Broadcasting on Random Networks

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ISIT 2019

A. Makur, E. Mossel, Y. Polyanskiy (MIT) Broadcasting on Random Networks

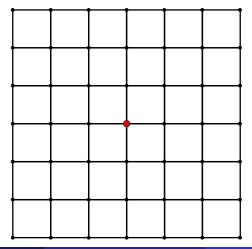
Outline

Introduction

- Motivation
- Formal Model and Broadcasting Problem
- Related Models in the Literature
- 2 Results on Random DAGs
- 3 Deterministic Broadcasting DAGs

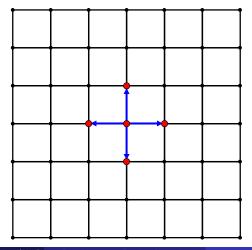


• How does information spread in time?



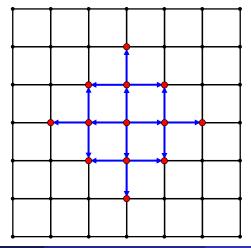
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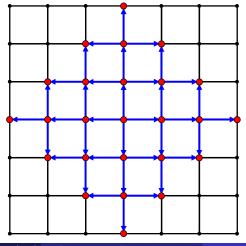
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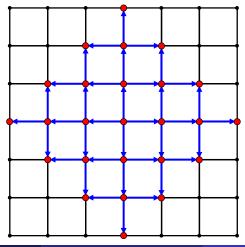
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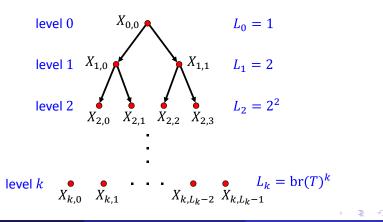
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- How does information spread in time?
- Can we invent relay functions so that far boundary contains non-trivial information about the original bit?

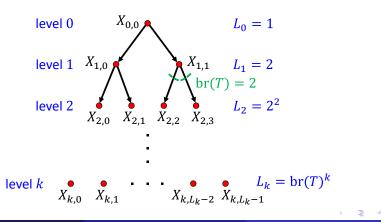


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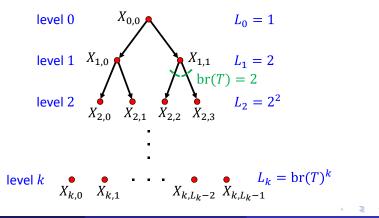
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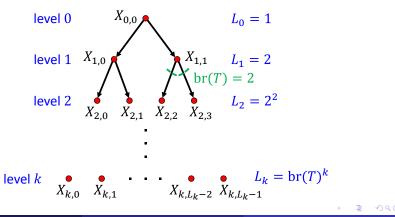
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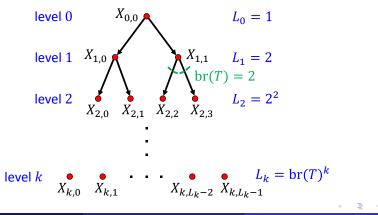
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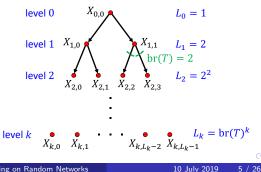


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- Let $P_{ML}^{(k)} = \mathbb{P}(\hat{X}_{ML}^{k}(X_{k}) \neq X_{0,0})$, where $X_{k} = (X_{k,0}, \dots, X_{k,br(\mathcal{T})^{k}-1})$.

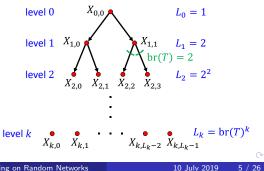


Theorem (Phase Transition for Trees [KS66, BRZ95, EKPS00])

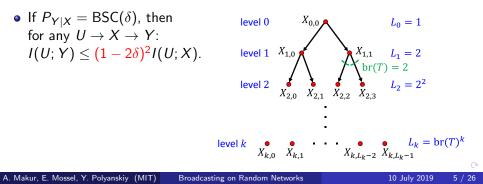
• If
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, then reconstruction possible: $\lim_{k \to \infty} P_{ML}^{(k)} < \frac{1}{2}$.
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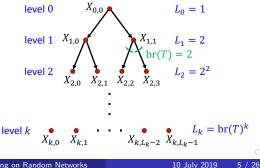


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- If $P_{Y|X} = BSC(\delta)$, then for any $U \to X \to Y$: $I(U; Y) < (1 - 2\delta)^2 I(U; X).$
- For any $0 \le i < br(T)^k$, $I(X_{0,0}; X_{k,i}) \leq (1-2\delta)^{2k}$



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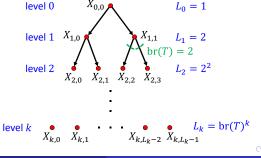
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• $br(T)^k$ paths from X_0 to X_k :
 $I(X_0; X_k) \le (br(T)(1 - 2\delta)^2)^k$.
• $br(T)^k$ level k
 $X_{k,0}$
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If (1 - 2δ)² br(T) < 1, then reconstruction impossible: lim_{k→∞} P^(k)_{ML} = ¹/₂.

Proof Idea: Strong data processing inequality [AG76, ES99]

Layers grow by br(T) and information contracts by $(1-2\delta)^2$. So, whichever effect wins determines reconstruction.



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Can there be any graph with sub-exponentially growing layer sizes such that reconstruction possible?

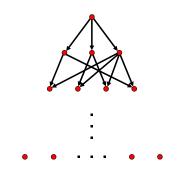
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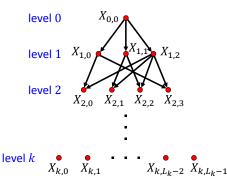
Surprise: Yes, and in fact, even logarithmic growth suffices (doubly-exponential reduction compared to trees (!)).

But need nice loops to aggregate information.

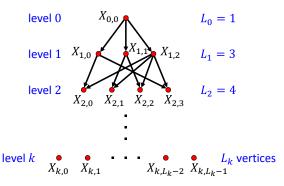
• Fix infinite directed acyclic graph (DAG) with single source node.



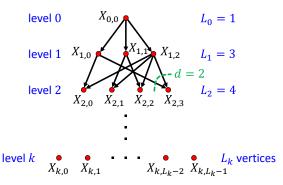
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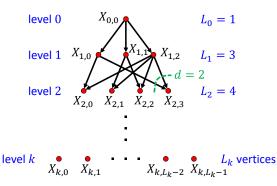
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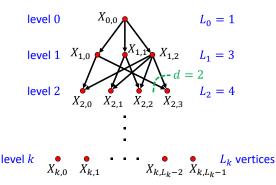


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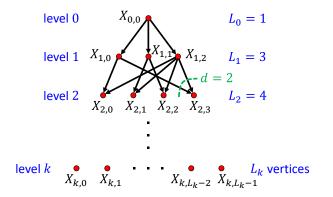
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- Nodes combine inputs with *d*-ary Boolean functions.
- This defines joint distribution of {X_{k,j}}.

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$$X_k \triangleq (X_{k,0}, \ldots, X_{k,L_k-1}).$$

• Can we decode X_0 from X_k as $k \to \infty$?



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and Broadcasting/Reconstruction impossible if:

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For which δ , d, $\{L_k\}$, and Boolean processing functions is reconstruction possible?

Related Models in the Literature

• Communication Networks:

Sender broadcasts single bit through network.

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 Reliable Computation and Storage: [vNe56, HW91, ES03, Ung07] Broadcasting model is noisy circuit to remember a bit using perfect gates and faulty wires.

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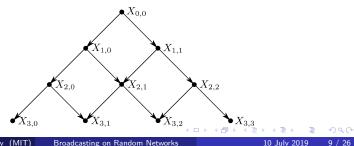
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Ferromagnetic Ising Models: [BRZ95, EKPS00] Reconstruction impossible on *tree* ⇔ Free boundary Gibbs state of Ising model on tree is extremal.

Introduction

2 Results on Random DAGs

- Phase Transition for Majority Processing
- Impossibility Results for Broadcasting
- Phase Transition for NAND Processing

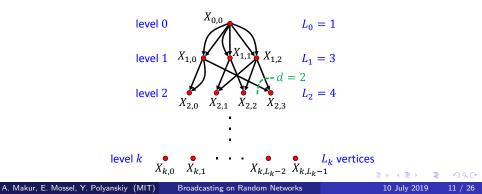
3 Deterministic Broadcasting DAGs



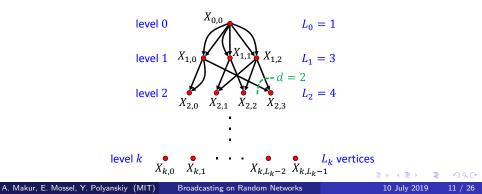
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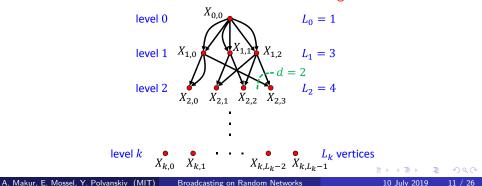
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- $P_{ML}^{(k)}(G)$ ML decoding probability of error for DAG G
- $\sigma_k \triangleq \frac{1}{L_k} \sum_{j=0}^{L_k-1} X_{k,j}$ sufficient statistic of X_k for $\sigma_0 = X_{0,0}$ in the absence of knowledge of G



Theorem (Phase Transition for $d \ge 3$)

Consider random DAG model with $d \ge 3$ and majority processing (with ties broken randomly). Let $\delta_{maj} \triangleq \frac{1}{2} - \frac{2^{d-2}}{\lceil d/2 \rceil \binom{d}{\lceil d/2 \rceil}}$.

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• Suppose $\delta \in (0, \delta_{maj})$. Then, there exists $C(\delta, d) > 0$ such that if $L_k \ge C(\delta, d) \log(k)$, then reconstruction possible:

$$\limsup_{k\to\infty} \mathbb{P}\Big(\hat{S}_k \neq X_{0,0}\Big) < \frac{1}{2}$$

where $\hat{S}_k \triangleq \mathbb{1}\left\{\sigma_k \geq \frac{1}{2}\right\}$ is majority decoder.

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$$\lim_{k\to\infty} P_{\mathsf{ML}}^{(k)}(G) = \frac{1}{2} \quad G\text{-a.s.}$$

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- Conditioned on $\sigma_{k-1} = \sigma \in [0, 1]$, level k has i.i.d. random bits

 $X_{k,j} \stackrel{\text{i.i.d.}}{\sim} \text{majority}(\text{Bernoulli}(\sigma * \delta), \text{Bernoulli}(\sigma * \delta), \text{Bernoulli}(\sigma * \delta))$

where $\sigma * \delta = \sigma(1-\delta) + \delta(1-\sigma)$

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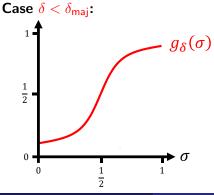
• Define the cubic polynomial:

$$g_{\delta}(\sigma) \triangleq \mathbb{E}[\sigma_k | \sigma_{k-1} = \sigma] = \mathbb{P}(X_{k,j} = 1 | \sigma_{k-1} = \sigma)$$

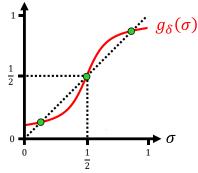
= $(\sigma * \delta)^3 + 3(\sigma * \delta)^2(1 - \sigma * \delta)$.

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- Define the cubic polynomial $g_{\delta}(\sigma) \triangleq (\sigma * \delta)^3 + 3(\sigma * \delta)^2(1 \sigma * \delta)$.
- **Concentration:** For large k, $\sigma_k \approx g_{\delta}(\sigma_{k-1})$ given σ_{k-1} .

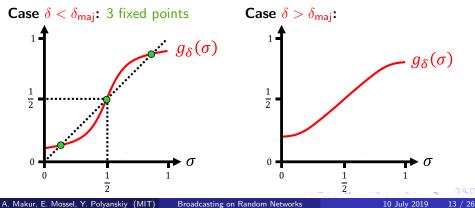
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- **Concentration:** For large k, $\sigma_k \approx g_{\delta}(\sigma_{k-1})$ given σ_{k-1} .
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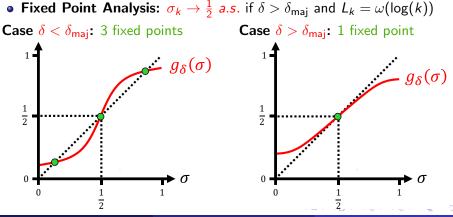
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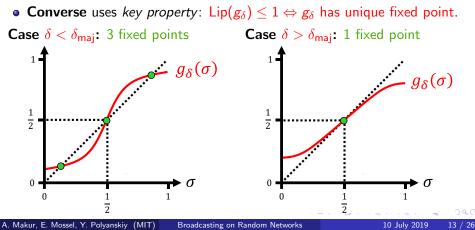
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Theorem (Phase Transition for $d \ge 3$)

Consider random DAG model with $d \ge 3$ and majority processing (with ties broken randomly). Let $\delta_{maj} \triangleq \frac{1}{2} - \frac{2^{d-2}}{\lceil d/2 \rceil \binom{d}{\lceil d/2 \rceil}}$.

- Suppose $\delta \in (0, \delta_{\text{maj}})$. Then, there exists $C(\delta, d) > 0$ such that if $L_k \ge C(\delta, d) \log(k)$, then $\lim_{k \to \infty} \mathbb{E} \Big[P_{\text{ML}}^{(k)}(G) \Big] < \frac{1}{2}$.
- Suppose $\delta \in (\delta_{\text{maj}}, \frac{1}{2})$. Then, there exists $D(\delta, d) > 1$ such that if $L_k = o(D(\delta, d)^k)$, then $\lim_{k \to \infty} P_{\text{ML}}^{(k)}(G) = \frac{1}{2}$ G-a.s.

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Remarks:

- $\delta_{maj} = \frac{1}{6}$ for d = 3 appears in reliable computation [vNe56, HW91].
- δ_{maj} for odd $d \ge 3$ also relevant in reliable computation [ES03].
- δ_{maj} for $d \ge 3$ relevant in recursive reconstruction on trees [Mos98].

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Questions:

- Broadcasting possible with sub-logarithmic *L_k*?
- Broadcasting possible when $\delta > \delta_{maj}$ with other processing functions?
- What about d = 2?

Optimality of Logarithmic Layer Size Growth

Broadcasting possible with sub-logarithmic L_k ?

Proposition (Layer Size Impossibility Result)

For any deterministic DAG, if:

$$L_k \leq rac{\log(k)}{d\log(rac{1}{2\delta})}\,,$$

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No, broadcasting impossible with sub-logarithmic L_k !

Partial Converse Results

Broadcasting possible when $\delta > \delta_{maj}$ with other processing functions?

Proposition (Single Vertex Reconstruction)

Consider random DAG model with $d \ge 3$.

If δ ∈ (0, δ_{maj}), L_k ≥ C(δ, d) log(k), and processing functions are majority, then single vertex reconstruction possible:

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• If $\delta \in [\delta_{maj}, \frac{1}{2})$, d is odd, $\lim_{k \to \infty} L_k = \infty$, and $\inf_{n \ge k} L_n = O(d^{2k})$, then single vertex reconstruction impossible for all processing functions (which may be graph dependent):

$$\lim_{k\to\infty} \mathbb{E}\Big[\Big\| P_{X_{k,0}|G,X_{0,0}=1} - P_{X_{k,0}|G,X_{0,0}=0}\Big\|_{\mathsf{TV}}\Big] = 0\,.$$

Remark: Converse uses reliable computation results [HW91, ES03].

Partial Converse Results

Broadcasting possible when $\delta > \delta_{maj}$ with other processing functions?

Proposition (Information Percolation [ES99, PW17])

For any deterministic DAG, if:

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What about d = 2?

Theorem (Phase Transition for d = 2)

Consider random DAG model with d = 2 and NAND processing functions. Let $\delta_{\text{nand}} \triangleq \frac{3-\sqrt{7}}{4}$.

Image: Image:

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Remark: δ_{nand} appears in reliable computation [EP98, Ung07].

A. Makur, E. Mossel, Y. Polyanskiy (MIT) Broad

Broadcasting on Random Networks

10 July 2019 17 / 26

Introduction

- 2 Results on Random DAGs
- 3 Deterministic Broadcasting DAGs
 - Existence of DAGs where Broadcasting is Possible
 - Construction of DAGs where Broadcasting is Possible

4 Conclusion

Existence of DAGs where Broadcasting is Possible

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Can we construct such DAGs for any $\delta \in (0, \frac{1}{2})$?

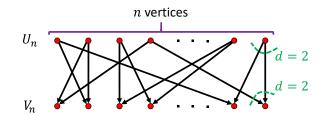
Regular Bipartite Expander Graphs

Proposition (Existence of Expander Graphs [Pin73, SS96])

For all (large) d and all sufficiently large n, there exists d-regular bipartite graph $B_n = (U_n, V_n, E_n)$ with disjoint vertex sets U_n, V_n of cardinality $|U_n| = |V_n| = n$, edge multiset E_n , and the lossless expansion property:

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where $\Gamma(S) \triangleq \{v \in V_n : \exists u \in S, (u, v) \in E_n\}$ is neighborhood of S.



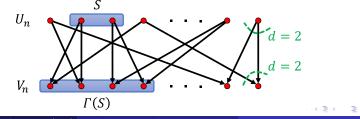
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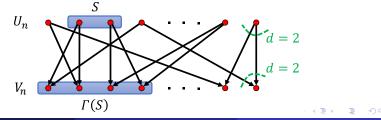
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Intuition: Expander graphs are sparse, but have high connectivity.



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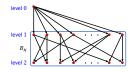
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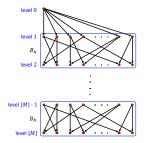
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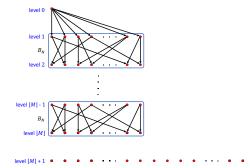
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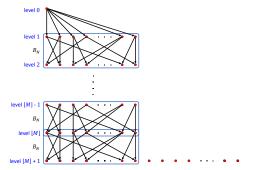
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Both edge multisets $X_k \rightarrow (X_{k+1,0}, \dots, X_{k+1,L_k-1})$ and
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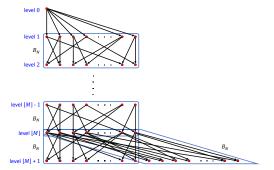












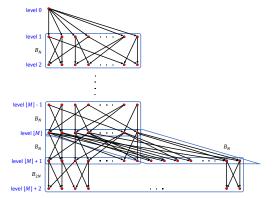
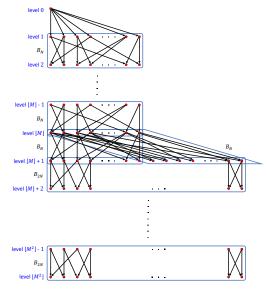


Illustration of "Expander DAG":



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Theorem (Broadcasting in Expander DAG)

For "expander DAG" with majority processing, reconstruction possible:

$$\limsup_{k\to\infty} \mathbb{P}\Big(\hat{S}_k \neq X_{0,0}\Big) < \frac{1}{2}$$

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Proof Sketch:

• Suppose edges from level k to k + 1 given by expander B_N .

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 If X_{0,0} = 0, then |S_k| likely to remain small as k → ∞.

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Proposition (Computational Complexity of DAG Construction)

For any $\delta \in (0, \frac{1}{2})$, the *d*-regular bipartite expander graphs for levels $0, \ldots, k$ of "expander DAG" can be constructed in:

• deterministic quasi-polynomial time $O(\exp(\Theta(\log(k) \log \log(k))))$,

Remark: Enumerate all *d*-regular bipartite graphs and test expansion.

Theorem (Broadcasting in Expander DAG)

For "expander DAG" with majority processing, reconstruction possible:

$$\limsup_{k\to\infty} \mathbb{P}\Big(\hat{S}_k \neq X_{0,0}\Big) < \frac{1}{2}$$

where $\hat{S}_k = \mathbb{1}\left\{\sigma_k \geq \frac{1}{2}\right\}$ is majority decoder.

Proposition (Computational Complexity of DAG Construction)

For any $\delta \in (0, \frac{1}{2})$, the *d*-regular bipartite expander graphs for levels $0, \ldots, k$ of "expander DAG" can be constructed in:

- deterministic quasi-polynomial time $O(\exp(\Theta(\log(k) \log \log(k))))$,
- randomized polylogarithmic time O(log(k) log log(k))
 with positive success probability (which depends on δ but not k).

Remark: Generate uniform random *d*-regular bipartite graphs.



- 2 Results on Random DAGs
- 3 Deterministic Broadcasting DAGs

4 Conclusion

Conclusion

Main Contributions:

• Broadcasting in random DAGs with $d \ge 3$ and majority processing

- Broadcasting in random DAGs with $d \ge 3$ and majority processing
- Broadcasting in random DAGs with d = 2 and NAND processing

- Broadcasting in random DAGs with $d \ge 3$ and majority processing
- Broadcasting in random DAGs with d = 2 and NAND processing
- Broadcasting in "expander DAG" construction

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Future Directions:

• Prove conjecture that for random DAG with odd $d \ge 3$ (or d = 2), reconstruction impossible for all processing functions when $\delta \ge \delta_{maj}$ (or $\delta \ge \delta_{nand}$).

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- Find polynomial time construction of DAGs with sufficiently large d given some δ such that broadcasting possible.
- Construct DAGs with arbitrary $d \ge 3$ and $\delta < \delta_{maj}$, or d = 2 and $\delta < \delta_{nand}$, such that broadcasting possible.

Thank You!

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