

Robust Distributed Estimation: Extending Gossip Algorithms to Ranking and Trimmed Means

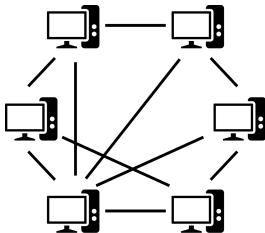
Can we design more robust gossip algorithms?

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Gossip Algorithms: Where and Why?

- When data is distributed over a **network**.
- If we have **resource** and **communication** constraints.
- If we don't have access to a **central server**.



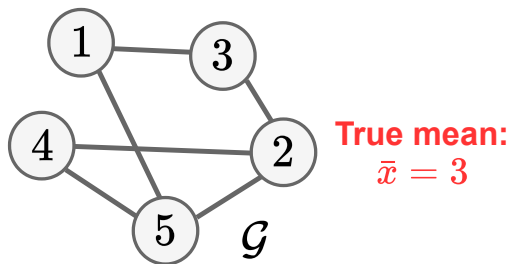
Peer-to-Peer (P2P) Networks



Wireless Sensor Networks

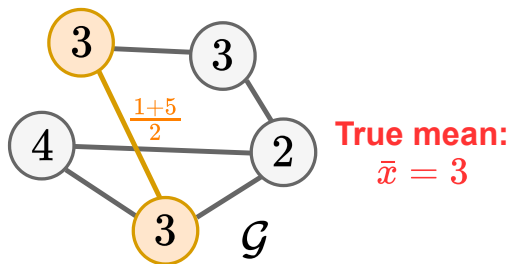
...and many more!

Simple Example: Gossip for Averaging



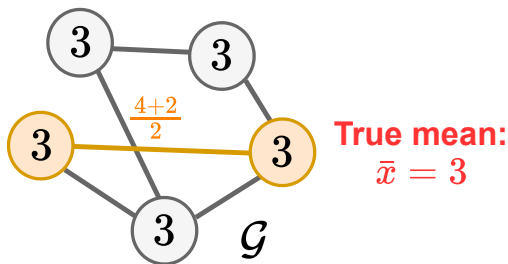
Select random $(i, j) \in E$, average X_i and X_j

Simple Example: Gossip for Averaging



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Simple Example: Gossip for Averaging



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What Makes the Theoretical Analysis Work?

- **Averaging matrix:** $t > 0$, for a random edge $(i, j) \in E$,

$$\mathbf{W}_2(t) = \mathbf{I}_n - \frac{1}{2} (\mathbf{e}_i - \mathbf{e}_j) (\mathbf{e}_i - \mathbf{e}_j)^\top.$$

- Its **expectation** with respect to the edge sampling process:

$$\mathbf{W}_2 = \mathbb{E} [\mathbf{W}_2(t)] = \mathbf{I}_n - \mathbf{L} / (2|E|).$$

Graph Laplacian

- **Properties:** symmetric, doubly stochastic and

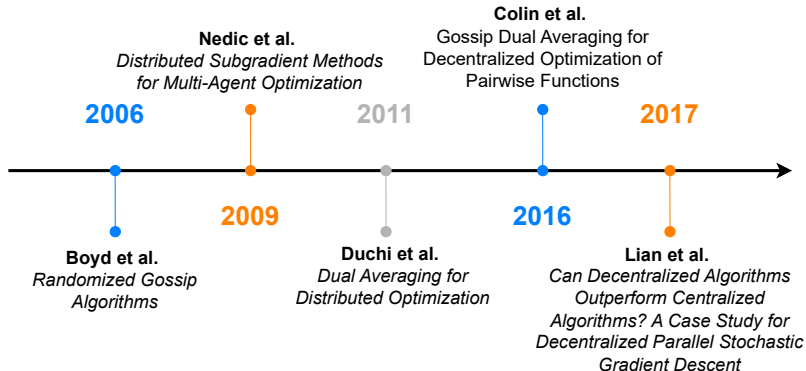
$$\|\mathbf{W}_2 - \mathbf{1}_n \mathbf{1}_n^\top / n\|_{\text{op}} \leq 1 - c / 2 < 1.$$

Graph's connectivity

- **Convergence in expectation:**

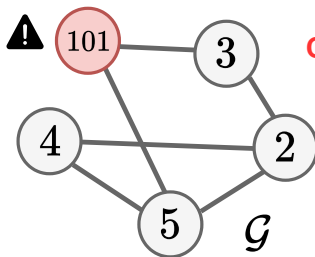
$$\|\mathbb{E}[\mathbf{Y}(t)] - \bar{x}_n \mathbf{1}_n\| \leq \left(1 - \frac{c}{2}\right)^t \|\mathbf{X} - \bar{x}_n \mathbf{1}_n\|.$$

Applications of Gossip for Decentralized Learning



When Gossip Goes Wrong...

- What if a node's value is **corrupted**? **All estimates will be corrupted!**
- The average is **not robust** to outliers. We need more robust statistics, e.g., **trimmed mean** (see Huber's robustness).



Corrupted mean:

$$\bar{x} = 23$$

True mean:

$$\bar{x} = 3$$

Robust Statistics: Trimmed Means

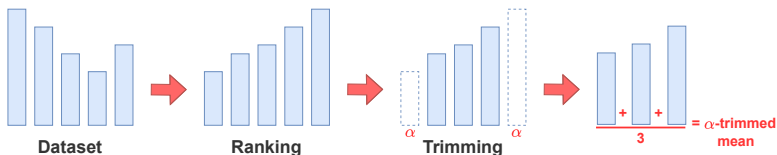
- Robust average: denoting $m = \lfloor n\alpha \rfloor$,

$$\bar{x}_\alpha = \frac{1}{n - 2m} \sum_{k=m+1}^{n-m} X_{n(k)}$$

α -trimmed mean

Order statistic

- Breakdown point is equal to α .



Problem Formulation and Framework

- **Communication network**: connected undirected graph $G = (V, E)$ with n nodes. Each node k holds X_k .
- **Huber's contamination model**: fraction ε of corrupted nodes.
- **Synchronous/asynchronous setting**: global/local iteration counter.

Using **ranks**, we can compute a **robust** average:

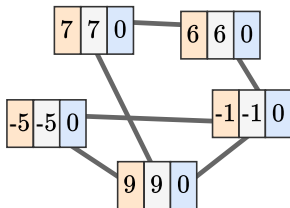
$$\begin{aligned} \bar{X}_\alpha &= \frac{1}{n - 2m} \sum_{k=m+1}^{n-m} X_{n(k)} \\ &= \frac{1}{n} \sum_k f\left(\underset{\text{Rank}}{r_k}\right) \cdot \underset{\text{Observation}}{X_k} \end{aligned}$$

α -trimmed mean

GoRank – A Gossip Algorithm for Ranking (Asynchronous)

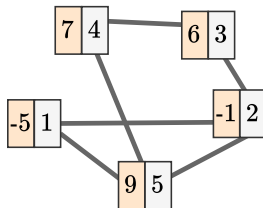
$$\text{Rank of node } k \uparrow \quad r_k = 1 + n \left(\underbrace{\frac{1}{n}}_{\# \text{ of nodes}} \sum_{l=1}^n \mathbb{I}_{\{ \underbrace{x_k > x_l}_{\text{Pairwise comparison}} \}} \right) = 1 + nr'_k$$

Estimates:



 Observation
 Auxiliary observation
 Rank estimate

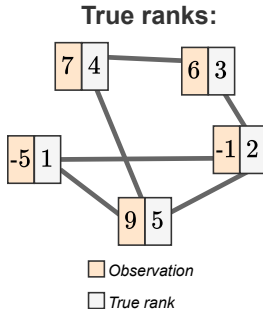
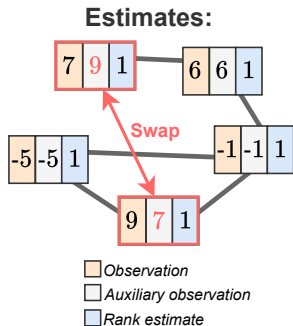
True ranks:



 Observation
 True rank

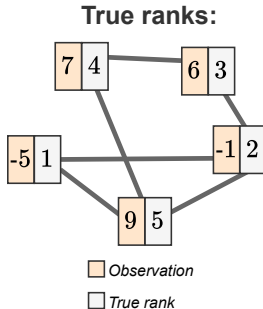
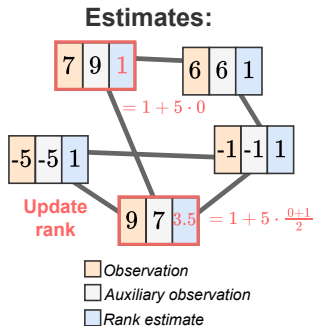
GoRank – A Gossip Algorithm for Ranking (Asynchronous)

$$\underset{\text{Rank estimate}}{\boxed{R_k(t)}} = 1 + n \left(\underset{\text{Counter}}{\boxed{\frac{1}{C_k(t)}}} \sum_{s=1}^{C_k(t)} \mathbb{I}_{\{X_k > \underset{\text{Auxiliary observation}}{\boxed{Y_k(s)}}\}} \right) = 1 + nR'_k(t)$$



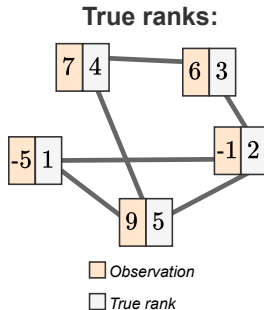
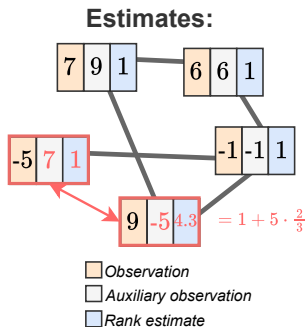
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 \begin{array}{c} \uparrow \text{Counter} \qquad \qquad \qquad \uparrow \text{Auxiliary observation} \end{array}
 \end{array}$$



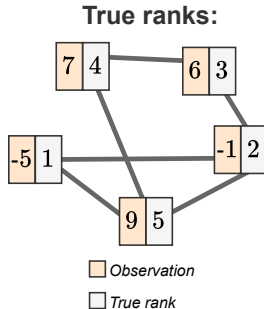
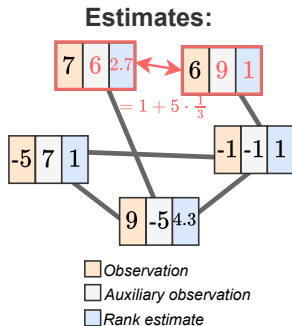
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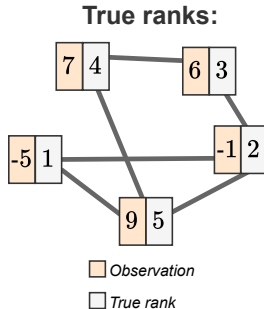
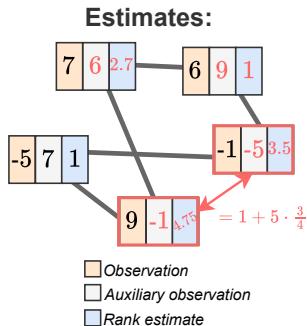
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 \uparrow & & \uparrow \\
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GoRank – A Gossip Algorithm for Ranking (Asynchronous)

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 \end{array}$$



GoRank Shows Great Empirical Performance

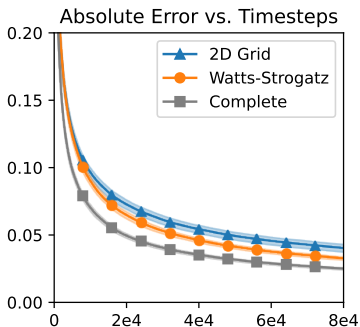


Figure 1: Graph topology has an impact on convergence.

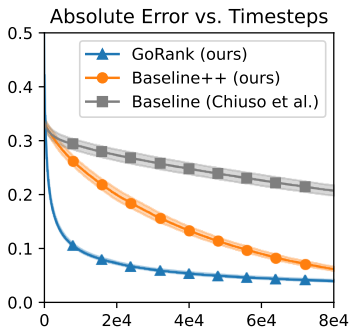


Figure 2: GoRank outperforms previous work in large graphs.

	GoRank (synchronous)
Rank Estimator of Node k	$1 + n \cdot \frac{1}{t} \sum_{s=1}^t \mathbb{I}_{\{X_k > Y_k(s)\}}$
Convergence in Expectation (Theorem 1)	$\mathcal{O}\left(\frac{\sigma_k}{ct}\right)$
Expected Abs. Error (Theorem 2)	$\mathcal{O}\left(\frac{\sigma_k}{\sqrt{ct}}\right)$

Table 1: Convergence Rate Bounds.

σ_k = standard deviation

c = spectral gap of the Laplacian

“The absolute error converges in $\mathcal{O}\left(\frac{1}{\sqrt{t}}\right)$.”

GoRank: What Makes the Theoretical Analysis Work?

- **Swapping matrix:** $t > 0$, for a random edge $(i, j) \in E$,

$$\mathbf{W}_1(t) = \mathbf{I}_n - (\mathbf{e}_i - \mathbf{e}_j)(\mathbf{e}_i - \mathbf{e}_j)^\top.$$

- Its **expectation** with respect to the edge sampling process:

$$\mathbf{W}_1 = \mathbb{E}[\mathbf{W}_1(t)] = \mathbf{I}_n - \mathbf{L}/|E|.$$

Graph Laplacian

- **Properties:** symmetric, doubly stochastic and

$$\|\mathbf{W}_1 - \mathbf{1}_n \mathbf{1}_n^\top / n\|_{\text{op}} \leq 1 - c < 1.$$

Graph's connectivity

GoTrim – A Gossip Algorithm for Trimmed Means

- Computes a **weighted average** using **current ranks**:

$$\frac{1}{n} \sum_k f(r_k) \cdot X_k.$$

- **Idea 1**: Perform standard (weighted) **gossip-based averaging** using current ranks:

$$\text{weight} = f(r_k).$$

- **Idea 2**: Since ranks vary, **correct past errors** by injecting:

$$(\text{weight}^{\text{new}} - \text{weight}^{\text{prev}}) \cdot X_k.$$

GoTrim Shows Great Empirical Performance

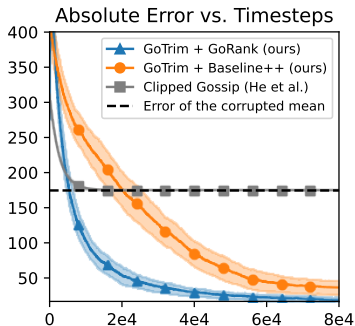


Figure 3: Simulated Dataset

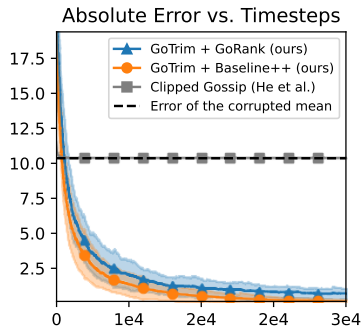


Figure 4: Basel Luftklima Dataset

“GoTrim quickly improves over the corrupted mean.”

	GoTrim (synchronous)
Trimmed Mean Estimator of Node k	$\frac{1}{n} \sum_{k=1}^n f(R_k) \cdot X_k$
Convergence in Expectation (Theorem 3)	$\mathcal{O}\left(\frac{1}{c^2 t}\right)$
τ -Breakdown Point (Theorem 4)	$\approx \alpha - \frac{1}{\sqrt{t-T}}$

Table 2: Convergence Rate Bounds.

c = spectral gap of the Laplacian

“The bias converges in $\mathcal{O}\left(\frac{1}{t}\right)$.”

Conclusion and Future Work

- We design novel gossip algorithms for **ranking** (GoRank) and **trimmed means** estimation (GoTrim).
- We show **strong empirical performance** and have solid **theoretical guarantees**.
- **Future work:**
 - Extension to multivariate data
 - Decentralized robust optimization
 - Byzantine Robustness

Our paper:



- [1] Peter J Huber and Elvezio M Ronchetti. **Robust statistics**. John Wiley & Sons, 2011.
- [2] Stephen Boyd et al. **“Randomized gossip algorithms”**. In: *IEEE transactions on information theory* 52.6 (2006), pp. 2508–2530.
- [3] Igor Colin et al. **“Extending gossip algorithms to distributed estimation of U-statistics”**. In: *NeurIPS* 28 (2015).
- [4] Alessandro Chiuso et al. **“Gossip algorithms for distributed ranking”**. In: *Proceedings of the 2011 American Control Conference*. IEEE. 2011, pp. 5468–5473.
- [5] Lie He, Sai Praneeth Karimireddy, and Martin Jaggi. **“Byzantine-robust decentralized learning via clippedgossip”**. In: *arXiv preprint arXiv:2202.01545* (2022).