

Concentration of measure (tail bounds)

The more you know about r.v. X , the better the bounds

① If only thing you know is mean & $X \geq 0$ (but not = 0)

Markov's Inequality

$$\Pr(X \geq t) \leq \frac{E(X)}{t} \quad t > 0 \quad \left[\Pr(X \geq cE(X)) \leq \frac{1}{c} \right] c > 0$$

Corollary

$$\text{If } 0 \leq X \leq B \Rightarrow \Pr(X \leq t) \leq \frac{E(X)}{B-t}$$

② If you know mean μ and variance σ^2

Chebyshev's Inequality

$$\forall t > 0 \quad \Pr(|X - \mu| \geq t\sigma) \leq \frac{1}{t^2}$$

\uparrow
std deviation

③ Sums of indep r.v.'s

Theorem

$X = X_1 + X_2 + \dots + X_n$ where X_i 's indep & $X_i \in [0, 1]$ with $E(X_i) = p_i$

$$\mu = E(X) = \sum_{i=1}^n p_i \quad p = \frac{\mu}{n}$$

$$\Pr(X \geq \mu + \lambda) \leq e^{-n H(p + \frac{\lambda}{n} \| p)} \quad (1)$$

$$\Pr(X \leq \mu - \lambda) \leq e^{-n H(1 - p + \frac{\lambda}{n} \| 1 - p)} \quad (2)$$

$$H(x \| p) = x \ln\left(\frac{x}{p}\right) + (1-x) \ln\left(\frac{1-x}{1-p}\right) \quad \text{relative entropy}$$

Today

- quick recap of tail bounds
- application to balls in bins
- Poisson approx for analyzing balls in bins
- estimating reachability

More useful forms (corollaries)

$$\Pr(X \geq \mu + \lambda) \leq e^{-\frac{\lambda^2}{n}}$$

$$\Pr(X \leq \mu - \lambda) \leq e^{-\frac{\lambda^2}{n}} \quad (3)$$

gives a CLT

$$X \sim \text{Bin}(n, p)$$

$$\sigma^2 = np(1-p)$$

$$\Pr(X \geq \mu + k\sigma) \leq e^{-\frac{2(k\sigma)^2}{n}}$$

$-k^2 \text{ const.}$

$$= e^{-2k^2}$$

$$\Pr(X \leq (1-\delta)\mu) \leq e^{-\frac{\delta^2 \mu}{2}}$$

$0 < \delta \leq 1$ $\Leftarrow \mu_L \leq \mu$

$$\Pr(X \geq (1+\delta)\mu) \leq e^{-\mu[(1+\delta)^2 - 1]}$$

$\mu \leq \mu_H$ $\Leftarrow \mu \leq \mu_H$

$$\leq \begin{cases} e^{-\frac{\delta^2 \mu}{3}} & \delta > 0 \\ e^{-\frac{\delta^2 \mu}{6}} & 0 < \delta \leq 1 \end{cases} \quad (4)$$

probably use most frequently.

$$X = X_1 + X_2 + \dots + X_n$$

X_i 's indep. X_i takes values in $[a_i, b_i]$ $E(X) = \mu$

$$\Pr(X \leq \mu - \lambda) \leq e^{-\frac{\lambda^2}{\sum_{i=1}^n (b_i - a_i)^2}}$$

$$\Pr(X \geq \mu + \lambda) \leq e^{-\frac{\lambda^2}{\sum_{i=1}^n (b_i - a_i)^2}} \quad (5)$$

Comments:

- many different versions (hold for Poisson r.v.s, Gaussian etc); will see more later.
- also hold for "negatively correlated r.v.s" [negatively associated]

$$E[e^{+(X+Y)}] \leq E[e^{+X}] E[e^{+Y}]$$

Example

- edges in random spanning trees

sampling random spanning trees.

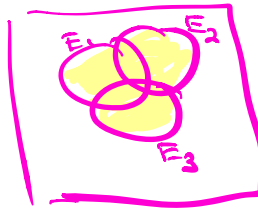
$$X_e = \begin{cases} 1 & e \in T \\ 0 & \text{o.w.} \end{cases}$$

One more simple probabilistic tool

Union Bound

Let E_1, E_2, \dots, E_k be any collection of events in prob space

Then $\Pr(E_1 \vee E_2 \vee \dots \vee E_k) \leq \sum_{i=1}^k \Pr(E_i)$



- Chernoff bounds
- union bound
- cleverness

Application(s): Balls in Bins

n bins 

Throw n balls, one at a time, independently at random into a bin. Prob \rightarrow i^{th} bin = $\frac{1}{n}$

$X_i = \#$ balls in i^{th} bin at end (after n balls) $\uparrow E(X_i) = 1$
 X_i 's not indep. $X_i \sim \text{Bin}(n, \frac{1}{n})$

jobs \rightarrow machines
 items \rightarrow hashtable
 requests \rightarrow servers

Theorem $\Pr(\max_i X_i \geq \frac{e \ln n}{\ln \ln n}) \leq \frac{1}{n^c}$ for some $c > 0$

proof idea: prove that prob that a particular bin so unlikely to exceed this bound that a union bound gives result

$E(\max_i X_i) = \Theta(\frac{\ln n}{\ln \ln n})$

Pf Fix bin X_i . $X_i \sim \text{Bin}(n, \frac{1}{n})$. $E(X_i) = 1$
 X_i & X_j dep. $X_i = B_1 + B_2 + \dots + B_n$ $B_i \sim \text{Ber}(\frac{1}{n})$

$\Pr(X_i \geq \frac{e \ln n}{\ln \ln n}) \leq e^{-\Omega(\frac{e \ln n}{\ln \ln n} - 1)}$
 $\leq e^{-\Omega(\frac{e \ln n}{\ln \ln n} - (1 + \frac{1}{\ln \ln n}))}$

$\frac{e \ln n}{\ln \ln n}$

$\leq e^{-\left[\frac{e \ln n}{\ln \ln n} - (1 + \frac{1}{\ln \ln n}) \right]} \leq e^{-c \frac{\ln n}{\ln \ln n}}$

$\ln c = 1 + \frac{\ln \ln n}{\ln \ln n} - \frac{\ln \ln \ln n}{\ln \ln n} \geq 1 + \frac{\ln \ln n}{2}$

$e^v = 1 + v + \frac{v^2}{2} + \dots$
 $e^v > 2v$ $v > 1$

needs $o(\frac{1}{n})$

$$\Pr(X_i \geq c) = e^{-c[1 + \frac{c-1}{2}]} = e^{-\frac{c^2}{2}}$$

plug c back in

$$= e^{-\frac{e \ln n}{2}} = n^{-\frac{1}{2}e} \approx n^{-1.35}$$

\forall bins i : $\Pr(X_i \geq \frac{e \ln n}{2}) \leq n^{-1.35} = \frac{-(1+c)}{n}$

$$\Pr(\exists \text{ bin } i \text{ with } X_i \geq \frac{e \ln n}{2}) = \Pr(E_1 \vee E_2 \vee \dots \vee E_n)$$

$$\leq \sum_{i=1}^n \Pr(E_i) \leq n \cdot n^{-1.35} = n^{-0.35} \rightarrow 0 \text{ as } n \rightarrow \infty$$

$\frac{1}{n^{0.35}}$

Poisson approx m balls $\rightarrow n$ bins

X_1, X_2, \dots, X_n

final loads in bins
 X_i # balls in bin i at end.

$$X_i \sim \text{Bin}(m, \frac{1}{n}) \xrightarrow[\frac{m}{n} \text{ is const.}]{\text{in limit } m \rightarrow \infty} \text{Poi}(m \cdot \frac{1}{n})$$

indep $\text{Poi}(\frac{m}{n})$ $Y_1 \ Y_2 \ \dots \ Y_n$

$\text{Bin}(n, p) \rightarrow \text{Poi}(np)$

$\bullet \frac{P_i(n) P_i(n) \dots P_i(n)}{Z_1 Z_2 \dots Z_n}$

$\Sigma Z_i \sim \text{Poi}(\sum_{i=1}^n \lambda_i)$

Observation.

$$\Pr(X_1=k_1, X_2=k_2, \dots, X_n=k_n) = \frac{\Pr(Y_1=k_1) \Pr(Y_2=k_2) \dots \Pr(Y_n=k_n)}{\Pr(\sum_{i=1}^n Y_i = m)}$$

$\sum_{i=1}^n k_i = m$

real loads behave like indep Poissons
 Conditioned on $\sum_{i=1}^n Y_i = m$

$$\Pr(Y_1=k_1 \dots Y_n=k_n | \sum_{i=1}^n Y_i = m)$$

Theorem m balls $\rightarrow n$ bins

Let \mathcal{E} be any event that depends only on (X_1, X_2, \dots, X_n)

st. $\left[\begin{array}{l} \Pr(\mathcal{E}) \text{ is monotone } \uparrow \text{ in } \# \text{ balls } (m) \\ \text{or monotone } \downarrow \end{array} \right.$

$\Pr(\mathcal{E})$ monotone \uparrow

$\max X_i \geq 1000$

$\Pr(\mathcal{E}^c)$ monotone \downarrow

$\forall i: X_i \leq 100$

read Alistair Sinclair's lecture

$\left[\begin{array}{l} \Pr(\mathcal{E}(X_1, \dots, X_n)) \leq 4 \Pr(\mathcal{E}(Y_1, \dots, Y_n)) \\ \text{unlikely} \quad \leftarrow \quad \text{unlikely} \end{array} \right.$

we showed w.h.p. $n \rightarrow n$ balls bins max load $O\left(\frac{\ln n}{\ln \ln n}\right)$
 now w.h.p. $1 - o(1)$ max load $\Omega\left(\frac{\ln n}{\ln \ln n}\right)$
 $o(1)$ goes to 0 as $n \rightarrow \infty$

show very unlikely that any bin has load $\geq (1-\beta) \frac{\ln n}{\ln \ln n}$
 indep $\text{Poi}(\lambda)$ pos const.

$$\Pr(\max(Y_1, \dots, Y_n) < k) = \prod_{i=1}^n \Pr(Y_i < k) = \prod_{i=1}^n (1 - \Pr(Y_i \geq k))$$

$$\leq \left(1 - \frac{e^{-k}}{k!}\right)^n$$

$$\leq e^{-\frac{ne^{-k}}{k!}}$$

$$\Pr(Y_i \geq k) = \sum_{j=k}^{\infty} \frac{e^{-k} k^j}{j!} \geq \frac{e^{-k}}{k!}$$

$1-x \leq e^{-x}$
 $0 < x < 1$

$\Pr(Z=k) = \frac{e^{-\lambda} \lambda^k}{k!}$

Proof?

to show this

$\frac{ne^{-k}}{k!} \rightarrow \infty$

$\ln n - 1 - \ln k! \rightarrow \infty$

$(1-\beta) \frac{\ln n}{\ln \ln n}$

$\sim k \ln k$

$k \ln k \sim (1-\beta) \frac{\ln n}{\ln \ln n} \left[\ln \ln n (1+o(1)) \right]$

$(1-\beta) \ln n (1+o(1))$

$\ln n - (1-\beta) \ln n \sim \beta \ln n$

$k! = \sqrt{2\pi k} \frac{k^k}{e^k}$

Stirling's formula

$\ln k! = \boxed{k \ln k} - k - \ln(\sqrt{2\pi k})$

Power of 2 choices

standard balls in bins

$n \rightarrow n$

$E[\text{max load}] = \frac{\ln n}{\ln \ln n}$

throw balls one at time.

n bins

each ball

puts itself

picks

into

2 random bins

the less loaded of 2 bins



$E[\text{max load after } n \text{ balls}] = \Theta\left(\frac{\ln n}{\ln \ln n}\right)$

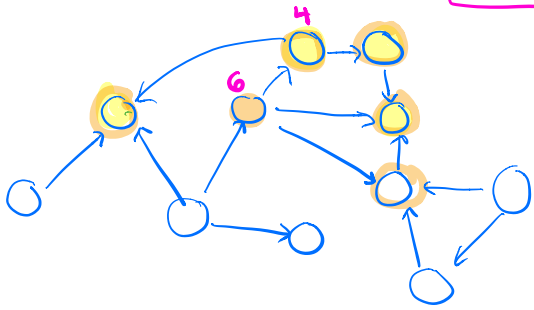
A cool application: reachability

n vertices m edges $m \geq n$.

Input: directed graph $G=(V,E)$

Output: $\forall v \in V, |S(v)|$ where

$S(v)$: set of nodes reachable from v



do BFS from every single node.

$O(nm)$

$O(n^{2.37...})$ best matrix multiply

$O(m \log^2 n)$

