Converse Results

Achievability 00 Random Graphs

Regenerating Codes on Graphs

Adway Patra & Alexander Barg

(University of Maryland)

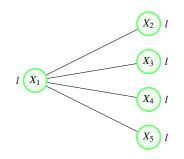
ISIT 2021

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Achievability

Random Graphs

Node repair in distributed storage

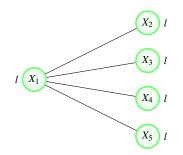


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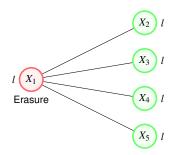
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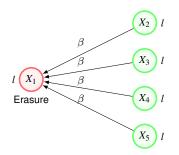
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- Total required transmission bounded by the Cut-set bound

$$B \leqslant \sum_{i=0}^{k-1} \min\{l, (d-i)\beta\}$$

Random Graphs

Moving away from traditional setting

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Question 1 : Is it possible to process the data to reduce communication?

Question 2 : If so, then to what extent?

Random Graphs

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Lemma

Let $v_f, f \in [n]$ be the failed node. For a subset of the helper nodes $E \subset D$ let R_E^f be a function of S_E^f such that

$$H(X_f|R_E^f, S_{D\setminus E}^f) = 0.$$

1) If $|E| \ge d - k + 1$, then

 $H(R_E^f) \ge l.$

2) If $|E| \leq d - k$, then

$$H(R_E^f) \geqslant \frac{|E|l}{d-k+1}.$$

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Lower bound on communication

Random Graphs

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Proposition

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Proof.

Take $E = \bigcup_{i=j}^{t} \Gamma_i(v_f)$.

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Proposition

Let $J_f = \{v \in V(T_f) \setminus \{v_f\} : |D^*(v)| \ge d - k + 2\}$. The total communication complexity β for the repair of node v_f on the repair tree T_f is bounded as

$$\beta \ge \sum_{v \in J_f} l + \sum_{v \in V(T_f) \setminus (\{v_f\} \cup J_f)} \frac{|D^*(v)|l}{d - k + 1}.$$

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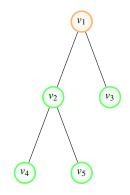
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- Every node $v \in J_f$ needs to transmit at least *l* symbols to its immediate parent.

Random Graphs

Achieving the bounds: Using MSR Product Matrix codes

Example

Take an [n = 5, k = 3, d = 4, l = 2, β = 1, B = 6] MSR Product Matrix code.



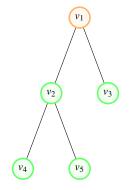
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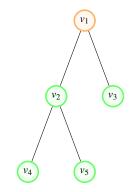
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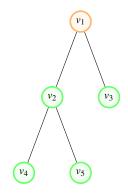
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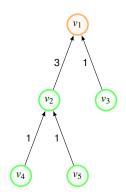
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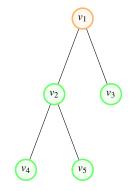
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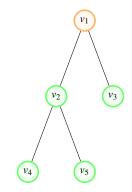
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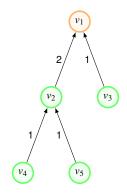
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Introduction 00

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Achievability 00 Random Graphs

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Application to random graphs

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- Operate in $p \gg \frac{\log n}{n}$ region, i.e., connected region.
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- > Threshold behavior: We say that *t*-layer repair of the failed node *v* is possible if

 $P(|N_t(v)| \ge d) \to 1 \text{ as } n \to \infty.$

Application to random graphs: Repair threshold

Proposition

Let $d = \delta n, 0 < \delta < 1$ be a constant and let t be a fixed integer. Then t is the threshold depth for repair if

$$(np)^{t-1} = o(n), \quad p^t n^{t-1} - 2\log n \to \infty.$$

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- Proof by classical results:
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 - If $(np)^{t-1} = o(n)$ and $d = \Theta(n)$, then with high probability, d nodes are not reached in t 1 layers [Chung et. al. 2001].

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Let *t* be the threshold for repair. For $d = \Theta(n)$ let $d - k = \chi(n)$ be a function of *n* such that $\chi(n)n^{s-1}p^s \to 0$ where $s \leq t-1$ is the largest integer for which this condition holds. Then $\mathbb{P}(\beta_{\mathrm{IP}} \leq (t-s)d + o(n)) \to 1$.

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• Using Intermediate Processing, the scaling of the bandwidth can be brought down from t to t - s.

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Achievability 00 Random Graphs

Concluding remarks

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Concluding remarks

- In sparsely connected graphs, it is possible to do better than simple relaying.
- The intermediate processing technique is applicable to all F-linear MSR codes and achieves the minimum possible communication in some cases.
- For random graphs $\mathcal{G}_{n,p}$, in certain regimes, intermediate processing can give significant reductions in communication overhead.