Perseus: A Fail-Slow Detection Framework for Cloud Storage Systems

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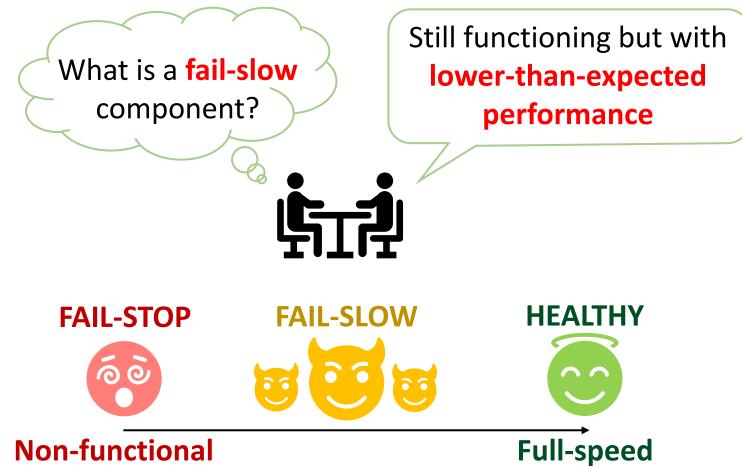




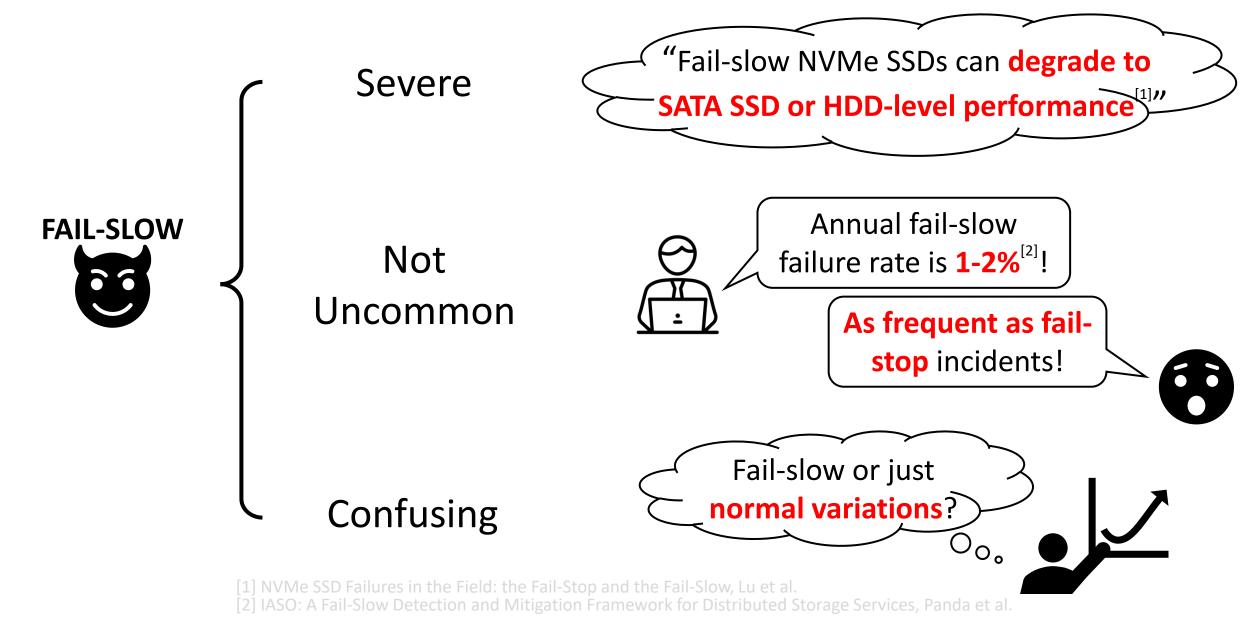
FAST¹ Data Center Instability

- Failures in The Wild
 - Fail-Slow
 - Fail-Stop
 - Byzantine

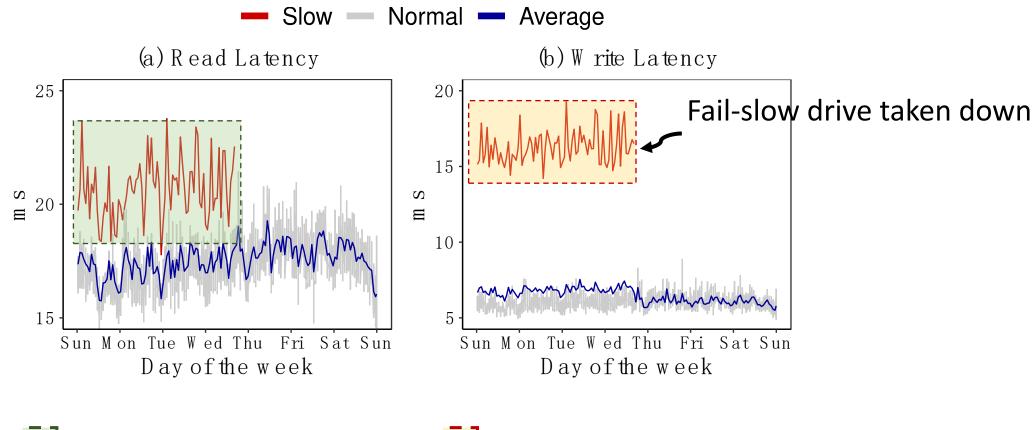
...



FAST⁷ Not A Problem?

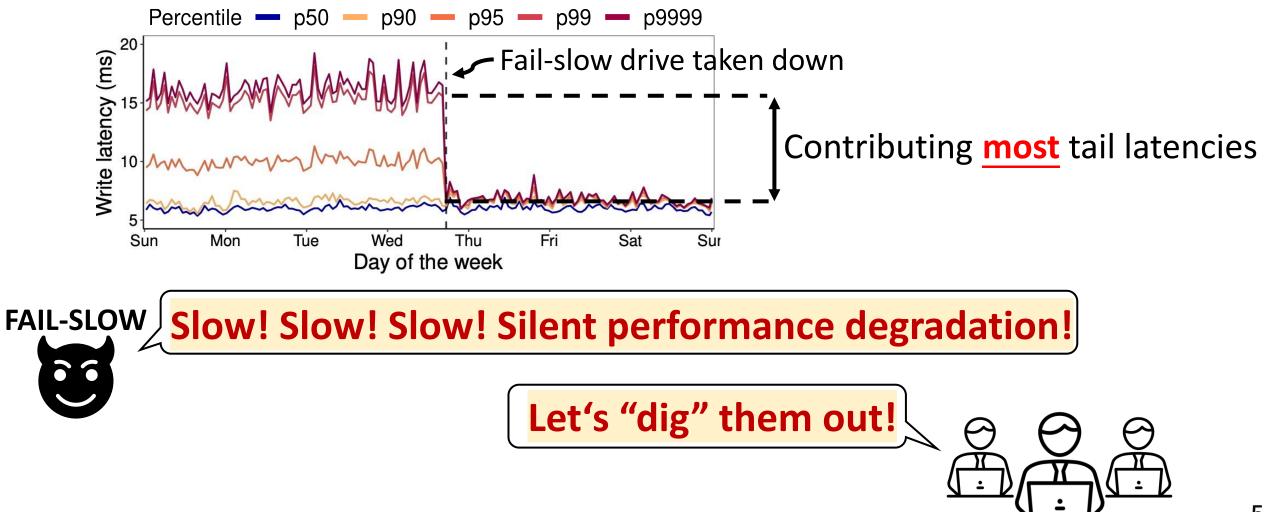


Fail-Slow in The Field:

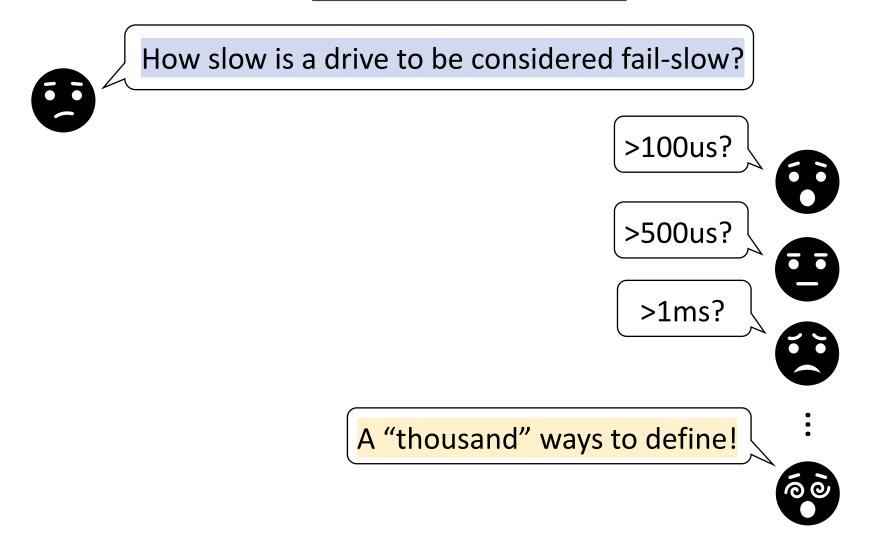


1.01-1.50X higher for read 2.06-3.65X higher for write

Fail-Slow in The Field:



• No Ground Truth in Identifying Fail-Slow



FAST⁷ Fail-Slow Detection (FSD)

• Previous FSD Studies Are

- Intrusive
 - Source Code Accessing/Altering
- Coarse-grained
 - Node-Level Detection

Capturing and Enhancing *In Situ* System Observability for Failure Detection

Peng Huang Johns Hopkins University Chuanxiong GuoJacob R.ByteDance Inc.M

Jacob R. Lorch Lidong Zhou Microsoft Research

Yingnong Dang Microsoft

IASO: A Fail-Slow Detection and Mitigation Framework for Distributed Storage Services

Biswaranjan Panda, Deepthi Srinivasan, Huan Ke*, Karan Gupta, Vinayak Khot, and Haryadi S. Gunawi*

Nutanix Inc.

University of Chicago*

Abstract

We address the problem of "fail-slow" fault, a fault where a hardware or software component can still function (does not fail-stop) but in much lower performance than expected. absolute failure of sub-components but can also gracefully handle the occurrence of performance faults.

In this context, our work in this paper makes the two following contributions:

(1) Design and implementation of a fail slave mitiastica

FAST^T₂₃ Fail-Slow Detection (FSD)

- Our Work Shares
 - Years of Experiences in FSD
 - A Practical FSD Framework named Perseus
 - Root Cause Analysis

FAST⁷ Outline



FAST¹/₂₃ Our Dataset

• <u>248K+</u> drives

- 55% NVMe SSD + 45% SATA HDD
- 4 manufacturers
- 9 major drive models
- Diverse cloud services:
 - Log service, big data, E-commerce, table storage, stream processing, database, object storage, data warehouse, block storage

FAST¹/₂₃ Our Dataset

- 248K+ drives
- <u>10-month</u> performance logs (iostat)
 - Latency/throughput time series
- Test dataset released
 - https://tianchi.aliyun.com/dataset/144479



FAST¹ Ideal Fail-Slow Detection Should Be ...?

Efficient Fail-Slow Detection

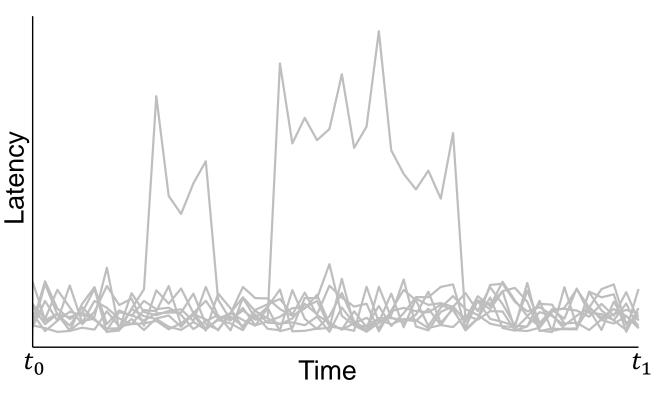
Non-intrusive

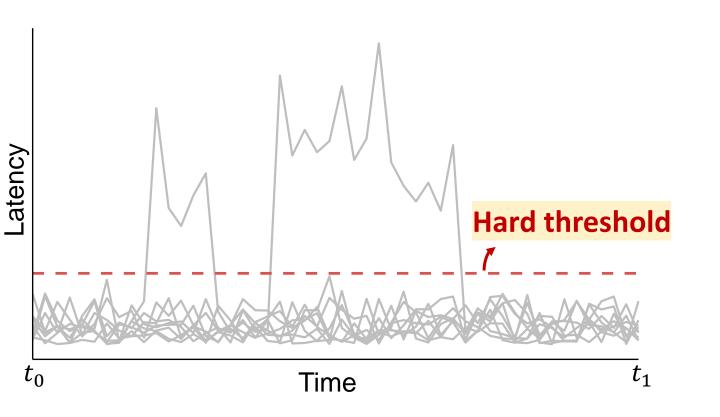
No source code altering External performance log-based

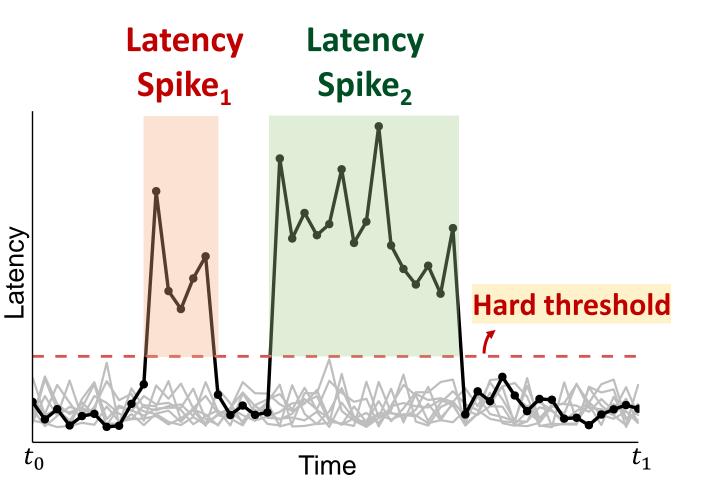


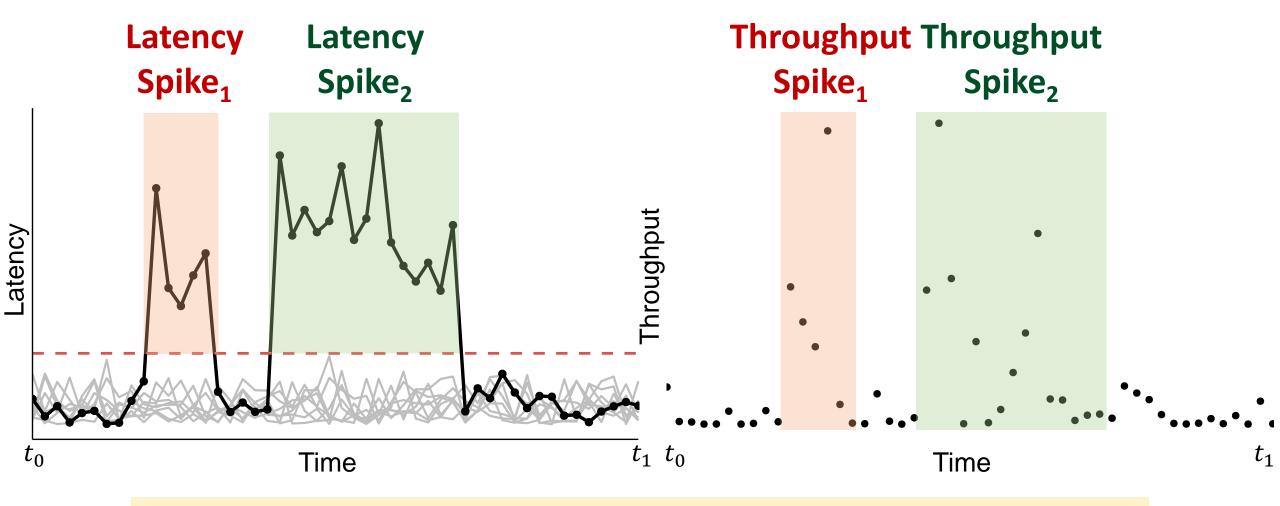
High precision/recall rate



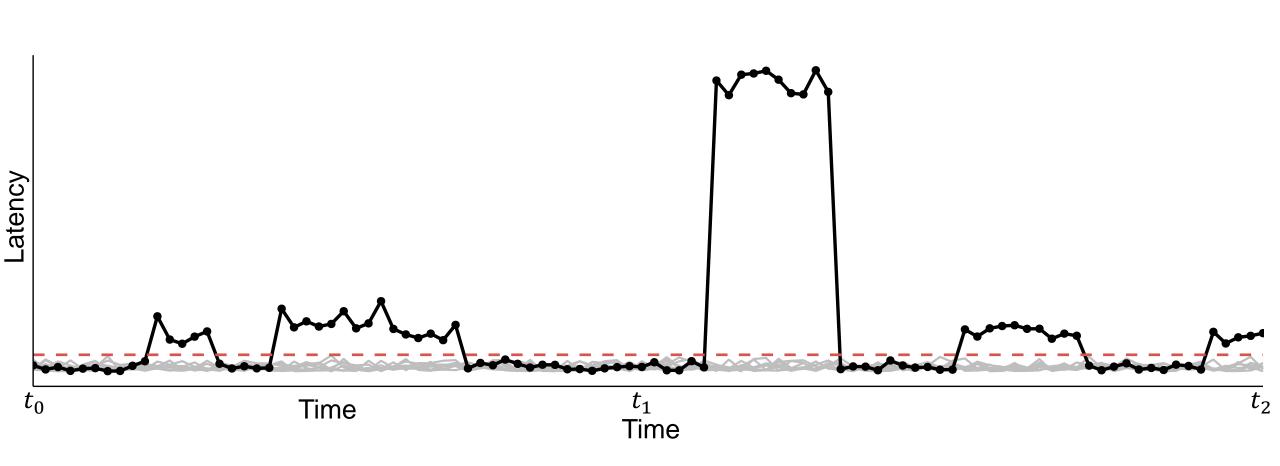


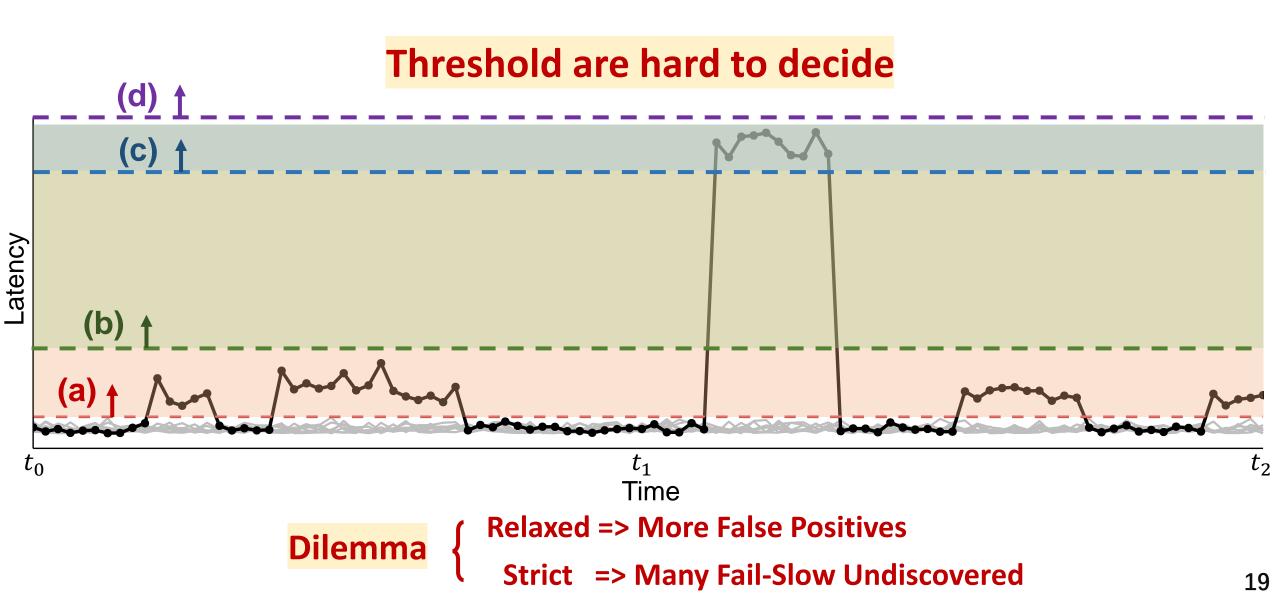




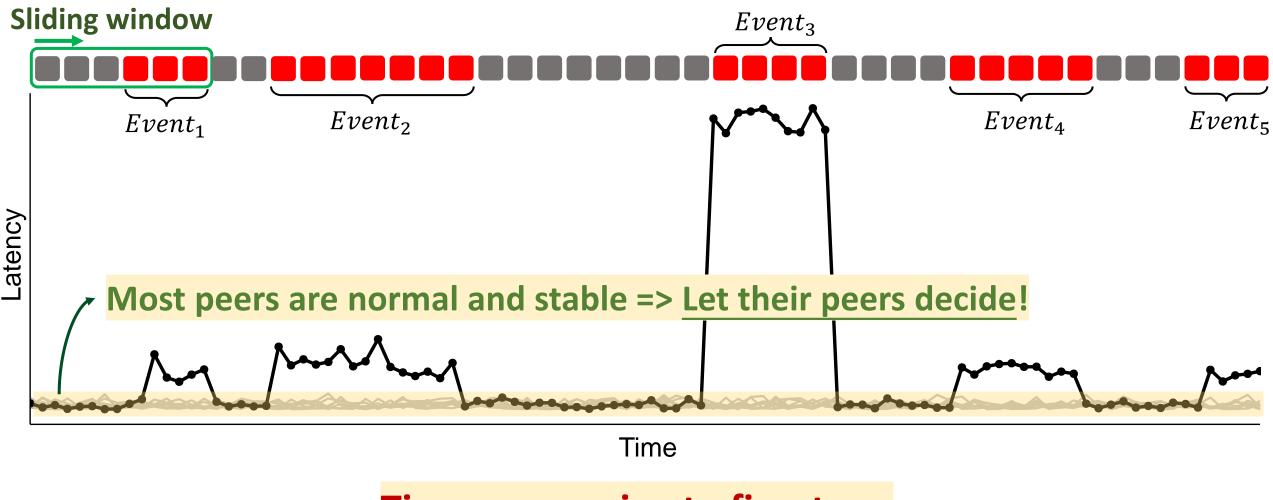


Workload bursts are common causes of latency variations





FAST³ Failed Attempt: Peer Evaluation

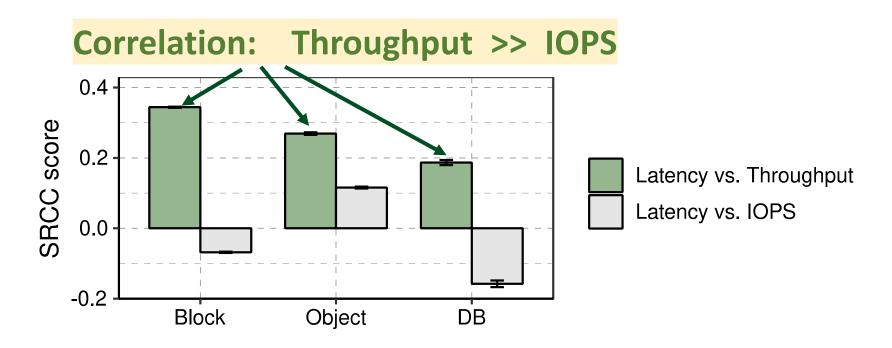


Time-consuming to fine-tune

FAST^T Design Guidelines (I)

Insight: "Workload pressure can affect latency variations"

• Throughput or IOPS?

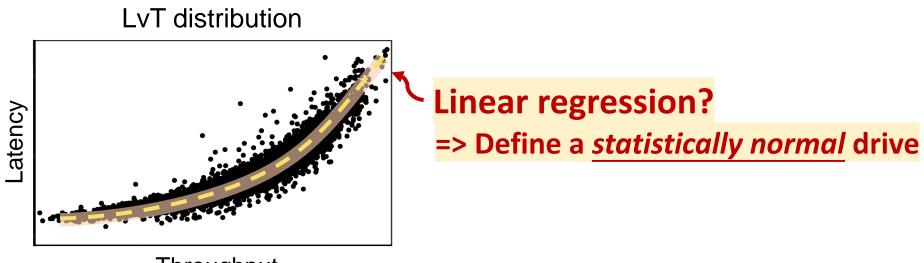


Guideline 1: Use throughput to model the workload pressure

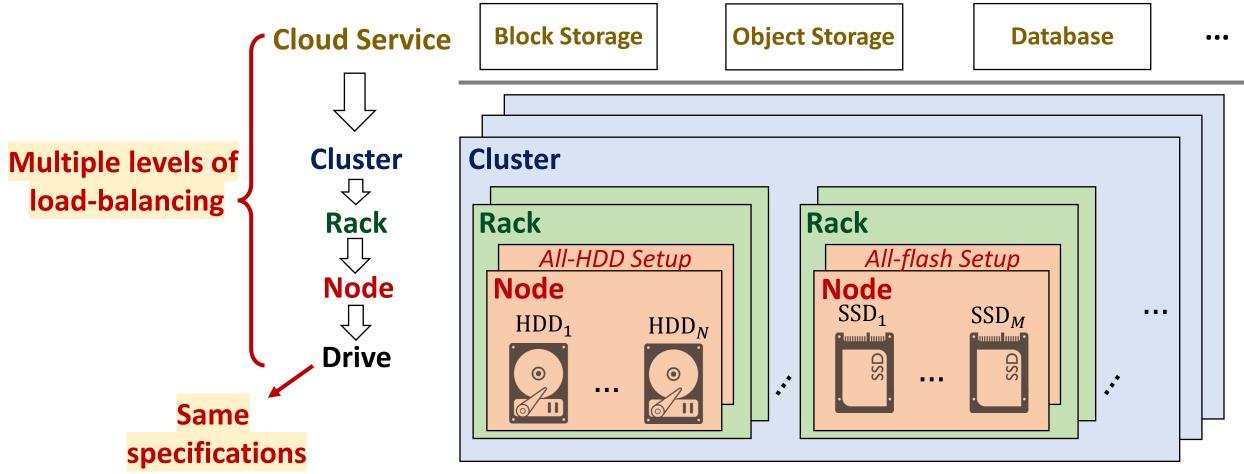
Insight: "Workload pressure can affect latency variations"

• How to model such a positive correlation?

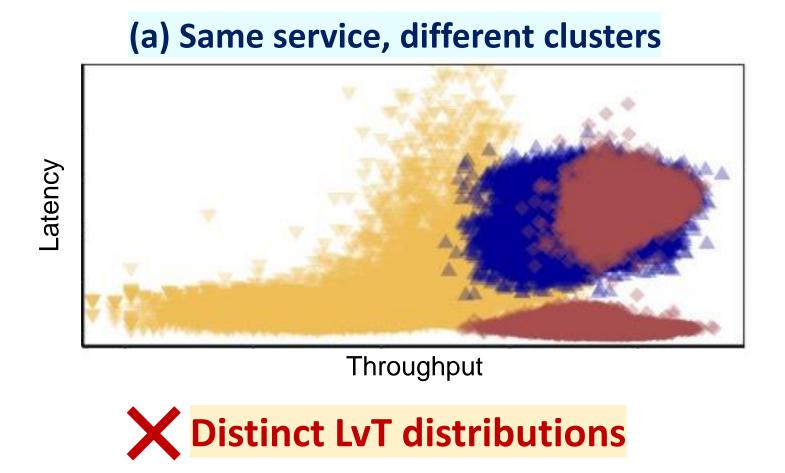
Guideline 2: Model the latency-vs-throughput (LvT) distribution

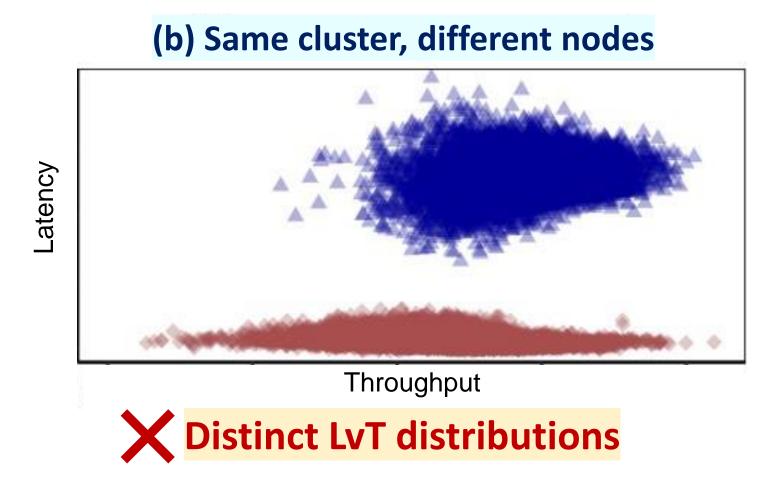


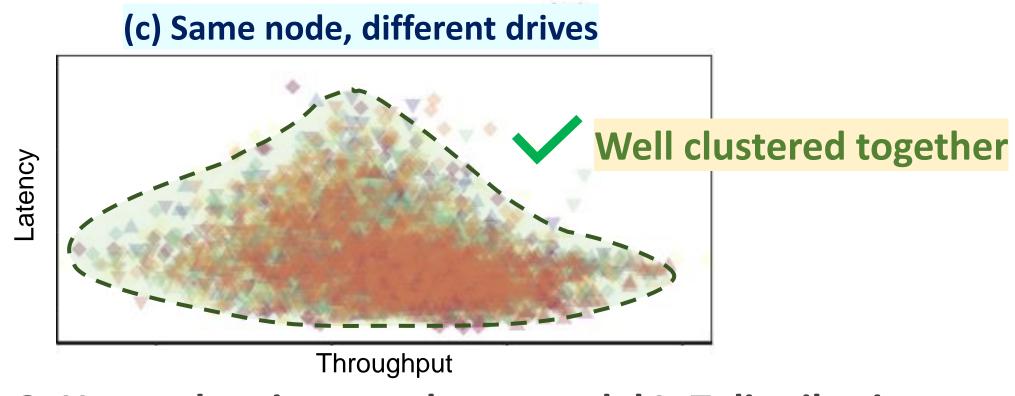
Throughput



- Need to determine the scope of drives to model
 - Drives from the same service?
 - Drives from the same cluster?
 - Drives from the same <u>node</u>?







Guideline 3: Use node-wise samples to model LvT distribution

Insight: "No golden standards to identify fail-slow "



Guideline 4: Non-binary output

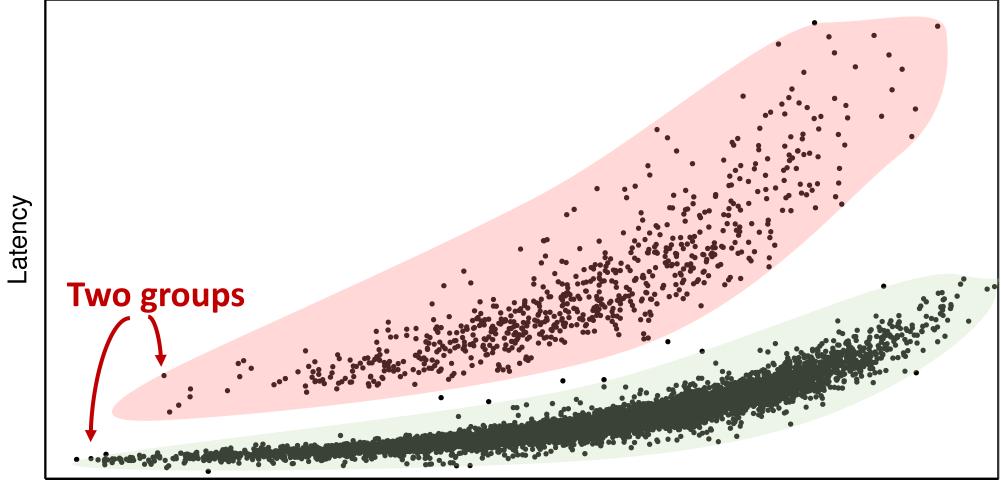
• Model the likelihood of fail-slow

FAST⁷ Outline

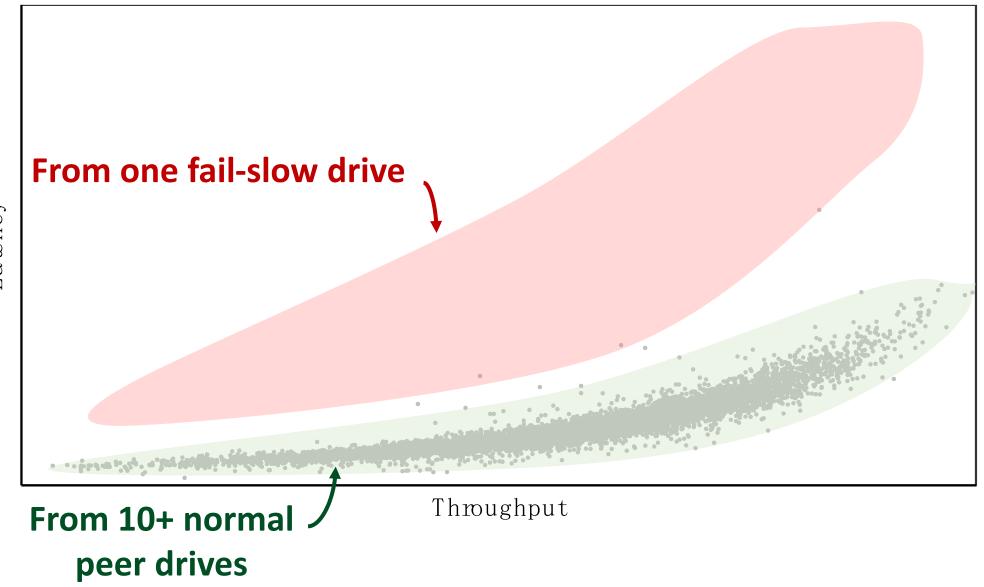


FAST¹/₂₃ Raw Data





Throughput



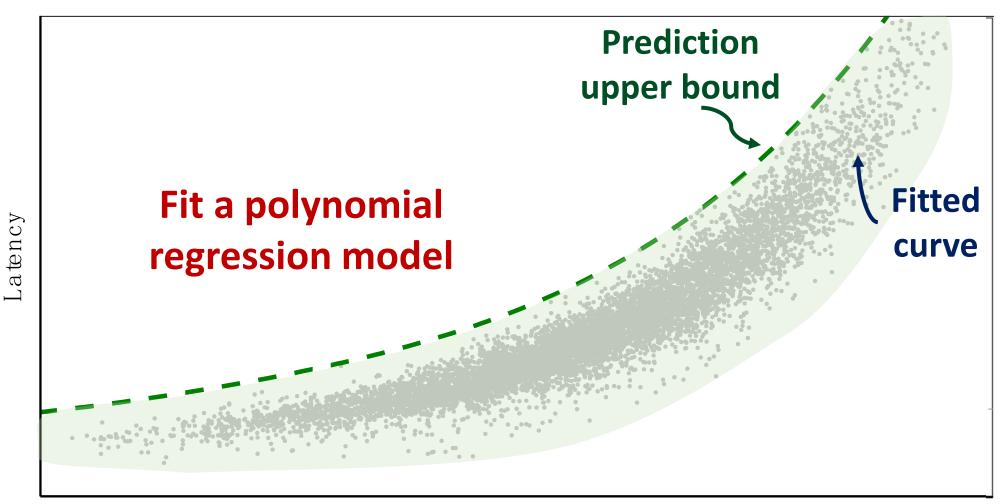
Latency

FAST¹/₂₃ Step 1: Outlier Detection



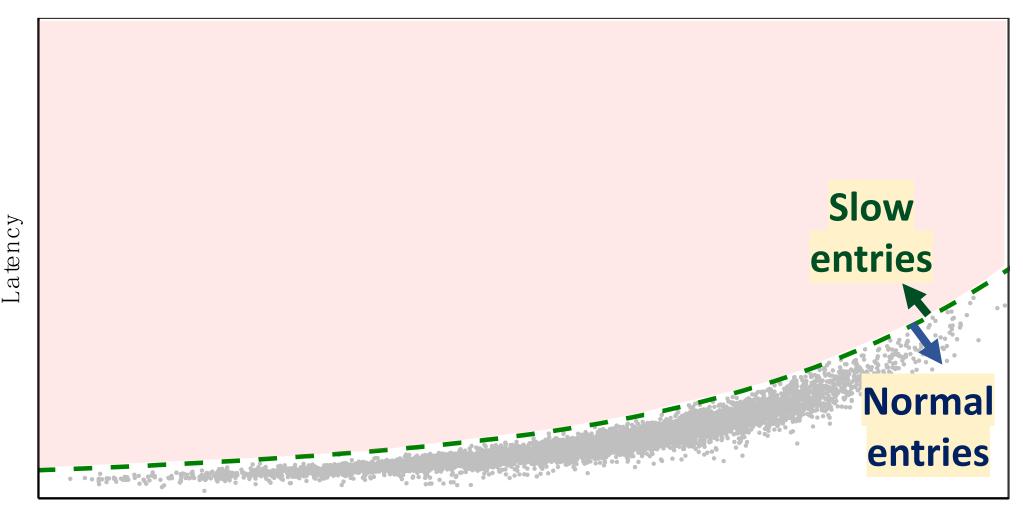
Throughput

FAST³ Step 2: Building Regression Model



Throughput

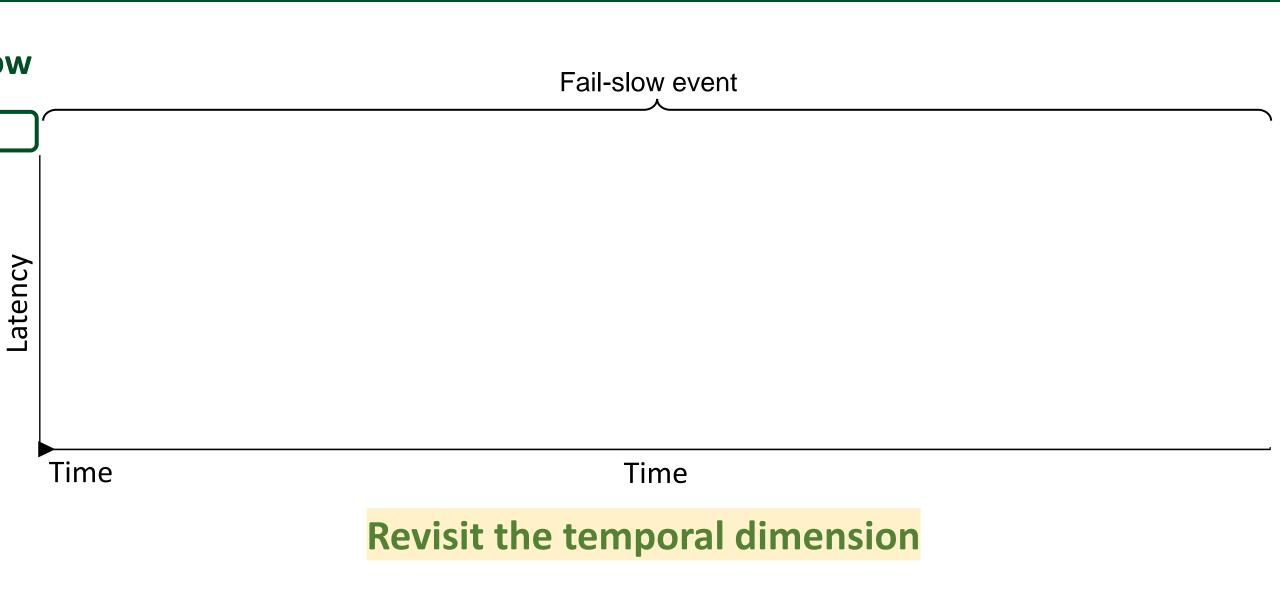
FAST³ Step 2: Building Regression Model



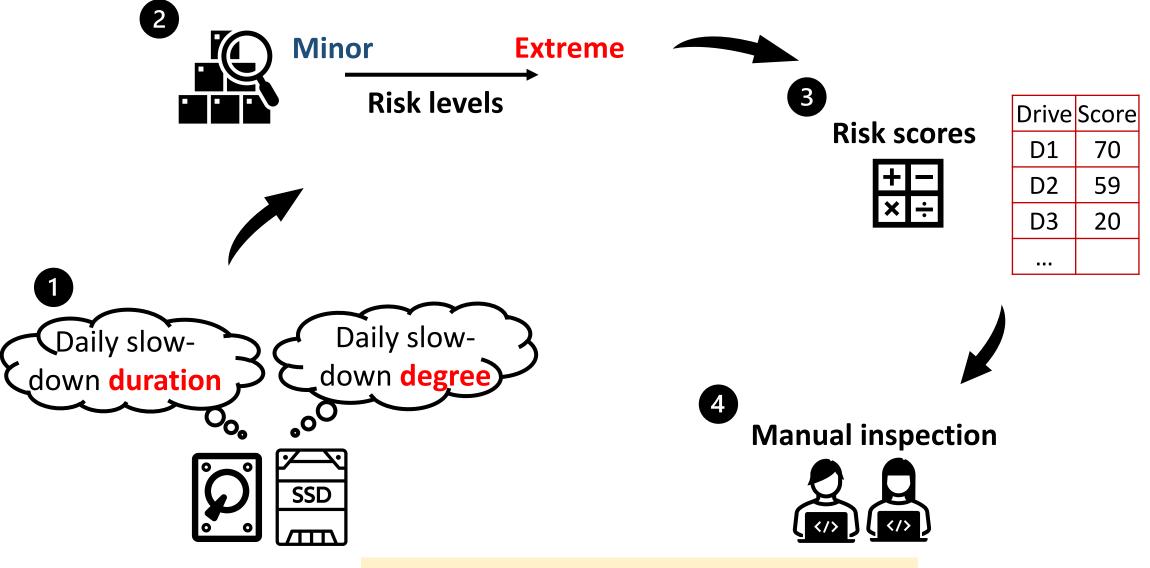
Throughput

Prediction upper bounds as adaptive latency thresholds without fine-tuning

FAST^T Step 3: Identifying Fail-Slow Event



FAST¹/₂₃ Step 4: Evaluating Risk



Quantify the slowness of drives

FAST⁷ Outline



FAST¹/₂₃ Evaluation Benchmark

- Built and released our self-assembled test dataset
 - Clear labels (fail-slow or not)
 - 15 days of operational traces
 - 41K drives
 - ~300 fail-slow drives

Fail-Slow Detection Open Dataset	CC BY-NC-SA 4.0		New a notebook
ontent Notebook Comment			
Description			
This dataset aims at fail-slow detection on storage devices. Please	refer to our paper (to appear i	n USENIX FAST 2023) for more details.	
Data List			
Name	Date	Size	Download
README.md	2023-01-13	1.42KB	يل.
1_cluster_ABCDE.zip	2023-01-25	379.70MB	يلى بل
2_cluster_FGHIJ.zip	2023-01-25	1.48GB	Ł
cluster_info.csv	2023-01-25	555.00Bytes	Ł
slow_drive_info.csv	2023-01-25	9.45KB	ىكى ئ
5_cluster_PQST.zip	2023-01-25	556.42MB	ىكى ئ
7_cluster_UVWXY.zip	2023-01-25	1.01GB	Ł
4_cluster_MNO.zip	2023-01-25	1.07GB	Ł
3_cluster_KL.zip	2023-01-25	1.42GB	소
6_cluster_R.zip	2023-01-25	1.86GB	يلى بل

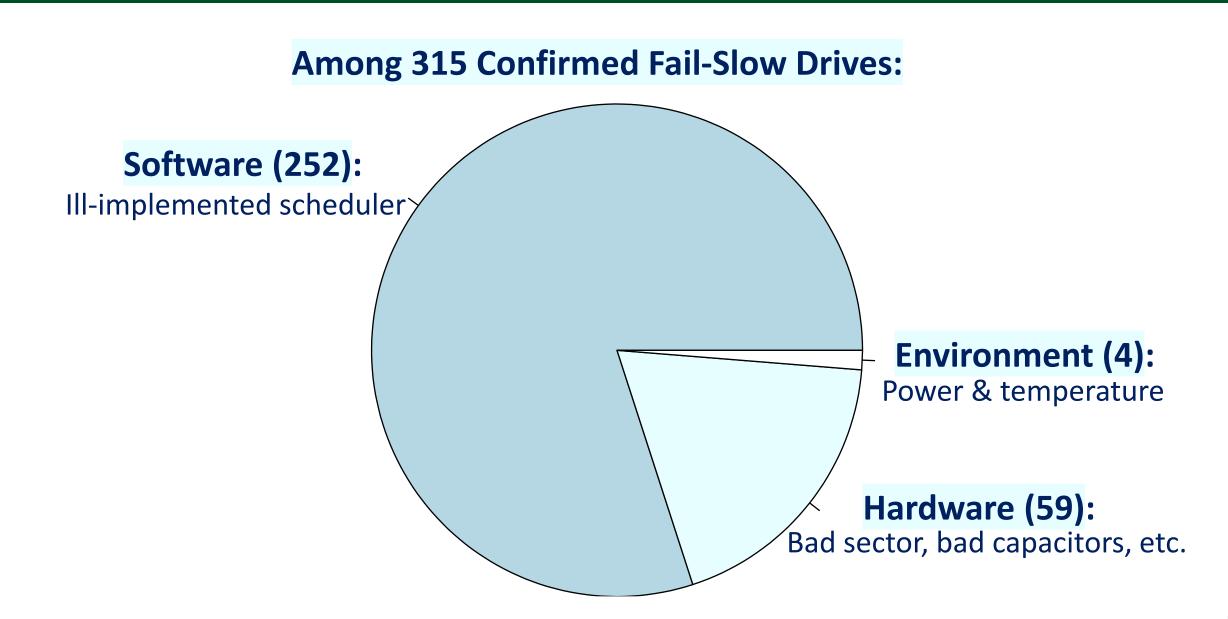
https://tianchi.aliyun.com/dataset/144479

FAST⁷₂₃ Evaluations

- Perseus outperforms all previous attempts (§5.4)
- Effectiveness of Perseus's Design Choices (§5.5)
- Reduce Tail Latency By 31-48% (§5.6)
- Root Cause Analysis (§6)

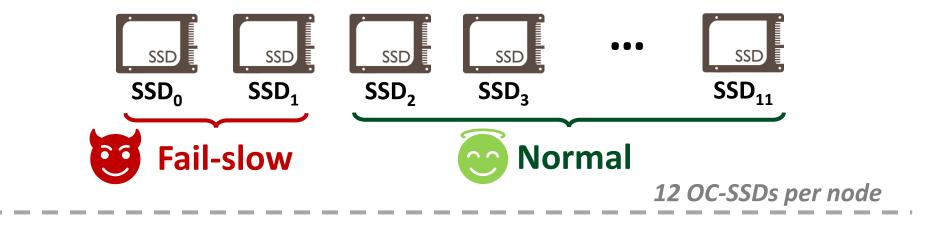
More details in the paper!

FAST¹ Root Cause Distribution



Case I: In Open-Channel SSD Cluster

1. Every node always has 2 fail-slow drives

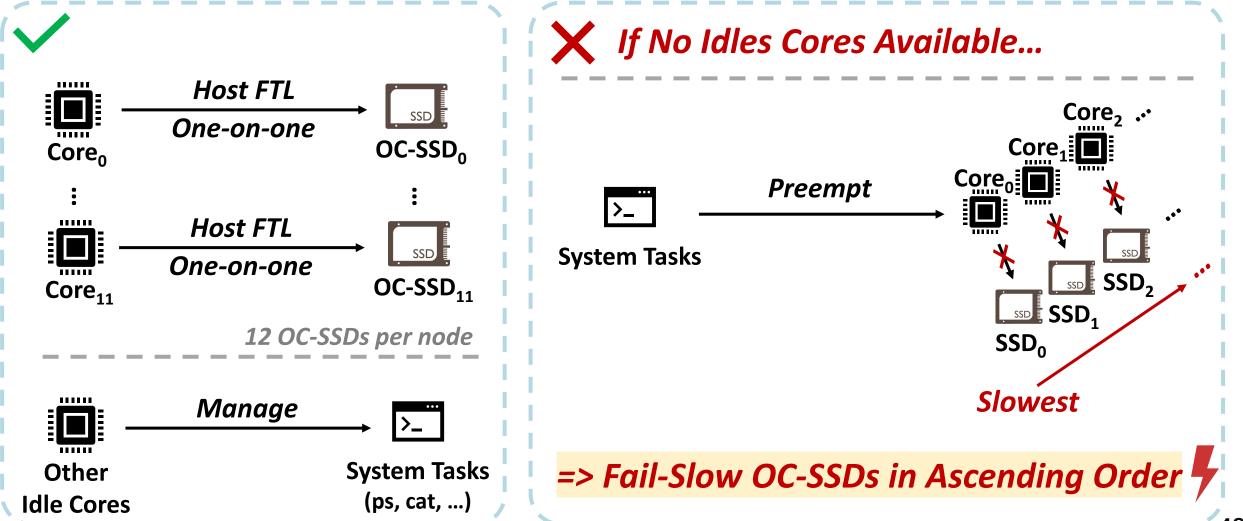


2. Latency levels follow ascending order of logical IDs



FAST^T Root Cause: Software

Case I: In Open-Channel SSD Cluster



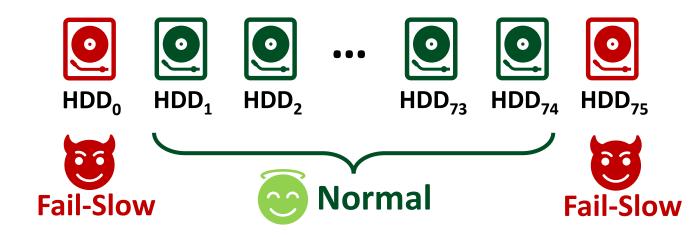
FAST^T Root Cause: Software

Case II: In All-HDD Cluster

1. Fail-slow drives always appear in fixed pairs

76 HDDs per node

Two fail-slow disks in a node:



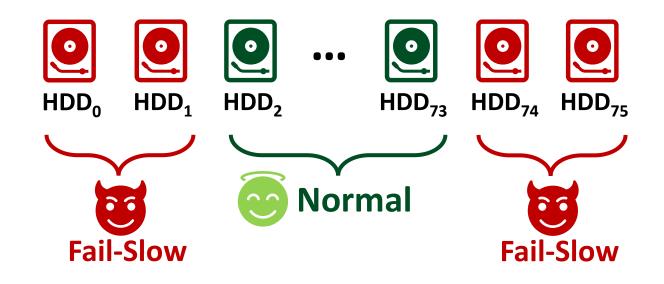
FAST^T Root Cause: Software

Case II: In All-HDD Cluster

1. Fail-slow drives always appear in fixed pairs

76 HDDs per node

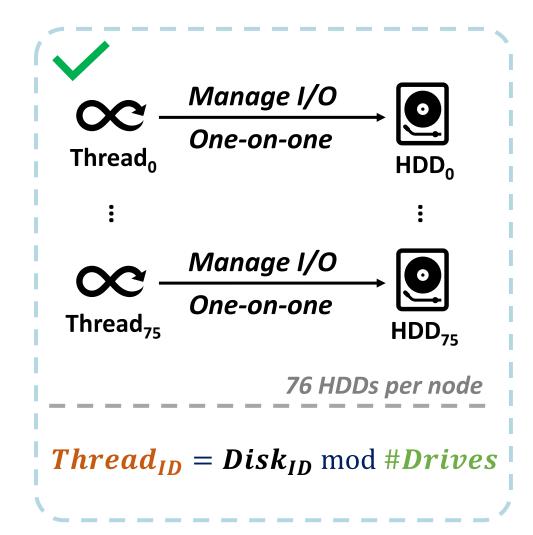
Four fail-slow disks in a node:

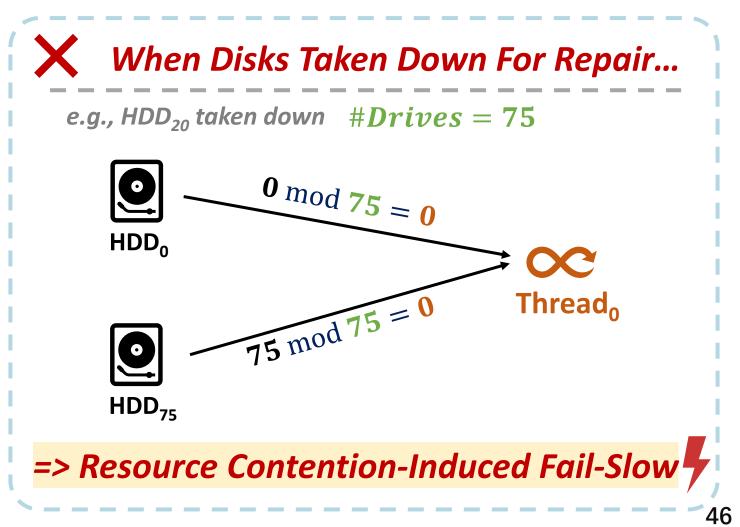


Case II: In All-HDD Cluster

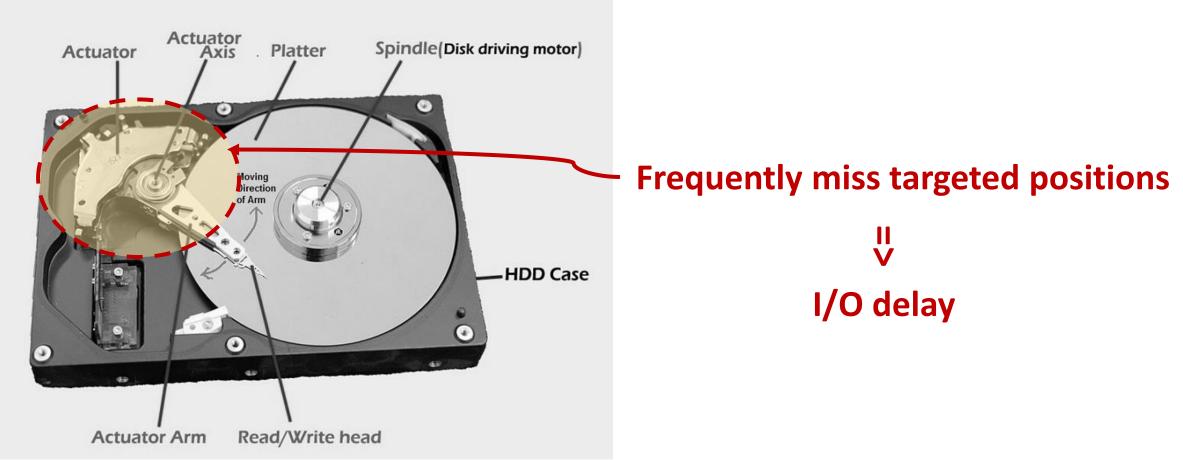
- **1.** Fail-slow drives always appear in fixed pairs
- 2. All fail-slow drives are experiencing similar slowdown
- **3.** #*Fail-slow* = $2 \times #Offline$

Case II: In All-HDD Cluster



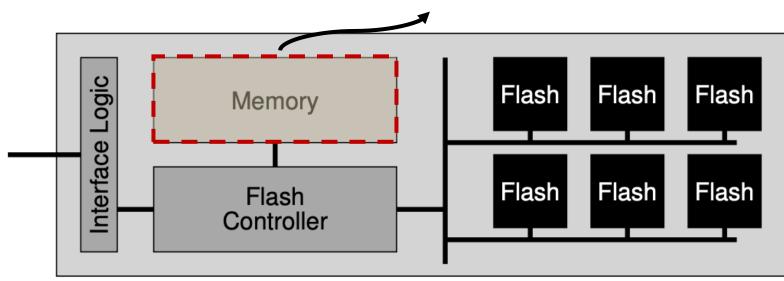


• Rotor Eccentricity



Source: https://www.techintangent.com/hard-disk-description/

- Rotor Eccentricity
- Bad Capacitors



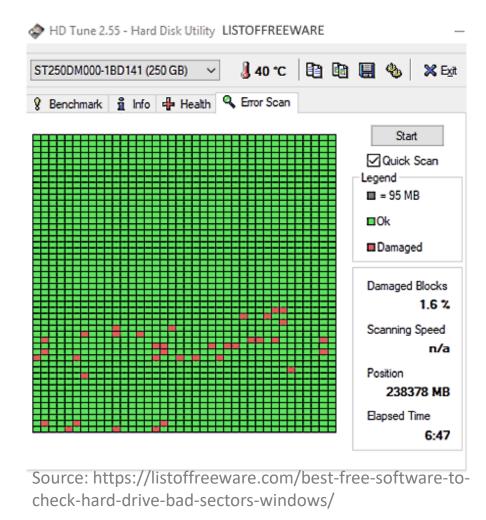
DRAM as an internal write-back cache

Source: Operating Systems: Three Easy Pieces

DRAM capacitors failed => **Delayed writes**

- Rotor Eccentricity
- Bad Capacitors
- Bad Sectors:

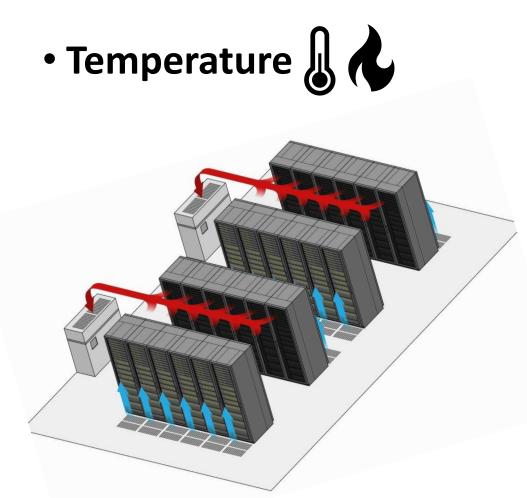
Data reallocate to spare sectors



- Rotor Eccentricity
- Bad Capacitors
- Bad Sectors:

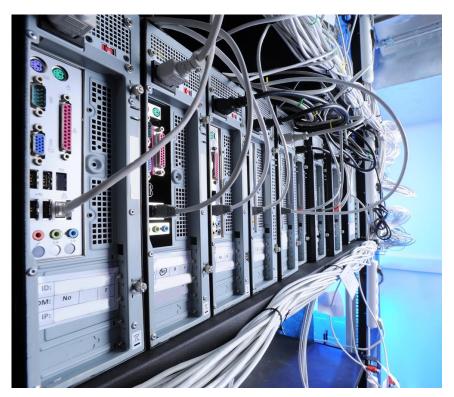


FAST¹/₂₃ Root Cause: Environment



Source: https://www.upsite.com/blog/helping-your-datacenter-breath-easier-with-good-air-flow-management/





Source: https://www.ecsintl.com/how-datacenters-can-effectively-manage-power-surges/

FAST⁷/₂₃ Summary

Perseus

Detection Framework

Non-intrusive (Performance) log-based No source code altering

Accurate

Recall/precision rate > 0.99

Fail-Slow Detection

Efficient

Fine-grained Device-level detection

✓ General

One set of parameters fits all scenarios

Storage Devices



...

Adaptable to Other Problem Domains



Thank you!

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FAST^T Evaluations

Effectiveness of Perseus's design
choices (§5.5)

Perseus's design tradeoffs (§5.5)

(a) Precision

Parameter	Range	Description						
S1: Outlier detection (§4.2)								
PCA	On/Off	Transform the coordinates w.r.t. the						
		principal components.						
DBSCAN On/Off Density-based outlier detection.								
	S3: Identifying fail-slow event (§4.4)							
X	95~99.9	Use the $X\%$ prediciton upper bound as						
Λ	95,099.9	the latency upper bound.						
	S4: Evaluating risk (§4.5)							
min_score	1~100	Risk score threshold.						
N	1~15	Evaluate the risk score of the most						
1		recent N days.						

Metric	w/o	w/o	p95	p99	p999	Deployed				
	Outlier	PCA								
Full-set										
Precision	0.98	0.55	0.99	1.00	1.00	0.99				
Recall	0.51	0.43	0.99	0.93	0.93	1.00				
MCC	0.71	0.49	0.99	0.96	0.96	0.99				
	Subset (excluding software-induced)									
Precision	0.95	0.36	0.94	0.98	1.00	0.94				
Recall	0.82	0.91	0.95	0.92	0.95	1.00				
MCC	0.88	0.57	0.95	0.95	0.98	0.97				

	15 -	0.46	0.81	98.0	96 0	0.97	0 99	1	1	1	1	1	1	1			- 1.0
ŝ																	
day(s)						0.97		1	1	1	1	1	1	1			
Last N da	7 -	0.46	0.81	0.86	0.96	0.97	0.99	1	1	1	1	1	1	1			
	5 -	0.46	0.81	0.86	0.96	0.97	1	1	1	1	1	1	1	1			
-as	3 -	0.46	0.81	0.86	0.96	0.97	1	1	1	1	1	1	1	1			- 0.8
_	1 -	0.46	0.81	0.86	0.95	0.90	1	1	1	1	1	1	1	1			
(b) Recall																	
	15 -	0.96	0.95	0.95	0.95	0.95	0.94	0.93	0.91	0.88	0.86	0.82	0.77	0.71			0.0
(s)	10 -	0.96	0.95	0.95	0.95	0.94	0.93	0.91	0.87	0.81	0.74	0.68	0.64	0.62			0.6
day(s)	7 -	0.96	0.95	0.95	0.95	0.94	0.92	0.87	0.76	0.70	0.64	0.61	0.58	0.57			
Last N	5 -	0.96	0.95	0.95	0.95	0.94	0.89	0.80	0.67	0.63	0.58	0.56	0.20	0.19			
as	3 -	0.96	0.95	0.95	0.94	0.92	0.71	0.65	0.51	0.21	0.18	0.17	0.17	0.16			
_	1 -	0.96	0.95	0.90	0.62	0.23	0.20	0.19	0.19	0.16	0.13	0.09	0.09	0.09			0.4
							(c)	MC	C								
	15 -	0.66	0.88	0.90	0.95	0.96	0.97	0.96	0.96	0.94	0.92	0.91	0.87	0.84			
(s)	10 -	0.66	0.88	0.90	0.95	0.95	0.96	0.95	0.93	0.90	0.86	0.82	0.80	0.78			0.2
ast N day(s)-	7 -	0.66	0.88	0.90	0.95	0.95	0.96	0.93	0.87	0.84	0.80	0.78	0.76	0.75			0.2
ţ	5 -	0.66	0.88	0.90	0.95	0.95	0.94	0.89	0.82	0.79	0.76	0.75	0.45	0.43			
as	3 -	0.66	0.88	0.90	0.95	0.94	0.84	0.81	0.71	0.45	0.43	0.42	0.41	0.40			
_	1 -	0.66	0.88	0.88	0.77	0.46	0.45	0.43	0.43	0.40	0.36	0.30	0.30	0.30			~ ~
		i	5	10	15	20	30	40	50	60	70	80	90	100			0.0
Risk score threshold (min_score)																	

- 1.0	Metric	Thresh-	Thresh-	Peer	IASO-	PERSEUS-					
		Stat	Emp	Eval	Based	Deployed					
	Full-set										
	Precision	1.00	1.00	0.98	0.48	0.99					
- 0.8	Recall	0.52	0.02	0.57	0.24	1.00					
- 0.0	MCC	0.72	0.14	0.74	0.32	0.99					
	Subset (excluding software-induced)										
	Precision	1.00	1.00	1.00	0.45	0.94					
	Recall	0.71	0.09	0.65	0.61	1.00					
- 0.6	MCC	0.84	0.30	0.80	0.52	0.97					