

# On a $T_1$ Transport inequality for the adapted Wasserstein distance

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## The weak topology

How can we define a topology on the space of probability measures ?

- **The weak topology** is the smallest topology for which

$$\mathbb{P} \mapsto \mathbb{E}^{\mathbb{P}}[\varphi(X)]$$

is continuous for all continuous and bounded  $\varphi$ .

- **The Wasserstein distance** metrizes the weak topology:

$$\mathcal{W}_1(\mathbb{P}, \mathbb{Q}) = \inf\{\mathbb{E}^\pi[|X - Y|] : \pi \text{ has marginals } \mathbb{P}, \mathbb{Q}\}.$$

## A topology for stochastic processes

$\mathbb{P}$  is a law of a stochastic process  $X = (X_1, X_2, \dots, X_N)$ . Ideally, we seek a topology for which the map

$$\mathbb{P} \mapsto \nu(\mathbb{P})$$

is continuous for time-dependent  $\nu$  such as

- (optimal stopping problem)  $\nu(\mathbb{P}) = \inf\{\mathbb{E}^{\mathbb{P}}[\varphi(X_\tau)] : \text{stopping time } \tau\}$ ,
- (superhedging error)  $\nu(\mathbb{P}) = \text{superhedging error under } \mathbb{P}$ ,
- (utility maximization)  $\nu(\mathbb{P}) = \text{maximum utility under } \mathbb{P}$ .

These maps are NOT continuous with respect to the weak topology.

## The adapted weak topology

How can we define a topology on the space of laws of processes ?

- **The adapted weak topology** is the smallest topology for which

$$\mathbb{P} \rightarrow \inf\{\mathbb{E}^{\mathbb{P}}[\varphi(X_\tau)] : \text{stopping time } \tau\}$$

is continuous for all continuous, bounded and adapted  $\varphi$ .

- **The adapted Wasserstein distance** metrizes the adapted weak topology:

$$\mathcal{AW}_1(\mathbb{P}, \mathbb{Q}) = \inf\{\mathbb{E}^\pi[|X - Y|] : \pi \text{ has marginals } \mathbb{P}, \mathbb{Q} \text{ and is bicausal}\}$$

where bicausal means that the transport at each time is independent of future information given the current information.

The adapted weak topology is finer than the weak topology. In particular,

$$\mathcal{W}_1(\mathbb{P}, \mathbb{Q}) \leq \mathcal{AW}_1(\mathbb{P}, \mathbb{Q}).$$

For the aforementioned operators  $\nu$ , we have

$$|\nu(\mathbb{P}) - \nu(\mathbb{Q})| \lesssim \mathcal{AW}_1(\mathbb{P}, \mathbb{Q}).$$

## Research question

In many applications, understanding the quantitative behavior of  $\mathcal{AW}_1$  is crucial. One natural direction is to establish inequalities of the form

$$\mathcal{AW}_1(\mathbb{P}, \mathbb{Q}) \lesssim \mathcal{J}(\mathbb{Q} | \mathbb{P})$$

for certain well-understood functionals  $\mathcal{J}$ .

- $\mathcal{J}(\mathbb{Q}, \mathbb{P}) = \text{TV}(\mathbb{P}, \mathbb{Q})$  (TV is the total variation distance): Eckstein–Pammer (2024).
- $\mathcal{J}(\mathbb{Q} | \mathbb{P}) = \sqrt{\mathcal{W}_1(\mathbb{P}, \mathbb{Q})}$ : Blanchet–Larsson–Park–Wiesel (2024), Acciaio–Hou–Pammer (2025).
- $\mathcal{J}(\mathbb{Q} | \mathbb{P}) = \sqrt{\mathcal{H}(\mathbb{Q} | \mathbb{P})}$  ( $\mathcal{H}$  is the relative entropy): Backhoff–Beiglböck–Lin–Zalashko (2017), Beiglböck–Zona (2025).

**Question:** The inequality  $\mathcal{W}_1 \lesssim \sqrt{\mathcal{H}}$  is well-known to characterize the Gaussian concentration. Can we connect the inequality  $\mathcal{AW}_1 \lesssim \sqrt{\mathcal{H}}$  with the Gaussian concentration ?

## Main result

**Theorem (Park, '25).** The following are equivalent.

1.  $\mathbb{P}$  satisfies the adapted  $T_1$  inequality: for some  $C > 0$ ,

$$\mathcal{AW}_1(\mathbb{P}, \mathbb{Q}) \leq C \sqrt{\mathcal{H}(\mathbb{Q} | \mathbb{P})} \text{ for all } \mathbb{Q}.$$

2.  $\mathbb{P}$  satisfies the  $T_1$  inequality: for some  $C > 0$ ,

$$\mathcal{W}_1(\mathbb{P}, \mathbb{Q}) \leq C \sqrt{\mathcal{H}(\mathbb{Q} | \mathbb{P})} \text{ for all } \mathbb{Q}.$$

3.  $\mathbb{P}$  exhibits the Gaussian concentration: for some  $C > 0$ ,

$$\mathbb{P}(\varphi(X) > \mathbb{E}^{\mathbb{P}}[\varphi(X)] + \varepsilon) \leq e^{-C\varepsilon^2} \text{ for all bdd, 1-Lipschitz } \varphi$$

4.  $\mathbb{P}$  satisfies the following moment condition: for some  $\alpha > 0$ ,

$$\mathbb{E}^{\mathbb{P}}[\exp(\alpha |X|^2)] < \infty.$$

**Theorem (Park, '25).** If  $\mathbb{P}$  satisfies the above statements,

$$\mathcal{AW}_1(\mathbb{P}, \mathbb{Q}) \leq (2\sqrt{N} + 1)\alpha^{-1/2} \left(1 + \log \mathbb{E}^{\mathbb{P}}[\exp(\alpha |X|^2)]\right)^{1/2} \sqrt{2\mathcal{H}(\mathbb{Q} | \mathbb{P})}$$

for all  $\mathbb{Q}$ .

## Comparison with existing results

### Regularity of kernels

Previous results typically impose certain regularity assumptions on the conditional distributions of  $\mathbb{P}$ . However, it turns out that such assumptions are not necessary.

### Dependence on the temporal dimension $N$

Our results show that the constant  $C$  in  $\mathcal{AW}_1 \leq C\sqrt{\mathcal{H}}$  grows sublinearly with  $N$ , specifically, as  $\sqrt{N}$  up to a logarithmic factor. This rate is consistent with the independent case and with the sharp adapted Pinsker inequality, while constants in previous results exhibit exponential growth in  $N$ .

## Generalization

The theorem extends to any Polish space equipped with an arbitrary metric.

## References

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