

Naive Utility Calculus2

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- 1 Introduction
- 2 Related Work
- 3 NUC Computational Framework
- 4 Experiments
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How do we make sense of other people's
behavior?

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- Why did you sleep late last night?

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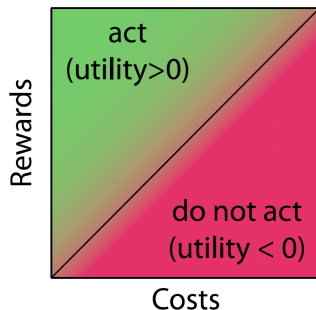
- Why did you sleep late last night?
- Why did you sign up for this course?

How do we make sense of other people's behavior?

- Why did you sleep late last night?
- Why did you sign up for this course?
- Why did you choose to eat out instead of cooking?

$$\text{Utility} = \text{Rewards} - \text{Costs}$$

- There is empirical support that humans intuitively use utility-based reasoning to make sense of other people's behavior

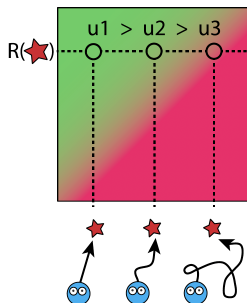


$$U(p, o) = R(o) - C(p)$$

- $U(p, o)$: utility expected from acting according to plan p to reach outcome o
- $R(o)$: subjective reward the agent expects from outcome o
- $C(p)$: subjective cost of executing plan p

- **Descriptive, not normative:** This is not about how people *should* make decisions (economic utility theory)
- **How we actually operate:** This describes how we *intuitively* make sense of other people's behavior
- People don't explicitly compute utilities when they act - this is the cognitive framework we use to understand others

Utility and Efficiency



- More efficient paths are less costly and therefore produce higher utilities
- When agents act, they will fulfill their goals as efficiently as possible to maximize utility

Graded Preference Inference

added

Costs Vary Across Agents

added

Rewards Vary Across Agents

added

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Inverse Decision-Making

added

Inverse Planning

- Inferring goals and preferences from observed actions
- Often modeled using Markov Decision Processes (MDPs)
- Agent state transitions and reward functions

added

Research Questions

added

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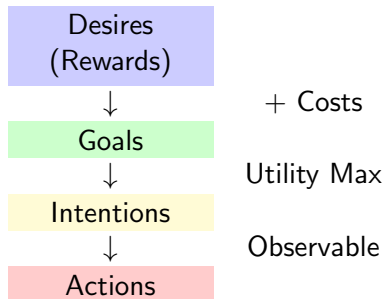
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Hierarchical Mind Model

Level	Component	Observable?
4	Desires (Reward functions)	No
3	Goals (World states)	No
2	Intentions (Goal sequences)	No
1	Actions (Behaviors)	Yes

↓ Inference Direction ↑

Generative Process



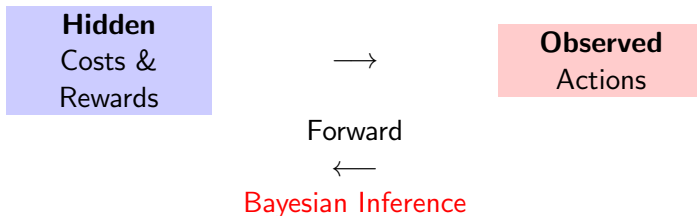
Goal: Reach Object A

$$V^*(s) = \max_a \sum_{s'} P(s'|s, a) [R(a, s) - C(a, s) + \gamma V^*(s')]$$

Policy: $p(a|s) \propto \exp(\sum_{s'} P(s'|s, a) V^*(s') / \alpha)$

Each goal \rightarrow Separate MDP \rightarrow Efficient path

The Inference Problem



$$p(C, R|A) \propto p(A|C, R) \cdot p(C, R)$$

Two Types of Rationality

Type	What	Formula
Rational Choice	Intention selection	$p(I C, R) \propto \exp(U(I)/\beta)$
Rational Action	Efficient execution	$p(A I)$ via MDP policy

Likelihood: $p(A|C, R) = \sum_I p(A|I) \cdot p(I|C, R)$

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Experimental Setup

added

Experiment 1

added

Experiment 2

added

Experiment 5

added

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- Summary of key points
- Main takeaways from this presentation
- Future directions and next steps
- Questions and discussion