

Importance Splitting for Statistical Model Checking Properties

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Probabilistic model checking

Quantify temporal logical properties of stochastic systems

- *Numerical* model checking
 - precise
 - exhaustive exploration of state space
 - limited model size
- *Statistical* model checking (SMC)
 - statistical model of *executions*
 - results within confidence bounds
 - trades off tractability with precision

Motivation

Objective :

- Standard Statistical technique for SMC: Monte Carlo.
- Rare events may cause serious problems and are difficult to simulate.
- Given a stochastic system, design a procedure for estimating a rare property in a reasonable time with SMC.
- Properties specified with time bounded temporal logic:

$$\phi = \alpha \mid \phi \vee \phi \mid \phi \wedge \phi \mid \neg \phi \mid \mathbf{X} \phi \mid \mathbf{F}^t \phi \mid \mathbf{G}^t \phi \mid \phi \mathbf{U}^t \phi$$

Monte Carlo model checking

Goal: Given a Markovian system and a property φ , compute the probability γ that a path ω satisfies φ ($\gamma = P[\omega \models \varphi]$).

The behavior of the system with respect to the property can be modeled by a Bernoulli random variable Z .

property indicator
function $z \in \{0,1\}$

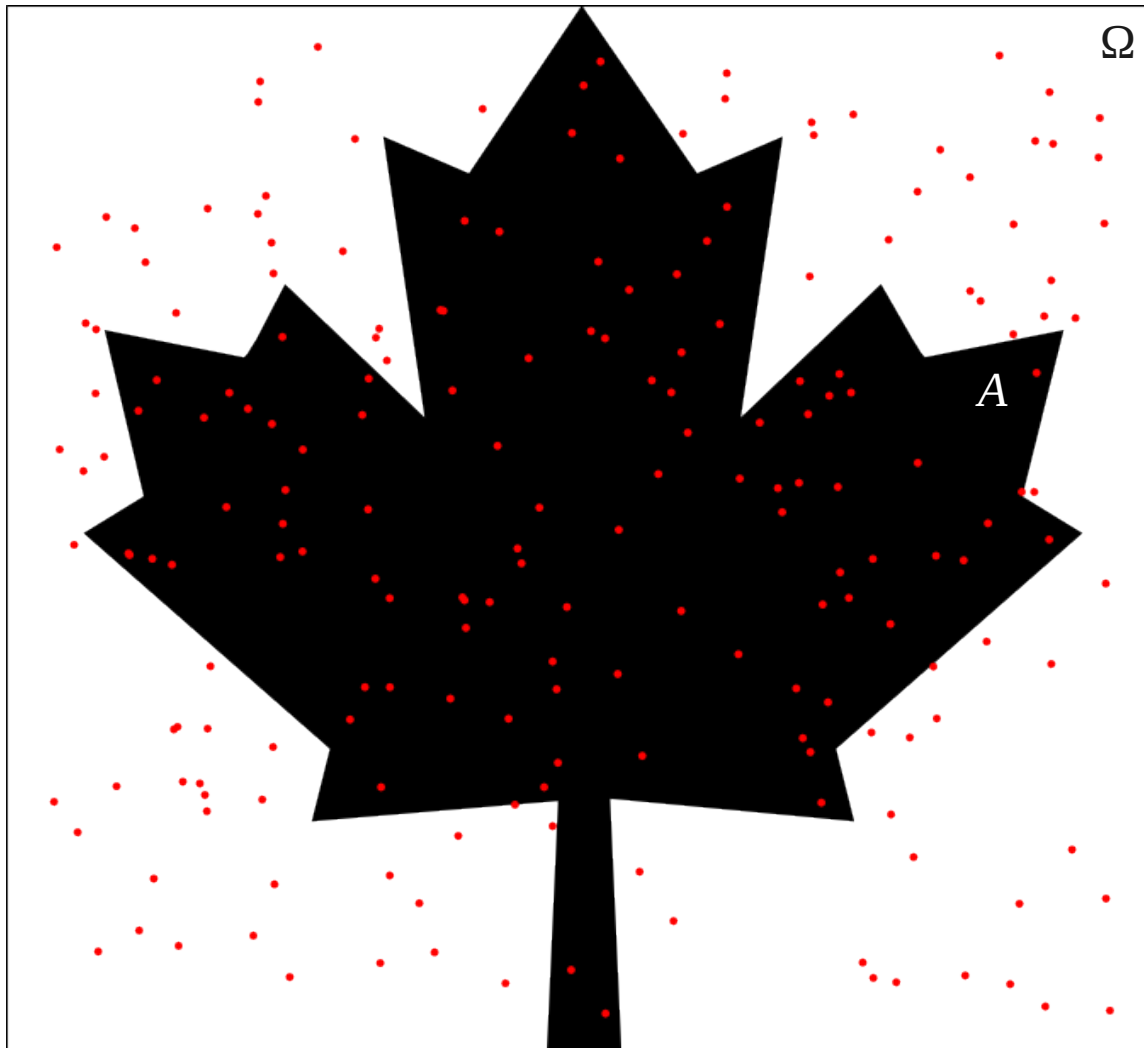
probability measure
function

$$\gamma \stackrel{\text{def}}{=} E_f[Z] = \int_{\Omega} z(\omega) f(\omega) d\omega$$

$$\tilde{\gamma} = \frac{1}{N} \sum_{i=1}^N z(\omega_i)$$

sample traces generated
under f

Monte Carlo estimation



$$A = \{\omega \in \Omega : z(\omega) = 1\}$$

$$\tilde{y} = \frac{1}{N} \sum_{i=1}^N z(\omega_i)$$

Absolute error = half the size of the confidence interval

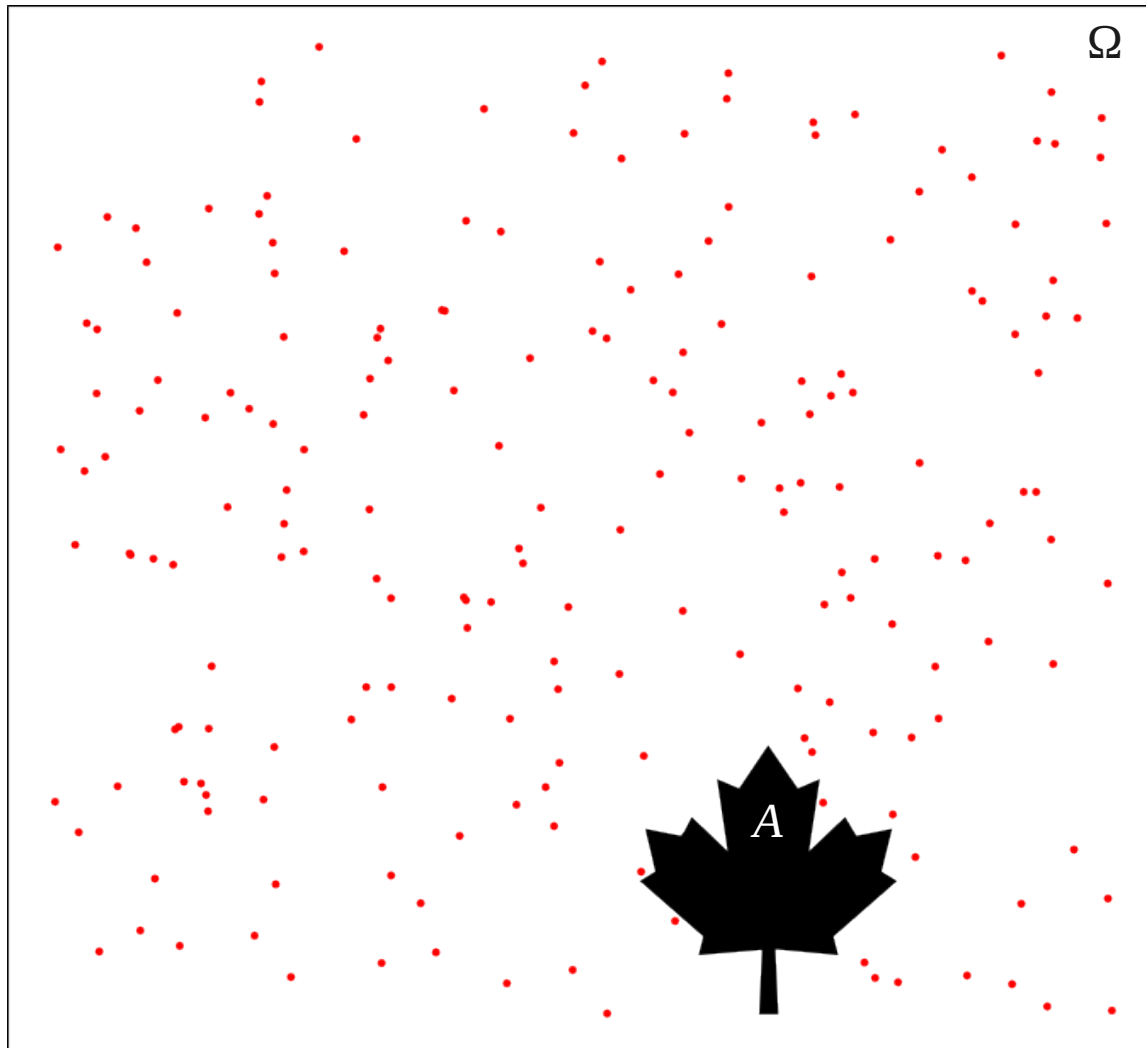
$$AE \propto \frac{\sqrt{y(1-y)}}{\sqrt{N}}$$

Problems of rare events

- Occur with small probability (e.g. $< 10^{-6}$)
 - appear rarely in stochastic simulations
 - need very large number of trials to see single example
 - without seeing, cannot quantify how low the probability
- The absolute error is not useful $(\gamma \pm \epsilon)$ not useful if $\epsilon \gg \gamma$
 - Bounds (e.g. Chernoff) not useful when γ small
 - Unbounded *relative* error:

$$RE = \frac{\sqrt{\text{Var}(z)}}{E(z)} = \frac{\sqrt{\gamma - \gamma^2}}{\gamma} \approx_{\gamma \rightarrow 0} \frac{1}{\sqrt{\gamma}}$$

High variance



$$\text{RE} \propto_{y \rightarrow 0} \frac{1}{\sqrt{N y}}$$

N very large to bound RE
with Monte Carlo simulation

Importance sampling

Monte Carlo

$$y = \int_{\Omega} z(\omega) f(\omega) d\omega$$

$$\tilde{y}_{MC} = \frac{1}{N} \sum_{i=1}^N z(\omega_i)$$

traces generated under f

$$y = \int_{\Omega} z(\omega) \frac{f(\omega)}{f'(\omega)} f'(\omega) d\omega$$

importance sampling distribution

likelihood ratio

$$\tilde{y}_{IS} = \frac{1}{N} \sum_{i=1}^N z(\omega_i) \frac{f(\omega_i)}{f'(\omega_i)}$$

traces generated under f'

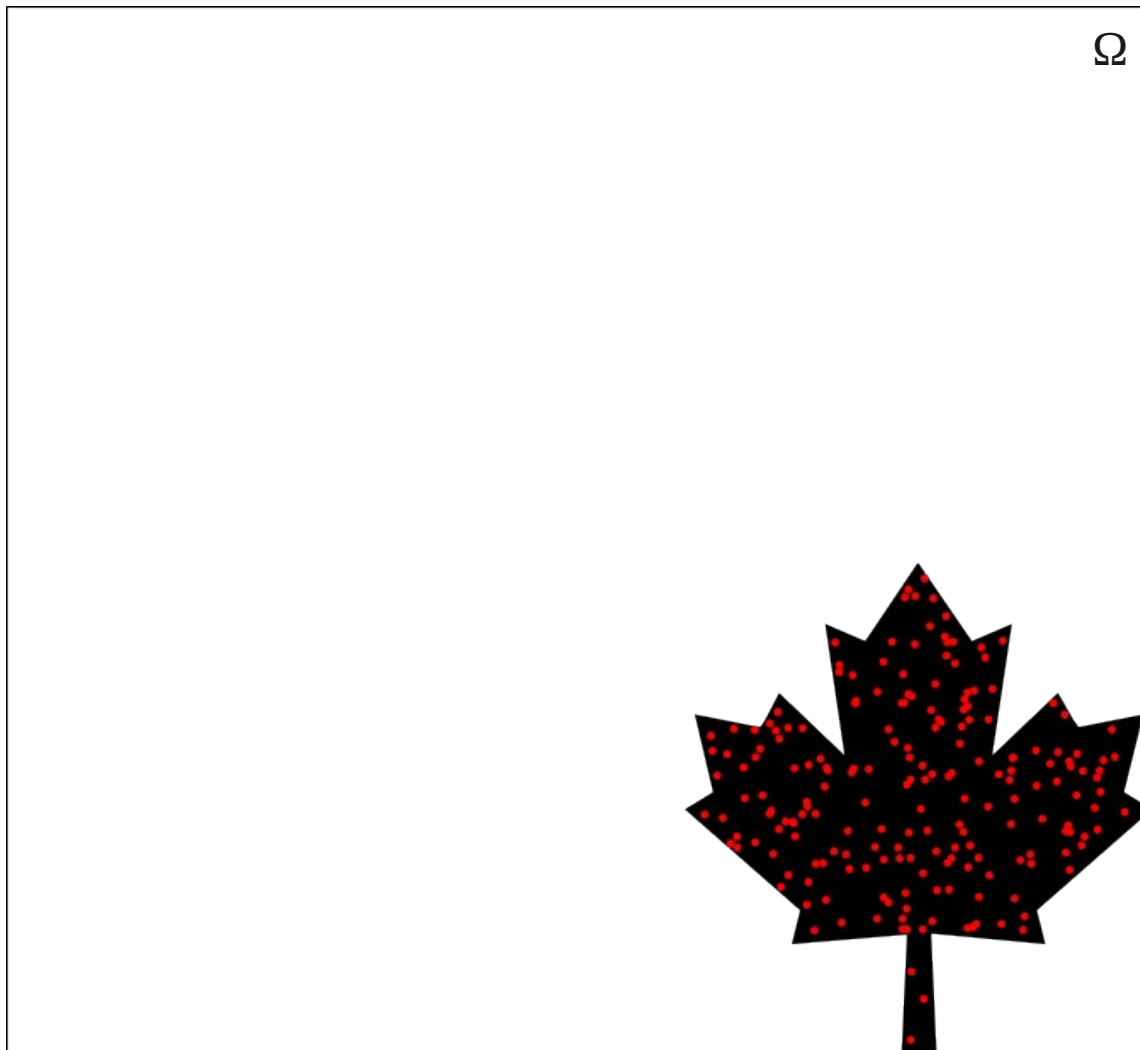
'Tilted' simulation



$$\tilde{y} = \frac{1}{N} \sum_{i=1}^N z(\omega'_i) \frac{f(\omega')}{f'(\omega'_i)}$$

traces generated under f'
(importance sampling dist.)

Optimal importance sampling



$$\tilde{y} = \frac{1}{N} \sum_{i=1}^N z(\omega'_i) \frac{f(\omega'_i)}{f'(\omega'_i)}$$

$$f^{opt} = \frac{z f}{\gamma}$$

f conditioned on the rare event

Limitations of Importance Sampling

- Quantifying the performance of apparently “good” distributions is an open problem.
- Problem of accuracy with long simulations: likelihood ratio vanishes and variance of the estimators increases.

=> need of an alternative technique: Importance Splitting.

Basics of Importance Splitting

Let A a rare event and $(A_k)_{0 \leq k \leq n}$ a sequence of nested events:

$$A_0 \supset A_1 \supset \dots \supset A_n = A$$

$$\gamma \stackrel{\text{def}}{=} P(A) = P(A_0)P(A_1|A_0)P(A_2|A_1)\dots P(A_n|A_{n-1})$$

Bayes formula

$$\forall k \quad P(A_k | A_{k-1}) = \gamma_k \geq \gamma$$

Less rare

Generation of traces in Importance Splitting

- Assuming a set of increasing *levels* k , generate traces starting from a distribution of the initial states.
- Simulations are stopped as soon as they reach the next level $k+1$.
- The final states become the empirical distribution of initial states for the next level (level $k+1$).
- Failed traces discarded. Successful traces continue from where they stopped.
- Avoid a reduction of simulations by resampling the discarded traces from empirical distribution of level $k+1$.

Illustration 1

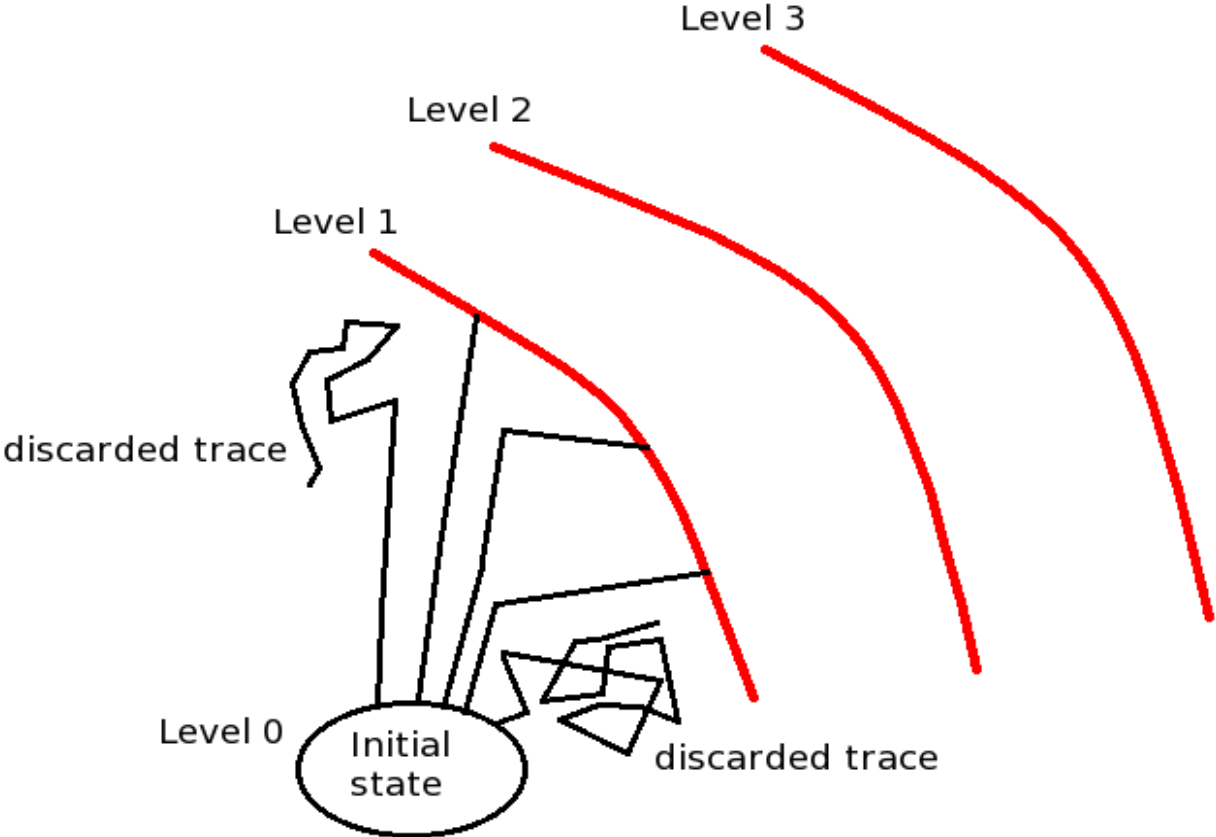
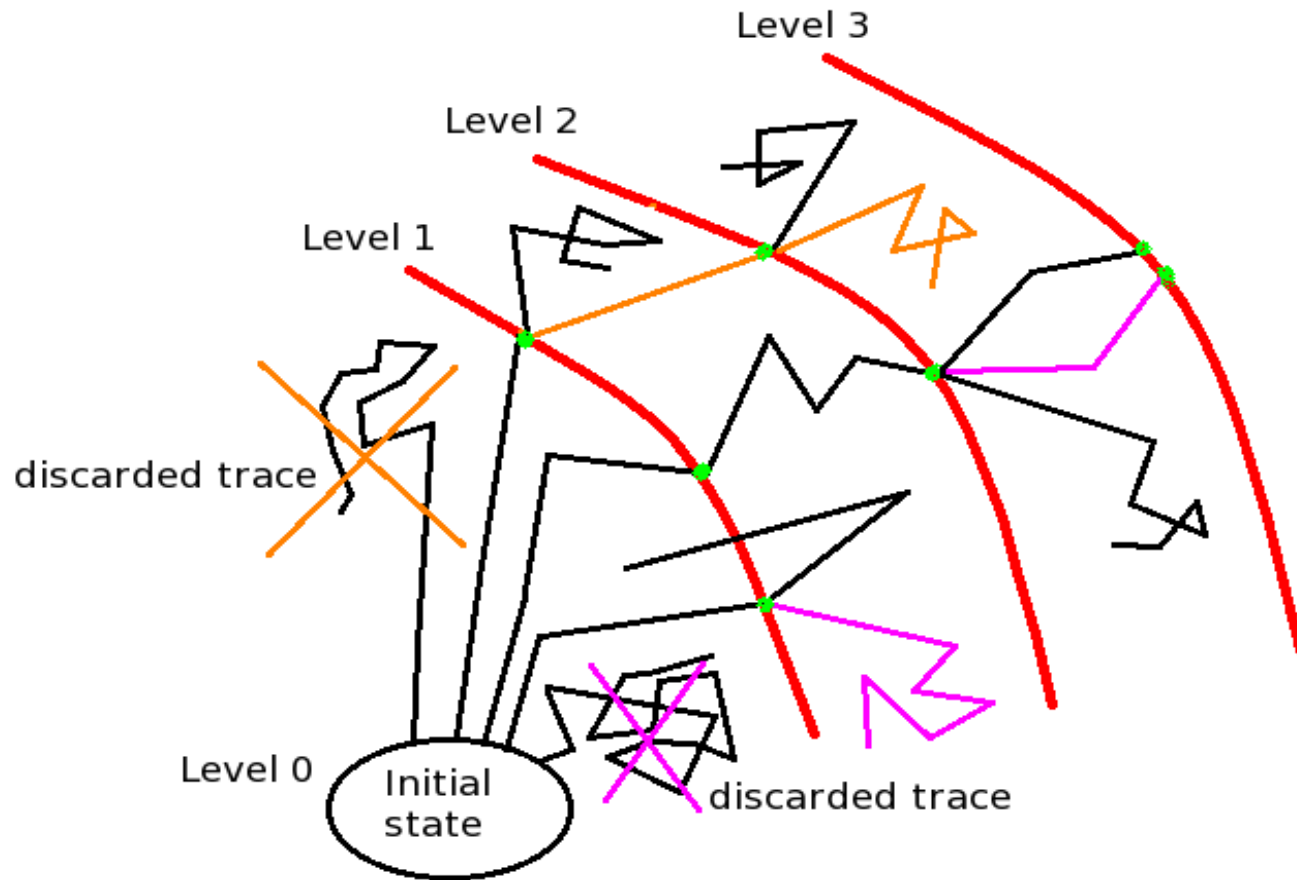


Illustration 2



$$P(\text{reaching Level 3}) = 3/5 * 2/5 * 2/5$$

Importance Splitting for (Temporal) Logic

Idea: given a rare property ϕ , define a set of levels based on a sequence of temporal properties such that:

$$(\phi_k)_{0 \leq k \leq n} : \phi_0 \Leftarrow \phi_1 \Leftarrow \dots \Leftarrow \phi_n = \phi$$

Thus,

$$\gamma = P(\omega \models \phi_0) \prod_{k=1}^n P(\omega \models \phi_k \mid \omega \models \phi_{k-1})$$

Level-based Score functions

- Goal: Generalise the concept of levels.

- Definition 1:

Let $J_0 \supset J_1 \supset \dots \supset J_n$ be a set of nested intervals of \mathbb{R} .

Let $\phi_0 \supset \phi_1 \supset \dots \supset \phi_n$ be a set of nested properties.

$S: \Omega \rightarrow \mathbb{R}$ is a level-based score function of property ϕ iff $\forall k$:

$$\omega \models \phi_k \Leftrightarrow S(\omega) \in J_k \text{ and } \forall i, j \in \{0, \dots, |\omega|\}: i < j \Rightarrow S(\omega_{\leq i}) \leq S(\omega_{\leq j})$$

- Example: given a set of nested properties, a simple score function may be defined as follows:

$$S(\omega) = \sum_{k=1}^n \mathbf{1}(\omega \models \phi_k)$$

General score functions

- Definition 2:

Let $J_0 \supset J_1 \supset \dots \supset J_n$ be a set of nested intervals of \mathbb{R} .

Let $\Omega = \Omega_0 \supset \Omega_1 \supset \dots \supset \Omega_n$ be a set of nested subsets of Ω .

$S: \Omega \rightarrow \mathbb{R}$ is a general score function of property ϕ iff $\forall k$:

(i) $\omega \in \Omega_k \Leftrightarrow S(\omega) \in J_k$

(ii) $\omega \models \phi \Leftrightarrow \omega \in \Omega_n$

(iii) $\forall i, j \in \{0, \dots, |\omega|\}: i < j \Rightarrow S(\omega_{\leq i}) \leq S(\omega_{\leq j})$

Score functions

- Goal: Generalise the concept of levels.
- Level-based score functions: Mapping from logical properties to the real numbers which give information on the number of satisfied sub-formulae.

$$\text{Example: } S(\omega) = \sum_{k=1}^n \mathbf{1}(\omega \models \phi_k)$$

- General score functions: Mapping from sets of paths to the real numbers s.t. higher scores assigned to paths that satisfy the overall property.

Use of Heuristics

- Level-based score functions correlate logic to score.
 - General score functions requires:
 - higher scores assigned to paths that satisfy the overall property.
 - Score of a path's prefix is non decreasing with increasing prefix length.
 - In some case, the shortest paths satisfying a rare property are the most likely.
- => possibility to exploit the length of a path to improve a score function based on coarse logical levels.

Simple decomposition

- When $\phi = \bigwedge_{j=1}^n \psi_j$, a decomposition into nested properties is:

$$\phi_i = \bigwedge_{j=1}^i \psi_j, \quad \forall i \in \{1, \dots, n\} \text{ with } \phi_0 \equiv \text{True}$$

- Possibility to choose an arbitrary order of sub-formulae:

Example: Given $\phi = a \wedge b \wedge c$,

$$\phi_3 = a \wedge b \wedge c, \quad \phi_2 = a \wedge b, \quad \phi_1 = a$$

$$\phi_3 = a \wedge b \wedge c, \quad \phi_2 = b \wedge c, \quad \phi_1 = c$$

Both decompositions are valid.

Natural decomposition

- Many rare events are defined with a natural notion of level, when some quantity of the system reaches a particular value.
- In Computational systems: might refer to a loop counter, a number of software objects, etc...
- In physical systems: might refer to a temperature, a distance, a number of molecules...
- Natural levels defined by nested atomic properties:
 $\phi_i = (l > l_i)$ with l a state variable and $\omega \models \phi_n \Leftrightarrow l \geq l_n$

Decomposition of temporal operators

$$(i) (\phi_n \Rightarrow \phi_{n-1}) \Rightarrow (S \phi_n \Rightarrow S \phi_{n-1}) \text{ with } S \in \{F^{\leq t}, G^{\leq t}, X, F^{\leq t} G^{\leq s}\}$$

$$(ii) (\phi_n \Rightarrow \phi_{n-1} \wedge \psi_m \Rightarrow \psi_{m-1}) \Rightarrow (\phi_n U \psi_m \Rightarrow \phi_{n-1} U \psi_{n-1})$$

$$(iii) (\phi_n \Rightarrow \phi_{n-1}) \Rightarrow (\forall \omega \models G^{\leq t} \phi_n : \exists t' \geq t \mid \omega \models G^{\leq t'} \phi_{n-1})$$

$$(iv) (\phi_n \Rightarrow \phi_{n-1}) \Rightarrow (\forall \omega \models F^{\leq t} \phi_n : \exists t' \leq t \mid \omega \models F^{\leq t'} \phi_{n-1})$$

$$(v) (t' \geq t \wedge s' \leq s) \Rightarrow (F^{\leq t} G^{\leq s} \phi_n \Rightarrow F^{\leq t'} G^{\leq s'} \phi_n)$$

$$(vi) (\phi_n \Rightarrow \phi_{n-1}) \Rightarrow (\forall \omega \models F^{\leq t} G^{\leq s} \phi_n : \exists t' \leq t \wedge s' \geq s \mid \omega \models F^{\leq t'} G^{\leq s'} \phi_{n-1})$$

Two algorithms

- Fixed level algorithm:
 - Exploits a score function based on “logical” levels
- Adaptive level algorithm:
 - Given a score function, finds itself the “best” levels
 - Requires a score function refined enough.

Fixed level algorithm

Let $(\tau_k)_{1 \leq k \leq M}$ be the sequence of thresholds

Let **stop** be a termination condition

for $1 \leq k \leq M$ **do**

$\forall 1 \leq j \leq N$, using prefix $\tilde{\omega}_j^k$, generate path ω_j^k until $S(\omega_j^k) \geq \tau_k \vee$ **stop**

$$I_k = \{ j : S(\omega_j^k) \geq \tau_k \} \text{ and } \tilde{y}_k = \frac{|I_k|}{N}$$

$$\forall j \in I_k, \tilde{\omega}_j^{k+1} = \omega_j^k$$

$\forall j \notin I_k$, let $\tilde{\omega}_j^{k+1}$ be a copy of ω_i^k with $i \in I_k$ chosen randomly

$$\tilde{y} = \prod_{k=1}^M \tilde{y}_k$$

Fluctuation analysis

- Estimator unbiased
- Confidence interval based on the relative variance:

$\sqrt{N} \frac{\tilde{y} - \gamma}{\gamma} \xrightarrow[n \rightarrow \infty]{D} N(0, \sigma^2)$ where N denotes a Gaussian distribution

$$\text{with } \sigma^2 \geq \sum_{k=0}^{n-1} \frac{1 - \gamma_k}{\gamma_k}$$

- Inequality arises because the independence of initial states diminishes with increasing levels.
- Several possibilities minimise this dependence effect.

Idealized version

- relative variance of the estimator: $\sigma^2 = \sum_{k=0}^{n-1} \frac{1-\gamma_k}{\gamma_k}$
- For a fixed number of levels, this variance is minimal if all the conditional probabilities are equal:

$$\underset{p_0, \dots, p_{n-1}}{\operatorname{argmin}} \sum_{k=0}^{n-1} \frac{1-\gamma_k}{\gamma_k} \quad \text{s.t.} \quad \prod_{k=0}^{n-1} \gamma_k = p$$

- It corresponds to the case where the levels are evenly spaced in terms of probability of success.
- Hence, the idea of an adaptive algorithm.

Adaptive level algorithm

Let N_k be the predefined number of paths to keep per iteration

Let τ_ϕ be the minimum score of paths that satisfy ϕ

$k=1. \forall 1 \leq j \leq N$, generate path ω_j^k

repeat (until $\tau_k \geq \tau_\phi$)

Let $T = \{S(\omega_j^k), \forall j \in \{1, \dots, N\}\}$

Find minimum $\tilde{\tau}_k$ s.t. $|\{\tau \in T : \tau > \tilde{\tau}_k\}| \geq N_k$

$I_k = \{j : S(\omega_j^k) \geq \tau_k\}$ and $\tilde{y}_k = \frac{|I_k|}{N}$

$\forall j \in I_k, \omega_j^{k+1} = \omega_j^k$

for $j \notin I_k$ do

Choose randomly $l \in I_k$

$\tilde{\omega}_j^{k+1} = \max \{\omega \in \text{pref}(\omega_l^k) : S(\omega) < \tau_k\}$

generate path ω_j^{k+1} with prefix $\tilde{\omega}_j^{k+1}$

$M, k = k, k + 1$

$$\tilde{y} = \prod_{k=1}^M \tilde{y}_k$$

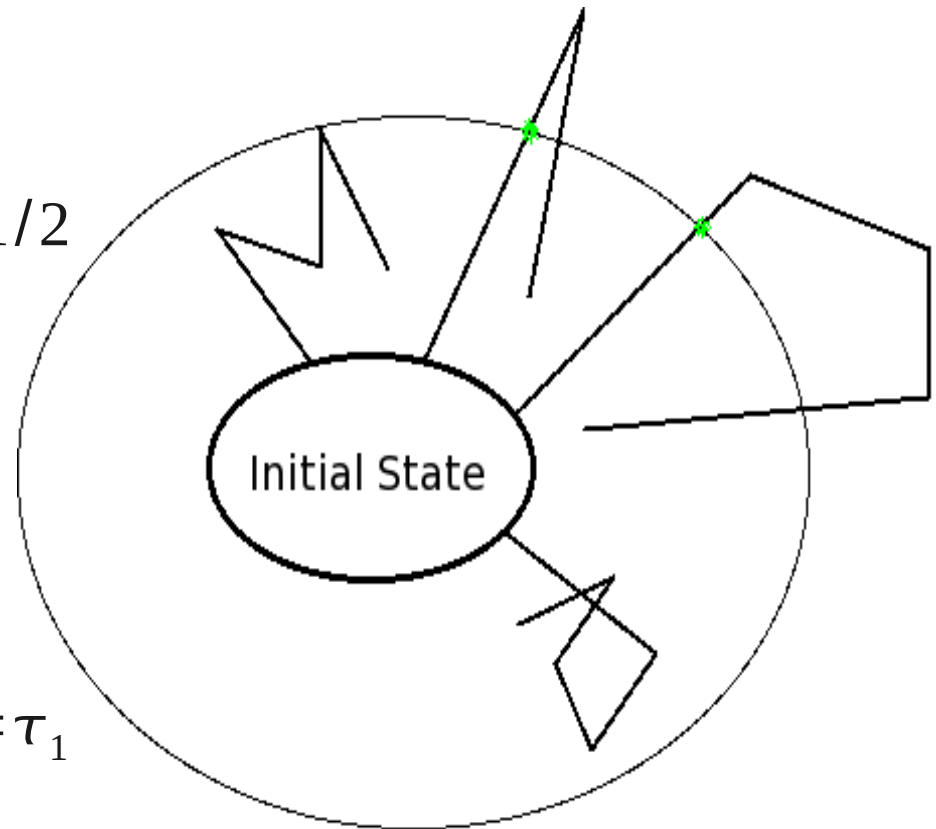
Adaptive algorithm illustration

1st step: trace generation

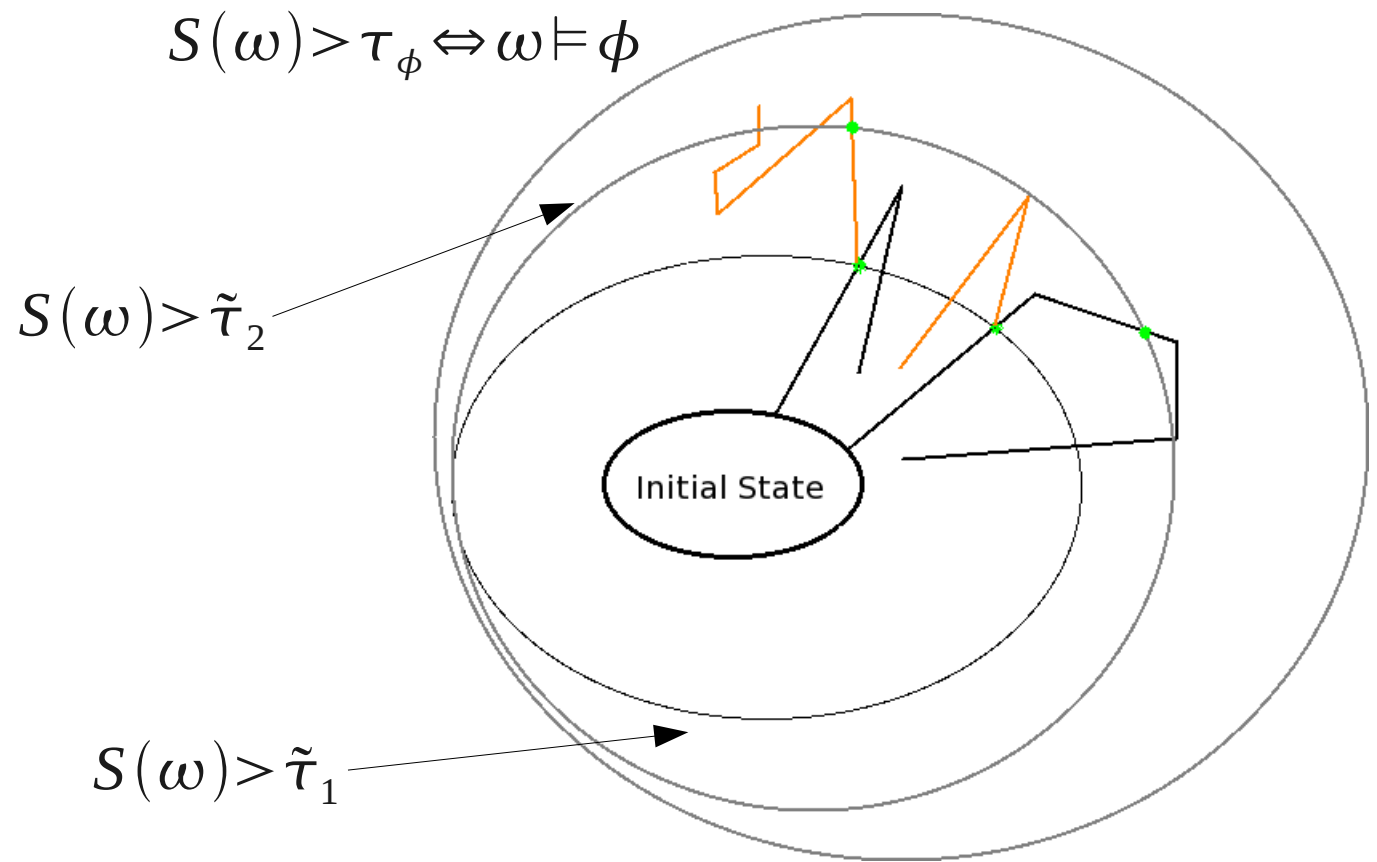
Predefine $\gamma_0 = 1/2$

Estimate τ_1 s.t. $P(\text{Score}(\omega) > \tau_1) = 1/2$

Ellipse corresponding to $\text{Score}(\omega) = \tau_1$



Adaptive algorithm illustration



Fluctuation analysis

- For simplicity, let us write: $\gamma = r \gamma_0^M$
with γ_0 the predefined conditionnal probability,
 M the number of levels
 r the number of traces ω in the last iteration s.t.: $S(\omega) \geq \tau_\phi$

$$\sqrt{N} \frac{\tilde{\gamma} - \gamma}{\gamma} \xrightarrow[n \rightarrow \infty]{D} N(0, \sigma^2) \quad \text{with } \sigma^2 \geq M \frac{1 - \gamma_0}{\gamma_0} + \frac{1 - r}{r}$$

$$E[\tilde{\gamma}] - \gamma \sim \frac{\gamma}{N} \frac{M(1 - \gamma_0)}{\gamma_0}$$

- Positive Bias of order $O(1/N)$ => Good news!

Bias, variance and Confidence interval

- $E[\tilde{y}] = p(1 + O(N^{-1}))$
- $Var(\tilde{y}) = \frac{p^2}{N} \left(M \frac{1 - \gamma_0}{\gamma_0} + \frac{1 - r}{r} \right) + o(N^{-1})$
- \Rightarrow Hence, the variance is reduced if γ_0 is chosen large.
- Confidence interval of level $(1 - \alpha)$ based on the relative variance:

$$\left[\tilde{y} \left(\frac{1}{1 + z_\alpha \sigma N^{-1/2}} \right), \tilde{y} \left(\frac{1}{1 - z_\alpha \sigma N^{-1/2}} \right) \right]$$

Example: Dining philosophers

Model: 150 philosophs

Property of interest:

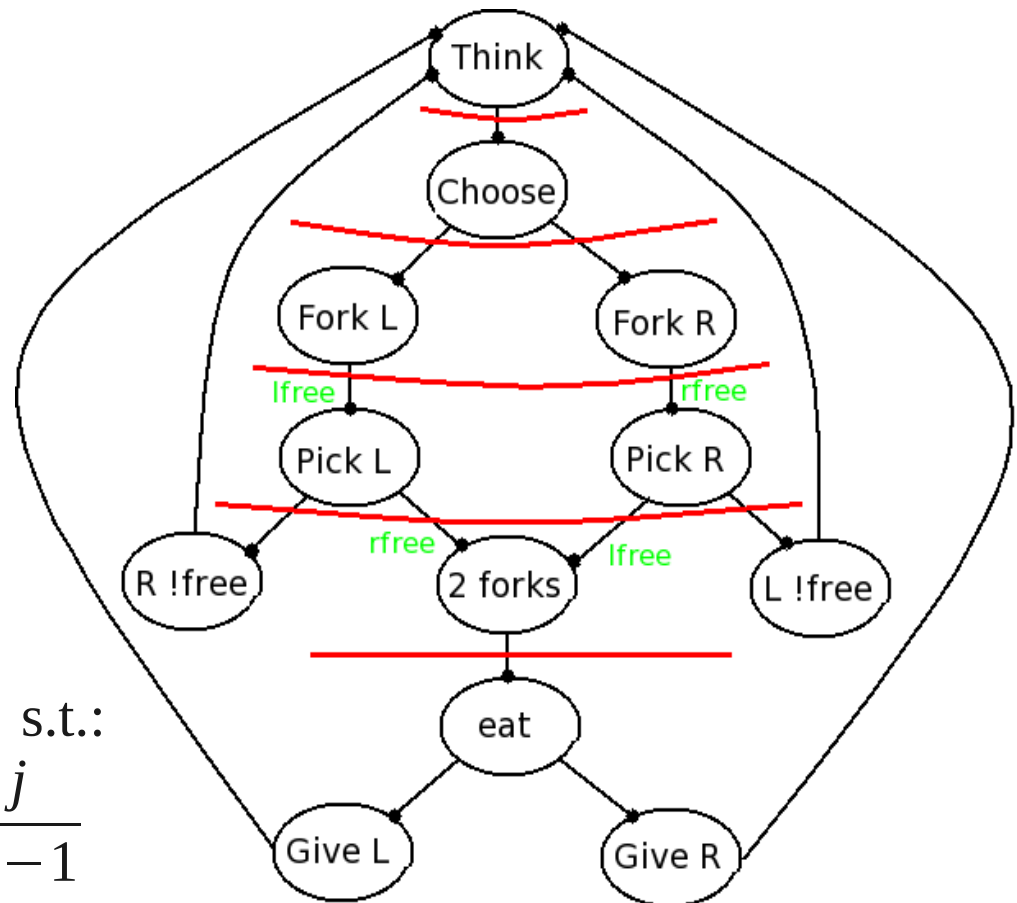
$$F^{\leq K} \text{ phil}_i \text{ eat}$$

$$S_1(\omega) = \sum_{k=1}^n \mathbf{1}(\omega \models \phi_k)$$

$$S_2(\omega) = \max_{1 \leq j \leq K} \Psi(\omega_{\leq j})$$

where j is prefix's length and Ψ s.t.:

$$\Psi(\omega_{\leq j}) = S_1(\omega_{\leq j}) - \frac{S_1(\omega_{\leq j}) - j}{S_1(\omega_{\leq j}) - K - 1}$$



Experimental results

- Description of the model: more than 10^{96} states
- MC probability based on 10^7 samples: $1.4 * 10^{-6}$
- With $N=1000$ samples, score function S_2 and $\gamma_0 \approx 1 - \frac{1}{N}$
 - Probability estimator: $1.581 * 10^{-6}$
 - Variance of the estimator: $0.119 * 10^{-6}$
 - Around 100 levels found adaptively.
- Roughly, the number of samples required for IS is between 1000 and 10000 times less important than with MC. => Gain of time

Ongoing work

- Quantifying performance of importance splitting:
 - Define more complex score functions to improve efficiency
 - Real case studies (biology, robotics?)
- Continuing the development of PLASMA