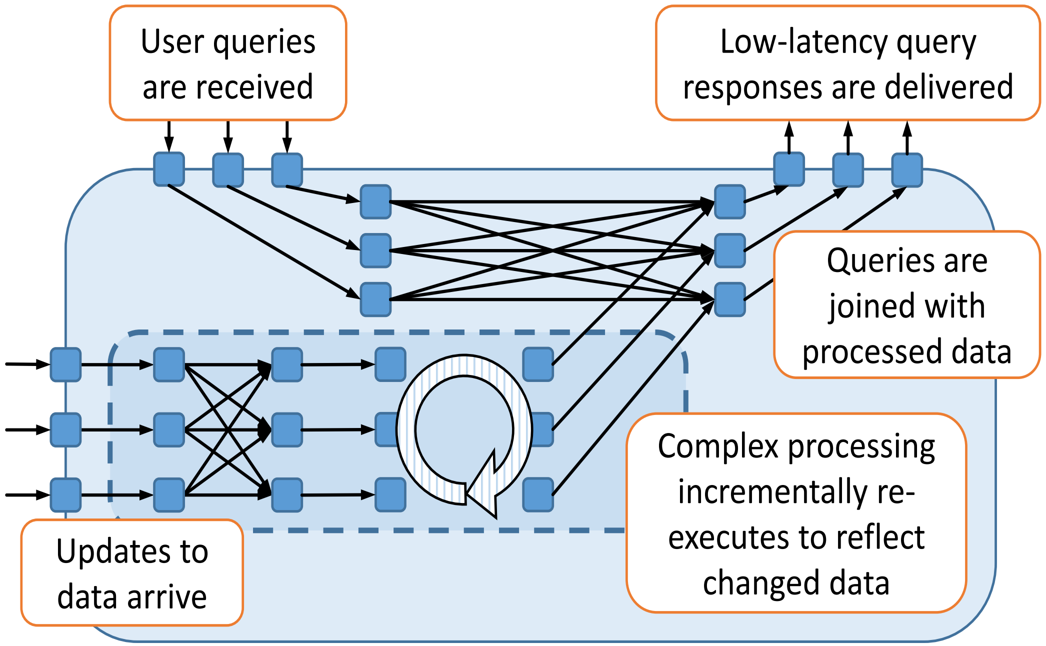
Paper Review
Naiad: A Timely Dataflow System[1]

Theo Long

19th October 2022

[1]All figures and information from Murray et. al (2013), unless otherwise specified

Naiad: High Performance Parallel Processing



Naiad: High Performance Parallel Processing

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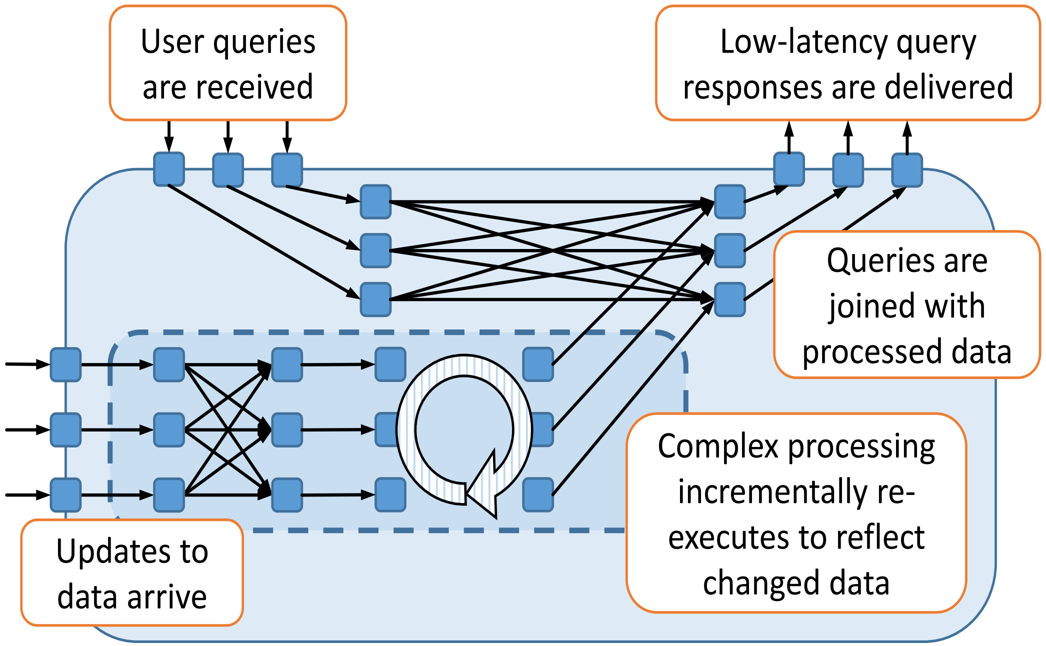

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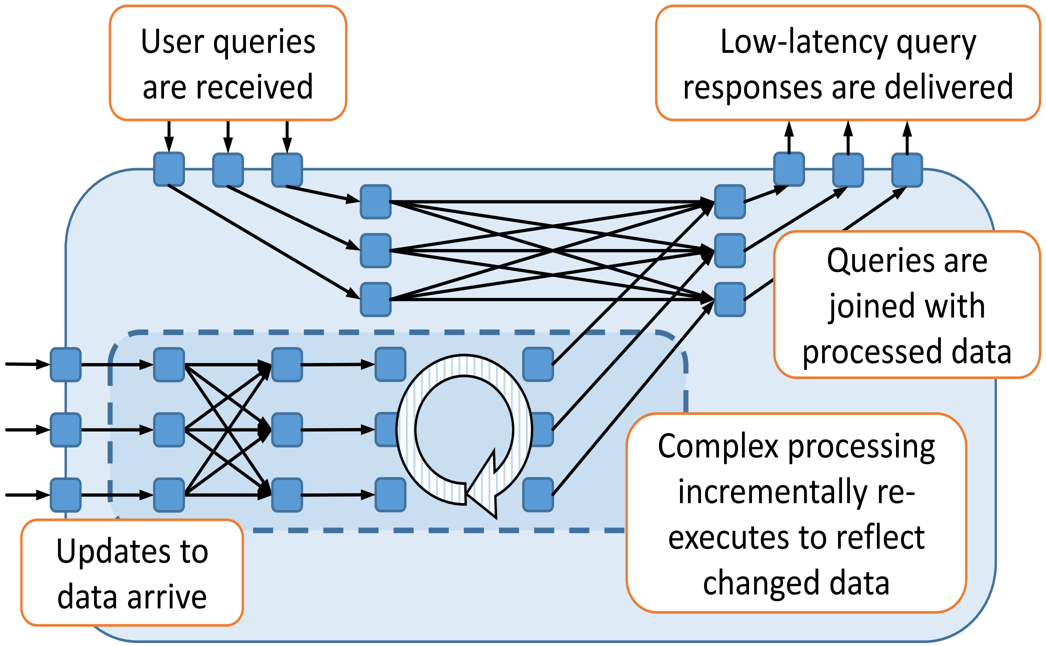

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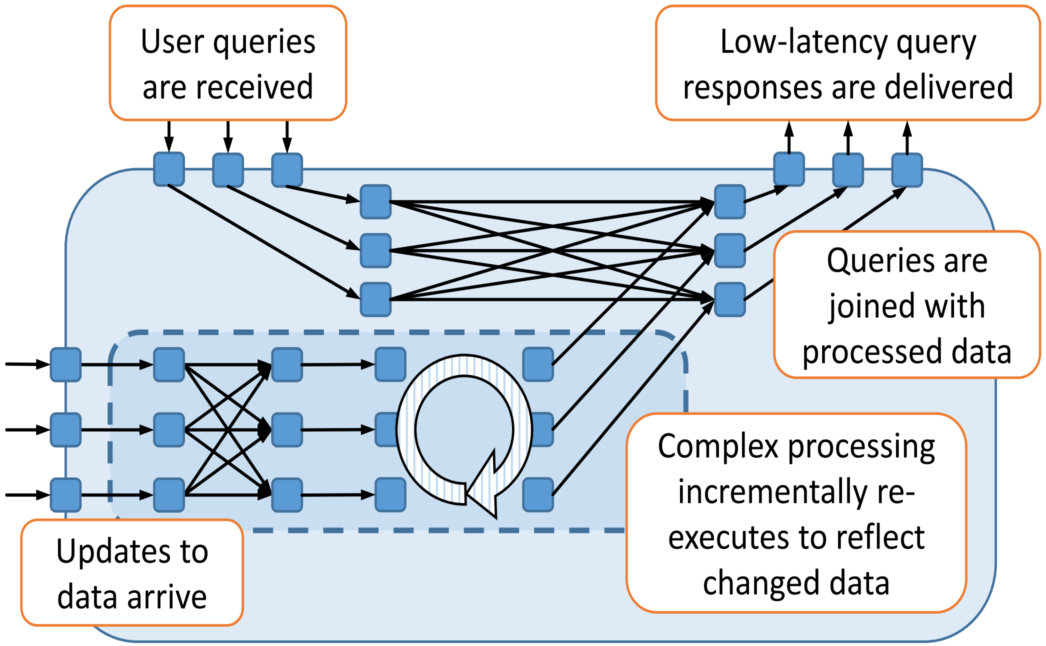

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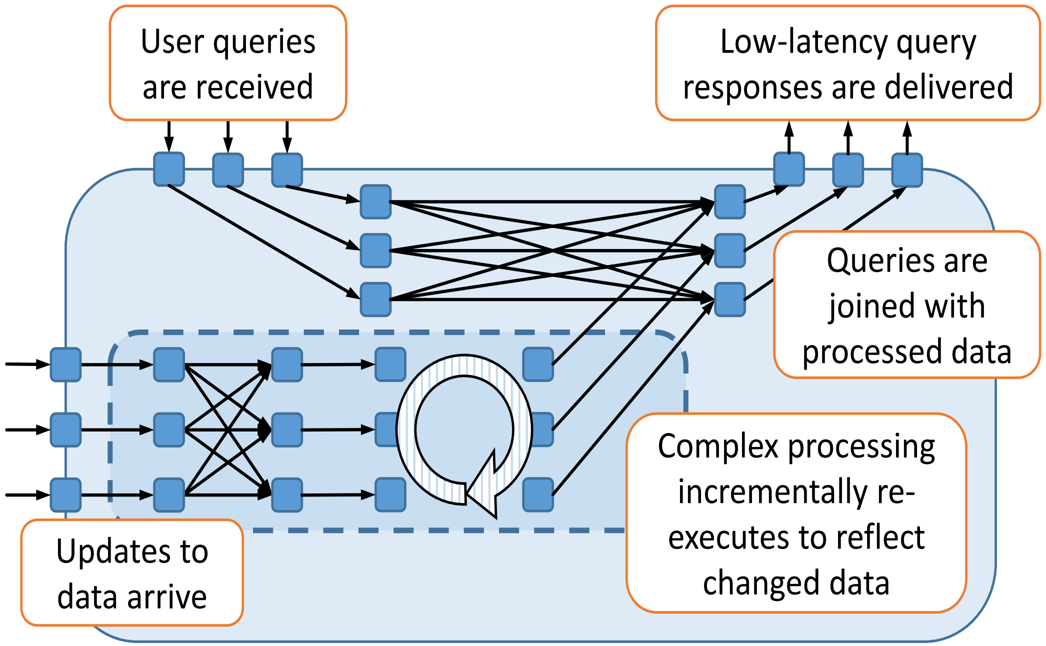
1. High throughput (like batch processing)
2. Low latency (like stream processing)
3. Iterative Computation – i.e. loops
4. Strong Consistency Guarantees



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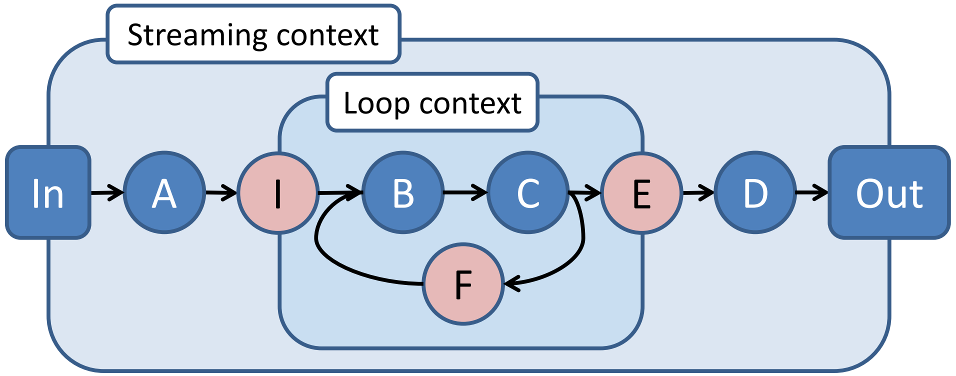
- Allows for nested cycles
- Vertices send and receive timestamped messages allowing for a partial ordering of computations that **includes time**
- This allows for parallel computation **across epochs**
- Global notification when all messages of given timestamp received -> Allows us to reason about result ‘as of’ a certain time

Key Abstraction: Timestamps



$$\text{Timestamp} : (\underbrace{e \in \mathbb{N}}_{\text{epoch}},\ \underbrace{\langle c_1, \ldots, c_k \rangle \in \mathbb{N}^k}_{\text{loop counters}})$$

Vertex	Input timestamp	Output timestamp
Ingress	$(e, \langle c_1, \ldots, c_k \rangle)$	$(e, \langle c_1, \ldots, c_k, 0 \rangle)$
Egress	$(e, \langle c_1, \ldots, c_k, c_{k+1} \rangle)$	$(e, \langle c_1, \ldots, c_k \rangle)$
Feedback	$(e, \langle c_1, \ldots, c_k \rangle)$	$(e, \langle c_1, \ldots, c_k + 1 \rangle)$

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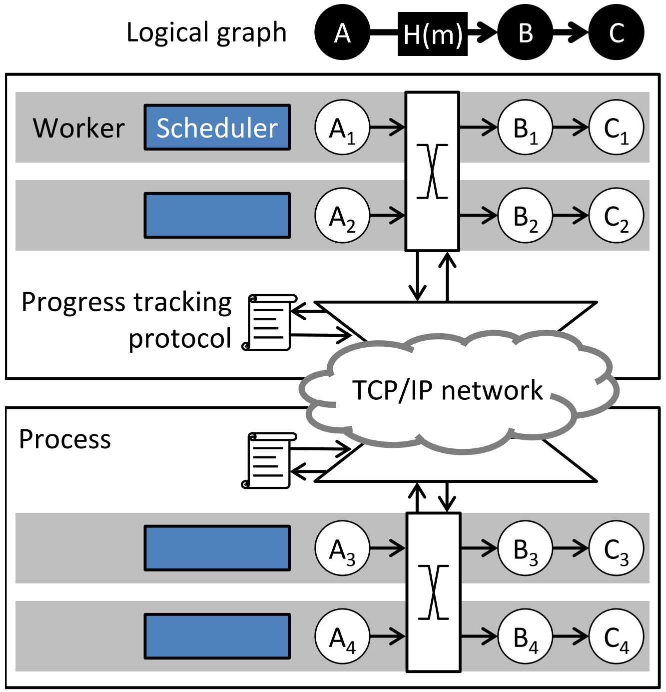
- When a pointstamp no longer has any predecessors (it is on the **frontier**), all corresponding events can be released

Making Timely Dataflow Distributed



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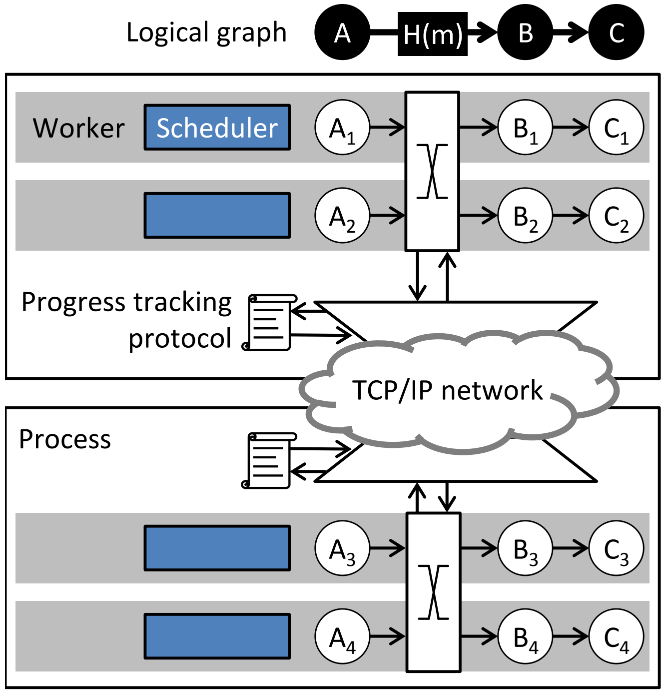

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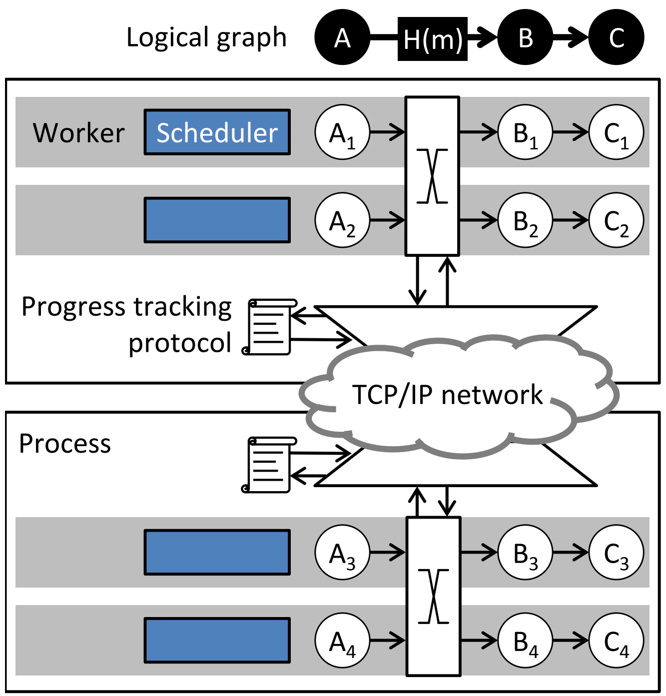
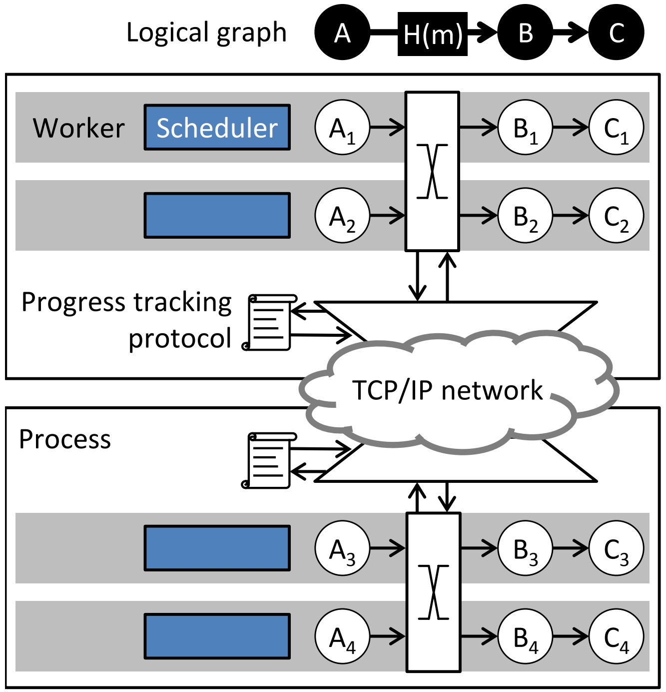


Making Timely Dataflow Distributed

- Naiad implements **data parallelism** – operating on multiple parts of the data at once
- Logical computation graph translated into **physical** graph
- Dependencies are always measured in the logical graph – this is not always optimal, but guarantees correctness



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- When an event is dispatched by a worker, it broadcasts update to all other workers
- By processing incoming updates from a given worker in FIFO order, we guarantee that the local frontier is always a subset of the global frontier

Optimizing Broadcasts

1. Progress tracking is done on logical graph, which is much smaller than physical graph

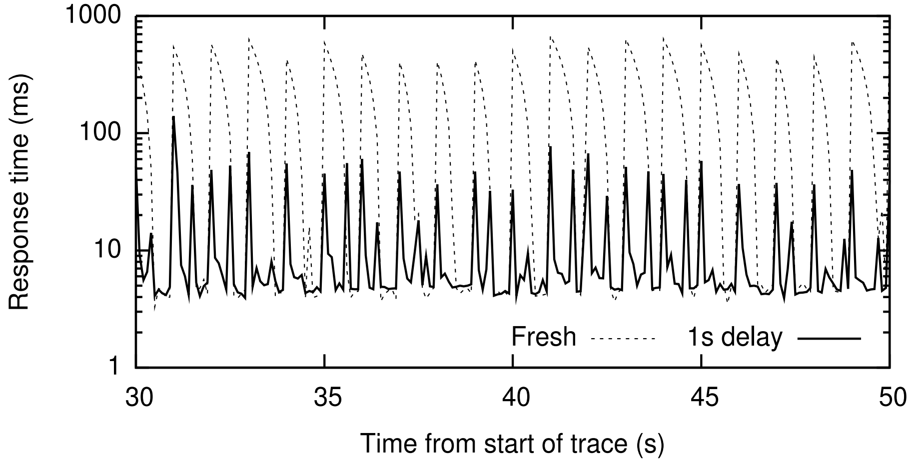
2. Updates are accumulated in a local buffer – updates with the same pointstamp are combined into one update

What do Naiad programs look like?

```
// 1a. Define input stages for the dataflow.
var input = controller.NewInput<string>();

// 1b. Define the timely dataflow graph.
// Here, we use LINQ to implement MapReduce.
var result = input.SelectMany(y => map(y))
                  .GroupBy(y => key(y),
                     (k, vs) => reduce(k, vs));

// 1c. Define output callbacks for each epoch
result.Subscribe(result => { ... });

// 2. Supply input data to the query.
input.OnNext(/* 1st epoch data */);
input.OnNext(/* 2nd epoch data */);
input.OnNext(/* 3rd epoch data */);
input.OnCompleted();
```

Naiad is Fast for Iterative Graph Computation

- Want to perform connected components on twitter mention graph
  - Also want to show top hashtag in each component
- One input stream of incoming tweets – 32k per second
- One query stream of usernames – 1 every 100ms



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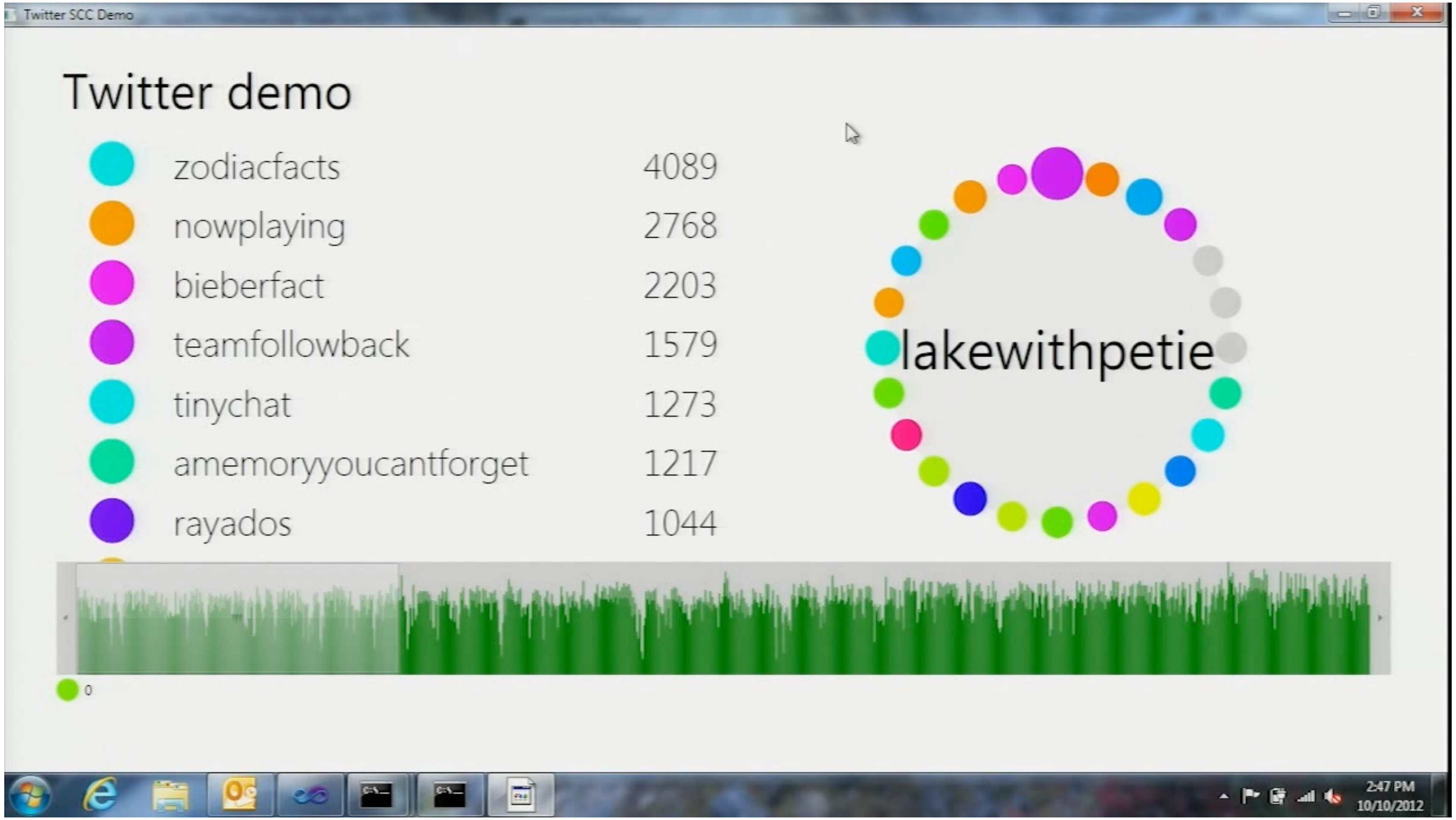

Source: 'Introducing Project Naiad and Differential Dataflow', https://www.youtube.com/watch?v=nRp3EQy6ccw

Thoughts, Comments, and Further Questions

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  - Many analytics workloads can be performed in batch mode

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- Cannot support dynamic computation graphs

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- Very well suited to real-time graph computation where number of iterations might be dynamic (e.g. BFS)
- Matches performance of many specialized systems of the time

Questions?