

4 - Relative entropy

There is another way to measure the discrepancy between two probability measures, which is so popular that it has several names depending on the field (up to an additive term or/and change of sign): Kullback-Leibler divergence, Shannon entropy, Boltzmann entropy, ...

Definition 33

Consider $\mu, \pi \in \mathcal{P}(V)$.

The relative entropy of μ wrt π is

$$Ent(\mu | \pi) = \begin{cases} \sum \ln\left(\frac{\mu(x)}{\pi(x)}\right) \mu(x) & \text{if } \mu \ll \pi \\ \infty & \text{otherwise} \end{cases}$$

The relative entropy is not a distance, as it is not symmetric in μ and π . It is similar in nature to the chi-square discrepancy, as shown by

the following generalization.

Let $\varphi: \mathbb{R}_+ \rightarrow \mathbb{R}_+$ be a convex function vanishing only at 1.

The φ -entropy is defined by

$$\forall \mu, \pi \in \mathcal{P}(V),$$

$$\text{Ent}_{\varphi}(\mu|\pi) := \begin{cases} \sum_{x \in V} \varphi\left(\frac{\pi(x)}{\mu(x)}\right) \pi(x) & \text{if } \mu \ll \pi \\ \infty & \text{otherwise} \end{cases}$$

We have $\text{Ent}_{\varphi}(\mu|\pi) \in [0, \infty]$

and $\text{Ent}_{\varphi}(\mu|\pi) = 0$ if and only if

$\mu = \pi$. But it is not a distance,

since, as the relative entropy, it can

take the value ∞ .

- Let, $\forall r \geq 0$, $\varphi_0(r) := |r - 1|$

Then $\forall \mu \ll \pi \in \mathcal{P}(V)$, $\text{Ent}_{\varphi_0}(\mu|\pi) = 2\|\mu - \pi\|_{TV}$

(the only difference between Ent_{φ_0} and $2\|\cdot\|_{TV}$ comes from the convention when $\mu \not\ll \pi$).

- Let, $\forall r \geq 0$ $\varphi_2(r) := (r - 1)^2$

Then $\forall \mu, \pi \in \mathcal{P}(V)$, $\pi \gg \mu$ $\underbrace{\text{Ent}_{\varphi_2}(\mu|\pi)}_{\text{extension to all } \mu, \pi \in \mathcal{P}(V)} = \chi^2(\mu, \pi)$

- Let, $\forall r \geq 0$, $\varphi_1(r) := r \ln r - (r - 1)$

Then $\forall \mu, \pi \in \mathcal{P}(V)$, $\text{Ent}_{\varphi_1}(\mu|\pi) = \text{Ent}(\mu|\pi)$

Indeed it is sufficient to check this relation for $\mu \ll \pi$. Then

$$\begin{aligned} & \sum_{x \in V} \left(\frac{\mu(x)}{\pi(x)} \ln \frac{\mu(x)}{\pi(x)} - \frac{\mu(x)}{\pi(x)} + 1 \right) \pi(x) \\ &= \sum_{x \in V} \ln \frac{\mu(x)}{\pi(x)} \mu(x) - \underbrace{\sum_{x \in V} \mu(x) + \sum_{x \in V} \pi(x)}_{= -1 + 1 = 0} \end{aligned}$$

Similarly to χ^2 , the relative entropy controls the total variation:

Lemma 34 (Pinsker's inequality)

$$\left| \begin{array}{l} \forall \mu, \pi \in \mathcal{P}(V), \\ \|\mu - \pi\|_{TV} \leq \frac{1}{\sqrt{2}} \sqrt{Ent(\mu | \pi)} \end{array} \right.$$

Proof

It is sufficient to prove this bound for $\mu \ll \pi$.

Denote then $\beta = \frac{\mu}{\pi}$ the density of μ / π .

We have seen that

$$\|\mu - \pi\|_{TV} = \frac{1}{2} \sum_{x \in V} (f(x) - 1) \pi(x)$$

$$\text{Ent}(\mu|\pi) = \sum_{x \in V} \varphi_1(f(x)) \pi(x)$$

One can check the elementary bound:

$$\forall r \geq 0, \quad 3(r-1)^2 \leq (2r+4)(r \vee r-r+1)$$

Thus Cauchy-Schwarz' inequality

implies

$$\sum (f-1) \pi \leq \sum \sqrt{\frac{2f+4}{3}} \sqrt{\varphi_1(f)} \pi$$

$$\leq \underbrace{\sqrt{\sum \frac{2f+4}{3} \pi}}_{\frac{2}{3} + \frac{4}{3} = 2} \underbrace{\sqrt{\sum \varphi_1(f) \pi}}_{\text{Ent}(\mu|\pi)}$$

$$\frac{2}{3} + \frac{4}{3} = 2$$

$$= \sqrt{2} \sqrt{\text{Ent}(\mu|\pi)}$$

□

When $(\mu_t)_{t \geq 0}$ is the family of time-marginal laws of a Markov process associated to L , ^{an irreducible and reversible generator} it is then

meaningful to estimate

$$\forall t \geq 0, \quad I_t := \mathbb{E}_t(\omega_t | \Pi)$$

Lemma 35

$$\left\{ \begin{array}{l} \text{We have} \\ \forall t \geq 0, \quad \partial_t I_t = - \mathbb{E}_t(\ln f_t, f_t) \\ \text{where } f_t = \frac{\omega_t}{\Pi} \end{array} \right.$$

Proof

Recall that as soon as $t > 0$, $\omega_t > 0$. Furthermore φ_1 is differentiable on $(0, +\infty)$ and we have

$$\begin{aligned} \forall r > 0, \quad \varphi_1'(r) &= \frac{d}{dr}(r(\ln r - r + 1)) \\ &= \ln(r) \end{aligned}$$

We deduce for any $t \geq 0$,

$$\begin{aligned} \partial_t I_t &= \sum_{x \in V} \ln f_t(x) \int_x f_t(x) \Pi(x) \\ &= \sum_{x \in V} \ln f_t(x) L[f_t](x) \Pi(x) \\ &= \Pi[\ln f_t L[f_t]] \end{aligned}$$

$$= - \mathcal{E}_L(\ln f_r, f_r)$$

□

It leads us to introduce the

Definition 36

The modified logarithmic Sobolev constant associated to L is

$$\tilde{\alpha}(L) := \inf_{f \in \mathcal{F}_+(V) \setminus \text{Vect}(1)} \frac{\mathcal{E}_L(\ln f, f)}{\text{Ent}_\pi(f)}$$

where $\mathcal{F}_+(V) = \{f \in \mathcal{F}(V) : f \geq 0\}$

and

$$\forall f \in \mathcal{F}_+(V),$$

$$\text{Ent}_\pi(f) = \sum_{x \in V} \pi(x) \varphi_1\left(\frac{f(x)}{\pi[f]}\right) \pi(x)$$

Equivalently, $\tilde{\alpha}(L)$ is the smallest constant $\tilde{\alpha} \geq 0$ such that

$$\forall f \in \mathcal{F}_+(V),$$

$$\tilde{\alpha} \text{Ent}_\pi(f) \leq \mathcal{E}_L(f, \ln f)$$

From Lemma 35, we deduce

The differential inequality

$$\forall L > 0, \quad \partial_r \mathbb{I}_r \leq -\tilde{\chi}(L) \mathbb{I}_r$$

taking into account that for any

$$f = \frac{\mu}{\Pi}, \quad \text{Ent}_{\Pi}(f) = \text{Ent}(\mu | \Pi).$$

Since furthermore

$$\lim_{h \rightarrow 0_+} \mathbb{I}_h = \mathbb{I}_0$$

we get

Corollary 37

For any $t \geq 0$, we have

$$\text{Ent}(\mu_t | \Pi) \leq e^{-\tilde{\chi}(L)t} \text{Ent}(\mu_0 | \Pi)$$

and

$$\|\mu_t - \Pi\|_{h_t} \leq e^{-\frac{\tilde{\chi}(L)t}{2}} \sqrt{\frac{\text{Ent}(\mu_0 | \Pi)}{2}} \quad (21)$$

One can be doubtful about this

last bound: from (17') the

rate $\frac{\tilde{\chi}(L)}{2}$ cannot be better than $\lambda(L)$,

i.e. we always have

$$\frac{\tilde{\chi}(L)}{2} \leq \lambda(L) \quad (21')$$

Worse: we did not check yet that $\tilde{\alpha}(L) > 0$, see Corollary 21 below.

The interest of (21) is in the factor

$\sqrt{\text{Ent}(\text{vol } \Pi)}$ which can be much

smaller than $\sqrt{\chi^2(\text{vol } \Pi)}$.

Thus (21) should not be applied as $t \rightarrow +\infty$, but in some

intermediate time scale, as it will

be illustrated at the end of this lesson.

Before, we must present some comparisons of ergodic constants

such as $\lambda(L)$ and $\tilde{\alpha}(L)$, but

also with the following one:

Definition 38

The logarithmic Sobolev constant associated to L is defined by

$$\alpha(L) := \inf_{f \in F(V) \setminus \text{Vect}(1)} \frac{\mathcal{E}_L(\sqrt{f}, \sqrt{f})}{\text{Ent}_\Pi(f)} \quad (22)$$

This constant $\alpha(L)$ comes from the investigation of hyperconvexity,

Write a short introduction?

initially in continuous infinite dimensional frameworks.

The interest for us is that it is simpler to approximate than its "modified" version.

Here is a first comparison:

Lemma 39

We have
$$\tilde{\alpha}(L) \geq \alpha(L)$$

Proof

The elementary bound

$$\forall t \geq 0, \quad \forall s \geq -t$$

$$(h+s) \ln(h+s) \geq h \ln h + (1 + \ln(h))s + (\sqrt{h+s} - \sqrt{h})^2 \quad (23)$$

is a refinement of the convexity of the mapping $(\mathbb{R}_+ \ni t \mapsto t \ln t)$

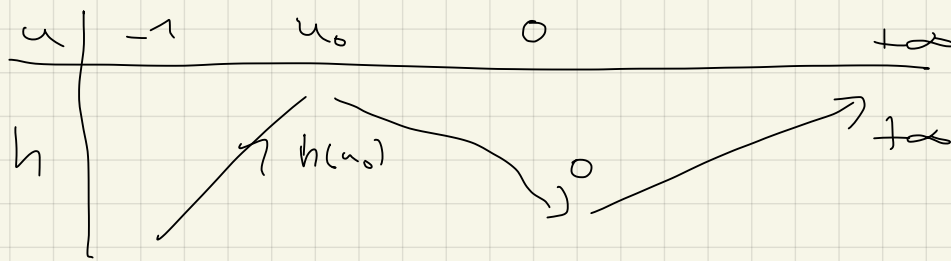
It is shown by posing

$u = s/r$ and considering

the function $h(u)$ obtained

by subtracting the r.h.s. to the l.h.s.

The variation table of h is



for a certain value $u_0 \in (-1, 0)$.

Consider $f \in \mathcal{F}_+(V)$ and $x, y \in V$

and apply (25) to $t+s = f(y)$

and $t = f(x)$, to get

$$f(y)(\ln f(y) - \ln f(x)) \geq f(y) - f(x) + (\sqrt{f(y)} - \sqrt{f(x)})^2$$

Multiply by $\pi(x) L(x, y)$ and sum

over $y, x \in V$ to get

$$\begin{aligned} \pi[f L[\ln f]] &\geq \pi[Lf] \\ &\quad + 2\mathcal{E}(\sqrt{f}, \sqrt{f}) \end{aligned}$$

$$= 2 \varepsilon_L(\sqrt{b}, \sqrt{f})$$

namely

$$\varepsilon_L(b, \ln f) \geq 2 \varepsilon_L(\sqrt{b}, \sqrt{f})$$

which leads to the desired bound
by minimizing over $f \in \mathcal{F}(V)$. $\square$

Let us consider the particular
case of the generator L_π

where $\pi \in \mathcal{F}(V)$, $\pi > 0$ is given

Lemma 40

We have

$$\alpha(L_\pi) \geq \frac{(1 - \sqrt{\pi_1})^2}{\ln \frac{1}{\pi_1} - 1 + \pi_1}$$

∴
 $\alpha \pi_1$

Proof

It is based on the elementary

bound:

$$\forall A > 1, \quad \forall r \in [0, A],$$

$$(\sqrt{r}-1)^2 \geq \frac{(\sqrt{A}-1)^2}{A \ln A - A + 1} (r \ln r - r + 1) \quad (24)$$

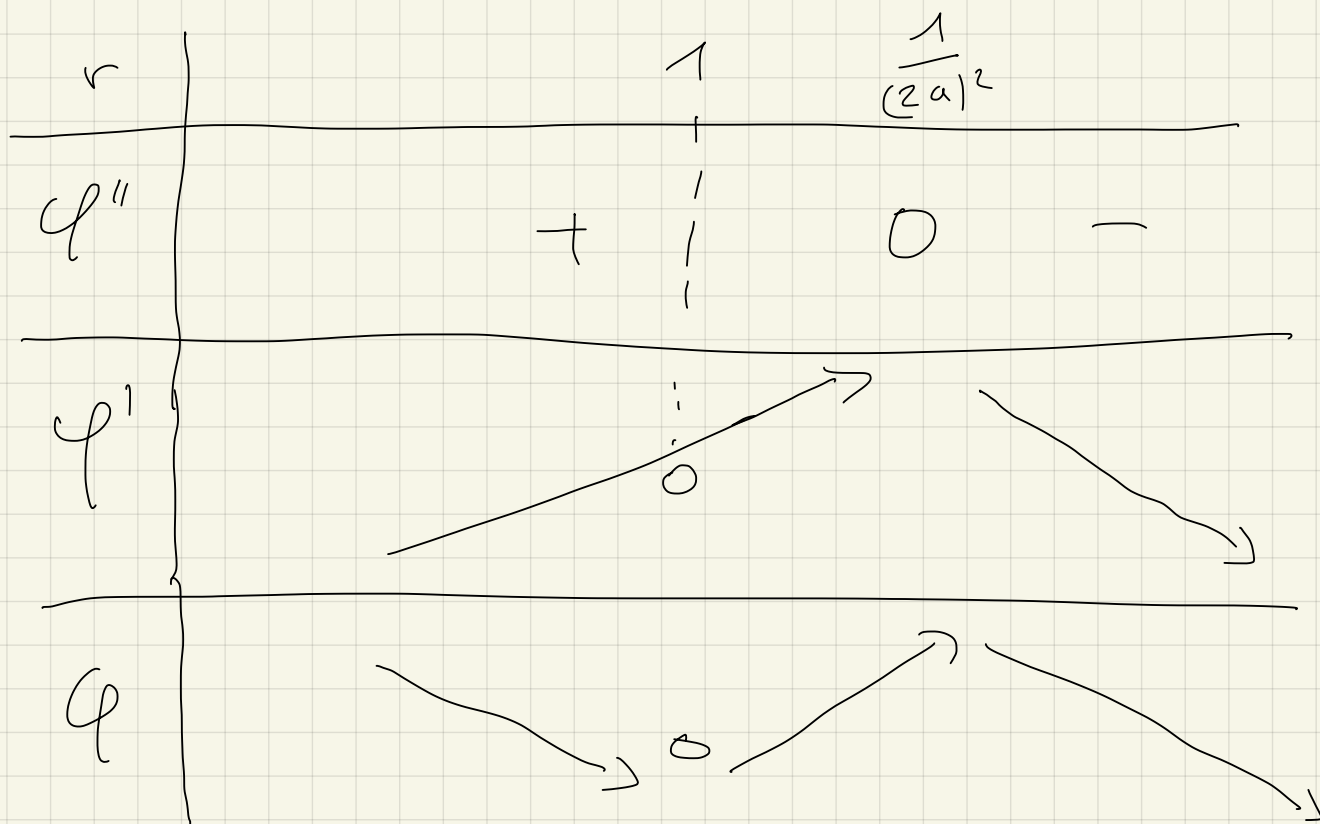
Indeed for any $a < \frac{1}{2}$, consider the mapping

$$\varphi_a: \mathbb{R}_+ \ni r \mapsto (\sqrt{r}-1)^2 - a(r \ln r - r + 1)$$

We compute

$$\forall r > 0, \quad \varphi_a''(r) = \frac{1}{r} \left(\frac{1}{2\sqrt{r}} - a \right)$$

We deduce the variation table



Thus taking $a < \frac{1}{2}$ such
 that $\phi_a(A) = 0$, for $A > 1$, we get
 that $\phi_a \geq 0$ on $[0, A]$,
 this amounts to (24).

By definition, we have

$$\begin{aligned} \alpha(L_\pi) &= \inf_{f \in \bigcup_{+} f(v) \setminus \text{Vect}(V)} \frac{\sum_{L_\pi} (f f)}{\text{Ent}_\pi(f)} \\ &= \inf_{\substack{f \in \bigcup_{+} f(v) \setminus \{0\} \\ \pi(f) = 1}} \frac{\sum_{L_\pi} (f f)}{\text{Ent}_\pi(f)} \end{aligned}$$

Since both the numerator and
 denominator are 1-homogeneous.

For $f \in \bigcup_{+} f(v)$, with $\pi(f) = 1$,
 we have

$$\forall x \in V \quad f(x) \leq \frac{1}{\pi(x)} \leq \frac{1}{\pi_1}$$

Applying (24) with $v = f(y)$

, For $f \in \mathcal{F}_+(V)$, $\pi(f)=1$, and $x \in V$

and integrating with respect to π

in x , we get

$$\begin{aligned} \pi[(\sqrt{f}-1)^2] &\geq \frac{(\sqrt{1/\pi_1}-1)^2}{\underbrace{\frac{1}{\pi_1} \ln \frac{1}{\pi_1} - \frac{1}{\pi_1} + 1}} E_{\pi_1}(f) \\ &\stackrel{(*)}{=} \text{Var}(\sqrt{f}, \pi) \\ &\stackrel{(**)}{\geq} \varepsilon_{L_\pi}(\sqrt{f}, \sqrt{f}) \quad \frac{(1-\sqrt{\pi_1})^2}{\ln \frac{1}{\pi_1} - 1 + \pi_1} \end{aligned}$$

which implies the wanted bound.

□

Remark

The true value of $\alpha(L_\pi)$ has been obtained by more involved computations:

$$\alpha(L_\pi) = \frac{1 - 2\pi_1}{\ln((1-\pi_1)/\pi_1)}$$

But our bound is not bad as

$$\pi_1 \rightarrow 0_+ :$$

$$a_{\pi_1} := \frac{(1 - \sqrt{\pi_1})^2}{\ln \frac{1}{\pi_1} - 1 + \pi_1} \sim \frac{1}{\ln \frac{1}{\pi_1}} \sim \alpha(L_\pi)$$

(But for $\pi_1 = 1/2$, $a_{1/2} \approx 0,444$

while $\alpha(L_\pi) = 1/2 = \frac{\alpha(L_\pi)}{2}$
 $(1/2, 1/2)$

Corollary 41

For any L irreducible and reversible with respect to π , we have

$$\tilde{\alpha}(L) \geq \alpha(L) \geq 2a_{\pi_1} \alpha(L)$$

In particular both $\tilde{\alpha}(L)$ and $\alpha(L)$ are positive

Proof

It is sufficient to show the bound

$$\alpha(L) \geq a_\pi \alpha(L)$$

Consider $f \in \bigcup_+ (V)$, we have

$$\mathcal{E}_L(\sqrt{f}, \sqrt{f}) \geq \lambda(L) \text{Var}(\sqrt{f}, \pi)$$

$$\geq \lambda(L) a_{\pi_L} \text{Ent}(f, \pi)$$

according to Lemma 40.

□

Both the modified log-Sob and the log-Sob constants enjoy the tensorization property.

Let us show it for $\tilde{\lambda}(L)$, leaving the $\lambda(L)$ case as an exercise. (write it!)

Consider $d \geq 2$ finite spaces

$V_1, \dots, V_d$ endowed with

irreducible Markov generators $L_1, \dots, L_d$,

reversible with respect to $\pi_1, \dots, \pi_d$.

Define on $V = V_1 \times \dots \times V_d$

$L = L_1^{(1)} + \dots + L_d^{(d)}$, which is ^{irred. and} reversible
 $\pi := \pi_1 \otimes \pi_2 \otimes \dots \otimes \pi_d$

where $L_a^{(a)}$ acts on the factor V_a as L_a , leaving the other factors free of action.

Theorem 42

$$\left\{ \begin{array}{l} \text{We have} \\ \alpha(L) = \min_{1 \leq k \leq d} \tilde{\alpha}(L_k) \end{array} \right.$$

Proof

By iteration, it is sufficient to consider the case $d=2$.

Consider any $f \in \mathcal{F}_+(V)$ with $\Pi(f)$, we want to check that

$$a \text{Ent}_H(f) \leq \mathcal{E}_L(f, \log f)$$

$$\text{where } a = \tilde{\alpha}(L_1) \wedge \tilde{\alpha}(L_2)$$

Write μ the probability measure admitting f as density / Π .

Let us decompose μ in

$$\forall (x_1, x_2) \in V, \quad \mu(x_1, x_2) = \underbrace{\mu_2(x_2 | x_1)}_{\text{conditional probability of } x_2 \text{ knowing } x_1} \underbrace{\mu_1(x_1)}_{\text{marginal of } \mu \text{ on } V_1}$$

$\mathcal{W}_e$ have

$$\mathbb{E}_{\pi}[\ell] = \sum_{(x_1, x_2) \in V} \ln \frac{\mu_2(x_2 | x_1) \mu_1(x_1)}{\pi_2(x_2) \pi_1(x_1)} \mu_2(x_2 | x_1) \mu_1(x_1)$$

$$= \sum_{(x_1, x_2) \in V} \ln \frac{\mu_2(x_2 | x_1)}{\pi_2(x_2)} \mu_2(x_2 | x_1) \mu_1(x_1)$$

$$+ \sum_{(x_1, x_2) \in V} \ln \frac{\mu_1(x_1)}{\pi_1(x_1)} \mu_2(x_2 | x_1) \mu_1(x_1)$$

$$= \sum_{x_1 \in V} \mathbb{E}_{\pi}(\mu_2(\cdot | x_1) | \pi_2) \mu_1(x_1)$$

$$+ \sum_{x_1 \in V} \ln \frac{\mu_1(x_1)}{\pi_1(x_1)} \mu_1(x_1)$$

$$= \sum_{x_1 \in V} \mathbb{E}_{\pi_2}(\beta_2(\cdot | x_1)) \mu_1(x_1)$$

$$+ \mathbb{E}_{\pi_1}(\beta_1) \quad (25)$$

where for all $(x_1, x_2) \in V$,

$$f_2(x_2 | x_1) = \frac{\mu_2(x_2 | x_1)}{\pi_2(x_2)}$$

$$f_1(x_1) = \frac{\mu_1(x_1)}{\pi_1(x_1)}$$

Let us first consider the part $L_2^{(2)}$ of L :

$$\begin{aligned} \mathbb{E}_{L_2^{(2)}}(\ln f, f) &= \\ &= \sum_{x_1, y \in V} f(x) (\ln f(y) - \ln f(x)) \pi(x) L_2^{(2)}(x, y) \\ &= \sum_{\substack{(x_1, x_2) \in V \\ y_2 \in V}} f(x_1, x_2) (\ln f(x_1, y_2) - \ln f(x_1, x_2)) \pi(x_1) \pi(x_2) L_2^{(2)}(x_1, y_2) \\ &= \sum_{x_1 \in V_1} \mathbb{E}_{L_2} \left(f_2(\cdot | x_1), \ln f_2(\cdot | x_1) \right) f(x_1) \pi(x_1) \end{aligned}$$

$$\geq \frac{1}{2(L_2)} \sum_{x_1 \in V_1} \mathbb{E}_{\pi_2} \left(f_2(\cdot | x_1) \right) \mu_1(x_1)$$

Which is the first part in (25).

Coming to $L_1^{(1)}$, we get

Symmetrically,

$$\sum_{L_1^{(1)}} (f, f) \geq \tilde{\alpha}(L_1) \sum_{x_2 \in V_2} \text{Ent}_{\pi_1}(f_1(\cdot | x_2)) \mu_2(x_2)$$

(Comparing with the second part
in (25), it remains to show

that

$$\sum_{x_2 \in V_2} \text{Ent}_{\pi_1}(f_1(\cdot | x_2)) \mu_2(x_2) \geq \text{Ent}_{\pi_1}(f_1) \quad (26)$$

Using Jensen's inequality we get

$$\begin{aligned} & \sum_{x_2 \in V_2} \text{Ent}_{\pi_1}(f_1(\cdot | x_2)) \mu_2(x_2) \\ &= \sum_{x_2 \in V_2} \pi_1 \left[\varphi_1(f_1(\cdot | x_2)) \right] \mu_2(x_2) \\ &\geq \pi_1 \left[\varphi_1 \left(\sum_{x_2 \in V_2} f_1(\cdot | x_2) \mu_2(x_2) \right) \right] \end{aligned}$$

Since φ_1 is convex,

For any $x_1 \in V_1$, we have

$$\sum_{x_2 \in V} f_1(x_1 | x_2) \mu_2(x_2) = \sum_{x_2 \in V} \frac{\mu_1(x_1 | x_2) \mu_2(x_2)}{\pi_1(x_1)}$$

$$= \frac{\mu_1(x_1)}{\pi_1(x_1)} = f_1(x_1)$$

thus (26) follows.

□

Let us come back to Example 29.

Since π is uniform over $\mathbb{Z}_N^d$,

$$\text{we have } \pi_1 = \frac{1}{N^d}.$$

Proposition 41 then implies as $N \rightarrow \infty$

$$\tilde{\alpha}(L_N^{(d)}) \geq \frac{2}{d \ln(N)} \alpha(L_N^{(d)})$$

$$\sim \frac{2}{d \ln(N)} \frac{4\pi^2}{N^2}$$

It is thus better to use

Theorem 42:

$$\tilde{\alpha}(L_N^{(1)}) = \tilde{\alpha}(L_N)$$

$$\geq \frac{2}{\ln(N)} \alpha(L_N)$$

$$\sim \frac{2}{\ln(N)} \frac{4\pi^2}{N^2} \quad (27)$$

We have for any $t \geq 0$,

$$\|m_t - \pi\|_{TV} \leq e^{-\tilde{\alpha}(L_N^{(d)})t} \sqrt{\frac{\text{Ent}(m_0 | \pi)}{2}}$$

Using Jensen, the worse case is when m_0 is a Dirac mass at some $x_0 \in V$

$$\text{Ent}(S_{x_0} | \pi)$$

$$= \ln \frac{1}{\pi(x_0)} \leq \ln \frac{1}{\pi_1}$$

Put that directly in (21)

Let be given $\varepsilon > 0$.

We will have $\|m_t - \pi\|_{TV} \leq \varepsilon$

as soon as

$$\sqrt{\frac{\ln 1/\pi_1}{2}} e^{-\tilde{\alpha}(L_N^{(d)})t} \leq \varepsilon$$

and using (27) it will satisfied for

$$\text{Some } t \sim \frac{N^2 \ln(N)}{8\pi^2} \left(\frac{1}{2} \ln \frac{\ln(N^4)}{2} + \ln 1/\varepsilon \right)$$

for fixed $\varepsilon > 0$, as $N, d \rightarrow \infty$

$$\sim \frac{N^2 \ln(N)}{16 d^2} (\ln d + \ln(\ln(N)))$$

which is much better in terms of $d \gg 1$
than the bound obtained using the
spectral gap.

Remark

In Corollary 4.1, the bound

$$\tilde{\alpha}(L) \geq 2 \alpha_{\pi_1} \geq \alpha(L)$$

can be far from optimal.

Indeed let us come back to

L_π , for $\pi > 0$ on V .

We compute that the spectral
decomposition of $f - L_\pi$ is

eigenvalue	multiplicity	eigenspace
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0	[1]	$\text{Vect}(1)$
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1	$[N-1]$	$\{f \in f(V) : \pi[f] = 0\}$
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so that $\Delta(L_\pi) = 1$

Furthermore, $\forall f \in \mathcal{F}_+(V)$ with $\pi[f]=1$, we have

$$\sum_{L_\pi} (f, \ln f) = \sum_{x, y \in V} \pi(x)\pi(y) f(x) (\ln f(x) - \ln f(y))$$

$$= \sum_{x \in V} \pi(x) f(x) \ln f(x) - \sum_{y \in V} \pi(y) \ln f(y)$$

$$= \sum_{x \in V} \pi(x) f(x) - \sum_{y \in V} \pi(y) \ln f(y)$$

$$= \mathbb{E}_{L_\pi}(f) - \pi[f] \pi[\ln f]$$

Note that by Jensen

$$\pi[\ln f] \leq \ln \pi[f] = 0$$

so $\sum_{L_\pi} (f, \ln f) \geq \mathbb{E}_{L_\pi}(f)$

and $\Delta(L_\pi) \geq 1$

But $a_{\pi_1} \xrightarrow{\pi_1 \rightarrow 0} +\infty$.