# Visualizing Distributed Traces in Aggregate

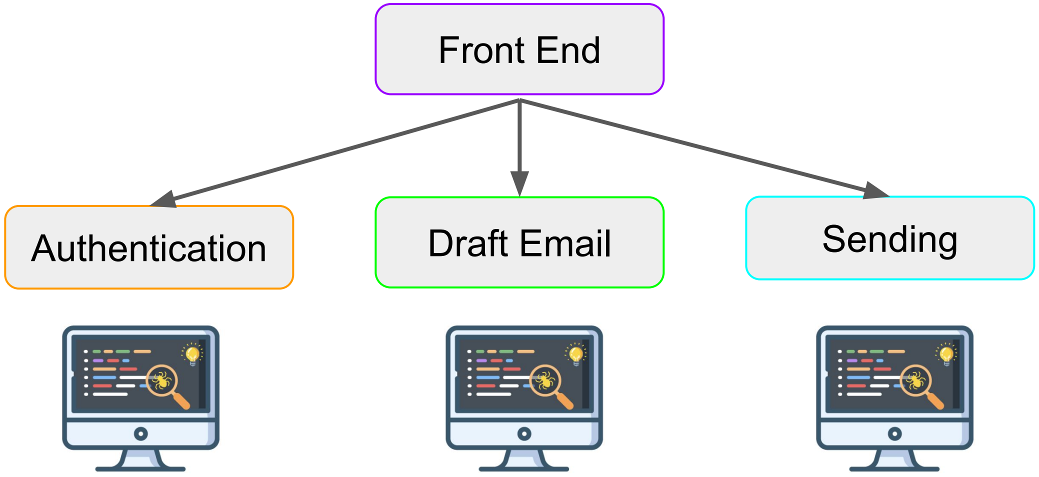
Adrita Samanta and Henry Han

Mentors: Darby Huye, Zhaoqi (Roy) Zhang, Lan (Max) Liu, Prof. Raja Sambasivan

# What are Distributed Systems?

Distributed systems are environments where multiple computers work on numerous tasks within a network.

Email example:

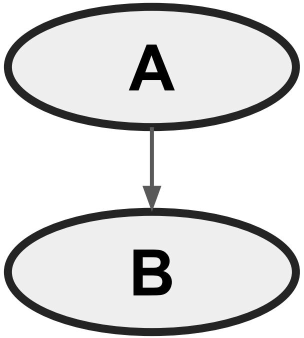


# What is Distributed Tracing?

Tracing is a method of looking into requests in distributed environments.

Each request – any task performed by the system – offers visibility into interactions between services. (Latency, errors, etc.)

Caller/Callee



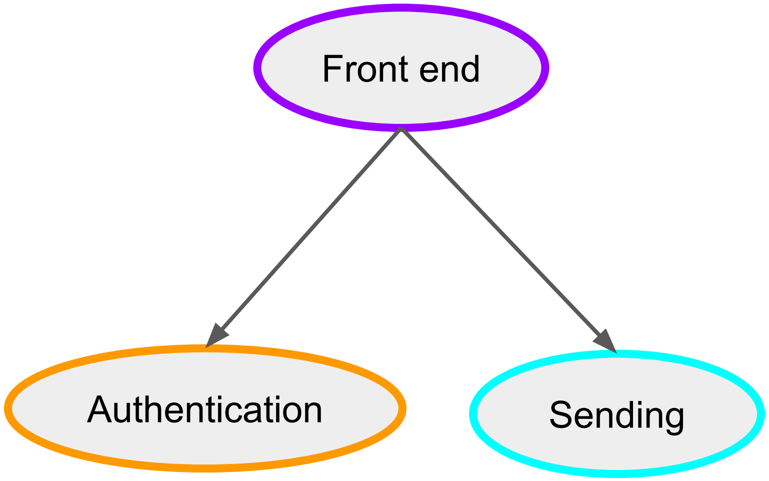
# What is Distributed Tracing?

Tracing is a method of looking into requests in distributed environments.

Each request – any task performed by the system – offers visibility into interactions between services. (Latency, errors, etc.)

Let’s say you sent an email to a coworker:

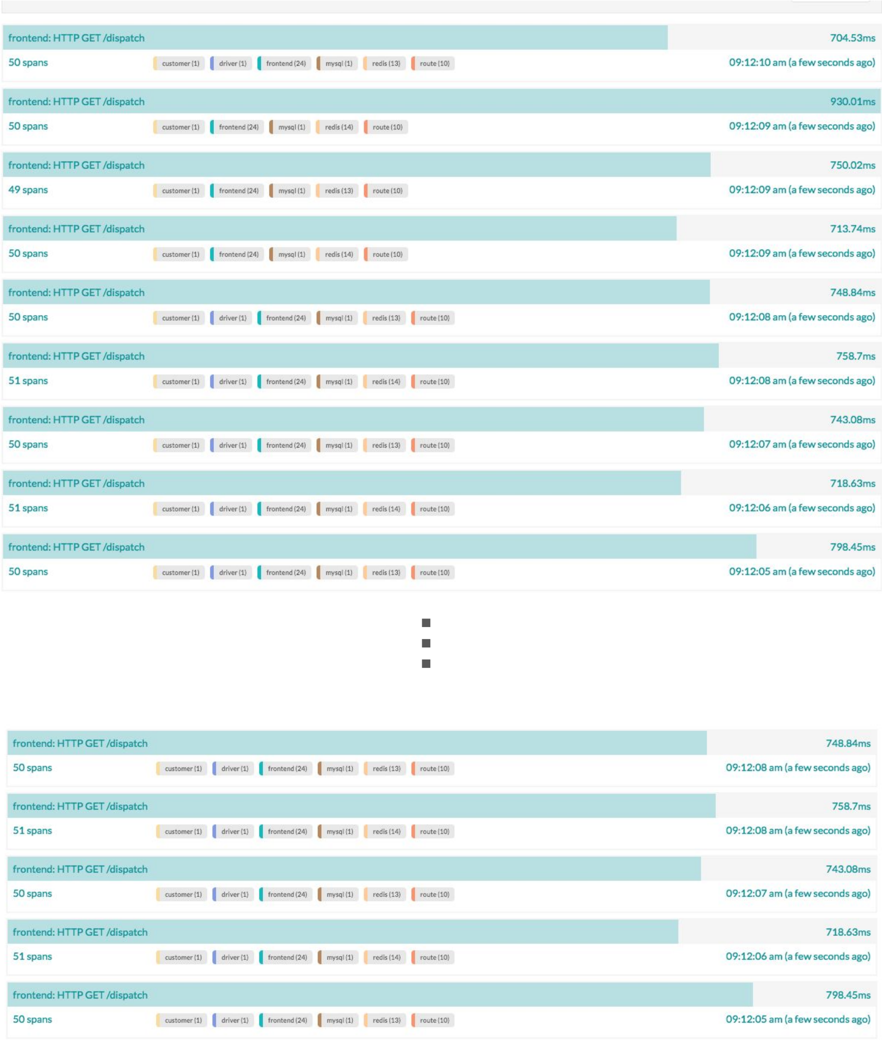
Send email trace:



# Current Issues with Tracing

Developers have a hard time understanding an entire trace dataset.

- Applications like Jaeger allow visualization of one or two traces at a time
- There can be millions of traces/services to look into



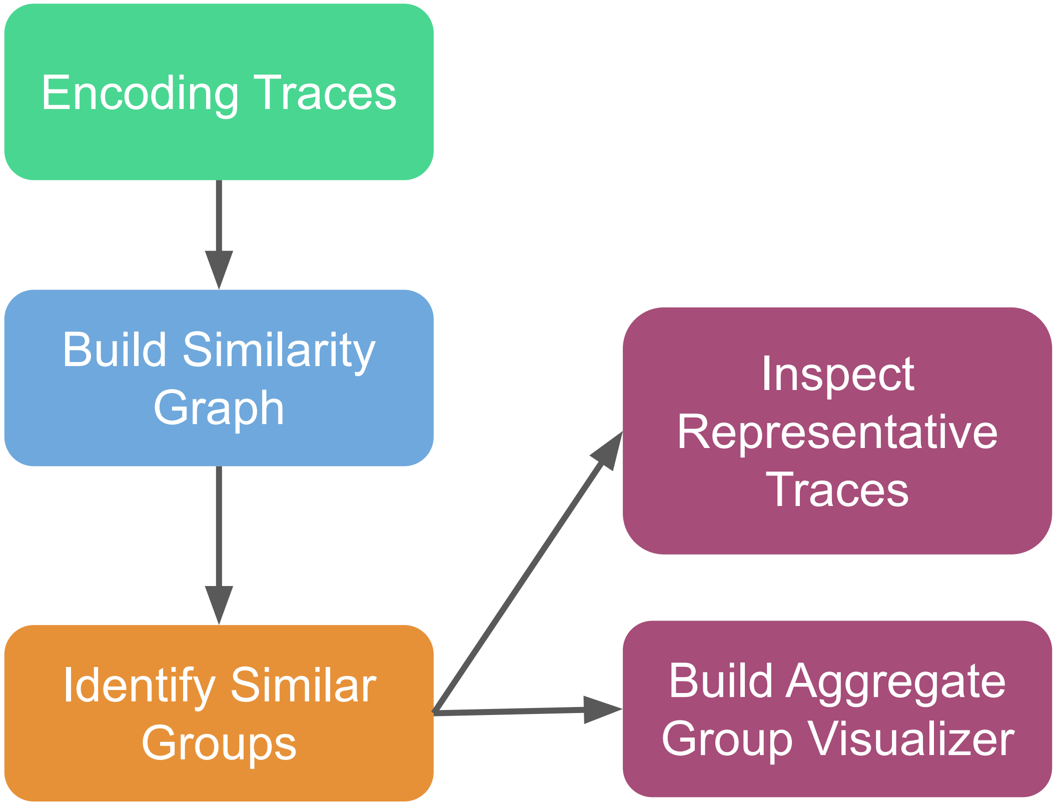
# Dealing with Millions of Traces

- Debugging and optimization becomes harder for developers without an understanding of the whole trace dataset.

- Software companies can generate millions of traces daily so, combing through all traces can be inefficient. But, often these traces can be similar [1].

- Group together similar traces → reduce traces needed to understand overall system

# Design



Encoding Traces
Build Similarity Graph
Identify Similar Groups
Inspect Representative Traces
Build Aggregate Group Visualizer

# Encoding Traces

1. Service names - for high level understand of system

2. Full trace topology - for details of services and their requests

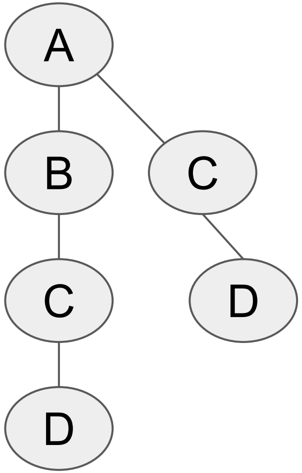
3. Latency - for optimizing applications

# Defining Trace Similarity

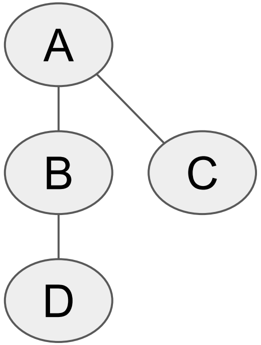
Keep track of service names in the trace.

Similar set of service names → traces are similar

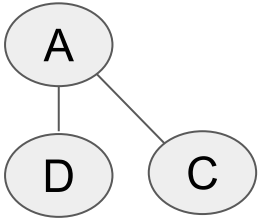
Trace 1




Trace 2




Trace 3




Set of service names:

- Trace 1: {A, B, C, D}
- Trace 2: {A, B, C, D}
- Trace 3: {A, C, D}

# Measuring Similarity Between Traces

Jaccardian Similarity:

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

For two traces (trace_a and trace_b):

- A = set of service names in trace_a, B = set of service names in trace_b
- Threshold = 0.8 (min value of J(A, B) to consider A and B similar)

- J(A, B) > threshold → similar set of service names → traces are similar

# Build Trace Similarity Graph

Trace 1

{A, B, C, D}

Trace 2

{A, B, C, D}

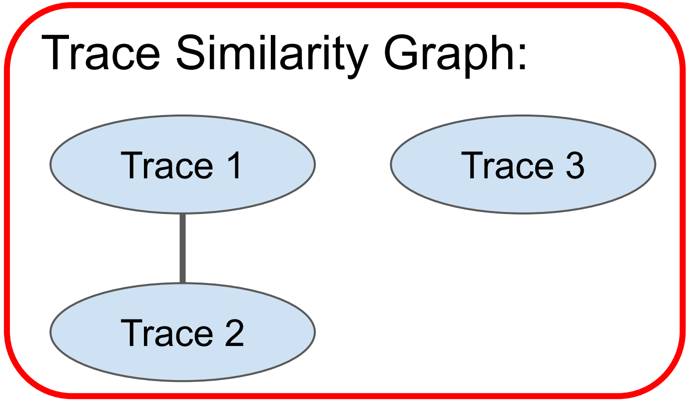
Trace 3

{A, C, D}

J(trace1, trace2) = 1 **> 0.8**

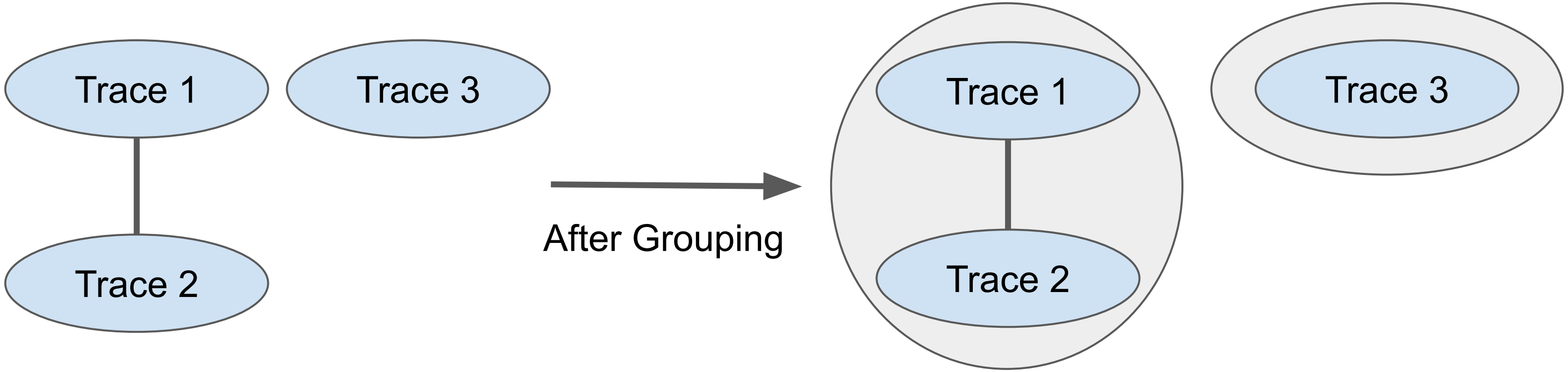
J(trace1, trace3) = 0.75 **< 0.8**

J(trace2, trace3) = 0.75 **< 0.8**



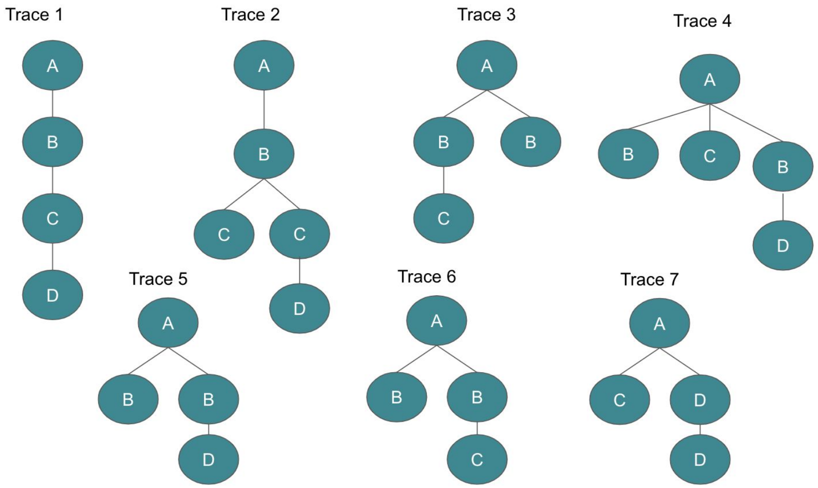
# Identify Similar Groups

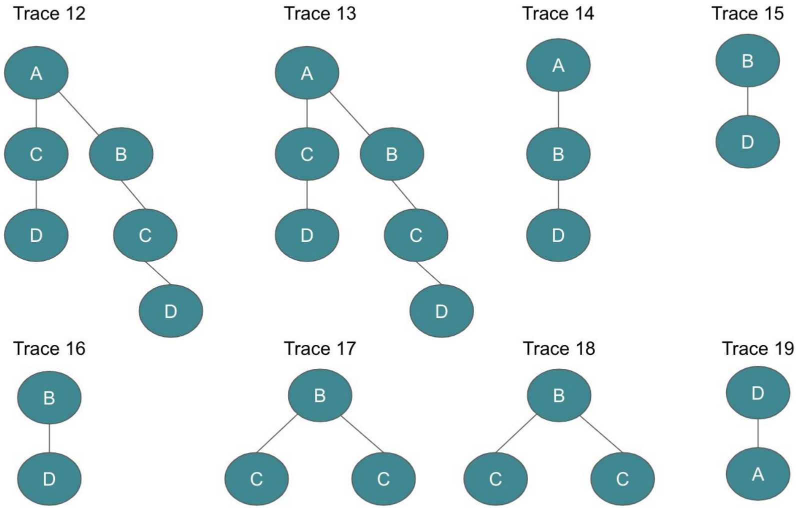
- Use **Disjoint Set Union (DSU)** algorithm to find connected groups in the trace similarity graph.



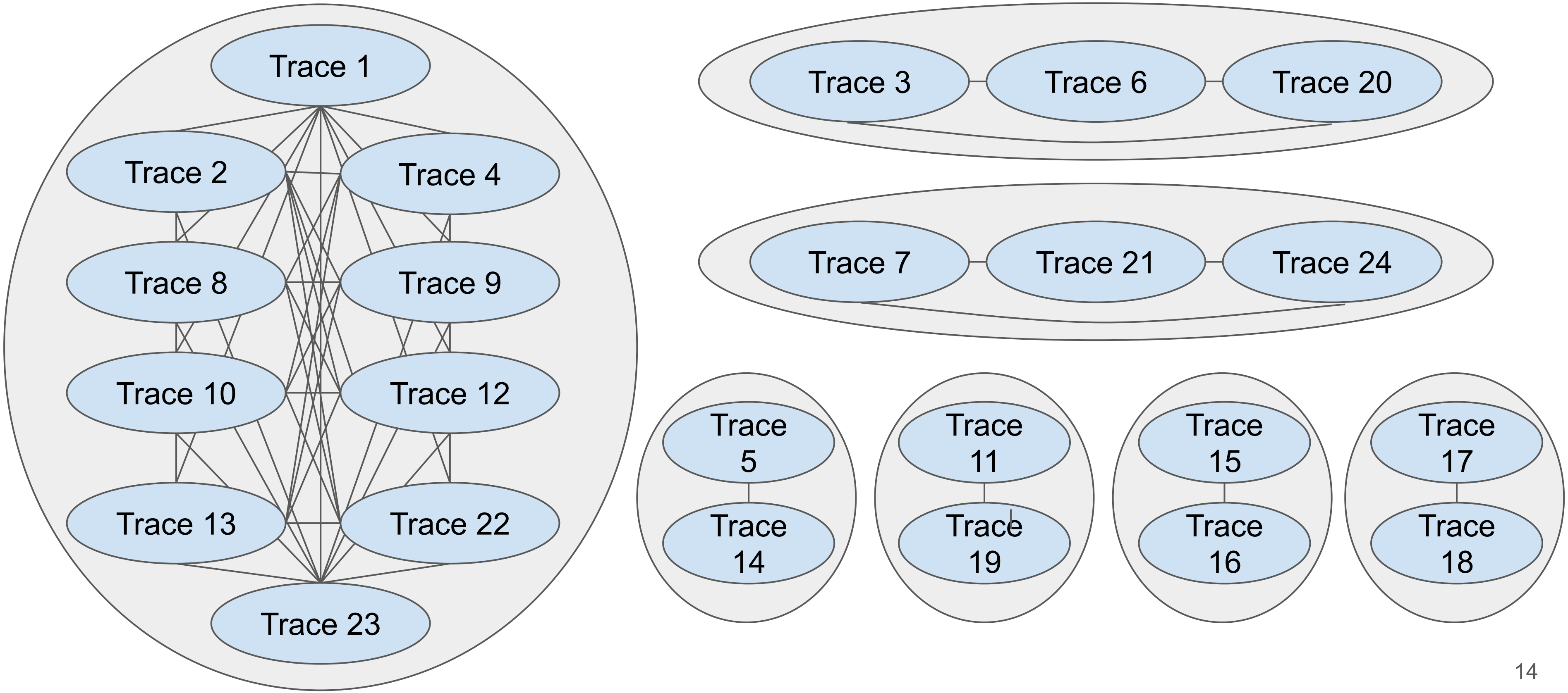
# Methodology

- Created a sample trace set of 24 traces that has variation.

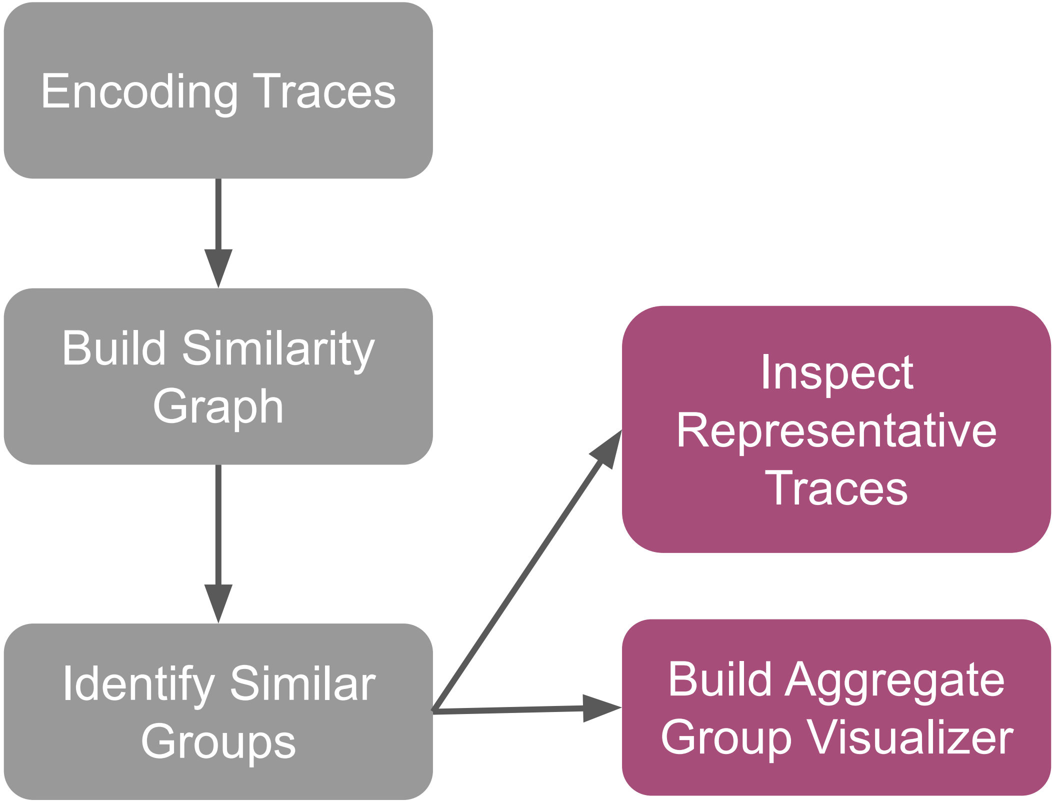


# Results


Trace 1
Trace 2
Trace 4
Trace 8
Trace 9
Trace 10
Trace 12
Trace 13
Trace 22
Trace 23
Trace 3
Trace 6
Trace 20
Trace 7
Trace 21
Trace 24
Trace 5
Trace 14
Trace 11
Trace 19
Trace 15
Trace 16
Trace 17
Trace 18

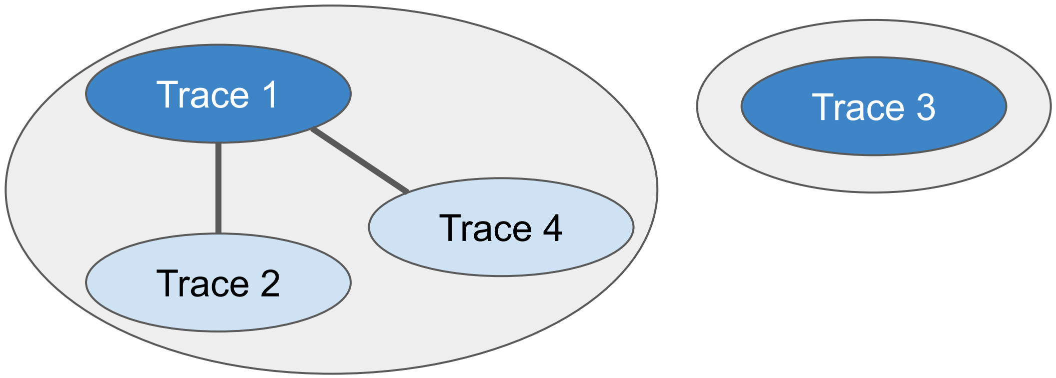
# Design



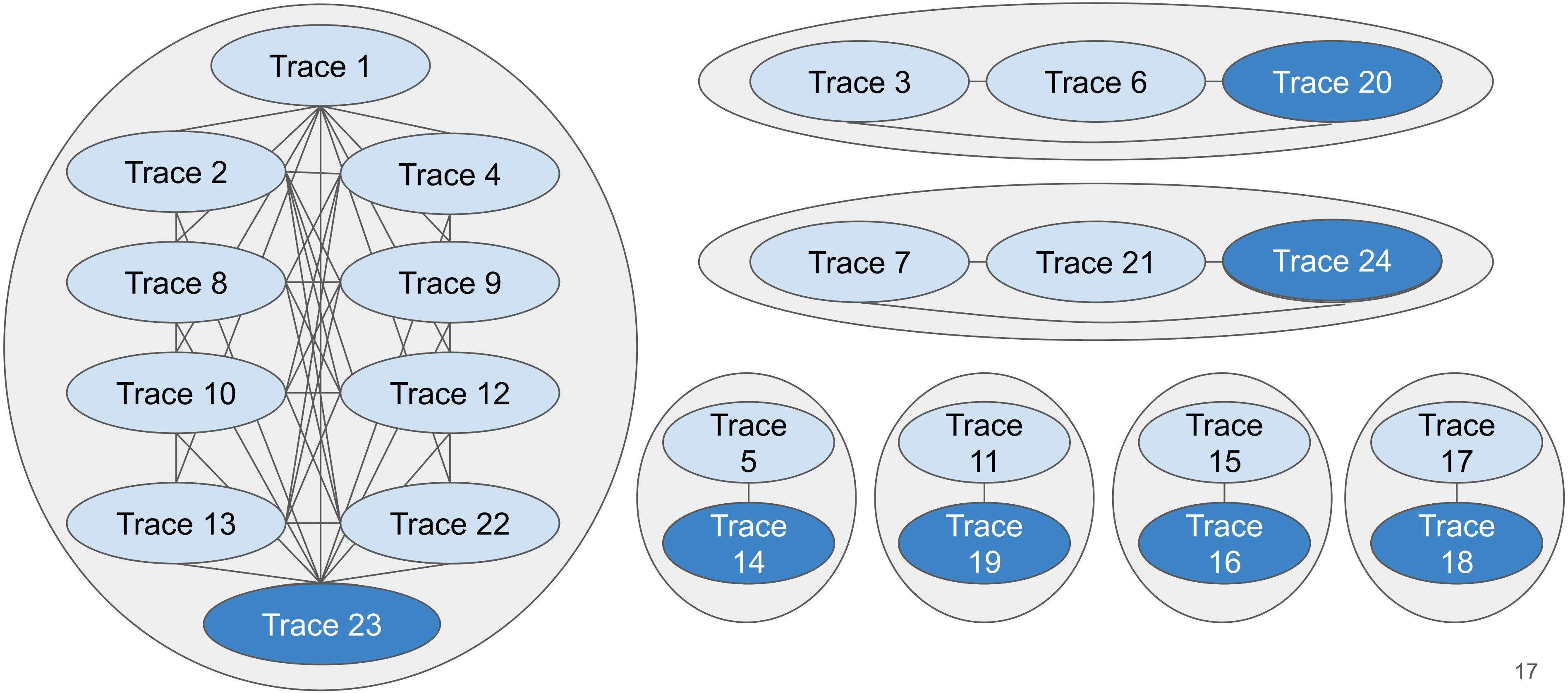
Encoding Traces
Build Similarity Graph
Identify Similar Groups
Inspect Representative Traces
Build Aggregate Group Visualizer

# Inspect Representative Traces

- Choose a trace from each group that represents the group:
  - Trace connected to the most other traces in the trace similarity graph (i.e. **trace with the highest degree**).



# Results

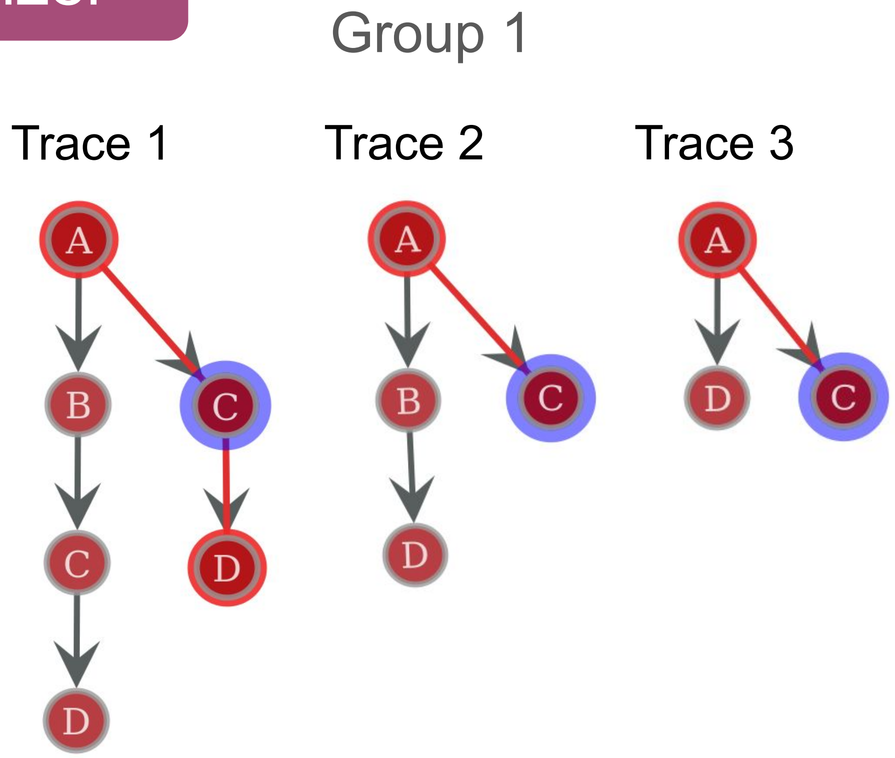


Trace 1
Trace 2
Trace 4
Trace 8
Trace 9
Trace 10
Trace 12
Trace 13
Trace 22
Trace 23
Trace 3
Trace 6
Trace 20
Trace 7
Trace 21
Trace 24
Trace 5
Trace 14
Trace 11
Trace 19
Trace 15
Trace 16
Trace 17
Trace 18

# Build Aggregate Group Visualizer

In addition to representative traces, we want to visualize traces such that developers can further their understanding of each group.

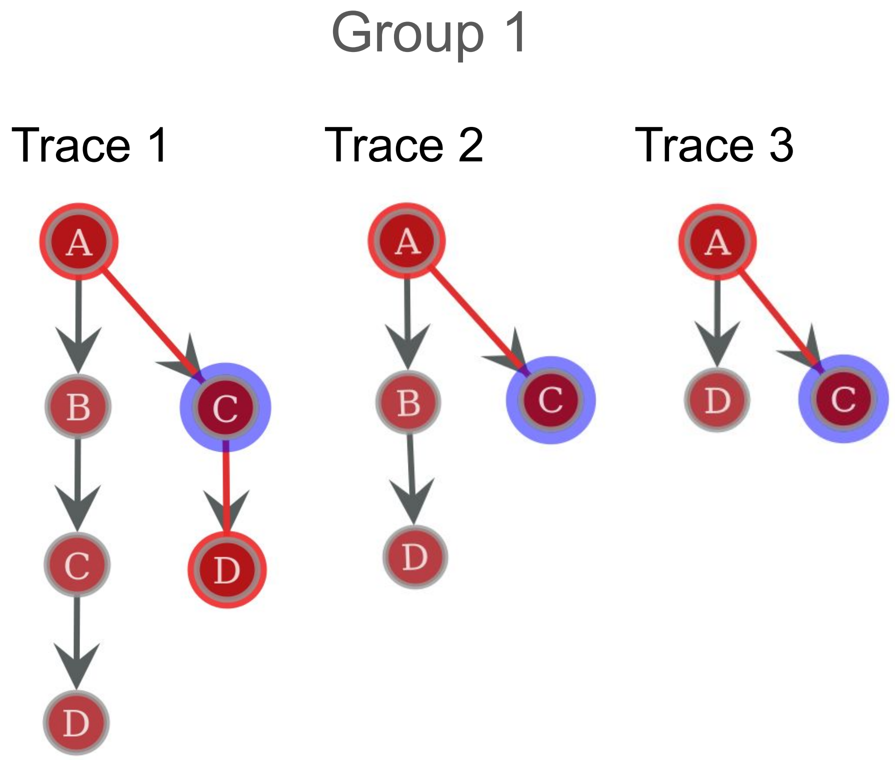
We want to highlight major services/interactions to show the most important information about a group.



# Collecting Group Data

We want to measure the frequency of each node within the group.

| | Node A | Node B | Node C | Node D |
|---|---|---|---|---|
| # Traces | 3 | 2 | 3 | 3 |

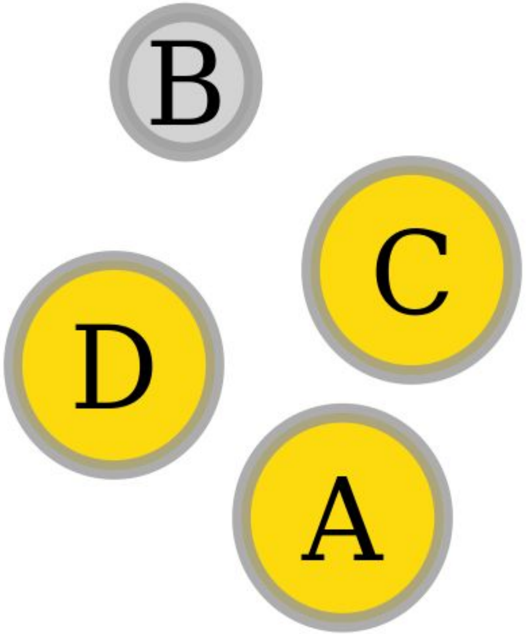


# Visualizing a Group

Rules:

1. Yellow nodes: present in all traces
2. Gray nodes: present in some traces
3. Node size: corresponds to # traces it is in vs. total # traces in the group.
    a. Node B is ⅔ the size of Node A

Aggregate visualization:



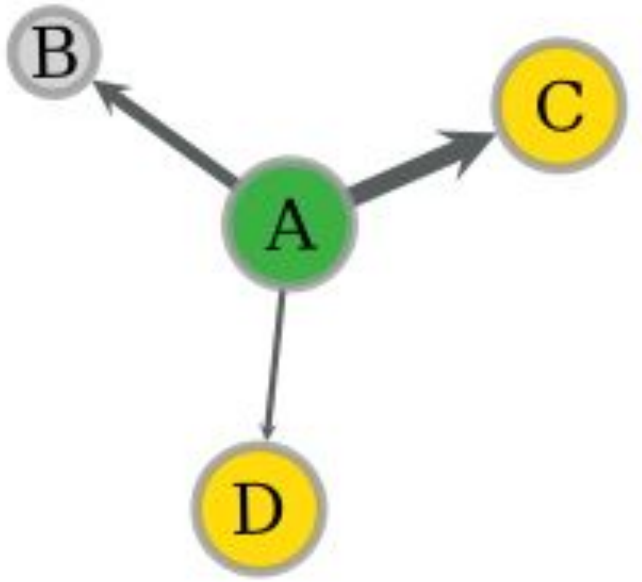
# Interacting with Group Visualizations

Say we want to look into Node A:

Rules:

1. Chosen service (A) is highlighted in green
2. Arrows are shown to indicate services which A calls
3. Arrow size corresponds to how often A calls another service

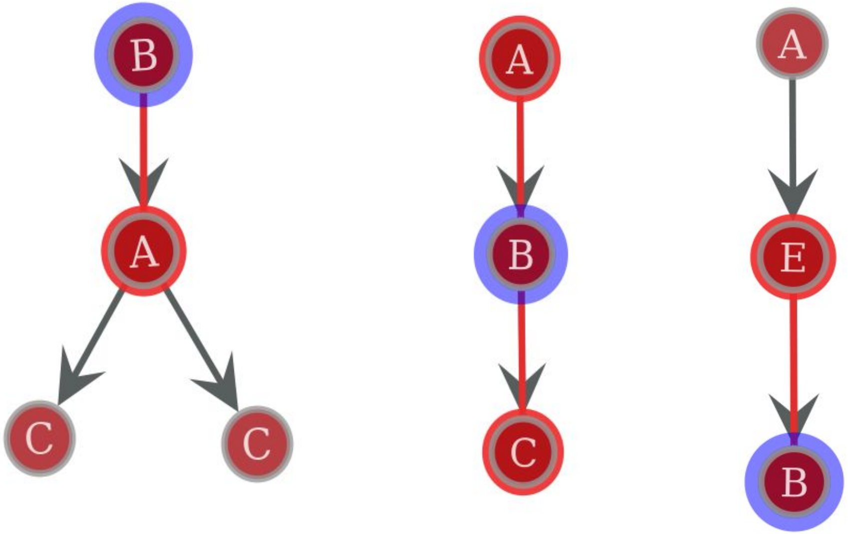
Node A visualization:



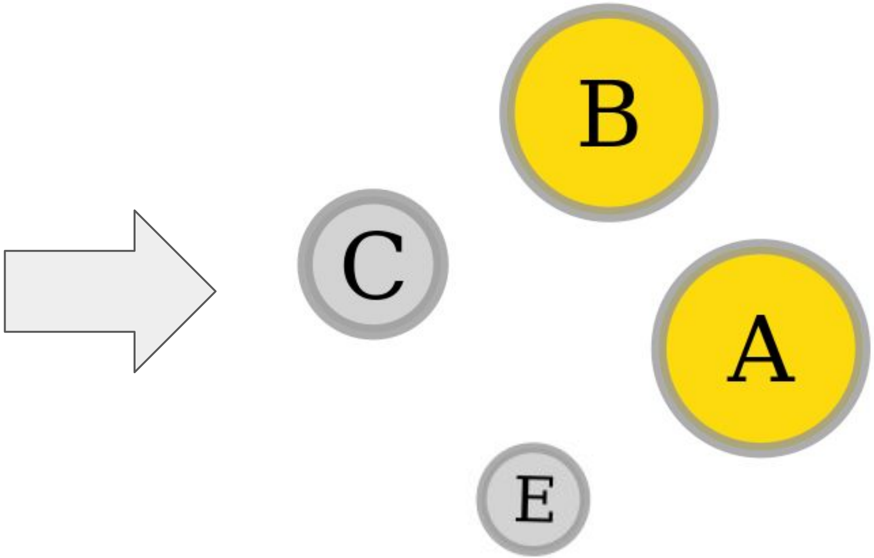
# Comparing Groups

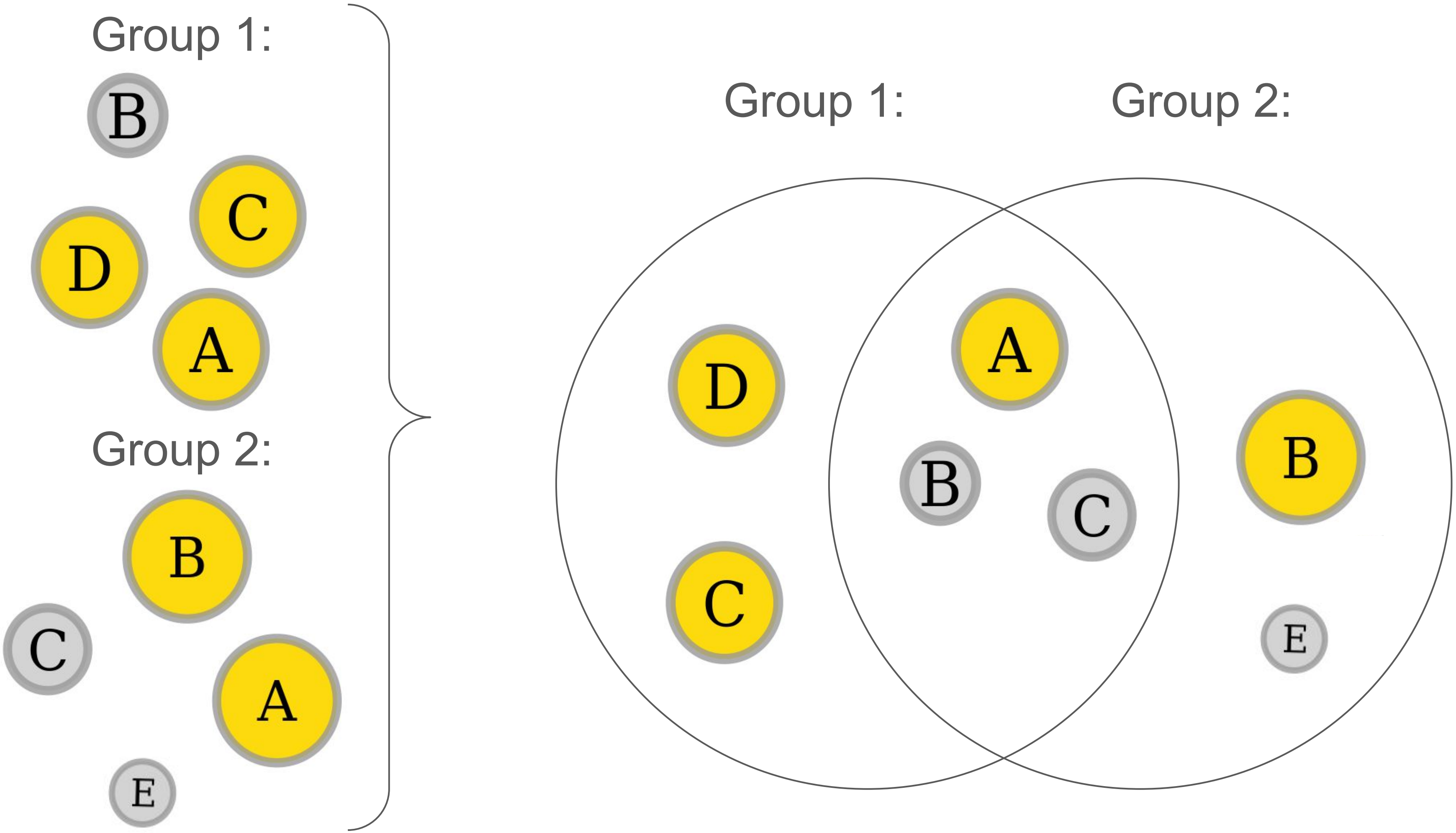
Group 2

Trace 1 Trace 2 Trace 3



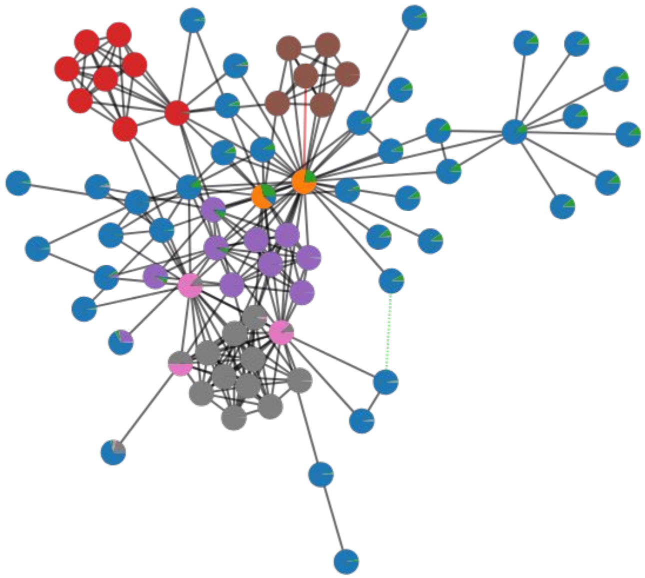

Group 2 visualization:




Group 1:
B
C
D
A
Group 2:
B
C
A
E
Group 1:
Group 2:
D
C
A
B
C
B
E

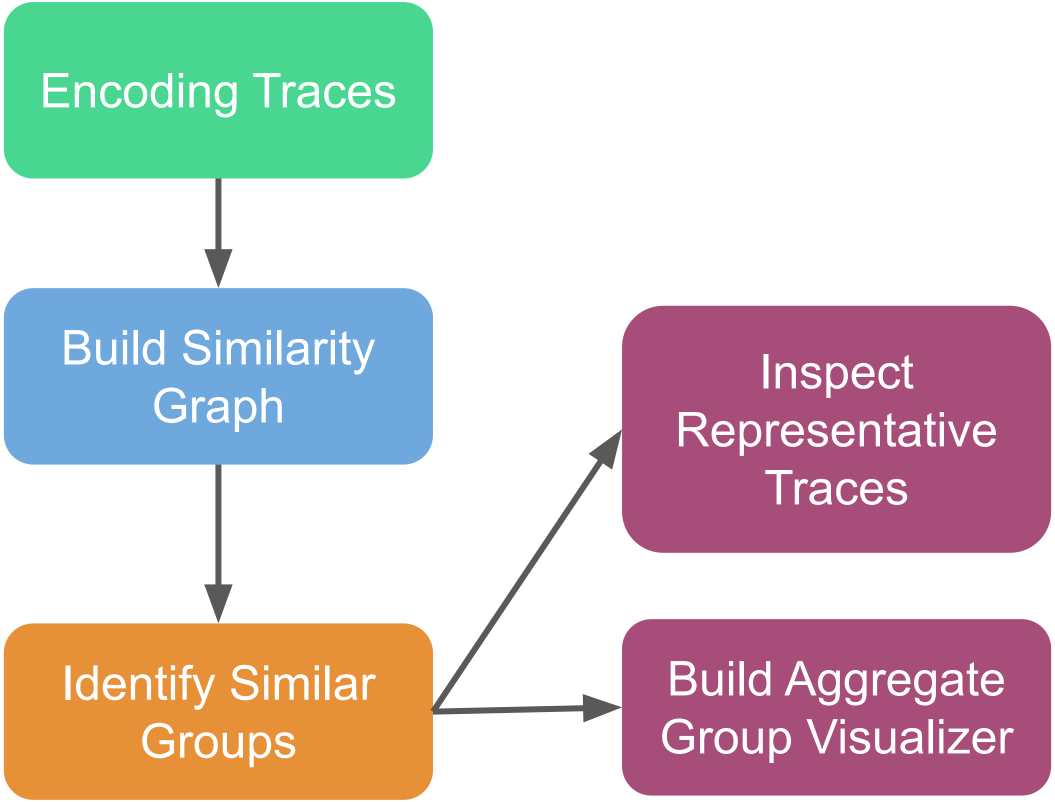
# Future Work

- Implement other methods of encoding traces.
  - Full trace topology
  - Latency
- Build trace similarity graph more efficiently
- Implement our aggregate visualization ideas using graph-tool.



https://graph-tool.skewed.de/static/doc/demos/inference/inference.html

# Visualizing Distributed Traces in Aggregate



# References

[1] Las-Casas, P., Papakerashvili, G., Anand, V., Mace, J.: Sifter: Scalable Sampling for Distributed Traces, without Feature Engineering. https://people.mpi-sws.org/~jcmace/papers/lascasas2019sifter.pdf

[2] Gias, A. Ul., Gao, Y., Sheldon, M., Peruspuía, J. A., O'Brien, O., Casale, G.: SampleHST: Efficient On-the-Fly Selection of Distributed Traces. In arXiv 2022. https://arxiv.org/abs/2210.04595

[3] Huang, L., Zhu, T.: tprof: performance profiling via structural aggregation and automated analysis of distributed systems traces. In: SoCC 2021, pp. 76–91. https://dl.acm. org/doi/10.1145/3472883.3486994

[4] Huye, D., Shkuro, Y., Sambasivan, R. R.: Lifting the veil on Meta's microservice architecture: Analyses of topology and request workflows. In: USENIX ATC 2023, pp. 419–432. https://www.usenix.org/conference/atc23/presentation/huye

[5] Wu, Y., Chen, A., Phan, L. T. X.: Zeno: Diagnosing Performance Problems with Temporal Provenance. In: NSDI 2019, pp. 395-420. https://www.usenix.org/system/ files/nsdi19-wu.pdf

# Acknowledgements

We'd like to thank

- Our mentors: Darby Huye, Zhaoqi (Roy) Zhang, Lan (Max) Liu, and Prof. Raja Sambasivan for their guidance and time.

- MIT PRIMES: Dr. Slava Gerovitch and Prof. Srini Devadas for this great opportunity.