Generating Realistic Wear Distributions for SSDs

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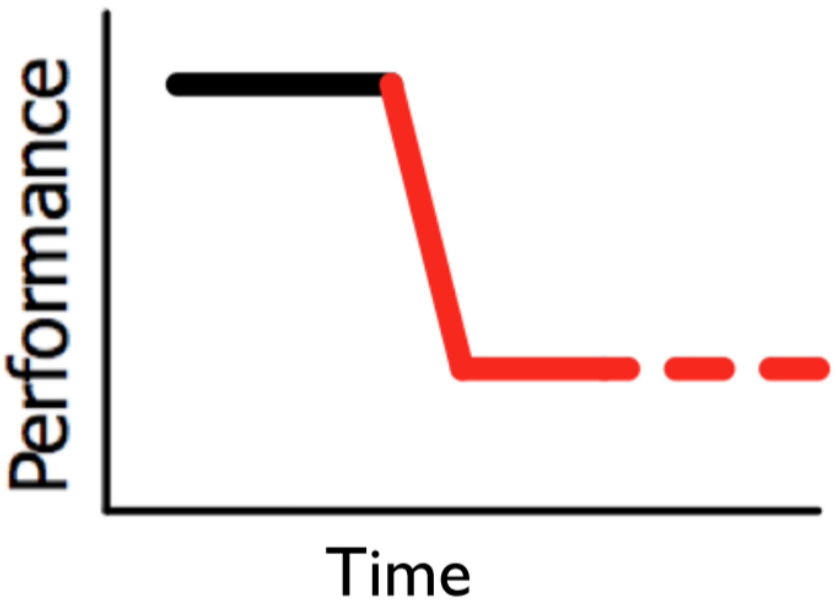
Overview

- The fail-slow symptom
- Challenges in SSD aging
- Related works
- Fast-forwardable SSD
- Evaluation
- Conclusion and future work

The fail-slow symptom of SSDs

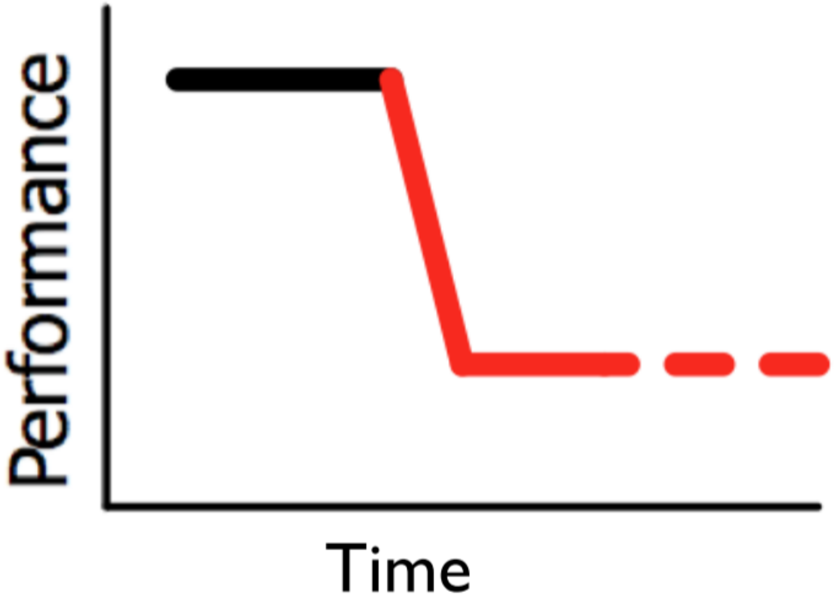
- Performance degradation



- Haryadi S. Gunawi et al, “Fail-Slow at Scale: Evidence of Hardware Performance Faults in Large Production Systems”, FAST 2018

The fail-slow symptom of SSDs

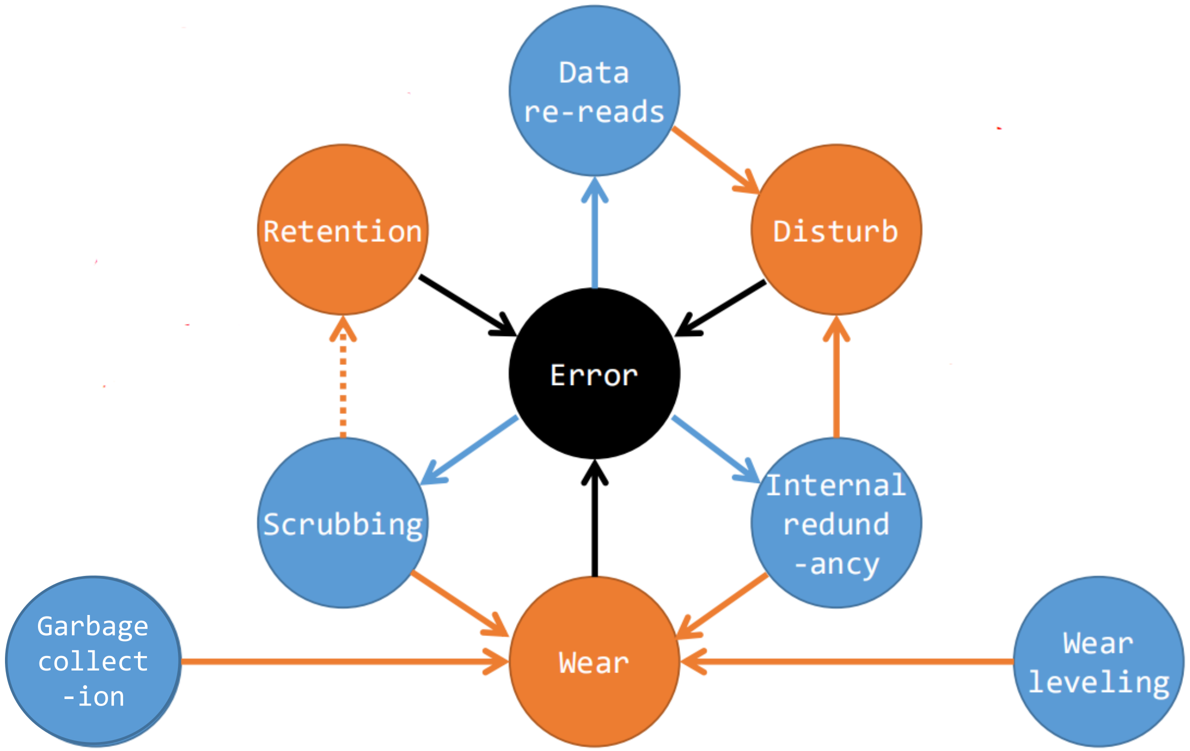
- Performance degradation
- No existing SSD development frameworks consider aging in their design



- Haryadi S. Gunawi et al, “Fail-Slow at Scale: Evidence of Hardware Performance Faults in Large Production Systems”, FAST 2018

Challenges

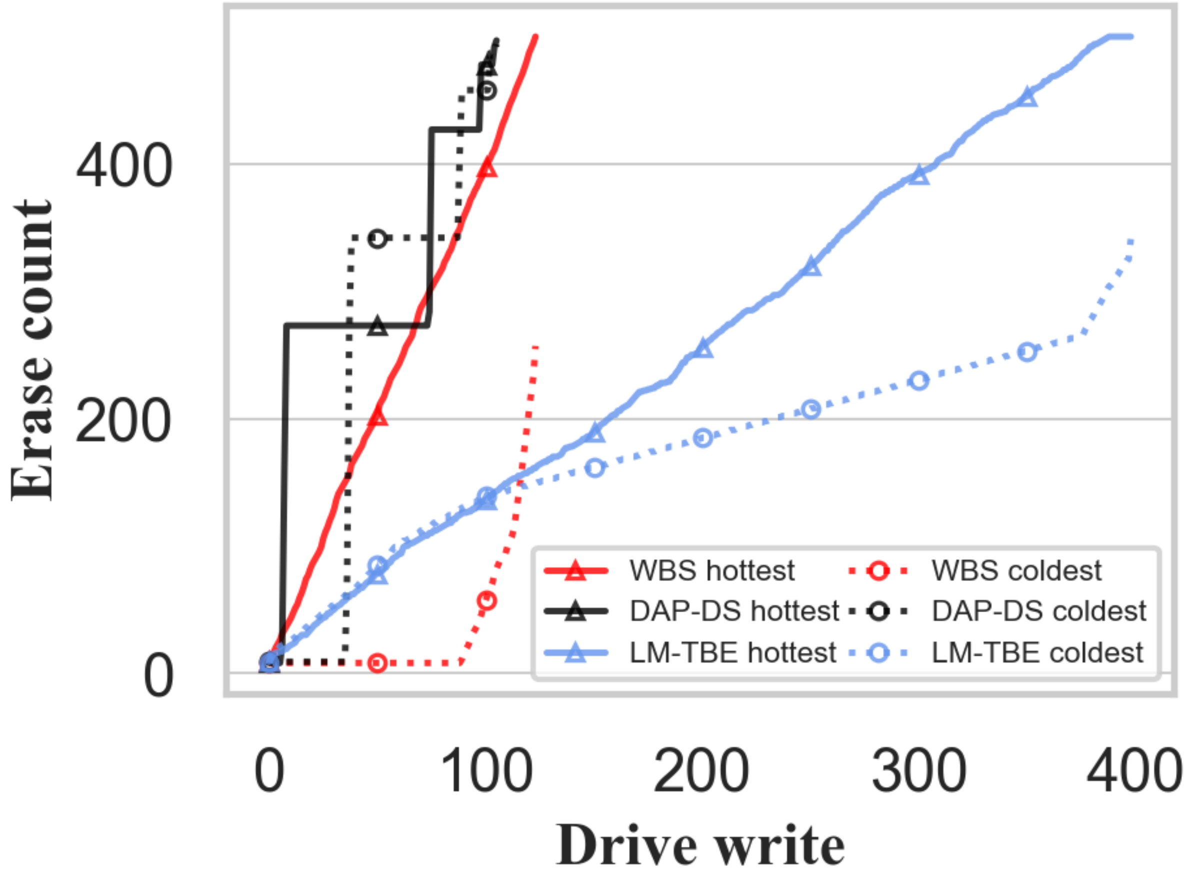
- The overhead of aging process → Efficiency
- The internal intricacy of SSDs → Accuracy



- Bryan S. Kim et al, "CPR for SSDs", HotOS 2019

Challenges

- The irregularity of block erasure



Current art

Preconditioning:

The process of writing data to the device to prepare it for steady state measurement.

Expensive:

- ✖ **Resources**
- ✖ **Time**

- https://www.snia.org/sites/default/files/technical-work/pts/release/SNIA-SSS-PTS-Enterprise-v1.1.pdf

File system aging

- FS aging is not applicable to SSD aging
  - FS aging: generate a fragmented state of logical block layouts
  - SSD aging: physical aging of blocks
- Preconditioning is more akin to FS aging
  - Populating and invalidating the address space
  - Cannot sufficiently age the device to an end-of-life state.

ML for simulation

- DEVS

  DEVS execution acceleration with machine learning.

  SpringSim 2016: https://dl.acm.org/doi/10.5555/2975389.2975399

  – Consider multiple model candidates

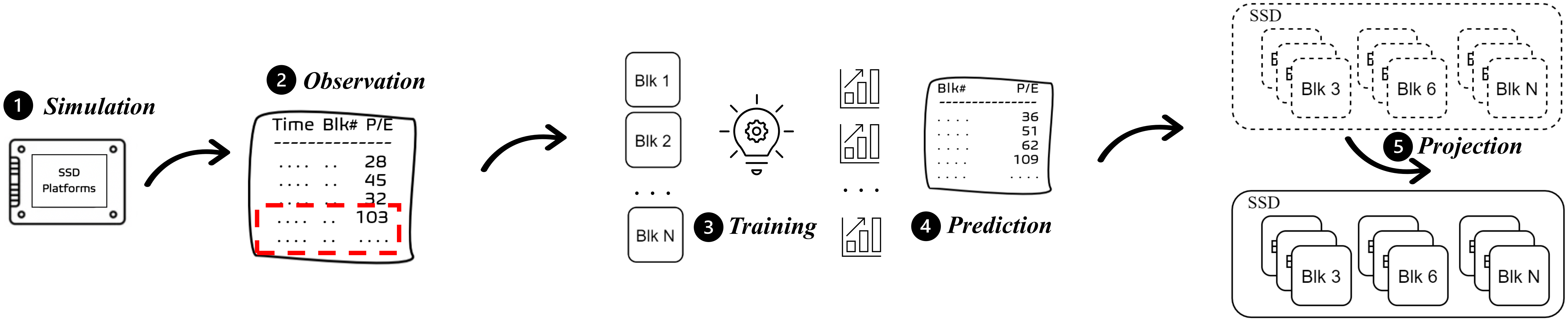
- CML

  Using continuous statistical machine learning to enable high-speed performance prediction in hybrid instruction-/cycle-accurate instruction set simulators.

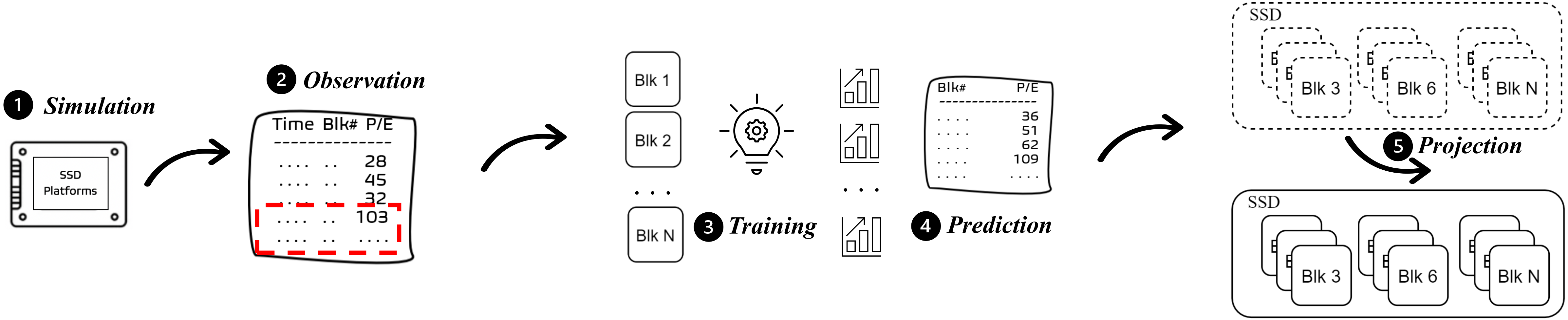
  CODES+ISSS 2009: https://dl.acm.org/doi/10.1145/1629435.1629478

  – Continuously incorporate the latest data to update model

Fast-forwardable SSD



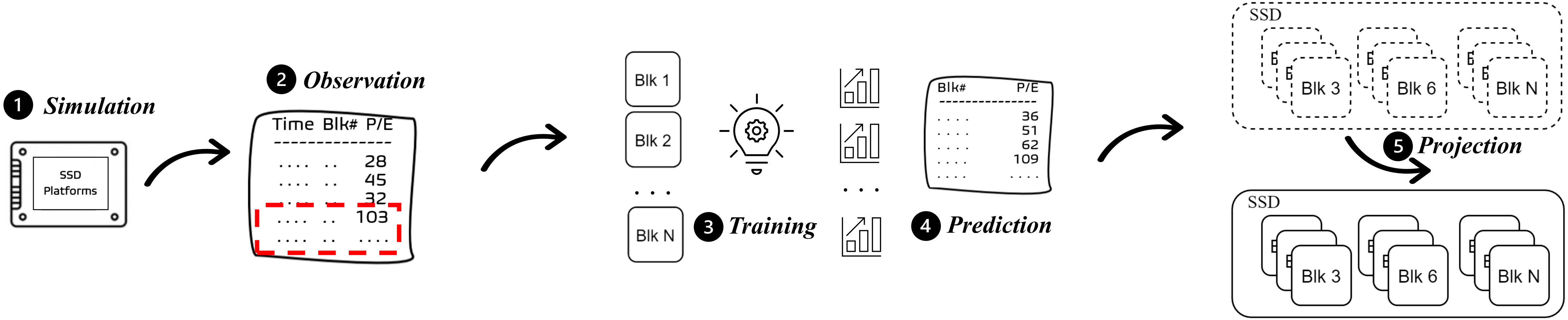
System overview



Simulation & Observation

- Observe SSD’s internal activities
- Output log periodically

System overview



Simulation & Observation → Training & Prediction

- Observe SSD's internal activities
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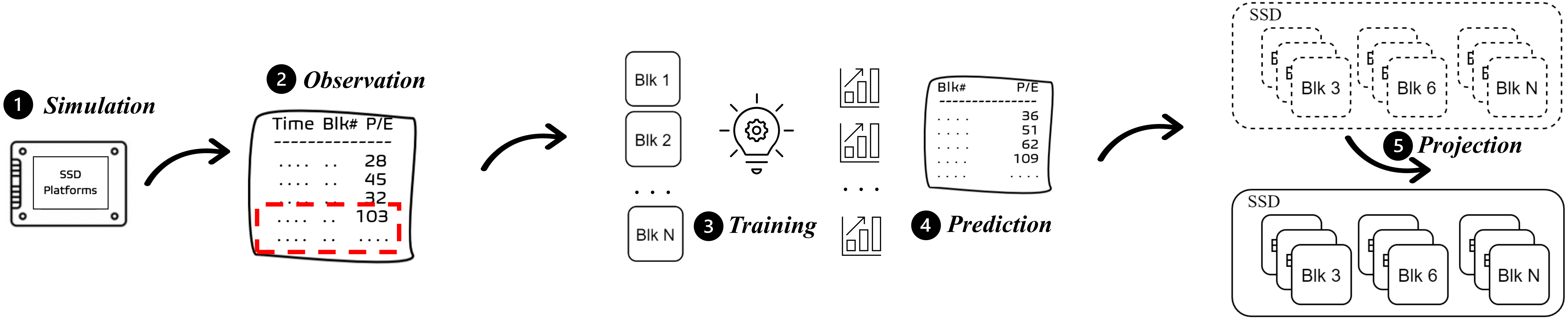
- Multiple lightweight regression models (LR)
- Predict future state based on the latest history
- $Acceleration\ Factor\ (AF)$
$$= \frac{simulated\ +\ predicted}{simulated}$$

System overview



Simulation & Observation → **Training & Prediction** → **Projection**

Simulation & Observation

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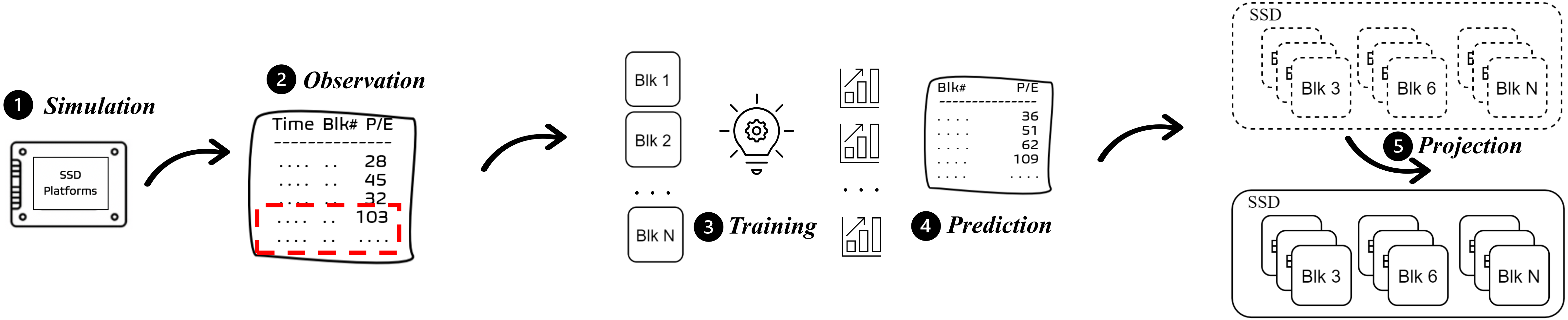
Projection

- Project SSD states based on the prediction results

System overview



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Enhancing efficiency

- Build models for each block:
  - The summed prediction overhead is proportional to the drive capacity (the # of blocks), although the model is lightweight itself.

- Two approaches to further enhancing efficiency:
  - A naïve approach: based on sampling
  - An analytic approach: based on distribution modeling

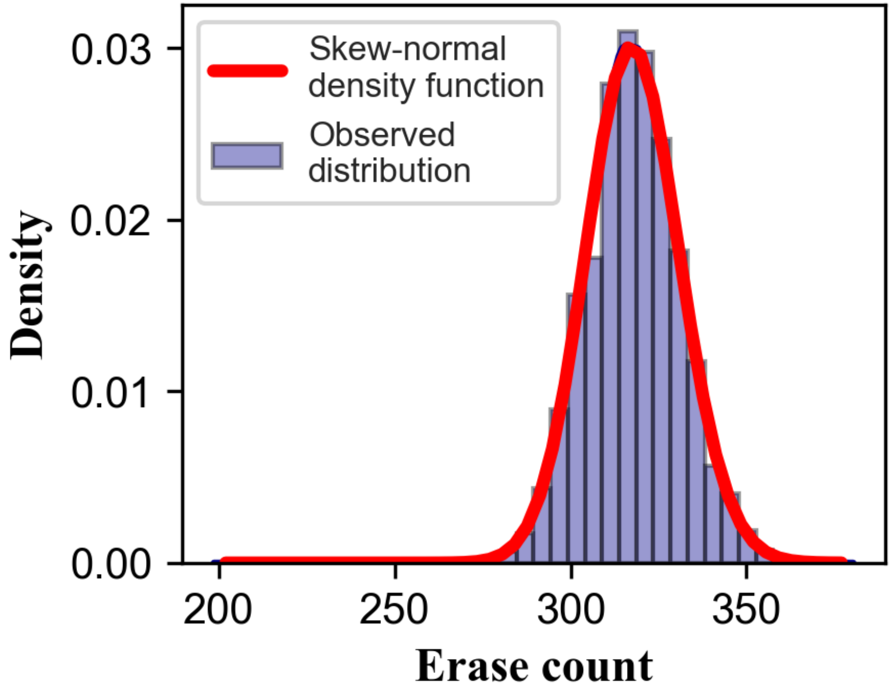
Approximation by distribution modeling

- Challenge: given only information of a subset of blocks, how can we estimate the blocks that behave distinctively than samples?

- Use extrapolation as the estimate method:
  - Assume that the wear distribution of blocks adheres to an underlying measurable distribution $\rho(\cdot)$
  - Estimate the future wear using the prediction result and the density function that models the underlying distribution.

Approximation by distribution modeling

- Approximation by distribution modeling:
  - $\rho(\cdot)$: a skew-normal distribution with skewness α, location μ, and scale parameter σ.
  - $\alpha=0.75$, $\mu=310$, $\sigma=15.1$
  - Fail to reject the null hypothesis on 10^5 samples with $p > 0.1$ using Kolmogorov–Smirnov goodness-of-fit test



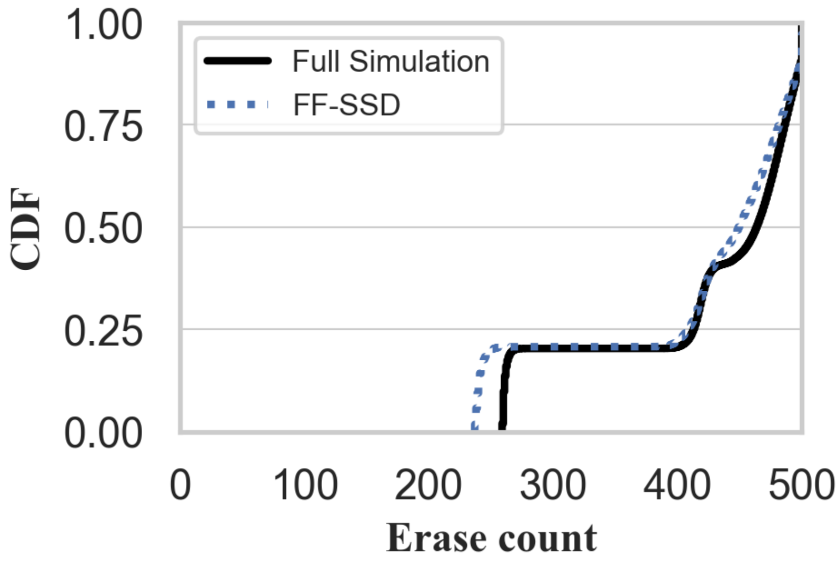
Skew norm fit to the measured distribution

Evaluation

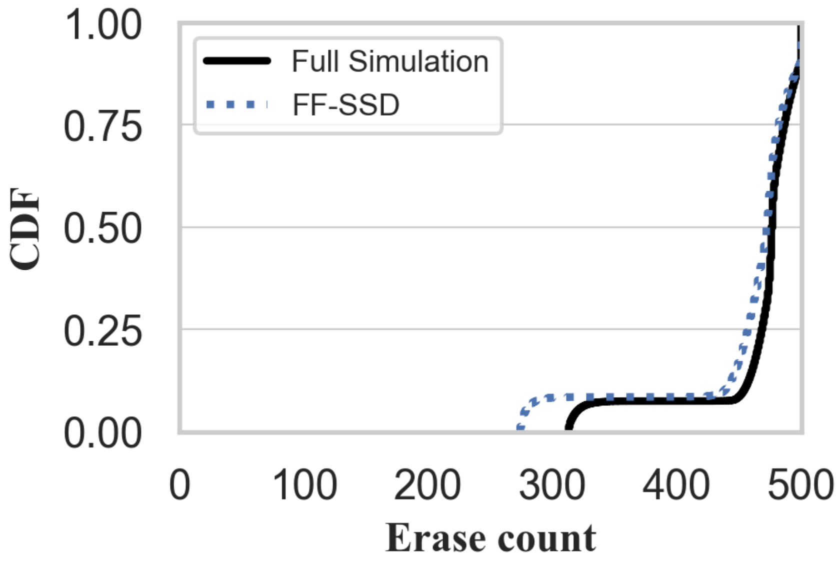
- SSD development platforms:
  - FTLSim - SYSTOR 2012
  - Amber - MICRO 2018
  - FEMU - FAST 2018
- Workloads:
  - YCSB
  - VDI (virtual desktop infrastructure)
  - Microsoft production servers
  - Microsoft enterprise servers

FTLSim			
Pages per block	256	Physical capacity	284 GiB
Page size	4 KiB	Logical capacity	256 GiB
Endurance limit	500	Over-provisioning	0.11
Wear leveling	PWL	Garbage collection	Greedy
Amber			
Channels	8	Page size	4 KiB
Packages per channel	4	Physical capacity	285 GiB
Dies per package	2	Logical capacity	256 GiB
Planes per die	2	Over-provisioning	0.11
Blocks per plane	1136	Garbage collection	Greedy
Pages per block	512	Wear leveling	Var-based
FEMU			
Channels	8	Page size	4 KiB
Luns per channel	8	Physical capacity	16 GiB
Planes per lun	1	Logical capacity	15 GiB
Blocks per plane	256	Over-provisioning	0.07
Pages per block	256	Garbage collection	Greedy

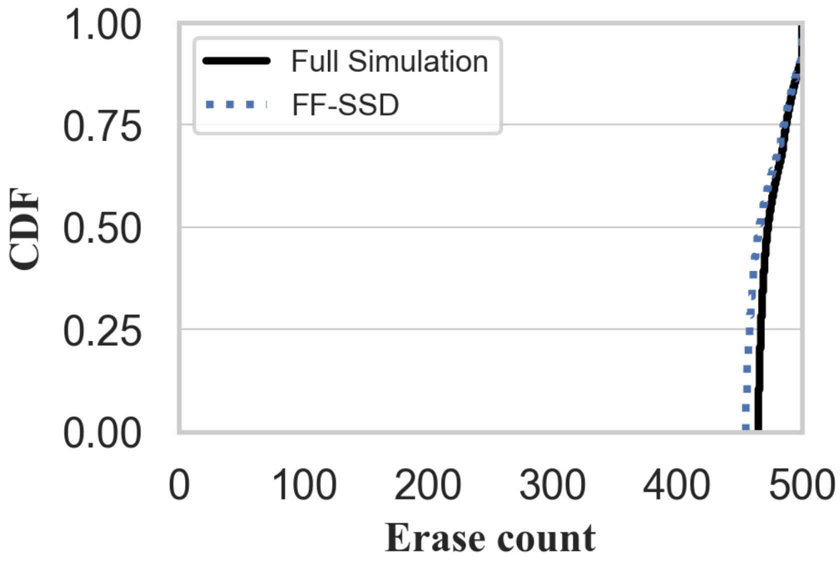
SSD aging until failure on FTLSim



Windows Build Server

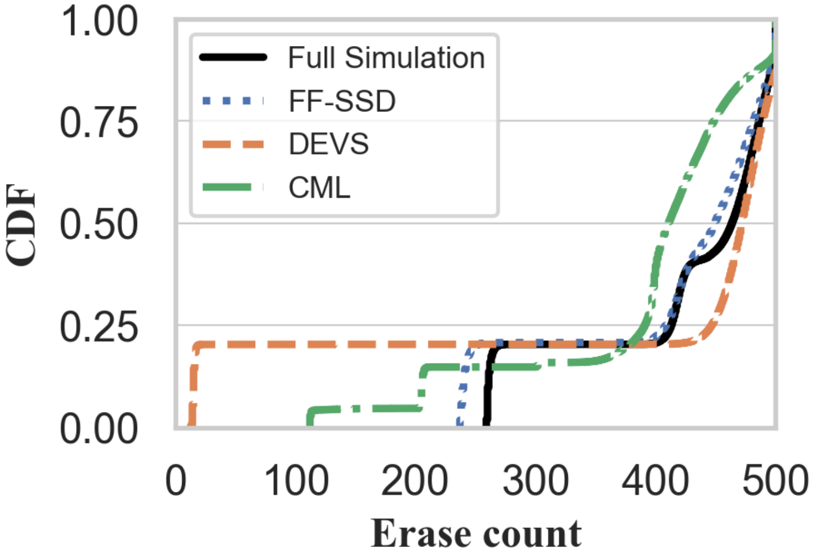


Developer Tools Release



Virtual Desktop Infra

SSD aging until failure on FTLSim



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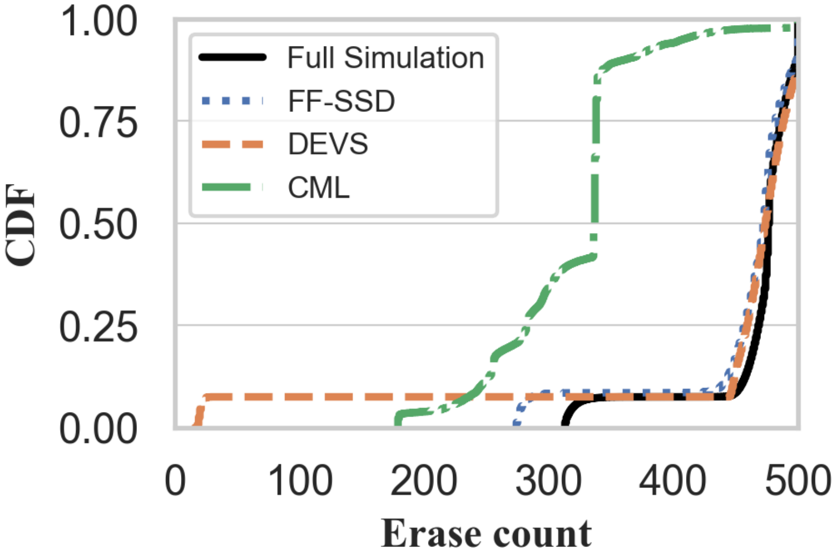

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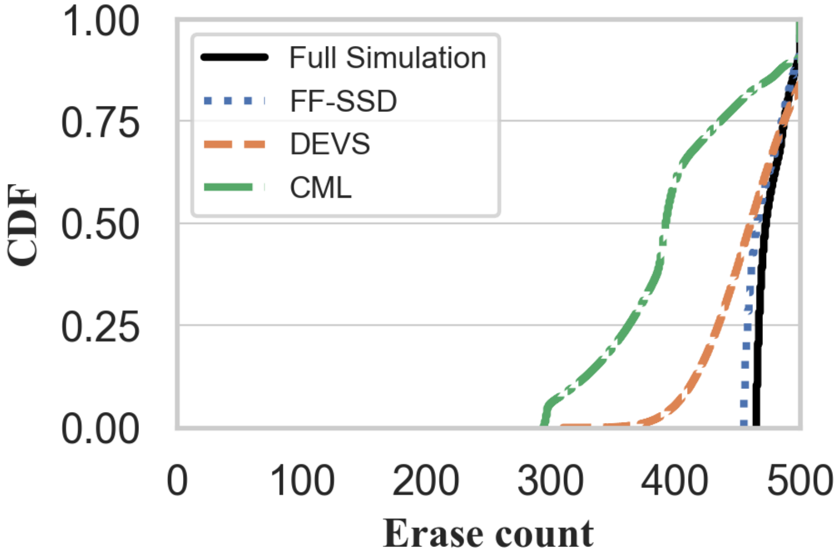

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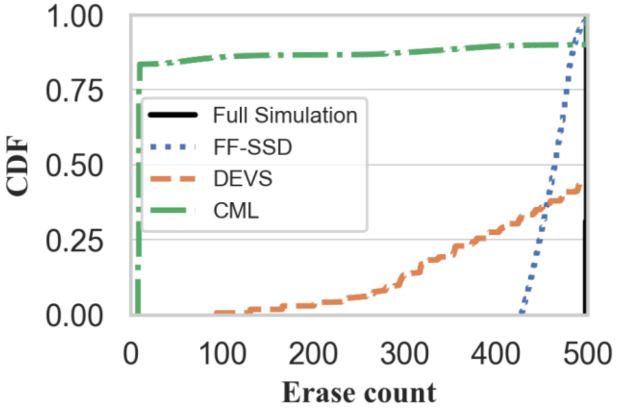
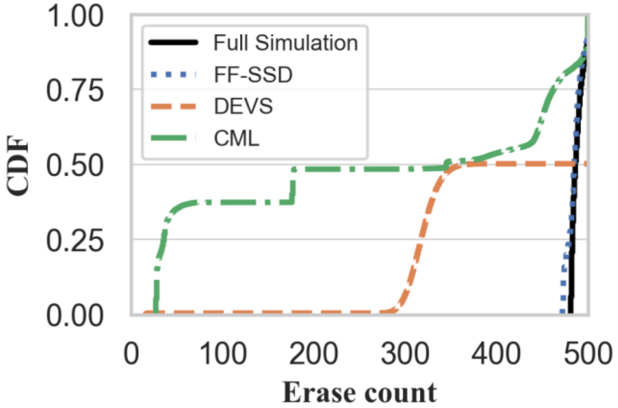
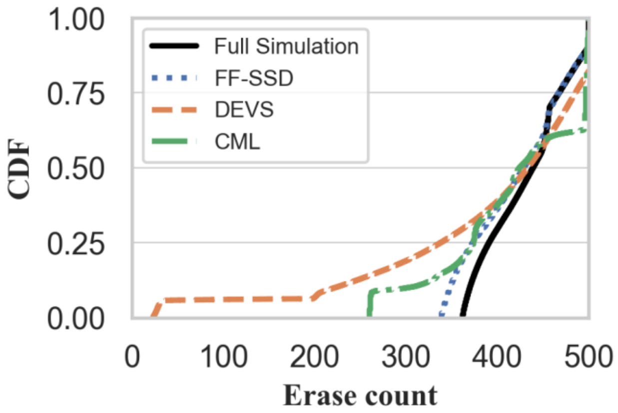


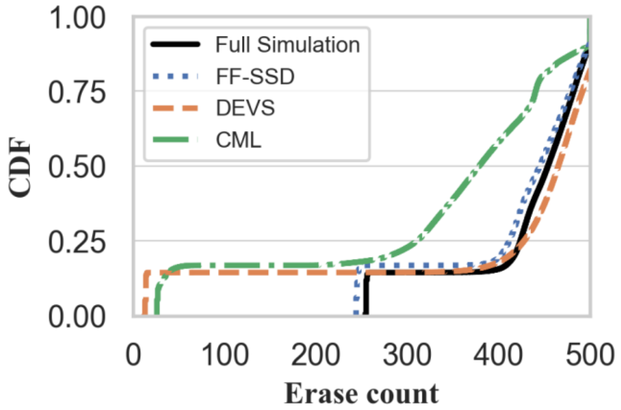
DAP-DS



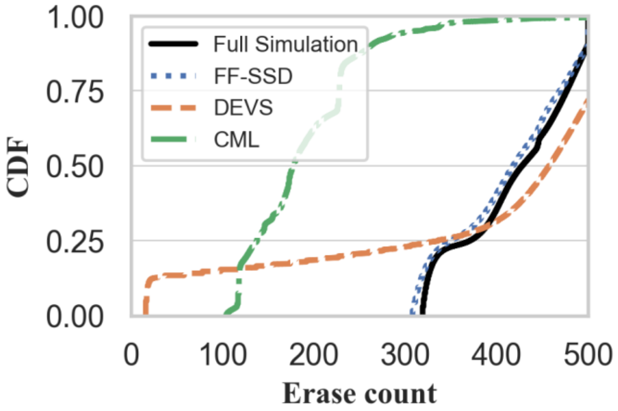
DAP-PS



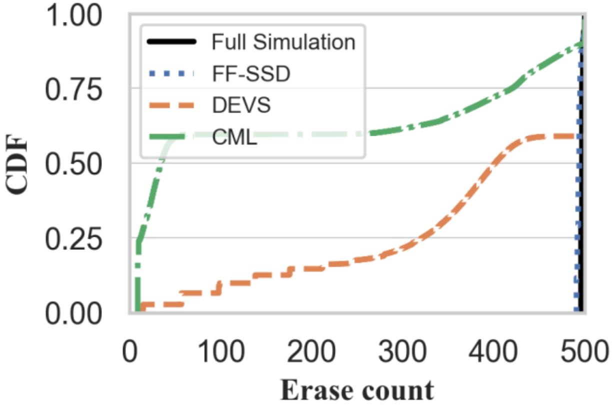
LM-TBE



MSN-BEFS

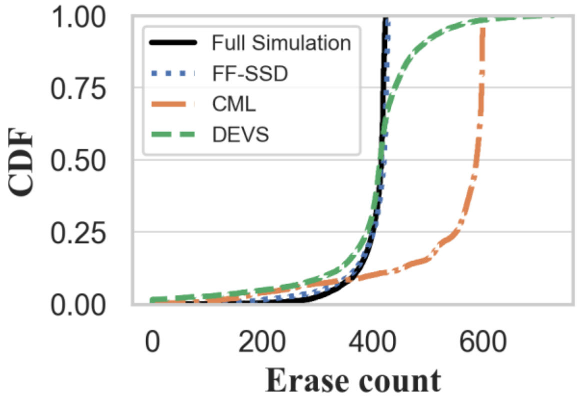


YCSB-A

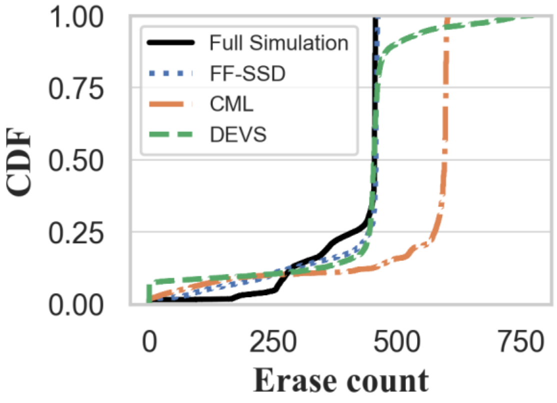


RAD-BE

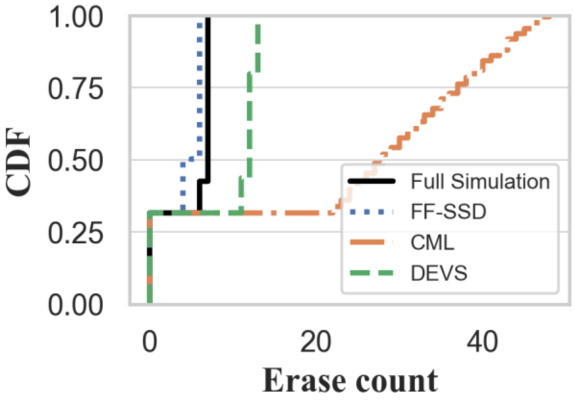
SSD aging on Amber



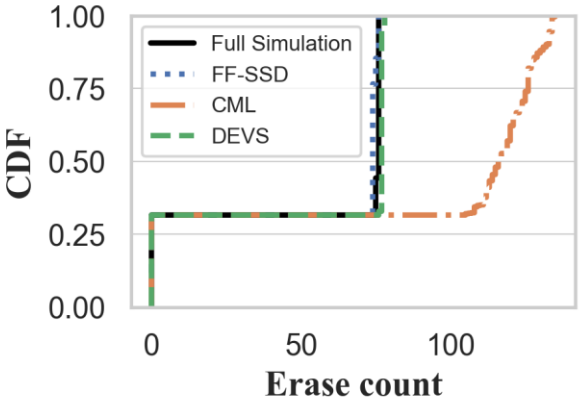
DTRS



WBS



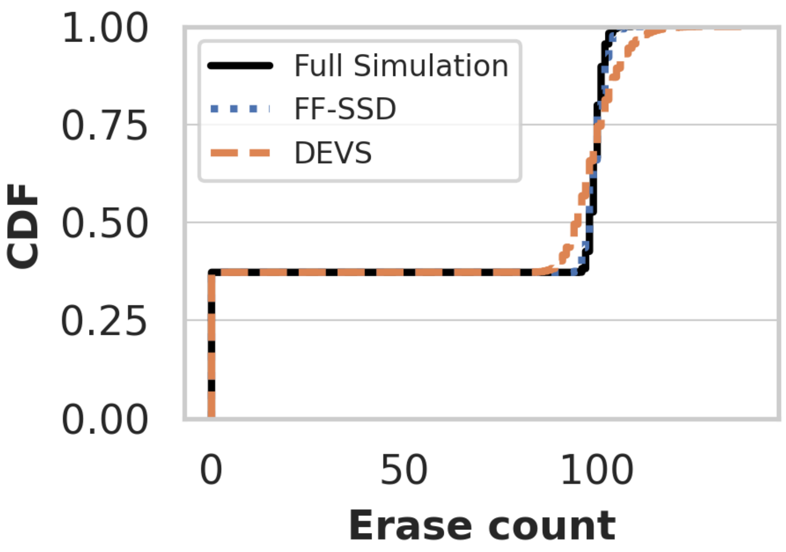
DAP-DS



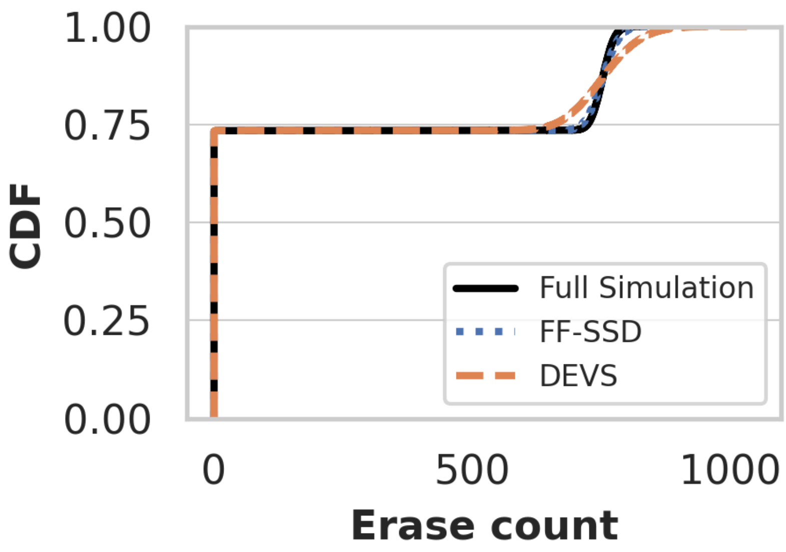
RAD-RS

SSD aging with 600 iterations of the workloads on Amber.

Without wear leveling



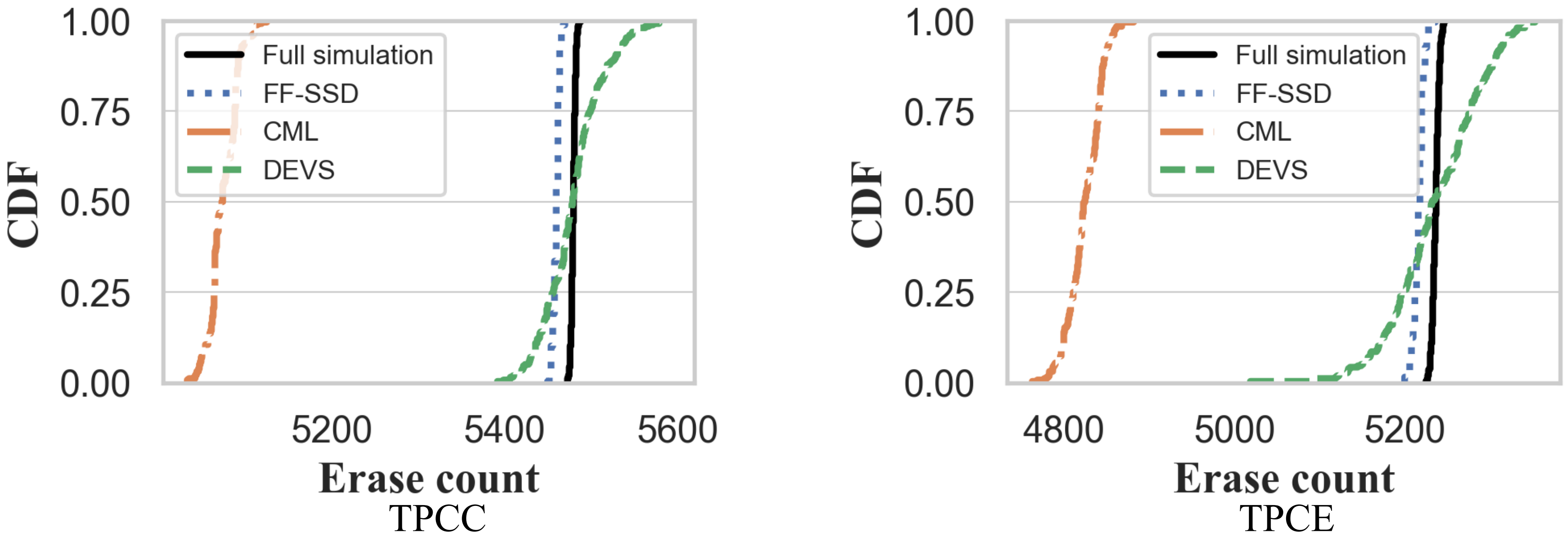
DTRS



WBS

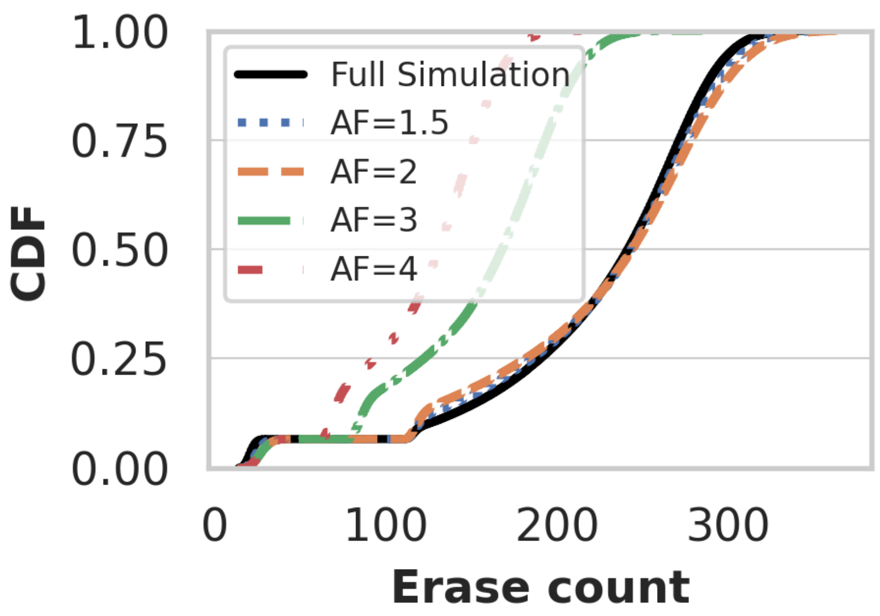
Performance comparison of FF-SSD and DEVS on FTLSim without WL.

SSD aging on FEMU

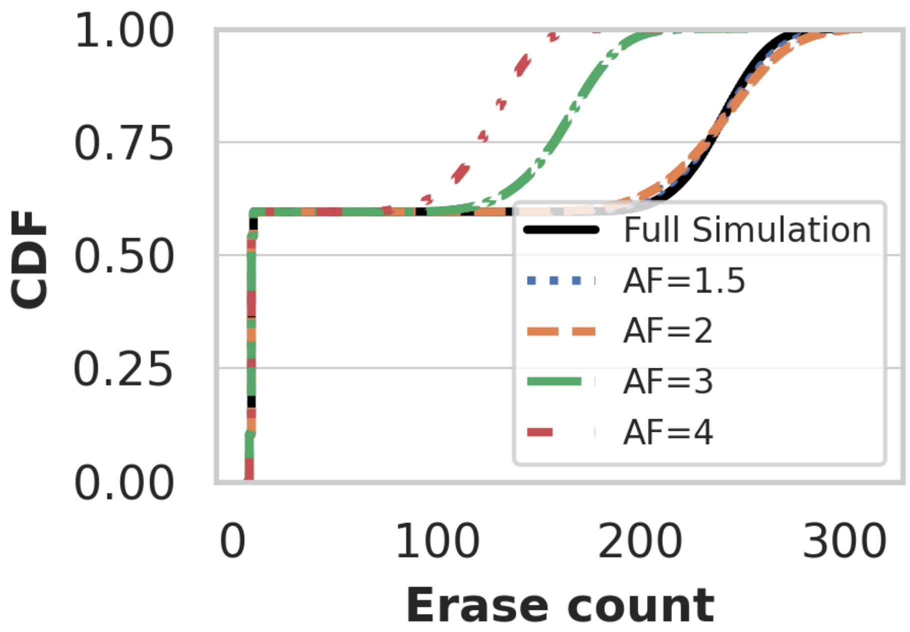


SSD aging with 50 iterations of the workloads on FEMU.

Accuracy and efficiency tradeoff



LM-TBE



RAD-BEFS

The tradeoff between aging accuracy and efficiency.

Conclusion & future work

- We present fast-forwardable SSD, an ML-based SSD aging framework that generates representative future wear-out states.
  - Accurate (up to 99% similarity)
  - Efficient (accelerates simulation time by 2×)
  - Modular (can be integrated with existing simulators and emulators)

- Codebase will be available soon
  - https://github.com/ZiyangJiao/FF-SSD

- Future work
  - Improving accuracy through adaptive acceleration.
  - Predicting on the wear states real SSDs
  - More promising directions…

Thank you!

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