The problem

We have a sequence of n (unknown) integers between

$$a_1, a_2, a_3, a_4, \ldots, a_n$$

Want to estimate $\overline{a} = \frac{a_1 + a_2 + ... + a_n}{n}$

We sample s integers (with replacement) and output the average.

Let X_i be a random variable associated with the i-th sample.

Algorithm's output:
$$X = \frac{1}{s}(X_1 + \ldots + X_s)$$

We know:
$$E[X] = \overline{a}$$

Deviation from Expectation

We want to know <u>how often</u> X <u>deviates</u> from E[X] by a considerable degree.

In other words, we want to bound this probability $(\epsilon \ge 0)$

$$Pr(\underbrace{|X - E[X]|}_{\text{the amount of deviation}} \ge \epsilon E[X])$$

We have some useful inequalities for this.

Deviation Bounds

Markov Inequality: For any non-negative random variable X,

$$Pr(X \ge t) \le \frac{E[X]}{t} \Rightarrow Pr(X \ge tE[X]) \le \frac{1}{t}$$

Chebyshev Inequality: For any random variable X and t > 0,

$$Pr(|X - E[X]| \ge t) \le \frac{Var[X]}{t^2}$$

Specially (when $t = \epsilon E[X]$),

$$Pr(|X - E[X]| \ge \epsilon E[X]) \le \frac{Var[X]}{\epsilon^2 E^2[X]}$$

Proof: Apply Markov inequality to the random variable $Y = (X - E[X])^2$.

Applying Chebyshev

We need an upper bound on Var[X].

Since X_i 's are independent,

$$Var[X] = Var[\frac{1}{s}(X_1 + ... + X_s)] = \frac{1}{s^2}(Var[X_1] + ... + Var[X_s])$$

Since X_i 's are identical, $Var[X] = \frac{1}{s^2} sVar[X_i] = \frac{1}{s} Var[X_i]$

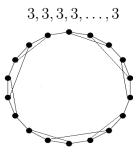
$$Var[X_i] = E[X_i^2] - E^2[X_i] = (\frac{a_1^2}{n} + \ldots + \frac{a_n^2}{n}) - \overline{a}^2$$

$$Pr(|X - E[X]| \ge \epsilon E[X]) \le \frac{\frac{1}{s} \left(\frac{a_1^2 + \dots + a_n^2}{n} - \overline{a}^2\right)}{\epsilon^2 \overline{a}^2}$$

$$= \frac{1}{\epsilon^2 s} \left(n \frac{a_1^2 + \dots + a_n^2}{(a_1 + \dots + a_n)^2} - 1\right)$$

How large the term $D = n \frac{a_1^2 + \dots + a_n^2}{(a_1 + \dots + a_n)^2}$ can be?

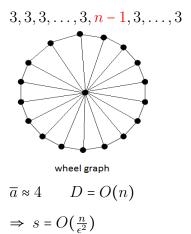
Lets consider two cases : (when a_1, \dots, a_n are degrees of nodes of a graph)



3-regular graph

$$\overline{a} = 3$$
 $D = 1$

$$\Rightarrow$$
 $s = 1$ is enough



- ▶ It can be shown that $D \le \frac{a_{max}}{\overline{a}}$ when $a_{max} = \max\{a_i\}$. It suggests $s = O(\frac{a_{max}}{\epsilon^2 \overline{a}})$ is enough.
- ► The above cases tell us we need random $\Omega(n)$ degree queries to distinguish between $\overline{a} = 3$ and $\overline{a} \approx 4$.
- ▶ This shows $\frac{3}{4} + \epsilon$ approximation is not possible using o(n) degree queries.
- ▶ Uriel Feige showed that $O(\frac{\sqrt{n}}{\epsilon})$ random degree queries is enough to get a $\frac{1}{2} \epsilon$ approximation of d.

Lets try a different tool: Chernoff bound

Chernoff Bound: Let $0 \le \epsilon \le 1$. Suppose Y_1, \ldots, Y_t are independent random variables taking values in the interval [0,1]. Let $Y = \sum_{i=1}^t Y_i$. Then

$$Pr(|Y - E[Y]| \ge \epsilon E[Y]) \le 2e^{-\frac{\epsilon^2 E[Y]}{3}}$$

Recall that $X = \frac{1}{s}(X_1 + \ldots + X_s)$ where $X_i \in \{1, \ldots, a_{max}\}.$

We define
$$Y_i = \frac{X_i}{a_{max}} \Rightarrow Y_i \in [0, 1]$$
.

$$Y = Y_1 + \ldots + Y_s \implies Y = \frac{s}{a_{max}} X$$

$$E[Y] = \frac{s}{a_{max}} \overline{a}$$

$$Pr(|X - E[X]| \ge \epsilon E[X]) = Pr(|\frac{sX}{a_{max}} - E[\frac{sX}{a_{max}}]| \ge \epsilon E[\frac{sX}{a_{max}}])$$

$$= Pr(|Y - E[Y]| \ge \epsilon E[Y])$$

$$\le 2e^{-\frac{\epsilon^2 E[Y]}{2}} - 2e^{-\frac{\epsilon^2 s}{3}} \frac{\bar{a}}{a_{max}}$$

A direct application of Chernoff bound suggest $s = O(\frac{a_{max}}{\bar{a}\epsilon^2})$.

This is the same bound that we obtained using Chebyshev!

In comparison with Chebyshev inequality:

- Chernoff does not need a knowledge of the variance. It only needs the expectation.
- Chernoff gives a much higher probability of concentration.

Comparing Chebyshev and Chernoff

Suppose we want to have error probability $\delta < 0$.

Using Chebyshev we should have:

$$Pr(|X - E[X]| \ge \epsilon E[X]) \le \frac{1}{\epsilon^2 s} (D - 1) < \frac{1}{\epsilon^2 s} (\frac{a_{max}}{\overline{a}}) \le \delta$$

$$s > \frac{1}{\delta} \frac{a_{max}}{\epsilon^2 \overline{a}}$$

Using Chernoff we should have:

$$Pr(|X - E[X]| \ge \epsilon E[X]) \le 2e^{-\frac{\epsilon^2 s}{3} \frac{\overline{a}}{a_{max}}} \le \delta$$

$$s \ge 3\ln(\frac{1}{2\delta})\frac{a_{max}}{\epsilon^2 \overline{a}}$$

Another application of Chernoff bound

Amplifying the success probability

Suppose we have a randomized algorithm A that processes the input data D and approximate some f(D) where

$$|A(D) - f(D)| \le \epsilon f(D)$$
 with probability at least 3/4.

How to amplify the success probability of A?

We want to have a randomized algorithm A' with error probability $\delta << 1/4$.

Idea: Run A on input data D, $O(\ln(\frac{1}{\delta}))$ times and output the median of the outcomes.

Each (independent) repetition of A succeeds with probability 3/4. Suppose a_i is the outcome of i-th repetition. We have

$$Pr(|a - f(D)| \ge \epsilon f(A)) \le 1/4.$$

We define $X_i = 1$ if *i*-th repetition is good (its error is less than $\epsilon f(A)$), otherwise we let $X_i = 0$.

 $X = X_1 + \ldots + X_t$ is the number of good outcomes in t repetitions.

The median of $\{a_1, \ldots, a_t\}$ is bad \Rightarrow Less than t/2 repetitions are good. In other words, X < t/2.

By Chernoff bound, we have

$$Pr(\text{median is bad}) \le Pr(X < t/2) \le e^{O(-t)} \le \delta \implies t = (\ln(\frac{1}{\delta}))$$