# An observation concerning the effect of the Random Batch Method on phase transition 

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Joint work with : Arnaud Guillin (LMBP, Clermont-Ferrand), Pierre Monmarché (LJLL, Paris)
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II. Understanding the problem on a toy model
II. 1 The Curie-Weiss model
II. 2 ...with the Random Batch Method

## I. Motivation

## Simulation of particle systems

Consider a $N$ particle system

$$
\begin{equation*}
d X_{t}^{i}=\frac{1}{N-1} \sum_{j \neq i} F\left(X_{t}^{i}-X_{t}^{j}\right) d t+\sqrt{2 \sigma} d B_{t}^{i}, \tag{IPS}
\end{equation*}
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which is linked to

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\left\{\begin{array}{c}
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\left\{\begin{array}{l}
X_{k}^{i, \delta}=X_{k}^{i, \delta}+\frac{\delta}{N-1} \sum_{j \neq 1} F\left(X_{k}^{i, \delta}-X_{k}^{j, \delta}\right)+\sqrt{2 \sigma \delta} G_{k}^{i},  \tag{D-IPS}\\
G_{k}^{+} \text {i.i.d } \sim \mathcal{N}(0,1), \quad t \in \mathbb{N} .
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X_{k+1}^{i, \delta}=X_{k}^{i, \delta}+\frac{\delta}{N-1} \sum_{j \neq i} F\left(X_{k}^{i, \delta}-X_{k}^{j, \delta}\right)+\sqrt{2 \sigma \delta} G_{k}^{i},  \tag{D-IPS}\\
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## Solution : Random Batch Method

## Références:

Shi Jin, Lei Li, and Jian-Guo Liu. Random batch methods (RBM) for interacting particles ystems. J. Comput. Phys. (2020).

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- Consider $\mathcal{P}_{k}=\left(\mathcal{P}_{k}^{1}, \ldots, \mathcal{P}_{k}^{N / p}\right)$ a partition of $\{1, \ldots, N\}$ into batches of size $p$ and define

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- Compute the numerical step

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\left\{\begin{array}{l}
Y_{k+1}^{i, \delta, p}=Y_{k}^{i, \delta, p}+\frac{\delta}{p-1} \sum_{j \in \mathcal{C}_{k}^{i} \backslash\{i\}} F\left(Y_{k}^{i, \delta, p}-Y_{k}^{j, \delta, p}\right)+\sqrt{2 \sigma \delta} G_{k}^{i} \\
G_{k}^{i} \text { i.i.d } \sim \mathcal{N}(0,1), \quad i \in\{1, \ldots, N\}
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## The Random Batch Method

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## The Random Batch Method



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$X_{1}^{6}$

An observation

## Addition of randomness

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Convergence as $N \rightarrow \infty$ with $p$ fixed (Jin-Li '22)

$$
\left\{\begin{array}{l}
\bar{Y}_{k+1}^{\delta, p}=\bar{Y}_{k}^{\delta, p}+\frac{\delta}{p-1} \sum_{j=1}^{p-1} F\left(\bar{Y}_{k}^{\delta, p}-Y^{j}\right)+\sqrt{2 \sigma \delta} G_{k},  \tag{D-RB-NL}\\
G_{k} \text { i.i.d } \sim \mathcal{N}(0,1),\left(Y^{j}\right)_{j} \text { ji.i.d } \sim \operatorname{Law}\left(\bar{Y}_{k}^{\delta, p}\right) .
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G_{k} \text { i.i.d } \sim \mathcal{N}(0,1), \quad\left(Y^{j}\right)_{j} \text { ji.i.d } \sim \operatorname{Law}\left(\bar{Y}_{k}^{\delta, p}\right) .
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Writing

$$
\begin{aligned}
& \xi_{k}=\frac{1}{p-1} \sum_{j=1}^{p-1} F\left(\bar{Y}_{k}^{\delta, p}-Y^{j}\right) \Longrightarrow \mathbb{E}\left(\xi_{t} \mid \bar{Y}_{k}^{\delta, p}\right)=F * \bar{\rho}_{k}^{\delta, p}\left(\bar{Y}_{k}^{\delta, p}\right), \\
& \text { and } \operatorname{Var}\left(\xi_{t} \mid \bar{Y}_{t}^{\delta, p}\right)=\frac{1}{p-1}\left(F^{2} * \bar{\rho}_{k}^{\delta, p}\left(\bar{Y}_{k}^{\delta, p}\right)-\left(F * \bar{\rho}_{k}^{\delta, p}\left(\bar{Y}_{k}^{\delta, p}\right)\right)^{2}\right) .
\end{aligned}
$$

Hence,

$$
\bar{Y}_{k}^{\delta, p}=\bar{Y}_{0}^{\delta, p}+\delta \sum_{l=0}^{k-1} F * \bar{\rho}_{l}^{\delta, p}\left(\bar{Y}_{l}^{\delta, p}\right)-\delta M_{k}+\sqrt{2 \sigma \delta} \sum_{l=0}^{k-1} G_{l}
$$

where $k \mapsto M_{k}:=\sum_{l=0}^{k-1}\left(\xi_{l}-F * \bar{\rho}_{l}^{\delta, p}\left(\bar{Y}_{l}^{\delta, p}\right)\right)$ is a martingale.

## Effective dynamics

By martingale CLT, (D-RB-IPS) is close to the effective dynamics:

$$
\left\{\begin{array}{l}
d \bar{X}_{t}^{e, \delta, p}=F * \bar{\rho}_{t}^{e, \delta, p}\left(\bar{X}_{t}^{e, \delta, p}\right) d t+\left(2 \sigma+\frac{\delta}{p-1} \Sigma\left(\bar{X}_{t}^{e, \delta, p}, \bar{\rho}_{t}^{e, \delta, p}\right)\right)^{1 / 2} d B_{t}  \tag{Eff}\\
\bar{\rho}_{t}^{e, \delta, p}=\operatorname{Law}\left(\bar{X}_{t}^{e, \delta, p}\right)
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where we denote $\Sigma(x, \rho)=F^{2} * \rho(x)-(F * \rho(x))^{2}$.

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Recall (NL):

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Recall (D-RB-IPS):

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## Question

If (NL) admits a phase transition, what about (Eff) ? And does the critical parameter $\sigma_{c}$ decreases as we would expect ?

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How does this added randomness affects the nonlinear limit, and more precisely its phase transition?

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## II. 1 The Curie-Weiss model

## Markov chain

Let $N$ spins $\sigma=\left(\sigma_{1}, \ldots, \sigma_{N}\right) \in \Omega_{N}=\{-1,1\}^{N}$ and consider

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\forall \sigma \in \Omega_{N}, \quad H_{N}(\sigma)=-\frac{1}{2 N} \sum_{i, j} \sigma_{i} \sigma_{j} .
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Consider $\sigma(k)$ the Markov chain on $\Omega_{N}$ such that at time step $k$ :

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- Accept $\sigma(k+1)=\sigma^{\prime}$ with probability $e^{-\beta\left(H_{N}\left(\sigma^{\prime}\right)-H_{N}(\sigma(k))\right)+}$ where $\beta$ is the inverse temperature.

An observation

## Mean magnetization

The system is entirely defined by its mean magnetization $m_{N}(\sigma):=\frac{1}{N} \sum_{i=1}^{N} \sigma_{i}$ as $H_{N}(\sigma)=-\frac{N}{2} m_{N}(\sigma)^{2}$.

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$m_{N}(k)=m_{N}(\sigma(k))$ is a Markov chain on $I_{N}=\left\{-1,-1+\frac{2}{N}, \ldots, 1-\frac{2}{N}, 1\right\}$ given by the transition probabilities

$$
r\left(m, m^{\prime}\right)= \begin{cases}\frac{1-m}{2} \exp \left(-\frac{\beta N}{2}\left(m^{2}-m^{\prime 2}\right)_{+}\right) & \text {if } m^{\prime}=m+\frac{2}{N} \\ \frac{1+m}{2} \exp \left(-\frac{\beta N}{2}\left(m^{2}-m^{\prime 2}\right)_{+}\right) & \text {if } m^{\prime}=m-\frac{2}{N} \\ 1-r\left(m, m+\frac{2}{N}\right)-r\left(m, m-\frac{2}{N}\right) & \text { if } m^{\prime}=m \\ 0 & \text { otherwise }\end{cases}
$$

## Phase transition

The process $t \mapsto m_{N}(\lfloor N t\rfloor)$ weakly converges to the solution $m(t)$ of the ODE

$$
\frac{d}{d t} m(t)=\left(e^{-2 \beta(-m(t))_{+}}-e^{-2 \beta(m(t))_{+}}\right)-m\left(e^{-2 \beta(-m(t))_{+}}+e^{-2 \beta(m(t))_{+}}\right) .
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- For $\beta>\beta_{c}=1$, the limit ODE has 3 equilibria, 0 is one of them and is unstable.
- For $\beta \leq \beta_{c}=1,0$ is the unique equilibrium and is stable.


Figure: $\beta=0.5, \beta=1, \beta=2$

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- For $\beta \leq \beta_{c}=1,0$ is the unique equilibrium and is stable.


Figure: $\beta=0.5, \beta=1, \beta=2$
Proof : consider the generator of $t \mapsto m_{N}(\lfloor N t\rfloor)$ and show its convergence to the generator associated to the ODE.

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## II. 2 ...with the Random Batch Method

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- Consider $\sigma^{\prime}$ where $\sigma_{P}(k)_{i}$ is switched.


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- Accept $\sigma(k+1)=\sigma^{\prime}$ with probability $\mathrm{e}^{-\beta\left(H_{p, \mathcal{N}}\left(\sigma^{\prime}, \mathcal{C}\right)-H_{p, N}(\sigma(k), \mathcal{C})\right)+}$ where

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H_{p, N}(\sigma, \mathcal{C})=-\frac{1}{2 p} \sum_{i, j \in \mathcal{C}} \sigma_{i} \sigma_{j} .
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H_{p, N}(\sigma, \mathcal{C})=-\frac{1}{2 p} \sum_{i, j \in \mathcal{C}} \sigma_{i} \sigma_{j} .
$$

Consider again the sequence $m_{P, N}(k)=\frac{1}{N} \sum_{i} \sigma(k)_{i}$.

## Transition probabilities

## Lemma

In a system of size $N$, the transition probabilities for the magnetization with random batches of size $p$ are given by

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\begin{aligned}
& \left(\frac{1-m}{2}\binom{N-1}{p-1}^{-1} \sum_{k=0}^{p-1}\binom{\left(\frac{1-m}{2}\right) N-1}{k}\binom{\left(\frac{1+m}{2}\right) N}{p-1-k} e^{-2 \beta\left(\frac{2 k+1-p}{p}\right)_{+}}\right. \\
& \text {if } m^{\prime}=m+\frac{2}{N}
\end{aligned}
$$

$$
\begin{aligned}
& \text { if } m^{\prime}=m-\frac{2}{N} \\
& 1-r_{p}\left(m, m+\frac{2}{N}\right)-r_{p}\left(m, m-\frac{2}{N}\right) \\
& \text { if } m^{\prime}=m \\
& \text { otherwise. }
\end{aligned}
$$

For instance

$$
r_{p}\left(m, m+\frac{2}{N}\right)=\frac{1-m}{2} \frac{1}{\binom{N-1}{p-1}} \sum_{k=0}^{p-1}\binom{\left(\frac{1-m}{2}\right) N-1}{k}\binom{\left(\frac{1+m}{2}\right) N}{p-1-k} e^{-2 \beta\left(\frac{2 k+1-p}{p}\right)_{+}}
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In a system of size $N$, the transition probabilities for the magnetization with random batches of size $p$ are given by

$$
r_{p}\left(m, m^{\prime}\right)=\left\{\begin{array}{c}
\frac{1-m}{2}\binom{N-1}{p-1}^{-1} \sum_{k=0}^{p-1}\binom{\left(\frac{1-m}{2}\right) N-1}{k}\binom{\left(\frac{1+m}{2}\right) N}{p-1-k} e^{-2 \beta\left(\frac{2 k+1-p}{p}\right)_{+}^{\prime}}=m+\frac{2}{N} \\
\text { if } m^{\prime} \\
\frac{1+m}{2}\binom{N-1}{p-1}^{-1} \sum_{\begin{array}{l}
p-1 \\
k=0
\end{array}\binom{\left(\frac{1-m}{2}\right) N}{k}\binom{\left(\frac{1+m}{2}\right) N-1}{p-1-k} e^{-2 \beta\left(\frac{p-1-2 k}{p}\right)_{+}}+}^{\text {if } m^{\prime}=m-\frac{2}{N}} \\
1-r_{p}\left(m, m+\frac{2}{N}\right)-r_{p}\left(m, m-\frac{2}{N}\right) \\
\text { if } m^{\prime}=m
\end{array}\right\} \begin{gathered}
\text { otherwise. }
\end{gathered}
$$

For instance

$$
r_{p}\left(m, m+\frac{2}{N}\right)=\overbrace{\frac{1-m}{2}}^{\text {Proportion of }-1} \frac{1}{\binom{N-1}{p-1}} \sum_{k=0}^{p-1}\binom{\left(\frac{1-m}{2}\right) N-1}{k}\binom{\left(\frac{1+m}{2}\right) N}{p-1-k} e^{-2 \beta\left(\frac{2 k+1-p}{p}\right)_{+}}
$$

## Transition probabilities

## Lemma

In a system of size $N$, the transition probabilities for the magnetization with random batches of size $p$ are given by

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\end{gathered}
$$

For instance
$r_{p}\left(m, m+\frac{2}{N}\right)=\overbrace{\frac{1-m}{2}}^{\overbrace{\# \text { of clusters }}^{\binom{N-1}{p-1}}} \sum_{k=0}^{p-1}\binom{\left.\frac{1-m}{2}\right) N-1}{k}\binom{\left(\frac{1+m}{2}\right) N}{p-1-k} e^{-2 \beta\left(\frac{2 k+1-p}{p}\right)}+$

## Transition probabilities

## Lemma

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\text { otherwise. }
\end{gathered}
$$

For instance
$r_{p}\left(m, m+\frac{2}{N}\right)=\overbrace{\frac{1-m}{2}}^{\underbrace{\left.\frac{1}{(N-1} \begin{array}{l}p-1\end{array}\right)}_{\# \text { of clusters }}} \overbrace{\sum_{k=0}^{\text {Proportion of }-1}\binom{\left.\frac{1-m}{2}\right) N-1}{k}\binom{\left(\frac{1+m}{2}\right) N}{p-1-k}}^{\text {Classifying the clusters based on the number of }-1} e^{-2 \beta\left(\frac{2 k+1-p}{p}\right)_{+}}$

## Transition probabilities

## Lemma

In a system of size $N$, the transition probabilities for the magnetization with random batches of size $p$ are given by

$$
\begin{aligned}
& \int \frac{1-m}{2}\binom{N-1}{p-1}^{-1} \sum_{k=0}^{p-1}\binom{\left(\frac{1-m}{2}\right) N-1}{k}\binom{\left(\frac{1+m}{2}\right) N}{p-1-k} e^{-2 \beta\left(\frac{2 k+1-p}{p}\right)_{+}} \\
& \text {if } m^{\prime}=m+\frac{2}{N}
\end{aligned}
$$

$$
\begin{aligned}
& \text { if } m^{\prime}=m-\frac{2}{N} \\
& \begin{array}{c}
1-r_{p}\left(m, m+\frac{2}{N}\right)-r_{p}\left(m, m-\frac{2}{N}\right) \\
\text { if } m^{\prime}=m
\end{array} \\
& 0 \text { otherwise. }
\end{aligned}
$$

For instance


## Limit ODE

## I. Motivation

The process $M_{t}^{(N, p)}=m_{N, p}(\lfloor N t\rfloor)$ weakly converges as $N \rightarrow \infty$ to the solution of

$$
\begin{gathered}
\frac{d}{d t} m(t)=f_{p}(\beta, m(t)) . \\
\text { with } f_{p}(\beta, m)=\left(S_{1}^{p, \beta}(m)-S_{2}^{p, \beta}(m)\right)-m\left(S_{1}^{p, \beta}(m)+S_{2}^{p, \beta}(m)\right) \text { where } \\
S_{1}^{p, \beta}(m)=\mathbb{E}\left(e^{-2 \beta\left(\frac{2 x_{m, p+1-p}^{p}}{p}\right)_{+}}\right), \quad S_{2}^{p, \beta}(m)=\mathbb{E}\left(e^{-2 \beta\left(\frac{p-1-2 x_{m, p}}{\rho}\right)_{+}}\right) \\
\text {and } \quad X_{m, p} \sim \mathcal{B}\left(p-1, \frac{1-m}{2}\right) .
\end{gathered}
$$

## Limit ODE

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S_{1}^{p, \beta}(m)=\mathbb{E}\left(e^{-2 \beta\left(\frac{2 X_{m, p+1-p}^{p}}{\rho}\right)_{+}}\right), \quad S_{2}^{p, \beta}(m)=\mathbb{E}\left(e^{-2 \beta\left(\frac{p-1-2 x_{m, p}}{\rho}\right)_{+}}\right) \\
\text {and } \quad X_{m, p} \sim \mathcal{B}\left(p-1, \frac{1-m}{2}\right) .
\end{gathered}
$$

Recall the limit with no random batches

$$
\frac{d}{d t} m(t)=\left(e^{-2 \beta(-m(t))+}-e^{-2 \beta(m(t))+}\right)-m\left(e^{-2 \beta(-m(t))+}+e^{-2 \beta(m(t))+}\right) .
$$

## Decreased critical temperature

Theorem
Let $p \in \mathbb{N} \backslash\{0,1\}$ and $\beta>0$.

- For all $\beta>0,0$ is an equilibrium state for the solution of the timit ODE.
- For $p \in\{2,3\}, 0$ is the unique equilibrium state, and it is stable.
- For $p \geq 4$, there exists $\beta_{c, p}$ such that for all $\beta>\beta_{c, p}$, the equilibrium state 0 is unstable, and for all $\beta \leq \beta_{c, p}$ it is stable. Furthermore, we have the estimate

$$
\beta_{c, p}=1+\sqrt{\frac{2}{p \pi}}+o\left(\frac{1}{\sqrt{p}}\right)
$$

An observation on Random Batch Method

## Decreased critical temperature



Figure: Numerical observation of the invariant distribution for the Curie-Weiss model
$\square$

## An observation on Random Batch Method <br> Pierre Le Bris <br> I. Motivation <br> II. Understanding the problem on a toy model <br> 11. 1 The Curie-Weiss model <br> II. 2 ...with the Random Batch Method <br> III. Double well potential <br> III. Double well potential

## Double well potential

Consider in dimension one

$$
\left\{\begin{array}{l}
d \bar{X}_{t}=-U^{\prime}\left(\bar{X}_{t}\right) d t-W^{\prime} * \bar{\rho}_{t}\left(\bar{X}_{t}\right) d t+\sqrt{2 \sigma} d B_{t},  \tag{DW-NL}\\
\bar{\rho}_{t}=\operatorname{Law}\left(\bar{X}_{t}\right),
\end{array}\right.
$$

with the potentials

$$
U(x)=\frac{x^{4}}{4}-\frac{x^{2}}{2}, \quad W(x)=L_{w} \frac{x^{2}}{2} \quad \text { with } L_{w}>0 .
$$

Theorem (Tugaut '14)
There exists $\sigma_{c}>0$ such that

- For all $\sigma \geq \sigma_{c}$, there exists a unique stationary distribution $\mu_{\sigma, 0}$ for (DW-NL). Furthermore, $\mu_{\sigma, 0}$ is symmetric.
- For all $\sigma<\sigma_{c}$, there exist three stationary distributions for (DW-NL). One is symmetric, also denoted $\mu_{\sigma, 0}$, and the other two, denoted $\mu_{\sigma,+}$ and $\mu_{\sigma,-}$, satisfy $\pm \int x d \mu_{\sigma, \pm}(d x)>0$.


## Double well potential - Effective

$$
\left\{\begin{array}{l}
d \bar{X}_{t}=-U^{\prime}\left(\bar{X}_{t}\right) d t-W^{\prime} * \bar{\rho}_{t}\left(\bar{X}_{t}\right) d t+\left(2 \sigma+\frac{\delta}{p-1} L_{W}^{2} \operatorname{Var}\left(\bar{\rho}_{t}\right)\right)^{1 / 2} d B_{t}  \tag{DW-Eff}\\
\bar{\rho}_{t}=\operatorname{Law}\left(\bar{X}_{t}\right)
\end{array}\right.
$$

Theorem
For $\delta / p$ sufficiently small, denoting

$$
\sigma_{c}^{e f f}=\sigma_{c}\left(1-\frac{\delta L_{w}}{2(p-1)}\right)
$$

we have the following phase transition for the dynamics (DW-Eff)

- For all $\sigma \geq \sigma_{c}^{\text {eff }}$, there exists a unique stationary distribution $\mu_{\sigma, 0}^{\delta, p}$ for (Eff). Furthermore, $\mu_{\sigma, 0}^{\delta, p}$ is symmetric.
- For all $\sigma \in\left[\sigma_{0}, \sigma_{c}^{\text {eff }}[\right.$, there exists exactly three stationary distributions for (Eff). One is symmetric, also denoted $\mu_{\sigma, 0}^{\delta, p}$, and the other two, denoted $\mu_{\sigma,+}^{\delta, p}$ and $\mu_{\sigma,-}^{\delta, p}$, satisfy $\pm \int x d \mu_{\sigma, \pm}^{\delta, p}(x)>0$.


## Idea of proof

## 1. Motivation

- Show that a stationary distribution for (DW-NL) is a stationary distribution for (DW-Eff), but for another diffusion coefficient.
- Study the variance around the critical parameter.

$$
\begin{array}{l|l}
\text { An observation } \\
\text { on Random } \\
\text { Batch Method } \\
\text { Pierre Le Bris } & \\
\text { I. Motivation } & \\
\text { II. Understanding } & \\
\text { the problem on a } \\
\text { toy model } & \\
\text { II.1 The Curie-Weiss } & \\
\text { model } \\
\text { II.2 with the } & \\
\text { Random Batch } & \text { Method } \\
\text { III. Double well } & \text { potential }
\end{array}
$$

