

On the Relative Sizes of Complements of Generalized Sumsets

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Definition

We say A is **MSTD** if $|A + A| > |A - A|$.

Existence of MSTD Sets

MSTD sets exist: $\{0, 2, 3, 4, 7, 11, 12, 14\}$ (Conway, 1960s).

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Question

What is the “right way of counting”?

Uniform Model

First try: Pick A uniformly at random from $2^{\{0,1,\dots,N\}}$.
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Theorem (Martin and O'Bryant, 2006)

For $N \geq 15$, there exists a constant $c > 0$ such that

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Intuition:

- With high probability, $A + A$ and $A - A$ will hit everything in the middle of $[0, 2N]$ and $[-N, N]$, respectively.
- We can then “rig” the fringes of $A + A$ and $A - A$ by carefully selecting the fringes of A .

Binomial Model

Second try: Keep the same model, but now let the inclusion probability be $p(N) \asymp N^{-\delta}$ for some $\delta \in (0, 1)$.

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Theorem (Hegarty and Miller, 2008)

- (Fast Decay) If $\delta > \frac{1}{2}$, $\frac{|A-A|}{|A+A|} \sim 2$.
- (Critical Decay) If $p(N) = cN^{-1/2}$, $\frac{|A-A|}{|A+A|} \sim f(c) \searrow 1$.
- (Slow Decay) If $\delta < \frac{1}{2}$, $\frac{|(A+A)^c|}{|(A-A)^c|} \sim 2$.

Generalized Sumsets

Definition

The **generalized sumset** $A_{s,d}$ of A with s sums, d differences is

$$A_{s,d} := \{a_1 + \cdots + a_s - b_1 - \cdots - b_d : a_1, \dots, a_s, b_1, \dots, b_d \in A\}.$$

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- (Critical Decay) If $p(N) = cN^{-\frac{h-1}{h}}$, $\frac{|A_{s_1, d_1}|}{|A_{s_2, d_2}|} \sim \frac{f(c, s_1, d_1)}{f(c, s_2, d_2)}$.

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Proposition (J., Miller, 2023++)

We have that $\frac{f(c,s_1,d_1)}{f(c,s_2,d_2)} \searrow 1$.

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Step (1) is easy for the complements when there are two summands:

$$\mathbb{E}[|(A + A)^c|] = \sum_{k=0}^{2N} \Pr[k \notin A + A],$$

and $k \notin A + A$ is the union of the mutually independent events

$$\{0, k\} \not\subseteq A, \{1, k-1\} \not\subseteq A, \dots, \{\lfloor k/2 \rfloor, \lceil k/2 \rceil\} \not\subseteq A.$$

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Harder to compute exclusion probabilities for three or more summands.

Main Result

We include each element in $\{0, 1, \dots, N\}$ in A independently with probability $p(N) \asymp N^{-\delta}$, where $\delta < \frac{h-1}{h}$.

Theorem (J., Miller, 2023++)

If $s_1 + d_1 = s_2 + d_2 = h$ and $\delta < \frac{h-1}{h}$,

$$\frac{|A_{s_1, d_1}^c|}{|A_{s_2, d_2}^c|} \sim \left(\frac{s_1! d_1!}{s_2! d_2!} \right)^{\frac{1}{h-1}}.$$

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Takeaways:

- When comparing sizes of complements in the slow decay regime, there is always a limit in probability.
- The limiting ratio of the main terms in the fast decay regime generalizes differently from the limiting ratio of the complements in the slow decay regime.

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- 3 The number of missing elements is strongly concentrated about its expectation.

Henceforth: Everything will be under the context of $A_{h,0}$, which takes values in $[0, hN]$. We also assume that we only allow distinct summands.

Step 1: The Fringes

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- 1 The $\frac{(1/p)^{\frac{1}{h-1}}}{h}$ th element of A is $\sim \frac{(1/p)^{\frac{h}{h-1}}}{h}$.
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We therefore have the asymptotic lower bound

$$\mathbb{E}[|A_{h,0}^c|] \gtrsim h \cdot \frac{(1/p)^{\frac{h}{h-1}}}{h} - \sum_{i=1}^{(1/p)^{\frac{1}{h-1}}} i^{h-1} \gtrsim (1/p)^{\frac{h}{h-1}}.$$

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Expected number of missing elements in $[\tau N, (h - \tau)N]$ is at most

$$\begin{aligned} \sum_{k \in [\tau N, (h - \tau)N]} e^{-k^{h-1}p^h} &\lesssim (1/p)^{\frac{h}{h-1}} \int_{\log \left[Np^{\frac{h}{h-1}} \right]}^{\infty} e^{-Cx^{h-1}} dx \\ &= o\left((1/p)^{\frac{h}{h-1}} \right). \end{aligned}$$

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Combined with Last Slide: All of the missing elements lie in $[\tau N, (h - \tau)N]^c = [0, \tau N] \cup [(h - \tau)N, hN]$, the fringes.

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For each possible sum k in the fringes, we invoke the Stein-Chen method (Arratia, Goldstein, Gordon, 1989) to prove that the number of ways k is hit converges to a Poisson.

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The expected number of missing elements in the left fringe, $[0, \tau N]$, is

$$\begin{aligned} \sum_{k=0}^{\tau N} \Pr[k \notin A_{h,0}] &\stackrel{(1)}{\sim} \sum_{k=0}^{\tau N} \Pr[\text{Pois}(\lambda_k) = 0] \sim \sum_{k=0}^{\tau N} e^{-\lambda_k} \\ &\stackrel{(2)}{\sim} (1/p)^{\frac{h}{h-1}} \int_0^{\infty} e^{-C_h x^{h-1}} dx. \end{aligned}$$

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- ① The probability that each Poisson random variable is 0 dominates the bound on the total variation distance from Stein-Chen.
- ② The rate λ_k is the expected number of combinations with h distinct terms that sum to k . The number of ways to partition k into h distinct parts, for large k , is $\sim C_h k^{h-1}$ (Knessl and Keller, 1990). So $\lambda_k \sim C_h p^h k^{h-1}$.

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Altogether, we have that

$$\frac{\mathbb{E} \left[\left| A_{s_1, d_1}^c \right| \right]}{\mathbb{E} \left[\left| A_{s_2, d_2}^c \right| \right]} \sim \frac{h^{-1} \sqrt{\binom{h}{d_2}}}{h^{-1} \sqrt{\binom{h}{d_1}}} = \left(\frac{s_1! d_1!}{s_2! d_2!} \right)^{\frac{1}{h-1}}.$$

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Proves the theorem for the expectations.

Step 3: Reductions from Martingale Machinery

For $k \in \{0, \dots, N\}$, define the quantities

$$\Delta_k(A) = \mathbb{E} \left[|A_{h,0}^c| \mid A \cap [0, k-1], k \in A \right] - \mathbb{E} \left[|A_{h,0}^c| \mid A \cap [0, k-1], k \notin A \right],$$

$$C(A) = \max_{0 \leq k \leq N} \Delta_k(A), \quad V(A) = p \sum_{k=0}^N (\Delta_k(A))^2.$$

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From a result of Vu (2002), for any $\lambda, V, C > 0$ such that $\lambda \leq \frac{4V}{C^2}$,

$$\mathbb{P} \left(\left| |A_{h,0}^c| - \mathbb{E} [|A_{h,0}^c|] \right| \geq \sqrt{\lambda V} \right) \leq 2e^{-\lambda/4} + \mathbb{P}(C(A) \geq C) + \mathbb{P}(V(A) \geq V).$$

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It will suffice to show the RHS vanishes if we take

$$\lambda \asymp \log(1/p), \quad V \asymp ((1/p) \log(1/p))^{1+\frac{h}{h-1}}, \quad C \asymp (1/p) \log(1/p),$$

since then, $\lambda \leq \frac{4V}{C^2}$, $\sqrt{\lambda V} = o\left((1/p)^{\frac{h}{h-1}}\right)$, and $e^{-\lambda/4}$ vanishes.

Step 3: Sketch of Strong Concentration

Fix some $k \in \{0, \dots, N\}$.

- 1 (Middle) Number of elements in $[\tilde{\tau}N, (h - \tilde{\tau})N]$ that adding k to A will add to $A_{h,0}$ is $o(1)$. (Adapt argument from Step 1, with a larger threshold $\tilde{\tau} \asymp \frac{(\log N)^{\frac{1}{h-1}}}{N\rho^{\frac{h}{h-1}}}$ separating the fringe from the middle.)

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- 1 (Middle) Number of elements in $[\tilde{\tau}N, (h - \tilde{\tau})N]$ that adding k to A will add to $A_{h,0}$ is $o(1)$. (Adapt argument from Step 1, with a larger threshold $\tilde{\tau} \asymp \frac{(\log N)^{\frac{1}{h-1}}}{Np^{\frac{h}{h-1}}}$ separating the fringe from the middle.)
- 2 (Fringes) Number of elements in $[\tilde{\tau}N, (h - \tilde{\tau})N]^c$ that adding k to A will add to $A_{h,0}$ is $\lesssim (1/p) \log(1/p)$. (Adding k to A cannot add more new sums to $A_{h,0}$ than \asymp (number of fringe elements of A) $^{h-1}$; Chernoff yields size of fringes to be $\asymp [(1/p) \log(1/p)]^{\frac{1}{h-1}}$.)

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A union bound with vanishing sum of error probabilities gives

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Furthermore, $V(A) \lesssim p\tilde{\tau}N [(1/p) \log(1/p)]^2 \asymp ((1/p) \log(1/p))^{1 + \frac{h}{h-1}}$, so

$$\mathbb{P}(V(A) \geq V) = \mathbb{P}(V(A) \geq \kappa_2 ((1/p) \log(1/p))^{1 + \frac{h}{h-1}}) \xrightarrow{N \rightarrow \infty} 0.$$

Thank You for Listening!

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