

Randomness and Computation

or, “Randomized Algorithms”

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RC (2018/19) – Lecture 9 – slide 1

warm-up: Birthday Paradox

Hence

$$p_{30\text{diff}} < \prod_{j=1}^{29} e^{-j/365} = \left(\prod_{j=1}^{29} e^{-j} \right)^{\frac{1}{365}} = \left(e^{-\sum_{j=1}^{29} j} \right)^{\frac{1}{365}} = \left(e^{-435} \right)^{\frac{1}{365}},$$

last step using $\sum_{j=1}^n j = \frac{n(n+1)}{2}$. And $(e^{-435})^{\frac{1}{365}} \sim e^{-1.19} \sim 0.3$. So with probability of at least 0.7, two people at the party share a birthday.

More general framework:

n birthday options, *m* party guests

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warm-up: Birthday Paradox

30 people in a room. What is the probability they share a birthday?

- ▶ Assume everyone is equally likely to be born any day (*uniform at random*). Exclude Feb 29 for neatness.
- ▶ Generate birthdays one-at-a-time from the pool of 365 (*principle of deferred decisions*).

Probability $p_{30\text{diff}}$ that all birthdays are *different* is

$$p_{30\text{diff}} = \prod_{i=1}^{30} \frac{365 - (i-1)}{365} = \prod_{i=1}^{30} \left(1 - \frac{(i-1)}{365} \right) = \prod_{j=1}^{29} \left(1 - \frac{j}{365} \right).$$

Recall that $1 + x < e^x$ for all $x \in \mathbb{R}$, hence $(1 - \frac{j}{365}) < e^{-j/365}$ for any j .

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warm-up: General Birthday Paradox

More general framework:

n birthday options, *m* party guests

Probability $p_{\text{all}-m\text{-diff}}$ that all are *different* is

$$p_{\text{all}-m\text{-diff}} = \prod_{j=1}^m \left(1 - \frac{(j-1)}{n} \right) = \prod_{j=1}^{m-1} \left(1 - \frac{j}{n} \right).$$

Continuing,

$$p_{\text{all}-m\text{-diff}} \leq \prod_{j=1}^{m-1} e^{-j/n} = \left(\prod_{j=1}^{m-1} e^{-j} \right)^{\frac{1}{n}} = \left(e^{-\sum_{j=1}^{m-1} j} \right)^{\frac{1}{n}} = e^{-\frac{(m-1)m}{2n}},$$

approximately $e^{-m^2/2n}$.

Suppose we set $m = \lfloor \sqrt{n} \rfloor$, then $e^{-m^2/2n}$ becomes $\sim e^{-0.5} \sim 0.6$.

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Balls in Bins

- ▶ m balls, n bins, and balls thrown *uniformly at random* into bins (usually one at a time).
- ▶ Magic bins with no upper limit on capacity.
- ▶ Common model of random allocations and their affect on overall *load* and *load balance*, typical *distribution* in the system.
- ▶ (by the birthdays analysis) we know that for $m = \Omega(\sqrt{n})$, then there is some constant probability $c > 0$ of a birthday clash (visualiser).
- ▶ "Classic" question - what does the distribution look like for $m = n$? Max load? (*with high probability* results are what we want).

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Balls in Bins maximum load

Proof of Lemma 5.1 cont'd.

So bin i gets $\geq M$ balls with probability at most

$$\left(\frac{e}{M}\right)^M.$$

Set $M =_{\text{def}} \frac{3 \ln(n)}{\ln \ln(n)}$. Then the probability that *any* bin gets $\geq M$ balls is (using the Union bound) at most

$$n \cdot \left(\frac{e \cdot \ln \ln(n)}{3 \ln(n)}\right)^{\frac{3 \ln(n)}{\ln \ln(n)}} \leq n \cdot \left(\frac{\ln \ln(n)}{\ln(n)}\right)^{\frac{3 \ln(n)}{\ln \ln(n)}} = e^{\ln(n)} \left(\frac{\ln \ln(n)}{\ln(n)}\right)^{\frac{3 \ln(n)}{\ln \ln(n)}}.$$

Again using properties of \ln , this expands as

$$e^{\ln(n)} \left(e^{\ln \ln \ln(n) - \ln \ln(n)}\right)^{\frac{3 \ln(n)}{\ln \ln(n)}} = e^{\ln(n)} \left(e^{-3 \ln(n) + 3 \frac{\ln(n) \ln \ln \ln(n)}{\ln \ln(n)}}\right).$$

□

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Balls in Bins maximum load

Lemma (5.1)

Let n balls be thrown independently and uniformly at random into n bins. Then for sufficiently large n , the maximum load is bounded above by $\frac{3 \ln(n)}{\ln \ln(n)}$ with probability at least $1 - \frac{1}{n}$.

Proof The probability that bin i receives $\geq M$ balls is at most

$$\binom{n}{M} \frac{n^{n-M}}{n^n} = \binom{n}{M} \frac{1}{n^M}.$$

Expanding $\binom{n}{M}$, this is

$$\frac{n \dots (n - M + 1)}{M!} \frac{1}{n^M} \leq \frac{1}{M!}.$$

To bound $(M!)^{-1}$ note that for any k , we have $\frac{k^k}{k!} \leq \sum_{i=0}^{\infty} \frac{k^i}{i!} = e^k$, hence $\frac{1}{k!} \leq \left(\frac{e}{k}\right)^k$. *Or use Stirling ...*

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Balls in Bins maximum load

Proof of Lemma 5.1 cont'd.

Grouping the $\ln(n)$ s in the exponents, and evaluating, we have

$$e^{-2 \ln(n)} \cdot e^{3 \frac{\ln(n) \ln \ln \ln(n)}{\ln \ln(n)}} = \frac{1}{n^2} n^{3 \frac{\ln \ln \ln(n)}{\ln \ln(n)}}.$$

If we take n "sufficiently large" ($n \geq e^{e^4}$ will do it), then $\frac{\ln \ln \ln(n)}{\ln \ln(n)} \leq 1/3$, hence the probability of *some* bin having $\geq M$ balls is at most

$$\frac{1}{n}.$$

□

Can derive a matching proof to show that "with high probability" there will be a bin with $\Omega\left(\frac{\ln(n)}{\ln \ln(n)}\right)$ balls in it.

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$\Omega(\cdot)$ bound on the maximum load (chat)

- ▶ We implicitly used the *Union Bound* in our proof of Lemma 5.1, when we multiplied by n on slide 7. However, in reality, bin i has a lower chance of being “high” (say $\Omega(\frac{\ln(n)}{\ln \ln(n)})$) if other bins are already “high” (the “high-bin” events are *negatively correlated*).
- ▶ This means that we can’t use the same approach as in Theorem 5.1 to prove a partner result of $\Omega(\frac{\ln(n)}{\ln \ln(n)})$.
- ▶ Solution is to use the fact that for the binomial distribution $B(m, \frac{1}{n})$ for an individual bin, that as $n \rightarrow \infty$,

$$\Pr[X = k] = \binom{m}{k} \left(\frac{1}{n}\right)^k \left(1 - \frac{1}{n}\right)^{m-k} \rightarrow \frac{e^{-m/n} (m/n)^k}{k!}$$

(ie, close to the probabilities for the Poisson distribution with parameter $\mu = m/n$)

- ▶ The Poisson’s aren’t independent but the dependance can be limited to an extra factor of $e^{\sqrt{m}}$ (Section 5.4).

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References and Exercises

- ▶ Sections 5.1, 5.2 of “Probability and Computing”.
- ▶ For Friday’s lecture, try to read Sections 5.3 and 5.4 with the Ω bound for the $\Theta(\frac{\ln(n)}{\ln \ln(n)})$ result; I plan to sketch this on Friday.

Exercises

- ▶ Exercise 5.3 (balls in bins when $m = c \cdot \sqrt{n}$).
- ▶ Exercise 5.10 (sequences of empty bins; this is a bit more tricky)

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Some preliminary observations, definitions

The probability is of a specific bin (bin i , say) being empty:

$$\left(1 - \frac{1}{n}\right)^m \sim e^{-m/n}.$$

Expected number of empty bins: $\sim ne^{-m/n}$

Probability p_r of a specific bin having r balls:

$$p_r = \binom{m}{r} \frac{1^r}{n^r} \left(1 - \frac{1}{n}\right)^{m-r}.$$

Note

$$p_r \sim \frac{e^{-m/n} m^r}{r! n}.$$

Definition (5.1)

A discrete *Poisson random variable* X with parameter μ is given by the following probability distribution on $j = 0, 1, 2, \dots$:

$$\Pr[X = j] = \frac{e^{-\mu} \mu^j}{j!}.$$

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