



let $N(s, \bar{s})$ be the number of times \bar{s} is used in s .

Then
$$A = \max_{\bar{s} \in \tilde{S}} \left\{ \frac{1}{\sqrt{|\bar{s}|}} \sum_{s \in S} \text{length}(s) N(s, \bar{s}) \mu(s) \right\}$$

Example: Consider S_n with random transpositions (Diaconis, Shah...)

deck of n cards
 left + right hand picks cards uniformly at random (maybe the same)
 Then transpose the cards.

[This is related to how DNA encodes information]

$S = \{ (a,b) \mid a \neq b \} \cup \{id\}$

We have $\mu(id) = \frac{1}{n}$ and $\mu(a,b) = \frac{2}{n^2}$

Since again S is a union of conjugacy classes, rep theory can be used to find eigenvalues and eigenfunctions.

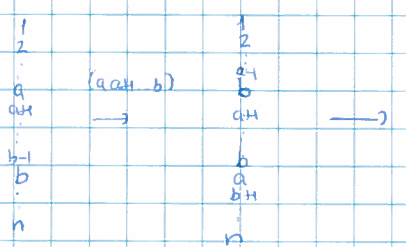
Can see that $\lambda_2 = 1 - \frac{2}{n}$

Random to random: deck of n cards. Pick a card uniformly at random, remove it from deck and insert it in a uniformly random position.

The generators of these transpositions are $\tilde{S} = \{ \text{cycles} \} \cup \{id\}$

Then $\nu(id) = \frac{1}{n}$ $\nu(a, a+1) = \frac{2}{n^2}$ $\nu(a, a+1, \dots, a+k) = \frac{1}{n^2}$

Given a transposition (a,b) can write it as a product of elements in \tilde{S} :



hence $\text{length}(a,b) = 2$
 $N((a,b), s) = 1$ for $s = (a, a+1, \dots, b)$

$A = n^2 \cdot \frac{2}{n^2} \cdot 2 \cdot 2 \cdot 1 = 8$ (2 transpositions at most)

We get the following formula for A : $A = 8$ for $s = (a, a+1, \dots, b)$ (this is the maximum you can get)

The inequality says

$\rho_2 \leq 1 - \frac{1 - (1 - \frac{2}{n})}{8} = 1 - \frac{1}{4n}$

Lecture 4: Lower bound techniques

Configuration space $X = (\mathbb{Z}/2\mathbb{Z})^n$ (hypercube)
 $= \{ (a_1, \dots, a_n) \mid a_i \in \mathbb{Z}/2\mathbb{Z} \}$

this is an abelian group \Rightarrow can use rep theory to find eigenvalues and eigenfunctions.

What to prove: If we consider the transition matrix

$$P(x,y) = \begin{cases} \frac{1}{2} & \text{if } y=x \\ \frac{1}{2n} & \text{if } y=x+e_i \quad e_i = (0, \dots, 0, 1, 0, \dots, 0) \\ 0 & \text{otherwise} \end{cases}$$

If $t = \frac{1}{2} n \log n - cn$ $\|P_0^t - U\|_{TV} \geq 1 - \frac{1}{2^c}$ (quite big) after.

The only prerequisite for today is Chebyshev's inequality

$$Z \text{ random variable } \boxed{P(|Z - E(Z)| \geq \alpha \sqrt{\text{Var}(Z)}) \leq \frac{1}{\alpha^2}}$$

- Eigenfunctions $f_1(x) = 1$, eigenvalue 1
 $f_2(x) = n - 2x$ eigenvalue $1 - \frac{1}{n}$
 $f_3(x) = \binom{n}{2} - 2nx + x^2$ eigenvalue $1 - \frac{2}{n}$

have for X_t two moments, $f(X_t) = f(\|X_t\|)$
 ↑
 number of 1s on X_t

for instance $f_2(x) = f_2(\|x\|) = n - 2$

New $(f_2(x))^2 = n f_1(x) + 2 f_3(x)$

1) Y a random variable on X $Y \sim U$ uniform distribution

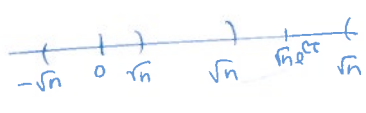
Let $U(f_2) = \sum_{\bar{x} \in X} \frac{1}{2^n} f_2(\bar{x}) = \sum_{\bar{x}} \frac{1}{2^n} f_2(x) f_1(x) = 0$ because $\langle f_1, f_2 \rangle = 0$

mean $E_U(f)$
 $\text{Var}_U(f_2) = U(f_2^2) - U(f_2)^2 = \sum_{\bar{x}} \frac{1}{2^n} (n - 2x)^2 = n$ (check)



2) $P_0^t(f_2) = \sum_{x \in X} P_0^t(x) f_2(x) = f_2(0) (1 - \frac{1}{n})^t = n (1 - \frac{1}{n})^t \sim \sqrt{n} e^{-\frac{t}{2}}$ if $t = \frac{1}{2} n \log n - cn$

$\text{Var}_{P_0^t}(f_2) = P_0^t(f_2^2) - (P_0^t(f_2))^2 = P_0^t(n f_1 + 2 f_3) - n^2 (1 - \frac{1}{n})^{2t} = n + n(n-1) (1 - \frac{2}{n})^t - n^2 (1 - \frac{2}{n} + \frac{1}{n^2})^t$
 ↑
 mean = $n (1 - \frac{1}{n})^t$
 $\approx n$ if $t = \frac{1}{2} n \log n - cn$



for appropriate t these intervals are disjoint \Rightarrow the measures are distant.
 Chebyshev

Chebyshev $A = \{x : |f_2(x)| \leq b\}$
 $U(A) \geq 1 - \frac{1}{b^2}$
 $U(A) - P_0^t(A) \geq 1 - \frac{1}{b^2} - \frac{1}{2^t}$
 $P_0^t(A) \leq \frac{1}{b^2} + \frac{1}{2^t}$

(this is in chapter 3 of Peres's book)

$\|P_0^t - U\|_{TV} = \max_{B \subseteq X} |P_0^t(B) - U(B)| \geq U(A) - P_0^t(A) \approx 1$ if $t = \frac{1}{2} n \log n - cn$

This method is ~~due~~ due to Diaconis + S and it is called the 2nd moment method (with the first moment we could get a lower bound of n)

Wilson's Lemma: P transition matrix of a Markov chain on X . $f: X \rightarrow \mathbb{R}$, $Pf = \lambda f$ and

$E((f(x) - f(x_0))^2 | x_0) \leq R$ then if $t = \frac{1}{2 \log(\frac{1}{\lambda})} \left[\log \frac{(1-\lambda) R}{2R} + \log \frac{\epsilon}{1-\epsilon} \right]$ then

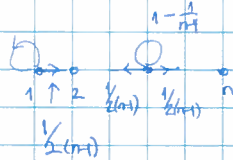
$\|P_x^t - M\|_{TV} \geq 1 - \epsilon$ [no need for reversibility, only need an eigenvalue and cn eigenfunction]



$$S = \{(a, a+1), a=1, 2, \dots, n-1\} \cup \{\text{id}\}$$

$$P(x, y) = \begin{cases} \frac{1}{2} & y=x \\ \frac{1}{2(n-1)} & y=x(a, a+1) \\ 0 & \text{otherwise} \end{cases}$$

Can project this to a much smaller Markov chain by looking at what happens to the first card. This has only n states rather than $n!$



The eigenvalues and eigenvectors are similar to the example about the circle:

$$\varphi(k) = \cos \frac{\pi(2k-1)}{2n} \quad \text{w/ eigenvalue } \frac{n-2}{n-1} + \frac{1}{n} \cos \left(\frac{\pi}{n} \right)$$

$$\varphi_k(\sigma) = \cos \frac{\pi(2\sigma(k)-1)}{n} \quad \sigma(k) = \text{card of position } k.$$

We could have considered any other card than the first. Let

$$\bar{\Phi}(\sigma) = \sum_{k=1}^{n/2} \varphi(k) \varphi_k(\sigma)$$

$$\bar{\Phi}(\text{id}) = \sum_{k=1}^{n/2} (\varphi(k))^2 = \sum_{k=1}^{n/2} \cos^2 \frac{\pi(2k-1)}{2n} \approx \frac{n}{4}$$

If we perform $(a, a+1)$

(all other terms cancel)

$$\begin{aligned} \left| \bar{\Phi}(\sigma \circ (a, a+1)) - \bar{\Phi}(\sigma) \right| &= \varphi(a) \varphi(\sigma(a+1)) + \varphi(a+1) \varphi(\sigma(a)) - \varphi(a) \varphi(\sigma(a)) - \varphi(a+1) \varphi(\sigma(a+1)) \\ &= |\varphi(a) - \varphi(a+1)| \underbrace{|\varphi(\sigma(a)) - \varphi(\sigma(a+1))|}_{\leq 2 \text{ (difference of cosines)}} \end{aligned}$$

$$|\varphi(a) - \varphi(a+1)| = |\varphi'(a)| \leq \frac{\pi}{n}$$

Hence $\mathbb{E}(\bar{\Phi}(\sigma_t) - \bar{\Phi}(\sigma_0))^2 / \sigma_0 \leq \frac{1}{2(n-1)} \frac{2\pi}{n} \sim \frac{1}{n^2} = R$ in Wilkins Theorem.

Using next term in Taylor series of cosine we see that $\lambda \approx 1 - \frac{1}{n^3}$ so $\frac{1}{n} \cos \frac{\pi}{n} = 1 - \frac{1}{n^2}$

$$t \geq - \frac{1}{2 \log(1 - \frac{1}{n^3})} \left[\log \frac{1}{n^3} \frac{n^2}{n^2} + \log \epsilon \right] \approx \frac{n^3 \log n}{2} + n^3 \log \frac{\epsilon}{n}$$

