

# Fluctuation results in spin glasses

Matthias Löwe

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# Today's menu

The mother of all models

Spin glasses

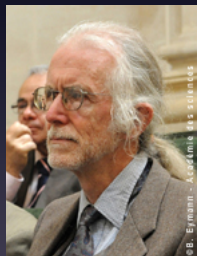
Fluctuations

Fluctuations in the REM

Fluctuations in the Hopfield model

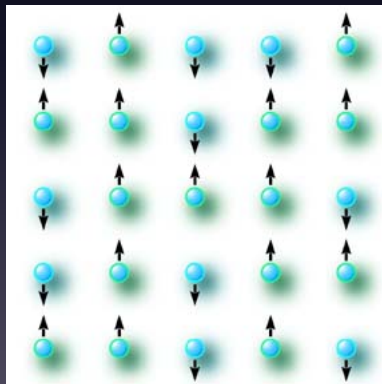
Conclusion

”Above all, it must be said, that this paper would not have been written without the encouragement of Erwin Bolthausen (the reader, will observe that, as what should have been a three months project, ended only after years of very intense struggle, the word 'grateful' was omitted in the acknowledgement)”  
(Michel Talagrand (1996))



# The mother of all models?

- Lenz and Ising ( $\sim 1922$ )
- How do you model a **ferromagnet**?
- Idea: Locate "atoms" at the sites of a subset of  $\Lambda \subset \mathbb{Z}^d$ .
- Each of them has a **magnetic dipole**, a **spin**  $\in \{-1, +1\}$



## The mother of all models? (cont.)

- These spins need to **cooperate**, to create a magnetic behavior.
- Introduce an **energy function**
- $H_{\Lambda}(\sigma) = - \sum_{\langle i,j \rangle \in \Lambda} \sigma_i \sigma_j (-h \sum_{j \in \Lambda} \sigma_j), \sigma \in \{\pm 1\}^{\Lambda}$
- and a **probability measure**
- $\mu_{\Lambda}(\sigma) = \frac{e^{-\beta H_{\Lambda}(\sigma)}}{Z_{\Lambda,\beta}}$  (**Gibbs measure**)
- with  $Z_{\Lambda,\beta} = \sum_{\sigma' \in \{\pm 1\}^{\Lambda}} e^{-\beta H_{\Lambda}(\sigma')}$
- and  $\beta > 0$ .

# Ising's prediction

- The model is **uninteresting** in dimension  $d = 1$  (Right!)
- It also does not model magnetic behavior in  $d = 2$  **Wrong!**
- Indeed, the model does show a **phase transition** from **paramagnetic** to **magnetic** behavior **in higher dimensions**.



## A related model

- An even simpler model with magnetic behavior:
- Replace interaction of  $\sigma_i$  and other  $\sigma'_j$ 's
- by interaction of  $\sigma_i$  with an **average** spin:  $\frac{1}{|\Lambda|} \sum_{j \in \Lambda_j} \sigma_j$
- The energy function becomes

$$H_N = -\frac{1}{2N} \sum_{i,j=1}^N \sigma_i \sigma_j$$

- This is known as the **Curie-Weiss model**
- Advantage:  $H_N$  is a function of the **mean magnetization**  
 $m_N(\sigma) = \frac{1}{N} \sum_{i=1}^N \sigma_i$ .

# A phase transition

- The Curie-Weiss model exhibits a **phase transition** at  $\beta = 1$
- This can be in various ways, e.g.
- For  $\beta \leq 1$ :  $m_N$  converges to 0 under  $\mu_{N,\beta}$
- For  $\beta > 1$ : The distribution of  $m_N$  under  $\mu_{N,\beta}$  converges to  $\frac{1}{2}\delta_{z(\beta)} + \delta_{-z(\beta)}$
- where  $z(\beta)$  is the largest solution of

$$z = \tanh(\beta z).$$



# Spin glasses

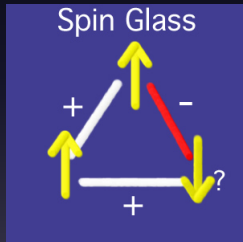
- In the early 1970's:
- Add **randomness** to the interactions
- i.e., consider the new energy function

$$H(\sigma) = - \sum_{i,j} \sigma_i \sigma_j J_{ij}$$

- where  $J_{ij}$  are random variables with
- $\mathbb{E} J_{ij} = 0$
- **tossed in advance**

# Frustration

- Spin glasses are on another level of difficulty
- compared to ferromagnets
- Basic reason: **frustration**



- Result: **Ground states** cannot be easily read off
- Many **metastable states**

# Spin glass models

- **Edwards-Anderson model**
- Disordered Ising model
- $H_{\Lambda}(\sigma) = - \sum_{\langle i,j \rangle \in \Lambda} \sigma_i \sigma_j J_{ij}$
- with e.g.  $J_{ij}$  i.i.d.  $\mathcal{N}(0, 1)$
- and the corresponding Gibbs measure
- **Way to difficult**

## Spin glass models (cont.)

- Sherrington-Kirkpatrick model (SK model)
- "Mean-field Spin glass"
- $H_N(\sigma) = -\frac{1}{\sqrt{N}} \sum_{1 \leq i < j \leq N} \sigma_i \sigma_j J_{ij}$
- with again  $J_{ij}$  i.i.d.  $\mathcal{N}(0, 1)$
- and the corresponding Gibbs measure
- still very difficult
- "Solved" by the physicists by the replica method"

## Spin glass models (cont.)

- **Hopfield model**
- Another "Mean-field Spin glass"
- with a device to tune the difficulty of the model
- $H_N(\sigma) = - \sum_{1 \leq i < j \leq N} \sigma_i \sigma_j J_{ij}$
- with  $J_{ij} = \frac{1}{N} \sum_{\mu=1}^M \xi_i^\mu \xi_j^\mu$
- and  $\xi_i^\mu$  i.i.d. **Bernoulli random variables**
- with  $\mathbb{P}(\xi_i^\mu = \pm 1) = \frac{1}{2}$
- and  $M$  may and will depend on  $N$

# The Hopfield model

- For  $M \equiv 1 \Rightarrow$  Curie-Weiss model
- For  $M = N$ , morally

$$\begin{aligned}
 J_{ij} &= \frac{1}{N} \sum_{\mu=1}^N \xi_i^\mu \xi_j^\mu \\
 &= \frac{1}{\sqrt{N}} \frac{1}{\sqrt{N}} \sum_{\mu=1}^N \xi_i^\mu \xi_j^\mu \\
 &\sim \frac{1}{\sqrt{N}} G_{ij}
 \end{aligned}$$

- with **standard Gaussian random variables**  $G_{ij}$
- Hence Hopfield model and SK-model can be expected to behave similarly.

# The Hopfield model

- The Hopfield model has various interpretations:
- As a spin glass (Pastur and Figotin, 1976)
- As a **neural network** (Hopfield 1982)
- Here the vectors  $\xi^\mu$  are interpreted as information to be stored in a brain
- so-called **patterns**
- It can be shown, that for
- $\beta > 1$  and  $M \ll N$
- the measure  $\mu_{N,\beta}$  is concentrated **on small balls centered in the  $\pm\xi^\mu$**  (Bovier/Gayrard)

# The Hopfield model

- The Hopfield can also be interpreted as a model of **social choice** (Cont/L. 2003 and 2009).
- Here the  $\sigma$  are **decisions to be made**.
- The  $\xi_i^\mu$  are characteristics of the  $i$ 'th individual.
- The more two individuals **resemble**
- the more likely is it, that **their decision is the same**.



# Spin glass models (cont.)

- **The Random Energy Model (REM)**
- Introduced by Derrida (1984)
- Basic idea: The energy function in the SK-model is a **Gaussian process** in the  $\sigma$
- Ignore its **covariance structure**
- Then we obtain an energy function of the form
- $H_N(\sigma) = \sqrt{N} X_\sigma$
- and the corresponding Gibbs measure
- This is a caricature of a spin glass.

# Types of Fluctuation

- Let  $X_n$  be a sequence of random variables (possibly in several dimensions)
- Assume there is a **Law of Large Numbers** on a scale  $a_n$
- i.e.  $\frac{X_n}{a_n}$  converges to some point or deterministic vector
- We distinguish the following three types of fluctuations

# Central Limit theorem

- There is a scale  $b_n \ll a_n$  such that
- $X_n/b_n$  converges to a **non-degenerate distribution**
- generic example (of course)
- $X_n$  is a sum of  $n$  i.i.d. random variables
- and  $b_n = \sqrt{n}$

# Large deviations

- We say that  $X_n$  obey a **Large Deviations Principle(LDP)**, if
- there exists a lower semi-continuous function  $I(\cdot)$
- with compact level sets  $\{x : I(x) \leq L\}$
- such that for all measurable sets  $A$
- and some scale  $\alpha_n$

$$\begin{aligned} \inf_{x \in A} I(x) &\leq \liminf \frac{1}{\alpha_n} \log \mathbb{P}(X_n/a_n \in A^\circ) \\ &\leq \limsup \frac{1}{\alpha_n} \log \mathbb{P}(X_n/a_n \in \bar{A}) \leq \inf_{x \in \bar{A}} I(x) \end{aligned}$$

- Example: Cramér's theorem

# Moderate deviations

- We say that  $X_n$  obey a **Moderate Deviations Principle(MDP)**, if
- there exists a lower semi-continuous function  $J(\cdot)$
- with compact level sets  $\{x : J(x) \leq L\}$
- such that for all measurable sets  $A$
- and scales  $c_n$  and  $\gamma_n$

$$\begin{aligned} \inf_{x \in A} I(x) &\leq \liminf_{\gamma_n} \frac{1}{\gamma_n} \log \mathbb{P}((X_n - \mathbb{E}X_n)/c_n \in A^\circ) \\ &\leq \limsup_{\gamma_n} \frac{1}{\gamma_n} \log \mathbb{P}((X_n - \mathbb{E}X_n)/c_n \in \overline{A}) \leq \inf_{x \in \overline{A}} I(x) \end{aligned}$$

# Connections

- General folklore (?):
- Often, most often, always (?)
- If a centered sequence  $X_n$  obeys an LDP with rate function  $I$
- and there is a CLT on scale  $b_n$  with limiting d.f.  $F$ , s.t.  
 $1 - F(x) \sim f(x)$  for  $x$  large
- Then there is also an MDP with rate function  $J$  and
- $J(x) = \log f(x)$
- and similarly for the large deviations:  $I(x) \sim J(x)$  for  $x$  small.

# The free energy in the REM

- Important quantity in statistical physics: the **free energy**
- $\Phi_{N,\beta} = \frac{1}{N} \log Z_{N,\beta}$
- In disordered systems, this is a **random variable** in the disorder
- Consider the **expected free energy**

$$f_N(\beta) = \frac{1}{N} \mathbb{E} \log Z_{N,\beta}$$

- and its **thermodynamical limit**

$$f(\beta) = \lim_{N \rightarrow \infty} f_N$$

# A phase transition in the REM

- In the REM  $Z_{N,\beta} = \frac{1}{2^N} \sum_{\sigma \in \{\pm 1\}^N} e^{\sqrt{N}X_\sigma}$
- Then one can prove the following result:

Theorem (Derrida?, Talagrand, Bovier)

*In the REM:*

$$f = \begin{cases} \beta^2/2 & \text{if } \beta \leq \beta_c \\ \beta_c^2/2 + (\beta - \beta_c)\beta_c & \text{if } \beta > \beta_c \end{cases}$$

where  $\beta_c = \sqrt{2 \log 2}$



# A phase transition in the REM

- This theorem constitutes a **phase transition** in the REM
- This phase transition is of **third order**, as
- the limiting free energy has a **jump** in its second derivative

## Fluctuations in the REM (cont.)

- But even in the **high temperature regime** there is **another surprise**

## Theorem

*The free energy of the REM has the following fluctuations:*

- *If  $\beta < \sqrt{\log 2/2}$ , then*

$$e^{\frac{N}{2}(\log 2 - \beta^2)} \log \frac{Z_{N,\beta}}{\mathbb{E}Z_{N,\beta}} \xrightarrow{\mathcal{D}} \mathcal{N}(0, 1).$$

- *If  $\beta = \sqrt{\ln 2/2}$ , then*

$$e^{\frac{N}{2}(\log 2 - \beta^2)} \log \frac{Z_{N,\beta}}{\mathbb{E}Z_{N,\beta}} \xrightarrow{\mathcal{D}} \mathcal{N}(0, 1/2).$$

## Fluctuations in the REM (cont.)

## Theorem

- Let  $\alpha \equiv \beta/\sqrt{2\log 2}$ . If  $\sqrt{\log 2/2} < \beta < \sqrt{2\log 2}$ , then

$$e^{\frac{N}{2}(\sqrt{2\log 2}-\beta)^2 + \frac{\alpha}{2}(\ln(N\log 2) + \log 4\pi)} \log \frac{Z_{N,\beta}}{\mathbb{E}Z_{N,\beta}}$$

$$\xrightarrow{\mathcal{D}} \int_{-\infty}^{\infty} e^{\alpha z} (\mathcal{P}(dz) - e^{-z} dz),$$

where  $\mathcal{P}$  denotes the Poisson point process on  $\mathcal{R}$  with intensity measure  $e^{-x} dx$ .

# Discussion

- This means, there is a **second phase transition** in the REM
- at  $\beta = \sqrt{\log 2/2} = \beta_c/2$ .
- For  $\beta < \beta_c/2$  the theorem is proved via showing that the **Lindeberg condition** for triangular arrays holds.
- This condition **breaks down** at  $\beta_c/2$ .
- Reason: influence of the **extreme values of the summands**.
- This is also reflected in the occurrence of the Poisson point processes for  $\beta_c/2 < \beta < \beta_c$ .

# Fluctuations in the Hopfield model

- Which quantity should be considered?
- Observe that in the Hopfield model

$$H_N(\sigma) = -\frac{N}{2} \|m_N(\sigma)\|^2$$

- where  $m_N(\sigma) = (m_N^\mu(\sigma))_{\mu=1}^M$  is the so-called **overlap vector**
- $m_N^\mu(\sigma) = \frac{1}{N} \sum_{i=1}^N \sigma_i \xi_i^\mu$
- The overlap is an **order parameter** of the system.

# A limit theorem for the overlap

- A **phase transition** in the Hopfield model can be **read off** from the behavior of the overlap parameter

Theorem (Bovier, Gayrard, Picco)

*For  $M \ll N$  and almost all choices of the  $\xi^\mu$*

- *For  $\beta \leq 1$  the distribution of  $m_N$  weakly converges to  $\delta_0$ .*
- *For  $\beta > 1$  for any metrics  $d$  metrizing weak convergence,*

$$d(\mathbb{P} \circ m_N^{-1}, \frac{1}{2M} \sum_{\mu=1}^M \delta_{e^\mu z^+(\beta)} + \delta_{-e^\mu z^+(\beta)}) \rightarrow 0$$

*with  $e_\mu$  the  $\mu$ 'th unit vector and  $z^+$  the largest solution to*

$$z = \tanh(\beta z)$$

# Fluctuations of the overlap

- The phase transition can also be read off **from the fluctuations**
- Bovier and Gayrard prove an **almost sure LDP** for the overlap in the above situation.
- The speed is  $n$
- and the rate function
  - has a **unique minimum in 0** for  $\beta \leq 1$
  - and **several minima** in all the  $\delta_{\pm e_\mu z^+}$  for  $\beta > 1$ .

# Fluctuations of the overlap (cont.)

- Can we also see something happening of the level of **Central Limit Theorem**?
- A partial answer is given by the following **classical CLT**

Theorem (Gentz, Bovier/Gayrard)

*If  $\beta < 1$  and  $M \ll N$ , the almost surely in the  $\xi^\mu$  every **finite-dimensional projection** of the rescaled-overlap vector  $\sqrt{N}m_N$  converges in distribution to  $\mathcal{N}(0, \Sigma)$ , where*

$$\Sigma = \frac{1}{1 - \beta} Id.$$



# Central idea in the proof (and the following proofs)

- The energy function  $H_N(\sigma) = \frac{N}{2} \|m_N(\sigma)\|^2$  is **quadratic** (and therefore makes the computation difficult).
- It can be linearised by the so called **Hubbard-Stratonovich transformation**.

$$\mu_{N,\beta} \circ (\sqrt{a_N N} m_N)^{-1} * \mathcal{N}(0, a_N/\beta) = \chi_{N,\beta,a_N,\xi}$$

where  $1/N \leq a_N \leq 1$

- This new measure possesses a density  $f_{N,\beta}$  w.r.t. to Lebesgue measure
- and

$$f_{N,\beta}(x) \sim \exp(-N\beta\Psi_{N,\beta}(x/\sqrt{Na_N}))$$

## Central idea in the proof (cont.)

- Here

$$\Psi_{N,\beta}(x) = \frac{1}{2} \|x\|_2^2 - \frac{1}{\beta N} \sum_{i=1}^N \log \cosh(\beta \langle \xi_i, x \rangle).$$

- Expand  $\Psi$
- Analyze  $f_{N,\beta}$  (and  $\chi$ )
- Relate this to the **original measure**.

# What about $\beta = 1$

- At  $\beta = 1$  the classical CLT obviously must **fail**.
- We have to **rescale**  $m_N$  **differently**.
- This is known from the Curie-Weiss model
- (by  $N^{1/4}$ )
- However, in the Hopfield model, there is a **surprise** waiting.

# What about $\beta = 1$ (cont).

Theorem (with B. Gentz)

If  $M$  is *independent* of  $N$ . Then the distribution of the random probability measure  $\mu_{N,\beta} \circ (\sqrt{N^{1/4} N m_N})^{-1}$  converges weakly to the distribution of a *random* probability measure  $Q_\eta$  on  $\mathbb{R}^M$ . Its density is proportional to

$$\exp \left( -\frac{1}{12} \|x\|_4^4 - \sum_{\mu < \nu} x_\mu^2 x_\nu^2 + \sum_{\mu < \nu} \eta_{\mu,\nu} x_\mu x_\nu \right)$$

where  $\eta_{\mu,\nu}$  are independent standard normally distributed r.v.s.

What about  $\beta = 1$  (cont).

- Note that **other than** for different values of  $\beta$
- there is **no almost sure** result
- The limiting object stays **random**
- A similar result can also be shown for **growing  $M$**
- as long as  $M \ll N^{1/3}$
- Talagrand analyzes  $M \ll N^{1/3}$

## Why?

- Taylor-expand  $\cosh$  in

$$\Psi_{N,\beta}(x) = \frac{1}{2} \|x\|_2^2 - \frac{1}{\beta N} \sum_{i=1}^N \log \cosh(\beta \langle \xi_i, x \rangle).$$

- At  $\beta = 1$  the quadratic term  $\frac{1}{2} \|x\|_2^2$  cancels with part of the second order term of  $\log \cosh(\cdot)$
- It remains  $\frac{1}{\sqrt{N}} \sum_{i=1}^N \sum_{\mu < \nu} \xi_i^\mu x^\mu \xi_i^\nu x^\nu$
- plus fourth order terms
- of which  $\frac{1}{12} \|x\|_4^4$  and  $\sum_{\mu < \nu} x_\mu^2 x_\nu^2$  survive

# What about moderate deviations

- Can the phase transition be detected from the moderate deviations analysis?
- For  $\beta < 1$  and  $M \ll N$  the moderate deviations of  $m_N$  behave as they should
- i.e. for  $1 \ll b_N \ll \sqrt{N}$  the rescaled overlap  $b_N m_N$
- almost surely obeys an MDP with speed  $N/b_N^2$  and quadratic rate function

# What about moderate deviations

- At  $\beta = 1$  the **situation changes**.
- **"Away" from the CLT**, i.e. for
- $M^6 \ll N$  and  $M^2 \ll N^{1-4\gamma}$
- the **rescaled overlap**  $N^\gamma m_N$ ,  $0 < \gamma < 1/4$
- almost surely obeys an MDP with speed  $N^{1-4\gamma}$  and rate function
- $I(x) = \frac{1}{12} \|x\|_4^4 - \sum_{\mu < \nu} x_\mu^2 x_\nu^2$
- However, even for **finite**  $M$ , for  $b_N \ll \sqrt[4]{\log \log N}$
- the sequence  $(N^{1/4}/b_N)m_N$  **does not obey an a.s. MDP**



# Conclusion

Today we have

- Met several disordered models from statistical physics
- Seen the **influence of a phase transition** on **fluctuation results**
- Seen that in the REM we can detect a **second phase transition** on the level of a CLT
- Seen that in the Hopfield model the phase transition is characterized by
- **a non-standard CLT** for the overlap
- and by **a breakdown of moderate deviations**

# Bedankt voor jullie aandacht!

