Behavior Modeling via Mathematical Methods

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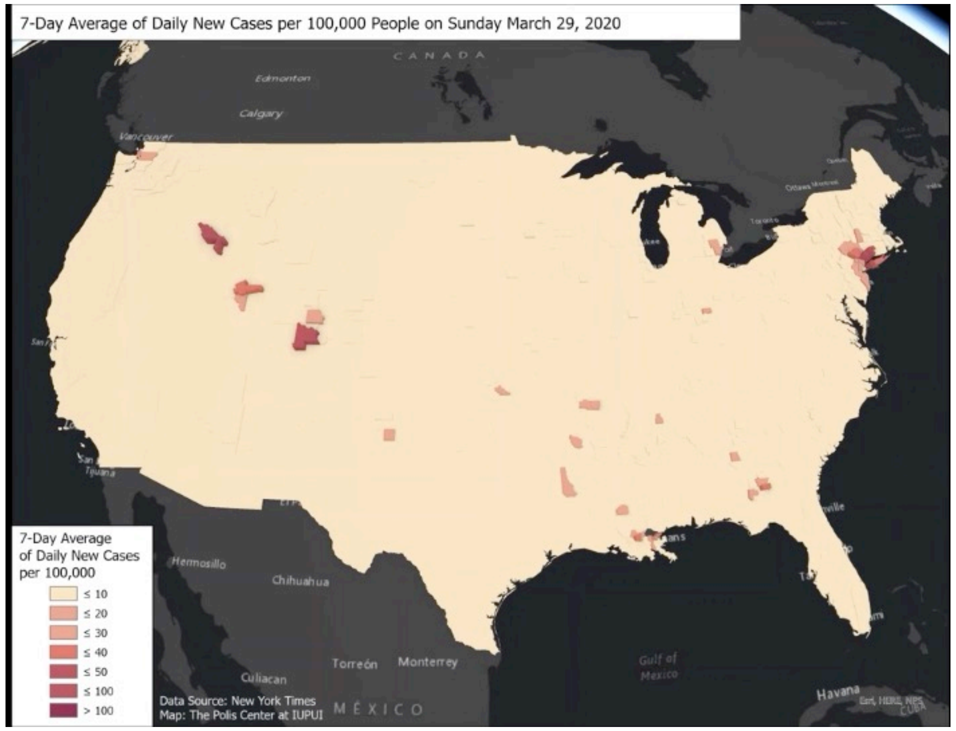
Math in Life

Casino

New cases of covid



transportation management

pharmacy

Research Goal

Many applications such as healthcare, social networks, urban mobility, e-commence…

Daily Routines

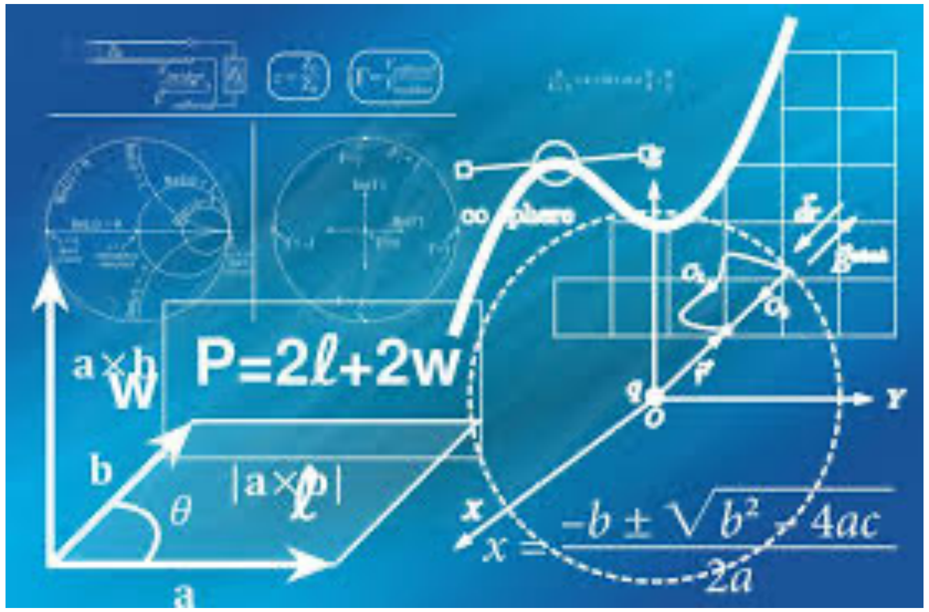
Automate Diagnoses

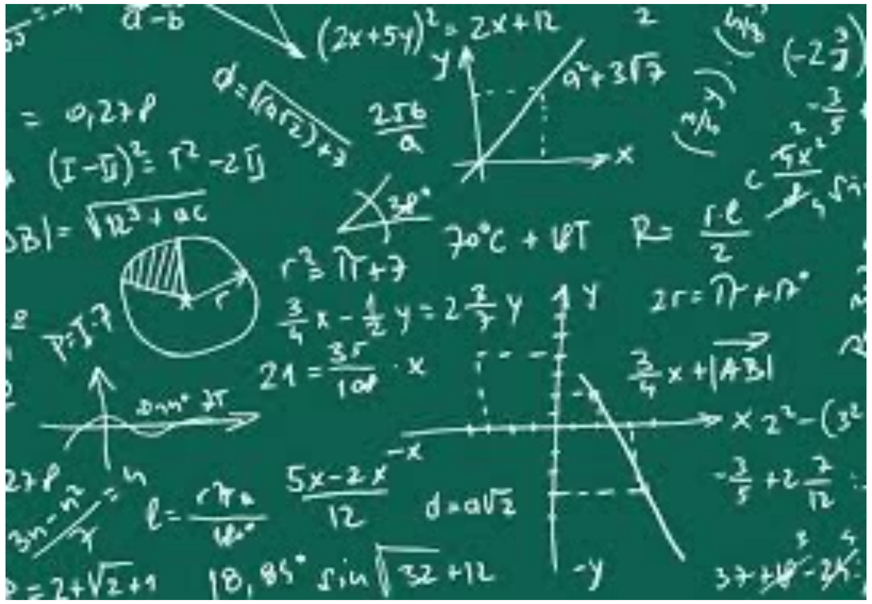
Sociology/Psychology/
Anthropology

Research Goal

- **Formally model human behavior from ambient sensor data**

- **Use these models to different real life problems**





Topics

Heavy Tail for Indoor Behavior

Markov Model for Indoor Behavior

Inverse Reinforcement Learning Model of Indoor Behavior

Formal Models of Indoor Behavior — Challenges

Why is this hard?

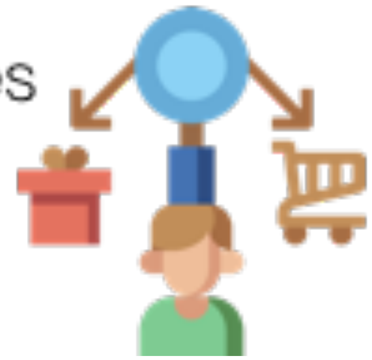
– Human behavior is highly complex

– Activities vary over time

– Interdependencies among activities

– Habit with periodic behaviors

– Individual preferences



Model requirements

– Capture activities in continuous time

– Predict the relationship between activities and health status

– Provide timely and interpretable prediction

Topic1

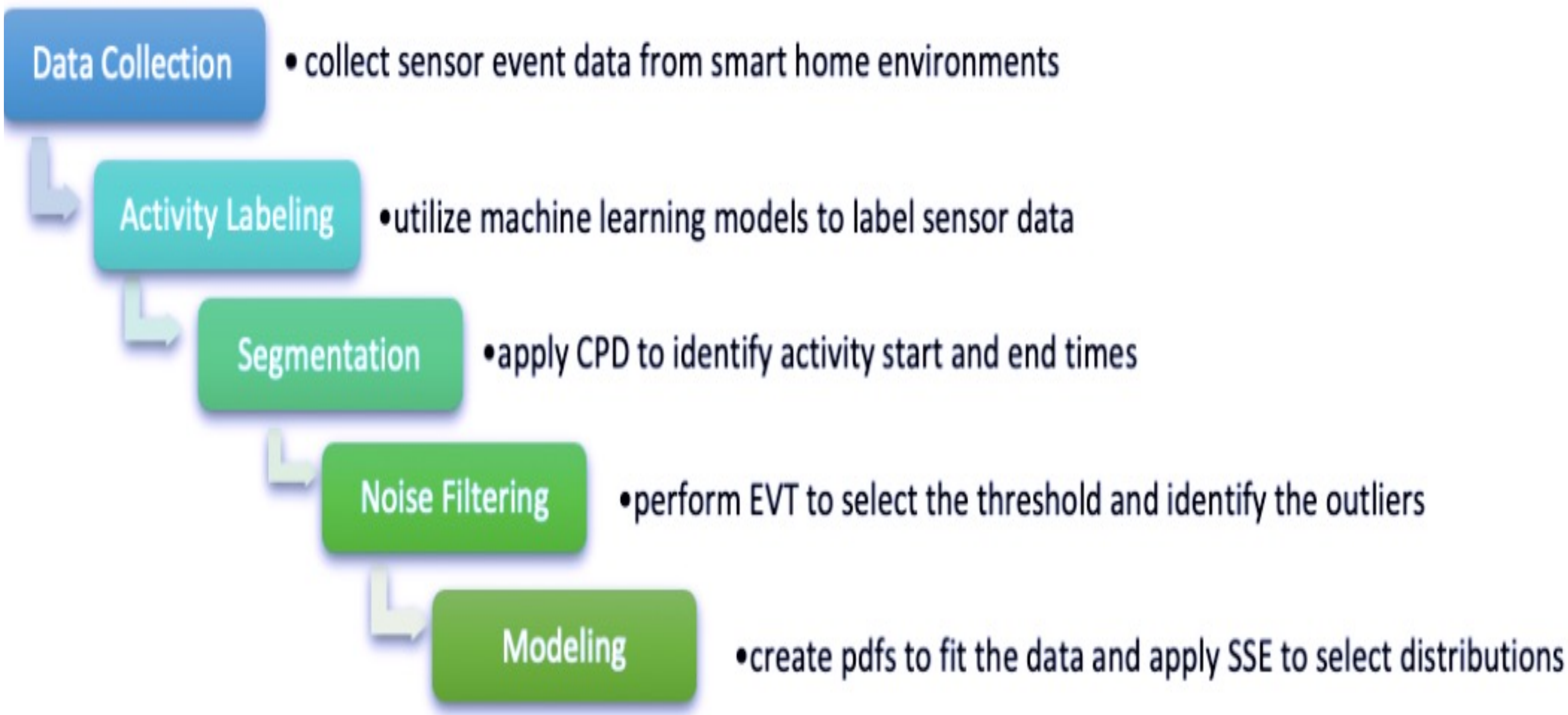
Heavy Tail for Indoor Behavior

Motivation --Formal Models of Indoor Behavior

Detect indoor behavior changes
Automatically recognize behavior patterns

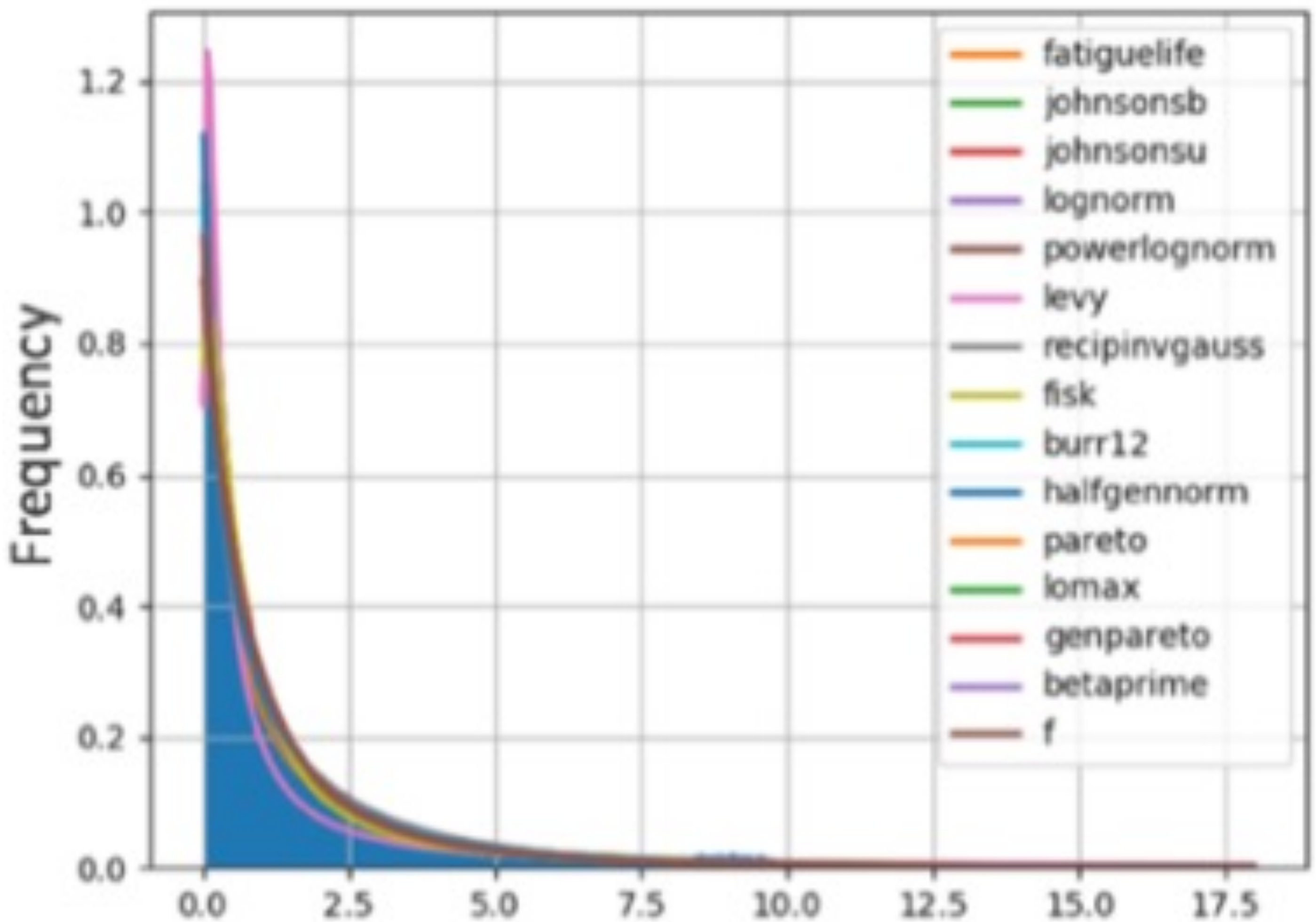
Automatic diagnosis systems
Deliver effective healthcare interventions

Methodology --Formal Models of Indoor Behavior



Methodology --Formal Models of Indoor Behavior

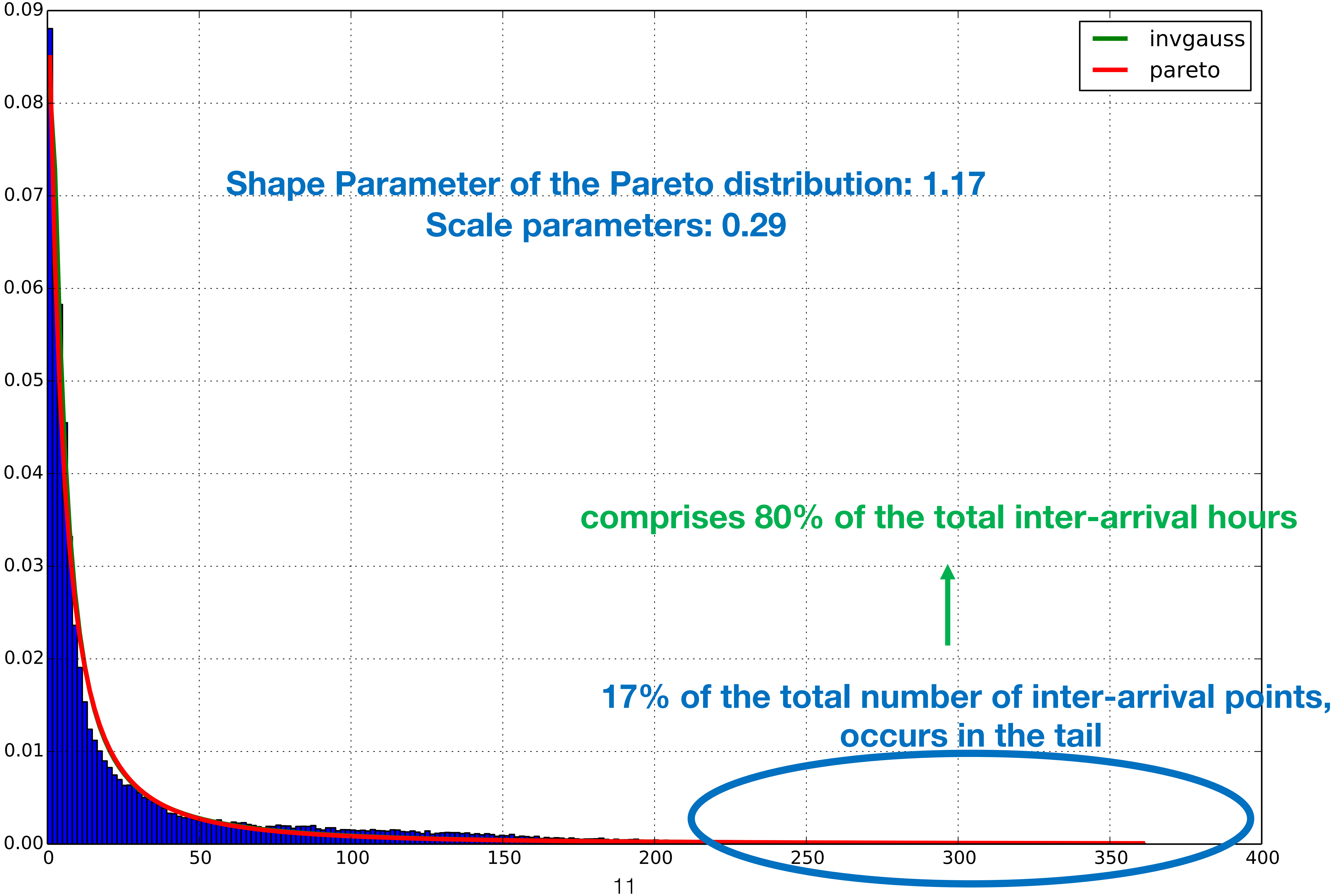
Stochastic approaches to study inter-arrival times of activities



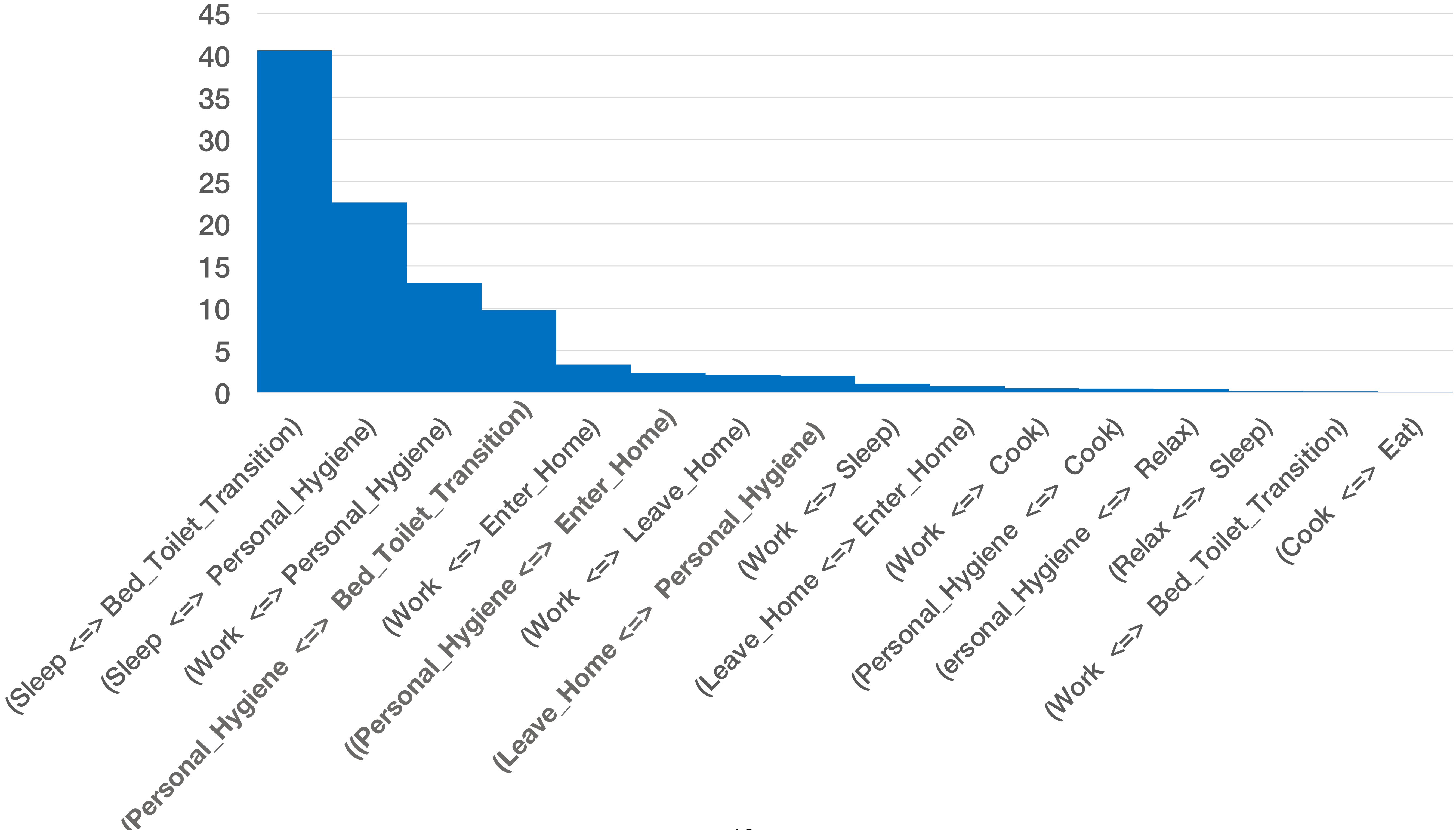
Inter-Arrival Time of Personal Hygiene (hours)

$$f(x; \alpha, \beta) = \alpha\beta^{\alpha} / x^{\alpha+1}$$

Results - Single-Person Analysis

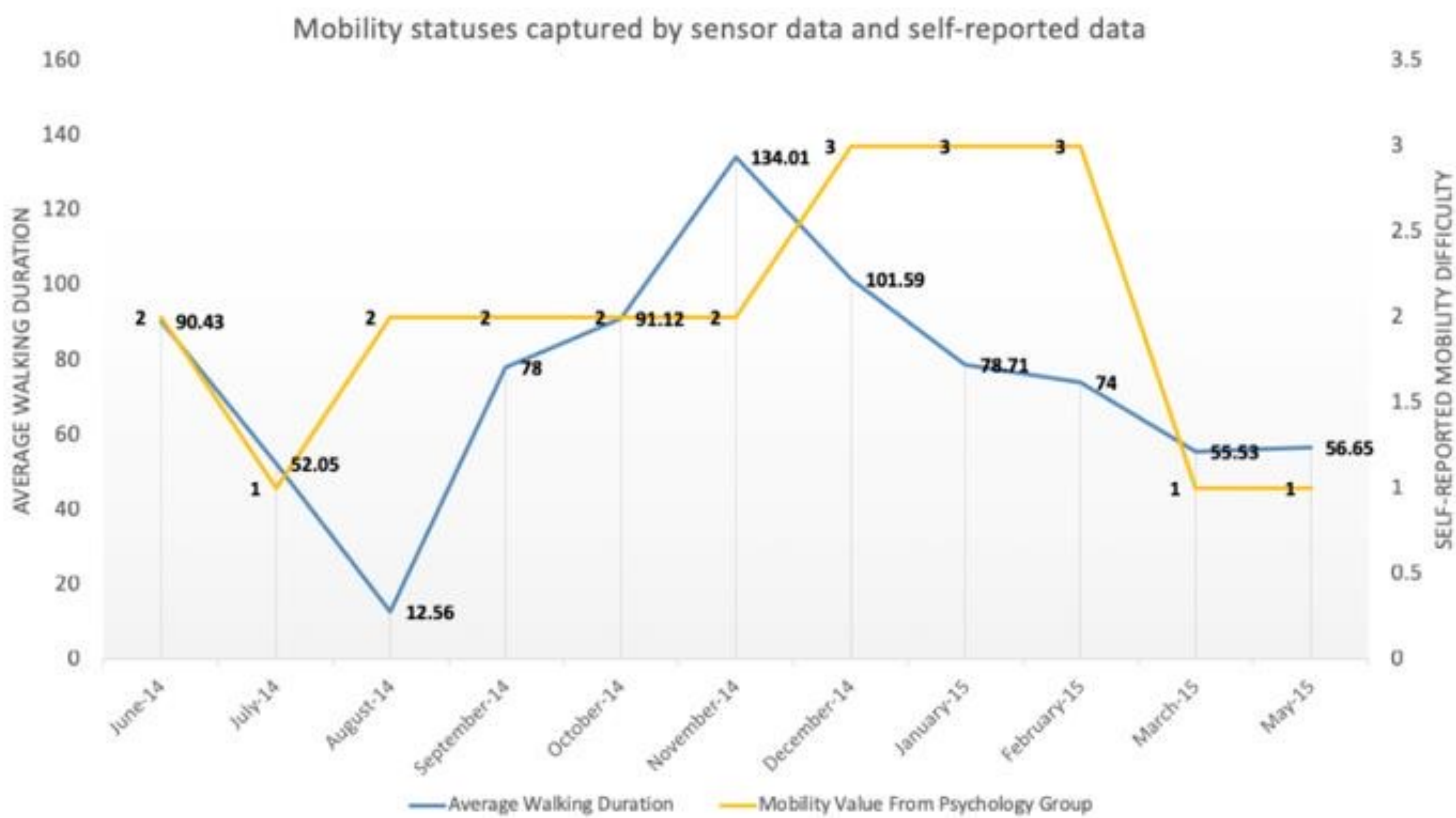


Results - Single-Person Analysis



Impact --Formal Models of Indoor Behavior

The trend of a resident's mobility difficulty



Topic2

Heavy Tail for Indoor Behavior

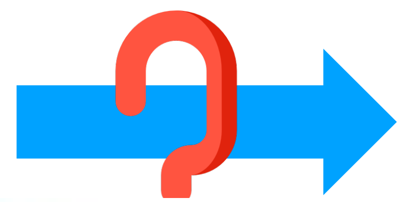
Markov Model for Indoor Behavior

Motivation --Formal Models of Indoor Behavior

Stochastic approaches to study behavior random walks on Markov chains (MC)

Cognitive Decline

shrm.org

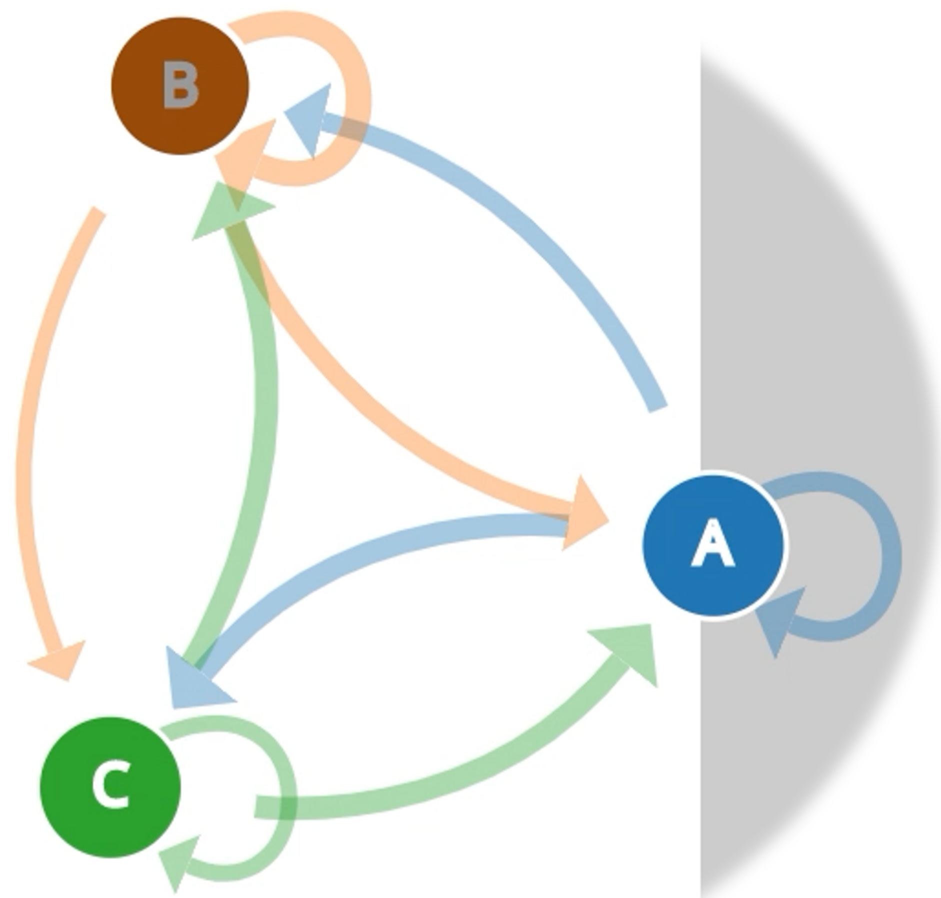


Behaviors are Random or Markovian

What is Markov Models?

Motivation --Formal Models of Indoor Behavior

Markov Chains



Markov Model of Indoor Behavior - Hypothesis

1. Examine the question of whether a person's indoor activities are Markovian.

2. Identify the Markov order that best fits behavior-driven sensor data.

3. Select the orders of Markov models that best capture resident activities.

4. Perform this process on different population subgroups.
   (health status on formal models of human behavior)

Markov Model of Indoor Behavior – Markovian

1. **Inter-arrival times of indoor activities can be described by Pareto distribution**

2. **A Pareto distribution is a special case of Lévy flight**

3. **A Lévy flight is a Markovian stochastic process**

↓

indoor resident behavior captured by sensors is a Markov process

Methodology --Formal Models of Indoor Behavior

Sensor Data → Select Models For Each subgroups

Propose new measures → Generate Synthetic Data → Test Measures Performance

Markov Model of Indoor Behavior – Order Selection

Current measures

$$\mathrm{AIC} = -2\log(\mathcal{L}(\hat{\theta}|\mathrm{data})) + 2\mathrm{K}$$

Good if N/K < 40

$$\cancel{\mathrm{AIC_c} = AIC + \frac{\mathrm{K(K+1)}}{\mathrm{N-K-1}}}$$

$$\cancel{\mathrm{CAIC} = -2\log(\mathcal{L}(\hat{\theta}|\mathrm{data})) + \mathrm{K}(\log(N)+1)}$$

$$\mathrm{BIC} = -2\log(\mathcal{L}(\hat{\theta}|\mathrm{data})) + \mathrm{K}\log(\mathrm{N})$$

$$\mathrm{HQIC} = -2\log(\mathcal{L}(\hat{\theta}|\mathrm{data})) + 2\mathrm{K}\log(\log(\mathrm{N}))$$

$\hat{\theta}$: maximum likelihood estimate

$\mathcal{L}(\hat{\theta}|\mathrm{data})$: likelihood of the model

K : # of model parameters

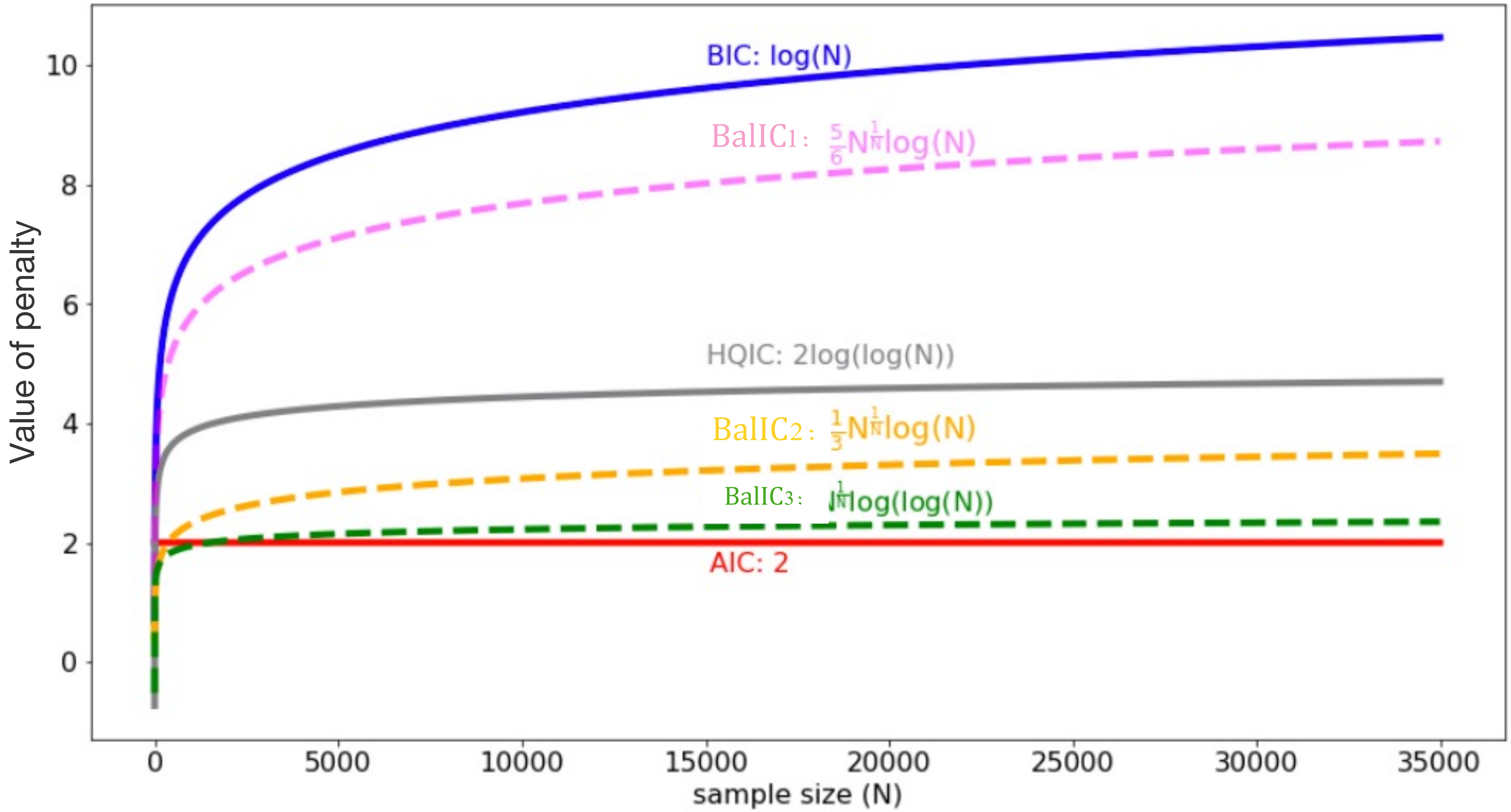
N : sample size

New Measure: BalIC (Balanced Information Criteria)

$$\mathrm{BalIC}_1 = -2\log(\mathcal{L}(\hat{\theta}|\mathrm{data})) + \frac{5}{6}\mathrm{K}N^{\frac{1}{N}}\log(\mathrm{N})$$

$$\mathrm{BalIC}_2 = -2\log(\mathcal{L}(\hat{\theta}|\mathrm{data})) + \frac{1}{3}\mathrm{K}N^{\frac{1}{N}}\log(\mathrm{N})$$

$$\mathrm{BalIC}_3 = -2\log(\mathcal{L}(\hat{\theta}|\mathrm{data})) + \mathrm{K}N^{\frac{1}{N}}\log(\log(\mathrm{N}))$$

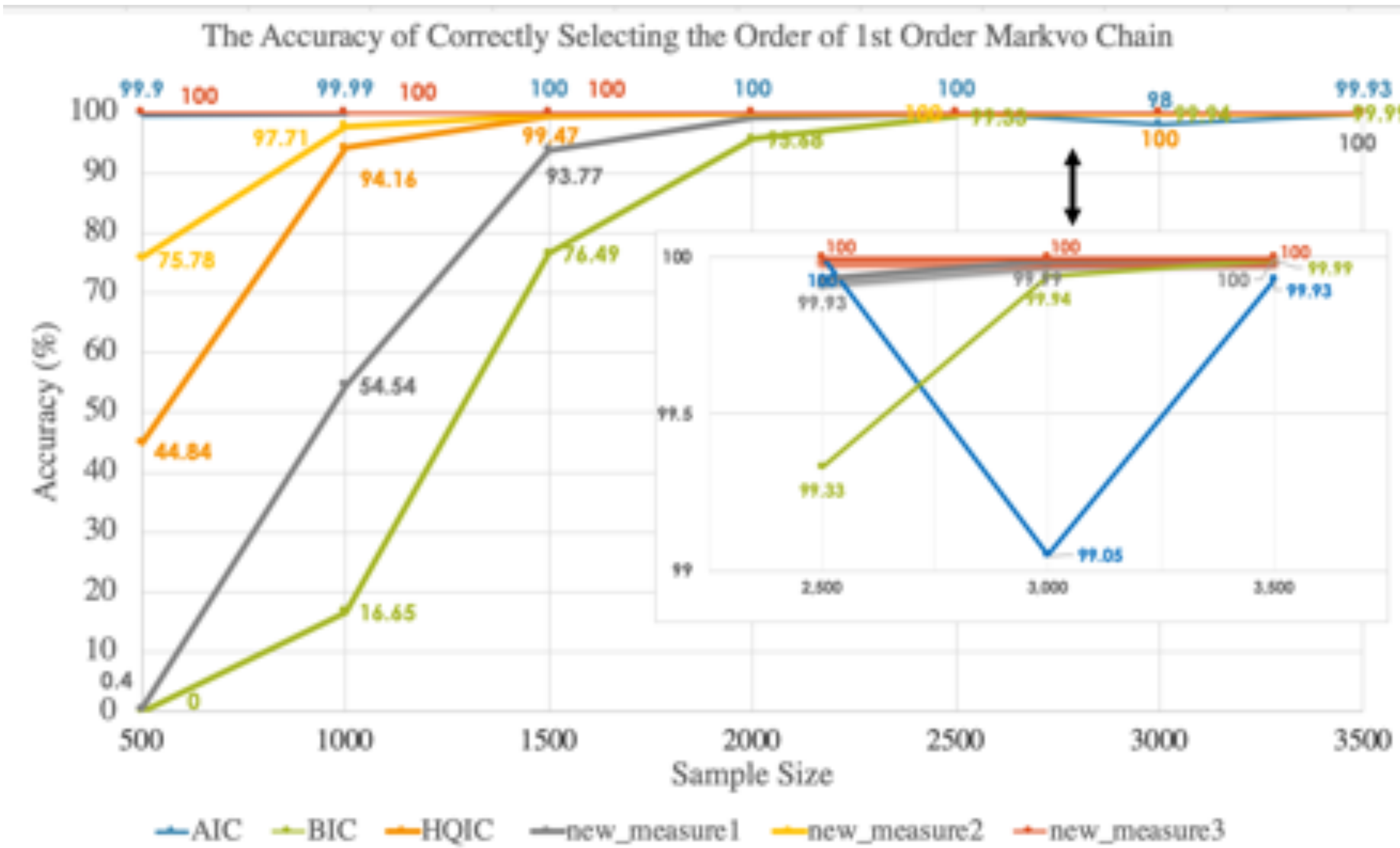


Methodology --Formal Models of Indoor Behavior

New Measure:

Convergence based on the sample size

Not select the over-simplified model



$$\text{new\_measure}_3 = -2\log(\mathcal{L}(\hat{\theta}|\text{data})) + KN^{\frac{1}{N}}\log(\log(N))$$

Markov Model of Indoor Behavior – Smart Home Data

2011-06-13 10:23:15.231817 Kitchen OFF Wash_Dishes
2011-06-13 10:23:16.156653 Kitchen ON Wash_Dishes
2011-06-13 10:23:17.277543 Kitchen OFF Wash_Dishes
2011-06-13 10:23:17.804728 Kitchen ON Wash_Dishes
2011-06-13 10:23:18.459437 Kitchen ON Cook
2011-06-13 10:23:19.612122 Kitchen OFF Cook
2011-06-13 10:23:19.739553 Kitchen OFF Cook
2011-06-13 10:23:20.253069 Kitchen ON Cook

Groups	The Selected Order Based on Different Measures			
	AIC	BIC	HQIC	BalIC$_3$
entire dataset	4	3	4	4
young	3	3	3	3
middle aged	3	2	3	3
middle aged double	3	2	3	3
middle aged single	3	2	2	3
middle aged healthy	3	2	3	3
middle aged health complaints	2	1	2	2
middle aged and senior	3	2	2	3
seniors	4	3	3	4
senior single	3	3	3	3
senior double	3	3	3	3
senior single healthy	3	3	3	3
senior single health complaints	3	3	3	3

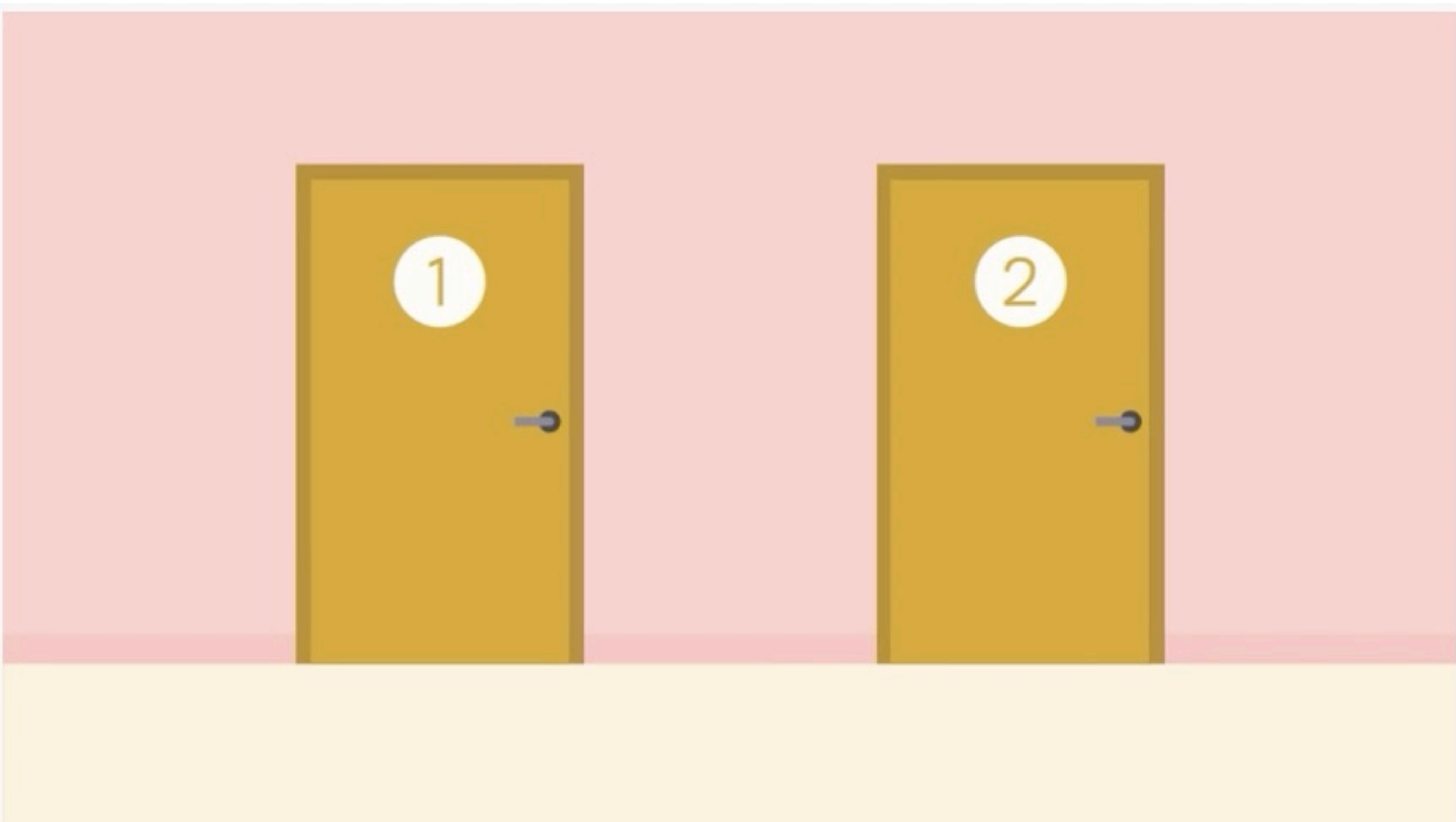
Topic3

Heavy Tail for Indoor Behavior

Markov Model for Indoor Behavior

Inverse Reinforcement Learning Model of Indoor Behavior

Decision Making



Motivation

Detect indoor behavior changes
Automatically recognize behavior patterns

Automatic diagnosis systems
Deliver effective healthcare interventions

Inverse Reinforcement Learning (IRL) of Indoor Behavior - Hypothesis

1. Model navigation patterns as a Markov decision process

2. Design the spatio-temporal features of indoor navigations

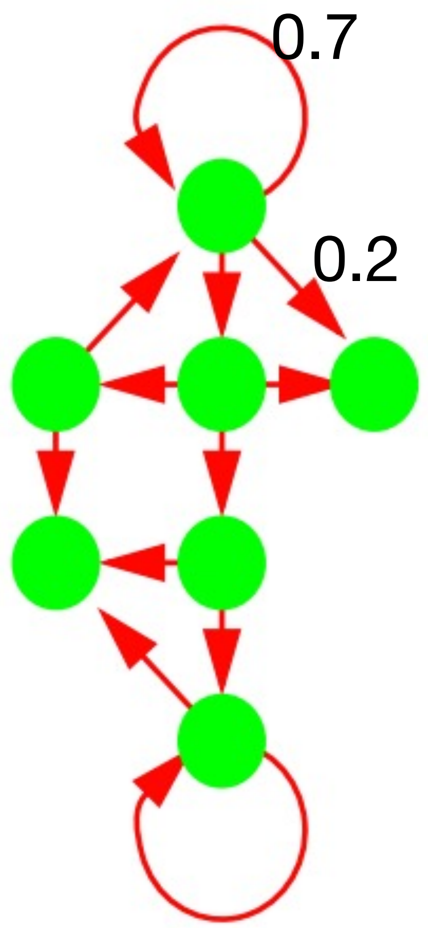
3. Learn a behavior strategy that is consistent with the observed movement patterns

4. Analyze behavior patterns and differences on different subgroups (eight actual smart homes)

Inverse Reinforcement Learning (IRL) of Indoor Behavior - Definitions

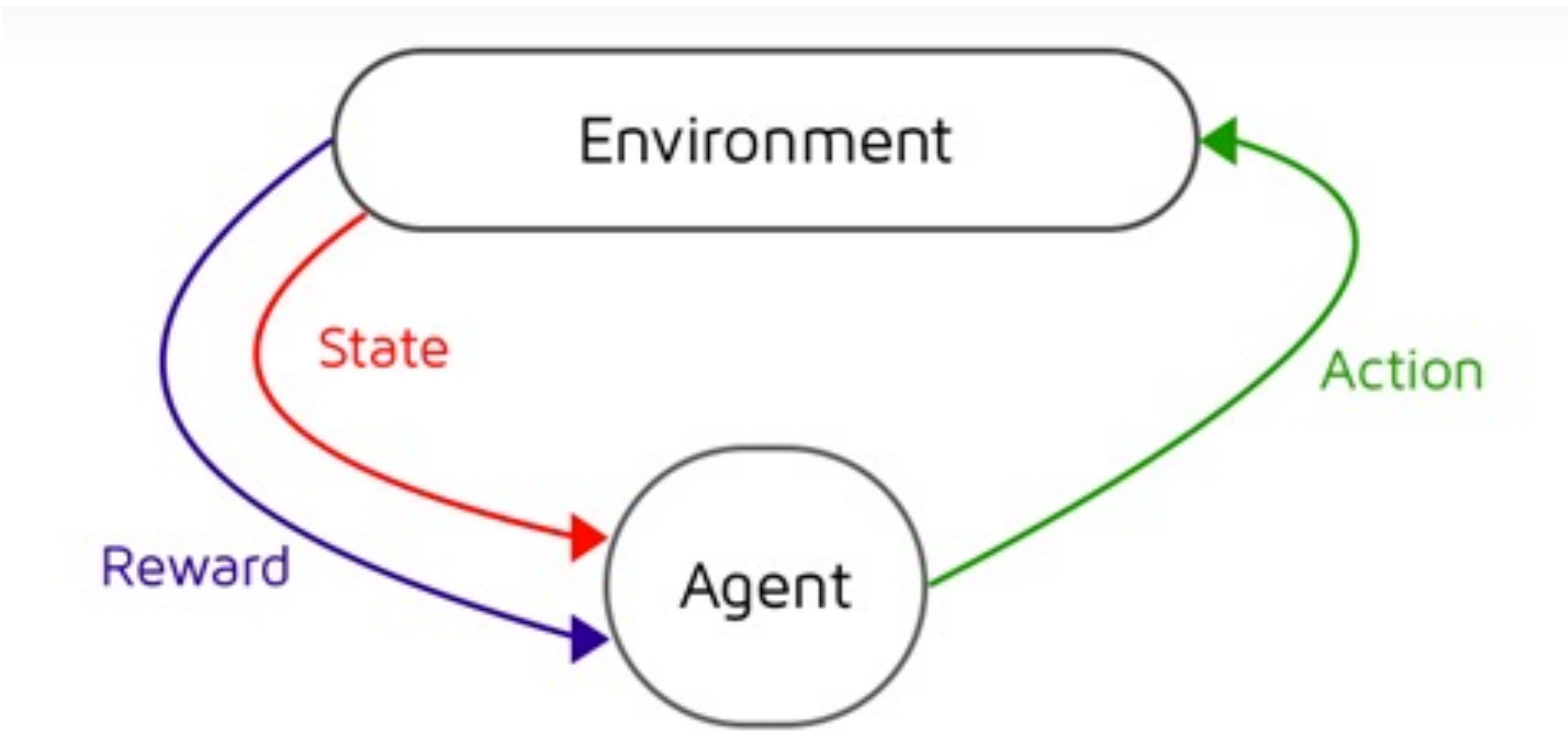
A *Markov Decision Process* (MDP) model contains:

- A set of possible states *S*
- A set of possible actions *A*
- A real valued reward function *R(s, a)*
- A transition matrix *P*

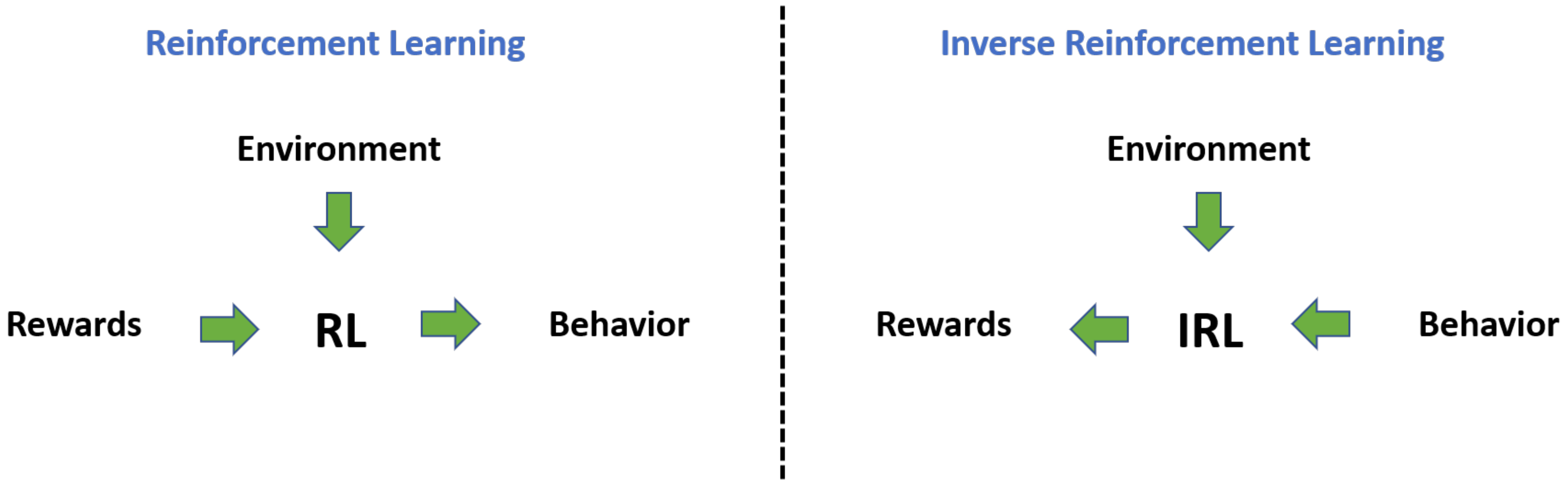


Inverse Reinforcement Learning (IRL) of Indoor Behavior - RL

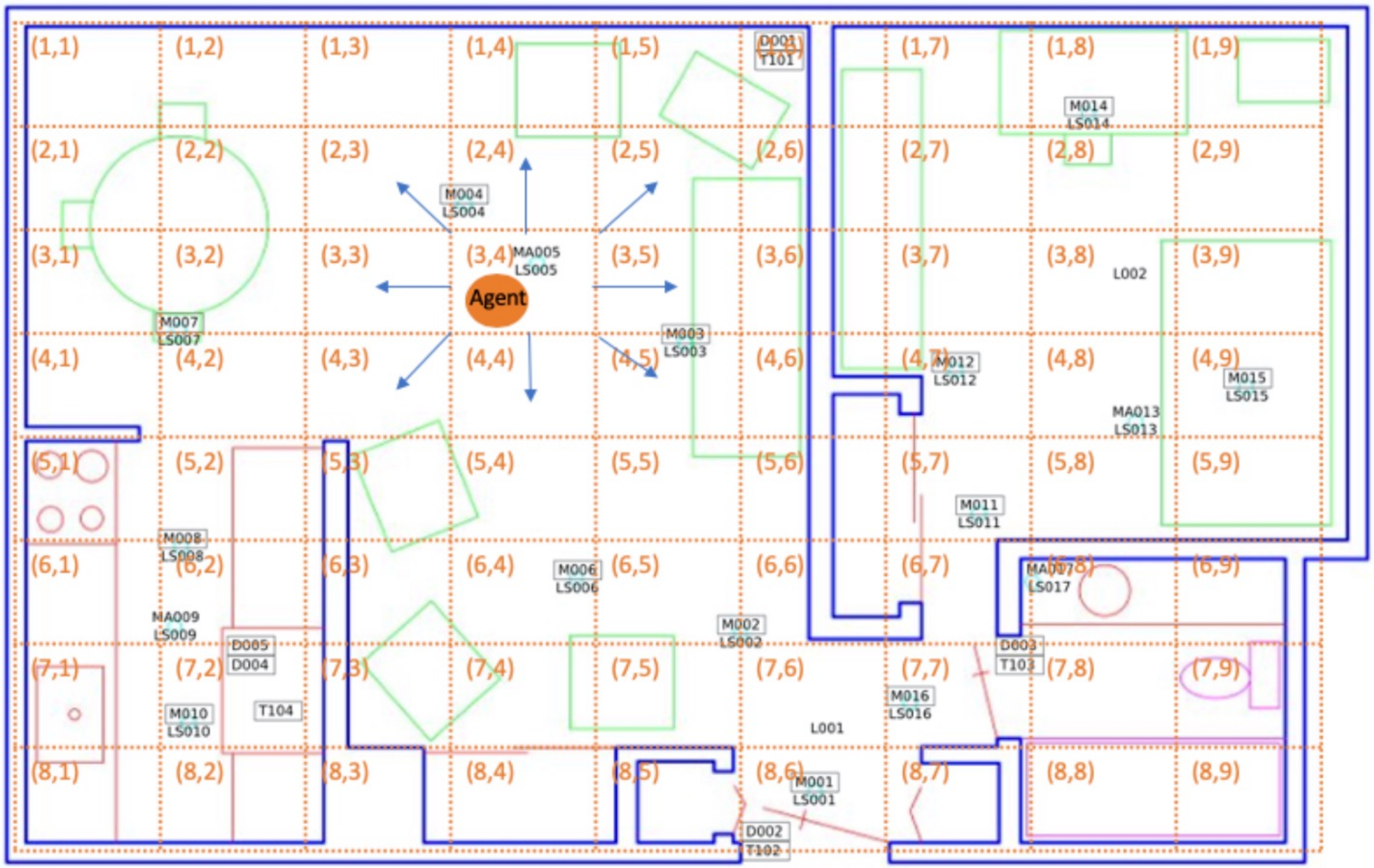
Reinforcement Learning (RL):



Inverse Reinforcement Learning (IRL) of Indoor Behavior – RL v.s. IRL



Inverse Reinforcement Learning (IRL) of Indoor Behavior – Navigation



d_toilet	d_bathroom_sink	d_livingroom_chair	d_kitchen_sink
d_bedroom	d_kitchen	d_livingroom	d_hallway
d_stove	d_office_chair	o_toilet	o_livingroom_chair
o_kitchen_sink	o_office_chair		

Inverse Reinforcement Learning (IRL) of Indoor Behavior – Algorithm

Algorithm : Resident Relative Entropy IRL (RRE-IRL)

input : a set of residents' trajectories $\mathcal{T}$

output : the reward function (the preference vector) θ

initialize: the preference vector θ

while $(\frac{\hat{\partial}}{\partial \theta_i} g(\theta) > \epsilon_i)$ **do**

calculate $\frac{\hat{\partial}}{\partial \theta_i} g(\theta) = \hat{\mu}_i - \frac{\sum_{\tau \in \mathcal{T}_N^\pi} \frac{A_{tran}}{\pi(\tau)} \exp(\theta \cdot \phi^\tau) \phi_i^\tau}{\sum_{\tau \in \mathcal{T}_N^\pi} \frac{A_{tran}}{\pi(\tau)} \exp(\theta \cdot \phi^\tau)} - \alpha_i \cdot \epsilon_i,$

update $\theta_i \longleftarrow \theta_i + \alpha_i \cdot \frac{\hat{\partial}}{\partial \theta_i} g(\theta)$

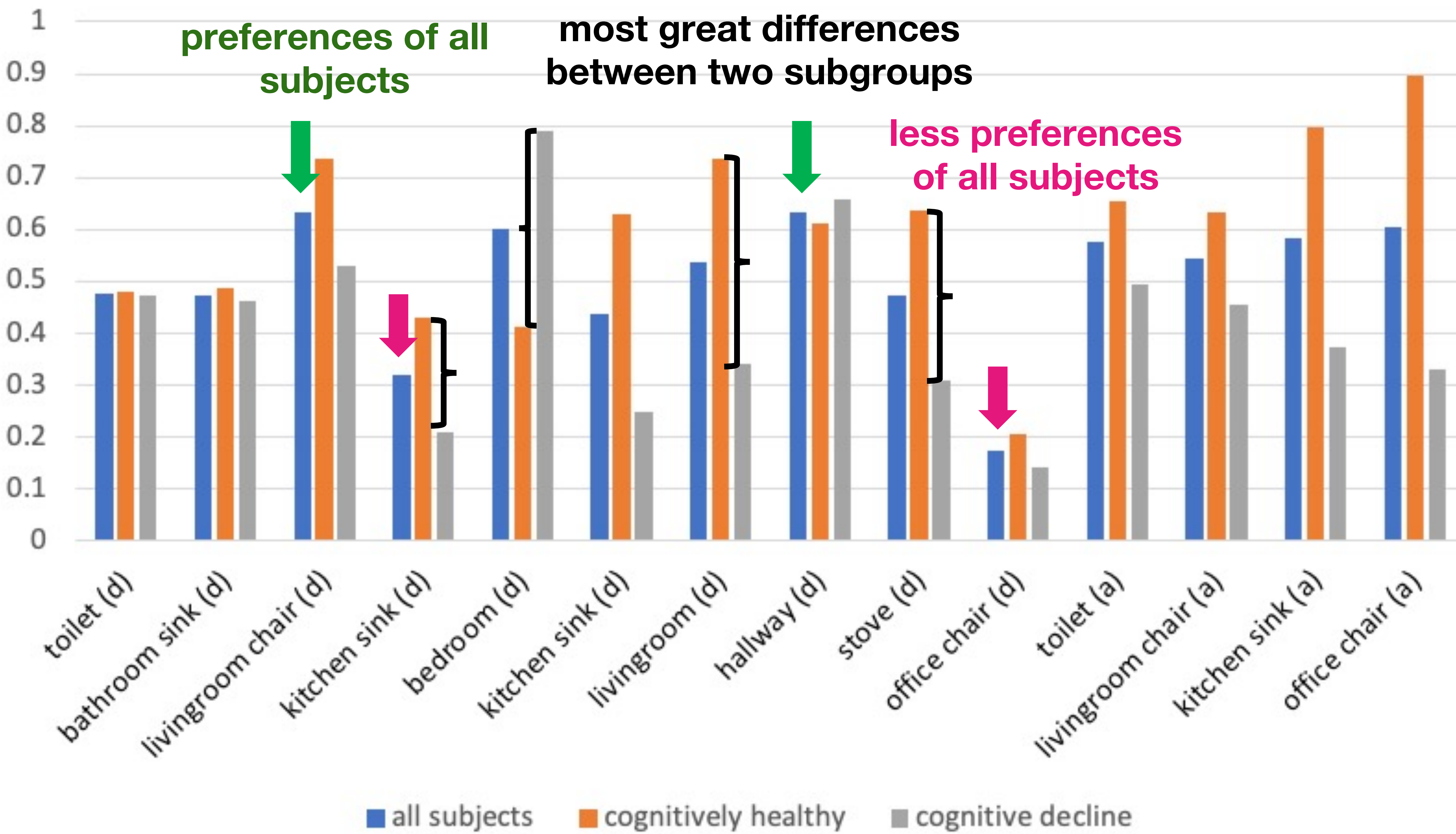
end

return θ

Inverse Reinforcement Learning (IRL) of Indoor Behavior – Datasets

Group	ID	Health Diagnosis	#Sensors	Duration of Data Collection	Number of Month-long Samples
Cognitive decline	Home 1	Mild Cognitive Impairment (MCI)	21 downward-facing motion (motion); 2 motion area (ma)	843 days	26
	Home 2	MCI	19 motion; 2 ma	223 days	7
	Home 3	MCI	26 motion; 0 ma	682 days	22
	Home 4	MCI, Early dementia	11 motion; 2 ma	149 days	5
Cognitively healthy	Home 5	Healthy	13 motion; 1 temperature	1788 days	56
	Home 6	Healthy	13 motion	1591 days	49
	Home 7	Healthy	18 motion; 2 ma	379 days	12
	Home 8	Healthy	10 motion; 1 ma	969 days	31

Inverse Reinforcement Learning (IRL) of Indoor Behavior – Results



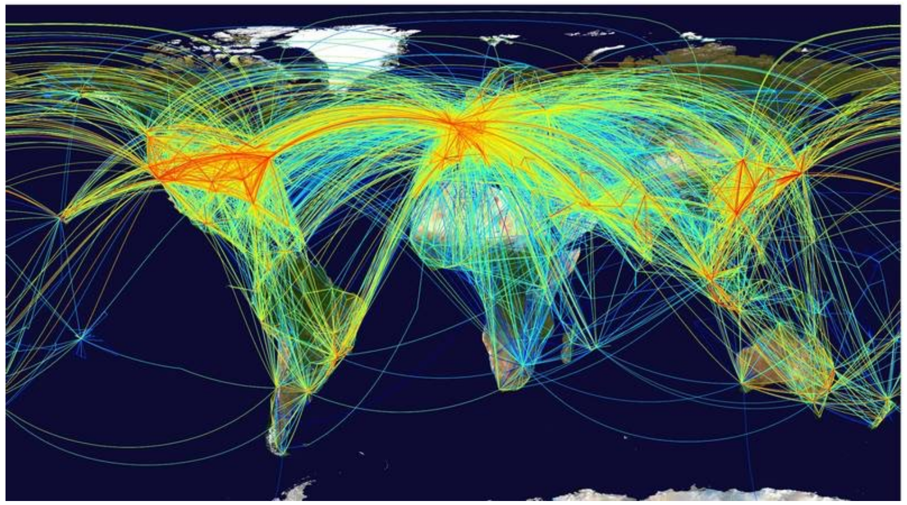
Future Work

Math Models and Machine Learning for Alzheimer's Diseases

1. **Behavior analysis**
2. **Gene analysis**

Math Models for human mobility patterns

1. **Transportation management**
2. **Resource allocation**



Thank you!