

Last time:

approx counting \Rightarrow approx sampling

Q: given \mathcal{R} & distr $\pi = (\pi_1, \dots, \pi_{|\mathcal{R}|})$
over elts of \mathcal{R}

how to approx sample from this distr?

Cool idea:

- design a MC whose stationary distr is π
- Show that it mixes in polynomial time

i.e. after $T = \text{poly}(n)$ steps
 $\Pr(X_T = j) \approx \pi_j \quad \forall j \in \mathcal{R}$

Today

- another example of coupling
- martingales

Coupling simple & elegant approach to bounding mixing time

Given a MC P on \mathcal{L} , a coupling is a MC on $\mathcal{L} \times \mathcal{L}$ defining stochastic process (X_t, Y_t) s.t.

① each X_t & Y_t in isolation is faithful copy of MC

$$\Pr(X_{t+1}=z \mid X_t=x) = P_{xz}$$

$$\Pr(Y_{t+1}=w \mid Y_t=y) = P_{yw}$$

② If $X_t=Y_t$ then $X_{t+1}=Y_{t+1}$

Coupling Lemma Let (X_t, Y_t) be a coupling

Suppose $\exists T$ s.t. $\forall x, y$

$$\Pr(X_T \neq Y_T \mid X_0=x, Y_0=y) \leq \epsilon$$

Then $T(\epsilon) \leq T$

$$\|D_1 - D_2\|_{TV} = \frac{1}{2} \sum_{x \in \mathcal{L}} |D_1(x) - D_2(x)| = \max_{A \subseteq \mathcal{L}} |D_1(A) - D_2(A)|$$

Graph coloring

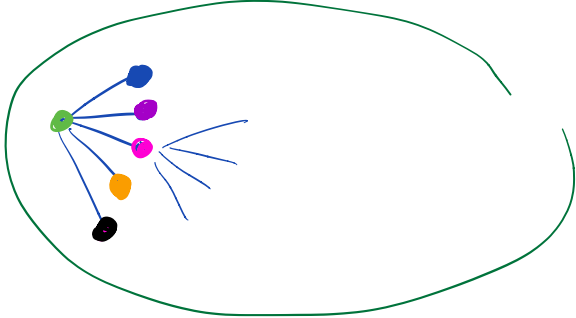
Input: $G=(V,E)$ undirected; max degree Δ . k colors

Recall if $k \geq \Delta + 1$,
 k -colorable

Markov chains

- ① pick vertex v & color c u.a.r.
- ② recolor v with c if legal

- aperiodic
- irreducible:



- π uniform

Conjecture: $\forall k \geq \Delta + 2$, this MC has poly mixing time
even $O(\ln \log n)$

Thm If $k \geq 4\Delta + 1$, then MC has mixing time $O(n \log n)$

Coupling: X_t & Y_t choose same v & c each step

$$D_t = \{v \mid X_t \text{ & } Y_t \text{ disagree on color } v\} \quad |D_t| = d_t$$

$$A_t = V - D_t$$

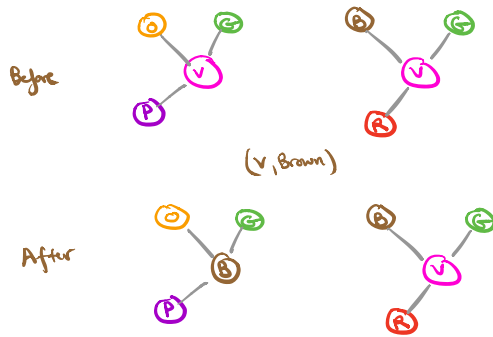
here d_t may \uparrow

Good moves $d_t \downarrow$

$$g_t = \# \text{ good moves} \geq d_t(k - 2\Delta)$$

Bad moves $d_t \uparrow$

$$b_t = \# \text{ bad moves} \leq 2d_t\Delta$$



$$\begin{aligned} & E(X|Y=y) \text{ w.p. } \Pr(Y=y) \\ & E(E(X|Y)) \\ &= \sum_y E(X|Y=y) \Pr(Y=y) \\ &= \sum_y \sum_x x \Pr(X=x|Y=y) \Pr(Y=y) \\ &= \sum_x x \sum_y \Pr(X=x \cap Y=y) \\ &= \sum_x x \Pr(X=x) \end{aligned}$$

All other moves cause no change in d_t
Prob of each move = $\frac{1}{kn}$

$$\begin{aligned} \Rightarrow E[d_{t+1} | d_t] &= d_t + \frac{b_t - g_t}{kn} \leq d_t + \frac{2d_t\Delta - d_t(k - 2\Delta)}{kn} \\ &= d_t \left(1 + \frac{4\Delta - k}{kn}\right) \leq d_t \left(1 - \frac{1}{kn}\right) \end{aligned}$$

since $k \geq 4\Delta + 1$

$$\Rightarrow E[d_t] = E[E[d_t | d_{t-1}]]$$

\Rightarrow for $T = kn \ln\left(\frac{n}{\epsilon}\right)$

$$\Pr(X_T \neq Y_T \mid X_0 = x, Y_0 = y) \leq \epsilon \quad \Rightarrow \tau(\epsilon) \leq kn \ln\left(\frac{n}{\epsilon}\right)$$

bound can be improved to $k \geq 2\Delta + 1$ with more clever coupling
see notes.

Martingales

A sequence of r.v.s X_0, X_1, \dots is a martingale with respect to the sequence Y_0, Y_1, \dots if $\forall n \geq 0$ the following conditions hold:

- X_n is a fn of Y_0, Y_1, \dots, Y_n
- $E(|X_n|) < \infty$
- $E(X_{n+1} | Y_0, \dots, Y_n) = X_n$

Sequence of r.v.s X_0, X_1, X_2, \dots called a martingale when it is a martingale wrt itself

- $E(|X_n|) < \infty$
- $E(X_{n+1} | X_0, X_1, \dots, X_n) = X_n$

Example: gambler plays sequence of fair games

Y_i : winnings on i th game $E(Y_i) = 0$

X_i : gambler's total winnings at end of i th game

$$E(X_{i+1} | Y_1, \dots, Y_n) = X_i + E(Y_{i+1}) = X_i$$

martingale regardless of amt bet each game, even if these amts are dependent on previous results

Examples

① Sums of indep random variables

$Y_0=0$ Y_1, \dots, Y_n iid w/ $E(Y_k)=0 \forall k$

Define $X_n = Y_0 + Y_1 + Y_2 + \dots + Y_n$

$\{X_t\}$ is a martingale wrt. $\{Y_t\}$

$$\begin{aligned} E(X_{n+1} | Y_0, \dots, Y_n) &= E(X_n + Y_{n+1} | Y_0, \dots, Y_n) \\ &= E(X_n | Y_0, \dots, Y_n) + E(Y_{n+1} | Y_0, \dots, Y_n) \\ &= X_n + E(Y_{n+1}) \\ &= X_n \end{aligned}$$

② Variance of a sum

Y_1, \dots, Y_n iid w/ $E(Y_k)=0 \forall k$ $E(Y_k^2)=\sigma^2$

Define $X_0=0$ $X_n = \left(\sum_{k=1}^n Y_k\right)^2 - n\sigma^2$

$\{X_t\}$ is a martingale wrt $\{Y_t\}$

$$\begin{aligned} E(X_{n+1} | Y_0, \dots, Y_n) &= E\left[\left(\sum_{k=1}^{n+1} Y_k\right)^2 - (n+1)\sigma^2 \mid Y_0, \dots, Y_n\right] \\ &= E\left[Y_{n+1}^2 + 2Y_{n+1}\left(\sum_{k=1}^n Y_k\right) + \left(\sum_{k=1}^n Y_k\right)^2 - (n+1)\sigma^2 \mid Y_0, \dots, Y_n\right] \end{aligned}$$

③ "Doob's" martingale process

Y_1, Y_2, \dots arbitrary seq of random vars

X r.v. with finite expectation

$X_n = E(X | Y_1, \dots, Y_n)$ forms martingale wrt $\{Y_n\}$

$X_0 = E(X)$

$$\begin{aligned} & E(X_{n+1} | Y_1, \dots, Y_n) \\ &= E(E(X | Y_1, \dots, Y_{n+1}) | Y_1, \dots, Y_n) \\ &= E(X | Y_1, \dots, Y_n) = X_n \end{aligned}$$

$E(V|W) = E[E(V|U, W) | W]$
 prove this ↑

Example: Edge exposure martingale

$G(n, p)$ random graph
 label $m = \binom{n}{2}$ potential edges e_1, e_2, \dots, e_m

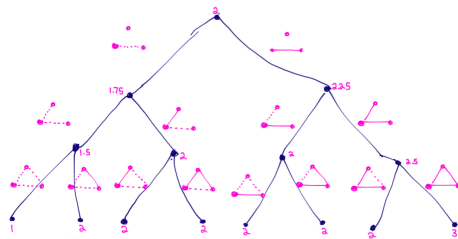
Let $f(G)$ be size of largest clique in G

$Y_j = \begin{cases} 1 & \text{if edge } e_j \text{ present} \\ 0 & \text{otherwise} \end{cases} \quad \Pr(Y_j=1) = p$

$X_k = E[f(G) | Y_1, \dots, Y_k] \quad X_0 = E[f(G)]$
 $X_m = f(G)$

$G(n, \frac{1}{2})$

- $X_0 = E(\text{max clique})$
- $X_1 = E(\text{max clique} | Y_1)$
- $X_2 = E(\text{max clique} | Y_1, Y_2)$
- $X_3 = E(\text{max clique} | Y_1, Y_2, Y_3)$



Some useful facts about martingales:

① $E(X_n) = E(X_0)$

by induction

$$E(X_{n+1} | Y_0, \dots, Y_n) = X_n$$

$$E\left[E(X_{n+1} | Y_0, \dots, Y_n)\right] = E(X_n)$$

$$= E(X_{n+1})$$

$$E(E(X|Y)) \stackrel{E(X|Y=y) \cdot \Pr(Y=y)}{=} \sum_y E(X|Y=y) \Pr(Y=y)$$

$$= E(X)$$

② Definition

A r.v. T is called a "stopping time" wrt $\{Y_t\}$ if

T takes values in $\{0, 1, 2, \dots\}$

and if $\forall n \geq 0$, the event $\{T \leq n\}$ is determined by Y_0, \dots, Y_n

i.e. can determine if $T \leq n$ or $T > n$ from knowledge of values Y_0, \dots, Y_n

"know it when you see it"

Optional Stopping Thm

$\{Z_t\}$ is a martingale wrt $\{X_t\}$

For T a stopping time "know it when you see it"

$$E(Z_T) = E(Z_0)$$

whenever any of the following hold

- Z_t 's bounded ($\exists c$ s.t. $\forall i |Z_i| \leq c$)
- T is bounded
- $E(T) < \infty$ and $\exists c$ s.t. $E(|Z_{t+1} - Z_t| | X_{1..t}, X_t) \leq c$

Applications of Optional Stopping Theorem

① unbiased r.w. on line starting at 0



$$Y_i = \begin{cases} 1 & \text{with prob } \frac{1}{2} \\ -1 & \text{" " } \frac{1}{2} \end{cases} \quad X_n = \sum_{i=1}^n Y_i \quad \text{martingale}$$

$$T = \min \{n \mid X_n = -a \text{ or } X_n = b\}$$

T is a stopping time

Let $v_a = \Pr(X_n \text{ reaches } -a \text{ before reaching } b)$

$$\text{By O.S.T.} \quad E(X_T) = E(X_0) = 0$$

② Same unbiased r.w. on line, same T

What is $E(T)$?

$$Z_n = X_n^2 - n \quad \text{is a martingale [variance of a sum } E(Y_i^2) = 1]$$

$$\text{By O.S.T.} \quad E(Z_T) = E(Z_0) = 0$$

Same question: biased r.w.

$$Y_i = \begin{cases} +1 & p \\ -1 & q \end{cases} \quad p > q \quad (=1-p)$$

$$\begin{aligned} X_n &= \sum_{i=1}^n Y_i - n(p-q) \\ X_n' &= \left(\frac{q}{p}\right)^{\sum_{i=1}^n Y_i} \quad X_0' = 1 \end{aligned} \quad \left. \vphantom{\begin{aligned} X_n \\ X_n' \end{aligned}} \right\} \begin{array}{l} \text{martingales wrt } \{Y_n\} \\ \text{check it!} \end{array}$$

$$\begin{aligned} T &= \min \left\{ n \mid \sum_{i=1}^n Y_i = -a \text{ or } = b \right\} \\ v_a &= \Pr \left(\sum_{i=1}^n Y_i \text{ reaches } -a \text{ before } b \right) \end{aligned}$$

$$E(X_T') = E(X_0') = 1$$

$$E(X_T') = v_a \left(\frac{q}{p}\right)^{-a} + (1-v_a) \left(\frac{q}{p}\right)^b = 1$$

$$\Rightarrow v_a = \frac{1 - \left(\frac{q}{p}\right)^b}{\left(\frac{q}{p}\right)^{-a} - \left(\frac{q}{p}\right)^b}$$

$$E(X_T) = v_a(-a) + (1-v_a)b - E(T)(p-q) = 0$$

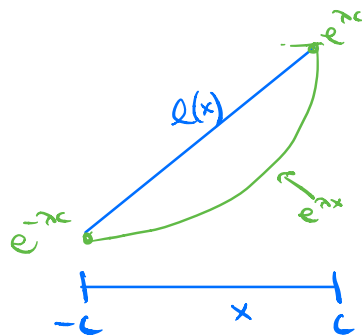
③ Tail inequalities

$E(X_n) = E(X_0)$ how far can it be from its expectation

Azuma-Hoeffding Inequality

X_0, \dots, X_n martingale s.t. $\forall k \quad |X_k - X_{k-1}| \leq c_k$
 c_k may depend on k

Then $\forall t \geq 0$, any $R > 0$
 $\Pr(|X_t - X_0| > R) \leq 2 e^{-\left[\frac{R^2}{2 \sum_{k=1}^t c_k^2} \right]}$



$$\Rightarrow E[e^{\lambda X_{t+1}} | H_t] = e^{\lambda X_t} E[e^{\lambda (X_{t+1} - X_t)} | H_t] \\ \leq e^{\lambda X_t} e^{\frac{(\lambda c_t)^2}{2}}$$

take expectation on both sides

$$E[e^{\lambda X_{t+1}}] \leq e^{\frac{(\lambda c_t)^2}{2}} E[e^{\lambda X_t}] \leq e^{\lambda^2 \sum_{i=1}^t c_i^2 / 2}$$

by induction on t

Finally,

$$\Pr(X_t \geq R) = \Pr(e^{\lambda X_t} \geq e^{\lambda R}) \leq e^{-\lambda R} E[e^{\lambda X_t}] \\ = e^{-\lambda R} e^{\lambda^2 \sum_{i=1}^t c_i^2 / 2}$$

Optimizing, we choose $\lambda = \frac{R}{\sum_{i=1}^t c_i^2}$

$$\Rightarrow \Pr(X_t \geq R) \leq e^{-\frac{R^2}{2 \sum_{i=1}^t c_i^2}}$$

$$-\left(\lambda R - \frac{\lambda^2 \sum c_i^2}{2}\right) = -\left(\frac{R^2}{\sum c_i^2} - \frac{R^2}{2 \sum c_i^2}\right)$$

Factor of 2 comes from $\Pr(X_t < -R)$