# Anticoncentration via the Strong Perfect Graph Theorem 

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## The Littlewood-Offord problem

Theorem (Erdős 45)
Let $\varepsilon_{1}, \ldots, \varepsilon_{n}$ be independent random variables such that $\mathbb{P}\left(\varepsilon_{i}= \pm 1\right)=\frac{1}{2}$. Then for $a_{i} \in \mathbb{R}$ with $\left|a_{i}\right| \geq 1$ we have

$$
\mathbb{P}\left(a_{1} \varepsilon_{1}+\cdots+a_{n} \varepsilon_{n} \in(x, x+2]\right) \leq \mathbb{P}\left(\varepsilon_{1}+\cdots+\varepsilon_{n} \in(-1,1]\right) .
$$

Answering a question of Erdős, Kleitman (70) extended the result to arbitrary normed spaces.

## Extension to other random variables

Theorem (Leader-Radcliffe 94)
Let $X_{1}, \ldots, X_{n}$ be independent random variables such that for all $x \in \mathbb{R}$

$$
\mathbb{P}\left(X_{i} \in(x, x+2)\right) \leq \frac{1}{k}
$$

Then

$$
\mathbb{P}\left(X_{1}+\cdots+X_{n} \in(x, x+2)\right) \leq \mathbb{P}\left(U_{1}+\cdots+U_{n} \in(-1,1]\right)
$$

where $U_{i}$ 's are independent uniform random variables on the $k$-point set $\{-k+1,-k+3, \ldots, k-3, k-1\}$.

Henceforth we shall denote the latter uniform distribution by $\nu^{k}$.

## Other values of concentration 1

Leader and Radcliffe asked about the situation with concentration bound being not an inverse of an integer.

Notation. For $\alpha \in\left[\frac{1}{k+1}, \frac{1}{k}\right]$ denote by $T(\alpha)$ a real random variable having distribution

$$
p \nu^{k+1}+(1-p) \nu^{k}, p=k(k+1) \alpha-k,
$$

where $p=k(k+1) \alpha-k$. The latter choise ensures that the sum of two consecutive atoms of $T(\alpha)$ is exactly $\alpha$.

## Other values of concentration 2

Theorem (J., 2015)
Let $X_{1}, \ldots, X_{n}$ be independent random variables such that for all $x \in \mathbb{R}$

$$
\mathbb{P}\left(X_{i} \in(x, x+2)\right) \leq \alpha_{i}
$$

Then
$\mathbb{P}\left(X_{1}+\cdots+X_{n} \in(x, x+2)\right) \leq \mathbb{P}\left(T_{1}\left(\alpha_{1}\right)+\cdots+T_{n}\left(\alpha_{n}\right) \in(-1,1]\right)$.
Setting $\alpha_{i}=\frac{1}{k}$ recovers the previous result by Leader-Radcliffe.

## A conjecture by Leader-Radcliffe

Let $\mathcal{M}$ be a normed space. Define a notion of concentration of a random vector $X$ by

$$
\tilde{Q}(X, D)=\sup _{A} \mathbb{P}(X \in A)
$$

where $A$ runs through all open sets of diameter $D$ in $\mathcal{M}$.
Conjecture. Let $X_{1}, \ldots, X_{n}$ be independent random vectors in some normed space $\mathcal{M}$ such that for all $i$ we have

$$
\tilde{Q}\left(X_{i}, 2\right) \leq \frac{1}{2}
$$

Then

$$
\tilde{Q}\left(X_{1}+\cdots+X_{n}, 2\right) \leq \mathbb{P}\left(\varepsilon_{1}+\cdots+\varepsilon_{n} \in(-1,1]\right)
$$

## A conjecture by Lee Jones 78

Definition. We shall call a set of $k$ points in a normed space $\mathcal{M}$ a $k$-block if their pairwise distances are at least 2 . We sometimes omit the parameter $k$ when it is convenient and just call such sets blocks.

Conjecture. Let $X_{1}, \ldots, X_{n}$ be independent random vectors in a normed space $\mathcal{M}$. Assume that each of them is uniform on some $k$-block. Then

$$
\tilde{Q}\left(X_{1}+\cdots+X_{n}, 2\right) \leq \tilde{Q}\left(U_{1}+\cdots+U_{n}, 2\right)
$$

where $U_{i}$ 's are independent and each distributed uniformly on the $k$-block $\{-k+1,-k+3, \ldots, k-3, k-1\}$.

## Main result

Theorem (J., V. Kurauskas 2023+)
Let $X_{1}, \ldots, X_{n}$ be independent random vectors in $\mathbb{R}^{d}$ with a norm $\|\cdot\|$. Assume that $\tilde{Q}\left(X_{i}, 2\right) \leq \alpha$ for some $\alpha \in[0,1]$. Then

$$
\tilde{Q}\left(X_{1}+\cdots+X_{n}, 2\right) \leq(1+o(1)) \tilde{Q}\left(T_{1}(\alpha)+\cdots+T_{n}(\alpha), 2\right)
$$

where the $o(1)$ term depends on $d$ and the underlying norm.

Remark. Apart from the $1+o(1)$ multiplicative factor, the latter inequality gives exactly the

1) bound in the Leader-Radcliffe conjecture taking $\alpha=2$;
2) bound in the conjecture of Lee Jones taking $\alpha=\frac{1}{k}$.

## Difficulties and a negative result

Difficulties of the proof - circumventing the Krein-Milman theorem (board).
It might be tempting to believe that the latter inequality is true without the parasitic $1+o(1)$ factor. We now show that this natural conjecture is false, even for $n=2$. A counterexample for 2-dimensional Euclidean space is when both $X_{1}$ and $X_{2}$ are chosen uniformly at random from the vertices of a regular octagon with radius $2(\sqrt{2}+2)^{-\frac{1}{2}} \approx 0.5412$. Then

$$
\tilde{Q}\left(X_{1}+X_{2}, 2\right)=\tilde{Q}\left(X_{1}, 2\right)=\frac{3}{8}
$$

This value is sharp when $\alpha=\frac{3}{8}$ since $\tilde{Q}\left(X_{1}+X_{2}, 2\right) \leq \tilde{Q}\left(X_{1}, 2\right)$. It is also strictly larger than $\tilde{Q}\left(T_{1}\left(\frac{3}{8}\right)+T_{2}\left(\frac{3}{8}\right), 2\right)$.

## Setup for today

In order to present the proof ideas we shall consider the problem in a more restricted setting:

1) Only the $I_{2}$ norm;
2) Finitely supported random variables with rational probabilities.

## Splitting into cases (idealized)

Case 1 (structured): all distributions lie close to a single line;
Case 2 (unstructured): distributions are substantially "high-dimensional", i.e., the spread of the sum is happening in multiple directions.

## Unstructured case

Use Halasz's concentration bound that gives probabilities of magnitude $o\left(n^{-1 / 2}\right)$.

## Structured case

Now every distribution is close to a single line (to be quantified later). Take any random vector $X$ in $\mathbb{R}^{d}$ with finite support and rational probabilities. We can assume that $X$ is uniformly distributed on some multiset $M$ (find a common denominator for the probabilities ant take each point appropriately many times).

## The Perfect Graph Theorem

Definition. A (finite simple) graph is called perfect iff the chromatic number and the clique number coincide on all of its induced subgraphs.

Theorem (Chudnovsky, Robertson, Seymour, Thomas 2003) A graph $G$ is perfect iff neither $G$ nor its complement have induced odd cycles of length $\geq 5$.

## The use in our setting

Recall that we are working with random vectors $X$ concentrated on some multiset $M \subset \mathbb{R}^{d}$ such that $\tilde{Q}(X, 2) \leq \alpha$.

Define a distance graph on $M$ in the following way - treat all elements of $M$ as distinct (repeating elements are distinguished) vertices of a graph $G$. Two vertices $x, y \in M$ are joined iff $d(x, y)<2$.
Theorem (J., V. Kurauskas)
Let $G$ be a distance graph of points $x_{1}, \ldots, x_{N}$ in $\mathbb{R}^{d}$, and assume each of the points is of distance at most $\frac{\sqrt{3}}{2}$ from the line generated by the vector $(1,0, \ldots, 0)^{T}$ (the " $x$ axis"). Then neigher $G$ nor its complement contain an induced cycles of odd length 5 or more.

## So what? Quite a lot, actually.

We now know that in the structured case our distance graph of the supporting multiset of each variable is perfect. The optimal coloring of any such graph produces a certain number of independent sets (color classes) which we can control via the clique number. The condition $\tilde{Q}(X, 2) \leq \alpha$ means that the largest clique in $G$ has at most $\alpha$-proportion of the vertices which is also a bound on the chromatic number.

Why care about the chromatic classes (independent sets)? They decompose the distribution of $X$ into blocks! And we can control the number of them (and thus, the sizes).

## Where are the bodies burried?

Lee Jones actually has proved his conjecture when the underlying normed space satisfies a certain partitioning condition (called the De Bruijn, Tengbergen, Kruyswijk or B.K.T. condition) of the sumset of blocks. Regrettably, that condition fails for $I_{2}$. Yet we can justify it in the structured case and we do not need it in the unrestricted case.

## Finishing up

To get the desired result we split the underlying product measure into product measures of blocks and use a more general version of Lee Jones's result when the B.K.T. condition is satisfied. This makes every distribution on a block into a distribution $\nu^{k}$. Putting it all back into a single product structure gives us a convolution of measures on the line by keeping the concentration condition $\tilde{Q}\left(X_{i}, 2\right) \leq \alpha$. Then we just apply what we know about the linear case.

THE END

