

Coupling and Importance Sampling for Statistical Model Checking

Benoît Barbot, Serge Haddad, and Claudine Picaronny

LSV, ENS Cachan & CNRS & INRIA, Cachan, France
`{barbot,haddad,picaronny}@lsv.ens-cachan.fr`

Abstract. Statistical model-checking is an alternative verification technique applied on stochastic systems whose size is beyond numerical analysis ability. Given a model (most often a Markov chain) and a formula, it provides a confidence interval for the probability that the model satisfies the formula. One of the main limitations of the statistical approach is the computation time explosion triggered by the evaluation of very small probabilities. In order to solve this problem we develop a new approach based on importance sampling and coupling. The corresponding algorithms have been implemented in our tool COSMOS. We present experimentations on several relevant systems, with time reductions reaching a factor of 10^{-120} .

Keywords: statistical model checking, rare events, importance sampling, coupling

1 Introduction

Quantitative model checking. Model checking [12] is an efficient verification method to check that the behaviour of a system fulfills properties expressed by some temporal logic. It has been successfully implemented in a variety of tools, thanks to its algorithmic simplicity. Although a method initially dedicated to discrete event systems, it has been adapted to performance evaluation in order to check quantitative properties and in particular to estimate probabilities [17]. **Statistical model-checking.** Analysis of stochastic systems requires *numerical* or *statistical* techniques. Numerical methods give exact results (up to numerical approximations) but significantly restrict the class of analysable systems (manageable size, Markov properties, etc.). Otherwise, statistical method may be used. By simulating a big sample of trajectories of the system and computing the ratio of these trajectories that satisfy a given property, it produces a probabilistic framing of the expected value. To generate the sample we only need to have an operational stochastic semantic of the system. This usually requires a very small state space compared to the numerical method and allows to deal with huge models [19].

Rare events. The main drawback of the statistical model-checking is its inefficiency in dealing with very small probabilities. The size of the sample of

simulations required to estimate these small probabilities exceeds achievable capacities. This difficulty is known as the *rare event* problem. Several methods have been developed to cope with this problem whose main one is *importance sampling*. Importance sampling consists in modifying the model and in substituting to the indicator random variable related to the satisfaction of the formula, another variable with same mean and, in the favourable cases, reduced variance. Most of the techniques related to importance sampling are based on heuristics and cannot provide any confidence interval for the estimated probability.

Our contribution. Here we propose a method based on importance sampling to estimate in a reliable way a very small probability¹.

We set up a theoretical framework using coupling theory [20], yielding an efficient importance sampling that guarantees a variance reduction and provides a confidence interval. This is done by performing numerical model checking on a small suitable reduction of the Markov chain associated with the system. The results are then used as parameters required for the importance sampling technique. Such a method deals with huge (possibly infinite) systems which are out of reach of numerical model checking and standard statistical model checking. It can be applied to a large variety of models compared to existing importance sampling methods which are usually put up in an ad-hoc way for particular families of models. Furthermore to the best of our knowledge, this is the first importance sampling method that provides a true (and not an approximate) confidence interval.

We implemented our method in the statistical model-checker COSMOS [5] using the tool PRISM for the numerical computation on the reduced model. We tested our tool on several models getting impressive time reductions.

Organisation. In section 2, we motivate this work and we give a state of the art related to rare event handling. Then we develop our method in section 3. Afterwards we present and discuss experimentations in section 4. Finally in section 5, we conclude and give some perspectives to this work.

2 Motivation and State of the Art

The temporal logics for probabilistic systems include both the qualitative and quantitative aspects of the systems. For instance, such logics can express (1) boolean assertions like “the probability of failure of a fixed component is below some threshold” and (2) numerical indices like “the mean delivery time of a packet assuming three collisions”. The semantics of such formula is based on the probability that a random path fulfills some property (in CSL [3]) or (in a more general setting) on the conditional expectation of a path random variable whose condition is the satisfaction of some property by the random path (in HASL [5]).

Model checking of these logics can be performed in a numerical or in a statistical way. The former approach builds the underlying stochastic process of the model and then computes probabilities or expectations using direct or

¹ We have presented in a previous paper [6] a preliminary approach of this method with stronger assumptions and without using the coupling theory.

iterative methods. Such methods have been implemented efficiently in tools like PRISM [16], LiQuor [9] or MRMC [15].

However these methods have two drawbacks. On the one hand, they rely on strong assumptions about the stochastic process that must be a Markov chain (see for instance [2]) or at least a regenerative process (see for instance [1]). On the other hand they suffer from the combinatorial explosion of the size of the stochastic process w.r.t. the size of the model.

Models with huge stochastic process are handled by statistical model checking. The corresponding methods randomly generate a (large) set of execution paths and check whether the paths fulfill the formula. The result is a probabilistic estimation of the satisfaction given by a confidence interval [4]. In principle, it only requires to maintain a current state (and some numerical values in case of a non Markovian process). Furthermore no regenerative assumption is required and it is easier to parallelize the methods. Several tools include statistical model checking: COSMOS [5], GREATSPN [8], PRISM [16], UPPAAL [7], VESTA [22], YMER [24].

Model checking of probabilistic systems is particularly important for events which have disastrous consequences (loss of human life, financial ruin, etc.), but occur with very small probability. Unfortunately statistical model checking of *rare events* triggers a computation time explosion, forbidding its use. To illustrate this point, suppose one wants to estimate an unknown probability $p = 10^{-13}$ and one chooses to generate 10^{10} paths (which is already a large number) for such an estimation. With probability larger than 0.999 the result is 0, giving no information on the value of p . With probability smaller than 0.001 the result will be greater or equal than 10^{-10} which is a very crude estimation.

Thus *acceleration* techniques [21] have been introduced to cope with this problem. The two main families of methods are *splitting* and *importance sampling*.

Splitting methods [18] duplicate or eliminate paths during their generation depending on their intermediate behaviour. When generation is ended, the bias introduced by these operations is taken into account for the estimation of the probability. Splitting methods are by nature heuristics, model dependent and very few theoretical results are known.

Importance sampling methods [13] generate paths of a system whose probability distribution of transitions have been changed to increase the probability of the event to occur. A weight is then affected to each path to correct the introduced bias. The goal is to substitute to the Bernoulli random variable corresponding to the occurrence of the rare event, another one with same mean value (the probability of event occurrence) but smaller variance. In Markov chains, an optimal change of distribution exists leading to a zero variance but it requires more information than the searched value! However this optimal importance sampling allows to design efficient heuristics for some classes of models.

The modification of the distribution can be performed at the model level (called *static*) or at the Markov chain level (called *dynamic*). The static importance sampling requires no additional memory but in general provides a smaller

reduction of variance than the dynamic importance sampling. More precisely, it is proved in [10] that asymptotic optimality (a weaker requirement than optimality) cannot be obtained even for very simple classes of models by static importance sampling. In full generality, the dynamic importance sampling [23] requires to maintain a memory whose size is proportional to the size of the Markov chain which is exactly what one wants to avoid. To deal with this problem, in [11] the authors develop the following method: (1) the possible distributions belong to the convex hull of a finite number of distributions, (2) the state space is partitioned and (3) a distribution is selected for each subset of this partition. They prove that for a simple class of models their method is asymptotically optimal. Other empirical approaches turn out to be efficient [14].

Summarizing, theoretical results (reduction of variance, asymptotical optimality, etc.) have been obtained for importance sampling. However none of these methods can produce a reliable confidence interval² for the mean value since the distribution of the modified random variable is unknown.

3 General Approach

3.1 Preliminaries

Definition 1. A discrete time Markov chain (DTMC) $\mathcal{C}$ is defined as a set of states S , an initial state s_0 , and a transition probability matrix $\mathbf{P}$ of size $S \times S$. The state of the chain at time n is a random variable X_n defined inductively by $\Pr(X_0 = s_0) = 1$ and $\Pr(X_{n+1} = s' \mid X_n = s, X_{n-1} = s_{n-1}, \dots, X_0 = s_0) = \Pr(X_{n+1} = s' \mid X_n = s) = \mathbf{P}(s, s')$.

Example 1. The figure 1(a) represents a Markov chain of a tandem queue system. This system contains two queues, the number of clients in the first queue is represented on the horizontal axis and the number of clients in the second one is represented on the vertical axis. In the initial state s_0 , the two queues are empty. Given some state, a new client comes in the first queue with probability λ , a client leaves the first queue for the second one with probability ρ_1 and a client leaves the second queue and exits with probability ρ_2 ($\lambda + \rho_1 + \rho_2 = 1$). An impossible event (due to the emptiness of some queue) corresponds to an event letting unchanged the state. These loops are not represented in the figure.

Usually the modeller does not specify its system with a Markov chain. He rather defines a higher level model $\mathcal{M}$ (a queueing network, a stochastic Petri net, etc.), whose operational semantic is a Markov chain $\mathcal{C}$.

In the context of model checking, the states of chain $\mathcal{C}$ are labelled with atomic propositions. The problem we address here is the computation of the probability that a random path starting from state s_0 satisfies a formula aUb where U is the *Until* operator and a, b are atomic propositions. Observe that in continuous time Markov chains, this probability only depends on its embedded

² In contrast to the empirical confidence interval based on approximations by the normal distribution.

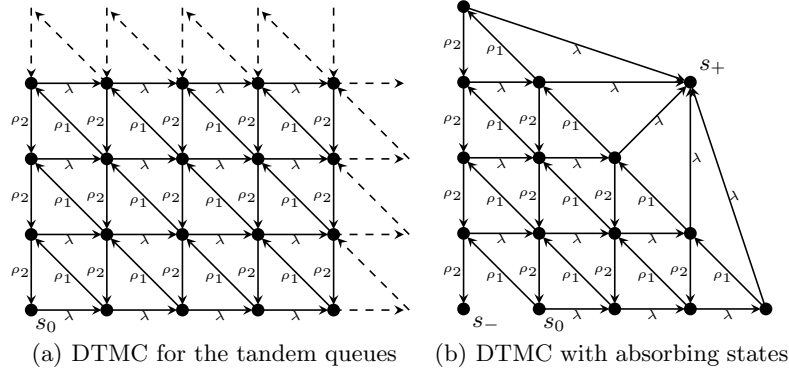


Fig. 1. DTMC for tandem queues

DTMC. Thus our results are also applicable in a continuous time setting. We (implicitly) transform $\mathcal{C}$ by lumping together all the states that satisfy b into an absorbing state s_+ (i.e. $\mathbf{P}(s_+, s_+) = 1$) and states that satisfy $\neg a \wedge \neg b$ into an absorbing state s_- . We assume that there is no terminal strongly connected component of $\mathcal{C}$ whose every state satisfies $a \wedge \neg b$ ³. Hence in the modified chain, the probability to reach s_+ or s_- is equal to 1 and probability of satisfying the formula is the probability to reach s_+ .

Example 1. The figure 1(b) shows the transformation of the tandem queues where the states have been lumped together w.r.t. the propositions a : *There is at least one client in some queue* and b : *the sum of clients in both queues is equal to 5*. The initial state s_0 is now the state with one client in the first queue (to avoid $s_0 = s_-$). We are looking for the probability to have simultaneously at least five clients between two idle periods.

The statistical approach consists in generating K paths of the Markov chain which ends in an absorbing state. Let K_+ be the number of paths ending in the s_+ state. The random variable K_+ follows a binomial distribution with parameters p and K . Thus the random variable $\frac{K_+}{K}$ has a mean value p and a variance $\frac{p-p^2}{K}$. When K goes to infinity the variance goes to 0. In order to be more precise on the estimation, we introduce the notion of confidence interval.

Definition 2. Let $X_1, \dots, X_n$ be independent random variables following a common distribution including a parameter θ . Let $0 < \gamma < 1$ be a confidence level. Then a confidence interval for θ with level at least γ is given by two random variables $l(X_1, \dots, X_n)$ and $u(X_1, \dots, X_n)$ such that for all θ :

$$\Pr(l(X_1, \dots, X_n) \leq \theta \leq u(X_1, \dots, X_n)) \geq \gamma$$

For standard parametrized distributions like the normal or the Bernoulli ones, it is possible to compute confidence intervals [4]. Thus, given a number of paths

³ There is currently no satisfactory solution for the statistical model checking of the unbounded until for chains that do not fulfill this assumption.

K and a confidence level $1 - \varepsilon$, the method produces a confidence interval. As discussed before when $p \ll 1$, the number of paths required for a small confidence interval is too large to be simulated.

The importance sampling method uses a modified transition matrix $\mathbf{P}'$ during the generation of paths. $\mathbf{P}'$ must satisfy:

$$\mathbf{P}(s, s') > 0 \Rightarrow \mathbf{P}'(s, s') > 0 \vee s = s_- \quad (1)$$

which means that this modification cannot remove transitions that have not s_- as target, but can add new transitions. The method maintains a correction factor called L initialized to 1; this factor represents the *likelihood* of the path. When a path crosses a transition $s \rightarrow s'$ with $s' \neq s_-$, L is updated by $L \leftarrow L \frac{\mathbf{P}(s, s')}{\mathbf{P}'(s, s')}$. When a path reaches s_- , L is set to zero. If $\mathbf{P}' = \mathbf{P}$ (i.e. no modification of the chain), the value of L when the path reaches s^+ (resp. s^-) is 1 (resp. 0).

Let V_s (resp. W_s) be the random variable associated with the final value of L for a path starting in s in the original model (resp. in the modified one). By definition, $\mathbf{E}(V_{s_0}) = p$. The following proposition establishes the correctness of the method.

Proposition 1. $\mathbf{E}(W_{s_0}) = p$.

A good choice of $\mathbf{P}'$ should reduce the variance of W_{s_0} w.r.t. to variance of V_{s_0} . The following proposition shows that there exists a matrix $\mathbf{P}'$ which leads to a null variance. We denote the probability to reach s_+ starting from s by $\mu(s)$.

Proposition 2. Let $\mathbf{P}'$ be defined by

$$\begin{aligned} - \forall s \text{ such that } \mu(s) \neq 0, \mathbf{P}'(s, s') &= \frac{\mu(s')}{\mu(s)} \mathbf{P}(s, s') \\ - \forall s \text{ such that } \mu(s) = 0, \mathbf{P}'(s, s') &= \mathbf{P}(s, s') \end{aligned}$$

Then for all s , we have $\mathbf{V}(W_s) = 0$.

This result has a priori no practical application since it requires the knowledge of μ for all states, whereas we only want to estimate $\mu(s_0)$!

The coupling method [20] is a classical method for comparing two stochastic processes, applied in different contexts (establishing ergodicity of a chain, stochastic ordering, bounds, etc.). In the sequel we will develop a new application for coupling. A coupling between two Markov chains is a chain whose space is a subset of the product of the two spaces which satisfies: (1) the projection of the product chain on any of its components behaves like the original corresponding chain, (2) an additional constraint which depends on the property to be proved (here related to the absorbing states).

Definition 3. Let $\mathcal{C} = (S, \mathbf{P})$ and $\mathcal{C}' = (S', \mathbf{P}')$ be two Markov chains with s_+ and s_- two absorbing states of $\mathcal{C}$ and s'_+ and s'_- two absorbing states of $\mathcal{C}'$. A coupling between $\mathcal{C}$ and $\mathcal{C}'$ is a DTMC $\mathcal{C}^\otimes = (S^\otimes, \mathbf{P}^\otimes)$ such that :

$$- S^\otimes \subseteq S \times S'$$

- $\forall s \neq s_1 \in S, \forall (s, s') \in S^\otimes, \mathbf{P}(s, s_1) = \sum_{s'_1 \in S'} \mathbf{P}^\otimes((s, s'), (s_1, s'_1))$ and
 $\forall s' \neq s'_1 \in S', \forall (s, s') \in S^\otimes, \mathbf{P}'(s', s'_1) = \sum_{s_1 \in S} \mathbf{P}^\otimes((s, s'), (s_1, s'_1))$
- $\forall (s, s') \in S^\otimes, s' = s'_+ \Rightarrow s = s_+$

The set $S^\otimes$ defines a coupling relation between the two chains.

The following proposition allows to compare probabilities without any numerical computation. As before, $\mu(s)$ (resp. $\mu'(s')$) denotes the probability to reach the state s_+ (resp. s'_+) in $\mathcal{C}$ (resp. in $\mathcal{C}'$) starting from s (resp. from s').

Proposition 3. *Let $\mathcal{C}^\otimes$ be a coupling between $\mathcal{C}$ and $\mathcal{C}'$. Then, for all $(s, s') \in S^\otimes$, we have:*

$$\mu(s) \geq \mu'(s')$$

Example 1. *Let us illustrate coupling for the Markov chain represented in figure 2 and called $\mathcal{C}^\bullet$. This chain is obtained from the tandem queues by lumping together states which have the same number of clients and at least R clients in the second queue (in the figure $R = 2$). Its set of state is $S^\bullet = [0..N] \times [0..R]$. Here there is a coupling of this chain with itself defined by $S^\otimes = \{(n_1, n_2), (n'_1, n'_2) \mid n_1 + n_2 \geq n'_1 + n'_2 \wedge n_1 \geq n'_1\}$.*

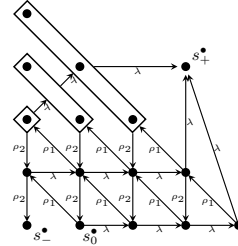


Fig. 2. Reduced DTMC

Lemma 1. $S^\otimes$ is a coupling relation.

Thus: $\forall ((n_1, n_2), (n'_1, n'_2)) \in S^\otimes, \mu^\bullet(n_1, n_2) \geq \mu^\bullet(n'_1, n'_2)$

3.2 An Importance Sampling Method with Variance Reduction and Confidence Interval

The proposed method combines statistical model checking on the original chain preceded by numerical model checking on a reduced chain whose formal definition is given below.

Definition 4. *Let $\mathcal{C}$ be a DTMC, a DTMC $\mathcal{C}^\bullet$ is called a reduction of $\mathcal{C}$ by a function f that maps S to $S^\bullet$, the state space of $\mathcal{C}^\bullet$, if, denoting $s_{-}^{\bullet} = f(s_{-})$ and $s_{+}^{\bullet} = f(s_{+})$, the following assertions are satisfied:*

- $f^{-1}(s_{-}^{\bullet}) = \{s_{-}\}$ and $f^{-1}(s_{+}^{\bullet}) = \{s_{+}\}$.
- $s_{-}^{\bullet}$ and $s_{+}^{\bullet}$ are absorbing states reached with probability 1.
- Let $s^{\bullet} \in S^\bullet$ and denote by $\mu^\bullet(s^{\bullet})$, the probability to reach $s_{+}^{\bullet}$ starting from $s^{\bullet}$. Then for all $s \in S$, we have $\mu^\bullet(f(s)) = 0 \Rightarrow \mu(s) = 0$.

The two first assertions entail that the reduced chain has two absorbing states reached with probability 1 which are images of the absorbing states of the original chain. The last assertion requires that when from the image of some state s , one cannot reach $s_{+}^{\bullet}$, then one cannot reach s_{+} from s . These (weak) assumptions ensure that the mapping f preserves the basic features of

the original chain. Two states s and s' are *equivalent* if $f(s) = f(s')$, in other words f^{-1} define equivalence classes for this reduction.

Example 1. *In the example of tandem queues, the reduced chain $\mathcal{C}^\bullet$ is obtained from the original chain by applying the following function to the state space.*

$$f(n_1, n_2) = \begin{cases} (n_1, n_2) & \text{if } n_2 \leq R \\ (n_1 + n_2 - R, R) & \text{otherwise} \end{cases}$$

Given some reduced chain $\mathcal{C}^\bullet$, our goal is to replace the random variable (r.v.) V_{s_0} which takes value in $\{0, 1\}$ by a r.v. W_{s_0} which takes value in $\{0, \mu^\bullet(f(s_0))\}$. This requires that $\mu(s_0) \leq \mu^\bullet(f(s_0))$. By applying an homogeneity principle, we get the stronger requirement $\forall s \in S, \mu(s) \leq \mu^\bullet(f(s))$. In fact, the appropriate requirement which implies the previous one (see later proposition 4) is expressed by the next definition.

Definition 5. *Let $\mathcal{C}$ be a DTMC and $\mathcal{C}^\bullet$ a reduction of $\mathcal{C}$ by f . $\mathcal{C}^\bullet$ is a reduction with guaranteed variance if for all $s \in S$ such that $\mu^\bullet(f(s)) > 0$ we have :*

$$\sum_{s' \in S} \mu^\bullet(f(s')) \cdot \mathbf{P}(s, s') \leq \mu^\bullet(f(s)) \quad (2)$$

Given $s \in S$, let $h(s)$ be defined by $h(s) = \sum_{s' \in S} \frac{\mu^\bullet(f(s'))}{\mu^\bullet(f(s))} \mathbf{P}(s, s')$. We can now construct an efficient important sampling based on a reduced chain with guaranteed variance.

Definition 6. *Let $\mathcal{C}$ be a DTMC and $\mathcal{C}^\bullet$ be a reduction of $\mathcal{C}$ by f with guaranteed variance. Then $\mathbf{P}'$ is transition matrix on S defined by:*

Let s be a state of S ,

- *if $\mu^\bullet(f(s)) = 0$ then for all $s' \in S$, $\mathbf{P}'(s, s') = \mathbf{P}(s, s')$*
- *if $\mu^\bullet(f(s)) > 0$ then for all $s' \in S \setminus \{s_-\}$,*

$$\mathbf{P}'(s, s') = \frac{\mu^\bullet(f(s'))}{\mu^\bullet(f(s))} \mathbf{P}(s, s') \text{ and } \mathbf{P}'(s, s_-) = 1 - h(s).$$

The following proposition justifies the definition of $\mathbf{P}'$.

Proposition 4. *Let $\mathcal{C}$ be a DTMC and $\mathcal{C}^\bullet$ be a reduction with guaranteed variance. The importance sampling based on matrix of $\mathbf{P}'$ definition 6 has the following properties:*

- *For all s such that $\mu(s) > 0$,*
 W_s *is a random variable which has value in $\{0, \mu^\bullet(f(s))\}$.*
- *$\mu(s) \leq \mu^\bullet(f(s))$ and $\mathbf{V}(W_s) = \mu(s)\mu^\bullet(f(s)) - \mu^2(s)$.*
- *One can compute a confidence interval for this importance sampling.*

Since $\mu(s_0) \ll 1$, $\mathbf{V}(W_{s_0}) \approx \mu(s_0)$. If $\mu(s_0) \ll \mu^\bullet(f(s_0))$, we obtain $\mathbf{V}(W_{s_0}) \approx \mu(s_0)\mu^\bullet(f(s_0))$, so the variance is reduced by a factor $\mu^\bullet(f(s_0))$. In the case where $\mu(s_0)$ and $\mu^\bullet(f(s_0))$ have same magnitude order, the reduction of variance is even bigger.

Unfortunately, Equation (2) requires to compute the function $\mu^\bullet$ in order to check that $\mathcal{C}^\bullet$ is a reduction with guaranteed variance. We are looking for a structural requirement that does not involve the computation of $\mu^\bullet$.

Proposition 5. *Let $\mathcal{C}$ be a DTMC, $\mathcal{C}^\bullet$ be a reduction of $\mathcal{C}$ by f . Assume there exists a family of functions $(g_s)_{s \in S}$, $g_s : \{t \mid \mathbf{P}(s, t) > 0\} \rightarrow S^\bullet$ such that:*

1. $\forall s \in S, \forall t^\bullet \in S^\bullet, \mathbf{P}^\bullet(f(s), t^\bullet) = \sum_{s' \mid g(s')=t^\bullet} \mathbf{P}(s, s')$
2. $\forall s, t \in S$ such that $\mathbf{P}(s, t) > 0$, $\mu^\bullet(f(t)) \leq \mu^\bullet(g_s(t))$

Then $\mathcal{C}^\bullet$ is a reduction of $\mathcal{C}$ with guaranteed variance.

The family of functions (g_s) assigns to each transition of $\mathcal{C}$ starting from s a transition of $\mathcal{C}^\bullet$ starting from $f(s)$. The first condition can be checked by straightforward examination of the probability transition matrices. The second condition still involves the mapping $\mu^\bullet$ but here there are only comparisons between its values. Thanks to proposition 3, it can be proved by exhibiting a coupling of $\mathcal{C}$ with itself.

We are now in position to describe the whole method for a model $\mathcal{M}$ with associated DTMC $\mathcal{C}$.

1. Specify a model $\mathcal{M}^\bullet$ with associated DTMC $\mathcal{C}^\bullet$, a function f and a family of functions $(g_s)_{s \in S}$. The specification of this family is done at the level of models $\mathcal{M}$ and $\mathcal{M}^\bullet$ as shown in the next example and in section 4.
2. Prove using a coupling on $\mathcal{C}^\bullet$ that proposition 5 holds. Again the proof is performed at the level of models.
3. Compute function $\mu^\bullet$ with a numerical model checker applied on $\mathcal{M}^\bullet$.
4. Compute $\mu(s_0)$ with a statistical model checker applied on $\mathcal{M}$ using the importance sampling of definition 6.

The last two steps are done by tools. The second step is currently done by hand (see appendix C) but could be handled by theorem provers. The only manual step is the specification of $\mathcal{M}^\bullet$ which requires to study $\mathcal{M}$ and the formula to be checked (see section 4).

Example 1. *To apply the method on the example it remains to specify the family of functions $(g_s)_{s \in S}$.*

$$\begin{aligned} g_{(n_1, n_2)}(n_1, n_2) &= f(n_1, n_2) \\ g_{(n_1, n_2)}(n_1 + 1, n_2) &= f(n_1 + 1, n_2) \\ g_{(n_1, n_2)}(n_1 - 1, n_2 + 1) &= f(n_1 - 1, n_2 + 1) \\ g_{(n_1, n_2)}(n_1, n_2 - 1) &= \begin{cases} (n_1, n_2 - 1) & \text{if } n_2 \leq R \\ (n_1 + n_2 - R, R - 1) & \text{otherwise} \end{cases} \end{aligned}$$

The condition 2 always trivially holds except for the last case with $n_2 > R$. We have to check that $\mu^\bullet(n_1 + n_2 - 1 - R, R) \leq \mu^\bullet(n_1 + n_2 - R, R - 1)$. As $(n_1 + n_2 - R, R - 1), (n_1 + n_2 - 1 - R, R)$ belongs to the coupling relation the inequality holds.

3.3 Generalisation

In this paragraph, we generalize the method but with no more guarantee about the variance reduction.

Definition 7. Let $\mathcal{C}$ be a DTMC and $\mathcal{C}^\bullet$ a reduction $\mathcal{C}$ of by f . We define a transition matrix $\mathbf{P}'$ on S by the following rules.

Let s be in S :

- if $\mu^\bullet(f(s)) = 0$ then for all $s' \in S$, $\mathbf{P}'(s, s') = \mathbf{P}(s, s')$
- if $\mu^\bullet(f(s)) > 0$ and $h(s) \leq 1$ then for all $s' \in S \setminus \{s_-\}$,

$$\mathbf{P}'(s, s') = \frac{\mu^\bullet(f(s'))}{\mu^\bullet(f(s))} \mathbf{P}(s, s') \text{ and } \mathbf{P}'(s, s_-) = 1 - h(s)$$
- if $h(s) > 1$, then for all $s' \in S$, $\mathbf{P}'(s, s') = \frac{\mu^\bullet(f(s'))}{h(s)\mu^\bullet(f(s))} \mathbf{P}(s, s')$

When Equation 2 does not hold for some state s , we have to “normalize” the matrix row $\mathbf{P}'(s, -)$. The following proposition characterises the range of the random variable W_s for this importance sampling.

Proposition 6. Let $\mathcal{C}$ be a DTMC and $\mathcal{C}^\bullet$ his reduction. The importance sampling of the definition 7 has the following property: for all s such that $\mu(s) > 0$, W_s is a random variable which takes its values in $\{0\} \cup [\mu^\bullet(f(s)), \infty[$.

As we do not have any additional information on the distribution of W_s , the precision of the estimator highly depends of the shape of the distribution of W_s .

4 Experimentation

4.1 Implementation

Tools. Our experiments⁴ have been performed on a modified version of COSMOS. COSMOS is a statistical model checker whose input model is a stochastic Petri net with general distributions and formulas are expressed by the Hybrid Automata Stochastic Logic [5]. The numerical model checking of the reduced model have been performed by PRISM whereas we have also used the statistical model checker PRISM for comparisons with our method.

Adaptation of COSMOS. Since COSMOS takes as input a stochastic Petri net with a continuous time semantic, we have adapted our method to work with continuous time Markov chains. As discussed before, for formulas that we consider, this does not present serious difficulty.

The importance sampling increases the computation time of simulation. First we have to compute the probability vector $\mu^\bullet$ of the reduced model in polynomial time w.r.t. the reduced Markov chain $\mathcal{C}^\bullet$.

a discuter

Moreover after each transition of the system we must to compute again the rate of all enabled transition. A hash table is used to store the value of $\mu^\bullet$. Another additional cost come from the computation of $P^\bullet(x, s_-)$ which require in the worst case an additional linear time in the number of transition in $\mathcal{M}$. Another minor additional time is inherent to the importance sampling method, usually paths to reach s_+ are longer than the ones to s_- so the mean length of a path is increased.

⁴ All the experiments have been performed on a computer with a 2.6Ghz processor and 48Go of memory without parallelism.

4.2 Example 1: Tandem

We use this classical example in order to compare our results with those of [11] who also use an importance sampling method. We take the same parameters with $\lambda = 0.1$, $\rho_1 = \rho_2 = 0.45$, $N = 50$ and we simulate 20000 trajectories. The parameter R is set to 4. Our result is $3.8017 \cdot 10^{-31}$ with confidence interval width of $9.63 \cdot 10^{-33}$ whereas the result in [11] is $3.75 \cdot 10^{-31}$ with a confidence interval of $6.4 \cdot 10^{-32}$ and the computation done using a numerical model checker is $3.8012 \cdot 10^{-31}$. With the same parameter our method provides a six times smaller confidence interval.

We also need to compare our method to both numerical model checking and statistical one without rare event method: we change the parameter of the model to $\lambda = 0.32$, $\rho_1 = \rho_2 = 0.34$ in order to test big values of N ; we use Prism with its numerical and statistical implementation. Results are depicted in table 1. To choose the value of R , we compute experimentally the minimal value of R such that $\frac{\mu(s_0)}{\mu \bullet (f(s_0))} < 1.5$. We found that R and N satisfy $R \approx 36.3 \log(N) - 126$. We use this to compute $\mu(s_0)$ for big values of N , the narrowness of the obtained confidence interval confirms the validity of this approximation. The reduced model has $O(n \log(n))$ states whereas the initial one has $O(n^2)$ states.

We find that our method computes a good approximation of the result whereas numerical method takes too much time because of the size of the model (25000000 states), and statistical model checking without rare event handling returns zero as value.

Table 1. Experimental results for tandem queues

N	Size of C	Prism num		Prism stat			Cosmos				
		T (s)	$\mu(s_0)$	T (s)	$\mu(s_0)$	Conf. Int.	R	T C*	T (s)	$\mu(s_0)$	Conf. Int.
50	2601	0.3	0.0929	1.45	0.091	0.016	4	0.03	7	0.090	0.017
100	10 201	1.6	0.01177	2.7	0.015	0.007	30	1	36	0.01156	8.6E-4
500	251 001	126	2.06E-12	2.3	0	#	87	23	145	2.075e-12	1.72E-13
1000	1E6	860	2.87E-25	#	#	#	111	113	263	2.906e-25	2.52E-26
5000	25E6	>12h	#	#	#	#	150	3061	1099	7.10e-130	1.21E-130

4.3 Example 2 : Parallel Ruin

The Petri net depicted in figure 3 describes a model of parallel ruin of N players. We represent on this figure the player i and his interactions with player $i + 1$. Each of the N players can move along a line of L cells. The player i in cell j can move forward using the transition $A_{i,j}$ of rate p if the player $i + 1$ is not in the cell j or if $i = N$. He can always move backward using transition $R_{i,j-1}$ of rate q . Cells 1 and L are absorbing. This models has L^N states. We are interested in the property **a majority of players have reached the cells L before a majority of player reaches the cells 1**, each player starts in the cell $L/2$.

This model is a paradigm of failure tolerant systems in which each player represents a process which finishes his job when he reaches the cell 1. Failure

can occur and move the process away of its goal. The reduced model removes all synchronisation between players. Behaviours of all players are then independent. A state of the system is now fully characterized by the number of players in each cell. The states space of the system is $\binom{N+L-1}{L-1}$.

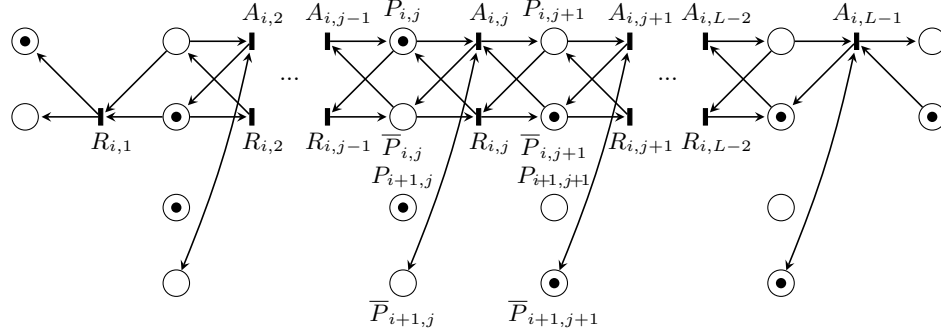


Fig. 3. The Petri net for the parallel ruin

For this model we were able to prove the proposition 5. The table 2 shows the experimental result with the following parameters $p = 0.3$, $q = 0.7$, $L = 15$. We stop the simulation when the confidence interval width reaches one tenth of the estimated value.

Table 2. Experimental results for players ruin

N	taille de	Prism num		Prism stat		Cosmos								
	C	T in s.	$\mu(s_0)$	T in s.	$\mu(s_0)$	Conf. Int.	Nb Traj.	T C*	T en s.	$\mu(s_0)$	Conf. Int.			
1	15	≈ 0	0.00113	12	1.15E-3	1E-4	1	≈ 0	≈ 0	0.00113	0			
5	7.5E5	6	1.88E-9	21	0	#	18000	0.5	13	1.94E-9	1.89E-10			
6	1.1E7	127	1.14E-12	No sample reach the rare event			53000	1	57	1.17E-12	1.17E-13			
7	1.7E8	2248	2.93E-12				#	50000	2.8	186	2.92E-12	2.89E-13		
8	2.0E9	Out of memory					145000	7.9	1719	1.86E-15	1.86E-16			
9	3.8E10						#	#	128000	24	3800	4.7E-15	4.75E-16	
10	5.7E11	#	#				371000	71	26000	3.12E-18	3.11E-19			
11	8.0E12	#	#				321000	228	67000	7.90E-18	7.89E-19			

This result shows that our method gives an estimation of the probability $\mu(s_0)$ with a good precision, the confidence interval width is one tenth of $\mu(s_0)$, for very big model ($8 \cdot 10^{12}$). Whereas the classical statistical model checking fails, returning *zero*, and numerical model checking fails because of the size of the system.

4.4 Example 3

We will now consider the tandem queues system again but with a different property to check. This property is **The second queue contains N clients**

($n_2 = N$) before that the second queue is empty ($n_2 = 0$). The state space is $S = \mathbb{N} \times [0..N]$ the initial state is moved to $(0, 1)$. The reduction function f of the first example is no longer suitable. We must define a new one in order to have a finite state space for the reduced model.

We define a new reduction function f'_R such that we have a finite reduced model. We choose to transform the model such that once the first queue reaches R clients it behave like a queue with an infinite number of clients. This model is depicted figure 4(a). The reduction function f' is defined as

$$f'_R(n_1, n_2) = \begin{cases} (n_1, n_2) & \text{if } n_1 \leq R \\ (R, n_2) & \text{otherwise} \end{cases}$$

This function is represented figure 4(b). We can prove that this model and this function guarantees the reduction of variance. The proof is very similar to the one of the first case of tandem queues.

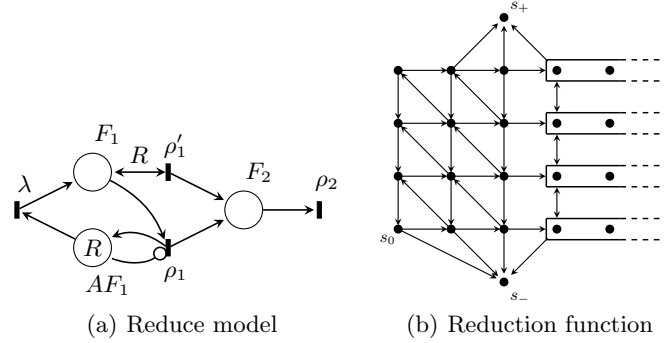


Fig. 4. Petri net for the infinite tandem queues ($R = 3, N = 5$)

Table 3. Experimental result for tandem queues

N	R	T (s)	Size of $\mathcal{C}^\bullet$	Size of $\mu^\bullet(f(s_0))$	Cosmos					Prism stat		
					$\mu(s_0)$	Conf. Int.	T (s)	Nb Traj.	T (s)	$\mu(s_0)$	Conf. Int.	
25	12	≈ 0	338	1.16E-5	1.48E-6	2.83E-7	2	5000	33	1.1E-6	1.6E-6	
50	29	≈ 0	1530	2.98E-10	3.81E-11	7.19E-12	13	5000	No sample reach the rare event			
100	66	1.44	6767	1.87E-19	4.22E-20	7.34E-21	17	3000				
500	370	1770	185871	1.03E-90	6.63E-91	8.05E-32	37	2000				
1000	740	24670	741741	3.24E-177	3.95E-179	4.00E-179	180	3000				#

Similarly to the first example we have to choose suitable values for R , we found by running experiments on small values of N and R that for $R > 0.74 \times N$ we have $\mu(s_0) \geq \mu^\bullet(f(s_0))/10$. This allows us to compute big values of N . This example shows that we can estimate a probability on an infinite model which is not possible with a numerical model checker like PRISM, the low probability of the outcome makes this computation too long for statistical model checker.

4.5 Example 4

The third property we choose to study for the tandem queues system is: **The second queue is full ($n_2 = N$) before the first one ($n_1 = N$).** The idea for the reduction is that in the initial state the second queue already contains R clients, then the second queue is full when it contains $N - R$ clients. This model is depicted figure 5(a). We define f_R'' the new reduction function:

$$f_R''(n_1, n_2) = \begin{cases} (n_1, R) & \text{if } n_2 \leq R \\ (n_1, n_2) & \text{otherwise} \end{cases}$$

This function is depicted figure 5(b). We prove that this model guarantees the reduction of variance.

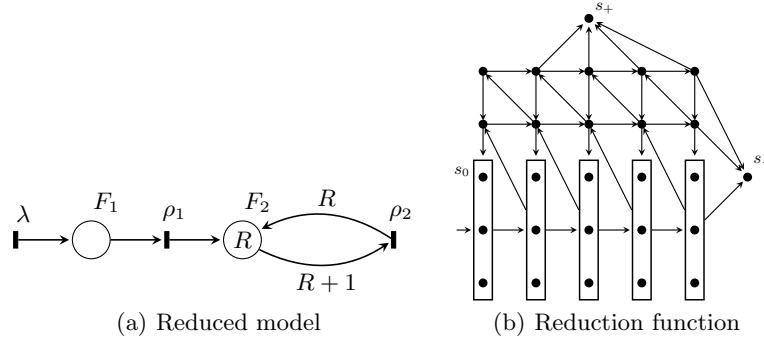


Fig. 5. Petri net for the tandem queues ($R = 2, N = 5$)

Even if our method guarantees the reduction of variance, the experimental results are not satisfactory. Because $\mu(s_0) \ll \mu^\bullet(f(s_0))$ when R is small compared to N . This shows that the reduced model needs to be carefully designed to obtain an efficient importance sampling. For this example we need to find a better reduced model to make our method work.

5 Conclusion

We proposed a method of statistical model checking which computes a reduced confidence interval for the probability of a rare event. Our method is based on importance sampling techniques. Other methods usually rely on heuristics and fail to provide a confidence interval. We have developed a theoretical framework ensuring the reduction of the variance and providing a confidence interval. This framework requires a structural analysis of the model but no numerical computation thanks to coupling theory. Our method is implemented in the statistical model checker COSMOS and we have done experiments with impressive results.

We plan to go further in three directions. First we want to deal with more complex infinite systems. Secondly we want to handle “bounded until” formulas

requiring to deal with non Markovian systems. Finally we would like to mechanize the proofs of coupling since they consist to check parametrized inequalities.

References

1. E. G. Amparore and S. Donatelli. Model checking CSL^{TA} with deterministic and stochastic petri nets. In *DSN*, pages 605–614, 2010.
2. C. Baier, B. R. Haverkort, H. Hermanns, and J.-P. Katoen. On the logical characterisation of performability properties. In *ICALP*, pages 780–792, 2000.
3. C. Baier, B. R. Haverkort, H. Hermanns, and J.-P. Katoen. Model-checking algorithms for continuous-time markov chains. *IEEE Trans. Software Eng.*, 29(6):524–541, 2003.
4. L. J. Bain and M. Engelhardt. *Introduction to Probability and Mathematical Statistics, Second Edition*. Duxbury Classic Series, 1991.
5. P. Ballarini, D. Hilal, M. Duflot, S. Haddad, and N. Pekergin. HASL: An expressive language for statistical verification of stochastic models. In *(VALUETOOLS’11)*, Cachan, France, May 2011. To appear.
6. B. Barbot, S. Haddad, and C. Picaronny. Échantillonnage préférentiel pour le model checking statistique. In É. Crayé and A. Gamatié, editors, *Actes du 8ème Colloque sur la Modélisation des Systèmes Réactifs (MSR’11)*, volume 45 of *Journal Européen des Systèmes Automatisés*, Lille, France, Nov. 2011. Hermès. To appear.
7. J. Bengtsson, K. G. Larsen, F. Larsson, P. Pettersson, and W. Yi. UPPAAL - a tool suite for automatic verification of real-time systems. In *Hybrid Systems*, pages 232–243, 1995.
8. G. Chiola, G. Franceschinis, R. Gaeta, and M. Ribaud. GreatSPN 1.7: Graphical editor and analyzer for timed and stochastic petri nets. *Perform. Eval.*, 24(1-2):47–68, 1995.
9. F. Ciesinski and C. Baier. LiQuor: A tool for qualitative and quantitative linear time analysis of reactive systems. In *QEST’06*, pages 131–132, 2006.
10. P.-T. de Boer. Analysis of state-independent importance-sampling measures for the two-node tandem queue. *ACM Trans. Model. Comput. Simul.*, 16(3):225–250, 2006.
11. P. Dupuis, A. D. Sezer, and H. Wang. Dynamic importance sampling for queueing networks. *Annals of Applied Probability*, 17:1306–1346, 2007.
12. E. A. Emerson and E. M. Clarke. Characterizing correctness properties of parallel programs using fixpoints. In *ICALP*, LNCS 85, 1980.
13. P. W. Glynn and D. L. Iglehart. Importance sampling for stochastic simulations. *Management Science*, 1989.
14. P. E. Heegaard and W. Sandmann. Ant-based approach for determining the change of measure in importance sampling. In *Winter Simulation Conference*, pages 412–420, 2007.
15. J.-P. Katoen, I. S. Zapreev, E. M. Hahn, H. Hermanns, and D. N. Jansen. The ins and outs of the probabilistic model checker MRMC. *Quantitative Evaluation of Systems, International Conference on*, 0:167–176, 2009.
16. M. Kwiatkowska, G. Norman, and D. Parker. PRISM: Probabilistic symbolic model checker. In T. Field, P. Harrison, J. Bradley, and U. Harder, editors, *Computer Performance Evaluation: Modelling Techniques and Tools*, volume 2324 of *LNCS*, pages 113–140. Springer Berlin / Heidelberg, 2002.

17. M. Kwiatkowska, G. Norman, and D. Parker. Stochastic model checking. In M. Bernardo and J. Hillston, editors, *SFM'07*, volume 4486 of *LNCS*), pages 220–270. Springer, 2007.
18. P. L'Ecuyer, V. Demers, and B. Tuffin. Splitting for rare-event simulation. In *Winter Simulation Conference*, pages 137–148, 2006.
19. A. Legay, B. Delahaye, and S. Bensalem. Statistical model checking: an overview. In *Proceedings of the First international conference on Runtime verification*, RV'10, pages 122–135. Springer-Verlag, 2010.
20. T. Lindvall. *Lectures on the coupling method*. Dover, 2002.
21. G. Rubino and B. Tuffin. *Rare Event Simulation using Monte Carlo Methods*. Wiley, 2009.
22. K. Sen, M. Viswanathan, and G. Agha. VESTA: A statistical model-checker and analyzer for probabilistic systems. *QEST*, 0:251–252, 2005.
23. R. Srinivasan. *Importance sampling – Applications in communications and detection*. Springer Verlag, Berlin, 2002.
24. H. Younes. Ymer: A statistical model checker. In K. Etessami and S. Rajamani, editors, *Computer Aided Verification*, volume 3576 of *LNCS*, pages 171–179. Springer Berlin / Heidelberg, 2005.

A Definitions

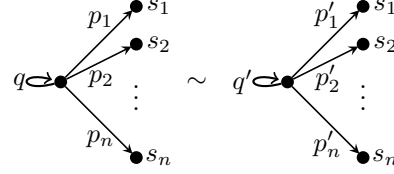
For our purpose, we need to enrich the usual definition of Markov chains with labels on transitions. When the transitions' labels are not useful, we simply omit them.

Definition 8. A discrete time Markov chain (DTMC) $\mathcal{C}$ is defined as a set of states S , an initial state s_0 , a finite set of events E , a successor function $\delta : S \times E \rightarrow S$, and a function $p : S \times E \rightarrow [0; 1]$ with the property that for all $s \in S$, $\sum_{e \in E} p(s, e) = 1$. We define the transition probability matrix $\mathbf{P}$ of size $S \times S$ by:

$$\forall s, s' \in S, \mathbf{P}(s, s') = \sum_{\delta(s, e) = s'} p(s, e)$$

Two Markov chains are *equivalent* if they have the same set of states S , respective probability distribution matrices $\mathbf{P}, \mathbf{P}'$ and for all state s with $q = \mathbf{P}(s, s)$, $q' = \mathbf{P}'(s, s)$ we have the following equality

$$\forall s' \neq s \frac{\mathbf{P}(s, s')}{1 - q} = \frac{\mathbf{P}'(s, s')}{1 - q'}$$



This equivalence is used in an implicit way in the proofs. We will often omit self-loops: we consider that a self-loop always exists with a probability such that the sum of all outgoing transitions probability is equal to 1.

B Proofs

Proof of proposition 1

In all states, the probability to reach s_- or s_+ is equal to 1. Then thanks to a classic result on Markov chains the expected value of the r.v. V_s is the unique solution of the following system of equations:

$$\mathbf{E}(V_{s_-}) = 0 \wedge \mathbf{E}(V_{s_+}) = 1 \wedge \forall s \notin \{s_-, s_+\} \mathbf{E}(V_s) = \sum_{s' \neq s_-} \mathbf{P}(s, s') \mathbf{E}(V_{s'}) \quad (3)$$

We now write the corresponding system for $\mathbf{P}'$ with correction factor:

$$\mathbf{E}(W_{s_-}) = 0 \wedge \mathbf{E}(W_{s_+}) = 1$$

$$\wedge \forall s \notin \{s_-, s_+\} \mathbf{E}(W_s) = \sum_{s' \neq s_- \wedge \mathbf{P}'(s, s') > 0} \mathbf{P}'(s, s') \left(\frac{\mathbf{P}(s, s')}{\mathbf{P}'(s, s')} \right) \mathbf{E}(W_{s'})$$

Thanks to the restriction of equation 1, the two systems are equal after simplification, and we have $\mathbf{E}(W_{s_0}) = \mathbf{E}(V_{s_0}) = p$.

c.q.f.d. $\diamond\diamond\diamond$

Proof of proposition 2

If $\mu(s) = 0$ then all trajectories starting in s end in s_- . Therefore the variance is null.

If $\mu(s) \neq 0$, thanks to the equation

$$\mu(s) = \sum_{s' | \mu(s') > 0} \mathbf{P}(s, s') \mu(s')$$

$\mathbf{P}'(s, -)$ is a distribution. A trajectory starting from a state s with $\mu(s) > 0$ visits only states s' with $\mu(s') > 0$, so it ends in s_+ , with $s = u_0, \dots, u_l = s_+$ such a trajectory then the value L is equal to $(\mu(u_0)/\mu(u_1)) \dots (\mu(u_{l-1})/\mu(u_l)) = \mu(s)$.

c.q.f.d. $\diamond\diamond\diamond$

Proof of proposition 3

Let ω be a finite random trajectory ending in one of the absorbing states in the coupled chain starting from (s, s') . We define the random variables $\mathbf{1}_{s_+}, \mathbf{1}_{s'_+}$ such that:

- $\mathbf{1}_{s_+} = 1$ if the first component of the ending state of ω is s_+ .
- $\mathbf{1}_{s'_+} = 1$ if the second component of the ending state of ω is s'_+ .

let $(s_f, s'_f) \in S^\otimes$ be the final state of ω . Using the hypothesis we have:

$$s'_f = s'_+ \Rightarrow s_f = s_+$$

then for all ω

$$\mathbf{1}_{s_+}(\omega) \geq \mathbf{1}_{s'_+}(\omega)$$

by taking mean values, we have:

$$\mathbf{E}(\mathbf{1}_{s_+}) \geq \mathbf{E}(\mathbf{1}_{s'_+})$$

which is equal to:

$$\mu(s) \geq \mu'(s')$$

c.q.f.d. $\diamond\diamond\diamond$

To simplify proofs of coupling we add a new proposition.

Proposition 7. *Let $\mathcal{C} = (S, E, \delta, p)$ be a DTMC and $S^\otimes \subset S \times S$ be a relation on $\mathcal{C}$ such that:*

1. $\forall e \in E, s_1, s_2 \in S, p(s_1, e) = p(s_2, e)$

$$2. \forall (s_1, s_2) \in S^\otimes, e \in E, (t_1, t_2) \in S^2 \\ (\delta(s_1, e) = t_1 \wedge \delta(s_2, e) = t_2) \Rightarrow (t_1, t_2) \in S^\otimes$$

We define $\delta^\otimes((s_1, s_2), e) = (\delta(s_1, e), \delta(s_2, e))$ and $p^\otimes((s_1, s_2), e) = p(s_1, e)$. Then the DTMC $\mathcal{C}^\otimes = (S^\otimes, E, \delta^\otimes, p^\otimes)$ and $S^\otimes$ is a coupling relation on $\mathcal{C}^2$.

Proof

The second hypothesis asserts that the chain is well defined. We will now prove that

$$\forall s \neq t \in S, \forall (s, s') \in S^\otimes, \mathbf{P}(s, t) = \sum_{t' \in S'} \mathbf{P}^\otimes((s, s'), (t, t'))$$

Using definition 8 we replace the sum on target states by a sum on events.

$$\sum_{t' \in S'} \mathbf{P}^\otimes((s, s'), (t, t')) = \sum_{e | \delta(s, e) = s'} p(s, e) = \mathbf{P}(s, t)$$

The other claim has a similar proof.

c.q.f.d. $\diamond\diamond\diamond$

Proof of proposition 4

Let $s = u_0, \dots, u_l = s_+$ be a trajectory starting in s ending in s_+ .

As the trajectory avoids s_- , its value is

$$(\mu^\bullet(f(u_0))/\mu^\bullet(f(u_1))) \dots (\mu^\bullet(f(u_{l-1}))/\mu^\bullet(f(u_l))) = \mu^\bullet(f(s))$$

We know that $\mathbf{E}(W_s) = \mu(s)$, then $\mathbf{P}(W_s = \mu^\bullet(f(s))) = \frac{\mu(s)}{\mu^\bullet(f(s))}$. This implies that $\mu(s) \leq \mu^\bullet(f(s))$ and $\mathbf{V}(W_s) = \mu(s)\mu^\bullet(f(s)) - \mu^2(s)$. As W_s takes only two values, the distribution is proportionnal to a binomial law and it is possible to compute a confidence interval.

c.q.f.d. $\diamond\diamond\diamond$

Proof of proposition 5

Let s be a state of S . We split the term of the sum of the inequation (2) by there mapping by g_s :

$$\sum_{s' | \mathbf{P}(s, s') > 0} \mu^\bullet(f(s')) \cdot \mathbf{P}(s, s') = \sum_{s^\bullet \in S^\bullet} \sum_{s' | g_s(s') = s^\bullet} \mu^\bullet(f(s')) \cdot \mathbf{P}(s, s')$$

We apply the second hypothesis:

$$\leq \sum_{s^\bullet \in S^\bullet} \sum_{s' | g_s(s') = s^\bullet} \mu^\bullet(s^\bullet) \cdot \mathbf{P}(s, s') = \sum_{s^\bullet \in S^\bullet} \mu^\bullet(s^\bullet) \sum_{s' | g_s(s') = s^\bullet} \mathbf{P}(s, s')$$

then the first hypothesis:

$$= \sum_{s^\bullet \in S^\bullet} \mu^\bullet(s^\bullet) \mathbf{P}(f(s), s^\bullet)$$

This term is equal to $\mu^\bullet(f(s))$ thanks to the equation (3) apply to the Markov chain $\mathcal{C}^\bullet$.

c.q.f.d. $\diamond\diamond\diamond$

Proof of proposition 6

Let $s = u_0, \dots, u_l = s_+$ be a trajectory starting in s ending in s_+ .
As the trajectory avoids s_- , its value is

$$\begin{aligned} & (\mu^\bullet(f(u_0) \max(h(u_0), 1)) / \mu^\bullet(f(u_1))) \dots (\mu^\bullet(f(u_{l-1}) \max(h(u_{l-1}), 1)) / \mu^\bullet(f(u_l))) \\ &= \mu^\bullet(f(s)) \prod_{0 \leq i < l | h(u_i) > 1} h(u_i) \geq \mu^\bullet(f(s)) \end{aligned}$$

c.q.f.d. $\diamond\diamond\diamond$

C Proofs of coupling

Proof of lemma 1

We recall the coupling relation

- a) $n_1 + n_2 \geq n'_1 + n'_2$
- b) $n_1 \geq n'_1$

We need to check that for all couples $((n_1, n_2), (n'_1, n'_2))$ in the relation, all successors are also in the relation. We have three different types of transitions in the system:

1. For transition λ , the successor of $((n_1, n_2), (n'_1, n'_2))$ is $((n_1 + 1, n_2), (n'_1 + 1, n'_2))$ which is inside the relation.
2. For transition ρ_1 , the successor of $((n_1, n_2), (n'_1, n'_2))$ is $((n_1 - \mathbf{1}_{\{n_1 > 0 \wedge n_2 < R\}}, n_2 + \mathbf{1}_{\{n_1 > 0 \wedge n_2 < R\}}), (n'_1 - \mathbf{1}_{\{n'_1 > 0 \wedge n'_2 < R\}}, n'_2 + \mathbf{1}_{\{n'_1 > 0 \wedge n'_2 < R\}}))$
the condition a) is satisfied as the sum is not modified.
 - If $n_1 > n'_1$ then $n_1 - \mathbf{1}_{\{n_1 > 0 \wedge n_2 < R\}} \geq n'_1 - \mathbf{1}_{\{n'_1 > 0 \wedge n'_2 < R\}}$ and condition b) is satisfied.
 - Else $n_1 = n'_1$ and with the condition a) we have $n_2 \geq n'_2$; then $n_1 > 0 \wedge n_2 < R \Rightarrow n'_1 > 0 \wedge n'_2 < R$ which implies : $n_1 - \mathbf{1}_{\{n_1 > 0 \wedge n_2 < R\}} \geq n'_1 - \mathbf{1}_{\{n'_1 > 0 \wedge n'_2 < R\}}$ then condition b) holds.
3. For transition ρ_2 , the successor of $((n_1, n_2), (n'_1, n'_2))$ is $((n_1, n_2 - \mathbf{1}_{\{n_2 > 0\}}), (n'_1, n'_2 - \mathbf{1}_{\{n'_2 > 0\}}))$.
As the first component is not modified, the condition b) holds.
 - If $n_1 + n_2 > n'_1 + n'_2$ then $n_1 + n_2 - \mathbf{1}_{\{n_2 > 0\}} \geq n'_1 + n'_2 - \mathbf{1}_{\{n'_2 > 0\}}$
 - Else $n_1 + n_2 = n'_1 + n'_2$ and with condition b) $n_2 \leq n'_2$ then $n_2 - \mathbf{1}_{\{n_2 > 0\}} \geq n'_2 - \mathbf{1}_{\{n'_2 > 0\}}$, the condition a) holds.

Then $S^\otimes$ is a coupling relation.

We now have to check the hypothesis of the proposition 3 on coupling of two chains. Let $((n_1, n_2), (n'_1, n'_2)) \in S^\otimes$. If $n'_1 + n'_2 = N$ is an absorbing state then by condition a) of coupling, $n_1 + n_2 = N$. Moreover, for all $n > 0$, $((n, R - 1), (n - 1, R)) \in S^\otimes$. We can apply proposition 3 which gives

$$\forall n > 0, \mu^\bullet(n, R - 1) \geq \mu^\bullet(n - 1, R)$$

c.q.f.d. $\diamond\diamond\diamond$

Proof of guaranteed variance reduction for example 3

Proposition 8. *The third example guarentees the variance reduction.*

Proof

We define the family function g_s .

$$\begin{aligned} g_{(n_1, n_2)}(n_1, n_2) &= f_R(n_1, n_2) \\ g_{(n_1, n_2)}(n_1 + 1, n_2) &= f_R(n_1 + 1, n_2) \\ g_{(n_1, n_2)}(n_1 - 1, n_2 + 1) &= \begin{cases} (n_1 - 1, n_2 + 1) & \text{if } n_1 < R \\ (R, n_2 + 1) & \text{otherwise} \end{cases} \\ g_{(n_1, n_2)}(n_1, n_2 - 1) &= f_R(n_1, n_2 - 1) \end{aligned}$$

We have to verify the condition 2 of property 5 with a coupling method. The only non trivial case is for transition ρ_1 with $n_1 = R$. We have to prove that

$$\forall n_2, \mu^\bullet(R - 1, n_2) \leq \mu^\bullet(R, n_2)$$

The pair $((n_1, n_2), (n'_1, n'_2))$ belongs to the coupling relation $S^\otimes$ if the two following conditions are satisfied:

- a) $n_1 \geq n'_1$
- b) $n_2 \geq n'_2$

For all couple $((n_1, n_2), (n'_1, n'_2))$ in the coupling relation we have to prove that all its successor also belong to the coupling relation. There is three possible transitions.

1. For transition λ , The successor of $((n_1, n_2), (n'_1, n'_2))$ is $((n_1 + \mathbf{1}_{\{n_1 < R\}}, n_2), (n'_1 + \mathbf{1}_{\{n'_1 < R\}}, n'_2))$
Condition b is satisfied. We split cases where $n_1 = n'_1$ and $n_1 > n'_1$ condition a is satisfied for both cases.
2. For transition ρ_1 , The successor of $((n_1, n_2), (n'_1, n'_2))$ is $((n_1 - \mathbf{1}_{\{n_1 > 0 \wedge n_1 < R\}}, n_2 + \mathbf{1}_{\{n_1 > 0\}}), (n'_1 - \mathbf{1}_{\{n'_1 > 0 \wedge n'_1 < R\}}, n'_2 + \mathbf{1}_{\{n'_1 > 0\}}))$
 - if $n_1 = n'_1$ then both conditions are satisfied
 - else $n_1 > n'_1$ and a is satisfied, and $\mathbf{1}_{\{n_1 > 0\}} \geq \mathbf{1}_{\{n'_1 > 0\}}$ then b holds
3. For transition ρ_2 , The successor of $((n_1, n_2), (n'_1, n'_2))$ is $((n_1, n_2 - \mathbf{1}_{\{n_2 > 0\}}), (n'_1, n'_2 - \mathbf{1}_{\{n'_2 > 0\}}))$.
As the first component is not modified the condition a) holds.

- if $n_2 > n'_2$ then $n_2 - \mathbf{1}_{\{n_2 > 0\}} \geq n'_2 - \mathbf{1}_{\{n'_2 > 0\}}$
- else $n_2 = n'_2$ then $n_2 - \mathbf{1}_{\{n_2 > 0\}} = n'_2 - \mathbf{1}_{\{n'_2 > 0\}}$

By applying proposition 7, we obtain a coupling.

We can now check the hypotheses of proposition 3 on coupling. Let $((n_1, n_2), (n'_1, n'_2))$ be in $S^\otimes$. If $n'_2 = N$, (n'_1, n'_2) is an absorbing state then using condition b) of coupling we have : $n_2 = N$. Moreover for all $n_1, n_2 < N$, $((n_1, n_2), (n_1, n_2)) \in S^\otimes$. We can then apply the property. We obtain

$$\forall n_1, n_2 < N, \mu^\bullet(n_1, n_2) \geq \mu^\bullet(n_1 - 1, n_2)$$

With $n_1 = R$ we have the needed property.

Other hypothesis of proposition 5 holds trivially. We then have guarantee variance reduction.

c.q.f.d. $\diamond\diamond\diamond$

Proof of guaranteed variance reduction for example 4

Proposition 9. *The fourth example guarantees the variance reduction.*

Proof

We define the family function g_s .

$$\begin{aligned} g_{(n_1, n_2)}(n_1, n_2) &= f_R(n_1, n_2) \\ g_{(n_1, n_2)}(n_1 + 1, n_2) &= f_R(n_1 + 1, n_2) \\ g_{(n_1, n_2)}(n_1 - 1, n_2 + 1) &= \begin{cases} (n_1 - 1, n_2 + 1) & \text{if } n_2 \geq R \\ (n_1 - 1, R + 1) & \text{otherwise} \end{cases} \\ g_{(n_1, n_2)}(n_1, n_2 - 1) &= f_R(n_1, n_2 - 1) \end{aligned}$$

We have to verify condition 2 of property 5 with a coupling method. The only non trivial case is for transition ρ_1 with $n_2 < R$. We have to prove that

$$\forall n_1, n_2 < R, \mu^\bullet(n_1, n_2 + 1) \leq \mu^\bullet(n_1, R + 1)$$

The pair $((n_1, n_2), (n'_1, n'_2))$ belongs to the coupling relation $S^\otimes$ if the two following conditions are satisfied:

- a) $n_1 = n'_1$
- b) $n_2 \geq n'_2$

For all couple $((n_1, n_2), (n'_1, n'_2))$ in the coupling relation we have to prove that all its successors also belong to the coupling relation. There are three possible type of transitions.

1. For transition λ , The successor of $((n_1, n_2), (n'_1, n'_2))$ is $((n_1 + 1, n_2), (n'_1 + 1, n'_2))$ which is indeed in the coupling relation.

2. For transition ρ_1 , The successor of $((n_1, n_2), (n'_1, n'_2))$ is $((n_1 - \mathbf{1}_{\{n_1 > 0\}}, n_2 + \mathbf{1}_{\{n_1 > 0\}}), (n'_1 - \mathbf{1}_{\{n'_1 > 0\}}, n'_2 + \mathbf{1}_{\{n'_1 > 0\}}))$.
Using condition a), $n_1 - n'_1$ then the difference between n'_2 and n_2 is unchanged. Then condition b) holds.
3. For transition ρ_2 , the successor of $((n_1, n_2), (n'_1, n'_2))$ is $((n_1, n_2 - \mathbf{1}_{\{n_2 > R\}}), (n'_1, n'_2 - \mathbf{1}_{\{n'_2 > R\}}))$.
As the first component is not modified the condition a) holds.
 - if $n_2 > n'_2$ then $n_2 - \mathbf{1}_{\{n_2 > R\}} \geq n'_2 - \mathbf{1}_{\{n'_2 > R\}}$
 - else $n_2 = n'_2$ then $n_2 - \mathbf{1}_{\{n_2 > R\}} = n'_2 - \mathbf{1}_{\{n'_2 > R\}}$

By applying proposition 7, we obtain a coupling.

We can now check the hypotheses of proposition 3 on coupling.

Let $((n_1, n_2), (n'_1, n'_2))$ be in $S^\otimes$. If $n'_2 = N$, (n'_1, n'_2) is an absorbing state then using condition b) of coupling we have : $n_2 = N$. Moreover for all $n_1, n_2 < N$, $((n_1, n_2), (n_1, n_2)) \in S^\otimes$. We can then apply the property. We obtain

$$\forall n_1, n_2 \geq n'_2, \mu^\bullet(n_1, n_2) \geq \mu^\bullet(n_1, n'_2)$$

The other hypothesis of proposition 5 holds trivially. We then have guarantee variance reduction.

c.q.f.d. $\diamond\diamond\diamond$