

# Pseudorandomness: Some Distributed Applications

Alexandre Nolin

CISPA Helmholtz Center for Information Security

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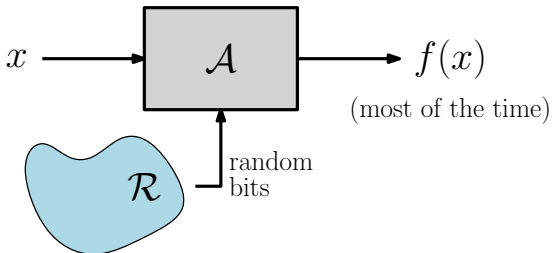
# What this talk will be about

## Goals of this talk

- Introduce several key ideas about pseudorandomness using a toy example.  
Existence via Probabilistic Method, connections to error correcting codes, hash functions.
- See (up to 3) examples how these ideas have been used in distributed computing.  
Low-congestion sampling, derandomization.
- See some extra pseudorandom objects on the way.  
Expander graphs, pairwise independent hash functions.

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Given a randomized algorithm, can we swap its source of random bits for a simpler one?

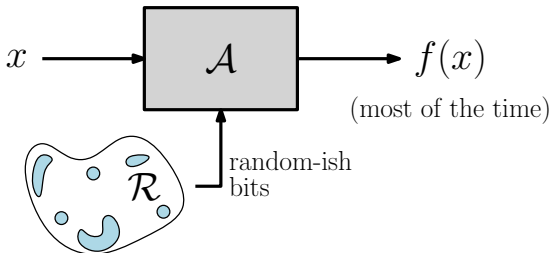


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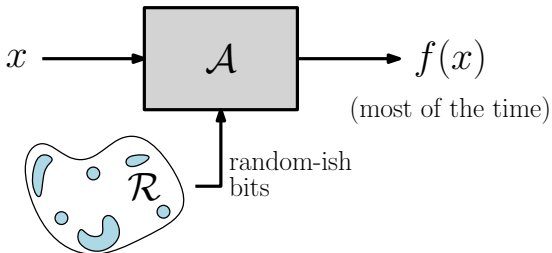


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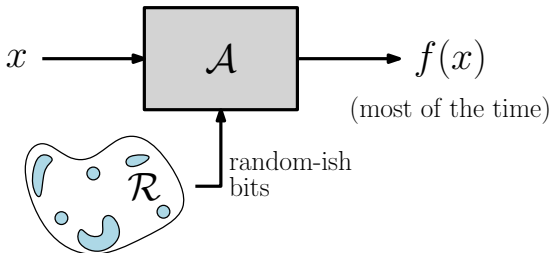


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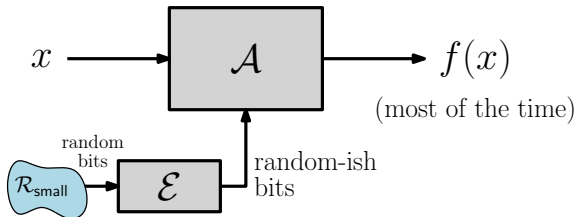


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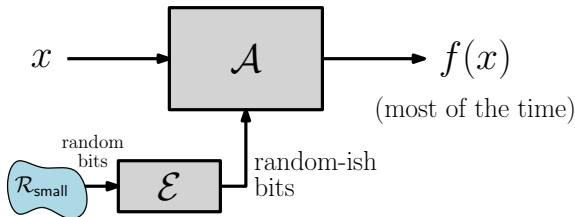
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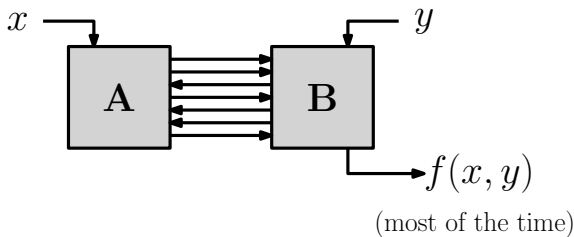
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Furthermore: is the sparsification **reasonably computable**?

**Pseudorandomness = study of when this is possible.**

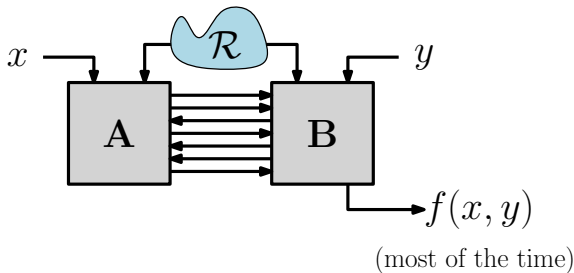


## Example: Equality in 2-party Communication Complexity



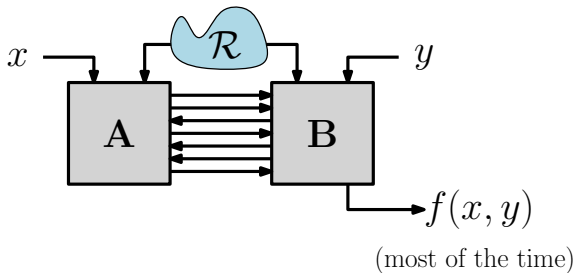
$$\text{Take } f = \text{EQ}_n: \text{EQ}_n(x, y) = \begin{cases} 1 & \text{if } x = y \\ 0 & \text{otherwise} \end{cases} \text{ with } x, y \in \{0, 1\}^n.$$

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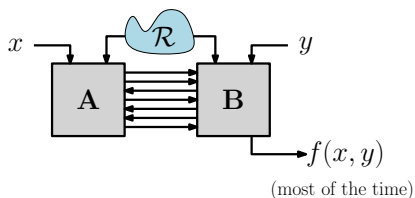
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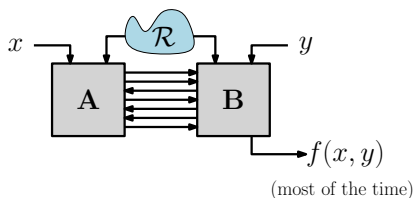
For error  $\epsilon < 1/2$ , simple algorithm using  $\lceil \log(1/\epsilon) \rceil$  bits?

# Algorithm for Equality with shared randomness



1. Repeat for  $t$  in  $[\lceil \log(1/\epsilon) \rceil]$ 
  - 1.1 Alice reads  $r^{(t)} \in \{0, 1\}^n$  from shared randomness.
  - 1.2 Alice computes  $\langle x, r^{(t)} \rangle = \sum_{i=1}^n x_i \cdot r_i^{(t)} \pmod 2$ , sends it to Bob.
2. Bob outputs “Equal” iff  $\langle x, r^{(t)} \rangle = \langle y, r^{(t)} \rangle, \forall t \in [\lceil \log(1/\epsilon) \rceil]$

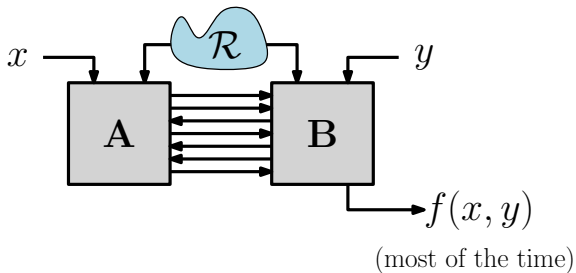
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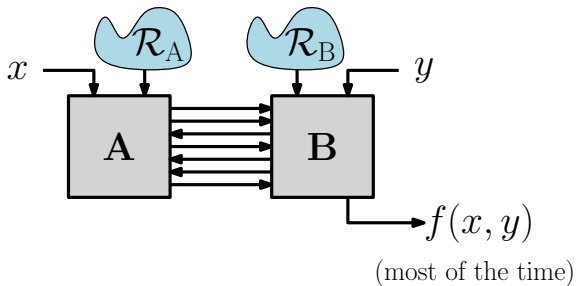
**Proof:** when  $x \neq y$ , each  $r^{(t)}$  has a probability  $1/2$  to be s.t.  $\langle x, r^{(t)} \rangle \neq \langle y, r^{(t)} \rangle$  (to see it, focus on any index  $i$  s.t.  $x_i \neq y_i$ ).

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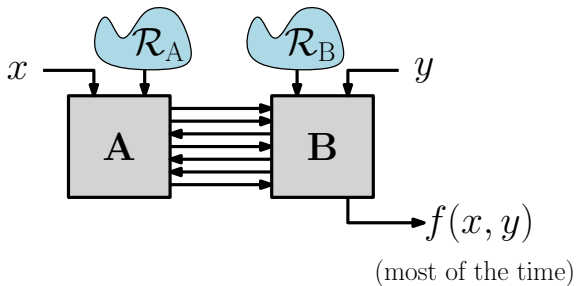
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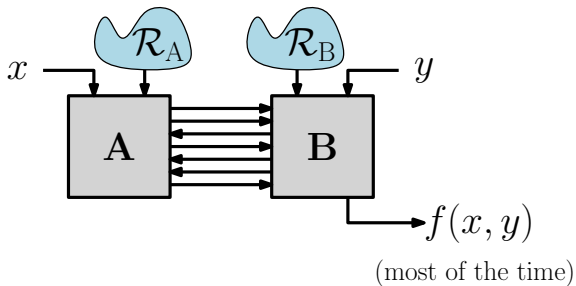


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Can we identify a subset of the randomness that works?

## First Important Idea: probabilistic method

**Goal:** find subset  $R \subseteq \{0, 1\}^n$  such that:

- (small)  $|R| \ll 2^n$ ,
- (useful)  $\forall x, y \in \{0, 1\}^n, x \neq y, \Pr_{r \in R}[\langle x, r \rangle \neq \langle y, r \rangle] \geq 1/4$ .

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**Proof:** Pick specific pair  $x, y$  with  $x \neq y$ . In  $k$  random strings  $r_1, \dots, r_k$ ,  $k/2$  in expectation are s.t.  $\langle x, r \rangle \neq \langle y, r \rangle$ .

Probability that less than  $k/4$  strings are s.t.  $\langle x, r \rangle \neq \langle y, r \rangle$  is bounded by:  $\exp(-k/12)$  (Chernoff bound)

Probability that less than  $k/4$  strings are s.t.  $\langle x, r \rangle \neq \langle y, r \rangle$  for some pair  $x, y$ :  $2^{2n} \cdot \exp(-k/12) < 1$  for  $k > (24 \ln(2)) \cdot n$ .

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# Probabilistic method at its fullest: pseudorandom generators

**More generally:** Consider any randomized algorithm with  $N$  inputs, failure probability  $\epsilon$ . We can identify a subset of its randomness of size  $O(\epsilon^{-1} \log N)$  such that the error is at most  $2\epsilon$  when using random strings from this sparse randomness.

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**Pseudorandom generators:** generators of such strings. An explicit construction would give  $P = BPP$ , by enumerating through all the strings.

## Second Important Idea: connection to other objects

Pick a set of random strings  $R \subseteq \{0, 1\}^n$  like we just constructed, i.e., for any  $x, y \in \{0, 1\}^n$  such that  $x \neq y$ :

$$\{r \in R : \langle x, r \rangle \neq \langle y, r \rangle\} \geq |R|/4 .$$

For each  $x \in \{0, 1\}^n$ , consider the  $|R|$ -bit word  $w_R(x)$ :

$$w_R(x) = \langle x, r_1 \rangle . \langle x, r_2 \rangle . \dots . \langle x, r_{|R|} \rangle .$$

**Property:**

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With parameters  $[24 \ln(2)n, n, 6 \ln(2)n]$ , over  $\mathbb{F}_2$ .

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**Conversely:** Can get more randomness-efficient algorithms from results on Error Correcting Codes.

## Second Important Idea continued: another connected object

We can also see each  $r \in R$  as a map  $h_r: \{0, 1\}^n \rightarrow 0, 1$ , with  $h_r(x) = \langle x, r \rangle$

### Definition (( $\epsilon$ -almost) Pairwise-Independent Hash Functions)

A set  $\mathcal{H}$  of functions  $h: [N] \rightarrow [M]$  s.t.:

$$\forall x \neq y \in [N]^2, z, z' \in [M]^2,$$

$$|\Pr_{h \in \mathcal{H}}[h(x) = z \wedge h(y) = z'] - 1/M^2| \leq \epsilon/M^2.$$

There exists a family of such hash functions of size  $\text{poly}(M, 1/\epsilon)(\log N / \log \log N)$ .

## Lessons learned so far

Given ANY randomized algorithm, we can reduce its use of randomness to  $O(\log n)$  bits without affecting its success/failure probability too much.

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Going the last mile requires finding some explicit structure that works in the given application (error correcting codes, families of hash functions, fields, polynomials, classes of graphs).

# Distributed applications

# Distributed application 1: random sampling

**Setting:** CONGEST model:

- Graph  $G = (V, E)$  is the input and the communication network.
- $n =$  number of nodes,  $\Delta =$  maximum degree. Known by all nodes.
- In a round, each node can send  $O(\log n)$  bits on each incident edge.
- Complexity is the number of rounds to achieve the wanted result.

LOCAL model: same with infinite bandwidth.

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- $k$ -coloring: each node must be properly colored with a value from  $\{1, \dots, k\}$ .
- $k$ -list-coloring: each node starts with a list of  $k$  colors, from which it must choose its color.
- palette  $\Psi_v$ : colors still available to a node  $v$  as it avoids colors already chosen by neighbors.
- edge-coloring: we have to color the edges instead of the nodes

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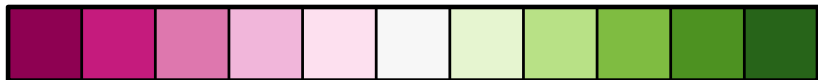
LOCAL model: same with infinite bandwidth.

Highlights from [HN23, HNT22], lowering the complexity in CONGEST to that in LOCAL (or almost):

- In  $O(\log^* n)$ :  $(1 + \epsilon)\Delta$  coloring,  $(1 + \epsilon)\Delta$  edge-coloring, when  $\Delta \in \Omega(\log^{1+1/\log^*} n)$ . [HN23]
- deg +1-list-coloring in  $O(\log^5 \log n)$  [HNT22],  $(2\Delta - 1)$ -edge coloring in  $O(\log^4 \log n)$  rounds. [HN23]  
(saving an additive  $\log \Delta$  in both cases)

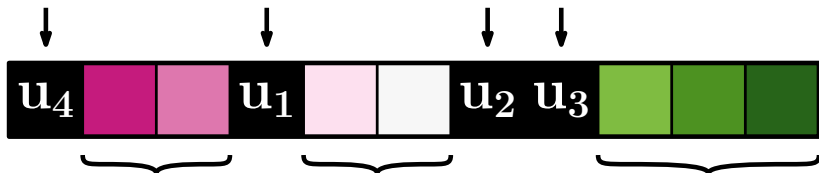
## Fast coloring with an excess of colors [SW10]

- Consider the nodes  $v$  s.t.  $|\Psi_v| \geq 2x \cdot d_v$ .  
(i.e., with  $\times 2x$  more available colors than active neighbors)
- Let each such node try  $x$  colors.
- They each get colored w.p.  $1 - 2^{-x}$ .



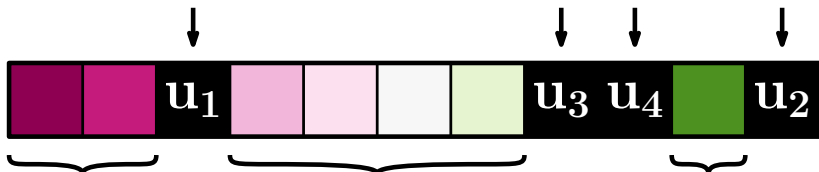
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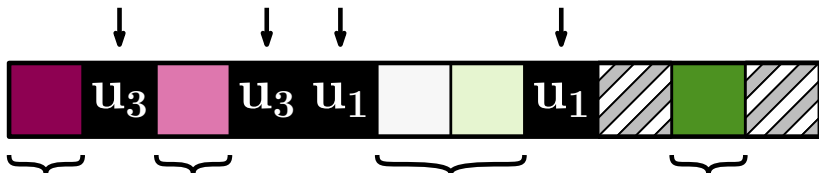
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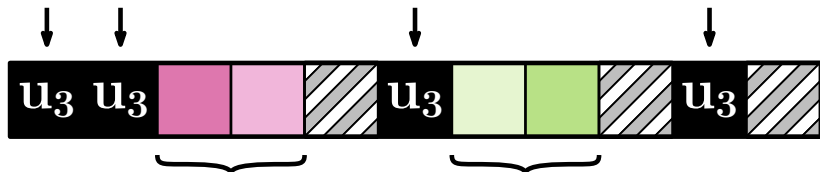
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## Fast coloring with an excess of colors [SW10]

Algorithm for  $2\Delta$ -coloring in LOCAL, for a node  $v$ , with neighbors of higher ID  $N^+(v)$ .

1. Set  $x \leftarrow 1$ .
2. For  $i = 1$  to  $O(\log^* n)$ 
  - 2.1 Repeat  $O(1)$  times:
    - 2.1.1  $v$  picks a set  $S_v$  of  $x$  random colors in its palette  $\Psi_v$ .
    - 2.1.2  $v$  sends  $S_v$  to  $N(v)$ , computes  $T_v = S_v \setminus \bigcup_{u \in N^+(v)} S_u$ .
    - 2.1.3 If  $T_v \neq \emptyset$ ,  $v$  permanently adopts a color in  $T_v$ .  
It sends its final color to its neighbors and stops the algorithm.
  - 2.2 Set  $x \leftarrow \min(2^x, \log n)$ .
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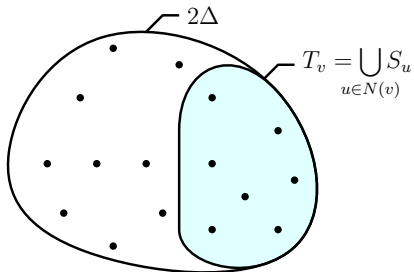
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**Proof idea:** the degree of each node is bounded by  $\max(\frac{2\Delta}{x}, O(\log n))$ , w.h.p., throughout the algorithm.

## Doing the same in CONGEST: the cost of sending a set

Basic argument of the algorithm is:

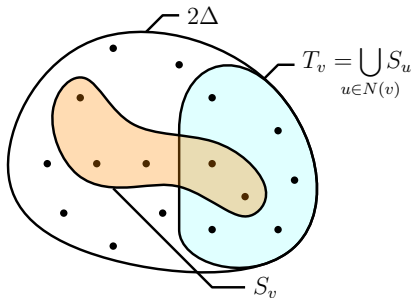
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- a subset  $T \subseteq \mathcal{C}$  of colors to avoid of size  $|T| \leq |\mathcal{C}|/2$ ,
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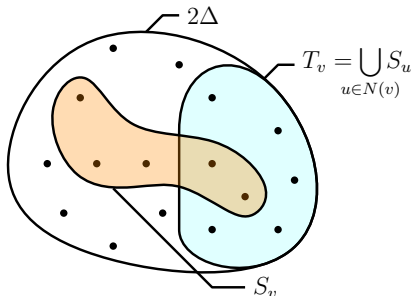
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**Issue for Congest:** describing an arbitrary set  $S \subseteq [2\Delta]$ ,  $|S_v| \in [1, \Theta(\log n)]$  requires  $\Theta(\log n \cdot \log \Delta)$  bits.

## Solution 1 (existential), by probabilistic method

### Same proof scheme as before:

- Fix  $T \subseteq [2\Delta]$ ,  $|T| \leq \Delta$ .
- For a random set  $S \subseteq [2\Delta]$  of size  $x$ ,  $\Pr[S \subseteq T] \leq 2^{-x}$ .
- Taking  $k$  random sets  $S_1 \dots S_k \subseteq [2\Delta]$ ,  $\leq k \cdot 2^{-x}$  are expected to be  $\subseteq T$ .
- The probability that  $\geq 2 \cdot k2^{-x}$  of the sets are  $\subseteq T$  is  $\leq e^{-k \cdot 2^{-x}/3}$ .
- There are  $\leq 2^{2\Delta}$  possible sets  $T$ .
- With  $x \in O(\log n)$ ,  $k \in \text{poly}(\log \Delta, n)$ ,  $k$  random sets are s.t.  $T \subseteq [2\Delta]$ ,  $|T| \leq \Delta$ ,  $|\{i : S_i \subseteq T\}| \leq 2k2^{-x}$  with probability  $> 0$ .



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**Can strengthen it a bit:** For any sufficiently large set  $T$ , most sets  $S_1 \dots S_{\text{poly}(\log \Delta, n)}$  intersect  $T$  in  $\approx S_i \cdot |T| / (2\Delta)$  elements.

# Representative sets

## Lemma (Representative sets)

Let  $U$  be a universe of size  $k$ . A family  $\mathcal{F} = \{S_1, \dots, S_t\}$  of  $s$ -sized sets is said to be an  $(\alpha, \delta, \nu)$ -representative family iff:

$$\forall T \subseteq U, |T| \geq \delta k : \Pr_{i \in_u [t]} \left[ \left| \frac{|S_i \cap T|}{|S_i|} - \frac{|T|}{k} \right| \leq \alpha \frac{|T|}{k} \right] \geq (1 - \nu), \quad (1)$$

$$\forall T \subseteq U, |T| < \delta k : \Pr_{i \in_u [t]} \left[ \frac{|S_i \cap T|}{|S_i|} - \delta \leq \alpha \delta \right] \geq (1 - \nu), \quad (2)$$

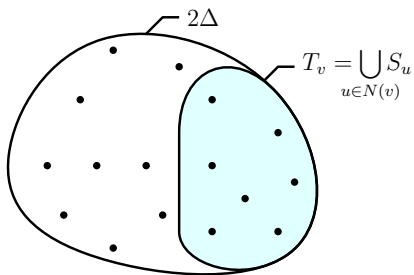
$$\forall u \in U : \Pr_{i \in_u [t]} [u \in S_i] \in [1 - \alpha, 1 + \alpha] \frac{s \cdot t}{k}. \quad (3)$$

Such families exist for  $t \in \Theta(k/\nu + k \log k)$  and  $s \in \Theta(\alpha^{-2} \delta^{-1} \log(1/\nu))$ .

**Proof:** probabilistic method.

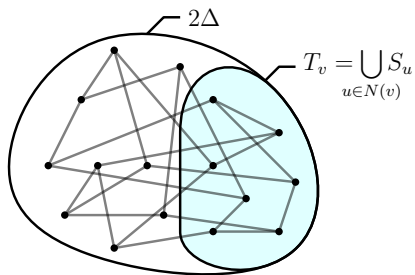
## Solution 2 (explicit), using expander graphs

We add a graph structure on the space of colors.



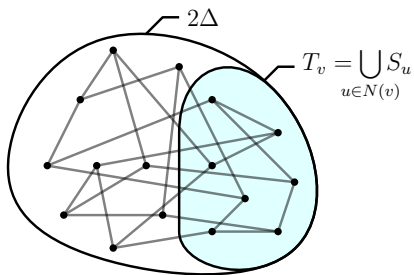
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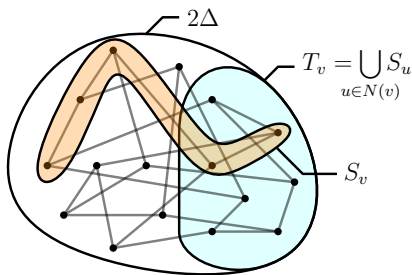
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On a graph of degree  $O(1)$ , describing a walk of length  $k$  takes  $O(\log \Delta)$  (to describe the starting vertex) +  $O(k)$  bits (to describe the  $k$  steps taken from this starting node).

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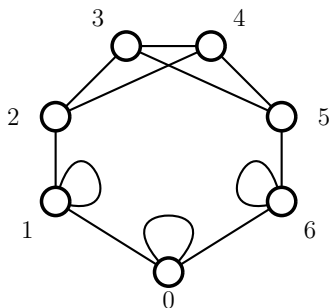
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**But why should such sets have the right properties?**

## Spectral expanders and random walks



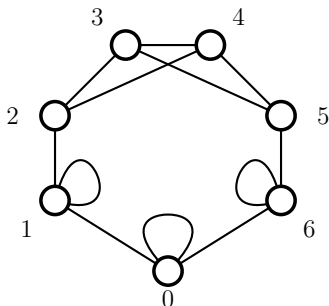
1	1	0	0	0	0	1
1	1	1	0	0	0	0
0	1	0	1	1	0	0
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0	0	1	1	0	1	0
0	0	0	1	1	1	1
1	0	0	0	0	1	0

Consider a connected, non-bipartite, regular digraph  $G$ , transition matrix  $M_G$ .

Consider eigenvalues of  $M_G$   $\lambda_1, \dots, \lambda_n$ , s.t.  $|\lambda_i| \geq |\lambda_{i+1}|$

The largest eigenvalue is always  $\lambda_1 = 1$  and corresponds to the uniform distribution, others are  $< 1$ .

## Spectral expanders and random walks



1/3	1/3	0	0	0	0	1/3
1/3	1/3	1/3	0	0	0	0
0	1/3	0	1/3	1/3	0	0
0	0	1/3	0	1/3	1/3	0
0	0	1/3	1/3	0	1/3	0
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## Expanders mix well

The spectral gap  $\gamma = 1 - |\lambda_2|$  captures how fast and close a random walk gets to the uniform distribution.

Theorem ([Hea08, WX05])

*Consider an expander graph  $G$  with spectral gap  $\gamma = 1 - |\lambda_2|$ , and a subset  $S \subseteq V$  of its nodes. Consider a random walk of length  $k$ , and let  $X$  measure how many steps of the walk are in  $S$ . For any  $\epsilon > 0$ :*

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Just need to find an expander over  $2\Delta$  nodes, with constant degree, spectral gap  $\Omega(1)$ .

# Existence of expanders

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But explicit constructions are also known.

Graphs defined by the structure of a prime fields, recursive constructions...

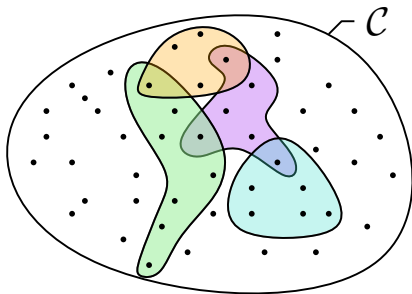
## Consequences [HN23]

$\Delta$	Coloring tasks	Complexity in CONGEST
$\Omega(\log^{1+1/\log^* n} n)$	$(1 + \epsilon)\Delta$ -vertex $(1 + \epsilon)\Delta$ -edge	$O(\log^* n)$
$O(\log^{1+1/\log^* n} n)$	$(1 + \epsilon)\Delta$ -vertex	$O(\log^3 \log n)$
	$(2\Delta - 1)$ -edge	$O(\log^4 \log n)$
$\Omega(\sqrt{\log^{1+1/\log^* n} n})$	$(1 + \epsilon)\Delta^2$ -vertex distance-2	$O(\log^* n)$
$O(\sqrt{\log^{1+1/\log^* n} n})$		$O(\log^4 \log n)$
$\Omega(\log^{1+1/c'} n)$	$\Delta \log^{(c)}$ -vertex $\Delta \log^{(c)}$ -edge	$O(1)$
$\Omega(\sqrt{\log^{1+1/c'} n})$	$\Delta^2 \log^{(c)}$ $n$ -vertex distance-2	

**Techniques:** Rödl nibble [DGP98] (for  $(1 + \epsilon)\Delta$ -edge coloring), shattering [BEPS16] and deterministic algorithm [GK21] (for smaller  $\Delta$ ).

## Harder case: non-shared color space [HNT22]

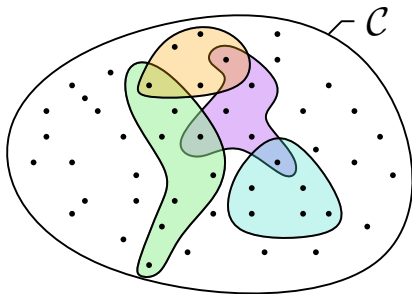
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The expander construction no longer works here. How do we extend the argument?

## Existential solution: pure hashing

Suppose nodes could sample and communicate a perfect hash function  $\mathcal{C} \rightarrow [4\Delta]$ . To try colors, nodes could:

1. Consider the part of their palette that hash to a value  $\leq \Theta(\log n)$ . ( $\Theta(\log n)$  do, in expectation)
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Extends all previous results to the list-setting, but with very large local computation.

## Doing without the existential arguments

1. Each node  $v$  finds an  $\epsilon/2$ -almost-pairwise independent hash function  $h_v : \mathcal{C} \rightarrow [4\Delta/\epsilon]$  with  $\leq \epsilon\Delta$  collisions.
2. Each node samples colors/ hashes using the expander graph structure applied to the hash space  $[2\Delta/\epsilon]$ .
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**General idea:** each node has at least  $(2 - \epsilon)\Delta$  colors which are not in collision with its hash function.

Each color tried by a neighbor removes at most one possible hash for  $v$ . As before, nodes sample more and more colors but always guaranteeing that each node has a constant fraction of its palette untried by neighbors in any given round.

Each node, when sampling hashes, should thus succeed in finding a color with the usual probability.

## The point of it

Allowed us to get a poly  $\log \log n$  algorithm for deg +1-list-coloring, and the list-coloring versions of all previously mentioned problems (with extra colors).

Also, the algorithm for deg +1-list-coloring finishes in  $O(\log^* n)$  for  $\Delta > \log^7 n$ .

Also useful in subsequent work: see distance-2 paper at this DISC [FHN23].



## Distributed application 2: derandomization

Pseudorandomness is also essential to derandomizing randomized algorithms: less random bits to deterministically choose, the better!

- MPC [CDP21a, CDP21b, CC22, FGG22, CCDM23a]
- Congested Clique [CPS20, CDP21c, CCDM23b]

## Concluding

To go further if this has piqued your interest, “Pseudorandomness” by Salil Vadhan is a great survey. [Vad12]

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The explicit solution presented before works for distance-1 node-coloring, not some other settings (edge-coloring, distance-2 coloring).

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The PRGs fit in low-space MPC, but requires exponential computation.

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**Thanks!**


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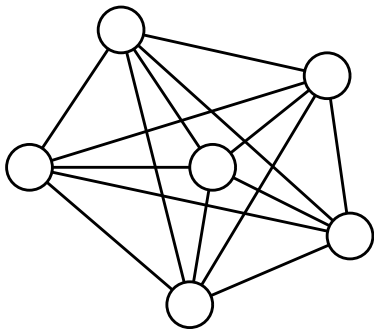


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## Creating slack: sparsity



**Intuition:** if your neighbors are mostly disconnected, it's likely some of them will pick the same color.

**Formally:**  $\zeta_v = \frac{1}{\Delta} \left( \binom{\Delta}{2} - |E[N(v)]| \right)$ .

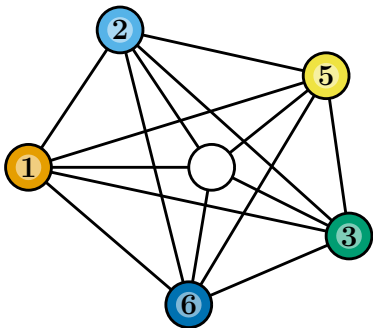
**Theorem ([EPS15]):** Let each node try a random color, then afterwards:

$$\Pr[s_v \leq c \cdot \zeta_v] \leq \exp(-c' \cdot \zeta_v).$$

for some universal constants  $c$  and  $c'$ .

Nodes of the line-graph  $L_G$  ( $e \in E_G$  iff  $v_e \in V_{L_G}$ ;  $v_e v_{e'} \in E_{L_G}$  iff  $e = uv, e' = uv'$ ) have sparsity  $\Omega(\Delta)$ . **In an edge-coloring setting, [EPS15]'s result gives  $\Omega(\Delta)$  slack.**

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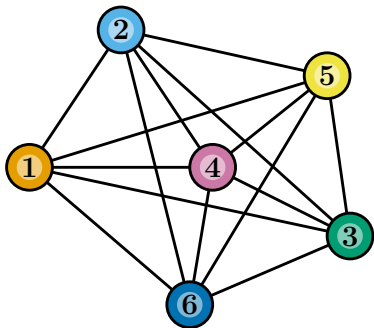
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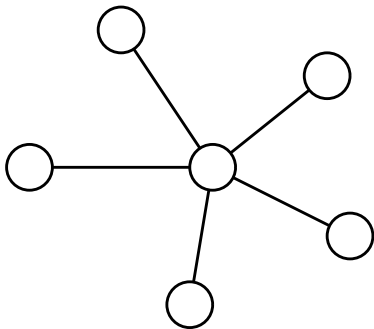
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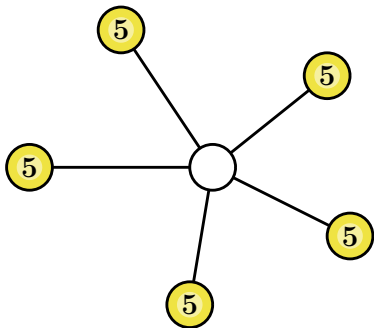
**Theorem ([EPS15]):** Let each node try a random color, then afterwards:

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for some universal constants  $c$  and  $c'$ .

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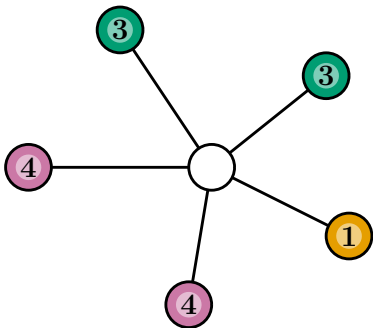
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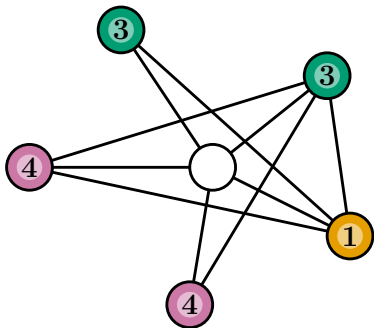
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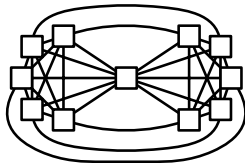
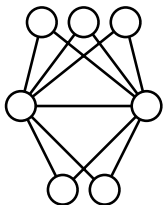
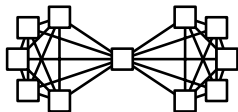
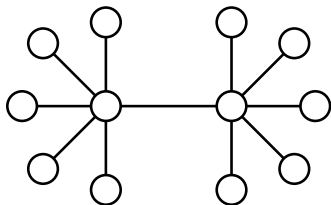
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## Inherent sparsity of line-graphs



# Pairwise-Independent Hash Functions

## Definition (( $\epsilon$ -almost) Pairwise-Independent Hash Functions)

A set  $\mathcal{H}$  of functions  $h : [N] \rightarrow [M]$  s.t.:

$$\forall x \neq y \in [N]^2, z, z' \in [M]^2,$$

$$|\Pr_{h \in \mathcal{H}}[h(x) = z \wedge h(y) = z'] - 1/M^2| \leq \epsilon/M^2.$$

Let  $p$  be a prime such that  $p \geq M^3 \cdot \log_p N / \epsilon$ .

Decompose  $x$  into basis  $p$ , i.e., compute  $x_1, \dots, x_{\lceil \log_p N \rceil}$  such that  $x = \sum_i x_i \cdot p^i$ .

Consider the polynomial  $P_x(X) = \sum_i x_i \cdot X^i$ , of degree  $\leq \log_p N$ .

Pick  $a, b, z$  uniformly at random in  $\{0, \dots, p-1\}$ .

Compute:  $h_{a,b,z} = ((a \cdot P_x(z) + b) \bmod p) \bmod M$ .

## Finite fields of size $p^k$ , $p$ prime

Example with  $p = 2$ .

Pick a degree  $k$  polynomial irreducible over  $\mathbb{F}_2$ . For  $p = 2$ ,  $P(X) = X^k + X + 1$  always works:  $P(0) = P(1) = 1 \pmod{2}$ .

Consider the  $\mathbb{F}_2[X]/P(X)$ , i.e., polynomials over  $\mathbb{F}_2 \pmod{P}$ .

It is equivalent to defining that there's an element  $a$  s.t.  $a^k = 1 + a$ , and considering the  $2^k$  possible words that can be written as combinations of  $1, a, \dots, a^{k-1}$ .

Example of a multiplication over this field: let  $k = 3$ ,  $(1 + a^2) \times a = a + a^3 = a + 1 + a = 1$ .