

Day 1

Introduction to Decoupling and Self-normalization

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Topics Preview

1 Introduction

2 Decoupling

- Complete Decoupling
- Conditional Independent (Tangent) Decoupling

3 Self-Normalization

- Canonical Assumptions
- Pseudo-maximization (Method of Mixtures)

4 Martingale

5 Probabilistic Inequalities

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Motivation and History

- Decoupling and self-normalization constitute domains that have evolved in response to the imperative of expanding martingale techniques to encompass high-dimensional, infinite-dimensional, and intricate nonlinear dependency structures.

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Motivation and History

- Decoupling and self-normalization constitute domains that have evolved in response to the imperative of expanding martingale techniques to encompass high-dimensional, infinite-dimensional, and intricate nonlinear dependency structures.
- **Decoupling** equips us with techniques to proficiently address dependent variables by treating them akin to independent entities. Notably, it offers a natural framework for constructing precise exponential inequalities tailored for self-normalized (super-)martingales.
- Prominent illustrations of **self-normalized processes** include the t-statistic with dependent random variables, alongside (self-normalized) extensions of the KOLMOGOROV's law of the iterated logarithm

$$\limsup_{n \rightarrow \infty} \frac{|S_n|}{\sqrt{2n\sigma^2 \log n}} = 1 \text{ } \mathbb{P}\text{-almost everywhere}$$

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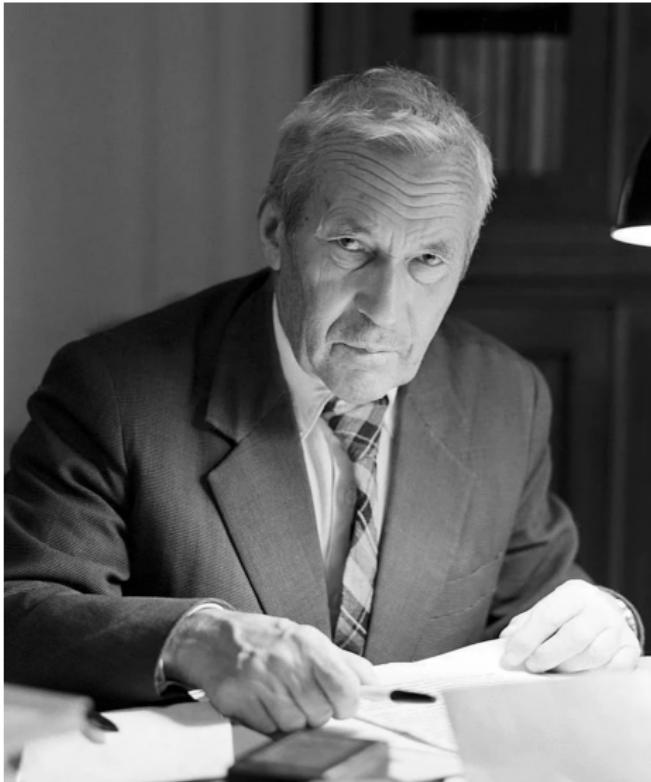
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Decoupling



"BEHIND EVERY LIMIT
THEOREM THERE IS AN
INEQUALITY."

This quote has been
attributed to
A.N. KOLMOGOROV.

Complete Decoupling

Let $\{d_i\}_{i=1}^n$ be a sequence of dependent random variables with $\mathbb{E}|d_i| < \infty$. Let $\{y_i\}_{i=1}^n$ be a sequence of independent variables where for each i , d_i and y_i have the same marginal distributions (denoted as $d_i \stackrel{\mathcal{L}}{=} y_i$ or $d_i \stackrel{d}{=} y_i$). Since $\mathbb{E}(d_i) = \mathbb{E}(y_i)$, linearity of expectations provides the first “complete decoupling” equality:

$$\mathbb{E} \sum_{i=1}^n d_i = \mathbb{E} \sum_{i=1}^n y_i \tag{1}$$

In **complete decoupling**, one compares $\mathbb{E}f(\sum d_i)$ to $\mathbb{E}f(\sum y_i)$ for more general functions $f(\cdot)$, taking the linear mapping $f(x) = cx$ as a special case. It remains possible to derive valuable inequalities based on specific assumptions.

Let the population C consist of N values c_1, \dots, c_N (e.g. a deck of cards, $N=52$), and let d_1, \dots, d_n ($n \leq N$) denote a random sample **without** replacement drawn from C , and y_1, \dots, y_n denote a random sample **with** replacement from C . The random variables y_1, \dots, y_n are i.i.d. and $d_i \stackrel{\mathcal{L}}{=} y_i$ for all i . HOEFFDING (1963, [9]) developed the following inequality:

$$\mathbb{E}\Phi\left(\sum d_i\right) \leq \mathbb{E}\Phi\left(\sum y_i\right). \quad (2)$$

for every continuous convex function Φ .

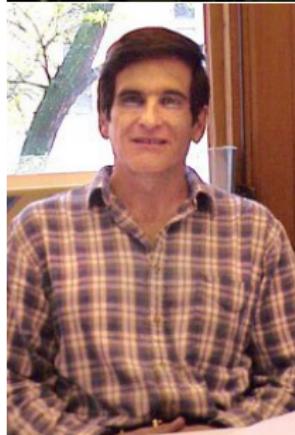
DE LA PEÑA (1990, [2]), extended the assumption such that for nonnegative dependent r.v.s (d_1, \dots, d_n) , such that for each i , y_i and d_i , have the same distribution and $\{y_i\}$ is a sequence of independent random variables. When $p \geq 2$, there exists a constant C_p depending on p only s.t.

$$\left\| \sum_{i=1}^n d_i \right\|_{L_p} \geq C_p \left\| \sum_{i=1}^n y_i \right\|_{L_p}. \quad (3)$$

And if Ψ is a nondecreasing concave function on $[0, \infty)$ such that $\Psi(0) = 0$ and $\Psi(x) > 0$ if $x > 0$, then there is a constant $C > 0$, not depending on anything, such that

$$\mathbb{E}\Psi\left(\sum_{i=1}^n d_i\right) \leq C\mathbb{E}\Psi\left(\sum_{i=1}^n y_i\right). \quad (4)$$

The Origin of Tangent Decoupling



The theory of martingale inequalities has been crucial in the development of modern probability theory. Recently it has been expanded widely through the introduction of the theory of conditionally independent (tangent) decoupling. This approach to decoupling can be traced back to a result of Burkholder and McConnell included in Burkholder [1] that represents a step in extending the theory of martingales to Banach spaces.

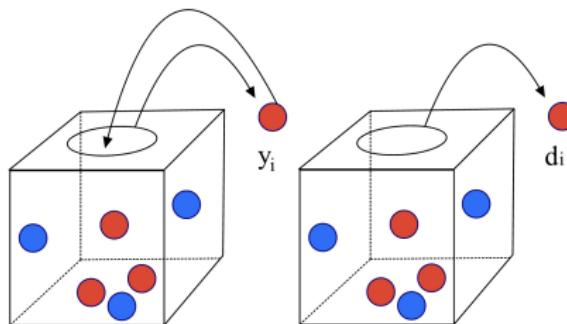
Construction of Tangent Sequence

Specifically, given $\{d_i\}$, we can construct a tangent sequence w.r.t. $\mathcal{F}_i = \sigma(d_1, \dots, d_i)$:

- First, we take d_1 and y_1 to be two independent copies of the same random mechanism.
- With $(d_1, \dots, d_{i-1}; y_1, \dots, y_{i-1})$, the i -th pair of variables d_i and y_i comes from i.i.d. copies of the same random mechanism given \mathcal{F}_i ,

$$\begin{array}{ccccccc} d_1 & \rightarrow & d_2 & \rightarrow & d_3 & \rightarrow & \dots \rightarrow d_n \\ y_1 & \searrow & y_2 & \searrow & y_3 & \searrow & \dots \searrow \\ & & & & & & y_n \end{array}$$

and y_i 's are conditionally independent w.r.t. $= \mathcal{F}_n$.



Tangent Decoupling: M.G.F.

In 1994, de la Peña [3] introduced the tangent decoupling equality, which compares the sum of dependent variables with the corresponding conditional independent sum.

Theorem

If y_i is a decoupled \mathcal{F}' -tangent version of d_i , then for all r.v. $g > 0$ \mathcal{G} -measurable ($\mathcal{G} = \sigma(d_1, \dots, d_n)$),

$$\mathbb{E} \left[g \exp \left(\lambda \sum_{i=1}^n d_i \right) \right] \leq \sqrt{\mathbb{E} \left[g^2 \exp \left(2\lambda \sum_{i=1}^n y_i \right) \right]}. \quad (5)$$

When setting $g = 1$ almost surely, one gets the decoupling inequality for the moment-generating function.

Remark: the y_i 's are conditionally independent given \mathcal{G} .

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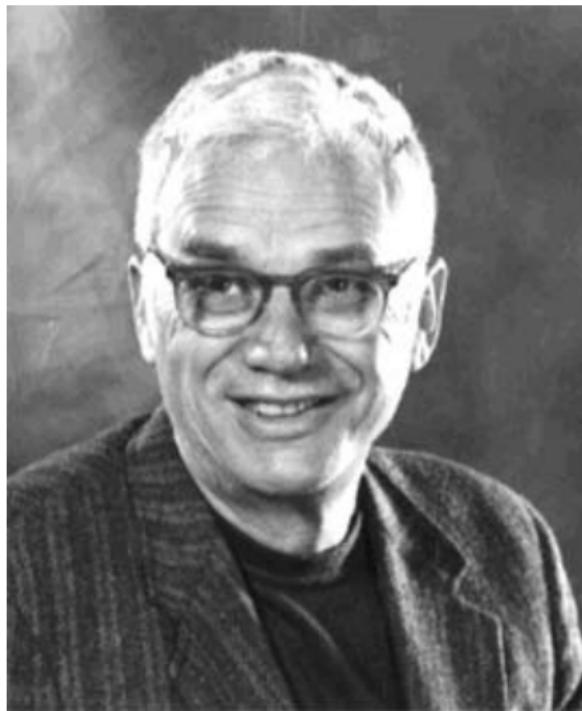
Self-Normalized statistics

- A self-normalized statistic, literally, takes the form $\frac{A_n}{B_n}$ (resp., $\frac{A_t}{B_t}$ for continuous cases), where both A_n and B_n are functions of X_1, \dots, X_n (resp., A_t, B_t the function of $(X_s)_{0 \leq s \leq t}$).
- Self-normalization can be traced back to the seminal work of **W.S. GOSSET** in 1908 ([8]), which is considered a breakthrough in science. Notably, his Student t-statistic allowed statistical inference about the value of the mean of a (Gaussian) distribution without knowledge of the actual value of the variance, provided one has a random sample from the target population.



Figure: William S. Gosset, June 13, 1876 - October 16, 1937

Joseph L. Doob, February 27, 1910 - June 7, 2004



Doob suggested the problem of self-normalization, in 1994.

Canonical Assumptions

Assume that for a pair of random variables A, B with $B > 0$,

$$\mathbb{E} \exp(\lambda A - \lambda^2 B^2 / 2) \leq 1, \quad (6)$$

holds for any one of the following schemes:

- for all real λ ;
- for all $\lambda \geq 0$;
- for all $0 \leq \lambda < \lambda_0$, where $0 < \lambda_0 < \infty$.

This assumption is valid in a wide array of scenarios involving discrete-time and continuous-time stochastic processes, particularly in the context of (super)martingales.

Example (Karatzas & Shreve (1991) [10])

Let M_t be a continuous, square-integrable martingale, with $M_0 = 0$. Then $\exp\{\lambda M_t - \lambda^2 \langle M \rangle_t / 2\}$ is a supermartingale for all $\lambda \in \mathbb{R}$.

Example (de la Peña (1999) [4])

Let $\{d_i\}$ be a sequence of variables adapted to an increasing sequence of σ -fields $\{\mathcal{F}_i\}$. Assume that the d_i 's are conditionally symmetric (i.e., $\mathcal{L}(d_i | \mathcal{F}_{i-1}) = \mathcal{L}(-d_i | \mathcal{F}_{i-1})$). Then $\exp(\lambda \sum_{i=1}^n d_i - \lambda^2 \sum_{i=1}^n d_i^2 / 2)$, $n \geq 1$, is a supermartingale with mean ≤ 1 , for all $\lambda \in \mathbb{R}$.

Remark: There is no integrability assumption made in this example.

Pseudo-maximization

Recall the canonical assumption for a pair of random variables A, B with $B > 0$,

$$\mathbb{E} \exp(\lambda A - \lambda^2 B^2 / 2) \leq 1,$$

If the "global maximizer" of $\lambda A - \lambda^2 B^2 / 2$, $\hat{\lambda} := \frac{A}{B^2}$ lies in the regime we are interested, and is of course, deterministic, then $\mathbb{E} \exp(A^2 / 2B^2) \leq 1$. And by CHEBYSHEV inequality, we have

$$\mathbb{P}\left(\frac{|A|}{|B|} > x\right) = \mathbb{P}\left(\frac{A^2}{2B^2} > \frac{x^2}{2}\right) \leq e^{-\frac{x^2}{2}} \mathbb{E} e^{\frac{A^2}{2B^2}} \leq e^{-\frac{x^2}{2}}.$$

Unfortunately, since $\frac{A}{B^2}$ is random, we need an alternative way,
pseudo-maximization, an informal framework of which can be stated as:

- (i) For $\lambda \in \Lambda$, a measurable set, we construct a probability measure of λ , with distribution function F independent of A and B .
- (ii) Now by FUBINI, we have that

$$\begin{aligned} 1 &\geq \mathbb{E} \exp \left(\lambda A - \frac{\lambda^2 B^2}{2} \right) \\ &= \mathbb{E} \left[\int_{\mathbb{R}} \exp \left(\lambda A - \frac{\lambda^2 B^2}{2} \right) dF \right] \\ &= \int_{\mathbb{R}} \mathbb{E} \left[\exp \left(\lambda A - \frac{\lambda^2 B^2}{2} \right) \right] dF. \end{aligned}$$

One application of pseudo-maximization is to construct a Gaussian bound for $\frac{A}{\sqrt{B^2 + \mathbb{E}^2 B}}$:

Theorem (de la Peña et al, 2004 [5])

Let A, B with $B > 0$ be random variables satisfying the canonical assumption

$$\mathbb{E} \exp(\lambda A - \lambda^2 B^2 / 2) \leq 1,$$

for all $\lambda \in \mathbb{R}$. Then

$$\mathbb{P} \left(\frac{|A|}{\sqrt{B^2 + \mathbb{E}^2 B}} \geq x \right) \leq \sqrt{2} \exp \left(-\frac{x^2}{4} \right). \quad (7)$$

Law of Iterated Logarithm Bound

Let $\{Y_n\}$ be independent, identically distributed random variables with means zero and variances σ^2 . Let $S_n = Y_1 + \dots + Y_n$. Then

$$\limsup_{n \rightarrow \infty} \frac{|S_n|}{\sqrt{2n\sigma^2 \log \log n}} = 1 \quad \text{a.s..}$$

Another application of pseudo-maximization, under the following refinement of the canonical assumption, leads an LIL bound.

Theorem

Assume that

$$\left\{ \exp \left(\lambda A_t - \lambda \frac{B_t^2}{2} \right), t \geq 0 \right\}$$

is a supermartingale with mean ≤ 1 . Then on the set $\{\lim_{t \rightarrow \infty} B_t^2 = \infty\}$,

$$\limsup_{t \rightarrow \infty} \frac{A_t}{\sqrt{2B_t^2 \log \log B_t^2}} \leq 1.$$

As formalized in the previous example:

Example (de la Peña (1999) [4])

Let $\{d_i\}$ be a sequence of variables adapted to an increasing sequence of σ -fields $\{\mathcal{F}_i\}$. Assume that the d_i 's are conditionally symmetric (i.e., $\mathcal{L}(d_i|\mathcal{F}_{i-1}) = \mathcal{L}(-d_i|\mathcal{F}_{i-1})$). Then $\exp(\lambda \sum_{i=1}^n d_i - \lambda^2 \sum_{i=1}^n d_i^2 / 2)$, $n \geq 1$, is a supermartingale with mean ≤ 1 , for all $\lambda \in \mathbb{R}$.

We can get, on the set $\{\lim_{n \rightarrow \infty} \sum_{i=1}^n d_i^2 = \infty\}$, that

$$\limsup_{n \rightarrow \infty} \frac{\sum_{i=1}^n d_i}{\sqrt{2 \left(\sum_{i=1}^n d_i^2 \right) \log \log \left(\sum_{i=1}^n d_i^2 \right)}} \leq 1,$$

a sharp extension of KOLMOGOROV's LIL without moment assumptions, which is also valid for i.i.d. centered Cauchy variables.

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Background and Definitions

Given a stochastic process $\{X_n\}_{n \in \mathbb{N}_0}$, as the time n increases, so does our knowledge about what has happened in the past, which can be modelled using filtration.

Definition (Filtration (Discrete))

Given the measurable space (Ω, \mathcal{F}) , a sequence of σ -algebras $\mathcal{F}_1, \mathcal{F}_2, \dots$, on Ω such that

$$\mathcal{F}_1 \subseteq \mathcal{F}_2 \subseteq \dots \subseteq \mathcal{F}$$

is called a filtration.

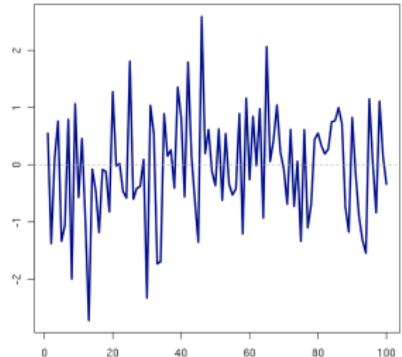
Here \mathcal{F}_n represents our knowledge at time n . It contains all events such that at time n it is possible to decide whether A has occurred or not. As n increases, there will be more such events A , i.e. the family \mathcal{F}_n representing our knowledge will become larger.

Definition (Discrete-time Martingales)

Given the probability space $(\Omega, \mathcal{F}, \mathbb{P})$, a sequence M_1, M_2, \dots , of random variables is called a martingale (resp, supermartingale, submartingale) with respect to a filtration $\mathcal{F}_1, \mathcal{F}_2, \dots$, if

- 1) M_n is integrable for each $n = 1, 2, \dots$;
- 2) M_1, M_2, \dots is adapted to $\mathcal{F}_1, \mathcal{F}_2, \dots$;
- 3) $\mathbb{E}(M_{n+1} | \mathcal{F}_n) = (\text{resp, } \leq, \geq) M_n$ a.s. for each $n = 1, 2, \dots$.

The concept of a martingale has its origin in gambling, namely, it describes a fair game of chance. Similarly, the notions of submartingale and supermartingale defined below are related to favourable and unfavourable games of chance.



Definition (Filtration)

Given the measurable space (Ω, \mathcal{F}) , a family of σ -algebras \mathcal{F}_t on Ω , parametrized by $t \in T \subset \mathbb{R}$, is called a filtration if

$$\mathcal{F}_s \subseteq \mathcal{F}_t \subseteq \mathcal{F}$$

for any $s, t \in T$ such that $s \leq t$.

Definition (Continuous-time Martingales)

Given the probability space $(\Omega, \mathcal{F}, \mathbb{P})$, a stochastic process ξ_t ($t \in T$) is called a martingale (resp, supermartingale, submartingale) with respect to a filtration \mathcal{F}_t , if

- 1) ξ_t is integrable for each $t \in T$;
- 2) ξ_t is adapted to \mathcal{F}_t for each $t \in T$;
- 3) $\mathbb{E}(\xi_t | \mathcal{F}_s) = (\text{resp, } \leq, \geq) \xi_s$ a.s. for every $s, t \in T$ and $s \leq t$.

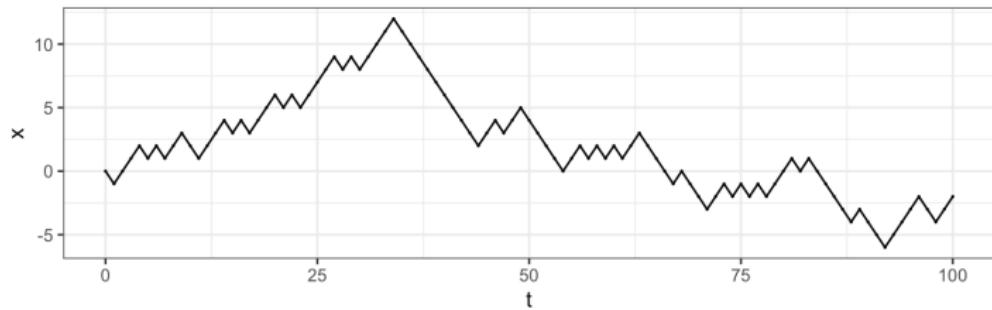
Examples

Example

Mean-corrected Sums of i.i.d. r.v.s & Simple Symmetric Random Walk

Let X_1, X_2, \dots be independent random variables each with mean μ . Let $S_0 = 0$ and for $n > 0$ let S_n be the partial sum $S_n = X_1 + \dots + X_n$. Then $M_n = S_n - n\mu$ is a martingale with respect to \mathcal{F}_n , the information contained in X_1, \dots, X_n .

If we now assume that X_i is the Rademacher variable, then this stochastic process is called a **simple symmetric random walk**.



Example

Brownian Motion The **Wiener process** (or **Brownian motion**) is a stochastic process $W(t)$ with values in \mathbb{R} defined for $t \in [0, \infty)$ such that

- 1) $W(0) = 0$ a.s.;
- 2) the sample paths $t \mapsto W(t)$ are a.s. continuous;
- 3) for any finite sequence of times $0 < t_1 < \dots < t_n$ and Borel sets $A_1, \dots, A_n \subset \mathbb{R}$

$$\mathbb{P}(W(t_1) \in A_1, \dots, W(t_n) \in A_n)$$

$$= \int_{A_1} \dots \int_{A_n} p(t_1, 0, x_1) p(t_2 - t_1, x_1, x_2) \dots p(t_n - t_{n-1}, x_{n-1}, x_n) dx_1 \dots dx_n,$$

where

$$p(t, x, y) = \frac{1}{\sqrt{2\pi t}} e^{\frac{(x-y)^2}{2t}}$$

defined for any $x, y \in \mathbb{R}$ and $t > 0$, called the transition density.

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Some Basic Probabilistic Inequalities

Now let us get familiar with rudimentary probabilistic inequalities including exponential inequalities, decoupling inequalities, and martingale inequalities.

MARKOV's Inequality

For any integrable random variable X (i.e. $\mathbb{E}X < \infty$), we have that, for any $a > 0$,

$$\mathbb{P}(|X| \geq a) \leq \frac{\mathbb{E}(|X|)}{a}. \quad (8)$$

HÖLDER's inequality/ CAUCHY-SCHWARZ Inequality

For any square-integrable random variable X, Y (i.e. $\mathbb{E}X^2, \mathbb{E}Y^2 < \infty$), we have that

$$\mathbb{E}|XY| \leq \sqrt{\mathbb{E}X^2\mathbb{E}Y^2}. \quad (9)$$

And I leave the random vector's version as an exercise.

JENSEN's Inequality

We assume X an integrable real-valued random variable and Φ a convex function. Then

$$\Phi(\mathbb{E}(X)) \leq \mathbb{E}(\Phi(X)). \quad (10)$$

BERNSTEIN's inequality

Let $\{x_i\}$ be a sequence of independent variables. Assume that $\mathbb{E}(x_i) = 0$ and $\mathbb{E}(x_i^2) = \sigma_i^2 < \infty$ and set $v_n^2 = \sum_{i=1}^n \sigma_i^2$. Furthermore, assume that there exists a constant $0 < c < \infty$ such that, $\mathbb{E}(|x_i|^k) \leq (k! / 2)\sigma_i^2 c^{k-2}$ for all $k > 2$ (satisfied by subexponential random variables). Then for all $x > 0$.

$$\mathbb{P}\left(\sum_{i=1}^n x_i > x\right) \leq \exp\left(-\frac{x^2}{2(v_n^2 + cx)}\right).$$

HOEFFING's Inequality for Sampling Without Replacement

Let the population C consist of N values c_1, \dots, c_N (e.g. a deck of cards, $N=52$), and let d_1, \dots, d_n ($n \leq N$) denote a random sample **without** replacement drawn from C , and y_1, \dots, y_n denote a random sample **with** replacement from C . The random variables y_1, \dots, y_n are i.i.d. and $d_i \stackrel{\mathcal{L}}{=} y_i$ for all i . And we have

$$\mathbb{E} \left[\Phi \left(\sum_{i=1}^n d_i \right) \right] \leq \mathbb{E} \left[\Phi \left(\sum_{i=1}^n y_i \right) \right]. \quad (11)$$

KOLMOGOROV's Maximal Inequality

If X_1, X_2, \dots, X_n are independent random variables with $E[X_i] = 0$ and $\text{Var}(X_i) = \sigma_i^2$, then for any $t > 0$,

$$P\left(\max_{1 \leq k \leq n} \left| \sum_{i=1}^k X_i \right| \geq t\right) \leq \frac{1}{t^2} \sum_{i=1}^n \sigma_i^2. \quad (12)$$

Doob's Maximal Inequalities

If X_1, X_2, \dots, X_n are martingale differences (i.e., $M_n := \sum_{i=1}^n X_i$ is a martingale with $M_0 = 0$), then for any $t > 0$,

$$\mathbb{P}\left(\max_{1 \leq k \leq n} |M_k| \geq t\right) \leq \frac{1}{t^2} \mathbb{E}[(M_n)^2]. \quad (13)$$

And for all $p > 1$,

$$\mathbb{E}\left(\max_{1 \leq k \leq n} |M_k|^p\right) \leq \left(\frac{p}{p-1}\right)^p \mathbb{E}|M_n|^p \quad (14)$$

We call it a day with the following important inequalities and one definition, which we will give further discussion on this Wednesday.

Theorem (BURKHOLDER-DAVIS-GUNDY's Square Function Inequality)

If X_1, X_2, \dots, X_n are martingale differences, then for any $p \geq 1$,

$$c_p E \left[\left(\sum_{i=1}^n X_i^2 \right)^{\frac{p}{2}} \right] \leq E \left[\left(\max_{1 \leq k \leq n} \left| \sum_{i=1}^k X_i \right| \right)^p \right] \leq C_p E \left[\left(\sum_{i=1}^n X_i^2 \right)^{\frac{p}{2}} \right], \quad (15)$$

where c_p and C_p are positive constants depending only on p .

KHINTCHINE inequality

Let $\epsilon_i, i = 1, \dots, m$ be i.i.d. Rademacher variables with $\mathbb{P}(\epsilon_i = \pm 1) = 1/2$.
Let $0 < p < \infty$ and let $x_1, \dots, x_n \in \mathbb{C}$. Then

$$A_p \left(\sum_{i=1}^n |x_i|^2 \right)^{1/2} \leq \left(\mathbb{E} \left| \sum_{i=1}^n \epsilon_i x_i \right|^p \right)^{1/p} \leq B_p \left(\sum_{i=1}^n |x_i|^2 \right)^{1/2} \quad (16)$$

for some constants $A_p, B_p > 0$ depending only on p .

Definition (K-function)

Consider a nontrivial centered random variable Y (i.e., $\mathbb{E}Y = 0$). Then the K-function, $K_Y(x)$, is implicitly defined by the inverse of

$$g(x) = \frac{x^2}{\int_0^x \mathbb{E}|Y|I_{|Y|>u} du}. \quad (17)$$

Exercise: Please verify the equivalent definition of K-function, which is the unique solution of

$$K_Y(x)^2 = x\mathbb{E}[Y^2 \wedge (|Y|K_Y(x))] = x\mathbb{E}Y^2 I_{|Y|\leq K_Y(x)} + xK_Y(x)\mathbb{E}|Y|I_{|Y|>K_Y(x)}. \quad (18)$$

You can find the proof in Section 1.4.3 of the book [7].

Theorem (K-function Bounds)

Consider $\{y_i\}_{i=1}^n$ a sequence of i.i.d. random centered variables such that $y_1 \sim Y$. Then we have

$$0.67K_Y(n) \leq \mathbb{E}\left|\sum_{i=1}^n y_i\right| \leq 2K_Y(n). \quad (19)$$

References I

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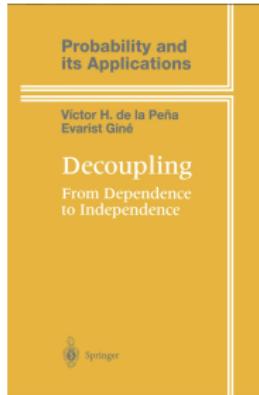
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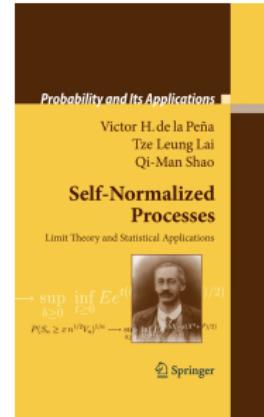
References III

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Two Recommended Books



*Decoupling: From
Dependence to Independence
(1999, [7])*
Victor H. de la Peña
Evarist Giné



*Self-normalized processes:
Limit theory and Statistical
Applications (2009, [6])*
Victor H. de la Peña
Tze Leung Lai
Qi-Man Shao