

CUTOFF PROFILE FOR RANDOM TRANSPOSITIONS

Lucas TEYSSIER

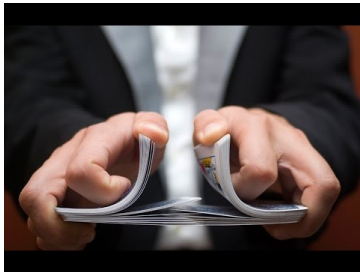
Universität Wien

BIRS Workshop on *Permutations and Probability*
Banff, 2021

♠ : Different ways to shuffle a deck of cards



Spacial motion (Diaconis, Pal, 2017)



Dovetail shuffle (Bayer, Diaconis, 1992)

♠ : The random transposition shuffle

Method :

- ▶ Pick two cards uniformly and independently;
- ▶ If different, interchange them;
- ▶ If they are the same card, do nothing.

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Interpretation :

- ▶ Random walk on \mathfrak{S}_n with

$$P(\sigma, \sigma\tau) = \mu_n(\tau) = \begin{cases} 1/n & \text{if } \tau = id \\ 2/n^2 & \text{if } \tau \text{ is a transp.} \end{cases}$$

P : transition matrix

μ_n : increment measure.

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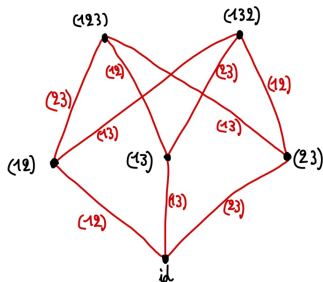
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Cayley graph for $n=3$

Question : In which sense do we converge to uniformity?

♠ : Distance to stationarity

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$\nu_n(t)$: distribution of the walk after t steps.

Définition

Distance to stationarity after t steps :

$$d_n(t) := d_{\text{TV}}(\nu_n(t), \text{Unif}_n).$$

where for probability measures μ and ν on \mathfrak{S}_n ,

$$d_{\text{TV}}(\mu, \nu) = \frac{1}{2} \sum_{\sigma \in \mathfrak{S}_n} |\mu(\sigma) - \nu(\sigma)| = \frac{1}{2} d_1(\mu, \nu).$$

♠ : Cutoff for random transpositions

Theorem (DIACONIS AND SHAHSHAHANI, 1981)

It takes $\frac{1}{2}n \ln(n)$ steps to mix a deck of n cards by random transpositions.

For every $0 < \epsilon < 1$,

$$d_n \left((1 - \epsilon) \frac{1}{2} n \ln(n) \right) \xrightarrow{n \rightarrow +\infty} 1 \quad \& \quad d_n \left((1 + \epsilon) \frac{1}{2} n \ln(n) \right) \xrightarrow{n \rightarrow +\infty} 0$$

That is what is called the **cutoff phenomenon**.

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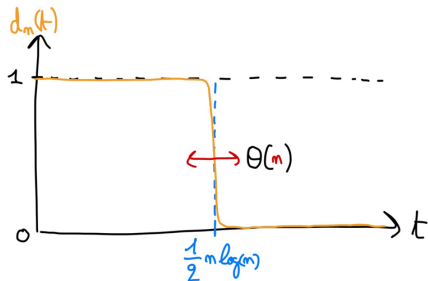
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More precisely, it takes $\frac{1}{2}n \ln(n) + \Theta(n)$ steps to mix.



♠ : Cutoff profile for random transpositions

Theorem (T., 2020)

For random transpositions, we have for every $c \in \mathbb{R}$,

$$d_n \left(\frac{1}{2} n \ln(n) + cn \right) \xrightarrow{n \rightarrow +\infty} f(c) := d_{\text{TV}}(\text{Poiss}(1 + e^{-2c}), \text{Poiss}(1)).$$

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Comments :

- ▶ We call f the **cutoff profile**.
- ▶ Question asked by N. Berestycki at an AIM workshop in 2016.
- ▶ The other known profiles can be written in a similar form.

♠ : Some related results

▶ **On random transpositions themselves**

Cutoff result : **Diaconis, Shahshahani**, 1981, *PTRF*

Precise lower bound : **Matthews**, 1988, *J. of Th. Prob.*

Phase transition result : **N. Berestycki, Durrett**, 2006, *PTRF*

Probability of long cycles : **Alon, Kozma**, 2013, *Duke*

Strong stationary time : **White**, 2019

Cutoff profile : **T.**, 2020, *Ann. Prob.*

▶ **Generalisations to other conjugacy classes :**

Cutoff for k -cycles : **N. Berestycki, Schramm, Zeitouni**, 2011, *Ann. Prob.*

Cutoff for conjugacy-invariant walks on \mathfrak{S}_n : **N. Berestycki, Şengül**, 2014, *PTRF*

Profile for k -cycles : **Nestoridi, Olesker-Taylor**, 2021, *PTRF*

▶ **Other generalisations :**

Biaised random transpositions : **Matheau-Raven**, 2020

Quantum random transpositions : **Freslon, T., Wang**, 2021

♡ : The non-commutative Fourier transform

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but instead the one of **finite groups** G , where for $\lambda \in \hat{G}$,

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Inverse Fourier transform, isometry between Hilbert spaces, Parseval identity.

Pierre-Loïc Méliot, *Representation Theory of Symmetric Groups*, chap. 1.

♡ : A method to prove a cutoff phenomenon on finite groups

- ▶ **Lower bound of the cutoff time** (not a problem)
- ▶ **The Diaconis-Shahshahani upper bound lemma:**
Note that $v_n(t) = \mu_n^{*t}$, and let $f = \mu_n^{*t} - \text{Unif}_n$.

$$\begin{aligned} 4d_n(t)^2 &= \left(\sum_{\sigma \in \mathfrak{S}_n} |f(\sigma)| \right)^2 \stackrel{CS}{\leq} n! \sum_{\sigma \in \mathfrak{S}_n} f(\sigma)^2 \stackrel{Pars.}{=} \sum_{\lambda \in \widehat{\mathfrak{S}_n}} d_\lambda \text{Tr}(\widehat{f}(\lambda) \widehat{f}(\lambda)^*) \\ &= \sum_{\lambda \in \widehat{\mathfrak{S}_n}^*} d_\lambda \text{Tr}(\widehat{\mu_n^{*t}}(\lambda) \widehat{\mu_n^{*t}}(\lambda)^*). \end{aligned}$$

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- ▶ For random transpositions : the increment measure μ_n is **conjugacy stable** (i.e. $\mu_n(\sigma) = \mu_n(\eta\sigma\eta^{-1})$), so each $\widehat{\mu_n}(\lambda)$ is a **multiple of the identity matrix** : $\widehat{\mu_n}(\lambda) =: s_\lambda \text{Id}_\lambda$. We deduce :

$$4d_n(t)^2 \leq \sum_{\lambda \in \widehat{\mathfrak{S}_n}^*} d_\lambda^2 s_\lambda^{2t}.$$

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- ▶ s_λ : eigenvalue of multiplicity d_λ^2 (of the transition matrix).

♡ : A method to find cutoff profiles

Method:

- ▶ Apply the inverse Fourier transform on the **finite group** \mathfrak{S}_n to the function $f = \mu_n^{*t} - \text{Unif}_n$:

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- ▶ Understand which λ matter, and the (complicated) terms $\text{ch}^\lambda(\sigma)$.
- ▶ Generalised to reversible Markov C. (Nestoridi, Olesker-Taylor, 2021).

♥ : Representations of the symmetric group

- ▶ Irreducible representations λ of $\mathfrak{S}_n \longleftrightarrow$ Young diagrams of size n .
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Example: $n = 5$.



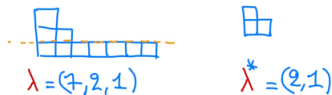
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- ▶ **Definition:** Let $\lambda = (\lambda_1, \lambda_2, \dots)$ be a partition of n . Associated *truncated partition* : Partition $\lambda^* := (\lambda_2, \lambda_3, \dots)$. **Example:**



♡ : Ideas of the proof for random transpositions

► **Starting point :**

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- ▶ **Eigenvalues** (known by D& S). For λ such that $\lambda_1 = n - j$,

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- ▶ **"Eigenvectors"** $\text{ch}^\lambda(\sigma)$: complicated.
(**Murnagham-Nakayama formula**).

♡ : The polynomial convergence lemma

For $j \geq 1$, let us define the *weighted average of characters*

$$A_j(\sigma) := \sum_{\lambda \in \widehat{\mathfrak{S}}_n : \lambda_1 = n-j} \frac{d_{\lambda^*}}{j!} \text{ch}^{\lambda}(\sigma). \quad (2)$$

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Lemma

Fix $j \geq 1$. Then for "almost all" permutations $\sigma \in \mathfrak{S}_n$,

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"almost all" permutations = permutations with a cycle of length $\geq j$.

♡ : Consequence on the profile

We now can deal with $d_{\lambda, s_{\lambda}}$ **and** $\text{ch}^{\lambda}(\sigma)$.

we have for each j at time $t_c = \frac{1}{2}n \log(n) + cn$,

$$\begin{aligned} \sum_{\lambda \in \widehat{\mathfrak{S}}_n : \lambda_1 = n-j} d_{\lambda} s_{\lambda}^{t_c} \text{ch}^{\lambda}(\sigma) &\approx \sum_{\lambda \in \widehat{\mathfrak{S}}_n : \lambda_1 = n-j} \frac{n^j}{j!} d_{\lambda^*} \frac{e^{-2jc}}{n^j} \text{ch}^{\lambda}(\sigma) \\ &= e^{-2jc} T_j(\text{Fix}(\sigma)), \end{aligned}$$

so we can rewrite

$$2d_n(t_c) \approx \frac{1}{n!} \sum_{\sigma \in \mathfrak{S}_n} \left| \sum_{j=1}^{\infty} e^{-2jc} T_j(\text{Fix}(\sigma)) \right|.$$

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Then simple computations and the fact that $\text{Fix}(\cdot) \rightarrow \text{Pois}(1)$ lead to


$$d_n(t_c) \xrightarrow{n \rightarrow +\infty} f(c) := d_{\text{TV}}(\text{Pois}(1 + e^{-2c}), \text{Pois}(1)).$$

♥ : The Murnagh-Nakayama formula

Murnagh-Nakayama formula :

Gives an exact formula for the characters $ch^\lambda(\sigma)$: we count how many times we can cover the diagram λ with ribbons corresponding to the cycle structure of σ .

Example 1:

$$ch^{\lambda}(\sigma) = 1$$




♡ : Playing with the Murnaghan-Nakayama formula

Example 2:

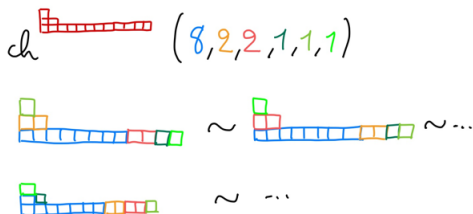
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Question : How many elements in the first class?

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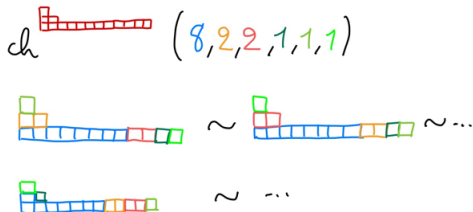
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Answer : $6 = \binom{N_1}{1} \binom{N_2}{1}$. $N_i :=$ number of i -cycles of σ .

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Answer : $6 = \binom{N_1}{1} \binom{N_2}{1}$. $N_i :=$ number of i -cycles of σ .

Then we need to understand how to cover the truncated diagram λ^* of size j with small ribbons \rightarrow Murnagham-Nakayama for diagrams of size j
 \rightarrow characters of \mathfrak{S}_j .

♡ : Playing with the Murnagham-Nakayama formula

Case $j = 2$.

$$\begin{aligned} 2! \cdot A_2(\sigma) &= \text{ch}^{(n-2,2)}(\sigma) + \text{ch}^{(n-2,1,1)}(\sigma) \\ &= \left(N_2 + \binom{N_1}{2} - N_1 \right) + \left(-N_2 + \binom{N_1}{2} - N_1 + 1 \right) \\ &= 2 \binom{\text{Fix}(\sigma)}{2} - 2\text{Fix}(\sigma) + 1. \end{aligned}$$

For larger j 's, the formulas become rapidly more voluminous. For example

$$\begin{aligned} \text{ch}^{(n-4,1,1,1,1)}(\sigma) &= + \left(\binom{N_1}{4} + N_3 N_1 + \binom{N_2}{2} - N_4 \right) \\ &\quad - \left(\binom{N_1}{3} - N_2 N_1 + N_3 \right) \\ &\quad + \left(\binom{N_1}{2} - N_2 \right) \\ &\quad - N_1 \\ &\quad + 1. \end{aligned}$$

◇ : Thank you for your attention!

$$d_{\text{TV}}(\text{Pois}(1 + e^{-c}), \text{Pois}(1))$$

$$d_{\text{TV}}(\mathcal{N}(e^{-c}, 1), \mathcal{N}(0, 1))$$

$$d_{\text{TV}}(\text{Meix}^+(-e^{-c}, 0) * \delta_{e^{-c}}, \text{Meix}^+(0, 0))$$