REscope: High-dimensional Statistical Circuit Simulation towards Full Failure Region Coverage

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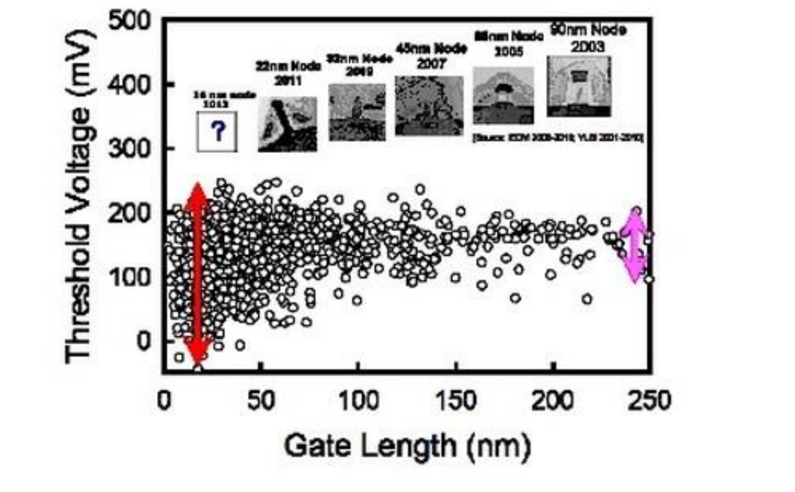
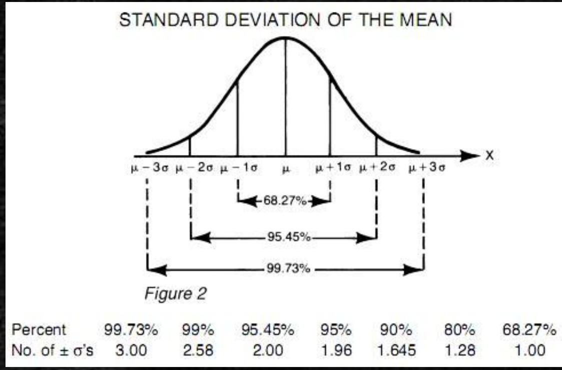
Need & Challenge of High Sigma analysis

- **Need for statistical circuit analysis**
  - Process technology continue to scale 45nm, 32nm, 22nm …
    - Shrinking devices → more prone to PVT variations
  - Statistical circuit analysis helps to **debug circuits in the pre-silicon phase**, and enhances yield rate



Courtesy of Prof. Yiming Li, National Chiao Tung University, Taiwan

- **Challenges**: **High Sigma** (Rare Failure Event) analysis
  - Memory cell (e.g. 6+ sigma)
  - Critical circuits (e.g. 4-5 sigma): I/O cell, PLL, etc.

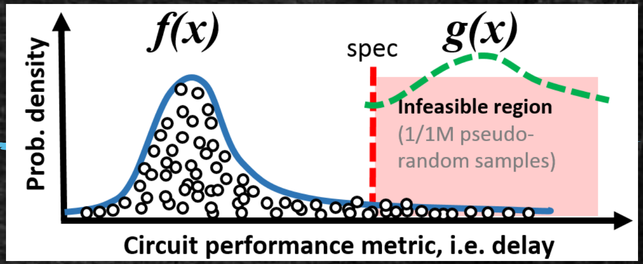


Sigma	Probability	# of Simulations
1	0.15866	700
2	0.02275	4,400
3	0.00135	74,100
4	3.17E-05	3,157,500
5	2.87E-07	348,855,600

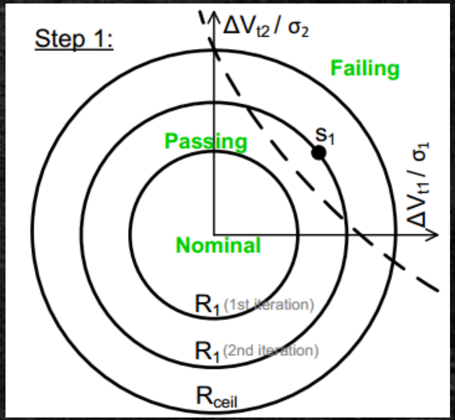
[LYL09] Kyu Won Lee, SM Yoon, SC Lee, W Lee, IM Kim, Cheol Eui Lee, and DH Kim. "Secondary electron eneration in electron-beam-irradiated solids: Resolution limits to nanolithography." *J Korean Phys Soc*,55:1720–1723, 2009

Existing Approaches

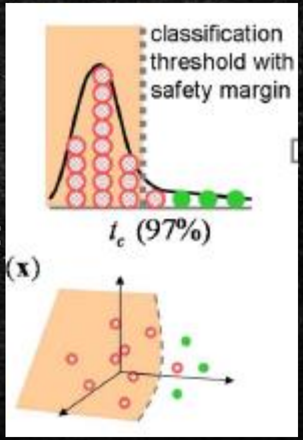
- Monte Carlo Simulation:
  - Monte Carlo is **infeasible** for high sigma analysis in terms of computational complexity
    - One post-layout PLL simulation may take several hours
- Importance Sampling methods:
  - Shift the sample distribution to more “important” region
  - e.g. Spherical sampling[QTD10], HDIS[WGC14]
- Classification based methods:
  - Statistical Blockade (Linear classifier)[SR08]



Spherical sampling[QTD10]:



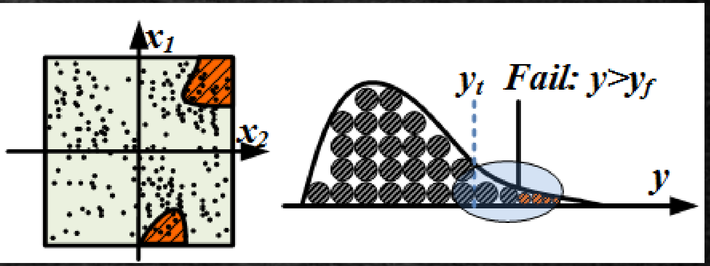
Statistical Blockade[QTD10]:



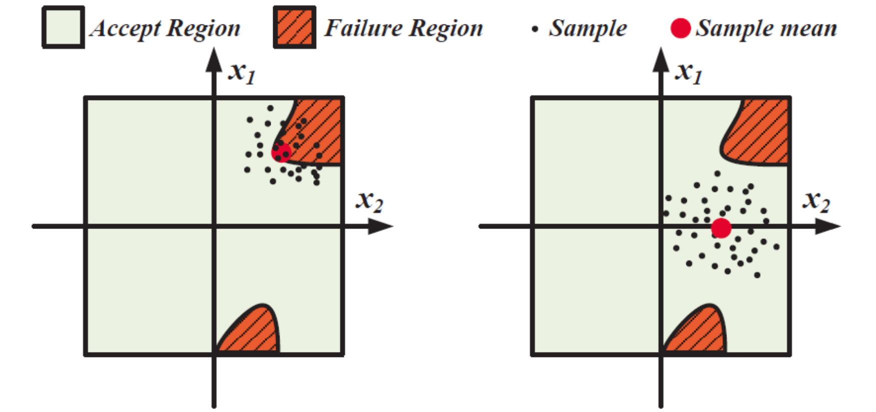
[QTD10] M. Qazi, M. Tikekar, L. Dolecek, D. Shah, and A. Chandrakasan, “Loop flattening and spherical sampling: Highly efficient model reduction techniques for SRAM yield analysis,” in DATE’2010, pp. 801 –806.
[12] W. Wu, F. Gong, G. Chen, and Lei He, “A Fast and Provably Bounded Failure Analysis of Memory Circuits in High Dimensions", ASPDAC’2014
[SR08] A Singhee, and RA Rutenbar. “Statistical blockade: Very fast statistical simulation and modeling of rare circuit events and its application to memory design,” in DATE’2008, pp. 235-251.

What if there are **multiple failure regions ?**

- What if failure samples fall in multiple disjoint regions



- Importance sampling works like this:

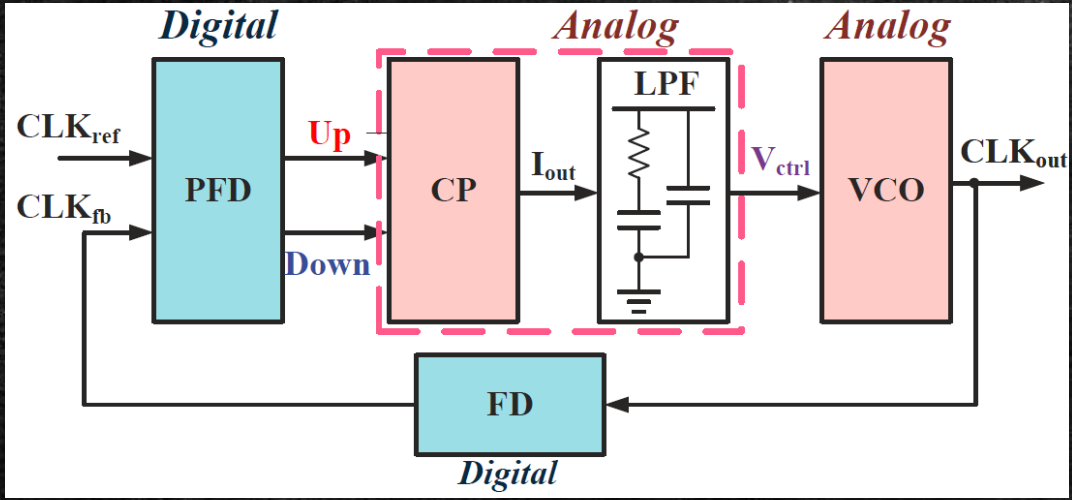


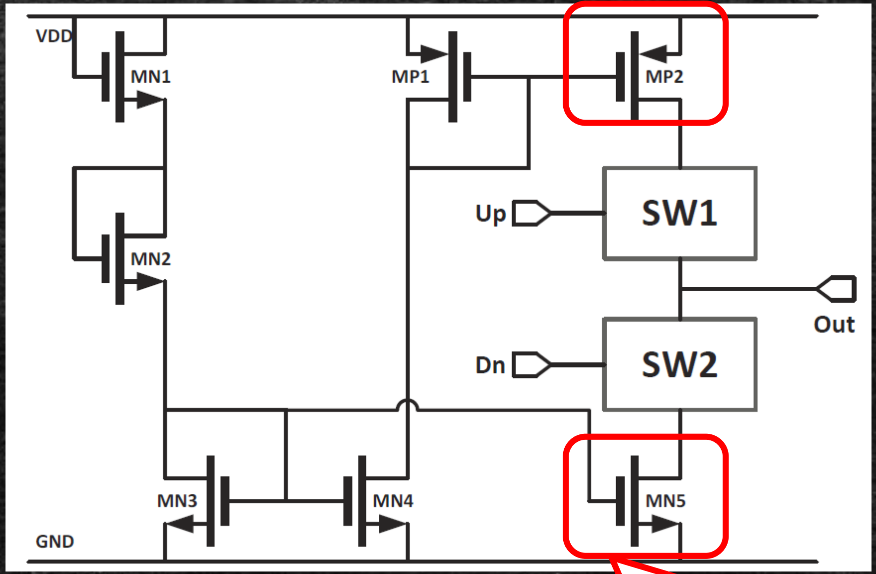
(a) Importance sampling with shifted mean on the boundary of failure region(s)

(b) Importance sampling with shifted mean on the centroid the failure region(s)

- Statistical blockade can't identify multiple failure regions. Even worse, the classifier scales poorly with the number of variation variables

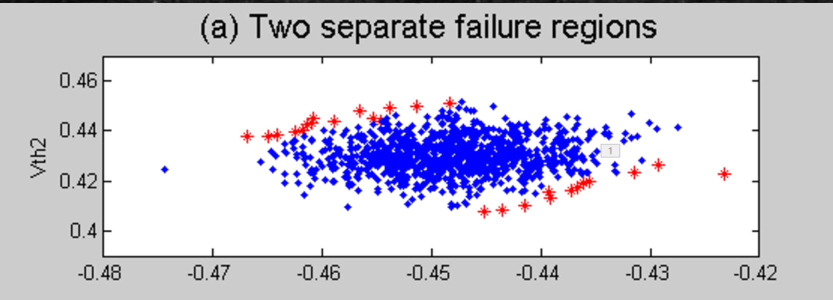
Unfortunately, multiple failure regions do exist





PFD: phase frequency detector; **CP: Charge pump**
FD: frequency divider; VCO: voltage controlled oscillator

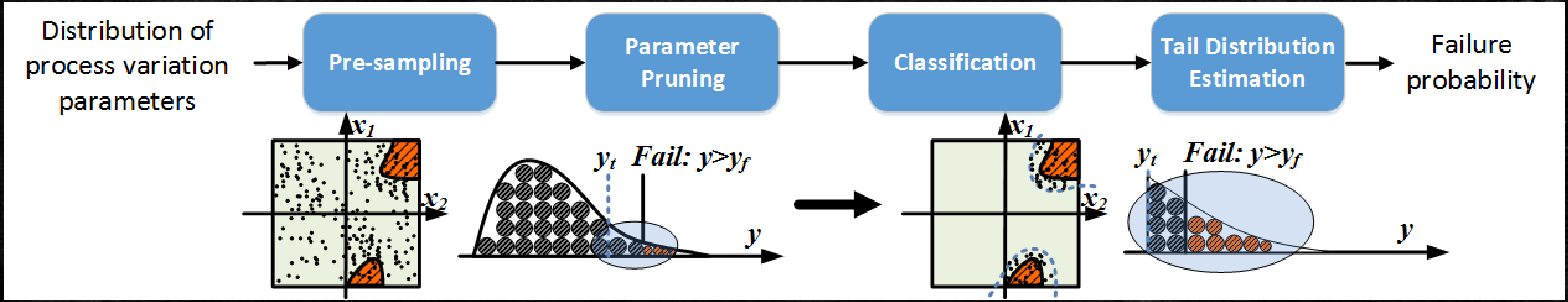
Mismatch between MP2 and MN5 may result in fluctuation of control voltage, which will lead to "jitter" in the clock.



Vths of MP2 and MN5 are variation parameters

Rare-Event Microscope (REscope)

- Make the classification based approach more practical, in terms of **accuracy and efficiency.**
  - Identifies **multiple failure regions**
  - Handles **high dimensional** problems
  - Approximates the tail as a **generalized pareto distribution (GPD)**
    - GPD: a good model for the distribution of the exceedence to a certain threshold in another distribution, i.e. the tail of PDF(y)

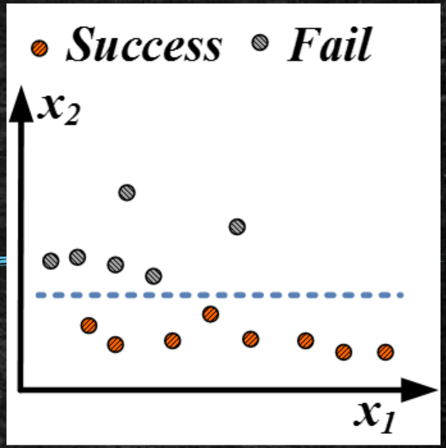


Pruning and Classification

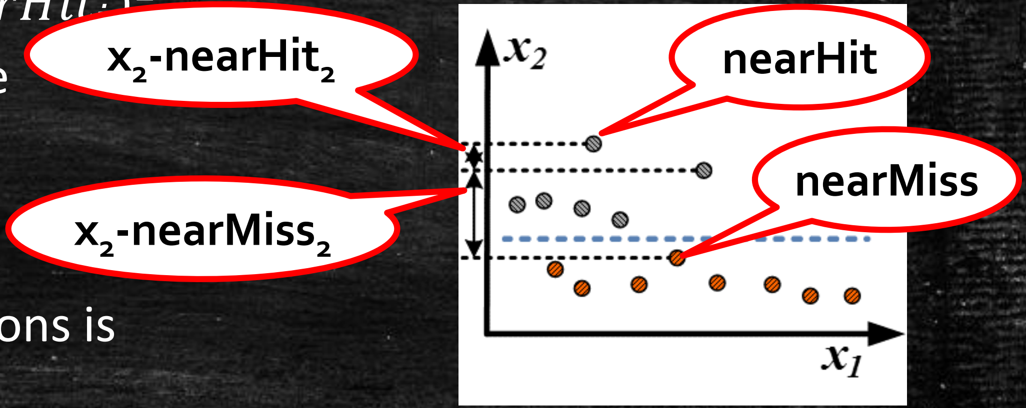
- **Parameter pruning (Feature selection)**
  - Evaluate the "**Importance**" of each parameter (feature)
  - RELIEF-F algorithm:

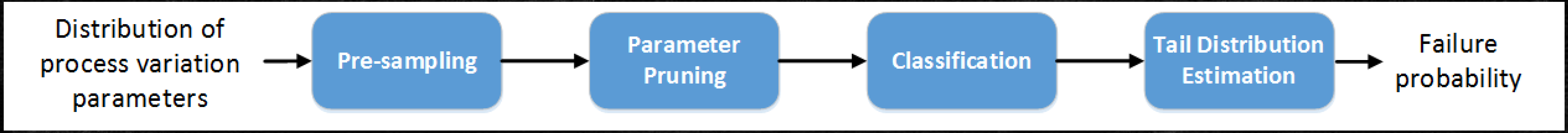
$$W_i = W_i + (x_i - nearMiss_i)^2 - (x_i - nearHit_i)^2$$

  - Sort parameters by "Importance", and prune the unimportant parameters
- **Classification**
  - The boundary separating accept and failure regions is usually nonlinear
  - Apply support vector machine (SVM) with radial basis function (RBF) kernel yields a good nonlinear boundary



Calculate W_2



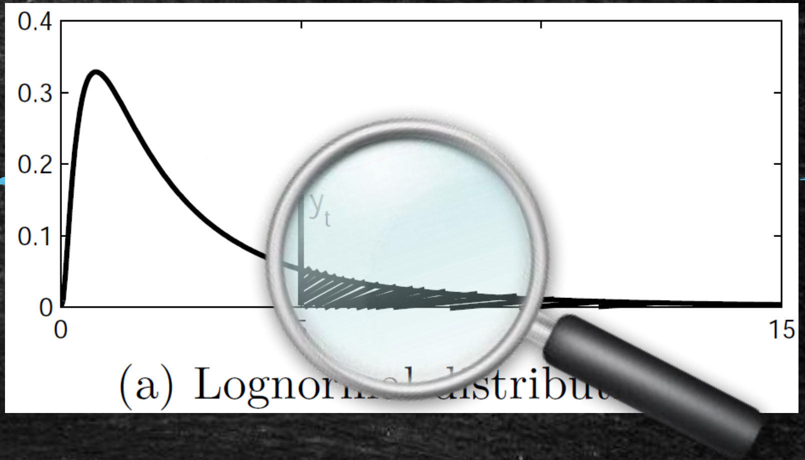


GPD Approximation

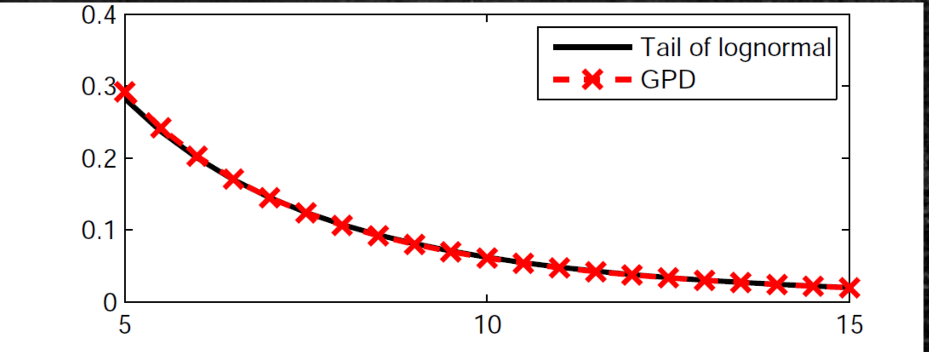
- **Approximate the tail of PDF by GPD with only 2 parameters**
  - Shape parameter(ξ), scale parameter(σ), starting point of the tail(μ)

$$F_{(\xi,\mu,\sigma)}(y) = \begin{cases} 1-(1-\frac{\xi(y-\mu)}{\sigma})^{\frac{1}{\xi}} & for\ \xi \neq 0 \\ 1-\exp(-\frac{(y-\mu)}{\sigma}) & for\ \xi = 0 \end{cases} \qquad (5)$$

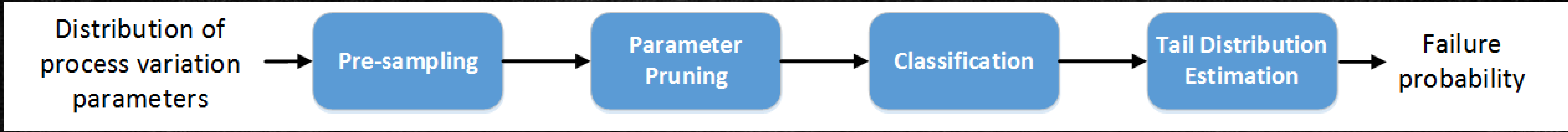
  - Calculate the initial solution by probability weighted moment matching
  - Refine the solution by Newton's method



(a) Logno... ...istribu...

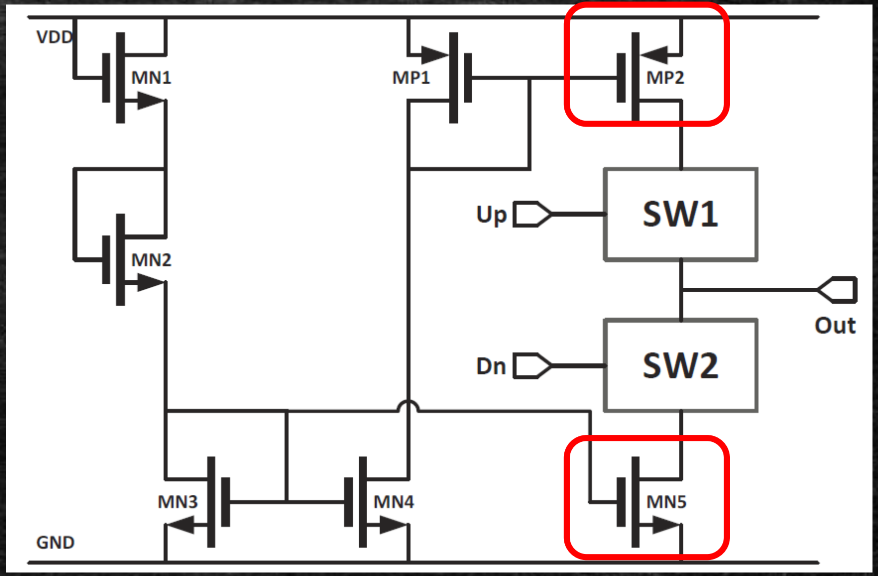


(b) Conditional PDF of the Lognormal tail

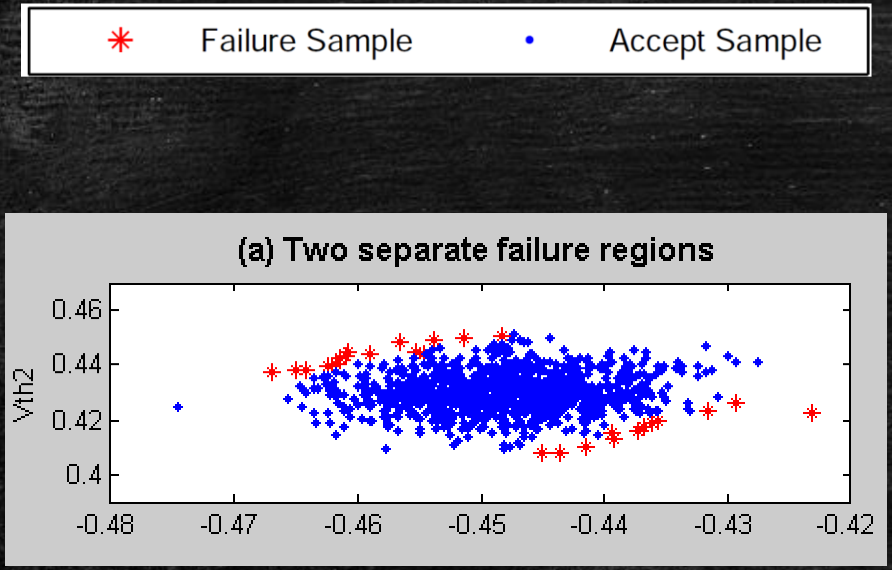


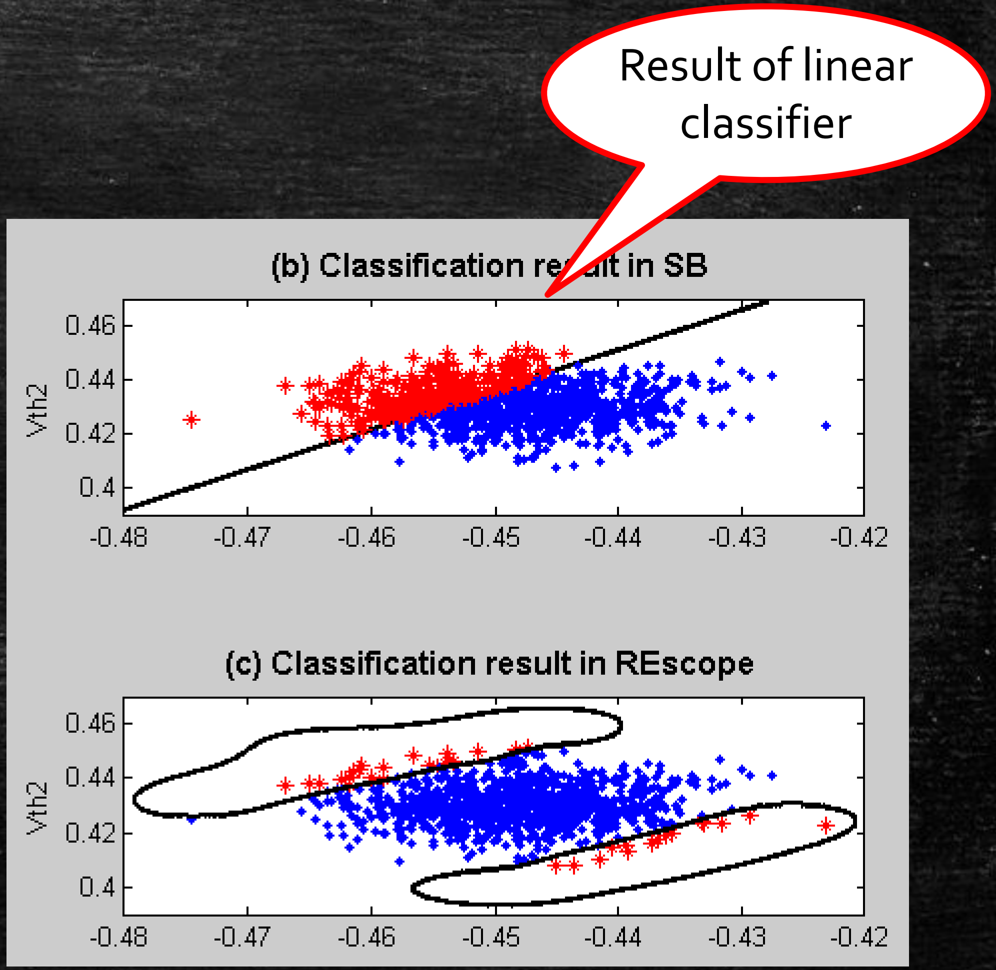
Experiments: REscope for Charge Pump

- One circuit, two configurations
  - An **illustrative** example: only **2** variation parameters
    - Vth of MP2 and MN5
  - A high dimensional example: **108** process variation parameters (27 transistors, 4 process variation parameters for each)
    - Channel length
    - Channel weight
    - Gate oxide thickness
    - Flat-band voltage
- Failure: current mismatch.



Experiment 1: Illustration of Classification results





Experiment 2: Handling high dimensional cases

- Parameter pruning results:
  - 27 important features are selected out of 108 variables

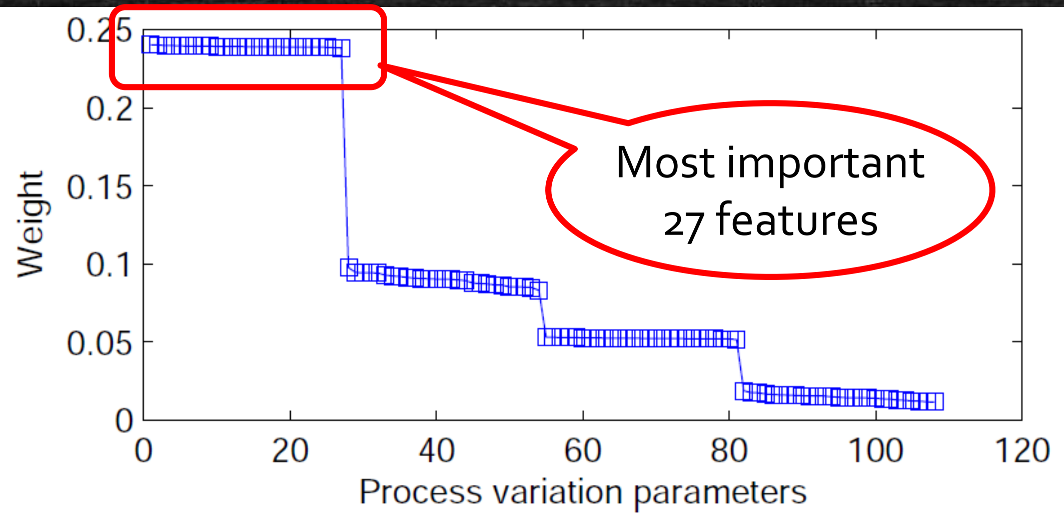
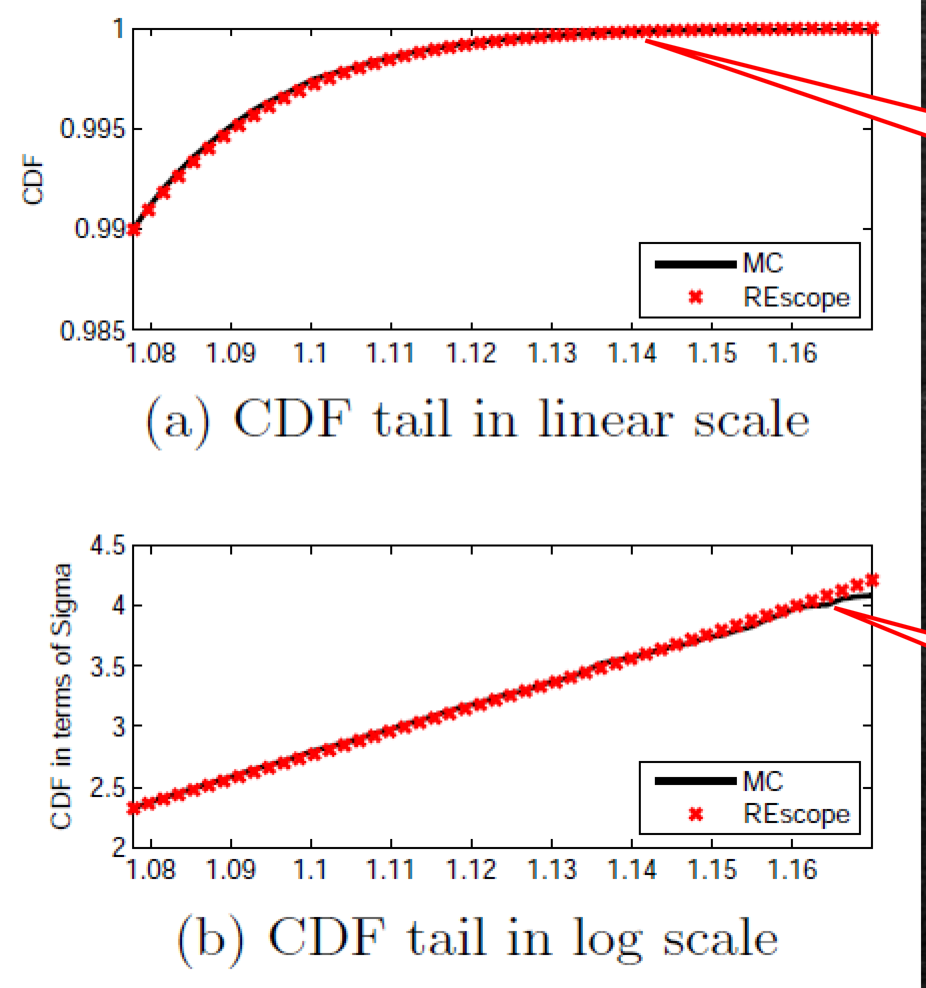


Figure 7: Weight of all 108 process variations in charge pump circuit

Accuracy of REscope

- Tail modeling after parameter pruning:



The estimated P_{fail} **overlap** with MC

Mismatch after 4.2 sigma because we don't have enough MC samples so far.

Comparison with existing methods

Table 1: Comparison of the accuracy and efficiency on charge pump circuit

	Monte Carlo (MC)	Importance sampling (HDIS)[12]	Proposed approach (REscope)
failure probability	2.279e-5 (0%)	1.136e-3	2.256e-5 (+1.05%)
#sim. runs	1.4e+6 (389x)	2e+4 (5.6x)	3.6e+3 (1x)

- **389x** speedup on MC with **1.05% error at 4 sigma**, while importance sampling and statistical blockade fail.

[12] Wei Wu, Fang Gong, Gengsheng Chen, and Lei He, “A Fast and Provably Bounded Failure Analysis of Memory Circuits in High Dimensions", ASPDAC’2014

Conclusions

- Strength:
  - Dimension reduction algorithm keeps the “important” parameters only.
  - Nonlinear classifier works perfectly on detecting multiple failure regions.
  - The tail is explicitly matched to a known distribution, such as GPD, to further reduce the number of sample.
  - Experiments show 389x speedup on MC with only 1.05% error, which importance sampling and statistical blockade fail.

- Limitation and Future direction:
  - Considering the correlation between variations sources
  - Algorithm to automatically adjust the classifier configuration

Thanks!

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