

# There is no stationary cyclically monotone Poisson matching in 2D

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## The random Euclidean bipartite matching problem

Let  $X_i, Y_i$  be i. i. d. uniformly distributed points  $(X_i)_{i=1}^n, (Y_i)_{i=1}^n$  on  $(0, 1)^d$  and consider the optimization problem

$$\min_{\sigma \in S_n} \sum_{i=1}^n |X_i - Y_{\sigma(i)}|^\gamma.$$

Define the **empirical measures**

$$\mu_n = \sum_{i=1}^n \delta_{X_i}, \quad \nu_n = \sum_{i=1}^n \delta_{Y_i}.$$

Recall the **Wasserstein distance**:

$$W_\gamma^\gamma(\mu_n, \nu_n) = \inf_{\pi \in \text{Cpl}} \int |x - y|^\gamma d\pi(x, y),$$

where Cpl is the set of **coupling** between  $\mu_n$  and  $\nu_n$ , namely the set of measures on the product space with first marginal equals to  $\mu_n$  and second marginal equals to  $\nu_n$ .

By Birkhoff's theorem

$$W_\gamma^\gamma(\mu_n, \nu_n) = \min_{\sigma \in S_n} \sum_{i=1}^n |X_i - Y_{\sigma(i)}|^\gamma.$$

## Macroscopic Behaviour

**Idea:** The typical distance is  $n^{-\frac{1}{d}}$  (points are spread as in a regular grid)

$$\min_{\sigma \in S_n} \sum_{i=1}^n |X_i - Y_{\sigma(i)}|^\gamma \approx n \cdot n^{-\frac{\gamma}{d}}.$$

**Achtung:** There are fluctuations! (CLT)

The asymptotic behaviour of  $W_\gamma(\mu_n, \nu_n)$  depends on the dimension  $d$ :

$$W_\gamma^\gamma(\mu_n, \nu_n) \sim \begin{cases} n \cdot n^{-\frac{\gamma}{2}} & \text{for } d = 1, \\ n \cdot \left(\frac{\log n}{n}\right)^{\frac{\gamma}{2}} & \text{for } d = 2, \\ n \cdot n^{-\frac{\gamma}{d}} & \text{for } d \geq 3. \end{cases}$$

The critical dimension  $d = 2$  has been firstly understood in the seminal paper by Ajtai, Komlós and Tusnády (1983).

## Topics

**Question:** Convergence of the rescaled cost.

Ambrosio-Stra-Trevisan (2016  $d = 2, \gamma = 2$ )

Goldman-Trevisan (2020  $d \geq 3, \gamma \geq 1$ )

Ambrosio-Goldman-Trevisan (2021 Lipschitz domain  $d = 2, \gamma = 2$ )

Bobkov-Ledoux (2019  $d = 1$ )

**Question:** Mesoscopic behaviour.

del Barrio-Giné-Utzet (2005)

Ledoux (2019)

Goldman-Huesmann (2021)

**Question:** Thermodynamic limit.

Huesmann-Sturm (2013  $d \geq 3$ )

Holroyd-Janson-Wästlund (2020)

↪ Today

## The Poisson Point Process

The **Poisson point process** on  $\mathbb{R}^d$  can be defined as a random variable taking values on locally finite atomic measures

$$\mu = \sum_i \delta_{X_i}$$

such that for every  $k \geq 1$ , for any disjoint Borel sets  $A_1, \dots, A_k \subseteq \mathbb{R}^d$ ,

- $\rightsquigarrow$  the random variables  $\mu(A_1), \dots, \mu(A_k)$  are independent,
- $\rightsquigarrow$  the random variable  $\mu(A_i)$  has a Poisson distribution of parameter  $|A_i|$  for every  $i = 1, \dots, k$ .

**Existence:** Superposition argument. On  $\Omega \subseteq \mathbb{R}^d$  bounded, conditionally on  $\mu(\Omega) = n$ , the measure  $\mu \llcorner \Omega$  has the same law as the random measure

$$\sum_{i=1}^n \delta_{X_i},$$

where  $(X_i)_{i=1}^n$  are i. i. d. with uniform law on  $\Omega$ .

**Notation:** I will often make use of the notation  $\{X\}$  to denote a Poisson point process.

## Motivation

**Definition:** Consider two Poisson point process  $\{X\}, \{Y\}$  in  $\mathbb{R}^d$  and let  $T$  be a bijection from  $\{X\}$  to  $\{Y\}$ . We call matching the triple  $(\{X\}, \{Y\}, T)$ .

**Definition:** A matching  $(\{X\}, \{Y\}, T)$  is  $\gamma$ -minimal if for any finite subset  $\{X_i\}_{i=1}^n \subset \{X\}, \{Y_i\}_{i=1}^n \subset \{Y\}$

$$\sum_{i=1}^n |T(X_i) - X_i|^\gamma = \min_{\sigma \in S_n} \sum_{i=1}^n |X_i - Y_{\sigma(i)}|^\gamma.$$

**Question:** (Peres 2002) For  $\{X\}, \{Y\}$  independent Poisson processes of intensity 1 in  $\mathbb{R}^2$ , does there exist a stationary *planar* matching?

**Question:** (Holroyd 2009) For  $\{X\}, \{Y\}$  independent Poisson processes of intensity 1 in  $\mathbb{R}^2$ , does there exist a stationary  $\gamma$ -*minimal* matching?

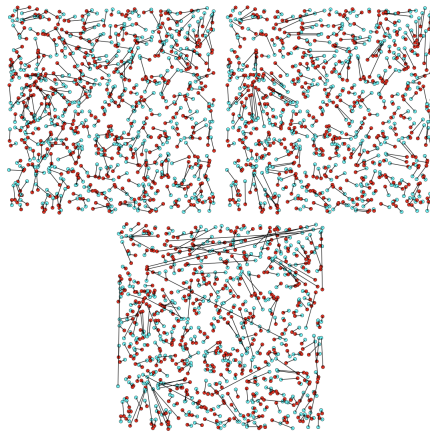
**Theorem (Holroyd-Janson-Wästlund 2020)**

*There exists a stationary  $\gamma$ -minimal matching if*

$$\rightsquigarrow d = 2, \gamma < 1;$$

$$\rightsquigarrow d \geq 3, \gamma < \infty.$$

## Simulations



**Figure:** Uniformly random red and blue points in equal numbers on a square, together with  $\gamma$ -minimal matchings for  $\gamma = \infty$  (top-left),  $\gamma = 1$  (top-right), and  $\gamma = -\infty$  (bottom).

Credits to Holroyd-Janson-Wästlund 2020.

## Our result

We are interested in the case  $\gamma = 2$ ,  $d = 2$ .

### Theorem (Huesmann-M.-Otto)

*There exists no stationary, ergodic and 2-minimal matching  $(\{X\}, \{Y\}, T)$  in  $d = 2$ .*

**Idea of the proof:** Contradiction argument. We argue by showing that 2-minimality together with stationarity will imply the following contradiction:

$$O(\ln^{\frac{1}{2}} R) \leq \frac{1}{R^d} \sum_{X \in B_R \text{ or } T(X) \in B_R} |T(X) - X| \leq o(\ln^{\frac{1}{2}} R).$$



# Proof in a nutshell

Step 1: Ergodic estimate

$$\#\left\{X \in (-R, R)^d : |T(X) - X| \gg 1\right\} \leq o(R^d).$$

Step 2:  $L^\infty$ -estimate

$$|T(X) - X| \leq o(R) \text{ provided that } X \in (-R, R)^d,$$

Step 3: Harmonic approximation

$$\frac{1}{R^d} \sum_{X \in B_R \text{ or } T(X) \in B_R} |T(X) - X|^2 \leq O(\ln R).$$

Step 4: Trading integrability against asymptotics.

$$\frac{1}{R^d} \sum_{X \in B_R \text{ or } T(X) \in B_R} |T(X) - X| \leq o(\ln^{\frac{1}{2}} R).$$

Step 5: Lower bound

$$\frac{1}{R^d} \sum_{X \in B_R \text{ or } T(X) \in B_R} |T(X) - X| \geq O(\ln^{\frac{1}{2}} R).$$

## Step 1: Ergodic estimate

**Definition:** a matching  $(\{X\}, \{Y\}, T)$  is said to be stationary if the joint law of  $(\{X\}, \{Y\}, T)$  is invariant under the action of the additive group  $\mathbb{Z}^d$

$$(\{X\}, \{Y\}, T) \mapsto (\{x + X\}, \{x + Y\}, T(\cdot - x) + x) \quad x \in \mathbb{Z}^d.$$

### Lemma

*For any  $\varepsilon > 0$  there exists a deterministic  $L$  and a random radius  $r_* < \infty$  a. s. such that for all  $R \geq r_*$*

$$\# \{X \in (-R, R)^2 \mid |T(X) - X| > L\} \leq (\varepsilon R)^2.$$

**Idea of the proof:** Use stationarity and ergodicity to apply Birkhoff-von Neumann's theorem to get

$$\begin{aligned} & \frac{1}{R^d} \# \{X \in (-R, R)^2 \mid |T(X) - X| > L\} \\ & \rightarrow \mathbb{E} [\# \{X \in (-1, 1)^2 \mid |T(X) - X| > L\}], \end{aligned}$$

as  $R \rightarrow \infty$ .

## Step 2: $L^\infty$ -estimate

### Lemma

*For every  $\varepsilon > 0$  there exists a random radius  $r_* < \infty$  a. s. such that for every  $R \geq r_*$*

$$|T(X) - X| \leq \varepsilon R \quad \text{provided that } X \in (-R, R)^2.$$

**Key ingredient:** Minimality implies that  $T$  is cyclically monotone, and in particular monotone, thus for  $\{X_i\}_{i=1}^3$  we have

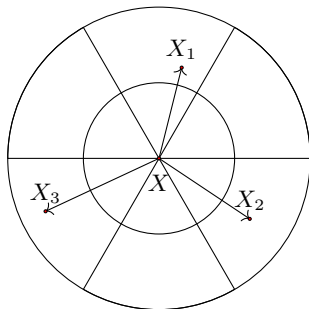
$$(T(X_i) - T(X)) \cdot (X_i - X) \geq 0.$$

In particular,

$$\begin{aligned} (T(X) - X) \cdot (X_i - X) &\leq (T(X_i) - X_i) \cdot (X_i - X) + |X_i - X|^2 \\ &\lesssim |T(X_i) - X_i|^2 + |X_i - X|^2. \end{aligned}$$

## Sketch of the proof

**Idea:** There are enough "good" points around  $X$ .



$$(T(X) - X) \cdot \frac{(X_i - X)}{|X_i - X|} \lesssim \frac{|T(X_i) - X_i|^2}{|X_i - X|} + |X_i - X| \lesssim \varepsilon R.$$

### Step 3: Harmonic approximation

**Aim:** Improve the  $L^\infty$ -estimate to the  $L^2$ -estimate of the local energy  $E(R) \leq O(\ln R)$ .

#### Lemma

*There exist a constant  $C$  and a random radius  $r_* < \infty$  a. s. such that for every  $R \geq r_*$  we have*

$$E(R) = \frac{1}{R^d} \sum_{X \in B_R \text{ or } T(X) \in B_R} |T(X) - X|^2 \leq C \ln R.$$

## Harmonic Approximation Theorem

Define the local energy

$$E(R) := \frac{1}{R^d} \sum_{X \in B_R \text{ or } T(X) \in B_R} |T(X) - X|^2.$$

Call  $\mu = \sum_{X \in (-R, R)^2} \delta_X$  and  $\nu = \sum_{Y \in (-R, R)^2} \delta_Y$  define the data term

$$D(R) := \frac{1}{R^d} W_{(-R, R)^2}^2(\mu, n_\mu) + \frac{R^2}{n_\mu} (n_\mu - 1)^2 + \frac{1}{R^d} W_{(-R, R)^2}^2(\nu, n_\nu) + \frac{R^2}{n_\nu} (n_\nu - 1)^2,$$

$$\text{where } n_\mu = \frac{\#\{X \in (-R, R)^2\}}{4R^2}, \quad n_\nu = \frac{\#\{Y \in (-R, R)^2\}}{4R^2}.$$

### Theorem (Goldman-Huesmann-Otto)

For any  $0 < \tau \ll 1$ , there exists an  $\varepsilon := \varepsilon(\tau) > 0$  and a  $C_\tau < \infty$  such that provided for some  $R$

$$\frac{1}{R^2} E(6R) + \frac{1}{R^2} D(6R) \leq \varepsilon$$

there exists a harmonic gradient field  $\Phi$  such that

$$\frac{1}{R^d} \sum_{X \in B_R \text{ or } T(X) \in B_R} |T(X) - X - \nabla \Phi(X)|^2 \leq \tau E(6R) + C_\tau D(6R),$$

$$\sup_{B_{2R}} |\nabla \Phi|^2 \leq C_\tau (E(6R) + D(6R)).$$

## Application of the harmonic approximation

**Idea:** Splitting the sum.

Consider the contribution given by the points which are transported by large distance

$$\begin{aligned} & \frac{1}{R^d} \sum_{(X \in B_R \text{ or } T(X) \in B_R) \text{ and } |T(X) - X| > L\tau} |T(X) - X|^2 \\ & \leq \frac{2}{R^d} \sum_{X \in B_R \text{ or } T(X) \in B_R} |T(X) - X - \nabla \Phi(X)|^2 \\ & \quad + \frac{2}{R^d} \sum_{(X \in B_R \text{ or } T(X) \in B_R) \text{ and } |T(X) - X| > L\tau} |\nabla \Phi(X)|^2 \\ & \leq 2\tau(1 + C_\tau) E(6R) + 2C_\tau(1 + \tau) \underbrace{D(6R)}_{\lesssim \ln R}. \end{aligned}$$

This combines to

$$E(R) \leq \tau E(6R) + C_\tau \ln R.$$

**Iteration:**

$$E(R) \leq \tau^k E(6^k R) + C_\tau \sum_{l=0}^{k-1} \tau^l \ln R \leq \varepsilon (36\tau)^k R^2 + C_\tau \sum_{l=0}^{k-1} \tau^l \ln R.$$

## Step 4: Upper bound

### Lemma

For every  $\varepsilon > 0$  there exists a random radius  $r_* < \infty$  a. s. such that

$$\frac{1}{R^d} \sum_{X \in B_R \text{ or } T(X) \in B_R} |T(X) - X| \leq \varepsilon \ln^{\frac{1}{2}} R.$$

**Proof:** We split again the sum into moderate and large transportation distance and apply Cauchy-Schwarz:

$$\begin{aligned} & \frac{1}{R^d} \sum_{X \in B_R \text{ or } T(X) \in B_R} |T(X) - X| \\ & \leq \frac{1}{R^d} \sum_{(X \in B_R \text{ or } T(X) \in B_R) \text{ and } |T(X) - X| \leq L} |T(X) - X| \\ & \quad + \frac{1}{R^d} \sum_{(X \in B_R \text{ or } T(X) \in B_R) \text{ and } |T(X) - X| > L} |T(X) - X| \\ & \leq CL + \varepsilon^{\frac{1}{2}} E(R)^{\frac{1}{2}} \leq C\varepsilon^{\frac{1}{2}} \ln^{\frac{1}{2}} R. \end{aligned}$$



# Conclusions

For  $\gamma = 2$ ,  $d = 2$  we proved the following:

## Theorem

*There exists no stationary, ergodic and 2-minimal matching  $(\{X\}, \{Y\}, T)$  in  $d = 2$ .*

Our proof relies on the **Harmonic Approximation Theorem** that requires  $\gamma = 2$ .

**Question:** What if  $\gamma \geq 1$ ?

↪ **Hope:** for  $\gamma > 1$  a similar argument might work.

↪ **Problem:**  $\gamma = 1$  requires a different argument.

## The Ansatz by Caracciolo-Lucibello-Parisi-Sicuro (2014)

Write  $\mu_n = \frac{1}{n} \sum_{i=1}^n \delta_{X_i}$ ,  $\nu_n = \sum_{i=1}^n \frac{1}{n} \delta_{Y_i}$ . The **optimal** coupling for  $W_2^2(\mu_n, \nu_n)$  is given by  $(\nabla\psi, \text{Id})_{\#} \nu_n$ .

A formal change of variable yields  $\mu_n \det \nabla^2 \psi = \nu_n$ .

Since  $\mu_n \approx 1$  we expect  $\nabla\psi(x) = x + \nabla\varphi(x)$  so that  $\nabla^2\psi = \text{Id} + \nabla^2\varphi$ .

Substitution and linearization yields

$$\mu_n (1 + \Delta\varphi) = \nu_n \quad \text{s. t. with } \mu_n \approx 1 \quad \Delta\varphi = \nu_n - \mu_n.$$

This ansatz leads to  $\nabla\varphi(x) = \nabla\psi(x) - x$  thus

$$\int |\nabla\varphi|^2 d\nu_n \approx W_2^2(\mu_n, \nu_n),$$

which gives several explicit description.

↪ Ambrosio-Stra-Trevisa (2019), Ambrosio-Glaudo-Trevisan (2019): true on macroscopic level for cost and transport map.

↪ Goldman-Huesmann-Otto (2021): Harmonic Approximation results. For  $\nu_n = \text{Leb}$  quantitative version from macro down to micro scale.

*Thank you for the attention!*