Fault-Tolerant Aggregation: Flow Update Meets Mass Distribution

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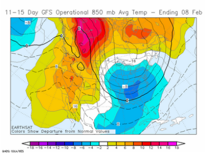
Motivation - Distributed Data Aggregation

- Important building block of distributed applications
- Transmission of raw data may not be scalable/economic
- Raw data may not fit in memory footprints
- Raw data may be highly redundant
- Applications often rely on data summaries

Motivation - Application Examples

- To obtain network statistics and administration information:
  - Network size
  - Total resources available
  - Average session time
  - Max./Min. network load
  - ...

- Monitor and control a covered area (WSN):
  - Min./Max. temperature
  - Average humidity
  - Concentration of a toxic substance
  - Noise level
  - ...



Aggregation Approaches

Several classes of aggregation algorithms

- Hierarchic: TAG
- Sketches: FM-Sketches, Extrema Propagation
- Sampling: Randomized Reports, Sample & Collide
- Averaging: Push-Sum, Push-Pull

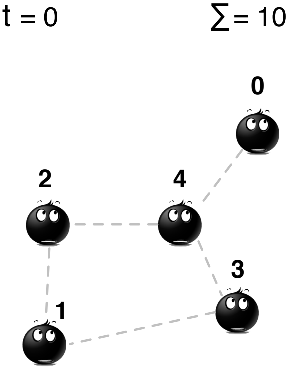
Both Hierarchic and Averaging allow high precision aggregates.

Existing Approaches

Averaging
(e.g. Push-Sum/Synopses, Push-Pull, DRG)

- Iterative *Averaging* process
- Topology independent
- Result produced at all nodes

- Correctness ⇒ "mass conservation":
  - $\sum_{i \in \mathcal{V}} v_i = \sum_{i \in \mathcal{V}} e_i^t = k$



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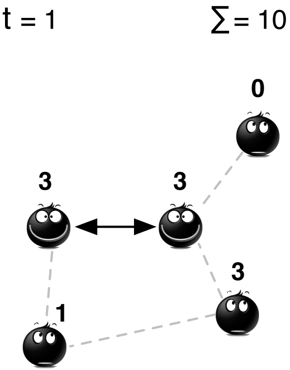

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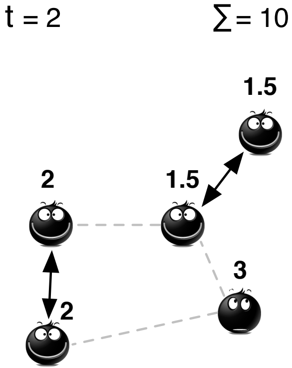

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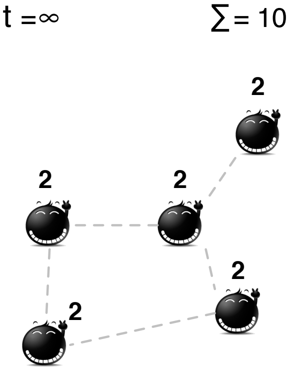
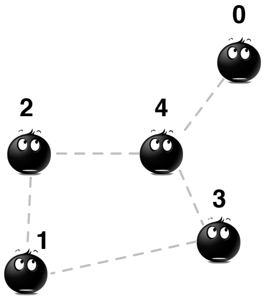


Dependability Issues of Averaging Approaches

Message loss:

$t = 0$ $\sum = 10$

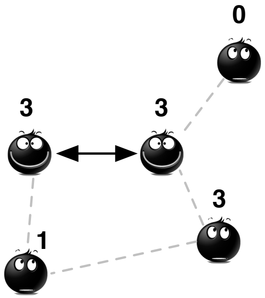


Problem:

- Loss of mass
- Violation of "mass conservation"
- Convergence to a wrong value

Dependability Issues of Averaging Approaches

Message loss: $t = 1$ $\sum = 10$



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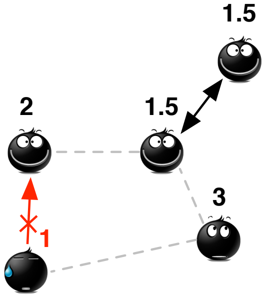
Dependability Issues of Averaging Approaches

Message loss:

$t = 2$ $\sum = 9$



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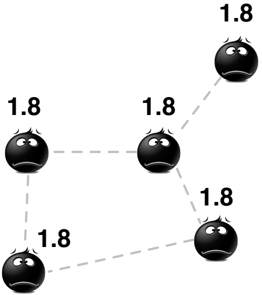
Dependability Issues of Averaging Approaches

Message loss:

t $=\infty$ $\sum = 9$



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Flow Updating

Flow Updating (DAIS 2009, IEEE SRDS 2010)

Robust aggregation algorithm for dynamic networks:

- Independent from the routing topology (gossip-based)
- Converges to the correct result at all nodes
- Supports message loss and node crashes
- Self-adapts to changes in input values

Flow Updating

- Based on the concept of flow from graph theory
  - Examples: water flow, electrical current
- Each node maintains flows to neighbors
  - Flows converge to symmetrical values
- Update flows by sending idempotent messages
- Keep the initial input values unchanged
- Compute the aggregate from the initial value and flows

Mass Distribution with Flow Updating

Flow Updating. Works very in empirical evaluations, but:

- Convergence in not monotonic
- Protocols have eluded analysis

MDFU was developed: Mass Distribution with Flow Updating

- Monotonic convergence
- Bounds for fault free and for stochastic message loss

Model and Notation

- Synchronous rounds
- Undirected connected graph G(V,E)
- For $i \in V$: neighbors N_i, degree $|N_i|$
- For $(i,j) \in E$: $D_{ij} = \max\{|N_i|, |N_j|\}$, $\Delta = \max_{i \in V} |N_i|$
- For edge and round, message failure probability f

Target Computation, and Node State

- Each nodes holds inputs value v_i
- Each nodes needs to compute $\overline{v} = \sum_{i=1}^{n} v_i / n$
- No global knowledge
  - n is unknown
  - Nodes only know: N_i and D_{ij}
  - Nodes compute e_i a local estimate of $\overline{v}$
- Nodes track for each neighbor:
  - *inbound flow* in F_{in}
  - *outbound flow* in F_{out}
- Nodes compute e_i a local estimate of $\overline{v}$
- $e_i = v_i + \sum_{j \in N_i} (F_{in}(j) - F_{out}(j))$

MDFU Algorithm

```
// initialization
```

$e_i \leftarrow v_i$;
foreach $j \in N_i$ **do**
    $F_{in}(j) \leftarrow 0$;
    $F_{out}(j) \leftarrow e_i / (2D_{ij})$;
end

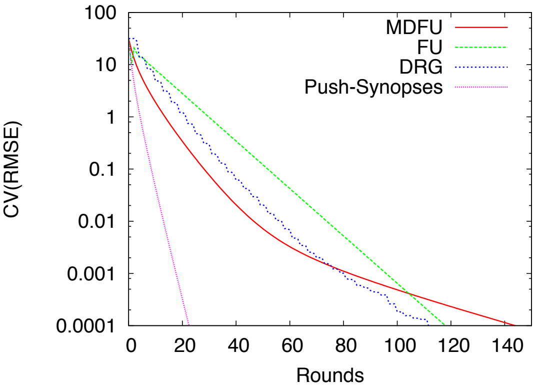
foreach *round* **do**
    `// communication phase`
    foreach $j \in N_i$ **do**
        Send j message $\langle i, F_{out}(j) \rangle$;
    end
    foreach $\langle j, F \rangle$ *received* **do**
        $F_{in}(j) \leftarrow F$;
    end
    `// computation phase`
    $e_i \leftarrow v_i + \sum_{j \in N_i} (F_{in}(j) - F_{out}(j))$;
    foreach $j \in N_i$ **do**
        $F_{out}(j) \leftarrow F_{out}(j) + e_i / (2D_{ij})$;
    end
end

Analytical Results

- For any target precision $0 < \xi < 1$
- Estimates within $[(1-\xi)\overline{v}, (1+\xi)\overline{v}]$
- For $f = 0$, a graph of size n and conductance $\Phi(G)$
- Convergence time (in rounds) is at most: $2 * \ln \frac{n}{\xi} * \frac{1}{\Phi(G)^2}$
- Precision grows exponentially with rounds
- Under $f > 0$ we derived multiplicative overheads over $f = 0$

Comparative Results (no message loss)

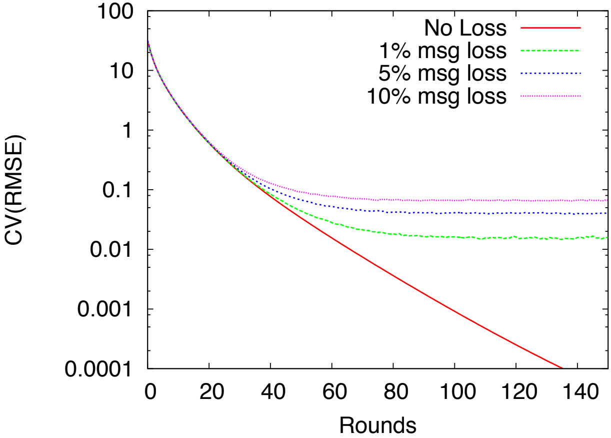
Erdos-Renyi Random Network $G(V, E)$, $|V| = 1000$, $|E| = 5000$



- DRG and Push-Synopses will not tolerate message loss
- CV(RMSE) $= \sqrt{\sum_{i \in V} (e_i - \overline{v})^2 / n} / \overline{v}$

MDFU under message loss f

Erdos-Renyi Random Network $G(V, E)$, $|V| = 1000$, $|E| = 5000$



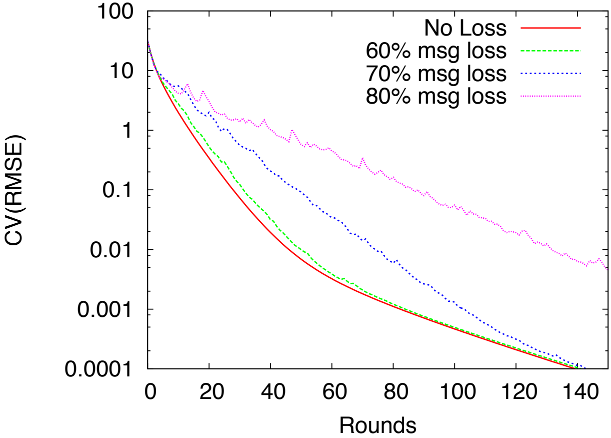
- Convergence, not to $\overline{v}$, but to a bias point in $[(1-f)\overline{v}, \overline{v}]$
- Mass is added as sent, in F_{out}, but not received in F_{in}

MDFU with Linear Prediction

- As node estimates converge, in neighbor nodes $e_x \approx e_y$
- Since flow F_{out} increases by $e_i/(2D_{ij})$
- In each edge flow growth velocities also converge
- When messages are not received, in an edge, one can (linearly) predict how F_{in} should have grown in an edge
- just multiply the last increase by the rounds with no message
- results are surprisingly good ...

MDFU-LP under very high message loss f

Erdos-Renyi Random Network $G(V, E)$, $|V| = 1000$, $|E| = 5000$



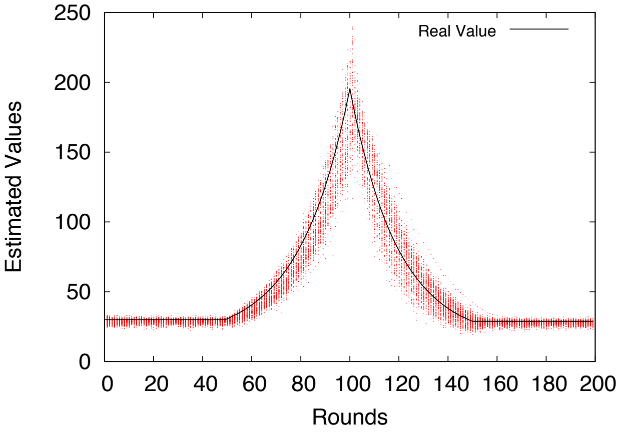
$$\mathrm{CV(RMSE)} = \sqrt{\sum_{i \in V} (e_i - \overline{v})^2 / n} / \overline{v}$$

MDFU-LP with input value variation

- Most averaging algorithms (PUSH-*) distribute mass
- They restart when node input value v_i changes
- Ongoing convergence is lost
- A recent exception is LiMoSense (ALGOSENSOR'11)
- MDFU (MDFU-LP) handle v_i variations with no modifications

MDFU-LP with input value variation

Erdos-Renyi Random Network $G(V, E)$, $|V| = 1000$, $|E| = 5000$, $f = 10\%$.



Closing remarks

- High precision distributed aggregation requires averaging
- Traditional "mass" exchange approaches should give way to idempotent algorithms, like *Flow Updating*
- Future work can include.
  - Asynchrony in MDFU (already studied in FU)
  - More complex aggregates: Cumulative Distribution Functions
  - Strategies to further increase convergence speed