

Utility Theory for Sequential Decision Making

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- We extend this theory to sequential decision making.

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$$\mathcal{O} = \{\square, \circ, \triangle\}$$

$$M = p_1 \square + p_2 \circ + p_3 \triangle \quad (p_1 + p_2 + p_3 = 1)$$

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Definition (Utility function)

A function $u : \mathcal{L} \rightarrow \mathbb{R}$, such that for all $M, N \in \mathcal{L}$,

$$M \succsim N \iff u(M) \geq u(N).$$

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- **Continuity:** For all lotteries $M \succsim N \succsim K$, there exists $p \in [0, 1]$ such that $pM + (1 - p)K \approx N$.

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- **Independence:** For all $M, N, K \in \mathcal{L}$ and for all $p \in [0, 1]$,

$$M \succsim N \iff (1 - p)M + pK \succsim (1 - p)N + pK.$$

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Theorem (VNM Utility Theorem)

\succsim satisfies the VNM axioms \iff there exists a utility function u such that

$$u \left(\sum_{x \in \mathcal{O}} p(x)x \right) = \sum_{x \in \mathcal{O}} p(x)u(x).$$

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- **Notation**
 - ▶ transitions: t, t_1, t_2, \dots
 - ▶ trajectories: τ, τ_1, τ_2
 - ▶ lotteries: M, N, J, K

Memoryless Sequential Decision Making

Axiom (Memorylessness)

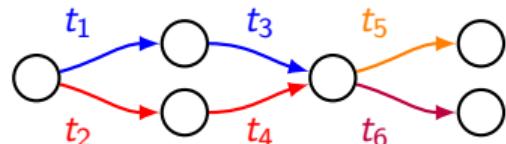
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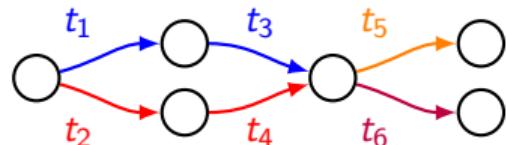
$$\langle t_1, t_3, t_5 \rangle \succsim \langle t_1, t_3, t_6 \rangle \iff \langle t_5 \rangle \succsim \langle t_6 \rangle$$

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Theorem

Utilities take the form $u(t \cdot \tau) = r(t) + m(t)u(\tau)$, where r is the reward function and m is the reward multiplier function.

An Axiom for Markov Decision Processes

Axiom (Additivity)

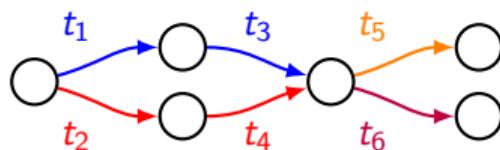
$$\begin{aligned} p(\tau_1 \cdot M) + (1 - p)J &\succsim p(\tau_1 \cdot N) + (1 - p)K \\ \iff p(\tau_2 \cdot M) + (1 - p)J &\succsim p(\tau_2 \cdot N) + (1 - p)K \end{aligned}$$

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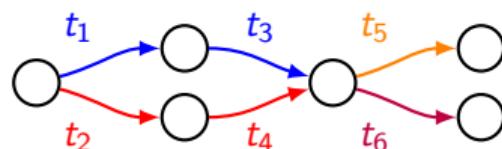
$$\langle t_1, t_3 \rangle \succsim \langle t_2, t_4 \rangle \text{ and } \langle t_5 \rangle \succsim \langle t_6 \rangle \implies \langle t_1, t_3, t_5 \rangle \succsim \langle t_2, t_4, t_6 \rangle$$

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Theorem

Utilities take the form $u(\tau) = \sum_{t \in \tau} r(t)$, where r is the reward function.

Discussion

*“That all of what we mean by **goals and purposes** can be well thought of as maximization of the expected value of the cumulative sum of a received scalar signal (called reward).”*

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- If the goal is to achieve a desired policy π^* , then we simply set

$$r(s, a, s') = \begin{cases} +1 & a = \pi^*(s) \\ -1 & \text{otherwise.} \end{cases}$$

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- goals and purposes = *rational preferences*
- Any two behaviours can be compared.
- If a given task can be represented as a *rational and additive* preference relation, then it can be modeled as an MDP.