Overview

Modeling and Verification of Probabilistic Systems

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http://moves.rwth-aachen.de/teaching/ss-14/movep14/

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Recall: continuous-time Markov chains Oniformization 4 Strong and weak bisimulation

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Recall: continuous-time Markov chains

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Negative exponential distribution

Density of exponential distribution

The density of an *exponentially distributed* r.v. Y with rate $\lambda \in \mathbb{R}_{>0}$ is:

$$f_Y(x) = \lambda \cdot e^{-\lambda \cdot x}$$
 for $x > 0$ and $f_Y(x) = 0$ otherwise

The cumulative distribution of r.v. *Y* with rate $\lambda \in \mathbb{R}_{>0}$ is:

$$F_Y(d) = \int_0^d \lambda \cdot e^{-\lambda \cdot x} dx = [-e^{-\lambda \cdot x}]_0^d = 1 - e^{-\lambda \cdot dx}$$

The rate $\lambda \in \mathbb{R}_{>0}$ uniquely determines an exponential distribution.

Variance and expectation

Let r.v. *Y* be exponentially distributed with rate $\lambda \in \mathbb{R}_{>0}$. Then:

- Expectation $E[Y] = \int_0^\infty x \cdot \lambda \cdot e^{-\lambda \cdot x} dx = \frac{1}{\lambda}$
- Variance $Var[Y] = \int_0^\infty (x E[X])^2 \lambda \cdot e^{-\lambda \cdot x} dx = \frac{1}{\lambda^2}$

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Continuous-time Markov chain

Continuous-time Markov chain

A CTMC is a tuple $(S, \mathbf{P}, \mathbf{r}, \iota_{\text{init}}, AP, L)$ where

- $(S, \mathbf{P}, \iota_{\text{init}}, AP, L)$ is a DTMC, and
- $r: S \to \mathbb{R}_{>0}$, the exit-rate function

Let $\mathbf{R}(s, s') = \mathbf{P}(s, s') \cdot r(s)$ be the transition rate of transition (s, s')

Interpretation

- residence time in state s is exponentially distributed with rate r(s).
- phrased alternatively, the average residence time of state s is $\frac{1}{r(s)}$.

Recall: continuous-time Markov chains

Recall: continuous-time Markov chains

CTMC semantics

Enabledness

The probability that transition $s \to s'$ is *enabled* in [0, t] is $1 - e^{-\mathbf{R}(s,s') \cdot t}$.

State-to-state timed transition probability

The probability to *move* from non-absorbing s to s' in [0, t] is:

$$\frac{\mathbf{R}(s,s')}{r(s)}\cdot\left(1-e^{-r(s)\cdot t}\right).$$

Residence time distribution

The probability to *take some* outgoing transition from s in [0, t] is:

$$\int_0^t r(s) \cdot e^{-r(s) \cdot x} \, dx = 1 - e^{-r(s) \cdot x}$$

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Transient distribution

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Transient distribution of a CTMC

Transient state probability

Let X(t) denote the state of a CTMC at time $t \in \mathbb{R}_{\geq 0}$. The probability to be in state *s* at time *t* is defined by:

$$p_{s}(t) = Pr\{X(t) = s\}$$

= $\sum_{s' \in S} Pr\{X(0) = s'\} \cdot Pr\{X(t) = s \mid X(0) = s'\}$

Theorem: transient distribution as linear differential equation

The transient probability vector $p(t) = (p_{s_1}(t), \dots, p_{s_k}(t))$ satisfies:

$$p'(t) = p(t) \cdot (\mathbf{R} - \mathbf{r})$$
 given $p(0)$

where \mathbf{r} is the diagonal matrix of vector \underline{r} .

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Transient distribution

Transient distribution theorem

Theorem: transient distribution as linear differential equation
The transient probability vector $\underline{p}(t) = (p_{s_1}(t), \dots, p_{s_k}(t))$ satisfies:
$p'(t) = p(t) \cdot (\mathbf{R} - \mathbf{r})$ given $p(0)$

where \mathbf{r} is the diagonal matrix of vector \underline{r} .

Proof:

On the blackboard.

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Computing transient probabilities

The transient probability vector $p(t) = (p_{s_1}(t), \dots, p_{s_k}(t))$ satisfies: $p'(t) = p(t) \cdot (\mathbf{R} - \mathbf{r})$ given p(0).

Transient distribution

Solution using standard knowledge yields: $p(t) = p(0) \cdot e^{(\mathbf{R}-\mathbf{r}) \cdot t}$.

Computing a matrix exponential

First attempt: use Taylor-Maclaurin expansion. This yields

$$\underline{p}(t) = \underline{p}(0) \cdot e^{(\mathbf{R}-\mathbf{r}) \cdot t} = \underline{p}(0) \cdot \sum_{i=0}^{\infty} \frac{((\mathbf{R}-\mathbf{r}) \cdot t)^i}{i!}$$

But: numerical instability due to fill-in of $(\mathbf{R}-\mathbf{r})^i$ in presence of positive and negative entries in the matrix $\mathbf{R}-\mathbf{r}$.

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Uniformization

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Uniformization

Let CTMC $C = (S, \mathbf{P}, \mathbf{r}, \iota_{init}, AP, L)$ with S finite.

Uniform CTMC

CTMC C is uniform if r(s) = r for all $s \in S$ for some $r \in \mathbb{R}_{>0}$.

Uniformization

[Gross and Miller, 1984]

Let $r \in \mathbb{R}_{>0}$ such that $r \ge max_{s \in S} r(s)$. Then unif(r, C) is the tuple $(S, \overline{\mathbf{P}}, \overline{r}, \iota_{\text{init}}, AP, L)$ with $\overline{r}(s) = r$ for all $s \in S$, and:

$$\overline{\mathbf{P}}(s,s') = \frac{r(s)}{r} \cdot \mathbf{P}(s,s') \text{ if } s' \neq s \quad \text{and} \quad \overline{\mathbf{P}}(s,s) = \frac{r(s)}{r} \cdot \mathbf{P}(s,s) + 1 - \frac{r(s)}{r}.$$

It follows that $\overline{\mathbf{P}}$ is a stochastic matrix and $unif(r, \mathcal{C})$ is a CTMC.

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Uniformization

Uniformization: example

Uniformization

Let $r \in \mathbb{R}_{>0}$ such that $r \ge \max_{s \in S} r(s)$. Then $unif(r, C) = (S, \overline{\mathbf{P}}, \overline{r}, \iota_{init}, AP, L)$ with $\overline{r}(s) = r$ for all $s \in S$, and:

$$\overline{\mathbf{P}}(s,s') = \frac{r(s)}{r} \cdot \mathbf{P}(s,s') \text{ if } s' \neq s \text{ and } \overline{\mathbf{P}}(s,s) = \frac{r(s)}{r} \cdot \mathbf{P}(s,s) + 1 - \frac{r(s)}{r}.$$



CTMC C and its uniformized counterpart unif(6, C)

Uniformization: intuition

Uniformization

Let $r \in \mathbb{R}_{>0}$ such that $r \ge \max_{s \in S} r(s)$. Then $unif(r, C) = (S, \overline{\mathbf{P}}, \overline{r}, \iota_{init}, AP, L)$ with $\overline{r}(s) = r$ for all $s \in S$, and:

Uniformizatio

$$\overline{\mathbf{P}}(s,s') = \frac{r(s)}{r} \cdot \mathbf{P}(s,s') \text{ if } s' \neq s \text{ and } \overline{\mathbf{P}}(s,s) = \frac{r(s)}{r} \cdot \mathbf{P}(s,s) + 1 - \frac{r(s)}{r}.$$

Intuition

- Fix all exit rates to (at least) the maximal exit rate r occurring in CTMC C.
- Thus, $\frac{1}{r}$ is the shortest mean residence time in the CTMC C.
- ▶ Then normalize the residence time of all states with respect to *r* as follows:
 - 1. replace an average residence time $\frac{1}{r(s)}$ by a shorter (or equal) one, $\frac{1}{r}$
 - 2. decrease the transition probabilities by a factor $\frac{r(s)}{r}$, and
 - 3. increase the self-loop probability by a factor $\frac{r-r(s)}{r}$

That is, slow down state s whenever r(s) < r.

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Strong and weak bisimulation

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Strong bisimulation on DTMCs

Probabilistic bisimulation	[Larsen & Skou, 1989]
Let $\mathcal{D} = (S, \mathbf{P}, \iota_{\text{init}}, AP, L)$ be a DTMC and $R \subseteq S$ Then: R is a <i>probabilistic bisimulation</i> on S if for an 1. $L(s) = L(t)$, and	× S an equivalence. ny $(s,t) \in R$:
2. $\mathbf{P}(s, C) = \mathbf{P}(t, C)$ for all equivalence classes C where $\mathbf{P}(s, C) = \sum_{s' \in C} \mathbf{P}(s, s')$.	$\in S/R$

For states in R, the probability of moving by a single transition to some equivalence class is equal.

Probabilistic bisimilarity

Let \mathcal{D} be a DTMC and s, t states in \mathcal{D} . Then: s is *probabilistically bisimilar* to t, denoted $s \sim_p t$, if there exists a probabilistic bisimulation R with $(s, t) \in R$.

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Strong and weak bisimulation

Strong bisimulation on CTMCs

Probabilistic bisimulation	[Buchholz, 1994]
Let $C = (S, \mathbf{P}, r, \iota_{init}, AP, L)$ be a CTMC and $R \subseteq S \times S$ a Then: R is a <i>probabilistic bisimulation</i> on S if for any (s, r)	an equivalence. $t) \in R$:
1. $L(s) = L(t)$, and 2. $r(s) = r(t)$, and	
3. $\mathbf{P}(s, C) = \mathbf{P}(t, C)$ for all equivalence classes $C \in S/R$?

The last two conditions amount to $\mathbf{R}(s, C) = \mathbf{R}(t, C)$ for all equivalence classes $C \in S/R$.

Probabilistic bisimilarity

Let C be a CTMC and s, t states in C. Then: s is *probabilistically bisimilar* to t, denoted $s \sim_m t$, if there exists a probabilistic bisimulation R with $(s, t) \in R$.

Strong and weak bisimulation

Weak bisimulation on DTMCs

Weak probabilistic bisimulation

[Baier & Hermanns, 1996]

Let $\mathcal{D} = (S, \mathbf{P}, \iota_{\text{init}}, AP, L)$ be a DTMC and $R \subseteq S \times S$ an equivalence. Then: *R* is a *weak probabilistic bisimulation* on *S* if for any $(s, t) \in R$:

- 1. L(s) = L(t), and
- 2. if $P(s, [s]_R) < 1$ and $P(t, [t]_R) < 1$, then:

$$\frac{\mathsf{P}(s,C)}{1-\mathsf{P}(s,[s]_R)} \;\;=\;\; \frac{\mathsf{P}(t,C)}{1-\mathsf{P}(t,[t]_R)} \quad \text{for all} C \in S/R, \, C \neq [s]_R = [t]_R.$$

3. s can reach a state outside $[s]_R$ iff t can reach a state outside $[t]_R$.

For states in R, the conditional probability of moving by a single transition to another equivalence class is equal. In addition, either all states in an equivalence class C almost surely stay there, or have an option to escape from C.

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Strong and weak bisimulation

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Weak bisimulation on DTMC: example



The equivalence relation R with $S/R = \{ \{s_1, s_2, s_3, s_4\}, \{u_1, u_2, u_3\} \}$ is a weak bisimulation. This can be seen as follows. For $C = \{ u_1, u_2, u_3 \}$ and s_1, s_2, s_4 with $\mathbf{P}(s_i, [s_i]_R) < 1$ we have:

 $\frac{\mathsf{P}(s_1, C)}{1 - \mathsf{P}(s_1, [s_1])} = \frac{1/8}{1 - 5/8} = \frac{1/4}{1 - 1/4} = \frac{\mathsf{P}(s_2, C)}{1 - \mathsf{P}(s_2, [s_2])} = \frac{1/3}{1} = \frac{\mathsf{P}(s_4, C)}{1 - \mathsf{P}(s_4, [s_4])}.$

Note that $\mathbf{P}(s_3, [s_3]_R) = 1$. Since s_3 can reach a state outside $[s_3]$ as s_1, s_2 and s_4 , it follows that $s_1 \approx_p s_2 \approx_p s_3 \approx_p s_4$.

Weak bisimulation on DTMCs

Weak probabilistic bisimulation

[Baier & Hermanns, 1996]

Let $\mathcal{D} = (S, \mathbf{P}, \iota_{\text{init}}, AP, L)$ be a DTMC and $R \subseteq S \times S$ an equivalence. Then: R is a *weak probabilistic bisimulation* on S if for any $(s, t) \in R$:

1. L(s) = L(t), and

2. if $P(s, [s]_R) < 1$ and $P(t, [t]_R) < 1$, then:

$$\frac{\mathsf{P}(s,C)}{1-\mathsf{P}(s,[s]_R)} \;\;=\;\; \frac{\mathsf{P}(t,C)}{1-\mathsf{P}(t,[t]_R)} \quad \text{for all}\, C \in S/R, \, C \neq [s]_R = [t]_R.$$

3. s can reach a state outside $[s]_R$ iff t can reach a state outside $[t]_R$.

Probabilistic weak bisimilarity

Let \mathcal{D} be a DTMC and s, t states in \mathcal{D} . Then: s is *probabilistically weak bisimilar* to t, denoted $s \approx_p t$, if there exists a probabilistic weak bisimulation R with $(s, t) \in R$.

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Strong and weak bisimulation

Reachability condition

Remark

Consider the following DTMC:

$$(s_1) \xrightarrow{1} (s_2) \xrightarrow{1} (u) 1$$

It is not difficult to establish $s_1 \approx s_2$. Note: $P(s_1, [s_1]) = 1$, but $P(s_2, [s_2]_R) < 1$. Both s_1 and s_2 can reach a state outside $[s_1]_R = [s_2]_R$. The reachability condition is essential to establish $s_1 \approx s_2$ and cannot be dropped: otherwise s_1 and s_2 would be weakly bisimilar to an equally labelled absorbing state.

Strong and weak bisimulation

Weak bisimulation on CTMCs

Weak probabilistic bisimulation[Bravetti, 2002]Let $C = (S, \mathbf{P}, r, \iota_{init}, AP, L)$ be a CTMC and $R \subseteq S \times S$ an equivalence.Then: R is a weak probabilistic bisimulation on S if for any $(s, t) \in R$:1. L(s) = L(t), and2. $\mathbf{R}(s, C) = \mathbf{R}(t, C)$ for all $C \in S/R$ with $C \neq [s]_R = [t]_R$

Weak probabilistic bisimilarity

Let C be a CTMC and s, t states in C. Then: s is *weak probabilistically bisimilar* to t, denoted $s \approx_m t$, if there exists a weak probabilistic bisimulation R with $(s, t) \in R$.

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Strong and weak bisimulation

Weak bisimulation on CTMCs: example



Equivalence relation R with $S/R = \{ \{s_1, s_2, s_3, s_4, s_5, s_6\}, \{u_1, u_2, u_3, u_4, u_5\} \}$ is a weak bisimulation on the CTMC depicted above. This can be seen as follows. For $C = \{u_1, u_2, u_3, u_4, u_5\}$, we have that all *s*-states enter C with rate 2. The rates between the *s*-states are not relevant.

A useful lemma

Let C be a CTMC and R an equivalence relation on S with $(s, t) \in R$. Then: the following two statements are equivalent:

1. If $P(s, [s]_R) < 1$ and $P(t, [t]_R) < 1$ then for all $C \in S/R$, $C \neq [s]_R = [t]_R$:

$$\frac{\mathsf{P}(s,C)}{1-\mathsf{P}(s,[s]_R)} = \frac{\mathsf{P}(t,C)}{1-\mathsf{P}(t,[t]_R)} \quad \text{and} \quad \mathsf{R}(s,S\setminus [s]_R) = \mathsf{R}(t,S\setminus [t]_R)$$

2. $\mathbf{R}(s, C) = \mathbf{R}(t, C)$ for all $C \in S/R$ with $C \neq [s]_R = [t]_R$.

Proof:

Left as an exercise.

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Strong and weak bisimulation

Properties (without proof)

Strong and weak bisimulation in uniform CTMCs

For all uniform CTMCs C and states s, u in C, we have:

 $s \sim_m u$ iff $s \approx_m u$ iff $s \sim_p u$.

For any CTMC C, we have: $C \approx_m unif(r, C)$ with $r \ge \max_{s \in S} r(s)$.

Preservation of transient probabilities

For all CTMCs C with states s, u in C and $t \in \mathbb{R}_{\geq 0}$, we have:

 $s \approx_m u$ implies p(t) = p(t)

where $\underline{p}(0) = \mathbf{1}_s$ and $\underline{p}(0) = \mathbf{1}_u$ where $\mathbf{1}_s$ is the characteristic function for state s, i.e., $\mathbf{1}_s(s') = \overline{1}$ iff s = s'.

Computing transient probabilities

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Computing transient probabilities

Computing transient probabilities

$$\underline{p}(t) = \underline{p}(0) \cdot e^{(\overline{\mathbf{R}} - \overline{\mathbf{r}}) \cdot t} = \underline{p}(0) \cdot e^{(\overline{\mathbf{P}} \cdot \mathbf{r} - \mathbf{l} \cdot \mathbf{r}) \cdot t} = \underline{p}(0) \cdot e^{(\overline{\mathbf{P}} - \mathbf{l}) \cdot \mathbf{r} \cdot t} = \underline{p}(0) \cdot e^{-rt} \cdot e^{r \cdot t \cdot \overline{\mathbf{P}}}.$$

Computing a matrix exponential

Exploit Taylor-Maclaurin expansion. This yields:

$$\underline{p}(0) \cdot e^{-rt} \cdot e^{r \cdot t \cdot \overline{\mathbf{P}}} = \underline{p}(0) \cdot e^{-rt} \cdot \sum_{i=0}^{\infty} \frac{(r \cdot t)^i}{i!} \cdot \overline{\mathbf{P}}^i = \underline{p}(0) \cdot \sum_{i=0}^{\infty} \underbrace{e^{-r \cdot t} \frac{(r \cdot t)^i}{i!}}_{\text{Poisson prob.}} \cdot \overline{\mathbf{P}}^i$$

As $\overline{\mathbf{P}}$ is a stochastic matrix, computing the matrix exponential $\overline{\mathbf{P}}^{i}$ is numerically stable.

Computing transient probabilities

The transient probability vector $\underline{p}(t) = (p_{s_1}(t), \dots, p_{s_k}(t))$ satisfies:

 $\underline{p}'(t) = \underline{p}(t) \cdot (\mathbf{R} - \mathbf{r})$ given $\underline{p}(0)$.

Standard knowledge yields: $\underline{p}(t) = \underline{p}(0) \cdot e^{(\mathbf{R}-\mathbf{r}) \cdot t}$.

As uniformization preserves transient probabilities, we replace $\mathbf{R}-\mathbf{r}$ by its variant for the uniformized CTMC, i.e., $\overline{\mathbf{R}}-\overline{\mathbf{r}}$. We have:

$$\overline{\mathsf{R}}(s,s') = \overline{\mathsf{P}}(s,s') \cdot \overline{r}(s) = \overline{\mathsf{P}}(s,s') \cdot r \quad \text{and} \quad \overline{\mathsf{r}} = \mathsf{I} \cdot r.$$

Thus:

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$$\underline{p}(0) \cdot e^{(\overline{\mathbf{R}} - \overline{\mathbf{r}}) \cdot t} = \underline{p}(0) \cdot e^{(\overline{\mathbf{P}} \cdot \mathbf{r} - \mathbf{l} \cdot \mathbf{r}) \cdot t} = \underline{p}(0) \cdot e^{(\overline{\mathbf{P}} - \mathbf{l}) \cdot \mathbf{r} \cdot t} = \underline{p}(0) \cdot e^{-rt} \cdot e^{r \cdot t \cdot \overline{\mathbf{P}}}.$$

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Computing transient probabilities

Intermezzo: Poisson distribution

Poisson distribution

The Poisson distribution is a discrete probability distribution that expresses the probability of a given number i of events occurring in a fixed interval of time [0, t] if these events occur with a known average rate r and independently of the time since the last event. Formally, the pdf is:

$$f(i; r \cdot t) = e^{-r \cdot t} \frac{(r \cdot t)^{i}}{i!}$$

where r is the mean of the Poisson distribution.

Remark

The Poisson distribution can be derived as a limiting case to the binomial distribution as the number of trials goes to infinity and the expected number of successes remains fixed.

Transient probabilities: example

$$\mathbf{P} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, \underline{r} = \begin{bmatrix} 3 \\ 2 \end{bmatrix} \text{ and } \overline{\mathbf{P}}_3 = \begin{bmatrix} 0 & 1 \\ \frac{2}{3} & \frac{1}{3} \end{bmatrix}$$

Let initial distribution p(0) = (1, 0), and time bound t=1. Then:

$$\underline{p}(1) = \underline{p}(0) \cdot \sum_{i=0}^{\infty} e^{-3} \frac{3^{i}}{i!} \cdot \overline{\mathbf{p}}^{i}$$

$$= (1,0) \cdot e^{-3} \frac{1}{0!} \cdot \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} + (1,0) \cdot e^{-3} \frac{3}{1!} \cdot \begin{bmatrix} 0 & 1 \\ \frac{2}{3} & \frac{1}{3} \end{bmatrix}$$

$$+ (1,0) \cdot e^{-3} \frac{9}{2!} \cdot \begin{bmatrix} 0 & 1 \\ \frac{2}{3} & \frac{1}{3} \end{bmatrix}^{2} + \dots$$

Summary

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Truncating the infinite sum

Computing transient probabilities

$$\underline{p}(t) = \underline{p}(0) \cdot \sum_{i=0}^{\infty} e^{-r \cdot t} \frac{(r \cdot t)^{i}}{i!} \cdot \overline{\mathbf{P}}^{i}$$

- Summation can be truncated *a priori* for a given error bound $\varepsilon > 0$.
- ▶ The *error* that is introduced by truncating at summand k_{ε} is:

$$\left\|\sum_{i=0}^{\infty} e^{-rt} \frac{(rt)^{i}}{i!} \cdot \underline{p}(i) - \sum_{i=0}^{k_{\varepsilon}} e^{-rt} \frac{(rt)^{i}}{i!} \cdot \underline{p}(i)\right\| = \left\|\sum_{i=k_{\varepsilon}+1}^{\infty} e^{-rt} \frac{(rt)^{i}}{i!} \cdot \underline{p}(i)\right\|$$

• Strategy: choose k_{ε} minimal such that:

$$\sum_{i=k_{\varepsilon+1}}^{\infty} e^{-rt} \frac{(rt)^i}{i!} = \sum_{i=0}^{\infty} e^{-rt} \frac{(rt)^i}{i!} - \sum_{i=0}^{k_{\varepsilon}} e^{-rt} \frac{(rt)^i}{i!} = 1 - \sum_{i=0}^{k_{\varepsilon}} e^{-rt} \frac{(rt)^i}{i!} \leqslant \varepsilon$$

Summary

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Summary

Main points

- Bisimilar states are equally labelled and their cumulative rate to any equivalence class coincides.
- Weak bisimilar states have equal conditional probabilities to move to some equivalence class, and can either both leave their class or both can't.
- Uniformization normalizes the exit rates of all states in a CTMC.
- Uniformization transforms a CTMC into a weak bisimilar one.
- Transient distribution are obtained by solving a system of linear differential equations.
- These equations can be solved conveniently on the uniformized CTMC.

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