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TRANSPORT-ENTROPY INEQUALITIES ON LOCALLY ACTING GROUPS OF PERMUTATIONS

PAUL-MARIE SAMSON

ABSTRACT. Following Talagrand's concentration results for permutations picked uniformly at random from a symmetric group [Tal95], Luczak and McDiarmid have generalized it to more general groups G of permutations which act suitably 'locally'. Here we extend their results by setting transport-entropy inequalities on these permutations groups. Talagrand and Luczak-Mc-Diarmid concentration properties are consequences of these inequalities. We also consider transport-entropy inequalities on G for a larger class of measures. By projection, we derive transport-entropy inequalities for the uniform law on the slice of the discrete hypercube and more generally for the multinomial law. These results are new examples, in discrete setting, of weak transport-entropy inequalities introduced in [GRST14], that contribute to a better understanding of the concentration properties of measures on permutations groups.

1. INTRODUCTION

Let S_n denote the symmetric group of permutations acting on a set Ω of cardinality n , and μ denote the uniform law on S_n , $\mu(\sigma) := \frac{1}{n!}$, $\sigma \in S_n$. A seminal concentration result on S_n obtained by Maurey is the following.

Theorem 1.1. [Mau79] *Let d_H be the Hamming distance on the symmetric group, for all $\sigma, \tau \in S_n$,*

$$d_H(\sigma, \tau) := \sum_{i \in \Omega} \mathbb{1}_{\sigma(i) \neq \tau(i)}.$$

Then for any subset $A \subset S_n$ such that $\mu(A) \geq 1/2$, and for all $t \geq 0$, one has

$$\mu(A_t) \geq 1 - 2e^{-\frac{t^2}{64n}},$$

where $A_t := \{y \in S_n, d_H(x, A) \leq t\}$.

Milman and Schechtman [MS86] generalized this result to some groups whose distance is invariant by translation. For example, in the above result we may replace (up to constants) the Hamming distance by the *transposition distance* $d_T(\sigma, \tau)$ that

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corresponds to the minimal number of transpositions t_1, \dots, t_k such that $\sigma t_1 \cdots t_k = \tau$. The distances d_T and d_H are comparable,

$$\frac{1}{2}d_H(\sigma, \tau) \leq d_T(\sigma, \tau) \leq d_H(\sigma, \tau) - 1, \quad \forall \sigma \neq \tau.$$

(We refer to [BHT06] for comments about these comparison inequalities).

A few years later, a stronger concentration property in terms of dependence in the parameter n , has been settled by Talagrand using the so-called ‘‘convex-hull’’ method [Tal95] (see also [Led01]). This property implies Maurey’s result with a slightly worse constant. Let us recall some notations from [Tal95]. For each $A \subset S_n$ and $\sigma \in S_n$, let $V(\sigma, A) \subset \mathbb{R}^\Omega$ be the set of vectors $z = (z_j)_{j \in \Omega} \in \mathbb{R}^\Omega$ with $z_j := \mathbb{1}_{\sigma(j) \neq y(j)}$ for $y \in A$. Let $\text{conv}(V(\sigma, A))$ denote the convex hull of $V(\sigma, A)$ in \mathbb{R}^Ω ,

$$V(\sigma, A) := \left\{ x = (x_j)_{j \in \Omega}, \exists p \in \mathcal{P}(A), \forall j \in \Omega, x_j = \int \mathbb{1}_{\sigma(j) \neq y(j)} dp(y) \right\},$$

where $\mathcal{P}(A)$ denotes the set of probability measures on A . Talagrand introduced the quantity

$$f(\sigma, A) := \inf \{ \|x\|_2^2; x \in \text{conv}(V(\sigma, A)) \}.$$

with $\|x\|_2^2 := \sum_{i \in \Omega} x_i^2$, that measures the distance from σ to the subset A .

Theorem 1.2. [Tal95] *For any subset $A \subset S_n$,*

$$\int_{S_n} e^{f(\sigma, A)/16} d\mu(\sigma) \leq \frac{1}{\mu(A)}.$$

Maurey’s concentration result easily follows by observing that

$$f(\sigma, A) \geq \frac{1}{n} \left(\inf \left\{ \sum_{i \in \Omega} x_i; x \in \text{conv}(V(\sigma, A)) \right\} \right)^2 = \frac{1}{n} d_H^2(\sigma, A)$$

and applying Tchebychev inequality with usual optimization arguments.

Talagrand’s result has been first extended to product of symmetric groups by McDiarmid [McD02], and then further by Luczak and McDiarmid to cover more general permutation groups which act suitably ‘‘locally’’ [LM03].

For any $\sigma \in S_n$, the *support* of σ , denoted by $\text{supp}(\sigma)$, is the set $\{i \in \Omega, \sigma(i) \neq i\}$ and the *degree* of σ , denoted by $\text{deg}(\sigma)$, is the cardinality of $\text{supp}(\sigma)$, $\text{deg}(\sigma) = |\text{supp}(\sigma)|$. By definition, according to [LM03], a subgroup G of S_n is ℓ -local, $\ell \in \{2, \dots, n\}$, if for any $\sigma \in G$ and any $i, j \in \Omega$ with $\sigma(i) = j$, there exists $\tau \in G$ such that $\text{supp}(\tau) \subset \text{supp}(\sigma)$, $\text{deg}(\tau) \leq \ell$ and $\tau(i) = j$.

As explained in [LM03], any 2-local group is a direct product of symmetric groups on its orbits, the alternating group (consisting of even permutations) is 3-local, and any 3-local group is a direct product of symmetric or alternating groups on its orbits.

In the present paper, the concentration result by Luczak-McDiarmid and Talagrand is a consequence of a weak transport-entropy inequality satisfied by the uniform law on G . We also prove weaker type of transport entropy inequalities for a larger class of probability measures on G , denoted by \mathcal{M} .

For a better comprehension of the class of measures \mathcal{M} , let us first consider the case of the symmetric group S_n on $[n] := \{1, \dots, n\}$. Let (i, j) denote the transposition in S_n that exchanges the elements i and j in $[n]$. One may easily check that the map

$$U : \begin{array}{ccc} \{1, 2\} \times \{1, 2, 3\} \times \dots \times \{1, \dots, n\} & \rightarrow & S_n \\ (i_2, i_3, \dots, i_n) & \mapsto & (i_2, 2)(i_3, 3) \dots (i_n, n), \end{array}$$

is one to one.

The set of measures \mathcal{M} consists of probability measures on S_n which are pushed forward by the map U of product probability measures on $\{1, 2\} \times \{1, 2, 3\} \times \dots \times \{1, \dots, n\}$,

$$\mathcal{M} := \{U\#\hat{\nu}, \hat{\nu} = \hat{\nu}_2 \otimes \dots \otimes \hat{\nu}_n \text{ with } \hat{\nu}_i \in \mathcal{P}([i]), \forall i \in [n]\},$$

where by definition $U\#\hat{\nu}(C) = \hat{\nu}(U^{-1}(C))$ for any subset C in S_n . The uniform measure μ on S_n belongs to \mathcal{M} since $\mu = U\#\hat{\mu}$ with $\hat{\mu} = \hat{\mu}_2 \otimes \dots \otimes \hat{\mu}_n$, where for each i , $\hat{\mu}_i$ denotes the uniform probability measure on $[i]$.

Let us now construct the class of measures \mathcal{M} for any ℓ -local group G . To clarify the notations, the elements of Ω are labelled with integers, $\Omega = [n]$.

The *orbit* of an element $j \in \Omega$, denoted by $\text{orb}(j)$, is the set of elements in Ω connected to j by a permutation of G ,

$$\text{orb}(j) := \{\sigma(j), \sigma \in G\}.$$

Let us observe that for any $j \in [n]$, $j \in \text{orb}(j)$ since the identity belongs to G . The identity will be denoted by id .

Lemma 1.1. *Let G be a ℓ -local subgroup of S_n . For any $j \in \{2, \dots, n\}$ let $I_j = \text{orb}(j) \cap [j]$. There exists a fixed family of permutations $\mathcal{T} = (t_{i,j})$ with $j \in \{2, \dots, n\}$ and $i_j \in I_j$ with $t_{j,j} = id$ and for every $i_j \neq j$*

$$t_{i_j,j}(i_j) = j, \quad \text{supp}(t_{i_j,j}) \subset [j], \quad \text{and} \quad \text{deg}(t_{i_j,j}) \leq \ell,$$

such that the map

$$(1) \quad \begin{array}{ccc} I_2 \times I_3 \times \dots \times I_n & \rightarrow & G \\ U_{\mathcal{T}} : (i_2, i_3, \dots, i_n) & \mapsto & t_{i_2,2} t_{i_3,3} \dots t_{i_n,n}, \end{array}$$

is one to one. Such a family \mathcal{T} is called “ ℓ -local base of G ” in the present paper.

The proof of this lemma simply follows from the definition of the ℓ -local property, the details of the proof are let to the reader.

As for the symmetric group, the class \mathcal{M} is made up of all probability measures on G which are pushed forward of product probability measures on $I_2 \times I_3 \times \dots \times I_n$ by a map $U_{\mathcal{T}}$ defined by (1),

$$(2) \quad \mathcal{M} := \{U_{\mathcal{T}}\#\hat{\nu}, \hat{\nu} = \hat{\nu}_2 \otimes \dots \otimes \hat{\nu}_n \text{ with } \hat{\nu}_i \in \mathcal{P}(I_i), \forall i \in \{2, \dots, n\}\},$$

where \mathcal{T} is a ℓ -local base of G . The class \mathcal{M} contains the uniform law on G , obtained by choosing for each $\hat{\nu}_i$ the uniform law on I_i .

In this paper, the concentration results are derived from weak transport-entropy inequalities, involving the relative entropy $H(\nu|\mu)$ between two probability measures μ, ν on G given by

$$H(\nu|\mu) := \int \log \left(\frac{d\nu}{d\mu} \right) d\nu,$$

if ν is absolutely continuous with respect to μ and $H(\nu|\mu) := +\infty$ otherwise.

The terminology “weak transport-entropy” introduced in [GRST14], encompass many kinds of transport-entropy inequalities from the well-known Talagrand’s transport inequality satisfied by the standard Gaussian measure on \mathbb{R}^n [Tal96], to the usual Csizár-Kullback-Pinsker inequality [Pin64, Csi67, Kul67] that holds for any (reference) probability measure μ on a Polish metric space \mathcal{X} , namely

$$(3) \quad \|\mu - \nu\|_{TV}^2 \leq 2H(\nu|\mu), \quad \forall \nu \in \mathcal{P}(\mathcal{X}).$$

where $\|\mu - \nu\|_{TV}$ denotes the total variation distance between μ and ν ,

$$\|\mu - \nu\|_{TV} := 2 \sup_A |\mu(A) - \nu(A)|,$$

above the supremum runs over all measurable subset A of \mathcal{X} . We refer to the survey [Sam16b, Sam16a] for other examples of weak transport-entropy inequalities and their connections with the concentration of measure principle.

The next theorem is one of the main result of this paper. It presents new weak transport inequalities for the uniform measure on G or measures in the class \mathcal{M} , that recover the concentration results of Theorems 1.1 and 1.2.

We also denote by d_H the Hamming distance on G : for any $\sigma, \tau \in G$,

$$d_H(\sigma, \tau) := \deg(\sigma\tau^{-1}) = \sum_{i=1}^n \mathbb{1}_{\sigma(i) \neq \tau(i)},$$

and the distance $d_T(\sigma, \tau)$ is defined as the minimal number of elements of G , t_1, \dots, t_k , with degree less than ℓ , such that $\sigma t_1 \cdots t_k = \tau$.

For any measures $\nu_1, \nu_2 \in \mathcal{P}(G)$, the set $\Pi(\nu_1, \nu_2)$ denotes the set of all probability measures on $G \times G$ with first marginal ν_1 and second marginal ν_2 . The Wasserstein distance between ν_1 and ν_2 , according to the distance $d = d_H$ or $d = d_T$, is given by

$$W_1(\nu_1, \nu_2) := \inf_{\pi \in \Pi(\nu_1, \nu_2)} \iint d(\sigma, \tau) d\pi(\sigma, \tau).$$

We also consider two other optimal weak transport costs, $\tilde{T}_2(\nu_2|\nu_1)$ and $\hat{T}_2(\nu_2|\nu_1)$ defined by

$$(4) \quad \tilde{T}_2(\nu_2|\nu_1) := \inf_{\pi \in \Pi(\nu_1, \nu_2)} \int \left(\int d(\sigma, \tau) dp_\sigma(\tau) \right)^2 d\nu_1(\sigma),$$

and

$$\hat{T}_2(\nu_2|\nu_1) := \inf_{\pi \in \Pi(\nu_1, \nu_2)} \int \sum_{i=1}^n \left(\int \mathbb{1}_{\sigma(i) \neq \tau(i)} dp_\sigma(\tau) \right)^2 d\nu_1(\sigma),$$

where p_σ represents any probability measure such that $\pi(\sigma, \tau) = \nu_1(\sigma)p_\sigma(\tau)$ for all $\sigma, \tau \in G$. By Jensen's inequality, these weak transport costs are comparable, namely

$$W_1^2(\nu_1, \nu_2) \leq \tilde{T}_2(\nu_2|\nu_1) \leq n\hat{T}_2(\nu_2|\nu_1),$$

where the last inequality only holds for $d = d_H$.

Theorem 1.3. *Let G be a ℓ -local subgroup of S_n , $G \neq \{id\}$.*

(a) *Let μ be a probability measure of the set \mathcal{M} defined by (2). Then, for all probability measures ν_1 and ν_2 on G ,*

$$(5) \quad \frac{2}{K_n c(\ell)^2} W_1^2(\nu_1, \nu_2) \leq \left(\sqrt{H(\nu_1|\mu)} + \sqrt{H(\nu_2|\mu)} \right)^2,$$

and

$$(6) \quad \frac{1}{2K_n c(\ell)^2} \tilde{T}_2(\nu_2|\nu_1) \leq \left(\sqrt{H(\nu_1|\mu)} + \sqrt{H(\nu_2|\mu)} \right)^2,$$

where K_n is the cardinality of the set $\{j \in \{2, \dots, n\}, I_j \neq \{j\}\}$, and

$$c(\ell) := \begin{cases} \min(2\ell - 1, n) & \text{if } d = d_H, \\ 2 & \text{if } d = d_T. \end{cases}$$

When μ is the uniform law on G , inequalities (5) and (6) hold with

$$c(\ell) := \begin{cases} \ell & \text{if } d = d_H, \\ 1 & \text{if } d = d_T. \end{cases}$$

(b) *Let μ denotes the uniform law on G . Then, for all probability measures ν_1 and ν_2 on G ,*

$$(7) \quad \frac{1}{2c(\ell)^2} \hat{T}_2(\nu_2|\nu_1) \leq \left(\sqrt{H(\nu_1|\mu)} + \sqrt{H(\nu_2|\mu)} \right)^2,$$

where $c(\ell)^2 = 2(\ell - 1)^2 + 2$.

The proofs of these results, given in the next section, are inspired by Talagrand seminal work on S_n [Tal95], and Luczak-McDiarmid extension to ℓ -local groups [LM03].

Comments :

- Here is a more popular dual formulation of the transport-entropy inequality (5): for all 1-Lipschitz functions $\varphi : G \rightarrow \mathbb{R}$ (with respect to the distance d),

$$(8) \quad \int e^\varphi d\mu \leq e^{\int \varphi d\mu + K_n c(\ell)^2 t^2 / 8}, \quad \forall t \geq 0.$$

For the uniform measure on S_n , $K_n = n - 1$ and this property is widely commented in [BHT06]; it is also a consequence of Hoeffding inequalities for bounded martingales (see page 18 of [Hoe63]). The concentration result derived from item (a) are of the same nature as the one obtained by the ‘‘bounded differences approach’’ in [Mau79, McD89, McD02, LM03].

- Similarly, by Proposition 4.5 and Theorem 2.7 of [GRST14] and using the identity

$$(\sqrt{u} + \sqrt{v})^2 = \inf_{\alpha \in (0,1)} \left\{ \frac{u}{\alpha} + \frac{v}{1-\alpha} \right\},$$

we may easily show that the weak transport-entropy inequality (6) is equivalent to the following dual property: for any real function φ on G and for any $0 < \alpha < 1$,

$$(9) \quad \left(\int e^{\alpha \tilde{Q}_{K_n} \varphi} d\mu \right)^{1/\alpha} \left(\int e^{-(1-\alpha)\varphi} d\mu \right)^{1/(1-\alpha)} \leq 1,$$

where the infimum-convolution operator $\tilde{Q}_t \varphi$, $t \geq 0$, is defined by

$$\tilde{Q}_t \varphi(\sigma) := \inf_{p \in \mathcal{P}(G)} \left\{ \int \varphi dp + \frac{1}{2c^2(\ell)t} \left(\int d(\sigma, y) dp(y) \right)^2 \right\}, \quad \sigma \in G.$$

Moreover, let us observe that following our proof of (9) in the next section, for each $\alpha \in (0, 1)$ the inequality (9) can be improved by replacing the square cost function by the convex cost $c_\alpha(u) \geq u^2/2, u \geq 0$ given in Lemma 2.2. More precisely, (9) holds replacing $\tilde{Q}_{K_n} \varphi$ by $\tilde{Q}_{K_n}^\alpha \varphi$ defined by

$$\tilde{Q}_t^\alpha \varphi(\sigma) := \inf_{p \in \mathcal{P}(S_n)} \left\{ \int \varphi dp + tc_\alpha \left(\frac{1}{c(\ell)t} \int d(\sigma, y) dp(y) \right)^2 \right\},$$

for any $\sigma \in G, t > 0$.

- Proposition 4.5 and Theorem 9.5 of [GRST14] also provide a dual formulation of the weak transport-entropy inequality (7): for any real function φ on G and for any $0 < \alpha < 1$,

$$(10) \quad \left(\int e^{\alpha \widehat{Q} \varphi} d\mu \right)^{1/\alpha} \left(\int e^{-(1-\alpha)\varphi} d\mu \right)^{1/(1-\alpha)} \leq 1,$$

where the infimum convolution operator $\widehat{Q} \varphi$ is defined by

$$\widehat{Q} \varphi(\sigma) = \inf_{p \in \mathcal{P}(G)} \left\{ \int \varphi dp + \frac{1}{2c(\ell)^2} \sum_{k=1}^n \left(\int \mathbb{1}_{\sigma(k) \neq y(k)} dp(y) \right)^2 \right\}, \quad \sigma \in G.$$

As explained at the end of this section, the property (10) directly provides the following version of the Talagrand's concentration result for the uniform law on G .

Corollary 1.1. *Let μ denotes the uniform law on a ℓ -local subgroup G of S_n . Then, for all $A \subset G$ and all $\alpha \in (0, 1)$, one has*

$$\int e^{\frac{\alpha}{2c(\ell)^2} f(\sigma, A)} d\mu(\sigma) \leq \frac{1}{\mu(A)^{\alpha/(1-\alpha)}},$$

with $c(\ell)^2 = 2(\ell - 1)^2 + 2$. As a consequence, by Tchebychev inequality, for any $\alpha \in (0, 1)$ and all $t \geq 0$,

$$\mu(\{\sigma \in G, f(\sigma, A) \geq t\}) \leq \frac{e^{-\frac{\alpha t}{2c(\ell)^2}}}{\mu(A)^{\alpha/(1-\alpha)}}.$$

For $\alpha = 1/2$, this result is exactly Theorem 2.1 by Luczak-McDiarmid [LM03], that generalizes Theorem 1.2 on S_n (since S_n is a 2-local group).

By projection arguments, Theorem 1.3 applied to the uniform law μ on the symmetric group S_n , also provides transport-entropy inequalities for the uniform law on the slices of the discrete cube $\{0, 1\}^n$. Namely, for $n \geq 1$, let us denote by $\mathcal{X}_{k,n-k}$, $k \in \{0, \dots, n\}$, the slices of discrete cube defined by

$$\mathcal{X}_{k,n-k} := \left\{ x = (x_1, \dots, x_n) \in \{0, 1\}^n, \sum_{i=1}^n x_i = k \right\}.$$

The uniform law on $\mathcal{X}_{k,n-k}$, denoted by $\mu_{k,n-k}$, is the pushed forward of μ by the projection map

$$\begin{aligned} S_n &\rightarrow \mathcal{X}_{k,n-k} \\ P : \sigma &\mapsto \mathbb{1}_{\sigma([k])}, \end{aligned}$$

where $\sigma([k]) := \{\sigma(1), \dots, \sigma(k)\}$ and for any subset A of $[n]$, $\mathbb{1}_A$ is the vector with coordinates $\mathbb{1}_A(i)$, $i \in [n]$. In other terms, $\mu_{k,n-k} = P\#\mu$ and $\mu_{k,n-k}(x) = \binom{n}{k}^{-1}$ for all $x \in \mathcal{X}_{k,n-k}$. Let d_h denotes the Hamming distance on $\mathcal{X}_{k,n-k}$ defined by

$$d_h(x, y) := \frac{1}{2} \sum_{i=1}^n \mathbb{1}_{x_i \neq y_i}, \quad x, y \in \mathcal{X}_{k,n-k}.$$

Theorem 1.4. *Let $\mu_{k,n-k}$ be the uniform law on $\mathcal{X}_{k,n-k}$, a slice of the discrete cube.*

(a) *For all probability measures ν_1 and ν_2 on $\mathcal{X}_{k,n-k}$,*

$$\frac{2}{C_{k,n-k}} W_1^2(\nu_1, \nu_2) \leq \left(\sqrt{H(\nu_1|\mu_{k,n-k})} + \sqrt{H(\nu_2|\mu_{k,n-k})} \right)^2,$$

and

$$\frac{1}{2C_{k,n-k}} \tilde{T}_2(\nu_2|\nu_1) \leq \left(\sqrt{H(\nu_1|\mu_{k,n-k})} + \sqrt{H(\nu_2|\mu_{k,n-k})} \right)^2,$$

where W_1 is the Wasserstein distance associated to d_h , \tilde{T}_2 is the weak optimal transport cost defined by (4) with $d = d_h$, and $C_{k,n-k} = \min(k, n-k)$.

(b) *For all probability measures ν_1 and ν_2 on $\mathcal{X}_{k,n-k}$,*

$$(11) \quad \frac{1}{8} \hat{T}_2(\nu_2|\nu_1) \leq \left(\sqrt{H(\nu_1|\mu_{k,n-k})} + \sqrt{H(\nu_2|\mu_{k,n-k})} \right)^2,$$

where

$$\hat{T}_2(\nu_2|\nu_1) := \inf_{\pi \in \Pi(\nu_1, \nu_2)} \int \sum_{i=1}^n \left(\int \mathbb{1}_{x_i \neq y_i} dp_x(y) \right)^2 d\nu_1(x),$$

with $\pi(x, y) = \nu_1(x)p_x(y)$ for all $x, y \in \mathcal{X}_{k,n-k}$.

Up to constants, the weak transport inequality (11) is the stronger one since for all $\nu_1, \nu_2 \in \mathcal{P}(\mathcal{X}_{k,n-k})$,

$$W_1^2(\nu_1, \nu_2) \leq \tilde{T}_2(\nu_2|\nu_1) \leq \frac{n}{4} \hat{T}_2(\nu_2|\nu_1).$$

The proof of Theorem 1.4 is given in section 3. The transport-entropy inequality (11) is derived by projection from the transport-entropy inequality (7) for the uniform measure μ on S_n . The same projection argument could be used to reach the results of (a) from the transport-entropy inequality of (a) in Theorem 1.3, but it provides worse constants. The constant $C_{k,n-k}$ is obtained by working directly on $\mathcal{X}_{k,n-k}$ and following similar arguments as in the proof of Theorem 1.3.

Remark : The results of Theorem 1.4 also extend to the multinomial law. Let $E = \{e_1, \dots, e_m\}$ be a set of cardinality m and let k_1, \dots, k_m be a collection of non-zero integers satisfying $k_1 + \dots + k_m = n$. The multinomial law μ_{k_1, \dots, k_m} is by definition the uniform law on the set

$$\mathcal{X}_{k_1, \dots, k_m} := \left\{ x \in E^n, \text{ such that for all } l \in [m], |\{i \in [n], x_i = e_l\}| = k_l \right\},$$

where we denote by $|A|$ the cardinality of a finite set A . For any $x \in \mathcal{X}_{k_1, \dots, k_m}$, one has $\mu_{k_1, \dots, k_m}(x) = \frac{k_1! \dots k_m!}{n!}$. As a result, the weak transport-entropy inequality (11) holds on $\mathcal{X}_{k_1, \dots, k_m}$ replacing the measure $\mu_{k,n-k}$ by the measure μ_{k_1, \dots, k_m} . The proof of this result is a simple generalization of the one on $\mathcal{X}_{k,n-k}$, by using the projection map $P : S_n \rightarrow \mathcal{X}_{k_1, \dots, k_m}$ defined by: $P(\sigma) = x$ if and only if

$$x_i = e_l, \quad \forall l \in [m], \forall i \in J_l,$$

where $J_l := \{i \in [n], k_0 + \dots + k_{l-1} < i \leq k_0 + \dots + k_l\}$, with $k_0 = 0$. The details of this proof are let to the reader.

A straightforward application of transport-entropy inequalities is deviation's bounds for different classes of functions. For more comprehension, we present below deviations bounds that can be reached from Theorem 1.3 for the uniform law μ on a ℓ -local subgroup of S_n . Obviously some of these results extend to the class of measures \mathcal{M} and a similar corollary can be derived from Theorem 1.4 on the slices of the discrete cube. For any $h : G \rightarrow \mathbb{R}$, the mean of h is denoted by $\mu(h) := \int h d\mu$.

Corollary 1.2. *Let μ be the uniform law on a ℓ -local subgroup G of S_n , $G \neq \{id\}$. Let g be a real function on G .*

(a) *Assume that there exists a function $\beta : G \rightarrow \mathbb{R}^+$ such that for all $\tau, \sigma \in G$,*

$$g(\tau) - g(\sigma) \leq \beta(\tau)d(\tau, \sigma),$$

where $d = d_T$ or $d = d_H$. Then for all $u \geq 0$, one has

$$\mu(g \geq \mu(g) + u) \leq \exp\left(-\frac{2u^2}{K_n c(\ell)^2 \sup_{\sigma \in G} \beta(\sigma)^2}\right).$$

and

$$\mu(g \leq \mu(g) - u) \leq \exp\left(-\frac{2u^2}{K_n c(\ell)^2 \min(\sup_{\sigma \in G} \beta(\sigma)^2, 4\mu(\beta^2))}\right),$$

where the constants $c(\ell)$ and K_n are defined as in (a) in Theorem 1.3.

(b) Assume that there exist functions $\alpha_k : G \rightarrow \mathbb{R}^+$, $k \in \{1, \dots, n\}$ such that for all $\tau, \sigma \in G$,

$$g(\tau) - g(\sigma) \leq \sum_{k=1}^n \alpha_k(\tau) \mathbb{1}_{\tau(k) \neq \sigma(k)}.$$

Then, for all $u \geq 0$, one has

$$\mu(g \geq \mu(g) + u) \leq \exp\left(-\frac{u^2}{2c(\ell)^2 \sup_{\sigma \in G} |\alpha(\sigma)|_2^2}\right),$$

and

$$\mu(g \leq \mu(g) - u) \leq \exp\left(-\frac{u^2}{2c(\ell)^2 \mu(|\alpha|_2^2)}\right),$$

where $|\alpha(\sigma)|_2^2 := \sum_{k=1}^n \alpha_k^2(\sigma)$ and $c(\ell)^2 = 2(\ell - 1)^2 + 2$.

Comments :

- The above deviation's bounds of g around its mean $\mu(g)$ are directly derived from the dual representations (8),(9),(10) of the transport-entropy inequalities of Theorem 1.3, when α goes to 0 or α goes to 1. By classical arguments (see [Led01]), Corollary 1.2 also implies deviation's bounds around a median $M(g)$ of g , but we loose in the constants with this procedure. However, starting directly from Corollary 1.1, we get the following bound under the assumption of (b): for all $u \geq 0$,

$$(12) \quad \mu(g \geq M(g) + u) \leq \frac{1}{2} \exp\left(-w\left(\frac{u}{\sqrt{2}c(\ell) \sup_{\sigma \in G} |\alpha(\sigma)|_2}\right)\right),$$

where $w(h) = h(h - 2\sqrt{\log 2})$, $h \geq 0$, and $c(\ell)^2 = 2(\ell - 1)^2 + 2$.

The idea of the proof is to choose the set $A = \{\sigma \in G, g(\sigma) \leq M(g)\}$ of measure $\mu(A) \geq 1/2$ and to show that the assumption of (b) implies

$$\{\sigma \in G, f(\sigma, A) < t\} \subset \left\{ \sigma \in G, g(\sigma) < M(g) + t \sup_{\sigma \in G} |\alpha(\sigma)|_2 \right\}, \quad t \geq 0.$$

Then, the deviation bound above the median directly follows from Corollary 1.1 by optimizing over all $\alpha \in (0, 1)$. With identical arguments, the same bound can be reached for $\mu(g \leq M(g) - u)$.

- In (a), the bound above the mean is a simple consequence of (8). As settled in (a), this bound also holds for the deviations under the mean, and it can be slightly improved by replacing $\sup_{\sigma \in G} \beta(\sigma)^2$ by $4\mu(\beta^2)$. This small improvement is a consequence of the weak transport inequality with stronger cost \tilde{T}_2 . The same kind of improvement could be reached for the deviations above the mean under additional Lipschitz regularity conditions on the function β .
- Let $\varphi : [0, 1]^n \rightarrow \mathbb{R}$ be a 1-Lipschitz convex function and let $x = (x_1, \dots, x_n)$ be a fixed vector of $[0, 1]^n$. For any $\sigma \in G$, let $x_\sigma := (x_{\sigma(1)}, \dots, x_{\sigma(n)})$. By applying the results of (b) (or even (12)) to the particular function

$g_x(\sigma) = \varphi(x_\sigma)$, $\sigma \in G$, we recover and extend to any ℓ -local group G , the deviation inequality by Adamczak, Chafaï and Wolff [ACW14] (Theorem 3.1) obtained from Theorem 1.2 by Talagrand. Namely, since for any $\sigma, \tau \in G$,

$$\varphi(x_\tau) - \varphi(x_\sigma) \leq \sum_{k=1}^n \partial_k \varphi(x_\tau)(x_{\tau(k)} - x_{\sigma(k)}) \leq \sum_{k=1}^n |\partial_k \varphi(x_\tau)| \mathbb{1}_{\tau(k) \neq \sigma(k)},$$

with $\sum_{k=1}^n |\partial_k \varphi(x_\tau)|^2 = |\nabla \varphi(x_\tau)|^2 \leq 1$, Corollary 1.2 implies, for any choice of vector $x = (x_1, \dots, x_n) \in [0, 1]^n$,

$$\mu(|g_x - \mu(g_x)| \geq u) \leq 2 \exp\left(-\frac{u^2}{2c(\ell)^2}\right), \quad u \geq 0.$$

This concentration property on S_n ($\ell = 2$) plays a key role in the approach by Adamczak and al. [ACW14], to study the convergence of the empirical spectral measure of random matrices with exchangeable entries, when the size of the matrices is increasing.

- The aim of this paper is to clarify the links between Talagrand's type of concentration results on the symmetric group and functional inequalities derived from the transport-entropy inequalities. For brevity's sake, applications of these functional inequalities are not developed in the present paper. However, let us briefly mention some other applications using concentration results on the symmetric group: the stochastic travelling salesman problem for sampling without replacement (see Appendix [Pau14]), graph coloring problems (see [McD02]). We also refer to the surveys and books [DP09, MR02] for other numerous examples of application of the concentration of measure principle in randomized algorithms.

Proof of Corollary 1.2. We start with the proof of (b). Under the assumption on the function g , for any $p \in \mathcal{P}(G)$

$$\int g d\sigma \geq g(\sigma) - \sum_{k=1}^n \alpha_k(\sigma) \int \mathbb{1}_{\sigma(k) \neq \tau(k)} dp(\tau) \geq g(\sigma) - |\alpha(\sigma)|_2 \left(\int \mathbb{1}_{\sigma(k) \neq \tau(k)} dp(\tau) \right)^{1/2}.$$

Let $\lambda \geq 0$. Plugging this estimate into the definition of $\widehat{Q}(\lambda g)$, we get for any $\sigma \in G$

$$\widehat{Q}(\lambda g)(\sigma) \geq \lambda g(\sigma) - \sup_{u \geq 0} \left\{ \lambda |\alpha(\sigma)|_2 - \frac{\lambda^2}{2c(\ell)^2} \right\} = \lambda g(\sigma) - \frac{\lambda^2 |\alpha(\sigma)|_2^2 c(\ell)^2}{2}.$$

As α goes to 1, (10) applied to the function λg yields

$$\int e^{\widehat{Q}(\lambda g)} d\mu \leq e^{\lambda \mu(g)},$$

and therefore

$$(13) \quad \int e^{\lambda g} d\mu \leq \exp\left(\lambda \mu(g) + \frac{\lambda^2 c(\ell)^2 \sup_{\sigma \in G} |\alpha(\sigma)|_2^2}{2}\right).$$

As α goes to 0, (10) yields

$$\int e^{-\lambda g} d\mu \leq e^{\lambda \mu(\widehat{Q}(\lambda g))},$$

and therefore

$$(14) \quad \int e^{-\lambda g} d\mu \leq \exp \left(-\lambda \mu(g) + \frac{\lambda^2 c(\ell)^2 \mu(|\alpha|_2^2)}{2} \right).$$

The deviation bounds of (b) then follows from (10) and (14) by Tchebychev inequality by optimizing over all $\lambda \geq 0$.

The deviation bounds of (a) are also obtained from (9) by Tchebychev inequality. As above, the improvement for the deviation under the mean is a consequence of (9) applied to λg , as α goes to 0, and using the estimate

$$\widetilde{Q}_{K_n}(\lambda g)(\sigma) \geq \lambda g(\sigma) - \frac{\lambda^2 \beta(\sigma)^2 c(\ell)^2 K_n}{2}.$$

□

Proof of Corollary 1.1. Take a subset $A \subset G$ and consider the function φ_λ which takes the values 0 on A and $\lambda > 0$ on $G \setminus A$. It holds

$$\begin{aligned} \widehat{Q}\varphi_\lambda(\sigma) &= \inf_{p \in \mathcal{P}(G)} \left\{ \lambda(1 - p(A)) + \frac{1}{2c(\ell)^2} \sum_{j=1}^n \left(\int \mathbb{1}_{\sigma(j) \neq y(j)} dp(y) \right)^2 \right\} \\ &= \inf_{\beta \in [0,1]} \{ \lambda(1 - \beta) + \psi(\beta, \sigma) \}, \end{aligned}$$

denoting by

$$\psi(\beta, \sigma) = \inf \left\{ \frac{1}{2c(\ell)^2} \sum_{j=1}^n \left(\int \mathbb{1}_{\sigma(j) \neq y(j)} dp(y) \right)^2 ; p(A) = \beta \right\}.$$

So it holds

$$\begin{aligned} \widehat{Q}\varphi_\lambda(\sigma) &= \min \left(\inf_{\beta \in [0,1-\varepsilon]} \{ \lambda(1 - \beta) + \psi(\beta, \sigma) \}; \inf_{\beta \in [1-\varepsilon,1]} \{ \lambda(1 - \beta) + \psi(\beta, \sigma) \}, \right) \\ &\geq \min \left(\lambda\varepsilon; \inf_{\beta \geq 1-\varepsilon} \psi(\beta, \sigma) \right) \rightarrow \inf_{\beta \geq 1-\varepsilon} \psi(\beta, \sigma), \end{aligned}$$

as $\lambda \rightarrow \infty$. It is easy to check that for any fixed σ , the function $\psi(\cdot, \sigma)$ is continuous on $[0, 1]$, so letting ε go to 0, we get $\liminf_{\lambda \rightarrow \infty} \widehat{Q}\varphi_\lambda(\sigma) \geq \psi(1, \sigma)$. On the other hand, $\widehat{Q}\varphi_\lambda(\sigma) \leq \psi(1, \sigma)$ for all $\lambda > 0$. This proves that $\lim_{\lambda \rightarrow \infty} \widehat{Q}\varphi_\lambda(\sigma) = \psi(1, \sigma)$. Applying (10) to φ_λ and letting λ go to infinity yields to

$$\int e^{\alpha \psi(1, \sigma)} d\mu \cdot \mu(A)^{\alpha/(1-\alpha)} \leq 1.$$

It remains to observe that $\psi(1, \sigma) = \frac{f(\sigma, A)}{2c(\ell)^2}$. □

2. PROOF OF THEOREM 1.3

Let G be a ℓ -local subgroup of S_n and $\mathcal{T}_n = (t_{i,j}, j \in \{2, \dots, n\}, i_j \in I_j)$ be a ℓ -local base of G (defined in Lemma 1.1). Let μ be a probability measure of the set \mathcal{M} . By definition of \mathcal{M} , there exists a product probability measure $\hat{\nu} = \hat{\nu}_1 \otimes \dots \otimes \hat{\nu}_n$ such that $\mu = U_{\mathcal{T}_n} \# \hat{\nu}$ where the map $U_{\mathcal{T}_n}$ is defined by (1).

Each transport-entropy inequality of Theorem 1.3 is obtained by induction over n and using the partition $(H_i)_{i \in \text{orb}(n)}$ of the group G defined by: for any $i \in \text{orb}(n)$,

$$(15) \quad H_i := \{\sigma \in G, \sigma(i) = n\}.$$

If $H_n = \{Id\}$, then $\text{orb}(n) = \{n\}$ and if $H_n \neq \{Id\}$, then $\text{orb}(n) \supsetneq \{n\}$. In any case, from the definition of the ℓ -local property, we may easily check that H_n is a ℓ -local group that realizes a natural embedding of a ℓ -local subgroup of S_{n-1} and \mathcal{T}_{n-1} is a ℓ -local base of this subgroup.

Moreover, it is rather easy to get that for any $i \in \text{orb}(n)$, H_i is the coset defined by $H_i = H_n t_{in}$. From the definition of μ , if $\sigma \in H_i$, then there exist i_2, \dots, i_{n-1} such that $\sigma = t_{i_2, 2} \cdots t_{i_{n-1}, n-1} t_{i, n}$ and therefore

$$\mu(\sigma) = \hat{\nu}_2(i_2) \cdots \hat{\nu}_{n-1}(i_{n-1}) \hat{\nu}_n(i).$$

As a consequence, one has $\mu(H_i) = \hat{\nu}_n(i)$. Let μ_i denote the restriction of μ to H_i defined by

$$\mu_i(\sigma) = \frac{\mu(\sigma)}{\mu(H_i)} \mathbb{1}_{\sigma \in H_i}.$$

From the construction of μ , $\mu_n = U_{\mathcal{T}_{n-1}} \#(\hat{\nu}_1 \otimes \cdots \otimes \hat{\nu}_{n-1})$. Moreover, for all $\sigma \in H_n$, $\sigma t_{i, n} \in H_i$, one has

$$(16) \quad \mu_n(\sigma) = \frac{\mu(\sigma)}{\mu(H_n)} = \frac{\mu(\sigma t_{i, n})}{\mu(H_i)} = \mu_i(\sigma t_{i, n}).$$

This property is needed in the induction step of the proofs.

Let us note that if i and l are elements of $\text{orb}(n)$, then from the ℓ -local property of G , there exists $t_{i, l} \in G$ such that $t_{i, l}(i) = l$ and $\deg(t_{i, l}) \leq \ell$. We also have $H_l = H_i t_{i, l}$. If moreover the measure μ is the uniform law on G , then for any $i, l \in \text{orb}(n)$, $\mu_i(H_i) = \mu_l(H_l) = \frac{|G|}{|\text{orb}(n)|}$. In that case we will use in the proofs the following property: for any $\sigma \in H_n$, $\sigma t_{i, n} t_{i, l}^{-1} \in H_l$ and

$$(17) \quad \mu_n(\sigma) = \mu_l(\sigma t_{i, n} t_{i, l}^{-1}).$$

Proof of (a) in Theorem 1.3. Since the distance W_1 satisfies a triangular inequality, the transport-entropy inequality (5) follows from the following one: for all probability measures ν_1 on G ,

$$\frac{2}{K_n c(\ell)^2} W_1^2(\nu_1, \mu) \leq H(\nu_1 | \mu).$$

A dual formulation of this property given by Theorem 2.7 in [GRST14] and Proposition 3.1 in [Sam16a] is the following: for all functions φ on G and all $\lambda \geq 0$,

$$(18) \quad \int e^{\lambda Q \varphi} d\mu \leq e^{\int \lambda \varphi d\mu + K_n c(\ell)^2 \lambda^2 / 8},$$

with

$$Q\varphi(\sigma) = \inf_{p \in \mathcal{P}(S_n)} \left\{ \int \varphi dp + \int d(\sigma, \tau) dp(\tau) \right\}$$

We will prove the inequality (18) by induction on n .

When $n = 2$, since $G \neq \{id\}$, G is the two points space, $G = S_2$, $\ell = 2$ and one has

$$Q\varphi(\sigma) = \inf_{p \in \mathcal{P}(S_2)} \left\{ \int \varphi dp + c(2) \int \mathbb{1}_{\sigma \neq \tau} dp(\tau) \right\}.$$

In that case, (18) exactly corresponds to the following dual form of the Csiszar-Kullback-Pinsker inequality (3) (see Proposition 3.1 in [Sam16a]): for any probability measure ν on a Polish space \mathcal{X} , for any measurable function $f : \mathcal{X} \rightarrow \mathbb{R}$,

$$(19) \quad \int e^{\lambda R^c f} d\nu \leq e^{\lambda \int f d\nu + \lambda^2 c^2 / 8}, \quad \forall \lambda, c \geq 0,$$

$$\text{with } R^c f(x) = \inf_{p \in \mathcal{P}(\mathcal{X})} \left\{ \int f dp + c \int \mathbb{1}_{x \neq y} dp(y) \right\}, x \in \mathcal{X}.$$

The induction step will be also a consequence of (19). Let $(H_i)_{i \in \text{orb}(n)}$ be the partition of G defined by (15). Any $p \in \mathcal{P}(G)$ admits a unique decomposition defined by

$$(20) \quad p = \sum_{i \in \text{orb}(n)} \hat{p}(i) p_i, \quad \text{with } p_i \in \mathcal{P}(H_i) \quad \text{and} \quad \hat{p}(i) = p(H_i).$$

This decomposition defines a probability measure \hat{p} on $\text{orb}(n)$. In particular, according to the definition of the measure $\mu \in \mathcal{M}$, one has

$$\mu = \sum_{i \in \text{orb}(n)} \hat{\nu}_n(i) \mu_i.$$

It follows that

$$\int e^{\lambda Q\varphi} d\mu = \sum_{i \in \text{orb}(n)} \hat{\nu}_n(i) \int e^{\lambda Q\varphi(\sigma)} d\mu_i(\sigma) = \sum_{i \in \text{orb}(n)} \hat{\nu}_n(i) \int e^{\lambda Q\varphi(\sigma t_{i,n})} d\mu_n(\sigma),$$

where the last equality is a consequence of property (16). Now, we will bound the right-hand side of this equality by using the induction hypotheses.

For any function $g : G \rightarrow \mathbb{R}$ and any $t \in G$, let $g^t : G \rightarrow \mathbb{R}$ denote the function defined by $g^t(\sigma) := g(\sigma t)$.

For any function $f : H_n \rightarrow \mathbb{R}$ and any $\sigma \in H_n$, let us note

$$Q^{H_n} f(\sigma) := \inf_{p \in \mathcal{P}(H_n)} \left\{ \int f dp + \int d(\sigma, \tau) dp(\tau) \right\}.$$

The next step of the proof relies on the following Lemma.

Lemma 2.1. *Let $i \in \text{orb}(n)$, for any function $\varphi : H_i \rightarrow \mathbb{R}$ and any $\sigma \in H_n$, one has*

$$(1) \quad Q\varphi(\sigma t_{i,n}) \leq \inf_{\hat{p} \in \mathcal{P}(\text{orb}(n))} \left\{ \sum_{l \in \text{orb}(n)} Q^{H_n} \varphi^{t_{n,l}}(\sigma) \hat{p}(l) + c(\ell) \sum_{l \in \text{orb}(n)} \mathbb{1}_{l \neq i} \hat{p}(l) \right\},$$

where $c(\ell) = \min(2\ell - 1, n)$ if $d = d_H$ and $c(\ell) = 2$ if $d = d_T$.

$$(2) \quad Q\varphi(\sigma t_{i,n}) \leq \inf_{\hat{p} \in \mathcal{P}(\text{orb}(n))} \left\{ \sum_{l \in \text{orb}(n)} Q^{H_n} \varphi^{t_{i,n} t_{i,l}^{-1}}(\sigma) \hat{p}(l) + c(\ell) \sum_{l \in \text{orb}(n)} \mathbb{1}_{l \neq i} \hat{p}(l) \right\},$$

where $c(\ell) = \ell$ if $d = d_H$ and $c(\ell) = 1$ if $d = d_T$, and $t_{i,l}$ denotes an element of G with $\deg(t_{i,l}) \leq \ell$ and such that $t_{i,l}(i) = l$.

This lemma is obtained using the decomposition (20) of the measures $p \in \mathcal{P}(G)$ on the H_j 's. Let $\sigma \in H_n$. By the triangular inequality and using the invariance by translation of the distance d , one has

$$\begin{aligned} \int d(\sigma t_{i,n}, \tau) dp(\tau) &= \sum_{l \in \text{orb}(n)} \int_{H_l} d(\sigma t_{i,n}, \tau) dp_l(\tau) \hat{p}(l) \\ &\leq \sum_{l \in \text{orb}(n)} d(\sigma t_{i,n}, \sigma t_{l,n}) \hat{p}(l) + \sum_{l \in \text{orb}(n)} \int_{H_l} d(\sigma t_{l,n}, \tau) dp_l(\tau) \hat{p}(l) \\ &= \sum_{l \in \text{orb}(n)} d(t_{i,n}, t_{l,n}) \hat{p}(l) + \sum_{l \in \text{orb}(n)} \int_{H_l} d(\sigma, \tau t_{l,n}^{-1}) dp_l(\tau) \hat{p}(l) \end{aligned}$$

and therefore, since $d(t_{i,n}, t_{l,n}) \leq c(\ell)$ with $c(\ell) = \min(2\ell - 1, n)$ if $d = d_H$ and $c(\ell) = 2$ if $d = d_T$,

$$(21) \quad \int d(\sigma t_{i,n}, \tau) dp(\tau) \leq \sum_{l \in \text{orb}(n)} \int_{H_l} d(\sigma, \tau t_{l,n}^{-1}) dp_l(\tau) \hat{p}(l) + c(\ell) \sum_{l \in \text{orb}(n)} \mathbb{1}_{l \neq i} \hat{p}(l).$$

It follows that

$$\begin{aligned} Q\varphi(\sigma t_{i,n}) &\leq \inf_{\hat{p} \in \mathcal{P}(\text{orb}(n))} \inf_{p_l \in \mathcal{P}(H_l), l \in \text{orb}(n)} \left\{ \sum_{l \in \text{orb}(n)} \left[\int \varphi dp_l + \int_{H_l} d(\sigma, \tau t_{l,n}^{-1}) dp_l(\tau) \right] \hat{p}(l) + c(\ell) \sum_{l \in \text{orb}(n)} \mathbb{1}_{l \neq i} \hat{p}(l) \right\} \\ &= \inf_{\hat{p} \in \mathcal{P}(\text{orb}(n))} \inf_{q_l \in \mathcal{P}(H_n), l \in \text{orb}(n)} \left\{ \sum_{l \in \text{orb}(n)} \left[\int \varphi^{t_{l,n}} dq_l + \int_{H_n} d(\sigma, \tau) dq_l(\tau) \right] \hat{p}(l) + c(\ell) \sum_{l \in \text{orb}(n)} \mathbb{1}_{l \neq i} \hat{p}(l) \right\} \\ &= \inf_{\hat{p} \in \mathcal{P}(\text{orb}(n))} \left\{ \sum_{l \in \text{orb}(n)} Q^{H_n} \varphi^{t_{l,n}}(\sigma) \hat{p}(l) + c(\ell) \sum_{l \in \text{orb}(n)} \mathbb{1}_{l \neq i} \hat{p}(l) \right\}. \end{aligned}$$

The proof of the second inequality of Lemma 2.1 is similar, starting from the following triangular inequality

$$\begin{aligned} \int d(\sigma t_{i,n}, \tau) dp(\tau) &= \sum_{l \in \text{orb}(n)} \int_{H_l} d(\sigma t_{i,n}, \tau) dp_l(\tau) \hat{p}(l) \\ &\leq \sum_{l \in \text{orb}(n)} \int d(\sigma t_{i,n}, \tau t_{i,l}) dp_l(\tau) \hat{p}(l) + \sum_{l \in \text{orb}(n)} \int_{H_l} d(\tau t_{i,l}, \tau) dp_l(\tau) \hat{p}(l) \\ &= \sum_{l \in \text{orb}(n)} \int d(\sigma, \tau t_{i,l} t_{i,n}^{-1}) dp_l(\tau) \hat{p}(l) + \sum_{l \in \text{orb}(n)} d(t_{i,l}, id) \hat{p}(l) \\ (22) \quad &\leq \sum_{l \in \text{orb}(n)} \int_{H_l} d(\sigma, \tau t_{i,l} t_{i,n}^{-1}) dp_l(\tau) \hat{p}(l) + c(\ell) \sum_{l \in \text{orb}(n)} \mathbb{1}_{l \neq i} \hat{p}(l), \end{aligned}$$

with $c(\ell) = \ell$ if $d = d_H$ and $c(\ell) = 1$ if $d = d_T$. The end of the proof of the second inequality of Lemma 2.1 is let to the reader.

The induction step of the proof of (18) continues by applying consecutively Lemma 2.1, the Hölder inequality, and the induction hypotheses to the measure μ_n .

If $I_n = \text{orb}(n) = \{n\}$ then $K_n = K_{n-1}$ and

$$\int e^{\lambda Q\varphi} d\mu = \int e^{\lambda Q\varphi(\sigma)} d\mu_n(\sigma) \leq e^{\int \lambda\varphi d\mu_n + K_{n-1}c(\ell)^2/8} = e^{\int \lambda\varphi d\mu + K_n c(\ell)^2/8}$$

If $I_n = \text{orb}(n) \neq \{n\}$ then $K_n = K_{n-1} + 1$ and for any $i \in \text{orb}(n)$,

$$\begin{aligned} \int e^{\lambda Q\varphi(\sigma_{t_{i,n}})} d\mu_n(\sigma) &\leq \inf_{\hat{p} \in \mathcal{P}(\text{orb}(n))} \left\{ \prod_{l \in \text{orb}(n)} \left(\int e^{\lambda Q^{H_n} \varphi^{t_{l,n}}} d\mu_n \right)^{\hat{p}(l)} e^{c(\ell)\lambda \sum_{l=1}^n \mathbb{1}_{l \neq i} \hat{p}(l)} \right\} \\ &\leq \exp \left[\inf_{\hat{p} \in \mathcal{P}(\text{orb}(n))} \left\{ \lambda \sum_{l \in \text{orb}(n)} \left(\int \varphi^{t_{l,n}} d\mu_n \right) \hat{p}(l) + K_{n-1}c(\ell)^2 \frac{\lambda^2}{8} + c(\ell)\lambda \sum_{l \in \text{orb}(n)} \mathbb{1}_{l \neq i} \hat{p}(l) \right\} \right] \\ &= \exp \left[\lambda \inf_{\hat{p} \in \mathcal{P}(\text{orb}(n))} \left\{ \sum_{l \in \text{orb}(n)} \hat{\varphi}(l) \hat{p}(l) + c(\ell) \sum_{l \in \text{orb}(n)} \mathbb{1}_{l \neq i} \hat{p}(l) \right\} + K_{n-1}c(\ell)^2 \frac{\lambda^2}{8} \right], \end{aligned}$$

where, by using property (16), $\hat{\varphi}(l) := \int \varphi d\mu_l = \int \varphi^{t_{l,n}} d\mu_n$. Let us consider again the above infimum-convolution $R^c \hat{\varphi}$ defined on the space $\mathcal{X} = \text{orb}(n)$, with $c = c(\ell)$, one has

$$R^c \hat{\varphi}(i) = \inf_{\hat{p} \in \mathcal{P}(\text{orb}(n))} \left\{ \sum_{l \in \text{orb}(n)} \hat{\varphi}(l) \hat{p}(l) + c \sum_{l \in \text{orb}(n)} \mathbb{1}_{l \neq i} \hat{p}(l) \right\}.$$

By applying (19) with the probability measure $\hat{\nu}_n$ on $\text{orb}(n)$, the previous inequality gives

$$\begin{aligned} \int e^{\lambda Q\varphi} d\mu &= \sum_{i \in \text{orb}(n)} \hat{\nu}_n(i) \int e^{\lambda Q\varphi(\sigma_{t_{i,n}})} d\mu_n(\sigma) \leq \left(\sum_{i \in \text{orb}(n)} e^{\lambda R^c \hat{\varphi}(i)} \hat{\nu}_n(i) \right) e^{K_{n-1}\lambda^2/8} \\ &\leq \exp \left[\sum_{i=1}^n \hat{\varphi}(i) \hat{\nu}_n(i) + \frac{\lambda^2 c(\ell)^2}{8} + K_{n-1}c(\ell)^2 \frac{\lambda^2}{8} \right] = \exp \left[\lambda \int \varphi d\mu + K_n c(\ell)^2 \frac{\lambda^2}{8} \right]. \end{aligned}$$

The scheme of the induction proof of (18), with a better constant $c(\ell)$ when μ is the uniform measure on G , is identical, starting from the second result of Lemma 2.1 and using the property (17). This is left to the reader.

We now turn to the induction proof of the dual formulation (9) of the weak transport-entropy inequality (6). The sketch of the proof is identical to the one of (18).

For the initial step $n = 2$, one has $G = S_2$ and $\ell = 2$, and one may easily check that

$$\tilde{Q}_1 \varphi(\sigma) = \inf_{p \in \mathcal{P}(S_2)} \left\{ \int \varphi dp + \frac{1}{2} \left(\int \mathbb{1}_{\sigma \neq \tau} dp(\tau) \right)^2 \right\}.$$

In that case, the result follows from the following infimum-convolution property.

Lemma 2.2. *For any probability measure ν on a Polish metric space \mathcal{X} , for all $\alpha \in (0, 1)$ and all measurable functions $f : \mathcal{X} \rightarrow \mathbb{R}$, bounded from below*

$$\left(\int e^{\alpha \tilde{R}^\alpha f} d\nu \right)^{1/\alpha} \left(\int e^{-(1-\alpha)f} d\nu \right)^{1/(1-\alpha)} \leq 1,$$

where for all $x \in \mathcal{X}$,

$$\tilde{R}^\alpha f(x) = \inf_{p \in \mathcal{P}(\mathcal{X})} \left\{ \int f(y) dp(y) + c_\alpha \left(\int \mathbb{1}_{x \neq y} dp(y) \right)^2 \right\},$$

and c_α is the convex function defined by

$$c_\alpha(u) = \frac{\alpha(1-u) \log(1-u) - (1-\alpha u) \log(1-\alpha u)}{\alpha(1-\alpha)}, \quad u \in [0, 1].$$

Observing that $c_\alpha(u) \geq u^2/2$ for all $u \in [0, 1]$, the above inequality also holds replacing $\tilde{R}^\alpha f$ by

$$(23) \quad \tilde{R}f(x) = \inf_{p \in \mathcal{P}(\mathcal{X})} \left\{ \int f(y) dp(y) + \frac{1}{2} \left(\int \mathbb{1}_{x \neq y} dp(y) \right)^2 \right\}, \quad x \in \mathcal{X}.$$

The proof of this Lemma can be founded in [Sam07] (inequality (4)). For a sake of completeness, we give in appendix a new proof of this result on finite spaces \mathcal{X} by using a localization argument (Lemma 4.1).

Let us now present the key lemma for the induction step of the proof. For any function $f : H_n \rightarrow \mathbb{R}$ and any $\sigma \in H_n$, we define

$$\tilde{Q}_t^{H_n} f(\sigma) := \inf_{p \in \mathcal{P}(H_n)} \left\{ \int f dp + \frac{1}{2c(\ell)^2 t} \left(\int d(\sigma, \tau) dp(\tau) \right)^2 \right\}.$$

Here, writing $\tilde{Q}_t^{H_n} f$, we omit the dependence in $c(\ell)$ to simplify the notations. The proof relies on the following Lemma.

Lemma 2.3. *Let $i \in \text{orb}(n)$. For any function $\varphi : H_i \rightarrow \mathbb{R}$ and any $\sigma \in H_n$, one has*

$$(1) \quad \tilde{Q}_{K_n} \varphi(\sigma t_{i,n}) \leq \inf_{\hat{p} \in \mathcal{P}(\text{orb}(n))} \left\{ \sum_{l \in \text{orb}(n)} \tilde{Q}_{K_{n-1}}^{H_n} \varphi^{t_{i,n}}(\sigma) \hat{p}(l) + \frac{1}{2} \left(\sum_{l \in \text{orb}(n)} \mathbb{1}_{l \neq i} \hat{p}(l) \right)^2 \right\},$$

with $c(\ell) = \min(2\ell - 1, n)$ if $d = d_H$ and $c(\ell) = 2$ if $d = d_T$.

$$(2) \quad \tilde{Q}_{K_n} \varphi(\sigma t_{i,n}) \leq \inf_{\hat{p} \in \mathcal{P}(\text{orb}(n))} \left\{ \sum_{l \in \text{orb}(n)} \tilde{Q}_{K_{n-1}}^{H_n} \varphi^{t_{i,n} \tau_{i,l}^{-1}}(\sigma) \hat{p}(l) + \frac{1}{2} \left(\sum_{l \in \text{orb}(n)} \mathbb{1}_{l \neq i} \hat{p}(l) \right)^2 \right\},$$

where $c(\ell) = \ell$ if $d = d_H$ and $c(\ell) = 1$ if $d = d_T$.

The proof of this lemma is similar to the one of Lemma 2.1. By (21) and the inequality

$$(u+v)^2 \leq \frac{u^2}{s} + \frac{v^2}{1-s}, \quad u, v \in \mathbb{R}, \quad s \in (0, 1),$$

we get for any $s \in (0, 1)$,

$$\begin{aligned}
 \left(\int d(\sigma t_{l,n}, \tau) dp(\tau) \right)^2 &\leq \left(\sum_{l \in \text{orb}(n)} \int_{H_l} d(\sigma, \tau t_{l,n}^{-1}) dp_l(\tau) \hat{p}(l) + c(\ell) \sum_{l \in \text{orb}(n)} \mathbb{1}_{l \neq i} \hat{p}(l) \right)^2 \\
 &\leq \frac{1}{s} \left(\sum_{l \in \text{orb}(n)} \int_{H_l} d(\sigma, \tau t_{l,n}^{-1}) dp_l(\tau) \hat{p}(l) \right)^2 + \frac{c(\ell)^2}{1-s} \left(\sum_{l \in \text{orb}(n)} \mathbb{1}_{l \neq i} \hat{p}(l) \right)^2 \\
 &\leq \frac{1}{s} \sum_{l \in \text{orb}(n)} \left(\int_{H_l} d(\sigma, \tau t_{l,n}^{-1}) dp_l(\tau) \right)^2 \hat{p}(l) + \frac{c(\ell)^2}{1-s} \left(\sum_{l \in \text{orb}(n)} \mathbb{1}_{l \neq i} \hat{p}(l) \right)^2.
 \end{aligned}$$

It follows that for any $\sigma \in H_n$,

$$\begin{aligned}
 &\tilde{Q}_{K_n} \varphi(\sigma t_{l,n}) \\
 &\leq \inf_{\hat{p} \in \mathcal{P}(\text{orb}(n))} \inf_{p_l \in \mathcal{P}(H_l), l \in \text{orb}(n)} \left\{ \sum_{l \in \text{orb}(n)} \left[\int \varphi dp_l + \frac{1}{2c(\ell)^2 s K_n} \left(\int_{H_l} d(\sigma, \tau t_{l,n}^{-1}) dp_l(\tau) \right)^2 \right] \hat{p}(l) + \frac{1}{2(1-s)K_n} \left(\sum_{l \in \text{orb}(n)} \mathbb{1}_{l \neq i} \hat{p}(l) \right)^2 \right\} \\
 &= \inf_{\hat{p} \in \mathcal{P}(\text{orb}(n))} \inf_{q_l \in \mathcal{P}(H_n), l \in \text{orb}(n)} \left\{ \sum_{l \in \text{orb}(n)} \left[\int \varphi^{t_{l,n}} dq_l + \frac{1}{2c(\ell)^2 s K_n} \left(\int_{H_n} d(\sigma, \tau) dq_l(\tau) \right)^2 \right] \hat{p}(l) + \frac{1}{2(1-s)K_n} \left(\sum_{l \in \text{orb}(n)} \mathbb{1}_{l \neq i} \hat{p}(l) \right)^2 \right\} \\
 &= \inf_{\hat{p} \in \mathcal{P}(\text{orb}(n))} \left\{ \sum_{l \in \text{orb}(n)} \tilde{Q}_{K_{n-1}}^{H_n} \varphi^{t_{l,n}}(\sigma) \hat{p}(l) + \frac{1}{2} \left(\sum_{l \in \text{orb}(n)} \mathbb{1}_{l \neq i} \hat{p}(l) \right)^2 \right\},
 \end{aligned}$$

where the last equality follows by choosing $s = K_{n-1}/K_n$, which ends the proof of the first inequality of Lemma 2.3. The second inequality of Lemma 2.3 is obtained identically starting from (22).

We now turn to the induction step of the proof. By the decomposition of the measure μ on the H_i 's, we want to bound

$$\int e^{\alpha \tilde{Q}_{K_n} \varphi} d\mu = \sum_{i \in \text{orb}(n)} \hat{\nu}_n(i) \int e^{\alpha \tilde{Q}_{K_n} \varphi(\sigma)} d\mu_i(\sigma) = \sum_{i \in \text{orb}(n)} \hat{\nu}_n(i) \int e^{\alpha \tilde{Q}_{K_n} \varphi(\sigma t_{i,n})} d\mu_n(\sigma),$$

where the last equality is a consequence of property (16).

If $\text{orb}(n) = \{n\}$, then the result simply follows from the induction hypotheses applied to the measure μ_n .

If $\text{orb}(n) \neq \{n\}$, then applying successively Lemma 2.3, the Hölder inequality, and the induction hypotheses, we get

$$\begin{aligned} \int e^{\alpha \tilde{Q}_{k_n} \varphi(\sigma t_{i,n})} d\mu_n(\sigma) &\leq \inf_{\hat{p} \in \mathcal{P}(\text{orb}(n))} \left\{ \prod_{l \in \text{orb}(n)} \left(\int e^{\alpha \tilde{Q}_{k_{n-1}} \varphi^{l,n}} d\mu_n \right)^{\hat{p}(l)} \exp \left[\frac{1}{2} \left(\sum_{l \in \text{orb}(n)} \mathbb{1}_{l \neq i} \hat{p}(l) \right)^2 \right] \right\} \\ &\leq \inf_{\hat{p} \in \mathcal{P}(\text{orb}(n))} \left\{ \prod_{l \in \text{orb}(n)} \left(\int e^{-(1-\alpha) \varphi^{l,n}} d\mu_n \right)^{-\frac{\hat{p}(l)\alpha}{1-\alpha}} \exp \left[\frac{1}{2} \left(\sum_{l \in \text{orb}(n)} \mathbb{1}_{l \neq i} \hat{p}(l) \right)^2 \right] \right\} \\ &= \exp \left[\alpha \inf_{\hat{p} \in \mathcal{P}(\text{orb}(n))} \left\{ \sum_{l \in \text{orb}(n)} \hat{\varphi}(l) \hat{p}(l) + \frac{1}{2} \left(\sum_{l \in \text{orb}(n)} \mathbb{1}_{l \neq i} \hat{p}(l) \right)^2 \right\} \right], \end{aligned}$$

where by property (16), we set

$$\hat{\varphi}(l) := \log \left(\int e^{-(1-\alpha) \varphi} d\mu_l \right)^{-\frac{1}{1-\alpha}} = \log \left(\int e^{-(1-\alpha) \varphi^{l,n}} d\mu_n \right)^{-\frac{1}{1-\alpha}}.$$

According to the definition of the infimum convolution $\tilde{R}\hat{\varphi}$ on the space $\mathcal{X} = \text{orb}(n)$ given in Lemma 2.2, the last inequality is

$$\int e^{\alpha \tilde{Q}_{k_n} \varphi(\sigma t_{i,n})} d\mu_n(\sigma) \leq e^{\alpha \tilde{R}\hat{\varphi}(i)},$$

and therefore Lemma 2.2 provides

$$\begin{aligned} \int e^{\alpha \tilde{Q}_{k_n} \varphi} d\mu &= \sum_{i \in \text{orb}(n)} e^{\alpha \tilde{R}\hat{\varphi}(i)} \hat{\nu}_n(i) \leq \left(\sum_{i \in \text{orb}(n)} e^{-(1-\alpha) \hat{\varphi}(i)} \hat{\nu}_n(i) \right)^{-\frac{\alpha}{1-\alpha}} \\ &= \left(\sum_{i \in \text{orb}(n)} \hat{\nu}_n(i) \int e^{-(1-\alpha) \varphi} d\mu_i \right)^{-\frac{\alpha}{1-\alpha}} = \left(\int e^{-(1-\alpha) \varphi} d\mu \right)^{-\frac{\alpha}{1-\alpha}}. \end{aligned}$$

The proof of (9) is completed for any measure $\mu \in \mathcal{M}$. To improve the constant when μ is the uniform probability measure on G , the proof is similar using the second inequality of Lemma 2.3 together with property (17). \square

Proof of (b) in Theorem 1.3. We prove the dual equivalent property (10) as a consequence of the stronger following result: for any real function φ on G , for any $j \in \{1, \dots, n\}$

$$(24) \quad \left(\int e^{\alpha Q^j \varphi} d\mu \right)^{1/\alpha} \left(\int e^{-(1-\alpha) \varphi} d\mu \right)^{1/(1-\alpha)} \leq 1,$$

where the infimum convolution operator $Q^j \varphi$ is defined as follows, for $\sigma \in G$

$$(25) \quad Q^j \varphi(\sigma) = \inf_{p \in \mathcal{P}(G)} \left\{ \int \varphi dp + \frac{1}{c(\ell)^2} \left(\int \mathbb{1}_{\sigma(j) \neq y(j)} dp(y) \right)^2 + \frac{1}{2c(\ell)^2} \sum_{k \in [n] \setminus \{j\}} \left(\int \mathbb{1}_{\sigma(k) \neq y(k)} dp(y) \right)^2 \right\}.$$

The proof of (24) relies on Lemma 2.2 and the following ones. For any $\sigma \in G$, we define

$$Q^{H_n} \varphi(\sigma) = \inf_{p \in \mathcal{P}(H_n)} \left\{ \int \varphi dp + \frac{1}{2c(\ell)^2} \sum_{k=1}^{n-1} \left(\int \mathbb{1}_{\sigma(k) \neq y(k)} dp(y) \right)^2 \right\},$$

and for $j \in [n-1]$,

$$Q^{H_n, j} \varphi(\sigma) = \inf_{p \in \mathcal{P}(H_n)} \left\{ \int \varphi dp + \frac{1}{c(\ell)^2} \left(\int \mathbb{1}_{\sigma(j) \neq y(j)} dp(y) \right)^2 + \frac{1}{2c(\ell)^2} \sum_{k \in [n-1] \setminus \{j\}} \left(\int \mathbb{1}_{\sigma(k) \neq y(k)} dp(y) \right)^2 \right\}.$$

Lemma 2.4. *Let $j \in [n]$. For any $\sigma \in G$, one has*

$$Q^j \varphi(\sigma) = Q^{\sigma(j)} \varphi^{\{-1\}}(\sigma^{-1}),$$

where $\varphi^{\{-1\}}(z) = \varphi(z^{-1})$, $z \in G$.

This result follows from the change of variables $\sigma(k) = l$ in the definition (25) of $Q^j \varphi(\sigma)$, one has

$$\begin{aligned} Q^j \varphi(\sigma) &= \inf_{p \in \mathcal{P}(G)} \left\{ \int \varphi dp + \frac{1}{c(\ell)^2} \left(\int \mathbb{1}_{y^{-1}(\sigma(j)) \neq \sigma^{-1}(\sigma(j))} dp(y) \right)^2 \right. \\ &\quad \left. + \frac{1}{2c(\ell)^2} \sum_{l, l \neq \sigma(j)} \left(\int \mathbb{1}_{l \neq y(\sigma^{-1}(l))} dp(y) \right)^2 \right\} \\ &= \inf_{q \in \mathcal{P}(G)} \left\{ \int \varphi(z^{-1}) dq(z) + \frac{1}{c(\ell)^2} \left(\int \mathbb{1}_{z(\sigma(j)) \neq \sigma^{-1}(\sigma(j))} dq(z) \right)^2 \right. \\ &\quad \left. + \frac{1}{2c(\ell)^2} \sum_{l, l \neq \sigma(j)} \left(\int \mathbb{1}_{z(l) \neq \sigma^{-1}(l)} dq(z) \right)^2 \right\}, \end{aligned}$$

where for the last equality, we use the fact that the map that associates to any measure $p \in \mathcal{P}(G)$ the image measure $q := R\#p$ with $R : \sigma \in G \mapsto \sigma^{-1} \in G$, is one to one from $\mathcal{P}(G)$ to $\mathcal{P}(G)$.

Here is the key lemma for the induction step of the proof of (24).

Lemma 2.5. (1) *Let $j \in \text{orb}(n)$. For any $\sigma \in H_n$, one has*

$$Q^j \varphi(\sigma t_{j,n}) \leq Q^{H_n} \varphi^{t_{j,n}}(\sigma).$$

(2) *If $\text{orb}(n) \neq \{n\}$, let $i, j \in \text{orb}(n)$ with $i \neq j$, and let $t_{i,j} \in G$ such that $t_{i,j}(i) = j$ and $\deg(t_{i,j}) \leq \ell$. We note $D_i = \text{supp}(t_{i,j}) \setminus \{i\}$ and $d = |D_i|$. For any $\sigma \in H_n$, for any $\theta \in [0, 1]$ one has*

$$Q^i \varphi(\sigma t_{i,n}) \leq \frac{1}{d} \sum_{l \in t_{i,n}(D_i)} \left[\theta Q^{H_n, l} \varphi^{t_{i,n}}(\sigma) + (1 - \theta) Q^{H_n} \varphi^{t_{i,n} l_{i,j}^{-1}}(\sigma) \right] + \frac{1}{2} (1 - \theta)^2.$$

Proof. The first part of this Lemma follows from the fact that $\mathcal{P}(H_j) \subset \mathcal{P}(G)$ and the fact that $\int \mathbb{1}_{\sigma t_{j,n}(j) \neq y(j)} dp(y) = 0$ for $\sigma \in H_n$ and $p \in \mathcal{P}(H_j)$. Therefore, according to the definition of $Q^j \varphi$, one has for $\sigma \in H_j$,

$$\begin{aligned} Q^j \varphi(\sigma t_{j,n}) &\leq \inf_{p \in \mathcal{P}(H_j)} \left\{ \int \varphi dp + \frac{1}{2c(\ell)^2} \sum_{k \in [n] \setminus \{j\}} \left(\int \mathbb{1}_{\sigma t_{i,n}(k) \neq y(k)} dp(y) \right)^2 \right\} \\ &= \inf_{q \in \mathcal{P}(H_n)} \left\{ \int \varphi^{t_{j,n}} dq + \frac{1}{2c(\ell)^2} \sum_{k \in [n] \setminus \{j\}} \left(\int \mathbb{1}_{\sigma t_{j,n}(k) \neq y_{t_{i,n}}(k)} dq(y) \right)^2 \right\} = Q^{H_n} \varphi^{t_{j,n}}(\sigma). \end{aligned}$$

For the proof of the second part of Lemma 2.5, let us consider $p_i^l, l \in D_i$, a collection of measures in $\mathcal{P}(H_i)$, and $p_j \in \mathcal{P}(H_j)$ ($j \neq i$). For $\theta \in [0, 1]$,

$$p := \frac{1}{d} \sum_{l \in D_i} [\theta p_i^l + (1 - \theta) p_j],$$

is a probability measure on G . Therefore, according to the definition of $Q^i \varphi$, for any $\sigma \in H_n$,

$$Q^i \varphi(\sigma t_{i,n}) \leq \frac{1}{d} \sum_{l \in D_i} \left[\theta \int f dp_i^l + (1 - \theta) \int f dp_j \right] + \frac{1}{2c(\ell)^2} (A + B + C),$$

with

$$A = \sum_{k \in [n] \setminus \text{supp}(t_{i,j})} \left(\int \mathbb{1}_{\sigma t_{i,n}(k) \neq y(k)} dp(y) \right)^2, \quad B = \sum_{k \in D_i} \left(\int \mathbb{1}_{\sigma t_{i,n}(k) \neq y(k)} dp(y) \right)^2,$$

$$\text{and } C = 2 \left(\int \mathbb{1}_{\sigma t_{i,n}(i) \neq y(i)} dp(y) \right)^2.$$

Since $\sigma \in H_n$ and $p_i^l \in \mathcal{P}(H_i)$, one has $\int \mathbb{1}_{\sigma t_{i,n}(i) \neq y(i)} dp_i(y) = 0$ and $\int \mathbb{1}_{\sigma(i) \neq y(i)} dp_j(y) = 1$. It follows that

$$C = 2(1 - \theta)^2.$$

For any $k \in [n]$ and $l \in D_i$, let us note

$$U_i(k, l) := \int \mathbb{1}_{\sigma t_{i,n}(k) \neq y(k)} dp_i^l(y), \quad \text{and} \quad U_j(k) := \int \mathbb{1}_{\sigma t_{i,n}(k) \neq y(k)} dp_j(y).$$

By the Cauchy-Schwarz inequality, one has

$$A \leq \frac{1}{d} \sum_{l \in D_i} \left[\theta \sum_{k \in [n] \setminus \text{supp}(t_{i,j})} U_i^2(k, l) + (1 - \theta) \sum_{k \in [n] \setminus \text{supp}(t_{i,j})} U_j^2(k) \right].$$

We also have

$$\begin{aligned}
B &= \sum_{k \in D_i} \left(\frac{\theta}{d} U_i(k, k) + (1 - \theta) U_j(k) + \frac{\theta}{d} \sum_{l \in D_i \setminus \{k\}} U_i(k, l) \right)^2 \\
&\leq \sum_{k \in D_i} \left[d \left(\frac{\theta}{d} U_i(k, k) + (1 - \theta) U_j(k) \right)^2 + \frac{\theta^2}{d} \sum_{l \in D_i \setminus \{k\}} U_i^2(k, l) \right] \\
&\leq \sum_{k \in D_i} \left[\frac{2\theta^2}{d} U_i^2(k, k) + 2(1 - \theta)^2 + \frac{\theta^2}{d} \sum_{l \in D_i \setminus \{k\}} U_i^2(k, l) \right] \\
&\leq 2d^2(1 - \theta)^2 + \frac{\theta}{d} \sum_{l \in D_i} \left[2U_i^2(l, l) + \sum_{k \in D_i \setminus \{l\}} U_i^2(k, l) \right]
\end{aligned}$$

All the above estimates together provide

$$\begin{aligned}
A + B + C &\leq (2d^2 + 2)(1 - \theta)^2 \\
&\quad + \frac{1}{d} \sum_{l \in D_i} \left[\theta \left(2U_i^2(l, l) + \sum_{k \in [n] \setminus \{l\}} U_i^2(k, l) \right) + (1 - \theta) \sum_{k \in [n] \setminus \text{supp}(t_{i,j})} U_j^2(k) \right].
\end{aligned}$$

Since $2d^2 + 2 \leq 2(\ell - 1)^2 + 2 = c(\ell)^2$, we get by optimizing over all $p_i^l \in \mathcal{P}(H_i)$ and all $p_j \in \mathcal{P}(H_j)$,

$$Q^i \varphi(\sigma_{t_{i,n}}) \leq \frac{1}{d} \sum_{l \in D_i} [\theta V_l + (1 - \theta) W_j] + \frac{1}{2} (1 - \theta)^2,$$

with

$$\begin{aligned}
V_l &:= \inf_{p_i \in \mathcal{P}(H_i)} \left\{ \int \varphi dp_i + \frac{1}{c(\ell)^2} \int \mathbb{1}_{\sigma_{t_{i,n}(l)} \neq y(l)} dp_i(y) + \frac{1}{2c(\ell)^2} \sum_{k \in [n] \setminus \{l\}} \int \mathbb{1}_{\sigma_{t_{i,n}(k)} \neq y(k)} dp_i(y) \right\} \\
&= \inf_{q_i \in \mathcal{P}(H_n)} \left\{ \int \varphi^{t_{i,n}} dq_i + \frac{1}{c(\ell)^2} \int \mathbb{1}_{\sigma_{(t_{i,n}(l))} \neq y(t_{i,n}(l))} dq_i(y) + \frac{1}{2c(\ell)^2} \sum_{k \in [n-1] \setminus \{t_{i,n}(l)\}} \int \mathbb{1}_{\sigma_{t_{i,n}(k)} \neq y(k)} dp_i(y) \right\} \\
&= Q^{H_n, t_{i,n}(l)} \varphi^{t_{i,n}}(\sigma)
\end{aligned}$$

and

$$\begin{aligned}
W_j &:= \inf_{p_j \in \mathcal{P}(H_j)} \left\{ \int \varphi dp_j + \frac{1}{2c(\ell)^2} \sum_{k \in [n] \setminus \text{supp}(t_{i,j})} \int \mathbb{1}_{\sigma t_{i,n}(k) \neq y(k)} dp_i(y) \right\} \\
&= \inf_{p_j \in \mathcal{P}(H_j)} \left\{ \int \varphi dp_j + \frac{1}{2c(\ell)^2} \sum_{k \in [n] \setminus \text{supp}(t_{i,j})} \int \mathbb{1}_{\sigma t_{i,n}(k) \neq y t_{i,j}(k)} dp_j(y) \right\} \\
&\leq \inf_{p_j \in \mathcal{P}(H_j)} \left\{ \int \varphi dp_j + \frac{1}{2c(\ell)^2} \sum_{k \in [n] \setminus \{i\}} \int \mathbb{1}_{\sigma t_{i,n}(k) \neq y t_{i,j}(k)} dp_j(y) \right\} \\
&\leq \inf_{q_j \in \mathcal{P}(H_n)} \left\{ \int \varphi^{t_{i,n} t_{i,j}^{-1}} dq_j + \frac{1}{2c(\ell)^2} \sum_{k \in [n] \setminus \{i\}} \int \mathbb{1}_{\sigma t_{i,n}(k) \neq y t_{i,n}(k)} dp_j(y) \right\} \\
&= \inf_{q_j \in \mathcal{P}(H_n)} \left\{ \int \varphi^{t_{i,n} t_{i,j}^{-1}} dq_j + \frac{1}{2c(\ell)^2} \sum_{k \in [n-1]} \int \mathbb{1}_{\sigma(k) \neq y(k)} dp_j(y) \right\} \\
&= Q^{H_n} \varphi^{t_{i,n} t_{i,j}^{-1}}
\end{aligned}$$

where we use successively the following arguments: $t_{i,j}(k) = k$ for any $k \in [n] \setminus \text{supp}(t_{i,j})$; the set $[n] \setminus \text{supp}(t_{i,j})$ is a subset of $[n] \setminus \{i\}$; for any $y \in H_j$ one has $y t_{i,j} t_{i,n}^{-1} \in H_n$. This ends the proof of Lemma 2.5. \square

We will now prove (24) by induction over n . For $n = 2$, G is the two points space S_2 which is 2-local. For $i \in \{1, 2\}$, and for any $p \in \mathcal{P}(G)$,

$$\begin{aligned}
\frac{1}{c(2)^2} \left(\int \mathbb{1}_{\sigma(i) \neq y(i)} dp(y) \right)^2 + \frac{1}{2c(2)^2} \sum_{k, k \neq i} \left(\int \mathbb{1}_{\sigma(k) \neq y(k)} dp(y) \right)^2 \\
= \frac{3}{8} \left(\int \mathbb{1}_{\sigma \neq y} dp(y) \right)^2 \leq \frac{1}{2} \left(\int \mathbb{1}_{\sigma \neq y} dp(y) \right)^2.
\end{aligned}$$

As a consequence, we get the expected result from Lemma 2.2 applied with $\mathcal{X} = G$.

Let us now present the induction step. We assume that (24) holds at the rank $n - 1$ for all $j \in \{1, \dots, n - 1\}$. By symmetry, we may assume without loss of generality that $j = n$ in (24) since μ is the uniform probability measure on G .

We assume that $\text{orb}(n) \neq \{n\}$, otherwise the induction step is obvious. We first apply Lemma 2.4,

$$\int e^{\alpha Q^n \varphi} d\mu = \int e^{\alpha Q^{\sigma(n)} \varphi^{(-1)(\sigma^{-1})}} d\mu(\sigma) = \int e^{\alpha Q^{\sigma^{-1}(n)} \varphi^{(-1)(\sigma)}} d\mu(\sigma).$$

Let $g = \varphi^{(-1)}$. According to the decomposition of the measure μ on the sets H_i , $i \in \text{orb}(n)$,

$$(26) \quad \int e^{\alpha Q^n \varphi} d\mu = \frac{1}{|\text{orb}(n)|} \sum_{i \in \text{orb}(n)} \int e^{\alpha Q^i g} d\mu_i,$$

where μ_i is the uniform probability measure on H_i . For $k \in \text{orb}(n)$, let us note

$$\hat{g}(k) := \log \left(\int e^{-(1-\alpha)g} d\mu_k \right)^{-1/(1-\alpha)}.$$

We choose $j \in \text{orb}(n)$ such that

$$\min_{k \in \text{orb}(n)} \hat{g}(k) = \hat{g}(j).$$

By property (16) and then applying Lemma 2.5, we get

$$\int e^{\alpha Q^j g} d\mu_j = \int e^{\alpha Q^j g(\sigma_{t_i,n})} d\mu_n(\sigma) \leq \int e^{\alpha Q^{H_n} g^{j,n}} d\mu_n.$$

By the induction hypotheses applied to the measure μ_n , it follows that

$$\begin{aligned} \int e^{\alpha Q^j g} d\mu_j &\leq \left(\int e^{-(1-\alpha)g^{j,n}} d\mu_n \right)^{-\alpha/(1-\alpha)} \\ (27) \qquad &= \left(\int e^{-(1-\alpha)g} d\mu_j \right)^{-\alpha/(1-\alpha)} = e^{\alpha \hat{g}(j)}. \end{aligned}$$

Let us now consider $i \neq j$, $i \in \text{orb}(n)$, property (16), the second part of Lemma 2.5 and Jensen's inequality yield: for any $\theta \in [0, 1]$,

$$\begin{aligned} \int e^{\alpha Q^i g} d\mu_i &= \int e^{\alpha Q^i g(\sigma_{t_i,n})} d\mu_n \\ &\leq \exp \left\{ \frac{1}{d} \sum_{l \in i_n(D_i)} \left[\theta \log \int e^{\alpha Q^{H_n,l} g^{i,n}} d\mu_n + (1-\theta) \log \int e^{\alpha Q^{H_n} g^{i,n,i,j}} d\mu_n \right] + \frac{\alpha}{2} (1-\theta)^2 \right\} \end{aligned}$$

By the induction hypotheses applied with the uniform measure μ_n on the ℓ -local subgroup H_n , and from property (17), it follows that

$$(28) \qquad \int e^{\alpha Q^i g} d\mu_i \leq \exp \left\{ \theta \alpha \hat{g}(i) + (1-\theta) \alpha \hat{g}(j) + \frac{\alpha}{2} (1-\theta)^2 \right\}.$$

According to the definition (23) of the infimum-convolution operator $\tilde{R}\hat{g}$ defined on the space $\mathcal{X} = \text{orb}(n)$, we may easily check that for every $i \in \text{orb}(n)$,

$$\tilde{R}\hat{g}(i) = \inf_{\theta \in [0,1]} \left\{ \theta \hat{g}(i) + (1-\theta) \min_{k \in \text{orb}(n)} \hat{g}(k) + \frac{1}{2} (1-\theta)^2 \right\}.$$

Therefore optimizing over all $\theta \in [0, 1]$, we get from (27) and (28): for all $i \in \text{orb}(n)$,

$$\int e^{\alpha Q^i g} d\mu_i \leq e^{\alpha \tilde{R}\hat{g}(i)}.$$

Finally, from Lemma 2.2 applied with the uniform probability measure $\hat{\mu}$ on $\text{orb}(n)$, the equality (26) gives

$$\begin{aligned} \int e^{\alpha Q^n \varphi} d\mu &\leq \int e^{\alpha \tilde{R} \hat{g}} d\hat{\mu} \leq \left(\int e^{-(1-\alpha)\hat{g}} d\hat{\mu} \right)^{-\alpha/(1-\alpha)} \\ &= \left(\frac{1}{|\text{orb}(n)|} \sum_{i \in \text{orb}(n)} \int e^{-(1-\alpha)g} d\mu_i \right)^{-\alpha/(1-\alpha)} = \left(\int e^{-(1-\alpha)g} d\mu \right)^{-\alpha/(1-\alpha)}. \end{aligned}$$

The proof of (24) is completed. \square

3. TRANSPORT-ENTROPY INEQUALITIES ON THE SLICE OF THE CUBE.

Proof of (a) in Theorem 1.4. We adapt to the space $\mathcal{X}_{k,n-k}$ the proof of (a) in Theorem 1.3. In order to avoid redundancy, we only present the main steps of the proof.

By duality, it suffices to prove that for all functions φ on $\mathcal{X}_{k,n-k}$ and all $\lambda \geq 0$,

$$(29) \quad \int e^{\lambda Q \varphi} d\mu_{k,n-k} \leq e^{\int \lambda \varphi d\mu_{k,n-k} + C_{k,n-k} \lambda^2 / 2},$$

where

$$Q\varphi(x) = \inf_{p \in \mathcal{P}(\mathcal{X}_{k,n-k})} \left\{ \int \varphi dp + \int d_h(x, y) dp(x) \right\}, \quad x \in \mathcal{X}_{k,n-k},$$

and for any $0 < \alpha < 1$,

$$(30) \quad \left(\int e^{\alpha \tilde{Q} \varphi} d\mu \right)^{1/\alpha} \left(\int e^{-(1-\alpha)\varphi} d\mu \right)^{1/(1-\alpha)} \leq 1,$$

where for $t > 0$,

$$\tilde{Q}\varphi(x) = \inf_{p \in \mathcal{P}(\mathcal{X}_{k,n-k})} \left\{ \int \varphi dp + \frac{1}{2t} \left(\int d_h(x, y) dp(y) \right)^2 \right\}, \quad x \in \mathcal{X}_{k,n-k}.$$

The proof is by induction over n and $0 \leq k \leq n$.

For any $n \geq 1$, if $k = n$ or $k = 0$, the set $\mathcal{X}_{k,n-k}$ is reduced to a singleton and the inequalities (29) or (30) are obvious.

For $n = 2$ and $k = 1$, $\mathcal{X}_{k,n-k}$ is a two points set, (29) and (30) directly follows from property (19) and Lemma 2.2 on $\mathcal{X} = \mathcal{X}_{1,1}$.

For the induction step, we consider the collection of subset $\Omega_{i,j}$, with $i, j \in \{1, \dots, n\}$, $i \neq j$, defined by

$$\Omega^{i,j} := \{x \in \mathcal{X}_{k,n-k}, x_i = 0, x_j = 1\}.$$

Since for any $x \in \mathcal{X}_{k,n-k}$,

$$\sum_{(i,j), i \neq j} \mathbb{1}_{\Omega^{i,j}}(x) = k(n-k),$$

any probability measure p on $\mathcal{X}_{k,n-k}$ admits a unique decomposition defined by

$$p = \sum_{(i,j), i \neq j} \hat{p}(i, j) p^{i,j}, \quad \text{with} \quad p^{i,j} = \frac{\mathbb{1}_{\Omega^{i,j}} p}{p(\Omega^{i,j})} \quad \text{and} \quad \hat{p}(i, j) = \frac{p(\Omega^{i,j})}{k(n-k)}.$$

Thus, we define probability measures $p^{i,j} \in \mathcal{P}(\Omega^{i,j})$ and a probability measure \hat{p} on the set $I(n) = \{(i, j) \in \{1, \dots, n\}^2, i \neq j\}$. For the uniform law μ on $\mathcal{X}_{k,n-k}$, one has

$$\mu = \frac{1}{n(n-1)} \sum_{(i,j) \in I(n)} \mu^{i,j},$$

where $\mu^{i,j}$ is the uniform law on $\Omega^{i,j}$, $\mu_{i,j}(x) = \binom{n-2}{k-1}$, for any $x \in \Omega^{i,j}$.

For any $(i, j), (l, m) \in I(n)$, let $s_{(i,j),(l,m)} : \mathcal{X}_{k,n-k} \rightarrow \mathcal{X}_{k,n-k}$ denote the map that exchanges the coordinates x_i by x_l and x_j by x_m for any point $x \in \mathcal{X}_{k,n-k}$. This map is one to one from $\Omega^{i,j}$ to $\Omega^{l,m}$. For any $(i, j) \in I(n)$, the set $\Omega^{i,j}$ can be identify to $\mathcal{X}_{k-1,n-k-1}$ and therefore the induction hypotheses apply for the uniform law $\mu^{i,j}$ on $\Omega^{i,j}$ with Hamming distance

$$d_h^{i,j}(x, y) = \frac{1}{2} \sum_{k \in [n] \setminus \{i,j\}} \mathbb{1}_{x_k \neq y_k}, \quad x, y \in \Omega^{i,j}.$$

For any function $f : \Omega^{i,j} \rightarrow \mathbb{R}$ and any $x \in \Omega^{i,j}$, we define

$$Q^{\Omega^{i,j}} f(x) := \inf_{p \in \mathcal{P}(\Omega^{i,j})} \left\{ \int f dp + \int d_h^{i,j}(x, y) dp(y) \right\},$$

and

$$\tilde{Q}_t^{\Omega^{i,j}} f(x) := \inf_{p \in \mathcal{P}(H_n)} \left\{ \int f dp + \frac{1}{2t} \left(\int d_h^{i,j}(x, y) dp(x) \right)^2 \right\}.$$

The key lemma of the proof that replaces Lemma 2.1 and 2.3 is the following.

Lemma 3.1. *For any function $\varphi : \Omega^{i,j} \rightarrow \mathbb{R}$ and any $x \in \Omega^{i,j}$, one has*

$$Q\varphi(x) \leq \inf_{\hat{p} \in \mathcal{P}(I(n))} \left\{ \sum_{(l,m) \in I(n)} Q^{\Omega^{i,j}}(\varphi \circ s_{(i,j),(l,m)})(x) \hat{p}(l, m) + \sum_{(l,m) \in I(n)} \mathbb{1}_{(l,m) \neq (i,j)} \hat{p}(l, m) \right\},$$

and

$$\begin{aligned} \tilde{Q}_{C_{k,n-k}} \varphi(x) \leq \inf_{\hat{p} \in \mathcal{P}(I(n))} \left\{ \sum_{(l,m) \in I(n)} \tilde{Q}_{C_{k-1,n-k-1}}^{\Omega^{i,j}}(\varphi \circ s_{(i,j),(l,m)})(x) \hat{p}(l, m) \right. \\ \left. + \frac{1}{2} \left(\sum_{(l,m) \in I(n)} \mathbb{1}_{(l,m) \neq (i,j)} \hat{p}(l, m) \right)^2 \right\}. \end{aligned}$$

The proof of this lemma is obtained by decomposition of the measures $p \in \mathcal{P}(\mathcal{X}_{k,n-k})$ on the sets $\Omega^{i,j}$, and using the following inequality

$$d_h(x, y) \leq d_h^{i,j}(x, s_{(i,j),(l,m)}(y)) + d_h(s_{(i,j),(l,m)}(y), y) \leq d_h^{i,j}(x, s_{(i,j),(l,m)}(y)) + 2,$$

for any $x \in \Omega^{i,j}$, $y \in \Omega^{l,m}$.

Finally, the proof of the induction step based on Lemma 3.1 and the identity $C_{k,n-k} = C_{k-1,n-k-1} + 1$, is let to the reader. \square

Proof of (b) in Theorem 1.4. We will explain the projection argument on the dual formulations of the transport-entropy inequalities. According to Proposition 4.5

and Theorem 9.5 of [GRST14], the weak transport-entropy inequality (11) is equivalent to the following property that we want to establish: for any real function f on $\mathcal{X}_{k,n-k}$ and for any $0 < \alpha < 1$,

$$(31) \quad \left(\int e^{\alpha \widehat{Q}f} d\mu_{k,n-k} \right)^{1/\alpha} \left(\int e^{-(1-\alpha)f} d\mu_{k,n-k} \right)^{1/(1-\alpha)} \leq 1,$$

where

$$\widehat{Q}f(x) := \inf_{p \in \mathcal{P}(\mathcal{X}_{k,n-k})} \left\{ \int \varphi dp + \frac{1}{8} \sum_{k=1}^n \left(\int \mathbb{1}_{x_k \neq y_k} dp(y) \right)^2 \right\}, \quad x \in \mathcal{X}_{k,n-k}.$$

Let us apply property (10) to the function $f \circ P : S_n \rightarrow \mathbb{R}$. Since $\mu_{k,n-k} = P\#\mu$, we get

$$\left(\int e^{\alpha \widehat{Q}(f \circ P)} d\mu \right)^{1/\alpha} \left(\int e^{-(1-\alpha)f} d\mu_{k,n-k} \right)^{1/(1-\alpha)} \leq 1.$$

The inequality (31) is an easy consequence of the following result.

Lemma 3.2. *For any $\sigma \in S_n$, $\widehat{Q}(f \circ P)(\sigma) \geq \widehat{Q}f(P(\sigma))$.*

It remains to prove this lemma. By definition, one has

$$\begin{aligned} \widehat{Q}(f \circ P)(\sigma) &= \inf_{p \in \mathcal{P}(S_n)} \left\{ \int f \circ P dp + \sum_{j=1}^n \left(\int \mathbb{1}_{\sigma(j) \neq \tau(j)} dp(\tau) \right)^2 \right\} \\ &= \inf_{q \in \mathcal{P}(\mathcal{X}_{k,n-k})} \inf_{p \in S_n, P\#p=q} \left\{ \int f \circ P dp + \sum_{j=1}^n \left(\int \mathbb{1}_{\sigma(j) \neq \tau(j)} dp(\tau) \right)^2 \right\} \\ &= \inf_{q \in \mathcal{P}(\mathcal{X}_{k,n-k})} \left\{ \int f dq + \inf_{p \in S_n, P\#p=q} \left[\sum_{j=1}^n \left(\int \mathbb{1}_{\sigma(j) \neq \tau(j)} dp(\tau) \right)^2 \right] \right\}. \end{aligned}$$

Let $p \in S_n$ such that $P\#p = q$.

$$\int \mathbb{1}_{\sigma(j) \neq \tau(j)} dp(\tau) = \sum_{y \in \mathcal{X}_{k,n-k}} \sum_{\tau \in S_n} \mathbb{1}_{U(\tau)=y, \sigma(j) \neq \tau(j)} P(\tau).$$

For $y \in \mathcal{X}_{k,n-k}$, let us note $Y = \{i \in [n], y_i = 1\}$. Then $P(\tau) = y$ if and only if $\tau([k]) = Y$.

Assume that $j \in [k]$, if $\tau([k]) = Y$ and $\sigma(j) \notin Y$ then $\tau(j) \neq \sigma(j)$. Therefore one has

$$\{\tau, \tau([k]) = Y, \sigma(j) \notin Y\} \subset \{\tau, P(\tau) = y, \sigma(j) \neq \tau(j)\}.$$

Assume now that $j \notin [k]$, if $\tau([k]) = Y$ and $\sigma(j) \in Y$ then we also have $\tau(j) \neq \sigma(j)$. It follows that

$$\{\tau, \tau([k]) = Y, \sigma(j) \in Y\} \subset \{\tau, P(\tau) = y, \sigma(j) \neq \tau(j)\}.$$

From these observations, we get

$$\begin{aligned}
 \sum_{j=1}^n \left(\int \mathbb{1}_{\sigma(j) \neq \tau(j)} dp(\tau) \right)^2 &\geq \sum_{j \in [k]} \left(\int \mathbb{1}_{P(\tau)=y, \sigma(j) \notin Y} dp(\tau) \right)^2 + \sum_{j \in [n] \setminus [k]} \left(\int \mathbb{1}_{P(\tau)=y, \sigma(j) \in Y} dp(\tau) \right)^2 \\
 &= \sum_{j \in [k]} \left(\int \mathbb{1}_{\sigma(j) \notin Y} dq(y) \right)^2 + \sum_{j \in [n] \setminus [k]} \left(\int \mathbb{1}_{\sigma(j) \in Y} dq(y) \right)^2 \\
 &= \sum_{i \in \sigma([k])} \left(\int \mathbb{1}_{i \notin Y} dq(y) \right)^2 + \sum_{i \notin \sigma([k])} \left(\int \mathbb{1}_{i \in Y} dq(y) \right)^2 \\
 &= \sum_{i \in \sigma([k])} \left(\int \mathbb{1}_{y_i=0} dq(y) \right)^2 + \sum_{i \notin \sigma([k])} \left(\int \mathbb{1}_{y_i=1} dq(y) \right)^2
 \end{aligned}$$

Setting $x = P(\sigma)$, it follows that

$$\begin{aligned}
 \sum_{j=1}^n \left(\int \mathbb{1}_{\sigma(j) \neq \tau(j)} dp(\tau) \right)^2 &\geq \sum_{i=1}^n \left[\mathbb{1}_{x_i=1} \left(\int \mathbb{1}_{y_i=0} dq(y) \right)^2 + \mathbb{1}_{x_i=0} \left(\int \mathbb{1}_{y_i=1} dq(y) \right)^2 \right] \\
 &= \sum_{i=1}^n \left(\int \mathbb{1}_{y_i \neq x_i} dq(y) \right)^2.
 \end{aligned}$$

This inequality provides

$$\widehat{Q}(f \circ P)(\sigma) \geq \widehat{Q}f(x) = \widehat{Q}f(P(\sigma)).$$

The proof of Lemma 3.2 and (b) in Theorem 1.4 is completed. \square

4. APPENDIX

Proof of Lemma 2.2. Let $\alpha \in (0, 1)$ and f be a real function on the finite set \mathcal{X} . We want to show that for any probability measure ν on \mathcal{X} ,

$$\left(\int e^{\alpha \widetilde{R}^\alpha f} d\nu \right)^{1/\alpha} \left(\int e^{-(1-\alpha)f} d\nu \right)^{1/(1-\alpha)} \leq 1.$$

We will apply the following lemma whose proof is given at the end of this section.

Lemma 4.1. *Let F be a real function on \mathcal{X} and $K \in \mathbb{R}$. Let us consider the set*

$$C := \left\{ \nu \in \mathcal{P}(\mathcal{X}), \int F d\nu = K \right\}.$$

If C is not empty, then the extremal points of this convex set are Dirac measures or convex combinations of two Dirac measures on \mathcal{X} .

Given a real function f on \mathcal{X} , for any $K \in \mathbb{R}$, let

$$C_K = \left\{ \nu \in \mathcal{P}(\mathcal{X}), \int e^{-(1-\alpha)f} d\nu = K \right\}.$$

One has

$$\sup_{\nu \in \mathcal{P}(\mathcal{X})} \left(\int e^{\alpha \widetilde{R}^\alpha f} d\nu \right)^{1/\alpha} \left(\int e^{-(1-\alpha)f} d\nu \right)^{1/(1-\alpha)} = \sup_{K, C_K \neq \emptyset} \left(\sup_{\nu \in C_K} \int e^{\alpha \widetilde{R}^\alpha f} d\nu \right)^{1/\alpha} K^{1/(1-\alpha)}$$

The supremum of the linear function $\nu \mapsto \int e^{\alpha \tilde{R}^\alpha f} d\nu$ on the non empty convex set C_K is reached at an extremal point of C_K . Therefore, by Lemma 4.1, we get

$$\begin{aligned} & \sup_{\nu \in \mathcal{P}(\mathcal{X})} \left(\int e^{\alpha \tilde{R}^\alpha f} d\nu \right)^{1/\alpha} \left(\int e^{-(1-\alpha)h} d\nu \right)^{1/(1-\alpha)} \\ &= \sup_{x,y \in \mathcal{X}} \sup_{\lambda \in [0,1]} \left((1-\lambda)e^{\alpha \tilde{R}^\alpha f(x)} + \lambda e^{\alpha \tilde{R}^\alpha f(y)} \right)^{1/\alpha} \left((1-\lambda)e^{-(1-\alpha)f(x)} + \lambda e^{-(1-\alpha)f(y)} \right)^{1/(1-\alpha)} \end{aligned}$$

Now, let x and y be some fixed points of \mathcal{X} . It remains to show that for any real function f on E and for any $x, y \in \mathcal{X}$,

$$\left((1-\lambda)e^{\alpha \tilde{R}^\alpha f(x)} + \lambda e^{\alpha \tilde{R}^\alpha f(y)} \right)^{1/\alpha} \left((1-\lambda)e^{-(1-\alpha)f(x)} + \lambda e^{-(1-\alpha)f(y)} \right)^{1/(1-\alpha)} \leq 1.$$

The left-hand side of this inequality is invariant by translation of the function f by a constant. Therefore, by symmetry, we may assume that $0 = f(y) \leq f(x)$. It follows that $\tilde{R}^\alpha f(y) = 0$. Therefore we want to check that for any non-negative function f on $\{x, y\}$, for any $\lambda \in [0, 1]$,

$$\left((1-\lambda)e^{\alpha \tilde{R}^\alpha f(x)} + \lambda \right)^{1/\alpha} \left((1-\lambda)e^{-(1-\alpha)f(x)} + \lambda \right)^{1/(1-\alpha)} \leq 1,$$

or equivalently, setting $\psi(\lambda) = \left((1-\lambda)e^{-(1-\alpha)f(x)} + \lambda \right)^{-\alpha/(1-\alpha)} - \lambda$,

$$e^{\alpha \tilde{R}^\alpha f(x)} \leq \inf_{\lambda \in [0,1]} \frac{\psi(\lambda) - \psi(1)}{1 - \lambda} = -\psi'(1) = \frac{\alpha}{1-\alpha} \left(1 - e^{-(1-\alpha)f(x)} \right) + 1,$$

since ψ is a convex function on $[0, 1]$.

So, it suffices to check that $\tilde{R}^\alpha f(x) \leq \phi(f(x))$, where

$$\phi(h) = \frac{1}{\alpha} \log \left(\frac{\alpha}{1-\alpha} \left(1 - e^{-(1-\alpha)h} \right) + 1 \right), \quad h \geq 0.$$

The function ϕ is concave and $\phi(0) = 0$. For all $h \geq 0$, one has

$$\phi'(h) = \frac{1-\alpha}{e^{(1-\alpha)h} - \alpha}.$$

The function ϕ' is a bijection from $[0, +\infty)$ to $(0, 1]$. It follows that

$$\phi(h) = \inf_{\theta \in (0,1]} \{\theta h + c_\alpha(1-\theta)\}, \quad h \geq 0,$$

where c_α is the convex function defined by

$$c_\alpha(1-\theta) = \sup_{h \in [0, +\infty)} \{-\theta h + \phi(h)\}, \quad \theta \in (0, 1].$$

After computations, we get

$$c_\alpha(u) := \frac{\alpha(1-u) \log(1-u) - (1-\alpha u) \log(1-\alpha u)}{\alpha(1-\alpha)},$$

and therefore we exactly have for any $x \in \mathcal{X}$,

$$\phi(f(x)) = \inf_{\theta \in [0,1]} \{\theta f(x) + c_\alpha(1-\theta)\} = \tilde{R}^\alpha f(x).$$

The proof of Lemma 2.2 is completed. \square

Proof of Lemma 4.1. We will show that, if $\nu \in C$ is a convex combination of three probability measures ν_1, ν_2, ν_3 ,

$$\nu = \alpha_1 \nu_1 + \alpha_2 \nu_2 + \alpha_3 \nu_3,$$

with $\alpha_1 \neq 0, \alpha_2 \neq 0, \alpha_3 \neq 0$, and $\alpha_1 + \alpha_2 + \alpha_3 = 1$, and $\nu_1(\mathcal{X}) > 0, \nu_2(\mathcal{X}) > 0, \nu_3(\mathcal{X}) > 0$, then there exists two measures $\hat{\nu}_1, \hat{\nu}_2$ in C and $\lambda \in [0, 1]$ such that

$$\nu = \lambda \hat{\nu}_1 + (1 - \lambda) \hat{\nu}_2.$$

Setting $F_i = \int F d\nu_i$, for $i = 1, 2, 3$, we may assume, without loss of generality, that $F_1 \leq F_2 \leq F_3$. Then one has either $F_1 \leq K \leq F_2$, either $F_2 \leq K \leq F_3$.

We will assume that $F_1 \leq K \leq F_2$. The case $F_2 \leq K \leq F_3$ can be treated identically and the proof in that case is left to the reader. Since $F_1 \leq K \leq F_2$ and $F_1 \leq K \leq F_3$, there exists $\beta, \gamma \in [0, 1]$ such that

$$(32) \quad K = \beta F_1 + (1 - \beta) F_2 \quad \text{and} \quad K = \gamma F_1 + (1 - \gamma) F_3.$$

If $F_1 = F_3$ then $F_1 = F_2 = F_3 = K$ and therefore $\nu_1, \nu_2, \nu_3 \in C$. We may choose $\lambda = \alpha_1, \hat{\nu}_1 = \nu_1$ and $\hat{\nu}_2 = \frac{\alpha_2 \nu_2 + \alpha_3 \nu_3}{\alpha_2 + \alpha_3}$.

If $F_1 = F_2$ then necessarily $F_1 = F_2 = F_3 = K$ and we are reduced to the previous case.

So, we may now assume that $F_1 \neq F_3$ and $F_1 \neq F_2$ and therefore $F_1 < K \leq F_2 \leq F_3$. In that case, we exactly have

$$\beta = \frac{F_2 - K}{F_2 - F_1} \quad \text{and} \quad \gamma = \frac{F_3 - K}{F_3 - F_1}.$$

Let us choose

$$\lambda = \frac{\alpha_2}{1 - \beta} = \alpha_2 \frac{F_2 - F_1}{K - F_1}, \quad \hat{\nu}_1 = \beta \nu_1 + (1 - \beta) \nu_2, \quad \hat{\nu}_2 = \gamma \nu_1 + (1 - \gamma) \nu_2.$$

The equalities (32) ensure that $\hat{\nu}_1 \in C$ and $\hat{\nu}_2 \in C$. The proof of Lemma 4.1 ends by checking that $\lambda \hat{\nu}_1 + (1 - \lambda) \hat{\nu}_2 = \hat{\mu}$. One has

$$(33) \quad \lambda \hat{\nu}_1 + (1 - \lambda) \hat{\nu}_2 = (\lambda \beta + (1 - \lambda) \gamma) \nu_1 + \lambda(1 - \beta) \nu_2 + (1 - \lambda)(1 - \gamma) \nu_3.$$

According to the definitions of λ, β, γ , we may easily check that $\lambda(1 - \beta) = \alpha_2$, and

$$(1 - \lambda)(1 - \gamma) = \frac{K - F_1}{F_3 - F_1} - \alpha_2 \frac{F_2 - F_1}{F_3 - F_1}.$$

Since $\hat{\mu} \in C$, one has $(1 - (\alpha_2 + \alpha_3))F_1 + \alpha_2 F_2 + \alpha_3 F_3$ and therefore

$$(1 - \lambda)(1 - \gamma) = \alpha_3.$$

As a consequence $\lambda \beta + (1 - \lambda) \gamma = 1 - \alpha_2 - \alpha_3 = \alpha_1$ and according to (33), we get

$$\lambda \hat{\nu}_1 + (1 - \lambda) \hat{\nu}_2 = \alpha_1 \nu_1 + \alpha_2 \nu_2 + \alpha_3 \nu_3 = \nu.$$

□

REFERENCES

- [ACW14] R. Adamczak, D. Chafaï, and P. Wolff. Circular law for random matrices with exchangeable entries. *ArXiv e-prints*, February 2014.
- [BHT06] S. G. Bobkov, C. Houdré, and P. Tetali. The subgaussian constant and concentration inequalities. *Israel J. Math.*, 156:255–283, 2006.
- [Csi67] I. Csiszár. Information-type measures of difference of probability distributions and indirect observations. *Studia Sci. Math. Hungar.*, 2:299–318, 1967.
- [DP09] D. Dubhashi and A. Panconesi. *Concentration of Measure for the Analysis of Randomized Algorithms*. Cambridge University Press, New York, NY, USA, 1st edition, 2009.
- [GRST14] N. Gozlan, C. Roberto, P.-M. Samson, and P. Tetali. Kantorovich duality for general transport costs and applications. *ArXiv e-prints*, December 2014.
- [Hoe63] W. Hoeffding. Probability inequalities for sums of bounded random variables. *Journal of the American Statistical Association*, 58(301):13–30, March 1963.
- [Kul67] S. Kullback. Lower bound for discrimination information in terms of variation. *IEEE Trans. Information Theory*, 4:126127, 1967.
- [Led01] M. Ledoux. *The concentration of measure phenomenon*, volume 89 of *Mathematical Surveys and Monographs*. American Mathematical Society, Providence, RI, 2001.
- [LM03] M. J. Luczak and C. McDiarmid. Concentration for locally acting permutations. *Discrete Math.*, 265(1-3):159–171, 2003.
- [Mau79] B. Maurey. Construction de suites symétriques. *C. R. Acad. Sci. Paris Sér. A-B*, 288(14):A679–A681, 1979.
- [McD89] C. McDiarmid. On the method of bounded differences. In *Surveys in combinatorics, 1989 (Norwich, 1989)*, volume 141 of *London Math. Soc. Lecture Note Ser.*, pages 148–188. Cambridge Univ. Press, Cambridge, 1989.
- [McD02] C. McDiarmid. Concentration for independent permutations. *Combin. Probab. Comput.*, 11(2):163–178, 2002.
- [MR02] M. Molloy and B. Reed. *Graph Colouring and the Probabilistic Method*. Algorithms and Combinatorics. Springer, 2002.
- [MS86] V. D. Milman and G. Schechtman. *Asymptotic theory of finite-dimensional normed spaces*, volume 1200 of *Lecture Notes in Mathematics*. Springer-Verlag, Berlin, 1986. With an appendix by M. Gromov.
- [Pau14] D. Paulin. The convex distance inequality for dependent random variables, with applications to the stochastic travelling salesman and other problems. *Electron. J. Probab.*, 19:no. 68, 34, 2014.
- [Pin64] M. S. Pinsker. *Information and information stability of random variables and processes*. Translated and edited by Amiel Feinstein. Holden-Day Inc., San Francisco, Calif., 1964.
- [Sam07] P.-M. Samson. Infimum-convolution description of concentration properties of product probability measures, with applications. *Ann. Inst. H. Poincaré Probab. Statist.*, 43(3):321–338, 2007.
- [Sam16a] P.-M. Samson. Concentration of measure principle and entropy inequalities. working paper or preprint, April 2016.
- [Sam16b] P.-M. Samson. *High dimensionnal concentration phenomena, transport of measure and functional inequalities*. Accreditation to supervise research, Université Paris-Est, June 2016.
- [Tal95] M. Talagrand. Concentration of measure and isoperimetric inequalities in product spaces. *Inst. Hautes Études Sci. Publ. Math.*, (81):73–205, 1995.
- [Tal96] M. Talagrand. Transportation cost for Gaussian and other product measures. *Geom. Funct. Anal.*, 6(3):587–600, 1996.

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