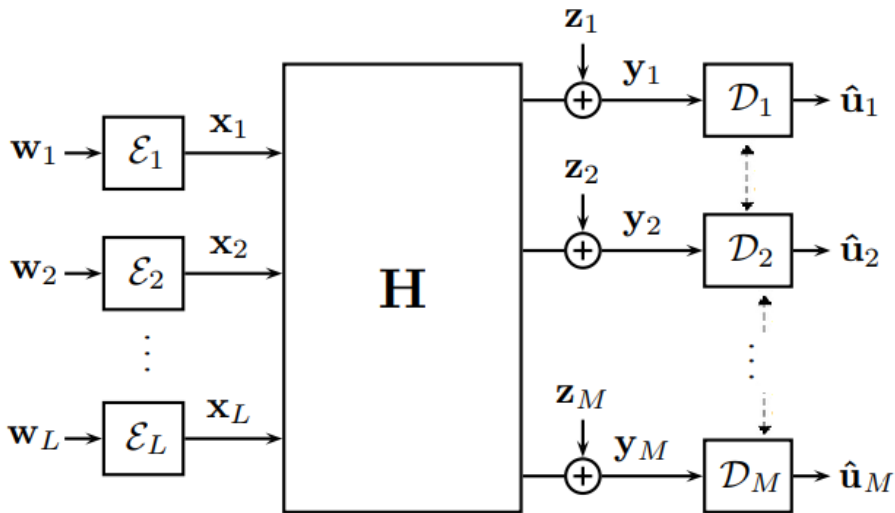


Lattice-based coding schemes and Diophantine approximations

Evgeniy Zorin

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23 January 2018



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The mutual information in this case is equal to

$$C = \log \det (\mathbf{I}_m + \text{SNR} \cdot \mathbf{H}^t \cdot \mathbf{H}).$$

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① Zero-forcing,

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- 1 Zero-forcing,
- 2 Minimum mean-squared error (MMSE).

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Each data stream is drawn from the same lattice codebook. The codebook structure ensures that any integer combination of codewords is itself a codeword, and thus decodable at high rates

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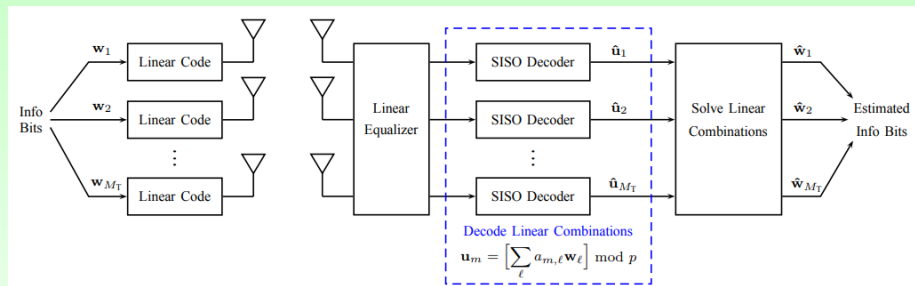
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Key step: selection of an integer matrix \mathbf{A} to approximate the channel matrix \mathbf{H} .

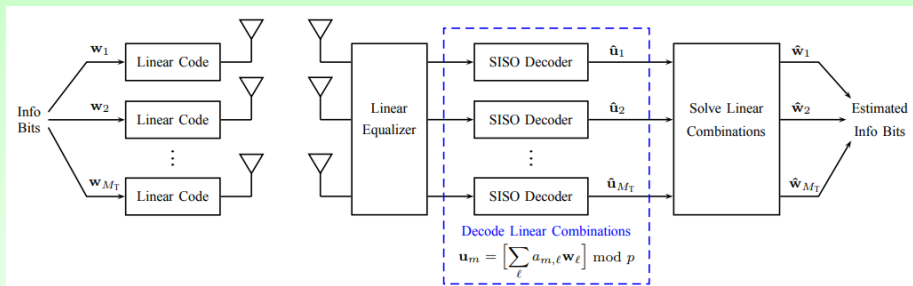
Integer-Forcing linear receiver

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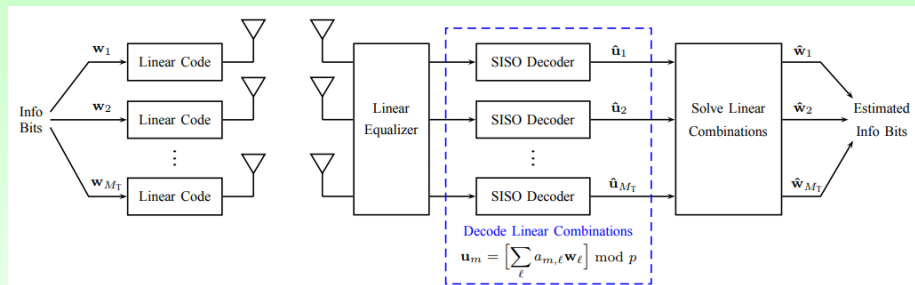
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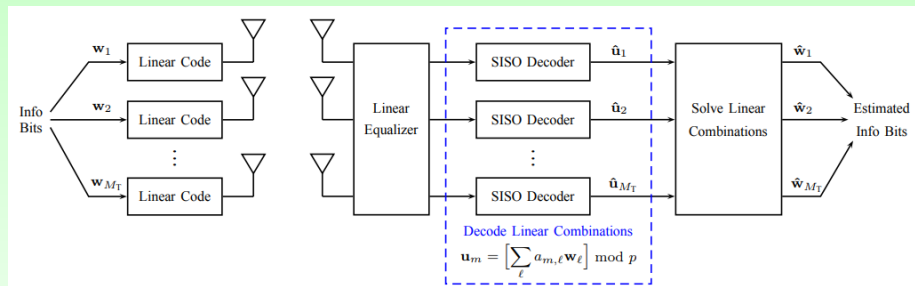


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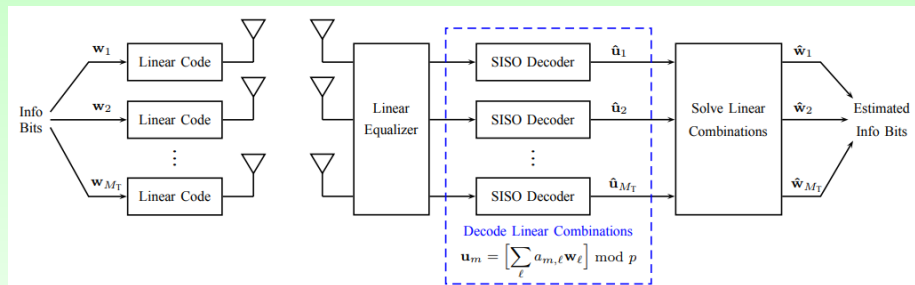
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To make the Integer-Forcing scheme to be successful, decoding over **all** sub-channels should be correct.

We define the effective SNR at the k th sub-channel as

$$\text{SNR}_{\text{eff},k} := \left(\mathbf{a}_k^T \left(\mathbf{I} + \text{SNR} \mathbf{H}^T \mathbf{H} \right) \mathbf{a}_k \right)^{-1},$$

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Theorem (Zhan, Nazer, Ordentlich and Gastbar)

Integer-forcing can achieve any rate

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Remark

The optimal choice of the matrix \mathbf{A} is given by

$$\mathbf{A}^{\text{opt}} := \operatorname{argmin}_{\substack{\mathbf{A} \in \mathbb{Z}^{n \times n} \\ \det \mathbf{A} \neq 0}} \max_{k=1,\dots,n} \mathbf{a}_k^T \left(\mathbf{I} + \text{SNR} \mathbf{H}^T \mathbf{H} \right) \mathbf{a}_k.$$

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Theorem (Ordentlich and Erez)

$$\frac{1}{n^2} M_n(\mathbf{I}_n + \text{SNR} \cdot \mathbf{H}^T \cdot \mathbf{H}) < \text{SNR}_{\text{eff}} \leq M_n(\mathbf{I}_n + \text{SNR} \cdot \mathbf{H}^T \cdot \mathbf{H}).$$

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Problem

Assume that the channel matrix \mathbf{H} has coefficients distributed with respect to a given law (e.g. Gaussian distribution independently for each entry). Let $\kappa \in (0, 1)$.

Find the best possible value of $s \geq 0$ such that the event $\text{SNR}_{\text{eff}} \geq s$ is realised with probability greater than κ .

Define

$$\mathcal{H}_{m,n}(C_0, \text{SNR}) := \left\{ \mathbf{H} \in \mathbb{R}^{n \times m} : \log \det \left(\mathbf{I}_m + \text{SNR} \cdot \mathbf{H}^T \cdot \mathbf{H} \right) = C_0 \right\}.$$

Refined version of the problem

Define

$$\mathcal{H}_{m,n}(C_0, \text{SNR}) := \left\{ \mathbf{H} \in \mathbb{R}^{n \times m} : \log \det \left(\mathbf{I}_m + \text{SNR} \cdot \mathbf{H}^T \cdot \mathbf{H} \right) = C_0 \right\}.$$

Problem

Assume that the channel matrix H is chosen randomly from the set $\mathcal{H}_{m,n}(C_0, \text{SNR})$, according to any given probability distribution on this set.

Let $\kappa \in (0, 1)$.

Find the best possible value of $s \geq 0$ such that the event $\text{SNR}_{\text{eff}} \geq s$ is realised with probability greater than κ ; equivalently, determine the cumulative distribution function of the quantity SNR_{eff} seen as a random variable.

Mathematical interpretation

So, we would like to find cumulative distribution function of

$$M_m(\mathbf{I}_m + \text{SNR}\mathbf{H}^T\mathbf{H})$$

when

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Problem (Mathematical version of the previous problem)

For a given probability measure μ on the set Σ_d^{++} , estimate the probability $\mu(M_d(\Sigma) \leq \delta)$ as a function of $\delta > 0$.

Mathematical Problem 2

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Then, there is a bijection between the locally symmetric set

$$X_d := \mathrm{SL}_d(\mathbb{Z}) \backslash \mathrm{SL}_d(\mathbb{R}) / \mathrm{SO}_d(\mathbb{R})$$

and $\Sigma_{d,red}^{++}$, given by

$$\phi : \bar{g} \in X_d \mapsto g^T \cdot g \in \Sigma_{d,red}^{++}$$

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Consider

$$\begin{aligned} p_{X_d}(\delta) &= (\phi_* \mu_{X_d}) \left(\left\{ \bar{\Sigma} \in \Sigma_{d,red}^{++} : M_d(\bar{\Sigma}) \leq \delta \right\} \right) \\ &= \mu_{X_d} \left(\left\{ \bar{g} \in X_d : M_d(\phi(\bar{g})) \leq \delta \right\} \right) \end{aligned}$$

D.Y. Kleinbock and G.A. Margulis, “Logarithm laws for flows on homogeneous spaces”, *Inventiones Mathematicae* (1998).

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$$V_d = \frac{\pi^{d/2}}{\Gamma\left(\frac{d}{2} + 1\right)} \quad \text{and} \quad A_d = \frac{2\pi^{d/2}}{\Gamma\left(\frac{d}{2}\right)}$$

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Theorem (Kleinbock & Margulis, 1998)

The following inequalities hold for any $\delta > 0$:

$$\frac{V_d}{2\zeta(d)} \delta^{d/2} - c_d \frac{V_d^2}{4} \delta^d \leq p_{X_d}(\delta) \leq \frac{V_d}{2\zeta(d)} \delta^{d/2}. \quad (1)$$

Here, ζ denotes the Riemann zeta function and c_d a strictly positive constant which, when $d \geq 3$, can be taken to be

$$c_d = \frac{1}{\zeta(d) \cdot \zeta(d-1)}.$$

Adiceam and Z., “On the Minimum of a Positive Definite Quadratic Form over Non–Zero Lattice points. Theory and Applications”, Journal de Mathematiques Pures et Appliques (2018)

Final Estimate

Adiceam and Z., “On the Minimum of a Positive Definite Quadratic Form over Non–Zero Lattice points. Theory and Applications”, Journal de Mathematiques Pures et Appliques (2018)

Let $f : \mathcal{S}_d^{++} \rightarrow \mathbb{R}_+$ be a density function supported on \mathcal{S}_d^{++} . The corresponding measure is denoted by ν_f .

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$$m_f(\delta) := \nu_f(\{Q \in \mathcal{S}_d^{++} : M_d(Q) \leq \delta\})$$

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Theorem (Adiceam and Z.)

Let $\delta \in (0, 1)$. Then,

$$0 \leq 1 - \int_{\sqrt{\delta}}^{\infty} g_f \leq m_f(\delta) \leq 1 - \int_{I_d(\delta)} G_f \leq 1, \quad (2)$$

where

$$I_d(\delta) := \left(\sqrt{\delta}, +\infty\right)^d.$$

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Given any $\beta = (\beta_1, \dots, \beta_d) \in (\mathbb{R}_{>0})^d$,

$$G_f(\beta) := 2^d \cdot \prod_{i=1}^d \beta_i^{d-i+1} \cdot \int_{\mathbb{R}^p} (f \circ \varphi_{chol})(\beta, \mathbf{u}) \cdot d\lambda_p(\mathbf{u}).$$

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and, given any $\beta_1 > 0$

$$g_f(\beta_1) := \int_{(\mathbb{R}_{>0})^{d-1}} G_f(\beta_1, \tilde{\beta}) \cdot d\lambda_{d-1}(\tilde{\beta}). \quad (4)$$

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Adiceam and Z., "On the Minimum of a Positive Definite Quadratic Form over Non-Zero Lattice points. Theory and Applications", Journal de Mathematiques Pures et Appliques (2018)

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$$\tilde{m}_f(\delta) := \tilde{\nu}_f(\{Q \in \Sigma_d^{++} : M_d(Q) \leq \delta\})$$

Theorem (Adiceam and Z.)

Let $\delta \in (0, 1)$. Then,

$$0 \leq 1 - \int_{\sqrt{\delta}}^{\infty} \tilde{g}_{\tilde{f}} \leq \tilde{m}_{\tilde{f}}(\delta) \leq 1 - \int_{\Delta_{d-1}(\delta)} \tilde{G}_{\tilde{f}} \leq 1, \quad (5)$$

$$\Delta_{d-1}(\delta) := \left\{ \beta' \in (\mathbb{R}_{>0})^{d-1} : \right.$$

$$\left. \left(\forall i = 1, \dots, d-1, \beta_i > \sqrt{\delta} \right) \wedge \left(\prod_{i=1}^{d-1} \beta_i < \frac{1}{\sqrt{\delta}} \right) \right\}.$$

Interference Alignment and Diophantine approximations

$$y = h_1x_1 + h_2x_2.$$

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$$y = \begin{cases} 0 & \text{if } x_1 = x_2 = 0 \\ h_1 & \text{if } x_1 = 0 \text{ and } x_2 = 1 \\ h_2 & \text{if } x_1 = 1 \text{ and } x_2 = 0 \\ h_1 + h_2 & \text{if } x_1 = x_2 = 1, \end{cases}$$

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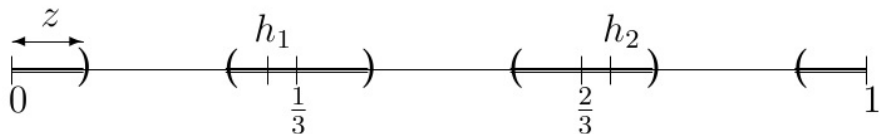
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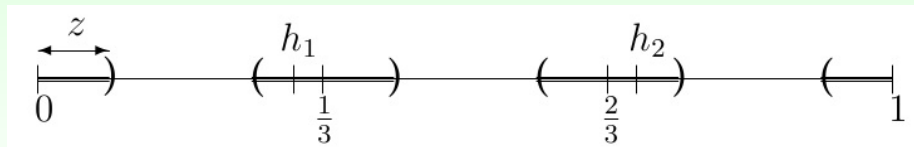
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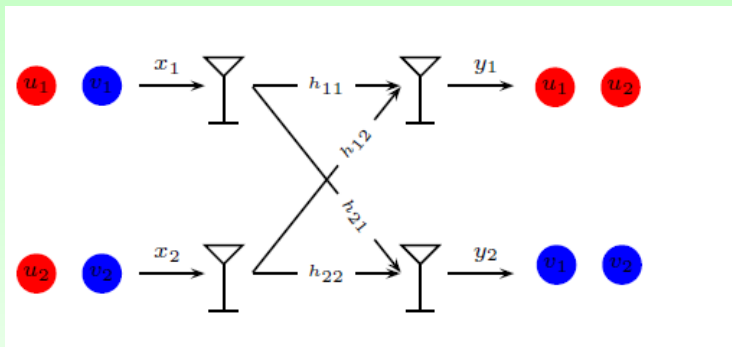
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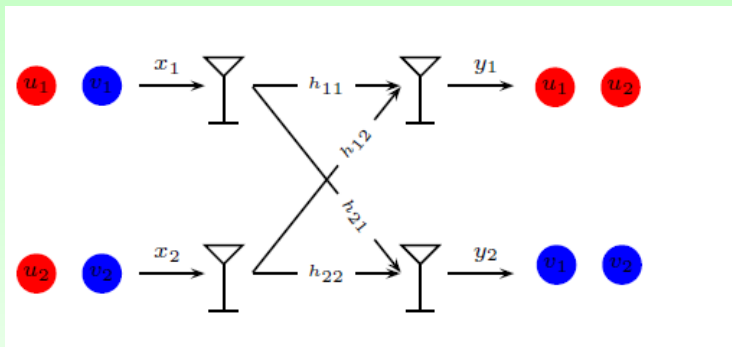
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Picture become more complicated if we transmit x_1 and x_2 from bigger interval, e.g. $x_1, x_2 \in [1, \dots, 16]$.

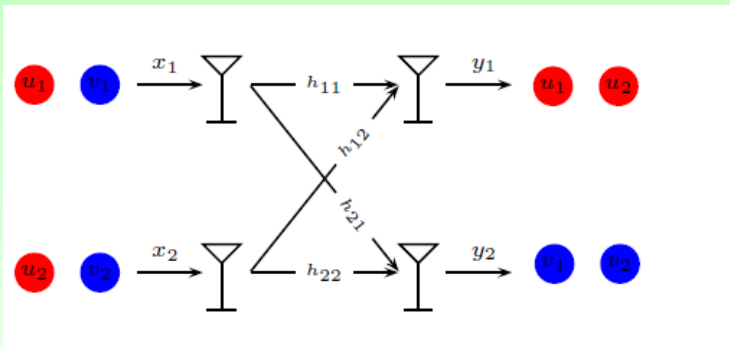




Precoding:

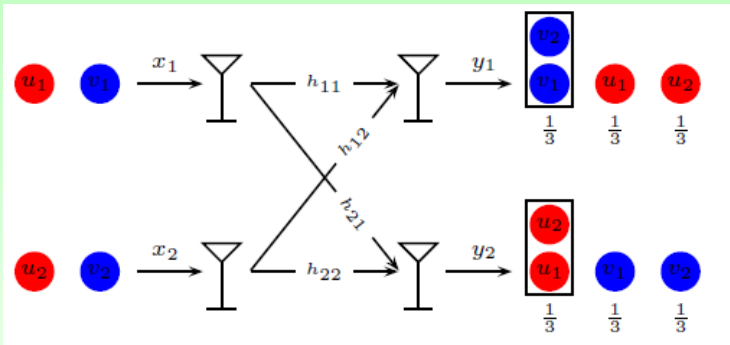
$$x_1 = h_{22}u_1 + h_{12}v_1$$

$$x_2 = h_{21}u_2 + h_{11}v_2$$



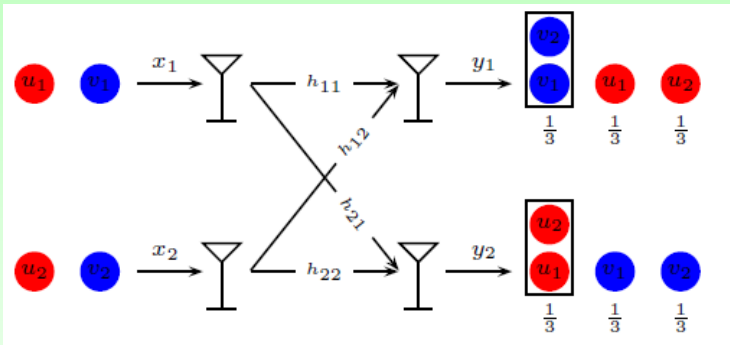
$$y_1 = (h_{11}h_{22})u_1 + (h_{21}h_{12})u_2 + (h_{11}h_{12})(v_1 + v_2)$$

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Problem

Estimate outage probability of this scheme.

- ① ...
- ② A. S. Motahari, S. Oveis-Gharan, M.A. Maddah-Ali, A. K. Khandani. Real interference alignment: exploiting the potential of single antenna systems, *IEEE Trans. Inform. Theory* 60 (2014), no. 8, 4799–4810.
- ③ A. S. Motahari, S. Oveis-Gharan, M.A. Maddah-Ali, A. K. Khandani. “Real Interference Alignment”, 2010.
- ④ ...

Definition

Given a real positive function $\psi : \mathbb{R}^+ \rightarrow \mathbb{R}^+$ with $\psi(r) \rightarrow 0$ as $r \rightarrow \infty$ (i.e. a so called approximating function), let

$$\mathcal{B}(\psi) := \{x \in \mathbb{R} : |qx - p| > \psi(q) \text{ for a.b.f.m. } (q, p) \in \mathbb{N} \times \mathbb{Z}\},$$

where 'for a.b.f.m.' reads 'for all but finitely many'.

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Theorem (Khintchine, 1924)

Let ψ be an approximating function. Then

$$|\mathcal{B}(\psi)| = \begin{cases} \text{FULL} & \text{if } \sum_{q=1}^{\infty} \psi(q) < \infty, \\ 0 & \text{if } \sum_{q=1}^{\infty} \psi(q) = \infty \text{ and } \psi \text{ is monotonic.} \end{cases}$$

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Example

Let $\log^+(q) := \max(1, \log(q))$. Set $\psi(q) = \frac{1}{q \log^+(q)^2}$. Clearly,

$$\sum_{q=1}^{\infty} \frac{1}{q \log^+(q)^2} < \infty,$$

so for almost all $x \in \mathbb{R}$ we have

$$\|qx\| > \frac{1}{q \log^+(q)^2} \text{ for a.b.f.m. } q \in \mathbb{N}.$$

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For almost all $x \in \mathbb{R}$ we have

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Moreover, the inequality

$$\|qx\| > \frac{10^{-100}}{q \log^+(q)^2} \quad (7)$$

fails for all integers $q \in [-1024; 1024]$ on a set of x of strictly positive Lebesgue measure. Indeed, it fails on, say,

$$x \in \left[2 - \frac{10^{-100}}{1024 \log(1024)^2}; 2 + \frac{10^{-100}}{1024 \log(1024)^2} \right]$$

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$$\mathcal{B}_m(\psi) := \{\mathbf{x} \in \mathbb{R}^m : \|\mathbf{a} \cdot \mathbf{x}\| > \psi(|\mathbf{a}|) \text{ for a.b.f.m. } \mathbf{a} \in \mathbb{Z}^m, \mathbf{a} \neq \mathbf{0}\},$$

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Theorem

Let $m \in \mathbb{N}$, ψ be an approximating function and

$$S_m(\psi) := \sum_{q=1}^{\infty} q^{m-1} \psi(q). \quad (8)$$

Then for any $m > 1$

$$|\mathcal{B}(\psi)|_m = \begin{cases} \text{FULL} & \text{if } S_m(\psi) < \infty, \\ 0 & \text{if } S_m(\psi) = \infty. \end{cases}$$

Corollary

Suppose that ψ is an approximating function and $S_m(\psi) < \infty$. Then for almost every $\mathbf{x} \in \mathbb{R}^m$ there exists a constant $\kappa(\mathbf{x}) > 0$ such that

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$$\kappa := \frac{1}{2} \min \left\{ \frac{1}{M_\Psi}, \left(\frac{\delta}{2\Sigma(\Psi)\Sigma_f} \right)^{1/m} \right\}.$$

Example

Assume that x follows the standard normal distribution, $\mathcal{N}(0, 1)$, and that $\psi(n) = \frac{1}{n \cdot \log(n)^2}$, $n \geq 2$, with $\psi(1) = 1$.

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Let δ takes the values 0.5, 0.25, 0.1 and 0.01. Then we have from previous calculations:

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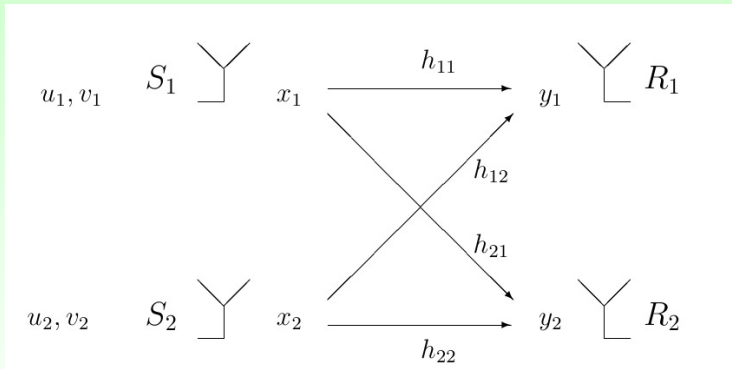
In particular, see that for 99% of the values of the random variable x that has normal distribution $\mathcal{N}(0, 1)$ the inequality

$$\|nx\| > \frac{3 \cdot 10^{-6}}{n \cdot \log(n)^2}$$

holds for all $n \in \mathbb{N}$.

MANIFOLDS

MANIFOLDS



Let \mathcal{M} be a manifold parametrized by $\mathbf{f} : \mathcal{U} \rightarrow \mathbb{R}^m$, where $\mathcal{U} \subset \mathbb{R}^d$ is an open set (might be all \mathbb{R}^d). Let $l \in \mathbb{N}$ and assume that at every point $\mathbf{x} \in \mathcal{U}$ among all partial derivatives of the order up to l , $\frac{\partial^k \mathbf{f}}{\partial x_1^{a_1} \dots \partial x_d^{a_d}}(\mathbf{x})$, $a_1, \dots, a_d \in \mathbb{N} \cup \{0\}$, $k = a_1 + \dots + a_d$, $1 \leq k \leq l$, there are d linearly independent vectors. Then we say that manifold \mathcal{M} is **non-degenerate**.

Example

Consider the simplest case, when \mathcal{M} is a planar curve, defined by a function $f : I \rightarrow \mathbb{R}$, where $I \subset \mathbb{R}$ is an interval. Then the condition that the curve \mathcal{M} is non-degenerate means that at every point \mathbf{x} at least one of derivatives of \mathbf{f} of an order up to l is non-zero.

Let $\Psi : \mathbb{Z}^m \setminus \{0\} \rightarrow (0, \infty)$ be a function satisfying

$$\Sigma(\Psi) := \sum_{\mathbf{q} \in \mathbb{Z}^m \setminus \{0\}} \Psi(\mathbf{q}) < \infty \quad (10)$$

$$\Psi(\mathbf{q}) \leq \frac{C_\Psi}{\prod_i \max(1, |q_i|)}, \quad (11)$$

where $C_\Psi > 0$.

$$\mathcal{B}_m(\Psi, \kappa, \mathcal{M}) := \{\mathbf{x} \in \mathcal{U} : \|\mathbf{a} \cdot \mathbf{f}(\mathbf{x})\| > \kappa \Psi(\mathbf{a}) \text{ for all } \mathbf{a} \in \mathbb{Z}^m, \mathbf{a} \neq \mathbf{0}\}.$$

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Theorem (Adiceam, Beresnevich, Leveseley, Velani and Z.)

Let $l \in \mathbb{N}$ and let \mathcal{M} be a compact d -dimensional C^{l+1} submanifold of \mathbb{R}^n and assume it is l -non-degenerate at every point. Let μ be a probability measure supported on \mathcal{M} absolutely continuous with respect to $|\cdot|_{\mathcal{M}}$. Let $\Psi : \mathbb{Z}^n \rightarrow \mathbb{R}^+$ be a monotonically decreasing function in each variable satisfying (10). Then there exist positive constants κ_0, C_0, C_1 depending on Ψ and \mathcal{M} only such that for any $0 < \delta < 1$, the inequality

$$\mu(\mathcal{B}_n(\Psi, \kappa) \cap \mathcal{M}) \geq 1 - \delta$$

holds with

$$\kappa := \min \left\{ \kappa_0, C_0 \Sigma_\Psi^{-1} \delta, C_1 \delta^{d(n+1)(2l-1)} \right\}.$$

One more example

So, admitting a small error $\delta > 0$ we can always find a constant κ such that for m -tuple of integers $\mathbf{a} \in \mathbb{Z}^m \setminus \{0\}$ we have

$$\|\mathbf{a} \cdot \mathbf{f}(\mathbf{x})\| > \kappa \Psi(\mathbf{a}).$$

For example for any $\delta > 0$, we can provide a constant κ such that with probability $> 1 - \delta$ we have

$$\|\mathbf{a} \cdot \mathbf{f}(\mathbf{x})\| > \frac{\kappa}{\prod_i \max(1, a_i \log(a_i)^2)}$$

Remark

If we transmit only such m -tuples $\mathbf{a} = (a_1, \dots, a_m)$ that $|a_i| \leq Q$, $i = 1, \dots, m$, we can optimize this result.

One more example

Define

$$\Psi(a_1, \dots, a_m) := \begin{cases} \frac{1}{Q^m}, & \text{if } |a_i| \leq Q \text{ for all } i = 1, \dots, m. \\ 0 & \text{otherwise.} \end{cases}$$

We have $S_\Psi = 1$. Then we have that for any $\delta > 0$ there exists an explicit constant κ such that for any $\mathbf{a} = (a_1, \dots, a_m)$ such that $|a_i| \leq Q$, $i = 1, \dots, m$ we have

$$\|\mathbf{a} \cdot \mathbf{f}(\mathbf{x})\| > \frac{\kappa}{Q^m}.$$

Thank you!