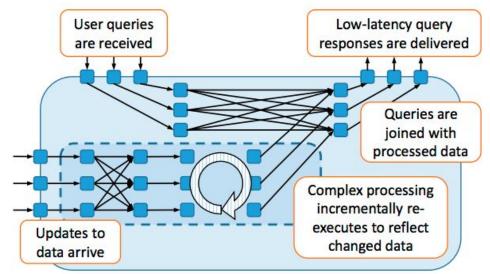
Naiad

James Thomas

Goals

- High-throughput batch processing
- Low-latency processing
- Iterative computation with streaming updates (novel contribution)
- For 100% in-memory workloads

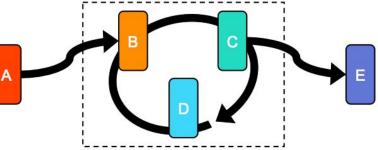


Novel Application, CIDR 2013 paper

- Maintaining connected components of graph formed by @username mentions on Twitter
- Connected components is iterative algorithm
- Batches of updates with new @username mentions coming in from Twitter, need to maintain connected components in real time
- First system that can do this

Solution: Lower-Level API, Vertex Model

 Philosophy: hack at lower level if performance needed, otherwise use higher-level library



v.ONRECV(e : Edge, m : Message, t : Timestamp)
v.ONNOTIFY(t : Timestamp).

this.SENDBY(e: Edge, m: Message, t: Timestamp) this.NOTIFYAT(t: Timestamp).

Low-level API Example

```
class DistinctCount<S,T> : Vertex<T>
 Dictionary<T, Dictionary<S, int>> counts;
 void OnRecv(Edge e, S msg, T time)
   if (!counts.ContainsKey(time)) {
     counts[time] = new Dictionary<S, int>();
     this.NotifyAt(time);
   if (!counts[time].ContainsKey(msg)) {
     counts[time][msg] = 0;
     this.SendBy(output1, msq, time);
   counts[time][msq]++;
 void OnNotify(T time)
   foreach (var pair in counts[time])
     this.SendBy (output2, pair, time);
   counts.Remove(time);
```

High-level Library Example

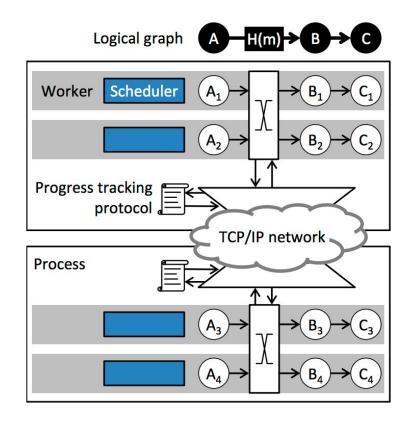
```
// la. Define input stages for the dataflow.
var input = controller.NewInput<string>();
```

```
// 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));
```

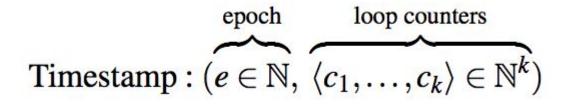
```
// 1c. Define output callbacks for each epoch
result.Subscribe(result => { ... });
```

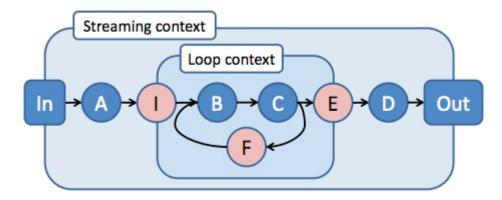
```
// 2. Supply input data to the query.
input.OnNext(/* 1st epoch data */);
input.OnNext(/* 2nd epoch data */);
input.OnNext(/* 3rd epoch data */);
input.OnCompleted();
```

Distributed Implementation



Distributed Progress Tracking -- Timestamps





Distributed Progress Tracking -- Pointstamps

Pointstamp : $(t \in \text{Timestamp}, \ \widetilde{l \in \text{Edge} \cup \text{Vertex}})$

OperationUv.SENDBY(e,m,t)Ov.ONRECV(e,m,t)Ov.NOTIFYAT(t)Ov.NOTIFYAT(t)O

Update

$$OC[(t,e)] \leftarrow OC[(t,e)] + 1$$

 $OC[(t,e)] \leftarrow OC[(t,e)] - 1$
 $OC[(t,v)] \leftarrow OC[(t,v)] + 1$
 $OC[(t,v)] \leftarrow OC[(t,v)] - 1$

Distributed Progress Tracking -- Putting it Together

- Can deliver OnNotify at a vertex if OC for all lower or equal timestamps at predecessor vertices or edges is 0
 - This OnNotify is in the "frontier"
- In distributed setting node's local frontier is conservative and assumes that other nodes haven't made progress until it explicitly hears from them

Fault Tolerance

- System calls user-defined Checkpoint() on vertices during a system-wide checkpoint, can Restore() them on failure
- Vertices can continuously log for better fault recovery at the expense of some throughput
- Higher burden on developer

Fault Tolerance -- Comparison with Spark/MR

- Since Spark/MR work with stateless tasks, on the failure of a node only the failed tasks need to be re-executed, reading from persisted barrier output
- Since vertices are continuously sending data to one another and updating mutable state and there is no system-imposed barrier like in Spark/MR, on the failure of ANY node Naiad must stop all nodes and restore them from the last system-wide checkpoint
- But scheduler needs to be on the path of every job to achieve this property (store lineage of ops), making Spark/MR less suitable for low-latency work

Optimizations -- Prevent Micro-Stragglers

- Tune TCP for this workload (e.g. reduce retransmission timeouts)
- Tune GC so there are fewer stop-the-worlds
- Shared memory contention
- Keep message queues small
- Can't solve stragglers if they still happen!