Naiad: A Timely Dataflow System

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 24^{th} ACM Symposium on Operating System Principles, 2013

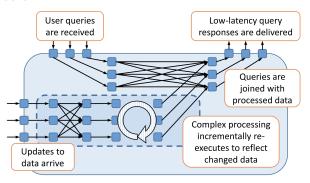
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Agenda

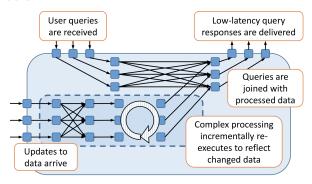
- Introduction
- Timely Data Flow
- Distributed Implementation
- Programming Model
- Performance Evaluation
- Real World Applications

Introduction





Introduction



Batch

- Iteration
- Consistency
- Poor latency

Stream

- No iteration
- No consistency
- Low latency

Graph

- Iteration
- Vertex-oriented Programming

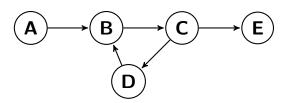
Introduction

- General purpose system
- Support high-level programming models
- Iteration on real-time data
- Supports interactive queries on fresh, consistent view of results
- Low latency specialized system performance

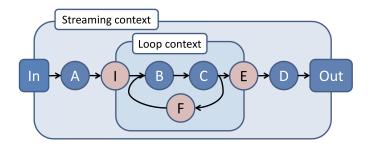
Timely Dataflow

Dataflow programming primitives based on time

- Structured Loops
- Stateful vertices
- Notification for vertices on iteration completion



Timely Dataflow - Graph Structure



- Time epoch on every input
- Streaming Context Process data and pass
- Loop Context
 - Loop Ingress (I) \Rightarrow Feedback (F) \Rightarrow Egress (E)
 - Monitors progress

Timely Dataflow - Concurrency Primitives



Vertices register callbacks

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

v.OnNotify(t: Timestamp)

Vertices generate events

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

this.NotifyAt(t: Timestamp)

Timely Dataflow - Concurrency Primitives



- ONRECV and ONNOTIFY are queued, no strict ordering
- Notify guarantee:

v. OnNotify(t) is invoked only after no further invocations of v. OnRecv(e, m, t'), for $t' \leq t$

Backward time constraint:

Callback methods at t should only call, SendBy(t') and NotifyAt(t') such that $t' \geq t$

Timely Dataflow - Timestamp

$$(e \in \mathbb{N}, \langle c_1, \dots, c_k \rangle \in \mathbb{N}^k)$$

Example: (epoch, counter) - (1, (0, 1, 2))

Vertex Behavior:

- Ingress $\langle c_1, \dots, c_k \rangle \Rightarrow \langle c_1, \dots, c_k, 0 \rangle$
- Egress $\langle c_1, \dots, c_k, c_{k+1} \rangle \Rightarrow \langle c_1, \dots, c_k \rangle$
- Feedback $\langle c_1, \dots, c_k \rangle \Rightarrow \langle c_1, \dots, c_k, c_{k+1} \rangle$

Ordering:

$$t_1 = (e_1, \vec{c_1}), t_2 = (e_2, \vec{c_2})$$

 $t_1 < t_2 \iff e_1 < e_2 \text{ and } \vec{c_1} < \vec{c_2}$

Future timestamps constrained by,

- Unprocessed events (SENDBY and NOTIFYAT)
- Graph structure



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for, v.SENDBY(e, m, t), pointstamp = (t, e) for, v.NotifyAt(t), pointstamp = (t, v)

Future timestamps constrained by,

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- Graph structure

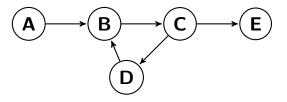
Pointstamp: $(t \in \mathsf{Timestamp}, \ l \in \mathsf{Edge} \cup \mathsf{Vertex})$

for,
$$v.SENDBY(e, m, t)$$
, pointstamp = (t, e)
for, $v.NotifyAt(t)$, pointstamp = (t, v)

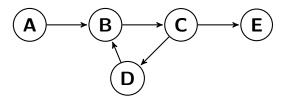
Structure constraint induces ordering:

 (t_1,l_1) could-result-in (t_2,l_2) \iff \exists path $\psi = \langle l_1,\ldots,l_2 \rangle$ such that t_1 is adjusted by each I, E or F, satisfies $\psi(t_1) \leq t_2$.

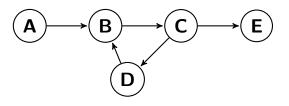




Is there a path between D and E?



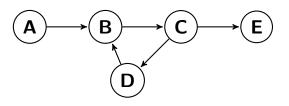
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((1,2),D) could-result-in ((1,4),C)?



Is there a path between D and E?

(1, A) could-result-in (1, E)?

((1,2),D) could-result-in ((1,4),C)?

((3,4),D) could-result-in (2,E) ?

Timely Dataflow - Single-Threaded Scheduler

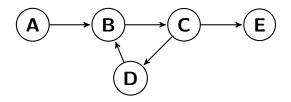
- A set of active pointstamps (at least 1 unprocessed event).
- For each active poinstamp, maintains,
 - occurrence count outstanding events.
 - precursor count how many active poinstamps precede.
- Update *occurrence count* for each event.

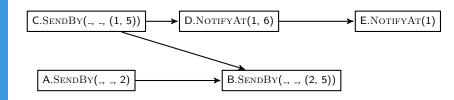
Timely Dataflow - Single-Threaded Scheduler

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Scheduler is a simple message sorting function, to deliver notifications

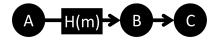
Visualizing the scheduler





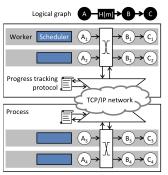
Distributed Implemenation

Naiad is the distributed implementation of timely dataflow



- A program consists of logical stages (A, B, C)
- H(m) Partitioning function
- H(m) controls exchange of data between stages

Data Parallelism



- Physical graph represents the chosen amount of workers and distributed connected hosts
- Programmer can select which way a message should flow in the system stages
- Naiad always uses the logical graph as a decision base where data has to flow

Worker

Delivers messages (data) and notifications to vertices

- Tie-breaker Always deliver messages before notifications
- Responsible for multiple vertices

Synchronization

- Communicate through shared queue
- \bullet Queue not necessary if $\mathrm{SEND}/\mathrm{RECV}$ are under same worker
- Re-entrancy due to loops enqueue for later, coalesce incoming messages in ONRECV to reduce memory.



Progress tracking

- Local occurrence counter don't get updated directly
- Change of occurrence gets broadcasted
- Change gets queued and modified in FIFO order
- Therefore the local counter is never before the global counter

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Optimize broadcast

- Rely on the logical graph, not the physical
- Buffer before broadcast
- Optimistically first broadcast via UDP to reduce latency
- Wake up threads with either broadcast or unicast with programming primitives



Fault tolerance and Availability

CHECKPOINT and RESTORE interface

- Vertex
 - Either log data or
 - Full checkpoint when requested
- Progress Tracking Protocol
 - Full checkpointing

Fault tolerance and Availability

CHECKPOINT and RESTORE interface

- Vertex
 - Either log data or
 - Full checkpoint when requested
- Progress Tracking Protocol
 - Full checkpointing

Checkpointing

- Message delivery gets stopped
- Outstanding ONRECV Events get delivered
- Save to disk

Restoring

- Revert from the last checkpoint
- Vertexes of failed process get reassigned



Micro Stragglers

Tiny latencies which can add up in a large system

Network

- Disable Nagle's algorithms
- Set smaller retry timeout for package loss
- Use different network protocols in datacenters for computing

Data structure contention

solved by smaller clock granularity

Garbage Collection

- avoid object allocation
- use buffer pools
- use value types



Naiad Program

- Provides public API with primitives
- Higher Level APIs
 - LINQ
 - MapReduce
 - Pregel
- Examples do not support coordination
 - to improve performance
 - concat, distinct, select
- Generic API for vertex programming
 - First define the behavior dataflow vertices
 - Second define the topology

Prototype Program

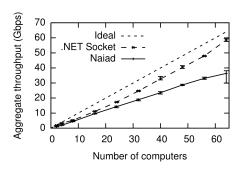
```
// la. Define input stages for the dataflow.
var input = controller.NewInput<string>();
// 1b. Define the timely dataflow graph.
// Here, we use LINQ to implement MapReduce.
var result = input.SelectMany(v => map(v))
                  .GroupBy(
                     y => key(y).
                     (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();
```

Performance Evaluation



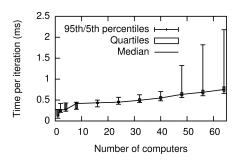
Performance Evaluation - Throughput

- Cyclic dataflow that repeatedly performs all-to-all data exchange of a fixed number of records.
- Ideal aggregate throughput based on Ethernet Bandwidth.
- .NET Socket demonstrates achievable throughput given network topology, TCP overheads and .NET API costs.
- Naiad throughput scales linearly.



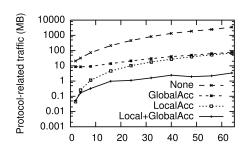
Performance Evaluation - Latency

- Minimal time required for Global Coordination.
- Request and receive completeness notifications.
- Median time per iteration small at $753\mu s$ for 64 computers.
- 95th percentile results adverse impact of micro-stragglers.



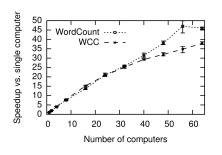
Performance Evaluation - Protocol Optimizations

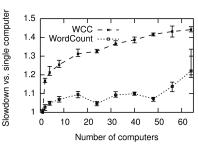
- Weakly Connected Components Computation (WCC) on random graph of 300 edges (2.2GB of raw input).
- Reduction in volume of protocol traffic depending on level of accumulation.
- In practice, reduction in messages from local accumulation is sufficient.



Performance Evaluation - Scaling

- Strong scaling Adding compute resources with fix input size.
- Weak scaling Adding compute resources and increasing input.
- Word Count 128GB uncompressed corpus.
- WCC Random Graph of 200M edges.





Real World Applications



Real World Applications - Batch Iterative Graph Computation

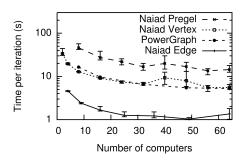
- Graph Computation on Large scale real world datasets.
- PDW Distributed Database
- DryadLINQ General Purpose Batch Processor
- SHS Purpose Built Distributed Graph Store
- Speedups demonstrate the power of being able to maintain application-specific state in memory between iterations.

Algorithm	PDW	DryadLINQ	SHS	Naiad
PageRank	156,982	68,791	836,455	4,656
SCC	7,306	6,294	15,903	729
WCC	214,479	160,168	26,210	268
ASP	671,142	749,016	2,381,278	1,131

Running time in seconds

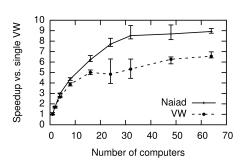
Batch Iterative Graph Computation

- Several systems have adopted the computation of PageRank on a Twitter follower graph as a standard benchmark.
- Naiad Vertex Partitions edges by source vertex.
- Naiad Edge Partitions edges using a space-filling curve.



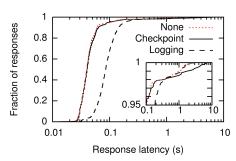
Batch Iterative Machine Learning

- Vowpal Wabbit (VW) open-source distributed machine learning library
- Modified VW –
 first and second phases run inside a Naiad vertex,
 third phase uses Naiad implementation of the AllReduce.



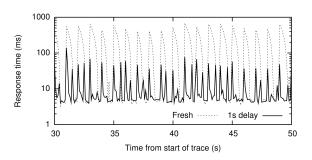
Streaming Acyclic Computation

- Kineograph ingests arriving graph data, takes regular snapshots for data parallel computation, and produces consistent results.
- The system is partitioned into ingest nodes and compute nodes.
- k-exposure metric for identifying controversial topics on Twitter.



Streaming Iterative Graph Analytics

- There are two input stages: stream of tweets and requests, specified by a user name and query identifier.
- "Fresh" queries being delayed behind tweet processing
- "1s delay" the benefit of querying stale but consistent data.
- Naiads support for overlapped computation by trading off responsiveness for staleness.





Thank you

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