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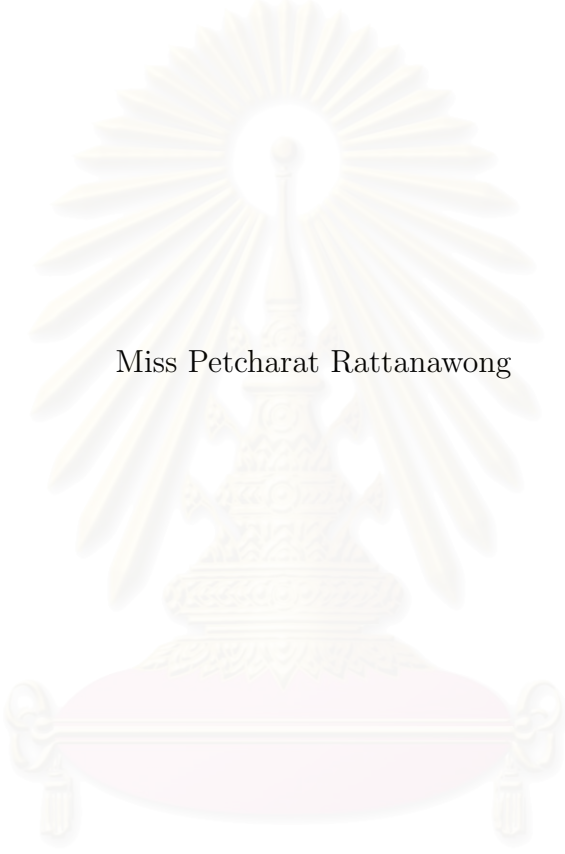
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BOUNDS ON A NORMAL APPROXIMATION FOR LATIN HYPERCUBE
SAMPLING



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A Dissertation Submitted in Partial Fulfillment of the Requirements
for the Degree of Doctor of Philosophy Program in Mathematics

Department of Mathematics

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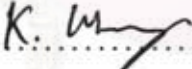

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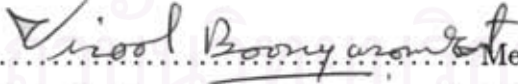
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ให้ X เป็นเวกเตอร์สุ่มที่มีการแจกแจงแบบสม่ำเสมอบน $[0,1]^d$ และ f เป็นฟังก์ชันจาก $[0,1]^d$
ไปยัง \mathbb{R} ซึ่งสามารถหาปริพันธ์ได้ วัตถุประสงค์หนึ่งของการทดลองทางคอมพิวเตอร์คือประมาณค่า

$$\mu = Ef(X) = \int_{[0,1]^d} f(x)dx$$

ในบรรดาเทคนิคต่างๆที่ใช้ในการประมาณค่าอินทิเกรต วิธีมอนติคาร์โลเป็นวิธีที่มีประสิทธิภาพและ
นิยมใช้ในการประมาณค่าอินทิเกรตบนโดเมนที่มีหลายมิติ ตัวอย่างค่าโดยวิธีมอนติคาร์โล
ของ μ คือ

$$\hat{\mu}_n = \frac{1}{n} \sum_{i=1}^n f(X_i)$$

โดยที่ X_1, X_2, \dots, X_n เป็นเวกเตอร์สุ่มบน $[0,1]^d$

แม็คเคย์ แม็คแมน และ โคนเวอร์(ค.ศ. 1979)เสนอการสุ่มตัวอย่าง X_1, X_2, \dots, X_n แบบลาตินไฮ
เพอร์คิวบ์ให้เป็นวิธีหนึ่งในการสุ่มเลือก ในวิทยานิพนธ์ฉบับนี้เราจะหาขอบเขตการประมาณค่าด้วยการ
แจกแจงปกติสำหรับ $\hat{\mu}_n$ ที่ใช้การสุ่มตัวอย่างแบบลาตินไฮเพอร์คิวบ์

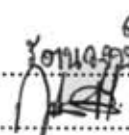
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PETCHARAT RATTANAWONG : BOUNDS ON A NORMAL
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Let X be a random vector uniformly distributed on $[0, 1]^d$ and let $f : [0, 1]^d \rightarrow \mathbb{R}$ be an integrable function. An objective of many computer experiments is to estimate

$$\mu = E(f(X)) = \int_{[0,1]^d} f(x)dx.$$

Among numerical integration techniques, Monte Carlo methods are efficient and competitive for high-dimensional integration. The Monte Carlo's estimator for the integral μ is given by

$$\hat{\mu}_n = \frac{1}{n} \sum_{i=1}^n f(X_i)$$

where X_1, X_2, \dots, X_n are random vectors on $[0, 1]^d$.

McKay, Beckman and Conover (1979) introduced Latin hypercube sampling(LHS) as an alternative method of generating X_1, X_2, \dots, X_n . In this work, we investigate normal approximation of error bounds in the distribution of $\hat{\mu}_n$ based on a Latin hypercube sampling.

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CHAPTER I

INTRODUCTION

In many problems multi-dimensional integrals occur, which have to be evaluated numerically. We consider an integral over the d -dimensional hypercube $[0, 1]^d$;

$$\mu = \int_{[0,1]^d} f(x)dx.$$

This is equivalent to finding $E(f(X))$, where the random vector X has a uniform distribution on the unit hypercube $[0, 1]^d$.

Among numerical integration techniques, Monte Carlo methods are especially useful and competitive for high-dimensional integration. The Monte Carlo estimate for the integral $\mu = E(f(X)) = \int_{[0,1]^d} f(x)dx$ is given by

$$\hat{\mu}_n = \frac{1}{n} \sum_{i=1}^n f(X_i)$$

where X_1, \dots, X_n is a random sampling on $[0, 1]^d$. There are various alternative ways to select the points X_i 's. For examples, simple random sampling, lattice sampling(see Patterson[22]), Latin hypercube sampling(see McKay, Beckman, Conover[16], Owen[18], Loh[14]), the orthogonal arrays(see Loh[13], Owen[20], Tang[28], Laipaporn and Neamma-nee[12]) and scrambled net(see Owen[21], and [19]).

In 1979, McKay, Beckman and Conover[16] proposed Latin hypercube sampling(LHS) as an attractive alternative to generate X_1, \dots, X_n . The main feature of Latin hypercube sampling is that, in contrast to simple random sampling, it simultaneously stratifies on all input dimensions. More precisely, let:

1. η_k , $1 \leq k \leq d$ be random permutations of $\{1, \dots, n\}$ each uniformly distributed over all the $n!$ possible permutations;
2. $U_{i_1, \dots, i_d, j}$ $1 \leq i_1, \dots, i_d \leq n$, $1 \leq j \leq d$, be $[0, 1]$ uniform random variables;
3. the $U_{i_1, \dots, i_d, j}$'s and η_k 's all be stochastically independent.

A Latin hypercube sample of size n (taken from the d -dimensional hypercube $[0, 1]^d$) is defined to be $\{X(\eta_1(i), \eta_2(i), \dots, \eta_d(i)) : 1 \leq i \leq n\}$, where for all $1 \leq i_1, \dots, i_d \leq n$,

$1 \leq j \leq d$,

$$X_j(i_1, \dots, i_d) = (i_j - U_{i_1, \dots, i_d, j})/n,$$

and

$$X(i_1, \dots, i_d) = (X_1(i_1, \dots, i_d), \dots, X_d(i_1, \dots, i_d)).$$

Hence the estimator for μ that based on a Latin hypercube sampling is

$$\hat{\mu}_n = \frac{1}{n} \sum_{k=1}^n f(X(\eta_1(k), \eta_2(k), \dots, \eta_d(k))).$$

Then $\hat{\mu}_n$ is an unbiased estimator for μ .

Assume that $Var(\hat{\mu}_n) > 0$, we define

$$L = \frac{\hat{\mu}_n - \mu}{\sqrt{Var(\hat{\mu}_n)}}. \quad (1.1)$$

In 1996, Loh[14] used Stein's method to show that the distribution of L can be approximated by normal distribution and gave a uniform bound on this approximation. The following is his result.

Theorem 1.1. For $1 \leq i_1, \dots, i_d \leq n$, let

$$\begin{aligned} \mu(i_1, \dots, i_d) &= E(f(X(i_1, \dots, i_d))), \\ \mu_{-k}(i_k) &= \frac{1}{n^{d-1}} \sum_{j \neq k} \sum_{i_j=1}^n \mu(i_1, \dots, i_d) \end{aligned}$$

and

$$V(i_1, \dots, i_d) = \frac{1}{n\sqrt{Var\hat{\mu}_n}} [f(X(i_1, \dots, i_d)) - \sum_{k=1}^d \mu_{-k}(i_k) + (d-1)\mu].$$

Then there exists a positive constant C_d which depends only on d such that for sufficiently large n ,

$$\sup_{z \in \mathbb{R}} |P(L \leq z) - \Phi(z)| \leq C_d \beta_3$$

where Φ is the standard normal distribution, and

$$\beta_3 = \frac{1}{n^{d-1}} \sum_{i_1=1}^n \dots \sum_{i_d=1}^n E|V(i_1, \dots, i_d)|^3.$$

The following is an immediate corollary.

Corollary 1.2. If $E|f(X)|^3 < \infty$, then

$$\sup_{z \in \mathbb{R}} |P(L \leq z) - \Phi(z)| \leq \frac{C_d}{\sqrt{n}}.$$

In this work, we give a constant C_d by using a concentration inequality approach of Stein's method and give a non-uniform bound of this approximation. These are our results.

Theorem 1.3. (A uniform bound for LHS) For $1 \leq i_1, \dots, i_d \leq n$, let

$$\begin{aligned}\mu(i_1, \dots, i_d) &= E(f(X(i_1, \dots, i_d))), \\ \mu_k(i_1, \dots, i_d) &= \frac{(-1)^k}{n^k} \sum_{1 \leq j_1 < j_2 < \dots < j_k \leq d} \sum_{q_{j_1}=1}^n \dots \sum_{q_{j_k}=1}^n \mu(l_1, \dots, l_d),\end{aligned}$$

where

$$l_p = \begin{cases} q_p & \text{if } p = j_1, \dots, j_k, \\ i_p & \text{otherwise,} \end{cases}$$

and

$$V(i_1, \dots, i_d) = \frac{1}{n\sqrt{\text{Var}(\hat{\mu}_n)}} [f(X(i_1, \dots, i_d)) + \sum_{k=1}^{d-1} \mu_k(i_1, \dots, i_d) + (-1)^d \mu].$$

Then for $n \geq 6^d + 3$,

$$\begin{aligned}\sup_{z \in \mathbb{R}} |P(L \leq z) - \Phi(z)| &\leq \frac{11.946}{\sqrt{n}} + \frac{1.037\sqrt{d}\beta_4^{\frac{1}{4}}}{n^{\frac{3}{8}}} + 8.314d^{\frac{1}{4}}\beta_4 + 11.765\beta_4 + \frac{5.014d\beta_4^{\frac{3}{4}}}{n^{\frac{1}{8}}} \\ &\quad + \frac{2\sqrt{2\pi}\beta_4^{\frac{3}{4}}}{n^{\frac{1}{8}}}\end{aligned}$$

where

$$\beta_4 = \frac{1}{n^{d-\frac{3}{2}}} \sum_{i_1=1}^n \dots \sum_{i_d=1}^n E|V(i_1, \dots, i_d)|^4.$$

Corollary 1.4. If $E|f(X)|^4 < \infty$, then

$$\sup_{z \in \mathbb{R}} |P(L \leq z) - \Phi(z)| \leq \frac{C_d(28.725 + 1.037\sqrt{d} + 8.314d^{\frac{1}{4}} + 5.014d)}{\sqrt{n}}.$$

where $C_d = \frac{27}{C^2} [2 + (d-1)^3 \sum_{k=1}^{d-1} \binom{d}{k}] E|f(X)|^4$ for some constant C .

Theorem 1.5. (A non-uniform bound for LHS) Let $z \in \mathbb{R}$. Then there exists a positive constant C which does not depend on z such that

$$|P(L \leq z) - \Phi(z)| \leq \frac{C}{1+|z|} \left\{ \frac{\beta_8^{\frac{1}{8}}}{n^{\frac{7}{16}}} + \frac{1}{n} + \beta_8 \right\}$$

where

$$\beta_8 = \frac{1}{n^{d-\frac{7}{2}}} \sum_{i_1=1}^n \dots \sum_{i_d=1}^n E|V(i_1, \dots, i_d)|^8.$$

Corollary 1.6. *If $E|f(X)|^8 < \infty$, then*

$$|P(L \leq z) - \Phi(z)| \leq \frac{C}{(1 + |z|)\sqrt{n}}.$$

In order to prove Theorem 1.3 and Theorem 1.5, we shall first show that

$$L = \sum_{i=1}^n Y(i, \pi_1(i), \dots, \pi_{d-1}(i)) \quad (1.2)$$

where $Y(i_1, \dots, i_d)$, $1 \leq i_1, \dots, i_d \leq n$, are random variables and π_1, \dots, π_{d-1} are random permutations of $\{1, \dots, n\}$ such that $Y(i_1, \dots, i_d)$'s and π_k 's are stochastically independent. In the case of $d = 1$, a theorem which has been proved under various conditions by Hoeffding([10]), Matoo([15]) and other authors states that the summation on the right-hand side of (1.2) is approximately standard normally distributed. This theorem is always called a combinatorial central limit theorem(CCLT). Thus from (1.2), it suffices to find a uniform bound and a non-uniform bound on normal approximation for the generalization of CCLT, the summation in the case of an arbitrary d . These are our theorems.

Theorem 1.7. *(A uniform bound for the generalization of a CCLT)*

Let d be a positive integer and let:

1. π_k , $1 \leq k \leq d$, be random permutations of $\{1, \dots, n\}$ each uniformly distributed over all the $n!$ possible permutations;
2. $Y(i_1, \dots, i_{d+1})$, $1 \leq i_1, \dots, i_{d+1} \leq n$, be random variables;
3. the $Y(i_1, \dots, i_{d+1})$'s and π_k 's all be stochastically independent.

We define

$$W = \sum_{i=1}^n Y(i, \pi_1(i), \dots, \pi_d(i)). \quad (1.3)$$

Suppose that

$$EW = 0 \quad \text{and} \quad \text{Var}W = 1, \quad (1.4)$$

and

$$\sum_{i_j=1}^n \tilde{\mu}(i_1, \dots, i_{d+1}) = 0 \quad \text{for every } j \in \{1, \dots, d+1\}$$

where $\tilde{\mu}(i_1, \dots, i_{d+1}) = EY(i_1, \dots, i_{d+1})$. Then for $n \geq 6^{d+1} + 3$,

$$\begin{aligned} \sup_{z \in \mathbb{R}} |P(W \leq z) - \Phi(z)| &\leq \frac{11.946}{\sqrt{n}} + \frac{1.037\sqrt{d+1}\delta_4^{\frac{1}{4}}}{n^{\frac{3}{8}}} + 8.314(d+1)^{\frac{1}{4}}\delta_4 + 11.765\delta_4 \\ &\quad + 5.014(d+1)\frac{\delta_4^{\frac{3}{4}}}{n^{\frac{1}{8}}} + \frac{2\sqrt{2\pi}\delta_4^{\frac{3}{4}}}{n^{\frac{1}{8}}} \end{aligned}$$

where

$$\delta_4 = \frac{1}{n^{d-\frac{1}{2}}} \sum_{i_1=1}^n \dots \sum_{i_{d+1}=1}^n E|Y(i_1, \dots, i_{d+1})|^4.$$

Furthermore, if $\delta_4 \sim n^{-1/2}$, then

$$\sup_{z \in \mathbb{R}} |P(W \leq z) - \Phi(z)| \leq \frac{28.725 + 1.037\sqrt{d+1} + 8.314(d+1)^{\frac{1}{4}} + 5.014(d+1)}{\sqrt{n}}. \quad (1.5)$$

Note that in the special case of $d = 1$, Neammanee and Suntornchost[17] yields the bound $\frac{216}{\sqrt{n}}$ while Theorem 1.7 gave a constant $C = 50.106$.

Theorem 1.8. (A non-uniform bound for the generalization of a CCLT) Let $z \in \mathbb{R}$. With the notation and assumptions of Theorem 1.7, there exists a positive constant C which does not depend on z such that

$$|P(W \leq z) - \Phi(z)| \leq \frac{C}{1+|z|} \left\{ \frac{\delta_8^{\frac{1}{8}}}{n^{\frac{7}{16}}} + \frac{1}{n} + \delta_8 \right\}$$

where

$$\delta_8 = \frac{1}{n^{d-\frac{5}{2}}} \sum_{i_1=1}^n \dots \sum_{i_{d+1}=1}^n E|Y(i_1, \dots, i_{d+1})|^8.$$

Furthermore, if $\delta_8 \sim n^{-1/2}$,

$$|P(W \leq z) - \Phi(z)| \leq \frac{C}{(1+|z|)\sqrt{n}}. \quad (1.6)$$

We observe that Corollary 1.4 and Corollary 1.6 are examples of (1.5) and (1.6), respectively.

In this thesis, we organize as follows. In chapter 2, we give some definitions in elementary probability theory, a background of Stein's method and some useful properties of Stein's solution. A proof of Theorem 1.5 is in chapter 3 while a proof of Theorem 1.6 is stated in chapter 4. A uniform bound and non-uniform bound for Latin hypercube sampling are proved in chapter 5 by applying Theorem 1.5 and Theorem 1.6 respectively.

CHAPTER II

PRELIMINARIES

In this chapter, we give some basic concepts in probability which will be used in our work and the idea of Stein's method. The proof is omitted but can be found in [[1], [2], [23], [26]].

2.1 Probability Space and Random Variables

A **probability space** is a measure space (Ω, \mathcal{F}, P) for which $P(\Omega) = 1$. The measure P is called a **probability measure**. The set Ω will be referred as a **sample space** and its elements are called **points** or **elementary events**. The elements of \mathcal{F} are called **events**. For any event A , the value $P(A)$ is called the **probability of A** .

Let (Ω, \mathcal{F}, P) be a probability space. A function $X : \Omega \rightarrow \mathbb{R}$ is called a **random variable** if for every Borel set B in \mathbb{R} , $X^{-1}(B)$ belongs to \mathcal{F} . We shall use the notation $P(X \in B)$ in place of $P(\{\omega \in \Omega \mid X(\omega) \in B\})$. In the case where $B = (-\infty, a]$ or $[a, b]$, $P(X \in B)$ is denoted by $P(X \leq a)$ or $P(a \leq X \leq b)$, respectively.

Let X be a random variable. A function $F : \mathbb{R} \rightarrow [0, 1]$ which is defined by

$$F(x) = P(X \leq x)$$

is called the **distribution function** of X .

Let X be a random variable with the distribution function F . Then X is said to be a **discrete random variable** if the image of X is countable and X is called a **continuous random variable** if F can be written in the form

$$F(x) = \int_{-\infty}^x f(t) dt$$

for some nonnegative integrable function f on \mathbb{R} . In this case, we say that f is the **probability density function** of X .

Now we will give some examples of random variables.

We say that X is a **normal** random variable with parameter μ and σ^2 , written as $X \sim N(\mu, \sigma^2)$, if its probability function is defined by

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2}(x - \mu)^2\right).$$

Moreover, if $X \sim N(0, 1)$ then X is said to be a **standard normal** random variable.

We say that X is a **uniform** random variable with parameter n if there exist x_1, x_2, \dots, x_n such that $P(X = x_i) = \frac{1}{n}$ for any $i = 1, 2, \dots, n$ and denoted by $X \sim U(n)$.

Furthermore, we say that π is a **random permutation** if π is a permutation-valued random variable.

2.2 Independence

Let (Ω, \mathcal{F}, P) be a probability space and \mathcal{F}_α a sub σ -algebra of \mathcal{F} for each $\alpha \in \Lambda$. We say that $\{\mathcal{F}_\alpha | \alpha \in \Lambda\}$ is **independent** if and only if for any subset $J = \{1, 2, \dots, k\}$ of Λ ,

$$P\left(\bigcap_{m=1}^k A_m\right) = \prod_{m=1}^k P(A_m)$$

where $A_m \in \mathcal{F}_m$ for $m = 1, \dots, k$.

Let $\mathcal{E}_\alpha \subseteq \mathcal{F}$ for all $\alpha \in \Lambda$. We say that $\{\mathcal{E}_\alpha | \alpha \in \Lambda\}$ is **independent** if and only if $\{\sigma(\mathcal{E}_\alpha) | \alpha \in \Lambda\}$ is independent where $\sigma(\mathcal{E}_\alpha)$ is the smallest σ -algebra with $\mathcal{E}_\alpha \subseteq \sigma(\mathcal{E}_\alpha)$.

We say that the set of random variables $\{X_\alpha | \alpha \in \Lambda\}$ is **independent** if $\{\sigma(X_\alpha) | \alpha \in \Lambda\}$ is independent, where $\sigma(X) = \{X^{-1}(B) | B \text{ is a Borel subset of } \mathbb{R}\}$.

Theorem 2.1. *Random variables X_1, X_2, \dots, X_n are **independent** if for any Borel sets B_1, B_2, \dots, B_n we have*

$$P\left(\bigcap_{i=1}^n \{X_i \in B_i\}\right) = \prod_{i=1}^n P(X_i \in B_i).$$

Proposition 2.2. *If $X_{ij}; i = 1, 2, \dots, n, j = 1, 2, \dots, m_i$ are independent and $f_i: \mathbb{R}^{m_i} \rightarrow \mathbb{R}$ are measurable, then $\{f_i(X_{i1}, X_{i2}, \dots, X_{im_i}) | i = 1, 2, \dots, n\}$ is independent.*

2.3 Expectation, Variance and Conditional Expectation

Let X be any random variable on a probability space (Ω, \mathcal{F}, P) .

If $\int_{\Omega} |X| dP < \infty$, then we define its **expected value** to be

$$E(X) = \int_{\Omega} X dP.$$

Proposition 2.3.

1. If X is a discrete random variable, then $E(X) = \sum_{x \in \text{Im}X} xP(X = x)$.

2. If X is a continuous random variable with probability function f , then

$$E(X) = \int_{\mathbb{R}} xf(x)dx.$$

Proposition 2.4. Let X and Y be random variables such that $E(|X|) < \infty$ and $E(|Y|) < \infty$ and $a, b \in \mathbb{R}$. Then we have the followings:

1. $E(aX + bY) = aE(X) + bE(Y)$.

2. If $X \leq Y$, then $E(X) \leq E(Y)$.

3. $|E(X)| \leq E(|X|)$.

4. If X and Y are independent, then $E(XY) = E(X)E(Y)$.

Let X be a random variable which $E(|X|^k) < \infty$. Then $E(|X|^k)$ is called the **k -th moment** of X about the origin and call $E[(X - E(X))^k]$ the **k -th moment** of X about the mean.

We call the second moment of X about the mean, the **variance** of X , denoted by $\text{Var}(X)$. Then

$$\text{Var}(X) = E[X - E(X)]^2.$$

We note that

1. $\text{Var}(X) = E(X^2) - E^2(X)$.

2. If $X \sim N(\mu, \sigma^2)$ then $E(X) = \mu$ and $\text{Var}(X) = \sigma^2$.

Proposition 2.5. If X_1, \dots, X_n are independent and $E|X_i| < \infty$ for $i = 1, 2, \dots, n$, then

1. $E(X_1X_2 \dots X_n) = E(X_1)E(X_2) \dots E(X_n)$,

2. $\text{Var}(a_1X_1 + \dots + a_nX_n) = a_1^2\text{Var}(X_1) + \dots + a_n^2\text{Var}(X_n)$ for any real number a_1, \dots, a_n .

Theorem 2.6. Let (X_n) be an increasing sequence of random variables on a probability space (Ω, \mathcal{F}, P) to $[0, \infty)$ and $\lim_{n \rightarrow \infty} X_n = X$ a.s. Then $\lim_{n \rightarrow \infty} E(X_n) = EX$.

The following inequalities are useful in our work.

1. **Hölder's inequality :**

$$E(|XY|) \leq E^{\frac{1}{p}}(|X|^p)E^{\frac{1}{q}}(|Y|^q)$$

where $0 < p, q < 1$, $\frac{1}{p} + \frac{1}{q} = 1$ and $E(|X|^p) < \infty, E(|Y|^q) < \infty$.

2. **Chebyshev's inequality :**

$$P(\{|X - E(X)| \geq \varepsilon\}) \leq \frac{\text{Var}(X)}{\varepsilon^2} \text{ for all } \varepsilon > 0$$

where $E(X^2) < \infty$.

Let X be a random variable with finite expected value on a probability space (Ω, \mathcal{F}, P) and \mathcal{D} a sub σ -algebra of \mathcal{F} . Define a probability measure $P_{\mathcal{D}} : \mathcal{D} \rightarrow [0, 1]$ by

$$P_{\mathcal{D}}(E) = P(E)$$

and a signed measure $\mathcal{Q}_X : \mathcal{D} \rightarrow \mathbb{R}$ by

$$\mathcal{Q}_X(E) = \int_E X dP.$$

Then, by Radon-Nikodym theorem we have $\mathcal{Q}_X \ll P_{\mathcal{D}}$ and there exists a unique measurable function $E^{\mathcal{D}}(X)$ on (Ω, \mathcal{F}, P) such that

$$\int_E E^{\mathcal{D}}(X) dP_{\mathcal{D}} = \mathcal{Q}_X(E) = \int_E X dP \text{ for any } E \in \mathcal{D}.$$

We will say that $E^{\mathcal{D}}(X)$ is the **conditional expectation** of X with respect to \mathcal{D} .

Moreover, for any random variables X and Y on the same probability space (Ω, \mathcal{F}, P) such that $E(|X|) < \infty$, we will denote $E^{\sigma(Y)}(X)$ by $E^Y(X)$.

Theorem 2.7. *Let X be a random variable on a probability space (Ω, \mathcal{F}, P) such that $E(|X|) < \infty$, then the followings hold for any sub σ -algebra \mathcal{D} of \mathcal{F} .*

1. *If X is a random variable on $(\Omega, \mathcal{D}, P_{\mathcal{D}})$, then $E^{\mathcal{D}}(X) = X$ a.s. $[P_{\mathcal{D}}]$.*
2. *$E^{\mathcal{F}}(X) = X$ a.s. $[P]$.*
3. *If $\sigma(X)$ and \mathcal{D} are independent, then $E^{\mathcal{D}}(X) = E(X)$ a.s. $[P_{\mathcal{D}}]$.*

Theorem 2.8. Let X and Y be random variables on the same probability space (Ω, \mathcal{F}, P) such that $E(|X|)$ and $E(|Y|)$ are finite. Then for any sub σ -algebra \mathcal{D} of \mathcal{F} the followings hold.

1. If $X \leq Y$, then $E^{\mathcal{D}}(X) \leq E^{\mathcal{D}}(Y)$ a.s. $[P_{\mathcal{D}}]$.
2. $E^{\mathcal{D}}(aX + bY) = aE^{\mathcal{D}}(X) + bE^{\mathcal{D}}(Y)$ a.s. $[P_{\mathcal{D}}]$ for any $a, b \in \mathbb{R}$.
3. $|E^{\mathcal{D}}(X)| \leq E^{\mathcal{D}}(|X|)$ a.s. $[P_{\mathcal{D}}]$.

Theorem 2.9. Let X and Y be random variables on the same probability space (Ω, \mathcal{F}, P) such that $E(|XY|)$ and $E(|Y|)$ are finite and $\mathcal{D}_1, \mathcal{D}_2$ be any sub σ -algebras of \mathcal{F} . If X is a random variable with respect to \mathcal{D}_1 , then

1. $E^{\mathcal{D}_1}(XY) = XE^{\mathcal{D}_1}(Y)$ a.s. $[P_{\mathcal{D}_1}]$,
2. $E^{\mathcal{D}_2}(XY) = E^{\mathcal{D}_2}(XE^{\mathcal{D}_1}(Y))$ a.s. $[P_{\mathcal{D}_2}]$.

Theorem 2.10. Let (X_n) are increasing sequence of non-negative random variables on the same probability space (Ω, \mathcal{F}, P) . If $X_n \rightarrow X$ a.s. and $E|X| \leq \infty$, then $0 \leq \lim_{n \rightarrow \infty} E^{\mathcal{D}}X_n = E^{\mathcal{D}}X$ a.s. $[P_{\mathcal{D}}]$ for any sub σ -algebra of \mathcal{F} .

Theorem 2.11. Let X be a random variable on the probability space (Ω, \mathcal{F}, P) such that $E(|X|)$ is finite and $\mathcal{D}_1, \mathcal{D}_2$ be any sub σ -algebra of \mathcal{F} . If $\sigma\{X, \mathcal{D}_1\}$ is independent of \mathcal{D}_2 , then

$$E^{\sigma\{\mathcal{D}_1, \mathcal{D}_2\}}(X) = E^{\mathcal{D}_1}(X) \text{ a.s. } [P].$$

2.4 Conditional Independence

Let (Ω, \mathcal{F}, P) be a probability space and \mathcal{D} a sub σ -algebra of \mathcal{F} . For any event A on \mathcal{F} , we define the **conditional probability of A given \mathcal{D}** by

$$P(A|\mathcal{D}) = E^{\mathcal{D}}\mathbb{I}(A)$$

where $\mathbb{I}(A)$ is an indicator function.

Let X, Y and Z be discrete random variables on a probability space (Ω, \mathcal{F}, P) . If $P(X \leq x, Y \leq y | Z = z) = P(X \leq x | Z = z)P(Y \leq y | Z = z)$ for all $x, y, z \in \mathbb{R}$ such that $P(Z = z) > 0$, then we say that X and Y are **conditionally independent** given Z .

Proposition 2.12. *Let X, Y and Z be discrete random variables on a probability space (Ω, \mathcal{F}, P) such that X and Y are conditionally independent given Z . Then the followings hold.*

1. X^+ and Y^+ are conditionally independent given Z ,
2. X^+ and Y^- are conditionally independent given Z ,
3. X^- and Y^+ are conditionally independent given Z ,
4. X^- and Y^- are conditionally independent given Z

where for any $f : \Omega \rightarrow [-\infty, \infty]$, we defined the **positive part** of f by $f^+ = \max\{f, 0\}$ and the **negative part** of f by $f^- = -\min\{f, 0\}$.

Proof. Assume that X and Y are conditionally independent given Z . Let $x, y, z \in \mathbb{R}$ be such that $P(Z = z) > 0$.

case 1. $\forall w \in \Omega, X(w) \geq 0$ or $\forall w \in \Omega, Y(w) \geq 0$.

WLOG, we assume that $\forall w \in \Omega, X(w) \geq 0$. If $y < 0$, then

$$P(X^+ \leq x, Y^+ \leq y \mid Z = z) = 0 = P(X^+ \leq x \mid Z = z)P(Y^+ \leq y \mid Z = z).$$

Let $y \geq 0$. We observe that

$$\begin{aligned} P(X^+ \leq x, Y^+ \leq y \mid Z = z) &= P(X \leq x, Y \leq y \mid Z = z) \\ &= P(X \leq x \mid Z = z)P(Y \leq y \mid Z = z) \\ &= P(X^+ \leq x \mid Z = z)P(Y^+ \leq y \mid Z = z). \end{aligned}$$

case 2. $\exists w \in \Omega, X(w) < 0$ and $\exists w \in \Omega, Y(w) < 0$.

If $x < 0$ or $y < 0$,

$$P(X^+ \leq x, Y^+ \leq y \mid Z = z) = 0 = P(X^+ \leq x \mid Z = z)P(Y^+ \leq y \mid Z = z).$$

If $x \geq 0$ and $y \geq 0$, then

$$\begin{aligned} P(X^+ \leq x, Y^+ \leq y \mid Z = z) &= P(X \leq x, Y \leq y \mid Z = z) \\ &= P(X \leq x \mid Z = z)P(Y \leq y \mid Z = z) \\ &= P(X^+ \leq x \mid Z = z)P(Y^+ \leq y \mid Z = z). \end{aligned}$$

Thus, we prove 1. Similarly, we have 2,3 and 4. □

Proposition 2.13. Let X, Y and Z be discrete random variables on a probability space (Ω, \mathcal{F}, P) such that X and Y are conditionally independent given Z . Then

$$EXY = E(E^Z X E^Z Y).$$

Proof. Assume that X and Y are conditionally independent given Z .

Step 1. X and Y are non-negative simple functions.

Let $X = \sum_{i=1}^n \alpha_i \mathbb{I}(E_i)$ and $Y = \sum_{j=1}^m \beta_j \mathbb{I}(F_j)$ where $\{E_1, E_2, \dots, E_n\}$ and $\{F_1, F_2, \dots, F_m\}$

are partitions of Ω . Thus $XY = \sum_{i=1}^n \sum_{j=1}^m \alpha_i \beta_j \mathbb{I}(E_i \cap F_j)$ and $\{E_i \cap F_j, |i = 1, 2, \dots, n \text{ and } j = 1, 2, \dots, m\}$ is a partition of Ω . Since X and Y are conditionally independent given Z , $P(X = x, Y = y | Z = z) = P(X = x | Z = z)P(Y = y | Z = z)$ for all $x, y, z \in \mathbb{R}$ such that $P(Z \leq z) > 0$. This implies

$$\begin{aligned} P(E_i \cap F_j | Z) &= \sum_{k \in \text{Im} Z} P(E_i \cap F_j | Z = k) \mathbb{I}(Z = k) \\ &= \sum_{k \in \text{Im} Z} P(X = \alpha_i, Y = \beta_j | Z = k) \mathbb{I}(Z = k) \\ &= \sum_{k \in \text{Im} Z} P(X = \alpha_i | Z = k) P(Y = \beta_j | Z = k) \mathbb{I}(Z = k) \\ &= \left[\sum_{k \in \text{Im} Z} P(X = \alpha_i | Z = k) \mathbb{I}(Z = k) \right] \left[\sum_{l \in \text{Im} Z} P(Y = \beta_j | Z = l) \mathbb{I}(Z = l) \right] \\ &= P(E_i | Z) P(F_j | Z) \end{aligned}$$

for every $i = 1, 2, \dots, n$ and $j = 1, 2, \dots, m$.

Then

$$\begin{aligned} EXY &= \sum_{i=1}^n \sum_{j=1}^m \alpha_i \beta_j E E^Z \mathbb{I}(E_i \cap F_j) \\ &= \sum_{i=1}^n \sum_{j=1}^m \alpha_i \beta_j E P(E_i \cap F_j | Z) \\ &= \sum_{i=1}^n \sum_{j=1}^m \alpha_i \beta_j E P(E_i | Z) P(F_j | Z) \\ &= E \left(\sum_{i=1}^n \alpha_i E^Z \mathbb{I}(E_i) \right) \left(\sum_{j=1}^m \beta_j E^Z \mathbb{I}(F_j) \right) \\ &= E(E^Z X E^Z Y). \end{aligned}$$

Step 2. X and Y are non-negative random variables.

Let (X_n) and (Y_n) are increasing sequences of non-negative simple functions such that $X_n \rightarrow X$ and $Y_n \rightarrow Y$. From step 1, Theorem 2.6 and Theorem 2.10, we have

$$EXY = \lim_{n \rightarrow \infty} E(X_n Y_n) = \lim_{n \rightarrow \infty} E(E^Z X_n E^Z Y_n) = E(E^Z X E^Z Y).$$

Step 3. X and Y are random variables.

It follows from Proposition 2.12 and step 2 that

$$\begin{aligned} E(X^+ Y^+) &= E(E^Z X^+ E^Z Y^+), & E(X^+ Y^-) &= E(E^Z X^+ E^Z Y^-) \\ E(X^- Y^+) &= E(E^Z X^- E^Z Y^+), & E(X^- Y^-) &= E(E^Z X^- E^Z Y^-). \end{aligned}$$

Thus

$$\begin{aligned} EXY &= E[(X^+ - X^-)(Y^+ - Y^-)] \\ &= E[X^+ Y^+ - X^+ Y^- - X^- Y^+ + X^- Y^-] \\ &= E(E^Z X^+ E^Z Y^+) - E(E^Z X^+ E^Z Y^-) - E(E^Z X^- E^Z Y^+) + E(E^Z X^- E^Z Y^-) \\ &= E[E^Z (X^+ - X^-) E^Z (Y^+ - Y^-)] \\ &= E(E^Z X E^Z Y). \end{aligned}$$

□

2.5 Stein's Method for Normal Approximation

In 1972, Stein[25] introduced a powerful and general method for obtaining an explicit bound for the error in the normal approximation to the distribution of a sum of dependent random variables. The technique used was novel. Stein's technique is free of Fourier methods and relied instead on the elementary differential equation. This method was adapted and applied to the Poisson approximation by Chen in 1975[5]. Since then, Stein's method has stimulated an area of intensive research in combinatorics, probability and statistics.

There are at least three approaches to use Stein's method when the limit distribution is normal, i.e., namely a concentration inequality approach (see, for examples, Ho and Chen[9], and Chen and Shao[6]), an inductive approach (see, for example, Bolthausen[3]), and a coupling approach (see, for example, Stein[26]). In this work, we use the concentration inequality approach.

In this section we give basic results on the Stein's equation and its solution.

Let Z be a standard normal distributed random variable and let C_{bd} be the set of continuous and piecewise continuously differentiable functions $g : \mathbb{R} \rightarrow \mathbb{R}$ with $E|g'(Z)| < \infty$.

For $g \in C_{bd}$ and any real valued function I with $E|I(Z)| < \infty$, the equation

$$g'(w) - wg(w) = I(w) - EI(Z) \quad (2.1)$$

is called **Stein's equation**. The Stein's equation for normal distribution function is

$$g'(w) - wg(w) = \mathbb{I}(w \leq z) - \Phi(z), \quad (2.2)$$

for $z \in \mathbb{R}$, where \mathbb{I} is an indicator function.

Hence

$$E(g'(W)) - EWg(W) = P(W \leq z) - \Phi(z) \quad (2.3)$$

for any random variable W and the solution g_z of (2.2) is given by

$$g_z(w) = \begin{cases} \sqrt{2\pi}e^{-\frac{w^2}{2}}\Phi(w)[1 - \Phi(z)] & , \text{ if } w \leq z, \\ \sqrt{2\pi}e^{-\frac{w^2}{2}}\Phi(z)[1 - \Phi(w)] & , \text{ if } w > z. \end{cases} \quad (2.4)$$

Thus, it suffices to find a bound for

$$E(g'_z(W)) - EWg_z(W)$$

instead of

$$P(W \leq z) - \Phi(z).$$

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CHAPTER III

A UNIFORM BOUND FOR THE GENERALIZATION OF A COMBINATORIAL CENTRAL LIMIT THEOREM

Let d be a positive integer and let:

1. π_k , $1 \leq k \leq d$, be random permutations of $\{1, \dots, n\}$ each uniformly distributed over all the $n!$ possible permutations;
2. $Y(i_1, \dots, i_{d+1})$, $1 \leq i_1, \dots, i_{d+1} \leq n$, be random variables;
3. the $Y(i_1, \dots, i_{d+1})$'s and π_k 's all be stochastically independent.

We define

$$W = \sum_{i=1}^n Y(i, \pi_1(i), \dots, \pi_d(i)). \quad (3.1)$$

This chapter is concerned with the normal approximation to the distribution of W . In the special case of $d = 1$, this is called a combinatorial central limit theorem (see, for examples, Wald and Walfowitz[29], Hoeffding[10], Matoo[15], Hajek[7], Robinson[24], Kolchin and Chistyakov[11], Von Bahr[30], Ho and Chen[9], Bolthausen [3], Bolthausen and Gotze[4] and Neammanee and Suntornchost[17]). In this chapter, we establish a uniform bound for W in the case of an arbitrary d by using technique from Ho and Chen[9] and Neammanee and Suntornchost[17]. This is our main result.

Theorem 3.1. *Suppose that*

$$EW = 0 \quad \text{and} \quad \text{Var}W = 1, \quad (3.2)$$

and

$$\sum_{i_j=1}^n \tilde{\mu}(i_1, \dots, i_{d+1}) = 0 \quad \text{for every } j \in \{1, \dots, d+1\} \quad (3.3)$$

where

$$\tilde{\mu}(i_1, \dots, i_{d+1}) = EY(i_1, \dots, i_{d+1}).$$

Then for $n \geq 6^{(d+1)} + 3$,

$$\begin{aligned} \sup_{z \in \mathbb{R}} |P(W \leq z) - \Phi(z)| &\leq \frac{11.946}{\sqrt{n}} + \frac{1.037\sqrt{d+1}\delta_4^{\frac{1}{4}}}{n^{\frac{3}{8}}} + 8.314(d+1)^{\frac{1}{4}}\delta_4 + 11.765\delta_4 \\ &\quad + 5.014(d+1)\frac{\delta_4^{\frac{3}{4}}}{n^{\frac{1}{8}}} + \frac{2\sqrt{2\pi}\delta_4^{\frac{3}{4}}}{n^{\frac{1}{8}}} \end{aligned}$$

where

$$\delta_4 = \frac{1}{n^{d-\frac{1}{2}}} \sum_{i_1=1}^n \dots \sum_{i_{d+1}=1}^n E|Y(i_1, \dots, i_{d+1})|^4.$$

Furthermore, if $\delta_4 \sim n^{-1/2}$, then

$$\sup_{z \in \mathbb{R}} |P(W \leq z) - \Phi(z)| \leq \frac{28.725 + 1.037\sqrt{d+1} + 8.314(d+1)^{\frac{1}{4}} + 5.014(d+1)}{\sqrt{n}}. \quad (3.4)$$

Note that in the special case of $d = 1$, Neammanee and Suntornchost[17] yields the bound $\frac{216}{\sqrt{n}}$ while Theorem 3.1 gave a constant $C = 50.106$.

We remark that no generality is lost in this work by assuming conditions (3.2) and (3.3). In the case of $d = 1$, this is showed by Neammanee and Suntornchost[17] as follow.

Let $(X(i, j))$ be an $n \times n$ matrix of independent random variables and π be a random permutation of $\{1, \dots, n\}$, such that π and $X(i, j)$'s are independent. Their work is concerned with the normal approximation to the distribution function of $W_n = \sum_{i=1}^n X(i, \pi(i))$.

For each $i, j \in \{1, 2, \dots, n\}$, let μ_{ij} and σ_{ij}^2 be the mean and variance of X_{ij} , respectively and

$$\begin{aligned} \mu_{i.} &= \frac{1}{n} \sum_j \mu_{ij}, \quad \mu_{.j} = \frac{1}{n} \sum_i \mu_{ij}, \quad \mu_{..} = \frac{1}{n^2} \sum_{i,j} \mu_{ij} \\ d^2 &= \frac{1}{(n-1)} \sum_{i,j} (\mu_{ij} - \mu_{i.} - \mu_{.j} + \mu_{..})^2 \quad \text{and} \quad \sigma^2 = \frac{1}{n} \sum_{i,j} \sigma_{ij}^2. \end{aligned}$$

From Ho and Chen[9], $VarW_n = d^2 + \sigma^2$. Then

$$W = \sum_{i=1}^n Y(i, \pi(i))$$

satisfies the conditions (3.2) and (3.3) where

$$Y(i, j) = \frac{1}{\sqrt{d^2 + \sigma^2}} (X(i, j) - \mu_{i.} - \mu_{.j} + \mu_{..})$$

(see[17],pp.560).

Next, we shall generalize this argument to the case of an arbitrary d . Let $X(i_1, \dots, i_{d+1})$, $1 \leq i_1, \dots, i_{d+1} \leq n$, be random variables and π_k , $1 \leq k \leq d$, be random permutations of $\{1, \dots, n\}$ each uniformly distributed over all the $n!$ possible permutations such that the $X(i_1, \dots, i_{d+1})$'s and π_k 's all are stochastically independent.

Assume that $\sigma^2 := \text{Var}(\sum_{i=1}^n X(i, \pi_1(i), \dots, \pi_d(i))) > 0$. We define

$$W = \sum_{i=1}^n Y(i, \pi_1(i), \dots, \pi_d(i)) \quad (3.5)$$

where

$$\begin{aligned} Y(i_1, \dots, i_{d+1}) &= \frac{1}{\sigma} [X(i_1, \dots, i_{d+1}) + \sum_{k=1}^d \mu_k(i_1, \dots, i_{d+1}) + (-1)^{(d+1)} \frac{\mu}{n}], \\ \mu_k(i_1, \dots, i_{d+1}) &= \frac{(-1)^k}{n^k} \sum_{1 \leq j_1 < j_2 < \dots < j_k \leq d+1} \sum_{q_{j_1}} \dots \sum_{q_{j_k}} \tilde{\mu}(l_1, \dots, l_{d+1}), \\ l_p &= \begin{cases} q_p & \text{if } p = j_1, \dots, j_k, \\ i_p & \text{otherwise,} \end{cases} \\ \tilde{\mu}(i_1, \dots, i_{d+1}) &= EX(i_1, \dots, i_{d+1}) \end{aligned} \quad (3.6)$$

and

$$\mu = \sum_{i=1}^n EX(i, \pi_1(i), \dots, \pi_d(i)).$$

Then W satisfies conditions (3.2) and (3.3). The proofs are shown in the following proposition.

Proposition 3.2.

1. $EW = 0$ and $\text{Var}W = 1$

2. $\sum_{i_j=1}^n EY(i_1, \dots, i_{d+1}) = 0$ for every $j = 1, \dots, d+1$.

Proof. 1. Note that

$$\mu = \frac{1}{n^d} \sum_{i_1=1}^n \dots \sum_{i_{d+1}=1}^n \tilde{\mu}(i_1, \dots, i_{d+1}).$$

By the fact that, for fixed i ,

$$\sum_{i_{j_1}=1}^n \dots \sum_{i_{j_k}=1}^n \tilde{\mu}(l_1, \dots, l_{d+1})$$

where $1 = j_1 < j_2 < \dots < j_k \leq d + 1$ and

$$l_p = \begin{cases} q_p & \text{if } p = 1, j_2, \dots, j_k, \\ \pi_p(i) & \text{otherwise} \end{cases}$$

is equal to

$$\frac{1}{n^{d+1-k}} \sum_{k_1=1}^n \dots \sum_{k_{d+1}=1}^n \tilde{\mu}(k_1, \dots, k_{d+1})$$

and the fact that, for fixed i ,

$$\sum_{q_{j_1}=1}^n \dots \sum_{q_{j_k}=1}^n \tilde{\mu}(l_1, \dots, l_{d+1})$$

where $1 < j_1 < j_2 < \dots < j_k \leq d + 1$ and

$$l_p = \begin{cases} i & \text{if } p = 1, \\ q_p & \text{if } p = j_1, j_2, \dots, j_k, \\ \pi_p(i) & \text{otherwise} \end{cases}$$

is equal to

$$\frac{1}{n^{d-k}} \sum_{k_2=1}^n \dots \sum_{k_{d+1}=1}^n \tilde{\mu}(i, k_2, \dots, k_{d+1}),$$

we have

$$\begin{aligned} \mu_k(i, \pi_1(i), \dots, \pi_d(i)) &= \frac{(-1)^k}{n^{d+1}} \sum_{1=j_1 < j_2 < \dots < j_k \leq d+1} \sum_{k_1=1}^n \dots \sum_{k_{d+1}=1}^n \tilde{\mu}(k_1, \dots, k_{d+1}) \\ &+ \frac{(-1)^k}{n^d} \sum_{1 < j_1 < j_2 < \dots < j_k \leq d+1} \sum_{k_2=1}^n \dots \sum_{k_{d+1}=1}^n \tilde{\mu}(i, k_2, \dots, k_{d+1}). \end{aligned}$$

Notice that

$$\begin{aligned} &\sum_{i=1}^n \sum_{k=1}^d \mu_k(i, \pi_1(i), \dots, \pi_d(i)) + (-1)^{(d+1)} \mu \\ &= \sum_{k=1}^d \frac{(-1)^k}{n^d} \sum_{1=j_1 < j_2 < \dots < j_k \leq d+1} \sum_{k_1=1}^n \dots \sum_{k_{d+1}=1}^n \tilde{\mu}(k_1, \dots, k_{d+1}) \\ &+ \sum_{k=1}^d \frac{(-1)^k}{n^d} \sum_{1 < j_1 < j_2 < \dots < j_k \leq d+1} \sum_{i=1}^n \sum_{k_2=1}^n \dots \sum_{k_{d+1}=1}^n \tilde{\mu}(i, k_2, \dots, k_{d+1}) + (-1)^{(d+1)} \mu \\ &= \sum_{k=1}^d (-1)^k \sum_{1=j_1 < j_2 < \dots < j_k \leq d+1} \mu + \sum_{k=1}^d (-1)^k \sum_{1 < j_1 < j_2 < \dots < j_k \leq d+1} \mu + (-1)^{(d+1)} \mu \end{aligned}$$

$$\begin{aligned}
&= \sum_{k=1}^d (-1)^k \sum_{1 \leq j_1 < j_2 < \dots < j_k \leq d+1} \mu + (-1)^{(d+1)} \mu \\
&= \sum_{k=1}^d (-1)^k \binom{d+1}{k} \mu + (-1)^{(d+1)} \mu \\
&= \sum_{k=1}^{d+1} (-1)^k \binom{d+1}{k} \mu \\
&= [(1-1)^{(d+1)} - 1] \mu \\
&= -\mu.
\end{aligned}$$

Thus

$$\begin{aligned}
W &= \frac{1}{\sigma} \left[\sum_{i=1}^n X(i, \pi_1(i), \dots, \pi_d(i)) + \sum_{i=1}^n \sum_{k=1}^d \mu_k(i, \pi_1(i), \dots, \pi_d(i)) + (-1)^{(d+1)} \mu \right] \\
&= \frac{1}{\sigma} \left[\sum_{i=1}^n X(i, \pi_1(i), \dots, \pi_d(i)) - \mu \right].
\end{aligned}$$

Hence $EW = 0$ and $VarW = 1$.

2. We shall first proof in the case of $j = 1$. Let $\mu_k(i_1, \dots, i_{d+1})$ and l_1, \dots, l_{d+1} be defined as in (3.6) and $i_2, \dots, i_{d+1} \in \{1, \dots, n\}$. We observe that

$$\begin{aligned}
&\sum_{i_1=1}^n \sum_{k=1}^d \mu_k(i_1, \dots, i_{d+1}) \\
&= \sum_{i_1=1}^n \sum_{k=1}^d \frac{(-1)^k}{n^k} \sum_{1 \leq j_1 < j_2 < \dots < j_k \leq d+1} \sum_{q_{j_1}} \dots \sum_{q_{j_k}} \tilde{\mu}(l_1, \dots, l_{d+1}) \\
&= \sum_{k=1}^d \frac{(-1)^k}{n^{k-1}} \sum_{1=j_1 < j_2 < \dots < j_k \leq d+1} \sum_{q_1} \sum_{q_{j_2}} \dots \sum_{q_{j_k}} \tilde{\mu}(q_1, l_2, \dots, l_{d+1}) \\
&\quad + \sum_{k=1}^d \frac{(-1)^k}{n^k} \sum_{i_1=1}^n \sum_{1 < j_1 < j_2 < \dots < j_k \leq d+1} \sum_{q_{j_1}} \dots \sum_{q_{j_k}} \tilde{\mu}(i_1, l_2, \dots, l_{d+1}) \\
&= - \sum_{q_1=1}^n \tilde{\mu}(q_1, i_2, \dots, i_{d+1}) + \sum_{k=2}^d \frac{(-1)^k}{n^{k-1}} \sum_{1=j_1 < j_2 < \dots < j_k \leq d+1} \sum_{q_1} \sum_{q_{j_2}} \dots \sum_{q_{j_k}} \tilde{\mu}(q_1, l_2, \dots, l_{d+1}) \\
&\quad + \sum_{k=1}^{d-1} \frac{(-1)^k}{n^k} \sum_{i_1=1}^n \sum_{1 < j_1 < j_2 < \dots < j_k \leq d+1} \sum_{q_{j_1}} \dots \sum_{q_{j_k}} \tilde{\mu}(i_1, l_2, \dots, l_{d+1})
\end{aligned}$$

$$\begin{aligned}
& + \frac{(-1)^d}{n^d} \sum_{i_1=1}^n \sum_{q_2} \dots \sum_{q_{d+1}} \tilde{\mu}(i_1, q_2, \dots, q_{d+1}) \\
& = - \sum_{q_1=1}^n \tilde{\mu}(q_1, i_2, \dots, i_{d+1}) + \sum_{k=2}^d \frac{(-1)^k}{n^{k-1}} \sum_{1=j_1 < j_2 < \dots < j_k \leq d+1} \sum_{q_1} \sum_{q_{j_2}} \dots \sum_{q_{j_k}} \tilde{\mu}(q_1, l_2, \dots, l_{d+1}) \\
& \quad + \sum_{k=2}^d \frac{(-1)^{k-1}}{n^{k-1}} \sum_{1 < j_1 < j_2 < \dots < j_{k-1} \leq d+1} \sum_{i_1=1}^n \sum_{q_{j_1}} \dots \sum_{q_{j_{k-1}}} \tilde{\mu}(i_1, l_2, \dots, l_{d+1}) + (-1)^d \mu \\
& = (-1)^d \mu - \sum_{q_1=1}^n \tilde{\mu}(q_1, i_2, \dots, i_{d+1}).
\end{aligned}$$

Thus

$$\begin{aligned}
& \sum_{i_1=1}^n EY(i_1, \dots, i_{d+1}) \\
& = \frac{1}{\sigma} \sum_{i_1=1}^n E[X(i_1, \dots, i_{d+1}) + \sum_{k=1}^d \mu_k(i_1, \dots, i_{d+1}) + (-1)^{(d+1)} \frac{\mu}{n}] \\
& = \frac{1}{\sigma} \left[\sum_{i_1=1}^n \tilde{\mu}(i_1, \dots, i_{d+1}) + \sum_{i_1=1}^n \sum_{k=1}^d \mu_k(i_1, \dots, i_{d+1}) + (-1)^{(d+1)} \mu \right] \\
& = 0.
\end{aligned}$$

For $j = 2, \dots, d+1$, we can prove this by using the same argument. \square

3.1 Auxiliary results

In this section, we give auxiliary results for proving our main theorem(Theorem 3.1).

We shall first construct the following system which generalizes the result from Ho and Chen[9] naturally by extending to d -dimensions. Let $I, K, L_1, \dots, L_d, M_1, \dots, M_d$ be uniformly distributed random variables on $\{1, 2, \dots, n\}$ and $\rho_1, \dots, \rho_d, \tau_1, \dots, \tau_d$ are random permutations of $\{1, 2, \dots, n\}$. Assume that

$$\{I, K, L_1, \dots, L_d, M_1, \dots, M_d, \rho_1, \dots, \rho_d, \tau_1, \dots, \tau_d\} \text{ is independent of } Y(i_1, \dots, i_{d+1})\text{'s,} \quad (3.7)$$

$$(I, K), (L_1, M_1), \dots, (L_d, M_d) \text{ are uniformly distributed on } \{(i, k) | i, k = 1, 2, \dots, n \text{ and } i \neq k\}, \quad (3.8)$$

$$(I, K), (L_1, M_1), \dots, (L_d, M_d) \text{ and } \tau_1, \dots, \tau_d \text{ are mutually independent,} \quad (3.9)$$

(I, K) and ρ_1, \dots, ρ_d are mutually independent, and (3.10)

$$\rho_i(\alpha) = \begin{cases} \tau_i(\alpha) & \text{if } \alpha \neq I, K, \tau_i^{-1}(L_i), \tau_i^{-1}(M_i) \\ L_i & \text{if } \alpha = I, \\ M_i & \text{if } \alpha = K, \\ \tau_i(I) & \text{if } \alpha = \tau_i^{-1}(L_i) \\ \tau_i(K) & \text{if } \alpha = \tau_i^{-1}(M_i), \end{cases} \quad (3.11)$$

where $\rho_i(\rho_i^{-1}(\alpha)) = \rho_i^{-1}(\rho_i(\alpha)) = \alpha$, for $i = 1, \dots, d$. In the case of $d = 1$, Ho[8] gave an example of random vectors $I, K, L, M, \pi, \rho, \tau$ and $Y(i, j), i, j = 1, 2, \dots, n$, which satisfy the conditions (3.7)-(3.11). It easy to generalize his example naturally by extending to d -dimensions. Let

$$S(\rho) = \sum_{i=1}^n Y(i, \rho_1(i), \dots, \rho_d(i)) \quad (3.12)$$

and

$$\tilde{S}(\rho) = S(\rho) - S_1 - S_2 + S_3 + S_4$$

where

$$\begin{aligned} S_1 &= Y(I, \rho_1(I), \dots, \rho_d(I)), & S_2 &= Y(K, \rho_1(K), \dots, \rho_d(K)) \\ S_3 &= Y(I, \rho_1(K), \dots, \rho_d(K)), & S_4 &= Y(K, \rho_1(I), \dots, \rho_d(I)). \end{aligned}$$

Clearly S_1 and S_2 have the same distribution and so do S_3 and S_4 . We observe that

$$P(S_1 \leq a) = \frac{1}{n^{d+1}} \sum_{i_1=1}^n \dots \sum_{i_{d+1}=1}^n P(Y(i_1, \dots, i_{d+1}) \leq a) = P(S_3 \leq a) \quad \text{for all } a \in \mathbb{R}.$$

Thus S_1, S_2, S_3, S_4 are identically distributed. (3.13)

Lemma 3.3. *Let $g : \mathbb{R} \rightarrow \mathbb{R}$ be a continuous and piecewise continuously differentiable function. Then*

$$ES(\rho)g(S(\rho)) = E \int_{-\infty}^{\infty} g'(S(\rho) + t)M(t)dt - \Delta g(S(\rho)) \quad (3.14)$$

and

$$|\Delta g(S(\rho))| \leq \frac{1}{n-1} [Eg^2(S(\rho))]^{1/2}, \quad (3.15)$$

where

$$M(t) = \frac{n}{4}(\tilde{S}(\rho) - S(\rho))\{\mathbb{I}(0 \leq t \leq \tilde{S}(\rho) - S(\rho)) - \mathbb{I}(\tilde{S}(\rho) - S(\rho) \leq t \leq 0)\}$$

and \mathbb{I} is an indicator function.

Proof. Let \mathcal{A} be the σ -algebra generated by

$$\{Y(i, \rho_1(i), \dots, \rho_d(i)) : 1 \leq i \leq n\}.$$

By the same argument as in Neammanee and Suntornchost([17],pp.565), we have

$$2E\{g(S(\rho))E^{\mathcal{A}}(\tilde{S}(\rho) - S(\rho))\} + E(\tilde{S}(\rho) - S(\rho))[g(\tilde{S}(\rho)) - g(S(\rho))] = 0. \quad (3.16)$$

We observe that for $i \neq k$ and $C \in \mathcal{A}$,

$$\begin{aligned} & \int_C Y(i, \rho_1(k), \dots, \rho_d(k)) dP \\ &= \sum_{j_1=1}^n \dots \sum_{j_d=1}^n \int_{\{\rho_1(k)=j_1, \dots, \rho_d(k)=j_d\} \cap C} Y(i, j_1, \dots, j_d) dP \\ &= \sum_{j_1=1}^n \dots \sum_{j_d=1}^n \int_{\Omega} Y(i, j_1, \dots, j_d) \mathbb{I}(\{\rho_1(k) = j_1, \dots, \rho_d(k) = j_d\} \cap C) dP \\ &= \sum_{j_1=1}^n \dots \sum_{j_d=1}^n EY(i, j_1, \dots, j_d) \mathbb{I}(\{\rho_1(k) = j_1, \dots, \rho_d(k) = j_d\} \cap C) \\ &= \sum_{j_1=1}^n \dots \sum_{j_d=1}^n \tilde{\mu}(i, j_1, \dots, j_d) P(\{\rho_1(k) = j_1, \dots, \rho_d(k) = j_d\} \cap C) \\ &= \sum_{j_1=1}^n \dots \sum_{j_d=1}^n \int_{\Omega} \tilde{\mu}(i, j_1, \dots, j_d) \mathbb{I}(\{\rho_1(k) = j_1, \dots, \rho_d(k) = j_d\} \cap C) dP \\ &= \sum_{j_1=1}^n \dots \sum_{j_d=1}^n \int_{\{\rho_1(k)=j_1, \dots, \rho_d(k)=j_d\} \cap C} \tilde{\mu}(i, j_1, \dots, j_d) dP \\ &= \int_C \tilde{\mu}(i, \rho_1(k), \dots, \rho_d(k)) dP. \end{aligned}$$

Thus

$$E^{\mathcal{A}}Y(i, \rho_1(k), \dots, \rho_d(k)) = E^{\mathcal{A}}\tilde{\mu}(i, \rho_1(k), \dots, \rho_d(k)) \text{ for any } i \neq k. \quad (3.17)$$

By this fact, we have

$$\begin{aligned}
E^{\mathcal{A}}(\tilde{S}(\rho) - S(\rho)) &= E^{\mathcal{A}}[-S_1 - S_2 + S_3 + S_4] \\
&= -E^{\mathcal{A}}Y(I, \rho_1(I), \dots, \rho_d(I)) - E^{\mathcal{A}}Y(K, \rho_1(K), \dots, \rho_d(K)) \\
&\quad + E^{\mathcal{A}}Y(I, \rho_1(K), \dots, \rho_d(K)) + E^{\mathcal{A}}Y(K, \rho_1(I), \dots, \rho_d(I)) \\
&= -\frac{2}{n} \sum_{i=1}^n Y(i, \rho_1(i), \dots, \rho_d(i)) \\
&\quad + \frac{2}{n(n-1)} \sum_{i=1}^n \sum_{\substack{k \\ k \neq i}} E^{\mathcal{A}}Y(i, \rho_1(k), \dots, \rho_d(k)) \\
&= -\frac{2}{n} S(\rho) + \frac{2}{n(n-1)} \sum_{i=1}^n \sum_{\substack{k \\ k \neq i}} E^{\mathcal{A}}\tilde{\mu}(i, \rho_1(k), \dots, \rho_d(k)) \\
&= -\frac{2}{n} S(\rho) + \frac{2}{n(n-1)} E^{\mathcal{A}} \sum_{i=1}^n \left\{ \sum_{k=1}^n \tilde{\mu}(i, \rho_1(k), \dots, \rho_d(k)) \right. \\
&\quad \left. - \tilde{\mu}(i, \rho_1(i), \dots, \rho_d(i)) \right\} \\
&= -\frac{2}{n} S(\rho) + \frac{2}{n(n-1)} E^{\mathcal{A}} \sum_{i=1}^n \sum_{k=1}^n \tilde{\mu}(i, \rho_1(k), \dots, \rho_d(k)) \\
&\quad - \frac{2}{n(n-1)} E^{\mathcal{A}} \sum_{i=1}^n \tilde{\mu}(i, \rho_1(i), \dots, \rho_d(i)). \tag{3.18}
\end{aligned}$$

We note from (3.3) that

$$\sum_{i=1}^n \sum_{k=1}^n \tilde{\mu}(i, \rho_1(k), \dots, \rho_d(k)) = 0.$$

This implies the second term on the right-hand side of (3.18) is zero.

Hence

$$E^{\mathcal{A}}(\tilde{S}(\rho) - S(\rho)) = -\frac{2}{n} S(\rho) - \frac{2}{n(n-1)} E^{\mathcal{A}} \sum_{i=1}^n \tilde{\mu}(i, \rho_1(i), \dots, \rho_d(i)). \tag{3.19}$$

We conclude from (3.16) and (3.19) that

$$\begin{aligned}
0 &= 2E\{g(S(\rho))[-\frac{2}{n} S(\rho) - \frac{2}{n(n-1)} E^{\mathcal{A}} \sum_{i=1}^n \tilde{\mu}(i, \rho_1(i), \dots, \rho_d(i))]\} \\
&\quad + E(\tilde{S}(\rho) - S(\rho))[g(\tilde{S}(\rho)) - g(S(\rho))].
\end{aligned}$$

This implies

$$\begin{aligned}
ES(\rho)g(S(\rho)) &= \frac{n}{4}E(\tilde{S}(\rho) - S(\rho))[g(\tilde{S}(\rho)) - g(S(\rho))] \\
&\quad - \frac{1}{n-1}E[g(S(\rho))E^{\mathcal{A}}\sum_{i=1}^n\tilde{\mu}(i, \rho_1(i), \dots, \rho_d(i))] \\
&= \frac{n}{4}E(\tilde{S}(\rho) - S(\rho))[g(\tilde{S}(\rho)) - g(S(\rho))] - \Delta g(S(\rho)) \\
&= \frac{n}{4}E(\tilde{S}(\rho) - S(\rho))\int_0^{\tilde{S}(\rho)-S(\rho)}g'(S(\rho)+t)dt - \Delta g(S(\rho)) \\
&= E\int_{-\infty}^{\infty}g'(S(\rho)+t)M(t)dt - \Delta g(S(\rho))
\end{aligned}$$

where

$$\Delta g(S(\rho)) = \frac{1}{n-1}E[g(S(\rho))E^{\mathcal{A}}\sum_{i=1}^n\tilde{\mu}(i, \rho_1(i), \dots, \rho_d(i))].$$

To finish the proof, we need to bound $|\Delta g(S(\rho))|$. We observe from (3.2) and (3.3) that

$$\begin{aligned}
&E\left[\sum_{i=1}^n\tilde{\mu}(i, \rho_1(i), \dots, \rho_d(i))\right]^2 \\
&= \sum_{i=1}^nE\tilde{\mu}^2(i, \rho_1(i), \dots, \rho_d(i)) + \sum_{i=1}^n\sum_{\substack{j \\ j \neq i}}E\tilde{\mu}(i, \rho_1(i), \dots, \rho_d(i))\tilde{\mu}(j, \rho_1(j), \dots, \rho_d(j)) \\
&= \frac{1}{n^d}\sum_{i_1=1}^n\cdots\sum_{i_{d+1}=1}^n\tilde{\mu}^2(i_1, \dots, i_{d+1}) \\
&\quad + \frac{1}{(n(n-1))^d}\sum_{i_1=1}^n\cdots\sum_{i_{d+1}=1}^n\tilde{\mu}(i_1, \dots, i_{d+1})\sum_{\substack{j_1 \\ j_1 \neq i_1}}\cdots\sum_{\substack{j_{d+1} \\ j_{d+1} \neq i_{d+1}}}\tilde{\mu}(j_1, \dots, j_{d+1}) \\
&= \frac{1}{n^d}\sum_{i_1=1}^n\cdots\sum_{i_{d+1}=1}^n\tilde{\mu}^2(i_1, \dots, i_{d+1}) + \frac{(-1)^{d+1}}{(n(n-1))^d}\sum_{i_1=1}^n\cdots\sum_{i_{d+1}=1}^n\tilde{\mu}^2(i_1, \dots, i_{d+1}) \\
&\leq \frac{1}{n^d}\sum_{i_1=1}^n\cdots\sum_{i_{d+1}=1}^nEY^2(i_1, \dots, i_{d+1}) + \frac{(-1)^{(d+1)}}{(n(n-1))^d}\sum_{i_1=1}^n\cdots\sum_{i_{d+1}=1}^n\tilde{\mu}^2(i_1, \dots, i_{d+1}) \\
&= \frac{1}{n^d}\sum_{i_1=1}^n\cdots\sum_{i_{d+1}=1}^nEY^2(i_1, \dots, i_{d+1}) \\
&\quad + \frac{1}{(n(n-1))^d}\sum_{i_1=1}^n\cdots\sum_{i_{d+1}=1}^nEY(i_1, \dots, i_{d+1})\sum_{\substack{j_1 \\ j_1 \neq i_1}}\cdots\sum_{\substack{j_{d+1} \\ j_{d+1} \neq i_{d+1}}}EY(j_1, \dots, j_{d+1})
\end{aligned}$$

$$\begin{aligned}
&= \sum_{i=1}^n EY^2(i, \rho_1(i), \dots, \rho_d(i)) + \sum_{i=1}^n \sum_{\substack{j \\ j \neq i}} EY(i, \rho_1(i), \dots, \rho_d(i))Y(j, \rho_1(j), \dots, \rho_d(j)) \\
&= E\left[\sum_{i=1}^n Y(i, \rho_1(i), \dots, \rho_d(i))\right]^2 \\
&= E(S(\rho))^2 \\
&= 1.
\end{aligned} \tag{3.20}$$

Hence, by Hölder's inequality and (3.20),

$$\begin{aligned}
|\Delta g(S(\rho))| &\leq \frac{1}{n-1} E[g^2(S(\rho))]^{\frac{1}{2}} \left\{ E\left[\sum_{i=1}^n \tilde{\mu}(i, \rho_1(i), \dots, \rho_d(i))\right]^2 \right\}^{\frac{1}{2}} \\
&\leq \frac{1}{n-1} E[g^2(S(\rho))]^{\frac{1}{2}}.
\end{aligned}$$

□

Lemma 3.4. *Let $S(\rho)$ be defined as in (3.12). Then in the special case of $d = 1$ and $n \geq 39$, we have*

$$ES^4(\rho) \leq 4.678\sqrt{n}\delta_4.$$

Proof. Note that

$$ES^4(\rho) = A_1 + A_2 + A_3 + A_4 + A_5 \tag{3.21}$$

where

$$\begin{aligned}
A_1 &= \sum_{i=1}^n EY^4(i, \rho_1(i)) \\
A_2 &= \sum_{i_1=1}^n \sum_{\substack{i_2 \\ i_2 \neq i_1}} EY^3(i_1, \rho_1(i_1))Y(i_2, \rho_1(i_2)) \\
A_3 &= \sum_{i_1=1}^n \sum_{\substack{i_2 \\ i_2 \neq i_1}} EY^2(i_1, \rho_1(i_1))Y^2(i_2, \rho_1(i_2)) \\
A_4 &= \sum_{i_1=1}^n \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{i_3 \\ i_3 \neq i_1, i_2}} EY^2(i_1, \rho_1(i_1))Y(i_2, \rho_1(i_2))Y(i_3, \rho_1(i_3)) \\
A_5 &= \sum_{i_1=1}^n \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{i_3 \\ i_3 \neq i_1, i_2}} \sum_{\substack{i_4 \\ i_4 \neq i_1, i_2, i_3}} EY(i_1, \rho_1(i_1))Y(i_2, \rho_1(i_2))Y(i_3, \rho_1(i_3))Y(i_4, \rho_1(i_4)).
\end{aligned}$$

By the fact that $n \geq 39$ and (3.3), we have

$$A_1 = \frac{1}{n} \sum_{i=1}^n \sum_{j=1}^n EY^4(i, j) = \frac{\delta_4}{\sqrt{n}} \leq 0.025\sqrt{n}\delta_4 \quad (3.22)$$

and

$$\begin{aligned} A_2 &= \frac{1}{n(n-1)} \sum_{i_1=1}^n \sum_{j_1=1}^n EY^3(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY(i_2, j_2) \\ &= \frac{1}{n(n-1)} \sum_{i_1=1}^n \sum_{j_1=1}^n EY^3(i_1, j_1) EY(i_1, j_1) \\ &\leq \frac{1}{n(n-1)} \sum_{i=1}^n \sum_{j=1}^n EY^4(i, j) \\ &= \frac{\delta_4}{\sqrt{n}(n-1)} \\ &\leq 0.0006\sqrt{n}\delta_4. \end{aligned} \quad (3.23)$$

We observe that

$$\left[\sum_{i=1}^n \sum_{j=1}^n EY^2(i, j) \right]^2 \leq n^2 \sum_{i=1}^n \sum_{j=1}^n [EY^2(i, j)]^2 \leq n^2 \sum_{i=1}^n \sum_{j=1}^n EY^4(i, j) = n^2 \sqrt{n}\delta_4. \quad (3.24)$$

By this fact,

$$\begin{aligned} A_3 &= \frac{1}{n(n-1)} \sum_{i_1=1}^n \sum_{j_1=1}^n EY^2(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY^2(i_2, j_2) \\ &\leq \frac{1}{n(n-1)} \left[\sum_{i=1}^n \sum_{j=1}^n EY^2(i, j) \right]^2 \\ &\leq \frac{n\sqrt{n}}{n-1} \delta_4 \\ &\leq 1.026\sqrt{n}\delta_4. \end{aligned} \quad (3.25)$$

Next, we will bound A_4 . Note that

$$\sum_{i_1=1}^n \sum_{j_1=1}^n EY^2(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY(i_2, j_2) \sum_{\substack{i_3 \\ i_3 \neq i_1, i_2}} \sum_{\substack{j_3 \\ j_3 \neq j_1, j_2}} EY(i_3, j_3) \quad (3.26)$$

consists of a sum of 4 terms each of the form

$$\sum_{i_1=1}^n \sum_{j_1=1}^n EY^2(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY(i_2, j_2) EY(k, l)$$

where $k = i_1$ or i_2 and $l = j_1$ or j_2 . By (3.3), for fixed i_1, j_1 ,

$$\sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY(i_2, j_2) EY(k, l) \leq \sum_{i=1}^n \sum_{j=1}^n (EY(i, j))^2 \leq \sum_{i=1}^n \sum_{j=1}^n EY^2(i, j).$$

This implies

$$\sum_{i_1=1}^n \sum_{j_1=1}^n EY^2(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY(i_2, j_2) \sum_{\substack{i_3 \\ i_3 \neq i_1, i_2}} \sum_{\substack{j_3 \\ j_3 \neq j_1, j_2}} EY(i_3, j_3) \leq 4 \left[\sum_{i=1}^n \sum_{j=1}^n EY^2(i, j) \right]^2.$$

From this fact, (3.24) and $n \geq 39$, we have

$$\begin{aligned} A_4 &= \frac{1}{n(n-1)(n-2)} \sum_{i_1=1}^n \sum_{j_1=1}^n EY^2(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY(i_2, j_2) \sum_{\substack{i_3 \\ i_3 \neq i_1, i_2}} \sum_{\substack{j_3 \\ j_3 \neq j_1, j_2}} EY(i_3, j_3) \\ &\leq \frac{4}{n(n-1)(n-2)} \left[\sum_{i=1}^n \sum_{j=1}^n EY^2(i, j) \right]^2 \\ &\leq \frac{4n\sqrt{n}}{(n-1)(n-2)} \delta_4 \\ &= 4 \left(\frac{n}{n-1} \right) \left(\frac{1}{n-2} \right) \sqrt{n} \delta_4 \\ &\leq 0.11 \sqrt{n} \delta_4. \end{aligned} \tag{3.27}$$

It remains to bound A_5 . Similarly to (3.26),

$$\begin{aligned} &\sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY(i_2, j_2) \sum_{\substack{i_3 \\ i_3 \neq i_1, i_2}} \sum_{\substack{j_3 \\ j_3 \neq j_1, j_2}} EY(i_3, j_3) \sum_{\substack{i_4 \\ i_4 \neq i_1, i_2, i_3}} \sum_{\substack{j_4 \\ j_4 \neq j_1, j_2, j_3}} \\ &EY(i_4, j_4) \end{aligned}$$

consists of a sum of 9 terms each of the form

$$B(k, l) = \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY(i_2, j_2) \sum_{\substack{i_3 \\ i_3 \neq i_1, i_2}} \sum_{\substack{j_3 \\ j_3 \neq j_1, j_2}} EY(i_3, j_3) EY(k, l)$$

where $k \in \{i_1, i_2, i_3\}$ and $l \in \{j_1, j_2, j_3\}$.

case 1. $(k, l) = (i_1, j_1)$

Note that

$$B(i_1, j_1) \leq A_{5,1} + A_{5,2} + A_{5,3} + A_{5,4}$$

where

$$\begin{aligned}
A_{5,1} &= \sum_{i_1=1}^n \sum_{j_1=1}^n (EY(i_1, j_1))^3 \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY(i_2, j_2), \\
A_{5,2} &= \sum_{i_1=1}^n \sum_{j_1=1}^n (EY(i_1, j_1))^2 \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY(i_2, j_2) EY(i_1, j_2), \\
A_{5,3} &= \sum_{i_1=1}^n \sum_{j_1=1}^n (EY(i_1, j_1))^2 \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY(i_2, j_2) EY(i_2, j_1), \\
\text{and} \quad A_{5,4} &= \sum_{i_1=1}^n \sum_{j_1=1}^n (EY(i_1, j_1))^2 \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} (EY(i_2, j_2))^2.
\end{aligned}$$

By (3.3),

$$\begin{aligned}
A_{5,1} &= \sum_{i=1}^n \sum_{j=1}^n (EY(i, j))^4 \leq \sqrt{n} \delta_4, \\
A_{5,2} &= - \sum_{i_1=1}^n \sum_{j_1=1}^n (EY(i_1, j_1))^2 \sum_{\substack{j_2 \\ j_2 \neq j_1}} (EY(i_1, j_2))^2 < 0, \\
A_{5,3} &= - \sum_{i_1=1}^n \sum_{j_1=1}^n (EY(i_1, j_1))^2 \sum_{\substack{i_2 \\ i_2 \neq i_1}} (EY(i_2, j_1))^2 < 0.
\end{aligned}$$

and by (3.24),

$$A_{5,4} \leq \left[\sum_{i=1}^n \sum_{j=1}^n EY^2(i, j) \right]^2 \leq n^2 \sqrt{n} \delta_4.$$

Thus

$$B(i_1, j_1) \leq \sqrt{n} \delta_4 + n^2 \sqrt{n} \delta_4.$$

case 2. $(k, l) = (i_2, j_2)$

We observe that

$$B(i_2, j_2) = A_{5,4} + A_{5,5} + A_{5,6} + A_{5,7}$$

where

$$A_{5,5} = \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} (EY(i_2, j_2))^2 EY(i_1, j_2),$$

$$A_{5,6} = \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} (EY(i_2, j_2))^2 EY(i_2, j_1),$$

$$\text{and } A_{5,7} = \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} (EY(i_2, j_2))^3.$$

By (3.3),

$$\begin{aligned} A_{5,5} &= \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY(i_1, j_2) \sum_{i_2=1}^n (EY(i_2, j_2))^2 \\ &\quad - \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{j_2 \\ j_2 \neq j_1}} (EY(i_1, j_2))^3 \\ &= \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{j_2=1}^n EY(i_1, j_2) \sum_{i_2=1}^n (EY(i_2, j_2))^2 \\ &\quad - \sum_{i_1=1}^n \sum_{j_1=1}^n (EY(i_1, j_1))^2 \sum_{i_2=1}^n (EY(i_2, j_1))^2 - \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{j_2=1}^n (EY(i_1, j_2))^3 \\ &\quad + \sum_{i_1=1}^n \sum_{j_1=1}^n (EY(i_1, j_1))^4 \\ &\leq \sum_{i_1=1}^n \sum_{j_1=1}^n EY^4(i_1, j_1) \\ &= \sqrt{n} \delta_4, \\ A_{5,6} &= \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} EY(i_2, j_1) \sum_{j_2=1}^n (EY(i_2, j_2))^2 \\ &\quad - \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} (EY(i_2, j_1))^3 \\ &= \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{i_2=1}^n EY(i_2, j_1) \sum_{j_2=1}^n (EY(i_2, j_2))^2 \\ &\quad - \sum_{i_1=1}^n \sum_{j_1=1}^n (EY(i_1, j_1))^2 \sum_{j_2=1}^n (EY(i_1, j_2))^2 \\ &\quad - \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{i_2=1}^n (EY(i_2, j_1))^3 + \sum_{i_1=1}^n \sum_{j_1=1}^n (EY(i_1, j_1))^4 \end{aligned}$$

$$\begin{aligned} &\leq \sum_{i_1=1}^n \sum_{j_1=1}^n EY^4(i_1, j_1) \\ &= \sqrt{n}\delta_4 \end{aligned}$$

and

$$\begin{aligned} A_{5,7} &= \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{j_2=1}^n (EY(i_2, j_2))^3 - \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} (EY(i_2, j_1))^3 \\ &= - \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{i_2=1}^n (EY(i_2, j_1))^3 + \sum_{i_1=1}^n \sum_{j_1=1}^n (EY(i_1, j_1))^4 \\ &\leq \sum_{i_1=1}^n \sum_{j_1=1}^n EY^4(i_1, j_1) \\ &= \sqrt{n}\delta_4. \end{aligned}$$

Thus

$$B(i_2, j_2) \leq 3\sqrt{n}\delta_4 + n^2\sqrt{n}\delta_4.$$

case 3. $(k, l) = (i_3, j_3)$

We note that

$$B(i_3, j_3) = A_{5,1} + A_{5,7} + A_{5,8} + A_{5,9} + A_{5,10} + A_{5,11} + A_{5,12} + A_{5,13} + A_{5,14}$$

where

$$\begin{aligned} A_{5,8} &= \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY(i_2, j_2) \sum_{i_3=1}^n \sum_{j_3=1}^n (EY(i_3, j_3))^2, \\ A_{5,9} &= - \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY(i_2, j_2) \sum_{j_3=1}^n (EY(i_1, j_3))^2, \\ A_{5,10} &= - \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY(i_2, j_2) \sum_{j_3=1}^n (EY(i_2, j_3))^2, \\ A_{5,11} &= - \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY(i_2, j_2) \sum_{i_3=1}^n (EY(i_3, j_1))^2, \\ A_{5,12} &= \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY(i_2, j_2) (EY(i_2, j_1))^2, \end{aligned}$$

$$A_{5,13} = - \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY(i_2, j_2) \sum_{i_3=1}^n (EY(i_3, j_2))^2, \quad \text{and}$$

$$A_{5,14} = \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY(i_2, j_2) (EY(i_1, j_2))^2.$$

By (3.3) and (3.24),

$$\begin{aligned} A_{5,8} &= \sum_{i_1=1}^n \sum_{j_1=1}^n (EY(i_1, j_1))^2 \sum_{i_3=1}^n \sum_{j_3=1}^n (EY(i_3, j_3))^2 \\ &\leq \left[\sum_{i=1}^n \sum_{j=1}^n EY^2(i, j) \right]^2 \\ &\leq n^2 \sqrt{n} \delta_4, \\ A_{5,9} &= - \sum_{i_1=1}^n \sum_{j_1=1}^n (EY(i_1, j_1))^2 \sum_{j_3=1}^n (EY(i_1, j_3))^2 \\ &< 0, \\ A_{5,10} &= \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{j_3=1}^n (EY(i_2, j_3))^2 EY(i_2, j_1) \\ &= \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{i_2=1}^n \sum_{j_3=1}^n (EY(i_2, j_3))^2 EY(i_2, j_1) \\ &\quad - \sum_{i_1=1}^n \sum_{j_1=1}^n (EY(i_1, j_1))^2 \sum_{j_3=1}^n (EY(i_1, j_3))^2 \\ &< 0, \\ A_{5,11} &= - \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{j_2=1}^n EY(i_2, j_2) \sum_{i_3=1}^n (EY(i_3, j_1))^2 \\ &\quad + \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} EY(i_2, j_1) \sum_{i_3=1}^n (EY(i_3, j_1))^2 \\ &= \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{i_2=1}^n EY(i_2, j_1) \sum_{i_3=1}^n (EY(i_3, j_1))^2 \\ &\quad - \sum_{i_1=1}^n \sum_{j_1=1}^n (EY(i_1, j_1))^2 \sum_{i_3=1}^n (EY(i_3, j_1))^2 \\ &< 0, \end{aligned}$$

$$\begin{aligned}
A_{5,12} &= \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}}^n \sum_{j_2=1}^n EY(i_2, j_2) (EY(i_2, j_1))^2 \\
&\quad - \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}}^n (EY(i_2, j_1))^3 \\
&= - \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{i_2=1}^n (EY(i_2, j_1))^3 + \sum_{i_1=1}^n \sum_{j_1=1}^n (EY(i_1, j_1))^4 \\
&\leq \sqrt{n}\delta_4, \\
A_{5,13} &= - \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}}^n \sum_{j_2=1}^n EY(i_2, j_2) \sum_{i_3=1}^n (EY(i_3, j_2))^2 \\
&\quad + \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}}^n EY(i_2, j_1) \sum_{i_3=1}^n (EY(i_3, j_1))^2 \\
&= \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{i_2=1}^n EY(i_2, j_1) \sum_{i_3=1}^n (EY(i_3, j_1))^2 \\
&\quad - \sum_{i_1=1}^n \sum_{j_1=1}^n (EY(i_1, j_1))^2 \sum_{i_3=1}^n (EY(i_3, j_1))^2 \\
&< 0, \quad \text{and} \\
A_{5,14} &= \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}}^n \sum_{j_2=1}^n EY(i_2, j_2) (EY(i_1, j_2))^2 \\
&\quad - \sum_{i_1=1}^n \sum_{j_1=1}^n (EY(i_1, j_1))^3 \sum_{\substack{i_2 \\ i_2 \neq i_1}}^n EY(i_2, j_1) \\
&= - \sum_{i_1=1}^n \sum_{j_1=1}^n (EY(i_1, j_1))^3 \sum_{i_2=1}^n EY(i_2, j_1) + \sum_{i_1=1}^n \sum_{j_1=1}^n (EY(i_1, j_1))^4 \\
&\leq \sqrt{n}\delta_4.
\end{aligned}$$

Thus

$$B(i_3, j_3) \leq n^2 \sqrt{n}\delta_4 + 4\sqrt{n}\delta_4.$$

case 4. $(k, l) = (i_1, j_2)$

We note that

$$B(i_1, j_2) = A_{5,2} + A_{5,5} + A_{5,14} + A_{5,15}$$

where

$$A_{5,15} = \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY(i_2, j_2) EY(i_1, j_2) EY(i_2, j_1).$$

Using the fact that $2ab \leq a^2 + b^2$,

$$\begin{aligned} A_{5,15} &\leq \frac{1}{2} \sum_{i_1=1}^n \sum_{j_1=1}^n E|Y(i_1, j_1)| \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} E|Y(i_2, j_2)| \{EY^2(i_1, j_2) + EY^2(i_2, j_1)\} \\ &\leq \frac{1}{2} \sum_{i_1=1}^n \sum_{j_1=1}^n E|Y(i_1, j_1)| \sum_{i_2=1}^n \sum_{j_2=1}^n E|Y(i_2, j_2)| \sum_{i_3=1}^n \sum_{j_3=1}^n EY^2(i_3, j_3) \\ &= \frac{1}{2} \left(\sum_{i=1}^n \sum_{j=1}^n E|Y(i, j)| \right)^2 \sum_{i=1}^n \sum_{j=1}^n EY^2(i, j) \\ &\leq \frac{n^2}{2} \left(\sum_{i=1}^n \sum_{j=1}^n EY^2(i, j) \right)^2 \\ &\leq \frac{n^4}{2} \sum_{i=1}^n \sum_{j=1}^n EY^4(i, j) \\ &= \frac{n^4 \sqrt{n}}{2} \delta_4. \end{aligned} \tag{3.28}$$

Thus

$$B(i_1, j_2) \leq 2\sqrt{n}\delta_4 + \frac{n^4 \sqrt{n}}{2} \delta_4.$$

case 5. $(k, l) = (i_1, j_3)$

We note that

$$B(i_1, j_3) = A_{5,1} + A_{5,3} + A_{5,5} + A_{5,9} + A_{5,14} + A_{5,16}$$

where

$$A_{5,16} = - \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY(i_2, j_2) \sum_{j_3=1}^n EY(i_2, j_3) EY(i_1, j_3).$$

By the same argument as (3.28), $A_{5,16} \leq \frac{n^4 \sqrt{n}}{2} \delta_4$. Thus

$$B(i_1, j_3) \leq 3\sqrt{n}\delta_4 + \frac{n^4 \sqrt{n}}{2} \delta_4.$$

case 6. $(k, l) = (i_2, j_1)$

Note that

$$B(i_2, j_1) \leq A_{5,3} + A_{5,6} + A_{5,12} + A_{5,15} \leq 2\sqrt{n}\delta_4 + \frac{n^4 \sqrt{n}}{2} \delta_4.$$

case 7. $(k, l) = (i_2, j_3)$

Note that

$$B(i_2, j_3) \leq A_{5,3} + A_{5,5} + A_{5,7} + A_{5,10} + A_{5,12} + A_{5,16} \leq 3\sqrt{n}\delta_4 + \frac{n^4\sqrt{n}}{2}\delta_4.$$

case 8. $(k, l) = (i_3, j_1)$

We observe that

$$B(i_3, j_1) = A_{5,1} + A_{5,2} + A_{5,6} + A_{5,11} + A_{5,12} + A_{5,17}$$

where

$$A_{5,17} = - \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY(i_2, j_2) \sum_{i_3=1}^n EY(i_3, j_1) EY(i_3, j_2).$$

We can use the same argument of (3.28), $A_{5,17} \leq \frac{n^4\sqrt{n}}{2}\delta_4$. Thus

$$B(i_3, j_1) \leq 3\sqrt{n}\delta_4 + \frac{n^4\sqrt{n}}{2}\delta_4.$$

case 9. $(k, l) = (i_3, j_2)$

Note that

$$B(i_3, j_2) = A_{5,2} + A_{5,6} + A_{5,7} + A_{5,13} + A_{5,14} + A_{5,17} \leq 3\sqrt{n}\delta_4 + \frac{n^4\sqrt{n}}{2}\delta_4.$$

It follows from cases 1-9 and $n \geq 39$ that

$$\begin{aligned} A_5 &= \frac{1}{n(n-1)(n-2)(n-3)} \sum_{i_1=1}^n \sum_{j_1=1}^n EY(i_1, j_1) \sum_{\substack{i_2 \\ i_2 \neq i_1}} \sum_{\substack{j_2 \\ j_2 \neq j_1}} EY(i_2, j_2) \sum_{\substack{i_3 \\ i_3 \neq i_1, i_2}} \sum_{\substack{j_3 \\ j_3 \neq j_1, j_2}} \\ &\quad EY(i_3, j_3) \sum_{\substack{i_4 \\ i_4 \neq i_1, i_2, i_3}} \sum_{\substack{j_4 \\ j_4 \neq j_1, j_2, j_3}} EY(i_4, j_4) \\ &= \frac{1}{n(n-1)(n-2)(n-3)} \sum_{k=1}^3 \sum_{l=1}^3 B(i_k, j_l) \\ &\leq \frac{(24\sqrt{n}\delta_4 + 3n^2\sqrt{n}\delta_4 + 3n^4\sqrt{n}\delta_4)}{n(n-1)(n-2)(n-3)} \\ &= \frac{24}{n(n-1)(n-2)(n-3)} \sqrt{n}\delta_4 + 3\left(\frac{n}{n-1}\right)\left(\frac{1}{n-2}\right)\left(\frac{1}{n-3}\right) \sqrt{n}\delta_4 \\ &\quad + 3\left(\frac{n}{n-1}\right)\left(\frac{n}{n-2}\right)\left(\frac{n}{n-3}\right) \sqrt{n}\delta_4 \\ &\leq 3.517\sqrt{n}\delta_4. \end{aligned} \tag{3.29}$$

Now, we conclude from (3.21), (3.22), (3.23), (3.25), (3.27) and (3.29) that

$$ES^4(\rho) \leq 4.678\sqrt{n}\delta_4.$$

□

Lemma 3.5. *Let $S(\rho)$ be defined as in (3.12). Then for $n \geq 6^{(d+1)} + 3$,*

$$ES^4(\rho) \leq 4.678\sqrt{n}\delta_4.$$

Proof. From Lemma 3.4, it suffices to proof the lemma in case of $d \geq 2$. Note that

$$ES^4(\rho) = A_1 + A_2 + A_3 + A_4 + A_5 \quad (3.30)$$

where

$$\begin{aligned} A_1 &= \sum_{j=1}^n EY^4(j, \rho_1(j), \dots, \rho_d(j)) \\ A_2 &= \sum_{j=1}^n \sum_{\substack{k \\ k \neq j}} EY^3(j, \rho_1(j), \dots, \rho_d(j))Y(k, \rho_1(k), \dots, \rho_d(k)) \\ A_3 &= \sum_{j=1}^n \sum_{\substack{k \\ k \neq j}} EY^2(j, \rho_1(j), \dots, \rho_d(j))Y^2(k, \rho_1(k), \dots, \rho_d(k)) \\ A_4 &= \sum_{j=1}^n \sum_{\substack{k \\ k \neq j}} \sum_{\substack{l \\ l \neq j, k}} EY^2(j, \rho_1(j), \dots, \rho_d(j))Y(k, \rho_1(k), \dots, \rho_d(k)) \\ &\quad \times Y(l, \rho_1(l), \dots, \rho_d(l)) \\ A_5 &= \sum_{j=1}^n \sum_{\substack{k \\ k \neq j}} \sum_{\substack{l \\ l \neq j, k}} \sum_{\substack{m \\ m \neq j, k, l}} EY(j, \rho_1(j), \dots, \rho_d(j))Y(k, \rho_1(k), \dots, \rho_d(k)) \\ &\quad \times Y(l, \rho_1(l), \dots, \rho_d(l))Y(m, \rho_1(m), \dots, \rho_d(m)). \end{aligned} \quad (3.31)$$

We observe that

$$\begin{aligned} \left(\frac{n}{n-1}\right)^d &= \left(1 + \frac{1}{n-1}\right)^d \\ &= 1 + \frac{d}{n-1} + \sum_{r=2}^d \binom{d}{r} \frac{1}{(n-1)^r} \\ &\leq 1 + \frac{d}{n-1} + \sum_{r=2}^d \frac{d^r}{r!(n-1)^r} \end{aligned}$$

$$\begin{aligned} &\leq 1 + \frac{d}{(n-1)} + \frac{1}{2} \sum_{r=2}^d \left(\frac{d}{n-1}\right)^r \\ &\leq 1.03 \end{aligned} \quad (3.32)$$

where we have used the fact that $\frac{d}{n-1} \leq \frac{d}{6^{(d+1)}+2} \leq \frac{1}{50}$ in the last inequality. By (3.32) and the fact that $n \geq 6^{(d+1)} + 3 \geq 219$, we can follow argument of Lemma 3.4 to show that

$$A_1 \leq 0.004\sqrt{n}\delta_4, \quad A_2 \leq 0.000002\sqrt{n}\delta_4, \quad A_3 \leq 1.03\sqrt{n}\delta_4, \quad A_4 \leq 1.09\sqrt{n}\delta_4. \quad (3.33)$$

Hence we need to bound only A_5 . Note that on expansion,

$$\begin{aligned} &\sum_{j=1}^n \sum_{j_1=1}^n \dots \sum_{j_d=1}^n EY(j, j_1, \dots, j_d) \sum_{\substack{k \\ k \neq j}} \sum_{\substack{k_1 \\ k_1 \neq j_1}} \dots \sum_{\substack{k_d \\ k_d \neq j_d}} EY(k, k_1, \dots, k_d) \sum_{\substack{l \\ l \neq j, k}} \sum_{\substack{l_1 \\ l_1 \neq j_1, k_1}} \dots \sum_{\substack{l_d \\ l_d \neq j_d, k_d}} \\ &EY(l, l_1, \dots, l_d) \sum_{\substack{m \\ m \neq j, k, l}} \sum_{\substack{m_1 \\ m_1 \neq j_1, k_1, l_1}} \dots \sum_{\substack{m_d \\ m_d \neq j_d, k_d, l_d}} EY(m, m_1, \dots, m_d) \end{aligned}$$

consists of a sum of 3^{d+1} terms each of the form

$$\begin{aligned} B(q_1, \dots, q_{d+1}) &= (-1)^{d+1} \sum_{j_1=1}^n \sum_{j_2=1}^n \dots \sum_{j_{d+1}=1}^n EY(j_1, j_2, \dots, j_{d+1}) \sum_{\substack{k_1 \\ k_1 \neq j_1}} \sum_{\substack{k_2 \\ k_2 \neq j_2}} \dots \sum_{\substack{k_{d+1} \\ k_{d+1} \neq j_{d+1}}} \\ &EY(k_1, k_2, \dots, k_{d+1}) \sum_{\substack{l_1 \\ l_1 \neq j_1, k_1}} \sum_{\substack{l_2 \\ l_2 \neq j_2, k_2}} \dots \sum_{\substack{l_{d+1} \\ l_{d+1} \neq j_{d+1}, k_{d+1}}} \\ &EY(l_1, l_2, \dots, l_{d+1}) EY(q_1, q_2, \dots, q_{d+1}) \end{aligned}$$

where $q_i \in \{j_i, k_i, l_i\}$ for $i = 1, \dots, d+1$.

case 1. $\forall i \in \{1, \dots, d+1\}, q_i = l_i$.

In this case, we have

$$\begin{aligned} &B(l_1, \dots, l_{d+1}) \\ &\leq \left(\sum_{j_1=1}^n \sum_{j_2=1}^n \dots \sum_{j_{d+1}=1}^n E|Y(j_1, j_2, \dots, j_{d+1})| \right)^2 \sum_{l_1=1}^n \sum_{l_2=1}^n \dots \sum_{l_{d+1}=1}^n (EY(l_1, l_2, \dots, l_{d+1}))^2 \\ &\leq n^{d+1} \left(\sum_{j_1=1}^n \sum_{j_2=1}^n \dots \sum_{j_{d+1}=1}^n EY^2(j_1, j_2, \dots, j_{d+1}) \right)^2 \\ &\leq n^{2(d+1)} \sum_{j_1=1}^n \sum_{j_2=1}^n \dots \sum_{j_{d+1}=1}^n EY^4(j_1, j_2, \dots, j_{d+1}) \\ &= n^{3d+1} \sqrt{n} \delta_4. \end{aligned}$$

case 2. $\exists i \in \{1, \dots, d+1\}$, $q_i \neq l_i$.

It suffices to prove only case $q_1 = l_1, \dots, q_s = l_s, q_{s+1} \neq l_{s+1}, \dots, q_{d+1} \neq l_{d+1}$ for some $s \in \{0, \dots, d\}$.

We observe that

$$\begin{aligned} B(q_1, \dots, q_{d+1}) &= (-1)^{d+1} \sum_{j_1=1}^n \sum_{j_2=1}^n \dots \sum_{j_{d+1}=1}^n EY(j_1, j_2, \dots, j_{d+1}) \sum_{\substack{k_1 \\ k_1 \neq j_1}} \sum_{\substack{k_2 \\ k_2 \neq j_2}} \dots \sum_{\substack{k_{d+1} \\ k_{d+1} \neq j_{d+1}}} \\ & EY(k_1, k_2, \dots, k_{d+1}) \sum_{\substack{l_1 \\ l_1 \neq j_1, k_1}} \dots \sum_{\substack{l_s \\ l_s \neq j_s, k_s}} EY(l_1, \dots, l_s, q_{s+1}, \dots, q_{d+1}) \\ & \sum_{\substack{l_{s+1} \\ l_{s+1} \neq j_{s+1}, k_{s+1}}} \dots \sum_{\substack{l_{d+1} \\ l_{d+1} \neq j_{d+1}, k_{d+1}}} EY(l_1, l_2, \dots, l_{d+1}). \end{aligned}$$

Note that for fixed $j_1, j_2, \dots, j_{d+1}, k_1, k_2, \dots, k_{d+1}$,

$$\begin{aligned} & \sum_{\substack{l_1 \\ l_1 \neq j_1, k_1}} \dots \sum_{\substack{l_s \\ l_s \neq j_s, k_s}} EY(l_1, \dots, l_s, q_{s+1}, \dots, q_{d+1}) \\ & \sum_{\substack{l_{s+1} \\ l_{s+1} \neq j_{s+1}, k_{s+1}}} \dots \sum_{\substack{l_{d+1} \\ l_{d+1} \neq j_{d+1}, k_{d+1}}} EY(l_1, l_2, \dots, l_{d+1}) \end{aligned}$$

consists of a sum of 2^{d-s+1} terms each of the form

$$\begin{aligned} C(r_{s+1}, \dots, r_{d+1}) &= (-1)^{d-s+1} \sum_{\substack{l_1 \\ l_1 \neq j_1, k_1}} \dots \sum_{\substack{l_s \\ l_s \neq j_s, k_s}} \\ & EY(l_1, \dots, l_s, q_{s+1}, \dots, q_{d+1}) EY(l_1, \dots, l_s, r_{s+1}, \dots, r_{d+1}) \end{aligned}$$

where $r_i \in \{j_i, k_i\}$ for $i = s+1, \dots, d+1$, and

$$\begin{aligned} & |C(r_{s+1}, \dots, r_{d+1})| \\ & \leq \frac{1}{2} \sum_{\substack{l_1 \\ l_1 \neq j_1, k_1}} \dots \sum_{\substack{l_s \\ l_s \neq j_s, k_s}} \{EY^2(l_1, \dots, l_s, q_{s+1}, \dots, q_{d+1}) + EY^2(l_1, \dots, l_s, r_{s+1}, \dots, r_{d+1})\} \\ & \leq \sum_{l_1=1}^n \dots \sum_{l_{d+1}=1}^n EY^2(l_1, \dots, l_{d+1}). \end{aligned}$$

By this fact and $s \geq 0$,

$$\begin{aligned}
B(q_1, \dots, q_{d+1}) &\leq 2^{d-s+1} \sum_{j_1=1}^n \sum_{j_2=1}^n \dots \sum_{j_{d+1}=1}^n E|Y(j_1, j_2, \dots, j_{d+1})| \\
&\quad \sum_{\substack{k_1 \\ k_1 \neq j_1}} \sum_{\substack{k_2 \\ k_2 \neq j_2}} \dots \sum_{\substack{k_{d+1} \\ k_{d+1} \neq j_{d+1}}} E|Y(k_1, k_2, \dots, k_{d+1})| \\
&\quad \sum_{l_1=1}^n \sum_{l_2=1}^n \dots \sum_{l_{d+1}=1}^n EY^2(l_1, l_2, \dots, l_{d+1}) \\
&\leq 2^{d-s+1} \left(\sum_{j_1=1}^n \sum_{j_2=1}^n \dots \sum_{j_{d+1}=1}^n E|Y(j_1, j_2, \dots, j_{d+1})| \right)^2 \\
&\quad \sum_{l_1=1}^n \sum_{l_2=1}^n \dots \sum_{l_{d+1}=1}^n EY^2(l_1, l_2, \dots, l_{d+1}) \\
&\leq 2^{d+1} n^{d+1} \left(\sum_{j_1=1}^n \sum_{j_2=1}^n \dots \sum_{j_{d+1}=1}^n EY^2(j_1, j_2, \dots, j_{d+1}) \right)^2 \\
&\leq 2^{d+1} n^{2d+2} \sum_{j_1=1}^n \sum_{j_2=1}^n \dots \sum_{j_{d+1}=1}^n EY^4(j_1, j_2, \dots, j_{d+1}) \\
&= 2^{d+1} n^{3d+1} \sqrt{n} \delta_4.
\end{aligned}$$

It follows from case 1. and case 2. that

$$\begin{aligned}
A_5 &\leq \frac{3^{d+1} 2^{d+1} n^{3d+1} \sqrt{n}}{(n(n-1)(n-2)(n-3))^d} \delta_4 \\
&= 6^{d+1} \left(\frac{n}{n-1} \right)^d \left(\frac{n}{n-2} \right)^d \left(\frac{n}{n-3} \right)^d \frac{1}{(n-3)^{d-1}} \sqrt{n} \delta_4 \\
&\leq 1.075 \sqrt{n} \delta_4
\end{aligned} \tag{3.34}$$

where we have used (3.32) and the fact that $n \geq 6^{(d+1)} + 3 \geq 219$ in the last inequality.

Now we conclude from (3.30), (3.33) and (3.34) that, for $d \geq 2$,

$$ES^4(\rho) \leq 3.199 \sqrt{n} \delta_4 \leq 4.678 \sqrt{n} \delta_4.$$

□

Lemma 3.6. *Let*

$$S(\tau) = \sum_{i=1}^n Y(i, \tau_1(i), \dots, \tau_d(i)).$$

Then $S(\tau)$ and $G^2\mathbb{I}(A)$ are conditionally independent given τ_1, \dots, τ_d where

$$A = \{\tau_i(I) \neq L_i, \tau_i(K) \neq M_i, \tau_i(I) \neq M_i, \tau_i(K) \neq L_i : i = 1, 2, \dots, d\}$$

and

$$G = Y(I, M_1, \dots, M_d) + Y(K, L_1, \dots, L_d) - Y(I, L_1, \dots, L_d) - Y(K, M_1, \dots, M_d).$$

Proof. We shall first prove lemma in case of $d = 1$. Let α be a permutation of $\{1, 2, \dots, n\}$ and $x, y \in \mathbb{R}$. We observe from (3.7) that

$$\begin{aligned} & P\left(\sum_{j=1}^n Y(j, \tau_1(j)) \leq x, G^2\mathbb{I}(A) \leq y, \tau_1 = \alpha\right) \\ &= P\left(\sum_{j=1}^n Y(j, \tau_1(j)) \leq x, G^2\mathbb{I}(A) \leq y, \tau_1 = \alpha, \mathbb{I}(A) = 0\right) \\ &\quad + P\left(\sum_{j=1}^n Y(j, \tau_1(j)) \leq x, G^2\mathbb{I}(A) \leq y, \tau_1 = \alpha, \mathbb{I}(A) = 1\right) \\ &= P\left(\sum_{j=1}^n Y(j, \tau_1(j)) \leq x, 0 \leq y, \tau_1 = \alpha, (\tau_1(I) = L) \vee (\tau_1(K) = M) \vee (\tau_1(I) = M) \right. \\ &\quad \left. \vee (\tau_1(K) = L)\right) + P\left(\sum_{j=1}^n Y(j, \tau_1(j)) \leq x, [Y(I, M) + Y(K, L) - Y(I, L) \right. \\ &\quad \left. - Y(K, M)]^2 \leq y, \tau_1 = \alpha, \tau_1(I) \neq L, \tau_1(K) \neq M, \tau_1(I) \neq M, \tau_1(K) \neq L\right) \\ &= P\left(\sum_{j=1}^n Y(j, \alpha(j)) \leq x, 0 \leq y, \tau_1 = \alpha, (\tau_1(I) = L) \vee (\tau_1(K) = M) \vee (\tau_1(I) = M) \right. \\ &\quad \left. \vee (\tau_1(K) = L)\right) + \sum_{i=1}^n \sum_{\substack{k \\ k \neq i}}^n \sum_{l=1}^n \sum_{\substack{m \\ m \neq l}}^n P\left(\sum_{j=1}^n Y(j, \alpha(j)) \leq x, [Y(i, m) + Y(k, l) \right. \\ &\quad \left. - Y(i, l) - Y(k, m)]^2 \leq y, \tau_1 = \alpha, \alpha(i) \neq l, \alpha(k) \neq m, \alpha(i) \neq m, \alpha(k) \neq l, I = i, \right. \\ &\quad \left. K = k, L = l, M = m\right) \\ &= P\left(\sum_{j=1}^n Y(j, \alpha(j)) \leq x\right) \{P(0 \leq y, \tau_1 = \alpha, (\tau_1(I) = L) \vee (\tau_1(K) = M) \vee (\tau_1(I) = M) \right. \\ &\quad \left. \vee (\tau_1(K) = L)\right) + \sum_{i=1}^n \sum_{\substack{k \\ k \neq i}}^n \sum_{l=1}^n \sum_{\substack{m \\ m \neq l}}^n P([Y(i, m) + Y(k, l) - Y(i, l) - Y(k, m)]^2 \leq y, \\ &\quad \tau_1 = \alpha, \alpha(i) \neq l, \alpha(k) \neq m, \alpha(i) \neq m, \alpha(k) \neq l, I = i, K = k, L = l, M = m)\} \end{aligned}$$

$$\begin{aligned}
&= P\left(\sum_{j=1}^n Y(j, \alpha(j)) \leq x\right) \{P(0 \leq y, \tau_1 = \alpha, (\tau_1(I) = L) \vee (\tau_1(K) = M) \vee (\tau_1(I) = M) \\
&\quad \vee (\tau_1(K) = L)) + P([Y(I, M) + Y(K, L) - Y(I, L) - Y(K, M)]^2 \leq y, \tau_1 = \alpha, \\
&\quad \tau_1(I) \neq L, \tau_1(K) \neq M, \tau_1(I) \neq M, \tau_1(K) \neq L)\} \\
&= P\left(\sum_{j=1}^n Y(j, \alpha(j)) \leq x\right) \{P(G^2\mathbb{I}(A) \leq y, \tau_1 = \alpha, \mathbb{I}(A) = 0) \\
&\quad + P(G^2\mathbb{I}(A) \leq y, \tau_1 = \alpha, \mathbb{I}(A) = 1)\} \\
&= \frac{1}{P(\tau_1 = \alpha)} P\left(\sum_{j=1}^n Y(j, \alpha(j)) \leq x, \tau_1 = \alpha\right) P(G^2\mathbb{I}(A) \leq y, \tau_1 = \alpha) \\
&= P\left(\sum_{j=1}^n Y(j, \tau_1(j)) \leq x, \tau_1 = \alpha\right) P(G^2\mathbb{I}(A) \leq y | \tau_1 = \alpha).
\end{aligned}$$

By this fact,

$$\begin{aligned}
&P\left(\sum_{j=1}^n Y(j, \tau_1(j)) \leq x, G^2\mathbb{I}(A) \leq y | \tau_1 = \alpha\right) \\
&= \frac{1}{P(\tau_1 = \alpha)} P\left(\sum_{j=1}^n Y(j, \tau_1(j)) \leq x, G^2\mathbb{I}(A) \leq y, \tau_1 = \alpha\right) \\
&= \frac{1}{P(\tau_1 = \alpha)} P\left(\sum_{j=1}^n Y(j, \tau_1(j)) \leq x, \tau_1 = \alpha\right) P(G^2\mathbb{I}(A) \leq y | \tau_1 = \alpha) \\
&= P\left(\sum_{j=1}^n Y(j, \tau_1(j)) \leq x | \tau_1 = \alpha\right) P(G^2\mathbb{I}(A) \leq y | \tau_1 = \alpha).
\end{aligned}$$

By the same argument, we can prove lemma in the case of an arbitrary d . □

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3.2 Proof of Theorem 3.1

Proof. We shall prove Theorem 3.1 by using Stein's method. Note from (2.3) and Lemma 3.3 that

$$\begin{aligned}
|P(W \leq z) - \Phi(z)| &= |Eg'_z(W) - EWg_z(W)| \\
&= |Eg'_z(S(\tau)) - ES(\rho)g_z(S(\rho))| \\
&= |Eg'_z(S(\tau)) - E \int_{-\infty}^{\infty} g'_z(S(\rho) + t)M(t)dt + \Delta g_z(S(\rho))| \\
&\leq |Eg'_z(S(\tau)) \int_{-\infty}^{\infty} M(t)dt - E \int_{-\infty}^{\infty} g'_z(S(\rho) + t)M(t)dt| \\
&\quad + |Eg'_z(S(\tau))E \int_{-\infty}^{\infty} M(t)dt - Eg'_z(S(\tau)) \int_{-\infty}^{\infty} M(t)dt| \\
&\quad + |Eg'_z(S(\tau)) - Eg'_z(S(\tau))E \int_{-\infty}^{\infty} M(t)dt| \\
&\quad + |\Delta g_z(S(\rho))| \\
&= |T_1| + |T_2| + |T_3| + |T_4|
\end{aligned} \tag{3.35}$$

where

$$\begin{aligned}
T_1 &= Eg'_z(S(\tau)) \int_{-\infty}^{\infty} M(t)dt - E \int_{-\infty}^{\infty} g'_z(S(\rho) + t)M(t)dt, \\
T_2 &= Eg'_z(S(\tau))E \int_{-\infty}^{\infty} M(t)dt - Eg'_z(S(\tau)) \int_{-\infty}^{\infty} M(t)dt, \\
T_3 &= Eg'_z(S(\tau)) - Eg'_z(S(\tau))E \int_{-\infty}^{\infty} M(t)dt
\end{aligned}$$

and $T_4 = \Delta g_z(S(\rho)).$

By the fact that

$$g'_z(w + u) - g'_z(w + v) \leq \begin{cases} 1 & \text{if } w + u < z, w + v > z, \\ (|w| + \frac{\sqrt{2\pi}}{4})(|u| + |v|) & \text{if } u \geq v, \\ 0 & \text{otherwise} \end{cases} \tag{3.36}$$

(see, [6],pp.247), we have

$$\begin{aligned}
T_1 &= E \int_{-\infty}^{\infty} [g'_z(S(\tau)) - g'_z(S(\rho) + t)]M(t)dt \\
&= E \int_{-\infty}^{\infty} [g'_z(S(\rho) + \Delta S) - g'_z(S(\rho) + t)]M(t)dt \quad \text{where } \Delta S = S(\tau) - S(\rho)
\end{aligned}$$

$$\begin{aligned}
&\leq E \int_{\substack{S(\rho)+\Delta S < z \\ S(\rho)+t > z}} M(t)dt + E \int_{t-\Delta S \leq 0} (|S(\rho)| + \frac{\sqrt{2\pi}}{4})(|\Delta S| + |t|)M(t)dt \\
&= M_1 + M_2
\end{aligned}$$

where

$$\begin{aligned}
M_1 &= E \int_{\substack{S(\rho)+\Delta S < z \\ S(\rho)+t > z}} M(t)dt \\
\text{and} \quad M_2 &= E \int_{t-\Delta S \leq 0} (|S(\rho)| + \frac{\sqrt{2\pi}}{4})(|\Delta S| + |t|)M(t)dt.
\end{aligned}$$

For each $\delta \geq 0$ and $a, b \in \mathbb{R}$ which is $a < b$, define a function f_δ by

$$f_\delta(t) = \begin{cases} -\frac{1}{2}(b-a) - \delta & \text{if } t < a - \delta, \\ -\frac{1}{2}(b+a) + t & \text{if } a - \delta \leq t \leq b + \delta, \\ \frac{1}{2}(b-a) + \delta & \text{if } b + \delta < t. \end{cases}$$

It is easy to see that

$$|f_\delta(t)| \leq \frac{1}{2}(b-a) + \delta \quad \text{for every } t \in \mathbb{R}, \quad (3.37)$$

and

$$\begin{aligned}
E \int_{-\infty}^{\infty} f'_\delta(S(\rho) + t)M(t)dt &\geq E \int_{\substack{a \leq S(\rho) \leq b \\ |t| \leq \delta}} f'_\delta(S(\rho) + t)M(t)dt \\
&= E \int_{\substack{a \leq S(\rho) \leq b \\ |t| \leq \delta}} M(t)dt \\
&= E \int_{|t| \leq \delta} \mathbb{I}(a \leq S(\rho) \leq b)M(t)dt. \quad (3.38)
\end{aligned}$$

By Lemma 3.3 and (3.38),

$$\begin{aligned}
E \int_{|t| \leq \delta} \mathbb{I}(a \leq S(\rho) \leq b)M(t)dt &\leq E \int_{-\infty}^{\infty} f'_\delta(S(\rho) + t)M(t)dt \\
&\leq ES(\rho)f_\delta(S(\rho)) + \frac{1}{n-1}[Ef_\delta^2(S(\rho))]^{\frac{1}{2}}. \quad (3.39)
\end{aligned}$$

We note that if $|t| > |\tilde{S}(\rho) - S(\rho)|$,

$$M(t) = 0.$$

Thus we conclude from (3.37) and (3.39) that

$$\begin{aligned}
M_1 &= E \int_{t-\Delta S > 0} \mathbb{I}(z-t < S(\rho) < z-\Delta S) M(t) dt \\
&\leq E \int_{-\infty}^{\infty} \mathbb{I}(z-t < S(\rho) < z-\Delta S) M(t) dt \\
&= E \int_{|t| \leq |\tilde{S}(\rho) - S(\rho)|} \mathbb{I}(z-t < S(\rho) < z-\Delta S) M(t) dt \\
&\leq E \int_{|t| \leq |\tilde{S}(\rho) - S(\rho)|} \mathbb{I}(z - |\tilde{S}(\rho) - S(\rho)| < S(\rho) < z - \Delta S) M(t) dt \\
&\leq ES(\rho) f_{|\tilde{S}(\rho) - S(\rho)|}(S(\rho)) + \frac{1}{n-1} [E f_{|\tilde{S}(\rho) - S(\rho)|}^2(S(\rho))]^{\frac{1}{2}} \\
&\leq E|S(\rho)| \left[\frac{3}{2} |\tilde{S}(\rho) - S(\rho)| - \frac{\Delta S}{2} \right] + \frac{1}{n-1} \left\{ E \left[\frac{3}{2} |\tilde{S}(\rho) - S(\rho)| - \frac{\Delta S}{2} \right]^2 \right\}^{\frac{1}{2}} \\
&\leq \frac{3}{2} E|S(\rho)| |\tilde{S}(\rho) - S(\rho)| + \frac{1}{2} E|\Delta S| |S(\rho)| \\
&\quad + \frac{1}{\sqrt{2}(n-1)} \{9E[\tilde{S}(\rho) - S(\rho)]^2 + E(\Delta S)^2\}^{\frac{1}{2}}. \tag{3.40}
\end{aligned}$$

By Lemma 3.3, when $g(w) = w$, we have

$$\begin{aligned}
E|\tilde{S}(\rho) - S(\rho)|^2 &= \frac{4}{n} E \int_{-\infty}^{\infty} M(t) dt \\
&\leq \frac{4}{n} (ES^2(\rho) + \frac{1}{n-1} [ES^2(\rho)]^{\frac{1}{2}}) \\
&= \frac{4}{n-1}. \tag{3.41}
\end{aligned}$$

Since $ES^2(\rho) = 1$ and (3.41),

$$E|S(\rho)| |\tilde{S}(\rho) - S(\rho)| \leq \sqrt{E|\tilde{S}(\rho) - S(\rho)|^2} \leq \frac{2}{\sqrt{n-1}}. \tag{3.42}$$

Let

$$\delta_2 = \frac{1}{n^{d+\frac{1}{2}}} \sum_{i_1=1}^n \dots \sum_{i_{d+1}=1}^n E|Y(i_1, \dots, i_{d+1})|^2.$$

Since $E|\Delta S|^k$ is a sum of $4(d+1)$ terms each of the form $E|Y(I, \rho_1(I), \dots, \rho_d(I))|^k$,

$$E|\Delta S|^k \leq \frac{4(d+1)\delta_k}{n^{\frac{k-1}{2}}} \tag{3.43}$$

for $k = 2, 4$. By this fact

$$E|\Delta S| |S(\rho)| \leq \sqrt{E|\Delta S|^2} \leq \frac{2\sqrt{d+1}\delta_2^{\frac{1}{2}}}{n^{\frac{1}{4}}}. \tag{3.44}$$

From (3.40)-(3.44),

$$\begin{aligned} M_1 &\leq \frac{3}{\sqrt{n-1}} + \frac{\sqrt{d+1}\delta_2^{\frac{1}{2}}}{n^{\frac{1}{4}}} + \frac{1}{\sqrt{2}(n-1)} \left\{ \frac{36}{n-1} + \frac{4(d+1)\delta_2}{\sqrt{n}} \right\}^{\frac{1}{2}} \\ &\leq \frac{3.202}{\sqrt{n}} + \frac{1.037\sqrt{d+1}\delta_2^{\frac{1}{2}}}{n^{\frac{1}{4}}} \end{aligned}$$

where we have used the fact that $n \geq 39$ in the last inequality. In order to bound M_2 , we need to bound $E|\tilde{S}(\rho) - S(\rho)|^k$, $k = 3, 4$.

Let

$$\delta_3 = \frac{1}{n^d} \sum_{i_1=1}^n \cdots \sum_{i_{d+1}=1}^n E|Y(i_1, \dots, i_{d+1})|^3.$$

We note that for $k = 3, 4$,

$$E|S_1|^k = \frac{1}{n^{d+1}} \sum_{i=1}^n \sum_{i_1=1}^n \cdots \sum_{i_d=1}^n |Y(i, i_1, \dots, i_d)|^k = \frac{\delta_k}{n^{\frac{k-1}{2}}} \quad (3.45)$$

which implies

$$E|\tilde{S}(\rho) - S(\rho)|^k = E|S_1 + S_2 - S_3 - S_4|^k \leq 4^k E|S_1|^k = \frac{4^k \delta_k}{n^{\frac{k-1}{2}}} \quad (3.46)$$

where we have used the fact that S_1, S_2, S_3 and S_4 have the same distribution in the first inequality. By Lemma 3.5, (3.43) and (3.46),

$$\begin{aligned} E \int_{\mathbb{R}} |S(\rho)| |\Delta S| M(t) dt &= \frac{n}{4} E|S(\rho)| |\Delta S| (\tilde{S}(\rho) - S(\rho))^2 \\ &\leq \frac{n}{4} \{ES^2(\rho)(\Delta S)^2\}^{\frac{1}{2}} \{E|\tilde{S}(\rho) - S(\rho)|^4\}^{\frac{1}{2}} \\ &\leq \frac{n}{4} \{ES^4(\rho)\}^{\frac{1}{4}} \{E(\Delta S)^4\}^{\frac{1}{4}} \{E|\tilde{S}(\rho) - S(\rho)|^4\}^{\frac{1}{2}} \\ &\leq \frac{n}{4} \{4.678\sqrt{n}\delta_4\}^{\frac{1}{4}} \left\{ \frac{4(d+1)\delta_4}{n\sqrt{n}} \right\}^{\frac{1}{4}} \left\{ \frac{256\delta_4}{n\sqrt{n}} \right\}^{\frac{1}{2}} \\ &= 8.314(d+1)^{\frac{1}{4}}\delta_4. \end{aligned} \quad (3.47)$$

Hence by Lemma 3.5, (3.43), (3.46) and (3.47),

$$\begin{aligned} M_2 &\leq E \int_{\mathbb{R}} |S(\rho)| |\Delta S| M(t) dt + E \int_{\mathbb{R}} |S(\rho)| |t| M(t) dt \\ &\quad + \frac{\sqrt{2\pi}}{4} E \int_{\mathbb{R}} |\Delta S| M(t) dt + \frac{\sqrt{2\pi}}{4} E \int_{\mathbb{R}} |t| M(t) dt \end{aligned}$$

$$\begin{aligned}
&\leq 8.314(d+1)^{\frac{1}{4}}\delta_4 + \frac{n}{8}E|S(\rho)||\tilde{S}(\rho) - S(\rho)|^3 \\
&\quad + \frac{\sqrt{2\pi n}}{16}E|\Delta S|(\tilde{S}(\rho) - S(\rho))^2 + \frac{\sqrt{2\pi n}}{32}E|\tilde{S}(\rho) - S(\rho)|^3 \\
&\leq 8.314(d+1)^{\frac{1}{4}}\delta_4 + \frac{n}{8}\{ES^4(\rho)\}^{\frac{1}{4}}\{E|\tilde{S}(\rho) - S(\rho)|^4\}^{\frac{3}{4}} \\
&\quad + \frac{\sqrt{2\pi n}}{16}\{E|\Delta S|^2\}^{\frac{1}{2}}\{E|\tilde{S}(\rho) - S(\rho)|^4\}^{\frac{1}{2}} + \frac{\sqrt{2\pi n}}{32}\{E|\tilde{S}(\rho) - S(\rho)|^4\}^{\frac{3}{4}} \\
&\leq 8.314(d+1)^{\frac{1}{4}}\delta_4 + 11.765\delta_4 + 5.014(d+1)\delta_2^{\frac{1}{2}}\delta_4^{\frac{1}{2}} + \frac{2\sqrt{2\pi}\delta_4^{\frac{3}{4}}}{n^{\frac{1}{8}}}
\end{aligned}$$

which implies that

$$\begin{aligned}
T_1 &\leq \frac{3.202}{\sqrt{n}} + \frac{1.037\sqrt{d+1}\delta_2^{\frac{1}{2}}}{n^{\frac{1}{4}}} + 8.314(d+1)^{\frac{1}{4}}\delta_4 + 11.765\delta_4 + 5.014(d+1)\delta_2^{\frac{1}{2}}\delta_4^{\frac{1}{2}} \\
&\quad + \frac{2\sqrt{2\pi}\delta_4^{\frac{3}{4}}}{n^{\frac{1}{8}}}. \tag{3.48}
\end{aligned}$$

By the same argument as in (3.48), by using the fact that

$$g'_z(w+u) - g'_z(w+v) \geq \begin{cases} -1 & \text{if } w+u > z, w+v < z, \\ -(|w| + \frac{\sqrt{2\pi}}{4})(|u| + |v|) & \text{if } u < v, \\ 0 & \text{otherwise} \end{cases}$$

(see[6],pp.247) instead of (3.36), we can show that

$$\begin{aligned}
T_1 &\geq -\frac{3.202}{\sqrt{n}} - \frac{1.037\sqrt{d+1}\delta_2^{\frac{1}{2}}}{n^{\frac{1}{4}}} - 8.314(d+1)^{\frac{1}{4}}\delta_4 - 11.765\delta_4 - 5.014(d+1)\delta_2^{\frac{1}{2}}\delta_4^{\frac{1}{2}} \\
&\quad - \frac{2\sqrt{2\pi}\delta_4^{\frac{3}{4}}}{n^{\frac{1}{8}}}.
\end{aligned}$$

Hence, we have

$$\begin{aligned}
|T_1| &\leq \frac{3.202}{\sqrt{n}} + \frac{1.037\sqrt{d+1}\delta_2^{\frac{1}{2}}}{n^{\frac{1}{4}}} + 8.314(d+1)^{\frac{1}{4}}\delta_4 + 11.765\delta_4 + 5.014(d+1)\delta_2^{\frac{1}{2}}\delta_4^{\frac{1}{2}} \\
&\quad + \frac{2\sqrt{2\pi}\delta_4^{\frac{3}{4}}}{n^{\frac{1}{8}}}. \tag{3.49}
\end{aligned}$$

Next, we shall bound T_2 by using the technique from Lemma 4.10 of Ho and Chen([9],pp.245).

Let A and G be defined as in Lemma 3.6, i.e.,

$$A = \{\tau_i(I) \neq L_i, \tau_i(K) \neq M_i, \tau_i(I) \neq M_i, \tau_i(K) \neq L_i : i = 1, 2, \dots, d\}$$

and

$$G = Y(I, M_1, \dots, M_d) + Y(K, L_1, \dots, L_d) - Y(I, L_1, \dots, L_d) - Y(K, M_1, \dots, M_d).$$

Note that $EG^2 = E^{\tau_1, \dots, \tau_d}G^2$ by independence of τ_1, \dots, τ_d and G . From this fact and (3.11),

$$\begin{aligned}
|T_2| &= \frac{n}{4} |Eg'_z(S(\tau))E(\tilde{S}(\rho) - S(\rho))^2 - Eg'_z(S(\tau))(\tilde{S}(\rho) - S(\rho))^2| \\
&= \frac{n}{4} |Eg'_z(S(\tau))EG^2 - Eg'_z(S(\tau))G^2| \\
&= \frac{n}{4} |Eg'_z(S(\tau))E^{\tau_1, \dots, \tau_d}G^2 - Eg'_z(S(\tau))G^2| \\
&\leq \frac{n}{4} |Eg'_z(S(\tau))E^{\tau_1, \dots, \tau_d}G^2\mathbb{I}(A) - Eg'_z(S(\tau))G^2\mathbb{I}(A)| \\
&\quad + \frac{n}{4} |Eg'_z(S(\tau))E^{\tau_1, \dots, \tau_d}G^2\mathbb{I}(A^c) - Eg'_z(S(\tau))G^2\mathbb{I}(A^c)|. \tag{3.50}
\end{aligned}$$

By Lemma 3.6 and Proposition 2.13,

$$\begin{aligned}
E[g'_z(S(\tau))G^2\mathbb{I}(A)] &= E\{[E^{\tau_1, \dots, \tau_d}g'_z(S(\tau))][E^{\tau_1, \dots, \tau_d}G^2\mathbb{I}(A)]\} \\
&= EE^{\tau_1, \dots, \tau_d}[g'_z(S(\tau))E^{\tau_1, \dots, \tau_d}G^2\mathbb{I}(A)] \\
&= E[g'_z(S(\tau))E^{\tau_1, \dots, \tau_d}G^2\mathbb{I}(A)].
\end{aligned}$$

This implies the first term on the right-hand side of (3.50) is zero. Hence

$$|T_2| \leq \frac{n}{4} |Eg'_z(S(\tau))E^{\tau_1, \dots, \tau_d}G^2\mathbb{I}(A^c) - Eg'_z(S(\tau))G^2\mathbb{I}(A^c)|. \tag{3.51}$$

Let \mathcal{B} be the σ -algebra generated by

$$\{I, K, L_1, \dots, L_d, M_1, \dots, M_d, Y(i_1, \dots, i_{d+1}) : 1 \leq i_1, \dots, i_{d+1} \leq n\}.$$

Note from Theorem 2.11 that

$$E^{\mathcal{B}}\mathbb{I}(A) = E^{I, K, L_1, \dots, L_d, M_1, \dots, M_d}\mathbb{I}(A).$$

By this fact,

$$\begin{aligned}
E^{\mathcal{B}}\mathbb{I}(A^c) &= 1 - E^{\mathcal{B}}\mathbb{I}(A) \\
&= 1 - E^{I, K, L_1, \dots, L_d, M_1, \dots, M_d}\mathbb{I}(A) \\
&= 1 - \left\{ \frac{(n-2)(n-3)[(n-2)]!}{n!} \right\}^d \\
&= 1 - \left[1 + \frac{6-4n}{n(n-1)} \right]^d \\
&\leq \sum_{r=1}^d \binom{d}{r} \left(\frac{4n-6}{n(n-1)} \right)^r
\end{aligned}$$

$$\begin{aligned}
&\leq \sum_{r=1}^d \binom{d}{r} \left(\frac{4}{n}\right)^r \\
&\leq \frac{4}{n} \sum_{r=1}^d \binom{d}{r}.
\end{aligned} \tag{3.52}$$

From (3.52) and the fact that $\sum_{r=1}^d \binom{d}{r} \leq \sqrt{n}$ for $n \geq 6^{(d+1)} + 3$, we have

$$E^{\mathcal{B}}\mathbb{I}(A^c) \leq \frac{4}{\sqrt{n}}. \tag{3.53}$$

By replacing $g(W)$ by W in Lemma 3.3 we have

$$\left|E \int_{-\infty}^{\infty} M(t)dt - 1\right| \leq \frac{1}{n-1} [E(S(\rho))^2]^{\frac{1}{2}} = \frac{1}{n-1}. \tag{3.54}$$

Thus, we conclude from the fact that

$$|g'_z(w)| \leq 1 \tag{3.55}$$

(see[26],pp.23), (3.51), (3.53) and (3.54),

$$\begin{aligned}
|T_2| &\leq \frac{n}{4} [E|g'_z(S(\tau))| |E^{\tau_1, \dots, \tau_d} G^2 \mathbb{I}(A^c)| + E|g'_z(S(\tau))| |G^2 \mathbb{I}(A^c)|] \\
&\leq \frac{n}{2} E[G^2 \mathbb{I}(A^c)] \\
&= \frac{n}{2} E[G^2 E^{\mathcal{B}} \mathbb{I}(A^c)] \\
&\leq 2\sqrt{n} E G^2 \\
&= \frac{8}{\sqrt{n}} E \int_{-\infty}^{\infty} M(t)dt \\
&\leq \frac{8.416}{\sqrt{n}}
\end{aligned} \tag{3.56}$$

where we have used the fact that $n \geq 39$ in the last inequality. Next, we will find a bound for T_3 and T_4 . From (3.54) and (3.55),

$$T_3 \leq \frac{1}{n-1} \tag{3.57}$$

and, from the fact that $0 \leq g_z(w) \leq 1$ (see[26],pp.23) and (3.15),

$$T_4 \leq \frac{1}{n-1}. \tag{3.58}$$

Hence we conclude from (3.35), (3.49), (3.56), (3.57) and (3.58) that

$$\begin{aligned}
|P(W \leq z) - \Phi(z)| &\leq \frac{11.946}{\sqrt{n}} + \frac{1.037\sqrt{d+1}\delta_2^{\frac{1}{2}}}{n^{\frac{1}{4}}} + 8.314(d+1)^{\frac{1}{4}}\delta_4 + 11.765\delta_4 \\
&\quad + 5.014(d+1)\delta_2^{\frac{1}{2}}\delta_4^{\frac{1}{2}} + \frac{2\sqrt{2\pi}\delta_4^{\frac{3}{4}}}{n^{\frac{1}{8}}} \\
&\leq \frac{11.946}{\sqrt{n}} + \frac{1.037\sqrt{d+1}\delta_4^{\frac{1}{4}}}{n^{\frac{3}{8}}} + 8.314(d+1)^{\frac{1}{4}}\delta_4 + 11.765\delta_4 \\
&\quad + 5.014(d+1)\frac{\delta_4^{\frac{3}{4}}}{n^{\frac{1}{8}}} + \frac{2\sqrt{2\pi}\delta_4^{\frac{3}{4}}}{n^{\frac{1}{8}}}
\end{aligned}$$

where we have used the fact that

$$\delta_2^2 \leq \frac{1}{n^{d+1}} \sum_{i_1=1}^n \dots \sum_{i_{d+1}=1}^n EY^4(i_1, \dots, i_{d+1}) = \frac{\delta_4}{\sqrt{n}} \quad (3.59)$$

in the last inequality. □

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CHAPTER IV

A NON-UNIFORM BOUND FOR THE GENERALIZATION OF A COMBINATORIAL CENTRAL LIMIT THEOREM

In this chapter, we use the same notation as in the previous chapter. In chapter 3, we give a uniform bound on the generalization of a combinatorial central limit theorem (Theorem 3.1). In this chapter, we give a non-uniform bound for the approximation of W by Φ .

Theorem 4.1. *Let $z \in \mathbb{R}$. With the notation and assumptions of Theorem 3.1, there exists a positive constant C which does not depend on z such that*

$$|P(W \leq z) - \Phi(z)| \leq \frac{C}{1 + |z|} \left\{ \frac{\delta_8^{\frac{1}{8}}}{n^{\frac{7}{16}}} + \frac{1}{n} + \delta_8 \right\}$$

where

$$\delta_8 = \frac{1}{n^{d-\frac{5}{2}}} \sum_{i_1=1}^n \dots \sum_{i_{d+1}=1}^n E|Y(i_1, \dots, i_{d+1})|^8.$$

Furthermore, if $\delta_8 \sim n^{-1/2}$,

$$|P(W \leq z) - \Phi(z)| \leq \frac{C}{(1 + |z|)\sqrt{n}}.$$

This chapter is organized as follows. Auxiliary results are in section 4.1 while the proof of main result is given in section 4.2.

From now on, C stands for a positive constant with possibly different values in different places.

4.1 Auxiliary Results

In this section, we shall give auxiliary results for proving our main theorem (Theorem 4.1).

Lemma 4.2. For each $i_1, \dots, i_{d+1} \in \{1, \dots, n\}$ and $z > 0$, let

$$Y_z(i_1, \dots, i_{d+1}) = Y(i_1, \dots, i_{d+1})\mathbb{I}(|Y(i_1, \dots, i_{d+1})| > 1 + z),$$

and $\widehat{Y}_z(i_1, \dots, i_{d+1}) = Y(i_1, \dots, i_{d+1})\mathbb{I}(|Y(i_1, \dots, i_{d+1})| \leq 1 + z).$

Then

$$E\left[\sum_{i=1}^n \sum_{k=1}^n \widehat{Y}_z(i, \rho_1(k), \dots, \rho_d(k))\right]^2 \leq Cn^{\frac{5}{4}}\delta_4^{\frac{1}{2}} + Cn^2\delta_4^2.$$

Proof. We observe from (3.3) that

$$\begin{aligned} & \sum_{i,k} \sum_{\substack{l,m \\ (l,m) \neq (i,k)}} EY(i, \rho_1(k), \dots, \rho_d(k))Y(l, \rho_1(m), \dots, \rho_d(m)) \\ &= \sum_{i=1}^n \sum_{k=1}^n \sum_{\substack{l \\ l \neq i}} \sum_{\substack{m \\ m \neq k}} EY(i, \rho_1(k), \dots, \rho_d(k))Y(l, \rho_1(m), \dots, \rho_d(m)) \\ & \quad + \sum_{i=1}^n \sum_{k=1}^n \sum_{\substack{l \\ l \neq i}} EY(i, \rho_1(k), \dots, \rho_d(k))Y(l, \rho_1(k), \dots, \rho_d(k)) \\ & \quad + \sum_{i=1}^n \sum_{k=1}^n \sum_{\substack{m \\ m \neq k}} EY(i, \rho_1(k), \dots, \rho_d(k))Y(i, \rho_1(m), \dots, \rho_d(m)) \\ &= \frac{1}{(n(n-1))^{d-1}} \sum_{k_1=1}^n \dots \sum_{k_{d+1}=1}^n EY(k_1, \dots, k_{d+1}) \sum_{\substack{m_1 \\ m_1 \neq k_1}} \dots \sum_{\substack{m_{d+1} \\ m_{d+1} \neq k_{d+1}}} EY(m_1, \dots, m_{d+1}) \\ & \quad + \frac{1}{n^{d-1}} \sum_{k_1=1}^n \dots \sum_{k_{d+1}=1}^n EY(k_1, \dots, k_{d+1}) \sum_{\substack{l \\ l \neq k_1}} EY(l, k_2, \dots, k_{d+1}) \\ & \quad + \frac{1}{(n(n-1))^{d-1}} \sum_{k_1=1}^n \dots \sum_{k_{d+1}=1}^n EY(k_1, \dots, k_{d+1}) \sum_{\substack{m_2 \\ m_2 \neq k_2}} \dots \sum_{\substack{m_{d+1} \\ m_{d+1} \neq k_{d+1}}} EY(k_1, m_2, \dots, m_{d+1}) \\ &\leq \frac{C}{n^{d-1}} \sum_{k_1=1}^n \dots \sum_{k_{d+1}=1}^n [EY(k_1, \dots, k_{d+1})]^2 \\ &\leq Cn\sqrt{n}\delta_2. \end{aligned}$$

Thus

$$\begin{aligned}
E\left[\sum_{i=1}^n \sum_{k=1}^n Y(i, \rho_1(k), \dots, \rho_d(k))\right]^2 &\leq \sum_{i=1}^n \sum_{k=1}^n EY^2(i, \rho_1(k), \dots, \rho_d(k)) + Cn\sqrt{n}\delta_2 \\
&= \frac{1}{n^{d-1}} \sum_{i_1=1}^n \dots \sum_{i_{d+1}=1}^n EY^2(i_1, \dots, i_{d+1}) + Cn\sqrt{n}\delta_2 \\
&= Cn\sqrt{n}\delta_2.
\end{aligned} \tag{4.1}$$

Note that

$$\begin{aligned}
&E|Y^m(i_1, \dots, i_{d+1})Y_z^n(i_1, \dots, i_{d+1})| \\
&\leq E|Y^m(i_1, \dots, i_{d+1})Y_z^n(i_1, \dots, i_{d+1})| \left(\frac{|Y_z(i_1, \dots, i_{d+1})|}{1+z}\right)^r \\
&\leq \frac{E|Y(i_1, \dots, i_{d+1})|^{m+n+r}}{(1+z)^r}
\end{aligned} \tag{4.2}$$

for any integers m, n and r which $m \geq 0, n, r > 0$. Using the fact that $2ab \leq a^2 + b^2$ and (4.2), we have

$$\begin{aligned}
&\sum_{i,k} \sum_{\substack{l,m \\ (l,m) \neq (i,k)}} EY_z(i, \rho_1(k), \dots, \rho_d(k))Y_z(l, \rho_1(m), \dots, \rho_d(m)) \\
&= \frac{1}{(n(n-1))^{d-1}} \sum_{k_1=1}^n \dots \sum_{k_{d+1}=1}^n EY_z(k_1, \dots, k_{d+1}) \sum_{\substack{m_1 \\ m_1 \neq k_1}} \dots \sum_{\substack{m_{d+1} \\ m_{d+1} \neq k_{d+1}}} EY_z(m_1, \dots, m_{d+1}) \\
&+ \frac{1}{n^{d-1}} \sum_{k_1=1}^n \dots \sum_{k_{d+1}=1}^n EY_z(k_1, \dots, k_{d+1}) \sum_{\substack{l \\ l \neq k_1}} EY_z(l, k_2, \dots, k_{d+1}) \\
&+ \frac{1}{(n(n-1))^{d-1}} \sum_{k_1=1}^n \dots \sum_{k_{d+1}=1}^n EY_z(k_1, \dots, k_{d+1}) \sum_{\substack{m_2 \\ m_2 \neq k_2}} \dots \sum_{\substack{m_{d+1} \\ m_{d+1} \neq k_{d+1}}} EY_z(k_1, m_2, \dots, m_{d+1}) \\
&\leq \frac{C}{n^{2(d-1)}} \left[\sum_{k_1=1}^n \dots \sum_{k_{d+1}=1}^n E|Y_z(k_1, \dots, k_{d+1})|^2 \right] \\
&+ \frac{1}{2n^{d-1}} \sum_{k_1=1}^n \dots \sum_{k_{d+1}=1}^n \sum_{\substack{l \\ l \neq k_1}} \{EY_z^2(k_1, \dots, k_{d+1}) + EY_z^2(l, k_2, \dots, k_{d+1})\} \\
&\leq \frac{C}{n^{2(d-1)}} \left[\sum_{k_1=1}^n \dots \sum_{k_{d+1}=1}^n E|Y_z(k_1, \dots, k_{d+1})|^2 \right] + \frac{C}{n^{d-2}} \sum_{k_1=1}^n \dots \sum_{k_{d+1}=1}^n EY_z^2(k_1, \dots, k_{d+1})
\end{aligned}$$

$$\begin{aligned} &\leq \frac{C}{n^{2(d-1)}} \left[\sum_{k_1=1}^n \cdots \sum_{k_{d+1}=1}^n \frac{EY^4(k_1, \dots, k_{d+1})}{(1+z)^3} \right]^2 + \frac{C}{n^{d-2}} \sum_{k_1=1}^n \cdots \sum_{k_{d+1}=1}^n \frac{EY^4(k_1, \dots, k_{d+1})}{(1+z)^2} \\ &= C\{n\delta_4^2 + n\sqrt{n}\delta_4\}. \end{aligned}$$

Thus

$$\begin{aligned} E\left[\sum_{i=1}^n \sum_{k=1}^n Y_z(i, \rho_1(k), \dots, \rho_d(k))\right]^2 &\leq \sum_{i=1}^n \sum_{k=1}^n EY_z^2(i, \rho_1(k), \dots, \rho_d(k)) + Cn\delta_4^2 + Cn\sqrt{n}\delta_4 \\ &= \frac{1}{n^{d-1}} \sum_{i_1=1}^n \cdots \sum_{i_{d+1}=1}^n EY_z^2(i_1, \dots, i_{d+1}) + Cn\delta_4^2 \\ &\quad + Cn\sqrt{n}\delta_4 \\ &\leq C\{n\sqrt{n}\delta_2 + n\delta_4^2 + n\sqrt{n}\delta_4\}. \end{aligned} \quad (4.3)$$

Now, we conclude from (4.1) and (4.3) that

$$\begin{aligned} &E\left[\sum_{i=1}^n \sum_{k=1}^n \widehat{Y}_z(i, \rho_1(k), \dots, \rho_d(k))\right]^2 \\ &= E\left[\sum_{i=1}^n \sum_{k=1}^n Y(i, \rho_1(k), \dots, \rho_d(k)) - \sum_{i=1}^n \sum_{k=1}^n Y_z(i, \rho_1(k), \dots, \rho_d(k))\right]^2 \\ &\leq 2E\left[\sum_{i=1}^n \sum_{k=1}^n Y(i, \rho_1(k), \dots, \rho_d(k))\right]^2 + 2E\left[\sum_{i=1}^n \sum_{k=1}^n Y_z(i, \rho_1(k), \dots, \rho_d(k))\right]^2 \\ &\leq C\{n\sqrt{n}\delta_2 + n\delta_4^2 + n\sqrt{n}\delta_4\} \\ &\leq C\{n^{\frac{5}{4}}\delta_4^{\frac{1}{2}} + n\delta_4^2 + n\sqrt{n}\delta_4\} \end{aligned} \quad (4.4)$$

where we have used the fact that $\delta_2^2 \leq \frac{\delta_4}{\sqrt{n}}$ (see eq.(3.59)) in the last inequality. We observe that

$$n\sqrt{n}\delta_4 = (n^{\frac{5}{4}}\delta_4^{\frac{1}{2}})(n^{\frac{1}{4}}\delta_4^{\frac{1}{2}}) \leq n^{\frac{5}{4}}\delta_4^{\frac{1}{2}},$$

in case of $n^{\frac{1}{4}}\delta_4^{\frac{1}{2}} \leq 1$, and

$$n\sqrt{n}\delta_4 \leq (n^{\frac{5}{4}}\delta_4^{\frac{1}{2}})(n^{\frac{1}{4}}\delta_4^{\frac{1}{2}})^3 = n^2\delta_4^2,$$

in case of $n^{\frac{1}{4}}\delta_4^{\frac{1}{2}} > 1$. Thus

$$n\sqrt{n}\delta_4 \leq n^{\frac{5}{4}}\delta_4^{\frac{1}{2}} + n^2\delta_4^2. \quad (4.5)$$

By this fact and (4.4),

$$E\left[\sum_{i=1}^n \sum_{k=1}^n \widehat{Y}_z(i, \rho_1(k), \dots, \rho_d(k))\right]^2 \leq C\{n^{\frac{5}{4}}\delta_4^{\frac{1}{2}} + n^2\delta_4^2\}.$$

□

Let $I, K, \rho_1, \dots, \rho_d$ be defined as in previous chapter. We define

$$\widehat{Y}(\rho) = \sum_{i=1}^n \widehat{Y}_z(i, \rho_1(i), \dots, \rho_d(i)) \quad (4.6)$$

and

$$\widetilde{Y}(\rho) = \widehat{Y}(\rho) - \widehat{S}_{1,z} - \widehat{S}_{2,z} + \widehat{S}_{3,z} + \widehat{S}_{4,z} \quad (4.7)$$

where

$$\begin{aligned} \widehat{S}_{1,z} &= \widehat{Y}_z(I, \rho_1(I), \dots, \rho_d(I)), \quad \widehat{S}_{2,z} = \widehat{Y}_z(K, \rho_1(K), \dots, \rho_d(K)), \\ \widehat{S}_{3,z} &= \widehat{Y}_z(I, \rho_1(K), \dots, \rho_d(K)), \quad \widehat{S}_{4,z} = \widehat{Y}_z(K, \rho_1(I), \dots, \rho_d(I)). \end{aligned}$$

Similarly to (3.13), $\widehat{S}_{i,z}$ for $i = 1, 2, 3, 4$ are identically distributed.

Lemma 4.3. *Let g be a continuous and piecewise continuously differential function.*

Then

$$E\widehat{Y}(\rho)g(\widehat{Y}(\rho)) = E \int_{-\infty}^{\infty} g'(\widehat{Y}(\rho) + t)K(t)dt + \Delta g(\widehat{Y}(\rho)) \quad (4.8)$$

and

$$|\Delta g(\widehat{Y}(\rho))| \leq C \left\{ \frac{\delta_4^{\frac{1}{4}}}{n^{\frac{3}{8}}} + \delta_4 \right\} \{Eg^2(\widehat{Y}(\rho))\}^{\frac{1}{2}} \quad (4.9)$$

where

$$K(t) = \frac{n-1}{4} (\widetilde{Y}(\rho) - \widehat{Y}(\rho)) (\mathbb{I}(0 \leq t \leq \widetilde{Y}(\rho) - \widehat{Y}(\rho)) - \mathbb{I}(\widetilde{Y}(\rho) - \widehat{Y}(\rho) \leq t < 0)).$$

Proof. Let \mathcal{C} be the σ -algebra generated by

$$\{\widehat{Y}_z(i, \rho_1(i), \dots, \rho_d(i)) : 1 \leq i \leq n\}.$$

Similarly to (3.16),

$$2E\{g(\widehat{Y}(\rho))E^{\mathcal{C}}(\widetilde{Y}(\rho) - \widehat{Y}(\rho))\} + E(\widetilde{Y}(\rho) - \widehat{Y}(\rho))[g(\widetilde{Y}(\rho)) - g(\widehat{Y}(\rho))] = 0. \quad (4.10)$$

Note that

$$\begin{aligned}
& E^C[\tilde{Y}(\rho) - \hat{Y}(\rho)] \\
&= -E^C \hat{Y}_z(I, \rho_1(I), \dots, \rho_d(I)) - E^C \hat{Y}_z(K, \rho_1(K), \dots, \rho_d(K)) \\
&\quad + E^C \hat{Y}_z(I, \rho_1(K), \dots, \rho_d(K)) + E^C \hat{Y}_z(K, \rho_1(I), \dots, \rho_d(I)) \\
&= -\frac{2}{n} \sum_{i=1}^n \hat{Y}_z(i, \rho_1(i), \dots, \rho_d(i)) + \frac{2}{n(n-1)} E^C \sum_{i=1}^n \sum_{\substack{k \\ k \neq i}}^n \hat{Y}_z(i, \rho_1(k), \dots, \rho_d(k)) \\
&= -\frac{2}{n} \hat{Y}(\rho) + \frac{2}{n(n-1)} E^C \sum_{i=1}^n \left\{ \sum_{k=1}^n \hat{Y}_z(i, \rho_1(k), \dots, \rho_d(k)) \right. \\
&\quad \left. - \hat{Y}_z(i, \rho_1(i), \dots, \rho_d(i)) \right\} \\
&= -\frac{2}{n-1} \hat{Y}(\rho) + \frac{2}{n(n-1)} E^C \sum_{i=1}^n \sum_{k=1}^n \hat{Y}_z(i, \rho_1(k), \dots, \rho_d(k)).
\end{aligned}$$

From this fact and (4.10), we have

$$\begin{aligned}
E\hat{Y}(\rho)g(\hat{Y}(\rho)) &= \frac{n-1}{4} E(\tilde{Y}(\rho) - \hat{Y}(\rho))[g(\tilde{Y}(\rho)) - g(\hat{Y}(\rho))] \\
&\quad + \frac{1}{n} Eg(\hat{Y}(\rho)) \sum_{i=1}^n \sum_{k=1}^n \hat{Y}_z(i, \rho_1(k), \dots, \rho_d(k)) \\
&= \frac{n-1}{4} E(\tilde{Y}(\rho) - \hat{Y}(\rho))[g(\tilde{Y}(\rho)) - g(\hat{Y}(\rho))] + \Delta g(\hat{Y}(\rho)) \\
&= \frac{n-1}{4} E(\tilde{Y}(\rho) - \hat{Y}(\rho)) \int_0^{\tilde{Y}(\rho) - \hat{Y}(\rho)} g'(\hat{Y}(\rho) + t) dt + \Delta g(\hat{Y}(\rho)) \\
&= E \int_{-\infty}^{\infty} g'(\hat{Y}(\rho) + t) K(t) dt + \Delta g(\hat{Y}(\rho))
\end{aligned}$$

where

$$\Delta g(\hat{Y}(\rho)) = \frac{1}{n} Eg(\hat{Y}(\rho)) \sum_{i=1}^n \sum_{k=1}^n \hat{Y}_z(i, \rho_1(k), \dots, \rho_d(k)).$$

By Lemma 4.2,

$$\begin{aligned}
|\Delta g(\hat{Y}(\rho))| &\leq \frac{1}{n} \{Eg^2(\hat{Y}(\rho))\}^{\frac{1}{2}} \left\{ E \left[\sum_{i=1}^n \sum_{k=1}^n \hat{Y}_z(i, \rho_1(k), \dots, \rho_d(k)) \right]^2 \right\}^{\frac{1}{2}} \\
&\leq C \left\{ \frac{\delta_4^{\frac{1}{4}}}{n^{\frac{3}{8}}} + \delta_4 \right\} \{Eg^2(\hat{Y}(\rho))\}^{\frac{1}{2}}.
\end{aligned}$$

□

Lemma 4.4.

$$E\hat{Y}^4(\rho) \leq C\{\sqrt{n}\delta_4 + n\delta_4^2\}.$$

Proof. We observe that

$$E\left(\sum_{i=1}^n Y_z(i, \rho_1(i), \dots, \rho_d(i))\right)^4 = M_1 + M_2 + M_3 + M_4 + M_5$$

where

$$\begin{aligned} M_1 &= \sum_{i=1}^n EY_z^4(i, \rho_1(i), \dots, \rho_d(i)), \\ M_2 &= \sum_{i=1}^n \sum_{\substack{j \\ j \neq i}} EY_z(i, \rho_1(i), \dots, \rho_d(i))Y_z^3(j, \rho_1(j), \dots, \rho_d(j)), \\ M_3 &= \sum_{i=1}^n \sum_{\substack{j \\ j \neq i}} EY_z^2(i, \rho_1(i), \dots, \rho_d(i))Y_z^2(j, \rho_1(j), \dots, \rho_d(j)), \\ M_4 &= \sum_{i=1}^n \sum_{\substack{j \\ j \neq i}} \sum_{\substack{k \\ k \neq i, j}} EY_z^2(i, \rho_1(i), \dots, \rho_d(i))Y_z(j, \rho_1(j), \dots, \rho_d(j)) \\ &\quad Y_z(k, \rho_1(k), \dots, \rho_d(k)) \quad \text{and} \\ M_5 &= \sum_{i=1}^n \sum_{\substack{j \\ j \neq i}} \sum_{\substack{k \\ k \neq i, j}} \sum_{\substack{l \\ l \neq i, j, k}} EY_z(i, \rho_1(i), \dots, \rho_d(i))Y_z(j, \rho_1(j), \dots, \rho_d(j)) \\ &\quad Y_z(k, \rho_1(k), \dots, \rho_d(k))Y_z(l, \rho_1(l), \dots, \rho_d(l)). \end{aligned}$$

We note that

$$|M_1| = \frac{1}{n^d} \sum_{i_1=1}^n \dots \sum_{i_{d+1}=1}^n EY_z^4(i_1, \dots, i_{d+1}) = \frac{\delta_4}{\sqrt{n}}.$$

It follows from (4.2) that

$$\begin{aligned} |M_2| &\leq \frac{C}{n^{2d}} \sum_{i_1=1}^n \dots \sum_{i_{d+1}=1}^n E|Y_z(i_1, \dots, i_{d+1})| \sum_{j_1=1}^n \dots \sum_{j_{d+1}=1}^n E|Y_z(j_1, \dots, j_{d+1})|^3 \\ &\leq \frac{C}{n^{2d}} \left[\sum_{i_1=1}^n \dots \sum_{i_{d+1}=1}^n EY^4(i_1, \dots, i_{d+1}) \right]^2 \\ &= \frac{C\delta_4^2}{n}, \end{aligned}$$

$$\begin{aligned}
|M_3| &\leq \frac{C}{n^{2d}} \sum_{i_1=1}^n \cdots \sum_{i_{d+1}=1}^n EY_z^2(i_1, \dots, i_{d+1}) \sum_{j_1=1}^n \cdots \sum_{j_{d+1}=1}^n EY_z^2(j_1, \dots, j_{d+1}) \\
&\leq \frac{C}{n^{2d}} \left[\sum_{i_1=1}^n \cdots \sum_{i_{d+1}=1}^n EY^4(i_1, \dots, i_{d+1}) \right]^2 \\
&= \frac{C\delta_4^2}{n}, \\
|M_4| &\leq \frac{C}{n^{3d}} \sum_{i_1=1}^n \cdots \sum_{i_{d+1}=1}^n EY_z^2(i_1, \dots, i_{d+1}) \left[\sum_{j_1=1}^n \cdots \sum_{j_{d+1}=1}^n E|Y_z(j_1, \dots, j_{d+1})| \right]^2 \\
&\leq \frac{C}{n^{3d}} \sum_{i_1=1}^n \cdots \sum_{i_{d+1}=1}^n EY^4(i_1, \dots, i_{d+1}) \left[\sum_{j_1=1}^n \cdots \sum_{j_{d+1}=1}^n E|Y(j_1, \dots, j_{d+1})|^2 \right]^2 \\
&= C\sqrt{n}\delta_4\delta_2^2 \quad \text{and} \\
|M_5| &\leq \frac{C}{n^{4d}} \left[\sum_{i_1=1}^n \cdots \sum_{i_{d+1}=1}^n E|Y_z(i_1, \dots, i_{d+1})| \right]^4 \\
&\leq \frac{C}{n^{4d}} \left[\sum_{i_1=1}^n \cdots \sum_{i_{d+1}=1}^n EY^2(i_1, \dots, i_{d+1}) \right]^4 \\
&= Cn^2\delta_2^4.
\end{aligned}$$

Thus

$$\begin{aligned}
E\left(\sum_{i=1}^n Y_z(i, \rho_1(i), \dots, \rho_d(i))\right)^4 &= \frac{\delta_4}{\sqrt{n}} + \frac{C\delta_4^2}{n} + C\sqrt{n}\delta_4\delta_2^2 + Cn^2\delta_2^4 \\
&\leq C \left\{ \frac{\delta_4}{\sqrt{n}} + \frac{\delta_4^2}{n} + \delta_4^2 + n\delta_4^2 \right\} \\
&\leq C \left\{ \frac{\delta_4}{\sqrt{n}} + n\delta_4^2 \right\}
\end{aligned}$$

where we have used the fact that $\delta_2^2 \leq \frac{\delta_4}{\sqrt{n}}$ in the first inequality. By this fact and Lemma 3.5,

$$\begin{aligned}
E\widehat{Y}^4(\rho) &= E\left(\sum_{i=1}^n Y(i, \rho_1(i), \dots, \rho_d(i)) - \sum_{i=1}^n Y_z(i, \rho_1(i), \dots, \rho_d(i))\right)^4 \\
&\leq CEW^4 + CE\left(\sum_{i=1}^n Y_z(i, \rho_1(i), \dots, \rho_d(i))\right)^4 \\
&\leq C\{\sqrt{n}\delta_4 + n\delta_4^2\}.
\end{aligned}$$

□

Lemma 4.5.

$$E|\tilde{Y}(\rho) - \hat{Y}(\rho)|^2 = \frac{4}{n} + \Delta$$

$$\text{where } |\Delta| \leq C \left\{ \frac{\delta_4^{\frac{1}{2}}}{n^{\frac{7}{4}}} + \frac{\delta_4}{n\sqrt{n}} + \frac{\delta_4^{\frac{3}{4}}}{n^{\frac{9}{8}}} \right\}.$$

Proof. Let

$$\begin{aligned} S_{1,z} &= Y_z(I, \rho_1(I), \dots, \rho_d(I)), & S_{2,z} &= Y_z(K, \rho_1(K), \dots, \rho_d(K)), \\ S_{3,z} &= Y_z(I, \rho_1(K), \dots, \rho_d(K)), & S_{4,z} &= Y_z(K, \rho_1(I), \dots, \rho_d(I)). \end{aligned}$$

By the same argument as in (3.13), $S_{1,z}, S_{2,z}, S_{3,z}, S_{4,z}$ have the same distribution. We observe that

$$\begin{aligned} E|\tilde{Y}(\rho) - \hat{Y}(\rho)|^2 &= E(-\hat{S}_{1,z} - \hat{S}_{2,z} + \hat{S}_{3,z} + \hat{S}_{4,z})^2 \\ &= E(-(S_1 - S_{1,z}) - (S_2 - S_{2,z}) + (S_3 - S_{3,z}) + (S_4 - S_{4,z}))^2 \\ &= \sum_{k=1}^4 ES_k^2 + \Delta_1 \end{aligned} \quad (4.11)$$

where

$$|\Delta_1| \leq \sum_{1 \leq i < j \leq 4} |ES_i S_j| + 4 \sum_{i=1}^4 ES_{i,z}^2 + \sum_{i=1}^n \sum_{j=1}^n E|S_i S_{j,z}|$$

and from (3.2) and (3.3),

$$\begin{aligned} ES_1^2 &= \frac{1}{n} \sum_{i=1}^n EY^2(i, \rho_1(i), \dots, \rho_d(i)) \\ &= \frac{1}{n} [EW^2 - \sum_{i=1}^n \sum_{\substack{j \\ j \neq i}} EY(i, \rho_1(i), \dots, \rho_d(i)) Y(j, \rho_1(j), \dots, \rho_d(j))] \\ &= \frac{1}{n} - \frac{1}{n^{d+1}(n-1)^d} \sum_{i_1=1}^n \dots \sum_{i_{d+1}=1}^n \sum_{\substack{j_1 \\ j_1 \neq i_1}} \dots \sum_{\substack{j_{d+1} \\ j_{d+1} \neq i_{d+1}}} EY(i_1, \dots, i_{d+1}) EY(j_1, \dots, j_{d+1}) \\ &= \frac{1}{n} - \frac{(-1)^{d+1}}{n^{d+1}(n-1)^d} \sum_{i_1=1}^n \dots \sum_{i_{d+1}=1}^n [EY(i_1, \dots, i_{d+1})]^2. \end{aligned} \quad (4.12)$$

By (4.11), (4.12) and the fact that S_1, S_2, S_3, S_4 have the same distribution,

$$E|\tilde{Y}(\rho) - \hat{Y}(\rho)|^2 = \frac{4}{n} + \Delta$$

where

$$|\Delta| \leq \frac{C\delta_2}{n\sqrt{n}} + \sum_{1 \leq i < j \leq 4} |ES_i S_j| + 4 \sum_{i=1}^4 ES_{i,z}^2 + \sum_{i=1}^n \sum_{j=1}^n E|S_i S_{j,z}|. \quad (4.13)$$

To prove the lemma, it suffices to find appropriate bounds for the terms on the right-hand side of (4.13). Note from (3.3) that

$$\begin{aligned} |ES_1 S_2| &= |EY(I, \rho_1(I), \dots, \rho_d(I))Y(K, \rho_1(K), \dots, \rho_d(K))| \\ &= \left| \frac{1}{n(n-1)} \sum_{i=1}^n \sum_{\substack{k \\ k \neq i}} EY(i, \rho_1(i), \dots, \rho_d(i))Y(k, \rho_1(k), \dots, \rho_d(k)) \right| \\ &= \left| \frac{1}{(n(n-1))^{d+1}} \sum_{i_1=1}^n \dots \sum_{i_{d+1}=1}^n EY(i_1, \dots, i_{d+1}) \sum_{\substack{k_1 \\ k_1 \neq i_1}} \dots \sum_{\substack{k_{d+1} \\ k_{d+1} \neq i_{d+1}}} EY(k_1, \dots, k_{d+1}) \right| \\ &= \left| \frac{1}{(n(n-1))^{d+1}} \sum_{i_1=1}^n \dots \sum_{i_{d+1}=1}^n (EY(i_1, \dots, i_{d+1}))^2 \right| \\ &\leq \frac{C\delta_2}{n^2\sqrt{n}}. \end{aligned}$$

By the same argument, we can show that

$$|ES_i S_j| \leq \frac{C\delta_2}{n^2\sqrt{n}} \quad (4.14)$$

for $1 \leq i < j \leq 4$. We note from (4.2) that

$$\begin{aligned} ES_{1,z}^2 &= \frac{1}{n} \sum_{i=1}^n EY_z^2(i, \rho_1(i), \dots, \rho_d(i)) \\ &= \frac{1}{n^{d+1}} \sum_{i_1=1}^n \dots \sum_{i_{d+1}=1}^n EY_z^2(i_1, \dots, i_{d+1}) \\ &\leq \frac{C}{n^{d+1}} \sum_{i_1=1}^n \dots \sum_{i_{d+1}=1}^n EY^4(i_1, \dots, i_{d+1}) \\ &= \frac{C\delta_4}{n\sqrt{n}}. \end{aligned} \quad (4.15)$$

By (3.45) and (4.15),

$$E|S_i S_{j,z}| \leq \{ES_i^2\}^{\frac{1}{2}} \{ES_{j,z}^2\}^{\frac{1}{2}} \leq \frac{C\delta_2^{\frac{1}{2}} \delta_4^{\frac{1}{2}}}{n} \quad (4.16)$$

for $i, j = 1, 2, 3, 4$. Now we conclude from (4.13)-(4.16) that

$$\begin{aligned} |\Delta| &\leq C \left\{ \frac{\delta_2}{n\sqrt{n}} + \frac{\delta_4}{n\sqrt{n}} + \frac{\delta_2^{\frac{1}{2}}\delta_4^{\frac{1}{2}}}{n} \right\} \\ &\leq C \left\{ \frac{\delta_4^{\frac{1}{2}}}{n^{\frac{7}{4}}} + \frac{\delta_4}{n\sqrt{n}} + \frac{\delta_4^{\frac{3}{4}}}{n^{\frac{9}{8}}} \right\} \end{aligned}$$

where we have used the fact that $\delta_2^2 \leq \frac{\delta_4}{\sqrt{n}}$ in the last inequality. \square

We define

$$\widehat{Y}(\tau) = \sum_{i=1}^n \widehat{Y}_z(i, \tau_1(i), \dots, \tau_d(i)).$$

Lemma 4.6. *Let $z > 0$ and g_z be defined as in (2.4). Then*

$$|Eg'_z(\widehat{Y}(\tau))E \int_{-\infty}^{\infty} K(t)dt - Eg'_z(\widehat{Y}(\tau)) \int_{-\infty}^{\infty} K(t)dt| \leq \frac{C}{1+z} \left\{ \frac{\delta_4^{\frac{1}{2}}}{n^{\frac{1}{4}}} + \delta_4 \right\}.$$

Proof. Let

$$\widehat{G} = \widehat{Y}_z(I, M_1, \dots, M_d) + \widehat{Y}_z(K, L_1, \dots, L_d) - \widehat{Y}_z(I, L_1, \dots, L_d) - \widehat{Y}_z(K, M_1, \dots, M_d)$$

and A be defined as in Lemma 3.6.i.e.,

$$A = \{\tau_i(I) \neq L_i, \tau_i(K) \neq M_i, \tau_i(I) \neq M_i, \tau_i(K) \neq L_i, \quad : \quad i = 1, 2, \dots, d\}.$$

By the same argument as (3.51),

$$|Eg'_z(\widehat{Y}(\tau))E \int_{-\infty}^{\infty} K(t)dt - E[g'_z(\widehat{Y}(\tau)) \int_{-\infty}^{\infty} K(t)dt]| \leq M_1 + M_2 \quad (4.17)$$

where

$$M_1 = \frac{n-1}{4} |Eg'_z(\widehat{Y}(\tau))\mathbb{I}(\widehat{Y}(\tau) \leq \frac{z}{2})[E^{\tau_1, \dots, \tau_d} \widehat{G}^2 \mathbb{I}(A^c) - \widehat{G}^2 \mathbb{I}(A^c)]|$$

$$\text{and} \quad M_2 = \frac{n-1}{4} |Eg'_z(\widehat{Y}(\tau))\mathbb{I}(\widehat{Y}(\tau) > \frac{z}{2})[E^{\tau_1, \dots, \tau_d} \widehat{G}^2 \mathbb{I}(A^c) - \widehat{G}^2 \mathbb{I}(A^c)]|.$$

To bound M_1 , we observe that for $w \leq \frac{z}{2}$,

$$\begin{aligned} |g'_z(w)| &= |[1 - \Phi(z)][1 + \sqrt{2\pi}we^{\frac{1}{2}w^2}\Phi(w)]| \\ &\leq \left\{ \frac{e^{-\frac{z^2}{2}}}{z} \right\} [1 + \sqrt{2\pi}\left(\frac{z}{2}\right)e^{\frac{z^2}{8}}\Phi\left(\frac{z}{2}\right)] \\ &\leq \frac{e^{-\frac{z^2}{2}}}{z} + \frac{\sqrt{2\pi}e^{-\frac{3z^2}{8}}}{2} \\ &\leq \frac{C}{1+z} \end{aligned} \quad (4.18)$$

where we have used the fact that $1 - \Phi(z) \leq \frac{e^{-\frac{z^2}{2}}}{z}$ for $z \geq 0$ (see [1], pp.11) in the first inequality. Let \mathcal{B} be defined as in chapter 3. By (3.52) and the fact that

$$E|\tilde{Y}(\rho) - \hat{Y}(\rho)|^k \leq C \sum_{i=1}^4 E|\hat{S}_{i,z}|^k \leq \frac{C\delta_k}{n^{\frac{k-1}{2}}} \quad (4.19)$$

for $k = 2, 4, 8$, we have

$$\begin{aligned} E[\hat{G}^2 \mathbb{I}(A^c)] &= E[\hat{G}^2 E^{\mathcal{B}} \mathbb{I}(A^c)] \\ &\leq \frac{CE\hat{G}^2}{n} \\ &= \frac{CE|\tilde{Y}(\rho) - \hat{Y}(\rho)|^2}{n} \\ &\leq \frac{C\delta_2}{n\sqrt{n}}. \end{aligned} \quad (4.20)$$

Then (4.18) and (4.20) yield

$$M_1 \leq \frac{Cn}{1+z} E|E^{\tau_1, \dots, \tau_d} \hat{G}^2 \mathbb{I}(A^c) - \hat{G}^2 \mathbb{I}(A^c)| \leq \frac{Cn}{1+z} E[\hat{G}^2 \mathbb{I}(A^c)] \leq \frac{C\delta_2}{(1+z)\sqrt{n}}. \quad (4.21)$$

To bound M_2 , we note that

$$\begin{aligned} E\hat{Y}^2(\tau) &= E\left[\sum_{i=1}^n \hat{Y}_z(i, \tau_1(i), \dots, \tau_d(i))\right]^2 \\ &= E\left[\sum_{i=1}^n Y(i, \tau_1(i), \dots, \tau_d(i)) - \sum_{i=1}^n Y_z(i, \tau_1(i), \dots, \tau_d(i))\right]^2 \\ &\leq 2E\left[\sum_{i=1}^n Y(i, \tau_1(i), \dots, \tau_d(i))\right]^2 + 2E\left[\sum_{i=1}^n Y_z(i, \tau_1(i), \dots, \tau_d(i))\right]^2 \\ &\leq 2EW^2 + 2n \sum_{i=1}^n EY_z^2(i, \tau_1(i), \dots, \tau_d(i)) \\ &= C + \frac{C}{n^{d-1}} \sum_{i_1=1}^n \dots \sum_{i_{d+1}=1}^n EY_z^2(i_1, \dots, i_{d+1}) \\ &\leq C + \frac{C}{n^{d-1}} \sum_{i_1=1}^n \dots \sum_{i_{d+1}=1}^n \frac{EY^4(i_1, \dots, i_{d+1})}{(1+z)^2} \\ &= C\{1 + \sqrt{n}\delta_4\}. \end{aligned} \quad (4.22)$$

From this fact, (3.55) and Chebyshev's inequality, we have

$$\begin{aligned}
M_2 &\leq CnE\mathbb{I}(\widehat{Y}(\tau) > \frac{z}{2})|E^{\tau_1, \dots, \tau_d}\widehat{G}^2\mathbb{I}(A^c) - \widehat{G}^2\mathbb{I}(A^c)| \\
&\leq Cn\left\{\frac{4E\widehat{Y}^2(\tau)}{z^2}\right\}^{\frac{1}{2}}\{E[E^{\tau_1, \dots, \tau_d}\widehat{G}^2\mathbb{I}(A^c) - \widehat{G}^2\mathbb{I}(A^c)]^2\}^{\frac{1}{2}} \\
&\leq \frac{Cn}{1+z}\{C + C\sqrt{n}\delta_4\}^{\frac{1}{2}}\{E[E^{\tau_1, \dots, \tau_d}\widehat{G}^2\mathbb{I}(A^c) - \widehat{G}^2\mathbb{I}(A^c)]^2\}^{\frac{1}{2}}.
\end{aligned}$$

To finish the proof, we need to bound $E[E^{\tau_1, \dots, \tau_d}\widehat{G}^2\mathbb{I}(A^c) - \widehat{G}^2\mathbb{I}(A^c)]^2$. We observe from (3.52) and (4.19) that

$$\begin{aligned}
E[E^{\tau_1, \dots, \tau_d}\widehat{G}^2\mathbb{I}(A^c) - \widehat{G}^2\mathbb{I}(A^c)]^2 &\leq 2E[E^{\tau_1, \dots, \tau_d}\widehat{G}^2\mathbb{I}(A^c)]^2 + 2E[\widehat{G}^2\mathbb{I}(A^c)]^2 \\
&= 2EE^{\tau_1, \dots, \tau_d}[\widehat{G}^2\mathbb{I}(A^c)E^{\tau_1, \dots, \tau_d}\widehat{G}^2\mathbb{I}(A^c)] + 2E\widehat{G}^4\mathbb{I}(A^c) \\
&\leq 2E\widehat{G}^2\mathbb{I}(A^c)E^{\tau_1, \dots, \tau_d}\widehat{G}^2 + 2E\widehat{G}^4\mathbb{I}(A^c) \\
&= 2E\widehat{G}^2\mathbb{I}(A^c)E\widehat{G}^2 + 2E\widehat{G}^4\mathbb{I}(A^c) \\
&= 2E\widehat{G}^2E^{\mathcal{B}}\mathbb{I}(A^c)E\widehat{G}^2 + 2E\widehat{G}^4E^{\mathcal{B}}\mathbb{I}(A^c) \\
&\leq \frac{CE\widehat{G}^4}{n} \\
&= \frac{CE|\widehat{Y}(\rho) - \widehat{Y}(\rho)|^4}{n} \\
&\leq \frac{C\delta_4}{n^2\sqrt{n}}.
\end{aligned}$$

So,

$$M_2 \leq \frac{C}{1+z} \left\{ \frac{\delta_4^{\frac{1}{2}}}{n^{\frac{1}{4}}} + \delta_4 \right\}. \quad (4.23)$$

Now, we conclude from (4.17), (4.21) and (4.23) that

$$\begin{aligned}
|Eg'_z(\widehat{Y}(\tau))E \int_{-\infty}^{\infty} K(t)dt - Eg'_z(\widehat{Y}(\tau)) \int_{-\infty}^{\infty} K(t)dt| &\leq \frac{C}{1+z} \left\{ \frac{\delta_2}{\sqrt{n}} + \frac{\delta_4^{\frac{1}{2}}}{n^{\frac{1}{4}}} + \delta_4 \right\} \\
&\leq \frac{C}{1+z} \left\{ \frac{\delta_4^{\frac{1}{2}}}{n^{\frac{1}{4}}} + \delta_4 \right\}
\end{aligned}$$

where we have used the fact that $\delta_2^2 \leq \frac{\delta_4}{\sqrt{n}}$ in the last inequality. \square

Lemma 4.7. *Let $z > 0$ and let*

$$h(w) = (wg_z(w))'.$$

Then

$$\begin{aligned} E\mathbb{I}(|\Delta\widehat{Y}| + |\widetilde{Y}(\rho) - \widehat{Y}(\rho)| < \frac{z}{4}) \int_{-\infty}^{\infty} \int_t^{\Delta\widehat{Y}} h(\widehat{Y}(\rho) + u)K(t)dudt \\ \leq \frac{C}{1+z} \left\{ \frac{\delta_{\frac{3}{8}}^{\frac{3}{8}}}{n^{\frac{5}{16}}} + \frac{\delta_{\frac{7}{8}}^{\frac{7}{8}}}{n^{\frac{1}{16}}} \right\} \end{aligned}$$

where $\Delta\widehat{Y} = \widehat{Y}(\tau) - \widehat{Y}(\rho)$.

Proof. Since $E|\Delta\widehat{Y}|^k$ is a finite sum of terms each of the form $E|\widehat{Y}_z(I, \rho_1(I), \dots, \rho_d(I))|^k$,

$$E|\Delta\widehat{Y}|^k \leq \frac{C\delta_k}{n^{\frac{k-1}{2}}} \quad (4.24)$$

for $k = 2, 4$. This implies

$$\begin{aligned} E\left(\int_{-\infty}^{\infty} \int_t^{\Delta\widehat{Y}} K(t)dudt\right)^k \\ \leq E\left(\int_{-\infty}^{\infty} (|\Delta\widehat{Y}| + |t|)K(t)dt\right)^k \\ = \left(\frac{n-1}{4}\right)^k E(|\Delta\widehat{Y}||\widetilde{Y}(\rho) - \widehat{Y}(\rho)|^2 + |\widetilde{Y}(\rho) - \widehat{Y}(\rho)|^3)^k \\ \leq Cn^k \{E|\Delta\widehat{Y}|^k |\widetilde{Y}(\rho) - \widehat{Y}(\rho)|^{2k} + E|\widetilde{Y}(\rho) - \widehat{Y}(\rho)|^{3k}\} \\ \leq Cn^k \{E|\Delta\widehat{Y}|^{2k}\}^{\frac{1}{2}} \{E|\widetilde{Y}(\rho) - \widehat{Y}(\rho)|^{4k}\}^{\frac{1}{2}} + Cn^k \{E|\widetilde{Y}(\rho) - \widehat{Y}(\rho)|^{4k}\}^{\frac{3}{4}} \\ \leq C \left\{ \frac{\delta_{\frac{1}{2}}^{\frac{1}{2}} \delta_{\frac{4k}{2}}^{\frac{1}{2}}}{n^{\frac{k-1}{2}}} + \frac{\delta_{\frac{3}{4}}^{\frac{3}{4}}}{n^{\frac{4k-3}{8}}} \right\} \quad (4.25) \end{aligned}$$

for $k = 1, 2$. By (4.25) and the fact that

$$h(w) \leq \begin{cases} C(1+z) & \text{if } \frac{z}{2} < w \leq z, \\ \frac{C}{(1+z)^2} & \text{if } w \leq \frac{z}{2} \text{ or } w > z \end{cases}$$

(see[12], pp.2357), we have

$$\begin{aligned} E\mathbb{I}(|\Delta\widehat{Y}| + |\widetilde{Y}(\rho) - \widehat{Y}(\rho)| < \frac{z}{4}) \int_{-\infty}^{\infty} \int_t^{\Delta\widehat{Y}} h(\widehat{Y}(\rho) + u)K(t)du dt \\ \leq E \int_{-\infty}^{\infty} \int_t^{\Delta\widehat{Y}} h(\widehat{Y}(\rho) + u)K(t)\mathbb{I}(\widehat{Y}(\rho) + u \leq \frac{z}{2} \text{ or } \widehat{Y}(\rho) + u > z)du dt \\ + E\mathbb{I}(|\Delta\widehat{Y}| + |\widetilde{Y}(\rho) - \widehat{Y}(\rho)| < \frac{z}{4}) \int_{-\infty}^{\infty} \int_t^{\Delta\widehat{Y}} h(\widehat{Y}(\rho) + u)K(t)\mathbb{I}(\frac{z}{2} < \widehat{Y}(\rho) + u \leq z)du dt \end{aligned}$$

$$\begin{aligned}
&\leq \frac{C}{(1+z)^2} \left\{ \delta_2^{\frac{1}{2}} \delta_4^{\frac{1}{2}} + \frac{\delta_4^{\frac{3}{4}}}{n^{\frac{1}{8}}} \right\} \\
&+ C(1+z) E \mathbb{I}(|\Delta \widehat{Y}| + |\widetilde{Y}(\rho) - \widehat{Y}(\rho)| < \frac{z}{4}) \int_{-\infty}^{\infty} \int_t^{\Delta \widehat{Y}} K(t) \mathbb{I}(\widehat{Y}(\rho) + u > \frac{z}{2}) du dt.
\end{aligned} \tag{4.26}$$

It remains to bound the second term on the right hand side of (4.1). By Lemma 4.4, (4.25) and the fact that $K(t) = 0$ for $|t| > |\widehat{Y}(\rho) - \widetilde{Y}(\rho)|$,

$$\begin{aligned}
&E \mathbb{I}(|\Delta \widehat{Y}| + |\widetilde{Y}(\rho) - \widehat{Y}(\rho)| < \frac{z}{4}) \int_{-\infty}^{\infty} \int_t^{\Delta \widehat{Y}} K(t) \mathbb{I}(\widehat{Y}(\rho) + u > \frac{z}{2}) du dt \\
&\leq E \mathbb{I}(|\Delta \widehat{Y}| + |\widetilde{Y}(\rho) - \widehat{Y}(\rho)| < \frac{z}{4}) \int_{-\infty}^{\infty} \int_t^{\Delta \widehat{Y}} K(t) \mathbb{I}(\widehat{Y}(\rho) + |\Delta \widehat{Y}| \\
&\quad + |\widetilde{Y}(\rho) - \widehat{Y}(\rho)| > \frac{z}{2}) du dt \\
&= E \int_{-\infty}^{\infty} \int_t^{\Delta \widehat{Y}} K(t) \mathbb{I}(\widehat{Y}(\rho) > \frac{z}{4}) du dt \\
&\leq \{P(\widehat{Y}(\rho) > \frac{z}{4})\}^{\frac{1}{2}} \{E(\int_{-\infty}^{\infty} \int_t^{\Delta \widehat{Y}} K(t) du dt)^2\}^{\frac{1}{2}} \\
&\leq C \left\{ \frac{E \widehat{Y}^4(\rho)}{z^4} \right\}^{\frac{1}{2}} \left\{ \frac{C \delta_4^{\frac{1}{2}} \delta_8^{\frac{1}{2}}}{\sqrt{n}} + \frac{C \delta_8^{\frac{3}{4}}}{n^{\frac{5}{8}}} \right\}^{\frac{1}{2}} \\
&\leq \frac{C}{z^2} \left\{ \delta_4^{\frac{3}{4}} \delta_8^{\frac{1}{4}} + \frac{\delta_4^{\frac{1}{2}} \delta_8^{\frac{3}{8}}}{n^{\frac{1}{16}}} + n^{\frac{1}{4}} \delta_4^{\frac{5}{4}} \delta_8^{\frac{1}{4}} + n^{\frac{3}{16}} \delta_4 \delta_8^{\frac{3}{8}} \right\}.
\end{aligned} \tag{4.27}$$

By (4.1) and (4.27),

$$\begin{aligned}
&E \mathbb{I}(|\Delta \widehat{Y}| + |\widetilde{Y}(\rho) - \widehat{Y}(\rho)| < \frac{z}{4}) \int_{-\infty}^{\infty} \int_t^{\Delta \widehat{Y}} h(\widehat{Y}(\rho) + u) K(t) du dt \\
&\leq \frac{C}{(1+z)^2} \left\{ \delta_2^{\frac{1}{2}} \delta_4^{\frac{1}{2}} + \frac{\delta_4^{\frac{3}{4}}}{n^{\frac{1}{8}}} \right\} + \frac{C}{1+z} \left\{ \delta_4^{\frac{3}{4}} \delta_8^{\frac{1}{4}} + \frac{\delta_4^{\frac{1}{2}} \delta_8^{\frac{3}{8}}}{n^{\frac{1}{16}}} + n^{\frac{1}{4}} \delta_4^{\frac{5}{4}} \delta_8^{\frac{1}{4}} + n^{\frac{3}{16}} \delta_4 \delta_8^{\frac{3}{8}} \right\} \\
&\leq \frac{C}{1+z} \left\{ \frac{\delta_8^{\frac{3}{8}}}{n^{\frac{5}{16}}} + \frac{\delta_8^{\frac{5}{8}}}{n^{\frac{3}{16}}} + \frac{\delta_8^{\frac{7}{8}}}{n^{\frac{1}{16}}} \right\}
\end{aligned}$$

where we have used the fact that $\delta_2^2 \leq \frac{\delta_4}{\sqrt{n}}$ and $\delta_4^2 \leq \frac{\delta_8}{\sqrt{n}}$ in the last inequality. By the same argument as (4.5), we can show that $\frac{\delta_8^{\frac{5}{8}}}{n^{\frac{3}{16}}} \leq \frac{\delta_8^{\frac{3}{8}}}{n^{\frac{5}{16}}} + \frac{\delta_8^{\frac{7}{8}}}{n^{\frac{1}{16}}}$. Thus, we have the lemma. \square

4.2 Proof of Theorem 4.1

Proof. To bound $|P(W \leq z) - \Phi(z)|$, it suffices to consider $z > 0$ as we have used the fact that $\Phi(z) = 1 - \Phi(-z)$ and apply the result to $-W$ when $z \leq 0$. So, from now on, we assume $z > 0$.

Let

$$\widehat{Y} = \sum_{i=1}^n \widehat{Y}_z(i, \pi_1(i), \dots, \pi_d(i)).$$

Note that

$$|P(W \leq z) - \Phi(z)| \leq P(W \neq \widehat{Y}) + |P(\widehat{Y} \leq z) - \Phi(z)|. \quad (4.28)$$

We observe that

$$\begin{aligned} P(W \neq \widehat{Y}) &= P\left(\sum_{i=1}^n \mathbb{I}(|Y(i, \pi_1(i), \dots, \pi_d(i))| > 1 + z) \geq 1\right) \\ &\leq \sum_{i=1}^n E\mathbb{I}(|Y(i, \pi_1(i), \dots, \pi_d(i))| > 1 + z) \\ &= \frac{1}{n^d} \sum_{i_1=1}^n \dots \sum_{i_{d+1}=1}^n P(|Y(i_1, \dots, i_{d+1})| > 1 + z) \\ &\leq \frac{1}{n^d} \sum_{i_1=1}^n \dots \sum_{i_{d+1}=1}^n \frac{E|Y(i_1, \dots, i_{d+1})|^4}{(1+z)^4} \\ &= \frac{\delta_4}{(1+z)^4 \sqrt{n}}. \end{aligned} \quad (4.29)$$

Next, we will bound the second term on the right hand side of (4.28). By the same argument as previous chapter, we can show that

$$\begin{aligned} |P(\widehat{Y} \leq z) - \Phi(z)| &\leq |Eg'_z(\widehat{Y}(\tau)) \int_{-\infty}^{\infty} K(t)dt - E \int_{-\infty}^{\infty} g'_z(\widehat{Y}(\rho) + t)K(t)dt| \\ &\quad + |Eg'_z(\widehat{Y}(\tau))E \int_{-\infty}^{\infty} K(t)dt - Eg'_z(\widehat{Y}(\tau)) \int_{-\infty}^{\infty} K(t)dt| \\ &\quad + |Eg'_z(\widehat{Y}(\tau)) - Eg'_z(\widehat{Y}(\tau))E \int_{-\infty}^{\infty} K(t)dt| \\ &\quad + |\Delta g_z(\widehat{Y}(\rho))| \\ &= |T_1| + |T_2| + |T_3| + |T_4| \end{aligned} \quad (4.30)$$

where

$$\begin{aligned}
T_1 &= E g'_z(\widehat{Y}(\tau)) \int_{-\infty}^{\infty} K(t) dt - E \int_{-\infty}^{\infty} g'_z(\widehat{Y}(\rho) + t) K(t) dt \\
T_2 &= E g'_z(\widehat{Y}(\tau)) E \int_{-\infty}^{\infty} K(t) dt - E g'_z(\widehat{Y}(\tau)) \int_{-\infty}^{\infty} K(t) dt \\
T_3 &= E g'_z(\widehat{Y}(\tau)) - E g'_z(\widehat{Y}(\tau)) E \int_{-\infty}^{\infty} K(t) dt \\
T_4 &= \Delta g_z(\widehat{Y}(\rho)).
\end{aligned}$$

By the fact that $0 \leq g_z(w) \leq \min(\frac{\sqrt{2\pi}}{4}, \frac{1}{|z|})$ (see [6], pp.246) and (4.9),

$$|T_4| \leq \left\{ \frac{C\delta_4^{\frac{1}{4}}}{n^{\frac{3}{8}}} + C\delta_4 \right\} \{E g_z^2(\widehat{Y}(\rho))\}^{\frac{1}{2}} \leq \frac{C}{1+z} \left\{ \frac{\delta_4^{\frac{1}{4}}}{n^{\frac{3}{8}}} + \delta_4 \right\}. \quad (4.31)$$

Next, we will bound T_3 . By the same argument as Chen and Shao ([6], pp.248), we can show that $E|g'_z(\widehat{Y}(\tau))| \leq \frac{C}{(1+z)^2} (1 + \sqrt{n}\delta_4)$, for $z > 0$. From this fact and Lemma 4.5, we have

$$\begin{aligned}
|T_3| &\leq E|g'_z(\widehat{Y}(\tau))| \left| 1 - E \int_{-\infty}^{\infty} K(t) dt \right| \\
&\leq \frac{C}{(1+z)^2} (1 + \sqrt{n}\delta_4) \left| 1 - \frac{n-1}{4} E|\widetilde{Y}(\rho) - \widehat{Y}(\rho)|^2 \right| \\
&\leq \frac{C}{(1+z)^2} \left\{ \frac{1}{n} + \frac{C\delta_4^{\frac{1}{2}}}{n^{\frac{3}{4}}} + \frac{C\delta_4^{\frac{3}{4}}}{n^{\frac{1}{8}}} + \frac{C\delta_4}{\sqrt{n}} + \frac{C\delta_4^{\frac{3}{2}}}{n^{\frac{1}{4}}} + C\delta_4^{\frac{7}{4}} n^{\frac{3}{8}} + \delta_4^2 \right\} \\
&\leq \frac{C}{(1+z)^2} \left\{ \frac{1}{n} + \frac{\delta_4^{\frac{1}{2}}}{n^{\frac{3}{4}}} + \frac{\delta_4^{\frac{3}{4}}}{n^{\frac{1}{8}}} + \delta_4^2 \right\} \quad (4.32)
\end{aligned}$$

where we have used the fact that $\frac{\delta_4}{\sqrt{n}}, \frac{\delta_4^{\frac{3}{2}}}{n^{\frac{1}{4}}, \delta_4^{\frac{7}{4}} n^{\frac{3}{8}}} \leq \frac{\delta_4^{\frac{1}{2}}}{n^{\frac{3}{4}}} + \delta_4^2$ in the last inequality. By Lemma 4.6, (4.31) and (4.32),

$$\begin{aligned}
|T_2| + |T_3| + |T_4| &\leq \frac{C}{1+z} \left\{ \frac{\delta_4^{\frac{1}{2}}}{n^{\frac{1}{4}}} + \delta_4^2 + \frac{1}{n} + \frac{\delta_4^{\frac{3}{4}}}{n^{\frac{1}{8}}} + \frac{\delta_4^{\frac{1}{4}}}{n^{\frac{3}{8}}} + \delta_4 \right\} \\
&\leq \frac{C}{1+z} \left\{ \frac{1}{n} + \frac{\delta_4^{\frac{1}{4}}}{n^{\frac{3}{8}}} + \sqrt{n}\delta_4^2 \right\} \quad (4.33)
\end{aligned}$$

where we have used the fact that $\frac{\delta_4^{\frac{1}{2}}}{n^{\frac{1}{4}}}, \frac{\delta_4^{\frac{3}{4}}}{n^{\frac{1}{8}}}, \delta_4 \leq \frac{\delta_4^{\frac{1}{3}}}{n^{\frac{3}{8}}} + \sqrt{n}\delta_4^2$ in the last inequality. To finish the proof of Theorem 4.1, it remains to bound T_1 . By the fact that

$$|g'_z(w+u) - g'_z(w+v) - \int_v^u h(w+u)du| \leq \mathbb{I}(z - \max(u, v) < w \leq z - \min(u, v))$$

(see[6],pp.250), we have

$$\begin{aligned} T_1 &= E \int_{-\infty}^{\infty} [g'_z(\widehat{Y}(\tau)) - g'_z(\widehat{Y}(\rho) + t)]K(t)dt \\ &= E \int_{-\infty}^{\infty} [g'_z(\widehat{Y}(\rho) + \Delta\widehat{Y}) - g'_z(\widehat{Y}(\rho) + t)]K(t)dt \\ &= T_{11} + T_{12} + T_{13} \end{aligned} \quad (4.34)$$

where

$$\begin{aligned} T_{11} &= E\mathbb{I}(|\Delta\widehat{Y}| + |\widetilde{Y}(\rho) - \widehat{Y}(\rho)| < \frac{z}{4}) \\ &\quad \int_{-\infty}^{\infty} \mathbb{I}(z - \max(\Delta\widehat{Y}, t) < \widehat{Y}(\rho) < z - \min(\Delta\widehat{Y}, t))K(t)dt, \\ T_{12} &= E\mathbb{I}(|\Delta\widehat{Y}| + |\widetilde{Y}(\rho) - \widehat{Y}(\rho)| < \frac{z}{4}) \int_{-\infty}^{\infty} \int_t^{\Delta\widehat{Y}} h(\widehat{Y}(\rho) + u)K(t)du dt, \\ T_{13} &= E\mathbb{I}(|\Delta\widehat{Y}| + |\widetilde{Y}(\rho) - \widehat{Y}(\rho)| \geq \frac{z}{4}) \int_{-\infty}^{\infty} [g'_z(\widehat{Y}(\rho) + \Delta\widehat{Y}) - g'_z(\widehat{Y}(\rho) + t)]K(t)dt. \end{aligned}$$

First, we consider T_{11} . For $\delta = |\Delta\widehat{Y}| + |\widetilde{Y}(\rho) - \widehat{Y}(\rho)|$, we used the idea from Chen and Shao([2],pp.243) to define $f_\delta : \mathbb{R} \rightarrow \mathbb{R}$ by

$$f_\delta(t) = \begin{cases} 0 & \text{if } t < z - 2\delta, \\ (1+t+\delta)(t-z+2\delta) & \text{if } z - 2\delta \leq t \leq z + 2\delta, \\ 4\delta(1+t+\delta) & \text{if } t > z + 2\delta. \end{cases}$$

Note that

$$|f_\delta(t)| \leq 4\delta|1+t+\delta| \quad \text{for every } t \in \mathbb{R} \quad (4.35)$$

and

$$f'_\delta(t) \geq \begin{cases} 1+z-\delta & \text{if } z - 2\delta \leq t \leq z + 2\delta, \\ 0 & \text{otherwise.} \end{cases} \quad (4.36)$$

By Lemma 4.3,

$$E \int_{-\infty}^{\infty} f'_\delta(\widehat{Y}(\rho) + t)K(t)dt = E\widehat{Y}(\rho)f_\delta(\widehat{Y}(\rho)) - \Delta f_\delta(\widehat{Y}(\rho)). \quad (4.37)$$

We conclude from Lemma 4.4, (4.19), (4.22), (4.24) and (4.35) that

$$\begin{aligned} & E|\widehat{Y}(\rho)f_\delta(\widehat{Y}(\rho))| \\ & \leq 4E|\widehat{Y}(\rho)|\delta|1 + \widehat{Y}(\rho) + \delta| \\ & = C\{E\widehat{Y}^2(\rho)\}^{\frac{1}{2}}\{[E|\Delta\widehat{Y}|^2]^{\frac{1}{2}} + [E|\widetilde{Y}(\rho) - \widehat{Y}(\rho)|^2]^{\frac{1}{2}}\} + [E|\Delta\widehat{Y}|^4]^{\frac{1}{2}} \\ & \quad + [E|\widetilde{Y}(\rho) - \widehat{Y}(\rho)|^4]^{\frac{1}{2}} + C[E\widehat{Y}^4(\rho)]^{\frac{1}{2}}\{[E|\Delta\widehat{Y}|^2]^{\frac{1}{2}} + [E|\widetilde{Y}(\rho) - \widehat{Y}(\rho)|^2]^{\frac{1}{2}}\} \\ & \quad + 2[E\widehat{Y}^2(\rho)|\Delta\widehat{Y}|^2]^{\frac{1}{2}}[E|\widetilde{Y}(\rho) - \widehat{Y}(\rho)|^2]^{\frac{1}{2}} \\ & \leq C \left\{ \frac{\delta_2^{\frac{1}{2}}}{n^{\frac{1}{4}}} + \frac{\delta_4^{\frac{1}{2}}}{n^{\frac{3}{4}}} + \delta_2^{\frac{1}{2}}\delta_4^{\frac{1}{2}} + \frac{\delta_4}{\sqrt{n}} + n^{\frac{1}{4}}\delta_4\delta_2^{\frac{1}{2}} + \frac{\delta_4^{\frac{1}{2}}\delta_2^{\frac{1}{2}}}{n^{\frac{1}{2}}} + \frac{\delta_2^{\frac{1}{2}}\delta_4^{\frac{3}{4}}}{n^{\frac{3}{8}}} \right\} \\ & \leq C \left\{ \frac{\delta_4^{\frac{1}{4}}}{n^{\frac{3}{8}}} + n^{\frac{1}{8}}\delta_4^{\frac{5}{4}} \right\}. \end{aligned} \quad (4.38)$$

By the same technique of (4.38), we can use Lemma 4.4, (4.9), (4.19), (4.22), (4.24) and (4.35) to show that

$$\Delta f_\delta(\widehat{Y}(\rho)) \leq \left\{ \frac{C\delta_4^{\frac{1}{4}}}{n^{\frac{3}{8}}} + C\delta_4 \right\} \{E f_\delta^2(\widehat{Y}(\rho))\}^{\frac{1}{2}} \leq C \left\{ \frac{\delta_4^{\frac{3}{4}}}{n^{\frac{9}{8}}} + \frac{\delta_4^{\frac{5}{2}}}{n^{\frac{1}{4}}} \right\}. \quad (4.39)$$

Thus, by (4.34), (4.36), (4.37), (4.38) and (4.39),

$$\begin{aligned} T_{11} & \leq E \int_{|t| \leq |\widetilde{Y}(\rho) - \widehat{Y}(\rho)|} \mathbb{I}(\delta < \frac{z}{4}) \mathbb{I}(z - (|\Delta\widehat{Y}| + |t|) < \widehat{Y}(\rho) < z + (|\Delta\widehat{Y}| + |t|)) K(t) dt \\ & \leq E \int_{|t| \leq |\widetilde{Y}(\rho) - \widehat{Y}(\rho)|} \mathbb{I}(\delta < \frac{z}{4}) \mathbb{I}(z - \delta < \widehat{Y}(\rho) < z + \delta) K(t) dt \\ & \leq \frac{C}{1+z} E \int_{|t| \leq |\widetilde{Y}(\rho) - \widehat{Y}(\rho)|} \mathbb{I}(\delta < \frac{z}{4}) (1+z-\delta) \mathbb{I}(z-\delta < \widehat{Y}(\rho) < z+\delta) K(t) dt \\ & \leq \frac{C}{1+z} E \int_{|t| \leq |\widetilde{Y}(\rho) - \widehat{Y}(\rho)|} f'_\delta(\widehat{Y}(\rho) + t) K(t) dt \\ & \leq \frac{C}{1+z} [E\widehat{Y}(\rho)f_\delta(\widehat{Y}(\rho)) - \Delta f_\delta(\widehat{Y}(\rho))] \\ & \leq \frac{C}{1+z} \left\{ \frac{\delta_4^{\frac{1}{4}}}{n^{\frac{3}{8}}} + n^{\frac{1}{8}}\delta_4^{\frac{5}{4}} + \frac{\delta_4^{\frac{3}{4}}}{n^{\frac{9}{8}}} + \frac{\delta_4^{\frac{5}{2}}}{n^{\frac{1}{4}}} \right\} \\ & \leq \frac{C}{1+z} \left\{ \frac{\delta_4^{\frac{1}{4}}}{n^{\frac{3}{8}}} + \frac{\delta_4^{\frac{5}{2}}}{n^{\frac{1}{4}}} \right\}. \end{aligned} \quad (4.40)$$

By the fact that $|g'_z(w) - g'_z(v)| \leq 1$ (see [6], pp.246), (4.19), and (4.24),

$$\begin{aligned}
T_{13} &\leq E\mathbb{I}(|\Delta\hat{Y}| + |\tilde{Y}(\rho) - \hat{Y}(\rho)| \geq \frac{z}{4}) \int_{-\infty}^{\infty} K(t) dt \\
&= \frac{n-1}{4} E\mathbb{I}(|\Delta\hat{Y}| + |\tilde{Y}(\rho) - \hat{Y}(\rho)| \geq \frac{z}{4}) E|\tilde{Y}(\rho) - \hat{Y}(\rho)|^2 \\
&\leq \frac{n-1}{4} \{P(|\Delta\hat{Y}| + |\tilde{Y}(\rho) - \hat{Y}(\rho)| \geq \frac{z}{4})\}^{\frac{1}{2}} \{E(\tilde{Y}(\rho) - \hat{Y}(\rho))^4\}^{\frac{1}{2}} \\
&\leq Cn \left\{ \frac{E[|\Delta\hat{Y}|^2 + |\tilde{Y}(\rho) - \hat{Y}(\rho)|^2]}{z^2} \right\}^{\frac{1}{2}} \left\{ \frac{\delta_4}{n\sqrt{n}} \right\}^{\frac{1}{2}} \\
&= \frac{C}{1+z} \delta_2^{\frac{1}{2}} \delta_4^{\frac{1}{2}} \\
&= \frac{C}{1+z} \delta_4^{\frac{3}{8}}.
\end{aligned} \tag{4.41}$$

Thus, by Lemma 4.7, (4.40) and (4.41),

$$\begin{aligned}
|T_1| &\leq \frac{C}{1+z} \left\{ \frac{\delta_4^{\frac{1}{4}}}{n^{\frac{3}{8}}} + \frac{\delta_4^{\frac{5}{2}}}{n^{\frac{1}{4}}} + \frac{\delta_4^{\frac{3}{4}}}{n^{\frac{1}{8}}} + \frac{\delta_8^{\frac{3}{8}}}{n^{\frac{5}{16}}} + \frac{\delta_8^{\frac{7}{8}}}{n^{\frac{1}{16}}} \right\} \\
&\leq \frac{C}{1+z} \left\{ \frac{\delta_8^{\frac{1}{8}}}{n^{\frac{7}{16}}} + n^{\frac{1}{8}} \delta_8^{\frac{5}{4}} \right\}.
\end{aligned} \tag{4.42}$$

So, by (4.28), (4.29), (4.30), (4.33) and (4.42),

$$\begin{aligned}
|P(W \leq z) - \Phi(z)| &\leq \frac{C}{1+z} \left\{ \frac{\delta_4}{\sqrt{n}} + \frac{\delta_8^{\frac{1}{8}}}{n^{\frac{7}{16}}} + n^{\frac{1}{8}} \delta_8^{\frac{5}{4}} + \frac{1}{n} + \frac{\delta_4^{\frac{1}{4}}}{n^{\frac{3}{8}}} + \sqrt{n} \delta_4^2 \right\} \\
&\leq \frac{C}{1+z} \left\{ \frac{\delta_8^{\frac{1}{8}}}{n^{\frac{7}{16}}} + \frac{1}{n} + \delta_8 \right\}.
\end{aligned}$$

Now, we prove the main theorem. □

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CHAPTER V

BOUNDS ON NORMAL APPROXIMATION FOR LATIN HYPERCUBE SAMPLING

In many problems, we are interested in estimating an integral over the d -dimensional hypercube $[0, 1]^d$;

$$\mu = \int_{[0,1]^d} f(x)dx.$$

This is equivalent to finding $E(f(X))$, where X is a random vector uniformly distributed on $[0, 1]^d$.

Among numerical integration techniques, Monte Carlo methods are especially useful and competitive for high-dimensional integration. The Monte Carlo estimate for the integral $\mu = E(f(X)) = \int_{[0,1]^d} f(x)dx$ is given by

$$\hat{\mu}_n = \frac{1}{n} \sum_{i=1}^n f(X_i)$$

where X_1, \dots, X_n is a random sampling on $[0, 1]^d$.

In 1979, McKay, Beckman and Conover[16] proposed Latin hypercube sampling(LHS) as an attractive alternative to generating X_1, \dots, X_n . Let

1. η_k , $1 \leq k \leq d$ be random permutations of $\{1, \dots, n\}$ each uniformly distributed over all the $n!$ possible permutations;
2. $U_{i_1, \dots, i_d, j}$ $1 \leq i_1, \dots, i_d \leq n$, $1 \leq j \leq d$, be $[0, 1]$ uniform random variables;
3. the $U_{i_1, \dots, i_d, j}$'s and η_k 's all be stochastically independent.

A Latin hypercube sample of size n (taken from the d -dimensional hypercube $[0, 1]^d$) is defined to be $\{X(\eta_1(i), \eta_2(i), \dots, \eta_d(i)) : 1 \leq i \leq n\}$, where for all $1 \leq i_1, \dots, i_d \leq n$, $1 \leq j \leq d$,

$$X_j(i_1, \dots, i_d) = (i_j - U_{i_1, \dots, i_d, j})/n,$$

and

$$X(i_1, \dots, i_d) = (X_1(i_1, \dots, i_d), \dots, X_d(i_1, \dots, i_d)).$$

Hence the estimator for μ that based on a Latin hypercube sampling is

$$\hat{\mu}_n = \frac{1}{n} \sum_{k=1}^n f \circ X(\eta_1(k), \eta_2(k), \dots, \eta_d(k)).$$

Then $\hat{\mu}_n$ is an unbiased estimator for μ .

Assume that $Var(\hat{\mu}_n) > 0$, we define

$$L = \frac{\hat{\mu}_n - \mu}{\sqrt{Var(\hat{\mu}_n)}}. \quad (5.1)$$

Loh[14] used Stein's method to show that the distribution of L can be approximated by normal distribution but he yield the convergence rate $\frac{C}{\sqrt{n}}$ under the finiteness of third moments without the value of C . In this chapter, we give a constant C by using Stein's method. Furthermore, we give a non-uniform bound of this approximation. These are our main results.

Theorem 5.1. (A uniform bound for LHS) For $1 \leq i_1, \dots, i_d \leq n$, let

$$\begin{aligned} \mu(i_1, \dots, i_d) &= Ef(X(i_1, \dots, i_d)), \\ \mu_k(i_1, \dots, i_d) &= \frac{(-1)^k}{n^k} \sum_{1 \leq j_1 < j_2 < \dots < j_k \leq d} \sum_{q_{j_1}=1}^n \dots \sum_{q_{j_k}=1}^n \mu(l_1, \dots, l_d), \end{aligned}$$

where

$$l_p = \begin{cases} q_p & \text{if } p = j_1, \dots, j_k, \\ i_p & \text{otherwise,} \end{cases} \quad (5.2)$$

and

$$V(i_1, \dots, i_d) = \frac{1}{n\sqrt{var(\hat{\mu}_n)}} [f(X(i_1, \dots, i_d)) + \sum_{k=1}^{d-1} \mu_k(i_1, \dots, i_d) + (-1)^d \mu]. \quad (5.3)$$

Then for $n \geq 6^d + 3$,

$$\begin{aligned} \sup_{z \in \mathbb{R}} |P(L \leq z) - \Phi(z)| &\leq \frac{11.946}{\sqrt{n}} + \frac{1.037\sqrt{d}\beta_4^{\frac{1}{4}}}{n^{\frac{3}{8}}} + 8.314d^{\frac{1}{4}}\beta_4 + 11.765\beta_4 + \frac{5.014d\beta_4^{\frac{3}{4}}}{n^{\frac{1}{8}}} \\ &\quad + \frac{2\sqrt{2\pi}\beta_4^{\frac{3}{4}}}{n^{\frac{1}{8}}} \end{aligned}$$

where

$$\beta_4 = \frac{1}{n^{d-\frac{3}{2}}} \sum_{i_1=1}^n \dots \sum_{i_d=1}^n E|V(i_1, \dots, i_d)|^4.$$

Corollary 5.2. *If $E|f(X)|^4 < \infty$, then*

$$\sup_{z \in \mathbb{R}} |P(L \leq z) - \Phi(z)| \leq \frac{C_d(28.725 + 1.037\sqrt{d} + 8.314d^{\frac{1}{4}} + 5.014d)}{\sqrt{n}}$$

where $C_d = \frac{27}{C^2} [2 + (d-1)^3 \sum_{k=1}^{d-1} \binom{d}{k}] E|f(X)|^4$ for some constant C .

Theorem 5.3. *(A non-uniform bound for LHS) Let $z \in \mathbb{R}$. Then there exists a positive constant C which does not depend on z such that*

$$|P(L \leq z) - \Phi(z)| \leq \frac{C}{1 + |z|} \left\{ \frac{\beta_8^{\frac{1}{8}}}{n^{\frac{7}{16}}} + \frac{1}{n} + \beta_8 \right\}$$

where

$$\beta_8 = \frac{1}{n^{d-\frac{7}{2}}} \sum_{i_1=1}^n \dots \sum_{i_d=1}^n E|V(i_1, \dots, i_d)|^8.$$

Corollary 5.4. *If $E|f(X)|^8 < \infty$, then*

$$|P(L \leq z) - \Phi(z)| \leq \frac{C}{(1 + |z|)\sqrt{n}}.$$

5.1 Proof of Main Results

5.1.1 Proof of 5.1 and Theorem 5.3

We shall prove Theorem 5.1 and Theorem 5.3 by applying Theorem 3.1 and Theorem 4.1, respectively. Note from (5.1) that $EL = 0$ and $VarL = 1$. Hence (3.2) holds. In order to apply Theorem 3.1 and Theorem 4.1, we need to prove the following:

a)

$$L = \sum_{i=1}^n V(i, \pi_1(i), \dots, \pi_{d-1}(i))$$

where $V(i_1, \dots, i_d)$ is defined by (5.3) and π_1, \dots, π_{d-1} are random permutations of $\{1, \dots, n\}$ such that $V(i_1, \dots, i_d)$'s and π_k 's are stochastically independent.

b)

$$\sum_{i_j}^n EV(i_1, \dots, i_d) = 0,$$

for every $j \in \{1, \dots, d\}$. There are proved in Lemma 5.5 and Lemma 5.6.

Lemma 5.5. *There are random permutations π_1, \dots, π_{d-1} of $\{1, \dots, n\}$ such that $V(i_1, \dots, i_d)$'s and π_k 's are stochastically independent and*

$$L = \sum_{i=1}^n V(i, \pi_1(i), \dots, \pi_{d-1}(i)).$$

Proof. Let S_n be the set of all permutations of $\{1, 2, \dots, n\}$. For $j \in \{1, \dots, d-1\}$, we define

$$\pi_j(w) = \eta_{j+1}(w)(\eta_1(w))^{-1}.$$

Since η_1, \dots, η_d are independent,

$$\begin{aligned} P(\pi_j = \gamma) &= P(\{w | \eta_{j+1}(w) = \gamma(\eta_1(w))\}) \\ &= P(\cup_{\alpha \in S_n} \{w | \eta_{j+1}(w) = \gamma(\eta_1(w)), \eta_1(w) = \alpha\}) \\ &= \sum_{\alpha \in S_n} P(\eta_{j+1} = \gamma(\alpha), \eta_1 = \alpha) \\ &= \sum_{\alpha \in S_n} P(\eta_{j+1} = \gamma(\alpha))P(\eta_1 = \alpha) \\ &= \frac{1}{n!} \end{aligned}$$

for any $j \in \{1, \dots, d-1\}$ and $\gamma \in S_n$. Hence π_1, \dots, π_{d-1} are random permutations. We observe that for $\gamma_1, \dots, \gamma_{d-1} \in S_n$,

$$\begin{aligned} &P(\pi_1 = \gamma_1, \dots, \pi_{d-1} = \gamma_{d-1}) \\ &= P(\{w | \eta_2(w) = \gamma_1(\eta_1(w)), \dots, \eta_d(w) = \gamma_{d-1}(\eta_1(w))\}) \\ &= P(\cup_{\alpha \in S_n} \{w | \eta_2(w) = \gamma_1(\eta_1(w)), \dots, \eta_d(w) = \gamma_{d-1}(\eta_1(w)), \eta_1(w) = \alpha\}) \\ &= \sum_{\alpha \in S_n} P(\{\eta_2 = \gamma_1(\alpha), \dots, \eta_d = \gamma_{d-1}(\alpha), \eta_1 = \alpha\}) \\ &= \frac{1}{(n!)^{d-1}} \\ &= P(\pi_1 = \gamma_1) \dots P(\pi_{d-1} = \gamma_{d-1}). \end{aligned}$$

So, π_j 's are independent. It's easy to see that $V(i_1, \dots, i_d)$'s and π_j 's are independent.

By the fact that, for fixed i ,

$$\sum_{i_{j_1}=1}^n \dots \sum_{i_{j_k}=1}^n \mu(l_1, \dots, l_d)$$

where $1 \leq j_1 < j_2 < \dots < j_k \leq d$ and

$$l_p = \begin{cases} i_p & \text{if } p = j_1, \dots, j_k, \\ \eta_p(i) & \text{otherwise} \end{cases}$$

is equal to

$$\frac{1}{n^{d-k}} \sum_{k_1=1}^n \dots \sum_{k_d=1}^n \mu(k_1, \dots, k_d)$$

and

$$\mu = E\hat{\mu}_n = \frac{1}{n^d} \sum_{k_1=1}^n \dots \sum_{k_d=1}^n \mu(k_1, \dots, k_d), \quad (5.4)$$

we have

$$\begin{aligned} \mu_k(\eta_1(i), \dots, \eta_d(i)) &= \frac{(-1)^k}{n^d} \sum_{1 \leq j_1 < j_2 < \dots < j_k \leq d} \sum_{k_1=1}^n \dots \sum_{k_d=1}^n \mu(k_1, \dots, k_d) \\ &= (-1)^k \sum_{1 \leq j_1 < j_2 < \dots < j_k \leq d} \mu \\ &= (-1)^k \binom{d}{k} \mu. \end{aligned}$$

So,

$$\begin{aligned} L &= \frac{1}{\sqrt{\text{Var}(\hat{\mu}_n)}} \left(\frac{1}{n} \sum_{i=1}^n f(X(\eta_1(i), \dots, \eta_d(i))) - \mu \right) \\ &= \frac{1}{\sqrt{\text{Var}(\hat{\mu}_n)}} \left(\frac{1}{n} \sum_{i=1}^n f(X(\eta_1(i), \dots, \eta_d(i))) + \mu[(1-1)^d - 1] \right) \\ &= \frac{1}{\sqrt{\text{Var}(\hat{\mu}_n)}} \left(\frac{1}{n} \sum_{i=1}^n f(X(\eta_1(i), \dots, \eta_d(i))) + \mu \sum_{k=1}^d (-1)^k \binom{d}{k} \right) \\ &= \frac{1}{\sqrt{\text{Var}(\hat{\mu}_n)}} \left(\frac{1}{n} \sum_{i=1}^n f(X(\eta_1(i), \dots, \eta_d(i))) + \frac{1}{n} \sum_{i=1}^n \sum_{k=1}^{d-1} \mu_k(\eta_1(i), \dots, \eta_d(i)) + (-1)^d \mu \right) \\ &= \sum_{i=1}^n V(\eta_1(i), \dots, \eta_d(i)). \end{aligned} \quad (5.5)$$

By this fact and the fact that

$$\eta_{k+1}(i)(w) = (\eta_{k+1}(w))(i) = (\eta_{k+1}(w)(\eta_1(w)^{-1}))(j) = (\pi_k(w))(j) = \pi_k(j)(w)$$

for $(\eta_1(w))(i) = j$ and $k = 1, \dots, d-1$, we have

$$L = \sum_{i=1}^n V(\eta_1(i), \dots, \eta_d(i)) = \sum_{j=1}^n V(j, \pi_1(j), \dots, \pi_{d-1}(j)).$$

□

Lemma 5.6. Let $V(i_1, \dots, i_d)$ be defined as in (5.3). Then

$$\sum_{i_j}^n EV(i_1, \dots, i_d) = 0,$$

for every $j \in \{1, \dots, d\}$.

Proof. First, we shall proof in the case of $j = 1$. For arbitrary j , it follows from the same way. Let $\mu_k(i_1, \dots, i_d)$ and l_1, \dots, l_d be defined as in (5.2). Then We observe that

$$\begin{aligned} & \sum_{i_1=1}^n \sum_{k=1}^{d-1} \mu_k(i_1, \dots, i_d) \\ &= \sum_{i_1=1}^n \sum_{k=1}^{d-1} \frac{(-1)^k}{n^k} \sum_{1 \leq j_1 < j_2 < \dots < j_k \leq d} \sum_{q_{j_1}=1}^n \dots \sum_{q_{j_k}=1}^n \mu(l_1, \dots, l_d) \\ &= \sum_{k=1}^{d-1} \frac{(-1)^k}{n^{k-1}} \sum_{1=j_1 < j_2 < \dots < j_k \leq d} \sum_{q_1=1}^n \sum_{q_{j_2}=1}^n \dots \sum_{q_{j_k}=1}^n \mu(q_1, l_2, \dots, l_d) \\ & \quad + \sum_{k=1}^{d-1} \frac{(-1)^k}{n^k} \sum_{i_1=1}^n \sum_{2 \leq j_1 < \dots < j_k \leq d} \sum_{q_{j_1}=1}^n \dots \sum_{q_{j_k}=1}^n \mu(i_1, l_2, \dots, l_d) \\ &= - \sum_{q_1=1}^n \mu(q_1, i_2, \dots, i_d) + \sum_{k=2}^{d-1} \frac{(-1)^k}{n^{k-1}} \sum_{1=j_1 < j_2 < \dots < j_k \leq d} \sum_{q_1=1}^n \sum_{q_{j_2}=1}^n \dots \sum_{q_{j_k}=1}^n \mu(q_1, l_2, \dots, l_d) \\ & \quad + \sum_{k=1}^{d-2} \frac{(-1)^k}{n^k} \sum_{i_1=1}^n \sum_{2 \leq j_1 < \dots < j_k \leq d} \sum_{q_{j_1}=1}^n \dots \sum_{q_{j_k}=1}^n \mu(i_1, l_2, \dots, l_d) \\ & \quad + \frac{(-1)^{(d-1)}}{n^{d-1}} \sum_{i_1=1}^n \sum_{q_2=1}^n \dots \sum_{q_d=1}^n \mu(i_1, q_2, \dots, q_d) \\ &= - \sum_{q_1=1}^n \mu(q_1, i_2, \dots, i_d) + \sum_{k=2}^{d-1} \frac{(-1)^k}{n^{k-1}} \sum_{1=j_1 < j_2 < \dots < j_k \leq d} \sum_{q_1=1}^n \sum_{q_{j_2}=1}^n \dots \sum_{q_{j_k}=1}^n \mu(q_1, l_2, \dots, l_d) \\ & \quad + \sum_{k=2}^{d-1} \frac{(-1)^{k-1}}{n^{k-1}} \sum_{2 \leq j_1 < \dots < j_{(k-1)} \leq d} \sum_{i_1=1}^n \sum_{q_{j_1}=1}^n \dots \sum_{q_{j_{(k-1)}}=1}^n \mu(i_1, l_2, \dots, l_d) + (-1)^{d-1} n \mu \\ &= - \sum_{q_1=1}^n \mu(q_1, i_2, \dots, i_d) + (-1)^{d-1} n \mu. \end{aligned}$$

Hence for fixed $i_2, \dots, i_d \in \{1, \dots, n\}$,

$$\begin{aligned} \sum_{i_1=1}^n EV(i_1, i_2, \dots, i_d) &= \frac{1}{n\sqrt{\text{Var}(\hat{\mu}_n)}} \sum_{i_1=1}^n E[f \circ X(i_1, \dots, i_d) + \sum_{k=1}^{d-1} \mu_k(i_1, \dots, i_d) + (-1)^d \mu] \\ &= \frac{1}{n\sqrt{\text{Var}(\hat{\mu}_n)}} \left\{ \sum_{i_1=1}^n \mu(i_1, \dots, i_d) + \sum_{i_1=1}^n \sum_{k=1}^{d-1} \mu_k(i_1, \dots, i_d) + (-1)^d n\mu \right\} \\ &= 0. \end{aligned}$$

□

5.1.2 Proof of Corollary 5.2 and Corollary 5.4

Proof. Let $\mu_k(i_1, \dots, i_d)$ and l_1, \dots, l_d be defined as in (5.2). From Stein[27], $\text{Var}(\hat{\mu}_n) \geq \frac{C}{n}$ for some constant C . Thus

$$\begin{aligned} &E|V(i_1, \dots, i_d)|^4 \\ &\leq \frac{1}{n^2 C^2} E[f(X(i_1, \dots, i_d)) + \sum_{k=1}^{d-1} \mu_k(i_1, \dots, i_d) + (-1)^d \mu]^4 \\ &\leq \frac{27}{n^2 C^2} [E|f(X(i_1, \dots, i_d))|^4 + E(\sum_{k=1}^{d-1} \mu_k(i_1, \dots, i_d))^4 + \mu^4] \\ &\leq \frac{27}{n^2 C^2} [E|f(X)|^4 + (d-1)^3 \sum_{k=1}^{d-1} E\mu_k^4(i_1, \dots, i_d) + E|f(X)|^4] \\ &= \frac{27}{n^2 C^2} [2E|f(X)|^4 + (d-1)^3 \sum_{k=1}^{d-1} \frac{1}{n^{4k}} E(\sum_{1 \leq j_1 < j_2 < \dots < j_k \leq d} \sum_{q_{j_1}} \dots \sum_{q_{j_k}} \mu(l_1, \dots, l_d))^4] \\ &\leq \frac{27}{n^2 C^2} [2E|f(X)|^4 + (d-1)^3 \sum_{k=1}^{d-1} \frac{1}{n^{4k}} \binom{d}{k} n^k]^4 E|f(X)|^4 \\ &= \frac{27}{n^2 C^2} [2 + (d-1)^3 \sum_{k=1}^{d-1} \binom{d}{k}^4] E|f(X)|^4. \end{aligned}$$

So, $\beta_4 \leq \frac{27}{\sqrt{n}C^2} [2 + (d-1)^3 \sum_{k=1}^{d-1} \binom{d}{k}^4] E|f(X)|^4$. By the same argument,

$$\beta_8 \leq \frac{2187}{\sqrt{n}C^4} [2 + (d-1)^7 \sum_{k=1}^{d-1} \binom{d}{k}^8] E|f(X)|^8.$$

Corollary 5.2 and Corollary 5.4 are proved by applying this fact to Theorem 5.1 and Theorem 5.3, respectively. □

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