If you hold a cat by the tail
you learn things you cannot learn any other way.
— Mark Twain

9 Tail Inequalities

The simple recursive structure of skip lists made it relatively easy to derive an upper bound on the expected *worst-case* search time, by way of a stronger high-probability upper bound on the worst-case search time. We can prove similar results for treaps, but because of the more complex recursive structure, we need slightly more sophisticated probabilistic tools. These tools are usually called *tail inequalities*; intuitively, they bound the probability that a random variable with a bell-shaped distribution takes a value in the *tails* of the distribution, far away from the mean.

9.1 Markov's Inequality

Perhaps the simplest tail inequality was named after the Russian mathematician Andrey Markov; however, in strict accordance with Stigler's Law of Eponymy, it first appeared in the works of Markov's probability teacher, Pafnuty Chebyshev.[1]

Markov's Inequality. *Let X be a non-negative integer random variable. For any $t > 0$, we have $\Pr[X \geq t] \leq \mathrm{E}[X]/t$.*

Proof: The inequality follows from the definition of expectation by simple algebraic manipulation.

$$\begin{aligned}
\mathrm{E}[X] &= \sum_{k=0}^{\infty} k \cdot \Pr[X = k] && [\text{definition of } \mathrm{E}[X]] \\
&= \sum_{k=0}^{\infty} \Pr[X \geq k] && [\text{algebra}] \\
&\geq \sum_{k=0}^{t-1} \Pr[X \geq k] && [\text{since } t < \infty] \\
&\geq \sum_{k=0}^{t-1} \Pr[X \geq t] && [\text{since } k < t] \\
&= t \cdot \Pr[X \geq t] && [\text{algebra}]
\end{aligned}$$

□

Unfortunately, the bounds that Markov's inequality implies (at least directly) are often very weak, even useless. (For example, Markov's inequality implies that with high probability, every node in an n-node treap has depth $O(n^2 \log n)$. Well, *duh!*) To get stronger bounds, we need to exploit some additional structure in our random variables.

[1]The closely related tail bound traditionally called Chebyshev's inequality was actually discovered by the French statistician Irénée-Jules Bienaymé, a friend and colleague of Chebyshev's.

9.2 Sums of Indicator Variables

Recall that random variables $X_1, X_2, \ldots, X_n$ are *mutually independent* if and only if

$$\Pr\left[\bigwedge_{i=1}^{n}(X_i = x_i)\right] = \prod_{i=1}^{n}\Pr[X_i = x_i]$$

for all possible values $x_1, x_2, \ldots, x_n$. For examples, different flips of the same fair coin are mutually independent, but the number of heads and the number of tails in a sequence of n coin flips are not independent (since they must add to n). Mutual independence of the X_i's implies that the expectation of the product of the X_i's is equal to the product of the expectations:

$$\mathrm{E}\left[\prod_{i=1}^{n} X_i\right] = \prod_{i=1}^{n}\mathrm{E}[X_i].$$

Moreover, if $X_1, X_2, \ldots, X_n$ are independent, then for any function f, the random variables $f(X_1)$, $f(X_2), \ldots, f(X_n)$ are also mutually independent.

Suppose $X = \sum_{i=1}^{n} X_i$ is the sum of n mutually independent random *indicator* variables X_i. For each i, let $p_i = \Pr[X_i = 1]$, and let $\mu = \mathrm{E}[X] = \sum_i \mathrm{E}[X_i] = \sum_i p_i$.

Chernoff Bound (Upper Tail). $\boxed{\Pr[X > (1+\delta)\mu] < \left(\dfrac{e^\delta}{(1+\delta)^{1+\delta}}\right)^{\mu}}$ *for any* $\delta > 0$.

Proof: The proof is fairly long, but it replies on just a few basic components: a clever substitution, Markov's inequality, the independence of the X_i's, The World's Most Useful Inequality $e^x > 1 + x$, a tiny bit of calculus, and lots of high-school algebra.

We start by introducing a variable t, whose role will become clear shortly.

$$Pr[X > (1+\delta)\mu] = \Pr[e^{tX} > e^{t(1+\delta)\mu}]$$

To cut down on the superscripts, I'll usually write $\exp(x)$ instead of e^x in the rest of the proof. Now apply Markov's inequality to the right side of this equation:

$$Pr[X > (1+\delta)\mu] < \frac{\mathrm{E}[\exp(tX)]}{\exp(t(1+\delta)\mu)}.$$

We can simplify the expectation on the right using the fact that the terms X_i are independent.

$$\mathrm{E}[\exp(tX)] = \mathrm{E}\left[\exp\left(t\sum_i X_i\right)\right] = \mathrm{E}\left[\prod_i \exp(tX_i)\right] = \prod_i \mathrm{E}[\exp(tX_i)]$$

We can bound the individual expectations $\mathrm{E}\left[e^{tX_i}\right]$ using The World's Most Useful Inequality:

$$\mathrm{E}[\exp(tX_i)] = p_i e^t + (1 - p_i) = 1 + (e^t - 1)p_i < \exp\big((e^t - 1)p_i\big)$$

This inequality gives us a simple upper bound for $\mathrm{E}[e^{tX}]$:

$$\mathrm{E}[\exp(tX)] < \prod_i \exp((e^t - 1)p_i) < \exp\left(\sum_i (e^t - 1)p_i\right) = \exp((e^t - 1)\mu)$$

Substituting this back into our original fraction from Markov's inequality, we obtain

$$Pr[X > (1+\delta)\mu] < \frac{\mathrm{E}[\exp(tX)]}{\exp(t(1+\delta)\mu)} < \frac{\exp((e^t-1)\mu)}{\exp(t(1+\delta)\mu)} = \big(\exp(e^t - 1 - t(1+\delta))\big)^\mu$$

Notice that this last inequality holds for *all* possible values of t. To obtain the final tail bound, we will choose t to make this bound as tight as possible. To minimize $e^t - 1 - t - t\delta$, we take its derivative with respect to t and set it to zero:

$$\frac{d}{dt}(e^t - 1 - t(1+\delta)) = e^t - 1 - \delta = 0.$$

(And you thought calculus would never be useful!) This equation has just one solution $t = \ln(1+\delta)$. Plugging this back into our bound gives us

$$Pr[X > (1+\delta)\mu] < \big(\exp(\delta - (1+\delta)\ln(1+\delta))\big)^\mu = \left(\frac{e^\delta}{(1+\delta)^{1+\delta}}\right)^\mu$$

And we're done! □

This form of the Chernoff bound can be a bit clumsy to use. A more complicated argument gives us the bound

$$\boxed{\Pr[X > (1+\delta)\mu] < e^{-\mu\delta^2/3} \text{ for any } 0 < \delta < 1.}$$

A similar argument gives us an inequality bounding the probability that X is significantly *smaller* than its expected value:

Chernoff Bound (Lower Tail). $\boxed{\Pr[X < (1-\delta)\mu] < \left(\frac{e^\delta}{(1-\delta)^{1-\delta}}\right)^\mu < e^{-\mu\delta^2/2}}$ *for any* $\delta > 0$.

9.3 Back to Treaps

In our analysis of randomized treaps, we defined the indicator variable A_k^i to have the value 1 if and only if the node with the ith smallest key ('node i') was a proper ancestor of the node with the kth smallest key ('node k'). We argued that

$$\Pr[A_k^i = 1] = \frac{[i \neq k]}{|k-i|+1},$$

and from this we concluded that the expected depth of node k is

$$\mathrm{E}[\mathrm{depth}(k)] = \sum_{i=1}^{n} \Pr[A_k^i = 1] = H_k + H_{n-k} - 2 < 2\ln n.$$

To prove a worst-case expected bound on the depth of the tree, we need to argue that the *maximum* depth of any node is small. Chernoff bounds make this argument easy, once we establish that the relevant indicator variables are mutually independent.

Lemma 1. *For any index k, the $k-1$ random variables A_k^i with $i < k$ are mutually independent. Similarly, for any index k, the $n-k$ random variables A_k^i with $i > k$ are mutually independent.*

Proof: To simplify the notation, we explicitly consider only the case $k = 1$, although the argument generalizes easily to other values of k. Fix $n-1$ arbitrary indicator values $x_2, x_3, \ldots, x_n$. We prove the lemma by induction on n, with the vacuous base case $n = 1$. The definition of conditional probability gives us

$$\begin{aligned}\Pr\left[\bigwedge_{i=2}^{n}(A_1^i = x_i)\right] &= \Pr\left[\bigwedge_{i=2}^{n-1}(A_k^i = x_i) \;\wedge\; A_1^n = x_n\right] \\ &= \Pr\left[\bigwedge_{i=2}^{n-1}(A_k^i = x_i) \,\middle|\, A_1^n = x_n\right] \cdot \Pr\left[A_1^n = x_n\right]\end{aligned}$$

Now recall that $A_1^n = 1$ if and only if node n has the smallest priority, and the other $n-2$ indicator variables A_1^i depend only on the order of the priorities of nodes 1 through $n-1$. There are exactly $(n-1)!$ permutations of the n priorities in which the nth priority is smallest, and each of these permutations is equally likely. Thus,

$$\Pr\left[\bigwedge_{i=2}^{n-1}(A_k^i = x_i) \,\middle|\, A_1^n = x_n\right] = \Pr\left[\bigwedge_{i=2}^{n-1}(A_k^i = x_i)\right]$$

The inductive hypothesis implies that the variables $A_1^2, \ldots, A_1^{n-1}$ are mutually independent, so

$$\Pr\left[\bigwedge_{i=2}^{n-1}(A_k^i = x_i)\right] = \prod_{i=2}^{n-1}\Pr\left[A_1^i = x_i\right].$$

We conclude that

$$\Pr\left[\bigwedge_{i=2}^{n}(A_1^i = x_i)\right] = \Pr\left[A_1^n = x_n\right] \cdot \prod_{i=2}^{n-1}\Pr\left[A_1^i = x_i\right] = \prod_{i=1}^{n-1}\Pr\left[A_1^i = x_i\right],$$

or in other words, that the indicator variables are mutually independent. □

Theorem 2. *The depth of a randomized treap with n nodes is $O(\log n)$ with high probability.*

Proof: First let's bound the probability that the depth of node k is at most $8\ln n$. There's nothing special about the constant 8 here; I'm being generous to make the analysis easier.

The depth is a sum of n indicator variables A_k^i, as i ranges from 1 to n. Our Observation allows us to partition these variables into two mutually independent subsets. Let $d_<(k) = \sum_{i<k} A_k^i$ and $d_>(k) = \sum_{i<k} A_k^i$, so that $depth(k) = d_<(k) + d_>(k)$. If $depth(k) > 8\ln n$, then either $d_<(k) > 4\ln n$ or $d_>(k) > 4\ln n$.

Chernoff's inequality, with $\mu = \mathrm{E}[d_<(k)] = H_k - 1 < \ln n$ and $\delta = 3$, bounds the probability that $d_<(k) > 4\ln n$ as follows.

$$\Pr[d_<(k) > 4\ln n] < \Pr[d_<(k) > 4\mu] < \left(\frac{e^3}{4^4}\right)^{\mu} < \left(\frac{e^3}{4^4}\right)^{\ln n} = n^{\ln(e^3/4^4)} = n^{3-4\ln 4} < \frac{1}{n^2}.$$

(The last step uses the fact that $4\ln 4 \approx 5.54518 > 5$.) The same analysis implies that $\Pr[d_>(k) > 4\ln n] < 1/n^2$. These inequalities imply the crude bound $\Pr[depth(k) > 4\ln n] < 2/n^2$.

Now consider the probability that the treap has depth greater than $10\ln n$. Even though the distributions of different nodes' depths are *not* independent, we can conservatively bound the probability of failure as follows:

$$\Pr\left[\max_k depth(k) > 8\ln n\right] = \Pr\left[\bigwedge_{k=1}^{n}(depth(k) > 8\ln n)\right] \le \sum_{k=1}^{n}\Pr[depth(k) > 8\ln n] < \frac{2}{n}.$$

This argument implies more generally that for any constant c, the depth of the treap is greater than $c \ln n$ with probability at most $2/n^{c \ln c - c}$. We can make the failure probability an arbitrarily small polynomial by choosing c appropriately. □

This lemma implies that any search, insertion, deletion, or merge operation on an n-node treap requires $O(\log n)$ time with high probability. In particular, the expected *worst-case* time for each of these operations is $O(\log n)$.

Exercises

1. Prove that for any integer k such that $1 < k < n$, the $n - 1$ indicator variables A_k^i with $i \neq k$ are *not* mutually independent. *[Hint: Consider the case $n = 3$.]*

2. Recall from Exercise 1 in the previous note that the expected number of descendants of any node in a treap is $O(\log n)$. Why doesn't the Chernoff-bound argument for depth imply that, with high probability, *every* node in a treap has $O(\log n)$ descendants? The conclusion is clearly bogus—Every treap has a node with n descendants!—but what's the hole in the argument?

3. A *heater* is a sort of dual treap, in which the priorities of the nodes are given, but their search keys are generate independently and uniformly from the unit interval $[0, 1]$. You can assume all priorities and keys are distinct.

   (a) Prove that for any r, the node with the rth smallest *priority* has expected depth $O(\log r)$.

   (b) Prove that an n-node heater has depth $O(\log n)$ with high probability.

   (c) Describe algorithms to perform the operations INSERT and DELETEMIN in a heater. What are the expected worst-case running times of your algorithms? In particular, can you express the expected running time of INSERT in terms of the priority rank of the newly inserted item?