

The coupling method for estimating  
 $\beta$ -mixing coefficients of Markov processes.

*Oleg Butkovsky*

(joint work with Alexander Yu. Veretennikov)

Department of Probability Theory  
Moscow State University

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## Two questions

Let  $X_n$ ,  $n \in \mathbb{Z}_+$  be a homogeneous Markov process. Suppose that  $X_n$  has a stationary distribution.

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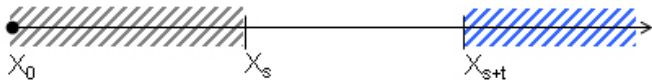
Let  $X_n$ ,  $n \in \mathbb{Z}_+$  be a homogeneous Markov process. Suppose that  $X_n$  has a stationary distribution.

- How fast is convergence to stationary regime?
- How fast is “mixing”?

# Motivation

# Mixing

- Sometimes it might be necessary to establish Central Limit Theorem (CLT) for dependent random variables.
- We can describe the dependence in terms of mixing coefficients.



- Roughly speaking, if the dependence between events separated by large number of time steps is “weak”, then CLT is satisfied.

## Mixing

Let  $\mathcal{F}_I^X$  be a  $\sigma$ -field generated by random variables  $\{X_s, s \in I\}$ .

$$\alpha(t) := \sup_{s \geq 0} \sup_{\substack{A \in \mathcal{F}_{\geq s+t}^X \\ B \in \mathcal{F}_s^X}} |P(AB) - P(A)P(B)|,$$

$$\beta(t) := \sup_{s \geq 0} E \sup_{A \in \mathcal{F}_{\geq s+t}^X} |P(A|\mathcal{F}_s^X) - P(A)|.$$



It is clear that  $\alpha(t) = 0$  and  $\beta(t) = 0$  for independent  $X_0, X_1, \dots$ . In general case, if these coefficients are “sufficiently small”, then under simple moment conditions the CLT holds.

## Mixing and CLT

**Theorem** (I.A. Ibragimov). *Let  $(X_n)_{n \in \mathbb{Z}_+}$  be a stationary process such that:*

1.  $E X_0 = 0$ ,  $E |X_0|^{2+\delta} < \infty$  for some  $\delta > 0$ ;
2.  $\sum_{n=1}^{\infty} \alpha(n)^{\frac{\delta}{2+\delta}} < \infty$ ;
3.  $\sigma^2 := E X_0^2 + 2 \sum_{k=1}^{\infty} E X_0 X_k \neq 0$ .

*Then*

$$\frac{X_0 + \cdots + X_n}{\sigma \sqrt{n}} \xrightarrow{d} N(0, 1), \quad n \rightarrow \infty.$$

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- We prove that for certain class of Markov processes  $\beta(n) = \underline{O}(e^{-cn})$ ,  $n \rightarrow \infty$ .
- Since  $\alpha(n) \leq \beta(n)$  this implies the CLT for these processes.



# The coupling method

## Total variation distance

- Let  $(\Omega, \mathcal{F})$  be a measurable space.
- If  $Q$  and  $\tilde{Q}$  are two measures on  $(\Omega, \mathcal{F})$ , then **total variation distance** between  $Q$  and  $\tilde{Q}$  is defined by

$$d_{TV}(Q, \tilde{Q}) := 2 \sup_{A \in \mathcal{F}} |Q(A) - \tilde{Q}(A)| = \sup_f \left| \int_{\Omega} f(\omega) dQ - \int_{\Omega} f(\omega) d\tilde{Q} \right|,$$

where the second supremum is taken over measurable functions bounded by 1.

- Obviously, if  $Q_n$  are probability measures and  $d_{TV}(Q_n, Q) \rightarrow 0$ ,  $n \rightarrow \infty$ , then  $Q_n \xrightarrow{d} Q$ .

## Total variation distance

- Similarly, the total variation distance between two random variables  $X$  and  $Y$  is defined to be the total variation distance between their distributions.

$$d_{TV}(X, Y) := 2 \sup_{A \in \mathcal{F}} |P(X \in A) - P(Y \in A)| = \sup_f |E f(X) - E f(Y)|.$$

- It follows from the definition, that

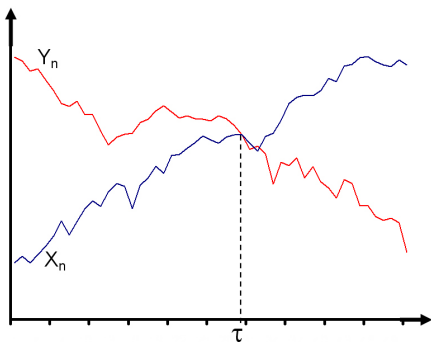
$$d_{TV}(X, Y) \leq 2P(X \neq Y).$$

## Setup

- Suppose  $(X_n)_{n \in \mathbb{Z}_+}$  and  $(Y_n)_{n \in \mathbb{Z}_+}$ , are homogeneous Markov processes with the same transition functions.
- Our goal is to estimate  $d_{TV}(X_n, Y_n)$ .
- If  $\mu$  is a stationary distribution of  $X_n$  and  $\text{Law}(Y_0) = \mu$ , then  $d_{TV}(X_n, Y_n) = d_{TV}(X_n, \mu)$

## Coupling: a simple example

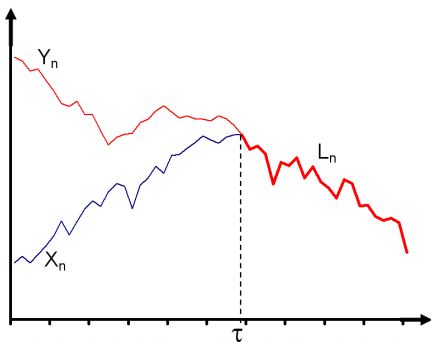
- To estimate  $d_{TV}(X_n, Y_n)$  we use the coupling method.
- Let  $\tau := \inf\{n : X_n = Y_n\}$  be the moment of the first meet of the processes.



- Then  $L_n := X_n \mathbb{1}(n < \tau) + Y_n \mathbb{1}(n \geq \tau)$  is distributed as  $X_n$ .
- Hence  $d_{TV}(X_n, Y_n) = d_{TV}(L_n, Y_n) \leq 2P(L_n \neq Y_n) \leq 2P(\tau > n)$ .

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## Coupling: definition

- A coupling is a bivariate process  $(\tilde{X}_n, \tilde{Y}_n)$ , such that
  - $\tilde{X}_n \stackrel{d}{=} X_n$  and  $\tilde{Y}_n \stackrel{d}{=} Y_n$ , for all  $n \in \mathbb{Z}_+$ ,
  - $\tilde{X}_n(\omega) = \tilde{Y}_n(\omega)$  for all  $n > \tau(\omega)$ .
- It is clear, that  $d_{TV}(X_n, Y_n) = d_{TV}(\tilde{X}_n, \tilde{Y}_n) \leq 2P(\tau > n)$ .
- For instance,  $(L_n, Y_n)$  is a coupling. This construction was suggested by Doeblin.
- Can Doeblin's coupling be improved?

## Doebelin's coupling vs Vaserstein's coupling

The Doebelin coupling

$(\tilde{X}_n, \tilde{Y}_n)$		$(\tilde{X}_{n+1}, \tilde{Y}_{n+1})$	$\tilde{p}_{..}$
$(i, i)$	$\rightarrow$	$(k, k)$	$p_{ik}$
$(i, j)$	$\rightarrow$	$(k, k)$	$p_{ik} p_{jk}$
$(i, j)$	$\rightarrow$	$(k, l)$	$p_{ik} p_{jl}$

The Vaserstein coupling

$(\tilde{X}_n, \tilde{Y}_n)$		$(\tilde{X}_{n+1}, \tilde{Y}_{n+1})$	$\tilde{p}_{..}$
$(i, i)$	$\rightarrow$	$(k, k)$	$p_{ik}$
$(i, j)$	$\rightarrow$	$(k, k)$	$p_{ik} \wedge p_{jk}$
$(i, j)$	$\rightarrow$	$(k, l)$	$c(i, j)(p_{ik} - p_{ik} \wedge p_{jk})(p_{jl} - p_{il} \wedge p_{jl})$



Suppose that processes  $X_n$  and  $Y_n$  have transition probability density  $p(u, v)$ .

Let us define

$$q(u, v) := \int_{-\infty}^{+\infty} p(u, t) \wedge p(v, t) dt.$$

Let  $\eta_n = (\eta_n^1, \eta_n^2)$  be a Markov process with transition probability density  $\varphi(x, y) := \varphi_1(x, y_1)\varphi_2(x, y_2)$ , where  $x = (x^1, x^2)$ ,  $y = (y^1, y^2)$  and

$$\varphi_1(x, u) := (1 - q(x^1, x^2))^{-1} (p(x^1, u) - p(x^1, u) \wedge p(x^2, u)),$$

$$\varphi_2(x, u) := (1 - q(x^1, x^2))^{-1} (p(x^2, u) - p(x^1, u) \wedge p(x^2, u)).$$

We also set  $\eta_0 = X_0$ .

**Lemma.** *It is possible to construct a coupling  $(\tilde{X}_n, \tilde{Y}_n)$  such that*

$$P(\tilde{X}_n \neq \tilde{Y}_n) \leq E \prod_{i=0}^{n-1} (1 - q(\eta_i^1, \eta_i^2)).$$

## Idea of the proof

Let  $\gamma_n = \mathbb{I}(\tau > n)$ .

Consider the following decomposition

$$\begin{aligned}\tilde{X}_n &= \eta_n^1 \mathbb{I}(\gamma_n = 1) + \zeta_n \mathbb{I}(\gamma_n = 0), \\ \tilde{Y}_n &= \eta_n^2 \mathbb{I}(\gamma_n = 1) + \zeta_n \mathbb{I}(\gamma_n = 0).\end{aligned}$$

Random processes  $\eta_n^1$  and  $\eta_n^2$  represent  $X_n$  and  $Y_n$ , correspondingly, under condition that coupling was not successful until time  $n$ .

On the other hand,  $\zeta_n$  represents both  $X_n$  and  $Y_n$  if the coupling occurs before time  $n$ .

It is possible to show, that  $(\eta_n^1, \eta_n^2, \zeta_n, \gamma_n)$  is a Markov process and

$$\mathbb{P}(\gamma_{n+1} = 1 | \gamma_n = 1, \eta_n^1 = x^1, \eta_n^2 = x^2) = 1 - q(x^1, x^2).$$

# Estimates of convergence rate

## Operator

Let us introduce operator  $A : C_b \rightarrow C_b$

$$Af(x) := (1 - q(x)) E_x f(\eta_1).$$

Operator  $A$  has an interesting property:

$$E A^n f(\eta_0) = E \prod_{i=0}^{n-1} (1 - q(\eta_i)) f(\eta_n).$$

Therefore,

$$\frac{1}{2} d_{TV}(X_n, Y_n) \leq E A^n 1(\eta_0) \leq \|A^n\|.$$

**Theorem.** *If operator  $A$  has a spectral radius  $r \neq 1$  then for any  $\varepsilon > 0$  and for sufficiently large  $n > n_0(\varepsilon)$*

$$d_{TV}(X_n, Y_n) \leq 2e^{-n(|\ln r| - \varepsilon)}.$$

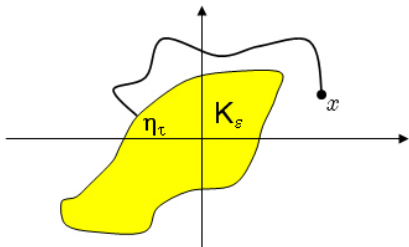
## Alternative approach

- In some cases it might be difficult to check whether  $r < 1$ .
- We developed also an alternative approach.
- Clearly,  $r \leq \|A\|$ , however  $\|A\| = 1 - \inf_x q(x) = 1$  in many cases.
- So we introduce operator  $B$  with  $\|B\| \leq 1 - \varepsilon$ .

## Alternative approach

Let us consider a “good” set  $K_\varepsilon := \{(x^1, x^2) : q(x^1, x^2) \geq \varepsilon\}$ .

We denote by  $\tau := \inf\{n > 0 : \eta_n \in K_\varepsilon\}$  a first hit time for the set  $K_\varepsilon$ .



Define operator  $B : C_b \rightarrow C_b$  by the following formula

$$Bf(x) := E_x((1 - q(\eta_1))(1 - q(\eta_2)) \cdots (1 - q(\eta_\tau))f(\eta_\tau)).$$



## Operator B

$$Af(x) := (1 - q(x)) E_x f(\eta_1).$$

$$Bf(x) := E_x((1 - q(\eta_1))(1 - q(\eta_2)) \cdot \dots \cdot (1 - q(\eta_\tau))f(\eta_\tau)).$$

We see, that since

$$Bf(x) \leq E_x((1 - q(\eta_\tau))f(\eta_\tau)) \leq (1 - \varepsilon) E_x f(\eta_\tau),$$

we have  $\|B\| \leq 1 - \varepsilon$ .

## Operator B

Moreover,

$$E(1 - q(\eta_0)B^n f(\eta_0)) = E \prod_{i=0}^{\tau_n} (1 - q(\eta_i)) f(\eta_{\tau_n}),$$

where  $\tau_n$  is a  $n$ -th hit time for the set  $K_\varepsilon$ .

On the other hand, it follows from Lemma that

$$P(\tilde{X}_{n+1} \neq \tilde{Y}_{n+1}) \leq E \prod_{i=0}^n (1 - q(\eta_i)).$$

## Operator B

Moreover,

$$\mathbb{E}(1 - q(\eta_0)B^n f(\eta_0)) = \mathbb{E} \prod_{i=0}^{\tau_n} (1 - q(\eta_i)) f(\eta_{\tau_n}),$$

where  $\tau_n$  is a  $n$ -th hit time for the set  $K_\varepsilon$ .

On the other hand, it follows from Lemma that

$$\mathbb{P}(\tilde{X}_{n+1} \neq \tilde{Y}_{n+1}) \leq \mathbb{E} \prod_{i=0}^n (1 - q(\eta_i)).$$

Therefore if we introduce a “bad” set  $\kappa_n := \{\omega : \tau_{\lfloor n/\Delta \rfloor} > n\}$  then

$$\mathbb{P}(\tilde{X}_{n+1} \neq \tilde{Y}_{n+1}) \leq \mathbb{E} B^{\lfloor n/\Delta \rfloor} 1(\eta_0) + \mathbb{E} 1(\kappa_n).$$

**Theorem.** Assume that there exist  $\varepsilon > 0$ ,  $\lambda > 0$ ,  $M > 0$  such that

1.  $E e^{\lambda\tau} < \infty$ .
2. For all  $x \in K_\varepsilon$  we have  $E_x e^{\lambda\tau} < M$ .

Then

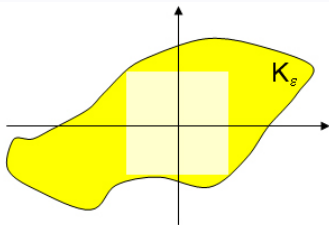
$$d_{TV}(X_n, Y_n) \leq C e^{-n\theta},$$

where  $C > 0$  and

$$\theta = \frac{|\ln(1 - \varepsilon)|\lambda}{\ln M + |\ln(1 - \varepsilon)|}.$$

- Recall that  $\tau$  is a first hit time for process  $\eta$ .
- Let us reformulate conditions 1 and 2 in terms of a first hit time for process  $X_n$ .

Let us assume that  $q(u, v) > \varepsilon$   
for all  $u, v$  such that  $|u| < K, |v| < K$ .



Define  $T := \inf\{n > 0 : |X_n| < K\}$ .

**Theorem.** Assume that there exist  $\lambda > 0, K > 0, M > 0, \varkappa > 0$ , such that

1.  $E_u e^{\lambda T} < \infty$  for all  $u$ .
2.  $E_u e^{\lambda T} < M$  for all  $|u| < K$ .
3.  $P_u(|X_1| < K) > \varkappa$  for all  $|u| < K$ .

Then

$$d_{TV}(X_n, Y_n) \leq C e^{-n\theta_1},$$

with some  $C > 0, \theta_1 > 0$ .

## Estimates of convergence rate: Summary

- If  $r < 1$  then  $d_{TV}(X_n, Y_n) \leq 2e^{-n(|\ln r| - \varepsilon)}$ .
- Under certain conditions on a first hit time for the set  $[-K, K]$  we have  $d_{TV}(X_n, Y_n) \leq Ce^{-n\theta}$ .

# Estimation of mixing coefficients

## $\beta$ -mixing

**Theorem.** Assume that  $X_n$  has a stationary distribution. If  $r \neq 1$  then for any  $\varepsilon > 0$

$$\beta(n) \leq C e^{-n(|\ln r| - \varepsilon)},$$

for some  $C > 0$  and sufficiently large  $n > N(\varepsilon)$ .



## Central Limit Theorem

- Therefore, CLT for dependent random variables implies

**Theorem.** *Suppose that  $X_n$  has a stationary distribution and  $r \neq 1$ .*

*Let  $X_n^\mu$ ,  $n \in \mathbb{Z}_+$ , be a stationary version of the process  $X_n$ .*

*Furthermore, assume that*

1.  $E |X_1^\mu|^{2+\delta} < \infty$ , for some  $\delta > 0$ ,
2.  $\sigma^2 := \text{Var } X_1^\mu + 2 \sum_{k=1}^{\infty} \text{cov}(X_1^\mu, X_{k+1}^\mu) \neq 0$ .

*Then the process  $X_n$  satisfies central limit theorem, i.e.*

$$\frac{\sum_{i=1}^n X_i - n E X_1^\mu}{\sqrt{n}} \xrightarrow{d} \mathcal{N}(0, \sigma^2) \quad \text{as } n \rightarrow \infty.$$