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More Concentration Inequalities & Applications

Review

Fact (Chernoff): Given independent random variables (RVs)

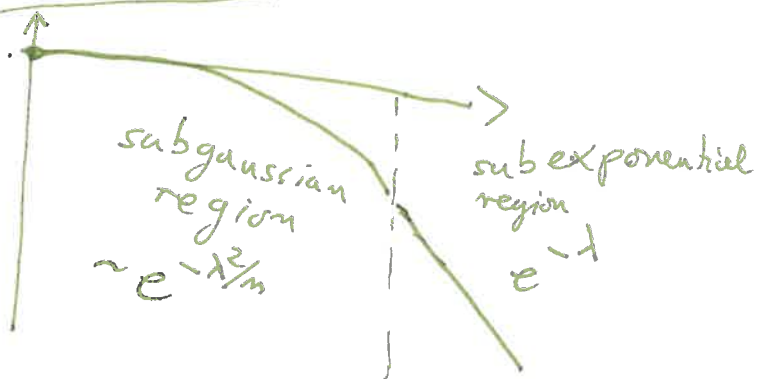
$X_1, X_2, \dots, X_n \in [0, 1]$, we have that

$$\Pr[|\sum X_i - E[\sum X_i]| \geq \lambda] \leq 2 \exp\left(-c \frac{\lambda^2}{E[\sum X_i] + \lambda}\right).$$

Here $c > 0$ is a sufficiently small constant.

Example: Let $X_1, X_2, \dots, X_n \in [-1, 1]$ be indep. RVs, then
 $\Pr[|\sum X_i| \geq \lambda] \leq 2 \exp\left(-c \frac{\lambda^2}{n + \lambda}\right)$. (actually not needed here)
 (we shift and scale st. X_i fit in $[0, 1]$).

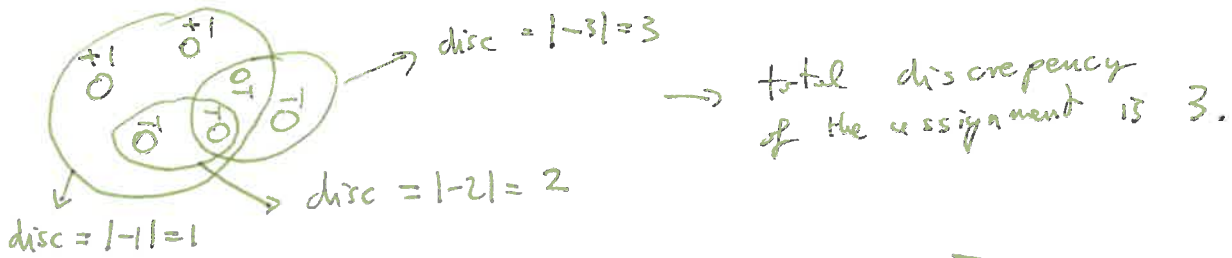
Behavior of tail bounds: consider $f(\lambda) = \exp\left(-c \frac{\lambda^2}{n + \lambda}\right)$.



Problem (set balancing / Discrepancy): Let $\mathcal{U} = \{1, 2, \dots, n\}$ be items and $S_1, S_2, \dots, S_m \subseteq \mathcal{U}$ be m sets of items.

For some assignment $f: \mathcal{U} \rightarrow \{-1, +1\}$ we define the discrepancy of a set S_i as $\text{disc}(S_i) = \left| \sum_{j \in S_i} f(j) \right|$ and the total discr. as $\max_i |\text{disc}(S_i)|$.

Prove there exist an assignment f s.t. $\text{t. discr.} \leq \sqrt{m \log n}$.



Note: [Spencer '85] proves $\text{disc} \leq 6\sqrt{m}$; more generally if $n = \# \text{items}$, $m = \# \text{sets}$, he proves $\text{disc} \leq O(\sqrt{n \log \frac{m}{n}})$.

Algo (uniform random assignments): for each $u \in \mathcal{U}$ we assign a random Rademacher RV. Namely, $f(u) \leftarrow \begin{pmatrix} +1 & -1 \\ .5 & .5 \end{pmatrix}$.

Analysis: we prove that, under the uniform rand. assignment, $\text{disc} \leq O(\sqrt{n \log n})$.

Pf $\sum_{u \in S_i} f(u) \sim \text{sum of } |S_i| \leq n \text{ Rad. RV's.}$

$$\Pr[|\sum_{u \in S_i} f(u)| \geq \lambda] \leq 2 \exp\left(c \cdot \frac{-\lambda^2}{n+\lambda}\right). \quad (\text{Chernoff})$$

$$\Pr[\max_i |\sum_{u \in S_i} f(u)| \geq \lambda] \leq n \cdot 2 \exp\left(c \cdot \frac{-\lambda^2}{n+\lambda}\right) \quad (\text{union bound})$$

$$\text{Setting } \lambda = C \cdot \sqrt{n \log n} \text{ we get } \Pr[\max_i \text{disc}(S_i)] \leq n \cdot n^{-c} = \frac{1}{n^{c-1}} < 1$$

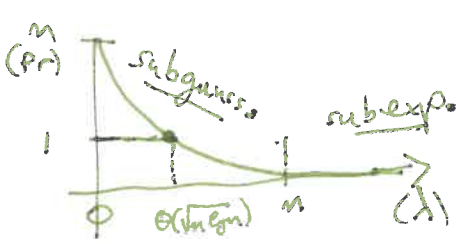
Note: if $n = \# \text{items}$ and $m = \# \text{sets}$, we can get $\text{disc} \leq O(\sqrt{n \log m})$.

Reconstructing the expectation from tail bounds

Fact: let $X \geq 0$ be an RV. Then

$$E[X] = \int_0^\infty \Pr[X > \lambda] d\lambda.$$

Ex (from set balancing). Suppose we have (S)
 $\Pr[Y \geq \lambda] \leq n \cdot \exp\left(-c \frac{\lambda^2}{n+\lambda}\right)$. ($Y = \max_i \text{disc}(S_i)$ in set balancing)



Note that for $\lambda \ll \sqrt{n \log n}$, the bound $\Pr \leq 1$ is better than the tail bound.

$$E[Y] = \int_0^\infty \Pr[Y \geq \lambda] d\lambda \leq \int_0^{c\sqrt{n \log n}} 1 + \int_{c\sqrt{n \log n}}^\infty O\left(\frac{1}{\lambda^2}\right) d\lambda = c\sqrt{n \log n} + o(1).$$

Unbiased Random Walk

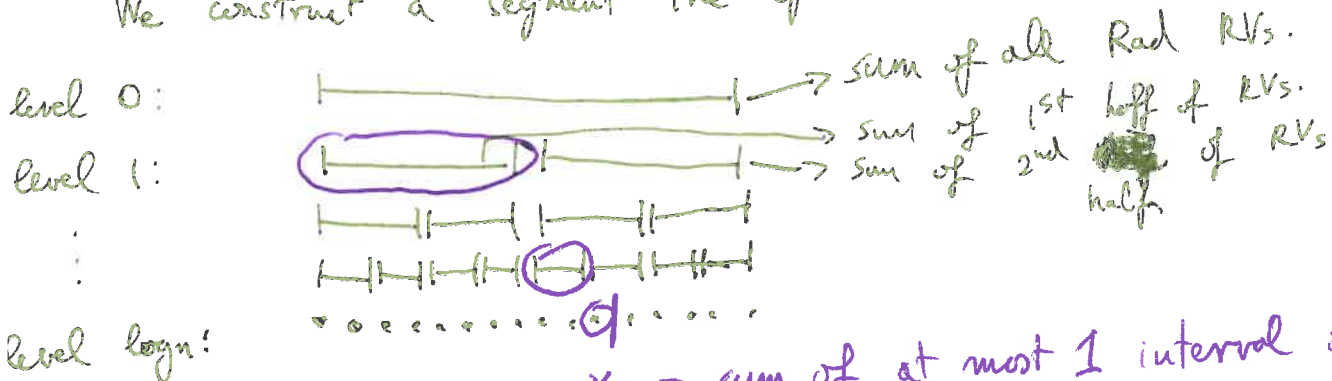
Def: let $X_0=0, X_1, \dots$ s.t. $X_{n+1} = X_n + \text{Rad} = X_n + \begin{pmatrix} +1 & -1 \\ 0.5 & 0.5 \end{pmatrix}$.
 then $E[X_n]=0$, $E[|X_n|] = O(\sqrt{n})$, $\Pr[|X_n| \geq \lambda] \leq 2 \exp\left(-c \frac{\lambda^2}{n+\lambda}\right)$.

Question: what is $E\left[\max_{i=1}^n |X_i|\right]$? Chernoff + Union bound will give us $O(\sqrt{n \log n})$, but this is not tight (unlike before). We can do better.

Thm: $E\left[\max_{i=1}^n |X_i|\right] = O(\sqrt{n})$.

Pf Let $\begin{matrix} \circ & \circ & \circ & \dots & \circ \\ \bullet & \bullet & \bullet & \dots & \bullet \end{matrix}$ be the individual Rad RVs.

We construct a segment tree of sums.



$X_k = \text{sum of at most 1 interval on every level.}$

Hence $X_k = \sum_{i=0}^{\log n} \left\{ \begin{array}{l} \text{either } 0, \text{ or} \\ \text{some interval on} \\ \text{level } i \end{array} \right\}$

Let $L_i =$ maximum absolute sum of an interval on level i .

Then $\max_k |X_k| \leq L_0 + L_1 + \dots + L_{\log n}$. Also $E[\max_k |X_k|] \leq \sum_{i=0}^{\log n} E[L_i]$.

However ~~$L_i \sim \sum_{j=1}^m \text{Rad}$~~ where ~~$m = 2^i$~~

$L_i \sim \max_{j=1}^m \sum_{t=1}^t \text{Rad}$, where $m = 2^i$
 $t = m/2^i$.

so $\Pr[L_i \geq \lambda] \leq \sqrt{t \cdot \log m} = o(\sqrt{n}) \cdot \frac{\sqrt{i}}{2^{i/2}}$

Hence $E \max |X_k| \leq o(\sqrt{n}) \cdot \sum_{i=0}^{\log n} \frac{\sqrt{i}}{2^{i/2}} = o(\sqrt{n})$

converges!



Martingales

Def A martingale is a sequence of RVs ~~X_0, X_1, \dots~~ s.t. (i) $E[X_{k+1} | X_k, X_{k-1}, \dots, X_1] = X_k$

$X_0 = 0, X_1, X_2, X_3, \dots$
and (ii) $E[|X_k|] < \infty$.

(for simplicity)

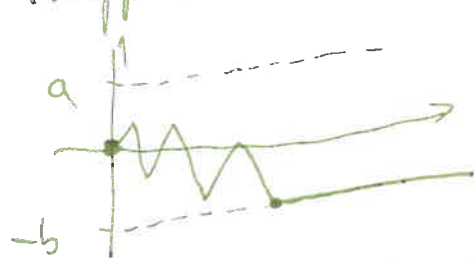
EX (unbiased random walk) $X_0 = 0, \dots, X_{k+1} = X_k + \text{Rad}$.
EX $Y_n = (X_n)^2 - n$ is a martingale.

Pf $E[Y_{n+1} | Y_n] = \frac{1}{2} (X_{n+1})^2 + \frac{1}{2} (X_{n-1})^2 - (n+1)$
 $= X_n^2 + 1 - n - 1 = X_n^2 - n = Y_n$

Fact: let $X_0=0, X_1, X_2, \dots$ be a martingale. Then $E[X_k] = E[X_0] = 0$. (5)

Pf (easy)

Ex (stopped random walk). $Z_0=0, \dots, Z_{k+1} = \begin{cases} Z_k & \text{if } Z_k \in \{a, -b\} \\ Z_k + \text{Rad} & \text{otherwise} \end{cases}$



↓ This is a martingale!

Fact: a martingale Z_k (stopped at $\{a, -b\}$) will stop at time τ where $E[\tau] < \infty$.

Fact: let $P_a = \Pr[Z_k \text{ stops at } a]$, $P_b = \Pr[Z_k \text{ stops at } -b]$. Then $P_a = \frac{b}{a+b}$ and $P_b = \frac{a}{a+b}$.

Pf: let N be such that $\Pr[Z_k \text{ stops before } N \text{ steps}] \geq 1 - \epsilon$.

$$0 = E[Z_N] = P_a^{(N)} \cdot a + P_b^{(N)} \cdot (-b) + \epsilon \cdot O(1)$$

$\hookrightarrow \leq \max(a, b)$

Also $P_a + P_b = 1 - O(\epsilon)$.

Plugging in & solving we get $P_a = \frac{b}{a+b} + O(\epsilon) \rightarrow \frac{b}{a+b}$
 $P_b = \frac{a}{a+b} + O(\epsilon) \rightarrow \frac{a}{a+b}$.

Fact: let Z_k be the unbiased rand. walk stopped at $\{a, -b\}$. Let τ be the stopping time. Then $E[\tau] = a \cdot b$.

idea: use $0 = E[Y_k]$ on $Y_k = (X_k)^2 - k$.

Fact (Azuma): let $0 = X_0, X_1, X_2, \dots$ be a martingale s.t. $|X_{k+1} - X_k| \leq 1$. Then $\Pr[|X_k| \geq \lambda] \leq 2 \exp\left(\frac{-\lambda^2}{2k}\right)$.

↳ note: we can use this on the stopped ~~Mobius~~ random walk to prove that $\max_{i=1}^n |X_i| \leq O(\sqrt{n})$ directly.