

# **Statistical Model Checking for Rare Events**

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### 4. Bounded Linear Temporal Logic 6. Importance Sampling

Extension of LTL with time bounds on temporal operators. No neXt operator = • Let  $\sigma = (s_0, t_0), (s_1, t_1), \dots$  be a trace of the model • the system stays in state *s<sub>i</sub>* for time *t<sub>i</sub>* = • The semantics of BLTL for trace  $\sigma$  starting at state k ( $\sigma^k$ ): •  $\sigma^k \models ap$ iff atomic proposition ap true in state  $s_k$ = iff  $\sigma^k \models \Phi_1$  or  $\sigma^k \models \Phi_2$ •  $\sigma^k \models \Phi_1 \lor \Phi_2$ iff  $\sigma^k \models \Phi$  does not hold •  $\sigma^k \models \neg \phi$ iff there exists natural *i* such that  $\bullet \sigma^k \models \Phi_1 \mathbf{U}^{\mathsf{t}} \Phi_2$ 1)  $\sigma^{k+i} \models \Phi_2$ 2)  $\Sigma_{j \le i} t_{k+j} \le t$ 3) for each  $0 \le j < i, \sigma^{k+j} \models \Phi_1$ "within time t,  $\Phi_2$  will be true and  $\Phi_1$  will hold until then" • In particular,  $\mathbf{F}^{t} \Phi = true \mathbf{U}^{t} \Phi$ ,  $\mathbf{G}^{t} \Phi = \neg \mathbf{F}^{t} \neg \Phi$ **Definition:** The time bound of *Φ*: ■#(*ap*) = 0  $\blacksquare \#(\neg \Phi) = \#(\Phi)$ = #( $\Phi_1 \vee \Phi_2$ ) = max (#( $\Phi_1$ ), #( $\Phi_2$ ))  $= #(\Phi_1 \mathbf{U}^t \Phi_2) = t + \max(\#(\Phi_1), \#(\Phi_2))$ Lemma: "Bounded simulations suffice" Let  $\Phi$  be a BLTL property, and k $\geq 0$ . For any two infinite traces  $\rho$ ,  $\sigma$  such that  $\rho^k$  and  $\sigma^k$  "equal up to time #( $\Phi$ )" we have  $\rho^{k} \models \Phi$  iff  $\sigma^{k} \models \Phi$ Sensors 5. Rare Events

• Estimate Prob(X $\geq t$ ) = p, when p is <u>small</u> (say 10<sup>-9</sup>)

Standard (Crude) Monte Carlo: generate K i.i.d. samples of X; return the estimator  $e_{\nu}$ 

$$\boldsymbol{e}_{\boldsymbol{K}} = \frac{1}{K} \sum_{i=1}^{K} I(X_i \ge t) = \frac{k_t}{K}$$

• Prob  $(e_{\kappa} \rightarrow p) = 1$  for  $K \rightarrow \infty$  (strong law LN) • Relative Error (RE) =  $\frac{\sqrt{\operatorname{var}[e_K]}}{2} = \frac{\sqrt{p(1-p)}}{2}$  $\mathrm{E}[e_{K}]$  $p\sqrt{K}$ 

• More accuracy  $\rightarrow$  more samples

• Want confidence interval of relative accuracy  $\delta$  and coverage probability c, i.e., estimate  $e_{\kappa}$  must satisfy:

 $Prob(|e_{\kappa} - p| < \delta \cdot p) \ge c$ 

From the CLT, a 99% (approximate) confidence interval of relative accuracy  $\delta$  needs about

$$X \approx \frac{1-p}{p\delta^2}$$
 samples ( $\rightarrow$  Prob( $|e_{\kappa} - p| < \delta p$ )  $\approx 0.99$ )

• Example:  $p = 10^{-9}$  and  $\delta = 10^{-2}$  (*ie*, 1% relative accuracy) we need about **10<sup>13</sup> samples**!!

$$=E_*[$$

$$\boldsymbol{p}_{k} = \frac{1}{K} \sum_{i=1}^{K} I(X_{i} \ge t) W(X_{i}), \qquad (X_{i} \sim f_{*})$$

- Need to choose a "good" biasing density (low variance)
- Optimal der
- Idea: search for a "good density" in a parameterized family







 $\boldsymbol{\rho} = E[I(X \ge t)]$ 

$$I(x \ge t)f(x) \ dx$$

$$I(x \ge t) \frac{f(x)}{f_*(x)} f_*(x) \ dx$$

- $I(x \ge t)W(x)f_*(x) \ dx$
- $[I(X \ge t)W(X)]$

where *f* is the density of *X*.

tance Sampling estimator is:

nsity: 
$$f_*(x) = \frac{I(x \ge t)f(x)}{p}$$

## 7. Cross-Entropy

The cross-entropy of densities g, h is

■ 
$$D(g,h) \neq D(h,g)$$
  
min  $D(f_*, f(-))$ 

optimal density  $f_*$ 

- The Cross-Entropy Method has two steps
- 1. find  $v_* = \arg \min D(f_*(\cdot), f(\cdot; v))$
- 2. run importance sampling with biasing density  $f(\cdot; v_*)$
- We can estimate v<sub>\*</sub> by Monte Carlo simulation

$$\bar{v}_{*} = \frac{\sum_{i=1}^{K} [I(X_{i} \ge t)W(X_{i};u,w)]}{\sum_{i=1}^{K} [I(X_{i} \ge t)W(X_{i};u,w)]}$$

where  $X_1, ..., X_k$  samples iid as  $f(\cdot; w)$ 

8. Applications

H2_press H2_pre H3_press H3_pre	55			
low_press Hydraulic Pressures	ess	Estimate	<b>Relative error</b>	Т
Samples	Step 1:100Step 2:1,000	1.58 x 10 <sup>-14</sup>	0.58	
	Step 1: 1,000 Step 2: 10,000	8.54 x 10 <sup>-14</sup>	0.24	
	Step 1: 10,000 Step 2: 100,000	8.11 x 10 <sup>-14</sup>	0.17	

### 9. References

• P. Zuliani, A. Platzer, E. M. Clarke. Bayesian Statistical Model Checking with Application to Stateflow/Simulink Verification.

• E. M. Clarke and P. Zuliani. Statistical Model Checking for Cyber-Physical Systems. In ATVA 2011, LNCS 6996, pages 1-12. P. Zuliani, C. Baier, E.M. Clarke. Rare-Event Verification for Stochastic Hybrid Systems. Submitted