

Lecture 14: November 16, 2015

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1 The power of two random choices

We will now show that two random choices can reduce the maximum load to $O(\ln \ln n)$. The proof technique is due to Azar et al. [ABKU94, ABKU99] and various applications were explored by Mitzenmacher in his thesis [Mit96]. We first provide the intuition for the proof.

For each i , let B_i denote the number of bins with at least i balls. Suppose $B_i \leq \beta_i$ for some bound β_i . Then B_{i+1} is bounded above by a binomial random variable corresponding to the number of heads in n independent coin tosses, where the probability of each toss being heads is at most $(\beta_i/n)^2$. This is because for a ball to land a bin such that the load of the bin becomes greater than i , it must happen that both the random bins which we chose to put it in, had load at least i . This happens with probability at most $(\beta_i/n)^2$. Thus, B_{i+1} is upper bounded by the above random variable, which we denote as $\text{Bin}\left(n, \left(\frac{\beta_i}{n}\right)^2\right)$.

This, $\mathbb{E}[B_{i+1}] \leq n \cdot \left(\frac{\beta_i}{n}\right)^2$ and B_{i+1} is at most $e \cdot \frac{\beta_i^2}{n}$ with high probability. We can then take β_{i+1} to be $e \cdot \frac{\beta_i^2}{n}$. For the above sequence, the value of β_i becomes less than 1 for $i_0 = O(\ln \ln n)$, and thus we can bound the maximum load by i_0 . The proof will follow this intuition, except that for the last step, when $\mathbb{E}[B_i]$ becomes very small, we will not be able to use a Chernoff bound and will have to resort to a slightly different analysis.

We first define the values β_i . Let $\beta_6 = \frac{n}{2e}$ and $\beta_{i+1} = e \cdot n \cdot \left(\frac{\beta_i}{n}\right)^2$.

$$\begin{aligned} \beta_6 &= \frac{n}{2e} \\ \Rightarrow \beta_7 &= e \left(\frac{n}{2e}\right)^2 = \frac{n}{4e} = \frac{n}{2^2 e} \\ \Rightarrow \beta_8 &= e \left(\frac{n}{4e}\right)^2 = \frac{n}{16e} = \frac{n}{2^{2^2} e} \\ \Rightarrow \beta_9 &= e \left(\frac{n}{16e}\right)^2 = \frac{n}{256e} = \frac{n}{2^{2^3} e} \\ &\vdots \\ \Rightarrow \beta_i &= \frac{n}{2^{2^{i-6}} e} \end{aligned}$$

Let E_i be the event that $B_i \leq \beta_i$. Note that E_6 holds for sure since there can be at most $n/6 \leq n/2e$ bins with 6 or more balls. We show that with high probability, if E_i holds then E_{i+1} holds provided $\beta_i^2 \geq 2n \ln n$.

Claim 1.1 *Let i be such that $\beta_i^2 \geq 2n \ln n$. Then,*

$$\mathbb{P}[\neg E_{i+1} \mid E_i] \leq \frac{1}{n^2} \cdot \frac{1}{\mathbb{P}[E_i]}.$$

Proof: The tricky part in proving the claim is the conditioning. Conditioning on the event E_i , the choices made by the various balls are no longer independent. To take care of this, we define the random variables Y_t as

$$Y_t = \begin{cases} 1 & \text{if at time } t \text{ there are at most } \beta_i \text{ bins with load } i \text{ and} \\ & \text{both bins chosen by the } t^{\text{th}} \text{ ball have load at least } i \\ 0 & \text{otherwise} \end{cases}$$

We can now write the event E_{i+1} in terms of the variables Y_t . We have

$$\mathbb{P}[\neg E_{i+1} \mid E_i] = \frac{\mathbb{P}[\sim E_{i+1} \wedge E_i]}{\mathbb{P}[E_i]} \leq \frac{\mathbb{P}[\sum_{t=1}^n Y_t \geq \beta_{i+1}]}{\mathbb{P}[E_i]}$$

Note that the variables Y_t are still *not* independent, but satisfy that

$$\mathbb{P}[Y_t = 1 \mid Y_1, \dots, Y_{t-1}] \leq \left(\frac{\beta_i}{n}\right)^2.$$

Prove that this implies

$$\mathbb{P}\left[\sum_{t=1}^n Y_t \geq \beta_{i+1}\right] \leq \mathbb{P}\left[\text{Bin}\left(n, \left(\frac{\beta_i}{n}\right)^2\right) \geq \beta_{i+1}\right],$$

where $\text{Bin}(n, p)$ denotes a binomial random variable with n independent trials and success probability p for each trial. Using Chernoff bounds, we get

$$\mathbb{P}\left[\text{Bin}\left(n, \left(\frac{\beta_i}{n}\right)^2\right) \geq \beta_{i+1}\right] = \mathbb{P}\left[\text{Bin}\left(n, \left(\frac{\beta_i}{n}\right)^2\right) \geq en \cdot \left(\frac{\beta_i}{n}\right)^2\right] \leq e^{-n \cdot (\beta_i/n)^2} \leq \frac{1}{n^2}$$

when $\beta^2 \geq 2n \ln n$. Thus,

$$\mathbb{P}[\neg E_{i+1} \mid E_i] = \frac{\mathbb{P}[\sim E_{i+1} \wedge E_i]}{\mathbb{P}[E_i]} \leq \frac{\mathbb{P}\left[\text{Bin}\left(n, \left(\frac{\beta_i}{n}\right)^2\right) \geq en \cdot \left(\frac{\beta_i}{n}\right)^2\right]}{\mathbb{P}[E_i]} \leq \frac{1}{n^2} \cdot \frac{1}{\mathbb{P}[E_i]}$$

when $\beta^2 \geq 2n \ln n$. ■

We can then use induction to show that for each i as above, the probability of the event E_i not happening is very low.

Claim 1.2 *For all i such that $\beta_i^2 \geq 2n \ln n$, we have*

$$\mathbb{P}[\neg E_{i+1}] \leq \frac{i+1}{n^2}.$$

Proof: We prove the claim by induction on i . We know from the definition of β_6 that $\mathbb{P}[\neg E_6] = 0$. Also, from the previous claim, we have that for any i as above,

$$\begin{aligned}\mathbb{P}[\neg E_{i+1}] &= \mathbb{P}[E_i] \cdot \mathbb{P}[\neg E_{i+1}|E_i] + \mathbb{P}[\neg E_i] \cdot \mathbb{P}[\neg E_{i+1}|\neg E_i] \\ &\leq \mathbb{P}[E_i] \cdot \frac{1}{n^2} \cdot \frac{1}{\mathbb{P}[E_i]} + \frac{i}{n^2} \\ &\leq \frac{i+1}{n^2}.\end{aligned}$$

■

We will need a slightly different analysis when $\beta_i^2 < 2n \ln n$. Let i_0 be the minimum i such that $\beta_i^2 < 2n \ln n$. Because $\beta_{i_0-1}^2 \geq 2n \ln n$, we have by the previous claim that $B_{i_0} \leq \beta_{i_0}$ with high probability. The probability that B_{i_0+1} is large can be bounded as before using

$$\begin{aligned}\mathbb{P}[(B_{i_0+1} \geq k) \wedge E_{i_0}] &\leq \mathbb{P}\left[\text{Bin}\left(n, \left(\frac{B_{i_0}}{n}\right)^2\right) \geq k\right] \\ &\leq \mathbb{P}\left[\text{Bin}\left(n, \left(\frac{\beta_{i_0}}{n}\right)^2\right) \geq k\right] \\ &\leq \mathbb{P}\left[\text{Bin}\left(n, \left(\frac{2n \ln n}{n}\right)^2\right) \geq k\right],\end{aligned}$$

where we use the fact that the probability of seeing a certain amount of heads increases as we increase the probability of heads. If we set $k = 6 \ln n$, then Chernoff bound gives

$$\mathbb{P}[(B_{i_0+1} \geq 6 \ln n) \wedge E_{i_0}] \leq e^{-2 \ln n} = \frac{1}{n^2},$$

which implies as before

$$\mathbb{P}[(B_{i_0+1} \geq 6 \ln n)] \leq \mathbb{P}[(B_{i_0+1} \geq 6 \ln n) \wedge E_{i_0}] + \mathbb{P}[\neg E_{i_0}] \leq \frac{i_0 + 1}{n^2}.$$

We further look at whether there even exists a bin with load more than $i_0 + 2$, and we see that

$$\mathbb{P}[B_{i_0+2} \geq 1] = \underbrace{\mathbb{P}[B_{i_0+2} \geq 1 | B_{i_0+1} > k]}_{\leq 1} \cdot \underbrace{\mathbb{P}[B_{i_0+1} > k]}_{\leq \frac{i_0+1}{n^2}} + \mathbb{P}[B_{i_0+2} \geq 1 | B_{i_0+1} \leq k] \cdot \underbrace{\mathbb{P}[B_{i_0+1} \leq k]}_{\leq 1}.$$

Because B_{i_0+1} is small enough, it suffices to bound the only term left in the above equation with Markov's inequality,

$$\mathbb{P}[B_{i_0+2} \geq 1 | B_{i_0+1} \leq k] \leq \mathbb{E}[B_{i_0+2} | B_{i_0+1} \leq k] \leq \mathbb{E}\left[\text{Bin}\left(n, \left(\frac{k}{n}\right)^2\right)\right] \leq \frac{k^2}{n}.$$

Recalling the expression for β_i

$$\beta_i = \frac{n}{2^{2^{i-6}} e},$$

we have

$$i_0 = \frac{\ln \ln n}{\ln 2} + O(1).$$

This completes the proof that if we choose two bins at random instead of one, we reduce the number of high-load bins from $O(\ln n)$ to $O(\ln \ln n)$ with high probability.

2 Martingales

We now relax the independence assumption we used in proving Chernoff-Hoeffding bounds. Martingale sequences capture the notion of somewhat limited independence which is still sufficient to prove similar concentration bounds. We first restate the a special case of Chernoff bounds slightly differently.

Let X_1, \dots, X_n be a sequence of independent random variables such that each X_i equals 1 with probability $1/2$ and -1 with probability $1/2$. Let

$$Z_i = X_1 + \dots + X_i.$$

We take $Z_0 = 0$ and notice that Chernoff bounds imply that the difference $|Z_n - Z_0|$ is small with high probability. Note that the above sequence satisfies the property that

$$\mathbb{E}[Z_i \mid X_1, \dots, X_{i-1}] = \mathbb{E}[Z_{i-1}],$$

which turns out to be sufficient to prove the required concentration bounds. The sequence of random variables $\{Z_i\}_{i=1}^n$ is known as a *Martingale sequence*.

Definition 2.1 Let $\mathcal{F}_0 \subseteq \mathcal{F}_1 \subseteq \dots \subseteq \mathcal{F}_n$ be an increasing sequence of σ -algebras, known as a *filter*, on a finite space Ω . A sequence of random variables $\{Z_i\}_{i=1}^n$ is known as *Martingale sequence* with respect to the above filter if for all $i \in [n]$, Z_i is measurable in the σ -algebra \mathcal{F}_i and

$$\mathbb{E}[Z_i \mid \mathcal{F}_{i-1}] = Z_{i-1}.$$

The sequence $Y_i = Z_i - Z_{i-1}$ is known as a *martingale difference sequence*, and satisfies that

$$\mathbb{E}[Y_i \mid \mathcal{F}_{i-1}] = 0.$$

Example 2.2 (Doob Martingale) Let A, X_1, \dots, X_n be random variables on the same finite space Ω . Then check that

$$Z_i = \mathbb{E}[A \mid X_1, \dots, X_i],$$

forms a martingale sequence. A case of particular interest is the one where $A = f(X_1, \dots, X_n)$ is a function of the random variables X_1, \dots, X_n .

We will prove a concentration inequality for such sequences, known as Azuma's inequality, in the next lecture.

References

- [ABKU94] Yossi Azar, Andrei Z Broder, Anna R Karlin, and Eli Upfal, *Balanced allocations*, Proceedings of the twenty-sixth annual ACM symposium on Theory of computing, ACM, 1994, pp. 593–602.
- [ABKU99] ———, *Balanced allocations*, SIAM journal on computing **29** (1999), no. 1, 180–200.
- [Mit96] Michael David Mitzenmacher, *The power of two random choices in randomized load balancing*, Ph.D. thesis, PhD thesis, Graduate Division of the University of California at Berkley, 1996.