Advanced Data Structures

Computer Science Department

Random Binary Search Trees: An empirical analysis

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March 4, 2025

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1 Introduction

Let T be a binary tree with subtrees T_l and T_r. We say that T is a *binary search tree* (BST) if it is either an empty binary tree or it contains at least one element x as its root such that

- T_l and T_r are also BSTs.
- $\forall y \in T_l, y < x$ and $\forall z \in T_r, z > x$.

Although it is well known that, in the worst case, a BST behaves like a linked list (with the height of the tree being $\Theta(n)$), in this report, we focus on *random BSTs* of size n.

By *random BSTs*, we mean the following: Given a universe of keys U with $|U| = n$, we construct the BST by inserting each element of U exactly once, choosing the insertion order uniformly at random.

2 Analysis of the Average Cost of Insertions

2.1 Theoretical Study

Let us first analyze the expected cost of inserting an element $u \in U$ into our BST T. For that, we will consider this cost as the cost of searching for u in our BST, which is valid since we can assume that, if u does not exist in T, our search terminates in any empty subtree with identical probability.

Let I_n be the expected cost of the insertion of a key x in a random BST of size n. Let, also, be $I_{n,q}$ be the expected cost of the insertion of a key x in a random BST which root is the $q-$th smallest element. Then, the expected cost of I_n is

$$
\begin{aligned}
I_n &= \frac{1}{n}\sum_{q=1}^{n} I_{n,q} \\
&= 1 + \frac{1}{n}\sum_{k=1}^{n}(\frac{1}{n}0 + \frac{k-1}{n}I_{k-1} + \frac{n-k}{n}I_{n-k}) \\
&= 1 + \frac{1}{n}\sum_{k=0}^{n-1}(\frac{k}{n}I_k + \frac{n-k-1}{n}I_{n-k-1}) \\
&= 1 + \frac{1}{n^2}\sum_{k=0}^{n-1}(kI_k + (n-k-1)I_{n-k-1}) \\
&= 1 + \frac{2}{n^2}\sum_{k=0}^{n-1} kI_k
\end{aligned}
$$

We can solve this recurrence using the continuous master theorem. The continuous master theorem solves recurrences of the form

$$F_n = t_n + \sum_{0 \le j < n} w_{n,j} F_j$$

with $t_n = \Theta(n^a(\log n)^b)$. We proceed as follows:

- Determine the values of a and b: Since $t_n = \Theta(1)$, it is straightforward to see that $a = b = 0$.
- Provide a shape function for the weights $w_{n,j}$: We use the following trick to determine the shape function:

$$w(z) = \lim_{n\to\infty} n \cdot w_{n,z\cdot n} = n \cdot \frac{2zn}{n^2} = 2z.$$

- Determine the value of

$$\mathcal{H} = 1 - \int_0^1 w(z) z^a dz.$$

Substituting the values, we obtain:

$$\mathcal{H} = 1 - \int_0^1 2z dz = 1 - (1 - 0) = 0.$$

- Since $\mathcal{H} = 0$, we need to compute

$$\mathcal{H}' = -(b+1) \int_0^1 w(z) z^a \ln z \, dz.$$

Substituting the known values,

$$\mathcal{H}' = -1 \int_0^1 2z \ln z \, dz.$$

This integral can be solved using integration by parts. For the purpose of applying the theorem, we skip the detailed calculation, giving the result:

$$\mathcal{H}' = -(x^2 \ln x - \frac{x^2}{2})\Big|_0^1 = \frac{1}{2}.$$

Since $\mathcal{H} = 0$ and $\mathcal{H}' \neq 0$, we use the result

$$F_n = \frac{t_n}{\mathcal{H}'} \ln n + o(t_n \log n).$$

Substituting the values, we obtain

$$I_n = 2 \ln n + o(\log n).$$

Thus, the expected cost of an insertion into a random binary search tree is bounded by $O(\log n)$.

2.2 Experimental Study

Once we have theoretical results on the expected cost of an insertion in a random BST, we can provide experimental results to assess how closely they match the theoretical predictions. For this, we will conduct the following experiment:

1. We create a random BST of size n by generating n random keys in the interval $[0, 1]$.
2. After constructing the BST, we generate $q = 2 \cdot n$ random numbers in the interval $[0, 1]$.
3. For each generated value, we perform a `find` operation in the BST, counting the number of nodes traversed during the operation.
4. We sum up the total number of nodes traversed across all q search operations and compute the average.
5. We repeat all previous steps with 20 different seeds and compute the final average.

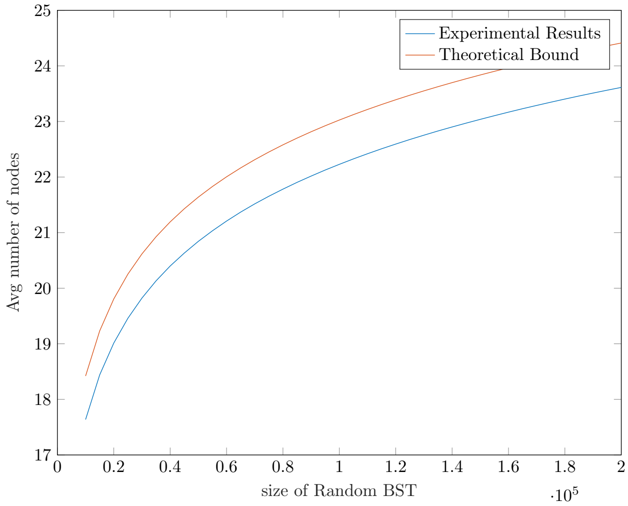

Figure 1: Plot

6. We repeat the entire experiment for different values of n.

I conducted the experiment previously explained with values of n ranging from $10,000$ to $200,000$ in increments of $5,000$, using seeds to generate random numbers from 1989 (in honor of the year of the first publication of the book *Introduction to Algorithms*, which was a great resource for refreshing my knowledge of BSTs and expected cost!) to 2008. Figure 1 provides a plot of the values obtained from this experiment, as well as the theoretical bound derived using the continuous master theorem. As we can see, the theoretical bound is respected within the experiment. Additionally, Table 1 presents the errors between the theoretical bound and the experimental results.

n	Experimental	Theoretical	Difference
10000	17.6373	18.4207	0.78335
15000	18.4401	19.2316	0.79148
20000	19.0132	19.807	0.79379
25000	19.4589	20.2533	0.79437
30000	19.8232	20.6179	0.79466
35000	20.1327	20.9262	0.79355
40000	20.3994	21.1933	0.79389
45000	20.6318	21.4288	0.79707
50000	20.8435	21.6396	0.79606
55000	21.0332	21.8302	0.79698
60000	21.2081	22.0042	0.79606
65000	21.3695	22.1643	0.79484
70000	21.5175	22.3125	0.79501
75000	21.6545	22.4505	0.79602
80000	21.7826	22.5796	0.79696
85000	21.9042	22.7008	0.79657
90000	22.0176	22.8151	0.79753
95000	22.1266	22.9233	0.79666
100000	22.2288	23.0259	0.7971
105000	22.3268	23.1234	0.79667
110000	22.4196	23.2165	0.79691
115000	22.5088	23.3054	0.79659
120000	22.5934	23.3905	0.79713
125000	22.6754	23.4721	0.7967
130000	22.7532	23.5506	0.79738
135000	22.8291	23.6261	0.79692
140000	22.901	23.6988	0.7978
145000	22.9706	23.769	0.79836
150000	23.0382	23.8368	0.79857
155000	23.1038	23.9024	0.79857
160000	23.1678	23.9659	0.79808
165000	23.2297	24.0274	0.79766
170000	23.2888	24.0871	0.79832
175000	23.3468	24.1451	0.79826
180000	23.4032	24.2014	0.79818
185000	23.4583	24.2562	0.79793
190000	23.5112	24.3096	0.79838
195000	23.5627	24.3615	0.79878
200000	23.6128	24.4121	0.79932

Table 1: xd