

A Note on the Quicksort Asymptotics

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January 28, 2013

Abstract

In a recent paper, Bindjeme and Fill obtained a surprisingly easy exact formula for the L_2 -distance of the (normalized) number of comparisons of Quicksort under the uniform model to its limit. Shortly afterwards, Neininger proved a central limit theorem for the error. As a consequence, he obtained the asymptotics of the L_3 -distance. In this short note, we use the moment transfer approach to re-prove Neininger's result. As a consequence, we obtain the asymptotics of the L_p -distance for all $1 \leq p < \infty$.

1 Introduction

Quicksort, an algorithm proposed by Hoare [6], is one of the most important sorting algorithms. It has been analyzed in many papers under the so-called uniform random model which assumes that the input is a random permutation of size n . One of the most popular characteristics is the number of comparison which we are going to denote by C_n .

First, it is straightforward to show that, as $n \rightarrow \infty$,

$$\mathbb{E}(C_n) = 2(n+1)H_n - 4n \sim 2n \log n,$$

where $H_n = \sum_{1 \leq j \leq n} (1/j)$ denotes the n -th harmonic number. Moreover, as $n \rightarrow \infty$,

$$\text{Var}(C_n) \sim \left(7 - \frac{2}{3}\pi^2\right)n.$$

As for more refined stochastic properties, Régnier [10] used martingale theory to prove that

$$Y_n := \frac{C_n - \mathbb{E}(C_n)}{n+1}$$

converges to a non-degenerate limit Y both almost surely and in L_p for all $1 \leq p < \infty$, i.e.,

$$\lim_{n \rightarrow \infty} \|Y_n - Y\|_p = 0,$$

*AMS 2010 subject classifications. 60F05, 68P10, 68Q25.

Key words. Quicksort, key comparisons, central limit theorem, L_p -distance, moment-transfer approach.

where $\|X\|_p = (\mathbb{E}|X|^p)^{1/p}$, $1 \leq p < \infty$, for a random variable X (here, Y_n and Y are all constructed on the same probability space which, for instance, can be done via random binary search trees). Régnier's result implies weak convergence of Y_n to Y . This was also proved by Rösler [11] who in addition constructed a random variable satisfying a distributional equation and proved that this random variable has the same distribution as Y . Recently, Bindjeme and Fill proved that the random variable constructed by Rösler is even almost surely equal to Y and they constructed random variables $Y^{(0)}$ and $Y^{(1)}$ with

$$Y = UY^{(0)} + (1 - U)Y^{(1)} + C(U),$$

where $U, Y^{(0)}$ and $Y^{(1)}$ are independent, $Y^{(0)}$ and $Y^{(1)}$ have the same distribution as Y , U is a uniform distributed random variable on $[0, 1]$ and

$$C(x) := 1 + 2x \log x + 2(1 - x) \log(1 - x).$$

Fill and Janson [3] further refined the above results by studying the rate of convergence of Y_n to Y . They proved that for the minimal L_p metric l_p , we have

$$l_p(Y_n, Y) = \mathcal{O}\left(\frac{1}{\sqrt{n}}\right), \quad l_p(Y_n, Y) = \Omega\left(\frac{\log n}{n}\right).$$

Moreover, they proved for the Kolmogorov–Smirnov distance ρ that for all $\epsilon > 0$, we have

$$\rho(Y_n, Y) = \mathcal{O}\left(\frac{1}{n^{(1/2)-\epsilon}}\right), \quad \rho(Y_n, Y) = \Omega\left(\frac{1}{n}\right).$$

Finally, Neininger and Rüschendorf [9] proved that for the Zolotarev metric ζ_3 , we have

$$\zeta_3(Y_n, Y) = \Theta\left(\frac{\log n}{n}\right).$$

Very recently, Bindjeme and Fill in [1] obtained the following surprisingly easy exact formula for the L_2 -distance of Y_n to Y :

$$\|Y_n - Y\|_2 = \left(\frac{1}{n+1} \left(2H_n + 1 + \frac{6}{n+1} \right) - 4 \sum_{j=n+1}^{\infty} \frac{1}{j^2} \right)^{1/2} \sim \sqrt{\frac{2 \log n}{n}}. \quad (1)$$

Also very recently, Neininger [8] proved the following central limit theorem (CLT):

$$\sqrt{\frac{n}{2 \log n}} (Y_n - Y) \xrightarrow{d} N(0, 1). \quad (2)$$

As a consequence of his proof, he obtained that, as $n \rightarrow \infty$,

$$\|Y_n - Y\|_3 \sim \frac{2}{\pi^{1/6}} \sqrt{\frac{\log n}{n}}.$$

The purpose of this note is two-fold. First, we are going to re-prove Neininger's result (2) with the moment-transfer approach. Second, as a consequence of our proof, we will obtain the following result.

Theorem 1. *We have for the L_p -distance of the (normalized) number of comparisons of quicksort Y_n to its limit Y that, as $n \rightarrow \infty$,*

$$\|Y_n - Y\|_p \sim \frac{2(\Gamma((p+1)/2))^{1/p}}{\pi^{1/(2p)}} \sqrt{\frac{\log n}{n}}.$$

2 CLT via the Moment-Transfer Approach

The moment-transfer approach was used in many recent papers in the analysis of algorithms. For instance, for Quicksort-type recurrences, it was applied by Hwang and Neininger [7]; see also Fill and Kapur [4] and the very general framework proposed by Chern, Hwang, and Tsai [2].

Before we can start with our proof, we collect some useful results.

First, we need the following result by Bindjeme and Fill [1]: for $n \geq 1$, we have the following (sample-pointwise) recurrence

$$\begin{aligned} Y_n - Y &= \frac{I_n + 1}{n + 1} (Y_{n,0} - Y^{(0)}) + \frac{n - I_n}{n + 1} (Y_{n,1} - Y^{(1)}) + \left(\frac{I_n + 1}{n + 1} - U \right) Y^{(0)} \\ &\quad + \left(\frac{n - I_n}{n + 1} - (1 - U) \right) Y^{(1)} + \frac{n}{n + 1} C_n(I_n + 1) - C(U), \end{aligned} \quad (3)$$

where $C(x), Y^{(0)}, Y^{(1)}$ and U are from the introduction; given $\{U = u\}$ we have that $I_n \stackrel{d}{=} \text{Binom}(n - 1, u)$; given $\{I_n = j\}$ we have that $Y_{n,0}$ and $Y_{n,1}$ are independent and distributed as Y_j and Y_{n-1-j} , respectively; and

$$C_n(i) := \frac{1}{n} (\mathbb{E}(C_{i-1}) + \mathbb{E}(C_{n-i}) - \mathbb{E}(C_n) + n - 1).$$

For the sake of simplicity, we will use the notation

$$T_n := \left(\frac{I_n + 1}{n + 1} - U \right) Y^{(0)} + \left(\frac{n - I_n}{n + 1} - (1 - U) \right) Y^{(1)} + \frac{n}{n + 1} C_n(I_n + 1) - C(U). \quad (4)$$

Next, we recall the following lemma which was obtained by Neininger in [8].

Lemma 1. *We have,*

$$\|T_n\|_p = \mathcal{O}\left(\frac{1}{\sqrt{n}}\right).$$

Proof. In Lemma 2.2 of [8], this was proved for $p = 3$. However, a careful inspection of the proof shows that it holds in fact for all $1 \leq p < \infty$. ■

Using the above notation, (3) becomes

$$(n + 1)(Y_n - Y) = (I_n + 1) (Y_{n,0} - Y^{(0)}) + (n - I_n) (Y_{n,1} - Y^{(1)}) + (n + 1)T_n. \quad (5)$$

Now, set

$$A_n^{[k]} = \mathbb{E} \left((n + 1)^k (Y_n - Y)^k \right).$$

Raising the above equation to the k -th power and taking expectation yields, for $n \geq 1$,

$$A_n^{[k]} = \frac{2}{n} \sum_{j=0}^{n-1} A_j^{[k]} + B_n^{[k]}, \quad (6)$$

where

$$B_n^{[k]} = \sum_{\substack{i_1 + i_2 + i_3 = k \\ 0 \leq i_1, i_2 < k}} \binom{k}{i_1, i_2, i_3} \mathbb{E} \left((I_n + 1)^{i_1} (Y_{n,0} - Y^{(0)})^{i_1} (n - I_n)^{i_2} (Y_{n,1} - Y^{(1)})^{i_2} (n + 1)^{i_3} T_n^{i_3} \right). \quad (7)$$

The above recurrence for $A_n^{[k]}$ was extensively studied. For instance, in [7], [4], and [2], the authors derived very general (asymptotic) transfer theorems. We recall one result which we will need in the sequel.

Lemma 2. Let $(b_n)_{n \geq 1}$ be a given sequence and define a sequence $(a_n)_{n \geq 0}$ by

$$a_n = \frac{2}{n} \sum_{j=0}^{n-1} a_j + b_n$$

for $n \geq 1$ with arbitrary initial value a_0 . Let $\alpha > 1$ and β be positive real numbers.

(i) If $b_n = n^\alpha \log^\beta n$, then

$$a_n = \frac{\alpha + 1}{\alpha - 1} n^\alpha \log^\beta n + \mathcal{O}(n^\alpha \log^{\beta-1} n).$$

(ii) If $b_n = \mathcal{O}(n^\alpha \log^\beta n)$, then

$$a_n = \mathcal{O}(n^\alpha \log^\beta n).$$

Using the above two lemmas and (6), we will prove the following result.

Proposition 1. For integers $m \geq 1$, we have

$$A_n^{[2m-1]} = \mathcal{O}(n^{m-(1/2)} \log^{m-1} n)$$

and

$$A_n^{[2m]} = g_m n^m \log^m n + \mathcal{O}(n^m \log^{m-1} n),$$

where $g_m = (2m)!/m!$.

Proof. We prove this result by induction on m , where in addition we prove that

$$\mathbb{E}((n+1)^{2m-1} |Y_n - Y|^{2m-1}) = \mathcal{O}(n^{m-(1/2)} \log^{m-(1/2)} n). \quad (8)$$

For $m = 1$, observe that the claim trivially holds for $A_n^{[1]}$ and by (1) holds for $A_n^{[2]}$. Also, (8) follows from (1) since

$$\|Y_n - Y\|_1 \leq \|Y_n - Y\|_2 = \mathcal{O}\left(\sqrt{\frac{\log n}{n}}\right).$$

Now, assume that the claim is true for all $m' < m$. We are going to prove it for m . We will only present the proof for $A_n^{[2m-1]}$ and $A_n^{[2m]}$. The proof of (8) is slightly different and will be done in an appendix (actually, (8) has to be proved first since it will be used below).

We start with $A_n^{[2m-1]}$. First consider (7) which we break into two parts

$$B_n^{[2m-1]} = \Sigma_0 + \Sigma_1$$

according to whether in the summation $i_3 = 0$ or $i_3 \geq 1$, respectively.

For Σ_0 , we obtain

$$\begin{aligned} \Sigma_0 &= \sum_{i=1}^{2m-2} \binom{2m-1}{i} \mathbb{E} \left((I_n + 1)^i (Y_{n,0} - Y^{(0)})^i (n - I_n)^{2m-1-i} (Y_{n,1} - Y^{(1)})^{2m-1-i} \right) \\ &= \sum_{i=1}^{2m-2} \binom{2m-1}{i} \frac{1}{n} \sum_{j=0}^{n-1} A_j^{[i]} A_{n-1-j}^{[2m-1-i]}. \end{aligned}$$

Note that either i is odd or $2m - 1 - i$ is odd. Consequently, by using the induction hypothesis,

$$\Sigma_0 = \mathcal{O} \left(n^{m-(1/2)} \log^{m-1} \right).$$

Next, we consider Σ_1 . Here, by an application of Hölder's inequality, we have

$$\begin{aligned} & \mathbb{E} \left((I_n + 1)^{i_1} |Y_{n,0} - Y^{(0)}|^{i_1} (n - I_n)^{i_2} |Y_{n,1} - Y^{(1)}|^{i_2} (n + 1)^{i_3} |T_n|^{i_3} \right) \\ & \leq \| (I_n + 1) (Y_{n,0} - Y^{(0)}) \|_{2m-1}^{i_1} \| (n - I_n) (Y_{n,1} - Y^{(1)}) \|_{2m-1}^{i_2} \| (n + 1) T_n \|_{i_3}^{i_3} \end{aligned} \quad (9)$$

Consequently, by using (8) and Lemma 1, we obtain

$$\Sigma_1 = \mathcal{O} \left(n^{m-(1/2)} \log^{m-1} \right).$$

Putting the above two estimates for Σ_0 and Σ_1 together gives

$$B_n^{[2m-1]} = \mathcal{O} \left(n^{m-(1/2)} \log^{m-1} \right).$$

From this, the claim for $A_n^{[2m-1]}$ follows from Lemma 2.

Next, we consider $A_n^{[2m]}$. We again start from (7) which we now break into three parts

$$B_n^{[2m]} = \Sigma_0 + \Sigma_1 + \Sigma_2$$

according to whether in the summation $i_3 = 0$, $i_3 = 1$ or $i_3 \geq 2$, respectively.

For Σ_0 , we have

$$\begin{aligned} \Sigma_0 &= \sum_{i=1}^{m-1} \binom{2m}{2i} \mathbb{E} \left((I_n + 1)^{2i} (Y_{n,0} - Y^{(0)})^{2i} (n - I_n)^{2m-2i} (Y_{n,1} - Y^{(1)})^{2m-2i} \right) \\ &+ \sum_{i=0}^{m-1} \binom{2m}{2i+1} \mathbb{E} \left((I_n + 1)^{2i+1} (Y_{n,0} - Y^{(0)})^{2i+1} (n - I_n)^{2m-2i-1} (Y_{n,1} - Y^{(1)})^{2m-2i-1} \right). \end{aligned}$$

Plugging the induction hypothesis into the first term on the right-hand side yields

$$\begin{aligned} \Sigma_{00} &:= \sum_{i=1}^{m-1} \binom{2m}{2i} \mathbb{E} \left((I_n + 1)^{2i} (Y_{n,0} - Y^{(0)})^{2i} (n - I_n)^{2m-2i} (Y_{n,1} - Y^{(1)})^{2m-2i} \right) \\ &= \sum_{i=1}^{m-1} \binom{2m}{2i} \frac{1}{n} \sum_{j=0}^{n-1} A_j^{[2i]} A_{n-1-j}^{[2m-2i]} \\ &= \sum_{i=1}^{m-1} \binom{2m}{2i} g_i g_{m-i} \frac{1}{n} \sum_{j=0}^{n-1} j^i (\log j)^i (n-1-j)^{m-i} (\log(n-1-j))^{m-i} + \mathcal{O} \left(n^m \log^{m-1} n \right). \end{aligned}$$

Now, observe that by an application of the Euler-Maclaurin summation formula (see Section 4.5 in Flajolet and Sedgewick [5]), we have

$$\begin{aligned} & \frac{1}{n} \sum_{j=0}^{n-1} j^i (\log j)^i (n-1-j)^{m-i} (\log(n-1-j))^{m-i} \\ &= n^m \log^m n \int_0^1 x^i (1-x)^{m-i} dx + \mathcal{O} \left(n^m \log^{m-1} n \right) \\ &= \frac{i!(m-i)!}{(m+1)!} n^m \log^m n + \mathcal{O} \left(n^m \log^{m-1} n \right). \end{aligned}$$

Consequently, by a simple computation,

$$\Sigma_{00} = \frac{m-1}{m+1} g_m n^m \log^m n + \mathcal{O}(n^m \log^{m-1} n).$$

As for the second term on the right-hand side of Σ_0 , again by the induction hypothesis,

$$\begin{aligned} \Sigma_{01} &:= \sum_{i=0}^{m-1} \binom{2m}{2i+1} \mathbb{E} \left((I_n + 1)^{2i+1} (Y_{n,0} - Y^{(0)})^{2i+1} (n - I_n)^{2m-2i-1} (Y_{n,1} - Y^{(1)})^{2m-2i-1} \right) \\ &= \sum_{i=0}^{m-1} \binom{2m}{2i+1} \frac{1}{n} \sum_{j=0}^{n-1} A_j^{[2i+1]} A_{n-1-j}^{[2m-2i-1]} = \mathcal{O}(n^m \log^{m-1} n). \end{aligned}$$

Next, we consider Σ_1 , where we plug (4) into Σ_1 and break the expectation into three parts according to the three terms in the definition of T_n . For the first part, we obtain

$$\begin{aligned} &\mathbb{E} \left((I_n + 1)^{i_1} (Y_{n,0} - Y^{(0)})^{i_1} (n - I_n)^{i_2} (Y_{n,1} - Y^{(1)})^{i_2} (I_n + 1 - (n+1)U) Y^{(0)} \right) \\ &= \sum_{j=0}^{n-1} (j+1)^{i_1} \mathbb{E} \left((Y_j - Y)^{i_1} Y \right) A_{n-1-j}^{[i_2]} \int_0^1 (j+1 - (n+1)u) \binom{n-1}{j} u^j (1-u)^{n-1-j} du. \end{aligned}$$

Note that

$$\int_0^1 (j+1 - (n+1)u) \binom{n-1}{j} u^j (1-u)^{n-1-j} du = \frac{j+1}{n} - \frac{j+1}{n} = 0.$$

Hence, the first part vanishes. Similarly, the second part vanishes. As for the third part, we have

$$\begin{aligned} &\mathbb{E} \left((I_n + 1)^{i_1} (Y_{n,0} - Y^{(0)})^{i_1} (n - I_n)^{i_2} (Y_{n,1} - Y^{(1)})^{i_2} (nC_n(I_n + 1) - (n+1)C(U)) \right) \\ &= \sum_{j=0}^{n-1} A_j^{[i_1]} A_{n-1-j}^{[i_2]} \int_0^1 (nC_n(j+1) - (n+1)C(u)) \binom{n-1}{j} u^j (1-u)^{n-1-j} du \\ &= \sum_{j=0}^{n-1} A_j^{[i_1]} A_{n-1-j}^{[i_2]} \left(C_n(j+1) - (n+1) \binom{n-1}{j} \int_0^1 C(u) u^j (1-u)^{n-1-j} du \right). \end{aligned}$$

We will show that

$$c_{j,n} := C_n(j+1) - (n+1) \binom{n-1}{j} \int_0^1 C(u) u^j (1-u)^{n-1-j} du = \mathcal{O}\left(\frac{1}{n}\right) \quad (10)$$

uniformly in j . Then, by using the induction hypothesis and the fact that $i_1 + i_2 = 2m - 1$, we have

$$\Sigma_1 = \mathcal{O}(n^{m-(1/2)} \log^{m-1} n).$$

In order to show (10), we use

$$\mathbb{E}(C_n) = 2(n+1) \log n + cn + \mathcal{O}(1)$$

for some constant c . Consequently,

$$\begin{aligned} C_n(j+1) &= \frac{1}{n} (\mathbb{E}(C_j) + \mathbb{E}(C_{n-j-1}) - \mathbb{E}(C_n) + n - 1) \\ &= \frac{2}{n} (j+1) \log j + \frac{2}{n} (n-j) \log(n-j-1) - \frac{2}{n} (n+1) \log n + 1 + \mathcal{O}\left(\frac{1}{n}\right). \end{aligned} \quad (11)$$

Next, to evaluate the integral in (10), we need

$$\begin{aligned} \int_0^1 u^\alpha (\log u) (1-u)^\beta du &= \frac{d}{dx} \int_0^1 u^x (1-u)^\beta du \Big|_{x=\alpha} \\ &= \frac{d}{dx} \frac{\Gamma(x+1)\Gamma(\beta+1)}{\Gamma(x+\beta+2)} \Big|_{x=\alpha} \\ &= \frac{\Gamma(\alpha+1)\Gamma(\beta+1)}{\Gamma(\alpha+\beta+2)} (\Psi(\alpha+1) - \Psi(\alpha+\beta+2)) \end{aligned}$$

for $\alpha, \beta > -1$, where Ψ is the digamma function. Recall that, as $x \rightarrow \infty$,

$$\Psi(x) = \log x + \mathcal{O}\left(\frac{1}{x}\right).$$

Using these results, we obtain for the integral in (10), uniformly in j ,

$$\begin{aligned} (n+1) \binom{n-1}{j} \int_0^1 C(u) u^j (1-u)^{n-1-j} du \\ = 1 + \frac{2}{n}(j+1)(\log j - \log n) + \frac{2}{n}(n-j)(\log(n-j-1) - \log n) + \mathcal{O}\left(\frac{1}{n}\right). \end{aligned}$$

Combining this with (11) proves (10).

Finally, we consider Σ_2 . Here, again from (9) together with (8) and Lemma 1, we obtain

$$\Sigma_2 = \mathcal{O}\left(n^m \log^{m-1} n\right).$$

Overall, by combining the above estimates for Σ_0, Σ_1 and Σ_2 ,

$$B_n^{[2m]} = \frac{m-1}{m+1} g_m n^m \log^m n + \mathcal{O}\left(n^m \log^{m-1} n\right).$$

From this, by applying Lemma 2,

$$A_n^{[2m]} = g_m n^m \log^m n + \mathcal{O}\left(n^m \log^{m-1} n\right).$$

This is the claimed result. Hence, the proof is finished. \blacksquare

The latter proposition together with the Fréchet-Shohat theorem implies (2).

3 Proof of Theorem 1

Here, we prove Theorem 1. First, observe that by Proposition 1, we have

$$\left\| \sqrt{\frac{n}{2 \log n}} (Y_n - Y) \right\|_p \leq \left\| \sqrt{\frac{n}{2 \log n}} (Y_n - Y) \right\|_{2\lceil p/2 \rceil} = \mathcal{O}(1). \quad (12)$$

Consequently,

$$\left(\frac{n}{2 \log n} \right)^{p/2} |Y_n - Y|^p$$

is uniformly integrable, for all $p \geq 1$. This together with (2) implies that

$$\lim_{n \rightarrow \infty} \left(\frac{n}{2 \log n} \right)^{p/2} \mathbb{E}|Y_n - Y|^p = \mathbb{E}|N(0, 1)|^p.$$

A standard computation yields

$$\mathbb{E}|N(0, 1)|^p = \frac{2^{p/2}}{\sqrt{\pi}} \Gamma\left(\frac{p+1}{2}\right).$$

Overall, as $n \rightarrow \infty$, we have

$$\|Y_n - Y\|_p \sim \frac{2}{\pi^{1/(2p)}} \Gamma\left(\frac{p+1}{2}\right)^{1/p} \sqrt{\frac{\log n}{n}}.$$

This proves the claimed result.

Remark 1. The property (12) was mentioned without proof on page 11 in [8].

Acknowledgments

We thank Jim Fill for many valuable suggestions and pointing out some bugs in a previous version of this paper.

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Appendix

Throughout this appendix, we will use the notation $\log_+(x) = \max\{\log x, 1\}$.

The goal of this appendix is to prove (8). We will use the notation

$$\bar{A}_n^{[k]} = \mathbb{E} \left((n+1)^k |Y_n - Y|^k \right).$$

Note that $\bar{A}_n^{[2m]} = A_n^{[2m]}$ and (8) becomes

$$\bar{A}_n^{[2m-1]} \leq cn^{m-(1/2)} \log_+^{m-(1/2)} n \quad (13)$$

for a suitable constant $c > 1$.

The proof will proceed by induction. Thus, we assume that (13) and the claims of Proposition 1 hold for all $m' < m$. Moreover, we assume that (13) holds for all $n' < n$ where we can assume that n is sufficiently large. We will show how to choose c such that (13) holds for all n .

In order to prove our claim, we start from (5). First, observe that

$$(n+1)|Y_n - Y| \leq (I_n + 1) |Y_{n,0} - Y^{(0)}| + (n - I_n) |Y_{n,1} - Y^{(1)}| + (n+1)|T_n|.$$

Raising this to the $2m - 1$ -st power gives

$$\bar{A}_n^{[2m-1]} \leq \frac{2}{n} \sum_{j=0}^{n-1} A_j^{[2m-1]} + \bar{B}_n^{[2m-1]}, \quad (14)$$

where $\bar{B}_n^{[2m-1]}$ is given by

$$\sum_{\substack{i_1+i_2+i_3=2m-1 \\ 0 \leq i_1, i_2 < 2m-1}} \binom{2m-1}{i_1, i_2, i_3} \mathbb{E} \left((I_n + 1)^{i_1} |Y_{n,0} - Y^{(0)}|^{i_1} (n - I_n)^{i_2} |Y_{n,1} - Y^{(1)}|^{i_2} (n+1)^{i_3} |T_n|^{i_3} \right).$$

As in the proof of Proposition (1) we will break $\bar{B}_n^{[2m-1]}$ into three parts

$$\bar{B}_n^{[2m-1]} = \Sigma_0 + \Sigma_1 + \Sigma_2$$

according to whether $i_3 = 0$, $i_3 = 1$, or $i_3 \geq 2$, respectively.

For Σ_0 , by using the induction hypothesis, we have

$$\Sigma_0 = \sum_{i=1}^{2m-2} \binom{2m-1}{i} \frac{2}{n} \sum_{j=0}^{n-1} \bar{A}_j^{[i]} \bar{A}_{n-1-j}^{[2m-1-i]} \leq d_1 n^{m-(1/2)} \log_+^{m-(1/2)} n$$

for a suitable constant d_1 .

Next, for Σ_1 , we use (9). From this, another application of the induction hypothesis and using Lemma (1), we obtain

$$\begin{aligned} \Sigma_1 &\leq \bar{d}_2 \sqrt{n} (2m-1) 4^{m-1} \left(\frac{1}{n} \sum_{j=0}^{n-1} \bar{A}_j^{[2m-1]} \right)^{(2m-2)/(2m-1)} \\ &\leq \bar{d}_2 c^{(2m-2)/(2m-1)} (2m-1) 4^{m-1} n^{m-(1/2)} \log_+^{m-1} n \leq d_2 c n^{m-(1/2)} \log_+^{m-1} n \end{aligned}$$

for suitable constants \bar{d}_2 and d_2 .

Finally, for Σ_2 , we again use (9) where $2m - 1$ is replaced by $2m - 2$. Consequently, again by the induction hypothesis

$$\Sigma_3 \leq d_3 n^{m-(1/2)} \log_+^{m-(3/2)} n \leq d_3 n^{m-(1/2)} \log_+^{m-(1/2)} n$$

for a suitable constant d_3 .

Putting the last three estimates together yields

$$\bar{B}_n^{[2m-1]} \leq \left(\frac{d_2 c}{\sqrt{\log_+ n}} + d_1 + d_3 \right) n^{m-(1/2)} \log_+^{m-(1/2)} n.$$

Plugging this into (14) and using once more the induction hypothesis yields

$$\begin{aligned} \bar{A}_n^{[2m-1]} &\leq 2c \frac{1}{n} \sum_{j=0}^{n-1} j^{m-(1/2)} \log_+^{m-(1/2)} j + \left(\frac{d_2 c}{\sqrt{\log_+ n}} + d_1 + d_3 \right) n^{m-(1/2)} \log_+^{m-(1/2)} n \\ &\leq \left(2c \int_0^1 u^{m-(1/2)} du \right) n^{m-(1/2)} \log_+^{m-(1/2)} n + \left(\frac{d_2 c}{\sqrt{\log_+ n}} + d_1 + d_3 \right) n^{m-(1/2)} \log_+^{m-(1/2)} n \\ &= \left(\frac{2c}{m + (1/2)} + \frac{d_2 c}{\sqrt{\log_+ n}} + d_1 + d_3 \right) n^{m-(1/2)} \log_+^{m-(1/2)} n. \end{aligned}$$

Note that for n large enough, we have

$$\frac{2}{m + (1/2)} + \frac{d_2}{\sqrt{\log_+ n}} < 1.$$

Hence, we can choose c such that

$$\frac{2c}{m + (1/2)} + \frac{d_2 c}{\sqrt{\log_+ n}} + d_1 + d_3 \leq c$$

which concludes our proof.