

CANDE 2008

From Finance to Flip Flops: Using the Mathematics of Money and Risk to Understand the Statistics of Nanoscale Circuits

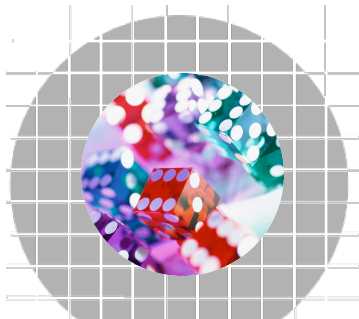
Rob A. Rutenbar (and Amith Singhee)
Professor, Electrical & Computer Engineering
rutenbar@ece.cmu.edu (and asinghee@us.ibm.com)

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CarnegieMellon

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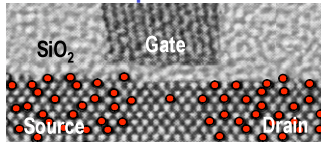
About This Talk



- **Statistics for nanoscale ckts**
 - The new challenge
- **Monte Carlo analysis**
 - How we do statistical analysis
- **Mathematics of money+risk**
 - Surprising source for very sophisticated Monte Carlo tools

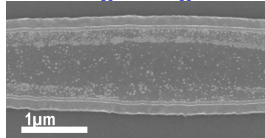
New Challenge: *Statistical Variation*

Random Dopant Fluctuations



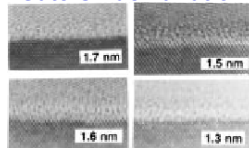
A. Brown et al., *IEEE Trans. Nanotechnology*, p. 195, 2002

Line Edge Roughness

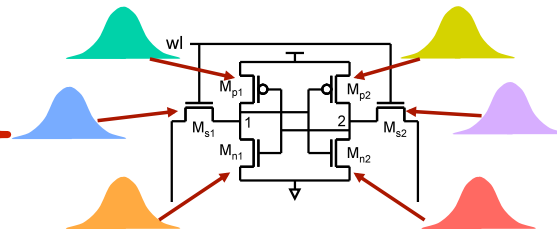


K. Shepard, U. Columbia

Gate Oxide Variation



Momose et al., *IEEE Trans. Electron Devices*, 45(3), 1998



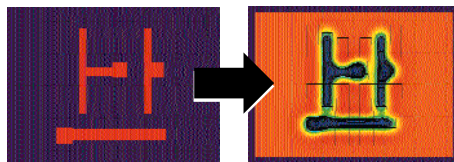
- At nanoscale, nothing is *deterministic* anymore
- Everything is *statistical*

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Statistical Variability: Two Flavors

■ Systematic variation

- Ex: Lithography
- Optics, chemistry to print small mask shapes

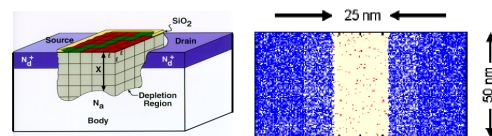


■ Not really random

- Physics is understood, expensive to compute

■ Random variation

- Ex: Dopant fluctuation
- How many individual dopant atoms; where?



■ Really (*really*) random

- Physics is fundamentally random for these effects

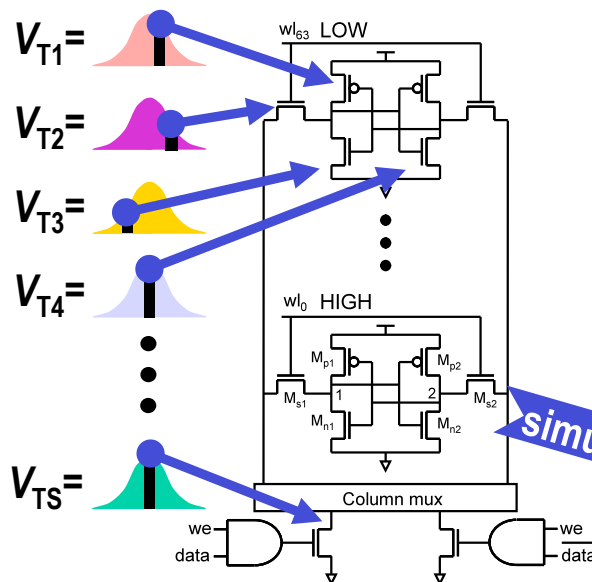
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End Result for Us Design/CAD Folks

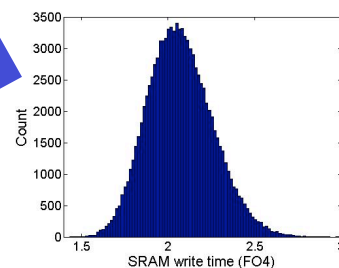


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To Evaluate Circuit Impact: *Monte Carlo*

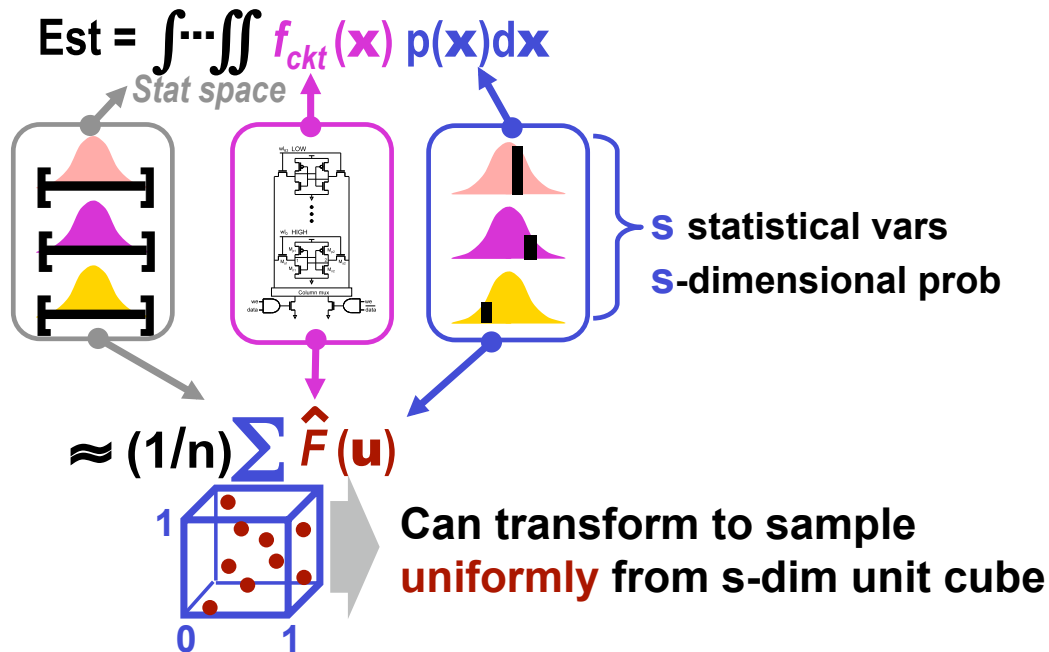


- Sample each statistical variable
- Parameterize one circuit, simulate it
- Repeat--n samples

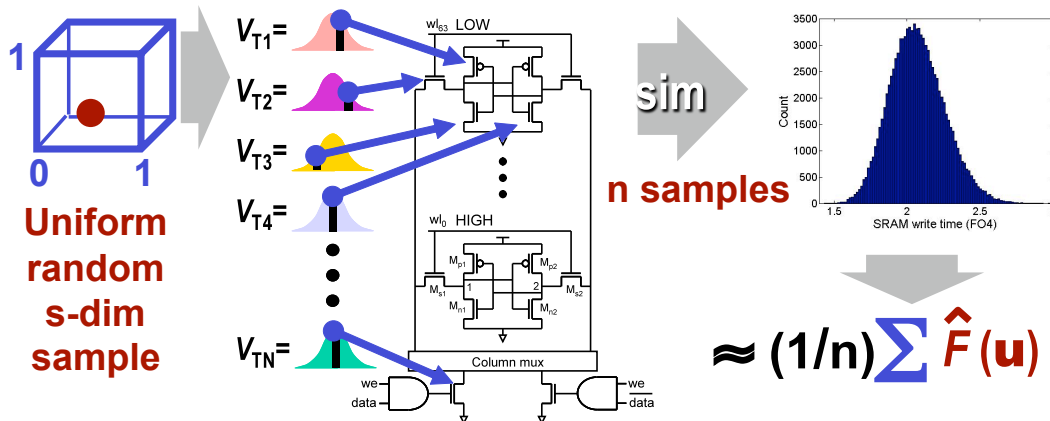


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Monte Carlo Math: Just A Big Integral



Evaluate Circuit Impact: Monte Carlo



- PRO: Accurate, flexible, general
- CON: Slow, slow, **s l o w**...

Why is Monte Carlo Painful?

- High-dim problems: *s is big (100-1000)*
- Profoundly nonlinear: *Nanoscale physics*
- Accuracy matters: *~1-5% error*
- Speed matters: *Many samples*
- Samples expensive: *Simulate each circuit*

Question: Who *Else* Has This Problem?



Computational finance

- Valuing complex financial instruments, derivatives
- High-dimensional, nonlinear, statistical integrals
- *Speed+accuracy* matters here, e.g., ~real-time decision-making

A Brief Aside: About the “F” Word...

- These recruiting signs common in my building at CMU...
- ...*last year*



A Brief Aside: About the “F” Word...

- ~1 year ago...
 - “Wow, analyzing yield is like pricing a bond? **Cool!**”
- ~ 1 month ago...
 - “Wow, you’re using the same stuff that **killed Wall Street?!**”



A Brief Aside: About the “F” Word...

HOME PAGE MY TIMES TODAY'S PAPER VIDEO MOST POPULAR TIMES TOPICS

The New York Times
Tuesday, September 23, 2008

Technology

Bits

Business • Innovation • Technology • Society

September 18, 2008, 7:52 AM

How Wall Street Lied to Its Computers

By SAUL HANSELL

CORRECTED 5 p.m.: Spelling of Leslie Rahl.

So where were the quants?

That's what has been running through my head as I watch some of the oldest and seemingly best-run firms on Wall Street implode because of what turned out to be really bad bets on mortgage securities.

Before I started covering the Internet in 1997, I spent 13 years covering trading and finance. I covered my share of trading disasters from junk bonds, mortgage securities and the financial blank canvas known as derivatives. And I got to know bunch of quantitative analysts ("quants"): mathematicians, computer scientists and economists who were working on Wall Street to develop the art and science of risk management.



(Credit: Fred R. Conrad/The New York Times)

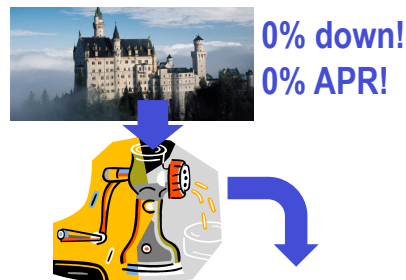
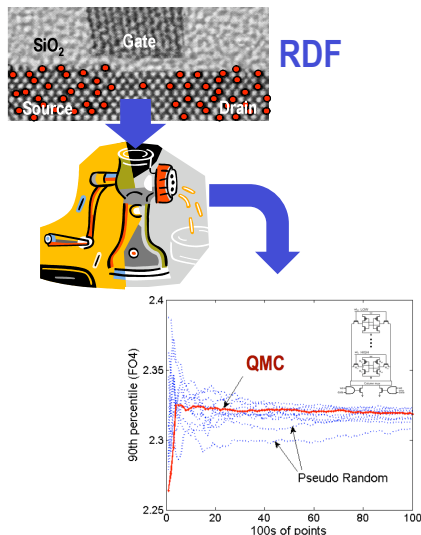
“The people who ran the financial firms **chose** to program their risk-management systems with **overly optimistic assumptions** and to feed them **oversimplified data**. ...

... Wall Street executives had **lots of incentives** to make sure their risk systems **didn't see much risk**.”

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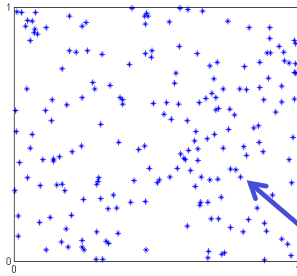
From Finance to Physics...

- Moral of story: If you start with **honest physics** as your input, you can get great results...



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Monte Carlo Revisited: Uniform Sampling



2-D example: unit cube is $[0,1]^2$

Independent, uniform
random samples
 (x,y) in 2-D cube

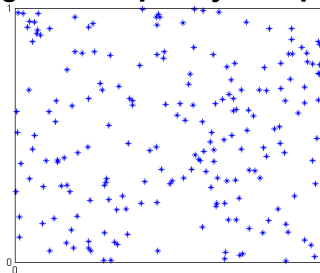
■ Classical Monte Carlo sampling

- Uses uniform pseudo-random pts (i.e, `rand()`)
- Surprise: *Not* very uniform (clumps, holes, etc)
- Turns out this is inefficient – we can do *better*

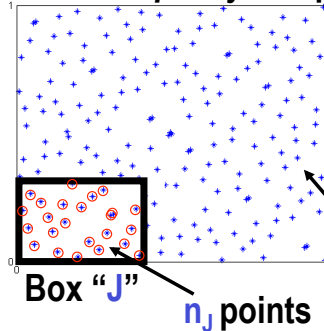
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Better == Low Discrepancy

High-discrepancy samples



Low-discrepancy samples



Mathematically: the **discrepancy**
is a measure of “uniformity”

$$D_n^* = \sup_J \left| \frac{n_J}{n} - Vol(J) \right|$$

Fraction of
points in J

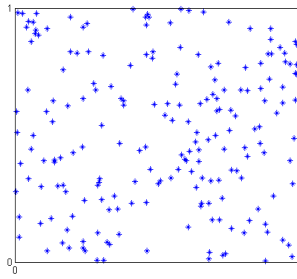
Fraction of volume
occupied by J

How well does sampled n_J / n
approximate *relative volume* of box?

For *low-discrepancy* sequences,
answer is: *always very well.*

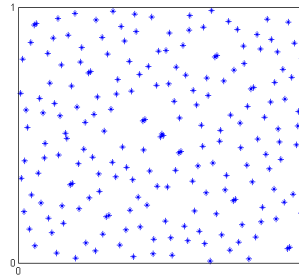
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Doing Better: Quasi Monte Carlo (QMC)



- Classical Monte Carlo
 - Uniform pseudo-random pts
 - Problem: *not* very uniform

- Error for n samples
 $O(1 / \sqrt{n})$



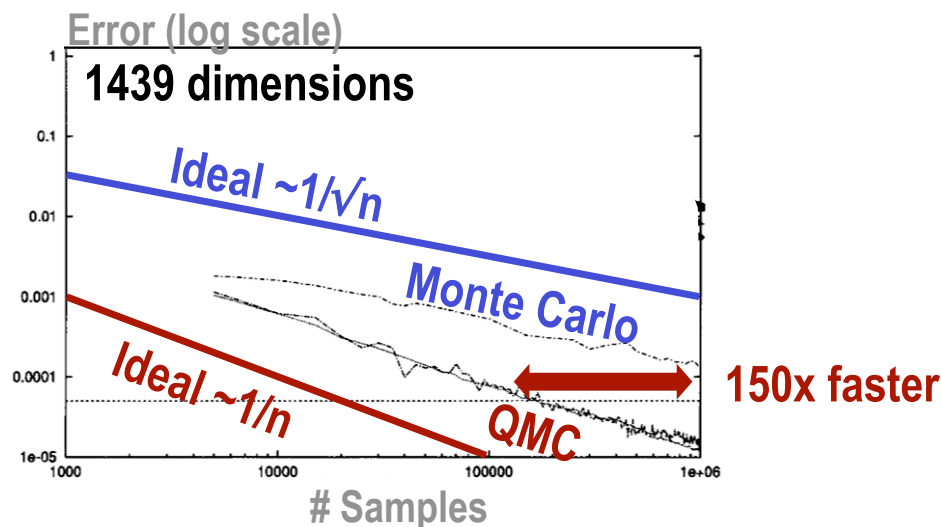
- Quasi Monte Carlo
 - “Low-discrepancy” seq’s
 - *Deterministic* samples

- Error for n samples
 $O(1 / n)$

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Computational Finance Example

- Eval 5-year discount price for a bond
 - From [Ninomiya, Tezuka, App Math Finance 1996]

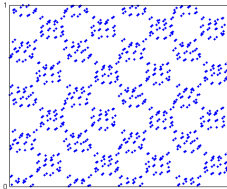


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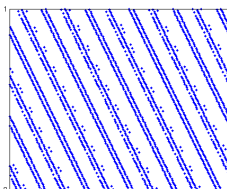
Engineering Detail: Pattern Artifacts

- Problem: Low Discrep Seq's show **patterns** in high dim's

- Need too many points for good uniformity



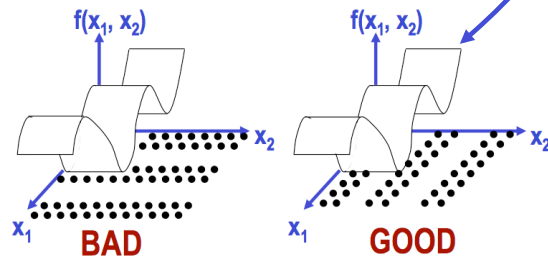
2 dims from 500-D Sobol' pts



2 dims from 500-D Faure pts

- Solution: Since *earlier* dimensions *less* affected...

- Calculate **statistical sensitivity** of all vars
- Put sensitive vars first
- Ex: in $f(x_1, x_2)$ if x_1 more important than x_2

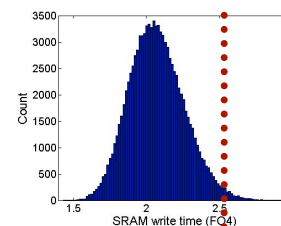
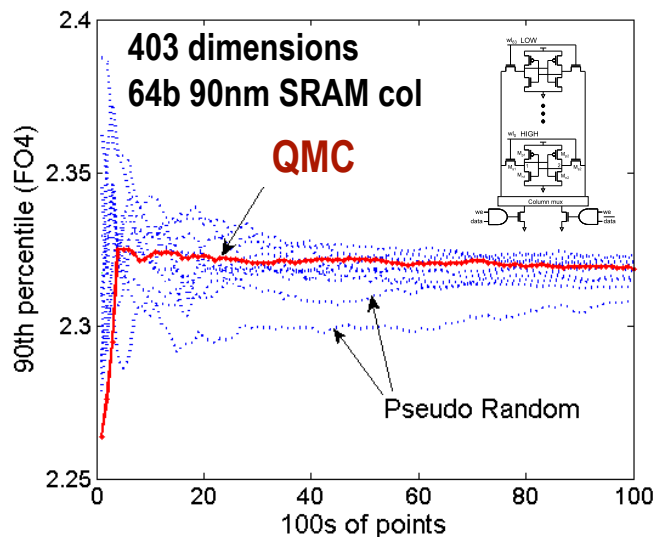


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Does QMC Work for Circuits?

- Yes!

- See: [Singhee, Rutenbar, ISQED 2007]
- Example: Complete SRAM column @ 90nm

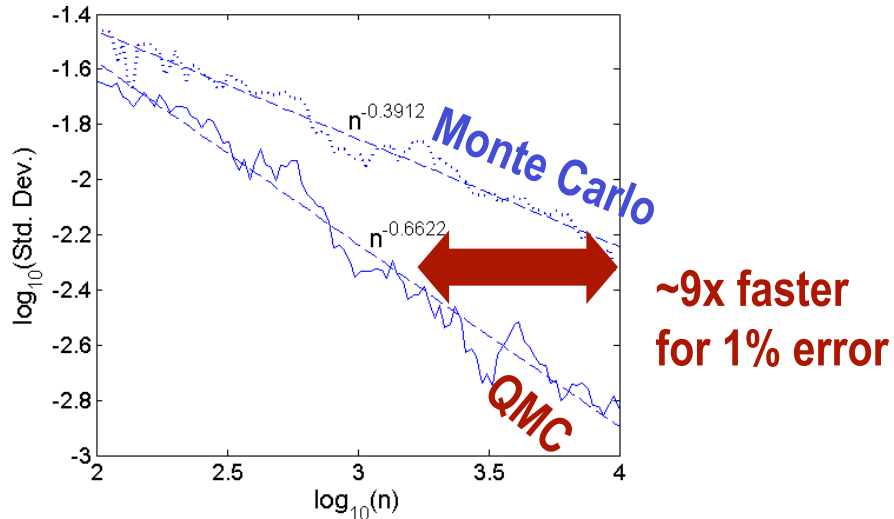


$$\Pr(\text{write} < t_w) = 0.9$$

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Very Promising Speedups

- Same 403-dimensional, 64b SRAM column

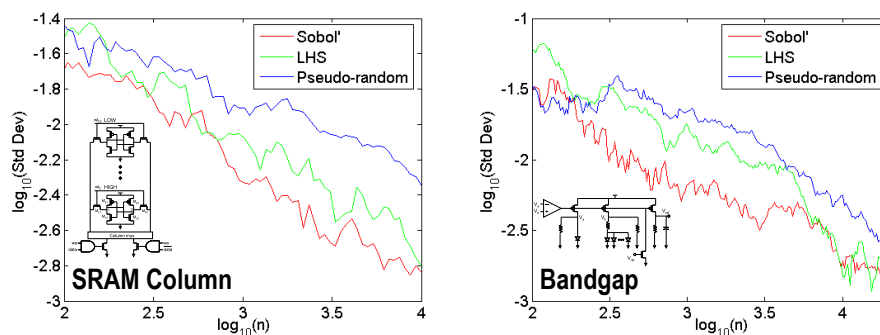


[Singhee, Rutenbar, ISQED 2007]

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Isn't This Just Latin Hypercube Sampling?

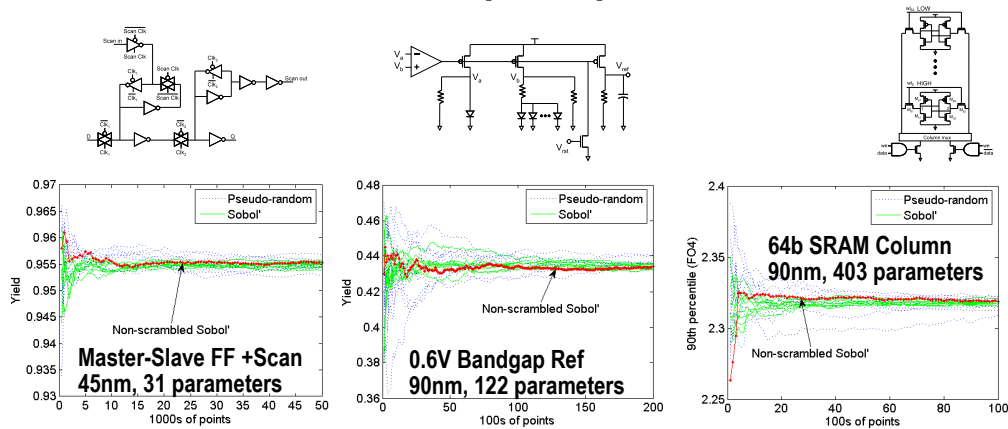
- No
 - LHS sample set actually a *randomized* low-discrep seq
 - Considered "advanced" in EDA, *but inferior* to QMC
 - (Nobody prices bonds with LHS – it's all QMC)

Plots: Error (est. variance across 10 runs) vs #samples n 

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Good Behavior on Other Circuits

- MC vs QMC variance, with #samples, n
 - 10 MC runs to compute MC variance
 - 1 QMC run + 9 *scrambled* QMC runs for variance
 - **General result: See speedups of 2X – 50X**



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Are We Done Yet? (Nope...)

- Lots of ideas to exploit in this space



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Another Aside: About the “F” Word...

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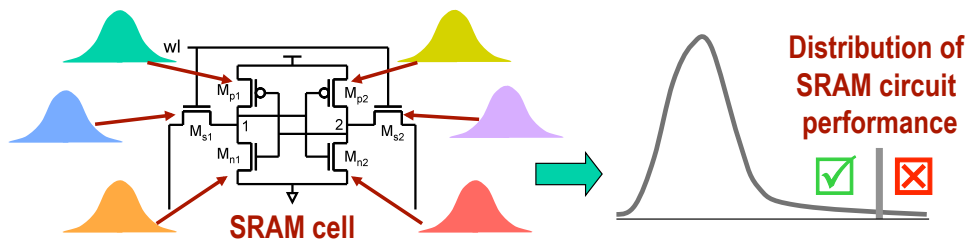
(Credit: Fred R. Conrad/The New York Times)

“In fact, most Wall Street computer models radically underestimated the risk of the complex mortgage securities ... partly because the level of financial distress is ‘the equivalent of the 100-year flood’...”

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Next Problem: “Rare Event” Statistics

- SRAM reliability is all about *far tails* of stats
 - Why? High replication ($\sim 10^8$ bits) of core circuits
 - 3σ doesn't cut it for 100M cells; need **6σ , 7σ , 8σ** ...

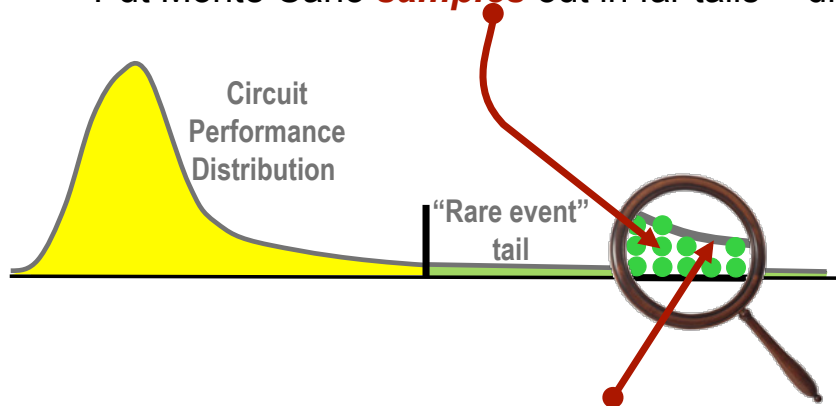


- Problem: *Intractable* Monte Carlo runs
 - 1M Monte Carlo sims predicts (unreliably) to **$\sim 4.5\sigma$**

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What Do We Need To Solve This...?

- Ultra fast *sampling* of rare events
 - Put Monte Carlo *samples* out in far tails -- directly



- Accurate analytical *pdf models* of rare tails
 - Using these samples, model lets us predict *farther*

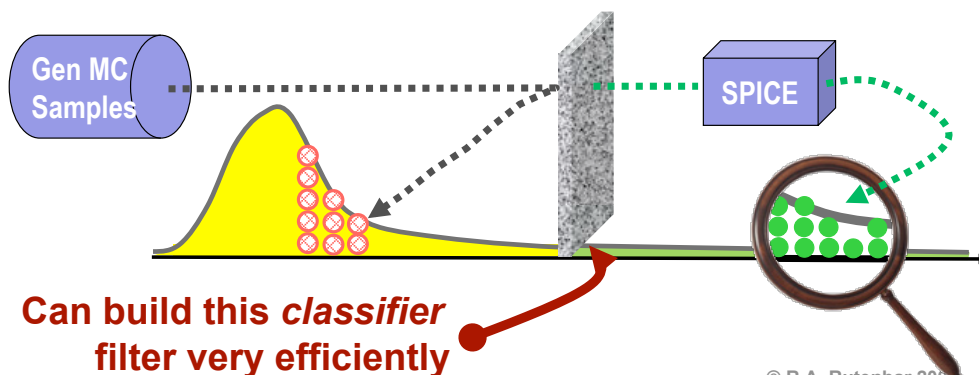
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Efficiently Sampling *Just* the Tail

- Note: *Generating* MC samples is cheap, *Simulating* these samples is costly

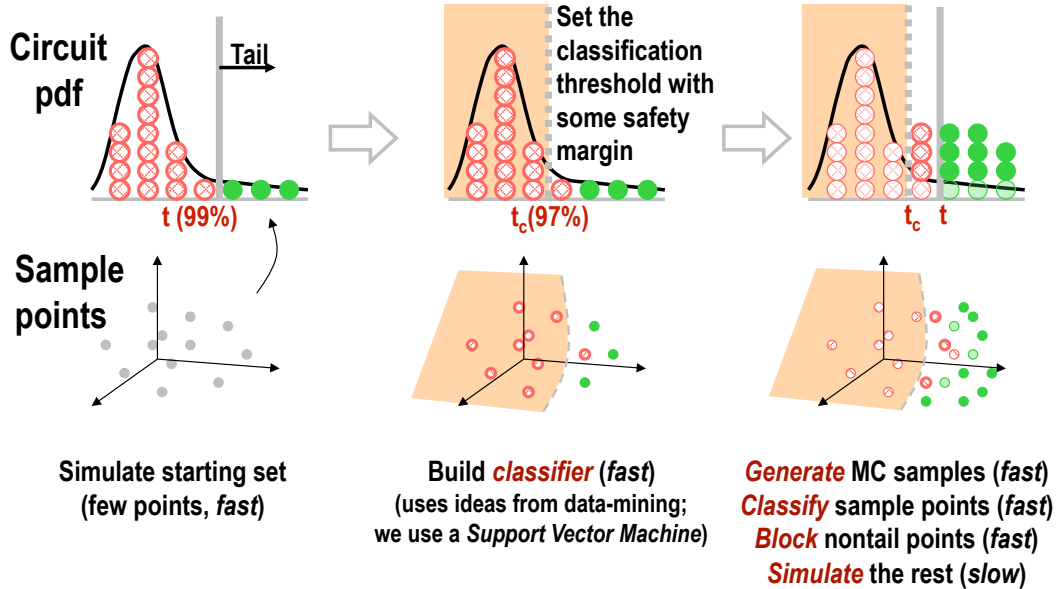
- Idea:

1. **Generate** regular MC samples...
2. ...but **block** points that are "very probably" **not** in tail
3. **Simulate** the rest – i.e., the points we do not block



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We Call the Idea: *Statistical Blockade*



[Singhee, Rutenbar DATE 2007]

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Modeling Statistics of Rare Events...?

■ Extreme Value Theory (EVT)

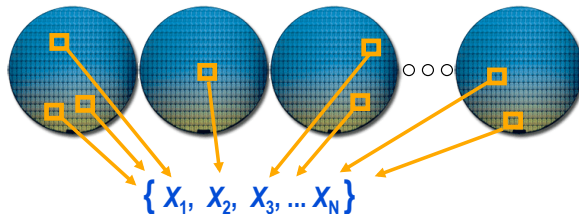
- Behavior of extreme (rare) values of distributions
- (If hurricanes are i.i.d random variables, we'd like to know the statistics of the *largest waves*...)

EVT: Modeling the PDF in the Tail

- Recall Central Limit Theorem: $\Sigma(\text{i.i.d. samples}) \rightarrow \text{Gaussian}$

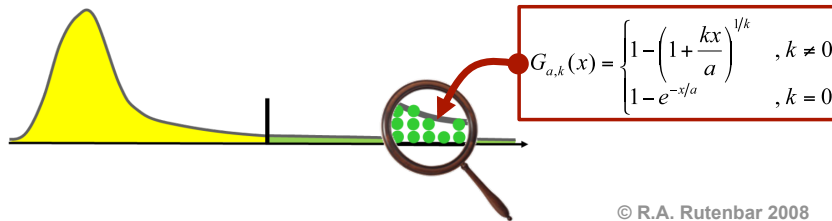
- Question: Is there a similar result for these tails of “extreme” results ...?

- Answer: YES – **Extreme Value Theory (EVT)**



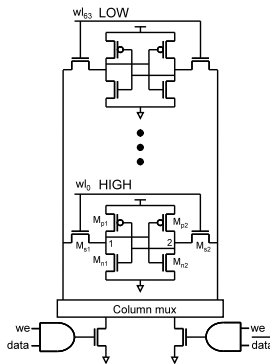
On each of N wafers, identify cells slower than threshold t . What is their distrib? EVT tells us!

- EVT gives simple analytical form for **conditional tail distrib**



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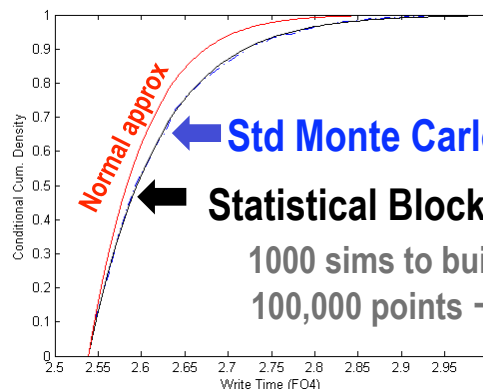
Result: Complete 64b SRAM Column



- 90nm 64b SRAM column with write driver and column mux

- ~ 400 devices; model **Write-time CDF**

- Speedup: ~16X**



Statistical Blockade: 6,314 sims

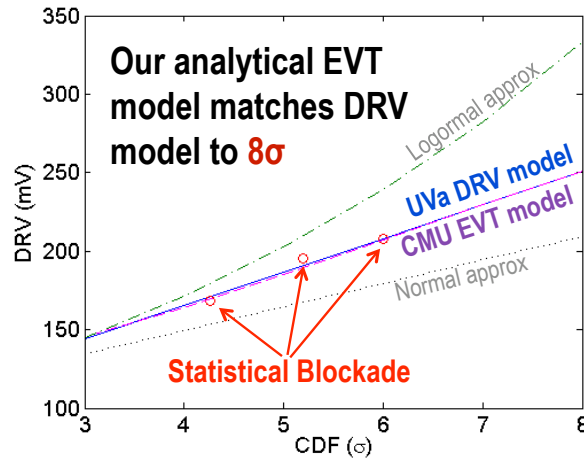
1000 sims to build classifier

100,000 points \rightarrow 5314 sims

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Result: Validating Model Out to 8σ

- Recently validated novel analytical DRV model
 - Model of Data Retention Voltage, [Calhoun et al. UVa, ESSCIRC'07]
 - Validated to 6σ , via **billion element** Monte Carlo run...
 - ...but only did 41,721 SPICE sims – **recursive** extension of Blockade
 - Speedup ~23,000X**

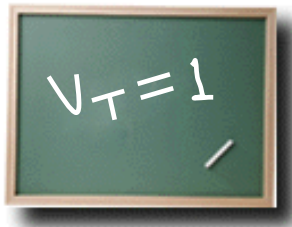


[Singhee et al,
2008 Conf on VLSI Design]

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Summarizing

Yesterday



Today, Tomorrow



- At nanoscale, nothing is deterministic...
- Brute-force Monte Carlo hurts (a lot)
- We can do ***much better with smart methods***
 - (Many of which involve \$\$\$ + risk...)
 - CMU results: **10x – 10,000x speedups**

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Thank You!

Acknowledgements

- My former student, Dr. Amith Singhee, whose PhD is the basis of all the results shown in this talk
- Prof. Benton Calhoun and Jiajing Wang of U Virginia, for sharing their statistical DRV model
- Funding from Semiconductor Research Corporation
- Funding from the Focus Center for Circuit & System Solutions (C2S2), one of five such focus centers managed by the Focus Center Research Program, an SRC program.