

# Rates of convergence in total variation norm for Markov processes

Joint work with  
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# Setup and notations

We consider a Markov process  $(X_t)_{t \geq 0}$ , with state space  $E$ , assumed to be ergodic with unique invariant probability measure  $\mu$ .

Let  $L$  be its generator, and  $(P_t)_{t \geq 0}$  the associated semigroup, acting on

- ▶ functions:

$$P_t f(x) = \mathbf{E}(f(X_t) \mid X_0 = x) = \mathbf{E}_x(f(X_t));$$

- ▶ measures:

$$\nu P_t = \mathcal{L}(X_t \mid \mathcal{L}(X_0) = \nu).$$

# Our aim

Get quantitative rates of convergence to equilibrium for  $X_t$ ,  
quantify the convergence

$$\nu P_t \xrightarrow[t \rightarrow +\infty]{} \mu.$$

One needs to choose a distance between probability measures.

# Wasserstein distances

## Definition

If  $(E, d)$  is a metric space, for  $p \geq 1$ , the Wasserstein distance of order  $p$  between two probability measures  $\nu, \tilde{\nu} \in \mathcal{P}(E)$  is

$$\begin{aligned} W_p(\nu, \tilde{\nu}) &= \inf \left\{ \left( \int_E d(x, y)^p d\pi(x, y) \right)^{1/p} : \pi \in \Pi(\nu, \tilde{\nu}) \right\} \\ &= \inf \left\{ \mathbf{E}(|X - Y|^p)^{1/p} : X \sim \nu, Y \sim \tilde{\nu} \right\}, \end{aligned}$$

where  $\Pi(\nu, \tilde{\nu})$  is the set of couplings of  $\nu$  and  $\tilde{\nu}$ , *i.e.* of probability measures on  $E^2$  with first (resp. second) marginal equal to  $\nu$  (resp. to  $\tilde{\nu}$ ).

# Wasserstein distances

## Interest

Among the many interesting features of Wasserstein distances

- ▶ “almost” metrizes the weak convergence (and more: Kantorovitch duality theorem);
- ▶ “easy” to bound from above: any coupling gives an upper bound (one has to find an efficient one).

See C. Villani, *Optimal transport. Old and new* for (much) more information...

# Wasserstein distances

## Coupling method for Markov processes

More specifically, for Markov processes, the typical coupling approach is to write

$$W_p(\nu P_t, \tilde{\nu} P_t)^p \leq \mathbf{E}(d(X_t, Y_t)^p),$$

where  $(X_t, Y_t)$  is a “trajectorial coupling” of the dynamics with initial measures  $\nu$  and  $\tilde{\nu}$ :

- ▶  $(X_t, Y_t)_{t \geq 0}$  is a Markov process on  $E^2$ ;
- ▶ both marginals are Markov processes with generator  $L$ ;
- ▶  $X_0 \sim \nu$  and  $Y_0 \sim \tilde{\nu}$ .

# Total variation distance

## Definition

The total variation distance between two probability measures  $\nu, \tilde{\nu} \in \mathcal{P}(E)$  is

$$\begin{aligned}\|\nu - \tilde{\nu}\|_{\text{TV}} &= \inf \left\{ \left( \int_E \mathbf{1}_{x \neq y} d\pi(x, y) \right) : \pi \in \Pi(\nu, \tilde{\nu}) \right\} \\ &= \inf \{ \mathbf{P}(X \neq Y) : X \sim \nu, Y \sim \tilde{\nu} \},\end{aligned}$$

- ▶ Total variation is (essentially) stronger than Wasserstein distances.
- ▶ Also defined via an infimum on couplings.

# Total variation distance

## Coupling method for Markov processes

As before, for Markov processes,

$$\|\nu P_t - \tilde{\nu} P_t\|_{\text{TV}} \leq \mathbf{P}(X_t \neq Y_t) \leq \mathbf{P}(T \geq t),$$

for any trajectorial coupling  $(X_t, Y_t)$ , where

$T = \inf\{t \geq 0 : X_t = Y_t\}$  is the coupling (coalescing) time.



# General idea

Construct an efficient coalescent coupling to derive quantitative estimates for the rate of convergence in total variation is difficult.

The approach “à la” Meyn & Tweedie hardly gives reasonable quantitative rates of convergence. One needs to develop alternative approaches.

Ours is the following:

1. First apply for a given time a Wasserstein coupling, *i.e.* a coupling which is adapted to the control of convergence in Wasserstein distance.
2. Once the two processes are “close enough”, find an adapted coalescent coupling.

# The TCP process

## Transmission Control Protocol window size process

Markov process on  $E = \mathbf{R}_+$  with generator

$$Lf(x) = f'(x) + x(f(x/2) - f(x)).$$

Modelization of the rate of transmission on the internet, to avoid congestions.

- ▶ non reversible;
- ▶ not stochastically monotone;
- ▶ not much randomness: all randomness comes from the jump times;
- ▶ not too complicated...

# The constant rate TCP process

## Definition

Markov process on  $E = \mathbf{R}_+$  with generator

$$Lf(x) = f'(x) + \lambda(f(x/2) - f(x)),$$

$\lambda$  being a positive constant.

A simplified version of the TCP process.

Constant jump rate: the jump times  $(T_n)_{n \geq 1}$  form a Poisson process of intensity  $\lambda$ .

# The constant rate TCP process

## Wasserstein distance

The best choice is to take the same jump times for both processes.

After  $n$  jumps, one has

$$|X_{T_n} - Y_{T_n}| = \frac{|X_0 - Y_0|}{2^n}, \text{ hence } |X_t - Y_t| = \frac{|X_0 - Y_0|}{2^{N_t}}.$$

By a simple computation this gives

$$W_p(\nu P_t, \tilde{\nu} P_t) \leq e^{-\lambda_p t} W_p(\nu, \tilde{\nu}),$$

with  $\lambda_p = \lambda(1 - 2^{-p})/p$  (optimal rate).

# The constant rate TCP process

Total variation norm

A simple geometric idea to coalesce in one jump:

if  $X_0 = x > Y_0 = y$  and  $T_1^X = T_1^Y + x - y < T_2^Y$ , then

$$X_{T_1^X} = Y_{T_1^X}.$$

We will combine this with the simple Wasserstein coupling used before.

# The constant rate TCP process

## Total variation norm

The complete coalescent coupling starting from  $x$  and  $y$  before time  $t$ :

- ▶ sample a Poisson process  $(T_k)$  of parameter  $\lambda$  on  $[0, t]$
- ▶ both  $X$  and  $Y$  will make exactly  $n = N_t$  jumps before time  $t$
- ▶ for  $1 \leq k \leq n - 1$ ,  $T_k^X = T_k^Y = T_k$ ; hence

$$X_{T_{n-1}} - Y_{T_{n-1}} = \frac{x - y}{2^{n-1}}$$

- ▶ the last jump of each process is chosen to maximize the probability that  $T_n^X = T_n^Y + \frac{x-y}{2^{n-1}}$ : optimal coupling of two continuous random variables

# The constant rate TCP process

Total variation norm

Conditionally on

$$\{N_t^X = N_t^Y = n; T_k^X = T_k^Y = T_k \forall 1 \leq k \leq n-1\},$$

$$\mathbf{P} \left( T_n^X = T_n^Y + \frac{x-y}{2^{n-1}} \right) \geq 1 - \frac{x-y}{2^{n-1}(t - T_{n-1})}$$

Gives

$$\begin{aligned} \|\delta_x P_t - \delta_y P_t\|_{\text{TV}} &\leq \mathbf{1} - \mathbf{E} \left[ \left( 1 - \frac{x-y}{2^{N_t-1}(t - T_{N_t-1})} \right) \mathbf{1}_{\{N_t \geq 1\}} \right] \\ &= e^{-\lambda t} + \lambda e^{-\lambda t/2} |x-y| \end{aligned}$$

New proof of a result by Perthame & Ryzhik (2005).

# The TCP process

## Wasserstein coupling

Defined on  $\mathbf{R}_+^2$  by

$$\begin{aligned}\mathcal{L}f(x, y) = & \partial_x f(x, y) + \partial_y f(x, y) + y(f(x/2, y/2) - f(x, y)) \\ & + (x - y)(f(x/2, y) - f(x, y))\end{aligned}$$

when  $x > y$  and symmetric expression when  $y < x$ .

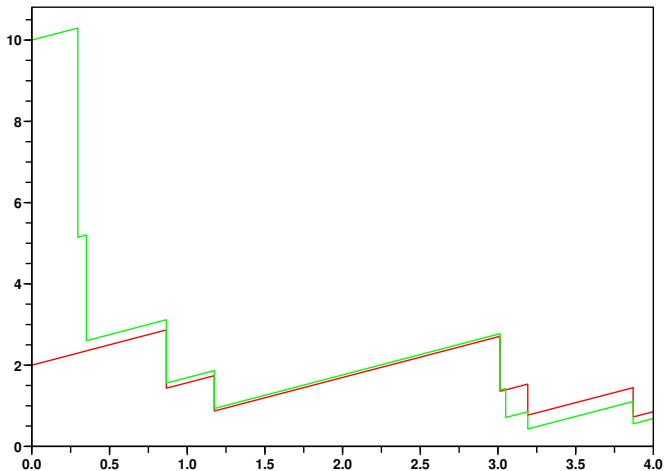
Introduced by Chafai, Malrieu & Paroux (2010).

The only trajectorial coupling of TCP process where the smallest process never jumps alone.



# The TCP process

Wasserstein coupling



# The TCP process

## Polynomial bound for $W_1$

For  $V_p(x, y) = |x - y|^p$ , one would like to get  $\mathcal{L}V_p \leq -\lambda_p V_p$   
hence  $\mathbf{E}(|X_t - Y_t|^p) \leq e^{-\lambda_p t} \mathbf{E}(|X_0 - Y_0|^p)$ .

By direct computation

$$\mathcal{L}V_1 = -\frac{3}{2} V_1^2$$

which only gives a polynomial rate of convergence (CMP, 2010).

It is even worse for  $p > 1$ .

# The TCP process

## Rate of convergence in Wasserstein distances

Things work better when  $p < 1$ .

With  $p = 1/2$ :

$$\mathcal{L}V_{1/2}(x, y) \leq -(x \vee y)(1 - M)V_{1/2}(x, y)$$

with  $M = \sqrt{2}(3 + \sqrt{3})/8 \sim 0.84$ .

### Proposition

For any  $x, y > 0$ ,

$$\mathbf{E} \left( |X_t - Y_t|^{1/2} \right) \leq \frac{1}{\sqrt{M}} e^{-\lambda t} |x - y|^{1/2},$$

with  $\lambda = \sqrt{2}(1 - \sqrt{M}) \sim 0.12$ .

# The TCP process

## Rate of convergence in Wasserstein distances

### Theorem

*For any  $\theta \in (0, 1)$ ,  $p \geq 1$  and  $t_0 > 0$ , there exists a constant  $C$  such that for any  $t \geq t_0$  and for all initial probability measures  $\nu$  and  $\tilde{\nu}$ :*

$$W_p(\nu P_t, \tilde{\nu} P_t) \leq C e^{-(\theta\lambda/p)t} W_{\theta/2}(\nu, \tilde{\nu})^{2/(p\theta)}.$$

For  $W_1$ :

- ▶ rate obtained by our method:  $\lambda \sim 0.12$
- ▶ rate for the Wasserstein coupling by simulation:  $\sim 0.5$
- ▶ rate for the true  $W_1$  distance by simulation:  $\sim 1.6$

# The TCP process

## Rate of convergence in total variation

There exists a constant  $K > 0$  such that for any  $t, x, y \leq 0$

$$\|\delta_x P_t - \delta_y P_t\|_{\text{TV}} \leq K(1+t)e^{K\sqrt{t}}e^{-(2\lambda/3)t}.$$

## Theorem

*For any  $\theta \in (0, 1)$  and  $t_0 > 0$ , there exists a constant  $C$  such that for any  $t \geq t_0$  and for all initial probability measures  $\nu$  and  $\tilde{\nu}$ :*

$$\|\nu P_t - \tilde{\nu} P_t\|_{\text{TV}} \leq C e^{-\theta(2\lambda/3)t}.$$

The best we could obtain via Meyn-Tweedie method:  $\sim 10^{-14}$ ...