Topic 4
Decoupling Inequalities for (Generalized) U-Statistics

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Topics Preview

1. U-statistics
2. The Generalized U-statistics with Applications
3. Decoupling Inequalities for U-statistics

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U-Statistics

Let $X_1, ..., X_n$ be a random sample (i.i.d. observations) from an unknown distribution F in $\mathbb{R}$. Given a known function $h : \mathbb{R} \to \mathbb{R}$, consider the estimation of the "parameter"

$$\theta = \theta(F) = \mathbb{E}[h(X_1, ..., X_m)],$$

Of course, you may interested in more complex spaces, which the random variables live in or h maps to, but now let us think about the simpler case.

A natural unbiased estimator of θ you propose is $h(X_1, ..., X_m)$, and since n observations (with $n \geq m$) are available, this simple estimator can be improved. Now you decide to get the average of $h(X_{\alpha_1}, ..., X_{\alpha_m})$, where $(X_{\alpha_1}, ..., X_{\alpha_m}) \in \Pi$, the set of all permutations of m integers such that

$$1 \leq \alpha_i \leq n, \quad \alpha_i \neq \alpha_j \ \ if \ \ i \neq j, \ \ (i, j = 1, ...m).$$

Congratulations! You successfully construct a U-Statistic, which in this context is defined by

$$U_n = U(X_1, ..., X_n) = \frac{1}{n(n-1)...(n-m+1)} \sum_{(X_{\alpha_1}, ..., X_{\alpha_m}) \in \Pi} h(X_{\alpha_1}, ..., X_{\alpha_m}). \tag{1}$$

If h is permutation invariant (for instance, when $r = 3$: $h((x_1, x_2, x_3)) = h((x_2, x_1, x_3)) = h((x_3, x_1, x_2)) = h((x_1, x_3, x_1)) = h((x_2, x_3, x_1)) = h((x_3, x_2, x_1))$), the definition (1) is equivalent to

$$U_n = \frac{1}{\binom{n}{m}} \sum_{1 \le \alpha_1 < \ldots < \alpha_m \le n} h(X_{\alpha_1}, \ldots, X_{\alpha_m}) \tag{2}$$

Although it may be the first time you hear U-Statistics, you have played with it for a long time. Look at equation (2), then set $h : \mathbb{R}^2 \to \mathbb{R}$ be such that $h(x_1, x_2) = \frac{1}{2}(x_1 - x_2)^2$, you can verify that U_n is exactly twice the sample variance, i.e.,

$$s_n^2 = \frac{\sum_{i=1}^{n}(X_i - \bar{X}_n)^2}{n-1} = \frac{\sum_{1 \le i < j \le n} \frac{1}{2}(X_i - X_j)^2}{\binom{n}{2}} = \frac{\sum_{1 \le i < j \le n}(X_i - X_j)^2}{n(n-1)}.$$

And by doing so, it is convenient to show that s_n^2 is an unbiasedness estimator. This is why we call such estimators U-statistics: the letter "U" stands for unbiased.

Examples

There are several examples of U-statistics. The sample mean is definitely a U-statistic. And when $X_1 \sim X \not\equiv 0$ is nonnegative a.s., the sample Gini mean difference (GMD), defined as

$$d = \frac{1}{n(n-1)} \sum_{i \neq j} |X_i - X_j| = \frac{2}{n(n-1)} \sum_{i<j} |X_i - X_j|,$$

is also a U-statistic. You can find several examples of U-statistics, together with many brilliant limiting theorems, in the giant paper by W. HOEFFDING (1948, [3]).

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Generalized U-statistics

We now extend this notion of U-statistics. Let $\{X_i\}$ be a sequence of independent random variables in a measurable space $(S, \mathcal{S})$ and $\boldsymbol{f} = \{f_{ij},\ 1 \leq i \neq j \leq n\}$, a family of functions of two variables taking $S \times S$ into $(D, \|\cdot\|)$. Then we define the generalized U-statistic U_n as

$$U_n = \sum_{1 \leq i \neq j \leq n} f_{ij}(X_i, X_j) \tag{3}$$

You can notice that the usual U-statistics can be obtained by letting $f_{ij} = f / \binom{n}{2}$. And such a generalized version may remind you more examples. For instance, the quadratic form $X^T A X = \sum_{1 \leq i \neq j \leq n} a_{ij} X_i X_j$, where the diagonal elements of the symmetric matrix A are set to be zero.

Random Graph

We can also link the generalized U-Statistic to random colored graph theory. Let $\{X_i\}_{i=1}^n$ a independent sequence of i.i.d. random variables, i.e., $X_i \overset{\mathcal{D}}{=} X$ for some random variables X. Consider the complete graph $G = (V, E)$, where $|V| = n$ and X_i is the color of the vertex i. Now we let $f_{ij} = f$ for some f fixed, and if f is symmetric, then

$$S_n(f) = \sum_{1 \leq i \neq j \leq n} f(X_i, X_j)$$

is a U-statistic (not averaged) representing some color information of vertices.

If we let $X \sim Ber(p)$, where the vertex $X_i = 1$ (resp, 0) indicates that this vertex is black (resp, white), and $f(x_1, x_2) = (1 - x_1)x_2$, which is not symmetric, then

$$S_n'(f) = \sum_{1 \le i < j \le n} f(X_i, X_j)$$

counts patterns beginning with a white vertex and ending with a black vertex in this random sequence. And with $f(x_1, x_2) = \mathbb{I}_{\{x_1 \neq x_2\}}$, the statistic

$$S_n"(f) = \sum_{1 \le i < j \le n} f(X_i, X_j)$$

counts the edges with one black and one white end-point.

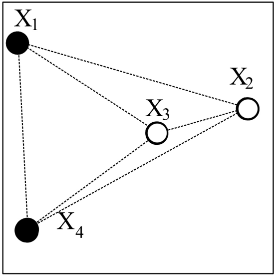

Figure: A example of a random graph, where $S_n' = 2$ and $S_n" = 4$.

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You may notice that, although $X_1, \dots, X_n$ are mutually independent, the random variables $f_{ij}(X_i, X_j)$'s are dependent, if i or j is fixed. This cause a difficulty in evaluating the expectation of $\|\sum_{1\le i<j\le n} f(X_i, X_j)\|$ and

$\Phi\left(\|\sum_{1\le i<j\le n} f(X_i, X_j)\|\right)$ for some $\Phi : \mathbb{R}_0^+ \to \mathbb{R}$ convex increasing.

Let us make the problem more complex, but give a formal statement: Let $X_1, ..., X_n$ be a sequence of independent random variables in a measurable space $(S, \mathcal{S})$ and let $\{f_{ij}\}$ be a family of integrable functions such that $f_{ij} : S \times S \mapsto D$ with $(D, \|\cdot\|)$ a Banach space. Let $\Phi : \mathbb{R}_0^+ \to \mathbb{R}$ be convex such that

$$\max_{1 \leq i \neq j \leq n} \mathbb{E}\Phi(\|f_{ij}(X_i, X_j)\|) < \infty.$$

Then how can we bound

$$\mathbb{E}\Phi(\| \sum_{1 \leq i \neq j \leq n} f_{ij}(X_i, X_j)\|)?$$

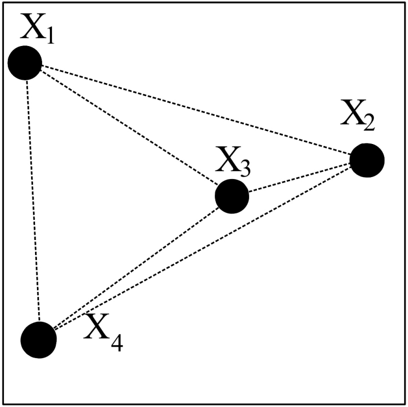
Remember that in the last lecture, I briefly introduced tangent decoupling. Think about the filtration $\mathcal{F}_i = \sigma(X_1, ..., X_i)$, and you can write

$$U_n = \sum_{1 \le i < j \le n} f_{ij}(X_i, X_j) = \sum_{j=2}^{n} \sum_{i=1}^{j-1} f_{ij}(X_i, X_j),$$

where $\sum_{i=1}^{j-1} f_{ij}(X_i, X_j)$ is adapted to $\mathcal{F}_j$. Suppose that we have $\{\tilde{X}_i\}_{i=1}^n$ an independent copy of $\{X_i\}_{i=1}^n$. Then

$$\sum_{j=2}^{n} \sum_{i=1}^{j-1} f_{ij}(X_i, \tilde{X}_j) = \sum_{j=2}^{n} T_j(\tilde{X}_j)$$

is a sum of conditionally independent variables given $\sigma(X_1, ..., X_n)$.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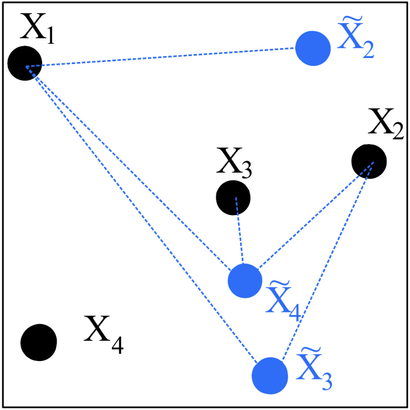
X_1
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X_2
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X_4
$\tilde{X}_3$

Theorem (de la Peña [1])

With the aforementioned setting ($\Phi : \mathbb{R}_0^+ \to \mathbb{R}$ convex increasing),

$$\begin{aligned} M &:= \mathbb{E}\Phi(\| \sum_{1\le i\ne j\le n} f_{ij}(X_i, X_j)\|) \\ &\le \mathbb{E}\Phi(8\| \sum_{1\le i\ne j\le n} f_{ij}(X_i, \tilde{X}_j)\|). \end{aligned} \tag{4}$$

And if $f_{ij} \in \Pi_{ij}$ satisfy the symmetry conditions

$$f_{ij} = f_{ji} \text{ and } f_{ij}(X_i, X_j) = f_{ij}(X_j, X_i),$$

then the reverse bound holds:

$$\mathbb{E}\Phi(\frac{1}{4}\| \sum_{1\le i\ne j\le n} f_{ij}(X_i, \tilde{X}_j)\|) \le M. \tag{5}$$

Remark

The fact that the lower bound does not hold for general f_{ij} follows trivially by using

$$f_{ij}(X_i, X_j) = X_j - X_i$$

because then $\sum_{i \neq j} f_{ij}(X_i, X_j) = 0$. But one may still obtain a lower bound by using the symmetrized kernels $\hat{f}_{ij} = [f_{ij}(X_i, X_j) + f_{ij}(X_j, X_i)]/2$ for $i \neq j$ and letting $\hat{f}_{ji} = \hat{f}_{ij}$

Remark

Considering the situation of quadratic forms, $X^T AX$, where the diagonal entries of A are zero and $A = A^T$, we have inequalities (4) and (5) as follows when X_i's are mean-zero:

$$\mathbb{E}\Phi(\frac{1}{4}|X^T A\tilde{X}|) \leq \mathbb{E}\Phi(|X^T AX|) \leq \mathbb{E}\Phi(4|X^T A\tilde{X}|).$$

I will explain the smaller constant 4 soon.

Warm-up Lemma

We demonstrate only the first equation (4) here, with a trivial lemma. But we first, for simplicity, denote by $\mathbb{E}_\sigma Y = \mathbb{E}[Y|\sigma]$, where Y is an r.v. and σ is a σ-field.

Let us first see the following warm-up lemma:

Lemma

For X_1, X_2 i.i.d., we have $\mathbb{E}(X_1|Z_1) = \frac{X_1+X_2}{2}$, where $Z_1 = (X_1, X_2)$ w.p. $1/2$ and $Z_1 = (X_2, X_1)$ w.p. $1/2$.

We extend this result to the bi-variate case in the following lemma:

Lemma

Let $\mathscr{Z} = \sigma(Z_i, i = 1, ..., n)$*, where* $\{Z_i\}$ *is a sequence of independent random vectors with* $Z_i = (X_i, \tilde{X}_i)$ *w.p.* $\frac{1}{2}$ *and* $Z_i = (\tilde{X}_i, X_i)$ *w.p.* $\frac{1}{2}$*. Then,*

$$\begin{aligned}
\mathbb{E}_{\mathscr{Z}} f_{ij}(X_i, X_j) = \mathbb{E}_{\mathscr{Z}} f_{ij}(X_i, \tilde{X}_j) = \mathbb{E}_{\mathscr{Z}} f_{ij}(\tilde{X}_i, X_j) = \mathbb{E}_{\mathscr{Z}} f_{ij}(\tilde{X}_i, \tilde{X}_j) \\
= \frac{1}{4} \mathbb{E}_{\mathscr{Z}} \left[f_{ij}(X_i, X_j) + f_{ij}(X_i, \tilde{X}_j) + f_{ij}(\tilde{X}_i, X_j) + f_{ij}(\tilde{X}_i, \tilde{X}_j) \right] \\
= \frac{1}{4} \left[f_{ij}(X_i, X_j) + f_{ij}(X_i, \tilde{X}_j) + f_{ij}(\tilde{X}_i, X_j) + f_{ij}(\tilde{X}_i, \tilde{X}_j) \right]
\end{aligned} \tag{6}$$

It is not hard to verify this lemma, by applying the same conditional law of $f_{ij}(X_i, \tilde{X}_j)$ and $f_{ij}(\tilde{X}_i, X_j)$ given $\mathscr{Z}$, and noticing that the sum of those four terms is measurable w.r.t. $\mathscr{Z}$.

Setting $\mathscr{X} = \sigma(X_1, ..., X_n)$, we use the following identity (remember we denote by $\mathbb{E}_\sigma Y = \mathbb{E}[Y|\sigma]$):

$$
\begin{aligned}
\sum_{1 \le i \neq j \le n} f_{ij}(X_i, X_j) = & \sum_{1 \le i \neq j \le n} [\mathbb{E}_{\mathscr{X}} f_{ij}(X_i, X_j) + \mathbb{E}_{\mathscr{X}} f_{ij}(X_i, \tilde{X}_j) \\
& + \mathbb{E}_{\mathscr{X}} f_{ij}(\tilde{X}_i, X_j) + \mathbb{E}_{\mathscr{X}} f_{ij}(\tilde{X}_i, \tilde{X}_j)] \\
& - \sum_{1 \le i \neq j \le n} [\mathbb{E}_{\mathscr{X}} f_{ij}(X_i, \tilde{X}_j) + \mathbb{E}_{\mathscr{X}} f_{ij}(\tilde{X}_i, X_j) \\
& + \mathbb{E}_{\mathscr{X}} f_{ij}(\tilde{X}_i, \tilde{X}_j)].
\end{aligned}
$$

A Simpler Version

Recall the Lemma 6, that

$$\mathbb{E}_{\mathscr{Z}} f(X_i, X_j) = \frac{1}{4}[f(X_i, X_j) + f(X_i, \tilde{X}_j) + f(\tilde{X}_i, X_j) + f(\tilde{X}_i, \tilde{X}_j)].$$

We **assume** that $\mathbb{E}_{\mathscr{X}} f(X_i, \tilde{X}_j) = \mathbb{E}_{\mathscr{X}} f(\tilde{X}_i, X_j) = \mathbb{E}_{\mathscr{X}} f(\tilde{X}_i, \tilde{X}_j) = 0$ (e.g., $f(x_1, x_2) = ax_1x_2$ for some constant a).
For the U-statistic $\sum\limits_{1 \leq i \neq j \leq n} f(X_i, X_j)$ with symmetric kernel f, we have

$$\begin{aligned}
\mathbb{E}\Phi(|\sum f(X_i, X_j)|) &= \mathbb{E}\Phi(|\sum f(X_i, X_j) + \mathbb{E}_{\mathscr{X}}[f(X_i, \tilde{X}_j) + f(\tilde{X}_i, X_j) + f(\tilde{X}_i, \tilde{X}_j)]|) \\
&\leq \mathbb{E}\Phi(|\sum \left(f(X_i, X_j) + f(X_i, \tilde{X}_j) + f(\tilde{X}_i, X_j) + f(\tilde{X}_i, \tilde{X}_j)\right) |) \\
&= \mathbb{E}\Phi(|\sum 4\mathbb{E}_{\mathscr{Z}} f(X_i, \tilde{X}_j)|) \\
&\leq \mathbb{E}\Phi(4|\sum f(X_i, \tilde{X}_j)|).
\end{aligned}$$

Proof

From the preceding and the triangle inequality,

$$
\begin{aligned}
&\mathbb{E}\Phi(\|\sum_{1\le i\ne j\le n} f_{ij}(X_i, X_j)\|) \\
&\le \mathbb{E}\Phi(\|\sum_{1\le i\ne j\le n} \mathbb{E}_{\mathscr{X}}[f_{ij}(X_i, X_j) + f_{ij}(X_i, \tilde{X}_j) + f_{ij}(\tilde{X}_i, X_j) + f_{ij}(\tilde{X}_i, \tilde{X}_j)]\| \\
&+ \|\mathbb{E}_{\mathscr{X}}[f_{ij}(X_i, \tilde{X}_j) + f_{ij}(\tilde{X}_i, X_j) + f_{ij}(\tilde{X}_i, \tilde{X}_j)]\|) \\
&\le \frac{1}{2}\mathbb{E}\Phi(2\|\sum_{1\le i\ne j\le n} \mathbb{E}_{\mathscr{X}}[f_{ij}(X_i, X_j) + f_{ij}(X_i, \tilde{X}_j) + f_{ij}(\tilde{X}_i, X_j) + f_{ij}(\tilde{X}_i, \tilde{X}_j)]\|) \\
&+ \frac{1}{2}\mathbb{E}\Phi(2\|\sum_{1\le i\ne j\le n} \mathbb{E}_{\mathscr{X}}[f_{ij}(X_i, \tilde{X}_j) + f_{ij}(\tilde{X}_i, X_j) + f_{ij}(\tilde{X}_i, \tilde{X}_j)]\|) \\
&\qquad\qquad [\text{by the convexity of } \Phi]
\end{aligned}
$$

Proof

$$\leq \frac{1}{2}\mathbb{E}\Phi(2\|\sum_{1\leq i\neq j\leq n}[f_{ij}(X_i,X_j)+f_{ij}(X_i,\tilde{X}_j)+f_{ij}(\tilde{X}_i,X_j)+f_{ij}(\tilde{X}_i,\tilde{X}_j)]\|)$$

$$+\frac{1}{2}\mathbb{E}\Phi(2\|\sum_{1\leq i\neq j\leq n}\mathbb{E}_{\mathscr{X}}[f_{ij}(X_i,\tilde{X}_j)+f_{ij}(\tilde{X}_i,X_j)+f_{ij}(\tilde{X}_i,\tilde{X}_j)\|)$$ [conditional JENSEN inequality]

$$\leq \frac{1}{2}\mathbb{E}\Phi(8\|\sum_{1\leq i\neq j\leq n}\mathbb{E}_{\mathscr{X}}f_{ij}(X_i,\tilde{X}_j)\|)+\frac{1}{6}[\mathbb{E}\Phi(6\|\sum_{1\leq i\neq j\leq n}\mathbb{E}_{\mathscr{X}}f_{ij}(X_i,\tilde{X}_j)\|)$$

$$+\mathbb{E}\Phi(6\|\sum_{1\leq i\neq j\leq n}\mathbb{E}_{\mathscr{X}}f_{ij}(\tilde{X}_i,X_j)\|)+\mathbb{E}\Phi(6\|\sum_{1\leq i\neq j\leq n}\mathbb{E}_{\mathscr{X}}f_{ij}(\tilde{X}_i,\tilde{X}_j)\|)]$$ [by (6) and Φ convex]

$$\leq \frac{1}{2}\mathbb{E}\Phi(8\|\sum_{1\leq i\neq j\leq n}f_{ij}(X_i,\tilde{X}_j)\|)+\frac{2}{6}\mathbb{E}\Phi(6\|\sum_{1\leq i\neq j\leq n}f_{ij}(X_i,\tilde{X}_j)\|)$$

$$+\frac{1}{6}\mathbb{E}\Phi(6\|\sum_{1\leq i\neq j\leq n}f_{ij}(\tilde{X}_i,\tilde{X}_j)\|)$$ [by conditional JENSEN, and $\mathbb{E}f_{ij}(\tilde{X}_i,\tilde{X}_j)=\mathbb{E}f_{ij}(X_i,\tilde{X}_j)$]

$$\leq \frac{1}{2}\mathbb{E}\Phi(8\|\sum_{1\leq i\neq j\leq n}f_{ij}(X_i,\tilde{X}_j)\|)+\frac{1}{2}\mathbb{E}\Phi(6\|\sum_{1\leq i\neq j\leq n}f_{ij}(X_i,\tilde{X}_j)\|)$$ [by JENSEN inequality]

$$\leq \mathbb{E}\Phi(8\|\sum_{1\leq i\neq j\leq n}f_{ij}(X_i,\tilde{X}_j)\|)$$ [by Φ increasing]

Decoupling Inequalities for General Kernels h

While this lecture primarily emphasizes the (generalized) U-statistics cases with kernels of the form $h : S^2 \to D$, it's worth noting that we have also established decoupling inequalities for the more general $h : S^k \to D$ Consequently, we arrive at a frequently employed concentration inequality (See de la Peña and Montgomery-Smith [4] in the Bulletin of the American Mathematical Society, or [2]).

Let $X_1, ..., X_n$ be a sequence of independent random variables on a measurable space $(S, \mathcal{S})$ and let $\{X_i^{(j)}\}$, $j = 1, ..., k$ be k independent copies of $\{X_i\}$. Let $f_{i_1,...,i_k}$ be family of functions of k variables taking S^k into a Banach space $(D, \|\cdot\|)$. Assume that each $f_{i_1,...,i_k}$ is permutation invariant. Then for all $n \geq k \geq 2$, $t > 0$, there exist numerical constants $C_k, \tilde{C}_k$ depending on k only such that (with $P_{n,k}$ the set of all permutations $(i_1, ..., i_k) \in \{1, ..., n\}^k$)

$$\mathbb{P}\left(\|\sum_{(i_1,...,i_k)\in P_{n,k}} f_{i_1,...,i_k}(X_{i_1}, ..., X_{i_k})\| \geq t\right)$$

$$\leq C_k \mathbb{P}\left(C_k \|\sum_{(i_1,i_2,...,i_k)\in P_{n,k}} f_{i_1,...,i_k}(X_{i_1}^{(1)}, ..., X_{i_k}^{(k)})\| \geq t\right).$$

In addition,

$$\tilde{C}_k \mathbb{P}\left(\tilde{C}_k \| \sum_{(i_1,i_2,\ldots,i_k)\in P_{n,k}} f_{i_1,\ldots,i_k}(X_{i_1},\ldots,X_{i_k})\| \geq t\right)$$
$$\geq \mathbb{P}\left(\| \sum_{(i_1,i_2,\ldots,i_k)\in P_{n,k}} f_{i_1,\ldots,i_k}(X_{i_1}^{(1)},\ldots,X_{i_k}^{(k)})\| \geq t\right).$$

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[1] V. H. de la Peña. "Decoupling and Khintchine's inequalities for U-statistics". In: *Ann. Proba.* (1992), pp. 1877–1892.

[2] Victor H de la Peña and Stephen J Montgomery-Smith. "Decoupling inequalities for the tail probabilities of multivariate U-statistics". In: *The Annals of Probability* (1995), pp. 806–816.

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[4] Victor H de la Peña and SJ Montgomery-Smith. "Bounds on the tail probability of U-statistics and quadratic forms". In: *the Bulletin of the American Mathematical Society* 31.2 (1994), pp. 223–227.