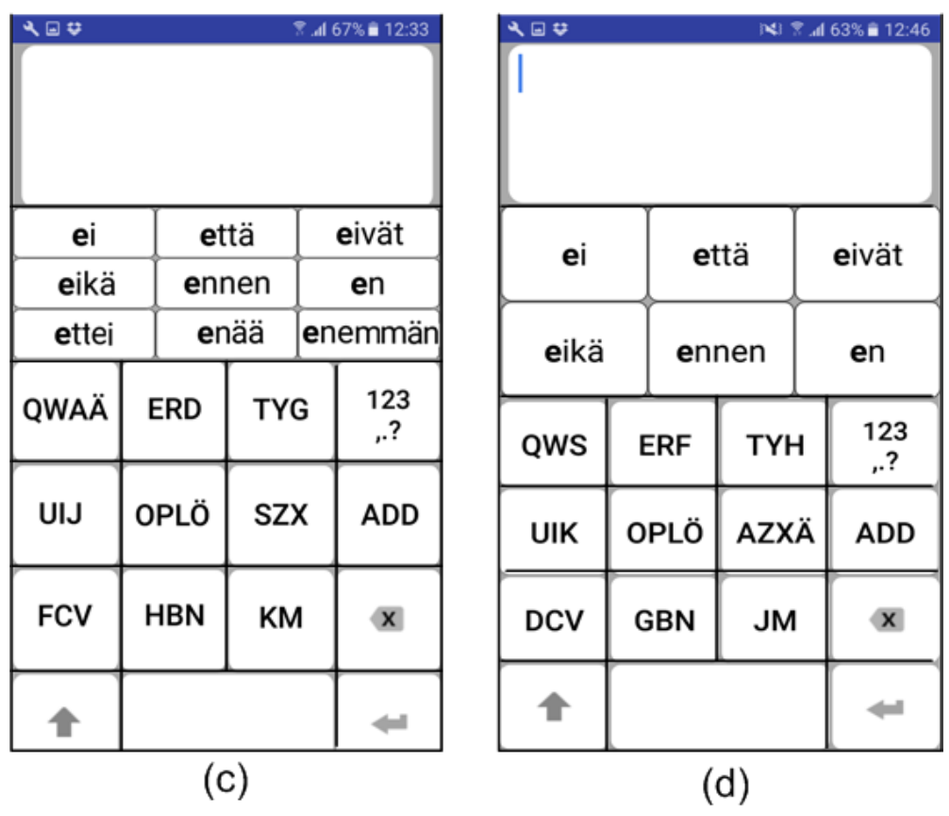
PRELIMINARY FM RESULTS

Essential tremor



Users unfamiliar with Qwerty

Reading disfluencies



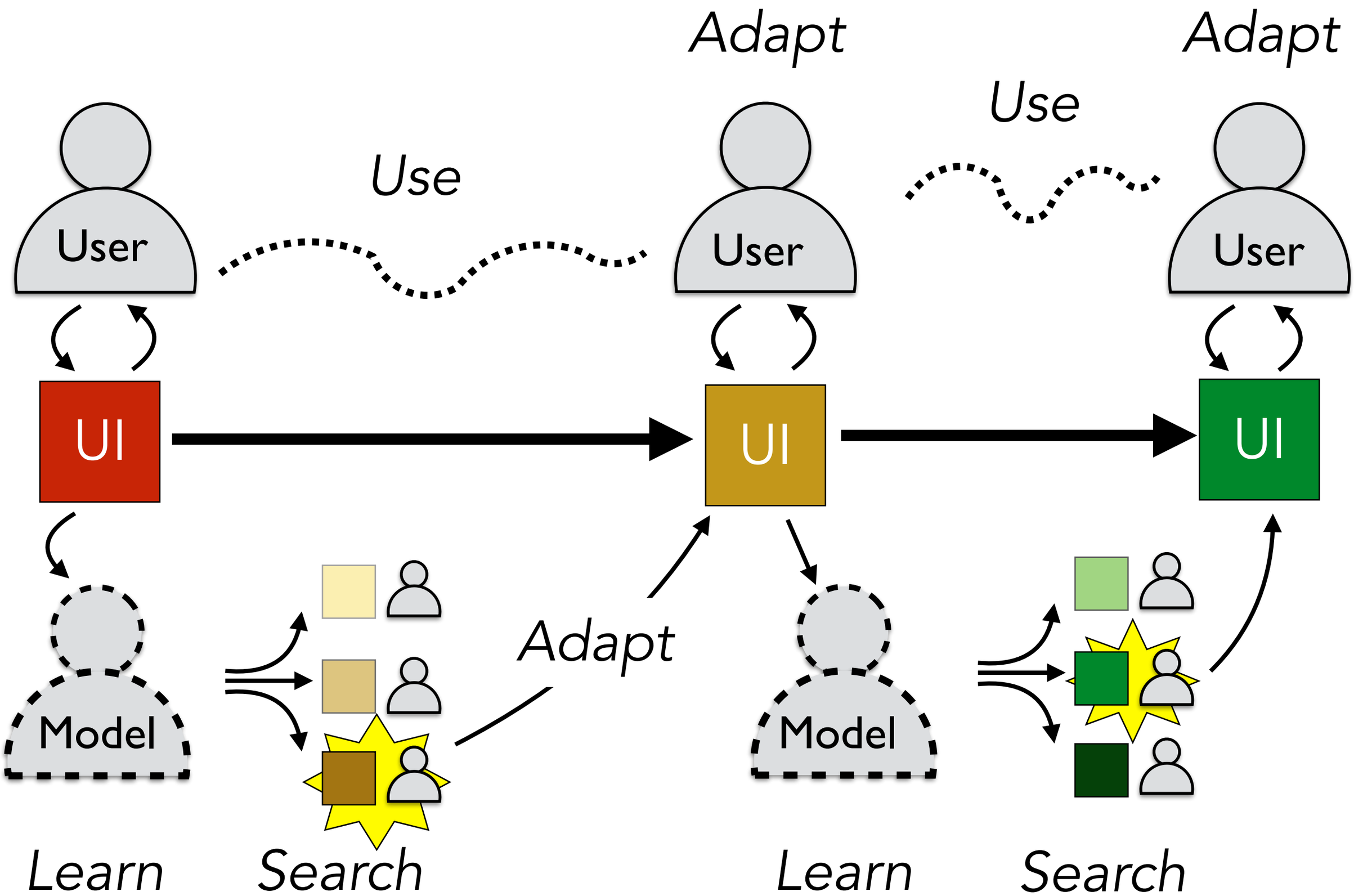
Reading disfluencies 2

“CO-ADAPTIVE TECHNOLOGY”

Inference of user simulators from naturalistic data

White-box models are interpretable and can be augmented by expert insight

They can drive online/offline optimization of UIs


Adapt
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Learn
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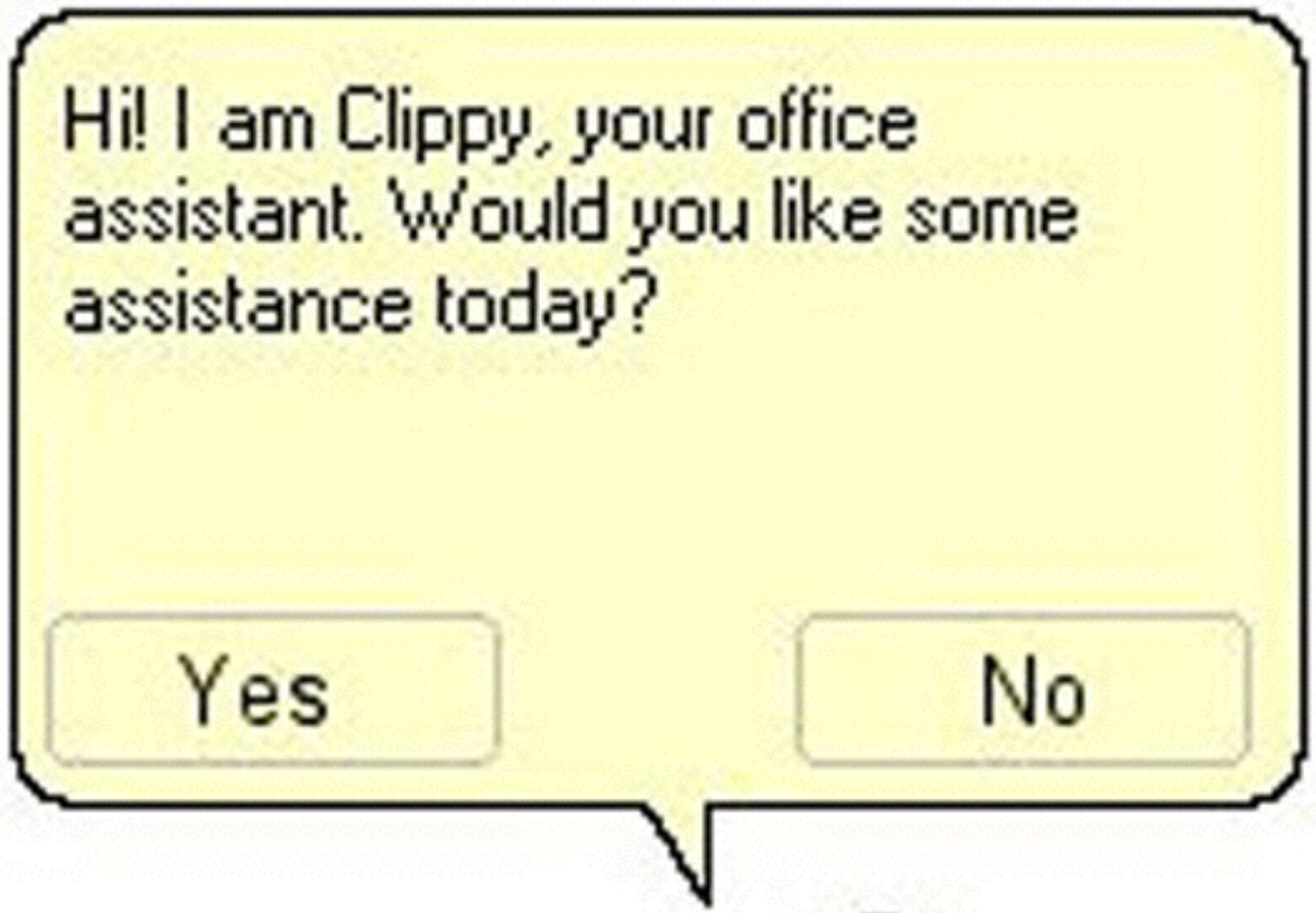

Adaptation considers individual diffs

And the benefits <u>and</u> costs of changes

END: GRAND OPPORTUNITIES

- **MACHINE LEARNING:** Improve capacity to condition white-box models to data
- **ARTIFICIAL INTELLIGENCE**: An approach to augment human capabilities with machine intelligence, instead of overriding them
- **COGNITIVE AND BEHAVIORAL SCIENCES**: Develop models that offer a better account of the incredibly rich space of human behaviors
- **HUMAN-COMPUTER INTERACTION**: Use these models to improve the fit of technology to individual differences and tasks

CHI 2017

ORE INNOVATE INSPIRE

Inferring Cognitive Models from Data using Approximate Bayesian Computation

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ABSTRACT
An important problem for HCI researchers is to estimate the parameter values of a cognitive model from behavioral data. This is a difficult problem, because of the substantial complexity and variety in human behavioral strategies. We report an investigation into a new approach using approximate Bayesian computation (ABC) to condition model parameters to data and prior knowledge. As the case study we examine menu interaction, where we have click time data only to infer a cognitive model that implements a search behaviour with parameters such as fixation duration and recall probability. Our results demonstrate that ABC (i) improves estimates of model parameter values, (ii) enables meaningful comparisons between model variants, and (iii) supports fitting models to individual users. ABC provides ample opportunities for theoretical HCI research by allowing principled inference of model parameter values and their uncertainty.

ACM Classification Keywords
H.1.2 User/Machine Systems: Human factors, Human information processing

Author Keywords
Approximate Bayesian computation; Cognitive models in HCI; Computational rationality; Inverse modeling

INTRODUCTION
It has become relatively easy to collect large amounts of data about complex user behaviour. This provides an exciting opportunity as the data has the potential to help HCI researchers understand and possibly predict such user behavior. Yet, unfortunately it has remained difficult to explain what users are doing and why in a given data set.

The difficulty lies in two problems: modeling and inference. The *modeling problem* consists of building models that are sufficiently general to capture a broad range of behaviors. Any model attempting to explain real-world observations must cover a complex interplay of factors, including what users are interested in, their individual capacities, and how they choose to process information (strategies). Recent research has shown progress in the direction of creating models for complex behavior [5, 13, 14, 16, 19, 21, 25, 27, 29, 36]. After constructing the model, we are then faced with the *inference problem*: how to set the parameter values of the model, such that the values agree with literature and prior knowledge, and that the resulting predictions match with the observations we have (Figure 1). Unfortunately, this problem has been less systematically studied in HCI. To this end, the goal of this paper is to report an investigation into a flexible and powerful method for inferring model parameter values, called *approximate Bayesian computation* (ABC) [42].

ABC has been applied to many scientific problems [7, 15, 42]. For example, in climatology the goal is to infer a model of climate from sensor readings, and in infectious disease epidemiology an epidemic model from reports of an infection spread. Inference is of great use both in applications and in theory-formation, in particular when testing models, identifying anomalies, and finding explanations to observations. However ABC, nor any other principled inference method, have, to our knowledge, been applied to complex cognitive models in HCI[1].

We are interested in principled methods for inferring parameter values, because they would be especially useful for process models of behaviour. This is because the models are usually defined as simulators, and thus the inference is very difficult to perform using direct analytical means[2]. Such process models in HCI have been created, for example, based on cognitive science [2, 9, 11, 16, 26, 41], control theory [23], biomechanics [4], game theory [10], foraging [38, 37], economic choice [3], and computational rationality [13]. In the absence of principled inference methods for such models, some approaches

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[1]For simpler models, such as regression models (e.g., Fitts' law), there exist well-known methods for finding parameter values, such as ordinary least squares.
[2]In technical terms, such models generally do not have a *likelihood function*—defining the likelihood of parameter values given the observations—that could be written in closed form.

A STORY OF A CHI PAPER

[Kangasrääsiö et al. Proc. CHI'17]