

(1)

$$\mathcal{F}_0 \subseteq \mathcal{F}_1 \subseteq \dots \subseteq \mathcal{F}_n = \Sigma. \quad (\Omega, \Sigma, P)$$

now  $X_i$  is measurable in  $\mathcal{F}_i$  ( $X$  is adapted to  $\mathcal{F}$ ).

and s.p.s.  $E[X_i | \mathcal{F}_{i-1}] = X_{i-1}$

$\uparrow$  take  $X_i$  and average over region  $\mathcal{F}_{i-1}$

then  $(X_0, X_1, \dots)$  is a martingale.

by induction  $E[X_t] = \boxed{\text{something}} = E[X_0]$ . typically set this to 0.

E.g. random walk.  
in line.

Example:  $X_{it} = X_{it} + Y_{it}$   $\leftarrow$  indep random var. (0 mean).

$\downarrow$  depends on past, but  $E[Y_{it} | X_0, \dots, X_{i-1}] = 0$ .

but could also take  $X_{it} = X_{it} + Y_{it}(X_{it})$  conditionally still 0 mean.

E.g. random walk with absorbing borders.

Stopping time measurable wrt filtration.

s.p.s.  $ET < \infty$  and all step sizes are bounded a.s.

then  $E[X_T] = E[X_0]$ . (Doob's Optional Stopping Thm)

E.g.:  $E[S_T] = E[S_0] = 0$  in random walk.

$$S_t = X_1 + X_2 + \dots + X_t$$

$$\text{s.o. } p_a(-a) + p_b(b) = 0 \Rightarrow ba = \frac{b}{atb}.$$

but also.  $S_T^2 - t$  is a martingale for the moments being 0 mean var 1.

$$\Rightarrow E[S_T^2] - E[t] = \frac{b}{atb} \cdot a^2 + \frac{a}{atb} b^2 = ab. \Rightarrow n^2 \text{ time to hit barrier at } \pm n.$$

Ville's thm: if  $S_n$  is a supermartingale, nonnegative then  $P_t(\sup_n S_n > x) \leq \frac{E[S_0]}{x}$ .

Like Markov but now for supermartingales.

And get supremum for free.

(2)

## Concentration bounds (Azuma-Hoeffding)

$0 = X_0, X_1, X_2, \dots$  martingale with  $|X_i - X_{i-1}| \leq c_i$ .

then  $P_\theta[|X_t| \geq \lambda] \leq \exp(-\lambda^2/2\sigma^2)$  where  $\sigma^2 = \sum_i c_i^2$ .

And we find like Ville's

$P_\theta[\max_{s \leq t} |X_s| \geq \lambda] \leq \exp(-\lambda^2/2\sigma^2)$  as well.

Example: s.p.s.  $f(\bar{X}) \in \mathbb{R}$   $\bar{X} = (X_1, X_2, \dots, X_n)$ .  $X_i$  i.i.d. r.v.s.

then  $\mathbb{E}[f] = Y_0 = E[f]$

$$Y_1 = E[f | X_1]$$

:

$$Y_n = E[f | X_1, X_2, \dots, X_n] = f.$$

Moreover: s.p.s. changing coordinate  $i$  changes  $f$  by  $\leq c_i \Rightarrow |Y_i - Y_{i-1}| \leq c_i$

Now apply Azuma:  $P_\theta[|f - E[f]| \geq \lambda] \leq \exp(-\lambda^2/2\sigma^2)$ . [McDiarmid]

Verify!!

Example: chromatic number  $\chi$  of random graph  $G_{n,p}$  is concentrated on  $S(n)$  values. [Shannon - Spencer]

[Bollobás: at most 4 values.]

[Alon-Kravitz, Achlioptas and Hajiaghayi: 2 values]

$$p \leq n^{1/2 - \epsilon}$$

$$p = d/n$$

Btw: instead of requiring that  $|X_i - X_{i-1}| \leq c_i$  a.s.

we could use that  $[X_i | X_{i-1} > 2]$  has ~~exp~~ subgaussian tails.

Azuma-Hoeffding  
and hence can extend to some f  
Subgaussian r.v.s.

## Discrepancy

$$S = S_1, S_2, \dots, S_m \subseteq \Omega$$

$$\chi: \Omega \rightarrow \{-1, 1\}^S.$$

$$\text{disc}_\chi(S) = \sum_{i \in S} \chi(i)$$

$$\text{disc}_\chi(S) = \max_{S \in \mathcal{S}} |\chi(S)|.$$

. Want  $\chi$  to get low discrepancy  $\text{disc}_\chi(S)$ .

Thm:  $\exists$  set systems such that  $\text{disc}_\chi(S) \geq \Omega(\sqrt{n})$ .

$m = \alpha(n)$  sets  $n$  elts

$$\text{take Hadamard matrix } H_1 = \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} \quad H_K = \begin{pmatrix} H_{K-1} & H_{K-1} \\ H_{K-1} & -H_{K-1} \end{pmatrix}.$$

now  $m = 2 \cdot 2^K$  sets for each row  $i$ ,  $A_i = +$  entries  $\bar{A}_i = -$  entries

$$\text{then } \chi(A_i) - \chi(\bar{A}_i) = \langle \chi, h_i \rangle$$

$$\Rightarrow |\langle \chi, h_i \rangle| \leq |\chi(A_i)| + |\chi(\bar{A}_i)| \quad (*)$$

But  $h_i$ 's form an orthogonal basis w.r.t. with vector  $\ell_2$  norm  $\|h_i\|^2 = 2^K$ .

$$\Rightarrow \sum_i (\langle \chi, h_i \rangle)^2 = \frac{\sum_i \langle \chi, h_i \rangle^2}{2^{2^K}} = \|\chi\|^2 = 2^K.$$

$$\Rightarrow \exists n \text{ s.t. } \|\chi\|^2 \geq 2^K$$

$$\Rightarrow |\langle \chi, h_i \rangle| \geq 2^{K/2}$$

using (\*) get  $\exists i$ ,  $\exists i$  in  $A_i \cap \bar{A}_i$  satisfying  $|\chi(S)| \geq \frac{1}{2} \sqrt{n}$ .

Sponn showed : Set system with  $m = O(n)$  sets,  
 Family with  $\text{disc}_X(S) \leq O(\sqrt{n})$ .

Recent proofs using CS-type ideas (based on making the results algorithmic)

Bansal, Lovett-Meka, Rothvoss, ~~Ellis~~, Ehsan-Singh, Bansal-Laddha-Vempala, ...

Give the Lovett-Meka proof

$$\text{Want } x(S_i) \leq c\sqrt{n \log(m/n)} \quad \forall i$$

$$x_i \in \{-1, 1\}.$$

↑  
relax to  $x_i \in [-1, 1]$ .

:(  $x_i = 0$  is a solution with discrepancy zero !!

So want to round.

by 1: independent rounding :-  $\Pr[\text{disc}(S_i) \geq \sqrt{n \log m}] \leq 1/\text{poly}(m)$   
 then union bound.

But : get  $\text{disc} \sqrt{n \log m}$  for  $m$  sets, and hence  $\sqrt{\log m}$  for  $n$  sets  
 "Penalty for union bound"

Smart idea: small steps, and fix problems as they arise

let's make this geometric:-

$$x(S_i) \leq \underbrace{\dots}_{\text{scale } a_i \in \mathbb{R}^n \text{ s.t. } \|a_i\|_1 = 1} \leq c\sqrt{n \log(m/n)} \Rightarrow \langle a_i, x \rangle \leq \|a_i\|_1 \cdot c \quad \forall i \in [m].$$

$x_j \in [-1, 1] \quad \forall j \in [n].$  think of this as  $\Theta(\sqrt{\log(m/n)}).$

start @  $x_0$  (think as 0).

Call constraint  $a_i$  dangerous if  $\langle a_i, x \rangle \geq c_i - \delta$

variable  $x_j$  frozen if  $|x_j| \geq 1 - \delta$ .

$\left. \begin{array}{l} \text{apx satisfied} \\ \end{array} \right\}$

Each time t: find subspace orthogonal to all dangerous constraints  
& all frozen variables.

until subspace dimension smaller than  $n/4$ .  
 $V_t$  (re. will have  $3n/4$  of these constraints/vars).

Idea: want to ensure that many of these are frozen vars.  
not dangerous constraints.

Pick  $g_t \sim N(V_t)$  gaussian from that subspace.

$X_0^t = x_0, X_t^t \leftarrow X_{t-1}^{t-1} + \gamma g_t$

$\delta \geq \gamma \sqrt{\log m}$

martingale.

Claim 1:  $\dim(V_{t+1}) \leq \dim(V_t)$ .

Claim 2: if we are not dangerous/frozen, it will not be violated w.h.p.

why? for a gaussian  $\Pr[|g| \geq \lambda] \leq 2\exp(-\lambda^2/2)$   
 now  $|\gamma g| \geq \delta \leq 2\exp(-(\delta/8)^2/2) = 2\exp\left(-\frac{\log(m/8)}{2}\right)$   
 $= \left(\frac{8}{m}\right)^{\text{O}(1)}$ .

⇒ uniform bound over all steps.

Claim 3:  $E[\|x^t\|^2] = E[\|x^{t-1}\|^2] + 2E[\langle x^{t-1}, \gamma g^t \rangle] + \gamma^2 E[\|g^t\|^2]$

$\downarrow$  0 indep       $\downarrow \gamma^2 \dim(V_t)$

$= \gamma^2 \sum_{i=t}^{t-1} \dim(V_i)$  ⇒ as long as  $\dim(V_t) \geq n/4$ , progress.