Randomness and Computation

or, “Randomized Algorithms”

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Coupon Collector Problem

> *"Coupon collecting" is the activity of buying cereal-packets, each of which will have a coupon inside. There are be n different types of "coupon" (eg cards with a photo of a foot-baller) and the goal is to collect one copy of each ... then stop buying.*

On Tuesday we showed that the expected number of purchases needed $\mathrm{E}[X]$ to collect all cards is $\sim n \ln(n)$.

Today we examine how likely a example "run" of the purchasing process is to come close to that expectation.

Results like *Markov's Inequality*, *Chebyshev's Inequality* and (Friday) *Chernoff/Hoeffding Bounds* help us show *concentration* about the mean.

Markov's Inequality

The simplest one.

Theorem (3.1, Markov's Inequality)

Let X be any random variable that takes only non-negative values. Then for any $a > 0$,

$$\Pr[X \geq a] \leq \frac{\mathrm{E}[X]}{a}.$$

Proof.

Define the indicator function $I = I(X)$ by

$$I(x) = \begin{cases} 0 & x < a \\ 1 & x \geq a \end{cases}$$

Then $X \geq a \cdot I(X)$, and hence $I(X) \leq \frac{X}{a}$.
Taking expectation of both sides, and using $\mathrm{E}[I] = \Pr[X \geq a]$, we have

$$\Pr[X \geq a] = \mathrm{E}[I] \leq \frac{1}{a}\mathrm{E}[X].$$

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Variance, Moments of a Random Variable

Definition (3.1)

The *kth moment* of a random variable X is defined to be $\mathrm{E}[X^k]$.

Definition (3.2)

The *variance* of a random variable is defined to be

$$\mathrm{Var}[X] =_{def} \mathrm{E}[(X - \mathrm{E}[X])^2] = \mathrm{E}[X^2] - \mathrm{E}[X]^2.$$

The *standard deviation* of a random variable X is defined as

$$\sigma[X] = \sqrt{\mathrm{Var}[X]}.$$

(we saw why $\mathrm{E}[(X - \mathrm{E}[X])^2]$ and $\mathrm{E}[X^2] - \mathrm{E}[X]^2$ were equal on Tuesday)

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Covariance of two Random Variables

Definition (3.3)

The *covariance* of two random variables X and Y is defined as

$$\mathrm{Cov}[X, Y] \;=\; \mathrm{E}\left[(X - \mathrm{E}[X])(Y - \mathrm{E}[Y])\right].$$

Theorem (3.2)

For any two random variables X, Y, we have

$$\mathrm{Var}[X + Y] \;=\; \mathrm{Var}[X] + \mathrm{Var}[Y] + 2\mathrm{Cov}[X, Y].$$

Proof.

The definition of Var gives $\mathrm{Var}[X + Y] \;=\; \mathrm{E}[(X + Y)^2] - \mathrm{E}[X + Y]^2$.
By squaring, and linearity of exp., this is
$\mathrm{E}[X^2] + \mathrm{E}[Y^2] + \mathrm{E}[2XY] - (\mathrm{E}[X]^2 + \mathrm{E}[Y]^2 + 2\mathrm{E}[X]\mathrm{E}[Y])$.
This is $\mathrm{Var}[X] + \mathrm{Var}[Y] + 2\mathrm{E}[XY] - 2\mathrm{E}[X]\mathrm{E}[Y]$.
Expanding $\mathrm{Cov}[X, Y]$, linearity of Exp., gives $2E[XY] - 2\mathrm{E}[X]\mathrm{E}[Y]$,so
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(pairwise) Independent Random Variables

Theorem (3.3)

If X, Y are a pair of independent random variables, then

$$\mathrm{E}[XY] = \mathrm{E}[X] \cdot \mathrm{E}[Y].$$

Proof is in the book, reasoning wrt Definition 2.2 (may do on visualiser).

Corollary (3.4)

If X, Y are a pair of independent random variables, then

$$\mathrm{Cov}[X, Y] = 0$$

and

$$\mathrm{Var}[X + Y] = \mathrm{Var}[X] + \mathrm{Var}[Y].$$

Proof is straightforward application of Thm 3.3.

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Chebyshev's Inequality

Theorem (3.2, Chebyshev's Inequality)

For every $a > 0$,

$$\Pr[|X - \mathrm{E}[X]| \geq a] \;\leq\; \frac{\mathrm{Var}[X]}{a^2}.$$

Proof.

Because the probability is of the *absolute value* of $X - \mathrm{E}[X]$, we know that for any $b > 0$, $|X - \mathrm{E}[X]| = b$ happens $\Leftrightarrow$ $(X - \mathrm{E}[X])^2 = b^2$ happens.

So $\Pr[|X - \mathrm{E}[X]| \geq a] \;=\; \Pr[(X - \mathrm{E}[X])^2 \geq a^2]$.

Applying Markov's Ineq. to the random variable $(X - \mathrm{E}[X])^2$, we know

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Bounding Coupon Collector purchases - Markov

Remember X are the number of packets bought until we have all n different cards, $\mathrm{E}[X] = n \ln(n) + \Theta(n)$ is the expected number.

Consider how likely we are to need *twice* the expected number of purchases ($2\mathrm{E}[X]$).By Markov's Ineq.,

$$\Pr[X \geq 2\mathrm{E}[X]] \leq \frac{\mathrm{E}[X]}{2\mathrm{E}[X]} = \frac{1}{2}.$$

Or, if we are willing to spend $10\mathrm{E}[X]$ (ie, $10n(\ln(n)+1)$), there is at most $1/10$ probability we fail to get all cards.

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We can do much better with Chebyshev's Ineq. ...

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- Looking back at Corollary 3.4, see that for independent Y, Z, $\mathrm{Var}[Y + Z] \;=\; \mathrm{Var}[Y] + \mathrm{Var}[Z]$.
- Recall that X_i, the *number of packets* bought to get the i-th new card, is independent of the value of X_{i-1} or any of the earlier X_h values. X_i only depends on the values n and i.
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- Hence the random variables $X_1, \ldots, X_n$ are all mutually independent.
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$$\mathrm{Var}[X] \;=\; \mathrm{Var}[X_1] + \mathrm{Var}[X_2] + \ldots + \mathrm{Var}[X_n].$$

Bounding Coupon Collector purchases - Chebyshev

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as claimed. □

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(using Euler's series for the $\frac{\pi}{6}$, see page 5 of "TCS cheat sheet").

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Bounding Coupon Collector purchases - Chebyshev

We know $\mathrm{Var}[X] \leq \frac{\pi^2 n^2}{6}$ for our coupon collector process.

Suppose we are willing to make $2\mathrm{E}[X]$ (about $2n\ln(n)$) purchases.

Buying this number of packets, the probability we fail to get all cards is

$$\begin{aligned} & \Pr[X > 2\mathrm{E}[X]] \\ = \; & \Pr[X - \mathrm{E}[X] > \mathrm{E}[X]] \\ \leq \; & \Pr[|X - \mathrm{E}[X]| > \mathrm{E}[X]] \end{aligned}$$

We can upper bound the probability of the bad event $|X - \mathrm{E}[X]| > \mathrm{E}[X]$ (aka "didn't get all cards") using Chebyshev's Inequality with $a = \mathrm{E}[X]$:

$$\Pr[|X - \mathrm{E}[X]| \geq \mathrm{E}[X]] \leq \frac{\mathrm{Var}[X]}{\mathrm{E}[X]^2} \leq \frac{\pi^2 n^2}{6n^2 H(n)^2}.$$

This value simplifies to $\frac{\pi^2}{6H(n)^2}$, which is less than $\frac{2}{\ln(n)^2}$, much better probability than $1/2$ (given by Markov for $2\mathrm{E}[X]$ purchases).

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Bounding Coupon Collector purchases - Chebyshev

If we are willing to make as many as $10\mathrm{E}[X]$ purchases, then we will upper-bound (probability of the "bad" scenario) $\Pr[|X - \mathrm{E}[X]| \geq 9\mathrm{E}[X]]$ by setting $a = 9\mathrm{E}[X]$ in Chebyshev's Inequality:

$$\Pr[|X - \mathrm{E}[X]| \geq 9\mathrm{E}[X]] \;\leq\; \frac{\mathrm{Var}[X]}{(9\mathrm{E}[X])^2} \;\leq\; \frac{\pi^2 n^2}{6 \cdot 81 \cdot n^2 H(n)^2}.$$

Working details with π, the right-hand side is at most $\frac{1}{49 \cdot H(n)^2}$, much much less/better than the $\frac{1}{10}$ we got with Markov's Ineq.

Wrapping up today

Next week we will continue the theme of “bounding deviation from the mean" by introducing some stronger concentration inequalities called Chernoff/Hoeffding bounds (which hold for iterations of independent Poisson trials, and related distributions).

First, on Friday (to give a break) we will look at a simple random algorithm to approximately calculate **Max** Cut, and show how to *derandomize* it.

- I have distributed the spec for coursework 1, deadline is 4pm, Thursday, 14th Feb, 2018.
- Tutorials are starting next week. I have distributed the first tutorial sheet today.