# Minimizing Markov chains Beyond Bisimilarity 

Giovanni Bacci, Giorgio Bacci, Kim G. Larsen, Radu Mardare Aalborg University, Denmark

I November 2016 - Rold Storkro, Denmark NWPT 2016

## The focus of the talk

- Probabilistic Models (Markov chains)
- Automatic verification (e.g., Model Checking)
- state space explosion (even after model reduction, symbolic tech., partial-order reduction)
- Still too large: one needs to compromise in the accuracy of the model (introduce an error)
- Our proposal: metric-based state space reduction


## Probabilistic Bisimulation

[Larsen \& Skou'91]


## Probabilistic Bisimulation

[Larsen \& Skou'91]


## Probabilistic Bisimulation

[Larsen \& Skou'91]


## Bisimilarity Distance

$$
\mathcal{M}=\left(\mathrm{M}, \tau, \ell, \mathrm{~m}_{0}\right)
$$

$$
\mathcal{N}=\left(\mathrm{N}, \theta, \alpha, \mathrm{n}_{0}\right)
$$



## Bisimilarity Distance

$$
\mathcal{M}=\left(\mathrm{M}, \tau, \ell, \mathrm{~m}_{0}\right)
$$

$$
\mathcal{N}=\left(\mathrm{N}, \theta, \alpha, \mathrm{n}_{0}\right)
$$



## Bisimilarity Distance

$$
\mathcal{M}=\left(\mathrm{M}, \tau, \ell, \mathrm{~m}_{0}\right) \quad \mathcal{N}=\left(\mathrm{N}, \theta, \alpha, \mathrm{n}_{0}\right)
$$



## Bisimilarity Distance

(fixed point characterization by van Breugel \& Worrell)
Given a parameter $\lambda \in(0, \mathrm{I}]$, called discount factor, the bisimilarity distance $\delta_{\lambda}$ is the least fixed point of

$$
\begin{gathered}
\Delta_{\lambda}(\mathrm{d})(\mathrm{m}, \mathrm{n})= \begin{cases}\mathrm{I} & \text { if } \ell(\mathrm{m}) \neq \alpha(\mathrm{n}) \\
\lambda \cdot \mathcal{K}(\mathrm{d})(\tau(\mathrm{m}), \theta(\mathrm{n})) & \text { otherwise }\end{cases} \\
\begin{array}{c}
\begin{array}{c}
\text { discount at } \\
\text { each step }
\end{array} \\
\underbrace{}_{\text {Kantorovich lifting }} \text { coupling }
\end{array} \\
\mathcal{K}(\mathrm{d})(\tau(\mathrm{m}), \theta(\mathrm{n}))=\min \left\{\sum \mathrm{d}(\mathrm{u}, \mathrm{v}) \cdot \mathrm{C}(\mathrm{u}, \mathrm{v}) \left\lvert\, \begin{array}{l}
\sum_{\mathrm{u} \in \mathrm{M}} \mathrm{C}(\mathrm{u}, \mathrm{v})=\theta(\mathrm{n})(\mathrm{v}) \\
\sum_{\mathrm{v} \in \mathrm{~N}} \mathrm{C}(\mathrm{u}, \mathrm{v})=\tau(\mathrm{m})(\mathrm{u})
\end{array}\right.\right\}
\end{gathered}
$$

## Approximate verification

[Chen, van Breugel, Worrell - FoSSaCS'12]

...imagine that $|\mathcal{M}| \gg|\mathcal{N}|$, we can use $\mathcal{N}$ in place of $\mathcal{M}$


## Some natural questions

- Given an MC $\mathcal{M}$, and $k \in \mathbb{N}$, what is its closest $k$-state approximant?
- Does this always exist?
- Can we find one? How hard is it to get?


## The CBA- $\lambda$ problem

[ The Closest Bounded Approximant w.r.t. $\delta_{\lambda}$
INSTANCE: An MC $\mathcal{M}$, and a positive integer $k$ OUTPUT: An MC $\mathcal{N}^{*}$ with at most k states minimizing $\delta_{\lambda}\left(\mathcal{M}, \mathcal{N}^{*}\right)$

$$
\text { MCs with } \leq \mathrm{k} \text { states }
$$

$$
\delta_{\lambda}\left(\mathcal{M}, \mathcal{N}^{*}\right)=\inf \left\{\delta_{\lambda}(\mathcal{M}, \mathcal{N}) \mid \mathcal{N} \in \operatorname{MC}(k)\right\}
$$

## CBA- $\lambda$ has always a solution

$$
\begin{gathered}
\quad \inf \left\{\delta_{\lambda}(\mathcal{M}, \mathcal{N}) \mid \mathcal{N} \in \operatorname{MC}(\mathrm{k})\right\}= \\
= \\
=\inf \left\{\mathrm{d}\left(\mathrm{~m}_{0}, \mathrm{n}_{0}\right) \mid \Delta_{\lambda}(\mathrm{d}) \subseteq \mathrm{d}, \mathcal{N} \in \operatorname{MC}(\mathrm{k})\right\}
\end{gathered}
$$

## Lemma (Meaningful labels)

For any $\mathcal{N}{ }^{\prime} \in \mathrm{MC}(k)$ there exists $\mathcal{N} \in \mathrm{MC}(k)$ with labels taken from $\mathcal{M}$, such that $\delta_{\lambda}(\mathcal{M}, \mathcal{N}) \leq \delta_{\lambda}\left(\mathcal{M}, \mathcal{N}^{\prime}\right)$.

$$
\begin{array}{lll}
\operatorname{mimimize} & d_{m_{0}, n_{0}} \\
\text { such that }
\end{array} \begin{array}{ll}
d_{m, n}=1 & \ell(m) \neq \alpha(n) \\
\lambda \sum_{(u, v) \in M \times N} c_{u, v}^{m, n} \cdot d_{u, v} \leq d_{m, n} & \ell(m)=\alpha(n) \\
\sum_{v \in N} c_{u, v}^{m, n}=\tau(m)(u) & m, u \in M, n \in N \\
\sum_{u \in M} c_{u, v}^{m, n}=\theta_{n, v} & m \in M, n, v \in N \\
c_{u, v}^{m, n} \geq 0 & m, u \in M, n, v \in N
\end{array}
$$

## CBA- $\lambda$ as bilinear program

$$
\begin{array}{ll}
\operatorname{mimimize} & d_{m_{0}, n_{0}} \\
\text { such that } & m \in M, n \in N \\
l_{m, n} \leq d_{m, n} \leq 1 & m \in M, n \in N \\
\lambda \sum_{(u, v) \in M \times N} c_{u, v}^{m, n} \cdot d_{u, v} \leq d_{m, n} & n \in N, \ell(m) \neq \ell(u) \\
l_{m, n} \cdot l_{u, n}=0 & n \in N, \ell(m) \neq \ell(u) \\
l_{m, n}+l_{u, n}=1 & n \in N, \ell(m)=\ell(u) \\
l_{m, n}=l_{u, n} & n \in N \\
\sum_{m \in M} l_{m, n} \leq|M|-1 & m, u \in M, n \in N \\
\sum_{v \in N} c_{u, v}^{m, n}=\tau(m)(u) & m \in M, n, v \in N \\
\sum_{u \in M} c_{u, v}^{m, n}=\theta_{n, v} & m, u \in M, n, v \in N \\
c_{u, v}^{m, n} \geq 0 & \\
\end{array}
$$

## The complexity of CBA- $\lambda$

We study its complexity by looking at its decision variant
The Bounded Approximant threshold w.r.t. $\delta_{\lambda}$ INSTANCE: An MC $\mathcal{M}$, a positive integer $k$, and a rational bound $\varepsilon$ OUTPUT: yes iff $\delta_{\lambda}(\mathcal{M}, \mathcal{N}) \leq \varepsilon$ for some $\mathcal{N} \in \operatorname{MC}(k)$

Theorem:
For any $\lambda \in(0, I], B A-\lambda$ is in PSPACE
proof sketch: we can encode the question $\langle\boldsymbol{\mathcal { M }}, k, \varepsilon\rangle \in B A-\lambda$ to that of asking for the feasibility of a set of bilinear inequalities. This is a decision problem in for the existential theory of the reals, thus it can be solved in PSPACE [Canny - STOC'88].

## The complexity of CBA- $\lambda$

We study its complexity by looking at its decision variant
The Bounded Approximant threshold w.r.t. $\delta_{\lambda}$ INSTANCE: An MC $\mathcal{M}$, a positive integer $k$, and a rational bound $\varepsilon$ OUTPUT: yes iff $\delta_{\lambda}(\mathcal{M}, \mathcal{N}) \leq \varepsilon$ for some $\mathcal{N} \in \operatorname{MC}(k)$

Theorem:
For any $\lambda \in(0, I], \mathrm{BA}-\lambda$ is in PSPACE
Theorem:
For any $\lambda \in(0, \mathrm{I}], \mathrm{BA}-\lambda$ is NP -hard proof idea: by reduction from VERTEX COVER
...the hardness of BA- $\lambda$ opens a new question: is it easy to choose a "good" bound $k$ ?

## $\mathcal{N}$ is a significant approximant if $\delta_{\lambda}(\mathcal{M}, \mathcal{N})<1$

## The MSAB- $\lambda$ problem

The Minimum Significant Approximant Bound w.r.t. $\delta_{\lambda}$
INSTANCE: An MC $\mathcal{M}$, and a positive integer $k$ OUTPUT: The smallest $k$ such that $\delta_{\lambda}(\mathcal{M}, \mathcal{N})<I$, for some $\mathcal{N} \in \operatorname{MC}(k)$

INSTANCE: An MC $\mathcal{M}$, and a for $\lambda=1$
OUTPUT: yes iff $\delta_{\lambda}(\mathcal{M}, \mathcal{N})<1$ for some $\mathcal{J N M C l}_{\boldsymbol{M}}$

## A practical solution: EM Algorithm

- Given $\mathcal{M}$ and a significant approximant $\mathcal{N}_{0}$
- it produces a sequence $\mathcal{N}_{0}, \ldots, \mathcal{N}_{\mathrm{h}}$ having successively decreased distance from $\mathcal{M}$
- $\mathcal{N}_{\mathrm{h}}$ is a sub-optimal solution of CBA- $\lambda$

Intuitive idea:
assign greater probability to transitions that are most representative of the behavior of $\boldsymbol{\mathcal { M }}$

| Case | $\|M\|$ | $k$ | $\lambda=1$ |  |  |  | $\lambda=0.8$ |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | $\delta_{\lambda}$-init | $\delta_{\lambda}$-final | \# | time | $\delta_{\lambda}$-init | $\delta_{\lambda}$-final | \# | time |
| IPv4 <br> (AM) | 23 | 5 | 0.775 | 0.054 | 3 | 4.8 | 0.576 | 0.025 | 3 | 4.8 |
|  | 53 | 5 | 0.856 | 0.062 | 3 | 25.7 | 0.667 | 0.029 | 3 | 25.9 |
|  | 103 | 5 | 0.923 | 0.067 | 3 | 116.3 | 0.734 | 0.035 | 3 | 116.5 |
|  | 53 | 6 | 0.757 | 0.030 | 3 | 39.4 | 0.544 | 0.011 | 3 | 39.4 |
|  | 103 | 6 | 0.837 | 0.032 | 3 | 183.7 | 0.624 | 0.017 | 3 | 182.7 |
|  | 203 | 6 | - | - | - | TO | - | - | - | TO |
| $\begin{aligned} & \mathrm{IPv4} \\ & (\mathrm{AE}) \end{aligned}$ | 23 | 5 | 0.775 | 0.109 | 2 | 2.7 | 0.576 | 0.049 | 3 | 4.2 |
|  | 53 | 5 | 0.856 | 0.110 | 2 | 14.2 | 0.667 | 0.049 | 3 | 21.8 |
|  | 103 | 5 | 0.923 | 0.110 | 2 | 67.1 | 0.734 | 0.049 | 3 | 100.4 |
|  | 53 | 6 | 0.757 | 0.072 | 2 | 21.8 | 0.544 | 0.019 | 3 | 33.0 |
|  | 103 | 6 | 0.837 | 0.072 | 2 | 105.9 | 0.624 | 0.019 | 3 | 159.5 |
|  | 203 | 6 | - | - | - | TO | - | - | - | TO |
| $\begin{gathered} \text { DrkW } \\ (\mathrm{AM}) \end{gathered}$ |  | 7 | 0.565 | 0.466 | 14 | 259.3 | 0.432 | 0.323 | 14 | 252.8 |
|  | 49 | 7 | 0.568 | 0.460 | 14 | 453.7 | 0.433 | 0.322 | 14 | 420.5 |
|  | 59 | 8 | 0.646 | - | - | TO | 0.423 | - | - | TO |
| $\begin{gathered} \text { DrkW } \\ (\mathrm{AE}) \end{gathered}$ | 39 | 7 | 0.565 | 0.435 | 11 | 156.6 | 0.432 | 0.321 | 2 | 28.6 |
|  | 49 | 7 | 0.568 | 0.434 | 10 | 247.7 | 0.433 | 0.316 | 2 | 46.2 |
|  | 59 | 8 | 0.646 | 0.435 | 10 | 588.9 | 0.423 | 0.309 | 2 | 115.7 |

Table 1. Comparison of the performance of EM algorithm on the IPv4 zeroconf protocol and the classic Drunkard's Walk w.r.t. the heuristics AM and AE.

## What we have seen

## Theoretical Results

We studied metric-based state space reduction for MCs
I. Closest Bounded Approximant

- encoded as a bilinear program

2. Bounded Approximant

- PSPACE \& NP-hard for all $\lambda \in(0, I]$

3. Significant Bounded Approximant

- NP-complete for $\lambda=1$
-Practical Results
We proposed an EM method to obtain a sub-optimal approximants


## Ongoing \& Future work

- Improve the encoding as bilinear program
- Study the CBA problem w.r.t. other - behavioral distances (e.g. Total Variation) - models (e.g. MDP, CTMC, Prob.Automata)


## Appendix

## Vertex Cover $\leq p$ BA- $\lambda$


$\langle\mathrm{G}, \mathrm{h}\rangle \in$ VertexCover $\Leftrightarrow\left\langle\boldsymbol{\mathcal { M }}_{\mathrm{G}}, \mathrm{m}+\mathrm{h}+2, \lambda^{2} / 2 \mathrm{~m}^{2}\right\rangle \in \mathrm{BA}-\lambda$

## Vertex Cover $\leq p$ BA- $\lambda$


$\langle\mathrm{G}, \mathrm{h}\rangle \in$ VertexCover $\Leftrightarrow\left\langle\boldsymbol{\mathcal { M }}_{\mathrm{G}}, \mathrm{m}+\mathrm{h}+2, \lambda^{2} / 2 \mathrm{~m}^{2}\right\rangle \in \mathrm{BA}-\lambda$

