

Lecture 28

*Lecture date: Oct 31, 2007**Scribe: Anand Sarwate***1 A recap**

For $\beta < 1/2$ in the Sherrington-Kirkpatrick (S-K) model, we showed a bound on the overlap R_{12} :

$$\mathbf{E} \left\langle (R_{12} - q)^{2k} \right\rangle \leq \frac{(Ck)^k}{N^k}, \quad (1)$$

where $q = \mathbf{E}[\tanh^2(\beta Z \sqrt{q} + h)]$ and $Z \sim \mathcal{N}(0, 1)$. This means that the overlap is concentrated. When $h = 0$ this implies that

$$\mathbf{E} \left\langle R_{12}^{2k} \right\rangle \leq \frac{(Ck)^k}{N^k}, \quad (2)$$

so R_{12} is close to 0 in this case. This result was crucial in showing that for $h = 0$ the quantity

$$l_1 = \frac{1}{\sqrt{N}} \sum_{j=2}^N g_{1j} \sigma_j \quad (3)$$

has a limiting annealed distribution

$$\frac{1}{2} \mathcal{N}(\beta, 1) + \frac{1}{2} \mathcal{N}(-\beta, 1). \quad (4)$$

We also proved that the quenched distribution of l_1 converges in probability to (4) by showing that

$$\langle f'(l_1) - (l_1 - \beta \tanh(\beta l_1)) f(l_1) \rangle \xrightarrow{P} 0. \quad (5)$$

Note that this convergence is in probability on the space of probability measures.

Finally, we also found a CLT for the Hamiltonian $\sum g_{ij} \sigma_i \sigma_j$ when $h = 0$. When $h \neq 0$ the limiting distribution of the Hamiltonian is not known.

2 The TAP equations

Today we will start looking at the Thouless-Anderson-Palmer (TAP) equations, which are a collection of self-consistent equations for the quenched average value for $i = 1, 2, \dots, N$:

$$\langle \sigma_i \rangle \approx \tanh \left(\frac{\beta}{\sqrt{N}} \sum_{j=1, j \neq i}^N g_{ij} \langle \sigma_j \rangle + h - \beta^2 (1 - q) \langle \sigma_i \rangle \right) \quad (6)$$

Furthermore, it is true that

$$\langle \sigma_i \rangle \xrightarrow{d} \tanh(\beta z \sqrt{q} + h) \quad (7)$$

where $z \sim \mathcal{N}(0, 1)$. Moreover, $\langle \sigma_1 \rangle, \langle \sigma_2 \rangle, \dots, \langle \sigma_p \rangle$ are asymptotically independent for fixed p as $N \rightarrow \infty$.

The concentration of the overlaps implies that

$$\langle \sigma_1 \sigma_j \rangle \cong \langle \sigma_i \rangle \langle \sigma_j \rangle, \quad (8)$$

which in turn implies

$$\frac{1}{N} \sum_{i=1}^N \sigma_i \cong \left\langle \frac{1}{N} \sum_{i=1}^N \sigma_i \right\rangle \quad (9)$$

$$= \frac{1}{N} \langle \sigma_i \rangle \quad (10)$$

$$\xrightarrow{P} \mathbf{E}[\tanh(\beta z \sqrt{q} + h)] . \quad (11)$$

Similarly, since $R_{12} \rightarrow q$,

$$R_{12} \cong \langle R_{12} \rangle \quad (12)$$

$$= \frac{1}{N} \sum_{i=1}^N \langle \sigma_i \rangle^2 \quad (13)$$

$$\xrightarrow{P} \mathbf{E}[\tanh^2(\beta z \sqrt{q} + h)] . \quad (14)$$

This shows why q must satisfy

$$q = \mathbf{E}[\tanh^2(\beta z \sqrt{q} + h)] . \quad (15)$$

For simplicity of notation, let us define

$$r_i = \frac{1}{\sqrt{N}} \sum_{j=1, j \neq i}^N g_{ij} \langle \sigma_j \rangle - \beta(1 - q) \langle \sigma_i \rangle \quad (16)$$

so that the TAP equations say

$$\langle \sigma_i \rangle \cong \tanh(\beta r_i + h) . \quad (17)$$

Note that r_i is a function of g only. It can be shown that $r_i \xrightarrow{d} \mathcal{N}(0, q)$.

3 A sketch of the proof

First, note that the conditional expectation of σ_1 given $\sigma_2, \dots, \sigma_N$ is just $\tanh(\beta l_1 + h)$, so

$$\langle \sigma_1 \rangle = \langle \tanh(\beta l_1 + h) \rangle . \quad (18)$$

Now the goal is to approximate the distribution of l_1 .

We first reparameterize Gaussian mixtures. Given a, b, μ, σ^2 , let ψ_{a,b,μ,σ^2} denote the probability density on \mathbb{R} proportional to

$$\cosh(ax + b) \exp\left(-\frac{(x - \mu)^2}{2\sigma^2}\right) . \quad (19)$$

Exercise Show that ψ_{a,b,μ,σ^2} is the same as $p\varphi_{\mu_1,\sigma^2} + (1-p)\varphi_{\mu_2,\sigma^2}$, where φ_{μ,σ^2} is the density $\mathcal{N}(\mu, \sigma^2)$, $\mu_1 = \mu + a\sigma^2$, $\mu_2 = \mu - a\sigma^2$, and

$$p = \frac{\exp(a\mu + b)}{\exp(a\mu + b) + \exp(-a\mu - b)} . \quad (20)$$

If $X \sim \psi_{a,b,\mu,\sigma^2}$, then

$$\mathbf{E}[\tanh(aX + b)] = \tanh(a\mathbf{E}[X] + b - (2p - 1)a^2\sigma^2) \quad (21)$$

$$= \tanh(a\mu + b) . \quad (22)$$

The term $-(2p - 1)a^2\sigma^2$ is called the Onsager correction term, and is what allows us to move the expectation inside the tanh. The quenched distribution of l_1 is approximately $\psi_{\beta,h,r_1,1-q}$, and so

$$\langle \tanh(\beta l_1 + h) \rangle \cong \tanh(\beta r_1 + h) \quad (23)$$

and $r_1 = \langle l_1 \rangle - \beta(1 - q)\langle \sigma_1 \rangle$. The quenched distribution is a random distribution with parameter r_1 .

The Stein characterizing operator for ψ_{a,b,μ,σ^2} is

$$Tf(x) = f'(x) - \left(\frac{x - \mu}{\sigma^2} - a \tanh(ax + b)\right) f(x) \quad (24)$$

To see this, look at

$$f'(x) + \left(\frac{d}{dx} \log \psi_{a,b,\mu,\sigma^2}(x)\right) f(x) . \quad (25)$$

Recall that for the characteristic operator, if $X \sim \psi_{a,b,\mu,\sigma^2}$ then $\mathbf{E}[Tf(x)] = 0$ for all f and conversely.

We have to show that

$$\mathbf{E} \left\langle f'(l_1) - \left(\frac{l_1 - r_1}{1 - q} - \beta \tanh(\beta l_1 + h) \right) f(l_1) \right\rangle^2 \longrightarrow 0 . \quad (26)$$

It is instructive to consider the contrast with the annealed equation. If $\mathbf{E}\langle \cdot \rangle \rightarrow 0$ then we've proved nothing. This comes from r_1 not being a constant. However, a quenched equation implies a distributional result because r_1 is a constant, given g .

The remaining steps are then

1. Start with

$$h_j(g) = \frac{1}{\sqrt{N}} \langle (\sigma_j - \langle \sigma_j \rangle) f(l_1) \rangle . \quad (27)$$

2. Then use the approximation Lemma to show that

$$\sum_{j=2}^N g_{1j} h_j \cong \sum_{j=2}^N \frac{\partial h_j}{\partial g_{1j}} . \quad (28)$$

3. Recognize, after some computation and using $R_{12} \cong q$, that (26) and (28) are the same.

The full details of these arguments can be found in the paper (S. Chatterjee, *Spin Glasses and Stein's Method*, arXiv:0706.3500v1 [math.PR]).