

Summary Part 3: Applications of Concentration Inequalities

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1 Applications

1.1 U-Statistics

1.2 Jackknife Estimation and Bootstrapping

1.3 Kernel-Density Estimation

- **Example (*Kernel Density Estimation*)**

Let Z_1, \dots, Z_n be i.i.d. samples drawn according to some (unknown) density ϕ on the real line. The density is estimated by the kernel estimate

$$\phi_n(z) = \frac{1}{n h_n} \sum_{i=1}^n K\left(\frac{z - Z_i}{h_n}\right),$$

where $h_n > 0$ is a *smoothing parameter*, and K is a nonnegative function with $\int K(z) = 1$. The performance of the estimate is typically measured by **the L_1 error**:

$$X(n) := f(Z_1, \dots, Z_n) = \int |\phi(z) - \phi_n(z)| dz.$$

It is easy to see that

$$\begin{aligned} |f(z_1, \dots, z_n) - f_i(z_1, \dots, z_{i-1}, z'_i, z_{i+1}, \dots, z_n)| &\leq \frac{1}{n h_n} \int \left| K\left(\frac{z - z_i}{h_n}\right) - K\left(\frac{z - z'_i}{h_n}\right) \right| dz \\ &\leq \frac{2}{n}, \end{aligned}$$

so without further work we obtain

$$\text{Var}(X(n)) \leq \frac{1}{n}$$

It is known that for every ϕ , $\sqrt{n} \mathbb{E}[X(n)] \rightarrow 0$, which implies, by *Chebyshev's inequality*, that for every $\epsilon > 0$

$$\mathbb{P}\left\{\left|\frac{X(n)}{\mathbb{E}[X(n)]} - 1\right| > \epsilon\right\} = \mathbb{P}\{|X(n) - \mathbb{E}[X(n)]| > \epsilon \mathbb{E}[X(n)]\} \leq \frac{\text{Var}(X(n))}{\epsilon^2 (\mathbb{E}[X(n)])^2} \rightarrow 0$$

as $n \rightarrow \infty$. That is, $\frac{X(n)}{\mathbb{E}[X(n)]} \rightarrow 1$ **in probability**, or in other words, $X(n)$ is **relatively stable**. This means that **the random L_1 -error** essentially **behaves like its expected value**.

By bounded difference inequality, we have

$$\mathbb{P}\{|X(n) - \mathbb{E}[X(n)]| \geq t\} \leq 2 \exp\left(-\frac{nt^2}{2}\right) \quad \blacksquare$$

1.4 Random Graph

1.5 Minimum Weight Spanning Tree

1.6 Rademacher Complexity

1.7 Dimensionality Reduction

2 Self-Bounding Functions

2.1 Definitions, Variance Bounds and Concentration

- Another simple property which is satisfied for many important examples is the so-called *self-bounding property*.

Definition (*Self-Bounding Property*)

A *nonnegative* function $f : \mathcal{X}^n \rightarrow [0, \infty)$ has the *self-bounding property* if there exist functions $f_i : \mathcal{X}^{n-1} \rightarrow \mathbb{R}$ such that for all $z_1, \dots, z_n \in \mathcal{X}$ and all $i = 1, \dots, n$,

$$0 \leq f(z_1, \dots, z_n) - f_i(z_1, \dots, z_{i-1}, z_{i+1}, \dots, z_n) \leq 1 \quad (1)$$

and also

$$\sum_{i=1}^n (f(z_1, \dots, z_n) - f_i(z_1, \dots, z_{i-1}, z_{i+1}, \dots, z_n)) \leq f(z_1, \dots, z_n). \quad (2)$$

- **Remark** Clearly if f has the *self-bounding property*,

$$\sum_{i=1}^n (f(z_1, \dots, z_n) - f_i(z_1, \dots, z_{i-1}, z_{i+1}, \dots, z_n))^2 \leq f(z_1, \dots, z_n) \quad (3)$$

Taking expectation on both sides, we have the following inequality

- **Corollary 2.1** [Boucheron et al., 2013]
If f has the *self-bounding property*, then

$$\text{Var}(f(Z)) \leq \mathbb{E}[f(Z)].$$

- **Remark (*Relative Stability*)** [Boucheron et al., 2013]
A sequence of nonnegative random variables $(Z_n)_{n \in \mathbb{N}}$ is said to be *relatively stable* if

$$\frac{Z_n}{\mathbb{E}[Z_n]} \xrightarrow{\mathbb{P}} 1.$$

This property guarantees that *the random fluctuations of Z_n around its expectation are of negligible size when compared to the expectation*, and therefore *most information about the size of Z_n is given by $\mathbb{E}[Z_n]$* .

Bounding the variance of Z_n by its expected value implies, in many cases, the relative stability of $(Z_n)_{n \in \mathbb{N}}$. If Z_n has the **self-bounding property**, then, by *Chebyshev's inequality*, for all $\epsilon > 0$,

$$\mathbb{P} \left\{ \left| \frac{Z_n}{\mathbb{E}[Z_n]} - 1 \right| > \epsilon \right\} \leq \frac{\text{Var}(Z_n)}{\epsilon^2 (\mathbb{E}[Z_n])^2} \leq \frac{1}{\epsilon^2 \mathbb{E}[Z_n]}.$$

Thus, for relative stability, it suffices to have $\mathbb{E}[Z_n] \rightarrow \infty$.

2.2 Configuration Function

- An important class of functions satisfying *the self-bounding property* consists of the so-called **configuration functions**.

Definition (Configuration Function)

Assume that we have a property Π **defined over the union of finite products** of a set \mathcal{X} , that is, a sequence of sets

$$\Pi_1 \subset \mathcal{X}, \Pi_2 \subset \mathcal{X} \times \mathcal{X}, \dots, \Pi_n \subset \mathcal{X}^n.$$

We say that $(z_1, \dots, z_m) \in \mathcal{X}^m$ **satisfies the property Π** if $(z_1, \dots, z_m) \in \Pi_m$.

We assume that Π is **hereditary** in the sense that if (z_1, \dots, z_m) satisfies Π then so does **any sub-sequence** $\{z_{i_1}, \dots, z_{i_k}\}$ of (z_1, \dots, z_m) .

The function f that maps any vector $z = (z_1, \dots, z_n)$ to **the size of a largest sub-sequence satisfying Π** is **the configuration function** associated with property Π .

- **Corollary 2.2** [Boucheron et al., 2013]

Let f be a **configuration function**, and let $X = f(Z_1, \dots, Z_n)$, where Z_1, \dots, Z_n are **independent** random variables. Then

$$\text{Var}(f(Z)) \leq \mathbb{E}[f(Z)].$$

2.3 VC-Dimension and Growth Function

2.4 Longest Increasing Subsequence

2.5 Weakly Self-Bounding Functions

3 Random Matrices

3.1 Definitions

3.2 Concentration Inequalities of Random Vectors

3.3 Concentration of Norm of Gaussian Vectors

3.4 Spectral Distribution of Hermitian Matrix: Semi-Circular Law

3.5 Largest Eigenvalue of Hermitian Random Matrix

4 Empirical Process

4.1 Definition

4.2 Uniform Law of Large Numbers

4.3 Suprema of Gaussian Process

4.4 Covering Number, Packing Number and Metric Entropy

4.5 Chaining

4.6 VC-Dimension

4.7 Variance Bounds

References

Stéphane Boucheron, Gábor Lugosi, and Pascal Massart. *Concentration inequalities: A nonasymptotic theory of independence*. Oxford university press, 2013.