

Compositionality for Markov Reward Chains with Fast Transitions

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Outline

Introduction

- Motivation

- Recapitulation: Markov Chains

Aggregation methods

- Discontinuous Markov reward chains

 - Ordinary lumping

 - Reduction

- Markov reward chains with fast transitions

 - τ -lumping

 - τ -reduction

- Relational properties

Parallel composition

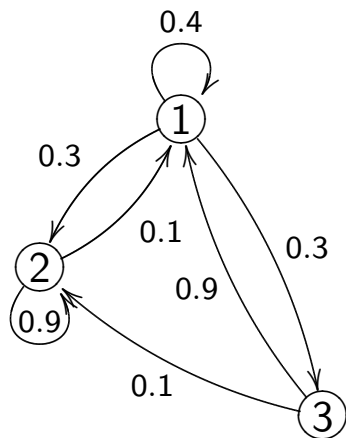
Markov Reward Chains

- ▶ Among most important and wide-spread analytical performance models
- ▶ Ever growing complexity of Markov reward chain systems
- ▶ Compositional generation: Composing a big system from several small components
- ▶ State space explosion: Result size is product of sizes of components
- ▶ Need aggregation methods...
- ▶ ...and they should be compositional
- ▶ We consider special models of Markov reward chains: Discontinuous Markov reward chains and Markov reward chains with fast transitions

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Discontinuous Markov reward chains and Markov reward chains with fast transitions

Recapitulation: Discrete time Markov chains

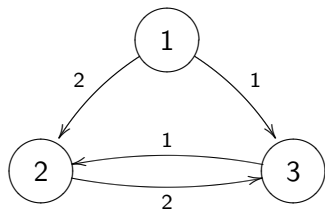


Transition probability matrix:

	1	2	3
1	0.4	0.3	0.3
2	0.1	0.9	0
3	0.9	0.1	0

- ▶ Graphs with nodes representing states
- ▶ Outgoing arrows determine stochastic behavior of each state
- ▶ Probabilities only depend on current state

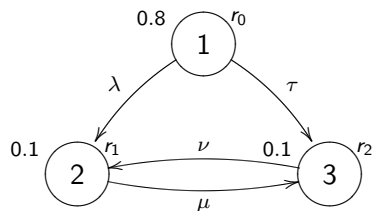
Continuous time Markov chains



► Generator matrix:

$$\begin{array}{c|ccc} & 1 & 2 & 3 \\ \hline 1 & -3 & 1 & 2 \\ 2 & 0 & -2 & 2 \\ 3 & 0 & 1 & -1 \end{array} = Q$$

Continuous time Markov reward chains



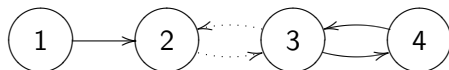
- ▶ $P = (\sigma, Q, \rho)$
- ▶ σ is a stochastic row initial probability vector $(0.8, 0.1, 0.1)$
- ▶ ρ is a state reward vector (r_0, r_1, r_2)
- ▶ Transition probability matrix

$$P(t) = \sum_{n=0}^{\infty} \frac{Q^n t^n}{n!} = e^{Qt}$$

- ▶ Rewards are used to measure performance (application dependent).

Discontinuous Markov reward chains

- ▶ Markov chains with instantaneous transitions \rightarrow discontinuous Markov chains
- ▶ Discontinuous Markov reward chain: $P = (\sigma, \Pi, Q, \rho)$
- ▶ Intuition: $\Pi[i, j]$ denotes probability that a process occupies two states via an instantaneous transition.
- ▶ $\Pi = I$ leads to a standard Markov chain \rightarrow generalization



Discontinuous Markov reward chains

Aggregation for discontinuous Markov reward chains

- ▶ Ordinary lumping
- ▶ Reduction

Ordinary lumping

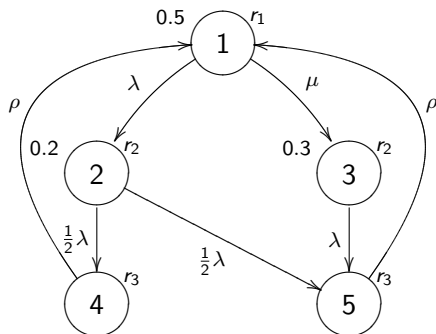
- ▶ We lump $P = (\sigma, \Pi, Q, \rho)$ to $\bar{P} = (\bar{\sigma}, \bar{\Pi}, \bar{Q}, \bar{\rho})$
- ▶ Partition \mathcal{L} is an ordinary lumping
- ▶ $P \xrightarrow{\mathcal{L}} \bar{P}$

Ordinary lumping

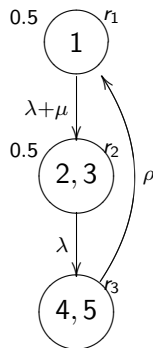
- ▶ $P \xrightarrow{\mathcal{L}} \bar{P}$
- ▶ Partition of the state space into classes
- ▶ States lumped together form a class
- ▶ Equivalent transition behavior to other classes (intuitively: probability of class is sum of probabilities of states)
- ▶ All states in a class have the same reward, total reward is preserved

Example

► $P \xrightarrow{\mathcal{L}} \bar{P}$



$\{\{1\}, \{2,3\}, \{4,5\}\}$



Reduction

- ▶ We reduce $P = (\sigma, \Pi, Q, \rho)$ to $\bar{P} = (\bar{\sigma}, I, \bar{Q}, \bar{\rho})$
- ▶ $P \rightarrow_r \bar{P}$
- ▶ Result is unique up to state permutation.
- ▶ Canonical product decomposition of Π
- ▶ Reduced states are given by ergodic classes of the original process (ergodic = each state can be reached from each other state in finite time)
- ▶ Total reward is preserved

Markov reward chains with fast transitions

Markov reward chains with fast transitions

- ▶ Definition
- ▶ Aggregation

Markov reward chains with fast transitions

- ▶ Adds parameterized (“fast”) transitions to a standard Markov reward chain.
- ▶ Uses two generator matrixes Q_s and Q_f , for slow and fast transitions.
- ▶ $P = (\sigma, Q_s, Q_f, \rho)$ is a function...
- ▶ ...where to each $\tau > 0$ a Markov reward chain $P_\tau = (\sigma, I, Q_s + \tau Q_f, \rho)$ is assigned
- ▶ The limit $\tau \rightarrow \infty$ makes fast transitions instantaneous, and we end up with a discontinuous Markov reward chain.

Markov reward chains with fast transitions

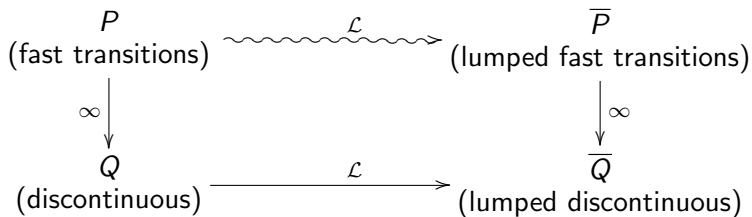
Aggregation for Markov reward chains with fast transitions

- ▶ τ -lumping
- ▶ τ -reduction

τ -lumping

- ▶ We τ -lump $P = (\sigma, Q_s, Q_f, \rho)$ to $\bar{P} = (\bar{\sigma}, \bar{Q}_s, \bar{Q}_f, \bar{\rho})$
- ▶ Can define it using the limiting discontinuous Markov reward chain.
- ▶ $P \xrightarrow{\mathcal{L}} \bar{P}$
- ▶ Not unique

τ -lumping

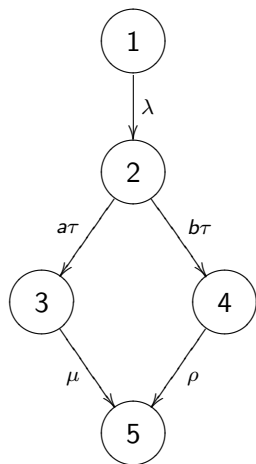


τ -reduction

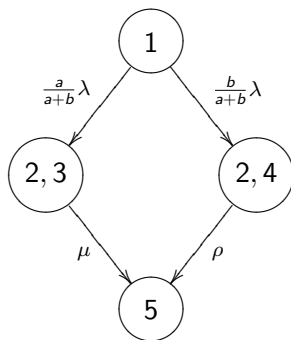
- ▶ We τ -reduce $P = (\sigma, Q_s, Q_f, \rho)$ to $R = (\bar{\sigma}, I, \bar{Q}, \bar{\rho})$
- ▶ $P \rightsquigarrow_r R$

Example

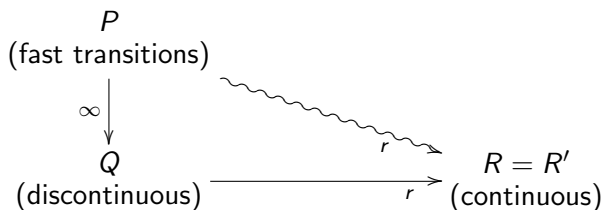
► $P \rightsquigarrow_r R$



τ -reduction \longrightarrow



τ -reduction



- ▶ if $P \rightsquigarrow_r R$
- ▶ and $P \xrightarrow{\infty} Q \xrightarrow{r} R'$
- ▶ then $R = R'$

Relational properties of ordinary lumping and τ -lumping

- ▶ Reduction works in one step, so no need to look at details of its relational properties.

Lumping:

- ▶ Need transitivity and strong confluence...
- ▶ ...to ensure that iterative application yields a uniquely determined process.
- ▶ Repeated application of ordinary lumping...
- ▶ ...can be replaced by single application of composition of individual lumpings.
- ▶ For τ -lumping, only the limit is uniquely determined.

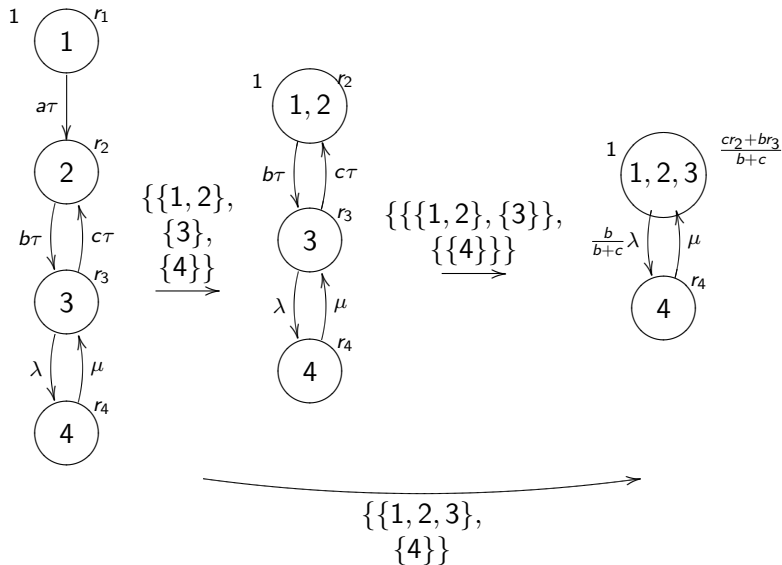
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Example



Parallel composition

- ▶ $P_1 \geq \bar{P}_1, P_2 \geq \bar{P}_2 \implies P_1 \parallel P_2 \geq \bar{P}_1 \parallel \bar{P}_2$
- ▶ Aggregate smaller components first...
- ▶ ...then combine them into the aggregated complete system.
- ▶ \geq is semantic preorder.
- ▶ $P \geq \bar{P}$ means \bar{P} is an aggregated version of P .
- ▶ \parallel is a parallel composition.

Composing discontinuous Markov reward chains

- ▶ Kronecker sum \oplus and Kronecker product \otimes
- ▶ Parallel composition $P_1 \parallel P_2 =$
 $(\sigma_1 \otimes \sigma_2, \Pi_1 \otimes \Pi_2, Q_1 \otimes \Pi_2 + \Pi_1 \otimes Q_2, \rho_1 \otimes \mathbf{1}^{|\rho_2|} + \mathbf{1}^{|\rho_1|} \otimes \rho_2)$
- ▶ If P_1 and P_2 are discontinuous Markov reward chains, then so is $P_1 \parallel P_2$

Composing discontinuous Markov reward chains

- ▶ Both lumping and reduction are compositional with respect to the parallel composition of discontinuous Markov reward chains
- ▶ If $P_1 \xrightarrow{\mathcal{L}_1} \bar{P}_1$ and $P_2 \xrightarrow{\mathcal{L}_2} \bar{P}_2$, then $P_1 \parallel P_2 \xrightarrow{\mathcal{L}_1 \otimes \mathcal{L}_2} \bar{P}_1 \parallel \bar{P}_2$.
- ▶ If $P_1 \rightarrow_r \bar{P}_1$ and $P_2 \rightarrow_r \bar{P}_2$, then $P_1 \parallel P_2 \rightarrow_r \bar{P}_1 \parallel \bar{P}_2$

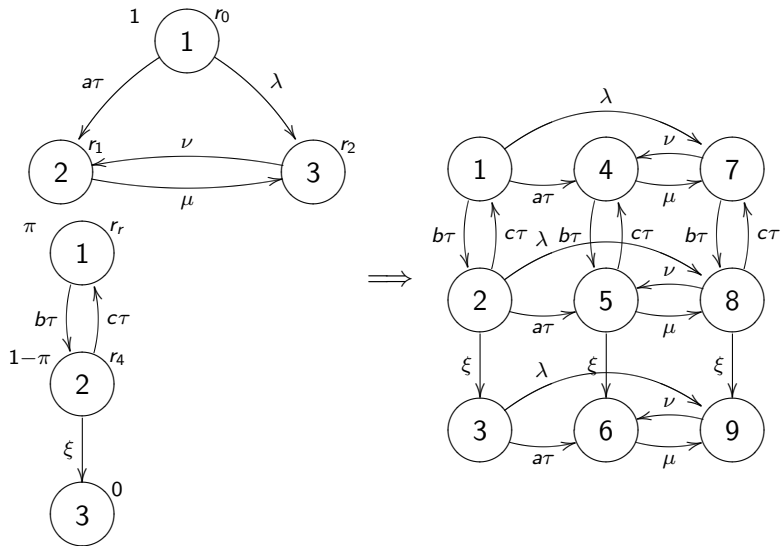
Composing Markov reward chains with fast transitions

- ▶ Parallel composition

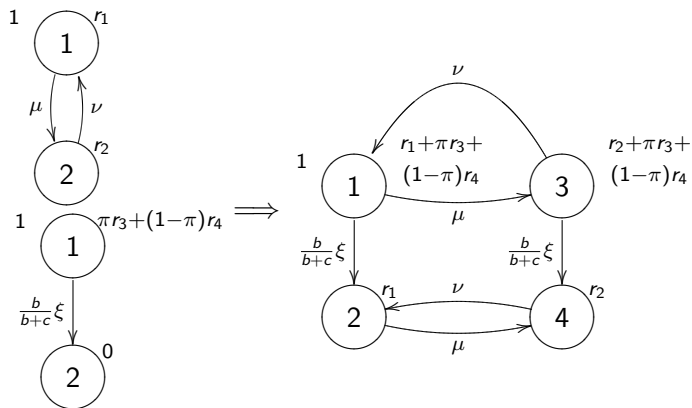
$$P_1 \parallel P_2 = (\sigma_1 \otimes \sigma_2, Q_{s,1} \oplus Q_{s,2}, Q_{f,1} \oplus Q_{f,2}, \rho_1 \otimes \mathbf{1}^{|\rho_2|} + \mathbf{1}^{|\rho_1|} \otimes \rho_2)$$

- ▶ If $P_1 \xrightarrow{\mathcal{L}_1} \bar{P}_1$ and $P_2 \xrightarrow{\mathcal{L}_2} \bar{P}_2$, then $P_1 \parallel P_2 \xrightarrow{\mathcal{L}_1 \otimes \mathcal{L}_2} \bar{P}_1 \parallel \bar{P}_2$.
- ▶ If $P_1 \rightsquigarrow_r \bar{P}_1$ and $P_2 \rightsquigarrow_r \bar{P}_2$, then $P_1 \parallel P_2 \rightsquigarrow_r \bar{P}_1 \parallel \bar{P}_2$

Example of parallel composition



Aggregated version of composition



Summary

$$\begin{array}{ccc} P_1 \xrightarrow{\mathcal{L}_1} \bar{P}_1 & P_2 \xrightarrow{\mathcal{L}_2} \bar{P}_2 & P_1 \parallel P_2 \xrightarrow{\mathcal{L}_1 \otimes \mathcal{L}_2} \bar{P}_1 \parallel \bar{P}_2 \\ \infty \downarrow & \infty \downarrow & \infty \downarrow \\ Q_1 \xrightarrow{\mathcal{L}_1} \bar{Q}_1 & Q_2 \xrightarrow{\mathcal{L}_2} \bar{Q}_2 & Q_1 \parallel Q_2 \xrightarrow{\mathcal{L}_1 \otimes \mathcal{L}_2} \bar{Q}_1 \parallel \bar{Q}_2 \end{array} \implies$$

$$\begin{array}{ccc} P_1 & P_2 & P_1 \parallel P_2 \\ \infty \downarrow \swarrow_r & \infty \downarrow \swarrow_r & \infty \downarrow \swarrow_r \\ Q_1 \xrightarrow{r} R_1 & Q_2 \xrightarrow{r} R_2 & Q_1 \parallel Q_2 \xrightarrow{r} R_1 \parallel R_2 \end{array} \implies$$

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End

▶ Questions?