Long-Term Values in MDPs, Corecursively

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Introduction

Joint work with Larry Moss (Indiana U.) and Frank Feys (Delft). (Paper at Coalgebraic Methods for Computer Science, 2018)

Background & Motivation:

- Coalgebra: categorical theory of systems, observable behaviour, non-wellfounded structures, modal logics.
- Markov Decision Processes (MDPs) are coalgebras.
- \Rightarrow Use coalgebraic techniques to reason about MDPs.



Decision-making Under Uncertainty

A startup company has to choose between Saving and Advertising.



- State set *S*, action set *A*.
- Probabilistic transitions: $t_a : S \to DS$ for all $a \in A$.
- Reward function: $u: S \to \mathbb{R}$.
- MDP is coalgebra $\langle u, t \rangle \colon S \to \mathbb{R} \times (\mathcal{D}S)^A$.

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Markov Decision Processes

State-based models of sequential decision-making under uncertainty

- In each state, the agent chooses actions, (but does not have full control over the system), and collects rewards.
- The decision maker wants to find a policy σ: S → A that maximizes future rewards
- Applications: maintenance schedules, inventory management, production planning, reinforcement learning, ...
- Classical theory is well-developed (see e.g. Puterman, 2014); uses analytic methods.
- Our motivation: develop high-level, coinductive methods.



Long-Term Value and Optimal Value Discounting criterion:

Take discounted infinite sum of expected future rewards.

Given an MDP *m* and a discounting factor $0 \le \gamma < 1$.

 The long-term value of policy σ: S → A in the state s is the discounted infinite sum:

$$V^{\sigma}(s) = \sum_{n=0}^{\infty} \gamma^n \cdot r_n^{\sigma}(s)$$

where $r_n^{\sigma}(s) =$ expected reward after *n* steps, starting from *s*, following σ .

• The optimal value of *m* in state *s* is

$$V^*(s) = \max_{\sigma} \{ V^{\sigma}(s) \}$$

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Fixpoint Characterisation of V^{σ}

Given an MDP *m* and a discounting factor $0 \le \gamma < 1$.

• The long-term value of policy $\sigma: S \to A$ is the unique function $V^{\sigma}: S \to \mathbb{R}$ such that for all $s \in S$:

$$V^{\sigma}(s) = u(s) + \gamma \sum_{s' \in S} t_{\sigma(s)}(s)(s') V^{\sigma}(s')$$

Our observation: This is equivalent to V^σ being coalgebra-to-algebra morphism:

$$S \xrightarrow{m_{\sigma} = \langle u, t_{\sigma} \rangle} \mathbb{R} \times \mathcal{D}S \qquad \text{fixpt of } \Psi_{\sigma}(v) = u + \gamma t_{\sigma} v$$
$$\downarrow^{\sigma} \downarrow \mathbb{R} \times \mathcal{D}(v^{\sigma}) \qquad \mathbb{R} \times \mathcal{D}\mathbb{R}$$

where $t_{\sigma}(s) = t_{\sigma(s)}(s)$, E: $\mathcal{D}\mathbb{R} \to \mathbb{R}$ computes expected value, and $\alpha_{\gamma} : \mathbb{R} \times \mathbb{R} \to \mathbb{R}$ maps $(x_1, x_2) \mapsto x_1 + \gamma \cdot x_2$.

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Fixpoint Characterisation of V^* Similarly,

• The optimal value of *m* is the unique function $V^*: S \to \mathbb{R}$ that satisfies the Bellman Equation:

$$V^{*}(s) = u(s) + \gamma \max_{A} \sum_{s' \in S} t(s)(a)(s')V^{*}(s')$$

• Our observation: This is equivalent to V* being coalgebra-to-algebra morphism:

where $\max_A : \mathbb{R}^A \to \mathbb{R}$.

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Universal Property as Definition Principle

• $\alpha: F(Y) \to Y$ is a corecursive algebra (for functor F)



- Our algebras are corecursive only for a subclass of f: X → F(X) (unique only among bounded maps).
- We give categorical conditions for how to obtain V^{σ} and V^* from a universal property (axiomatise properties of bounded maps).

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Coinductive Reasoning About Optimal Policies

We say $\sigma \ge \tau$ if $V^{\sigma} \ge V^{\tau}$ (pointwise). A policy σ is optimal if for all policies τ , $\sigma \ge \tau$.

Some basic facts, see e.g. (Puterman, 2014)

- If σ is optimal, then $V^{\sigma} = V^*$.
- Optimal policies need not be unique.
- Stationary (memory-free), deterministic policies suffice.
- Several algorithms for computing optimal policy:
 - policy iteration
 - value iteration
 - linear programming
 - (plus variations)



Policy Improvement

1 Initialise σ_0 to any policy.

- **2** Compute V^{σ_k} (e.g. by solving system of linear equations).
- **3** Define σ_{k+1} by

$$\sigma_{k+1}(s) \quad := \quad \operatorname{argmax}_{a \in \mathcal{A}} \sum_{s' \in \mathcal{S}} t(s, a, s') V^{\sigma_k}(s')$$

4 If $\sigma_{k+1} = \sigma_k$ then stop, else go to step 2. Why is $\sigma_k \le \sigma_{k+1}$?

Policy Improvement Lemma:

$$t_{\sigma}V^{\sigma} \leq t_{\tau}V^{\sigma} \quad \Rightarrow \quad V^{\sigma} \leq V^{\tau}$$

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Contraction Coinduction Principle

Theorem Let (M, d, \leq) be a non-empty, complete ordered metric space. If $f: M \to M$ is contractive and order-preserving, then the fixpoint x^* of f is a least pre-fixpoint (if $f(x) \leq x$, then $x^* \leq x$), and also a greatest post-fixpoint (if $x \leq f(x)$, then $x \leq x^*$).

Proof of policy improvement: Apply to contractive and order-preserving

$$\Psi_{\sigma} \colon \mathbb{R}^{S} \to \mathbb{R}^{S} \qquad \Psi_{\sigma}(v) = u + \gamma T_{\sigma} v.$$

$$t_ au V^\sigma \geq t_\sigma V^\sigma \quad \Rightarrow \quad \Psi_ au(V^\sigma) \geq \Psi_\sigma(V^\sigma) = V^\sigma \quad \Rightarrow \quad V^ au \geq V^\sigma$$

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Concluding

We have:

- identified coalgebraic and algebraic structure in the theory of MDPs
- given coinductive proof of policy improvement.

Related work

- Equilibria in infinite games without discounting (Abramsky & Winschel)
- Semantics of equilibria (Pavlovic)
- Open games (Hedges, Ghani,...)

