CENSUS: Counting Interleaved Workloads on Shared Storage

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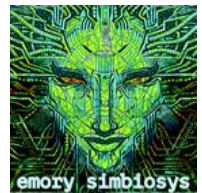


How to choose the right storage for workload?

Cost efficiency: higher throughput, less latency, less cost

Sequential write → LSM-tree based Key-value store

Fast random read → Flash memory

Random write → SSD

Lower speed read and write → HDD

…

And the best configuration?

Fair Resource Provisioning for Shared Storage is hard!

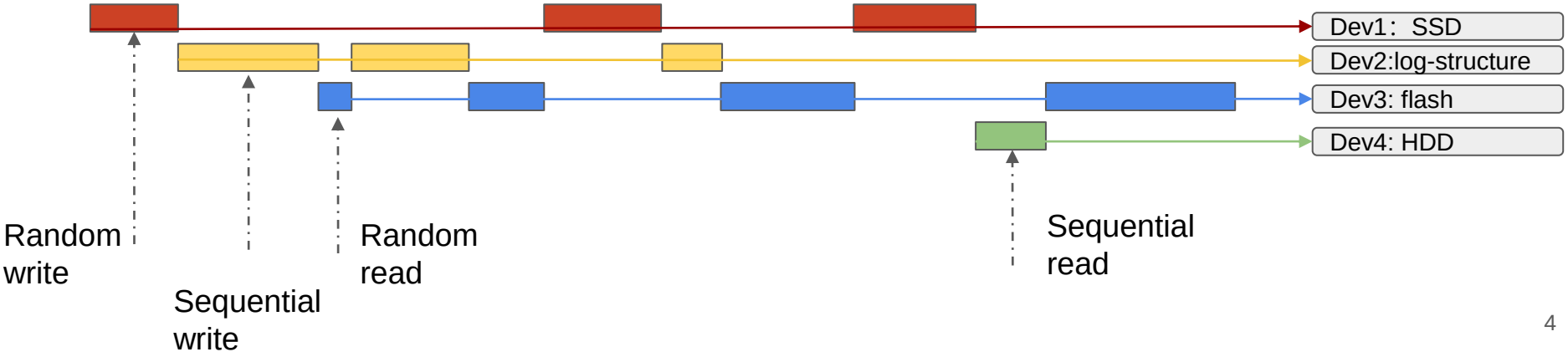
Challenge: shared storage, dynamic, interleaved,

Smart storage: capacity prediction and performance management

Deep understanding the workload!

Workload separation for shared storage

Workload
Separation !



What exactly shall we separate?

Application specific workload

Fully isolation does not really means shared storage.

Single workload has several functional usage of storage.

Functionally distinct usage of a storage system

Fworkload

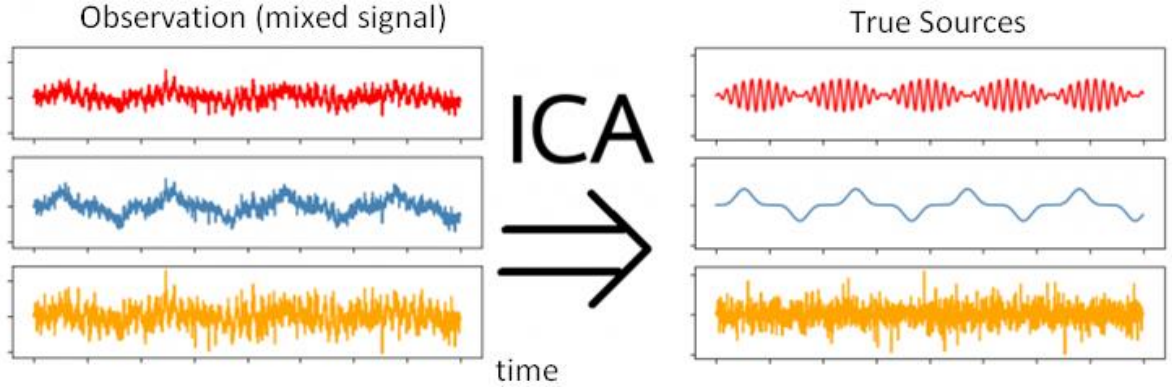
Process ID (PID) is a stand-in for non-existent labels

Motivation

Existing approaches fail to distinguish interleaved storage fworkloads.

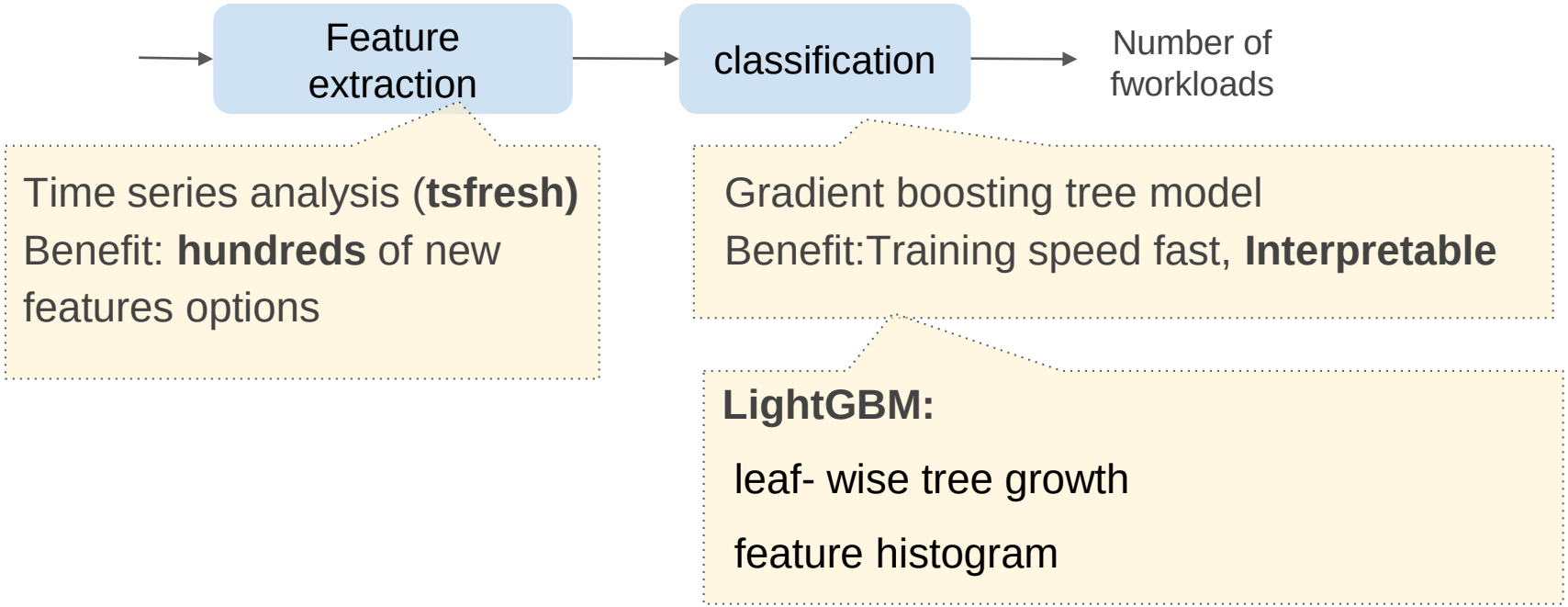
Traditional workload characterization only have limited features.
(read/write ratio, sequentiality...)

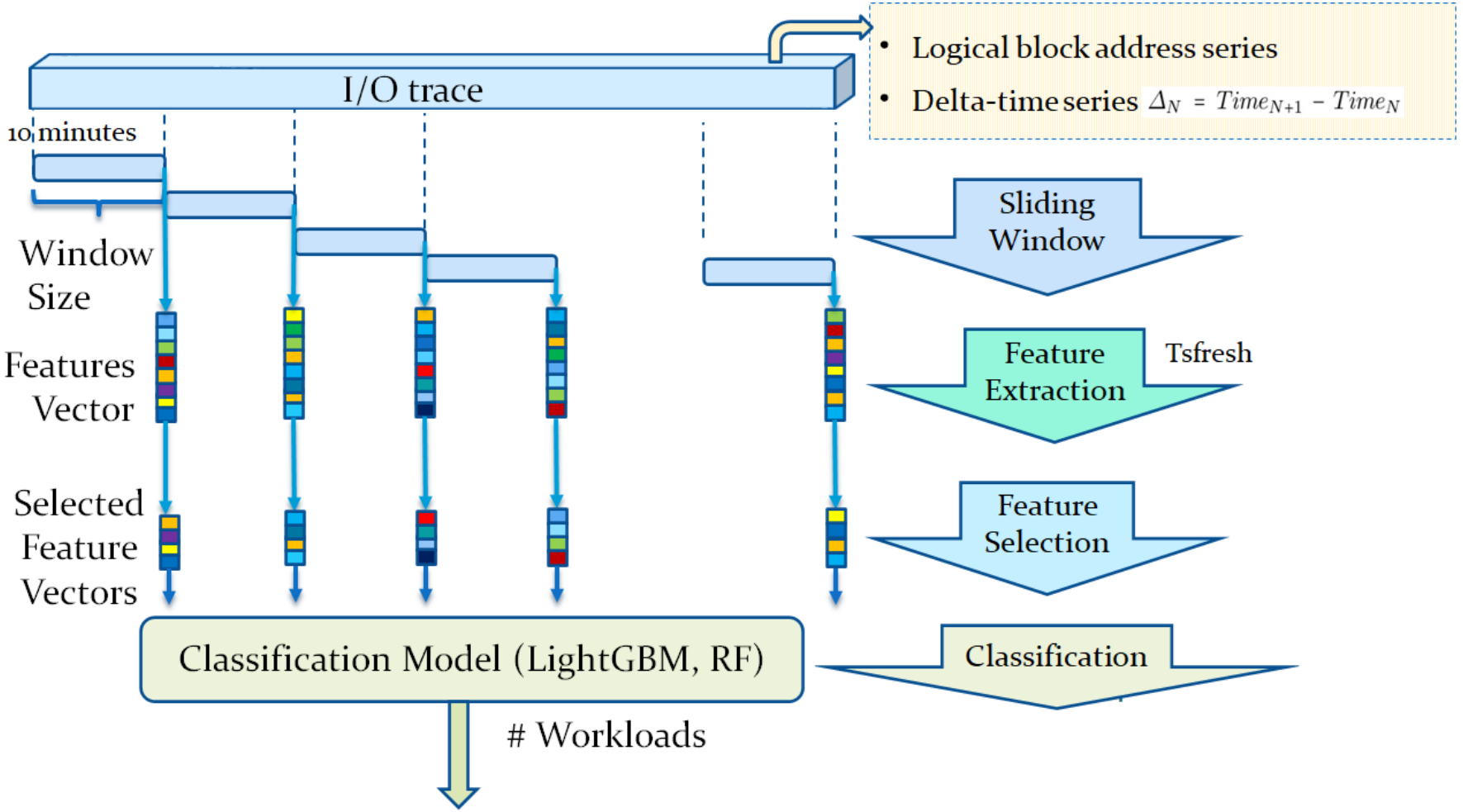
The **number** of concurrent fworkloads is precursor for separation

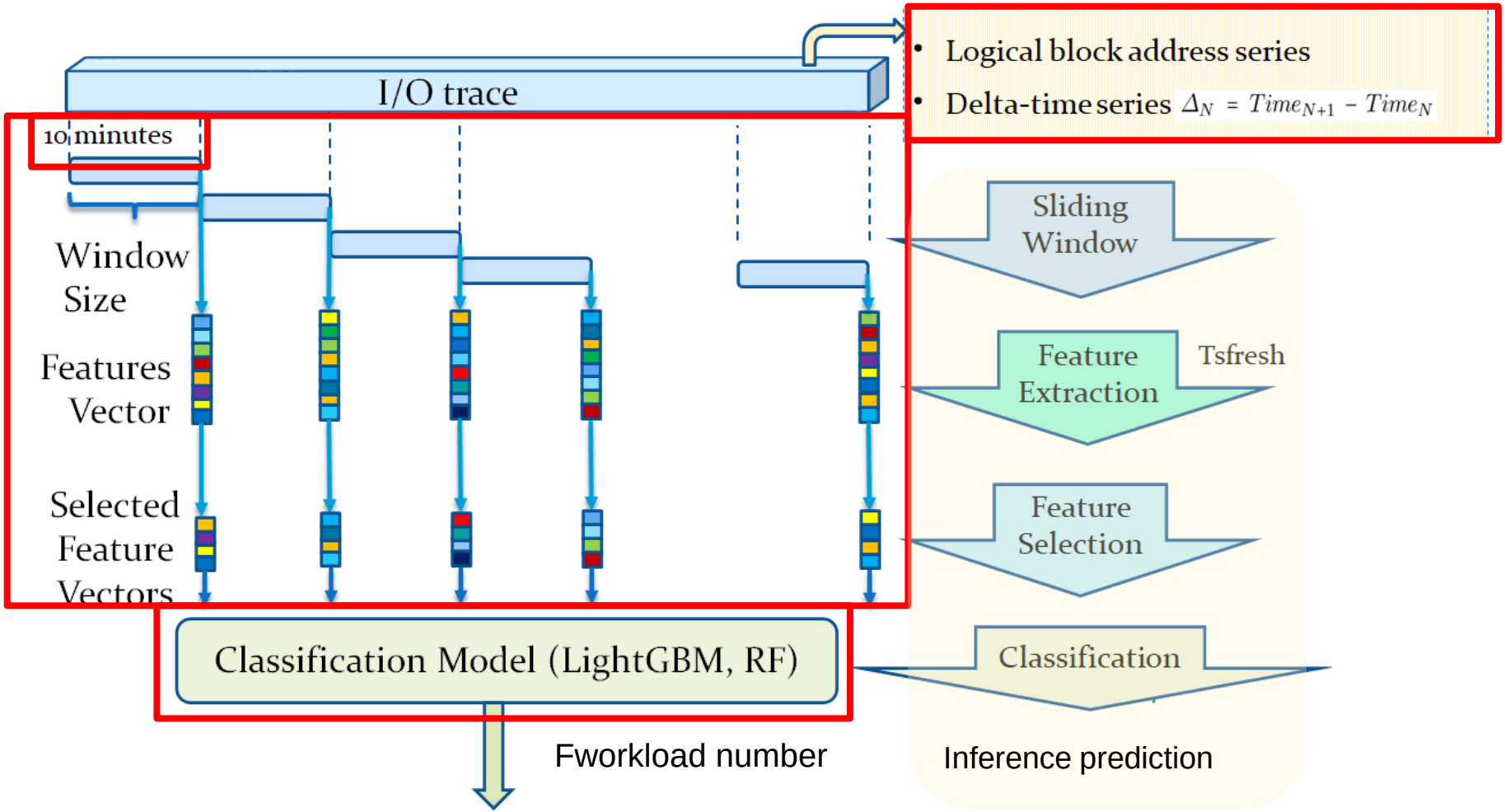


Goal: Given a block I/O trace, we are able to identify the **number** of fworkloads in a storage system.

Our Approach: Census




I/O trace
Logical block address series
Delta-time series $\Delta_N = Time_{N+1} - Time_N$
10 minutes
Window Size
Features Vector
Selected Feature Vectors
Sliding Window
Feature Extraction
Tsfresh
Feature Selection
Classification Model (LightGBM, RF)
Classification
Workloads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Classification
Classification Model (LightGBM, RF)
Fworkload number
Inference prediction

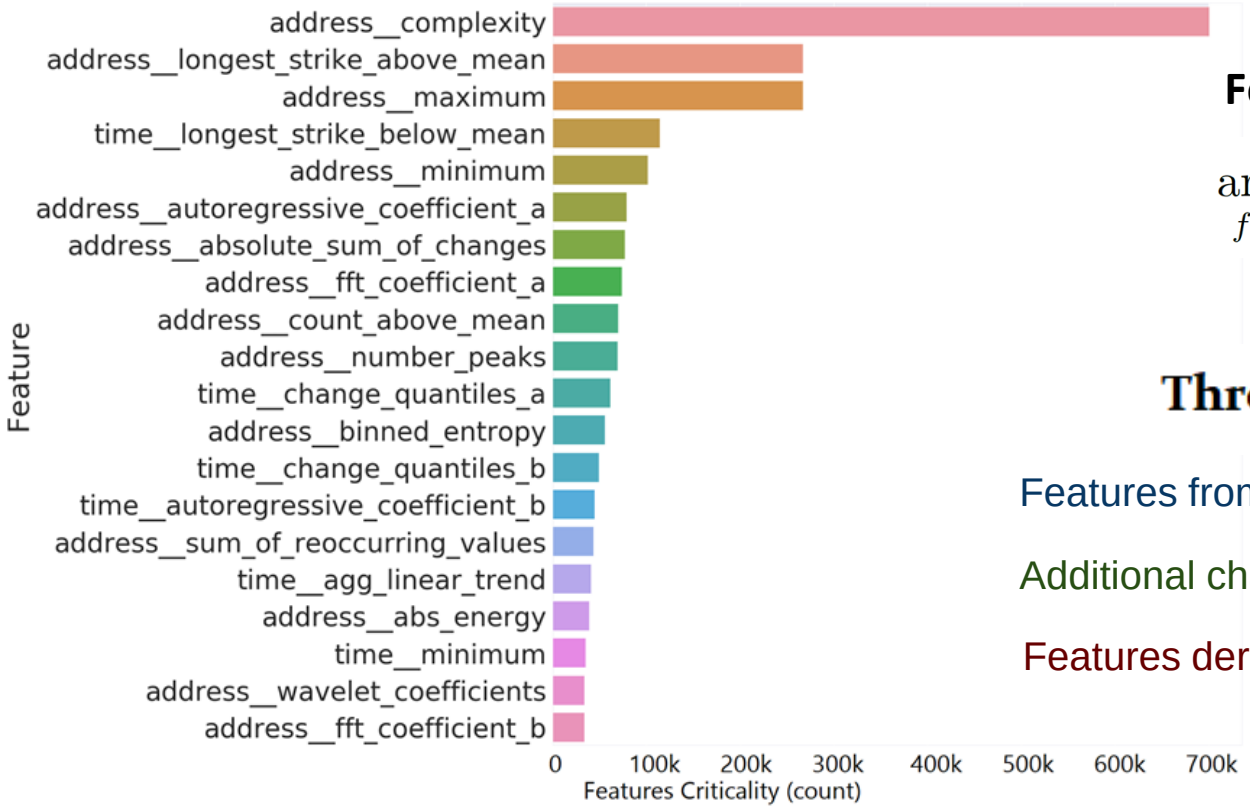
Dataset

- **FIU** (Florida International University)
  nearly three weeks of block I/O traces. Include web related, home related domain.

- **MSR** (Microsoft Research (MSR), Cambridge)
  1 week of block I/O traces from 36 different volumes on 13 enterprise servers

- **EmoryML (**newly collected**)**
  30 days of block I/O traces collected by blktrace from our local server, running machine learning workloads

Extracted features



Feature criticality = the count of

$$\arg\max_{feature} \sum_{Tree} Gain(Tree, feature)$$

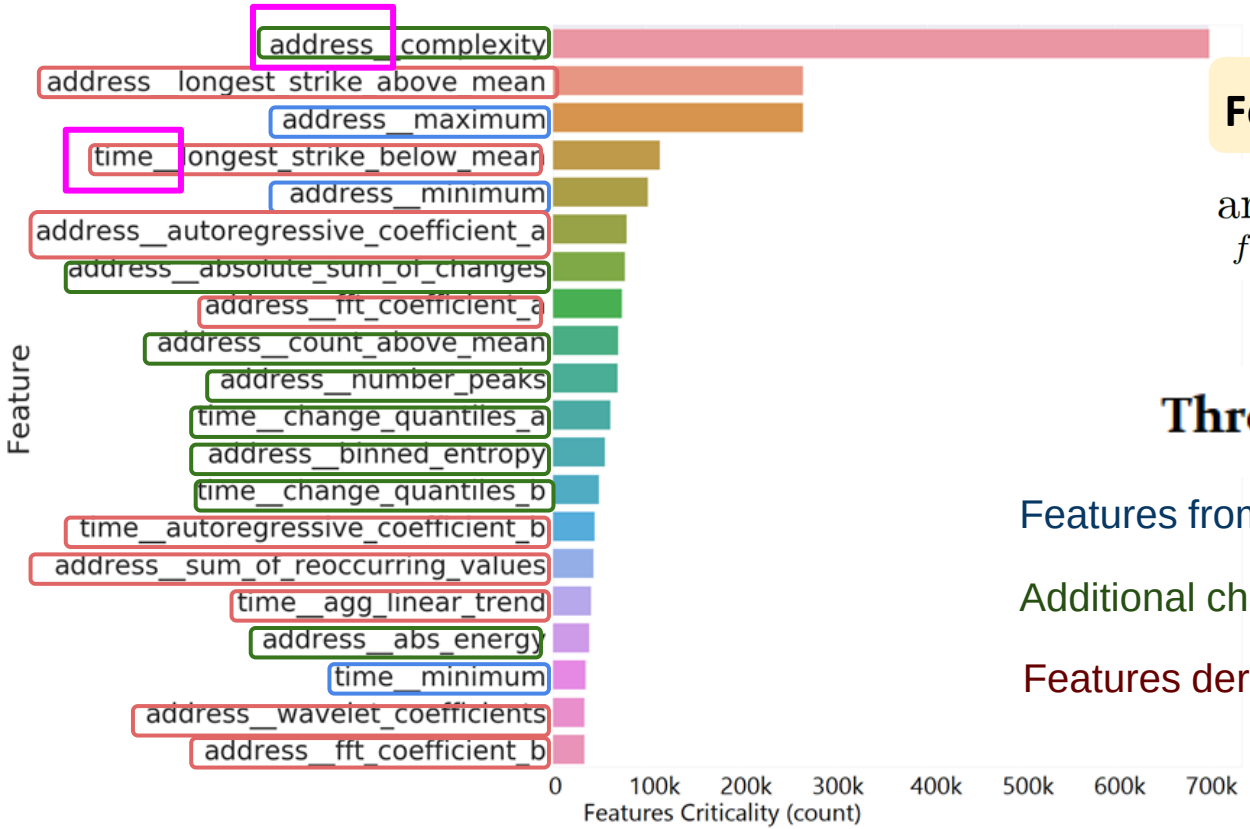
Three kinds of features

Features from summary statistics

Additional characteristics of sample distribution

Features derived from observed dynamics

Extracted features



Feature criticality = the count of

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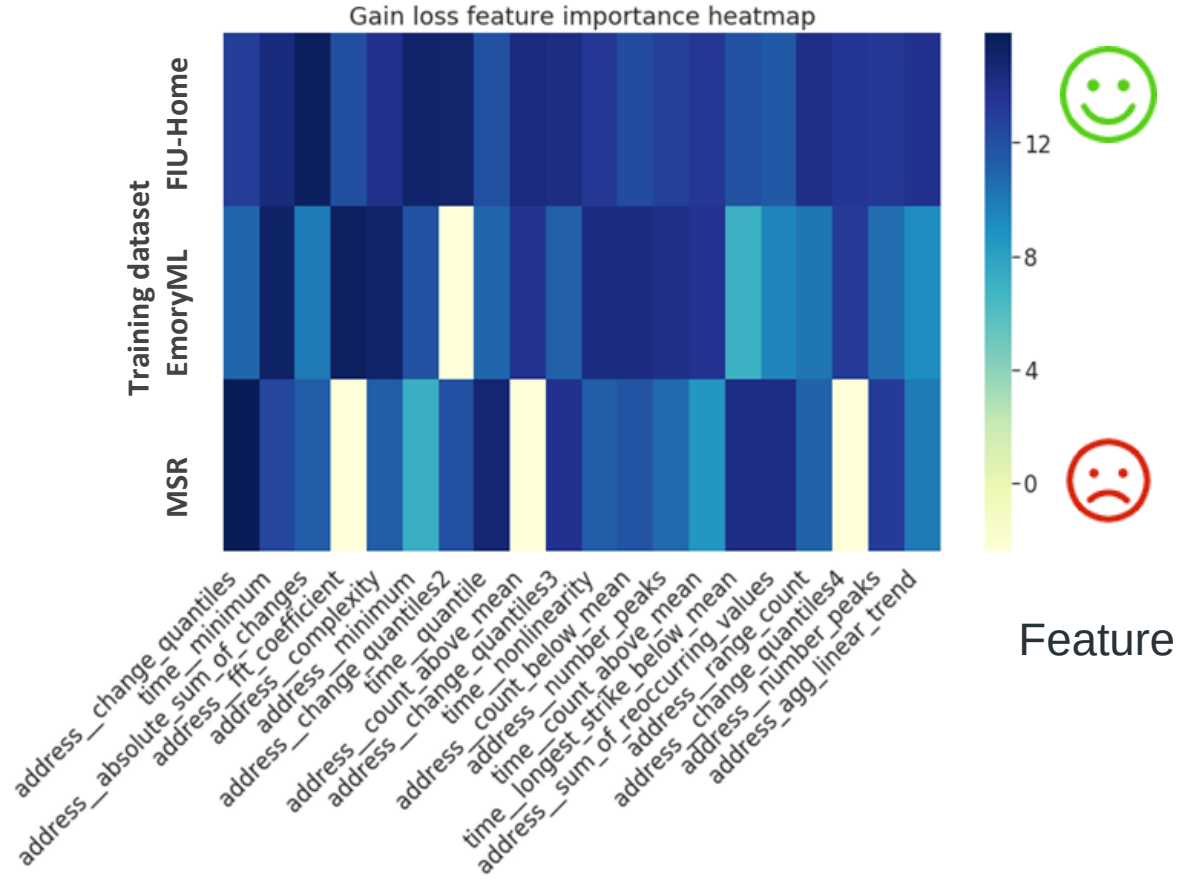
Feature Importance Heatmap



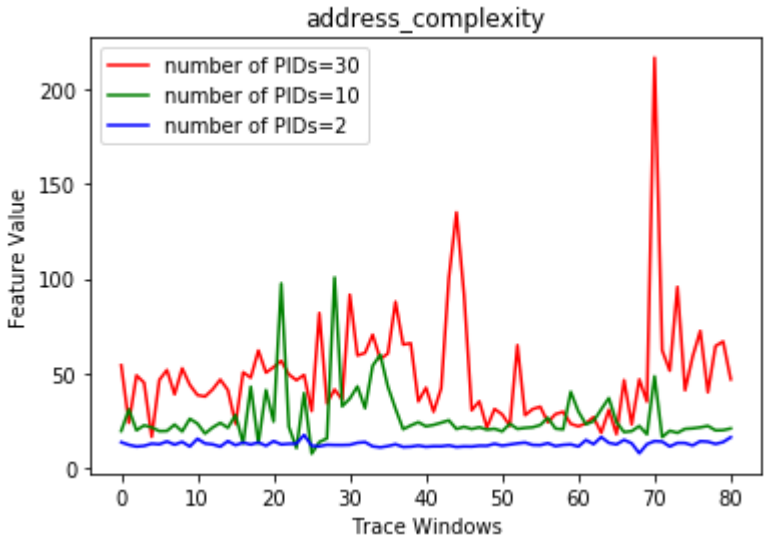
Feature criticality is trace dependent.

Sample features 1) address complexity

It measures the complexity of the address series

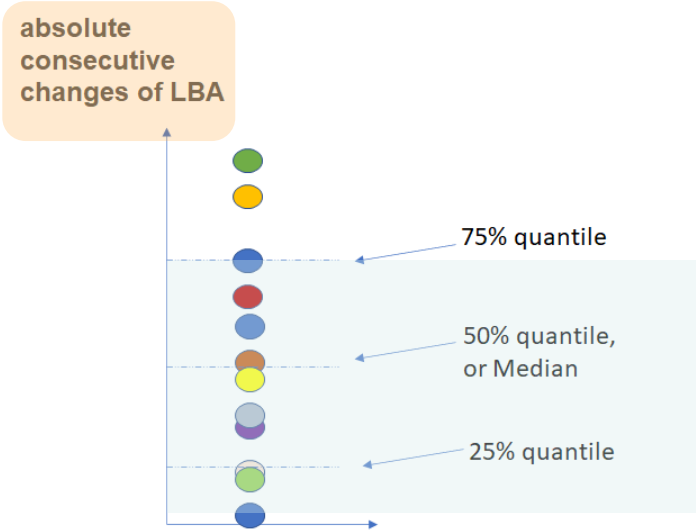
$$\sqrt{\sum_{i=0}^{n-2} (x_i - x_{i+1})^2}$$

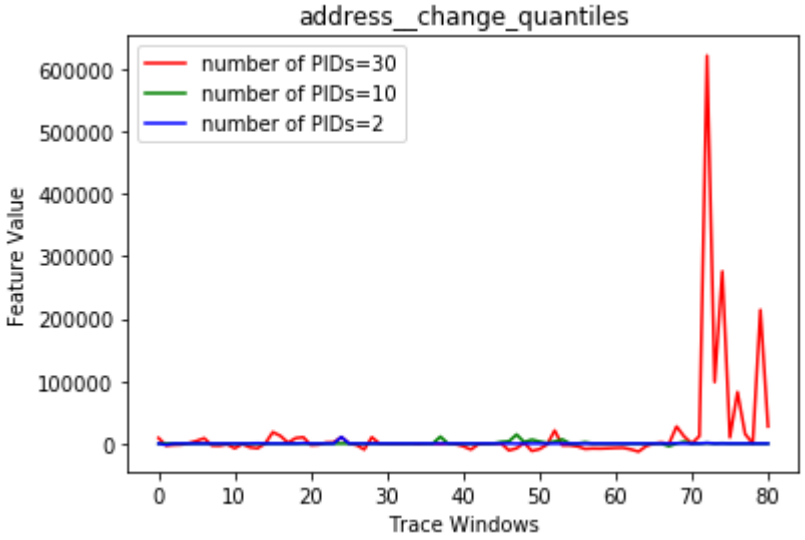
A **high** feature value indicates that **more random accesses** and less sequential accesses are in the trace, which implies **more** concurrent workloads during that time window.



Sample features 2) address change quantiles

Quantiles: divide data into equally sized groups.





It returns the **average absolute consecutive changes** of the address series identified between given higher and lower **quantiles**.

Model Evaluation

x-accuracy

Considers the instances with prediction error within 1 or 2, respectively as accurate.

MAPE (mean absolute percentage error)

Measures the size of the prediction error.

Identifies instances that are approximately correct.

$$\mathrm{M} = 100 \times \frac{1}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right|$$

Baseline (fairest guess):

Randomly generating labels based on the fworkload number distribution in the training set.

Training method

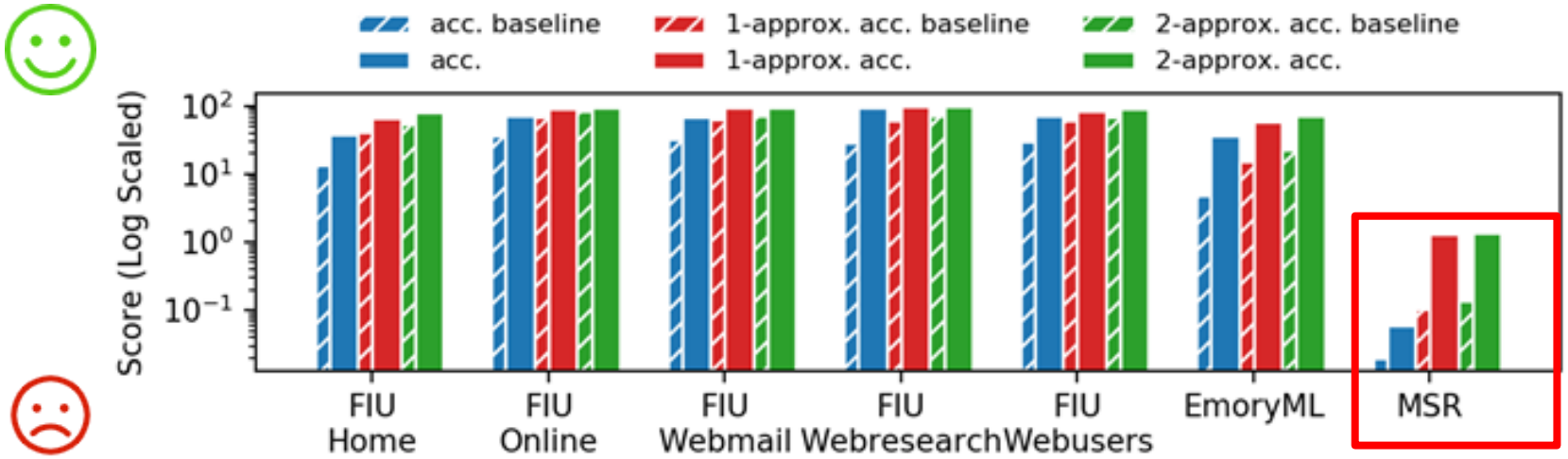
Generalized model:

Consider multiple domains

ID model:

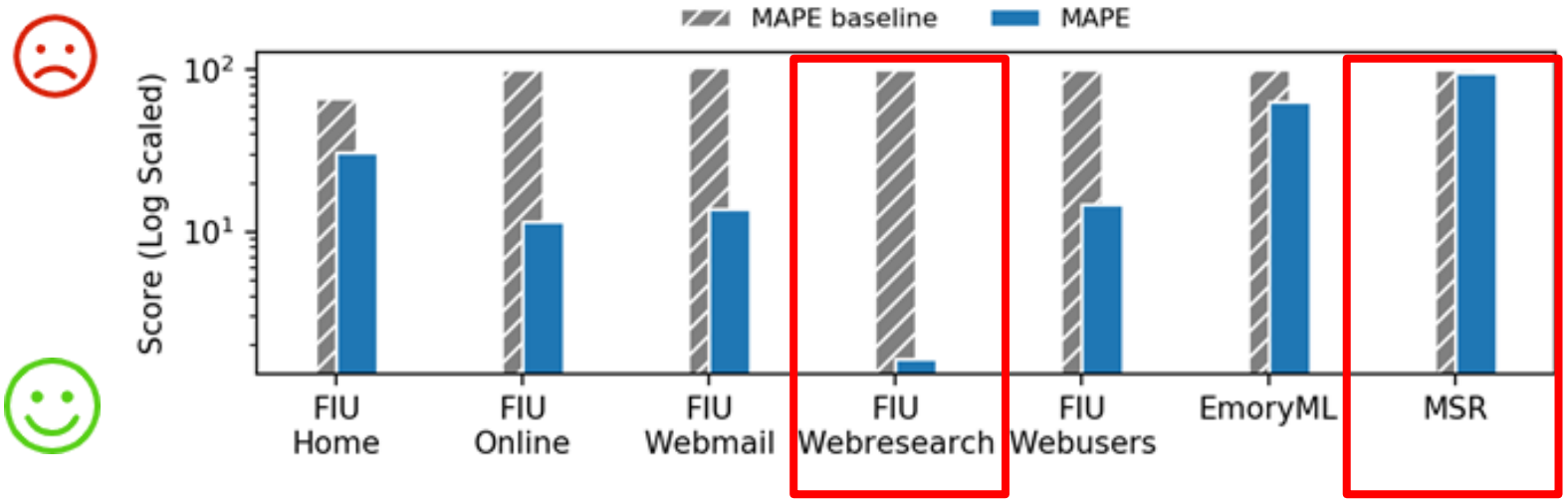
Domain specific

Result of Generalized model



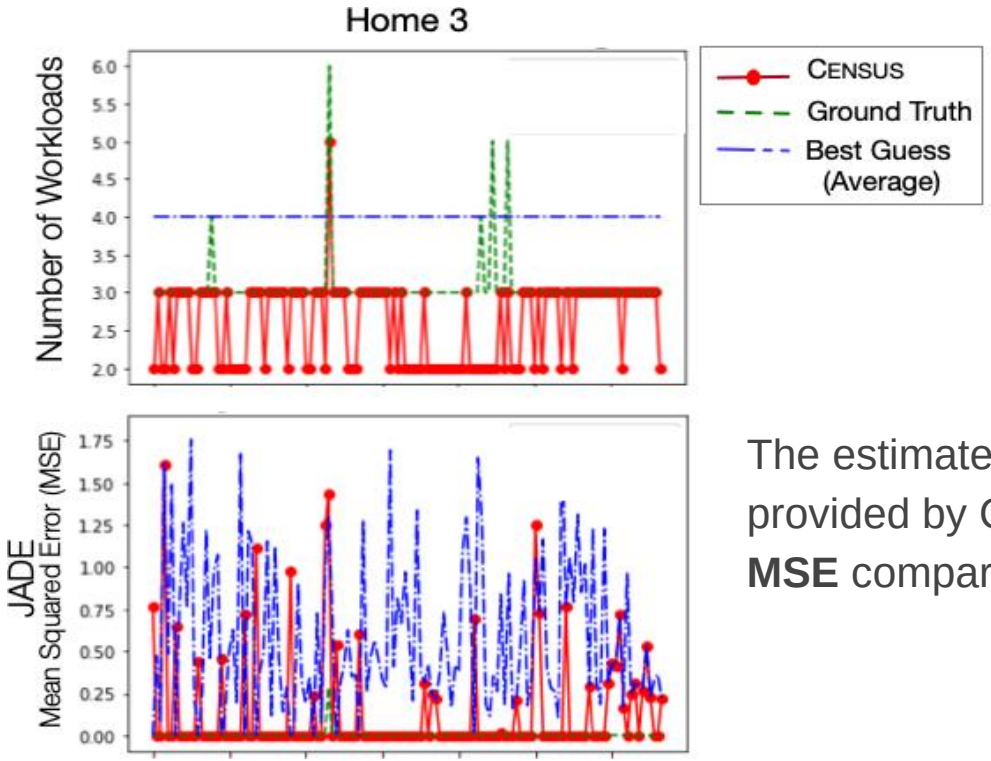
Accuracy score: CENSUS is 23% higher than baseline on average

Result of Generalized model



MAPE: CENSUS is 57% better than baseline on average

Application: Separating Interleaved fworkloads



The estimate for the number of fworkloads provided by CENSUS **decreases the average MSE** compared to the fair guess MSE

Summary

- CENSUS could **identify the number** of concurrent fworkloads with as little as 5% error.
- CENSUS opens the field to insights derivable from formerly overlooked **metrics**.
- LBA carries more effective information than **time interval**. Only 30% top features are related to time, affecting 1% of the final result.
- CENSUS improves fworkload separation in a test case.

Discussion and Future work

- Online model, recurrently training the model when unknown fworkload emerge.
- Find better fworkload label instead of PID, e.g. UID, process name.
- Add more trace attributes for workload characterization, e.g. latency.
- Try the workload separation on large-scale dataset.

Thank you! Questions!

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https://github.com/meditates/CENSUS