# Diluted spin glass models 

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## Overview

- discrete probability measures
- extremality and pinning
- the cut metric and pure state decompositions
- limits and compactness


## Discrete probability measures

Notation

- let $\Omega \neq \varnothing$ be a finite set
- $\mathscr{P}(\Omega)$ comprises all probability distributions on $\Omega$
- recall the total variation distance:

$$
d_{\mathrm{TV}}(\mu, v)=\frac{1}{2} \sum_{\omega \in \Omega}|\mu(\omega)-v(\omega)| \quad(\mu, v \in \mathscr{P}(\Omega))
$$

## Discrete probability measures

Probability measures on cubes

- consider a distribution $\mu \in \mathscr{P}\left(\Omega^{n}\right)$
- $\mu_{i}$ is the marginal of the $i$-th entry:

$$
\mu_{i}(s)=\mu\left(\left\{\boldsymbol{\sigma}_{i}=s\right\}\right)
$$

- more generally, for a set $I \subset[n]$ let

$$
\mu_{I}(\boldsymbol{s})=\mu\left(\left\{\forall i \in I: \boldsymbol{\sigma}_{i}=s_{i}\right\}\right) \quad\left(\boldsymbol{s} \in \Omega^{I}\right)
$$

## Discrete probability measures

Example 1

- $\Omega=\{ \pm 1\}$ and $n=3$ with

$$
\mu(\boldsymbol{\sigma})=\frac{\mathbf{l}\left\{\boldsymbol{\sigma}_{1} \boldsymbol{\sigma}_{2} \boldsymbol{\sigma}_{3}=1\right\}}{4} \quad\left(\boldsymbol{\sigma} \in \Omega^{n}\right)
$$

- $\mu_{1}( \pm 1)=\mu_{2}( \pm 1)=\mu_{3}( \pm 1)=1 / 2$
- $\mu_{i, j}( \pm 1, \pm 1)=1 / 4$ for all $1 \leq i<j \leq 3$
- however, $\boldsymbol{\sigma}_{1}, \boldsymbol{\sigma}_{2}, \boldsymbol{\sigma}_{3}$ are not independent


## Discrete probability measures

Example 2

- $\Omega=\{ \pm 1\}^{n}$ for $n \gg 1$
- $\mu=\mu_{K_{n}, \beta}=$ Curie-Weiss Boltzmann distribution with $\beta=b / n$
- if $b<1$ then for any set $I$ of size $|I|=O(1)$

$$
\mu_{I}(\sigma)=\prod_{i \in I} \mu_{i}\left(\sigma_{i}\right)=2^{-|I|} \quad\left(\sigma \in\{ \pm 1\}^{I}\right)
$$

- if $b>1$ then

$$
\mu_{I}(\sigma) \nsim \prod_{i \in I} \mu_{i}\left(\sigma_{i}\right)=2^{-|I|} \quad\left(\sigma \in\{ \pm 1\}^{I}\right)
$$

- however,

$$
\mu_{I}\left(\sigma \mid \sum_{i \leq n} \boldsymbol{\sigma}_{i} \geq 0\right) \sim \prod_{i \in I} \mu_{i}\left(\sigma_{i} \mid \sum_{i \leq n} \boldsymbol{\sigma}_{i} \geq 0\right)
$$

## Extremality and pinning

## Extremality

[BCO16]

- A distribution $\mu \in \mathscr{P}\left(\Omega^{n}\right)$ is $\varepsilon$-extremal if

$$
\frac{1}{n^{2}} \sum_{i, j=1}^{n}\left|\mu_{i, j}(s, t)-\mu_{i}(s) \mu_{j}(t)\right| \leq \varepsilon \quad(s, t \in \Omega)
$$

- not the similarity with (static) "replica symmetry" [KMRTSZ07]


## Extremality and pinning

## Extremality

- A distribution $\mu \in \mathscr{P}\left(\Omega^{n}\right)$ is $(\varepsilon, \ell)$-extremal if

$$
\sum_{i_{1}, \ldots, i_{\ell}=1}^{n}\left|\mu_{i_{1}, \ldots, i_{\ell}}\left(s_{1}, \ldots, s_{\ell}\right)-\prod_{j=1}^{\ell} \mu_{i_{j}}\left(s_{j}\right)\right| \leq \varepsilon n^{\ell} \quad\left(s_{i} \in \Omega\right)
$$

## Extremality and pinning

Lemma
For any $\Omega, \varepsilon>0, \ell>2$ there exist $\delta>0, n_{0}>0$ such that any $\delta$-extremal $\mu \in \mathscr{P}\left(\Omega^{n}\right)$ is $(\varepsilon, \ell)$-extremal.
"approximate pairwise independence implies approximate $\ell$-wise independence"

## Extremality and pinning

The pinning operation
[T08,M08,RT12,CKPZ17]

- consider $\mu \in \mathscr{P}\left(\Omega^{n}\right)$
- for a set $I \subset[n]$ and $\chi \in \Omega^{n}$ let

$$
\mathscr{S}^{I, \chi}=\left\{\sigma \in \Omega^{n}: \forall i \in I: \sigma_{i}=\chi_{i}\right\}
$$

- define

$$
\mu^{I, \chi}(\sigma)=\mu\left(\sigma \mid \mathscr{S}^{I, \chi}\right)
$$

- pin the coordinates I according to $\sigma$


## Extremality and pinning

Randomised pinning

## [T08,M08,RT12,CKPZ17]

- let $1 \leq \Theta \leq n$ and choose $1 \leq \ell \leq \Theta$ randomly
- consider a random set $I \subset[n]$ of size $\ell$
- draw $\chi$ from $\mu$
- then define

$$
\hat{\mu}(\cdot)=\mu^{[\Theta]}(\cdot)=\mu^{I, \chi}(\cdot)
$$

- observe that $\hat{\mu}(\cdot)$ is random!
- pin a random set of coordinates according to a sample from $\mu$


## Extremality and pinning

Theorem
[T08,M08,RT12,CKPZ17]
For any $\Omega, \varepsilon>0$ there exist $\Theta>0, n_{0}>\Theta$ such that for all $n>n_{0}$ and all $\mu \in \mathscr{P}\left(\Omega^{n}\right)$,

$$
\mathrm{P}[\hat{\mu} \text { is } \varepsilon \text {-extremal }]>1-\varepsilon .
$$

crucially, $\Theta$ depends on $\Omega$ and $\varepsilon$ only, but not on $\mu$ or even $n$

## Extremality and pinning





Example: the Curie-Weiss model with $b>1$

- fix a small $\varepsilon>1$ and let $n \gg 1$
- $\mu=\mu_{K_{n}, \beta}$ fails to be $\varepsilon$-extremal
- however, $\mu^{[\ell]}$ is $\varepsilon$-extremal for large enough $\ell$


## Extremality and pinning

## Proof

- the conditional mutual information

$$
\begin{aligned}
I(X, Y \mid Z)=\sum_{x, y, z \in \mathscr{X}} \mathrm{P}[ & X=x, Y=y, Z=z] \\
& \cdot \log \frac{\mathrm{P}[X=x, Y=y \mid Z=z]}{\mathrm{P}[X=x \mid Z=z] \mathrm{P}[Y=y \mid Z=z]}
\end{aligned}
$$

- the conditional entropy

$$
H(X \mid Y)=\sum_{x, y \in \mathscr{X}} \mathrm{P}[X=x, Y=y] \log \mathrm{P}[X=x \mid Y=y] .
$$

- they satisfy

$$
I(X, Y \mid Z)=H(X \mid Z)-H(X \mid Y, Z)
$$

## Extremality and pinning

## Proof

- let $\boldsymbol{i}, \boldsymbol{i}^{\prime}, \boldsymbol{i}_{1}, \boldsymbol{i}_{2}, \ldots \in[n]$ be independent and uniform
- for every $\theta \geq 0$,

$$
\begin{aligned}
& I\left(\boldsymbol{\sigma}_{\boldsymbol{i}}, \boldsymbol{\sigma}_{\boldsymbol{i}^{\prime}} \mid \boldsymbol{\sigma}_{\boldsymbol{i}_{1}}, \ldots, \boldsymbol{\sigma}_{\boldsymbol{i}_{\theta}}\right) \\
& \quad=H\left(\boldsymbol{\sigma}_{\boldsymbol{i}} \mid \boldsymbol{\sigma}_{\boldsymbol{i}_{1}}, \ldots, \boldsymbol{\sigma}_{\boldsymbol{i}_{\theta}}\right)-H\left(\boldsymbol{\sigma}_{\boldsymbol{i}} \mid \boldsymbol{\sigma}_{\boldsymbol{i}_{1}}, \ldots, \boldsymbol{\sigma}_{\boldsymbol{i}_{\theta}}, \boldsymbol{\sigma}_{\boldsymbol{i}^{\prime}}\right) \\
& \quad \stackrel{\mathrm{d}}{=} H\left(\boldsymbol{\sigma}_{\boldsymbol{i}} \mid \boldsymbol{\sigma}_{\boldsymbol{i}_{1}}, \ldots, \boldsymbol{\sigma}_{\boldsymbol{i}_{\theta}}\right)-H\left(\boldsymbol{\sigma}_{\boldsymbol{i}} \mid \boldsymbol{\sigma}_{\boldsymbol{i}_{1}}, \ldots, \boldsymbol{\sigma}_{\boldsymbol{i}_{\theta}}, \boldsymbol{\sigma}_{\boldsymbol{i}_{\theta+1}}\right)
\end{aligned}
$$

- summing on $\theta=1, \ldots, T$ (with $\mathrm{E}[\cdot]$ referring to the choice of $\left.\boldsymbol{i}, \boldsymbol{i}^{\prime}, \ldots\right)$, we thus obtain

$$
\sum_{\theta=0}^{T} \mathrm{E}\left[I\left(\boldsymbol{\sigma}_{i}, \boldsymbol{\sigma}_{i^{\prime}} \mid \boldsymbol{\sigma}_{i_{1}}, \ldots, \boldsymbol{\sigma}_{\boldsymbol{i}_{\theta}}\right)\right]=\mathrm{E}\left[H\left(\boldsymbol{\sigma}_{i}\right)\right]-\mathrm{E}\left[H\left(\boldsymbol{\sigma}_{i} \mid \boldsymbol{\sigma}_{\boldsymbol{i}_{1}}, \ldots, \boldsymbol{\sigma}_{\boldsymbol{i}_{T+1}}\right)\right]
$$

## Extremality and pinning

## Proof

- since $H\left(\boldsymbol{\sigma}_{i}\right) \leq \log |\Omega|$ and $H\left(\boldsymbol{\sigma}_{i} \mid \boldsymbol{\sigma}_{i_{1}}, \ldots, \boldsymbol{\sigma}_{\boldsymbol{i}_{T+1}}\right) \geq 0$, we obtain

$$
\sum_{\theta=0}^{T} \mathrm{E}\left[I\left(\boldsymbol{\sigma}_{\boldsymbol{i}}, \boldsymbol{\sigma}_{\boldsymbol{i}^{\prime}} \mid \boldsymbol{\sigma}_{\boldsymbol{i}_{1}}, \ldots, \boldsymbol{\sigma}_{\boldsymbol{i}_{\theta}}\right)\right] \leq \log |\Omega|
$$

- recalling the definition of the mutual information, we conclude that

$$
\mathrm{E}\left[D_{\mathrm{KL}}\left(\hat{\mu}_{i, i^{\prime}} \| \hat{\mu}_{\boldsymbol{i}} \otimes \hat{\mu}_{i^{\prime}}\right)\right] \leq \frac{\log |\Omega|}{T}
$$

## Extremality and pinning

## Proof

- finally, let us recall Pinsker's inequality:

$$
d_{\mathrm{TV}}(\mu, v) \leq \sqrt{D_{\mathrm{KL}}(\mu \| v) / 2}
$$

- applying Pinsker's inequality and Jensen's inequality, we see

$$
\begin{aligned}
\mathrm{E}\left[\left\|\hat{\mu}_{\boldsymbol{i}, \boldsymbol{i}^{\prime}}-\hat{\mu}_{\boldsymbol{i}} \otimes \mu_{\boldsymbol{i}^{\prime}}\right\|_{\mathrm{TV}}\right] & \leq \mathrm{E}\left[\sqrt{D_{\mathrm{KL}}\left(\hat{\mu}_{\boldsymbol{i}, \boldsymbol{i}^{\prime}} \| \hat{\mu}_{\boldsymbol{i}} \otimes \hat{\mu}_{\boldsymbol{i}^{\prime}}\right) / 2}\right] \\
& \leq \sqrt{\mathrm{E}\left[D_{\mathrm{KL}}\left(\hat{\mu}_{\boldsymbol{i} \boldsymbol{i}^{\prime}} \| \hat{\mu}_{\boldsymbol{i}} \otimes \hat{\mu}_{\boldsymbol{i}^{\prime}}\right)\right] / 2} \\
& \leq \sqrt{\frac{\log |\Omega|}{2 T}}
\end{aligned}
$$

thereby completing the proof

## The cut metric and pure states

## Couplings

- suppose that $\mu, v \in \mathscr{P}(\Omega)$
- a coupling of $\mu, v$ is a probability $\gamma$ on $\Omega \times \Omega$ such that

$$
\begin{array}{ll}
\sum_{y \in \Omega} \gamma(x, y)=\mu(x) & (x \in \Omega) \\
\sum_{y \in \Omega} \gamma(y, x)=v(x) & (x \in \Omega)
\end{array}
$$

- let $\Gamma(\mu, v)$ comprise all couplings of $\mu, v$
- Example: the product measure $\mu \otimes v$


## The cut metric and pure states

Coupling lemma
For any $\mu, v \in \mathscr{P}(\Omega)$ we have

$$
\max \left\{\sum_{x \in \Omega} \gamma(x, x): \gamma \in \Gamma(\mu, v)\right\}+d_{\mathrm{TV}}(\mu, v)=1
$$

## The cut metric and pure states

The cut metric
[FK99,BCO16,COHK21]
For two probability distributions $\mu, v \in \mathscr{P}\left(\Omega^{n}\right)$ define

$$
d_{\square}(\mu, v)=\frac{1}{n} \min _{\gamma \in \Gamma(\mu, v)} \max _{\substack{I \subset\{1, \ldots, n\} \\ B \in \Omega^{n} \times \Omega^{n} \\ \omega \in \Omega}}\left|\sum_{i \in I} \sum_{\substack{(\sigma, \tau) \in B}} \gamma(\sigma, \tau)\left(\mathbf{1}\left\{\sigma_{i}=\omega\right\}-\mathbf{1}\left\{\tau_{i}=\omega\right\}\right)\right|
$$

Explanation

- first couple $\mu, v$ as best as possible $\rightsquigarrow \gamma$
- then identify the largest discrepancy $\rightsquigarrow I, B, \omega$
- (the cut metric satisfies the triangle inequality)


## The cut metric and pure states





Example: Curie-Weiss

- let $v$ be the uniform distribution on $\{ \pm 1\}$
- then for any $b<1$,

$$
\lim _{n \rightarrow \infty} d_{\square}\left(\mu_{K_{n}, \beta}(\cdot), v^{\otimes n}\right)=0
$$

## The cut metric and pure states





Example: Curie-Weiss

- suppose $b>1$
- let $\lambda_{ \pm}$be the positive/negative maximiser
- let $v_{ \pm} \in \mathscr{P}(\{ \pm 1\})$ have mean $\lambda_{ \pm}$

$$
\lim _{n \rightarrow \infty} d \square\left(\mu_{K_{n}, \beta}(\cdot), \frac{1}{2}\left(v_{+}^{\otimes n}+v_{-}^{\otimes n}\right)\right)=0
$$

## The cut metric and pure states

## Product measures

- suppose that $\mu \in \mathscr{P}\left(\Omega^{n}\right)$
- then we let

$$
\bar{\mu}=\bigotimes_{i=1}^{n} \mu_{i}
$$

be the product measure with the same marginals as $\mu$

## The cut metric and pure states

## Lemma

For any $\Omega, \varepsilon>0$ there exist $\delta>0, n_{0}>0$ such that for all $n>n_{0}$ and all $\mu \in \mathscr{P}\left(\Omega^{n}\right)$ :

- if $\mu$ is $\delta$-extremal, then $d_{\square}(\mu, \bar{\mu})<\varepsilon$
- if $d \square(\mu, \bar{\mu})<\delta$, then $\mu$ is $\varepsilon$-extremal


## The cut metric and pure states

Decomposition theorem
[BCO16,COHK21]
For any $\Omega, \varepsilon>0$ there exist $n_{0}>0, \Theta>0$ such that for a random $1 \leq \boldsymbol{\theta}<\Theta$ for all $n>n_{0}$ and $\mu \in \mathscr{P}\left(\Omega^{n}\right)$ :

- let $I \subset[n]$ be a random subset of size $\boldsymbol{\theta}$
- let

$$
\bar{\mu}^{I}=\sum_{\chi \in \Omega^{I}} \mu_{I}(\chi) \bar{\mu}^{I, \chi}
$$

- then

$$
\mathrm{E}\left[d \square\left(\mu, \bar{\mu}^{I}\right)\right]<\varepsilon
$$

## The cut metric and pure states

Explanation

- $\boldsymbol{\theta}$ is bounded independently of $n, \mu$
- actually $\Theta \leq\left(\varepsilon^{-1} \log |\Omega|\right)^{c}$
- proof: pinning lemma and triangle inequality
- related to the "Szemerédi regularity lemma"
- "any distribution can be approximated by a mixture of a small number of product measures"


## The cut metric and pure states

Pure states

- we obtain a decomposition of the phase space $\Omega^{n}$ into

$$
\mathscr{S}^{I, \chi}\left\{\sigma \in \Omega^{n}: \forall i \in I: \sigma_{i}=\chi_{i}\right\} \quad\left(\chi \in \Omega^{I}\right)
$$

- for all but an $\varepsilon$-measure of $\chi$, the conditional

$$
\mu\left(\cdot \mid \mathscr{S}^{I, \chi}\right)
$$

is $\varepsilon$-extremal

- think of the $\mathscr{S}^{I, \chi}$ as "pure states"


## The cut metric and pure states

Example: Curie-Weiss

- suppose $b>1$
- actually the model has two pure states
- the decomposition theorem renders a partition that is "too fine"
- ... but not by "too much"
- ... and under the cut metric, the sub-states amalgamate


## The cut metric and pure states



Example: sparse random factor graphs

- in the RS/dRSB phase we obtain an approximation by a single product measure $\rightsquigarrow$ one pure state
- in the static RSB phase, we obtain several pure states
- their number diverges (slowly) as $\varepsilon \rightarrow 0$ and $n \rightarrow \infty$


## Limits and Aldous-Hoover

Limit objects

- let's stick to $\Omega=\{ \pm 1\}$
- let $\mathscr{S}$ contain all measurable $s:[0,1] \rightarrow[-1,1]$
- equip $\mathscr{S}$ with the $L^{1}$ metric:

$$
d_{1}(s, t)=\int_{0}^{1}|s(x)-t(x)| \mathrm{d} x
$$

- let $\mathbb{S}$ contain all measurable bijections $[0,1] \rightarrow[0,1]$


## Limits and Aldous-Hoover

Limit objects

- for probability measures $\mu, v$ on $\mathscr{S}$ define

$$
d_{\square}(\mu, v)=\min _{\substack{\gamma \in \Gamma(\mu, v) \\ \varphi \in \mathbb{S}}} \max _{\substack{I \subset[0,1] \\ B \subset \mathscr{S} \times \mathscr{S}}}\left|\int_{I} \int_{B} s(x)-t(x) \mathrm{d} \gamma(s, t) \mathrm{d} x\right|
$$

- obtain a space $L_{\square}(\{ \pm 1\})$ by identifying $\mu, v$ with $d_{\square}(\mu, v)=0$


## Limits and Aldous-Hoover

## Proposition

Endowed with $d_{\square}(\cdot, \cdot)$, the space $L_{\square}(\{ \pm 1\})$ is compact and separable.

## Limits and Aldous-Hoover

Embedding discrete mesures

- any configuration $\sigma \in\{ \pm 1\}^{n}$ yields a step function

$$
s:[0,1] \rightarrow[-1,1], \quad x \mapsto s(\lceil n x\rceil)
$$

- this turns a distribution $\mu \in \mathscr{P}\left(\{ \pm 1\}^{n}\right)$ into an element of $L_{\square}(\{ \pm 1\})$


## Limits and Aldous-Hoover

Random probability measures

- the Boltzmann distribution $\mu_{\mathbb{G}, \beta}$ of, say, an Ising model on the random regular graph $\mathbb{G}=\mathbb{G}(n, d)$ is random itself
- hence, $\mu_{\mathbb{G}, \beta}$ induces a distribution on $L_{\square}(\{ \pm 1\})$
- thus, disordered systems map to the space

$$
\mathscr{P}\left(L_{\square}(\{ \pm 1\})\right)
$$

- this is a compact separable space


## Limits and Aldous-Hoover

Aldous-Hoover

- this embedding is equivalent to the Aldous-Hoover representation of exchangeable arrays
- specifically, given $p \in \mathscr{P}\left(L_{\square}(\{ \pm 1\})\right)$, we ultimately represent the Boltzmann disordered as follows:
- choose a random measure $\mu \in L_{\square}(\{ \pm 1\})$ from $p$
- choose $s \in \mathscr{S}$ from $\mu$
- draw $x \in[0,1]$ randomly
- draw $\sigma \in\{ \pm 1\}$ from a Rademacher with mean $s(x)$


## Limits and Aldous-Hoover

Example: Curie-Weiss

- the Boltzmann distributions $\mu_{K_{n}, \beta}$ coverges to a limit $\mu^{*} \in L_{\square}(\{ \pm 1\})$
- in the case $b \leq 1$ we obtain

$$
\mu^{*}=\delta_{0}
$$

- in the case $b>1$ we obtain

$$
\mu^{*}=\frac{1}{2}\left(\delta_{\lambda_{-}}+\delta_{\lambda_{+}}\right)
$$

## Summary

- the pinning operation
- decomposition into pure states
- embedding into a compact space
- Aldous-Hoover

