Random Variables and Expectation (II)

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Most if the material included here is based on Chapter 13 of Kleinberg & Tardos Algorithm Design book.

Waiting for a first success

- A coin is heads with probability p and tails with probability $1-p$.
- How many independent flips we expect to get heads for the first time?
- Let X the random variable that gives the number of flips until (and including) the first head.
  Observe that
  $$\mathbb{P}[X=j] = (1-p)^{j-1}p$$
  and
  $$\mathbb{E}[X] = \sum_{j=1}^{\infty} j\,\mathbb{P}[X=j] = \sum_{j=1}^{\infty}(1-p)^{j-1}p = \frac{p}{1-p}\sum_{j=1}^{\infty} j(1-p)^j$$
  as $\sum_{j=1}^{\infty} jx^j = \frac{x}{(1-x)^2}$, we have
  $$\mathbb{E}[X] = \frac{p}{1-p}\frac{1-p}{p^2} = \frac{1}{p}$$

Bernoulli process

- A Bernoulli process denotes a sequence of experiments, each of them a with binary output: success (1) with probability p, and failure (0) with prob. $q = 1 - p$.
- A nice thing about Bernoulli distributions: it is natural to define a indicator r.v.

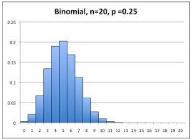
$$X = \begin{cases} 1 & \text{if the output is 1,} \\ 0 & \text{otherwise.} \end{cases}$$

Clearly, $\mathbb{E}[X] = \mathbb{P}[X = 1] = p$

The binomial distribution

A r.v. X has a Binomial distribution with parameters n and p ($X \sim \text{Bin}(n,p)$) if X counts the number of successes during n trials, each trial an independent Bernoulli experiment having probability of success p.

$$\mathbb{P}[X = k] = \binom{n}{k} p^k (1-p)^{n-k}.$$

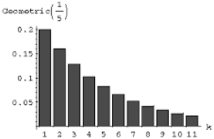


Let $X \sim \text{Bin}(n,p)$. To compute $\mathbb{E}[X]$, we define indicator r.v. $\{X_i\}_{i=1}^n$, where $X_i = 1$ iff the i-th output is 1, otherwise $X_i = 0$, that is, each X_i is the indicator rv of a Bernouilli experiment. Then $X = \sum_{i=1}^n X_i \Rightarrow \mathbb{E}[X] = \mathbb{E}[\sum_{i=1}^n X_i] = \sum_{i=1}^n \underbrace{\mathbb{E}[X_i]}_{=p} = np$.

The Geometric distribution

A r.v. X has a Geometric distribution with parameter p ($X \sim \text{Geom}(p)$) if X counts the number of Bernouilli trials until the first success.

If $X \sim \text{Geom}(p)$ then
$\mathbb{P}[X = k] = (1-p)^{k-1}p$,
$\mathbb{E}[X] = \frac{1}{p}$.



Random generators

Consider a sequential random generator of n bits, so that the probability that a bit is 1 is p.

- If $X =$ # number of 1's in the generated n bit number, $X \sim \text{Bin}(n, p)$.
- If $Y =$ # bits in the generated number until the first 1, $Y \sim \text{Geom}(p)$.

Coupon collector

Each box of cereal contains a coupon. There are n different types of coupons. Assuming all boxes are equally likely to contain each coupon, how many boxes before you have at least 1 coupon of each type?

Claim

The expected number of steps is $\Theta(n \log n)$.

Proof

- Phase j = number of steps between j and $j+1$ distinct coupons.
- Let $X_j =$ number of steps you spend in phase j.
- Let $X =$ total number of steps, of course, $X = X_0 + X_1 + \cdots + X_{n-1}$.

Coupon collector

Proof (cont'd)

$X_j =$ number of steps you spend in phase j.

- We can consider a Bernoulli experiment that succeeds when we hit one of the still not collected coupons.
- Conditioned on the event that we have already collected j distinct coupons, the probability of success is $p_j = \frac{n-j}{n}$.
- X_j counts the time until the Bernoulli process reaches a success, therefore $X_j \sim \text{Geom}(p_j)$, hence

$$\mathbb{E}[X_j] = \frac{n}{n-j}$$

Coupon collector

Proof (cont'd)

$X =$ total number of steps

Using linearity of expectations, we have

$$\begin{aligned}\mathbb{E}[X] &= E[X_0] + E[X_1] + \cdots + E[X_{n-1}] \\ &= \sum_{j=0}^{n-1} \frac{n}{n-j} = n \sum_{j=1}^{n} \frac{1}{j} = nH_n = n \ln n + \mathcal{O}(n).\end{aligned}$$

□

A randomized approximation algorithm for MAX 3-SAT

A 3-SAT formula is a Boolean formula in CNF such that each clause has exactly 3 literals and each literal corresponds to a different variable.

$$(x_2 \vee \overline{x_3} \vee \overline{x_4}) \wedge (x_2 \vee x_3 \vee \overline{x_4}) \wedge (\overline{x_1} \vee x_2 \vee x_4) \wedge (\overline{x_1} \vee \overline{x_2} \vee x_3) \wedge (x_1 \vee \overline{x_2} \vee \overline{x_4})$$

MAXIMUM 3-SAT. Given a 3-SAT formula, find a truth assignment that satisfies as many clauses as possible.

The problem is NP-hard. We can try to design a randomized algorithm that produces a good assignment, even if it is not optimal.

A randomized approximation algorithm for MAX 3-SAT

Algorithm. For each variable, flip a fair coin, and set the variable to **true** (1) if it is heads, to **false** (0) otherwise.

Note that a variable gets 1 with probability $\frac{1}{2}$, and this assignment is made independently of the other variables.

What is the expected number of satisfied clauses?

Assume that the 3-SAT formula has n variables and m clauses.

- Let $Z =$ number of clauses satisfied by the random assignment
- For $1 \leqslant j \leqslant m$, define the random variables $Z_j = 1$ if clause j is satisfied, 0 otherwise.
- By definition, $Z = \sum_{j=1}^{m} Z_j$.
- $\mathbb{P}[Z_j = 1] = 1 - (1/2)^3 = 7/8$, so $\mathbb{E}[Z_j] = 7/8$. Therefore ,

$$\mathbb{E}[Z] = \sum_{j=1}^{m} \mathbb{E}[Z_j] = \frac{7}{8}m$$

A randomized approximation algorithm for MAX 3-SAT

How good is the solution computed by the random algorithm?

- For a 3-CNF formula let $\mathrm{opt}(F)$ be the maximum number of clauses than can be satisfied by an assignment.
- As for any assignment x the number of satisfied clauses is always $\leqslant \mathrm{opt}(F)$, we have that $\mathbb{E}[Z] \leqslant \mathrm{opt}(F)$.
- Of course $\mathrm{opt}(F) \leqslant m$, that is $\frac{7}{8}\mathrm{opt}(F) \leqslant \frac{7}{8}m = \mathbb{E}[Z]$, then

$$\frac{\mathrm{opt}(F)}{\mathbb{E}[Z]} \leqslant \frac{8}{7}$$

We have a $\frac{8}{7}$-approximation algorithm for MAX 3-SAT.

The probabilistic method

Claim

For any instance of 3-SAT, there exists a truth assignment that satisfies at least a 7/8 fraction of all clauses.

Proof

For any random variable X there must exist one event ω for which the measured value $X(\omega)$ is at least as large as the expectation of X. $\square$

Probabilistic method. [Paul Erdős] Prove the existence of a non-obvious property by showing that a random construction produces it with positive probability

Random Quicksort

Input: An array A holding n keys. For simplicity we assumed that all keys are different.
Output: A sorted in increasing order.

I'm assuming that all of you known:

- The Quicksort algorithm which has $\mathcal{O}(n^2)$ cost
- and $\mathcal{O}(n \log n)$ average cost.
- One randomized version randomly sorts the input and then applies the deterministic algorithm, having average running time $\mathcal{O}(n \log n)$
- Here we consider another randomized version of Quicksort.

Random-Quicksort

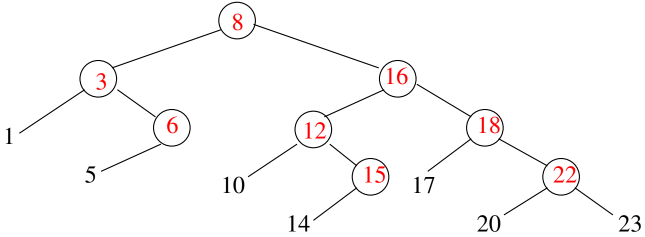
procedure RAND-QUICKSORT(A)
  if A.SIZE() $\leqslant 3$ **then**
    Sort A using insertion sort
    return A
  end if
  Choose an element $a \in A$ uniformly at random
  Put in A^- all elements $< a$ and in A^+ all elements $> a$
  RAND-QUICKSORT(A^-)
  RAND-QUICKSORT(A^+)
  $A := A^- \cdot a \cdot A^+$
end procedure

The main difference is that we perform a random partition in each call around the random pivot a.

Example

A={1,3,5,6,8,10,12,14,15,16,17,18,20,22,23}

Ran–Partition of input



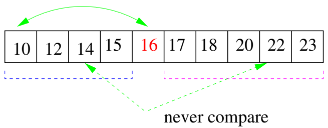
Expected Complexity of Ran-Partition

Taken from CMU course 15451-07
https://www.cs.cmu.edu/afs/cs/academic/class/15451-s07/www/lecture_notes/lect0123.pdf

- The expected running time $T(n)$ of Rand-Quicksort is dominated by the number of comparisons.
- Every Rand-Partition has cost
  $\Theta(1) + \Theta(\underbrace{\text{number of comparisons}}_{A.size()})$
- If we can count the number of comparisons, we can bound the the total time of Quicksort.
- Let X be the number of comparisons made in all calls of Ran-Quicksort
- X is a r.v. as it depends of the random choices of the element used to do a Ran-Partition

Expected Complexity of Ran-Partition

- Note: In the first application of Ran-Partition the selected a compares with all $n-1$ elements.
- Key observation: Any two keys are compared iff one of them is selected as pivot, and they are compared at most one time.



Denote the i-th smallest element in the array by z_i and define the indicator r.v.:

$$X_{ij} = \begin{cases} 1 & \text{if } z_i \text{ is compared to } z_j, \\ 0 & \text{otherwise.} \end{cases}$$

Then, $X = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} X_{i,j}$
(this is true because we never compare a pair more than once)

$$\mathbb{E}[X] = \mathbf{E}\left[\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} X_{i,j}\right] = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathbb{E}\left[X_{i,j}\right]$$

$\mathbb{E}\left[X_{i,j}\right] = \mathbb{P}\left[X_{i,j} = 1\right] = \mathbb{P}\left[z_i \text{ is compared to } z_j\right]$

- If the pivot we choose is between z_i and z_j then we never compare them to each other.
- If the pivot we choose is either z_i or z_j then we do compare them.
- If the pivot is less than z_i or greater than z_j then both z_i and z_j end up in the same partition and we have to pick another pivot.
- So, we can think of this like a dart game: we throw a dart at random into the array: if we hit z_i or z_j then X_{ij} becomes 1, if we hit between z_i and z_j then X_{ij} becomes 0, and otherwise we throw another dart.
- At each step, the probability that $X_{ij} = 1$ conditioned on the event that the game ends in that step is exactly $2/(j - i + 1)$. Therefore, overall, the probability that $X_{ij} = 1$ is $2/(j - i + 1)$.

End of the computation

$$
\begin{aligned}
\mathbb{E}[X] &= \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathbb{E}\left[X_{i,j}\right] \\
&= \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \frac{2}{j-i+1} \\
&= 2 \cdot \sum_{i=1}^{n} \left(\frac{1}{2} + \frac{1}{3} + \cdots + \frac{1}{n-i+1}\right) \\
&< 2 \cdot \sum_{i=1}^{n} \left(\frac{1}{2} + \frac{1}{3} + \cdots + \frac{1}{n}\right) \\
&= 2 \cdot \sum_{i=1}^{n} H_n = 2 \cdot n \cdot H_n = \mathcal{O}(n \lg n).
\end{aligned}
$$

Therefore, $\mathbb{E}[X] \leqslant 2n \ln n + \Theta(n)$.

Main theorem

Theorem

The expected complexity of Ran-Quicksort is $\mathbb{E}[T_n] = \mathcal{O}(n \lg n)$.

Selection and order statistics

Problem: Given a list A of n of unordered distinct keys, and a $i \in \mathbb{Z}$, $1 \leqslant i \leqslant n$, select the element $x \in A$ that is larger than exactly $i - 1$ other elements in A.

Notice if:

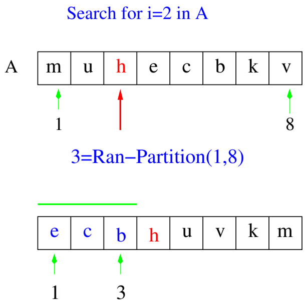
1. $i = 1 \Rightarrow$ MINIMUM element
2. $i = n \Rightarrow$ MAXIMUM element
3. $i = \lfloor \frac{n+1}{2} \rfloor \Rightarrow$ the MEDIAN
4. $i = \lfloor 0.9 \cdot n \rfloor \Rightarrow$ order statistics

Sort A ($\mathcal{O}(n \lg n)$) and search for $A[i]$ ($\Theta(n)$).
Can we do it in linear time?
Yes, there are deterministic linear time algorithms for selection—but with a bad constant factor.

Quickselect

Given unordered $A[1,\ldots,n]$ return the i-th. element

- Quickselect $(A[p,\ldots,q],i)$
- $r =$ Ran-Partition (p,q) to find position of pivot and partition the array
- if $i = r$ return $A[r]$
- if $i < r$ Quickselect $(A[p,\ldots,r-1],i)$
- else Quickselect $(A[r+1,\ldots,q],i-r)$



Analysis of Quickselect

In the worst-case, the cost of QUICKSELECT is $\Theta(n^2)$. But on avergae its coste is $\Theta(n)$.

Theorem

Given $A[1, \ldots, n]$ and i, the expected number of steps for Quickselect to find the i-th. element in A is $O(n)$

Analysis of Quickselect

- The algorithm is in phase j when the size of the set under consideration is at most $n(3/4)^j$ but greater than $n(3/4)^{j-1}$
- We bound the expected number of iterations spent in phase j.
- An element is central if at least a quarter of the elements are smaller and at least a quarter of the elements are larger.
- If a central element is chosen as pivot, at least a quarter of the elements are dropped. So, the set shrinks by a $3/4$ factor or better.
- Since half of the elements are central, the probability of choosing as pivot a central element is $1/2$.
- So the expected number of iterations in phase j is 2.

Analysis of Quickselect

- Let $X =$ number of steps taken by the algorithm.
- Let $X_j =$ number of steps in phase j. We have $X = X_0 + X_1 + X_2 + \dots$
- An iteration in phase j requires at most $cn(3/4)^j$ steps, for some constant c.
- Therefore, $\mathbb{E}\left[X_j\right] \leqslant 2cn(3/4)^j$ and by linearity of expectation.

$$\mathbb{E}[X] = \sum_j \mathbb{E}\left[X_j\right] \leqslant \sum_j 2cn\left(\frac{3}{4}\right)^j = 2cn\sum_j\left(\frac{3}{4}\right)^j \leqslant 8cn$$

Analysis of Quickselect

We have proved that its average cost is $\Theta(n)$. The proportionality constant depends on the ratio i/n. $C_n^{(i)}$, the expected number of comparisons to find the smallest i-th element among n is

$$C_n^{(i)} \sim f(\alpha) \cdot n + o(n), \qquad \alpha = i/n,$$
$$f(\alpha) = 2 - 2\left(\alpha \ln \alpha + (1-\alpha)\ln(1-\alpha)\right)$$

More precisely, Knuth (1971) proved that

$$\begin{aligned} C_n^{(i)} &= 2\big((n+1)H_n - (n+3-j)H_{n+1-j} \\ &\quad - (j+2)H_j + n + 3\big) \end{aligned}$$

The maximum average cost corresponds to finding the median ($i = \lfloor n/2 \rfloor$); then we have

$$C_n^{(\lfloor n/2 \rfloor)} = 2(\ln 2 + 1)n + o(n).$$

The Continuous Master Theorem

CMT considers divide-and-conquer recurrences of the following type:

$$F_n = t_n + \sum_{0 \leqslant j < n} \omega_{n,j} F_j, \qquad n \geqslant n_0$$

for some positive integer n_0, a function t_n, called the *toll function*, and a sequence of *weights* $\omega_{n,j} \geqslant 0$. The weights must satisfy two conditions:

1. $W_n = \sum_{0 \leqslant j < n} \omega_{n,j} \geqslant 1$ (at least one recursive call).
2. $Z_n = \sum_{0 \leqslant j < n} \frac{j}{n} \cdot \frac{\omega_{n,j}}{W_n} < 1$ (the size of the subinstances is a fraction of the size of the original instance).

The next step is to find a *shape function* $\omega(z)$, a continuous function approximating the discrete weights $\omega_{n,j}$.

The Continuous Master Theorem

Definition

Given the sequence of weights $\omega_{n,j}$, $\omega(z)$ is a shape function for that set of weights if

1. $\int_0^1 \omega(z)\,dz \geqslant 1$
2. there exists a constant $\rho > 0$ such that

$$\sum_{0 \leqslant j < n} \left| \omega_{n,j} - \int_{j/n}^{(j+1)/n} \omega(z)\,dz \right| = \mathcal{O}(n^{-\rho})$$

A simple trick that works very often, to obtain a convenient shape function is to substitute j by $z \cdot n$ in $\omega_{n,j}$, multiply by n and take the limit for $n \to \infty$.

$$\omega(z) = \lim_{n \to \infty} n \cdot \omega_{n,z \cdot n}$$

The Continuous Master Theorem

The extension of discrete functions to functions in the real domain is immediate, e.g., $j^2 \to z^2$. For binomial numbers one might use the approximation

$$\binom{z \cdot n}{k} \sim \frac{(z \cdot n)^k}{k!}.$$

The continuation of factorials to the real numbers is given by Euler's Gamma function $\Gamma(z)$ and that of harmonic numbers by Ψ function: $\Psi(z) = \frac{d \ln \Gamma(z)}{dz}$.
For instance, in quicksort's recurrence all wright are equal: $\omega_{n,j} = \frac{2}{n}$. Hence a simple valid shape function is $\omega(z) = \lim_{n \to \infty} n \cdot \omega_{n, z \cdot n} = 2$.

The Continuous Master Theorem

Theorem (Roura, 1997)

Let F_n *satisfy the recurrence*

$$F_n = t_n + \sum_{0 \leqslant j < n} \omega_{n,j} F_j,$$

with $t_n = \Theta(n^a (\log n)^b)$, *for some constants* $a \geqslant 0$ *and* $b > -1$, *and let* $\omega(z)$ *be a shape function for the weights* $\omega_{n,j}$. *Let* $\mathcal{H} = 1 - \int_0^1 \omega(z) z^a \, dz$ *and* $\mathcal{H}' = -(b+1) \int_0^1 \omega(z) z^a \ln z \, dz$. *Then*

$$F_n = \begin{cases} \frac{t_n}{\mathcal{H}} + o(t_n) & \text{if } \mathcal{H} > 0, \\ \frac{t_n}{\mathcal{H}'} \ln n + o(t_n \log n) & \text{if } \mathcal{H} = 0 \text{ and } \mathcal{H}' \neq 0, \\ \Theta(n^\alpha) & \text{if } \mathcal{H} < 0, \end{cases}$$

where $x = \alpha$ *is the unique non-negative solution of the equation*

$$1 - \int_0^1 \omega(z) z^x \, dz = 0.$$

Solving Quicksort's Recurrence

We apply CMT to quicksort's recurrence with the set of weights $\omega_{n,j} = 2/n$ and toll function $t_n = n - 1$. As we have already seen, we can take $\omega(z) = 2$, and the CMT applies with $a = 1$ and $b = 0$. All necessary conditions to apply CMT are met. Then we compute

$$\mathcal{H} = 1 - \int_0^1 2z\,dz = 1 - z^2\Big|_{z=0}^{z=1} = 0,$$

hence we will have to apply CMT's second case and compute

$$\mathcal{H}' = -\int_0^1 2z \ln z\,dz = \frac{z^2}{2} - z^2 \ln z\Big|_{z=0}^{z=1} = \frac{1}{2}.$$

Finally,

$$\begin{aligned} q_n &= \frac{n \ln n}{1/2} + o(n \log n) = 2n \ln n + o(n \log n) \\ &= 1.386\ldots n \log_2 n + o(n \log n). \end{aligned}$$

Analyzing Quickselect

Let us now consider the analysis of the expected cost C_n of Quickselect when sought rank i takes any value between 1 and n with identical probability. Then

$$
\begin{aligned}
&C_n = n + \mathcal{O}(1) \\
&+ \frac{1}{n} \sum_{1 \leqslant k \leqslant n} \mathbb{E}[\text{remaining number of comp.} \mid \text{pivot is the } k\text{-th element}]\,,
\end{aligned}
$$

as the pivot will be the k-th smallest element with probability $1/n$ for all k, $1 \leqslant k \leqslant n$.

Analyzing Quickselect

The probability that $i = k$ is $1/n$, then no more comparisons are need since we would be done. The probability that $i < k$ is $(k-1)/n$, then we will have to make C_{k-1} comparisons. Similarly, with probability $(n-k)/n$ we have $i > k$ and we will then make C_{n-k} comparisons. Thus

$$\begin{aligned} C_n &= n + \mathcal{O}(1) + \frac{1}{n} \sum_{1 \leqslant k \leqslant n} \frac{k-1}{n} C_{k-1} + \frac{n-k}{n} C_{n-k} \\ &= n + \mathcal{O}(1) + \frac{2}{n} \sum_{0 \leqslant k < n} \frac{k}{n} C_k. \end{aligned}$$

Applying the CMT with the shape function

$$\lim_{n \to \infty} n \cdot \frac{2}{n} \frac{z \cdot n}{n} = 2z$$

we obtain $\mathcal{H} = 1 - \int_0^1 2z^2 \, dz = 1/3 > 0$ and $C_n = 3n + o(n)$.