Sifter: Scalable Sampling for Distributed Traces, without Feature Engineering

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MAX PLANCK INSTITUTE
FOR SOFTWARE SYSTEMS

Sifter: a sampler for distributed traces

Part of distributed tracing backends

Problem: too many traces

Biased trace sampling

Which traces should we keep?

Which traces should we discard?

What constitutes an “interesting” trace?

Distributed Tracing

UBER

JAEGER

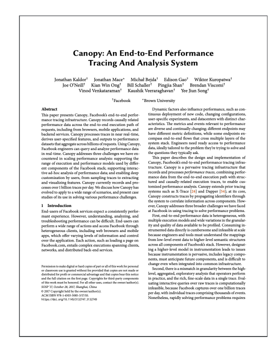
Google

Dapper

twitter

ZIPKIN

OPENTRACING

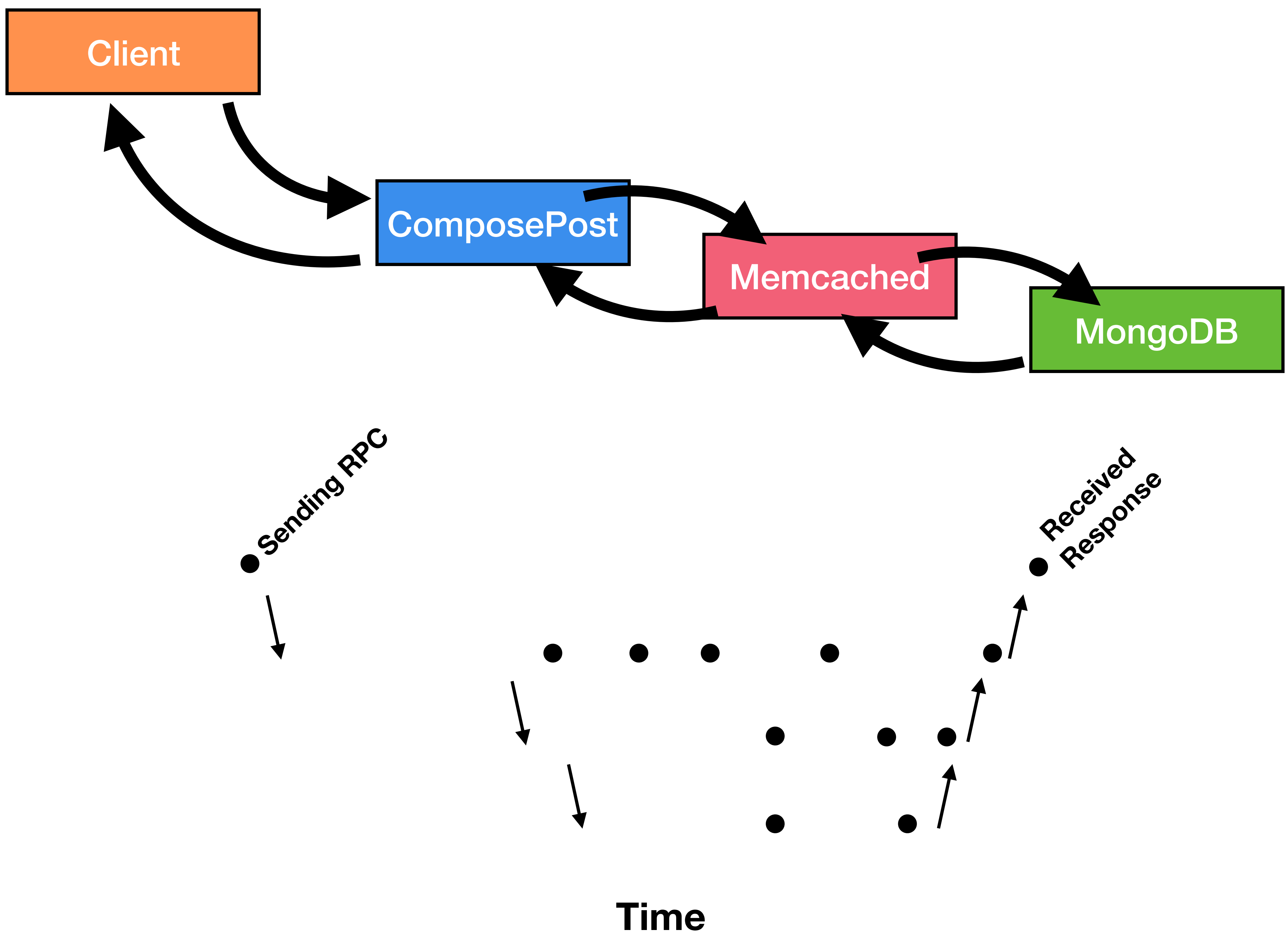


facebook

Canopy

Distributed Trace

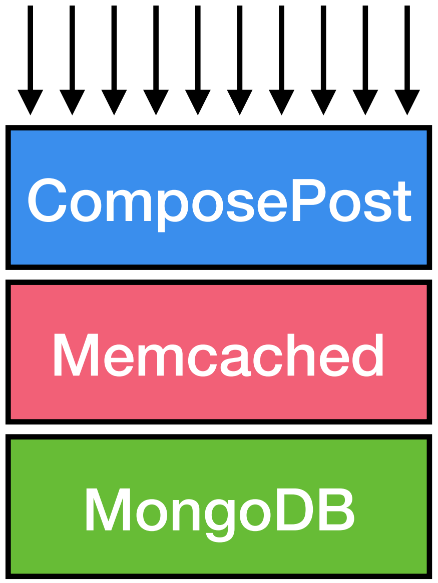
An end-to-end recording of one request

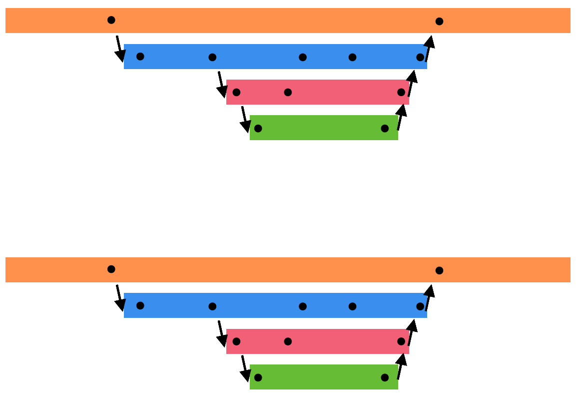


Distributed Trace

An end-to-end recording of one request

Each request generates a new trace





Distributed Trace

An end-to-end recording of one request

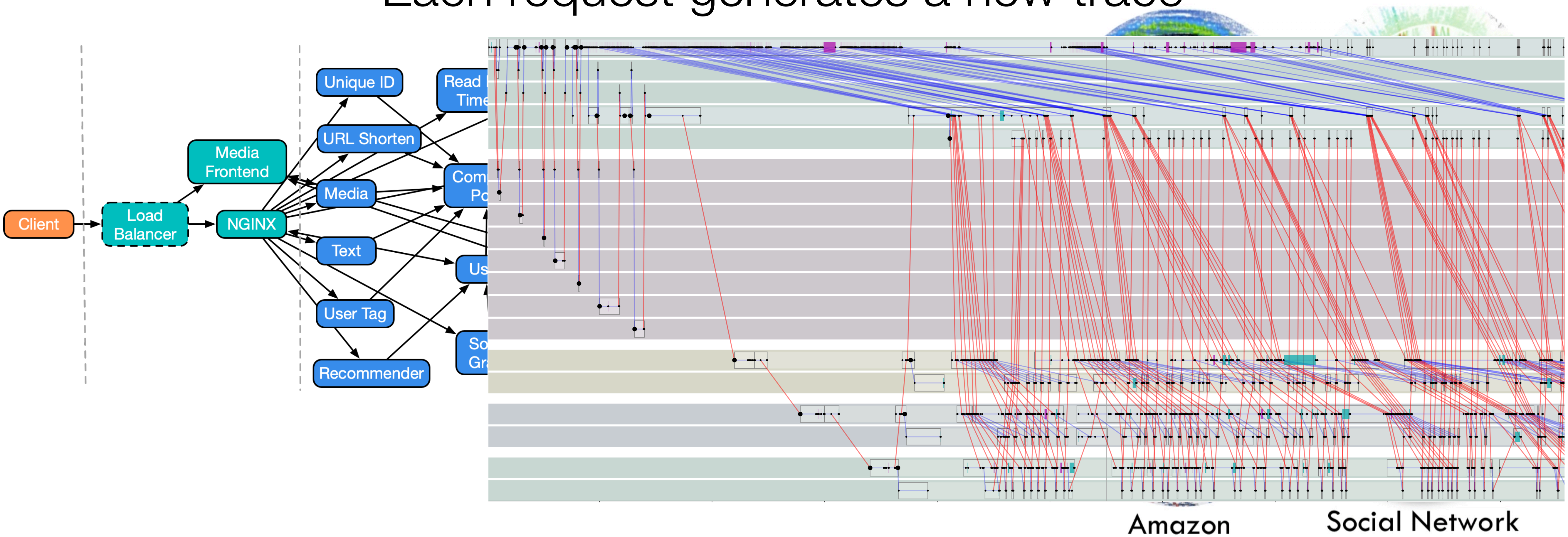
Each request generates a new trace

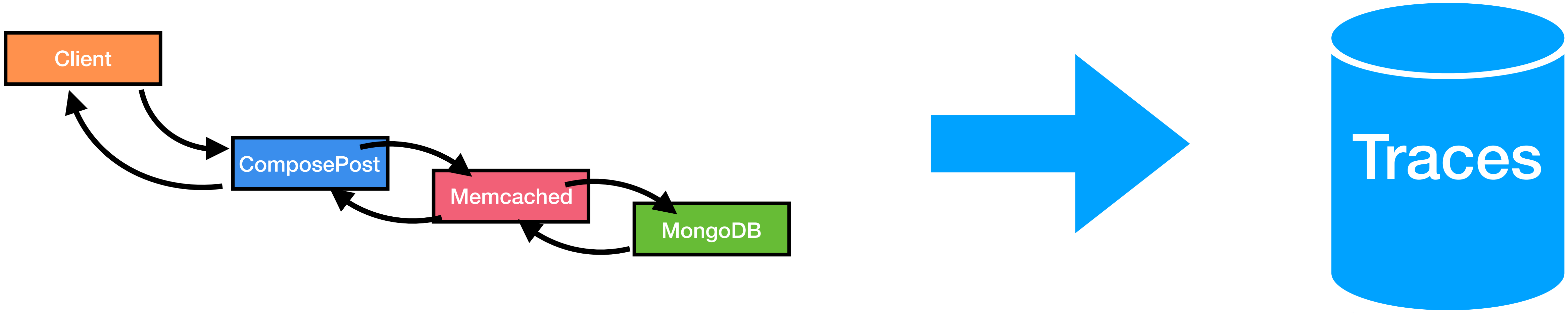
Traces with different execution paths == Traces with different structure

Distributed Trace

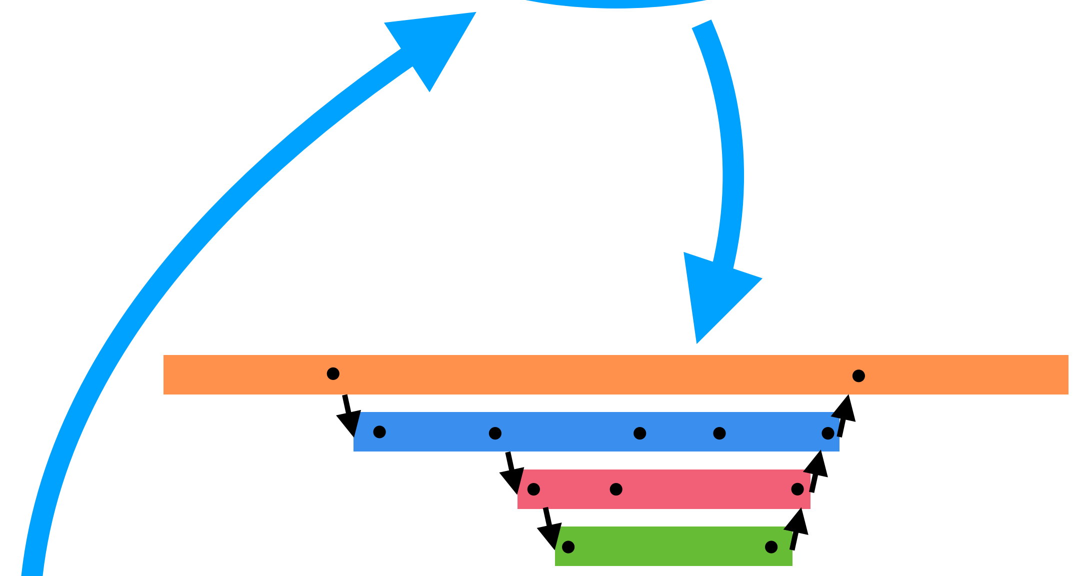
An end-to-end recording of one request

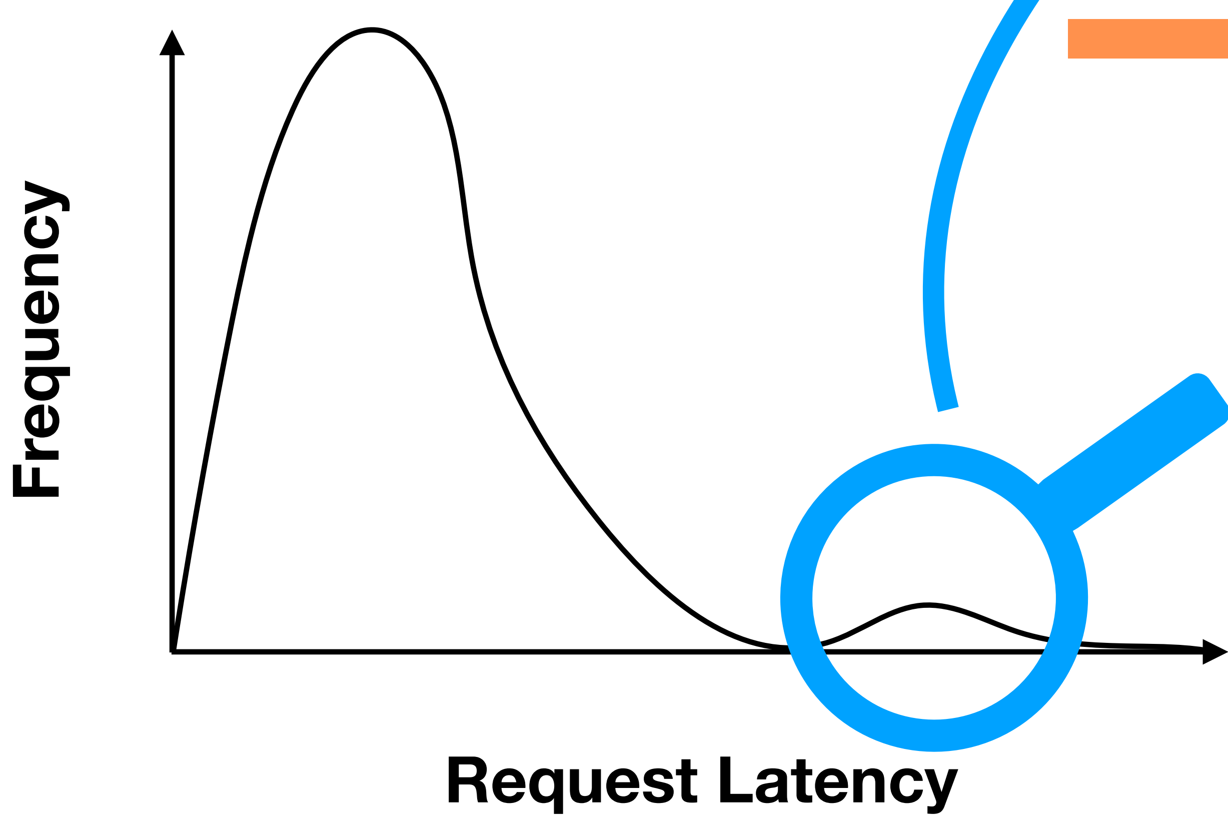
Each request generates a new trace





- Diagnosing latency problems
- Investigating bugs





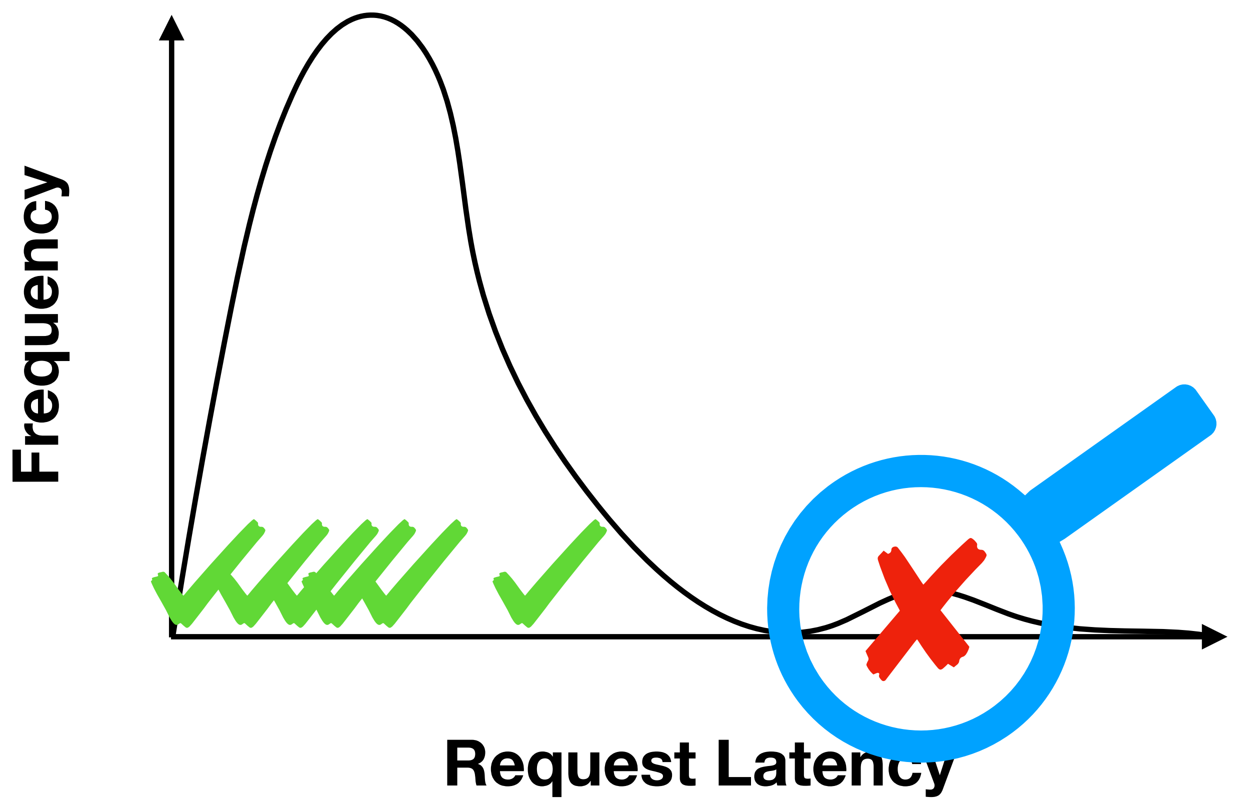
Sampling

Trace sampling

Individual traces can be very detailed

Tracing every request = too much data

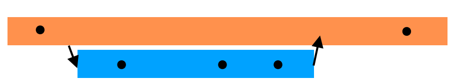
Uniform random sampling

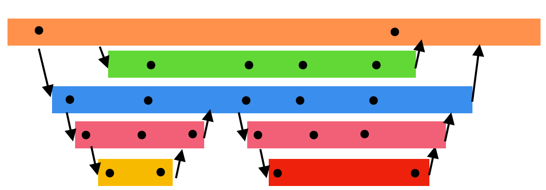


Biased Sampling

Adjust sampling probability based on how “interesting” trace is

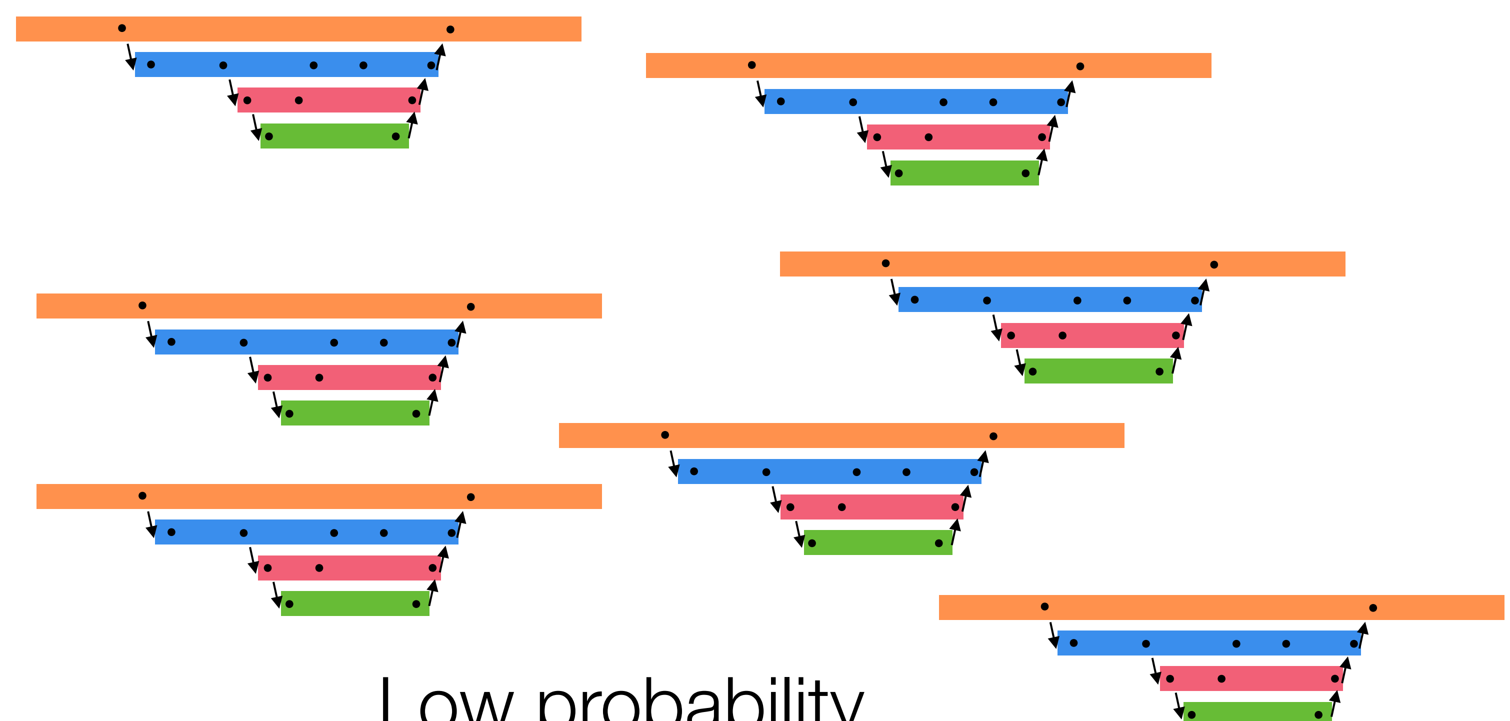
Uncommon cases
Infrequently seen
Interesting





High probability

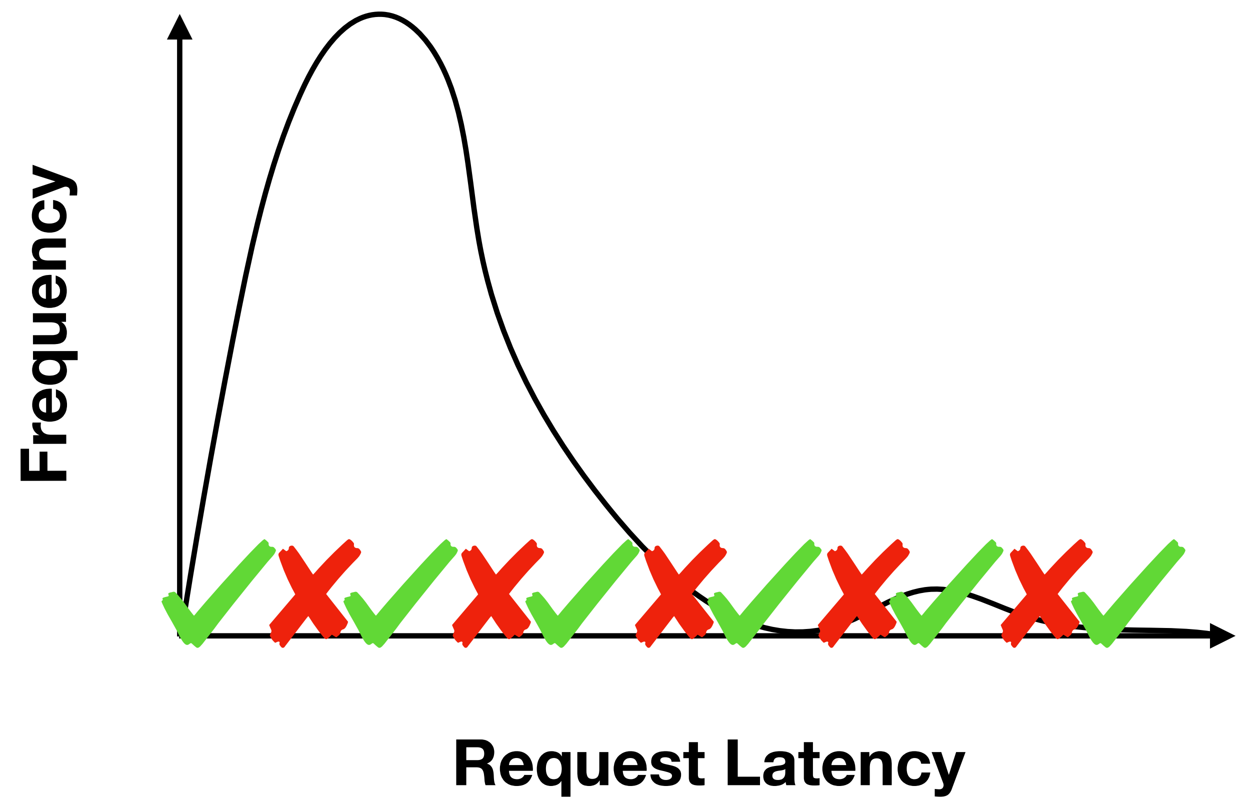
Common-cases
Frequently seen
Not very interesting



Low probability

Biased Sampling

Adjust sampling probability based on how “interesting” trace is



Sample traces across latency distribution

Sifter: a sampler for distributed traces

Part of distributed tracing backends

Biased trace sampling

Use traces to model the system’s behaviors

Low-dimensional probabilistic model forces approximation

Challenges

Operational requirements

Continuous operation over a stream of traces

Low overhead per sampling decision

Large volume of traces

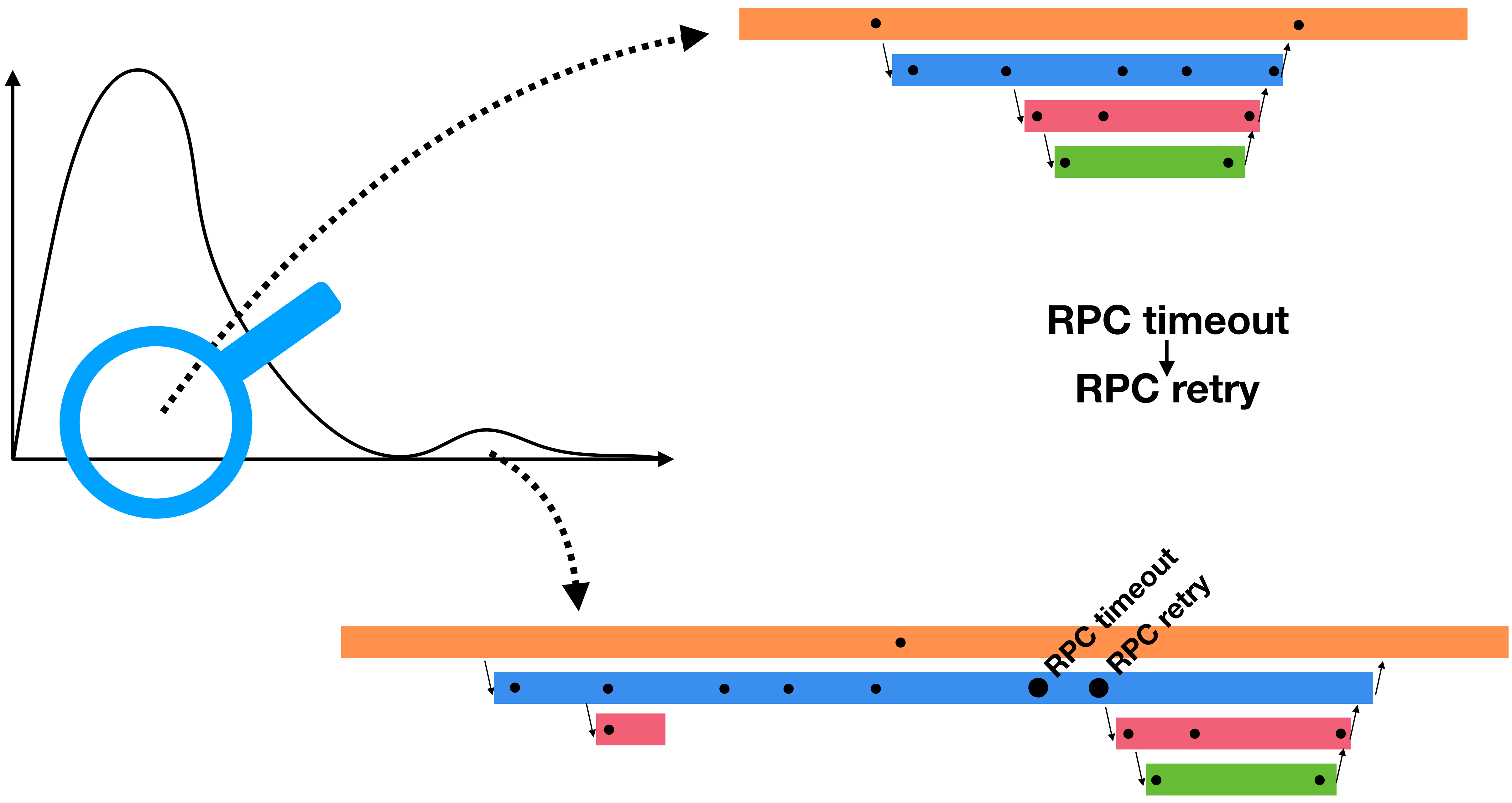
What is an interesting trace?

Lack of standard techniques or metrics

Feature engineering is undesirable

Differences manifest structurally

If two traces are conceptually different
then they will also differ in their
events, spans, timing, and ordering



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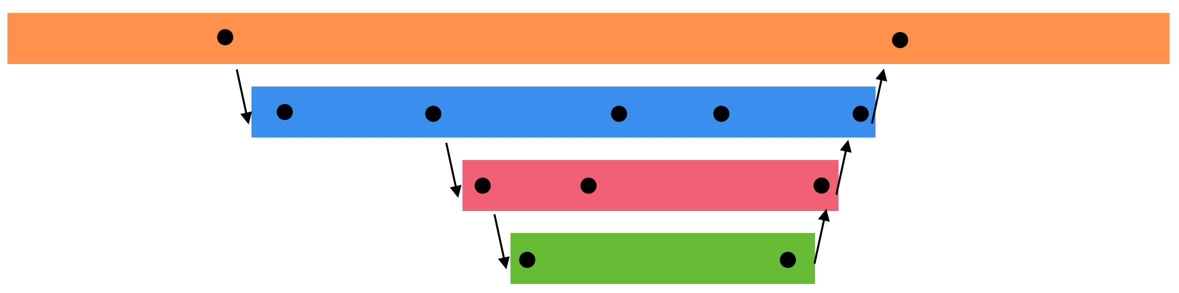
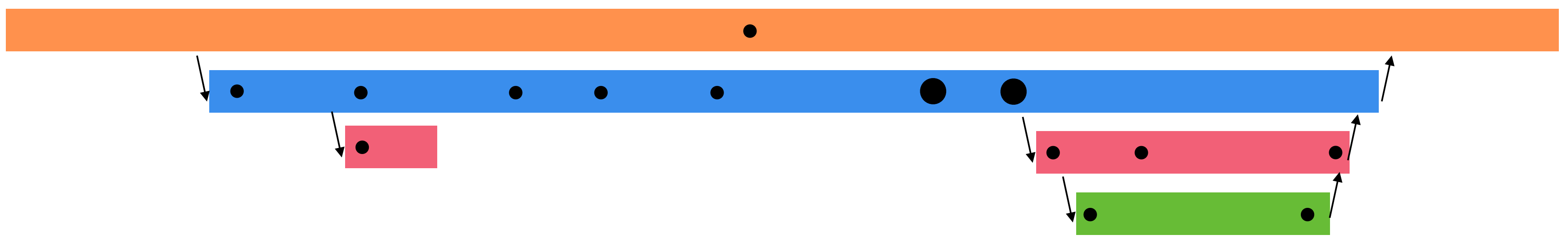
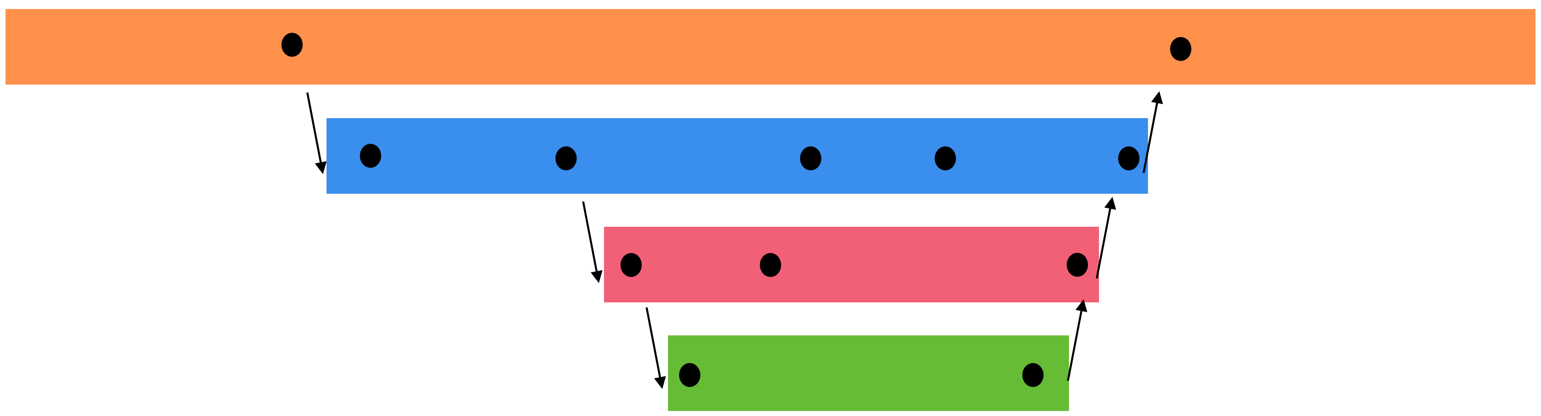


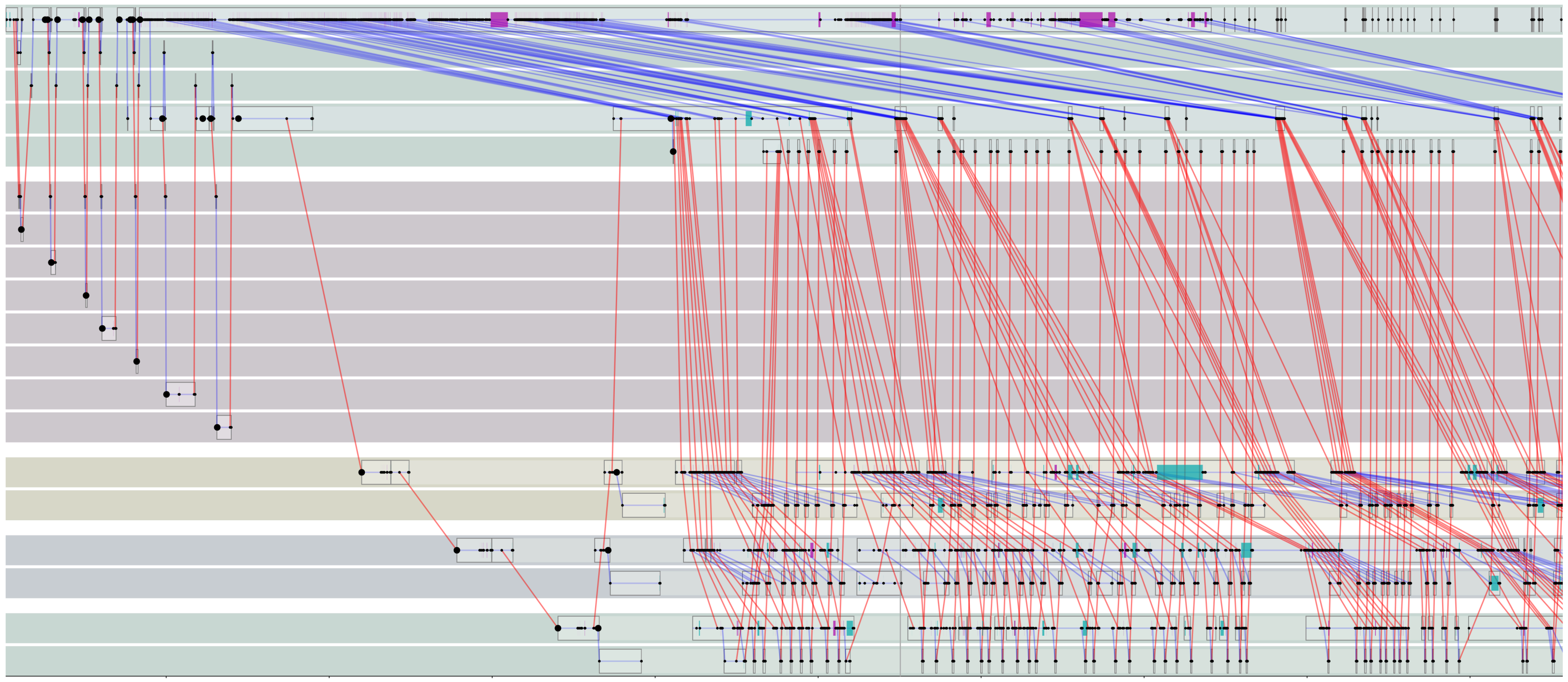
Sifter’s approach:

Unsupervised sampling decisions
Directly on trace data
No pre-defined high-level features



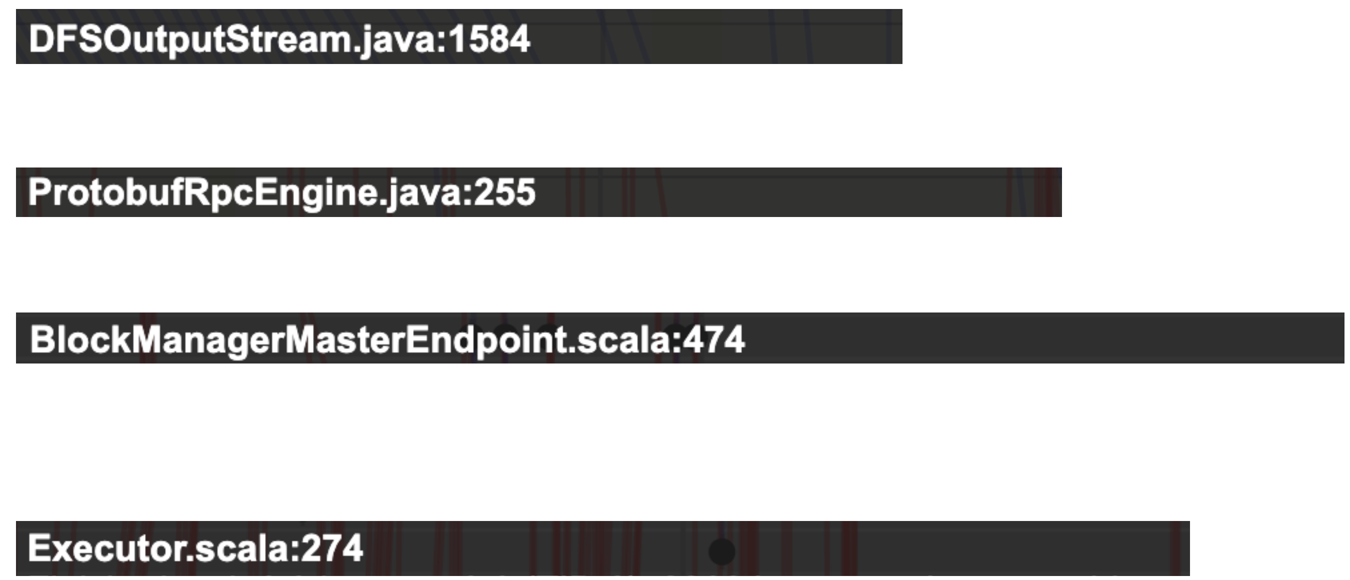
Sifter: Trace Representation

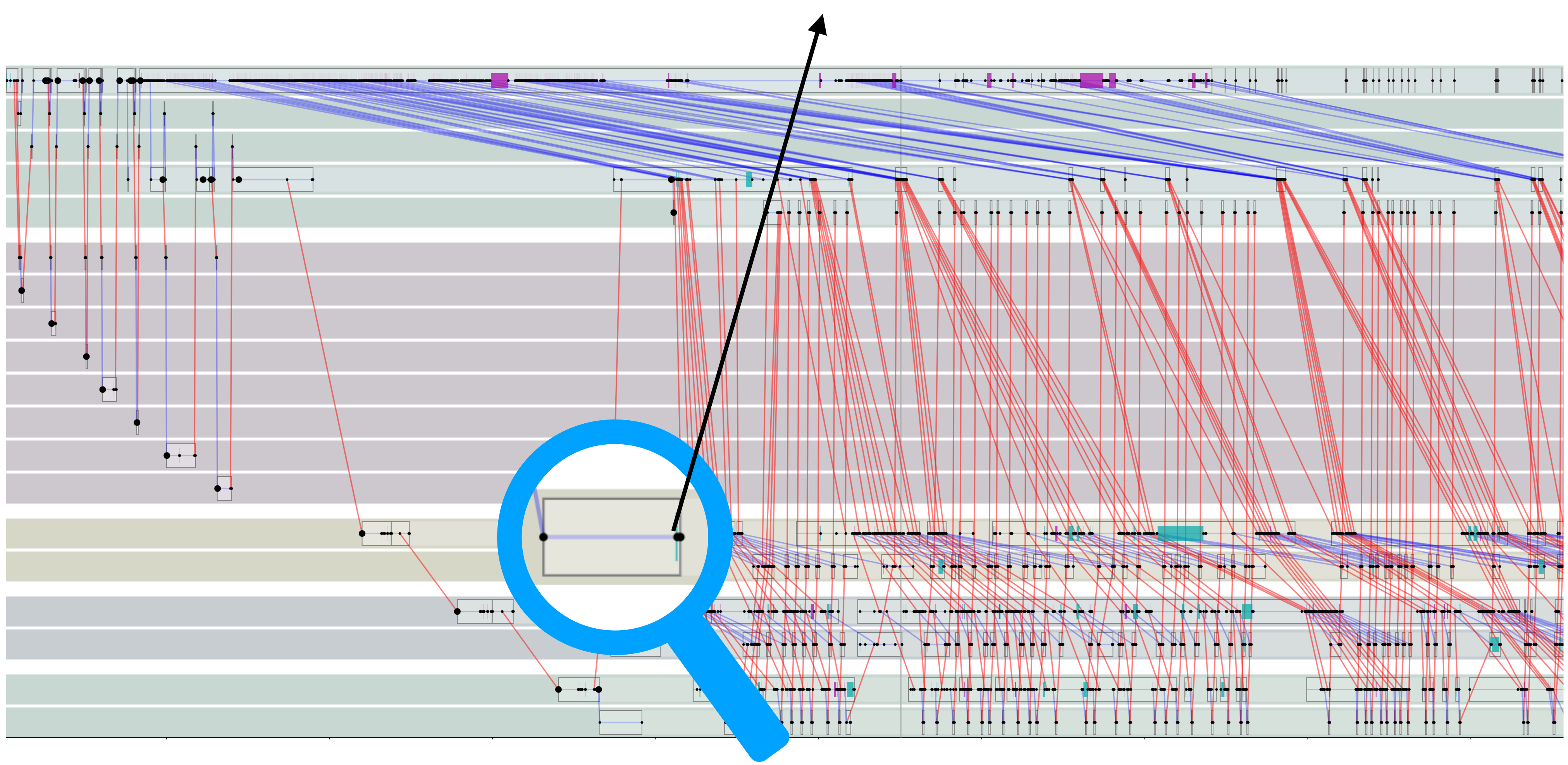




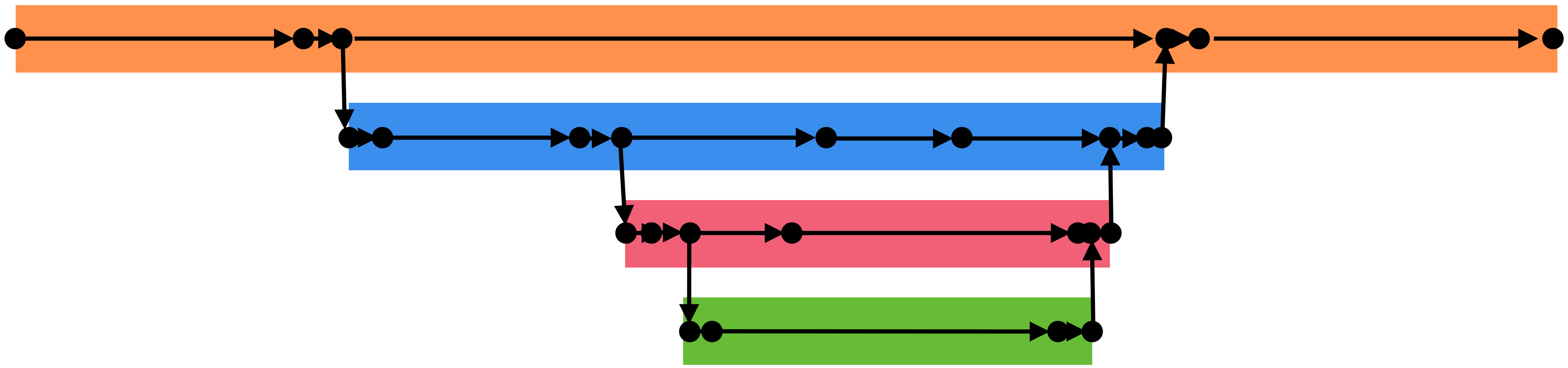
Sifter: Trace Representation

We rely on the system's source code information for the events



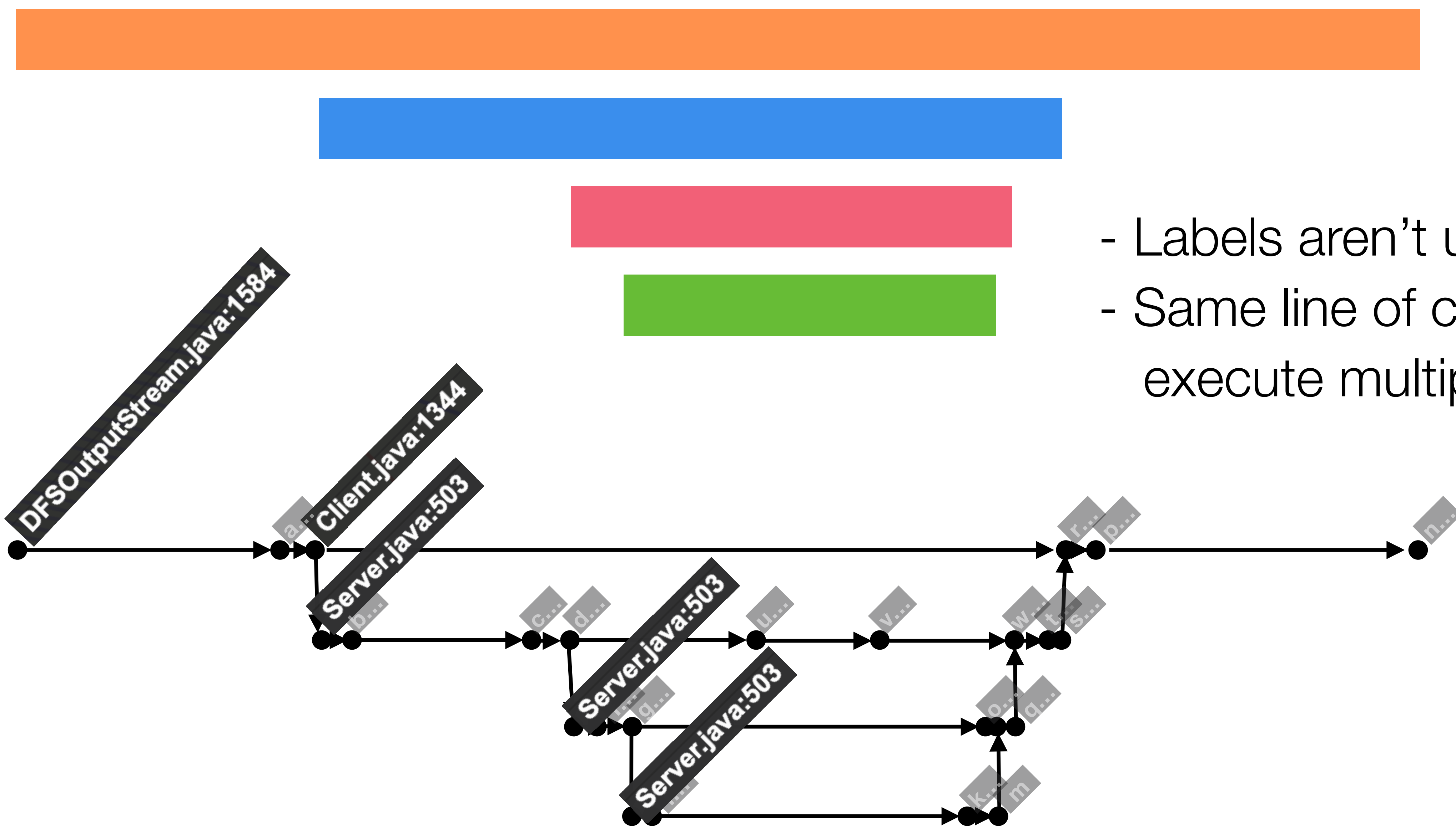


Sifter: Trace Representation



We represent our traces as a directed acyclic graph (DAG), instead of a span

Sifter: Trace Representation



- Labels aren’t unique
- Same line of code can execute multiple times

We represent our traces as a directed acyclic graph (DAG), instead of a span

Sifter: Probabilistic Modeling

Traces are examples

Each trace executes some code paths

The stream of traces tell us path frequencies

Use traces to build a probabilistic model

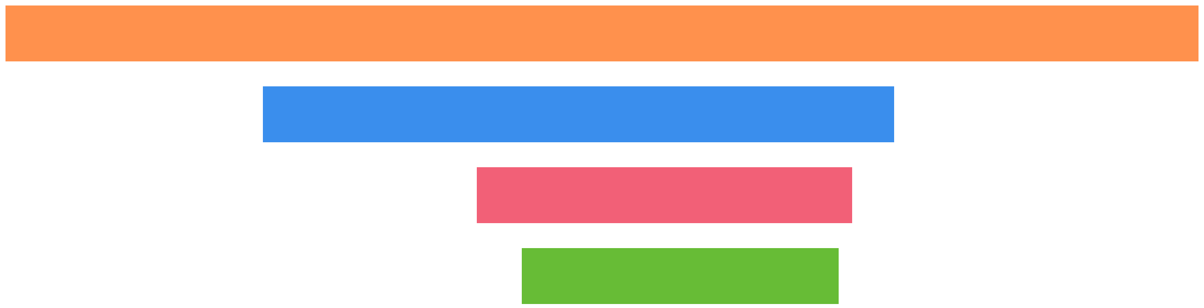
Unbiased model

Sifter sees *all* traces, regardless of sampling decision

Unbiased model can identify outliers to sample

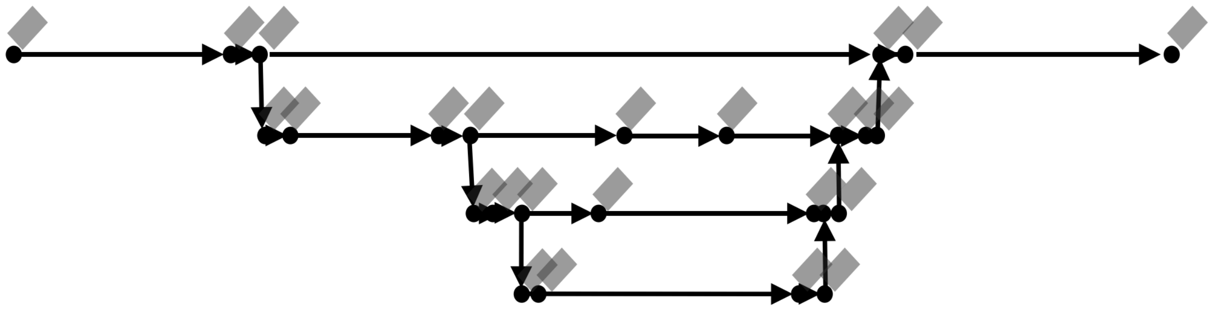
Sifter Workflow

(1)



Receive trace

(2)



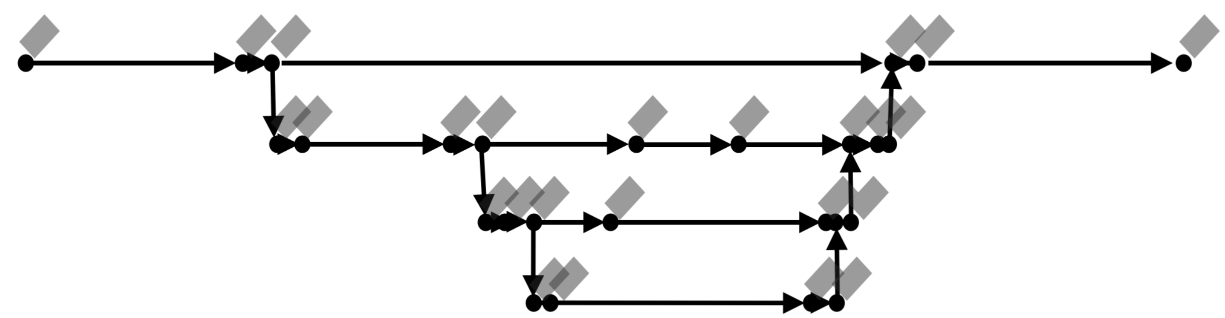
Convert it into a DAG

Sifter Workflow

(1)

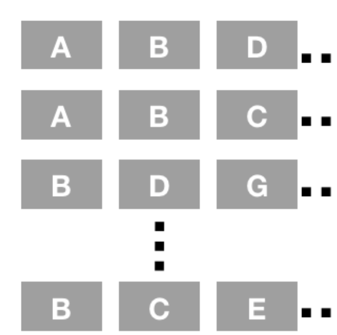
Receive trace

(2)



Convert it into a DAG

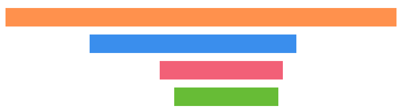
(3)



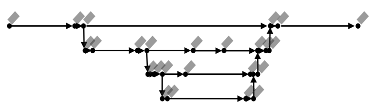
Extract all N-length paths

Sifter Workflow

(1)



(2)



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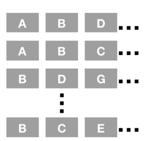
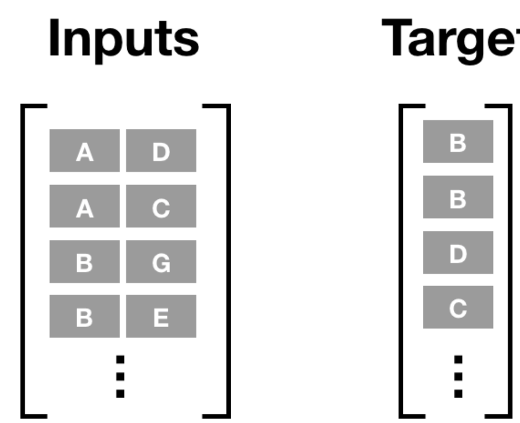
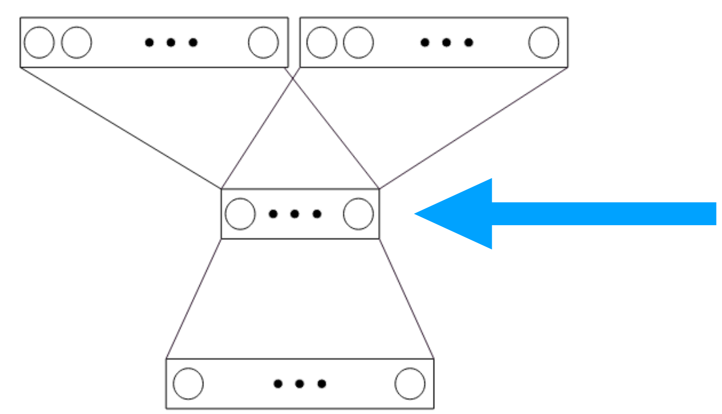


(4)



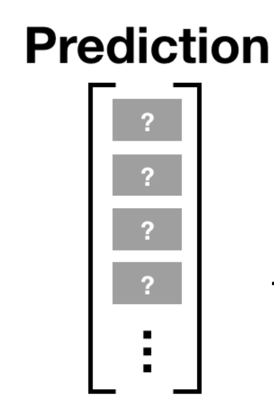
Use paths as input to Sifter's model

(5)



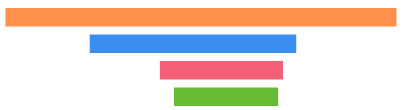
Sifter's internal model

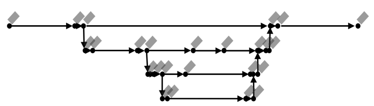
(6)

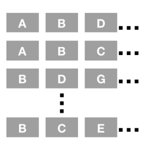


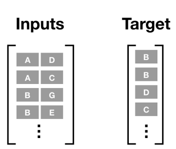
Model outputs a prediction of the middle event in the path

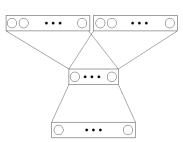
Sifter Workflow

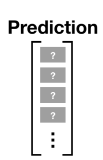
(1) 

(2) 

(3) 

(4) 

(5) 

(6) 

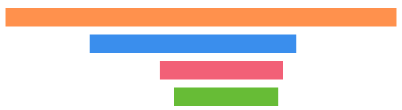
(7) ***Loss***

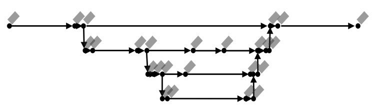
Error between predictions labels and actual labels

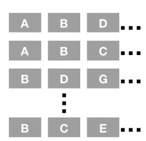
(8) **Backpropagation**

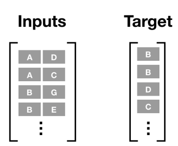
updates model weights
incorporates new trace

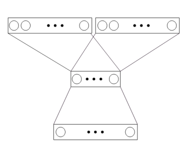
Sifter Workflow

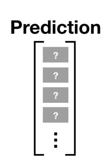
(1) 

(2) 

(3) 

(4) 

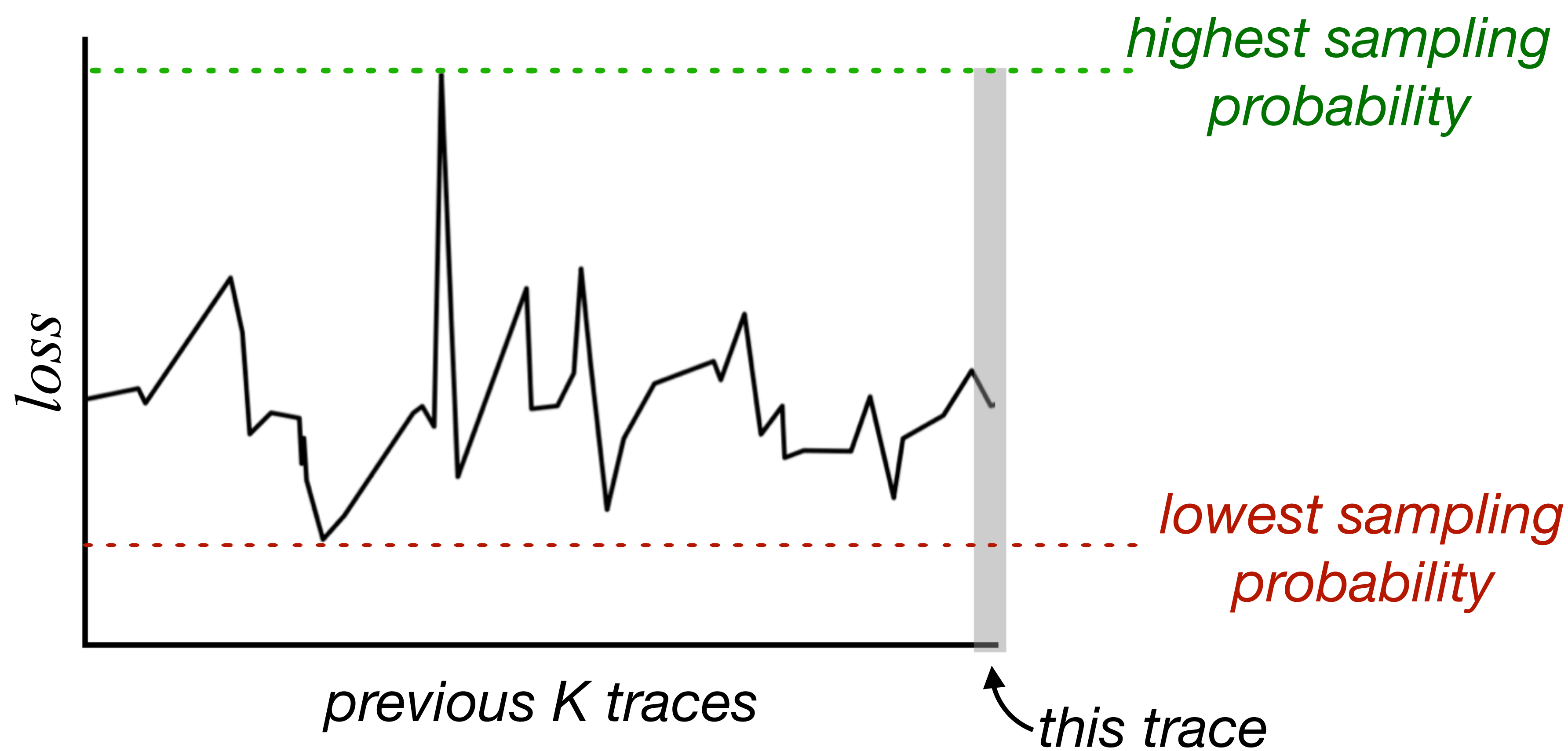
(5) 

(6) 

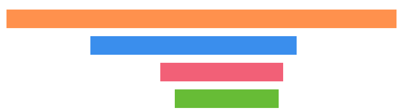
(7) *loss*

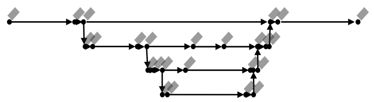
(8) **Backpropagation**

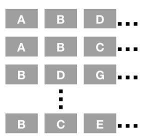
(9) **Sampling probability**

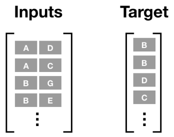


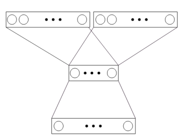
Sifter Workflow

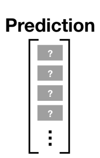
(1) 

(2) 

(3) 

(4) 

(5) 

(6) 

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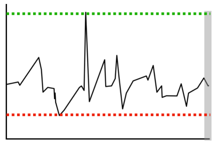
(9) 

Unbiased model

Sifter sees *all* traces, regardless of sampling decision

Every trace updates the model

Unbiased model can identify outliers to sample

No pretraining necessary

Evaluation

Operational requirements

Is Sifter fast?

Does Sifter scale?

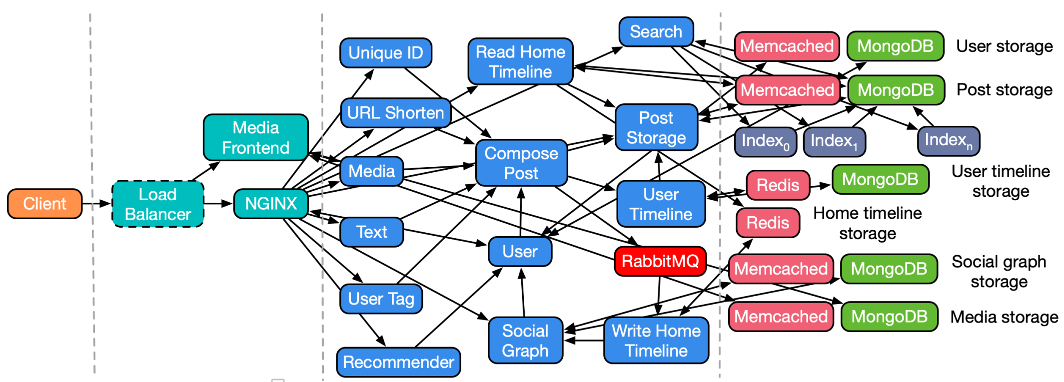
What is an interesting trace?

Do we detect uncommon and outlier traces?

Can we manage imbalanced classes?

Evaluation

Sifter's implementation using Tensorflow



DeathStarBench
social network benchmark

Hadoop Distributed File System

Production traces

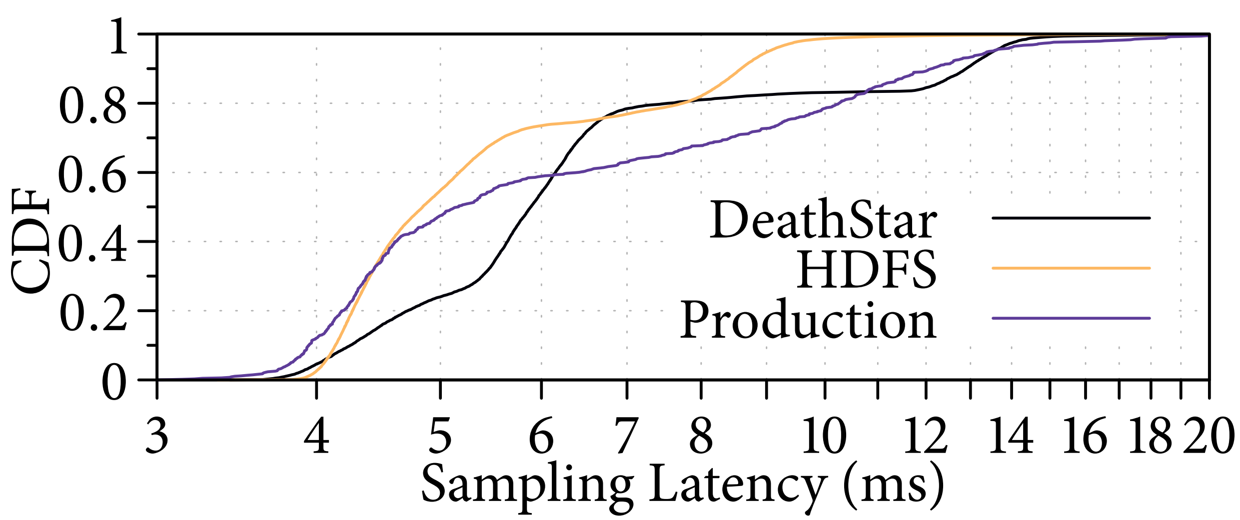
Operational requirements

Is Sifter fast?

Does Sifter scale?

Sifter's internal state is explicitly constrained

Computational cost depends only on:
(1) number of paths in the trace
(2) number of unique labels in the trace



Sampling latencies range from **3 and 20 milliseconds**

(N=5)

Dataset	Avg. Labels	Avg. Walks
HDFS	38	2547
DeathStar	82	155
Production	56	130

Does Sifter detect uncommon and outlier traces?

Replay a stream of traces

Inject traces from unrepresented / underrepresented classes

Known features:

(1) different API types

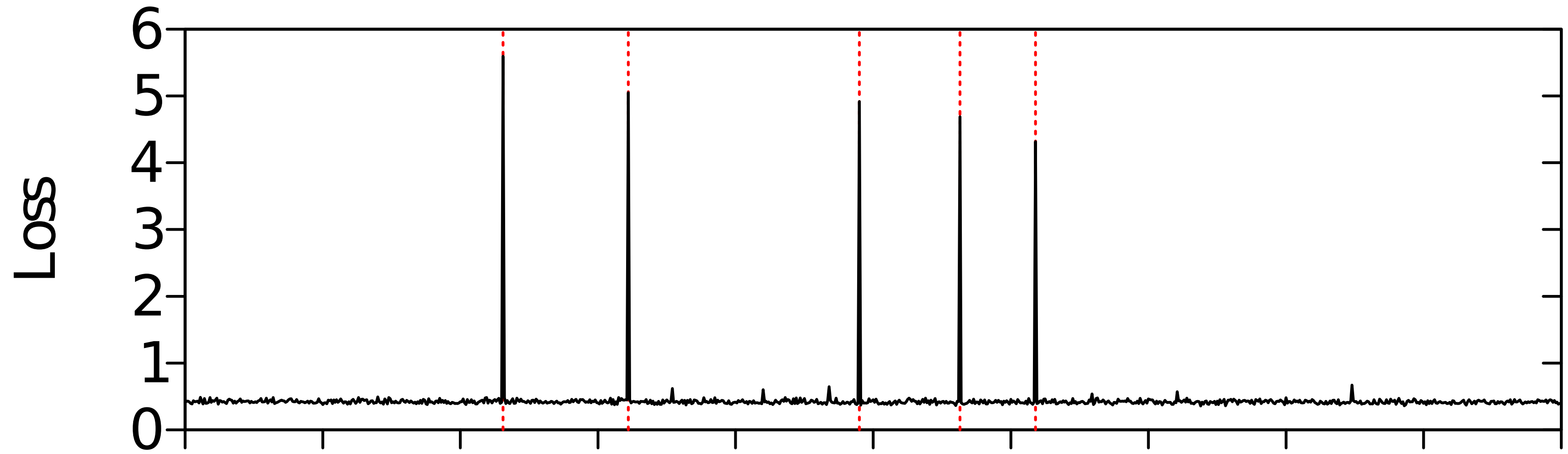
(2) parameters to API calls

(3) known errors / exceptions

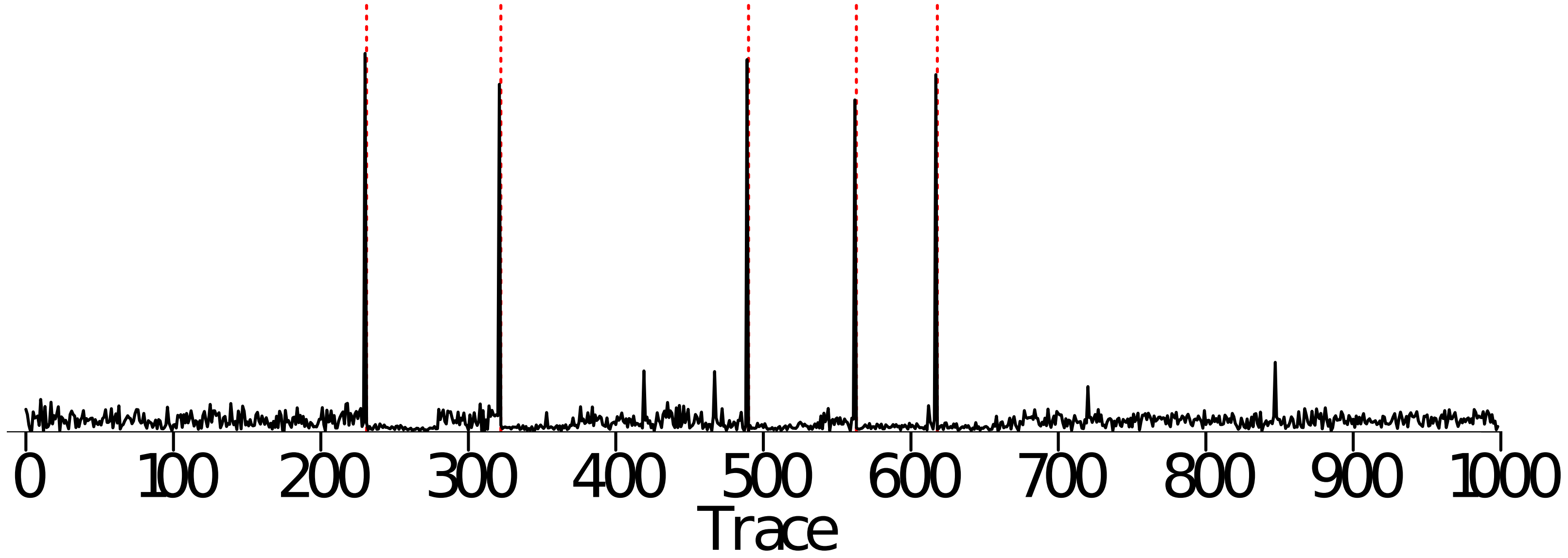
Does Sifter detect uncommon and outlier traces?

995 HDFS read API calls

5 HDFS write API calls

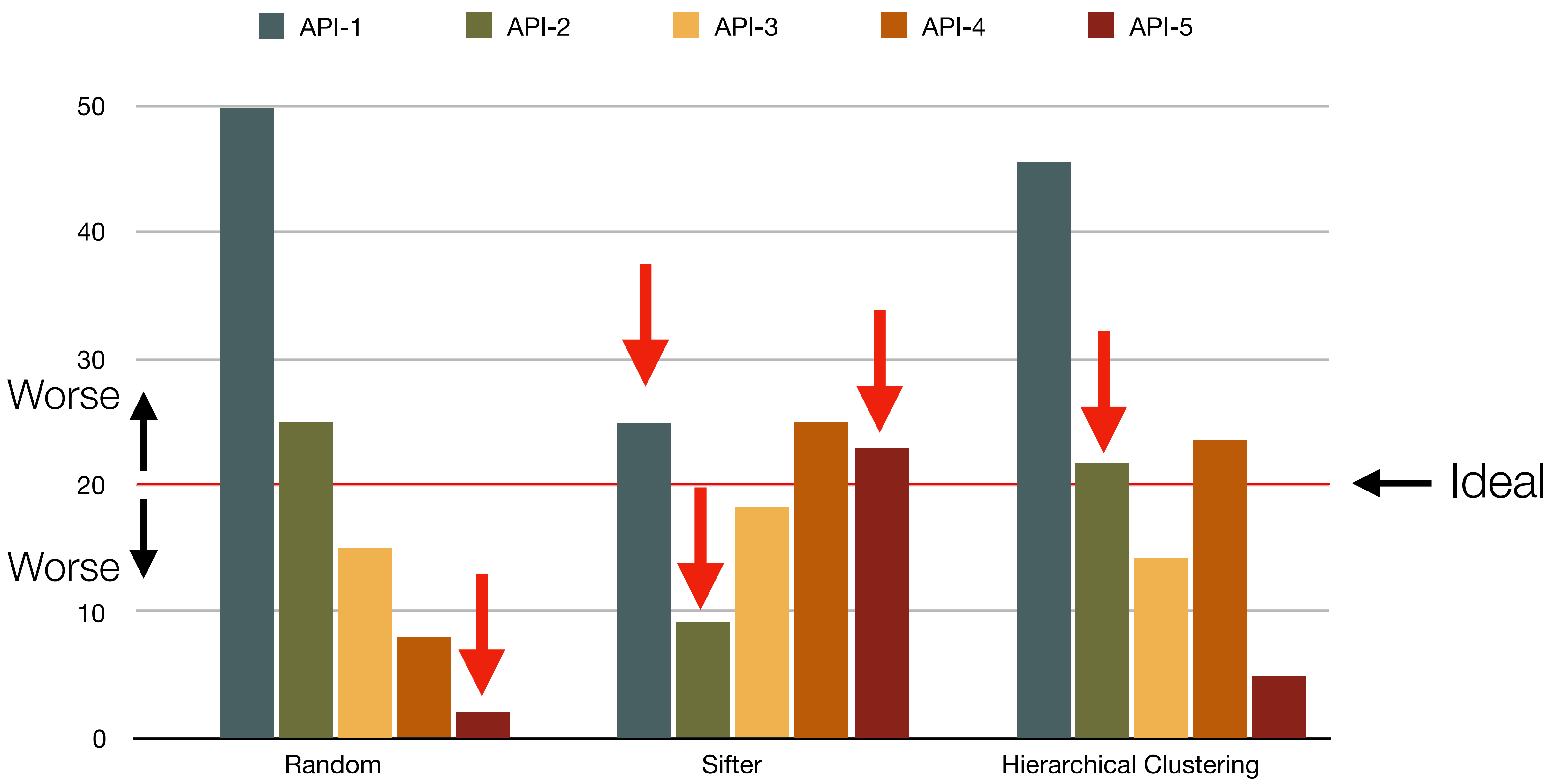


1% sampling rate



How does Sifter manage imbalanced classes?

Production traces - **10,000** traces in **5** different classes



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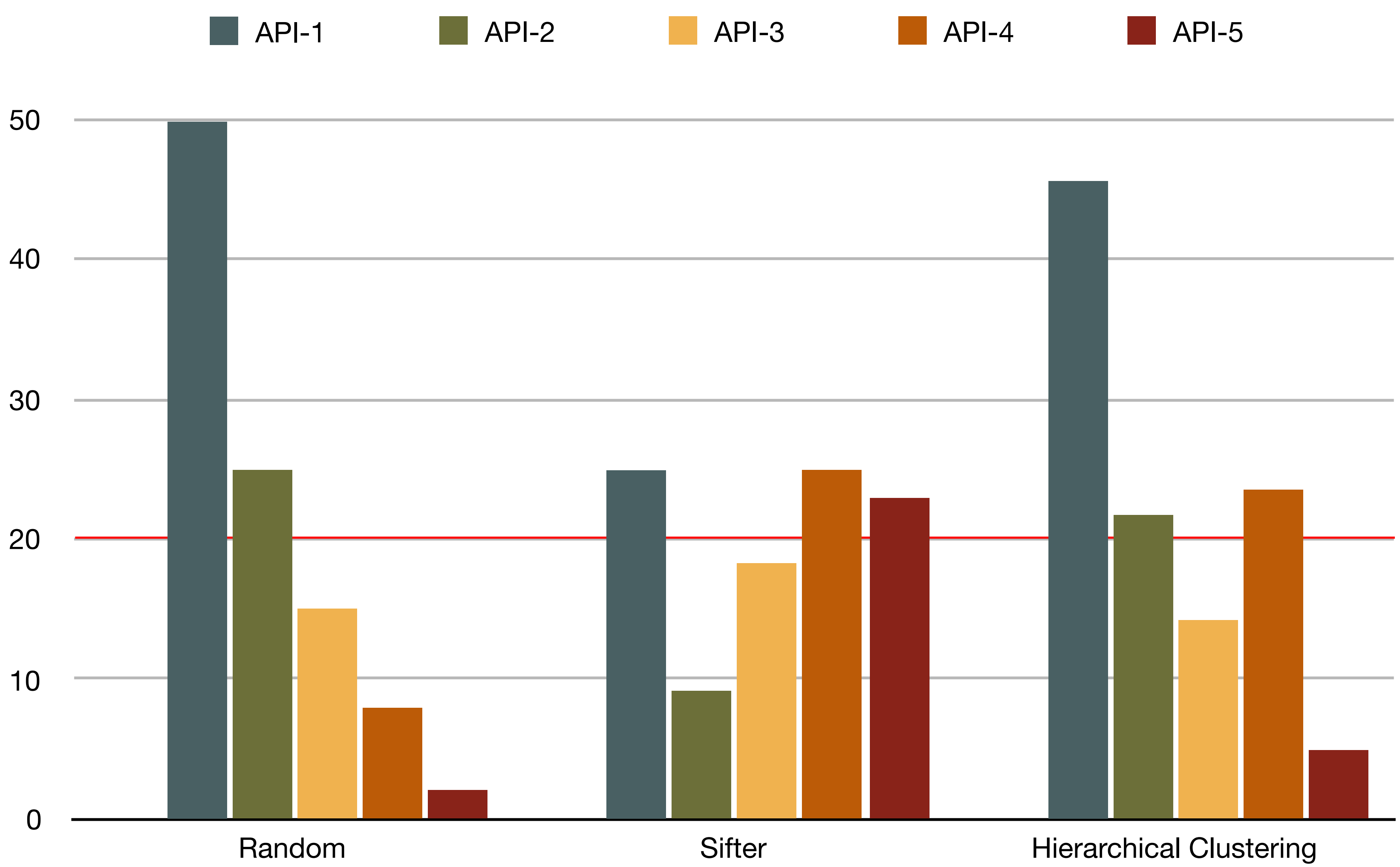

Mean-squared error

Sifter	**35.95**
Hierarchical Clustering	**193.12**
Random	**283.60**

How does Sifter manage imbalanced classes?

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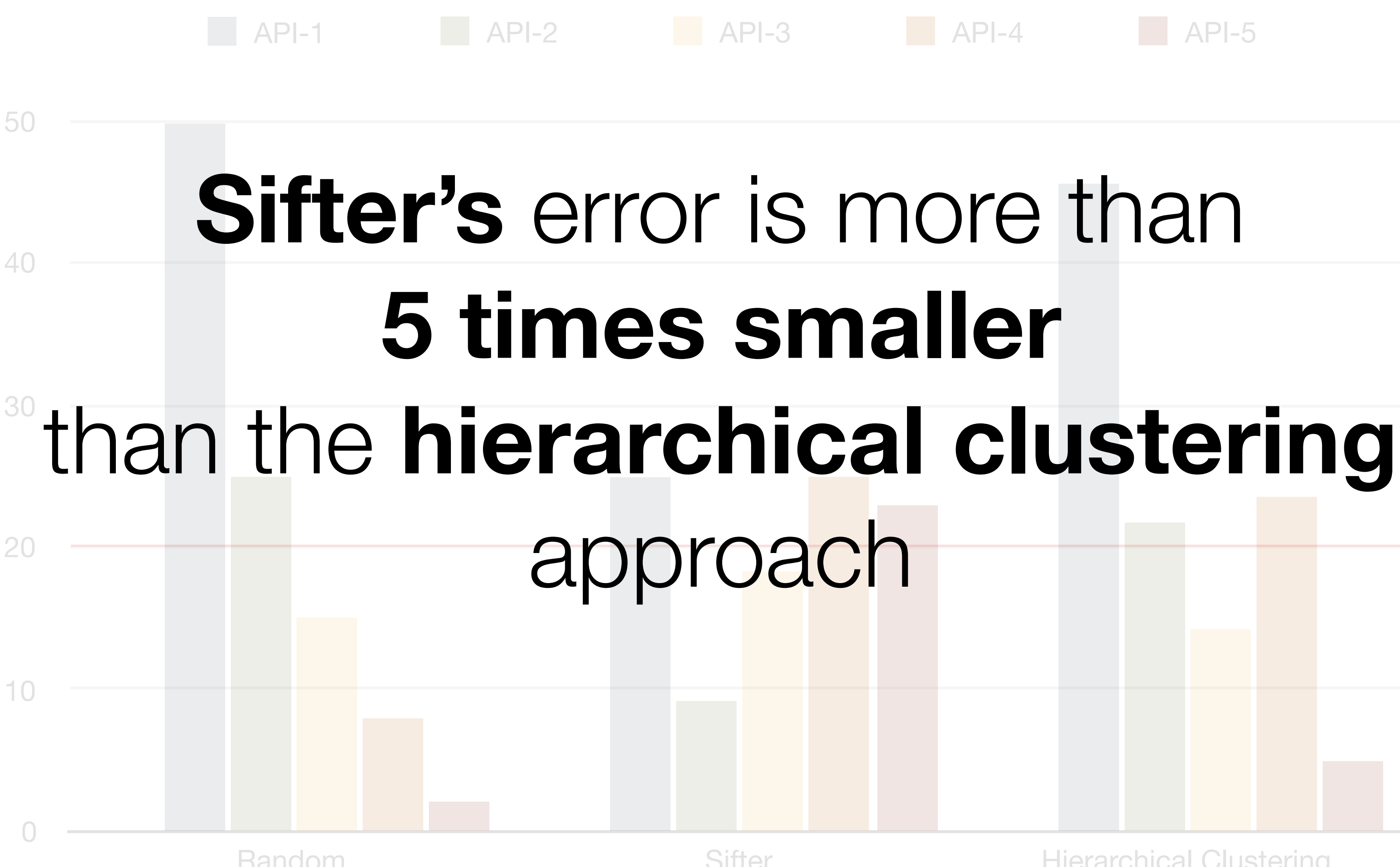
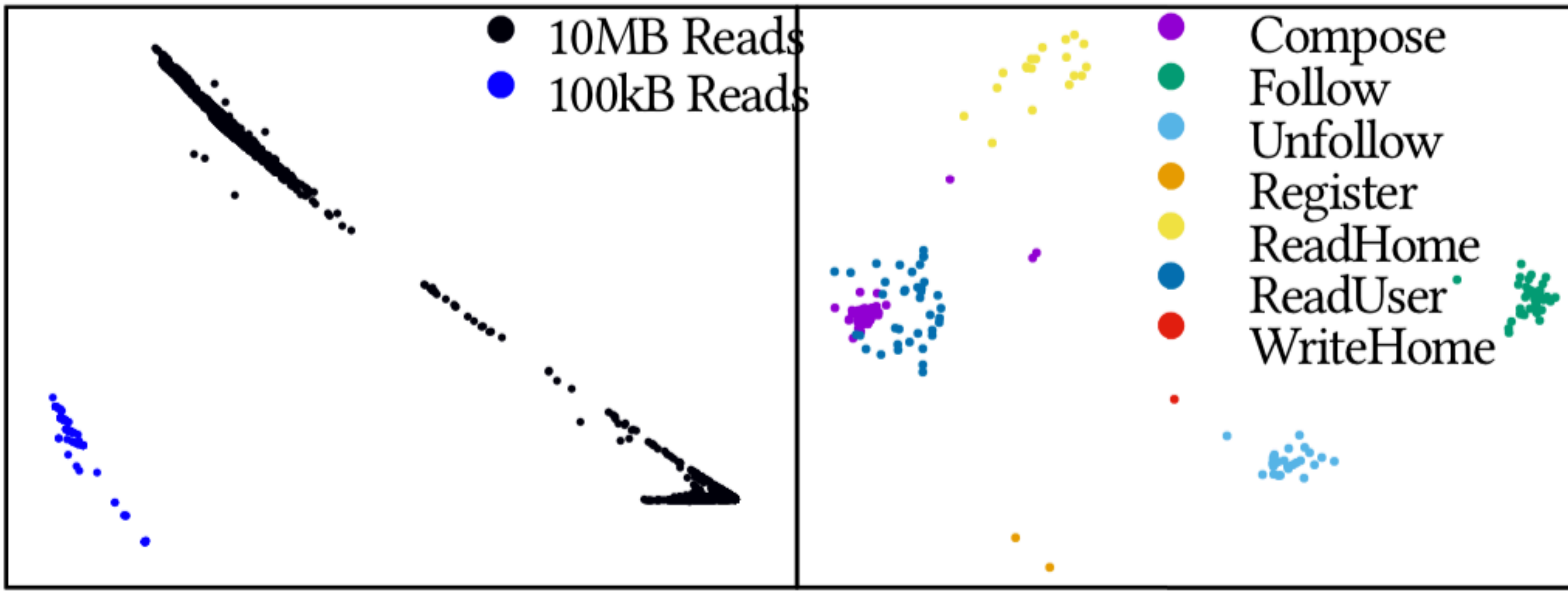


Sifter's error is more than
5 times smaller
than the **hierarchical clustering**
approach

Mean-squared error

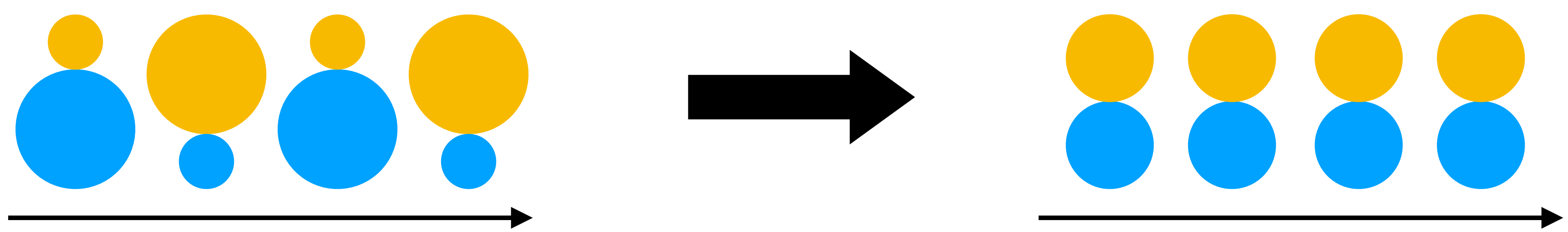
Sifter	**35.95**
Hierarchical Clustering	**193.12**
Random	**283.60**

Side effect: clustering traces



Some other results obtained by Sifter

Adapts over time



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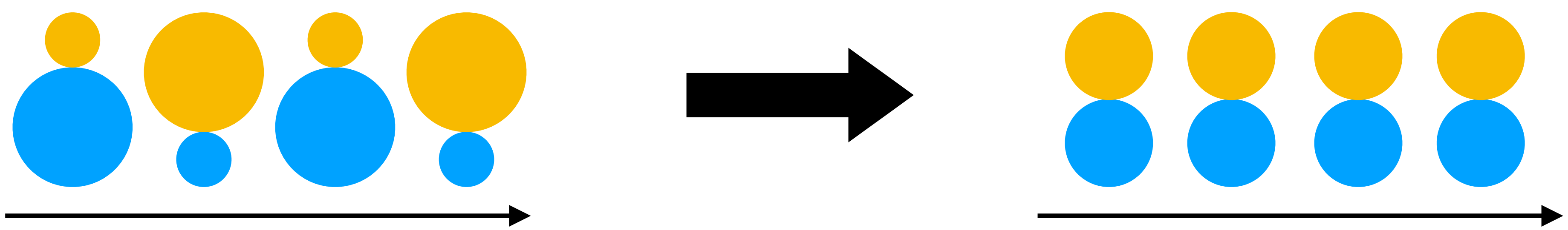
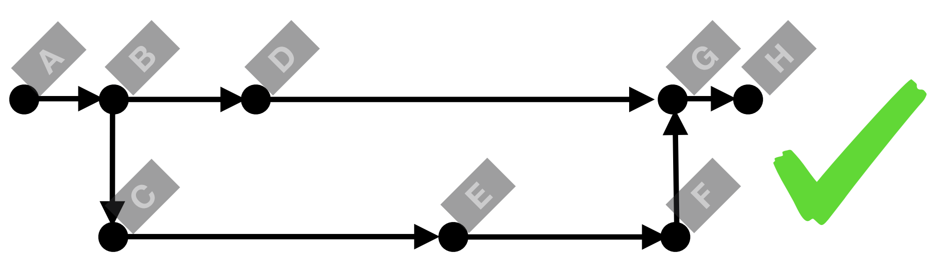
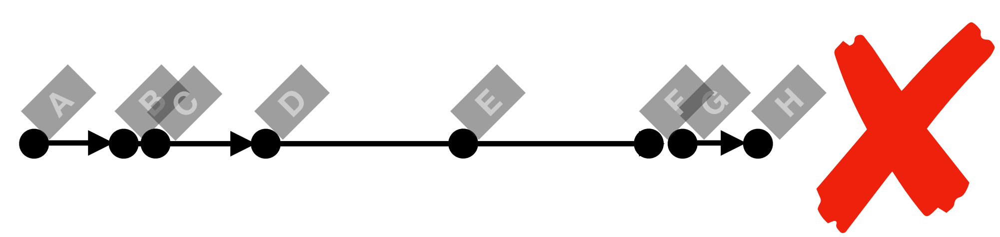


Structure discriminates!





Biased trace sampling

What constitutes an “interesting” trace?

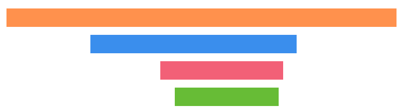
Efficient + Scalable

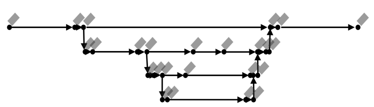
Sifter: a sampler for distributed traces

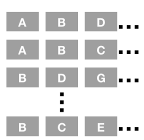
Use traces to model the system’s behaviors

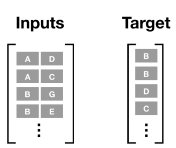
Low-dimensional probabilistic model forces approximation

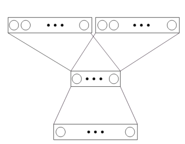
Sifter: Scalable Sampling for Distributed Traces, without Feature Engineering

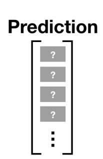
(1) 

(2) 

(3) 

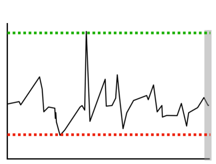
(4) 

(5) 

(6) 

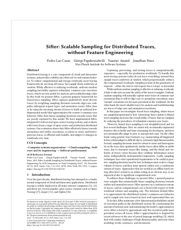
(7) *loss*

(8) **Backpropagation**

(9) 

Thank you!

Questions?



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ACM Symposium on Cloud Computing (SoCC), 2019
Pedro Las-Casas, Giorgi Papakerashvili, Vaastav Anand, Jonathan Mace