

CRISP: Critical Path Analysis of Large-Scale Microservice Architectures

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What is microservice architecture?

- Distributed system
- Independent business logic -> independent programs
- Communicate over well-defined APIs
- Loosely coupled
- Owned by small, self-contained team



Why microservices?

- Scalable development
- Independent development
- Easier deployment
- 71% organizations adopted microservices in 2021

Microservice Challenges: Complexity

- Evolution of microservices often leads to complex interactions
- Extremely complicated to analyze
- Deeply nested
- Asynchronous
- Tens of thousands of endpoints interact with each other



Distributed tracing

- Jaeger: System for capturing RPC caller-callee relationships among services
- Widely deployed at Uber
- Supports multiple languages: Go, Java, Python...
- Collect trace on sampling basis
- Retains in different storage systems
 - Cassandra, Elasticsearch, memory

https://www.jaegertracing.io/

How to **<u>pinpoint</u>** and **<u>quantify</u>** the root cause of end-to-end latency of a request?



Gives example visualize



Our solution

Critical Path Analysis (CPA) on distributed traces

It supports:

- Top-down: service owner debuggings and optimizations
- Bottom-up: systemic analysis and optimizations
- Anomaly detection: for building automatic alerting system

Outline

- Intro
- What is Critical Path Analysis
- Challenges applying CPA in real data center
- CRISP design
- Top-down analysis
- Bottom-up analysis
- Anomaly detection

Critical Path Analysis (CPA)

- Technique to identify longest stretch of dependent tasks
- End-to-end latency = length (CP)
- \downarrow length (CP) $\Rightarrow \downarrow$ end-to-end latency
- Naturally <u>simplifies</u> the complex dependency graph from distributed tracing
- How to compute: iterate backwards and recursively

CPA example



Challenges applying CPA on real-world traces

- "sync" (last arriver) are NOT designated events in Jaeger traces
 - "Sync" needs to be inferred via timestamp
- Machine clocks are not synchronized
- Missing spans

Critical Path on Perfect Traces



Critical Path on Real Traces



0

1000

0

T(1st end) - T(2nd start) in µs

Solution: allow some degree of overlap between child endpoints

Design of CRISP (Critical path and Span)

Jaeger traces



Top-Down Analysis



Differential Analysis

Root cause the tail latency by diffing P50 vs. P95

Recommend developer to cache the result instead of query database

[dosa-gateway] cassandraRead	1200	
[dosa-gateway] Dosa::read	T20	[fulfillent] google.spanner.v1.Sp [fulfillment] google.spann
[courier-task-platform] Dosa::read		[fulfillment] uber.marketplace.fulfill [fulfillment] uber.marketpla
[courier-task-platform] repository.dosa.get_task_completion_status		[fulfillment-compatible] uber.marketp [fulfillment-compatible] ube
[courier-task-platform] controller.couriertaskplatform.get_task_completion_status	[[fulfillment-compatible] GET:/supply/{uuid}
[courier-task-platform] handler.couriertaskplatformthrift.get_task_completion_status	[o	[mp-proxy] GET:fulfillment-http
[courier-task-platform] CourierTaskPlatform::getTaskCompletionStatus	[order	[mp-proxy] relay::mpx-prod-9
[driver-presentation] CourierTaskPlatform::getTaskCompletionStatus	[driver [d	[driver-presentation] supply.ReadSupply(Supply::readSupply)
[driver-presentation] DriverTasks::getDriverTasks		

Bottom-Up Analysis



Almost 10X difference!

Anomaly detection

- Important to detect anomaly to debug
- Auto-encoder decoder (Liu et al. ISSRE 2020)
- Use critical path as the training data instead of full graph
- Run on numerous real important services from Uber
 - 200~1500 unique endpoints on each service
 - 1500~11000 spans in the trace

Recall Improvement

recall Liu et al. (SOTA) CRISP service 1 0.986 0.98 service 2 0.958 0.98 service 3 0.5 0.98 service 4 0.928 0.93 service 5 0.5 0.98 service 6 0.912 0.912						
Liu et al. (SOTA) CRISP service 1 0.986 0.98 service 2 0.958 0.98 service 3 0.5 0.98 service 4 0.928 0.97 service 5 0.5 0.98 service 6 0.912 0.912		r	recall			
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service 3 0.5 0.98 service 4 0.928 0.97 service 5 0.5 0.98 service 6 0.912 0.97	service 2		0.958	0.984		
service 4 0.928 0.97 service 5 0.5 0.92 service 6 0.912 0.912	service 3		0.5	0.982		
service 5 0.5 0.98 service 6 0.912 0.912	service 4		0.928	0.978		
service 6 0.912 0.9 ⁻	service 5		0.5	0.982		
	service 6		0.912	0.977		

Training and Inferencing Speedup



Conclusion

- CRISP: critical path to analyze complex microservice traces
- Top-down for service-level insights
- Bottom-up for system-wide insights
- Anomaly detection to aid alerting systems

Available at: https://github.com/uber-research/CRISP

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Thanks!

Questions?