On mimicking Rademacher sums and on some extensions of the FKN theorem

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Discrete cube - notation

$$[n] := \{1, 2, \dots, n\}$$

Discrete cube (hypercube) $C_n := \{-1,1\}^n$, equipped with the normalized counting (uniform probability) measure $(\frac{1}{2}\delta_{-1} + \frac{1}{2}\delta_1)^{\otimes n}$

Expectation of $f: C_n \longrightarrow \mathbb{R}$ is thus given by

$$\mathbb{E}[f] = 2^{-n} \sum_{x \in C_n} f(x).$$

L^p-norm: $||f||_p = (\mathbb{E}[|f|^p])^{1/p}$ for $p \ge 1$.

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L²-structure

Scalar product: For $f,g:C_n\longrightarrow \mathbb{R}$ let

$$\langle f, g \rangle = \mathbb{E}[f \cdot g] = 2^{-n} \cdot \sum_{x \in C_n} f(x)g(x).$$

Note that $\langle f, f \rangle = ||f||_2^2$.

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$$\mathcal{H}_n := L^2(C_n, \mathbb{R}); \quad \dim \mathcal{H}_n = 2'$$

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Orthonormality

$$\mathbb{E}[w_A] = 0$$
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eq \emptyset$, and $\mathbb{E}[w_\emptyset] = 1$

Indeed, expectation of the product of independent random variables is equal to the product of their expectations (and they are all equal to zero).

Orthonormality:
$$w_A \cdot w_B = w_{A\Delta B}$$
 thus

$$\langle w_A, w_B \rangle = \mathbb{E}[w_{A \Delta B}] = \delta_{A,B}$$

Here Δ denotes a symmetric set difference (XOR) while $\delta_{A,B}=1$ if A=B and $\delta_{A,B}=0$ if $A\neq B$ (Kronecker's delta).

Example:
$$w_{\{1,2\}} \cdot w_{\{2,3\}} = r_1 r_2 \cdot r_2 r_3 = r_1 r_2^2 r_3 = r_1 r_3$$

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Walsh-Fourier expansion

The Walsh functions $(w_A)_{A\subseteq [n]}$ form an orthonormal system of cardinality 2^n , which is equal to the linear dimension of \mathcal{H}_n . Thus the system is complete and every $f\in\mathcal{H}_n$ admits the unique Walsh-Fourier expansion:

$$f = \sum_{A \subseteq [n]} \hat{f}(A) w_A,$$

with coefficients given by

$$\hat{f}(A) = \langle f, w_A \rangle = \mathbb{E}[f \cdot w_A].$$

Question

Let $N \ge 2$ and let us denote by V_N the linear span of $(w_A)_{A\subseteq [n]:|A|>N}$.

Problem (R. Bogucki, P. Nayar, M. Wojciechowski): Let $S: \{-1,1\}^n \to \mathbb{R}$ be defined by $S = r_1 + r_2 + \ldots + r_n$. Estimate $\operatorname{dist}_{L^1}(S, V_N)$.

There is $\operatorname{dist}_{L^1}(S, V_N) \simeq \min(N, \sqrt{n})$.

Actually, for $S = \sum_{i=1}^{n} a_i r_i$ there is

$$\operatorname{dist}_{L^1}(S, V_N) \leq CN \cdot \max_i |a_i|,$$

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Main result

Theorem

There exists a universal $\kappa > 0$ such that for any integers $N \geq 2$ and $n \geq 1$ there is a function $f: \{-1,1\}^n \to \mathbb{R}$ with $\mathbb{E}[|f|] \leq \kappa N$ and such that $\hat{f}(\{i\}) = 1$ for $1 \leq i \leq n$, and $\hat{f}(A) = 0$ for all $A \subseteq \{1,2,\ldots,n\}$ of cardinality $0,2,3,4,\ldots,N$.

Moreover, the O(N) bound is of optimal order. For N=2 one can even find f satisfying the above conditions and such that $\mathbb{E}[|f|]=1$.

Proof: For N=2 it suffices to consider the function $f=\frac{1}{2}\prod_{i=1}^n(1+r_i)-\frac{1}{2}\prod_{i=1}^n(1-r_i)$. Obviously, $\mathbb{E}[|f|]=1$. No better bound can be hoped for since $\mathbb{E}[fr_i]=1$ implies $\mathbb{E}[|f|]\geq 1$.

For general $N \ge 2$ let us consider a function of Fejér type:

$$\psi_N(x) = \sum_{k=1}^{N} k \sin kx + \sum_{k=1}^{N} (N-k) \sin(N+k)x,$$

or, equivalently, $\psi_N(x) = \sin Nx \cdot \sin^2(Nx/2)/\sin^2(x/2)$.

For some universal constants $\kappa_1, \kappa_2 > 0$ we have $|\psi_N(x)| \le \kappa_1 N^2$ on [-1/N, 1/N] and $|\psi_N(x)| \le \kappa_2/x^2$ for |x| > 1/N.

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Proof of the bound - the end

Recall that we have $\psi_N(x) = \sin Nx \cdot \sin^2(Nx/2)/\sin^2(x/2)$ and $\frac{1}{\pi} \int_{-\pi}^{\pi} |\psi_N(x)| dx \le \kappa N$.

One easily checks that $\int_{-\pi}^{\pi} \psi_N(x) \sin x \, \mathrm{d}x = \pi$, $\int_{-\pi}^{\pi} \psi_N(x) \, \mathrm{d}x = 0$, and $\int_{-\pi}^{\pi} \psi_N(x) \sin^m x \, \mathrm{d}x = 0$ for $2 \le m \le N$ (for even m this is obvious and for odd m one can use simple induction on m, expressing $\sin mx$ as a polynomial in $\sin x$).

Choosing f(x) defined by the formula

$$\frac{1}{\pi} \int_{-\pi}^{\pi} \psi_{N}(x) \prod_{i=1}^{n} (1 + r_{i} \sin x) dx = \sum_{A \subseteq [n]} \frac{1}{\pi} \int_{-\pi}^{\pi} \psi_{N}(x) \sin^{|A|} x dx \cdot w_{A},$$

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Optimality

Now we will prove that in general the linear order of the estimate cannot be improved:

There exists a universal constant $\eta > 0$ with the following property. For every $N \geq 2$ and every function $f: \{-1,1\}^{N^2} \to \mathbb{R}$ such that $\hat{f}(\{i\}) = 1$ for $1 \leq i \leq N^2$ and $\hat{f}(A) = 0$ for all $A \subseteq \{1,2,\ldots,N^2\}$ of cardinality $0,2,3,4,\ldots,N$ there is $\mathbb{E}[|f|] \geq \eta N$.

Proof of optimality

Let

$$W_N(t) = \sum_{k=0}^{\left[\frac{N-1}{2}\right]} \frac{(-1)^k t^{2k+1}}{(2k+1)!}, \quad R_N(t) = \sum_{\left[\frac{N+1}{2}\right]}^{\infty} \frac{(-1)^k t^{2k+1}}{(2k+1)!}.$$

Obviously, $W_N(t) + R_N(t) = \sin t$ and for $t \in [-N/6, N/6]$ we have

$$|R_N(t)| \le \sum_{\lfloor \frac{N+1}{2} \rfloor}^{\infty} (e/6)^{2k+1} \le 2^{-N},$$

since $m! \ge (m/e)^m$. Hence $|W_N(t)| \le 2$ for $|t| \le N/6$. Thus

$$2\mathbb{E}[|f|] \geq \mathbb{E}fW_N\left(\frac{1}{6N}\sum_{i=1}^{N^2}r_i\right) = \mathbb{E}\left[\left(\sum_{i=1}^{N^2}r_i\right)W_N\left(\frac{1}{6N}\sum_{i=1}^{N^2}r_i\right)\right].$$

Indeed, deg $W_N \leq N$, so that $W_N(\frac{1}{6N}\sum_{i=1}^{N^2}r_i)$ is a Walsh-Fourier chaos of order not exceeding N.

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Proof of optimality - the end

On the other hand,

$$\mathbb{E}\left[\left(\sum_{i=1}^{N^2} r_i\right) W_N \left(\frac{1}{6N} \sum_{i=1}^{N^2} r_i\right)\right] =$$

$$\mathbb{E}\left[\left(\sum_{i=1}^{N^2} r_i\right) \sin \left(\frac{1}{6N} \sum_{i=1}^{N^2} r_i\right)\right] - \mathbb{E}\left[\left(\sum_{i=1}^{N^2} r_i\right) R_N \left(\frac{1}{6N} \sum_{i=1}^{N^2} r_i\right)\right]$$

$$\geq N^2 \mathbb{E} r_1 \sin \left(\frac{1}{6N} \sum_{i=1}^{N^2} r_i\right) - 2^{-N} \cdot N^2 =$$

$$N^2 \sin \left(\frac{1}{6N} \right) \cos^{N^2 - 1} \left(\frac{1}{6N} \right) - 2^{-N} \cdot N^2 \sim N.$$

The case of $n < N^2$

The preceding proof can be easily modified to cover the case $n \ge N^2$ instead of $n = N^2$.

The lower bound in the case $n < N^2$ follows - indeed, let N' denote the integer part of \sqrt{n} , so that $n \ge N'^2$. Then we have $N' \le N$ and thus $V_N \subseteq V_{N'}$, so that

$$\operatorname{dist}_{L^1}(S, V_N) \ge \operatorname{dist}_{L^1}(S, V_{N'}) \ge \eta N' \simeq \sqrt{n}$$

Note that we have also a trivial upper bound

$$\operatorname{dist}_{L^1}(S, V_N) \leq \mathbb{E}[|S|] \leq (\mathbb{E}[S^2])^{1/2} = \sqrt{n}.$$

This ends the proof of the $\operatorname{dist}_{L^1}(S, V_N) \simeq \min(N, \sqrt{n})$ estimate.

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On some extensions of the FKN theorem

The classical theorem of Friedgut, Kalai and Naor (2002), re-proved and extended by Kindler and Safra (2002), states that there exists a universal positive constant C such that for any positive integer n and any $f: \{-1,1\}^n \to \{-1,1\}$ we have

$$\mathbb{E}[(f-g)^2] \leq C \cdot \sum_{A \subseteq [n]: |A| \geq 2} \left(\hat{f}(A)\right)^2$$

for some g of the form r_k , $-r_k$ (for some $k \in [n]$), 1, or -1.

We will discuss several new extensions to this theorem obtained in a joint paper with J. Jendrej and J. O. Wojtaszczyk, to appear in Theory of Computing soon (hopefully).

On some extensions of the FKN theorem

The classical theorem of Friedgut, Kalai and Naor (2002), re-proved and extended by Kindler and Safra (2002), states that there exists a universal positive constant C such that for any positive integer n and any $f: \{-1,1\}^n \to \{-1,1\}$ we have

$$\mathbb{E}[(f-g)^2] \leq C \cdot \sum_{A \subseteq [n]: |A| \geq 2} \left(\hat{f}(A)\right)^2$$

for some g of the form r_k , $-r_k$ (for some $k \in [n]$), 1, or -1.

We will discuss several new extensions to this theorem obtained in a joint paper with J. Jendrej and J. O. Wojtaszczyk, to appear in Theory of Computing soon (hopefully).

Main trick

Step 1 ([FKN]): Instead of the Boolean f defined on the discrete cube $\{-1,1\}^n$ (or, more generally, some product probability space), consider its orthogonal projection to the linear subspace of affine functions. On the discrete cube it reads as

$$\sum_{A\subseteq [n]:|A|\leq 1}\hat{f}(A)w_A=a_0+a_1r_1+\ldots+a_nr_n.$$

Step 2: Prove an appropriate lemma of the following form. Let X and Y be independent. If their sum X + Y is "concentrated" then at least one of the variables X, Y is *concentrated* (in a different sense).

Example: $\min(\operatorname{Var}(X), \operatorname{Var}(Y)) \leq C \cdot \operatorname{Var}(|X + Y|).$

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Reduction from *n* to two summands

Step 3: For a sum S of independent X_1, X_2, \ldots, X_n , deduce from Step 2 a lemma of the following form. If S is "concentrated" then there exists $k \in [n]$ such that $S - X_k$ is *concentrated*. Do it in the following way.

For $I\subseteq [n]$ let $S_I=\sum_{i\in I}X_i$. Choose a minimal I such that S_I is not *concentrated*. This implies, in particular, that I is nonempty. Choose any $k\in I$. Use Step 2 for $X=S_I$, $Y=S_{[n]\setminus I}$: S=X+Y is "concentrated" and, by the choice of I, the summand X is not *concentrated*, so that $Y=S_{[n]\setminus I}$ must be *concentrated*. Also, $S_{I\setminus \{k\}}$ is *concentrated* because of the minimality of I. Thus $S_{[n]\setminus \{k\}}=S_{[n]\setminus I}+S_{I\setminus \{k\}}$ is *concentrated* as well.

Potential for extensions and modifications: for example "concentrated" may be replaced by "small", and instead of sums one may consider maxima, etc.

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Symmetric case

Let X and Y be independent square-integrable random variables, at least one of them symmetric. Then

$$\min\left(\operatorname{Var}(X),\operatorname{Var}(Y)\right) \leq \frac{7+\sqrt{17}}{4} \cdot \operatorname{Var}(|X+Y|).$$

Let $(X_i)_{i=1}^n$ be a sequence of independent symmetric random variables. Then for some $k \in \{1, 2, ..., n\}$ we have

$$\operatorname{Var}\left(\sum_{i \leq n: i \neq k} X_i\right) \leq C \cdot \inf_{x \in \mathbb{R}} \operatorname{Var}\left(\left|x + \sum_{i \leq n} X_i\right|\right),$$

where C is a universal constant.

The result holds true with $C = (7 + \sqrt{17})/2 \approx 5.56$. A simple example of n = 3 and X_1, X_2, X_3 i.i.d. symmetric ± 1 random variables indicates that the constant C cannot be less than $8/3 \approx 2.67$ (it suffices to check it for x = 0).

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FKN theorem

The result from the preceding slide contains the FKN theorem, with a reasonable constant, as its special case. Actually, by using a less elementary method, specific to the case of the discrete cube, we were able to further improve the bounds in the FKN theorem (independently an analogous strengthening was obtained by Ryan O'Donnell).

Extension

Let X and Y be independent square-integrable random variables. Assume $\mathbb{E}(|X+Y|-1)^2 \leq \rho^2$ for some $\rho \in (0,1]$. Then $\mathrm{Var}(X) \leq 25\rho$ or $\mathrm{Var}(Y) \leq 25\rho$.

Let X_1, X_2, \ldots, X_n be independent square-integrable random variables and let $S = \sum_{i=1}^n X_i$. Assume $\mathbb{E}(|S|-1)^2 \leq \rho^2$ for some $\rho \in (0,1]$. Then there exists some $k \in [n]$ such that

$$\operatorname{Var}(S - X_k) \leq 50\rho.$$

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This Rubinstein-type bound immediately implies the estimate from the preceding slide (unsurprisingly, taking into account an additional parameter adds some precision). The new two-variable lemma has essentially the same proof as the old one.

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Structural theorem

Let $\varepsilon, \delta > 0$. Let A be a finite subset of a separable Banach space V, with $|A| \geq 2$, such that $||x-y|| \geq 3|A|\varepsilon$ for any distinct $x,y \in A$. Let ξ_1,\ldots,ξ_n be independent V-valued random vectors and $S = \sum_{i=1}^n \xi_i$. Assume that $\mathbb{P}(\mathrm{dist}(S,A) > \varepsilon) \leq \delta$. For $I \subseteq [n]$ let $S_I = \sum_{i \in I} \xi_i$. Then there exists a nonnegative integer k < |A| and $\{i_1,\ldots,i_k\} \subseteq [n]$ such that for some $v \in V$

$$\mathbb{P}\left(\left\|S_{[n]\setminus\{i_1,\ldots,i_k\}}-\nu\right\|>|A|\varepsilon\right)\leq |A|^2\delta^{1/|A|}$$

for some $v \in V$.

Moreover, if V is a Hilbert space and k>0 then there exist vectors $v_1,\ldots,v_k\in V$ and nonempty sets $B_1,\ldots,B_k\subseteq A$ with $\sum_{m=1}^k(|B_m|-1)<|A|$ such that

$$\mathbb{P}\left(\operatorname{dist}(\xi_{i_m}, \nu_m + B_m) > \varepsilon\right) \le 2|A|\delta^{1/(|A|-1)}$$

for every $m \in [k]$.

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Geometric problem

For a general Banach space V a slightly weaker result holds true. Its proof goes via essential reduction to a 2|A|-dimensional linear subspace and use of F. John's theorem therein to deduce the general case from the result in Hilbert spaces.

We will say that a subset of a metric space is Δ -separated if it does not contain a pair of distinct points whose distance is less than Δ .

Question: Let A and B be finite 1-separated subsets of a normed linear space. Does it imply that there exists $C \subseteq A + B$ with $|C| \ge |A| + |B| - 1$ which is also 1-separated?

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