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Subtree Sizes in Recursive Trees and Binary Search Trees: Berry–Esseen Bounds and Poisson Approximations

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We study the number of subtrees on the fringe of random recursive trees and random binary search trees whose limit law is known to be either normal or Poisson or degenerate depending on the size of the subtree. We introduce a new approach to this problem which helps us to further clarify this phenomenon. More precisely, we derive optimal Berry–Esseen bounds and local limit theorems for the normal range and prove a Poisson approximation result as the subtree size tends to infinity.

1. Introduction and results

In this paper, we are interested in the quantity $X_{n,k}$ that counts the number of subtrees of size k on the fringe of certain random trees of size n. This number is an important tree characteristic carrying a lot of information about the shape of a tree. It can be considered as another kind of 'profile', the latter notation usually reserved for the number of nodes at a fixed level. The profile attracted a lot of attention in recent research; for random recursive trees and random binary search trees see Drmota and Hwang [8] and Fuchs, Hwang and Neininger [14]; for other classes of random trees see [9], [16], [17]. Apart from being an important shape parameter, $X_{n,k}$ also has practical relevance due to its close relationship with some fundamental quantities of trees arising in molecular biology and genetics: see Blum and François [4] and Rosenberg [18] for more details.

In this paper, we will focus on recursive trees and binary search trees as underlying classes of trees. Due to the similarity of our approach for those two families, we will mainly restrict our attention to recursive trees. One way to define these trees is as rooted, non-plane trees with nodes labelled by positive integers, where the labels of any path from the root to the leaf form an increasing sequence. We consider the uniform random model on the class of recursive trees which assumes that every tree is equally likely. The resulting random tree is then called a *random recursive tree*. A different way to define a random recursive tree is by a tree evolution

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process: first start with the root and then randomly attach nodes, where the parent for an incoming node is chosen uniformly from the already existing nodes. Recursive trees have found many applications in diverse fields: see [14] and references therein.

The number of subtrees of random recursive trees seems to have appeared first in a paper of Aldous [1], who obtained the weak law of large numbers,

$$\frac{X_{n,k}}{n} \longrightarrow \frac{1}{k(k+1)} \quad \text{in probability.}$$

This result was then re-derived by Devroye in [7] with a different approach. Moreover, Devroye obtained the following expressions for mean value,

$$\mu_{n,k} := \mathbb{E}(X_{n,k}) = \frac{n}{k(k+1)} \qquad (k < n),$$

and variance,

$$\sigma_{n,k}^2 := \mathbb{V}(X_{n,k}) = \frac{(2k^2-1)n}{k(k+1)^2(2k+1)} \qquad (2k < n),$$

and proved that for fixed k a central limit theorem holds:

$$\frac{X_{n,k} - \mu_{n,k}}{\sigma_{n,k}} \to N(0,1) \qquad (n \to \infty).$$

Devroye's results were re-discovered in a recent paper by Feng, Mahmoud and Su [11]. The methods of the latter authors were, however, completely different, namely, they applied the contraction method and Pólya urns, whereas Devroye's approach was based on central limit theorems for m-dependent random variables.

The above form of the mean value motivates the subdivision of the range of k into the following three distinct subranges: (i) *subcritical* when $1 \leqslant k = o(\sqrt{n})$, (ii) *critical* when $k \sim c\sqrt{n}$, and (iii) *supercritical* when $k < n$ and $k/\sqrt{n} \longrightarrow \infty$. Feng, Mahmoud and Su posed in [11] the problem of extending the central limit theorem for fixed k to the whole subcritical range. This problem was then solved in a subsequent paper by Feng, Mahmoud and Panholzer [10]. More precisely, they derived all possible limit laws of $X_{n,k}$ as k varies: in the subcritical range, the limit law of $(X_{n,k} - \mu_{n,k})/\sigma_{n,k}$ is standard normal; in the critical range, the limit law of $X_{n,k}$ is Poisson with parameter $1/c^2$; in the supercritical range, the limit law of $X_{n,k}$ is degenerate.

The method of proof proposed by Feng, Mahmoud and Panholzer rested on an exact expression for all factorial moments. In an unpublished paper, we independently obtained the same results by a completely different approach. More precisely, our approach was based on the crucial observation that all moments (centered or non-centered) satisfy the same type of recurrence. Proving asymptotic transfer theorems for the latter recurrence then provided a scheme for recursively obtaining first-order asymptotics of all higher moments. The limit distribution is then identified via these asymptotics. Such a procedure, occasionally nicknamed 'moment pumping', was successfully applied in a great variety of problems: see Chern, Fuchs and Hwang [6] and references therein. The current situation is, however, more involved due to the dependence on two indices; see the above references for the profile, where a similar two-indexed situation was encountered.

One of the main aims of this paper and a companion paper is to demonstrate that our approach based on moments is very general in the sense that it applies to a great variety of problems and lends itself to refinements to give much deeper results.

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First, the approach of Feng, Mahmoud and Panholzer can be used to work out the above result for random recursive trees and also to prove a corresponding result for random binary search trees, but it is not clear how to amend their method to other classes of random trees. Our approach, however, can be more straightforwardly adapted to treat other classes of random trees. This will be done in a companion paper, where we will prove similar limit results for many other classes of random trees. These results then demonstrate that the above phenomenon exhibits great universality, thereby further emphasizing the importance of the number of subtrees as a fundamental tree characteristic.

In this paper, we will propose refinements of our recursive method above. These refinements will all be based on a method introduced by Hwang [15] for obtaining second phase change results in random m-ary search trees (for more information see Section 3). Our refined approaches will also exhibit some universality; we will demonstrate this by showing that they straightforwardly apply to random binary search trees as well. Technically, the main new challenges again arise from the dependence of the problem on two indices.

We will use our refined methods to shed further light on the phenomenon discovered by Feng, Mahmoud and Panholzer. In order to do so, we will prove two different types of results. First, in the subcritical range, we deduce the optimal Berry–Esseen bound and a local limit theorem. In particular, from the Berry–Esseen bound, we see that the convergence gets weaker and weaker as k approaches $\sqrt{n}$, thereby identifying the latter as the critical point.

Theorem 1.1. *Let $k = k_n$ be a sequence with $1 \leqslant k_n = o(\sqrt{n})$. Then,*

$$\sup_{-\infty<x<\infty}\left|P\left(\frac{X_{n,k}-\mu_{n,k}}{\sigma_{n,k}} \leqslant x\right) - \Phi(x)\right| = \mathcal{O}\left(\frac{k}{\sqrt{n}}\right),$$

where the rate is (up to the implied constant) optimal.

Theorem 1.2. *Let $k = k_n$ be a sequence with $1 \leqslant k_n = o(\sqrt{n})$. Then,*

$$P\left(X_{n,k} = \lfloor \mu_{n,k} + x\sigma_{n,k} \rfloor\right) = \frac{e^{-x^2/2}}{\sqrt{2\pi\sigma_{n,k}^2}}\left(1 + \mathcal{O}\left(\left(1+|x|^3\right)\frac{k}{\sqrt{n}}\right)\right)$$

uniformly in $x = o(n^{1/6}/k^{1/3})$.

Our second explanation of the above result of Feng, Mahmoud and Panholzer was inspired by a study of predecessors in random mappings due to Baron, Drmota and Mutafchiev [3]. First, observe that that the above expressions for mean value and variance imply

$$\mathbb{E}(X_{n,k}) \sim \mathbb{V}(X_{n,k}) \sim \frac{n}{k^2}$$

for $k = k_n < 2n$, where $k \to \infty$ as $n \to \infty$. This suggests that a Poisson approximation result should hold for $k \to \infty$ (with the latter range being optimal). This is in fact the case.

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Theorem 1.3. *Let $k = k_n$, where $k < n$ and $k \to \infty$ as $n \to \infty$. Then, the total variation distance between $X_{n,k}$ and a Poisson random variable with rate $\mu_{n,k}$ tends to 0, i.e.,*

$$d_{TV}(X_{n,k}, \mathrm{Po}(\mu_{n,k})) = \frac{1}{2}\sum_{l\geqslant 0}\left|P(X_{n,k} = l) - e^{-\mu_{n,k}}\frac{(\mu_{n,k})^l}{l!}\right| \to 0 \qquad (n \to \infty).$$

The proof of the above result will rely on the local limit theorem for the normal range as well as a similar local limit theorem for the critical and supercritical range that will be obtained below. Apart from proving convergence to 0, the proof will also yield a rate which, however, is quite poor (see the remark at the end of Section 4 for further details).

We give a short sketch of the paper. In the next section, we give some general asymptotic transfer results and re-derive the above two explicit formulas for mean value and variance. In Section 3, we will introduce our first refined moment approach and use it to prove the above two results for the normal range. Section 4 is then dedicated to obtaining a local limit theorem for the non-normal range via a second refinement of the moment approach. This result together with the local limit theorem above will then be used to prove Theorem 1.3. In a final section, we will outline similar results for random binary search trees.

Notation. Throughout the paper, c_0 will denote a constant whose value might change from one occurrence to the next.

2. Preliminaries

First, it is easy to see that $X_{n,k}$ satisfies the following recurrence:

$$X_{n,k} \stackrel{d}{=} X_{I_n,k} + X^*_{n-I_n,k} - \mathbf{1}_{\{n-I_n=k\}} \qquad (k < n) \tag{2.1}$$

with $X_{n,k} = 0$ for $n < k$ and $X_{k,k} = 1$, where $I_n = \mathrm{Unif}\{1, n-1\}$, $X^*_{n,k}$ is an independent copy of $X_{n,k}$, and the sequences $X_{n,k}$, $X^*_{n,k}$, and I_n are all independent.

Roughly speaking, this recurrence can be explained as follows: the number of subtrees of size k are counted by first counting the number of subtrees of size k in the leftmost subtree of the root and then adding the number of subtrees of size k in the remaining tree, where we have counted one subtree too many if the remaining tree itself is of size k; for a more detailed explanation we direct the reader to [11].

From this recurrence, we immediately obtain corresponding recurrences for the (centered or non-centered) moments of $X_{n,k}$, all of them having the following general shape:

$$a_{n,k} = \frac{2}{n-1}\sum_{j=1}^{n-1} a_{j,k} + b_{n,k} \qquad (k < n), \tag{2.2}$$

where $b_{n,k}$ is a suitable sequence, $a_{n,k} = 0$ for $n < k$, and $a_{k,k}$ is fixed.

For instance, for the mean value we get the above recurrence with $b_{n,k} = -1/(n-1)$ for $k < n$ and $a_{k,k} = 1$ and for the variance the 'toll' sequence $b_{n,k}$ becomes

$$b_{n,k} = \frac{1}{n-1}\sum_{j=1}^{n-1}(\mu_{j,k} + \mu_{n-j,k} - \mu_{n,k} - \mathbf{1}_{\{j=n-k\}})^2$$

and $a_{k,k} = 0$.

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We start by solving recurrence (2.2).

Lemma 2.1. *For $k < l < n$,*

$$a_{n,k} = \frac{n}{l} a_{l,k} + 2n \sum_{l<j<n} \frac{b_{j,k}}{j(j+1)} + b_{n,k} - \frac{n(l-1)}{l(l+1)} b_{l,k} \tag{2.3}$$

$$= \frac{2n}{k(k+1)} a_{k,k} + 2n \sum_{k<j<n} \frac{b_{j,k}}{j(j+1)} + b_{n,k}. \tag{2.4}$$

Proof. Consider $(n-1)a_{n,k} - (n-2)a_{n-1,k}$ and iterate the resulting recurrence. □

Using the above solution of (2.2), we can re-derive the explicit formulas for mean value and variance obtained by Feng, Mahmoud and Su.

First, for the mean value,

$$\begin{aligned}
\mu_{n,k} &= \frac{2n}{k(k+1)} \mathbb{E}X_{k,k} - 2n \sum_{k<j<n} \frac{1}{(j-1)j(j+1)} - \frac{1}{n-1} \\
&= \frac{2n}{k(k+1)} - 2n\left(-\frac{1}{2(n-1)n} + \frac{1}{2k(k+1)}\right) - \frac{1}{n-1} \\
&= \frac{n}{k(k+1)},
\end{aligned}$$

where this holds for $k < n$. Overall,

$$\mu_{n,k} = \begin{cases} n/(k(k+1)), & \text{if } k < n, \\ 1, & \text{if } k = n, \\ 0, & \text{if } k > n. \end{cases}$$

For the variance, slightly more work is necessary. Here, we are going to use (2.3) with $l = 2k+1$. First, for $n > 2k$,

$$\begin{aligned}
b_{n,k} &= \frac{1}{n-1} \sum_{j=1}^{n-1} (\mu_{j,k} + \mu_{n-j,k} - \mu_{n,k} - \mathbf{1}_{\{j=n-k\}})^2 \\
&= \frac{2}{n-1} \sum_{j<k} \left(\frac{n-j}{k(k+1)} - \frac{n}{k(k+1)}\right)^2 + \frac{1}{n-1}\left(\frac{n-k}{k(k+1)} + 1 - \frac{n}{k(k+1)}\right)^2 \\
&\quad + \frac{1}{n-1}\left(\frac{n-k}{k(k+1)} - \frac{n}{k(k+1)}\right)^2 \\
&= \frac{3k^2 - k + 1}{3k(k+1)(n-1)} = \frac{c_k}{n-1}.
\end{aligned}$$

Now, observe that all terms except the first one on the right-hand side of (2.3) add to 0 for toll functions of the form $b_{n,k} = c_k/(n-1)$. So, for $n > 2k$,

$$\sigma^2_{n,k} = \frac{n}{2k+1} \sigma^2_{2k+1,k}.$$

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It is easy to see that

$$X_{2k+1,k} = \begin{cases} 0, & \text{with probability } (k-1)(2k^2-1)/(2k^2(k+1)), \\ 1, & \text{with probability } (2k^2-1)/(k^2(k+1)), \\ 2, & \text{with probability } 1/(2k^2). \end{cases}$$

Thus,

$$\sigma^2_{2k+1,k} = \frac{2k^2-1}{k(k+1)^2}.$$

Plugging the latter into the above formula proves the claimed result. As for the remaining range of n, observe that for $k < n \leqslant 2k$ we have

$$X_{n,k} = \begin{cases} 0, & \text{with probability } 1 - n/(k(k+1)), \\ 1, & \text{with probability } n/(k(k+1)). \end{cases} \tag{2.5}$$

Consequently, for $k < n \leqslant 2k$,

$$\sigma^2_{n,k} = \frac{n}{k(k+1)}\left(1 - \frac{n}{k(k+1)}\right).$$

Overall,

$$\sigma^2_{n,k} = \begin{cases} (2k^2-1)n/(k(k+1)^2(2k+1)), & \text{if } n > 2k, \\ n/(k(k+1))(1-n/(k(k+1))), & \text{if } k < n \leqslant 2k, \\ 0, & \text{if } n < k. \end{cases} \tag{2.6}$$

Subsequently, we will need the following simple transfer result.

Proposition 2.2. *Let $a_{k,k} = 0$.*

(i) *Assume that $|b_{n,k}| \leqslant c_1 c_k$, where $c_1 > 0$ is a constant. Then, $|a_{n,k}| \leqslant 2c_1 c_k n/k$.*
(ii) *Assume that*

$$|b_{n,k}| \leqslant c_1 \big(c_k n\big)^v,$$

where $c_1 > 0$ and $v > 1$. Then,

$$|a_{n,k}| \leqslant \frac{2c_1 v}{v-1}\big(c_k n\big)^v.$$

Proof. We first prove part (i). Therefore, we use the above lemma. Consequently,

$$|a_{n,k}| \leqslant 2c_1 c_k n \sum_{k<j<n} \frac{1}{j(j+1)} + c_1 c_k = \frac{2c_1 c_k n}{(k+1)} - c_1 c_k \leqslant \frac{2c_1 c_k n}{k}.$$

For the second part, we use similar reasoning and obtain

$$|a_{n,k}| \leqslant 2c_1 c_k^v n \sum_{k<j<n} j^{v-2} + c_1 \big(c_k n\big)^v \leqslant \frac{2c_1 v}{v-1}(c_k n)^v.$$

This proves the claimed result. □

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3. Subcritical range: Berry–Esseen bounds and local limit theorems

In this section, we are going to prove Theorems 1.1 and 1.2. Therefore, we will propose a new version of Hwang's refined method of moments, which was introduced in [15] for proving second phase change results for random m-ary search trees; see also [6] and Bai, Hwang and Tsai [2] for other applications of the latter method. As already explained in the Introduction, the main new feature of the current situation is that we have to deal with a double-indexed recurrence. This will make the analysis much more involved. In particular, the crucial bound from Proposition 3.1 below must hold uniformly in both k and n. While the case of n large compared with k resembles the situations encountered in previous studies, the remaining range of n and k has to be treated quite differently.

Now, we will provide more details. Therefore, let

$$\phi_{n,k}(y) = e^{-\sigma_{n,k}^2 y^2/2}\mathbb{E}\big(e^{(X_{n,k}-\mu_{n,k})y}\big).$$

Then, (2.1) implies the following recurrence for $\phi_{n,k}(y)$,

$$\phi_{n,k}(y) = \frac{1}{n-1}\sum_{j=1}^{n-1}\phi_{j,k}(y)\phi_{n-j,k}(y)e^{\Delta_{j,n,k}y+\delta_{j,n,k}y^2} \qquad (k<n),$$

with $\phi_{n,k}(y) = 1$ for $n \leqslant k$,

$$\Delta_{j,n,k} := \mu_{j,k} + \mu_{n-j,k} - \mu_{n,k} - \mathbf{1}_{\{j=n-k\}},$$

and

$$\delta_{j,n,k} := \big(\sigma_{j,k}^2 + \sigma_{n-j,k}^2 - \sigma_{n,k}^2\big)/2.$$

Next, let $\phi_{n,k}^{(m)}$ denote the mth derivative of $\phi_{n,k}(y)$ at 0. From the above recurrence, we then obtain

$$\phi_{n,k}^{(m)} = \frac{2}{n-1}\sum_{j=1}^{n-1}\phi_{j,k}^{(m)} + \psi_{n,k}^{(m)} \qquad (k<n), \tag{3.1}$$

with $\phi_{n,k}^{(m)} = 0, n \leqslant k$ and

$$\psi_{n,k}^{(m)} = \sum_{\substack{i_1+i_2+i_3+2i_4=m\\ 0\leqslant i_1,i_2<m}} \frac{m!}{i_1!i_2!i_3!i_4!}\cdot\frac{1}{n-1}\sum_{j=1}^{n-1}\phi_{j,k}^{(i_1)}\phi_{n-j,k}^{(i_2)}\Delta_{j,n,k}^{i_3}\delta_{j,n,k}^{i_4}.$$

Our main aim is to prove the following proposition.

Proposition 3.1. *For $n,k \geqslant 1$ and $m \geqslant 0$,*

$$|\phi_{n,k}^{(m)}| \leqslant m!A^m \max\left\{\left(\frac{n}{k^2}\right)^{m/3}, \frac{n}{k^2}\right\},$$

where A is a suitable constant.

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We will first prove the claim for some small m. Therefore, note that it trivially holds for $m = 0, 1, 2$. Next, we consider $m = 3$. Here, (3.1) becomes

$$\phi_{n,k}^{(3)} = \frac{2}{n-1}\sum_{j=1}^{n-1}\phi_{j,k}^{(3)} + \psi_{n,k}^{(3)} \qquad (k < n)$$

with $\phi_{n,k}^{(3)} = 0, n \leqslant k$ and

$$\psi_{n,k}^{(3)} = \frac{6}{n-1}\sum_{j=1}^{n-1}\Delta_{j,n,k}\delta_{j,n,k} + \frac{1}{n-1}\sum_{j=1}^{n-1}\Delta_{j,n,k}^{3}.$$

Now, observe that

$$\Delta_{j,n,k} = \begin{cases} 0, & \text{if } k < j < n-k, \\ \mathcal{O}(1), & \text{if } j = k, \\ \mathcal{O}\big(1/k\big), & \text{otherwise} \end{cases} \tag{3.2}$$

and

$$\delta_{j,n,k} = \begin{cases} 0, & \text{if } 2k < j < n-2k, \\ \mathcal{O}\big(1/k\big), & \text{otherwise.} \end{cases} \tag{3.3}$$

From those two estimates we obtain $\psi_{n,k}^{(3)} = \mathcal{O}(1/k)$, where the implied constant is absolute. Applying Proposition 2.2 then yields

$$\phi_{n,k}^{(3)} = \mathcal{O}\left(\frac{n}{k^2}\right).$$

This proves our assertion for $m = 3$.

Next, assume that we have already proved that

$$|\phi_{n,k}^{(m)}| \leqslant m! A_0^m \frac{n}{k^2} \tag{3.4}$$

for all $n \leqslant 2k^2$ and $m \geqslant 1$, where A_0 is a suitable constant. This is in fact already half of the claim above and will be proved later on. To prove the other half, we have to show that

$$|\phi_{n,k}^{(m)}| \leqslant m! A_1^m \left(\frac{n}{k^2}\right)^{m/3} \tag{3.5}$$

for all $n > 2k^2$ and $m \geqslant 0$, where A_1 is a suitable constant. Without loss of generality we can assume that $A_1 \geqslant A_0$. In order to prove (3.5), we will use induction and (3.4).

We already know that (3.5) holds for $m = 0, 1, 2, 3$. Now, assume we have proved it for all m' with $m' < m$.

In order to prove the claim for m, we first consider $\psi_{n,k}^{(m)}$ and break it into three parts:

$$\begin{aligned}\psi_{n,k}^{(m)} &= \sum_{\substack{i_1+i_2+i_3+2i_4=m \\ 0\leqslant i_1,i_2<m}} \sum_{2k^2<j<n-2k^2} + \sum_{\substack{i_1+i_2+i_3+2i_4=m \\ 0\leqslant i_1,i_2<m}} \sum_{j\leqslant 2k^2} + \sum_{\substack{i_1+i_2+i_3+2i_4=m \\ 0\leqslant i_1,i_2<m}} \sum_{j\geqslant n-2k^2} \\ &=: \Sigma_1 + \Sigma_2 + \Sigma_3.\end{aligned}$$

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We start by treating the first sum. Note that, due to (3.2), and (3.3) it simplifies to

$$\Sigma_1 = \sum_{i=1}^{m-1} \binom{m}{i} \frac{1}{n-1} \sum_{2k^2<j<n-2k^2} \phi_{j,k}^{(i)} \phi_{n-j,k}^{(m-i)}.$$

Using the induction hypotheses, the latter sum can be estimated as follows:

$$\begin{aligned}
|\Sigma_1| &\leqslant m! A_1^m \sum_{i=1}^{m-1} \frac{1}{n-1} \sum_{2k^2<j<n-2k^2} \left(\frac{j}{k^2}\right)^{i/3} \left(\frac{n-j}{k^2}\right)^{(m-i)/3} \\
&\leqslant c_0 m! A_1^m \left(\frac{n}{k^2}\right)^{m/3} \sum_{i=1}^{m-1} \frac{\Gamma(i/3+1)\Gamma((m-i)/3+1)}{\Gamma(m/3+2)} \\
&\leqslant c_0 (m-1)! A_1^m \left(\frac{n}{k^2}\right)^{m/3},
\end{aligned}$$

where the last step follows from [15, Lemma 3].

As for the second sum, we first break it into the following two parts:

$$\Sigma_2 = \sum_{\substack{i_1+i_2+i_3+2i_4=m \\ 0\leqslant i_1,i_2<m}} \sum_{j\leqslant 2k^2,\ j<n-2k^2} + \sum_{\substack{i_1+i_2+i_3+2i_4=m \\ 0\leqslant i_1,i_2<m}} \sum_{j\leqslant 2k^2,\ j\geqslant n-2k^2} =: \Sigma_{2,1} + \Sigma_{2,2}.$$

We will use the induction hypotheses and the two estimates (3.2) and (3.3) to bound the latter two parts separately. First,

$$\begin{aligned}
|\Sigma_{2,1}| &\leqslant 2m! A_1^m \sum_{\substack{i_1+i_2+i_3+2i_4=m \\ 0\leqslant i_1,i_2<m}} \frac{1}{i_3!i_4!} \frac{1}{n-1} \sum_{j\leqslant 2k^2,\ j<n-2k^2} \left(\frac{n-j}{k^2}\right)^{i_2/3} C^{i_3} D^{i_4} \\
&\leqslant c_0 m! A_1^m \sum_{i=0}^{m} \sum_{l=0}^{i} \left(\frac{n}{k^2}\right)^{l/3} \frac{1}{n-1} \sum_{1\leqslant j<n} \left(1-\frac{j}{n}\right)^{l/3} \\
&\leqslant c_0 m! A_1^m \sum_{i=0}^{m} \sum_{l=0}^{i} \frac{1}{l} \left(\frac{n}{k^2}\right)^{l/3} \leqslant c_0 (m-1)! A_1^m \left(\frac{n}{k^2}\right)^{m/3},
\end{aligned}$$

where the last line follows from $n > 2k^2$ (otherwise the sum would be 0 and the bound trivially holds). The second sum above is once again broken into two parts:

$$\Sigma_{2,2} = \sum_{\substack{i_1+i_2+i_3+2i_4=m \\ i_3\neq 0 \text{ or } i_4\neq 0}} \sum_{j\leqslant 2k^2,\ j\geqslant n-2k^2} + \sum_{\substack{i_1+i_2=m \\ i_1,i_2\geqslant 1}} \sum_{j\leqslant 2k^2,\ j\geqslant n-2k^2} =: \Sigma_{2,2,1} + \Sigma_{2,2,2}.$$

We crudely bound the first part by

$$|\Sigma_{2,2,1}| \leqslant c_0 m! A_0^m \frac{1}{k} \sum_{i=0}^{m} \sum_{l=0}^{i} 1 \leqslant c_0 m^2 m! A_0^m \frac{1}{k}.$$

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For the second part, we use (3.4) and obtain

$$|\Sigma_{2,2,2}| \leqslant m! A_0^m \sum_{i=1}^{m-1} \frac{1}{n-1} \sum_{1 \leqslant j < n} \left(\frac{j}{k^2}\right) \left(\frac{n-j}{k^2}\right)$$
$$\leqslant c_0 m m! A_0^m \left(\frac{n}{k^2}\right)^2 \leqslant c_0 m m! A_0^m \left(\frac{n}{k^2}\right)^{7/6},$$

where the last line follows from $n \leqslant 4k^2$ (otherwise the sum would be 0). The sum Σ_3 can be bounded similarly.

Overall, we obtain for $n > k$

$$|\psi_{n,k}^{(m)}| \leqslant c_0 m! A_1^m \left(\frac{1}{m}\left(\frac{n}{k^2}\right)^{m/3} + m^2 \frac{1}{k} + m\left(\frac{n}{k^2}\right)^{7/6}\right).$$

Applying Proposition 2.2 then yields

$$|\phi_{n,k}^{(m)}| \leqslant c_0 m! A_1^m \left(\frac{1}{m-3}\left(\frac{n}{k^2}\right)^{m/3} + m^2 \left(\frac{n}{k^2}\right) + m\left(\frac{n}{k^2}\right)^{7/6}\right). \tag{3.6}$$

For $n > 2k^2$ the latter in turn implies

$$|\phi_{n,k}^{(m)}| \leqslant c_0 \left(\frac{1}{m-3} + m^2 2^{-(m-3)/3} + m 2^{-(2m-7)/6}\right) m! A_1^m \left(\frac{n}{k^2}\right)^{m/3} \leqslant m! A_1^m \left(\frac{n}{k^2}\right)^{m/3},$$

where the last line holds for n large enough. Hence, by suitable tuning of the constant A_1, the proof of (3.5) is finished.

Looking at (3.6), we see that we cannot prove (3.4) by the same approach. Hence, we will use a different (and more direct) proof. Since the claimed bound is for moderately small n, it is better to look at the factorial moments. Therefore, let $P_{n,k}(z) = \mathbb{E}\big(z^{X_{n,k}}\big)$. Then, (2.1) translates into

$$P_{n,k}(z) = \frac{1}{n-1} \sum_{j=1}^{n-1} P_{j,k}(z) P_{n-j,k}(z) z^{\mathbf{1}_{\{j=n-k\}}}$$
$$= \frac{1}{n-1} \sum_{j=1}^{n-1} P_{j,k}(z) P_{n-j,k}(z) - \frac{1}{n-1}(z-1) P_{n-k,k}(z), \tag{3.7}$$

where $P_{n,k}(z) = 1$ for $n < k$ and $P_{k,k}(z) = z$. Next let $A_{n,k}^{(m)}$ denote the mth derivative of $P_{n,k}(z)$ with respect to z evaluated at $z = 1$. The above recurrence in turn yields for $m \geqslant 2$

$$A_{n,k}^{(m)} = \frac{2}{n-1} \sum_{j=1}^{n-1} A_{j,k}^{(m)} + B_{n,k}^{(m)},$$

where $A_{n,k}^{(m)} = 0$ for $n \leqslant k$ and

$$B_{n,k}^{(m)} = \sum_{i=1}^{m-1} \binom{m}{i} \frac{1}{n-1} \sum_{j=1}^{n-1} A_{j,k}^{(i)} A_{n-j,k}^{(m-i)} - \frac{m}{n-1} A_{n-k,k}^{(m-1)}.$$

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Now, we will use the same approach as above to prove the uniform bound

$$|A_{n,k}^{(m)}| \leqslant m! A^m \left(\frac{n}{k^2}\right)^m. \tag{3.8}$$

with a suitable constant A and $m \geqslant 0$ (with the sole exception of $m = 1$ and $n = k$).

First observe that (3.8) trivially holds for $m = 0, 1$. Next, we look at $m = 2$. Here, we have

$$B_{n,k}^{(2)} = \frac{2}{n-1} \sum_{j=1}^{n-1} A_{j,k}^{(1)} A_{n-j,k}^{(1)} - \frac{2}{n-1} A_{n-k,k}^{(1)} = \mathcal{O}\left(\left(\frac{n}{k^2}\right)^2 + \frac{1}{n-1}\left(\frac{n}{k^2}\right)\right) = \mathcal{O}\left(\left(\frac{n}{k^2}\right)^2\right). \tag{3.9}$$

Note that in the above estimate, we have to be careful with $j = k$ and $j = n - k$: (i) if either $j \neq k$ or $j \neq n - k$, then we can exclude both cases from the above first sum and replace $-$ by $+$ in front of the second term; (ii) if $n = 2k$ then we can exclude the case $j = k$ from the first sum and completely drop the second term. Now, applying Proposition 2.2 yields (3.8) with $m = 2$.

For the general case, assume that the assertion holds for all m' with $m' < m$. To prove it for m, first consider

$$\begin{aligned}
|B_{n,k}^{(m)}| &\leqslant m! A^m \sum_{i=1}^{n-1} \frac{1}{m-1} \sum_{j=1}^{n-1} \left(\frac{j}{k^2}\right)^i \left(\frac{n-j}{k^2}\right)^{m-i} + \frac{m!}{n-1} A^{m-1} \left(\frac{n-k}{k^2}\right)^{m-1} \\
&\leqslant c_0 m! A^m \left(\frac{n}{k^2}\right)^m \sum_{i=0}^{m} \frac{i!(m-i)!}{(m+2)!} + m! A^{m-1} \left(\frac{n}{k^2}\right)^m \\
&\leqslant c_0 m! A^m \left(\frac{n}{k^2}\right)^m \left(\frac{1}{m} + A^{-1}\right),
\end{aligned}$$

where in the first estimate we again have to be careful with the cases $j = k$ and $j = n - k$ (but a remark similar to that above holds) and the last line follows from [15, Lemma 3]. Applying Proposition 2.2 then yields

$$|A_{n,k}^{(m)}| \leqslant c_0 \left(\frac{1}{m-1} + A^{-1} \frac{m}{m-1}\right) m! A^m \left(\frac{n}{k^2}\right)^m \leqslant m! A^m \left(\frac{n}{k^2}\right)^m,$$

where the last step follows for m and A large enough. Suitable tuning of A completes the induction step.

Remark. Note that (3.8) is simpler than the bound previously obtained for $\phi_{n,k}^{(m)}$. This is essentially due to the simpler nature of the toll sequence $B_{n,k}^{(m)}$ in this case. In particular, computing $\phi_{n,k}^{(3)}$ would reveal that a similar simple bound would not hold in the previous situation.

Moreover, we should mention that the following weaker result for $n \leqslant ck^2$ was obtained in [10]:

$$|A_{n,k}^{(m)}| \leqslant c_0 (m-1)! \frac{n}{k^2}$$

for $m \geqslant 2$. Actually, this bound would be sufficient for us as well. The reason why we proved the above stronger bound is because the proof is more in the spirit of our paper and hence makes our paper more self-contained. Moreover, we will also encounter a very similar situation in the next section.

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Using the following well-known relation between moments and factorial moments,

$$\mathbb{E}X_{n,k}^m = \sum_{i=1}^m S(n,i)A_{n,k}^{(i)},$$

where $S(n,i)$ are the Stirling numbers of second kind, we obtain for $k < n \leqslant 2k^2$ and $m \geqslant 1$

$$\begin{aligned}|\mathbb{E}X_{n,k}^m| &\leqslant \sum_{i=1}^m S(n,i)i!A^i\left(\frac{n}{k^2}\right)^i\\ &\leqslant \frac{n}{k^2}(2A)^m\sum_{i=1}^m S(n,i)m(m-1)\cdots(m-i+1)\\ &= \frac{n}{k^2}(2A)^m m^m \leqslant m!\bar{A}^m\frac{n}{k^2},\end{aligned}$$

where the last line follows by the definition of Stirling numbers of second kind and Stirling's formula. The latter estimate then in turn implies for $k < n \leqslant 2k^2$ and $m \geqslant 1$

$$\begin{aligned}|\mathbb{E}(X_{n,k}-\mu_{n,k})^m| &\leqslant \sum_{i=1}^m \binom{m}{i}\mathbb{E}X_{n,k}^i\big(\mu_{n,k}\big)^{m-i} + (\mu_{n,k})^m\\ &\leqslant m!\bar{A}^m\frac{n}{k^2}\sum_{i=1}^m\frac{2^{m-i}}{(m-i)!} + \left(\frac{n}{k^2}\right)^m\\ &\leqslant m!\tilde{A}^m\frac{n}{k^2}.\end{aligned}$$

Finally, we have

$$\phi_{n,k}^{(m)} = \sum_{i=0,\ i\ \text{even}}^m \binom{m}{i}\frac{i!}{(i/2)!}\big(-\sigma_{n,k}^2/2\big)^{i/2}\mathbb{E}(X_{n,k}-\mu_{n,k})^{m-i}.$$

Consequently, for $k < n \leqslant 2k^2$ and $m \geqslant 2$,

$$|\phi_{n,k}^{(m)}| \leqslant m!\tilde{A}^m\frac{n}{k^2}\sum_{i=0,\ i\ \text{even}}^m\frac{C^{i/2}}{(i/2)!} + D^m\left(\frac{n}{k^2}\right)^{m/2} \leqslant m!A_0^m\frac{n}{k^2}.$$

This concludes the proof of (3.5).

Overall, our proof of Proposition 3.1 is finished.

Next, we will apply the latter proposition to deduce the following two results for the characteristic function of $X_{n,k}$:

$$\varphi_{n,k}(y) := \mathbb{E}\big(e^{iy(X_{n,k}-\mu_{n,k})/\sigma_{n,k}}\big) = e^{-iy\mu_{n,k}/\sigma_{n,k}}P_{n,k}\big(e^{iy/\sigma_{n,k}}\big).$$

Proposition 3.2. *Let $k = k_n$ with $1 \leqslant k_n = o(\sqrt{n})$.*

(i) *For n large enough,*

$$\varphi_{n,k}(y) = e^{-y^2/2}\left(1 + \mathcal{O}\left(|y|^3\frac{k}{\sqrt{n}}\right)\right)$$

uniformly for y with $|y| \leqslant \epsilon n^{1/6}/k^{1/3}$, where $\epsilon > 0$ is sufficiently small.

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(ii) *For n large enough and $|y| \leqslant \pi\sigma_{n,k}$,*

$$|\varphi_{n,k}(y)| \leqslant e^{-\epsilon y^2/2},$$

where $\epsilon > 0$ is sufficiently small.

Proof. The first part follows from Taylor series expansion and Proposition 3.1; see [15]. So, we just have to concentrate on the second part. Here, we will prove a slightly more general result: for $n \geqslant 3, 1 \leqslant k < n$ and $|y| \leqslant \pi$, we have

$$|P_{n,k}(e^{iy})| \leqslant e^{-\epsilon y^2(n/k^2+c/k)} \tag{3.10}$$

with (dependent) constants ϵ and c, which will be chosen below. From this, the above claim is then immediate.

In order to prove the latter result, first observe that, from (3.7),

$$|P_{n,k}(e^{iy})| \leqslant \frac{1}{n-1}\sum_{j=1}^{n-1} |P_{j,k}(e^{iy})||P_{n-j,k}(e^{iy})|.$$

We will establish our claim by induction on n. Note that for $n > 3k$ the induction step is deduced from the above recurrence as follows:

$$\begin{aligned}
|P_{n,k}(e^{iy})| &\leqslant \frac{2}{n-1}\sum_{j\leqslant k} |P_{j,k}(e^{iy})||P_{n-j,k}(e^{iy})| + \frac{1}{n-1}\sum_{k<j<n-k} |P_{j,k}(e^{iy})||P_{n-j,k}(e^{iy})| \\
&\leqslant e^{-\epsilon y^2(n/k^2+c/k)}\left(\frac{2}{n-1}\sum_{j\leqslant k} e^{\epsilon y^2 j/k^2} + \left(1-\frac{2k}{n-1}\right)e^{-\epsilon y^2 c/k}\right) \\
&\leqslant e^{-\epsilon y^2(n/k^2+c/k)}\left(\frac{2k}{n-1}e^{\epsilon y^2(1/k+1/k^2)} + \left(1-\frac{2k}{n-1}\right)e^{-\epsilon y^2 c/k}\right) \\
&\leqslant e^{-\epsilon y^2(n/k^2+c/k)}\left(\frac{2k}{n-1}(1+c_0\epsilon y^2/k) + \left(1-\frac{2k}{n-1}\right)(1-c_1\epsilon y^2 c/k)\right),
\end{aligned}$$

where c_0, c_1 are suitable absolute constants (here, we need that ϵc is small; see below). Now, choose $c > 2c_0/c_1$. Then,

$$|P_{n,k}(e^{iy})| \leqslant e^{-\epsilon y^2(n/k^2+c/k)}\left(1-\epsilon y^2\frac{(n-1-2k)cc_1-2kc_0}{k(n-1)}\right) \leqslant e^{-\epsilon y^2(n/k^2+c/k)}.$$

This establishes the induction step for $n > 3k$. As for the remaining range we first consider $n \leqslant 2k$. Here, we can directly work with (2.5) and obtain

$$\begin{aligned}
|P_{n,k}(e^{iy})|^2 &= \left(\left(1-\frac{n}{k(k+1)}\right)+\cos(y)\frac{n}{k(k+1)}\right)^2 + \sin^2(y)\frac{n^2}{k^2(k+1)^2} \\
&= 1+2\sigma_{n,k}^2(\cos y - 1) \leqslant e^{-2\epsilon_0 y^2\sigma_{n,k}^2},
\end{aligned}$$

where ϵ_0 is chosen so small that $\cos(y) - 1 \leqslant -\epsilon_0 y^2$ for $|y| \leqslant \pi$. Thus,

$$|P_{n,k}(e^{iy})| \leqslant e^{-\epsilon_0 y^2\sigma_{n,k}^2} \leqslant e^{-(\epsilon_0/(6+6c))y^2(n/k^2+c/k)}.$$

So, with $\epsilon := \epsilon_0/(6+6c)$, the above claim is established (note that ϵc is also small as required). The final range of $2k < n \leqslant 3k$ can be treated by a similar (but slightly more complicated)

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computation, where for this range we have

$$X_{n,k} = \begin{cases} 0, & \text{with probability } 1 + \mu_{n,k}(\mu_{n,k} - 3)/2 + \sigma_{n,k}^2/2, \\ 1, & \text{with probability } \mu_{n,k}(2 - \mu_{n,k}) - \sigma_{n,k}^2, \\ 2, & \text{with probability } \mu_{n,k}(\mu_{n,k} - 1)/2 + \sigma_{n,k}^2/2. \end{cases}$$

Of course, the above-chosen ϵ then has to be adjusted accordingly.

As for $n = 3, 1 \leqslant k < 3$, note that these cases are already covered by the previous arguments. This concludes the induction proof and hence (3.10) is established. Finally, we remark that (3.10) does not hold for any other possible choices of n and k. □

Theorems 1.1 and 1.2 now follow from the latter proposition by standard tools; see [15].

4. Poisson approximations

In this section we will prove Theorem 1.3. The proof will be based on the local limit theorem from the supercritical range, together with the following result.

Proposition 4.1. *For $k < n$ and $n \to \infty$,*

$$P(X_{n,k} = l) = e^{-\mu_{n,k}} \frac{(\mu_{n,k})^l}{l!} + \mathcal{O}\left(\frac{n}{k^3}\right)$$

uniformly in l.

This result will be proved with yet another variation of Hwang's refined method of moments. Therefore, let

$$\tilde{\phi}_{n,k}(z) = e^{-\mu_{n,k}(z-1)} \mathbb{E}\left(z^{X_{n,k}}\right) = e^{-\mu_{n,k}(z-1)} P_{n,k}(z),$$

where we use the convention that $\mu_{k,k} = 0$ (this will simplify the proof below). Then, (3.7) can be rewritten as

$$\tilde{\phi}_{n,k}(z) = \frac{1}{n-1} \sum_{j=1}^{n-1} \tilde{\phi}_{j,k}(z) \tilde{\phi}_{n-j,k}(z) e^{\Lambda_{j,n,k}(z-1)} - \frac{1}{n-1}(z-1) \tilde{\phi}_{n-k,k}(z) e^{\lambda_{n,k}(z-1)},$$

where $\tilde{\phi}_{n,k}(z) = 1$ for $n < k$, $\tilde{\phi}_{k,k} = z$, and

$$\Lambda_{j,n,k} = \mu_{j,k} + \mu_{n-j,k} - \mu_{n,k}, \quad \lambda_{n,k} = \mu_{n-k,k} - \mu_{n,k}.$$

Next, let $\tilde{\phi}_{n,k}^{(m)}$ be the mth derivative of $\tilde{\phi}_{n,k}(z)$ with respect to z evaluated at $z = 1$. Then, the above recurrence in turn implies for $m \geqslant 2$

$$\tilde{\phi}_{n,k}^{(m)} = \sum_{j=1}^{n-1} \tilde{\phi}_{j,k}^{(m)} + \tilde{\psi}_{n,k}^{(m)},$$

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where $\tilde{\phi}_{n,k}^{(m)} = 0$ for $n \leqslant k$, and

$$\tilde{\psi}_{n,k}^{(m)} = \sum_{\substack{i_1+i_2+i_3=m \\ 0\leqslant i_1,i_2<m}} \binom{m}{i_1,i_2,i_3} \frac{1}{n-1} \sum_{j=1}^{n-1} \tilde{\phi}_{j,k}^{(i_1)} \tilde{\phi}_{n-j,k}^{(i_2)} \Lambda_{j,n,k}^{i_3} - \frac{m}{n-1} \sum_{i=0}^{m-1} \binom{m-1}{i} \tilde{\phi}_{n-k,k}^{(i)} \lambda_{n,k}^{m-1-i}.$$

We will use a method similar to that in the previous section to obtain the following uniform bound.

Proposition 4.2. *For all $n > k$ and $m \geqslant 0$,*

$$|\tilde{\phi}_{n,k}^{(m)}| \leqslant m! A^m \left(\frac{n}{k^3}\right)^{m/2},$$

where A is a suitable constant.

Note that the latter bound (once proved) will also hold for $n \leqslant k$, the only exception being $n = k$ and $m = 1$. So, the situation here is very similar to the situation encountered in the proof of (3.8). This is also the main reason for setting $\mu_{k,k} = 0$ in the definition of $\tilde{\phi}_{n,k}(z)$.

As for the proof of the above bound, we will proceed by induction. Note that our claim trivially holds for $m = 0, 1$. We next consider the case $m = 2$. Here, direct computation yields for $n > k$

$$\tilde{\phi}_{n,k}^{(2)} = \sigma_{n,k}^2 - \mu_{n,k}.$$

Now, we use (2.6). First, for $n > 2k$,

$$\tilde{\phi}_{n,k}^{(2)} = \frac{n}{2k+1} \tilde{\phi}_{2k+1,k}^{(2)} = -\frac{n(3k+2)}{k(k+1)^2(2k+1)} = \mathcal{O}\left(\frac{n}{k^3}\right).$$

Next, for $k < n \leqslant 2k$,

$$\tilde{\phi}_{n,k}^{(2)} = \frac{-n^2}{k^2(k+1)^2} = \mathcal{O}\left(\frac{n}{k^3}\right).$$

Overall, the claim is proved for $n = 2$.

Now, assume that it holds for all $m' < m$. We want to show that it holds for m as well. Therefore, observe that $1/k \leqslant (n/k^3)^{1/2}$. Using this together with the induction hypothesis, we obtain

$$|\tilde{\psi}_{n,k}^{(m)}| = \left| \sum_{\substack{i_1+i_2+i_3=m \\ 0\leqslant i_1,i_2<m}} \binom{m}{i_1,i_2,i_3} \frac{1}{n-1} \sum_{j=1}^{n-1} \tilde{\phi}_{j,k}^{(i_1)} \tilde{\phi}_{n-j,k}^{(i_2)} \Lambda_{j,n,k}^{i_3} - \frac{m}{n-1} \sum_{i=0}^{m-1} \binom{m-1}{i} \tilde{\phi}_{n-k,k}^{(i)} \lambda_{n,k}^{m-1-i} \right|$$

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$$\begin{aligned}
&\leqslant m! \sum_{\substack{i_1+i_2+i_3=m\\ 0\leqslant i_1,i_2<m}} \frac{1}{i_3!}\frac{1}{(n-1)} A^{i_1+i_2} \sum_{j=1}^{n-1} \left(\frac{j}{k^3}\right)^{i_1/2} \left(\frac{n-j}{k^3}\right)^{i_2/2} \left(\frac{C}{k}\right)^{i_3} \\
&\quad + \frac{m!}{n-1} A^{m-1} \sum_{i=0}^{m-1} \frac{1}{(m-1-i)!} \left(\frac{n}{k^3}\right)^{i/2} \left(\frac{D}{k}\right)^{m-1-i} \\
&\leqslant c_0 \left(m! \left(\frac{n}{k^3}\right)^{m/2} \sum_{i=0}^{m} A^i \sum_{l=0}^{i} \frac{\Gamma(l/2+1)\Gamma((i-l)/2+1)}{\Gamma(i/2+2)} + m! A^{m-1} \left(\frac{n}{k^3}\right)^{m/2} \right) \\
&\leqslant c_0 m! A^m \left(\frac{n}{k^3}\right)^{m/2} \left(\frac{1}{m} + \frac{1}{A}\right),
\end{aligned}$$

where the last line follows from [15, Lemma 3]. Note that in the first estimate above we have to be careful with the case where the induction hypothesis does not hold (see the remark below Proposition 4.2); however, a similar cancellation occurs as explained following (3.9). Now, we can apply Proposition 2.2 and obtain

$$|\tilde{\phi}_{n,k}^{(m)}| \leqslant c_0 \left(\frac{1}{m-2} + \frac{m}{m-2}\frac{1}{A} \right) m! A^m \left(\frac{n}{k^3}\right)^{m/2} \leqslant m! A^m \left(\frac{n}{k^3}\right)^{m/2},$$

where the last estimate holds for m and A large enough. By suitable tuning of A, the proof of the proposition is finished.

From the previous proposition, we can now deduce Proposition 4.1.

Proof of Proposition 4.1. First, observe that the assertion is trivial for $k \leqslant cn^{1/3}$ with $c > 0$. Hence, we can restrict ourselves to k with $k \geqslant cn^{1/3}$, where c is large.

Next, from Proposition 4.2 we get

$$\begin{aligned}
P_{n,k}(z) - e^{\mu_{n,k}(z-1)} &= e^{\mu_{n,k}(z-1)} \big(\tilde{\phi}_{n,k}(z) - 1 \big) \\
&= e^{\mu_{n,k}(z-1)} \mathcal{O}\left(\sum_{m=2}^{\infty} \frac{|\tilde{\phi}_{n,k}^{(m)}|}{m!} |z-1|^m \right) \\
&= e^{\mu_{n,k}(z-1)} \mathcal{O}\left(\sum_{m=2}^{\infty} \left(A \frac{\sqrt{n}}{k^{3/2}} |z-1| \right)^m \right) \\
&= e^{\mu_{n,k}(z-1)} \mathcal{O}\left(\frac{n}{k^3} \right),
\end{aligned}$$

where the last line holds for all z for which $|z-1| \leqslant \epsilon k^{3/2}/\sqrt{n}$, with ϵ suitably small. Finally, by making the above c large enough, we see that the above expansion holds uniformly in z with $|z| = 1$.

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Next, we apply Cauchy's formula. Hence,

$$\begin{aligned} P(X_{n,k} = l) &= \frac{1}{2\pi i} \int_{|z|=1} P_{n,k}(z) z^{-l-1} \mathrm{d}z \\ &= \frac{1}{2\pi i} \int_{|z|=1} e^{\mu_{n,k}(z-1)} z^{-l-1} \left(1 + \mathcal{O}\left(\frac{n}{k^3}\right)\right) \mathrm{d}z \\ &= e^{-\mu_{n,k}} \frac{(\mu_{n,k})^l}{l!} + \mathcal{O}\left(\frac{n}{k^3}\right) \end{aligned}$$

as was claimed. □

Now, we are ready to prove our main result.

Proof of Theorem 1.3. First, consider k with $k \geqslant n^{2/5}$. Then, break the sum in the total variation distance into two parts:

$$\sum_{l \geqslant 0} \left| P(X_{n,k} = l) - e^{-\mu_{n,k}} \frac{(\mu_{n,k})^l}{l!} \right| = \sum_{|l-\mu_{n,k}| \leqslant \eta \sqrt{\mu_{n,k}}} |\cdots| + \sum_{|l-\mu_{n,k}| > \eta \sqrt{\mu_{n,k}}} |\cdots| =: \Sigma_1 + \Sigma_2.$$

The second part can easily be estimated by Chebyshev's inequality,

$$\Sigma_2 \leqslant \frac{\sigma_{n,k}^2}{\eta^2 \mu_{n,k}} + \frac{1}{\eta^2} = \mathcal{O}\big(\eta^{-2}\big).$$

For the first sum, we use Proposition 4.1 and obtain

$$\Sigma_1 = \mathcal{O}\left(\eta \sqrt{\mu_{n,k}} \frac{n}{k^3}\right) = \mathcal{O}\big(\eta n^{3/2} k^{-4}\big).$$

Now, choose $\eta = k^{4/3} n^{-1/2}$. Then,

$$d_{TV}(X_{n,k}, \mathrm{Po}(\mu_{n,k})) = \mathcal{O}\big(\eta^{-2} + \eta n^{3/2} k^{-4}\big) = \mathcal{O}\big(n k^{-8/3}\big) = \mathcal{O}\big(n^{-1/15}\big),$$

which proves the result for $k \geqslant n^{2/5}$.

Next, we consider k with $n^{1/5} \leqslant k < n^{2/5}$ and choose $\eta = n^{1/12} k^{-1/6}$. We again use the above partition, where Σ_2 is estimated as above. As for bounding Σ_1, we use Theorem 1.2 together with the following two expansions,

$$e^{-\mu_{n,k}} \frac{(\mu_{n,k})^l}{l!} = \frac{1}{\sqrt{2\pi \mu_{n,k}}} \exp\left(-\frac{(l-\mu_{n,k})^2}{2\mu_{n,k}}\right) \big(1 + \mathcal{O}\big(\eta \mu_{n,k}^{-1}\big)\big)$$

and

$$\frac{1}{\sqrt{2\pi \sigma_{n,k}^2}} \exp\left(-\frac{(l-\mu_{n,k})^2}{2\sigma_{n,k}^2}\right) = \frac{1}{\sqrt{2\pi \mu_{n,k}}} \exp\left(-\frac{(l-\mu_{n,k})^2}{2\mu_{n,k}}\right) \big(1 + \mathcal{O}\big(\eta^2 k^{-1}\big)\big),$$

where the latter expansions hold uniformly for all l with $|l - \mu_{n,k}| \leqslant \eta \sqrt{\mu_{n,k}}$. Consequently,

$$\Sigma_1 = \mathcal{O}\big(\eta^3 k^{-1} + \eta^4 n^{-1/2} k\big) = \mathcal{O}\big(n^{-1/20}\big).$$

Overall, we obtain

$$d_{TV}(X_{n,k}, \mathrm{Po}(\mu_{n,k})) = \mathcal{O}\big(n^{-1/20} + \eta^{-2}\big) = \mathcal{O}\big(n^{-1/20}\big).$$

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For the final range of k with $k < n^{1/5}$, we choose $\eta = k^{1/5}$. Then, as above, we obtain

$$d_{TV}(X_{n,k}, \mathrm{Po}(\mu_{n,k})) = \mathcal{O}\big(k^{-2/5} + n^{-7/50}\big).$$

Hence, our result is established. □

Remark. As mentioned in the Introduction, the above proof also gives a rate for the convergence of the total variation distance to 0. However, the rate is quite poor and can be further improved by incorporating estimates for higher moments. We will restrain ourselves from doing this here and postpone the issue of deriving sharp bounds for the total variation distance to the related paper [5], which discusses applications of the techniques of this paper to random trees arising from molecular biology and genetics.

5. Binary search trees

In [10], a result similar to that described in the Introduction was derived for random binary search trees as well: see [7], Feng, Miao and Su [12] and Flajolet, Gourdon and Martinez [13] for earlier and/or related results in this direction.

A random binary search tree is recursively built from a random permutation of the sequence of records $1, \dots, n$ as follows: place the first record into the root and direct the other records either to the left or right subtree according to whether the record is smaller or larger than the record stored in the root; proceed like this to recursively build the left and right subtree. Binary search trees are a fundamental data structure in computer science and they have found numerous applications; see [14] and references therein.

Again, denote by $X_{n,k}$ the number of subtrees of size k on the fringe of a random binary search of size n. Then, $X_{n,k}$ satisfies the following recurrence:

$$X_{n,k} \stackrel{d}{=} X_{I_n,k} + X^*_{n-1-I_n,k} \qquad (k < n)$$

with $X_{n,k} = 0$ for $n < k$ and $X_{k,k} = 1$, where $I_n = \mathrm{Unif}\{0, n-1\}$, $X^*_{n,k}$ is an independent copy of $X_{n,k}$, and the sequences $X_{n,k}$, $X^*_{n,k}$ and I_n are all independent.

The latter recurrence can also be explained as the corresponding recurrence for recursive trees; see the paragraph below (2.1) in Section 2.

Now, the above recurrence again implies that all (centered or non-centered) moments satisfy a recurrence of the following shape:

$$a_{n,k} = \frac{2}{n} \sum_{j=0}^{n-1} a_{j,k} + b_{n,k},$$

where $b_{n,k}$ is a suitable sequence (again called a 'toll sequence'), $a_{n,k} = 0$ for $n < k$ and $a_{k,k}$ is fixed. Using the same method that was applied to (2.2), the above recurrence can easily be solved:

$$a_{n,k} = \frac{2(n+1)}{(k+1)(k+2)} a_{k,k} + 2(n+1) \sum_{k<j<n} \frac{b_{j,k}}{(j+1)(j+2)} + b_{n,k},$$

where $n > k$.

We already see here that things are very similar to the previous situation of random recursive trees. So, our methods will work with only minor modifications and yield similar results for

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random binary search trees, too. It should be pointed out that this is quite different to the situation encountered by Feng, Mahmoud and Panholzer [10], whose approach when applied to random binary search trees was technically much more involved than when applied to random recursive trees.

Due to the similarities to random recursive trees, we do not give any details, and instead only state the final results. The reader should have no difficulties in using the tools introduced in the previous sections to work out full proofs.

Firstly, for the mean value and variance, we obtain the following explicit formulas:

$$\mu_{n,k} := \mathbb{E}(X_{n,k}) = \frac{2(n+1)}{(k+1)(k+2)} \qquad (n > k)$$

and

$$\sigma^2_{n,k} := \mathbb{V}(X_{n,k}) = \frac{2k(4k^2+5k-3)(n+1)}{(k+1)(k+2)^2(2k+1)(2k+3)} \qquad (n > 2k+1).$$

Our results in this situation then read as follows.

Theorem 5.1.

(i) (*Berry–Esseen bound.*) *Let $k = k_n$ be a sequence with $1 \leqslant k_n = o(\sqrt{n})$. Then,*

$$\sup_{-\infty<x<\infty} \left| P\left(\frac{X_{n,k} - \mu_{n,k}}{\sigma_{n,k}} \leqslant x \right) - \Phi(x) \right| = \mathcal{O}\left(\frac{k}{\sqrt{n}} \right),$$

where the rate is (up to the implied constant) optimal.

(ii) (*Local limit theorem.*) *Let $k = k_n$ be a sequence with $1 \leqslant k_n = o(\sqrt{n})$. Then,*

$$P\left(X_{n,k} = \lfloor \mu_{n,k} + x\sigma_{n,k} \rfloor\right) = \frac{e^{-x^2/2}}{\sqrt{2\pi\sigma^2_{n,k}}} \left(1 + \mathcal{O}\left(\left(1+|x|^3\right) \frac{k}{\sqrt{n}} \right) \right)$$

uniformly in $x = o(n^{1/6}/k^{1/3})$.

(iii) (*Poisson approximation.*) *Let $k = k_n$, where $k < n$ and $k \to \infty$ as $n \to \infty$. Then, the total variation distance between $X_{n,k}$ and a Poisson random variable with rate $\mu_{n,k}$ tends to 0, i.e.,*

$$d_{TV}(X_{n,k}, \mathrm{Po}(\mu_{n,k})) = \frac{1}{2} \sum_{l \geqslant 0} \left| P(X_{n,k} = l) - e^{-\mu_{n,k}} \frac{(\mu_{n,k})^l}{l!} \right| \to 0 \qquad (n \to \infty).$$

6. Conclusion

In this paper, we introduced a new approach to the limit law of the number of subtrees on the fringe of random trees. Our new approach is based on the method of moments and its refinement. Compared to previous approaches, our method is capable of yielding much deeper results and it applies more uniformly to different types of random trees. We demonstrated here the validity of the first claim by considerably refining recent results of Feng, Mahmoud and Panholzer. In particular, our results further explain why the number of subtrees exhibits the phenomenon discovered by the latter authors.

Our method is likely to have many more applications. In particular, other classes of random trees also seem to be treatable by our approach. This will be postponed to future work.

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