

# Spin glasses and Stein's method

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# Spin glasses

- ▶ Magnetic materials with strange behavior.
- ▶ Not explained by ferromagnetic models like the Ising model.
- ▶ Theoretically studied since the 70's. An important example: Sherrington-Kirkpatrick model.
- ▶ High temperature phase: **Thouless-Anderson-Palmer**. Low temperature phase: **Mézard and Parisi**.
- ▶ Mathematically almost intractable until the late 90's.
  - ▶ Early results due to Aizenman, Lebowitz, Ruelle ('87), Fröhlich and Zegarliński ('87).
  - ▶ Notable papers due to Comets and Neveu ('95), Shcherbina ('99) etc.
  - ▶ Series of breakthroughs from **Talagrand** (1998 - present).
  - ▶ Groundbreaking contributions from **Guerra & Toninelli** ('02) and **Guerra** ('03), taken to completion by Talagrand in 2006.  
**The Parisi formula.** *Ann. Math. (2)* **163** no 1, 221–263.
  - ▶ Still, a lot of mysteries.

# The Sherrington-Kirkpatrick model

- ▶  $N$  spins. State space:  $\Sigma_N = \{-1, 1\}^N$ .
- ▶ Gibbs measure on  $\Sigma_N$  for the SK model:

$$G_N(\sigma) = Z_N^{-1} \exp\left(\frac{\beta}{\sqrt{N}} \sum_{i < j \leq N} g_{ij} \sigma_i \sigma_j + h \sum_{i \leq N} \sigma_i\right)$$

where

- ▶  $(g_{ij})_{i < j \leq N}$  is a fixed realization of independent standard gaussian random variables (the **disorder**),
  - ▶  $\beta$  and  $h$  are parameters,
  - ▶  $Z_N$  is the normalizing constant (partition function).
- ▶ Notation:

$$\langle f(\sigma) \rangle := \sum_{\sigma \in \Sigma_N} f(\sigma) G_N(\sigma).$$

# High temperature phase

- ▶ Let  $z$  be a standard gaussian r.v. Then

$$\lim_{N \rightarrow \infty} \frac{\log Z_N}{N} = \log 2 + \mathbb{E} \log \cosh(\beta z \sqrt{q} + h) + \frac{\beta^2}{4} (1 - q)^2,$$

where  $q$  is determined by

$$q = \mathbb{E} \tanh^2(\beta z \sqrt{q} + h).$$

Rigorously proven to hold for  $\beta < 1/2$ , all  $h$  (Talagrand).

- ▶ **Conjectured** description of the full high temperature regime: All  $(\beta, h)$  such that

$$\beta^2 \mathbb{E} \frac{1}{\cosh^4(\beta z \sqrt{q} + h)} < 1.$$

The line where equality holds is called the **Almeida-Thouless line**.

# The Gibbs measure at high temperature

- ▶ Spins are approximately independent, i.e. with high probability,

$$\langle \sigma_{i_1} \sigma_{i_2} \cdots \sigma_{i_k} \rangle \approx \langle \sigma_{i_1} \rangle \langle \sigma_{i_2} \rangle \cdots \langle \sigma_{i_k} \rangle.$$

*This is a deep fact and surprisingly hard to prove. Both sides are nondegenerate random variables in the limit.*

- ▶ Moreover,  $\langle \sigma_{i_1} \rangle, \dots, \langle \sigma_{i_k} \rangle$  are approximately i.i.d.
- ▶ First proved by Talagrand using his cavity argument.
- ▶ If  $h = 0$ , then  $\langle \sigma_i \rangle \equiv 0$  for all  $i$ .
- ▶ What if  $h \neq 0$ ? No simple formulas for  $\langle \sigma_1 \rangle, \dots, \langle \sigma_N \rangle$ .

# The TAP equations

When  $(\beta, h) \in$  the high temperature regime, the random quantities  $\langle \sigma_1 \rangle, \dots, \langle \sigma_N \rangle$  satisfy

$$\langle \sigma_i \rangle \approx \tanh \left( \frac{\beta}{\sqrt{N}} \sum_{j \neq i} g_{ij} \langle \sigma_j \rangle + h - \beta^2 (1 - q) \langle \sigma_i \rangle \right),$$

where  $q$  solves  $q = \mathbb{E} \tanh^2(\beta z \sqrt{q} + h)$ ,  $z$  being a standard gaussian r.v.

- ▶ Discovered by Thouless, Anderson, and Palmer ('77).
- ▶ Rigorous proof by Talagrand ('03) using the cavity method.
- ▶ Unique solution if  $\beta$  is smaller than a constant.
- ▶ Talagrand also shows that  $\langle \sigma_i \rangle$  converges in law to  $\tanh(\beta z \sqrt{q} + h)$ .

# The cavity method

- ▶ Basically, a very complex induction over  $N$ .
- ▶ Coefficient of  $\sigma_N$  in the Hamiltonian is

$$\frac{\beta}{\sqrt{N}} \sum_{j=1}^{N-1} g_{Nj} \sigma_j + h.$$

- ▶ Replace this by an independent gaussian r.v. to get a new Hamiltonian.
- ▶ Determine the mean and variance of this r.v. such that the annealed measures remain 'approximately the same'.
- ▶ Using gaussian interpolation and a certain recursive argument, Talagrand shows that it is possible to do this if  $\beta$  is sufficiently small. This is the foundation of the cavity induction.
- ▶ We will follow a different route, starting from the next slide.

# Explaining the TAP equations: (I) Local fields

- ▶ **Local field** at site  $i$ :

$$l_i = \frac{1}{\sqrt{N}} \sum_{j \neq i} g_{ij} \sigma_j.$$

- ▶ Easy to show: The conditional expectation of  $\sigma_i$  given  $(\sigma_j)_{j \neq i}$  is exactly  **$\tanh(\beta l_i + h)$** .
- ▶ This gives the equations

$$\langle \sigma_i \rangle = \langle \tanh(\beta l_i + h) \rangle.$$

- ▶ Thus, if we knew the **limiting distribution of  $l_i$** ,  $\langle \sigma_i \rangle$  could be computed directly. But this was not known previously.



# Explaining the TAP equations: (II) The Onsager correction

- ▶ If  $X$  is a random variable with small variance, then

$$\mathbb{E} \tanh(aX + b) \approx \tanh(a\mathbb{E}(X) + b).$$

This is the usual mean-field approximation.

- ▶ Applying the naïve mean-field logic (although  $\text{Var}(\ell_i) \not\rightarrow 0$ ), we may wonder whether

$$\begin{aligned} \langle \sigma_i \rangle &= \langle \tanh(\beta \ell_i + h) \rangle \stackrel{?}{\approx} \tanh(\beta \langle \ell_i \rangle + h) \\ &= \tanh\left(\frac{\beta}{\sqrt{N}} \sum_{j \neq i} g_{ij} \langle \sigma_j \rangle + h\right). \end{aligned}$$

Not surprisingly, this is incorrect.

- ▶ In the TAP equations, we have

$$\langle \sigma_i \rangle \approx \tanh\left(\frac{\beta}{\sqrt{N}} \sum_{j \neq i} g_{ij} \langle \sigma_j \rangle + h - \beta^2(1 - q)\langle \sigma_i \rangle\right).$$

The extra term is called the **Onsager correction term** in physics.

# Onsager correction and mixture gaussians

- ▶ Let  $\phi_{\mu, \sigma^2}$  be the gaussian density with mean  $\mu$  and variance  $\sigma^2$ . Let  $\psi_{p, \mu_1, \mu_2, \sigma^2}$  be the mixture gaussian density

$$\psi_{p, \mu_1, \mu_2, \sigma^2} = p\phi_{\mu_1, \sigma^2} + (1 - p)\phi_{\mu_2, \sigma^2}.$$

- ▶ Suppose  $\mu_2 > \mu_1$ , and we define

$$a = \frac{\mu_2 - \mu_1}{2\sigma^2}, \quad b = \frac{1}{2} \log \frac{p}{1-p} - \frac{\mu_2^2 - \mu_1^2}{4\sigma^2}.$$

Then, if  $X \sim \psi_{p, \mu_1, \mu_2, \sigma^2}$ , then

$$\mathbb{E} \tanh(aX + b) = \tanh(a\mathbb{E}(X) + b - (2p - 1)a^2\sigma^2).$$

- ▶ This is what happens! The local fields have mixture gaussian laws and the highlighted term is the Onsager correction term.

# Our main result: Limit law of local fields

- ▶ Recall: The local field at site  $i$  is defined as

$$\ell_i := \frac{1}{\sqrt{N}} \sum_{j \neq i} g_{ij} \sigma_j.$$

- ▶ For each  $i$ , let  $r_i$  be the random variable

$$r_i := \frac{1}{\sqrt{N}} \sum_{j \neq i} g_{ij} \langle \sigma_j \rangle - \beta(1-q) \langle \sigma_i \rangle.$$

- ▶ Let  $\nu_i$  be the (random) mixture gaussian probability measure with density function

$$p_i \phi_{r_i + \beta(1-q), 1-q} + (1 - p_i) \phi_{r_i - \beta(1-q), 1-q},$$

where

$$p_i = \frac{e^{\beta r_i + h}}{e^{\beta r_i + h} + e^{-\beta r_i - h}}.$$

- ▶ Under the Gibbs measure,  $\nu_i$  approximates the law of  $\ell_i$  for large  $N$ .

# Our main result: Limit law of local fields

## Theorem

Suppose  $(\beta, h)$  is in the high temperature regime and  $q$  satisfies

$$q = \mathbb{E} \tanh^2(\beta z \sqrt{q} + h),$$

where  $z$  is a standard gaussian r.v. Let  $\ell_1, \dots, \ell_N$  be the local fields and let  $\nu_1, \dots, \nu_N$  be defined as in the previous slide. Then for any **bounded measurable**  $f : \mathbb{R} \rightarrow \mathbb{R}$  and any  $1 \leq i \leq N$ , we have

$$\mathbb{E} \left( \langle f(\ell_i) \rangle - \int_{\mathbb{R}} f(x) \nu_i(dx) \right)^2 \leq \frac{C(\beta, h) \|f\|_{\infty}^2}{\sqrt{N}},$$

where  $C(\beta, h)$  is a constant depending only on  $\beta$  and  $h$ .

- ▶ Recall:  $\langle \sigma_i \rangle = \langle \tanh(\beta \ell_i + h) \rangle$ . Taking  $f(x) = \tanh(\beta x + h)$ , the TAP equations follow easily.
- ▶ Proof is by Stein's method.

# Stein's method

- ▶ Let  $X$  and  $Z$  be two random variables. Suppose we want to show that they approximately have the same distribution.
- ▶ Basic steps in Stein's method:

1. Identify an operator  $T$  such that for all functions  $h$ ,

$$\mathbb{E}(Th(Z)) = 0.$$

( $T$  is called a **Stein characterizing operator**.) For example, if  $Z$  is standard gaussian, then  $Th(x) = h'(x) - xh(x)$  is a characterizing operator.

2. Given a function  $f$ , find  $h$  such that

$$Th(x) = f(x) - \mathbb{E}(f(Z)).$$

Relate the properties of  $h$  to those of  $f$ .

3. By the definition of  $h$  it follows that

$$|\mathbb{E}f(X) - \mathbb{E}f(Z)| = |\mathbb{E}(Th(X))|.$$

Compute a bound on  $|\mathbb{E}(Th(X))|$  by whatever means possible.

# Stein's method for gaussian approximation

- ▶ Let  $Z$  be a standard gaussian r.v. Then for all  $h$ ,

$$\mathbb{E}(h'(Z) - Zh(Z)) = 0.$$

Thus,  $Th(x) := h'(x) - xh(x)$  is a characterizing operator for the standard gaussian distribution.

- ▶ Thus, to show that a r.v.  $W$  is approximately standard gaussian, one has to show that for all  $h$ ,

$$\mathbb{E}(h'(W) - Wh(W)) \approx 0.$$

# Stein's method for mixture gaussians

- ▶ For the mixture gaussian density

$$p\phi_{\mu_1, \sigma^2} + (1 - p)\phi_{\mu_2, \sigma^2}$$

the characterizing operator is

$$Th(x) = h'(x) - \left( \frac{x - \mu}{\sigma^2} - a \cdot \tanh(ax + b) \right) h(x),$$

where  $\mu, a, b$  are defined as

$$\mu = \frac{\mu_1 + \mu_2}{2}, \quad a = \frac{\mu_2 - \mu_1}{2\sigma^2},$$
$$b = \frac{1}{2} \log \frac{p}{1 - p} - \frac{\mu_2^2 - \mu_1^2}{4\sigma^2}.$$

- ▶ Appears to be naturally connected to physical models. Does not occur in the literature on Stein's method.

# The Approximation Lemma

## Lemma

Suppose  $g = (g_1, \dots, g_n)$  is a collection of independent standard gaussian random variables, and  $h_1, \dots, h_n$  are absolutely continuous functions of  $g$ . Then

$$\begin{aligned} & \mathbb{E} \left( \sum_{i=1}^n g_i h_i - \sum_{i=1}^n \frac{\partial h_i}{\partial g_i} \right)^2 \\ &= \sum_{i=1}^n \mathbb{E}(h_i^2) + \sum_{i,j=1}^n \mathbb{E} \left( \frac{\partial h_i}{\partial g_j} \frac{\partial h_j}{\partial g_i} \right). \end{aligned}$$

**Idea:** If the right hand side is small, then the lemma 'generates' the equation

$$\sum_{i=1}^n g_i h_i \approx \sum_{i=1}^n \frac{\partial h_i}{\partial g_i}.$$

Can be used to obtain **Stein characterizing equations** for highly complex functions of gaussian random variables.



# Example

- ▶ Consider the SK model with zero external field (the simple case):

$$G_N(\sigma) = Z_N^{-1} \exp\left(\frac{\beta}{\sqrt{N}} \sum_{i < j \leq N} g_{ij} \sigma_i \sigma_j\right).$$

- ▶ We wish to generate a characterizing equation for the local field at site 1:

$$\ell_1 = \frac{1}{\sqrt{N}} \sum_{j=2}^N g_{1j} \sigma_j.$$

- ▶ Fix a smooth function  $f$ . For each  $j = 2, \dots, N$ , let

$$h_j = \frac{1}{\sqrt{N}} \langle \sigma_j f(\ell_1) \rangle.$$

- ▶ Then

$$\sum_{j=2}^N g_{1j} h_j = \langle \ell_1 f(\ell_1) \rangle.$$

## Example contd.

- ▶ On the other hand, an easy computation gives

$$\frac{\partial h_j}{\partial g_{1j}} = \frac{\langle f'(l_1) \rangle + \beta \langle \sigma_1 f(l_1) \rangle - \beta \langle \sigma_j f(l_1) \rangle \langle \sigma_1 \sigma_j \rangle}{N}.$$

- ▶ **The 2nd term.** Note that  $l_1$  does not depend on  $\sigma_1$ , and the conditional expectation of  $\sigma_1$  given  $\sigma_2, \dots, \sigma_N$  is  $\tanh(\beta l_1)$ . Thus,

$$\langle \sigma_1 f(l_1) \rangle = \langle \tanh(\beta l_1) f(l_1) \rangle.$$

- ▶ **The 3rd term.** It follows from the high temperature theory for  $\beta < 1$  that for  $2 \leq j \leq N$ ,

$$\langle \sigma_1 \sigma_j \rangle \approx \langle \sigma_1 \rangle \langle \sigma_j \rangle = 0.$$

## Example contd.

- ▶ Thus, if we can apply the Approximation Lemma, we get the approximation

$$\sum_{j=2}^N g_{1j} h_j \approx \sum_{j=2}^N \frac{\partial h_j}{\partial g_{1j}}$$

which is equivalent to

$$\langle \ell_1 f(\ell_1) - f'(\ell_1) - \beta \tanh(\beta \ell_1) f(\ell_1) \rangle \approx 0.$$

- ▶ Now, the operator

$$Tf(x) = xf(x) - f'(x) - \beta \tanh(\beta x) f(x)$$

is a Stein characterizing operator for the **mixture gaussian density**

$$\frac{1}{2} \phi_{\beta,1} + \frac{1}{2} \phi_{-\beta,1}.$$

- ▶ This procedure 'discovers' the limiting distribution of  $\ell_1$ .

## When $h \neq 0$

- ▶ When  $h \neq 0$ ,  $\ell_1$  does not have a nonrandom limiting distribution. The situation becomes more complex.
- ▶ Given a function  $u$ , we start with a solution  $f(x, y)$  of the p.d.e.

$$\begin{aligned} & \frac{\partial f}{\partial x}(x, y) - \left( \frac{x-y}{\sigma^2} - \beta \tanh(\beta x + h) \right) f(x, y) \\ &= u(x) - \int_{\mathbb{R}} u(t) \frac{\cosh(\beta t + h) e^{-\frac{(t-y)^2}{2(1-q)}}}{\sqrt{2\pi(1-q)} \cosh(\beta \mu + h) e^{\frac{1}{2}\beta^2(1-q)}} dt. \end{aligned}$$

- ▶ Then, defining

$$r_1 = \frac{1}{\sqrt{N}} \sum_{j=2}^N g_{1j} \langle \sigma_j \rangle - \beta(1-q) \langle \sigma_1 \rangle,$$

we let

$$h_j = \frac{1}{\sqrt{N}} \langle (\sigma_j - \langle \sigma_j \rangle) f(\ell_1, r_1) \rangle.$$

- ▶ The proof is completed by an application of the Approximation Lemma with these  $h_j$ 's.

# Distribution of $\langle \sigma_1 \rangle$

- ▶ By the TAP equations,

$$\langle \sigma_1 \rangle \approx \tanh(\beta r_1 + h),$$

where

$$r_1 = \frac{1}{\sqrt{N}} \sum_{j=2}^N g_{1j} \langle \sigma_j \rangle - \beta(1 - q) \langle \sigma_1 \rangle.$$

- ▶ Thus, it suffices to find the limiting distribution of  $r_1$ .
- ▶ Repeatedly integrating by parts, we can get

$$\mathbb{E}(r_1 f(r_1)) \approx q \mathbb{E}(f'(r_1) \langle \eta_1 \rangle)$$

where

$$\eta_1 = 1 + \frac{\beta \sigma_1}{\sqrt{N}} \sum_{j=2}^N g_{1j} (\sigma_j - \langle \sigma_j \rangle) - \beta^2(1 - q)(1 - \langle \sigma_1 \rangle^2).$$

## Distribution of $\langle \sigma_1 \rangle$ contd.

- ▶ Applying the Approximation Lemma with

$$h_j = \frac{\beta}{\sqrt{N}} (\langle \sigma_1 \sigma_j \rangle - \langle \sigma_1 \rangle \langle \sigma_j \rangle),$$

we can show that  $\langle \eta_1 \rangle \approx 1$ .

- ▶ Combined with the earlier approximation

$$\mathbb{E}(r_1 f(r_1)) \approx q \mathbb{E}(f'(r_1) \langle \eta_1 \rangle),$$

this shows that  $\mathbb{E}(r_1 f(r_1)) \approx q \mathbb{E}(f'(r_1))$ .

- ▶ Thus,  $r_1$  is a gaussian r.v. with mean zero and variance  $q$  in the large  $N$  limit.

# Summary and future directions

- ▶ Often in spin glasses and other models we have the situation that for some random quantity  $X$ ,

$$\mathbb{E} \tanh(aX + b) = \tanh(a\mathbb{E}(X) + b + \text{a correction term}).$$

- ▶ We show that this happens if the distribution of  $X$  is a mixture of two gaussian densities.
- ▶ Following this line, we derive the **TAP equations** for the SK model by showing that the local field is indeed a mixture of two gaussians in the limit.
- ▶ Gives **total variation** error bounds.
- ▶ The key tool is the **Approximation Lemma** that generates characterizing equations for Stein's method.
- ▶ The Approximation Lemma can possibly be used to derive/discover limiting distributions of other objects.
- ▶ Results apply only to the high temperature phase. Possible to extend to **low temperature???**