EVAN WEST, STONY BROOK UNIVERSITY

GRAPHZEPPELIN

PROCESSING ENORMOUS, CHANGING GRAPHS

GRADUATE RESEARCH DAY, 2022

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PROCESSING ENORMOUS, CHANGING GRAPHS WITH LINEAR-SKETCHING MADE USEFUL VIA ALGORITHMIC IMPROVEMENTS AND EXTERNAL MEMORY DATA-STRUCTURES

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Rutgers University

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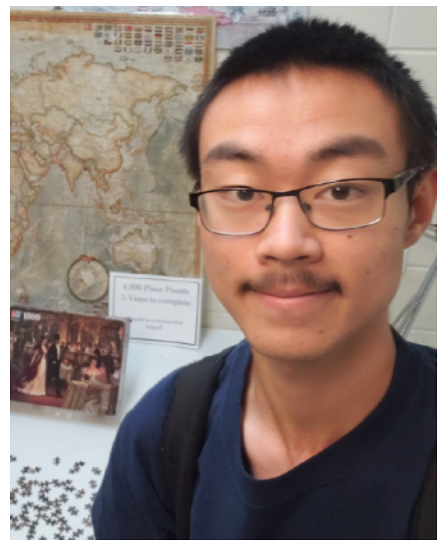
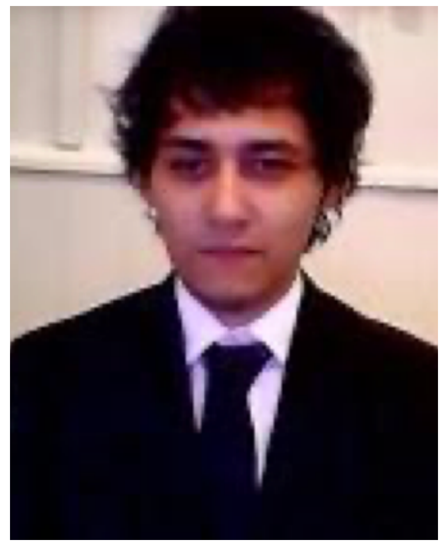


Kenny Zhang
Stony Brook University



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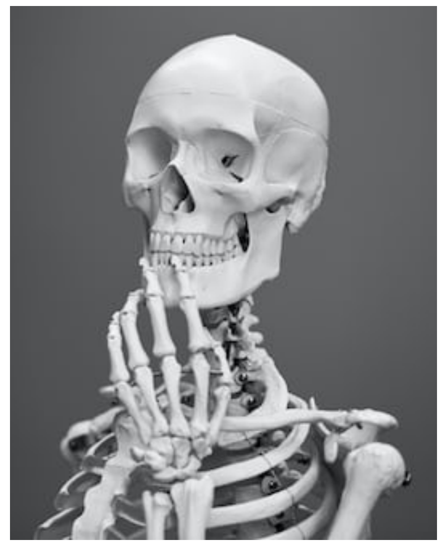

Tyler Seip
MongoDB

TWO YEARS AGO . . .

Hi David! I'd like to do research
and use my coding skills

A group of us are implementing Ahn,
Guha, and McGregor's algorithm
[SODA12] for the dynamic streaming
connected components problem.
It should be an easy publication …

TWO YEARS AGO . . .

This algorithm is useful! It can analyze massive changing graphs even when they're bigger than RAM. *So weird* it hasn't already been implemented. It uses this really cool technique called linear ske-

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David. You had me at easy publication

Oh yes. This algorithm uses asymptotically smaller memory than storing the entire graph. A straightforward implementation will *definitely* outperform state of the art systems.

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FORESHADOWING!

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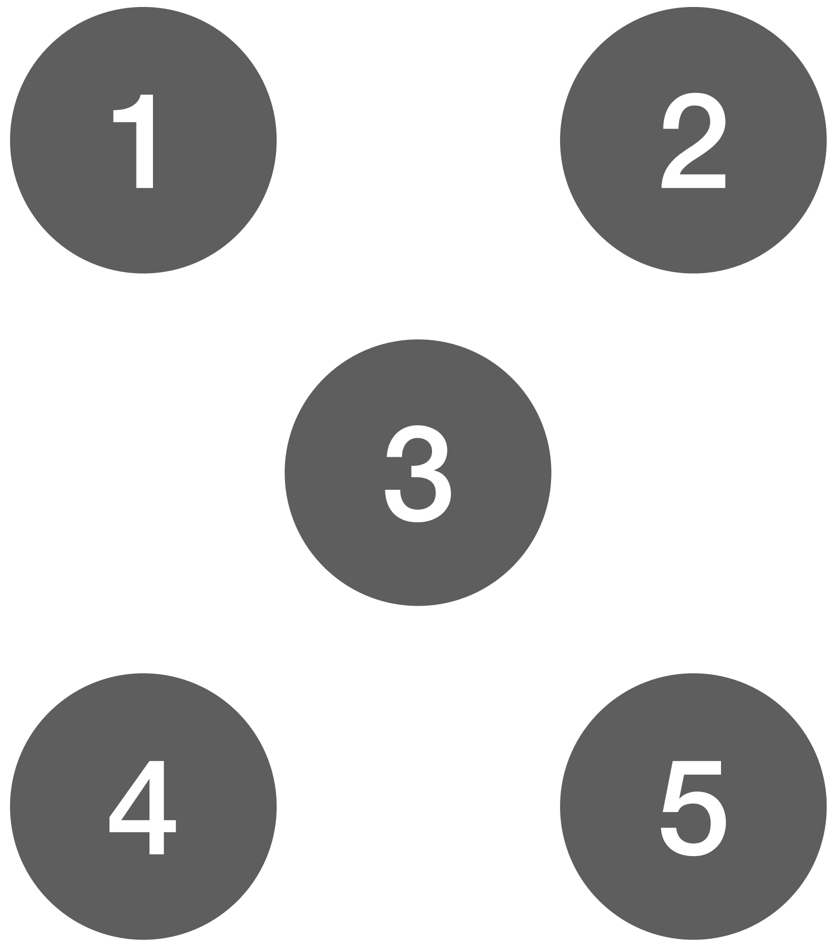
PROCESSING ENORMOUS, CHANGING GRAPHS WITH LINEAR-SKETCHING MADE USEFUL VIA ALGORITHMIC IMPROVEMENTS AND EXTERNAL MEMORY DATA-STRUCTURES

DYNAMIC STREAMING CONNECTED COMPONENTS

Goal: Find connected components of a graph with n nodes subject to stream of edge insertions and deletions.



{{1}, {2}, {3}, {4}, {5}}
Initial State

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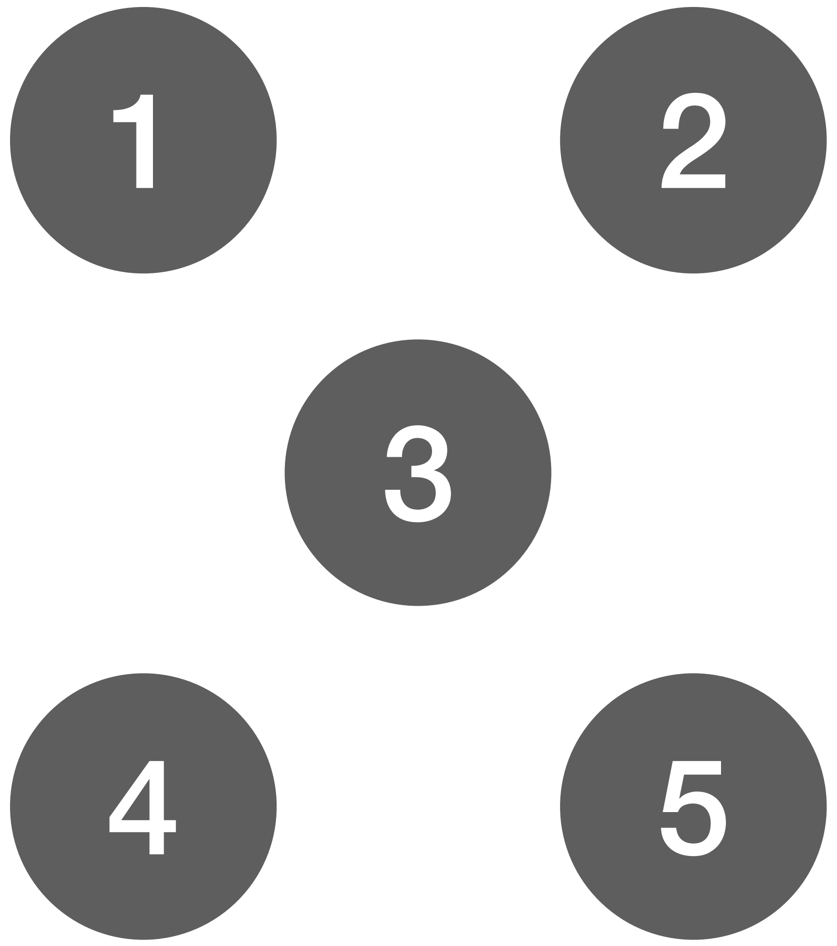

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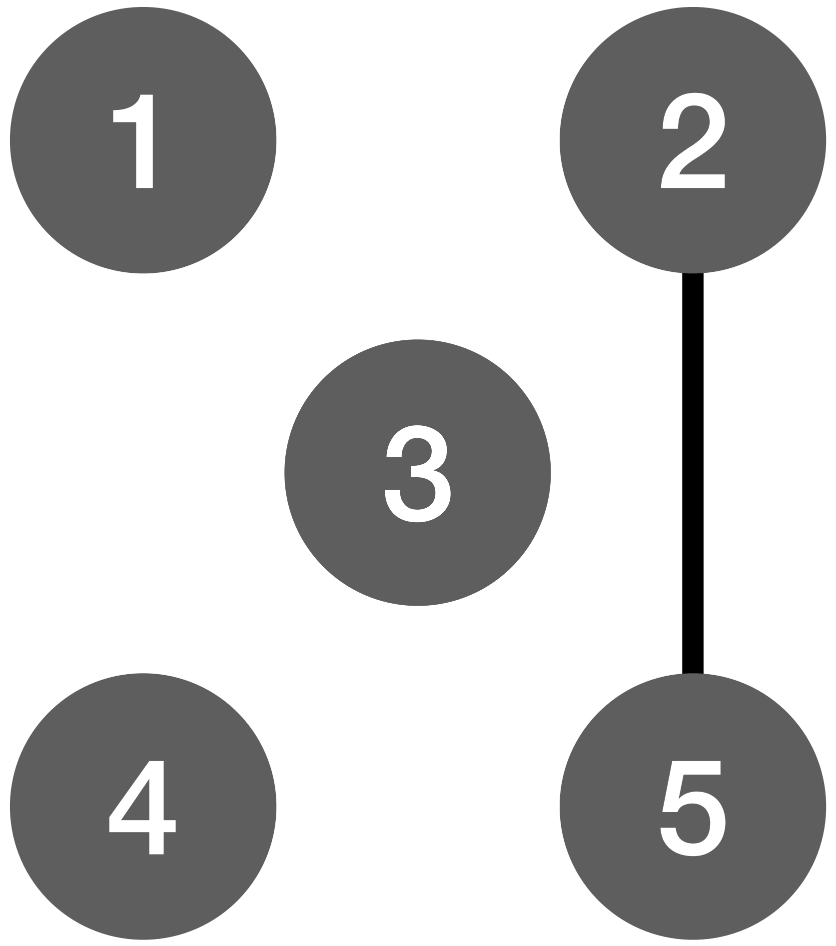

{{1}, {2, 5}, {3}, {4}}
Insert Edge 2,5

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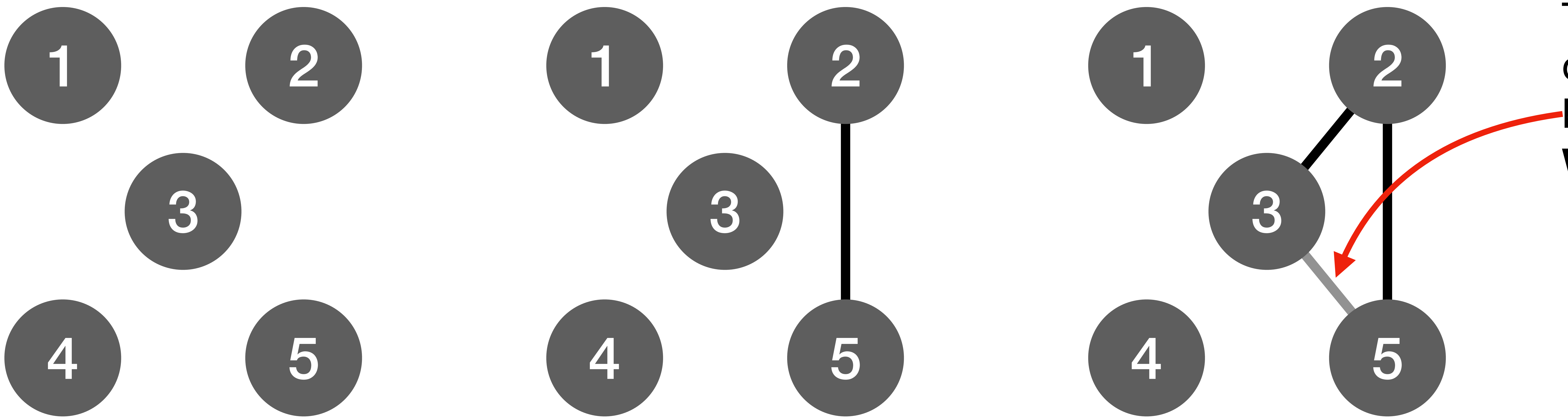

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Initial State

{{1}, {2, 5}, {3}, {4}}
Insert Edge 2,5

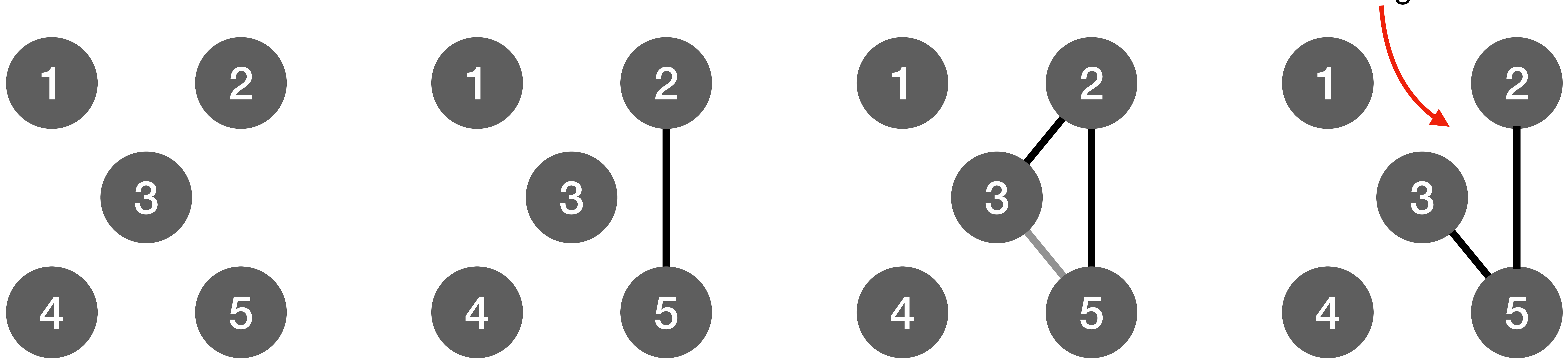
{{1}, {2, 3, 5}, {4}}
Insert Edges 2,3 3,5

This edge is redundant for defining the components but we still need to store it. **Why?**

DYNAMIC STREAMING CONNECTED COMPONENTS

Goal: Find connected components of a graph with n nodes subject to stream of edge insertions and deletions.

To return the correct answer we need to retain redundant edges in case other edges are deleted



{{1}, {2}, {3}, {4}, {5}}
Initial State

{{1}, {2, 5}, {3}, {4}}
Insert Edge 2,5

{{1}, {2, 3, 5}, {4}}
Insert Edges 2,3 3,5

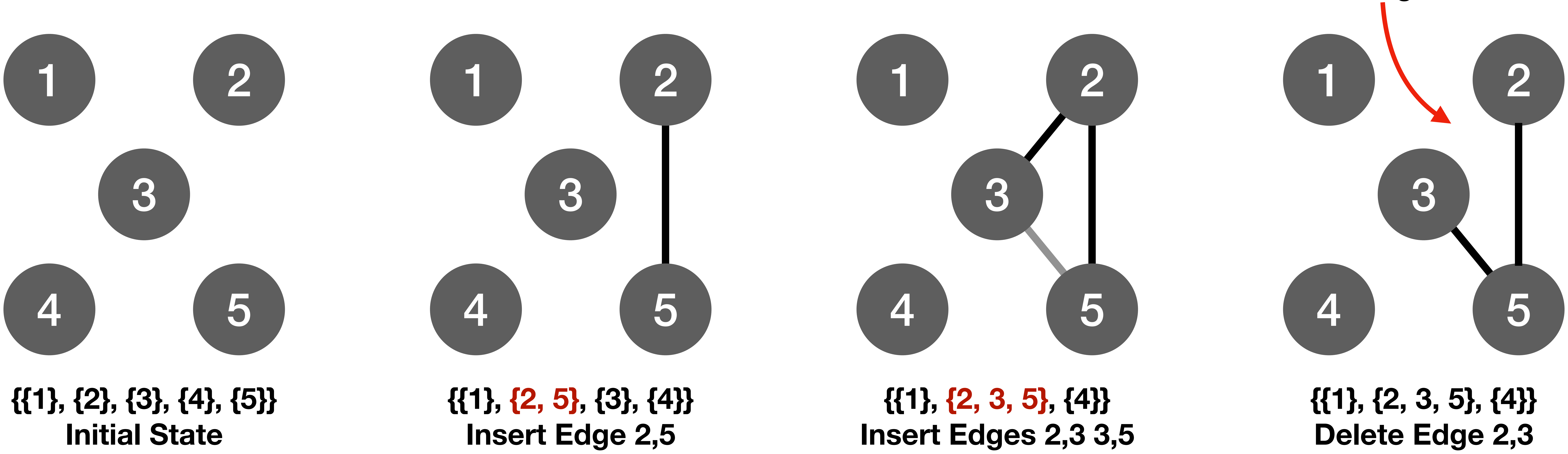
{{1}, {2, 3, 5}, {4}}
Delete Edge 2,3

DYNAMIC STREAMING CONNECTED COMPONENTS

Goal: Find connected components of a graph with n nodes subject to stream of edge insertions and deletions.

Semi-Streaming constraint: $O(n \times \text{polylog}(n))$ space

To return the correct answer we need to retain redundant edges in case other edges are deleted



PROCESSING ENORMOUS, CHANGING GRAPHS WITH LINEAR-SKETCHING MADE USEFUL VIA ALGORITHMIC IMPROVEMENTS AND EXTERNAL MEMORY DATA-STRUCTURES

Hi David! I'd like to do research and use my coding skills

A group of us are implementing **Ahn, Guha, and McGregor's algorithm [SODA12]** for the dynamic streaming connected components problem.
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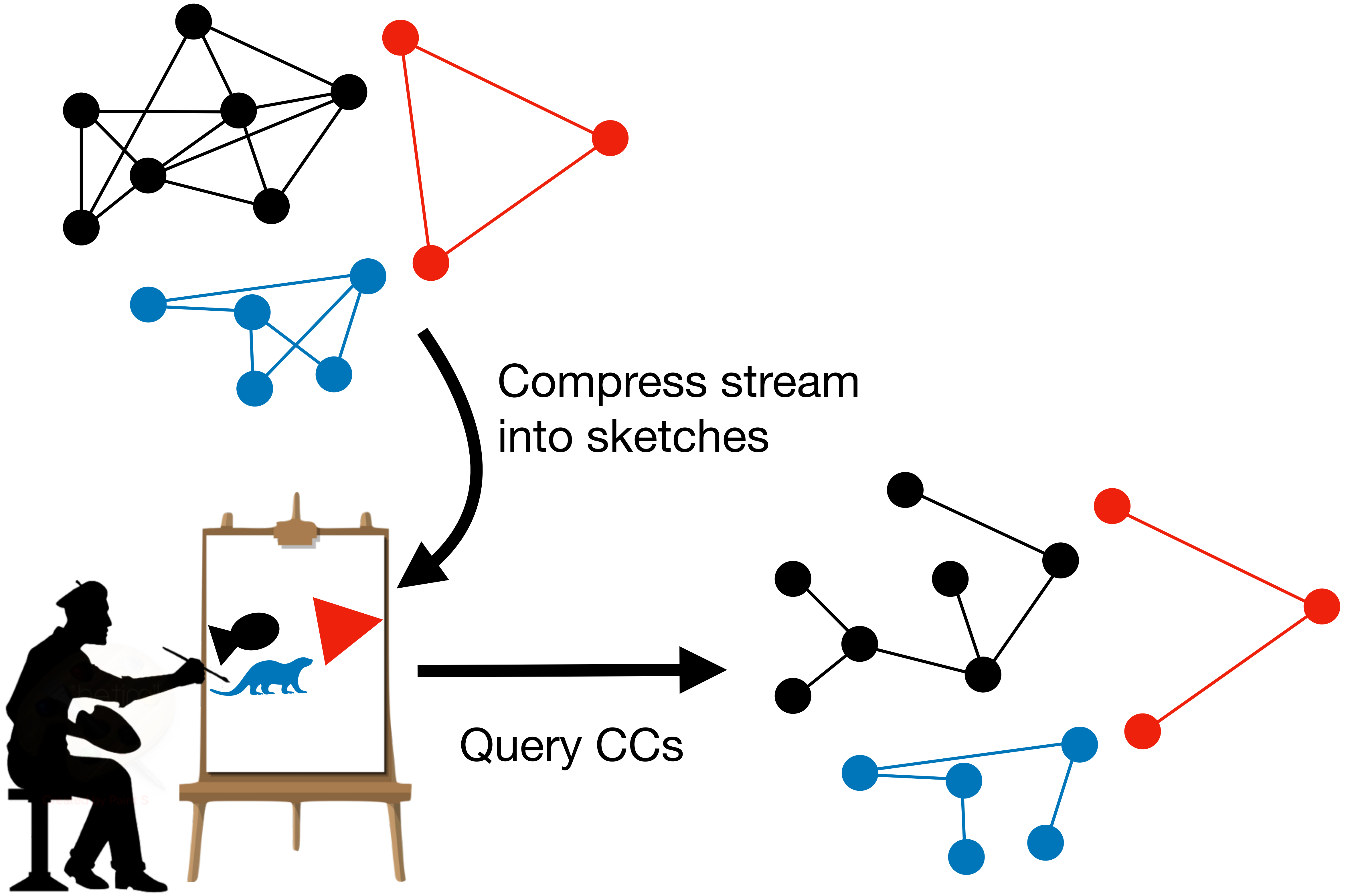
AHN, GUHA, & MCGREGOR'S ALGORITHM: CONNECTIVITY IN SMALL SPACE



Even though edge insertion/deletion updates are received one by one in stream order.

Compresses graph stream via **linear sketching** to a size of only $O(n \log^3 n)$. The graph may be much larger than this, but the algorithm can still recover connected components **w.h.p.**

[Ahn, Guha, McGregor SODA 2012]

IMPLEMENTATION TIME!


TO BOLDLY GO . . .


TO BOLDLY IMPLEMENT . . .


It’s too big!
Back of the envelope math for graph on 1 billion nodes:
$10^9 \log^3(10^9) = 2.7 \times 10^{13}$
Before constants, roughly **25 TB** of RAM.
It’s too slow!
BOLDLY IMPLEMENTED . . . POORLY?

MAKE SKETCHES SMALLER?

Let's improve the asymptotic space cost!

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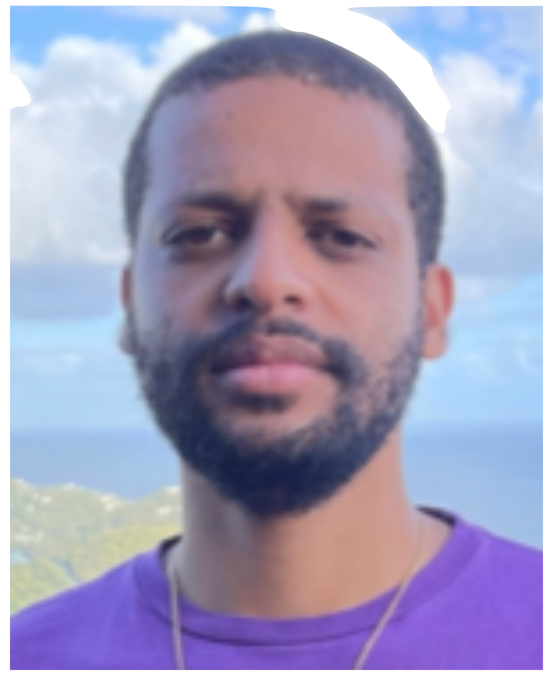
Great idea Evan, I always knew you'd finally contribute something to this project.

MAKE SKETCHES SMALLER?

Let's improve the asymptotic space cost!

<u>You cannot</u>: Lower bound: $\Omega(n \log^3 n)$

[Nelson & Yu, SODA 2019]



CANNOT MAKE SKETCHES SMALLER

<u>You cannot</u>: Lower bound: $\Omega(n \log^3 n)$
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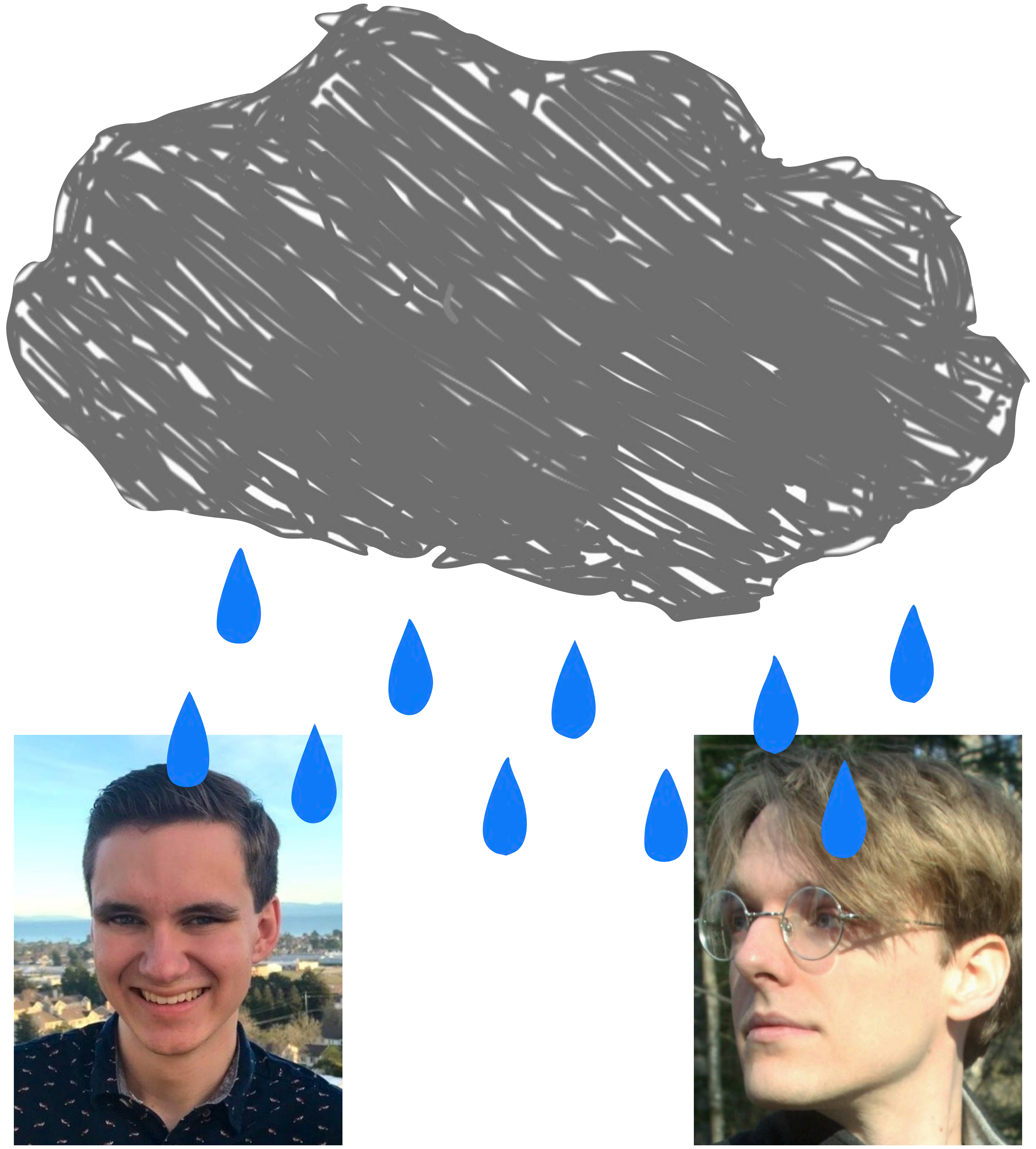
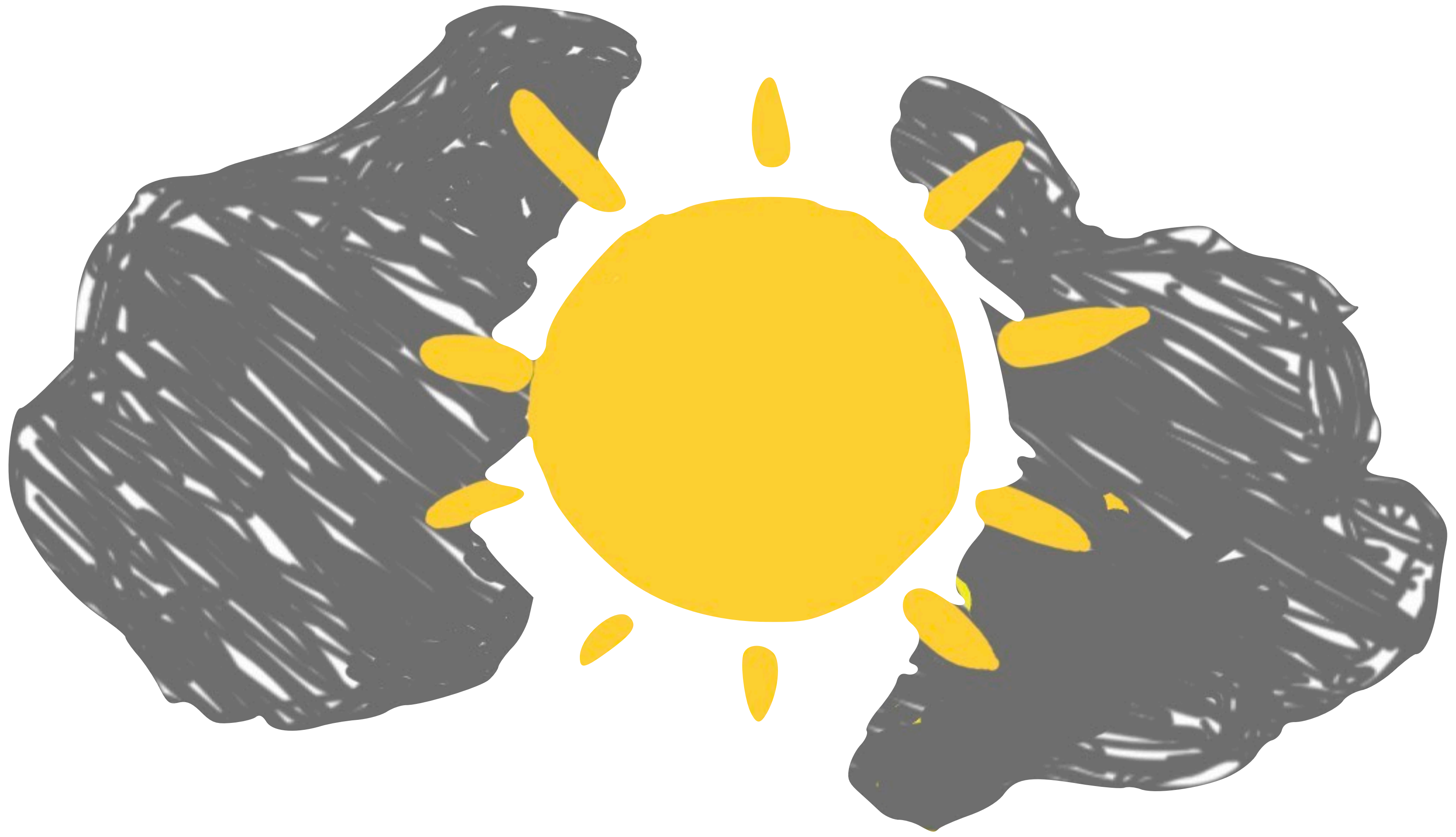


For our purposes:
This might as well be infinite RAM

How can we overcome this lower bound?

CANNOT MAKE SKETCHES SMALLER: MAKE THEM USEFUL ANYWAY



GraphZeppelin:
We built a system that solves dynamic streaming connected components for a critical use case.

To do this we designed an algorithm which works well **despite the space lower bound.**

PROCESSING ENORMOUS, CHANGING GRAPHS WITH LINEAR-SKETCHING MADE USEFUL VIA ALGORITHMIC IMPROVEMENTS AND EXTERNAL MEMORY DATA-STRUCTURES

WHAT MAKES A STREAMING ALGORITHM "USEFUL"?

1. Can be run on
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WHAT MAKES A STREAMING ALGORITHM "USEFUL"?

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2. Keeps pace with **high-speed streams.**

How can we achieve our other goals while remaining fast?

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3. Meets an **unmet need**

When are existing systems for processing graph streams unable to find CCs?

WHAT MAKES A STREAMING ALGORITHM "USEFUL"?

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SPACE

2. Keeps pace with **high-speed streams.**

How can we achieve our other goals while remaining fast?

SPEED

3. Meets an **unmet need**

When are existing systems for processing graph streams unable to find CCs?

DENSITY

UNMET NEED: PROCESSING DENSE GRAPHS

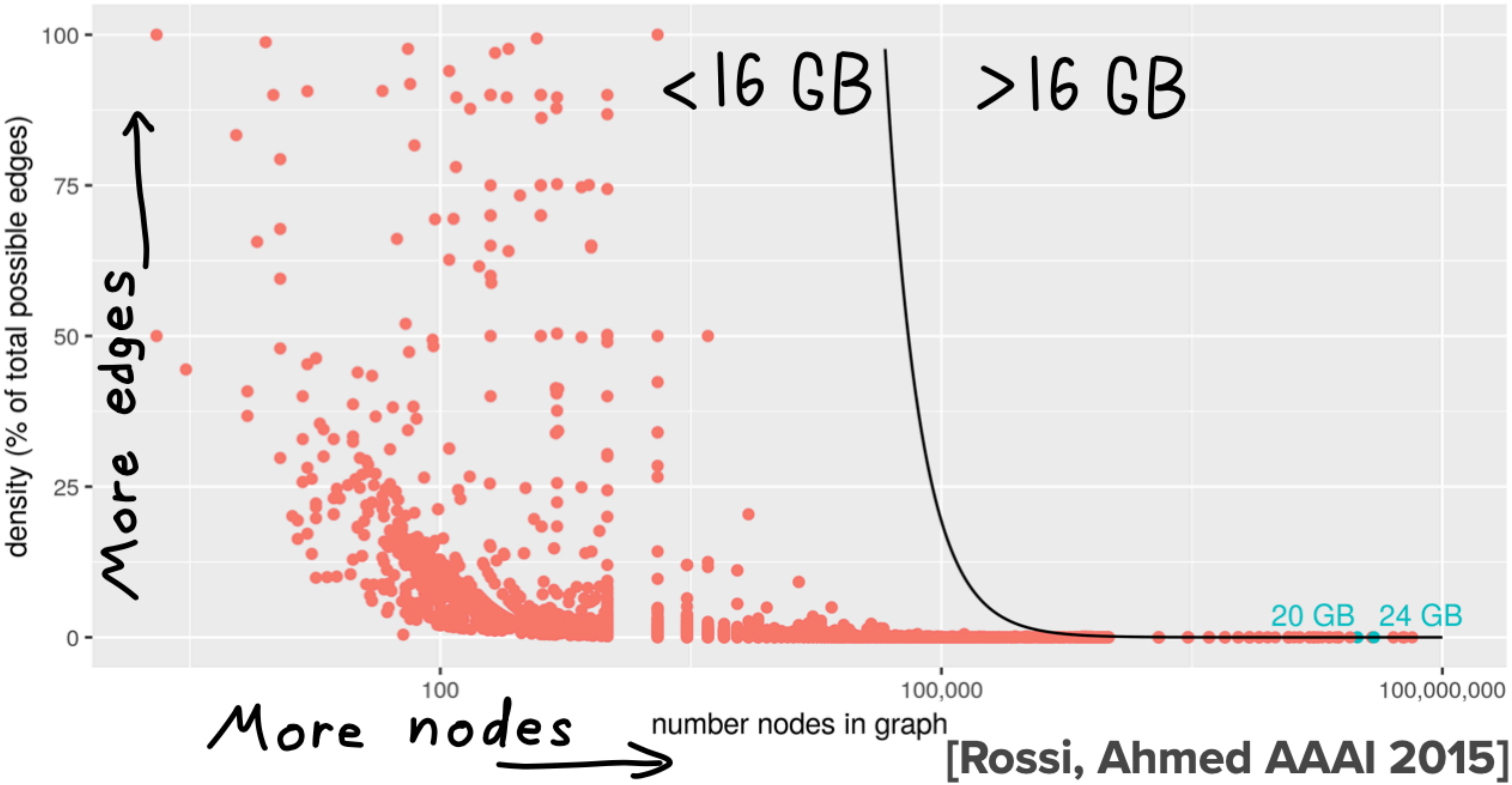
Memory usage of semi-streaming algorithms scales with n the number of nodes, **but not the number of edges E.**

Get the greatest gains when E is large, i.e., **graph is dense.**

Folk wisdom: "**Large dense graphs don't exist** in practice. Real-world graphs are **sparse**."

Other dynamic graph processing systems optimize for sparse graphs.
Aspen [Dhulipala, Blelloch, Shun 2019]
Terrace [Pandey, Wheatman, Xu, Buluç 2021]

UNMET NEED: PROCESSING DENSE GRAPHS



[Rossi, Ahmed AAAI 2015]

UNMET NEED: PROCESSING DENSE GRAPHS

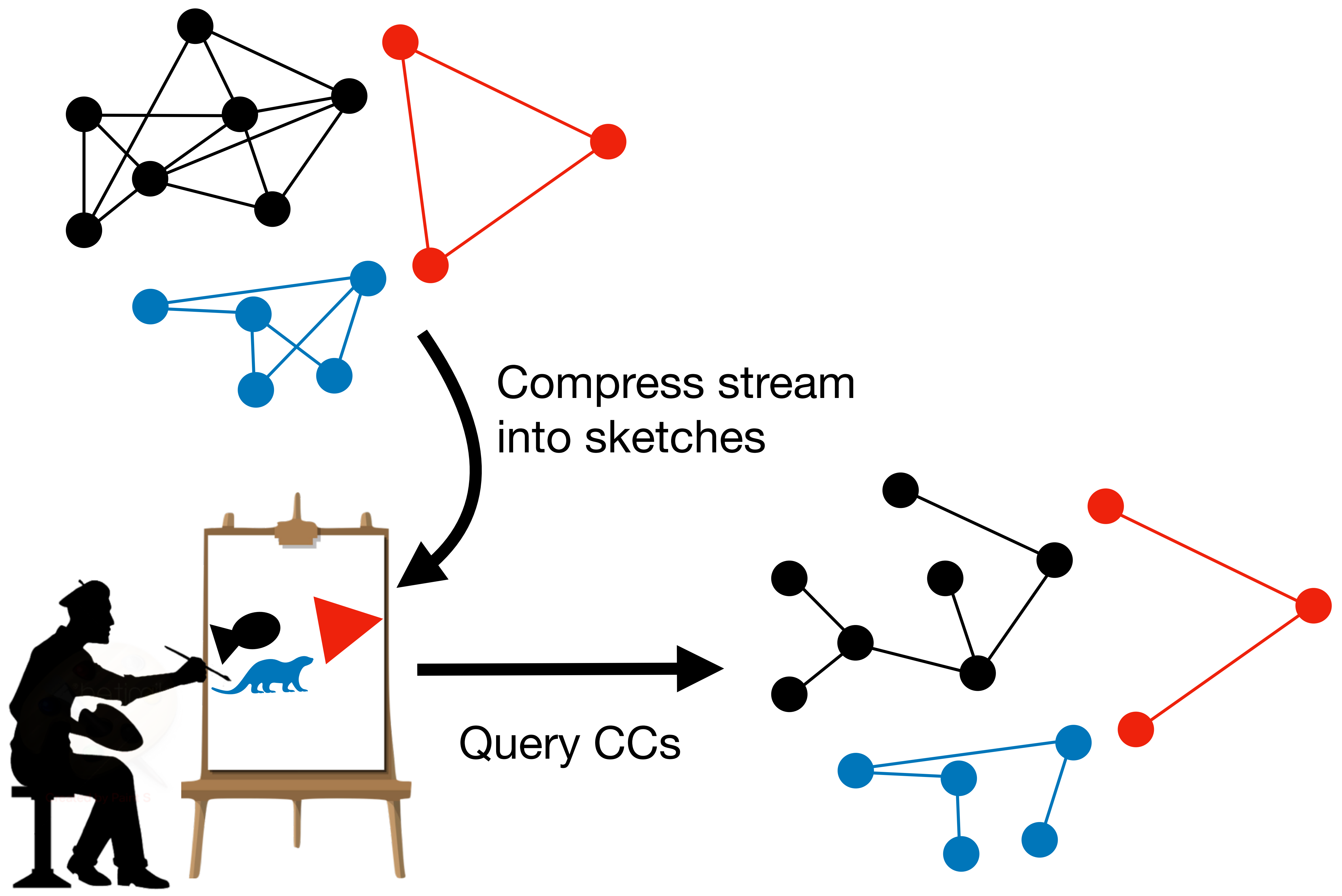
Facebook works with large, dense graphs (40 million nodes and larger) since at least 2015.
They do so at great cost on supercomputing clusters.
[Ching, Edunov, Kabiljo, Logothetic, Muthukrishnan VLDB 2015]

The folk wisdom is in fact observing a **selection effect**
We lack the tools to process large, dense graph streams so they are rarely studied.

DENSITY

PROCESSING ENORMOUS, CHANGING GRAPHS WITH LINEAR-SKETCHING MADE USEFUL VIA ALGORITHMIC IMPROVEMENTS AND EXTERNAL MEMORY DATA-STRUCTURES

SKETCHES ARE TOO LARGE FOR MODERN HARDWARE: OR ARE THEY?



The problem:

- $O(n \log^3 n)$ space is big actually. On top of that sketches have huge constants. Easily overflows RAM.

- Streams and sketches are random so data out-of-core is EXTREMELY slow

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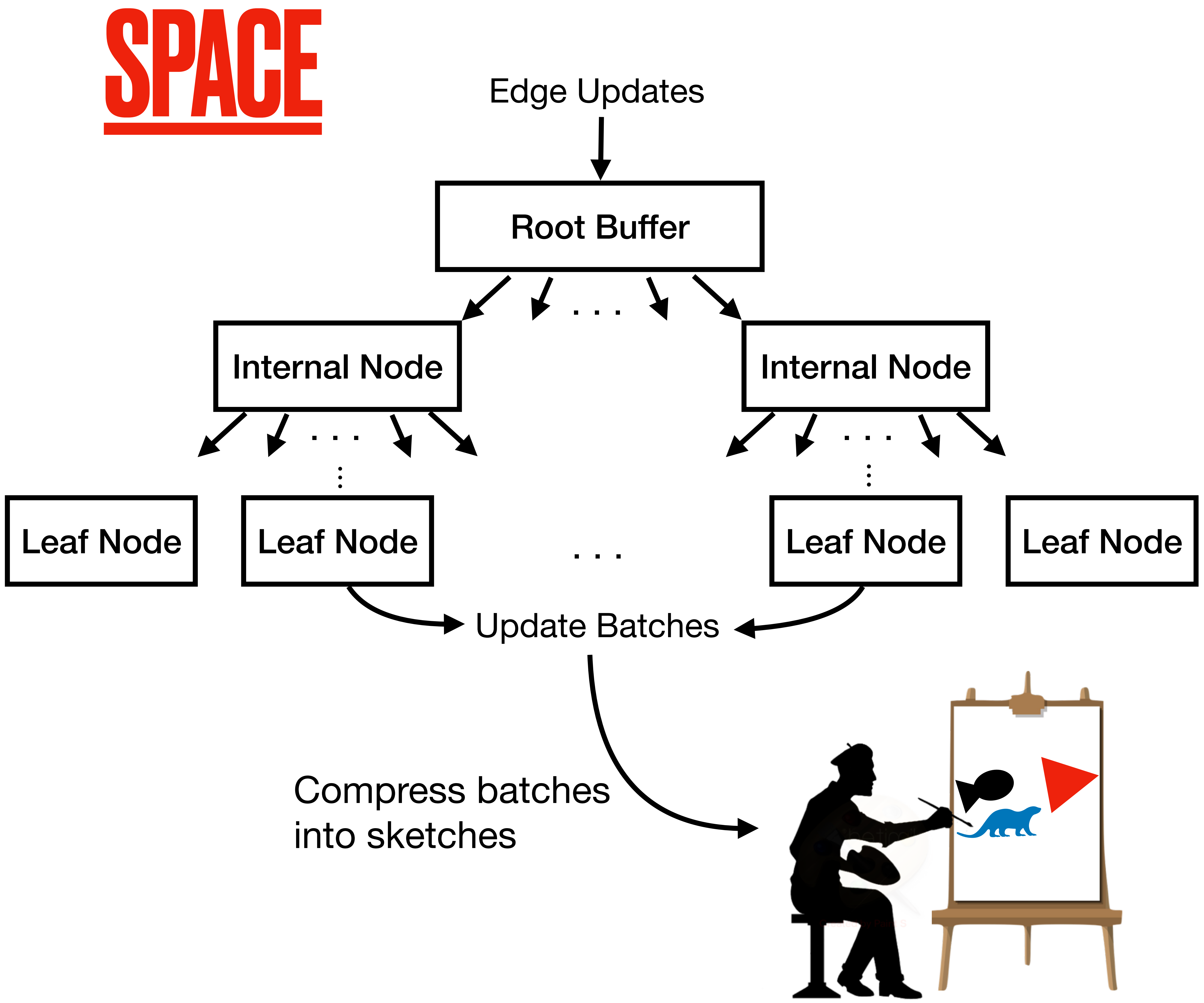

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Solve the space problem:

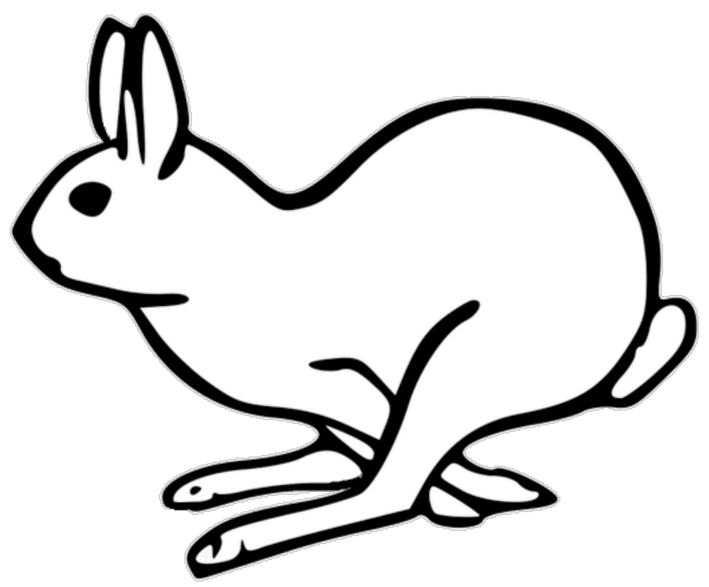
- GraphZeppelin uses a GutterTree to efficiently buffer updates on disk.
- Buffering updates **amortizes the cost of accessing the disk.**
- Still a **space optimal** connected components

EXTERNAL MEMORY ALGORITHMS

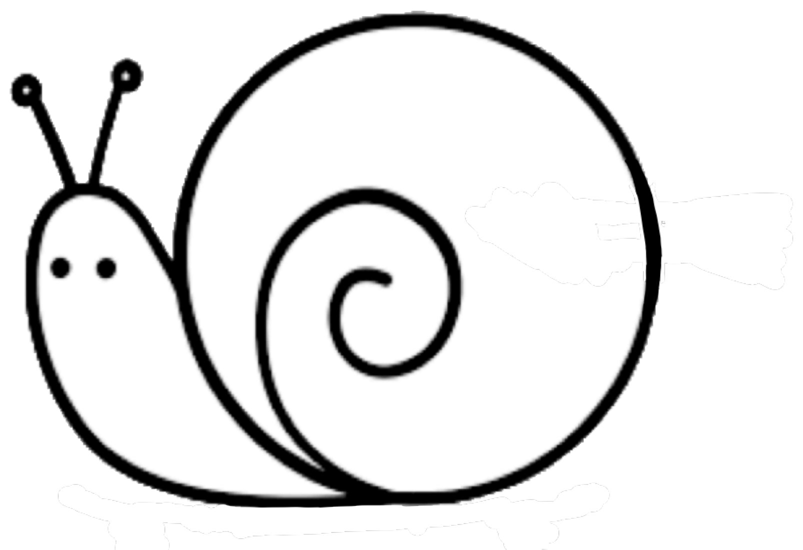
Fetching a block from disk into RAM is expensive. Latency of disk is much higher than that of RAM.

External memory algorithms: basic idea is to delay accessing the disk until we have a bunch of operations that touch the same block.

Therefore, latency of disk is shared (amortized) among all these operations



RAM



SSD with standard algorithms

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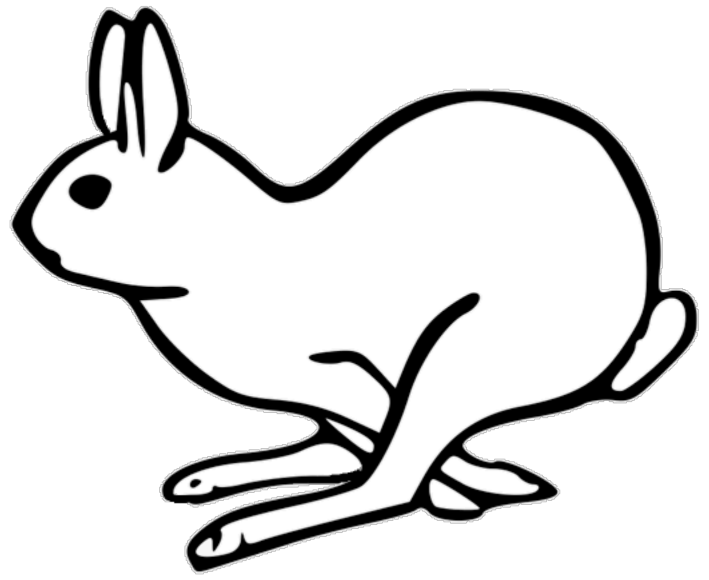

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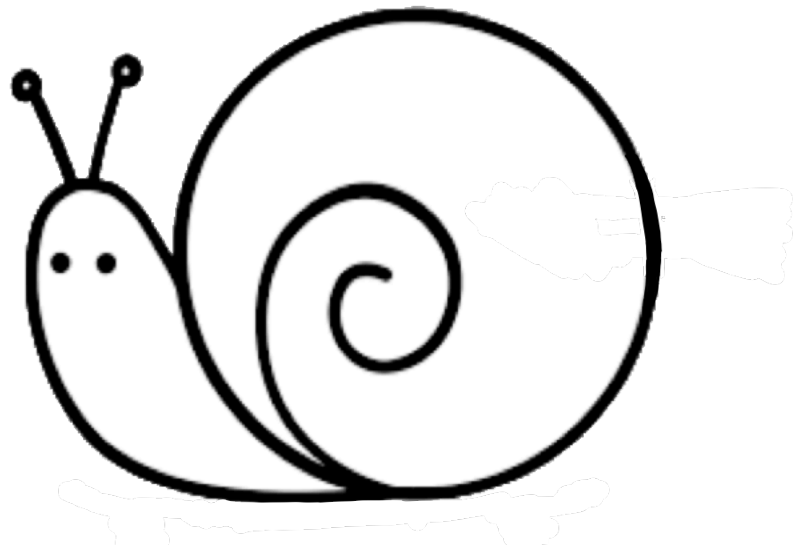
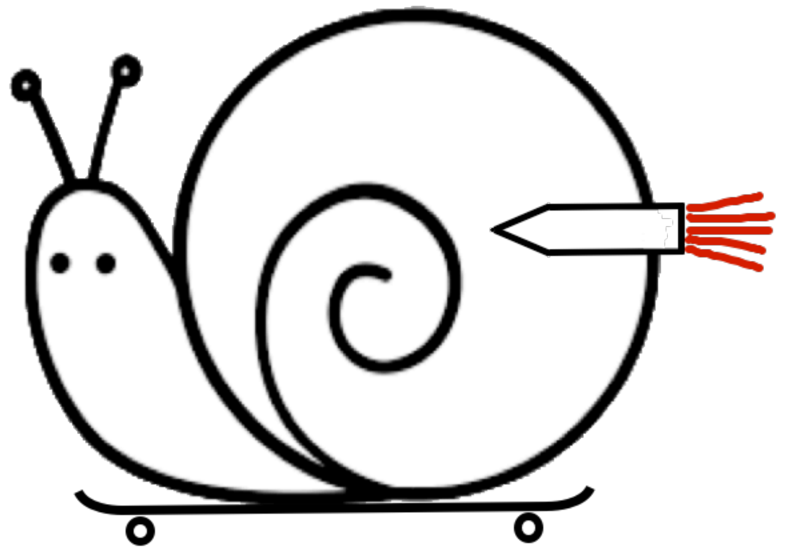
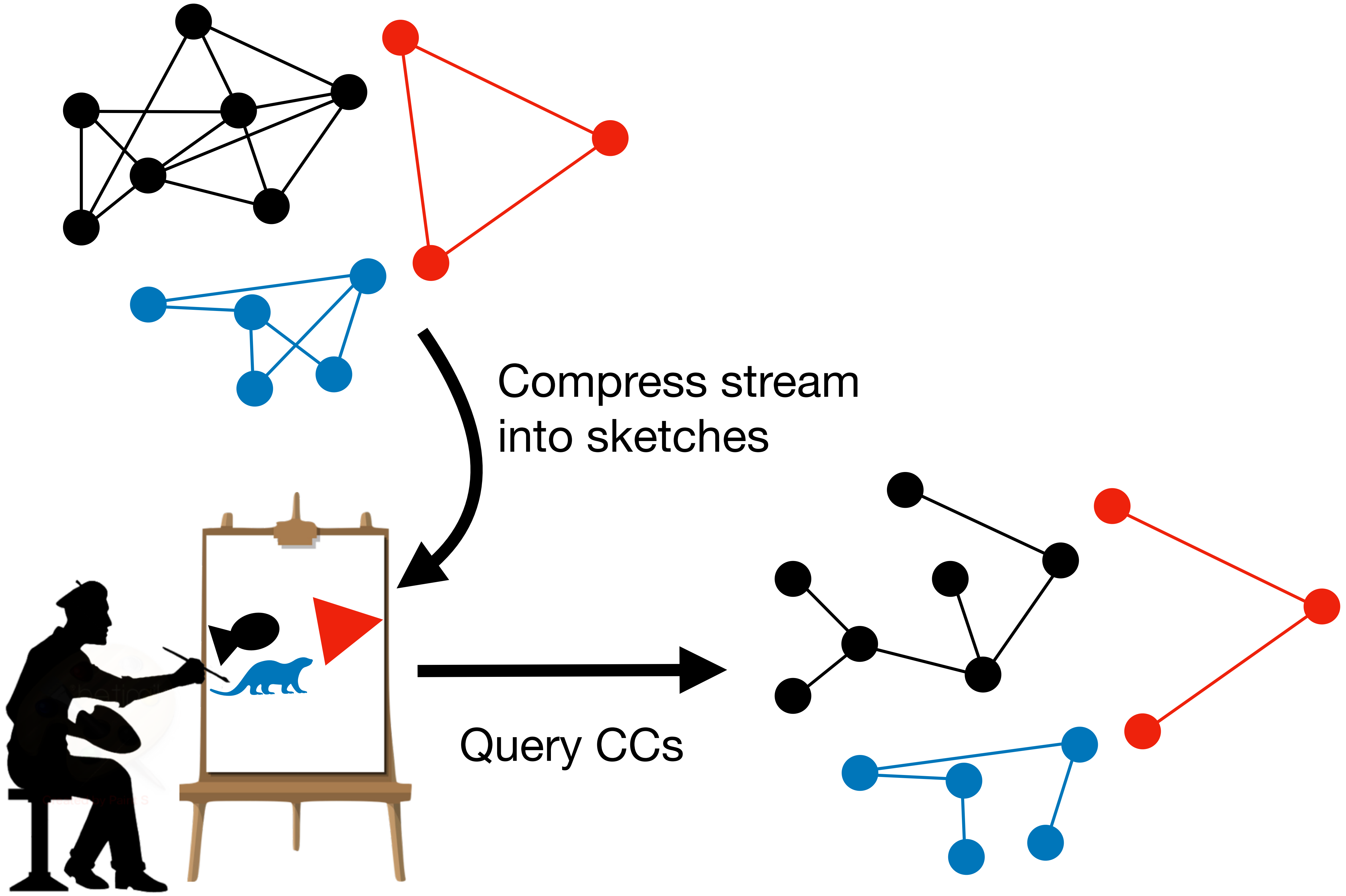


SSD with standard algorithms



SSD with external memory algorithms

SKETCHES ARE TOO SLOW FOR MODERN HARDWARE

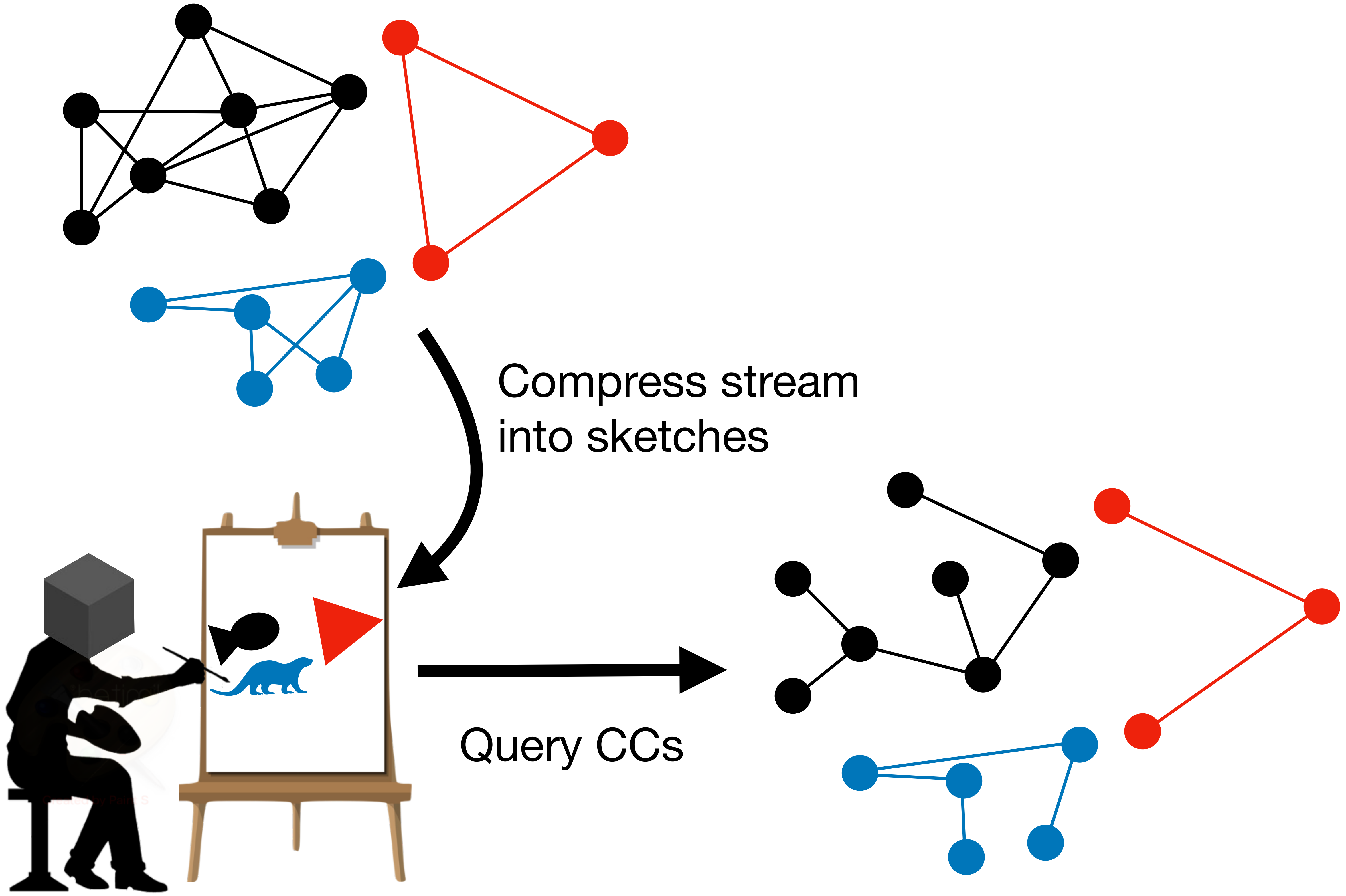


The problem:

- Linear-sketching algorithm by AGM uses modular exponentiation
- Also requires 128 bit integers
- This is very, very slow
  - For a graph on 10^6 nodes update rate is only 833 per second

SKETCHES ARE TOO SLOW FOR MODERN HARDWARE: IMPROVE THEM!

SPEED



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CubeSketch:

- Linear-sketching algorithm for connected components
- Updates $> 10^3$ times faster
- Uses 8 times less space

GRAPHZEPPELIN: C++ LINEAR-SKETCHING LIBRARY

GRAPHZEPPELIN: AVOIDING DATA EXPLOSION IN GRAPH STREAMS

Graf-Zeppelin, **NOT** the Hindenburg, did not explode

GraphZeppelin: Solves streaming connected components using CubeSketch.

Fast:

- 3-5 million updates/sec in RAM
- >2.5 million updates/sec on consumer SSD

Compact:

- Compresses >200 GB stream into 45 GB sketch (2^{18} node graph)

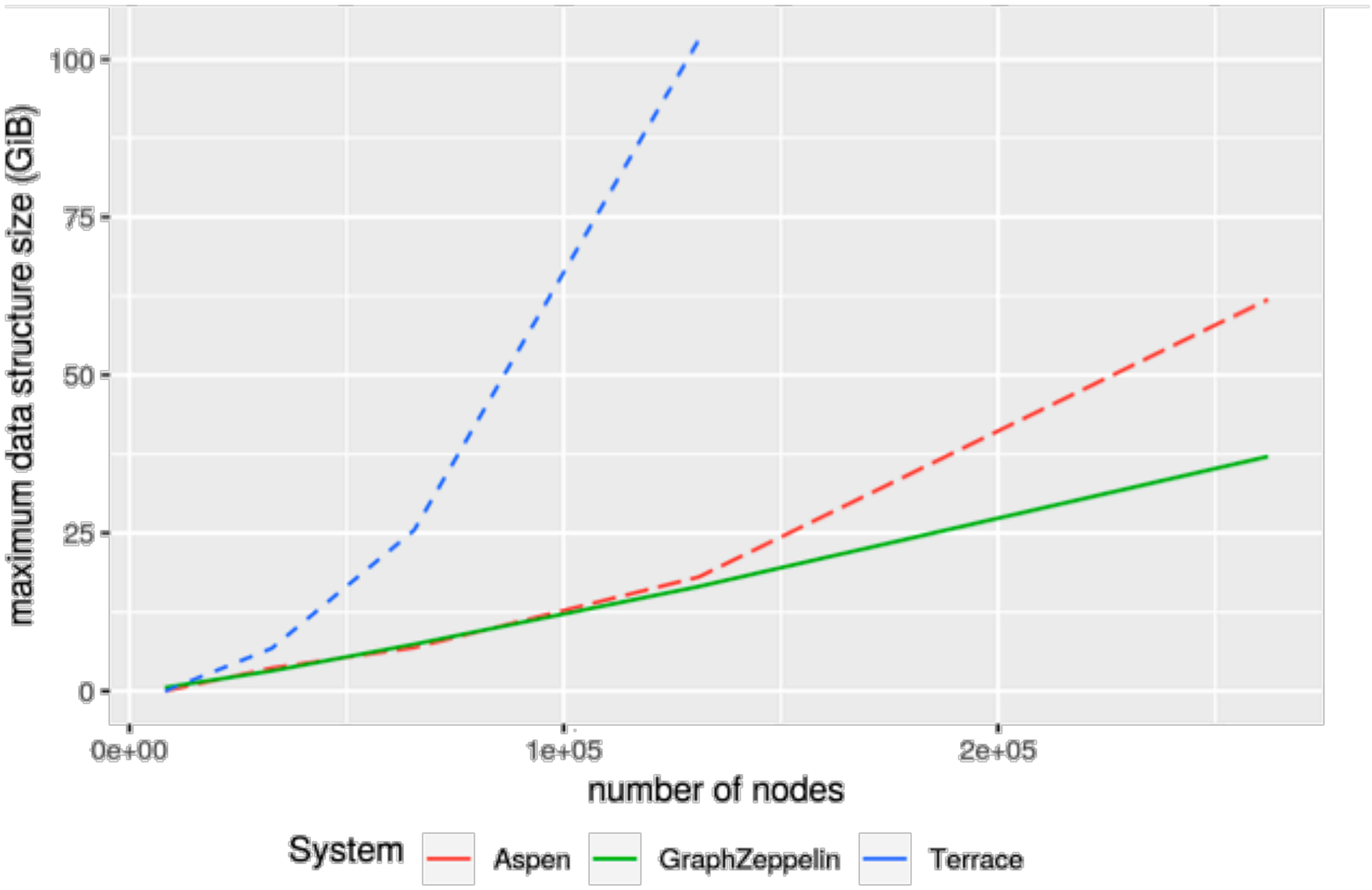
SMALLER ON DENSE GRAPHS

State-of-the-art:
Aspen **[Dhulipala, Blelloch, Shun 2019]**
Terrace **[Pandey, Wheatman, Xu, Buluç 2021]**

More compact:

- Aspen is 2x larger than GraphZeppelin
- Terrace is 10x larger than GraphZeppelin

Trend will continue - GraphZeppelin is asymptotically smaller: $O(n \log^3 n)$ vs $O(n^2)$



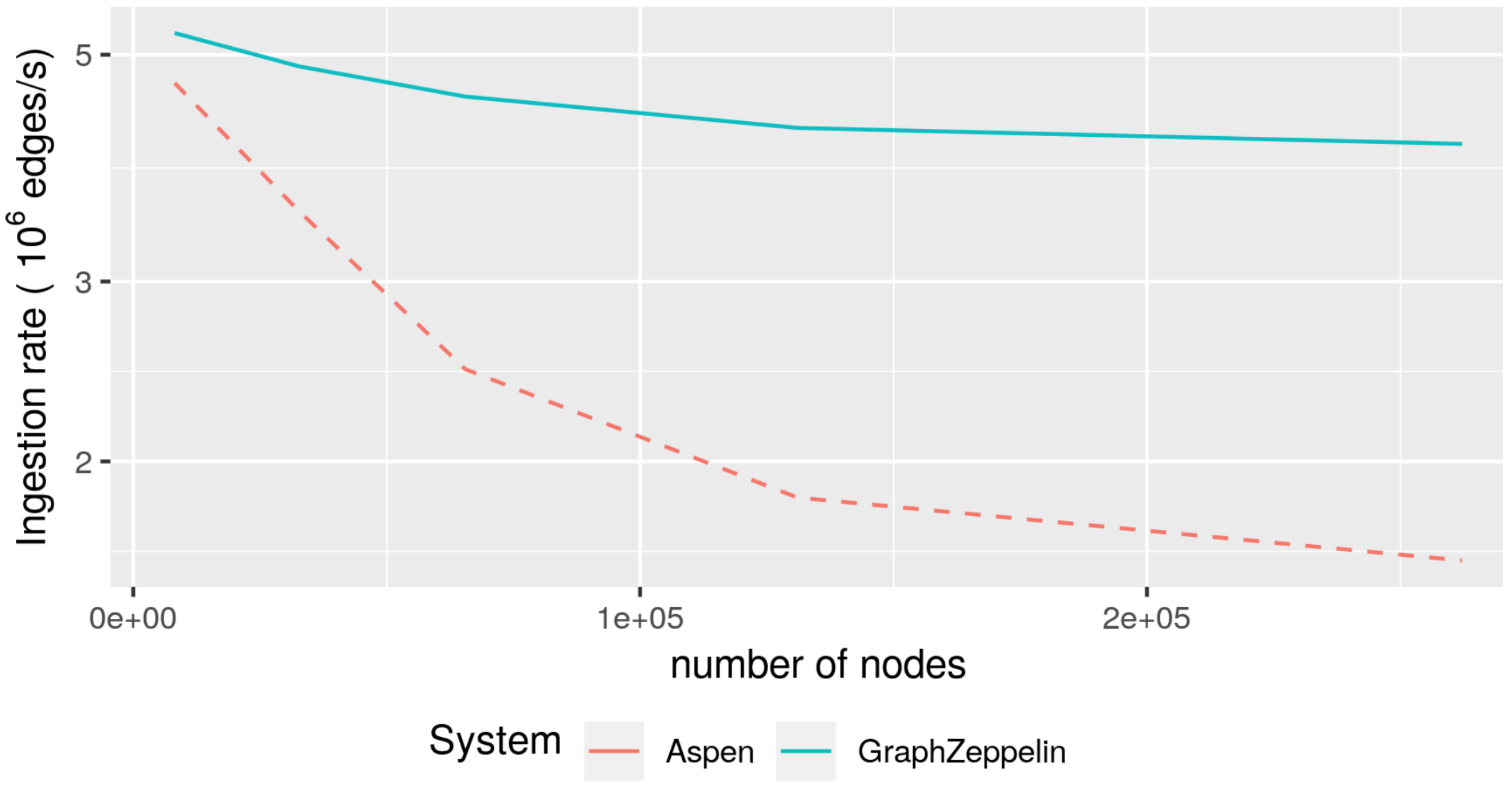
FASTER ON DENSE GRAPHS

Faster:

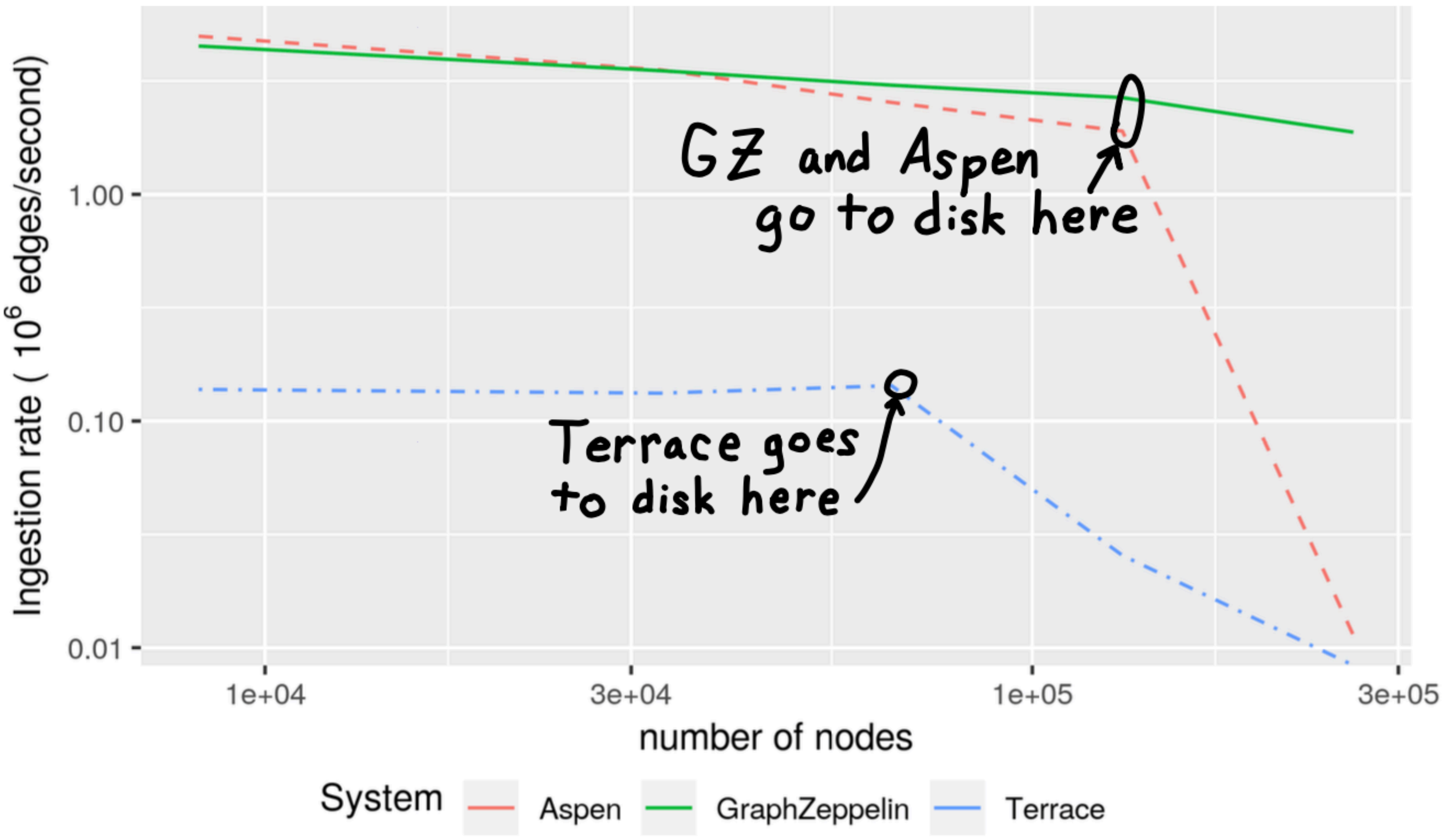
On dense graphs* in RAM,

- GraphZeppelin is 2x faster than Aspen
- GraphZeppelin is 30x faster than Terrace

*Aspen and Terrace are very fast on sparse graphs in RAM (10-50 million edges/sec)



FAST ON SSD

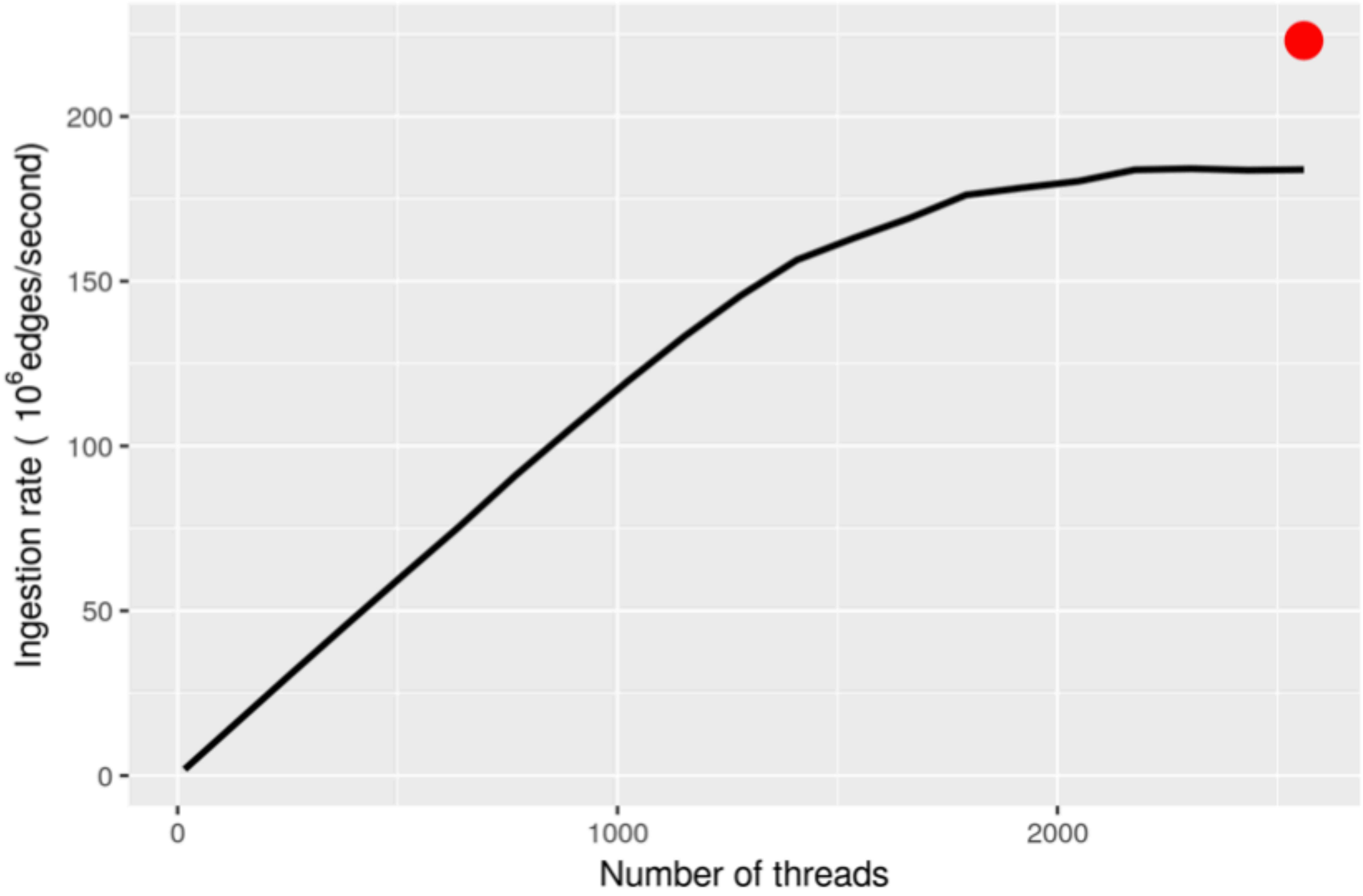

Ingestion rate (10^6 edges/second)
1.00
0.10
0.01
1e+04
3e+04
1e+05
3e+05
number of nodes
GZ and Aspen go to disk here
Terrace goes to disk here
System
Aspen
GraphZeppelin
Terrace

QUESTIONS? PLEASE ASK!

MORE DETAILS . . .

DISTRIBUTED SKETCHING

- Overcome GraphZeppelin's CPU bottleneck by distributing update work
- Sketching lets us avoid communication bottleneck of distributed graph systems
- Scale near-linearly until system bottlenecked by sequential RAM bandwidth



FUTURE WORK

- **Improve query performance**

  Current query times are comparable to Aspen/Terrace, but likely can be improved with a better algorithm.

- **Support more graph algorithms**

  E.g., k-connectivity, correlation clustering, triangle counting, spectral sparsification, minimum cut.