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## PATRICIA TRIES AGAIN REVISITED

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#### PATRICIA TRIES AGAIN REVISITED

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#### Abstract

This paper studies the average complexity of Patricia tries from the successful and unsuccessful search point of view. It is assumed that the Patricia trie is built over a V-element alphabet, and keys are strings of elements from the alphabet. The occurrence of the *i*th element from the alphabet in a key is given by a probability  $p_i$ , i = 1, 2, ..., V. We also assume that *n* keys are stored in the Patricia trie. These assumptions determine the so called Bernoulli model. Let  $S_n$  and  $U_n$  denote the successful search and unsuccessful search in the Patricia, respectively. We prove that the *m*-th moment of the successful search,  $E(S_n)^m$ , satisfies  $\lim_{n\to\infty} E(S_n)^m/ln^m n = 1/h_1^m$ , where  $h_1 = -\sum_{i=1}^{V} p_i \ln p_i$ . In particular, we show that the variance of  $S_n$  is var  $S_n = c \ln n + O(1)$  (*c* is a constant dependent on  $p_i$ , i = 1, 2, ..., V) for an asymmetric Patricia, and var  $S_n = O(1)$  for a symmetric Patricia (e.g. if V = 2 var  $S_n = 1.00$ ). The unsuccessful search  $U_n$ , is studied only for binary symmetric Patricia tries. We prove that  $\lim_{n\to\infty} E(U_n)^m/lg^m n = 1$ . In particular, the variance of  $U_n$ , is given by var  $U_n = 0.8790$ .

#### 1. INTRODUCTION

Digital searching is a well-known technique for storing and retrieving information using lexicographical (digital) structure of words. Let A be an alphabet containing V elements,  $A = \{\sigma_1, \ldots, \sigma_V\}$  and we define a set S which consists of finite numbers, say n, of (possible infinite) strings (keys) from A. A *trie or radix search trie* is a V-ary digital search tree in which edges are labelled by elements from A and leaves (external nodes) contain the keys [2], [7], [10], [12], [14], [18]. The access path from the root to the leaf is a minimal prefix of the information contained in the leaf. The radix trie has an annoying flaw: there is "one-way branching" which leads to the creation of extra nodes in the tree. D.R. Morrison discovered a way to avoid this problem in a structure which he named the *Patricia trie*. In such a tree all nodes have branching degree greater equal than two. This is achieved by collapsing one-way branches on internal nodes. For more details see [7], [10], [14], [18]. The Patricia tree finds many applications e.g. in \*and Technical University of Gainsk, Poland

lexicographical order [16], dynamic hashing algorithms [4], and most recently in conflict resolution algorithms [9], [21]. (For more examples see [10], [14].)

Two quantities are of interest for tries in general, and in particular for the Patricia trie, namely successful search and unsuccessful search. A successful search occurs whenever a new key added to the Patricia is already in the trie. If a new key is not in the Patricia, then an unsuccessful search occurs. The average complexity analysis of the Patricia is very scarce, (see [7], [13], [14]) and in fact restricted to binary symmetric Patricia, that is, V = 2 is assumed with equal probability of occurrence of the elements over a binary alphabet. Moreover, only average values were studied. These simplifications are dropped in this paper. For the successful search, we assume that a sequence of elements from the alphabet A is an independent sequence of Bernoulli trials (*Bernoulli model*), and the probability of occurrence of an element  $\sigma_i \in A$  in a key is equal to  $p_i$ , i = 1, 2, ..., V. Under these assumptions we study all moments of the successful search,  $S_n$ . It is shown that  $\lim_{n \to \infty} E(S_n)^m / \ln^m n = 1/h_1^m$ , where  $h_1 = -\sum_{i=1}^V p_i \ln p_i$  and m is an integer. In particular, we prove that the variance of  $S_n$  is  $(h_2 - h_1^2)h_1^{-3} \ln n + O(1)$  for an asymmetric Patricia, where  $h_2 = \sum_{i=1}^{V} p_i \ln^2 p_i$ . Note that this implies that the variance in the symmetric Patricia is equal to O(1) (e.g. for V = 2 the variance var  $S_n = 1.00$ , for V = 3 we find var  $S_n = 0.6309$  and so on). These results extend the works of Knuth [14], Flajolet and Sedgewick [7], and Kirschenhofer and Prodinger [13].

The results for the unsuccessful search are even more scarce, and to the author's knowledge only the mean value of  $U_n$  was obtained by Knuth [14]. The problem is also much more intricate, therefore, symmetric binary Patricia tries are assumed. However, asymptotic analysis of all moments of the unsuccessful search is discussed. It is proved that that the *m*-th moment of  $U_n$ satisfies  $\lim_{n\to\infty} E(U_n)^m/lg \ n = 1$  for any integer *m*, where  $lgn = \log_2 n$ . In particular, the variance of  $U_n$  is equal to 0.8790. The paper is organized as follows. In the next section we present some notation and preliminary results. In particular, we derive a recurrence equation for the generating function of the V-ary asymmetric Patricia trie. Then, in Section 3, we study the successful search. At the beginning we present some recurrence equations, show how to solve them using the results obtained by the author in [19], [22], and we also give final results of this section. In the last part of the section we show how to prove the main results. In a similar way, we organize Section 4 where unsuccessful search for binary symmetric Patricia trie is discussed.

## 2. NOTATIONS AND PRELIMINARY RESULTS

Let us consider a family  $T_n$  of Patricia tries with *n* keys (records) built over and alphabet  $A = \{\sigma_1, \ldots, \sigma_V\}$ . A key is a string of (possible infinite) elements from *A*, such that the *i*-th element  $\sigma_i \in A$  occurs independently of other elements, and with probability  $p_i$ ,  $i = 1, 2, \ldots, V$ ,  $\sum_{i=1}^{V} p_i = 1$ . A trie  $t \in T_n$  built over *A* is called *V*-ary asymmetric Patricia trie since the alphabet contains *V* elements which are distributed according to the probabilities  $p_i$ ,  $i = 1, 2, \ldots, V$ . The keys are stored in external nodes, while internal nodes determine branching strategy. The degree of each internal node is greater equal than two ,that is, one-way branches are collapsed on internal modes by including in the nodes the number of bits to skip over before making the next decision (for details see [7], [10], [19], [18]). Two parameters of tries are of particular interest: *successful search* and *unsuccessful search*. The successful search, called also the depth of a leaf, is the number of internal nodes in the trie on the path from the root to a given key (external node) if the key *is* already in the trie. If the new key *is not* in the trie, then an unsuccessful search occurs. The unsuccessful search is not simply related to the successful search, since unsuccessful search search new likely to occur at external nodes near the root.

We study properties of successful and unsuccessful searches in a random family of Patricia tries  $T_n$ . Let  $S_n$  and  $U_n$  (random variables) denote the successful search and the unsuccessful

search in  $T_n$ . The *m*-th factorial moments of  $S_n$  and  $U_n$  are defined as follows

$$s_n^{\frac{def}{def}} = E \{ S_n (S_n - 1) (S_n - 2) \cdots (S_n - m + 1) \},$$
 (2.1)

$$u_n^m = E \{ U_n (U_n - 1) (U_n - 2) \cdots (U_n - m + 1) \}, \qquad (2.2)$$

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where the expectations in (2.1) and (2.2) is taken over all tries in  $T_n$  and over all external nodes in a given trie  $t \in T_n$ . It is shown (see next sections) that these moments are related to *m*-th derivatives of the so called generating functions of  $T_n$ . Let  $H_n(z)$  denote this generating function with the coefficient at  $z^k$  being the expected number of external nodes at level k in our family of trees.

There is no explicit formula for  $H_n(z)$  but a rather sophisticated recurrence. To find it, let us denote by  $\mathbf{j} = (j_1, j_2, \dots, j_V)$  a vector such that  $j_1 + j_2 + \dots + j_V = n$ . Also let  $\begin{pmatrix} n \\ \mathbf{j} \end{pmatrix} \stackrel{def}{=} \begin{pmatrix} n \\ j_1, \dots, j_V \end{pmatrix} = \frac{n!}{j! j_2! \cdots j_V!}$  be a multinomial coefficient, and let  $\sum_{\{j_x = n\}} f(j_1, \dots, j_V)$  denote a sum of  $f(j_1, \dots, j_V)$  over all  $\mathbf{j}$  such that  $j_1 + j_2 + \dots + j_V = n$  for a given function  $f(\cdot)$ . Then the following recurrence on  $H_n(z)$  may be established.

Lemma 1. For any natural *n* the generating function  $H_n(z)$  of the random family of Patricia tries,  $T_n$ , satisfies the recurrence

$$H_0(z) = 0, \qquad H_1(z) = 1$$

$$H_n(z) = z \sum_{\{jz=n\}} {n \choose j} p_1^{j_1} \cdots p_V^{j_V} [H_{j_1}(z) + \cdots + H_{j_V}(z)] - (z-1)[p_1^n + p_2^n + \cdots + p_V^n]$$
(2.3)

*Proof*: Consider V subtrees of the root, each with  $j_1, j_2 \cdots j_V$  keys,  $j_1 + j_2 + \cdots + j_V = n$ . Then, for a given trie  $t \in T_n$ 

$$H_n(z) = [H_{j_1}(z) + \cdots + H_{j_{\nu}}(z)][z + \delta_{j_1,n}(1-z) + \delta_{j_2,n}(1-z) + \cdots + \delta_{j_{\nu},n}(1-z)].$$

where  $\delta_{j,k}$  is the Kronecker delta. In the second squared bracket the first z shows the fact that the subtrees are one level below the root, and the other terms are responsible for avoiding oneway branches (e.g. if  $j_1 = n$ , then the leftmost branch would be one-way branch, but  $z + \delta_{j_1,n}(1-z) = 1$ , hence the subtree starts at the root). Taking now the expectation of the last recurrence over all tries in  $T_n$ , and noting that in our Bernoulli model the probability of  $j_1, \ldots, j_V$  keys in the subtrees is equal to  $\binom{n}{j}p_1^{j_1}\cdots p_V^{j_V}$ , we finally obtain (2.3).

## 3. SUCCESSFUL SEARCH

In this section we analyze the successful search, that is, we derive an asymptotic approximations for all moments of  $S_n$ . We start with some initial results follow by our final results. In the further part of this section, we show how to derive these results.

#### 3.1. Initial and final results

Let  $L_n$  denote an external path in a trie  $t \in T_n$ , that is, it is the sum of all paths from the root to external nodes. We generalize the definition of  $L_n$  as follows. Let  $S_n(i)$  be a path from root to the *i*-th external node. For a given integer *m* we define

$$L_n^{\underline{m}} = \sum_{i=1}^n S_n(i)[S_n(i) - 1][S_n(i) - 2] \cdots [S_n(i) - m + 1]$$
(3.1)

and let  $l_n^m = EL_n^m$ . The quantity  $l_n^m$  is not exactly the *m*-th factorial moment of  $L_n$ , but it is closely related to it. We call  $l_n^m$  the *m*-th semi-factorial moment of the external path length.

Denote now by  $H_n^{(m)}(1)$  the *m*-th derivative of  $H_n(z)$  at z = 1. Then the following is easily to establish (see [14], [22])

Property 1. For integers n and m the below relationships hold

$$H_n(1) = n$$
  $l_n^m = H_n^{(m)}(1)$  (3.2)

$$s_n^m = l_n^m / n \tag{3.3}$$

Using Lemma 1 and (3.2) we derive a recurrence equation for  $l_n^m$ , hence by (3.3) also on  $s_n^m$ . We shall work at the beginning with  $l_n^m$ . For simplicity of computations, assume now that V = 2

and  $p_1 = p$ ,  $p_2 = 1 - p_1 = q$ . Then for m = 1 we find immediately that

$$l_n^{1} = n(1 - p^n - q^n) + \sum_{k=0}^n {n \choose k} p^k q^{n-k} [l_k^{1} + l_{n-k}^{1}].$$
(3.4)

Computing the second derivative of  $H_n(z)$  one shows that

$$l_n^2 = 2\left[\sum_{k=0}^n \binom{n}{k} p^k q^{n-k} (l_n^1 + l_{n-k}^1) - l_n(p^n + q^n)\right] + \sum_{k=0}^n \binom{n}{k} p^k q^{n-k} [l_n^2 + l_{n-k}^2].$$

But, the first term of the above is by (3.4) equal to  $l_n^{\perp} - n$ , hence

$$l_n^2 = 2(1 - p^n - q^n)[l_n^1 - n] + \sum_{k=0}^n \binom{n}{k} p^k q^{n-k}[l_k^2 + l_{n-k}^2].$$
(3.5)

Note that (3.4) and (3.5) is a system of recurrences, i.e., to find  $l_n^2$  we need  $l_n^1$ . Generalizing the above, we can prove that

Lemma 2. For any integers m and n, the m-th semi-factorial moment of  $L_n$  satisfies the following recurrence

$$l_{0}^{m} = l_{1}^{m} = 0$$

$$l_{n}^{m} = m! (1 - \sum_{i=1}^{V} p_{i}^{m}) \sum_{k=1}^{m} (-1)^{m-k} \frac{l_{n}^{k-1}}{(k-1)!} + \sum_{\{j_{k}=n\}} {n \choose j} p_{1}^{j_{1}} \cdots p_{V}^{j_{V}} [l_{j_{1}}^{m} + \cdots + l_{j_{V}}^{m}]$$
(3.6)

where in (3.6) we have defined  $l_n^0 = n$ .

Proof: The proof uses induction arguments applied to (2.3), and is left to the reader.

As noted before, (3.6) is a system of recurrences. To compute  $l_n^m$  we need  $l_n^1$ ,

 $l_n^2, \ldots, l_n^{m-1}$  from the previous recurrences. Note also that (3.6) has a common pattern and the recurrences differ only by the first term in (3.6) which we call the *additive term* and denote by  $a_n$ . This type of recurrence has been solved by Szpankowski in [19], [22] ( see also [14] ). Since we use it extensively in the further part of the paper we quote below, without proofs, some of these results.

#### Solution of a recurrence equation

Let  $x_0, x_1, \ldots, x_n$  be a sequence of numbers satisfying the following linear recurrence

given 
$$x_0 = x_1 = 0$$
  
solve  $x_n = a_n + \sum_{\{j_x = n\}} {n \choose j} p_1^{i_1} \cdots p_v^{j_v} [x_{j_1} + \cdots + x_{j_v}]$ 
(3.7)

where  $a_n$  is any sequence of numbers. We call  $a_n$  an additive term of the recurrence (3.7). To solve (3.7) we introduce the so called *binomial inverse relations*. Let us, for a given sequence  $a_n$ , define a new sequence  $\hat{a}_n$  as

$$\hat{a}_{n} = \sum_{k=0}^{n} (-1)^{k} \left[ \begin{array}{c} n \\ k \end{array} \right] a_{k} \qquad a_{n} = \sum_{k=0}^{n} (-1)^{k} \left[ \begin{array}{c} n \\ k \end{array} \right] \hat{a}_{k}$$
(3.8)

(The second equation justify the name binomial inverse relations). For more details see Riordan [23]. Using the above we proved in [19] that

Theorem 1. The recurrence (3.7) possesses the following solution

$$x_{n} = \sum_{k=2}^{n} (-1)^{k} {n \choose k} \frac{\hat{a}_{k} + ka_{1} - a_{0}}{1 - \sum_{i=1}^{V} p_{i}^{k}}.$$
(3.9)

From the numerical point of view the solution (3.9) is not better than the recurrence (3.7), however, (3.9) might be used to derive asymptotic approximation for  $x_n$ . In most computer science applications  $a_n$  is a linear combination of the following terms  $\binom{n}{r}c^n$ , where r is an

integer, and c is a constant. From [23] [14], we know that

$$a_n = \left(\begin{array}{c}n\\r\end{array}\right) c^n \rightarrow \hat{a}_n = \left(\begin{array}{c}n\\r\end{array}\right) (-c)^r (1-c)^{n-r}.$$
(3.10)

Since the recurrence (3.7) is linear, from the asymptotic point of view we need an approximation for large n of the following

$$T_{n,r}(c) \stackrel{def}{=} \sum_{k=2}^{n} (-1)^k {\binom{n}{k}} {\binom{k}{r}} \frac{c^k}{1 - \sum_{i=1}^{V} p_i^k}.$$
(3.11)

Let  $h_k = (-1)^k \sum_{i=1}^V p_i \ln^k p_i$ . Then in [19] we have proved that (for some details of the derivation

see also this section)

Theorem 2. For any r, c and large n the following holds

$$T_{n,r}(c) = \begin{cases} nc \left\{ \frac{ln(nc) + \gamma - \delta_{n,0}}{h_1} + \frac{h_2}{2h_1^2} + (-1)^r f_r(nc) \right\} + O(1) & r = 0, 1 \\ (-1)^r nc \left\{ \frac{1}{r(r-1)h_1} + f_r(nc) \right\} + O(1) & r \ge 2 \end{cases}$$
(3.12)

where  $\gamma = 0.571$  is the Euler constant, and  $f_r(n)$  is a fluctuating function with a small amplitude defined as

$$f_r(n) = -\sum_{\{z'_k \neq 0, r-1\}} \frac{\Gamma(z'_k) n^{r-z'_k}}{\sum_{i=1}^{V} p_i^{r+1-zk} \ln p_i}.$$
(3.13)

The number  $z_k^r$ ,  $k = 0, 1, \ldots, r = 0, 1, \ldots, n$  are roots of the equation

$$1 - \sum_{i=1}^{V} p_i^{r-2} = 0.$$
 (3.14)

It is shown [6], [7], [10], [12], [19] that the function  $f_r(n)$  has a very small amplitude and may be safely ignored in practice.

#### Final results of this section

Using Property 1, Lemma 2 and Theorem 1,2 we prove our main results of this section. Let us, in addition to  $h_n$  defined before, introduce a new notation  $\overline{h_n} = (-1)^n \sum_{i=1}^V p_i \ln^n (1-p_i)$ . Then

#### Proposition 1.

(i) The mean of the successful search  $S_n$  for large *n* is given by

$$ES_n = \frac{1}{h_1} \{ \ln n + \rho + F_1(n) \} + O(n^{-1})$$
(3.15)

where  $\rho = \gamma - \bar{h_1} + \frac{h_2}{2h_1}$  and  $F_1(n)$  is a fluctuating function with a small amplitude.

## (ii) The variance, var $S_n$ , of the successful search for large n satisfies

var 
$$S_n = \frac{h_2 - h_1^2}{h_1^3} \ln n + \alpha - 2\beta + F_2(n) + O(n^{-1}),$$
 (3.16)

where

$$\alpha = \frac{1}{h_1^2} \left[ \frac{\pi^2}{6} + \gamma^2 + \frac{3}{2} \frac{h_2^2}{h_1^3} + \frac{2\gamma h_2}{h_1} - \frac{2}{3} \frac{h_3}{h_1} + h_2 + \bar{h}_2 + 2h_1 \bar{h}_1 \right] - 2(h_1 + \bar{h}_1) \frac{\gamma h_1 + h_2}{h_1^3} + \frac{\rho}{h_1} \left( 1 - \frac{\rho}{h_1} \right)$$
(3.17)

and

$$\beta = \frac{1}{h_1} \sum_{\lambda=1}^{V} \sum_{\nu=1}^{V} p_{\nu} p_{\lambda} \sum_{i=0}^{\infty} \sum_{\{i_{\Sigma}=i\}} \left[ \begin{array}{c} l \\ \mathbf{i} \end{array} \right] \prod_{\mu=1}^{V} p_{\mu}^{i_{\mu}} \ln\{1 + \frac{p_{\lambda}(1-p_{\nu})}{1-p_{\lambda}} \prod_{\mu=1}^{V} p_{\mu}^{i_{\mu}}\}.$$
(3.18)

In particularly, for V-ary symmetric Patricia tries  $h_2 = h_1^2$  and (3.16) is reduced to (the coefficient at  $\ln n$  is equal to zero)

$$\operatorname{var} S_n = \frac{\pi^2}{6\ln^2 V} + \frac{1}{12} - \frac{2}{\ln V} \ln\{\prod_{l=1}^{\infty} (1 + \frac{1}{V^l})\} + F_2(n) + O(n^{-1}). \tag{3.19}$$

(iii) The *n*-th moment  $E(S_n)^m$ , of the successful search satisfies

$$\lim_{n \to \infty} \frac{E(S_n)^m}{\ln^m n} = \frac{1}{h_1^m}$$
(3.20)

We now compare the successful search for regular tries and Patricia tries. Let  $S_n^{[T]}$  and  $S_n^{[P]}$  denote  $S_n$  for the regular trie and the Patricia trie respectively. Then by the proposition and the results from [22] we easily see that  $ES_n^{[T]} - ES_n^{[P]} = \overline{h_1}/h_1$ . The variance of  $S_n$  for a regular trie is given by (3.16) with  $\beta = 0$  [22]. Table 1 compares the variances for tries and the Patricia tries in the symmetric case. For V = 2 (symmetric case) the result was previously obtained by Kirschenhofer and Prodinger [13] (see also [12]).

V	$\operatorname{var} S_n^{[T]}$	$\operatorname{var} S_n^{[P]}$
2	3.507	1.000
3	1.446	0.630
4	0.939	0.500
5	0.718	0.430
6	0.596	0.387

Finally, let us mention that the recurrence for the variance is very slowly "convergent" to its asymptotic approximation (at least 150 terms must be computed), so the above results are particularly useful.

## 3.2 The first two moments of $S_n$

The mean value of  $S_n$  is  $l_n^{\frac{1}{n}}/n$ , where  $l_n^{\frac{1}{n}}$  is given by (3.4). But (3.4) is a recurrence of type (3.7) with  $a_n = n (1 - \sum_{i=1}^{V} p_i^n)$ . Using (3.8) we find  $\hat{a}_n = n \sum_{i=1}^{V} p_i^{n-1}$  for  $n \ge 2$ , hence by Theorem 1

the solution of (3.4) is

$$l_{n}^{1} = \sum_{k=2}^{n} (-1)^{k} {\binom{n}{k}} {\binom{k}{1}} \frac{\sum_{i=1}^{V} p_{i} (1-p_{i})^{k-1}}{1-\sum_{i=1}^{V} p_{i}^{k}}$$
(3.21)

To find an asymptotic approximation of (3.21) we apply Theorem 2. Note that

$$l_n^{1} = \sum_{i=1}^{V} \frac{p_i}{1 - p_i} T_{n,1}(1 - p_i)$$

hence, by (3.3) and (3.12) we obtain our result (3.15) with

$$F_{1}(n) = \sum_{i=1}^{V} p_{i} f_{1}[n(1-p_{i})].$$
(3.22)

The second moment  $l_n^2$  is more difficult to compute. As before assume for simplicity V = 2. Note that by (3.5)  $l_n^2$  satisfies the recurrence (3.7), but now  $a_n = (1 - p^n - q^n)(l_n^1 - n)$ . Hence, the inverse sequence  $d_n$  is (we use (3.8))

$$\hat{a}_n = 2l_n^{\underline{1}} + 2(\delta_{n,1} - npq^{n-1} - npq^{n-1}) - 2I(p^n l_n^{\underline{1}}) - 2I(q^n l_n^{\underline{1}}).$$
(3.23)

where  $I(p^n l_n^{\frac{1}{2}})$  is the inverse relation to  $p^n l_n^{\frac{1}{2}}$ . Two problems are encountered in obtaining the exact expression for  $\mathcal{A}_n$ . Namely, we must know  $\hat{l}_n^{\frac{1}{2}}$ , and - what is more intricate - the inverse sequence to  $p^n l_n^{\frac{1}{2}}$ . The first problem is easy. We know that  $l_n^{\frac{1}{2}}$  is given by (3.21). But by the definition of the inverse relations  $l_n^{\frac{1}{2}} = \sum_{k=0}^n (-1)^k {n \choose k} l_k^{\frac{1}{2}}$  and  $\hat{l}_0 = \hat{l}_1 = 0$ . Hence combining this

with (3.21) we immediately find

$$\hat{l}_{k}^{1} = k \frac{\sum_{i=1}^{V} p_{i} (1-p_{i})^{k-1}}{1 - \sum_{i=1}^{V} p_{i}^{k}}.$$
(3.24)

Let us compute now  $I(p^n l_n^{\perp})$ . We first prove

Lemma 3. Let  $a_n$  and  $\hat{a}_n$  are given, and let  $b_n = p^n a_n$ , where  $0 \le p < 1$ . Then

$$\hat{b_n} = \sum_{j=0}^n \left[ \begin{array}{c} n \\ j \end{array} \right] \, \hat{a_j} \, p^j (1-p)^{n-j}. \tag{3.25}$$

Proof. Using well known relationships for binomial coefficients (see Riordan [23]) we find

$$b_{n} = \sum_{k=0}^{n} (-1)^{k} {\binom{n}{k}} a_{k} p^{k} = \sum_{k=0}^{n} (-1)^{k} {\binom{n}{k}} p^{k} \sum_{j=0}^{k} (-1)^{j} {\binom{k}{j}} \hat{a}_{j} = \sum_{j=0}^{n} {\binom{n}{j}} \hat{a}_{j} p^{n} \sum_{k=0}^{n-j} (-1)^{k} {\binom{n-j}{k}} (1/p)^{n-k-j} = \sum_{j=0}^{n} {\binom{n}{j}} \hat{a}_{j} p^{j} (1-p)^{n-j}.$$

Using Lemma 3 and (3.24) (once again for V = 2) we immediately obtain that

$$I(p^{n}l_{n}^{1}) = \sum_{j=0}^{n} {n \choose j} {j \choose 1} p^{j}(1-p)^{n-j} \frac{pq^{j-1}+qp^{j-1}}{1-\sum_{i=1}^{V} p_{i}^{j}}$$
(3.26)

Therefore, using (3.26), (3.23), (3.24) and (3.9) from Theorem 1, we finally derive an exact solution for  $l_n^2$ .

**Theorem 3.** The second semi-factorial moment  $l_n^2$  has the following solution

$$l_{n}^{2} = 2 \sum_{k=2}^{n} (-1)^{k} {\binom{n}{k}} {\binom{k}{1}} {\binom{k}{1}} \frac{\{\sum_{i=1}^{V} p_{i}(1-p_{i})^{k-1}\} \{\sum_{i=1}^{V} p_{i}^{k}\}}{(1-\sum_{i=1}^{V} p_{i}^{k})^{2}} - \frac{2 \sum_{k=2}^{n} (-1)^{k}}{1-\sum_{i=1}^{V} p_{i}^{k}} \sum_{j=2}^{k} {\binom{k}{j}} {\binom{j}{1}} \frac{\{\sum_{i=1}^{V} p_{i}^{j}(1-p_{i})^{k-j}\} \{\sum_{i=1}^{V} p_{i}(1-p_{i})^{j-1}\}}{1-\sum_{i=1}^{V} p_{i}^{k}} \sum_{j=2}^{k} {\binom{k}{j}} {\binom{j}{1}} \frac{\frac{\{\sum_{i=1}^{V} p_{i}^{j}(1-p_{i})^{k-j}\} \{\sum_{i=1}^{V} p_{i}(1-p_{i})^{j-1}\}}{1-\sum_{i=1}^{V} p_{i}^{j}}}$$
(3.27)

*Proof.* The details of algebraic manipulations are left to the reader.

## Asymptotic approximation for var $S_n$

We compute here the asymptotic approximation for the variance, var  $S_n$ , of the successful search. For this we need asymptotic expression for (3.27). Let us denote by  $A_n$  and  $B_n$  the first and the second term in (3.27), that is,  $l_n^2 = 2A_n - 2B_n$ .

The expression for  $A_n$  does not fall into (3.11) (since the denominator is raised to the

power two ), hence Theorem 2 cannot be applied. However, for asymptotic approximation of  $A_2$  we need to evaluate the following

$$T_{n}^{(2)}(c) = \sum_{k=2}^{n} (-1)^{k} {\binom{n}{k}} {\binom{k}{1}} \frac{c^{k}}{(1-\sum_{i=1}^{V} p_{i}^{k})^{2}}$$
(3.28)

which generalized (3.11). We use the Mellin transform technique [4], [11], [14], [22]. Performing some algebra over (3.28) we can prove that (for details see [22])

$$T_{n}^{(2)}(c) = -\frac{nc}{2\pi i} \int_{-\frac{1}{2}-\infty}^{-\frac{1}{2}+i\infty} \frac{\Gamma(z)(nc)^{-2}}{(1-\sum_{i=1}^{V}p_{i}^{1-2})^{2}} dz + O(1)$$
(3.29)

where  $\Gamma(z)$  is the gamma function [1]. The evaluation of the integral is standard: we must compute residues of the function under the integral to the right of the line  $(\frac{1}{2} - i \infty, -\frac{1}{2} + i \infty)$ . Let  $z_k \ k = 0,\pm 1,\pm 2,...$  denote roots of the denominator, that is,

$$1 - \sum_{i=1}^{V} p_i^{1-z} = 0.$$
 (3.30)

Note that  $z_0 = 0$ , while the other roots are complex. For more detailed treatment of (3.30) see [6], [12], [22]. The most difficult to handle is the pole  $z_0 = 0$  since it is the double pole of the denominator and, in addition, singular point of the gamma function. But, the following Taylor expansions of the functions under the integral are available [1], [4], [11]

$$\Gamma(z) = z^{-1} - \gamma + \frac{1}{2} \left[ \frac{\pi^2}{6} + \gamma^2 \right] z + O(z^2)$$
$$(nc)^{-z} = 1 - z \ln nc + \frac{z^2}{2} \ln^2 nc + O(z^3)$$
$$(1 - \sum_{i=1}^{V} p_i^{1-z})^2 = z^2 [b_0 + b_1 z + b_2 z^2] + O(z^5)$$

where  $b_0 = h_1^2$ ,  $b_1 = h_1h_2$ ,  $b_2 = \frac{1}{4}h_2^2 + \frac{1}{3}h_1h_3$  (for details see [22]), and as before  $h_k = (-1)^k \sum_{i=1}^V p_i \ln^k p_i$ . The algorithm to compute the residue at  $z_0 = 0$  is provided in [11],

[22]. Let g(z) denote the function under the integral in (3.29). Then, after some algebra

$$res_{z_0}g(z) = \frac{1}{2h_1^2} \ln^2 nc + \varepsilon \ln nc + \delta$$
(3.31)

where

$$\varepsilon = \frac{\gamma h_1 + h_2}{h_1^3}$$

$$\delta = \frac{1}{h_1^2} \left[ \frac{\pi^2}{12} + \frac{\gamma^2}{2} + \frac{3h_2^2}{4h_1^2} + \frac{\gamma h_2}{h_1} - \frac{h_3}{3h_1} \right].$$
(3.32)

On the other hand, the residues of g(z) at  $z_k$ ,  $k \neq 0$  are

$$res_{z_{k}}g(z) = \frac{\Gamma(z_{k})(nc)^{-z_{k}}}{h_{1}^{2}(z_{k})}$$
(3.33)

where  $h_1(z_k) \stackrel{def}{=} -\sum_{i=1}^{V} p_i^{-2k} \ln p_i$ . So finally by (3.29)–(3.33) we obtain

$$T_n^{(2)} = \frac{1}{2h_1^2} \ln^2 nc + \varepsilon \ln nc + \delta + f^{(2)}(nc) + O(1)$$
(3.34)

where

$$f^{(2)}(n) = \sum_{\substack{k \neq -\infty \\ k \neq 0}}^{\infty} \frac{\Gamma(z_k) n^{-z_k}}{h_1^2(z_k)}$$

Using the above we prove

Lemma 4. The coefficient  $A_n$  (the first term in (3.27)) for large *n* is equal to

$$A_n = n \left\{ \frac{1}{2h_1^2} \ln^2 n + \left( \epsilon - \frac{h_1 + \bar{h}_1}{h_1^2} \right) \ln n + \eta + F_A(n) \right\} + O(1)$$
(3.35a)

where

$$\eta = \frac{1}{2h_1^2} (h_2 + \bar{h}_2 + 2h_1 \bar{h}_1) - \varepsilon (h_1 + \bar{h}_1) + \delta$$
(3.35b)

$$\overline{h}_{k} = (-1)^{k} \sum_{i=1}^{V} p_{i} \ln^{k} (1-p_{i}) \text{ and}$$

$$F_{A}(n) = \sum_{i=1}^{V} \sum_{j=1}^{V} p_{i} p_{j} f^{(2)}[n p_{j}(1-p_{i})]$$
(3.36)

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Proof: To prove (3.35) it is enough to note that (3.27) and (3.28) imply

$$A_n = \sum_{i=1}^n \frac{p_i}{1 - p_i} \sum_{j=1}^V T_n^{(2)} \left[ p_j (1 - p_i) \right]$$

Using (3.34) after some algebra one finds (3.35).

To evaluate the second term in (3.27), namely  $B_n$ , we need some additional computations.

Let

$$B_{n} = \sum_{k=2}^{n} (-1)^{k} {\binom{n}{k}} \frac{B_{k}}{1 - \sum_{i=1}^{V} p_{i}^{k}}$$
(3.37a)

where, after some simple algebra, one obtains

$$B_{k}^{'} = \sum_{j=2}^{k} \left[ \begin{array}{c} k \\ j \end{array} \right] \left[ \begin{array}{c} j \\ 1 \end{array} \right] \frac{\sum_{\lambda=1}^{V} p_{\lambda}^{j} (1-p_{\lambda})^{k-j} \sum_{\nu=1}^{V} p_{\nu} (1-p_{\nu})^{j-1}}{1-\sum_{i=1}^{V} p_{i}^{j}}$$
(3.37b)

Now we develop the denominator in a geometric series and for  $i = (i_1, i_2, \ldots, i_V)$  such that

 $i_1 + i_2 + \cdots + i_V = l$  (*l* is an integer) we denote  $c_1 = \prod_{\mu=1}^{V} p_{\mu}^{i_{\mu}}$ . Then (3.37b) becomes

$$B_{k}' = k \sum_{\lambda=1}^{V} \sum_{\nu=1}^{V} p_{\nu} p_{\lambda} \sum_{l=0}^{\infty} \sum_{\{i_{z}=l\}} {l \choose i} c_{i} \{ [c_{i} p_{\lambda}(1-p_{\nu}) + 1-p_{\lambda}]^{k-1} - (1-p_{\lambda})^{k-1} \}$$

But by (3.37a) and our notation (3.11) one finds that

$$B_{k}' = \sum_{\lambda=1}^{V} \sum_{\nu=1}^{V} p_{\nu} p_{\lambda} \sum_{l=0}^{\infty} \sum_{\{l=1, l\}} \left[ l \atop i \right] c_{i} \left\{ \frac{T_{k,1}[c_{1}p_{\lambda}(1-p_{\nu})+1-p_{\lambda}]}{c_{1}p_{\lambda}(1-p_{\nu})+1-p_{\lambda}} - \frac{T_{k,1}(1-p_{\lambda})}{1-p_{\lambda}} \right\}$$

Hence by Theorem 2 (see (3.12)) we finally obtain

$$B_{n} = n \ \beta = n \left\{ \frac{1}{h_{1}} \sum_{\lambda=1}^{V} \sum_{\nu=1}^{V} p_{\lambda} p_{\nu} \sum_{l=0}^{\infty} \sum_{\{i_{\ell}=l\}} {l \choose i} c_{l} \ln[1 + p_{\lambda}(1 - p_{\nu})c_{l}/(1 - p_{\lambda})] + F_{B}(n) \right\} (3.38)$$

where

$$F_B(n) = \sum_{\lambda=1}^{V} \sum_{\nu=1}^{V} p_{\nu} p_{\lambda} \sum_{i=0}^{\infty} \sum_{\{i_{\nu}=i\}} \left[ l \atop i \right] c_1 \{f_1[n (c_i p_{\lambda}(1-p_{\nu})+1-p_{\lambda})] - f_1(n(1-p_{\lambda})) \}$$
(3.39)

and the constant  $\beta$  is defined as  $B_n/n$ . Note that we prove in fact that  $B_n = O(n)$ . This we shall use later to derive higher moments of  $S_n$ .

Finally, taking into account (3.3), (3.27), (3.35) and (3.38) we prove

**Theorem 4.** The second factorial moment  $s_n^2$  of the successful search  $S_n$  is given by

$$s_n^2 = 2 A_n / n - 2B_n / n = \frac{1}{h_1^2} ln^2 n + 2 \left[\varepsilon - \frac{h_1 + \overline{h_1}}{h_1^2}\right] \ln n + 2\eta - 2\beta + 2F_A(n) - 2F_B(n) + O(n^{-1})$$
(3.40)

where  $\eta$  and  $\beta$  are given by (3.35b) and (3.38), and  $F_A(n)$ ,  $F_B(n)$  are presented in (3.36) and (3.39).

To compute the variance of  $S_n$  we note that  $\operatorname{var} S_n = s_n^2 + ES_n - (ES_n)^2$ , hence the Proposition 1(ii) follows with  $\alpha = 2\eta + \frac{\rho}{h_1}(1 - \frac{\rho}{h_1})$  (see definition of  $\rho$  just after (3.15) and for  $\eta$  see (3.35b)). The function  $F_2(n)$  in (3.17) is

$$F_2(n) = 2F_A(n) - 2F_B(n) + F_1(n) - [F_1(n)]^2$$
(3.41)

where the terms of (3.41) are defined in (3.36), (3.39) and (3.22). Note also that for the symmetric Patricia trie  $h_1 = \ln V$  and  $h_k = h_1^k$ . In particular, the coefficient at  $\ln n$  disappears and  $\operatorname{var} S_n = \alpha - 2\beta + O(n^{-1})$  where  $\alpha = \frac{\pi^2}{6 \ln^2 V} + \frac{1}{12}$  and  $2\beta$  is the third term in (3.19). It is interesting that for a regular symmetric V-ary trie  $\operatorname{var} S_n = \alpha + O(n^{-1})$  with  $\alpha$  the same as for the Patricia.

## 3.3 Higher moments of $S_n$

In Lemma 2 we have established the recurrence equation (3.6) for the *m*-th semi-factorial moment of the external path length. By Property 1 the *m*-th factorial moment of  $S_n$ ,  $s_n^m$ , is equal to  $l_n^m/n$ . Note that the recurrence (3.6) is of type (3.7) with the additive term  $a_n$  equal to

$$a_{n} = m! \sum_{k=1}^{m} (-1)^{m-k} \frac{l_{n}^{k-1}}{(k-1)!} - m! \left\{ \sum_{i=1}^{V} p_{i}^{n} \right\} \left\{ \sum_{k=1}^{n} (-1)^{m-k} \frac{l_{n}^{k-1}}{(k-1)!} \right\}.$$
 (3.42)

Let us denote the first and the second term in (3.42) by  $a_n^{(1)}$  and  $a_n^{(2)}$ , respectively, that is,  $a_n = a_n^{(1)} + a_n^{(2)}$ . But (3.6) is a linear recurrence, hence  $l_n^m = \overline{l_n^m} - \underline{l_n^m}$ , where  $a_n^{(1)}$  contributes to  $\overline{l_n^m}$  and  $a_n^{(2)}$  to  $\underline{l_n^m}$ . We prove that  $\underline{l_n^m} = O(n)$ , hence  $s_n^m = \overline{l_n^m}/n + O(1)$ .

Lemma 5. For any *n* and  $m l_n^{\underline{m}} \leq \overline{l_n^{\underline{m}}}$  and

$$\overline{l}_{n}^{m} = \frac{n}{h_{1}^{m}} \ln^{m} n + n \frac{m}{h_{1}^{m}} \ln^{m-1} n \left[ \gamma + \frac{m}{2} \frac{h_{2}}{h_{1}} - (m-1)h_{1} - h_{1}^{m}F(n) \right] + O(n \ln^{m-2}n)$$
(3.43)

where F(n) is a fluctuating function with a small amplitude.

*Proof*: We recognize that  $\overline{l_n^m}$  is the *m*-th semi-factorial moment of the external path length in a regular digital trie (see [22]). Then (3.43) is proved in [22].

We now prove that  $\underline{l}_n^{\underline{m}} = O(n)$ . Note that by  $\underline{l}_n^{\underline{m}} \leq \overline{l}_n^{\underline{m}}$ , and by (3.43) we can find such constants  $\xi_0, \xi_1, \ldots, \xi_m$  that  $a_n^{(2)}$  is bounded, and

$$a_n^{(2)} \leq \sum_{i=1}^{V} p_i^n \sum_{r=0}^{m} \xi_k \binom{n}{r}^{def} = A_n^m$$

Let now  $y_n$  be a sequence

$$y_n^m = A_n^m + \sum_{\{j_x = n\}} {n \choose j} p_1^{j_1} \cdots p_V^{j_V} [y_{j_1}^m + \cdots + y_{j_V}^m]$$
(3.44)

By linearity of the recurrence for  $\underline{l_n^m}$  we have for each m

$$l_n^m \le y_n^m \tag{3.45}$$

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Hence, to prove that  $l_n^m$  is O(n) it is enough to show that  $y_n^m = O(n)$ . But

Lemma 6. For any m and large n

$$y_n^m = O(n)$$

*Proof*: The recurrence (3.44) is of type (3.7), hence Theorem 1 and 2 may be applied. By (3.12) after some algebra we find

$$y_n^m = \frac{n}{h_1} \sum_{i=1}^V \left\{ \xi_0[p_i + (1 - p_i)\ln(1 - p_i)] + \xi_1 p_i \ln(1 - p_i) + \sum_{r=2}^m \xi_r \frac{p_i^r}{r(r-1)(1 - p_i)^{r-1}} \right\} = O(n)$$

Finally by Lemma 5, 6 and (3.45) we prove our last result of this section.

**Theorem 6.** For m > 2 the *m*-th factorial moment of the successful search  $S_n$  is

$$s_n^{\underline{m}} = \frac{1}{h_1^m} \ln^m n + \frac{n}{h_1^m} \ln^{m-1} n \left[ \gamma + \frac{m}{2} \frac{h_2}{h_1} - (m-1)h_1 - h_1^m F(n) \right] + O(\ln^{m-2} n)$$
(3.46)

This, in a trivial way, implies our Proposition 1(iii).

### 4. UNSUCCESSFUL SEARCH

The unsuccessful search is neither simply related to the external path length nor to the successful search, since unsuccessful searches are more likely to occur at external nodes near the root. This makes the analysis much more difficult. Therefore, we consider only binary symmetric Patricia tries, that is, V = 2 and  $p_1 = p_2 = 0.5$  is assumed, however, we derive asymptotic approximation for all moments of the unsuccessful search. The organization of this section is the same as for Section 3.

### 4.1. Initial and final results

Let  $H_n^{(m)}(\frac{1}{2})$  denote the *m*-th derivative of the generating function  $H_n(z)$  (see (2.3) in Lemma 1) at  $z = \frac{1}{2}$ . Then one proves

Property 2. For any integer m the following holds

$$H_n(1/2) = 1$$
 (4.1a)

$$u_n^m = \frac{1}{2^m} H_n^{(m)}(\frac{1}{2}) \tag{4.1b}$$

*Proof.* For binary symmetric Patricia tries (V = 2,  $p_1 = p_2 = 0.5$ ) the generating function  $H_n(z)$  from Lemma 1 becomes

$$H_n(z) = z \ 2^{1-n} \sum_{k=1}^n {n \choose k} H_k(z) - 2^{1-n}(z-1) H_n(z), \quad n \ge 2$$
(4.2)

Substituting  $z = \frac{1}{2}$  in (4.2) one proves (4.1a). The average value of the unsuccessful search,  $u_n^{\perp}$ is  $\sum_{i=0}^{\infty} l H_i 2^{-1} = \frac{1}{2} H_n^{(1)}(\frac{1}{2})$ , since we end up at a given external node on level l with probability  $2^{-l}$  (by  $H_l$  we denote the number of external nodes at level l). For m = 2 we have  $u_n^2 = \sum_{i=0}^{\infty} l(l-1)H_i 2^{-l} = (\frac{1}{2})^2 H_n(\frac{1}{2})$ , and so on. This proves (4.16).

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To compute the factorial moments  $u_n^m$  we must find the derivatives of the recurrence (4.2). Differentiating (4.2) and using (4.1b) for m = 1 one immediately obtains

$$u_{0}^{1} = u_{1}^{1} = 0$$

$$u_{n}^{1}(2^{n} - 2) = 2^{n} - 2 + \sum_{k=1}^{n-1} {n \choose k} u_{k}^{1}$$
(4.3)

For the second factorial moment we must differentiate (4.2) twice. Then

$$u_n^2(2^n - 2) = 2\sum_{k=1}^{n-1} \binom{n}{k} u_k^{\frac{1}{2}} + \sum_{k=1}^{n-1} \binom{n}{k} u_k^{\frac{2}{2}}$$

But the first term of the above might be computed from (4.3). Then finally

$$u_n^2(2^n - 2) = 2(2^n - 2)(u_n^1 - 1) + \sum_{k=1}^{n-1} {n \choose k} u_k^2$$
(4.4)

Generalizing the above, we find

Lemma 7. For any integers n and m, the m-th factorial moment of  $U_n$  satisfies

$$u_0^m = u_1^m = 0$$

$$u_n^m (2^n - 2) = m(2^m - 2) \left[ u_n^{m-1} + \sum_{k=1}^m (-1)^k (m-k) u_n^{m-k} \right] + \sum_{k=1}^{n-1} \left[ n \atop k \right] u_k^m \qquad (4.5)$$
and  $u_n^{\underline{0}} \stackrel{\text{def}}{=} 1$ 

Proof. The proof uses induction arguments and is left to the reader.

Note that (4.5) is a system of recurrences. To compute  $u_n^m$  we need  $u_n^1$ ,  $u_n^2$ , ...,  $u_n^{m-1}$ . But recurrences of type (4.5) have a common pattern, and for various *m* they differ only by additive terms. To solve (4.5) we shall use extensively a solution of a recurrence discussed in Szpankowski [20]. Below, we summarize the most important results from [20].

## Solution of a recurrence equation

Let  $x_0, x_1, \ldots, x_n$  be a sequence of number such that

given 
$$x_0 = x_1 = 0, x_2, ..., x_N$$
  
solve  $x_n(2^n - 2) = 2^n a_n + \sum_{k=1}^{n-1} {n \choose k} x_k \quad n > N$ 

$$(4.6)$$

where N is an integer, and  $a_n$  is a given, but otherwise arbitrary sequence. It turns out that the solution of (4.6) depends on the so called *Bernoulli inverse relations* (see Riordan [23]). Define for an  $a_n$  a new sequence  $\bar{a}_n$  as

$$\vec{a}_n = \sum_{k=0}^n \left( \begin{array}{c} n \\ k \end{array} \right) B_k a_{n-k} \tag{4.7a}$$

where  $B_k$  are the Bernoulli numbers defined as the coefficients of the Taylor expansion of  $z(e^2 - 1)^{-1}$ , that is,

$$\frac{z}{e^z - 1} = \sum_{k=0}^{\infty} B_k \frac{z^k}{k!}$$
(4.8)

For more details about Bernoulli numbers see [1], [15], [20], [23]. The sequence  $\bar{a}_n$  and  $a_n$  are called inverse pair since [23]

$$a_{n} = \sum_{k=0}^{n} {n \choose k} \frac{\bar{a}_{n-k}}{k+1} = \frac{1}{n+1} \sum_{k=0}^{n} {n+1 \choose k} \bar{a}_{k}$$
(4.7b)

hence also  $d_n = a_n$ . Using the above, we have proved in [20] that

Theorem 7. The solution of (4.6) is given by

$$x_n = b_n + \frac{1}{n+1} \sum_{k=2}^n \left( \begin{array}{c} n+1 \\ k \end{array} \right) \frac{\bar{b_k}}{2^{k-1} - 1}$$
(4.9)

where

$$b_n = a_n + g_n \chi_{(n \le N)} \tag{4.10a}$$

$$g_k = x_k(1-2^{-k}) - a_k - 2^{-k} \sum_{i=1}^k {k \choose i} x_i \quad k = 1, 2, \dots, N$$
 (4.10b)

$$\vec{b_k} = \vec{a_k} - a_0 B_k + \sum_{i=1}^N \begin{pmatrix} k \\ i \end{pmatrix} g_i B_{k-i}$$
(4.11)

and  $\chi_{(n \leq N)}$  is the indicator function.

Note also that (4.9) and (4.7b) imply that the inverse sequence  $\tilde{x_n}$ , to  $x_n$  defined in the recurrence

(4.6) is

$$\vec{x_n} = \vec{b_n} + \frac{\vec{b_n}}{2^{n-1}-1} \quad n \ge 2$$
 (4.12)

To find asymptotic approximation of  $x_n$  we need more information about  $a_n$  and  $\bar{a}_n$ . In particular, it is proved that [20], [23]

$$a_n = \begin{bmatrix} n \\ r \end{bmatrix} q^n \to \tilde{a_n} = \begin{bmatrix} n \\ r \end{bmatrix} q^r B_{n-r}(q)$$
(4.13)

where r is an integer, and 0 < q < 1, while  $B_n(q)$  denotes the Bernoulli polynomial defined as [1], [15], [20]

$$\frac{ze^{tz}}{e^z - 1} = \sum_{k=0}^{\infty} B_k(t) \frac{z^k}{k!}$$
(4.14)

Some more inverse pairs the reader may find is [23]. For example, it is easy to prove that

$$a_n = \frac{1}{n+1} \qquad \tilde{a_n} = \delta_{n0} \tag{4.15a}$$

$$a_n = 1 \qquad \vec{a_n} = B_n + \delta_{n1} \tag{4.15b}$$

Let us now restrict our considerations to  $a_n$  given by (4.13), and define

$$R_{n,r}(q) = \frac{1}{n+1} \sum_{k=2}^{n} \binom{n+1}{k} \binom{k}{r} \frac{B_{k-r}(q)}{2^{k-1}-1}$$
(4.16)

The following is proved in [20].

Theorem 8. For large n the below holds

$$R_{n,0}(q) = (\frac{1}{2} + \delta_{q,1} - q)(lg n - \frac{1}{2} + \frac{\gamma}{\ln 2}) + \frac{\zeta'(1 - q + \delta_{q,1})}{\ln 2} + f_0(n) + O(n^{-1}) \quad (4.17a)$$

$$R_{n,1}(q) = lgn - \frac{1}{2} + \frac{\gamma}{\ln 2} - \frac{\psi(1 - q + \delta_{q,1})}{\ln 2} + f_1(n) + O(n^{-1})$$
(4.17b)

$$R_{n,r}(q) = \frac{1}{r \ln 2} \zeta(r, 1 - q + \delta_{q,1}) + \frac{1}{r!} f_r(n) + O(n^{-1}), \quad r \ge 2$$
(4.17c)

where  $\psi(x)$  is the psi function,  $\zeta(z,q)$  is the generalized Riemman zeta function ( $\zeta(z) = \zeta(z,1)$ ) [1], [11], [24], and

$$f_r(n) = \frac{1}{\ln 2} \sum_{\substack{k = -\infty \\ k \neq 0}}^{\infty} \zeta(r + 2\pi i k / \ln 2) \Gamma(r + 2\pi i k / \ln 2) \exp[-2\pi i k \, lgn]$$
(4.17d)

and  $lgn = lg_2n$ .

The function  $f_r(n)$  is a fluctuating function with a small amplitude and may be safely ignored in practice [14], [20].

## Final results of this section

Using the recurrence (4.5), and Theorems 7 and 8 we prove our main result of this section.

## **Proposition 2.**

(i) The mean of the unsuccessful search is

$$EU_{n} = lgn - \theta + F_{1}(n) + O(n^{-1})$$
(4.18)

where

$$\theta = \frac{\ln \pi - \gamma}{\ln 2} - \frac{1}{2} = 0.31875 \tag{4.19}$$

and  $F_1(n)$  is a fluctuating function with a small amplitude.

(ii) The variance, var  $U_n$ , of  $U_n$  satisfies

var 
$$U_n = 4(\alpha - \beta - \theta - 2) - \theta - \theta^2 + F_2(n) + O(n^{-1})$$
  
 $\approx 0.87904$ 
(4.20)

where

$$\alpha = \frac{1}{2} \theta + \frac{23}{24} + \frac{1}{\ln^2 2} \left[ \frac{\pi^2}{24} + \frac{\gamma^2}{4} - \frac{\gamma \ln 2\pi}{2} - \zeta_2 \right]$$
(4.21a)

$$\zeta_2 = \frac{1}{2} \zeta''(0) = \frac{\gamma^2}{4} + \frac{c_1}{2} - \frac{\pi^2}{48} - \frac{\ln^2(2\pi)}{4}$$
(4.21b)

with  $c_1 = -0.0728158$  and

$$\beta = \theta + \frac{1}{2} + \frac{2}{\ln 2} \sum_{k=2}^{\infty} \frac{\zeta(k)2^{-k}}{k} \left\{ \sum_{\lambda=2}^{\infty} 2^{-k(\lambda-1)} \left[ \sum_{i=1}^{2^{\lambda-1}-1} i^{k} - \frac{2^{\lambda-1}}{k+1} + \frac{1}{2} \right] - \frac{1}{2(k+1)} \right\}$$
  
$$\approx 0.48738.$$
(4.21c)

and  $F_2(n)$  is a fluctuating function with a small amplitude.

(iii) The *m*-th moment,  $E(U_n)^m$ , of  $U_n$  satisfies

$$\lim_{n \to \infty} \frac{E(U_n)^m}{lg^m n} = 1.$$
(4.22)

## 4.2. The first two moments of $U_n$

The mean value of  $U_n$  is given by recurrence (4.3). This falls into our general recurrence (4.6) with N = 2 and  $a_n = 1 - 2^{1-n}$ , and  $b_n = a_n$  and  $\overline{b_n} = 2[B_k - B_k(\frac{1}{2})] = 4B_k[1 - 2^{-k}]$  (we use here the following identity  $B_n(\frac{1}{2}) = B_n(2^{1-n} - 1)$  [1]). Hence, by Theorem 7 we obtain

$$u_n^{1} = 2 - \frac{4}{n+1} + 2\delta_{n0} + \frac{2}{n+1} \sum_{k=2}^{n} \left( \begin{array}{c} n+1\\ k \end{array} \right) \frac{B_k}{2^{k-1} - 1}$$
(4.23)

Note also that by (4.12) and (4.15) the inverse sequence to  $u_n^{\frac{1}{2}}$  is given by

$$\vec{u}_n^{\underline{1}} = 4B_n + 2\delta_{n1} - 4\delta_{n0} + (1 - \delta_{n0} - \delta_{n1}) \frac{2B_n}{2^{n-1} - 1}$$
(4.24)

The asymptotic approximation of (4.23) follows directly from (4.16) and Theorem 8. Namely, for large n

$$U_n^{1} = 2R_{n,0}(1) = lg - \theta + f_0(n) + O(n^{-1})$$

as needed in Proposition 2(i).

The analysis of the second moment is much more intricate. The recurrence is given by (4.4). This recurrence does *not* fall exactly in our general recurrence (4.6). Therefore, let us split

the additive term into two parts, namely

$$2(2^n - 2)[u_n^{\perp} - 1] = 2 \cdot 2^n [u_n^{\perp} - 1 + 2^{1-n}] + 4u_n^{\perp}$$

and let the solution of (4.4) derived from the first part of the above be denoted as  $U_n^{(1)}$ , while the solution that follows from the second part is defined as  $U_n^{(2)}$ . By linearity of (4.4) we have

$$u_n^2 = U_n^{(1)} - U_n^{(2)} \tag{4.25}$$

Note that for  $U_n^{(1)}$  we have the following recurrence

$$U_0^{(1)} = U_1^{(1)} = 0$$

$$(2^n - 2)U_n^{(1)} = 2^n \cdot 2[u_n^1 - 1 + 2^{1-n}] + \sum_{k=1}^{n-1} {n \choose k} U_k^{(1)}$$

and this falls into (4.6) with  $a_n = 2[u_n^1 - 1 + 2^{1-n}]$ . Since  $\bar{a_n} = 2[\bar{u_n}^1 - B_n - \delta_{n1} + 2B_n(\frac{1}{2})]$ , and by (2.24) we immediately obtain from Theorem 7 (we use the following identity  $B_n(\frac{1}{2}) = B_n(2^{1-n} - 1)[1]$ )

$$U_n^{(1)} = \frac{8}{n+1} \sum_{k=2}^n \left( \begin{array}{c} n+1\\ k \end{array} \right) \frac{B_k}{2^{k-1}-1} + \frac{4}{n+1} \sum_{k=2}^n \left( \begin{array}{c} n+1\\ k \end{array} \right) \frac{B_k}{(2^{k-1}-1)^2}$$
(4.26)

The analysis of  $U_n^{(2)}$  is much more difficult. Note that the recurrence for  $U_n^{(2)}$  is not exactly of type (4.6), since the additive term is  $4u_n^{1}$  (not  $2^n a_n$  as required). But  $u_n^{1} = 2^n (2^{-n} u_n^{1})$ , and for the solution, we need the inverse sequence to  $2^{-n} u_n^{1}$ . But

Lemma 8. Let  $A_n = q^n a_n$ , and  $\bar{a_n}$  is given. Then

$$\bar{A_n} = \sum_{j=0}^n \left( \begin{array}{c} n \\ j \end{array} \right) \, \bar{a_j} q^{j-1} \, \frac{B_{n+1-j}(q) - B_{n+1-j}}{n+1-j} \tag{4.27}$$

Proof. In the proof we use identities from [1], [23] and (4.7). We have

$$\tilde{A_n} = \sum_{k=0}^n {n \choose j} B_{n-k} q^k a_k = \sum_{k=0}^n {n \choose k} B_{n-k} q^k \sum_{j=0}^k {k \choose j} \frac{1}{k+1-j} \tilde{a_j} = \sum_{j=0}^n {n \choose j} \tilde{a_j} q^j \sum_{k=0}^{n-1} {n-j \choose k} \frac{1}{k+1} B_{n-j-k} q^k = \sum_{j=0}^n {n \choose j} \tilde{a_j} q^{j-1} \frac{1}{n-j+1} \sum_{k=1}^{n-j+1} {n+1-j \choose k} B_{n+1-j-k} q^k = \sum_{j=0}^n {n \choose j} \tilde{a_j} q^{j-1} \frac{1}{n-j+1} \sum_{k=1}^{n-j+1} {n+1-j \choose k} B_{n+1-j-k} q^k = \sum_{j=0}^n {n \choose j} \tilde{a_j} q^{j-1} \frac{1}{n-j+1} \sum_{k=1}^{n-j+1} {n+1-j \choose k} B_{n+1-j-k} q^k = \sum_{j=0}^n {n \choose j} \tilde{a_j} q^{j-1} \frac{1}{n-j+1} \sum_{k=1}^{n-j+1} {n+1-j \choose k} B_{n+1-j-k} q^k = \sum_{j=0}^n {n \choose j} \tilde{a_j} q^{j-1} \frac{1}{n-j+1} \sum_{k=1}^{n-j+1} {n+1-j \choose k} B_{n+1-j-k} q^k = \sum_{j=0}^n {n \choose j} \tilde{a_j} q^{j-1} \frac{1}{n-j+1} \sum_{k=1}^{n-j+1} {n+1-j \choose k} B_{n+1-j-k} q^k q^k = \sum_{j=0}^n {n \choose j} \tilde{a_j} q^{j-1} \frac{1}{n-j+1} \sum_{k=1}^{n-j+1} {n+1-j \choose k} B_{n+1-j-k} q^k q^k q^k$$

$$\sum_{j=0}^{n} \left( \begin{array}{c} n \\ j \end{array} \right) \bar{a_j} q^{j-1} \frac{B_{n+1-j}(q) - B_{n+1-j}}{n+1-j}$$

Let now  $A_n = 2^{-n} u_n^{\frac{1}{2}}$ . Then, using (4.27) and (4.24) one shows that

$$\bar{A_n} = 2[B_n(\frac{1}{2}) - B_n] - 8 \frac{B_{n+1}(\frac{1}{2}) - B_{n+1}}{n+1} + 2V_n$$

where

$$V_{k} = \sum_{j=2}^{k} \binom{k}{j} \frac{B_{j}}{2^{j-1} - 1} 2^{1-j} \frac{B_{k+1-j}(\frac{1}{2}) - B_{k+1-j}}{k+1-j}$$

Finally, applying Theorem 7 and the above we obtain

Theorem 9. The solution to  $u_n^2$  given by recurrence (4.4) is  $u_n^2 = U_n^{(1)} - U_n^{(2)}$  where  $U_n^{(1)}$  is done in (4.26) and

$$U_{n}^{(2)} = 4 \cdot 2^{-n} u_{n}^{1} + \frac{8}{n+1} \sum_{k=2}^{n} \left[ \begin{array}{c} n+1\\ k \end{array} \right] \frac{B_{k}(\frac{1}{2}) + B_{k}}{2^{k-1} - 1} - \frac{32}{n+1} \sum_{k=2}^{n} \left[ \begin{array}{c} n+1\\ k \end{array} \right] \frac{B_{k+1}(\frac{1}{2}) - B_{k+1}}{(k+1)(2^{k-1} - 1)} + \frac{32}{n+1} \sum_{k=2}^{n} \left[ \begin{array}{c} n+1\\ k \end{array} \right] \frac{B_{k+1}(\frac{1}{2}) - B_{k+1}}{(k+1)(2^{k-1} - 1)} + \frac{32}{n+1} \sum_{k=2}^{n} \left[ \begin{array}{c} n+1\\ k \end{array} \right] \frac{B_{k+1}(\frac{1}{2}) - B_{k+1}}{(k+1)(2^{k-1} - 1)} + \frac{32}{n+1} \sum_{k=2}^{n} \left[ \begin{array}{c} n+1\\ k \end{array} \right] \frac{B_{k+1}(\frac{1}{2}) - B_{k+1}}{2^{k-1} - 1} \sum_{j=2}^{k} \left[ \begin{array}{c} k\\ j \end{array} \right] \frac{B_{j}}{2^{j-1} - 2} 2^{1-j} \frac{B_{k+1-j}(\frac{1}{2}) - B_{k+1-j}}{k+1 - j} + \frac{32}{n+1} \sum_{j=2}^{n} \left[ \begin{array}{c} n+1\\ k \end{array} \right] \frac{B_{k+1}(\frac{1}{2}) - B_{k+1-j}}{2^{j-1} - 1} \sum_{j=2}^{n} \left[ \begin{array}{c} k\\ j \end{array} \right] \frac{B_{k+1-j}(\frac{1}{2}) - B_{k+1-j}}{k+1 - j} + \frac{32}{n+1} \sum_{j=2}^{n} \left[ \begin{array}{c} n+1\\ k \end{array} \right] \frac{B_{k+1-j}(\frac{1}{2}) - B_{k+1-j}}{k+1 - j} + \frac{32}{n+1} \sum_{j=2}^{n} \left[ \begin{array}{c} n+1\\ k \end{array} \right] \frac{B_{k+1-j}(\frac{1}{2}) - B_{k+1-j}}{k+1 - j} + \frac{32}{n+1} \sum_{j=2}^{n} \left[ \begin{array}{c} n+1\\ k \end{array} \right] \frac{B_{k+1-j}(\frac{1}{2}) - B_{k+1-j}}{k+1 - j} + \frac{32}{n+1} \sum_{j=2}^{n} \left[ \begin{array}{c} n+1\\ k \end{array} \right] \frac{B_{k+1-j}(\frac{1}{2}) - B_{k+1-j}}{k+1 - j} + \frac{32}{n+1} \sum_{j=2}^{n} \left[ \begin{array}{c} n+1\\ k \end{array} \right] \frac{B_{k+1-j}(\frac{1}{2}) - B_{k+1-j}}{k+1 - j} + \frac{32}{n+1} \sum_{j=2}^{n} \left[ \begin{array}{c} n+1\\ k \end{array} \right] \frac{B_{k+1-j}(\frac{1}{2}) - B_{k+1-j}}{k+1 - j} + \frac{32}{n+1} \sum_{j=2}^{n} \left[ \begin{array}{c} n+1\\ k \end{array} \right] \frac{B_{k+1-j}(\frac{1}{2}) - B_{k+1-j}}{k+1 - j} + \frac{32}{n+1} \sum_{j=2}^{n} \left[ \begin{array}{c} n+1\\ k \end{array} \right] \frac{B_{k+1-j}(\frac{1}{2}) - B_{k+j}}{k+1 - j} + \frac{32}{n+1} \sum_{j=2}^{n} \left[ \begin{array}{c} n+1\\ k \end{array} \right] \frac{B_{k+1-j}(\frac{1}{2}) - B_{k+j}}{k+1 - j} + \frac{32}{n+1} \sum_{j=2}^{n} \left[ \begin{array}{c} n+1\\ k \end{array} \right] \frac{B_{k+1-j}(\frac{1}{2}) - B_{k+j}}{k+1 - j} + \frac{32}{n+1} \sum_{j=2}^{n} \left[ \begin{array}{c} n+1\\ k \end{array} \right] \frac{B_{k+1-j}(\frac{1}{2}) - B_{k+j}}{k+1 - j} + \frac{32}{n+1} \sum_{j=2}^{n} \left[ \begin{array}{c} n+1\\ k \end{array} \right] \frac{B_{k+1-j}(\frac{1}{2}) - B_{k+j}}{k+1 - j} + \frac{32}{n+1} \sum_{j=2}^{n} \left[ \begin{array}{c} n+1\\ k \end{array} \right] \frac{B_{k+1-j}(\frac{1}{2}) - B_{k+j}}{k+1 - j} + \frac{32}{n+1} \sum_{j=2}^{n} \left[ \begin{array}{c} n+1\\ k \end{array} \right] \frac{B_{k+1-j}(\frac{1}{2}) - B_{k+j}}{k+1 - j} + \frac{32}{n+1} \sum_{j=2}^{n} \left[ \begin{array}[c] n+1\\ k \end{array} \right] \frac{B_{k+1-j}(\frac{1}{2}) - B$$

Asymptotic	approximation for	$r U_n^{(1)}$
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Let

$$R_n^{(2)} = \frac{1}{n+1} \sum_{k=2}^n \left( \begin{array}{c} n+1\\ k \end{array} \right) \frac{B_k}{(2^{k-1}-1)^2}$$
(4.30)

Then by (4.26), (4.16) and the above  $U_n^{(1)} = 8 R_{n,0}(1) + 4 R_n^{(2)}$ . But by Theorem 8 we have

$$R_{n,0}(1) = \frac{1}{2} lg \ n \ -\frac{1}{2} \theta - 1 + f_0(n) + O(n^{-1})$$
(4.31)

Hence to find approximation for  $U_n^{(1)}$  we need asymptotic analysis for  $R_n^{(2)}$ . But applying the Mellin transform to (4.30) one proves (see [3], [20].)

$$R_n^{(2)} = \frac{1}{2\pi i} \int_{-\frac{1}{2} + i\infty}^{-\frac{1}{2} + i\infty} \frac{\zeta(z)\Gamma(z)n^{-2}}{(2^{-2} - 1)^2} dz$$
(4.32)

and to evaluate  $R_n^{(2)}$  we need residues of the function under the integral. Note that the roots of the denominator are  $z_k = 2\pi i k / \ln 2$ , with  $z_0 = 0$ . In addition, there is a single pole of the zeta function  $\zeta(z)$ , at z = 1 [1]. The root  $z_0 = 0$  is a triple pole since  $z_0 = 0$  is also a singular point of the gamma function,  $\Gamma(z)$ . It turns out also that this pole makes the biggest contribution to the asymptotic analysis of (4.32). To find the residue at  $z_0 = 0$  we use the following Taylor expansions [1], [4], [11], [24].

$$n^{-z} = 1 - z \ln n + \frac{\ln^2 n}{2} z^2 + O(z^3)$$
  

$$\Gamma(z) = z^{-1} - \gamma + \frac{1}{2} \left[\frac{\pi^2}{6} + \gamma^2\right] z + O(z^2)$$
  

$$\frac{1}{(2^{-z} - 1)} = \frac{1}{\ln^2 2} z^{-2} + \frac{1}{\ln 2} z^{-1} + \frac{5}{12} + O(z)$$

and

$$\zeta(z) = -\frac{1}{2} - \frac{z}{2} \ln 2\pi + \zeta_2 z + O(z^2)$$

where  $\zeta_2 = \frac{1}{2} \zeta''(0)$ . The value of  $\zeta_2$  is computed in [3, p.204], and

$$\zeta_2 = \frac{1}{2} \zeta''(0) = \frac{\gamma^2}{4} + \frac{c_1}{2} - \frac{\pi^2}{48} - \frac{1}{4} \ln^2(2\pi) = -1.0032$$
(4.33)

where  $c_1 = -0.0728158$ . Multiplying the above and taking the coefficient at  $z^{-1}$  one finds the desired residue. In a similar way the residues at  $z_k$  might be obtained. Computations show that

$$R_n^{(2)} = \frac{1}{4} lg^2 n - \frac{1}{2} [2.5 + \theta] lg n + \delta + F_0(n) + f_0(n) + O(n^{-1})$$

where

$$\delta = \frac{1}{2} \theta + \frac{23}{24} + \frac{1}{\ln^2 2} \left[ \frac{\pi^2}{24} + \frac{\gamma^2}{4} - \frac{\gamma \ln 2\pi}{2} - \zeta_2 \right]$$

$$F_0(n) = \frac{1}{\ln^2 2} \sum_{\substack{k = -\infty \\ k \neq 0}}^{\infty} \left[ \zeta(z_k) \right] \Gamma'(z_k) + \Gamma(z_k) \zeta'(z_k) - \ln n \Gamma(z_k) \exp[-2\pi i k \lg n]$$
(4.34)

Finally using the above and (4.31) we find

$$U_n^{(1)} = lg^2 n - [1 + 2\theta] lg n + 4(\delta - \theta - 1) + 12f_0(n) + 4F_0(n) + O(n^{-1})$$
(4.35)

where  $\theta$  and  $\delta$  are defined in (4.19) and (4.34).

## Upper and lower bounds for $U_n^{(2)}$

We now study  $U_n^{(2)}$ . It is easy to show that  $U_n^{(2)}$  satisfies the following recurrence

$$(2^{n} - 2)U_{n}^{(2)} = 4u_{n}^{1} + \sum_{k=1}^{n-1} {n \choose k} U_{k}^{(2)} \quad n \ge 2$$
(4.36)

with  $U_0^{(2)} = U_1^{(2)} = 0$ . Since (4.36) is not of type (4.6), hence we explore some other methods to evaluate  $U_n^{(2)}$ . In this subsection, we give a tight lower bound and a tight upper bound on  $U_n^{(2)}$ . In fact, we prove that  $U_n^{(2)} = O(1)$ .

Note that by Proposition 2 (i)  $u_n^1 = lg \ n + O(1)$ , hence we can find such constants  $\xi_0$ ,  $\xi_1$ and  $\xi_2$  that  $\xi_0 \le u_n^1 \le \xi_1 n + \xi_2$ . This implies that upper and lower bound for  $u_n^1$  might be established through Theorem 7 and 8, since for the lower bound we assume  $a_n = \xi_0 2^{-n}$  while for the upper bound we set  $a_n = \xi_1 \ n 2^{-n} + \xi_2 2^{-n}$ , and these fall into our recurrence (4.6). The accuracy of our evaluation depends, in fact, on a good approximation of  $u_n^1$  for small values of n, say,  $n \le N$ . In fact, we assume that we know  $u_0^1 = u_1^1 = 0$  and  $u_2^1, \ldots, u_N^1$ . Then

Lemma 9. For n > N the following holds

$$\xi_0 \le u_n^1 \le \xi_1 n + \xi_2 \tag{4.37}$$

with  $\xi_0 = u_{N+1}^1$ ,  $\xi_1 = [(N+1)\ln^2]^{-1}$ ,  $\xi_2 = \xi_0 - 1/\ln 2$ .

*Proof.* The proof uses induction applied to recurrence (4.3), and is left to the reader.

Let us now define two sequences  $\underline{x}_n$  and  $\overline{x}_n$  as

$$\underline{x}_{0} = \underline{x}_{1} = 0, \ \underline{x}_{2} = U_{2}^{(2)}/4 , \dots, \ \underline{x}_{N} = U_{N}^{(2)}/4 (2^{n} - 2)\underline{x}_{n} = \xi_{0} + \sum_{k=1}^{n-1} {n \choose k} \underline{x}_{k} \quad n > N$$
(4.38)

and

$$\overline{x}_{0} = \overline{x}_{1} = 0, \quad \overline{x}_{2} = U_{2}^{(2)}/4, \quad \dots, \quad \overline{x}_{N} = U_{N}^{(2)}/4$$

$$(2^{n} - 2)\overline{x}_{n} = \xi_{2} + \xi_{1} \quad n + \sum_{k=1}^{n-1} \left[ \begin{array}{c} n \\ k \end{array} \right] \quad \overline{x}_{k} \quad n > N.$$
(4.39)

Note that by Lemma 9  $4\underline{x}_n \leq U_n^{(2)} \leq 4\overline{x}_n$ . The asymptotic approximations for (4.38) and (4.39) are available by Theorem 7 and 8 with  $a_n = \xi_0 2^{-n}$  and  $a_n = \xi_1 n 2^{-n} + \xi_2 2^{-n}$  respectively. Hence

Theorem 10. For large n the following holds

$$\underline{x}_{n} = 0.5\xi_{0}[\theta + 0.5] + \frac{1}{\ln 2} \sum_{r=2}^{N} \frac{\zeta(r)G_{r}}{r} + O(n^{-1})$$
(4.40a)

with

$$G_r = \underline{x}_r - 2^{-r} [\underline{x}_k + \xi_0 + \sum_{i=1}^r {r \choose k} \underline{x}_i], \quad r = 1, 2, \ldots, N$$

and

$$\vec{x}_n = \xi_1 + 0.5\xi_2(\theta + 0.5) + \frac{1}{\ln 2} \sum_{r=2}^N \frac{\zeta(r)g_r}{r} + O(n^{-1})$$
(4.40b)

with

$$g_r = \bar{x}_r - 2^{-r} [\bar{x}_r + \xi_1 r + \xi_2 + \sum_{i=1}^N {r \choose i} \bar{x}_i] \quad r = 1, 2, \dots, N$$

Note that by Theorem 10 we have proved that  $U_n^{(2)} = O(1)$ . Let  $U_n^{(2)} = 4\beta$ , and  $\underline{\beta}$ ,  $\overline{\beta}$  be the lower and the upper bound for  $\beta$ , that is,  $\underline{x}_n = \underline{\beta}$  and  $\overline{x}_n = \overline{\beta}$ . The accuracy of  $\beta$  evaluation depends on N. Table 2 contains  $\underline{\beta}$  and  $\overline{\beta}$  for  $2 \le N \le 6$ .

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N	ß	β
2	0.46574	0.49869
3	0.48020	0.49031
4	0.48479	0.48824
5	0.486411	0.48766
6	0.48701	0.48748

We prove in the next subsection that  $\beta = 0.487385$ , which confirms the above approximations. In fact, the method established here can be used to solve the recurrence (4.6) in the case when Theorem 7 and 8 are not applicable, that is, when the additive term is not of the form  $2^n a_n$ . For example, if the additive term in (4.6) is lg n, then using our approach, we can prove that  $0.4997 \le x_n \le 0.5001$ .

# Exact asymptotic analysis of $U_n^{(2)}$

Although we have obtained above very tight bounds for  $U_n^{(2)}$  it is interesting to see if exact asymptotic analysis of  $U_n^{(2)}$  is possible. This interest follows not only from "pure mathematical whim", but such a solution enables to extend the analysis of (4.6) to the case when the additive term is any sequence of numbers, not particularly  $2^n a_n$ . This finds many applications in practice,

An asymptotic solution of  $U_n^{(2)}$  depends on finding an appropriate approximation on the last term of (4.29), that is

$$V_n^{(1)} \stackrel{def}{=} \frac{1}{n+1} \sum_{k=2}^n \left( \begin{array}{c} n+1\\ k \end{array} \right) \frac{V_k}{2^{k-1} - 1}$$
(4.41a)

where  $V_k$  is given by (4.28), i.e.

$$V_{k} \stackrel{def}{=} \sum_{j=2}^{k} {k \choose j} \frac{B_{j}}{2^{j-1} - 1} 2^{1-j} \frac{B_{k+1-j}(\frac{1}{2}) - B_{k+1-j}}{k+1-j}$$
(4.41b)

To apply Theorem 8 we must express  $V_n$  in terms of Bernoulli polynomials  $B_n(x)$  as (4.16)

suggests. Note that developing the denominator  $(2^{j-1} - 1)$  in (4.41b) in a geometric series we obtain

$$V_n = \sum_{\lambda=2}^{\infty} \sum_{j=2}^{n} {n \choose j} B_j 2^{-\lambda(j-1)} \frac{B_{n+1-j}(\frac{j}{2}) - B_{n+1-j}}{n+1-j}$$
(4.42)

We prove

Lemma 10. Let  $q = \frac{1}{2}$  and define

$$T_{\lambda}^{n} = \sum_{j=0}^{n} \left[ \begin{array}{c} n \\ j \end{array} \right] B_{j} q^{\lambda(j-1)} \frac{B_{n+1-j}(q) - B_{n+1-j}}{n+1-j}$$
(4.43)

Then

$$T_{\lambda}^{n} = \sum_{l=1}^{2^{k-1}-1} B_{n}(lq^{l}) + B_{n}$$
(4.44)

*Proof.* Let  $T_{\lambda}(z)$  be the exponential generating function for  $T_{\lambda}^{n}$ . Then multiplying both sides of (4.43) by  $z^{k}/k!$  one finds

$$T_{\lambda}(z) = \frac{z}{e^{z} - 1} \frac{e^{z/2} - 1}{e^{z^{2^{-1}} - 1}}$$
(4.45)

(The easiest way to show (4.45) is by using so called generalized Bernoulli polynomials as defined in [15]). Now use the fact that  $(e^{z/2} - 1) = (e^{z/4} - 1)(e^{z/4} + 1) = (e^{z/8} - 1)(e^{z/8} + 1)(e^{z/4} + 1)$  and so on. Finally we obtain  $(q = \frac{1}{2})$ 

$$T_{\lambda}(z) = \frac{z}{e^{z} - 1} \prod_{k=2}^{\lambda} (1 + e^{zq^{k}})$$
(4.46)

For example, for  $\lambda = 3$ 

$$T_{3}(z) = \frac{z}{e^{z} - 1} \frac{e^{zq} - 1}{e^{zq^{1}} - 1} = \frac{z}{e^{z} - 1} (e^{zq^{1}} + 1)(e^{zq^{2}} + 1) = \frac{ze^{z(q^{2} + q^{3})}}{e^{z} - 1} + \frac{ze^{zq^{2}}}{e^{z} - 1} + \frac{ze^{zq^{3}}}{e^{z} - 1} + \frac{z}{e^{z} - 1} + \frac{ze^{zq^{3}}}{e^{z} - 1} + \frac{z}{e^{z} -$$

Hence by finding explicit formula for the product in (4.46) we obtain terms as above. But each of this term is the generating function for a Bernoulli polynomial. For example, the first term in the above is the generating function for  $B_n(q^2 + q^3)$ . This proves, after some additional algebra,

(4.44).

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Comparing now (4.42) and (4.43) we find that

$$V_n = \sum_{\lambda=2}^{\infty} \left[ T_{\lambda}^n - 2^{\lambda} \frac{B_{n+1}(\lambda) - B_{n+1}}{n+1} + \frac{B_n(\lambda) - B_n}{2} \right]$$
(4.47)

Because of (4.44), (4.41a) and Theorem 8 the asymptotic approximation of  $V_n^{(1)}$  is easy to obtain, if one evaluates the following

$$r_n(q) = \frac{1}{n+1} \sum_{k=0}^n \left( \begin{array}{c} n+1 \\ k \end{array} \right) \frac{B_{k+1}(q) - B_{k+1}}{(k+1)(2^{k-1} - 1)}$$
(4.48)

Then  $U_n^{(2)} = 4\beta$ , where by (4.29) and the above

$$\beta = 2[R_{n,0}(\frac{1}{2}) + R_{n,0}(1)] - 8r_n(\frac{1}{2}) + 2\sum_{\lambda=2}^{\infty} [R_{n,0}(\lambda 2^{-\lambda}) + \frac{1}{2}R_{n,0}(1) - 2^{\lambda}r_n(\frac{1}{2}) + \frac{1}{2}R_{n,0}(\frac{1}{2})]$$
(4.49)

The appropriate approximation of  $R_{n,0}(q)$  is given in Theorem 8. We need only asymptotic approximation for  $r_n(\frac{1}{2})$ .

Lemma 11. For large n the following holds

$$r_n(\frac{1}{2}) = \frac{1}{8}(lgn + \frac{\gamma}{\ln 2} - \frac{1}{2}) + \frac{1}{\ln 2}\int_0^{\frac{1}{2}} \zeta'(1-t)dt + \frac{1}{2}f_0(n) + O(n^{-1})$$
(4.50a)

where

$$\int_{0}^{\frac{1}{2}} \zeta'(1-t)dt = \frac{\gamma}{8} - \frac{\ln 2\pi}{4} + \sum_{k=2}^{\infty} \frac{\zeta(k)2^{-k-1}}{k(k+1)}$$
(4.50b)

Proof. We know that [1], [15]

$$\frac{B_{k+1}(q) - B_{k+1}}{n+1} = \int_0^q B_k(t) dt$$

$$r_n(q) = \int_0^q \frac{1}{n+1} \sum_{k=2}^n \left( \begin{array}{c} n+1 \\ k \end{array} \right) \frac{B_k(t)}{2^{k-1}-1} dt = \int_0^q R_{n,0}(t) dt$$

Therefore, Theorem 8 (4.17a) might be used. Noting that [4]  $\zeta'(1-t) = \ln\Gamma(1-t) - \frac{1}{2} \ln 2\pi$ and [4]

$$\ln\Gamma(1-t) = \gamma t + \sum_{k=2}^{\infty} \frac{\zeta(k)t^k}{k}$$

we finally obtain (4.50).

Using (4.49), (4.50) and (4.17) we easily figure out the constant  $\beta$ . In fact, all coefficients at *lg n* disappear, and the first two terms of (4.49) give

$$2[R_{n,0}(\frac{1}{2}) + R_{n,0}(1)] - 8r_n(\frac{1}{2}) = \theta + 0.5 - \frac{8}{\ln 2} \sum_{k=2}^{\infty} \frac{\zeta(k)2^{-k-1}}{k(k+1)}$$

while the sum in (4.49) is

$$\frac{2}{\ln 2} \sum_{k=2}^{\infty} \frac{\zeta(k) 2^{-k}}{k} \sum_{\lambda=2}^{\infty} \left\{ 2^{-k(\lambda-1)} \sum_{i=1}^{2^{\lambda-1}} i^k - \frac{2^{\lambda-1}}{k+1} + \frac{1}{2} \right\}$$

This gives  $\beta$  as established in (4.21c). The Proposition 2(ii) follows from the above, (4.35) and (4.18) if one notes that  $\operatorname{var} U_n = u_n^2 + u_n^1 - (u_n^1)^2$ . The fluctuating function  $F_2(n)$  in (4.21) is equal to  $F_2(n) = 12f_0(n) + 4F_0(n)$ , where  $f_0(n)$  and  $F_0(n)$  are given by (4.17d) and (4.34).

Finally note that the above approach might be used to extend the solution of our general recurrence (4.6) to the case when the additive term is  $a_n$  without the coefficient  $2^n$  at  $a_n$ .

## 4.3. Higher moments of the unsuccessful search

Let

$$a_n = m \left[ u_n^{m-1} + \sum_{k=1}^m (-1)^k (m-k) u_n^{m-k} \right]$$
(4.51)

Then by Property 2 the *m*-th factorial moment of the unsuccessful search satisfies the recurrence  $u_n^m = 2^n a_n - 2a_n + \sum_{k=1}^n {n \choose k} u_k^m$ , and by linearity we can split  $u_n^m$  into two parts, namely  $u_n^m = \overline{U}_n^{(m)} = \underline{U}_n^{(m)}$  where the first component of the above is associated with  $2^n a_n$ , while the second with  $2a_n$ . We prove that  $\overline{U}_n^m = lg^m n + O(lg^{m-1}n)$  and  $\underline{U}_n^{(m)} = O(1)$ .

To solve for  $\overline{U}_n^{(m)}$  we apply the same approach as in the case m = 2. Since the additive term is  $2^n a_n$  we may use Theorem 7, and after some algebra one proves that

$$\overline{U}_{n}^{(m)} = \frac{2m!}{n+1} \sum_{k=2}^{n} \left[ \begin{array}{c} n+1\\ k \end{array} \right] \frac{B_{k}}{(2^{k-1}-1)^{m}} + \frac{1}{n+1} \sum_{l=1}^{m-1} \chi_{l} \sum_{k=2}^{n} \left[ \begin{array}{c} n+1\\ k \end{array} \right] \frac{B_{k}}{(2^{k-1}-1)^{l}}$$
(4.52)

where  $\chi_l$ , l = 1, 2, ..., m-1 are some constants. Using the Mellin transform as in Section 4.2 for (4.30) we prove that

$$R_n^{(m)} \stackrel{def}{=} \frac{1}{n+1} \sum_{k=2}^n \left( \begin{array}{c} n+1 \\ k \end{array} \right) \frac{B_k}{\left(2^{k-1}-1\right)^m} = \frac{1}{2\pi i} \int_{-\frac{1}{2}-i\infty}^{-\frac{1}{2}+i\infty} \frac{\zeta(z)\Gamma(z)n^{-z}}{\left(2^{-z}-1\right)^m} \, dz + O(n^{-1})$$

and finding the residue of the function under the integral we show that

$$R_n^{(m)} = \frac{1}{2m!} lg^m n + O(lg^{m-1}n)$$
(4.53)

Hence by (4.52) and (4.53) we prove that  $\overline{U}_{n}^{(m)} = lg^{m}n + O(lg^{m-1}n)$ .

To prove  $\underline{U}_n^{(m)} = O(1)$  note that by (4.51)–(4.53) we can find such constants  $\xi_i$ ,  $i = 0, 1, \ldots, m$  that  $a_n \leq \sum_{r=0}^m \xi_r {n \choose r} \frac{def}{r} = \overline{a}_n$ . Let us solve now (4.6) with the additive term  $2^n (2^{-n} \overline{a}_n)$ . This is possible since  $\overline{a}_n$  is of form (4.13). Direct applications of (4.17a)–(4.17b) shows that  $\underline{U}_n^{(m)} = O(1)$  (for more details see proof of Theorem 10). This together with (4.53) establishes Proposition 2(iii).

#### 5. FINAL REMARKS

In this paper a family of Patricia tries with *n* records was studied from the successful and unsuccessful point of view. We proved that the *m*-th moment of successful and unsuccessful searches are of order of magnitude  $\ln^m n$ . We gave a detailed analysis of the first two moments of  $S_n$  and  $U_n$  for large value of *n*. For example, we showed the the variances of  $S_n$  and  $U_n$  for binary symmetric Patricia tric are 1.000 and 0.879 respectively. These results have been achieved through extensive applications of two types of recurrences for which the solutions and asymptotic approximations were obtained elsewhere by the author. However, in deriving the variance of the unsuccessful search we had to generalize the solution of the second recurrence equation to a wider class of additive terms. This finds a number of new applications in computer science and telecommunication, e.g. in the average complexity of an algorithm generating exponentially distributed variates [8], in the performance evaluation of conflict resolution algorithm in a broadcast communication environment [9], [21], in the analysis of the refined lexicographical sorting [16] and extendible hashing [5], [6], and so on.

There are still some open problems related to an analysis of the Patricia trie. First of all, it is interesting to determine an asymptotic distribution for the successful and unsuccessful search. It is reasonable to predict that the successful search in the *asymmetric* Patricia is normally distributed with the parameters established in Proposition 1 (i)-(ii), for large n (see [12]). The symmetric case needs some additional work. Moreover, the analysis of unsuccessful search should be extended to asymmetric Patricia tries. In this paper, we have not considered at all the height of the Patricia, which is another open problem. Note that if  $H_n$  denotes the height of the Patricia with n records, then  $H_n$  is bounded in probability (on the contrary to the regular tries), that is,  $Pr \{lg_V n \le H_n \le n\} = 1$ . A simple upper and lower bound for the average of the height is possible. Indeed, using the above and noting that the height in the Patricia is not greater than the height in a regular trie, one shows immediately that for the binary case  $lgn < EH_n \le 2lgn$  (for the height of a trie see [6] [17]). It seems that  $EH_n$  is closer to the upper bound than the lower

one. However, a detailed analysis is necessary.

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