

Review

- Relationship between t_{mix} & t_{rel} :

$$\frac{1}{1-|\lambda|} \leq O\left(\frac{t_{\text{mix}}(\varepsilon)}{\lg \frac{1}{\varepsilon}}\right) \leftarrow \begin{array}{l} \text{even for} \\ \text{nonreversible} \end{array}$$

t_{rel} when $\lambda = \lambda_2$ \leftarrow tighter as $\varepsilon \rightarrow 0$

$$t_{\text{mix}}(\varepsilon) \leq O\left(t_{\text{rel}} \cdot \lg\left(\frac{1}{\varepsilon \cdot \mu_{\min}}\right)\right) \leftarrow \begin{array}{l} \text{reversible} \\ \& \lambda_2 \geq |\lambda_n| \end{array}$$

Informally, t_{rel} is the coefficient of $\lg \frac{1}{\varepsilon}$.

- Functional analysis:

$$D_f(\nu \parallel \mu) := \mathbb{E}_{x \sim \mu} \left[f\left(\frac{\nu(x)}{\mu(x)}\right) \right] - f\left(\mathbb{E}_{x \sim \mu} \left[\frac{\nu(x)}{\mu(x)} \right]\right)$$

\downarrow
this is just $\sum_x \nu(x)$

* $f(x) = x^2$: $\chi^2(\nu \parallel \mu)$ or $\text{Var}_{\mu} \left[\frac{\nu}{\mu} \right]$

* $f(x) = x \lg x$: $D_{\text{KL}}(\nu \parallel \mu)$ or $\text{Ent}_{\mu} \left[\frac{\nu}{\mu} \right]$

$$d_{\text{TV}}(\nu, \mu) \leq \frac{1}{2} \sqrt{\chi^2(\nu \parallel \mu)} \quad d_{\text{TV}}(\nu, \mu) \leq \sqrt{\frac{1}{2} D_{\text{KL}}(\nu \parallel \mu)}$$

- Contraction:

$$D_f(\nu P \parallel \mu P) \leq (1-\rho) D_f(\nu \parallel \mu)$$

\downarrow
because stationary

- For any stochastic $N \in \mathbb{R}_{\geq 0}^{2 \times 2}$ we have

$$\sup_{\nu} \frac{\chi^2(\nu N \parallel \mu N)}{\chi^2(\nu \parallel \mu)} = \lambda_2(N N^{\circ})$$

\downarrow
time-reversal

Contraction in $\chi^2 \leftrightarrow$ bound on spectrum

- Fourier analysis

$$G = \mathbb{Z}_{n_1} \times \dots \times \mathbb{Z}_{n_k}$$

\rightarrow additive group

For dist π on G we get Abelian walk:

$$X \xrightarrow{P} X + Z \leftarrow \text{fresh sample from } \pi$$

* Eigenvectors = characters:

$$\chi: G \rightarrow \mathbb{C} \setminus \{0\} \text{ s.t. } \chi(x+y) = \chi(x)\chi(y)$$

* There are $n_1 \dots n_k$ of them

$$\chi((x_1, \dots, x_k)) = \omega_1^{x_1} \dots \omega_k^{x_k}$$

\uparrow
with root of unity

Plan for Today

- Examples of Fourier analysis
- Continuous time
- Comparison method
- Trading approx for time \leftarrow if time

Thm: If P is an Abelian walk, every character χ is an eigenvector.

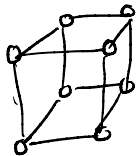
$$\begin{aligned}(\chi P)(y) &= \sum_{x \in G} \chi(x) P(x, y) = \\ &= \sum_{x \in G} \chi(x) \pi(y-x) = \sum_z \pi(z) \chi(y-z) \\ &= \underbrace{\left(\sum_z \pi(z) \chi(z)^{-1} \right)}_{\text{Corresponding eigenvalue}} \chi(y).\end{aligned}$$

Since there are $n_1 - n_k$ many, these are an eigenbasis!

$$\text{Eigenvalue for } \chi: \mathbb{E} \left[\chi(-z) \right]_{z \sim \pi}$$

Example: (Hypercube)

$$G = \mathbb{Z}_2^n$$



- Characters are

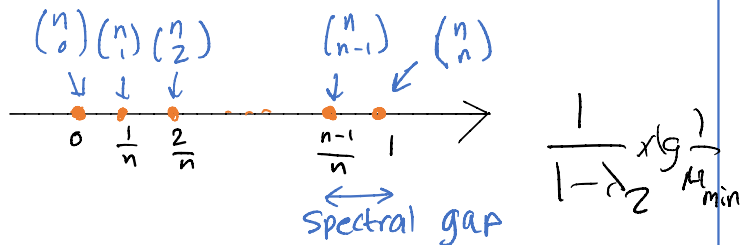
$$\chi(x_1, \dots, x_n) = \omega_1^{x_1} \dots \omega_n^{x_n}$$

$$\omega_1, \dots, \omega_n \in \{\pm 1\}$$

- Glauber dynamics:

$z \sim \Pi$: pick $i \in [n]$ u.a.r. and
let $z = e_i$ w.p. $\frac{1}{2}$ and 0 w.p. $\frac{1}{2}$

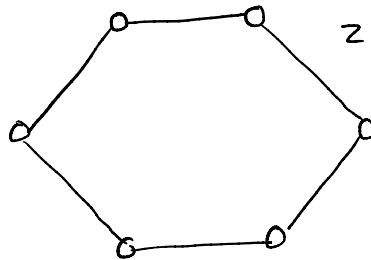
Eigenvalue: $\mathbb{E}_{z \sim \Pi} [\chi(z)] = \mathbb{P}_{i \in [n]} [\omega_i = 1]$



$$t_{rel} = O(n) \Rightarrow t_{mix} = O(n^2) \leftarrow \text{not tight}$$

Example: (Cycle)

$$G = \mathbb{Z}_n$$

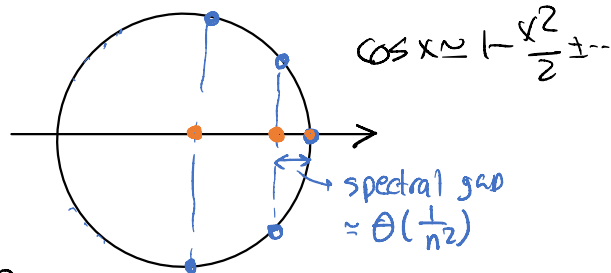


$z \sim \Pi$: pick ± 1 w.p. $\frac{1}{2}$

- Characters are

$$\chi(x) = \omega^x \rightarrow \exp\left(\frac{2\pi i \cdot t}{n}\right)$$

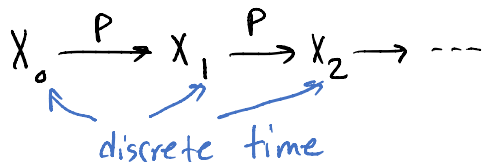
Eigenvalue: $\mathbb{E}_{z \sim \Pi} [\chi(z)] = \frac{\omega + \omega^{-1}}{2} = \cos\left(\frac{2\pi}{n} \cdot t\right)$



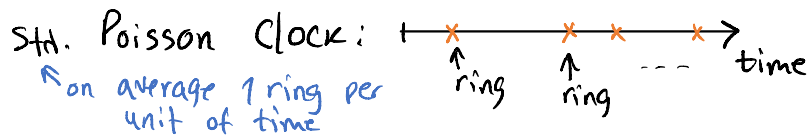
$$t_{rel} = O(n^2) \Rightarrow t_{mix} = O(n^2 \lg n), \text{ unnecessary}$$

Continuous time

- So far we have been running



- We can run a chain in continuous time too:



Everytime the clock rings we take a step of P .

X_t : location at time t
makes sense for $t \in \mathbb{R}_{\geq 0}$

Remark. Algorithmically to simulate X_t we can just sample $n \sim \text{Pois}(t)$ and run n steps of P .

Remark. For any t , conditioned on X_t , past & future are independent.

→ Poisson clock is memoryless.

Remark. For any t , $X_t | X_0$ follows a Markov chain. Same as $X_{t+s} | X_s$.

Think of dividing time into ε -sized intervals ε w.p. ε taking a P in each interval.

$$\underbrace{\left((1-\varepsilon)I + \varepsilon P \right)^{t/\varepsilon}}_{\text{transition for an interval}} = \left(I + \varepsilon(P-I) \right)^{\frac{t}{\varepsilon}} \xrightarrow{\text{Markov chain matrix}} \exp(t(P-I)) \quad \downarrow \text{as } \varepsilon \rightarrow 0$$

Remark. Main benefit of continuous time is "periodicity" goes away.

↓

Ultimate lazification: $P_t \rightarrow (1-\varepsilon)I_t + \varepsilon P$

Functional analysis in continuous time

- In discrete time we wanted

$$D_f(vP \| \mu) \leq (1-\rho) D_f(v \| \mu)$$

- In cont. time the analogous condition is:

$$\left. \frac{d}{dt} D_f(v_t \| \mu) \right|_{t=0} \leq -\rho \cdot D_f(v_0 \| \mu)$$

$$v_t = v_0 \cdot \exp(t \cdot (P-I))$$

* Corollary: $D_f(v_t \| \mu) \leq e^{-t\rho} \cdot D_f(v \| \mu)$

So we again get mixing time bounds.

- Poincaré: This for χ^2

- Modified Log-Sobolev: This for D_{KL}
 should be called Gross's inequality

Note. Discrete time contraction \Rightarrow cont. time

If P contracts by $1-\rho$ then $(1-\varepsilon)I_t + \varepsilon P$ contracts by $1-\varepsilon\rho$.

$$\begin{aligned} D_f((1-\varepsilon)v + \varepsilon vP \| \mu) &\leq (1-\varepsilon) D_f(v \| \mu) + \varepsilon D_f(vP \| \mu) \\ &\leq \underbrace{(1-\varepsilon)}_{1-\varepsilon\rho} + \varepsilon \underbrace{(1-\rho)}_{f \text{ is convex}} D_f(v \| \mu) \end{aligned}$$

$$\Rightarrow \frac{d}{dt} D_f(v_t \| \mu) \leq -\rho D_f(v_0 \| \mu)$$

Mini-proof: $e^{t\rho} \cdot D_f(v_t \| \mu) = z_t$
 $\frac{d}{dt} z_t = e^{t\rho} \cdot \rho \cdot D_f(v_t \| \mu) - \left(\frac{d}{dt} D_f(v_t \| \mu) \right) \cdot e^{t\rho}$

Remark: In general the reverse doesn't hold ☹️

Example: Periodic chains.



However:

For reversible & lazy chains in \mathcal{X}^2 :

say $\lambda_n \geq 0$
or $\lambda_n \geq -\lambda_2$

discrete time \iff continuous time

Sketch:

- Poincare $\iff 2(1 - \lambda_2(P))$

This is because $(1 - \lambda_2((1 - \epsilon)I + \epsilon P)) = \epsilon(1 - \lambda_2(P))$

So \mathcal{X}^2 contracts by $\simeq 2\epsilon(1 - \lambda_2(P))$

Derivative in ϵ is $2(1 - \lambda_2(P))$

- Discrete time \mathcal{X}^2 contraction $\iff 1 - \max(\lambda_2^2(P), \lambda_n^2(P))$

by assumption this dominates

Dirichlet form

Convenient to write $\frac{d}{dt} D_f(v_t \| \mu)$ in terms of quantity called Dirichlet form.

* Assume time-reversible

$$v_{dt} \simeq (1 - dt)v + dt \cdot vP = v + dt \cdot v(P - I)$$

$$\frac{d}{dt} \mathbb{E}_\mu \left[f\left(\frac{v_{dt}}{\mu}\right) \right] \Big|_{t=t_0} = \mathbb{E}_\mu \left[f'\left(\frac{v}{\mu}\right) \cdot \frac{\frac{d}{dt} v_t \Big|_{t=t_0}}{\mu} \right] v(P - I)$$

$$-\frac{1}{2} \sum_{x,y} Q(x,y) \left(f'\left(\frac{v(x)}{\mu(x)}\right) - f'\left(\frac{v(y)}{\mu(y)}\right) \right) \left(\frac{v(x)}{\mu(x)} - \frac{v(y)}{\mu(y)} \right)$$

ergodic flow: $\mu(x)P(x,y) = \mu(y)P(y,x)$

Dirichlet form:

$$\mathcal{E}(g, h) := \frac{1}{2} \mathbb{E}_{(x,y) \sim Q} \left[(g(x) - g(y))(h(x) - h(y)) \right]$$

$$\sum_{x,y} \mu(x)P(x,y) \left(f'\left(\frac{v(x)}{\mu(x)}\right) - f'\left(\frac{v(y)}{\mu(y)}\right) \right) \left(\frac{v(x)}{\mu(x)} - \frac{v(y)}{\mu(y)} \right)$$

- For χ^2 , we get $f(x) = x^2$
 $f' = 2x$

$$\frac{d}{dt} (\chi^2(v_t \| \mu)) = -2\mathcal{E}\left(\frac{v_t}{\mu}, \frac{v_t}{\mu}\right)$$

Poincaré: $2\mathcal{E}\left(\frac{v_t}{\mu}, \frac{v_t}{\mu}\right) \geq \rho \text{Var}_{\mu}\left[\frac{v_t}{\mu}\right]$

- For D_{KL} , we get $f(x) = x \log x$
 $f' = \log x + 1$

$$\frac{d}{dt} (D_{KL}(v_t \| \mu)) = -\mathcal{E}\left(\frac{v_t}{\mu}, \log \frac{v_t}{\mu}\right)$$

MLSI: $\mathcal{E}\left(\frac{v_t}{\mu}, \log \frac{v_t}{\mu}\right) \geq \rho \text{Ent}_{\mu}\left[\frac{v_t}{\mu}\right]$

Remark: There is something called LSI too:

$$\mathcal{E}\left(\sqrt{\frac{v_t}{\mu}}, \sqrt{\frac{v_t}{\mu}}\right) \geq \rho \text{Ent}_{\mu}\left[\frac{v_t}{\mu}\right]$$

Thm: $LSI \Rightarrow MLSI \leftarrow HW$

\leftarrow strictly stronger

$$(\sqrt{a} - \sqrt{b})^2 \leq (a-b)(\log a - \log b)$$

Remark: For continuous-space $MLSI \Leftrightarrow LSI$,
 but absolutely NOT in discrete space.

Comparison of Markov chains

Suppose we have two chains P, P'
 that "look similar" and have **same stationary dist μ** , but we can only analyze P . How do we transfer to P' ?

Example. (Coloring) Metropolis \leftrightarrow Glauber

Idea 1: Suppose $P(x,y) \stackrel{C}{\sim} P'(x,y)$ for $x \neq y$.
 \leftarrow multiplicative

For colorings

$$\frac{1}{q^n} \stackrel{\leftarrow \text{up to } \frac{q}{q-a}}{\sim} \frac{1}{n \cdot (q-a)} \leftarrow \text{Glauber}$$

\uparrow Metropolis \downarrow $\in [0, A]$

Comparison method (easy version)

$$\mathcal{E}\left(f\left(\frac{\nu}{\mu}\right), \frac{\nu}{\mu}\right) =$$

$$\frac{1}{2} \sum_{x,y} Q(x,y) \left(f\left(\frac{\nu(x)}{\mu(x)}\right) - f\left(\frac{\nu(y)}{\mu(y)}\right) \right) \left(\frac{\nu(x)}{\mu(x)} - \frac{\nu(y)}{\mu(y)} \right)$$

≥ 0 because
 f' is monotone

Thm: If $P \stackrel{c}{\approx} P'$ and P, P' have the same stationary dist, for any D_f ,

$$P(P) \stackrel{c}{\approx} P(P')$$

continuous time contraction factors

Comparison method (hard version)

What if P, P' are not this similar?

Routing: Suppose we have dist π

over paths $x_0 \sim x_1 \sim x_2 \sim \dots \sim x_\ell$,

s.t. $(x_0, x_\ell) \sim Q$

ergodic flow
for P

We call π a routing.

Congestion: $\frac{P_{\text{path} \sim \pi} [x \sim y \text{ in path}]}{Q'(x,y)}$

think of as capacities.

Length: Maximum ℓ .

Low congestion + Low length \Rightarrow

$c \cdot \mathcal{E}_P(g, g) \leq \mathcal{E}_{P'}(g, g)$ have to be equal!