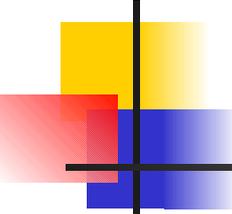


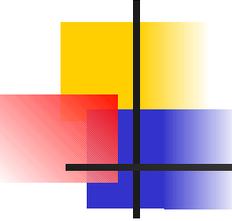
Acceptance Sampling and its Use in Probabilistic Verification

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The Problem

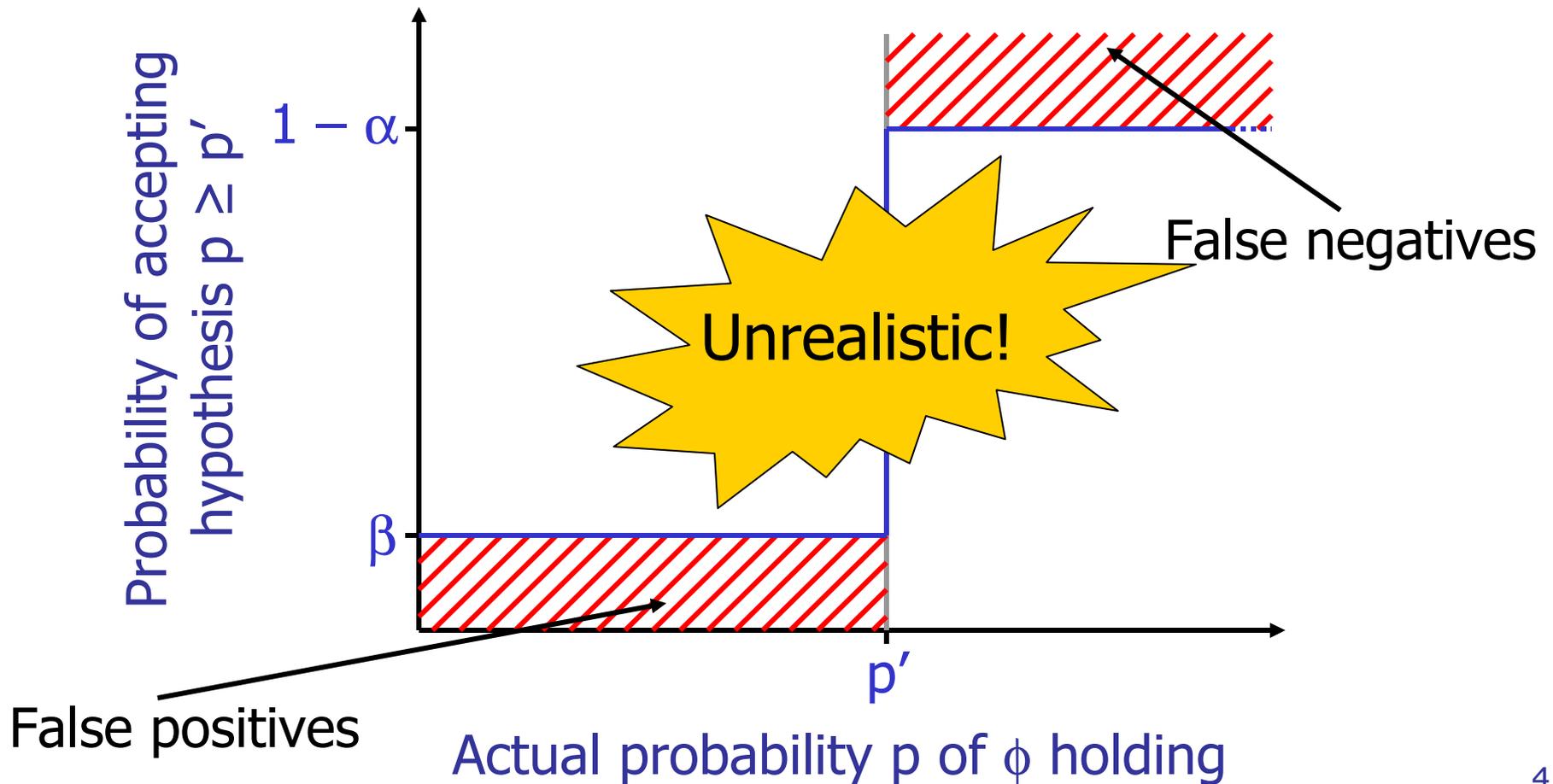
- Let ϕ be some property of a system holding with unknown probability p
- We want to **approximately** verify the hypothesis $p \geq p'$ using sampling
- This problem comes up in PCTL/CSL model checking: $\Pr_{\geq p'}(\phi)$
 - A sample is the truth value of ϕ over a sample execution path of the system

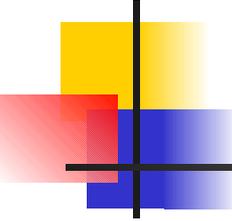


Quantifying “Approximately”

- Probability of accepting the hypothesis $p < p'$ when in fact $p \geq p'$ holds: $\leq \alpha$
- Probability of accepting the hypothesis $p \geq p'$ when in fact $p < p'$ holds: $\leq \beta$

Desired Performance of Test

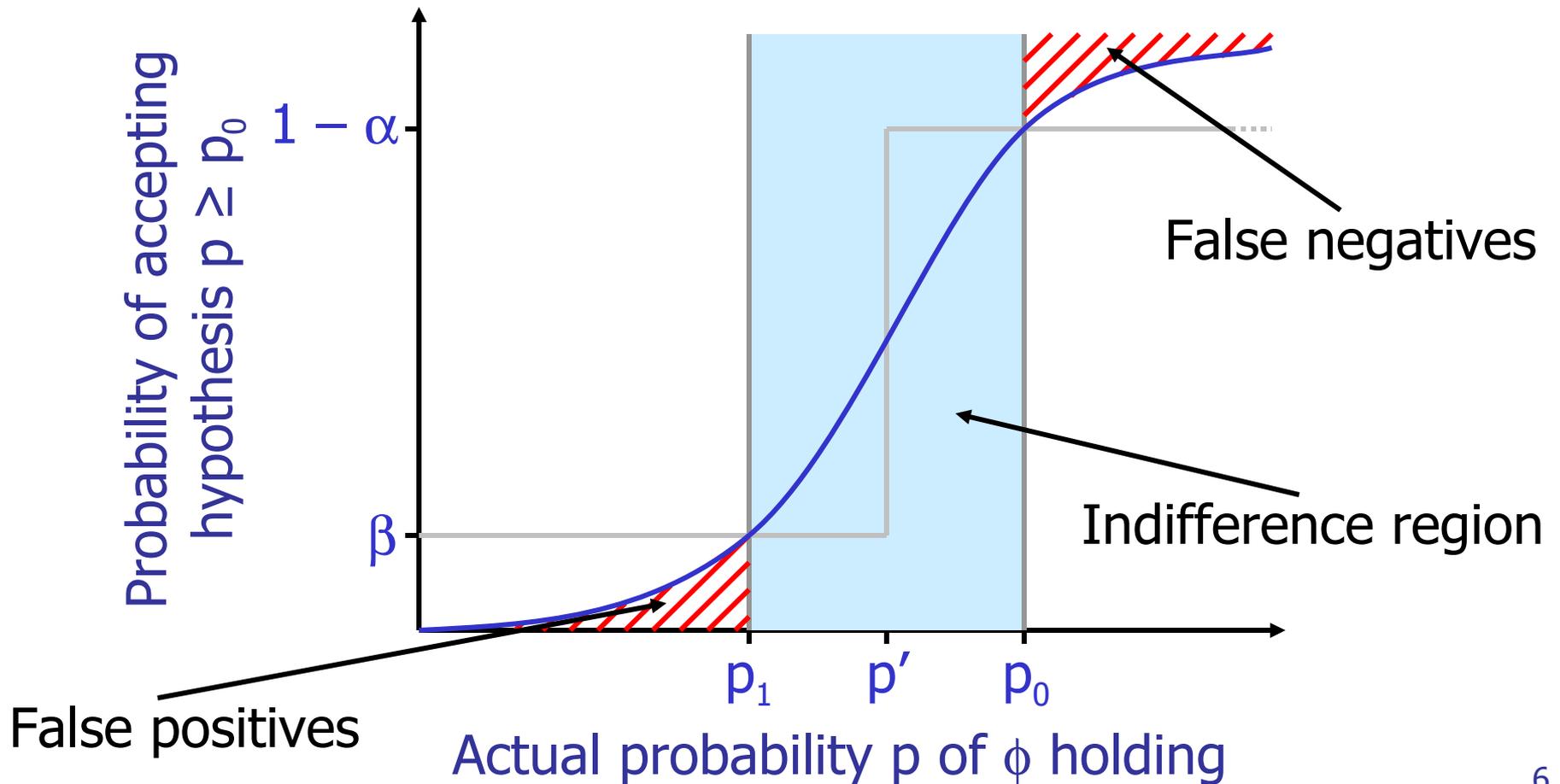




Relaxing the Problem

- Use two probability thresholds: $p_0 > p_1$
 - (e.g. specify p' and δ and set $p_0 = p' + \delta$ and $p_1 = p' - \delta$)
- Probability of accepting the hypothesis $p \leq p_1$ when in fact $p \geq p_0$ holds: $\leq \alpha$
- Probability of accepting the hypothesis $p \geq p_0$ when in fact $p \leq p_1$ holds: $\leq \beta$

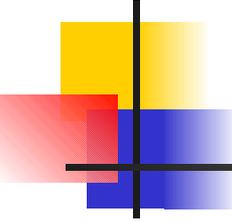
Realistic Performance of Test



Method 1:

Fixed Number of Samples

- Let n and c be two non-negative integers such that $c < n$
 - Generate n samples
 - Accept the hypothesis $p \leq p_1$ if at most c of the n samples satisfy ϕ
 - Accept the hypothesis $p \geq p_0$ if more than c of the n samples satisfy ϕ



Method 1: Choosing n and c

- Each sample is a Bernoulli trial with outcome **0** (ϕ is false) or **1** (ϕ is true)
- The sum of n iid Bernoulli variates has a binomial distribution

$$F(c, n, p) = \sum_{i=0}^c \binom{n}{i} p^i (1-p)^{n-i}$$

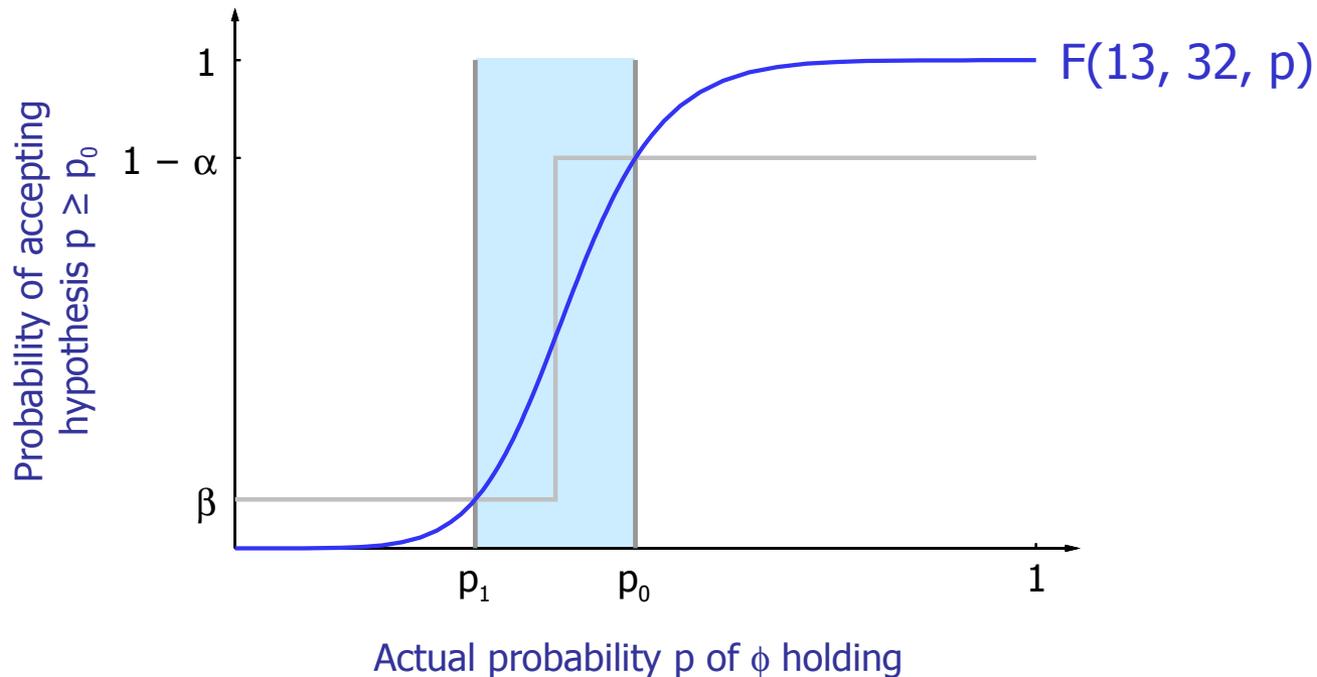
Method 1:

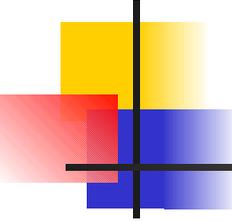
Choosing n and c (cont.)

- Find n and c simultaneously satisfying:
 1. ~~$\forall p' \in [p_0, 1]$~~ , $F(c, n, p_0) \leq \alpha$
 2. ~~$\forall p' \in [0, p_1]$~~ , $1 - F(c, n, p_1) \leq \beta$
- Non-linear system of inequalities, typically with multiple solutions!
 - Want solution with **smallest n**
 - Solve non-linear optimization problem using numerical methods

Method 1: Example

- $p_0 = 0.5$, $p_1 = 0.3$, $\alpha = 0.2$, $\beta = 0.1$:
 - Use $n = 32$ and $c = 13$



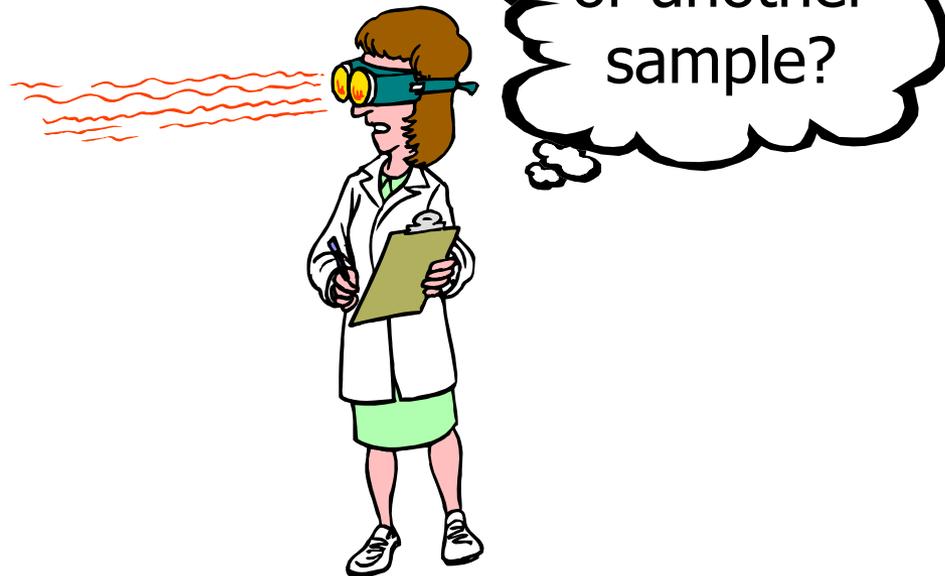


Idea for Improvement

- We can sometimes stop before generating all n samples
 - If after m samples more than c samples satisfy ϕ , then accept $p \geq p_0$
 - If after m samples only k samples satisfy ϕ for $k + (n - m) \leq c$, then accept $p \leq p_1$
- Example of a **sequential test**
- Can we explore this idea further?

Method 2: Sequential Acceptance Sampling

- Decide after each sample whether to accept $p \geq p_0$ or $p \leq p_1$, or if another sample is needed



The Sequential Probability Ratio Test [Wald 45]

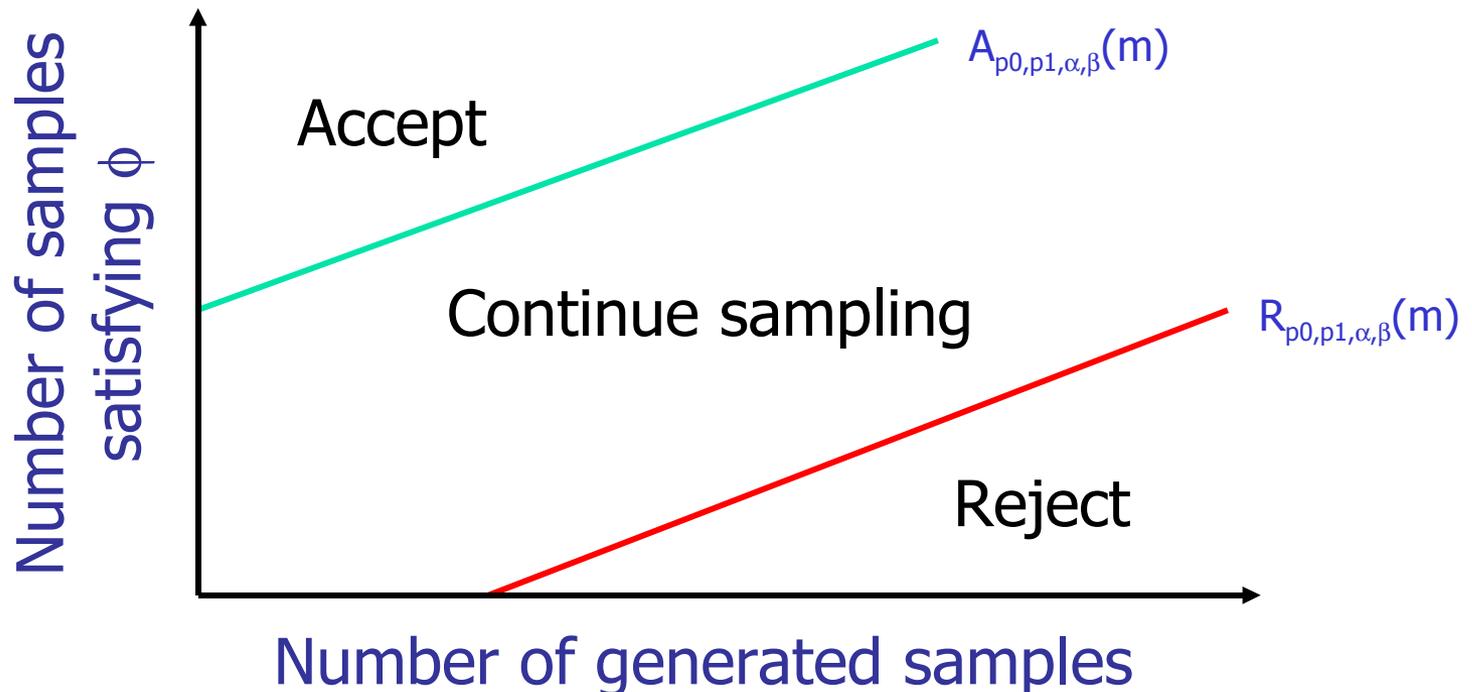
- An efficient sequential test:
 - After m samples, compute the quantity

$$f = \prod_{i=1}^m \frac{\Pr[X = x_i \mid p = p_1]}{\Pr[X = x_i \mid p = p_0]}$$

- Accept $p \geq p_0$ if $f \leq \beta/(1 - \alpha)$
- Accept $p \leq p_1$ if $f \geq (1 - \beta)/\alpha$
- Otherwise, generate another sample

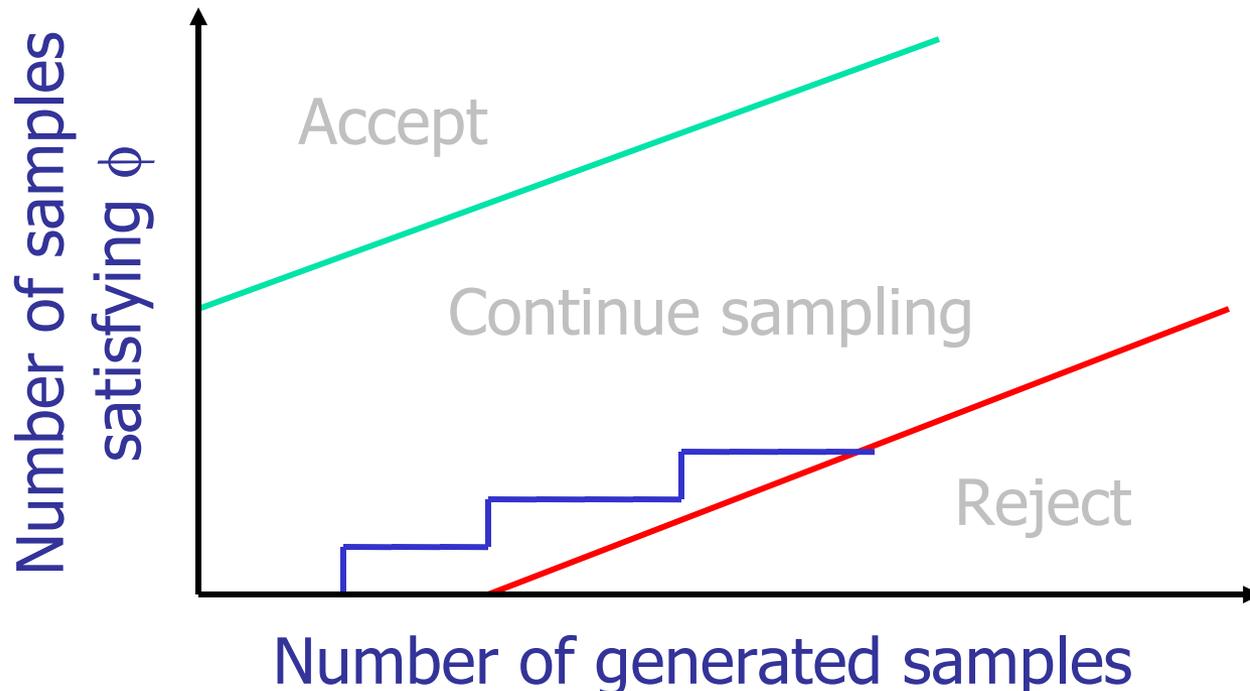
Method 2: Graphical Representation

- We can find an acceptance line and a rejection line give p_0 , p_1 , α , and β :



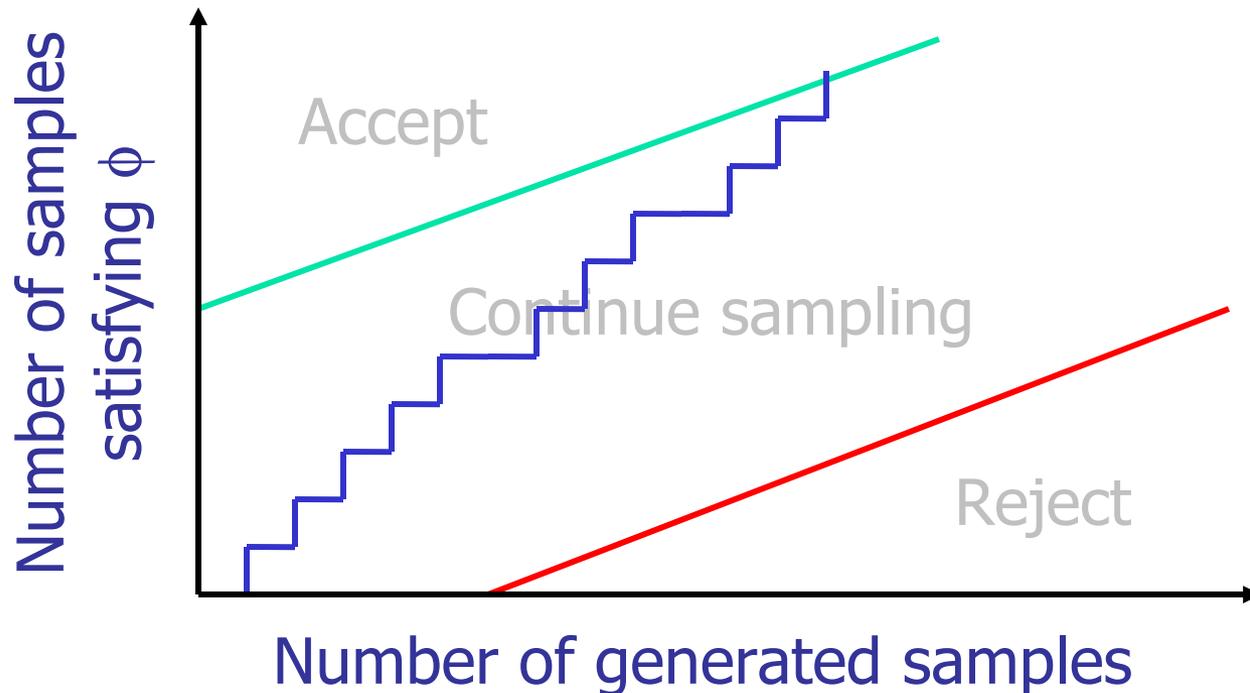
Method 2: Graphical Representation

- Reject hypothesis $p \geq p_0$ (accept $p \leq p_1$)



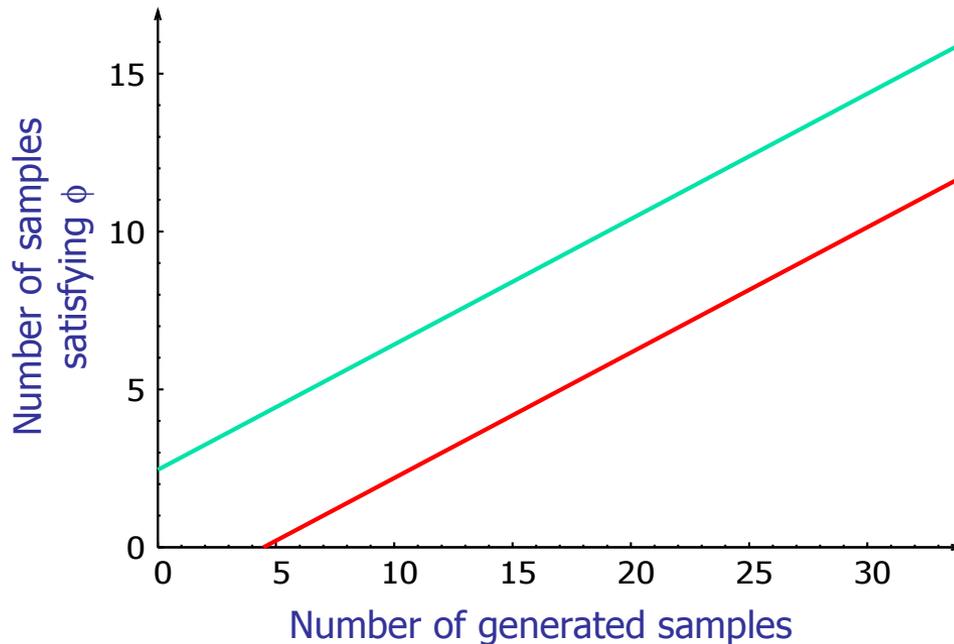
Method 2: Graphical Representation

- Accept hypothesis $p \geq p_0$



Method 2: Example

- $p_0 = 0.5$, $p_1 = 0.3$, $\alpha = 0.2$, $\beta = 0.1$:



Method 2:

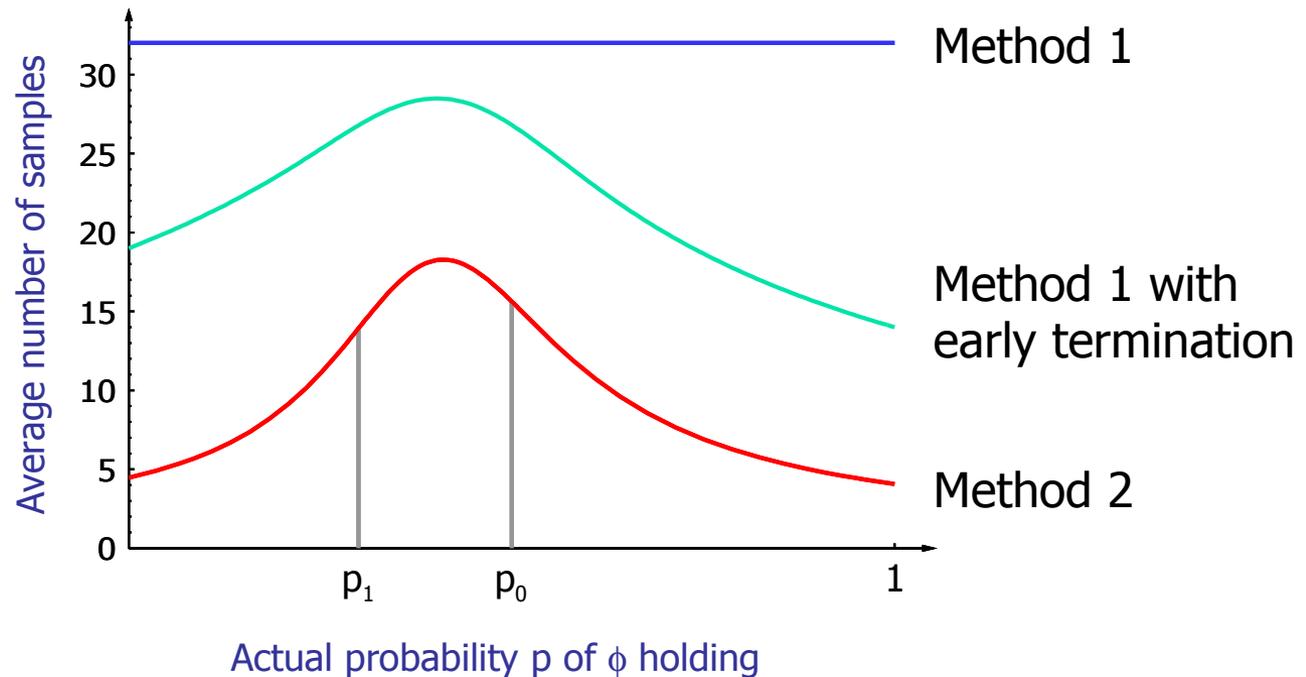
Number of Samples

- No upper bound, but terminates with probability one (“almost surely”)
- On **average** requires many fewer samples than a test with fixed number of samples

Method 2:

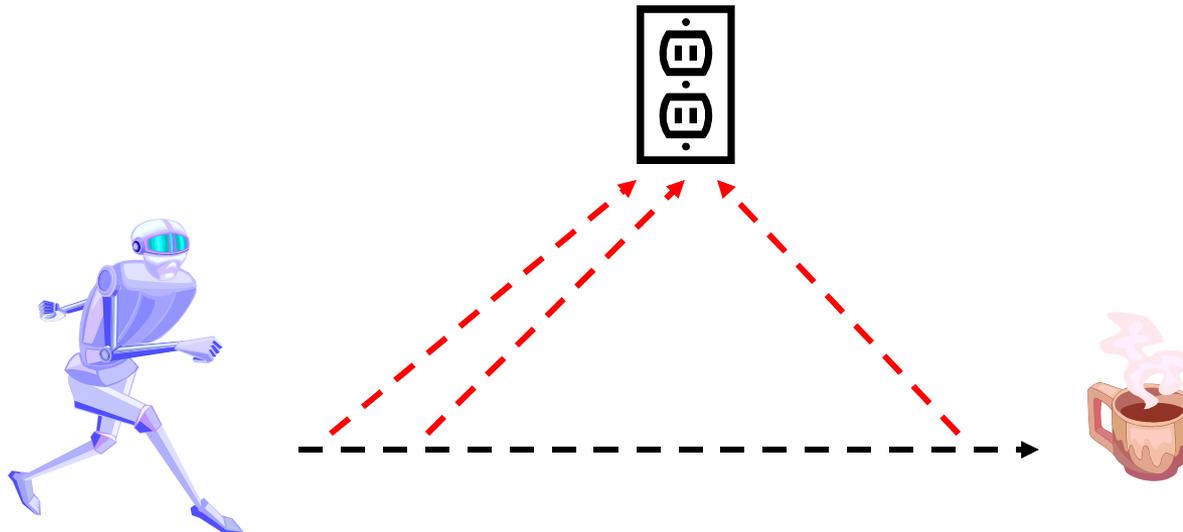
Number of Samples (cont.)

- $p_0 = 0.5$, $p_1 = 0.3$, $\alpha = 0.2$, $\beta = 0.1$:



Acceptance Sampling with Partially Observable Samples

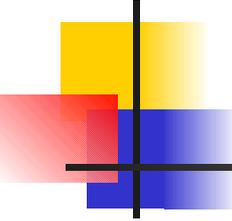
- What if we cannot observe the sample values without error?
 - $\Pr_{\geq 0.5}(\Pr_{\geq 0.7}(\diamond^{\leq 9} \text{ recharging}) U^{\leq 6} \text{ have tea})$



Acceptance Sampling with Partially Observable Samples

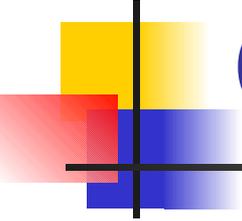
- What if we cannot observe the sample values without error?





Modeling Observation Error

- Assume prob. $\leq \alpha'$ of observing that ϕ does not satisfy a sample when it does
- Assume prob. $\leq \beta'$ of observing that ϕ satisfies a sample when it does not

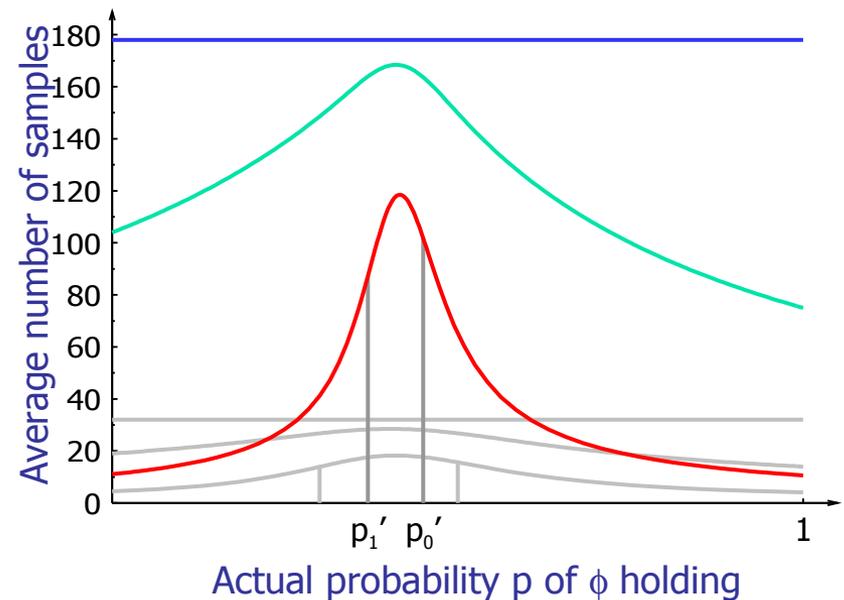
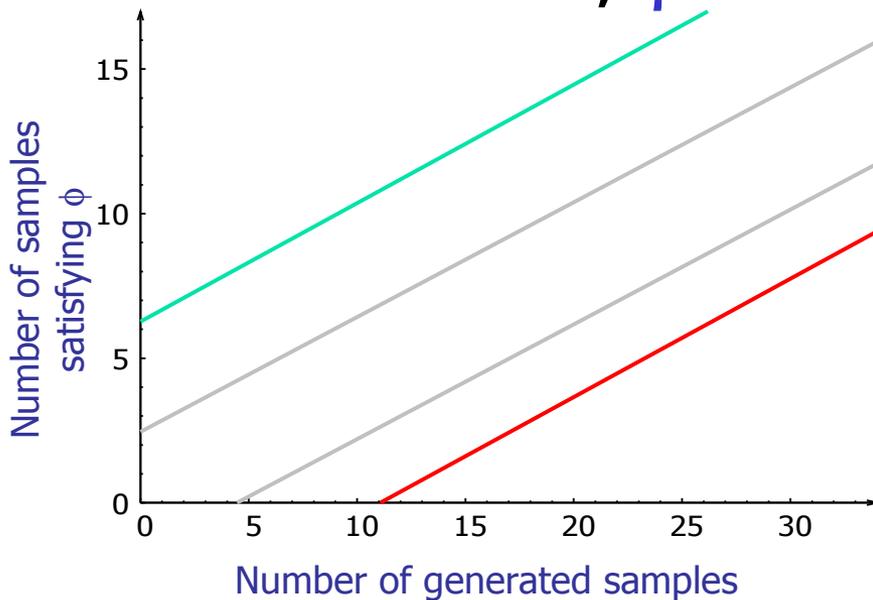


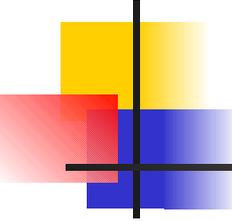
Accounting for Observation Error

- Use narrower indifference region:
 - $p_0' = p_0(1 - \alpha')$
 - $p_1' = 1 - (1 - p_1)(1 - \beta')$
- Works the same for both methods!

Observation Error: Example

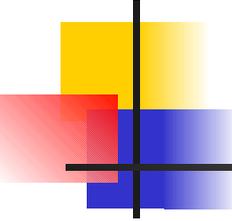
- $p_0 = 0.5, p_1 = 0.3, \alpha = 0.2, \beta = 0.1$
- $\alpha' = 0.1, \beta' = 0.1$





Application to CSL Model Checking [Younes & Simmons 02]

- Use acceptance sampling to verify probabilistic statements in CSL
- Can handle CSL **without** steady-state and unbounded until
 - Nested probabilistic operators
 - Negation and conjunction of probabilistic statements

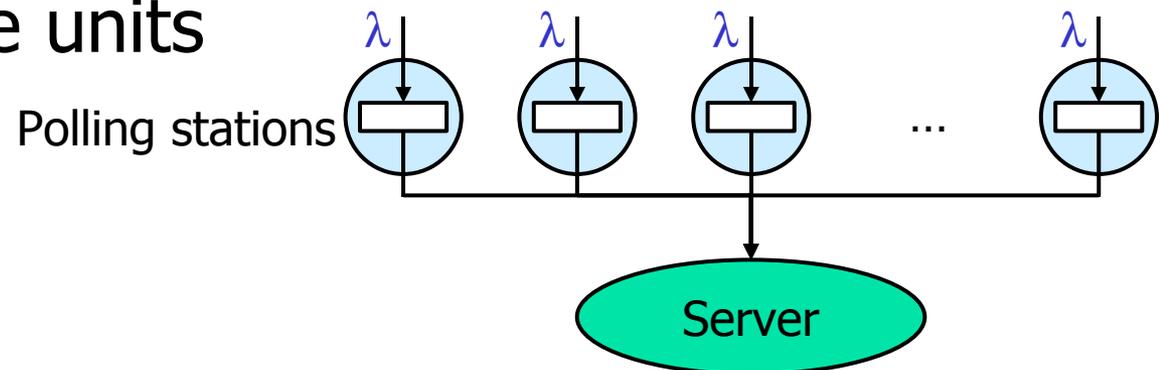


Benefits of Sampling

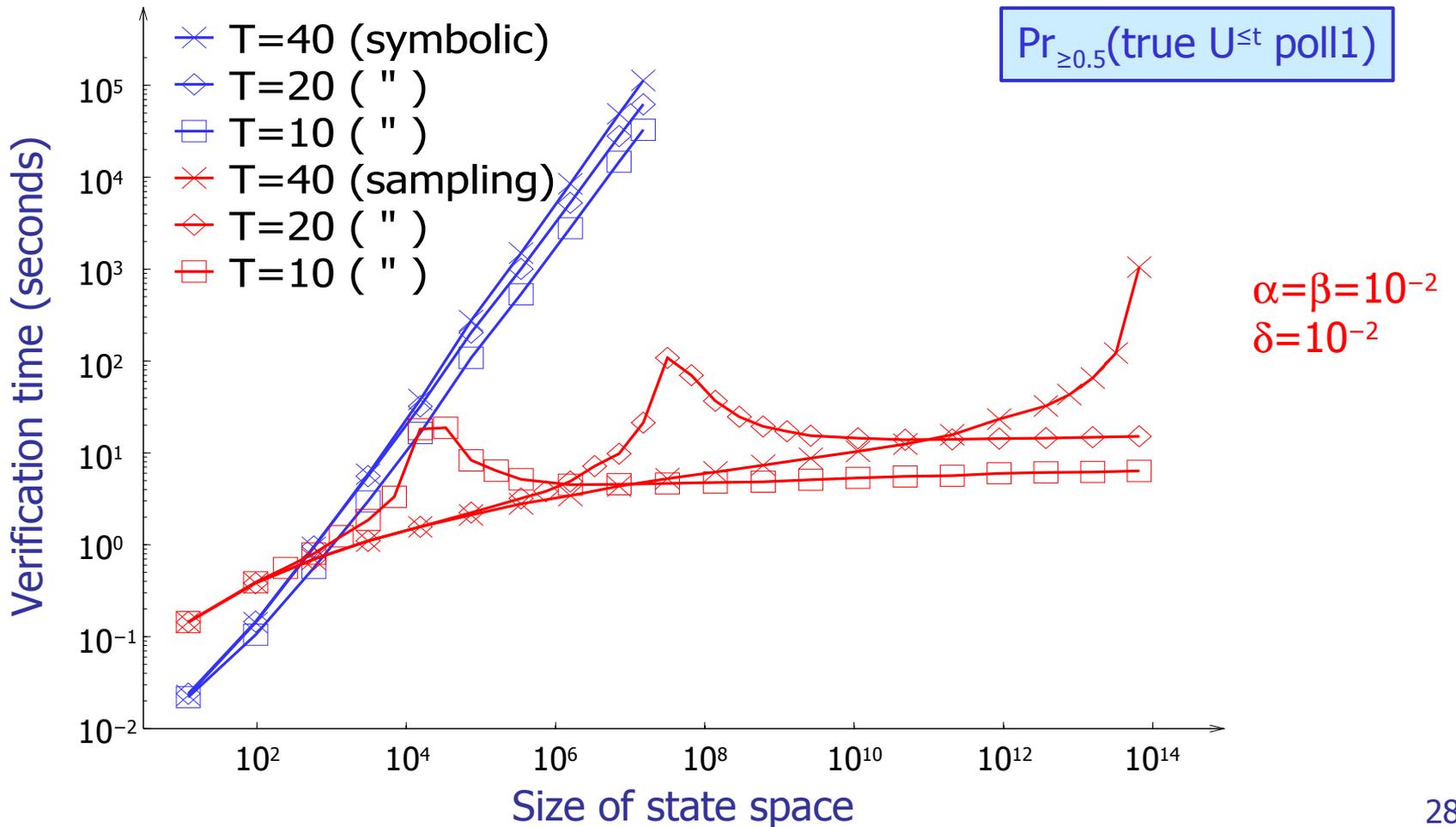
- Low memory requirements
- Model independent
- Easy to parallelize
- Provides “counter examples”
- Has “anytime” properties

CSL Model Checking Example: Symmetric Polling System

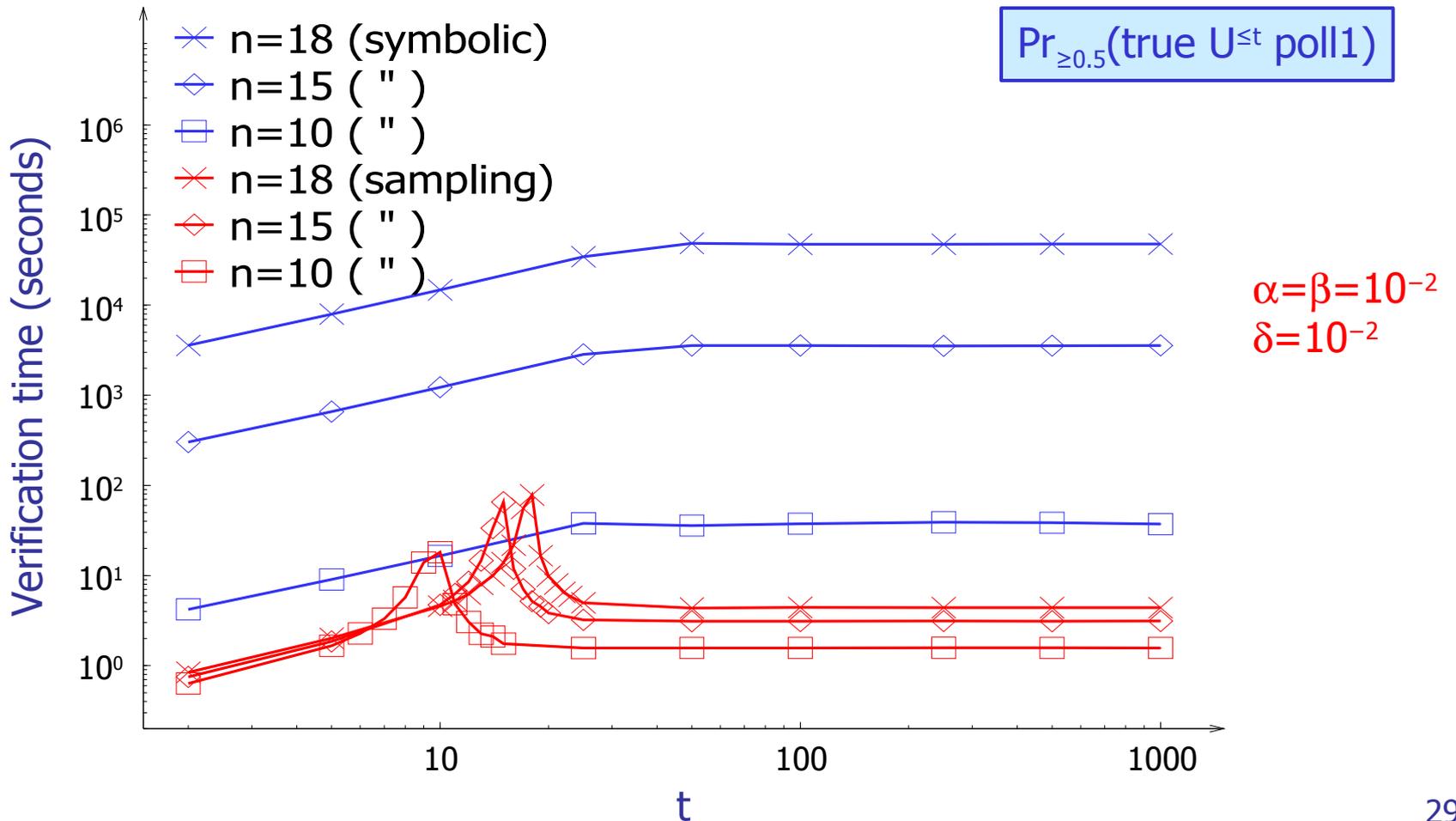
- Single server, n polling stations
- State space of size $O(n \cdot 2^n)$
- Property of interest:
 - When full and serving station 1, probability is at least 0.5 that station 1 is polled within t time units



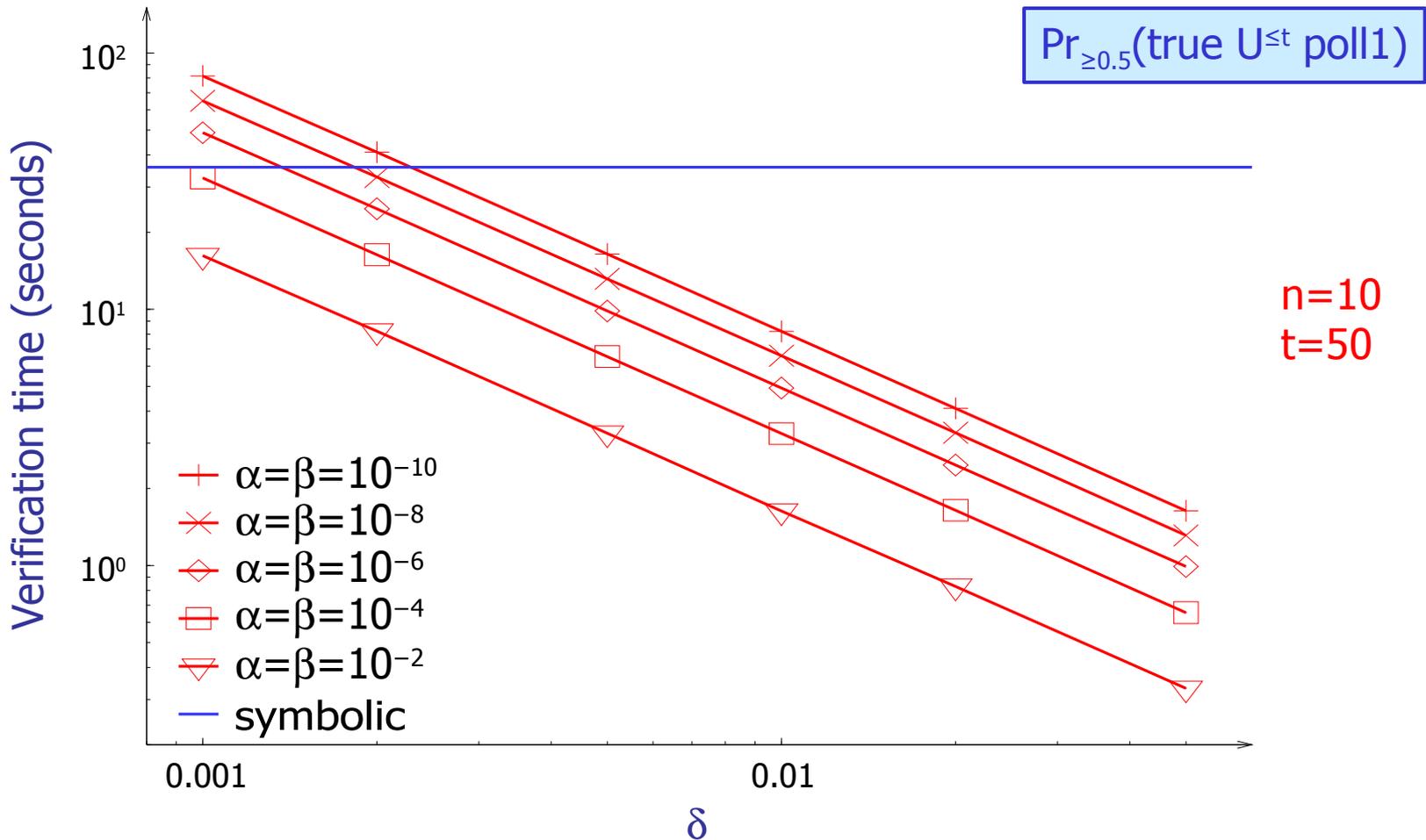
Symmetric Polling System (results) [Younes et al. ??]

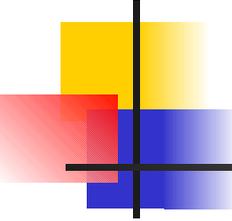


Symmetric Polling System (results) [Younes et al. ??]



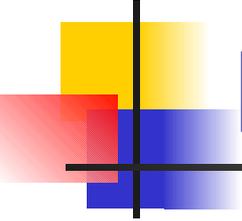
Symmetric Polling System (results) [Younes et al. ??]





Notes Regarding Comparison

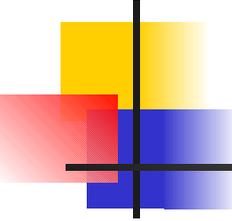
- Single state vs. all states
- Hypothesis testing vs. probability calculation/estimation
- Bounds on error probability vs. convergence criterion



Relevance to Planning

[Younes et al. 03]

- Planning for CSL goals in continuous-time stochastic domains
- Verification guided policy search:
 - Start with initial policy
 - Verify if policy satisfies goal in initial state
 - **Good**: return policy as solution
 - **Bad**: use sample paths to guide policy improvement and iterate



Summary

- Acceptance sampling can be used to verify probabilistic properties of systems
- Have shown method with fixed number of samples and sequential method
- Sequential method better on average and adapts to the difficulty of a problem