## Systemizing and Mitigating Topological Inconsistencies in Alibaba's Microservice Call-graph Dataset

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## **Everything is microservices**

Modern day distributed applications often built with microservices

- Decomposing applications' functionalities into many services that coordinate over well-defined APIs to process requests
- E.g. Google, Meta, Bytedance, Alibaba, etc.



Lots of interest in doing research on microservices



- But, little is known about concrete characteristics of microservice deployments at companies...

## Alibaba released microservice call graph datasets\*

*Call graphs* are trees showing path of request being processed by services Alibaba released two tabular call graph datasets:

- 2021: 12-hour time period, 20 million traces
- 2022: 13-day time period, ~13 billion traces

Datasets are popular:

- 1.5k stars on GitHub, 137 papers cite the original paper
- Comparing microservice architectures [Google SOSP '23], simulating realistic workloads and applications[Mbench] for profiling tail latency [Erms ASPLOS'23], testing QoS recovery mechanisms[Nodens ATC'23], and latency distribution predictions [LatenSeer]



\*https://github.com/alibaba/clusterdata/



### **Errors in the call graph datasets**

- Many missing edges resulting in disconnected trace trees
- Incorrect edge identifiers (*rpcids*) prevent constructing the tree accurately

### Key insight: hidden redundancies in their trace model that give us a starting point for fixing errors



Example call graph





### Key Contributions

- 1. Identify categories of errors in the datasets
- 2. Method to use hidden redundancies in the dataset to recover from errors
- 3. Analysis of changes in the topological characteristics as a result of fixing errors
- 4. Released corrected trace data and code

- Introduction
- Using Alibaba's datasets
- Casper: Remedying errors using redundancies in trace model
- Evaluation
- Implications of errors in trace data

### Outline

### Alibaba's (assumed) data collection

### Example trace



\* focusing on 2021 dataset during this talk



Delimeter between sequential calls





rpcid	UM	DM	rpctype	rt
0	A	В	http	8
0	A	В	http	-7
0.1	B	C	db	0
0.2	B	D	db	0

Example trace

# Build a call graph for a trace \* in an ideal world





rpcid	UM	DM	rpctype	rt
0	A	B	http	8
0	A	В	http	-7
0.1	B	C	mq	0
0.1.1.1	D	E	http	2
0.1.1.1.1	E	F	db	0
0.1.1.1.1	E	G	db	0

Example trace

# Build a call graph for a trace \* in the real world





- 99.5% are missing a duplicate row for two-way communication
- 35.2% are missing all rows for a call

Disconnected graphs likely caused by *data loss* 

30.2% of traces have non-unique rpcids

• Non-unique rpcids are propagated to all calls downstream (rendering them non-unique) Ambiguous edges likely caused by *context* propagation errors (where the rpcid is not updated)



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### **Casper: high-level approach**

**Goal**: build the <u>largest accurate trace topologies</u> • Omit ambiguous edges that remain after error correction

### **Approach**: Breadth-first reconstruction, level-by level from the table

- At each level look for *data loss* or *CPEs* & correct inconsistencies
  - call graph

Data loss: easy, add missing upstream rpcids until connects to existing

• CPE: complicated, use redundancies in the table to differentiate calls



Legend Captured rpcid **Recovered rpcid** A. .... Unrecoverable rpcid Microservice **Recovered calls** Unrecoverable calls





### **Recovery at source of CPE: # of unique calls**



- True number of calls is unknown (due to data loss), but can find the <u>minimum</u>
- rt values are rounded down, anything below a threshold is rounded to 0
- -rt rows cannot be paired with 0 rt rows

rpcid	UM	DM	rpctype	rt	
0.3.1	В	C	http	2 —	
0.3.1	В	C	http	0 —	
0.3.1	В	C	http	0 -	
0.3.1	В	C	http	0 -	
0.3.1	В	D	mq	0	

Calculating the number of calls to a DM

1) Number of fast calls (0 rt):  $\int \frac{(1)}{10} dt$ 

$$rt ==$$

- 2) Extra fast row: (rt == 0)%2
- 3) Number of slow calls: max(+rt,abs(-rt+extra\_fast\_row))

Total number of calls: fast + slow calls





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### Additional complete traces are different from original complete traces Casper increases the number of *complete* traces from 58% to 84%



### Additional 26% of traces are larger, wider, and deeper than original set of complete traces



### Methods of building traces

rpcid	UM	DM	rpctype	rt
0.1	A	B	http	+/-
0.1.1.1	C	D	http	+/-
0.1.1.1	C	E	db	+

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Naive-rpcid[Alibaba]: using assumptions provided in paper Naive-accurate: only preserve traces that meet all assumptions



Partial [LatenSeer]: keep portions of trace that meet assumptions, remove anything downstream from an inconsistency



### Casper traces are larger, deeper, and wider than other methods





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### **Implications & future work**





from errors



Proper context propagation is essential for observability in distributed systems

- Users of Alibaba's call graph data should be aware of the data quality issues and the impact they can have on research
  - Redundancies in trace models can be powerful for recovering

### **Casper Summary**

- Classify inconsistencies in Alibaba's call graph dataset
- Present Casper: a tool that uses redundancies in Alibaba's trace model to fix errors
- Showed Casper traces are larger and wider than other rebuild methods
- Released corrected traces and Casper's code

Dataverse https://github.com/ https://doi.org/ 10.7910/DVN/SS9SIY docc-lab/casper



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