

## Lecture 4 — Sep 9, 2015

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## 1 Overview

In previous lectures, we introduced some basic probability, the Chernoff bound, the coupon collector problem, and game tree evaluation.

In this lecture, we will introduce concentration inequalities.

## 2 Coupon Collector Problem

Draw numbers (coupons) independently from  $[n] = \{1, 2, \dots, n\}$ . How long does it take to see all of the numbers?

Suppose  $T_i$  is the number of draws to get the  $i$ -th new number. Let  $T = \sum_i T_i$ .

**Fact 1.** *The  $T_i$ 's are independent of each other.*

**Fact 2.**  *$T_i$  follows geometric distribution with success probability,  $p = \frac{n+1-i}{n}$ .*

**Fact 3.** *If  $X \sim \text{Geometric}(p)$ ,*

$$\begin{aligned} E[X] &= p \cdot 1 + (1-p) \cdot (E[X|X \geq 2]) \\ &= p + (1-p)(1 + E[X]) \\ \Rightarrow E[X] &= \frac{1}{p} \end{aligned}$$

$$\begin{aligned} E[X^2] &= p \cdot 1^2 + (1-p) \cdot E[X^2|X \geq 2] \\ &= p + (1-p)E[(X+1)^2] \\ &= p + (1-p)(E[X^2] + 2E[X] + 1) \\ &= p + (1-p)E[X^2] + 2(1-p)/p + (1-p) \\ \Rightarrow E[X^2] &= \frac{2-p}{p^2} \end{aligned}$$

$$\begin{aligned} \text{Var}(X) &= E[(X - E(X))^2] = E[X^2] - (E[X])^2 \\ \Rightarrow \text{Var}(X) &= \frac{1-p}{p^2} \leq \frac{1}{p^2} \end{aligned}$$

Therefore in the Coupon Collector Problem,

$$E[T] = \sum_{i=1}^n E[T_i] = \sum_{i=1}^n \frac{n}{n+1-i} = nH_n \approx n \log n$$

$$\begin{aligned} \text{Var}[T_i] &\leq \frac{1}{p_i^2} = \left( \frac{n}{n+1-i} \right)^2 \\ \Rightarrow \text{Var}[T] &= \sum_{i=1}^n \text{Var}[T_i] \leq n^2 \left( \sum_{i=1}^n \frac{1}{i^2} \right) \leq n^2 \cdot \frac{\pi^2}{6} = O(n^2) \end{aligned}$$

### 3 Concentration Inequalities

$$\forall i, \Pr[T_i \geq 1 + \alpha] \leq \left( 1 - \frac{n+1-i}{n} \right)^\alpha$$

Assume  $\delta$  is some failure probability. Setting  $\alpha_i = \left( \frac{n}{n+1-i} \right) \log \frac{n}{\delta}$  and because  $(1 - \frac{1}{x})^x < \frac{1}{e}$ , we have

$$\forall i, \Pr[T_i \geq 1 + \alpha_i] \leq \frac{\delta}{n}$$

**Definition 4.** *Union Bound*

$$\Pr[X_1 \cup X_2 \cup \dots \cup X_n] \leq \sum_i \Pr[X_i]$$

Using a union bound, we have

$$\begin{aligned} &\Pr \left[ T \geq n + n \log n \log \frac{n}{\delta} \right] \\ &= \Pr \left[ \sum_i T_i \geq n + \sum_i \alpha_i \right] \\ &= \Pr[T_1 \geq 1 + \alpha_1 \cup \dots \cup T_n \geq 1 + \alpha_n] \\ &\leq \sum_i \Pr[T_i \geq 1 + \alpha_i] \\ &\leq \delta \end{aligned}$$

**Definition 5.** *With High Probability (w.h.p.)*

$$X \leq O(y) \text{ w.h.p.} \Leftrightarrow \forall c_2, \exists c_1, \text{ s.t. } \Pr[X \leq c_1 y] \leq n^{-c_2}$$

$T = O(n \log^2 n)$  with high probability.

### 3.1 Markov's Inequality

For a non-negative random variable  $T$  and any non-negative  $\alpha$ ,

$$\begin{aligned} E[T] &\geq Pr[T \geq \alpha] \cdot \alpha \\ \Rightarrow Pr[T \geq \alpha] &\leq \frac{E[T]}{\alpha} \end{aligned}$$

In the Coupon Collector Problem,

$$\begin{aligned} \alpha &= \frac{E[T]}{\delta} = \frac{nH_n}{\delta} \\ \Rightarrow Pr\left[T \geq \frac{nH_n}{\delta}\right] &\leq \delta \end{aligned}$$

### 3.2 Chebyshev's Inequality

For a random variable,  $X$ , let  $\mu = E[X]$  denote the expectation and  $\sigma^2 = Var[X]$  denote the variance. Starting from Markov's Inequality, we find

$$Pr[(X - \mu)^2 \geq \alpha^2] \leq \frac{E[(X - \mu)^2]}{\alpha^2} = \frac{\sigma^2}{\alpha^2}$$

Setting  $\alpha \rightarrow \alpha\sigma$

$$Pr[(X - \mu)^2 \geq \alpha^2\sigma^2] \leq \frac{1}{\alpha^2}$$

Taking the square root, we find

$$\begin{aligned} Pr[X \geq \mu + \alpha\sigma] &\leq \frac{1}{\alpha^2} \\ Pr[X \leq \mu - \alpha\sigma] &\leq \frac{1}{\alpha^2} \end{aligned}$$

Using this result in the Coupon Collector Problem, gives us

$$Pr[T \geq nH_n + \frac{1}{\sqrt{\delta}}O(n)] \leq \delta$$

Setting  $\delta = \frac{1}{\log^2 n}$

$$Pr[T \geq nH_n + O(n \log n)] \leq O\left(\frac{1}{\log^2 n}\right)$$

Most of the time, the typical deviation is  $O(\sigma)$ .

$$Pr[|x - \mu| \leq O(\sigma)] \approx 1 - \delta$$

### 3.3 Moment Method

If  $f$  is non-negative, by Markov's inequality,

$$\Pr[f(X - \mu) \geq f(\alpha)] \leq \frac{E[f(X - \mu)]}{f(\alpha)}$$

For  $f$  increasing,

$$\Pr[X - \mu \geq \alpha] \leq \frac{E[f(X - \mu)]}{f(\alpha)}$$

Set  $f = |t|^k$ ,

$$\Pr[|X - \mu|^k \geq |\alpha|^k] \leq \frac{E[|x - \mu|^k]}{|\alpha|^k}$$

For one side,

$$\Pr[X \geq \mu + \alpha] \leq \frac{E[|x - \mu|^k]}{|\alpha|^k}$$

Setting  $\delta = \frac{E[|x - \mu|^k]}{|\alpha|^k}$ , we have

$$\Pr \left[ X \leq \mu + E[|x - \mu|^k]^{1/k} \cdot \left( \frac{1}{\delta} \right)^{1/k} \right] \geq 1 - \delta$$

If we consider  $X \sim N(0, \sigma^2)$ , we know

$$E[|x|^k] \approx (k\sigma^2)^{k/2} \quad \forall k > 0$$

which means

$$\Pr \left[ X \geq \mu + O \left( \sqrt{k} \cdot \sigma \cdot \left( \frac{1}{\delta} \right)^{1/k} \right) \right] \leq \delta$$

Setting  $k = \log \frac{1}{\delta}$ , we get

$$\Pr \left[ X \geq \mu + O \left( \sqrt{\log \frac{1}{\delta}} \right) \right] \leq \delta$$

### 3.4 Moment Generating Function

**Definition 6.** The moment generating function, parameterized by  $\lambda$ , is defined as

$$MGF_X(\lambda) = E[e^{\lambda(X - \mu)}]$$

Assume  $X$  is centered ( $E[X] = 0$ ).

$$e^{\lambda x} = 1 + \lambda x + \frac{(\lambda x)^2}{2} + \frac{(\lambda x)^3}{3!} + \dots + \frac{(\lambda x)^k}{k!}$$

We can use parameter  $\lambda$  to adjust the weights on each term. When  $\lambda$  is larger, more weight is on higher order terms.

From the derivation of the Moment Method, setting  $f(x) = e^{\lambda x}$ ,

$$Pr[X \geq \mu + \alpha] \leq \frac{MGF_X(\lambda)}{e^{\lambda \alpha}}$$

**Fact 7.** If  $X \sim N(0, \sigma^2)$ ,  $MGF_X(\lambda) = E[e^{\lambda x}] \leq e^{\lambda^2 \sigma^2 / 2} \forall \lambda \in \mathbb{R}$

Using this,

$$\begin{aligned} Pr[X \geq \mu + \alpha] &\leq \frac{MGF_X(\lambda)}{e^{\lambda \alpha}} \\ &= e^{\frac{\lambda^2 \sigma^2}{2} - \lambda \alpha} \\ &= e^{\frac{1}{2}(\lambda \sigma - \frac{\alpha}{\sigma})^2 - \frac{\alpha^2}{2\sigma^2}} \end{aligned}$$

Set  $\lambda = \frac{\alpha}{\sigma^2}$ , we get

$$Pr[X \geq \mu + \alpha] \leq e^{-\frac{\alpha^2}{2\sigma^2}}$$

If  $\delta = e^{-\frac{\alpha^2}{2\sigma^2}}$ , we have

$$\alpha = \sigma \sqrt{2 \log \frac{1}{\delta}}$$

Note that this is the same  $O\left(\sqrt{\log \frac{1}{\delta}}\right)$  bound as we found in the method of moments, except that now we know the constant.

### 3.5 Subgaussian Variables

**Claim 8.** The following three statements are equivalent if we only care up to a constant for  $\sigma$  (i.e.  $\forall i, j \in \{1, 2, 3\}, \sigma_i = \theta(\sigma_j)$ )

$$X \text{ is subgaussian with parameter } \sigma, \text{ i.e. } \forall \lambda \in \mathbb{R}, MGF_X(\lambda) \leq e^{\frac{\lambda^2 \sigma^2}{2}} \quad (1)$$

$$Pr[X \geq \mu + t] \leq e^{-\frac{t^2}{2\sigma^2}} \quad (2)$$

$$E[|x|^k]^{1/k} \leq O\left(\sigma \sqrt{k}\right) \quad (3)$$

**Fact 9.** The sum of subgaussian variables are subgaussian.

$$X = X_1 + \dots + X_n$$

$$\begin{aligned} MGF_X(\lambda) &= E[e^{\lambda X}] = E[e^{\lambda(\sum_i x_i)}] = E\left[\prod_i e^{\lambda x_i}\right] \\ &= \prod_i E[e^{\lambda x_i}] \quad (\text{by independence}) \\ &= \prod_i MGF_{X_i}(\lambda) \\ &\leq \prod_i e^{\lambda^2 \sigma_i^2 / 2} \quad (\text{by subgaussian}) \\ &= e^{\frac{\lambda^2}{2}(\sum_i \sigma_i^2)} \end{aligned}$$

This implies  $X$  is subgaussian with parameter  $\sqrt{\sum_i \sigma_i^2}$ .

**Fact 10.** If  $X \in [0, 1]$ , then  $X$  is subgaussian with  $\sigma = 1/2$  by Hoeffding's Lemma.<sup>1</sup>

Let  $X = \sum_i X_i$  where  $X_i \in [0, 1]$ .  $X$  is subgaussian with  $\sigma = \sqrt{n}/2$ . Plug this into (2), we have

$$\Pr[x \geq \mu + \alpha] \leq e^{-\frac{2\alpha^2}{n}}$$

which is exactly the Chernoff bound.

## 4 Next Class

In the Coupon Collector Problem, we had

$$\Pr[T_n \geq \alpha] \leq \left(1 - \frac{1}{n}\right)^\alpha \approx e^{-\alpha}$$

This is not of the form  $e^{-\alpha^2}$  so we cannot use the subgaussian results. We will relax the subgaussian requirement to subexponential and subgamma. This will lead to Bernstein's inequality.

$$MGF_X(\lambda) = E[e^{\lambda X}] \leq e^{\frac{\lambda^2 \sigma^2}{2}} \quad \forall |\lambda| \leq B$$

## References

- [MR] Rajeev Motwani, Prabhakar Raghavan Randomized Algorithms. *Cambridge University Press*, 0-521-47465-5, 1995.
- [RV] Roman Vershynin Introduction to the non-asymptotic analysis of random matrices. *CoRR*, abs-1011-3027, 2010.

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<sup>1</sup>[https://en.wikipedia.org/wiki/Hoeffding%27s\\_inequality](https://en.wikipedia.org/wiki/Hoeffding%27s_inequality)