

# Consistency of likelihood estimation for Gibbs point processes

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## General problem

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- Mase(2000) The MLE is consistent for exponential models.
- Other estimators are consistent and asymptotically normal : MPLE, Takacs-Fiksel estimators, variational estimators.

# Finite volume Gibbs point process

Let  $\Lambda$  be a bounded window in  $\mathbb{R}^d$ ,  $\mathcal{C}_\Lambda$  the space of finite configurations in  $\Lambda$  and  $\pi_\Lambda$  the law of the Poisson Point Process in  $\Lambda$  with intensity 1.

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The energy  $H$  is a functional from  $\Omega_\Lambda$  to  $\mathbb{R} \cup \{+\infty\}$ .

## Definition

The Finite volume Gibbs point process in  $\Lambda$  is the probability measure on  $\Omega_\Lambda$  which is absolutely continuous with respect to  $\pi_\Lambda$  with density

$$f_\Lambda = \frac{1}{Z_\Lambda} e^{-H}.$$

## Examples : pairwise potential interactions

$$H_{\Lambda}(\gamma) = z N_{\Lambda}(\gamma) + \sum_{\{x,y\} \in \gamma} \phi(x - y).$$

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- **The Lennard-Jones pair potential :**

$$\phi(x) = A|x|^{-n} - B|x|^{-m}, \quad x \in \mathbb{R}^d.$$

(The standard Lennard-Jones model,  $n = 12$  and  $m = 6$ ).

## Examples :

**The area interaction :**

$$H_{\Lambda}(\gamma) = z N_{\Lambda}(\gamma) + \beta \text{Volume} \left( \bigcup_{x \in \gamma} B(x, R) \right).$$

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**The Quermass interaction :**

$$H_{\Lambda}(\gamma) = z N_{\Lambda}(\gamma) + \sum_{i=1}^{d+1} \beta_i M_i \left( \bigcup_{x \in \gamma} B(x, R) \right).$$

$((M_i)_{1 \leq i \leq d+1})$  are the Minkowski's functionals)



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A *family of interaction energies* is a collection  $\mathcal{H} = (H_\Lambda)$  of measurable functions from  $\Omega$  to  $\mathbb{R} \cup \{+\infty\}$  such that for  $\Lambda \subset \Lambda'$

$$H_{\Lambda'}(\gamma) = H_\Lambda(\gamma) + \varphi_{\Lambda, \Lambda'}(\gamma_{\Lambda^c}).$$

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$$H_{\Lambda'}(\gamma) = H_\Lambda(\gamma) + \varphi_{\Lambda, \Lambda'}(\gamma_{\Lambda^c}).$$

The local conditional densities :

$$f_\Lambda(\gamma) = \frac{1}{Z_\Lambda(\gamma_{\Lambda^c})} e^{-H_\Lambda(\gamma)},$$

## Definition

A probability measure  $P$  on  $\Omega$  is a *Gibbs measure* if for every  $\Lambda$ ,

$$P(d\gamma_\Lambda | \gamma_{\Lambda^c}) = f_\Lambda(\gamma) \pi_\Lambda(d\gamma_\Lambda).$$

# The MLE procedure

We consider a family of parametric energy functionals  $(H_{\Lambda}^{\theta})$  where  $\theta \in \mathring{\Theta} \subset \mathbb{R}^p$ .

$P^*$  is a Gibbs point process for  $(H_{\Lambda}^{\theta^*})$  with unknown  $\theta^*$ .

$\gamma^*$  is a realization of  $P^*$ .

$\Lambda_n = [-n, n]^d$  are the observation windows.

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## Definition

Let  $\mathcal{K}$  be a compact subset of  $\mathring{\Theta}$  such that  $\theta^* \in \mathcal{K}$ . The MLE of  $\theta^*$  from the observation  $\gamma_{\Lambda_n}^*$  is defined by

$$(\hat{\theta}_n) = \operatorname{argmax}_{\theta \in \mathcal{K}} f_{\Lambda_n}^{\theta}(\gamma_{\Lambda_n}^*).$$

## Corollaries of our main Theorems

- The MLE of  $(z^*, \beta^*, R^*)$  in the Strauss model is consistent

$$\phi(x) = \begin{cases} \beta & \text{if } |x| < R, \\ 0 & \text{if } |x| \geq R. \end{cases}$$

- The MLE of  $(z^*, A^*, B^*, n^*, m^*)$  in the Lennard-Jones model is consistent

$$\phi(x) = A|x|^{-n} - B|x|^{-m}, \quad x \in \mathbb{R}^d.$$

- The MLE of  $(z^*, \beta^*, R^*)$  in the Area Process is consistent

$$H_\Lambda(\gamma) = z N_\Lambda(\gamma) + \beta \text{Volume} \left( \bigcup_{x \in \gamma} B(x, R) \right).$$

## Assumptions of our main Theorem

**[Stability]** : For any compact set  $\mathcal{K} \subset \Theta$ , there exists a constant  $\kappa \geq 0$  such that for any  $\Lambda$ , any  $\theta \in \mathcal{K}$  and any  $\gamma \in \Omega$

$$H_{\Lambda}^{\theta}(\gamma_{\Lambda}) \geq -\kappa N_{\Lambda}(\gamma)$$

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**[MeanEnergy]** : The following decompositions holds

$$H_{\Lambda_n}^{\theta} = \sum_{k \in \{-n, n-1\}^d} H_0^{\theta} \circ \tau_{-k} + \partial H_{\Lambda_n}^{\theta}$$

with for any  $P \in \mathcal{G}$

$$E_P(H_0^{\theta}) < +\infty$$

and

$$\lim_{n \rightarrow \infty} \frac{1}{|\Lambda_n|} \sup_{\theta \in \mathcal{K}} \left| \partial H_{\Lambda_n}^{\theta} \right| \stackrel{P-as}{=} 0.$$



# Assumptions of our main Theorem

**[Boundary]** : For all  $P \in \mathcal{G}$ , for any compact set  $\mathcal{K} \subset \Theta$  and for  $P$ -almost every  $\gamma \in \Omega$

$$\lim_{n \rightarrow \infty} \frac{1}{|\Lambda_n|} \sup_{\theta \in \mathcal{K}} \left| H_{\Lambda_n}^{\theta}(\gamma_{\Lambda_n}) - H_{\Lambda_n}^{\theta}(\gamma) \right| = 0.$$

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**[Regularity]** : For all  $P \in \mathcal{G}$ , for any compact set  $\mathcal{K} \subset \Theta$

$$E_P \left( \sup_{\substack{\theta' \in \mathcal{K} \\ |\theta - \theta'| \leq r}} \left| H_0^{\theta} - H_0^{\theta'} \right| \right) \xrightarrow{r \rightarrow 0} 0.$$

# Assumptions of our main Theorem

**[Regularity]** : (second part)

For any  $\eta > 0$  and any  $\theta_0 \in \Theta$ , there exists  $\theta \subset B(\theta_0, \eta)$  and  $r_0 > 0$  such that for any  $\Lambda$  and any  $\gamma_\Lambda$

$$\inf_{\theta' \in B(\theta_0, r_0)} \left( \frac{H_\Lambda^\theta(\gamma_\Lambda) - H_\Lambda^{\theta'}(\gamma_\Lambda)}{N_\Lambda(\gamma_\Lambda)} \right) \geq g(r_0) \xrightarrow{r_0 \rightarrow 0} 0$$

where  $g$  is a function such that  $g(r) \rightarrow 0$  when  $r \rightarrow 0$ .

# Assumptions of our main Theorem

**[Variational Principle]** : The *pressure* exists ;

$$p(\theta) := \lim_{n \rightarrow \infty} \frac{1}{|\Lambda_n|} \ln(Z_{\Lambda_n}^\theta).$$

In addition, for any  $\theta, \theta'$  in  $\Theta$  and  $\mu^{\theta'} \in \mathcal{G}^{\theta'}$  ,

$$\mathcal{I}(\mu^{\theta'}) + E_{\mu^{\theta'}}(H_0^\theta) \geq -p(\theta)$$

and the equality holds if and only if  $\theta' = \theta$ .

( $\mathcal{I}(\mu^{\theta'})$  is the specific entropy of  $\mu^{\theta'}$  with respect to  $\pi$ )

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This assumption is satisfied for any finite range interaction

(Der. 2015)

# Main Theorems

## Theorem (Dereudre, Lavancier)

*Under the assumptions [Stability], [MeanEnergy], [Boundary], [Regularity] and [VariationalPrinciple], for any  $\theta^* \in \mathcal{K}$  and any  $P^* \in \mathcal{G}^{\theta^*}$ , the MLE  $\hat{\theta}_n$  converges  $P^*$ -almost surely to  $\theta^*$  when  $n$  goes to infinity.*

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Variants of this theorem are given in the paper :

- with an hardcore part
- in the pairwise setting
- in the linear setting

## Sketch of the proof

$$\hat{\theta}_n(\gamma) = \operatorname{argmax}_{\theta \in \mathcal{K}} f_{\Lambda_n}^{\theta}(\gamma_{\Lambda_n}).$$

- **Step 1 (A limiting contrast function) :**

$$K_n(\theta, \gamma) := \frac{1}{|\Lambda_n|} \log f_{\Lambda_n}^{\theta}(\gamma) \xrightarrow{P^* \text{-as}} K(\theta).$$

(Classical thermodynamic arguments)



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- **Step 2 (Identification) :**

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(Variational principle)

- **Step 3 (Convergence of argmax) :**

$$\operatorname{argmax}_{\theta} K_n(\theta, \gamma) \xrightarrow{P^* - as} \operatorname{argmax}_{\theta} K(\theta).$$

(main contribution in the present work)

## Step 1 : A limiting contrast function

$$\begin{aligned}K_n(\theta, \gamma) &= \frac{1}{|\Lambda_n|} \log f_{\Lambda_n}^\theta(\gamma) \\ &= \frac{1}{|\Lambda_n|} \left( -\log(Z_{\Lambda_n}^\theta) + H_{\Lambda_n}^\theta(\gamma_{\Lambda_n}) \right)\end{aligned}$$

We assume that  $P^*$  is ergodic. So, For  $P^*$ -almost all  $\gamma$

$$K_n(\theta, \gamma) \longmapsto -p(\theta) - E_{P^*}(H_0^\theta) := K(\theta).$$

## Step 2 : Identification

Recall the variational principle,  
for any  $\theta, \theta'$  in  $\Theta$  and  $\mu^{\theta'} \in \mathcal{G}^{\theta'}$

$$\mathcal{I}(\mu^{\theta'}) + E_{\mu^{\theta'}}(H_0^\theta) \geq -p(\theta) \quad (1)$$

with equality if and only if  $\theta = \theta'$ .

So

$$\begin{aligned} K(\theta) &= -p(\theta) - E_{P^*}(H_0^\theta) \\ &\leq I(P^*), \end{aligned}$$

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## Step 3 : Convergence of argmax

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### Lemma (Dereudre-Lavancier)

If a family of random contrast functions  $(K_n^\theta)$  satisfies

- $K_n^\theta \xrightarrow{P^*} K^\theta$  almost surely
- $\text{argmax}_\theta K^\theta = \{\theta^*\}$
- $\theta \mapsto \mathcal{K}^\theta$  is upper semicontinuous
- There exists a function  $g : \mathbb{R}^+ \rightarrow \mathbb{R}^+$  with  $g(x) \mapsto 0$  when  $x \mapsto 0$  such that  $\forall \varepsilon > 0, \forall \theta, \exists \theta' \in B(\theta, g(\varepsilon)), \exists r > 0$

$$P^* \left( \limsup_{n \rightarrow \infty} \left\{ \sup_{B(\theta, r)} K_n^\theta - K_n^{\theta'} \geq \varepsilon \right\} \right) = 0.$$

Then the  $\text{argmax}_\theta K_n^\theta$  converges  $P^*$ -almost surely to  $\text{argmax}_\theta K^\theta$ .

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