

# On the Gardner formula for the perceptron

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Consider  $M$  independent, uniformly distributed, half-spaces  $H_k$ , with  $0 \in \partial H_k$ . How many  $\sigma \in \{-1, 1\}^N$  are in  $\bigcap_{k=1}^M H_k$ ? Take  $M = \alpha N$ , and define

$$f(\alpha) := \lim_{N \rightarrow \infty} \frac{1}{N} \log \# \left[ \{-1, 1\}^N \cap \bigcap_{k=1}^{\alpha N} H_k \right].$$

Gardner's formula, first derived (non-rigorously) by Gardner-Derrida:

**Theorem** (Gardner-Derrida, Mézard, Talagrand). *If  $\alpha$  is small enough, then*

$$f(\alpha) = \log 2 - \frac{\alpha r}{2} (1 - q) + E_Z \log \cosh(\sqrt{\alpha r} Z) + \alpha E_Z \log \Phi\left(\frac{\sqrt{q} Z}{\sqrt{1 - q}}\right),$$

where  $Z$  is a standard Gaussian,  $\Phi$  the Gaussian distribution function, and  $r = r(\alpha)$  and  $q = q(\alpha)$  solve

$$q = E \operatorname{th}^2(\sqrt{\alpha r} Z), \quad r = E \psi_q^2(\sqrt{q} Z), \quad \psi_q(x) := \frac{1}{\sqrt{1 - q}} \frac{\varphi(x/\sqrt{1 - q})}{\Phi(x/\sqrt{1 - q})}.$$

$\varphi$  the standard normal density.

**Remark:** Gardner-Derrida claim (based on replica computation) that the formula is correct up to

$$\alpha^* := \sup \{ \alpha > 0 : f(\alpha) > 0 \} < 1,$$

and that  $\# = 0$  a.s. for  $\alpha > \alpha^*$ .

**Remark:** For  $\alpha > 0$  is it true that  $f(\alpha)$  equals

$$f_{\text{ann}}(\alpha) := \lim_{N \rightarrow \infty} \frac{1}{N} \log \mathbb{E} \# \left[ \{-1, 1\}^N \cap \bigcap_{k=1}^{\alpha N} H_k \right] = (1 - \alpha) \log 2.$$

Talagrand: Consider  $u : \mathbb{R} \rightarrow [-\infty, \infty)$ , with some upper bound (square increase is not allowed), and with i.i.d. standard Gaussians  $(J_{ik})_{i \leq N, k \leq M}$

$$Z_{N, \alpha, u} := \sum_{\sigma \in \{-1, 1\}^N} \exp \left[ \sum_{k=1}^{\alpha N} u \left( \sum_{i=1}^N \sigma_i \frac{J_{ik}}{\sqrt{N}} \right) \right].$$

The half-space case is  $u(x) := -\infty \mathbf{1}_{x < 0}$ . For general  $u$ , one has

$$\psi_q(x) := \frac{1}{\sqrt{1-q}} \frac{E(Z \exp[u(x + \sqrt{1-q}Z)])}{E(\exp[u(x + \sqrt{1-q}Z)])},$$

and the replica symmetric formula for  $f(\alpha, u) := \lim_{N \rightarrow \infty} N^{-1} \log Z_{N, \alpha, u}$  is

$$\begin{aligned} f(\alpha, u) = & \log 2 - \frac{\alpha r}{2} (1 - q) + E_Z \log \cosh(\sqrt{\alpha r} Z) \\ & + \alpha E_Z \log E_{Z'} \exp\left[u\left(\sqrt{q} Z + \sqrt{1-q} Z'\right)\right]. \end{aligned}$$

again with  $q = E \operatorname{th}^2(\sqrt{\alpha r} Z)$ ,  $r = E \psi_q^2(\sqrt{q} Z)$ . Talagrand first proves the result for smooth  $u$  by a perturbative method, and then uses a complicated approximation for  $u = -\infty \mathbf{1}_{x < 0}$ .

**Remark:**  $\psi_q$  is smooth for non-smooth  $u$ .

The problem comes up in connection with the memory capacity in neural nets, in particular the **perceptron**, but it is also related to other models, e.g. in compressed sensing.

**Standard second moment method:** one tries to prove, for a sequence  $\{Z_N\}$  of random partition functions, that

$$\mathbb{E}Z_N^2 \leq \text{const} \times (\mathbb{E}Z_N)^2$$

in which case one obtains, with a self-averaging property

$$\lim_{N \rightarrow \infty} \frac{1}{N} \log Z_N = f_{\text{ann}} := \lim_{N \rightarrow \infty} \frac{1}{N} \log \mathbb{E}Z_N$$

which evidently cannot work in our case. Also for the **Sherrington-Kirkpatrick model** with *non-vanishing* external field:

$$Z_{N,\beta,h} := \sum_{\sigma} 2^{-N} \exp \left[ \frac{\beta}{\sqrt{2N}} \sum_{1 \leq i < j \leq N} J_{ij} \sigma_i \sigma_j + h \sum_{i=1}^N \sigma_i \right], \quad h \neq 0,$$

For *no*  $\beta > 0$ ,  $h \neq 0$ , one has  $f = f_{\text{ann}}$ .

**Morita argument:** find a “proper” sequence of  $\sigma$ -fields  $\mathcal{G}_N$  and prove

$$\mathbb{E} \left( Z_N^2 \mid \mathcal{G}_N \right) \leq C_N \mathbb{E} \left( Z_N \mid \mathcal{G}_N \right)^2,$$

$C_N = e^{o(N)}$ , and  $\lim_{N \rightarrow \infty} N^{-1} \log \mathbb{E} \left( Z_N \mid \mathcal{G}_N \right) = f$ . Then  $f = \lim_{N \rightarrow \infty} N^{-1} \log Z_N$ .

For the SK and the perceptron, take  $\mathcal{G}_N = \sigma \left( m_i : i \leq N \right)$ , where  $m_i := \langle \sigma_i \rangle$ .

**Thouless-Anderson-Palmer equations.** For SK:

$$m_i = \text{th} \left( h + \beta \sum_{j=1}^N \frac{J_{ij}}{\sqrt{N}} m_j - \underbrace{\beta^2 \left( 1 - N^{-1} \sum_j m_j^2 \right)}_{\text{Onsager correction}} m_i \right).$$

Heuristic derivation by belief propagation (at high temperature)

$$m_i = \text{th} \left( h + \beta \sum_{j=1}^N \frac{J_{ij}}{\sqrt{N}} m_j^{\text{cut } i} \right), \quad \frac{1}{N} \sum_i m_i^2 \approx q, \quad q = E_Z \text{th}^2 \left( h + \beta \sqrt{q} Z \right)$$

For the perceptron, TAP equations were first derived by Mézard: Best also by belief propagation (see Mézard 2017 for the Hopfield model). Formally, one relates the  $m_i$  to

$$n_k := \langle u'(S_k) \rangle, \quad S_k := \sum_{i=1}^N \sigma_i \frac{J_{ik}}{\sqrt{N}}$$

The equations are

$$\begin{aligned} m_i &= \text{th} \left( N^{-1/2} \sum_{k=1}^{M=\alpha N} J_{ik} n_k - \alpha E_Z \psi'_q(\sqrt{q}Z) m_i \right) \\ n_k &= \psi_q \left( N^{-1/2} \sum_{i=1}^N m_i J_{ik} - (1 - q) n_k \right), \end{aligned}$$

where  $q$  comes from the fixed point equation above.

For  $q \in (0, 1)$ ,  $\psi_q$  is smooth regardless if  $u$  is: The equations make sense for non-smooth  $u$ .

The proper way to construct directly TAP solutions (in high temperature) for SK was done in my 2015 CMP paper. The method can be adapted for the perceptron: joint work with **Shuta Nakaijma**, Kyoto University.

Take  $m_i^{[0]} := 0$ ,  $m_i^{[1]} := \sqrt{q}$ ,  $n_k^{[0]} = 0$ ,  $n_k^{[1]} := \sqrt{r}$ , and

$$\begin{aligned} m_i^{[t+1]} &= \text{th} \left( N^{-1/2} \sum_{k=1}^{\alpha N} J_{ik} n_k^{[t]} - m_i^{[t-1]} \alpha E \psi'_q(\sqrt{q} Z) \right), \\ n_k^{[t+1]} &= \psi_q \left( N^{-1/2} \sum_{i=1}^N m_i^{[t]} J_{ik} - n_k^{[t-1]} (1 - q) \right). \end{aligned}$$

The time shift for the Onsager corrections were “observed” before my paper by Donoho & Montanari for compressed sensing algorithms, and they checked the effectivity numerically.



**Theorem** Assume  $\sup_x |\psi'_q(x)| < \infty$  (which is satisfied for  $u = -\infty \mathbf{1}_{x < 0}$ ), and that  $q = E \operatorname{th}^2(\sqrt{\alpha r} Z)$ ,  $r = E \psi_q^2(\sqrt{q} Z)$  has a unique solution (which is easy for small  $\alpha$ , and may be correct for all  $\alpha$ ). Then

$$\lim_{s,t \rightarrow \infty} \limsup_{N \rightarrow \infty} \mathbb{E} \frac{1}{N} \sum_i \left( m_i^{[s]} - m_i^{[t]} \right)^2 = 0,$$

$$\lim_{s,t \rightarrow \infty} \limsup_{M \rightarrow \infty} \mathbb{E} \frac{1}{M} \sum_k \left( n_k^{[s]} - n_k^{[t]} \right)^2 = 0$$

under a condition resembling the de Almeida–Thouless condition for SK:

$$\alpha E \frac{1}{\cosh^4(\sqrt{\alpha r} Z)} E \left[ \psi'_q(\sqrt{q} Z) \right]^2 \leq 1.$$

The dependence of the iterates  $m^{[t]}$  and  $n^{[t]}$  on  $(J_{ij})$  can precisely be described (which would not be the case without the time shift of the Onsager correction).

For fixed  $t$ , and  $N \rightarrow \infty$ , there is a representation

$$\begin{aligned} m_i^{[t+1]} &\approx \text{th} \left( N^{-1/2} \sum_{k=1}^{\alpha N} J_{ik}^{[t]} n_k^{[t]} + \gamma_1 \xi_i^{[1]} + \cdots + \gamma_{k-1} \xi_i^{[t-1]} \right), \\ n_k^{[t+1]} &\approx \psi_q \left( N^{-1/2} \sum_{i=1}^N J_{ik}^{[t]} m_i^{[t]} + \delta_1 \eta_k^{[1]} + \cdots + \delta_{k-1} \eta_k^{[t-1]} \right), \end{aligned}$$

with inductively defined  $\gamma_i, \delta_i \in \mathbb{R}$ , random variables  $\xi_i^{[s]}, \eta_i^{[s]}$  which asymptotically ( $N \rightarrow \infty$ ) are Gaussian, and matrices  $\left( J_{ik}^{[t]} \right)_{i \leq N, k \leq \alpha N}$  that are *conditionally* Gaussian given  $\mathcal{G}_{t-1} := \sigma \left( \xi^{[s]}, \eta^{[s]} : s \leq t-1 \right)$ .

They have the following covariances:

$$\mathbb{E} \left( J_{ij}^{[t]} J_{kl}^{[t]} \middle| \mathcal{G}_{t-1} \right) = \left( \delta_{ik} - \alpha_{ik}^{[t-1]} \right) \left( \delta_{jl} - \beta_{jl}^{[t-1]} \right),$$

with

$$\alpha_{ij}^{[m]} := \frac{1}{N} \sum_{s=1}^m \phi_i^{[s]} \phi_j^{[s]}, \quad \beta_{ij}^{[m]} := \frac{1}{M} \sum_{s=1}^m \psi_i^{[s]} \psi_j^{[s]},$$

where  $\phi^{[s]} \in \mathbb{R}^N$  are from the  $m^{[s]}$  by Gram-Schmidt, and  $\psi^{[s]}$  the same in  $\mathbb{R}^M$ . The  $J^{[t]}$  are obtained from  $J$  with a series of rank one corrections:

$$J_{ij}^{[t]} = J_{ij} - \sum_{s=1}^{t-1} \rho_{ij}^{[s]}, \quad \rho_{ij}^{[s]} := \frac{\xi_i^{[s]} \psi_j^{[s]}}{\sqrt{N}} + \frac{\phi_i^{[s]} \eta_j^{[s]}}{\sqrt{N}} + \text{correction}.$$

Two crucial points:

- The AT-condition is satisfied iff the first parts  $N^{-1/2} \sum_{k=1}^{\alpha N} J_{ik}^{[t]} n_k^{[t]}$ ,  $N^{-1/2} \sum_{i=1}^N m_i^{[t]} J_{ik}$ , disappear asymptotically ( $N \rightarrow \infty$  first, and then  $t \rightarrow \infty$ ). This is due to combined properties of  $J^{[t]}$  and  $n^{[t]}, m^{[t]}$ . From this one derives the above theorem.
- The  $J^{[t]}$  stays “close” to  $J$ , as  $N \rightarrow \infty$ , for instance if  $x \in \mathbb{R}^N$  then the vector  $Y := xJ^{[t]}$  has a covariance matrix of rank  $N - t + 1$ .

The key idea for the free energy is to tilt the coin tossing measure  $p_0(\sigma) := 2^{-N}$ , to

$$p^{[t+1]}(\sigma) = \prod_{i=1}^N p_i^{[t+1]}(\sigma_i), \quad p_i^{[t+1]}(\sigma_i) = \frac{1}{2} \frac{e^{h_i^{[t+1]} \sigma_i}}{\cosh\left(h_i^{[t+1]}\right)}, \quad m_i^{[t+1]} = \text{th}\left(h_i^{[t+1]}\right),$$

and to write

$$\sum_{\sigma} 2^{-N} \exp \left[ \sum_k u(S_k) \right] = \prod_i \cosh \left( h_i^{[t+1]} \right) Z'_N,$$

$$Z'_N \quad : \quad = \sum_{\sigma} p^{[t+1]}(\sigma) \exp \left[ \sum_k u(S_k) - \sum_i h_i^{[t+1]} \sigma_i \right]$$

$$\lim_{N \rightarrow \infty} \frac{1}{N} \sum_{i=1}^N \log \cosh \left( h_i^{[t+1]} \right) = E_Z \log \cosh \left( \sqrt{\alpha r} Z \right)$$

a.s. and in  $L_1$ .  $p^{[t+1]}(\sigma)$  is  $\mathcal{G}_t$ -m.b., and one would like to prove that as  $N \rightarrow \infty$ ,  $t \rightarrow \infty$

$$\begin{aligned} N^{-1} \log \mathbb{E}_t Z'_N &= N^{-1} \log \sum_{\sigma} p^{[t+1]}(\sigma) \mathbb{E}_t \exp \left[ \sum_k u(S_k) - \sum_i h_i^{[t+1]} \sigma_i \right] \\ &\rightarrow -\frac{\alpha r}{2} (1 - q) + \alpha E_Z \log E_{Z'} \exp \left[ u \left( \sqrt{q} Z + \sqrt{1 - q} Z' \right) \right], \end{aligned}$$

plus an estimate of the second moment.  $\mathbb{E}_t := \mathbb{E}(\cdot | \mathcal{G}_t)$ .

The SK is simpler (and done): After a simple computation (and some approximations), one gets with  $\hat{\sigma}_i = \sigma_i - m_i^{[t+1]}$ , and with  $\langle x, y \rangle := N^{-1} \sum_{i=1}^N x_i y_i$

$$\mathbb{E}_t Z'_N = \exp \left[ N \frac{\beta^2 (1-q)^2}{4} \right] \\ \times \sum_{\sigma} p^{[t+1]}(\sigma) \mathbb{E}_t \exp \left[ \frac{\beta \sqrt{N}}{\sqrt{2}} \langle \hat{\sigma}, J \hat{\sigma} \rangle - \frac{\beta^2 N \|\hat{\sigma}\|^4}{4} + \beta^2 N \langle m^{[t+1]}, \hat{\sigma} \rangle^2 \right],$$

with  $q$  satisfying  $q = E \operatorname{th}^2 \left( h + \beta \sqrt{q} Z \right)$ . If  $\sum_{\sigma} \dots = e^{o(N)}$ , we are done (for the first moment).

Assume *wrongly* that  $J_{ij}$ , under  $\mathbb{E}_t$  are i.i.d. and independent of  $m_i^{[t+1]}$ , then

$$\sum_{\sigma} \dots = \sum_{\sigma} p^{[t+1]}(\sigma) \exp \left[ \beta^2 N \langle m^{[t+1]}, \hat{\sigma} \rangle^2 \right]$$

and we are left with a Curie-Weiss type term, which is  $e^{o(N)}$  below AT. A similar straightforward (but wrong!) argument gives the Gardner-formula in the perceptron.

For SK: Replace  $J$  by  $J^{[t+1]} + \sum$  of rank one corrections, which essentially adds in the Hamiltonian

$$\beta \sum_{s=1}^t N \langle \hat{\sigma}, \xi^{[s]} \rangle \langle \hat{\sigma}, \phi^{[s]} \rangle$$

which is still of Curie-Weiss type. We still have to evaluate

$$\mathbb{E}_t \exp \left[ \frac{\beta \sqrt{N}}{\sqrt{2}} \langle \hat{\sigma}, J^{[t+1]} \hat{\sigma} \rangle - \frac{\beta^2 N \|\hat{\sigma}\|^4}{4} \right].$$

$J^{[t+1]}$  is conditionally Gaussian given  $\mathcal{G}_t$ , leading to no additional trouble, *except* one has infinitely many Curie-Weiss terms in the  $t \rightarrow \infty$  limit, and one has to check that they are not destroying the picture

This step is however rather delicate for the perceptron, as the Gaussians are inside the function  $u$ , which may even be discontinuous e.g.  $u(x) = -\infty \mathbf{1}_{x < 0}$ .

The second conditional moment is similar, with additional Curie-Weiss terms. The result (for SK) is

$$\lim_{t \rightarrow \infty} \limsup_{N \rightarrow \infty} \mathbb{E} \left| \frac{1}{N} \log \mathbb{E}_t Z_N - \text{RS}(\beta, h) \right| = 0,$$

$$\lim_{t \rightarrow \infty} \limsup_{N \rightarrow \infty} \mathbb{E} \left| \frac{1}{N} \log \mathbb{E}_t Z_N^2 - 2 \text{RS}(\beta, h) \right| = 0,$$

where

$$\text{RS}(\beta, h) = E_Z \log \cosh(h + \beta \sqrt{q} Z) + \frac{\beta^2 (1 - q)^2}{4},$$

which proves

$$\lim_{N \rightarrow \infty} \frac{1}{N} \mathbb{E} \log Z_N = \text{RS}(\beta, h).$$



## Remarks:

- a) “In principle”, the method is non-perturbative. The only place where we have to rely on “small  $\beta$ ” are the Curie-Weiss computations for which the correct critical value is a bit delicate. For the first moment, I think it is OK up to AT, but certainly not for the second. For the perceptron, we in addition need the uniqueness of the fixed point equation for  $(q, r)$ .
- b) The method seems to be applicable in cases where there are TAP type equations.
- c) A somewhat similar idea is used in a paper by Fan, Mei, and Montanari (Aug 2018).
- d) Similar TAP-type structures appear in connection with compressed sensing, and variants of the above representations have been obtained in this context by Bayati, Donoho, Montanari, Lelarge, and others.

**e)** It is suggestive to conjecture that the Curie-Weiss terms describe the finite size corrections.

**d)** The main shortcoming is that the method is for the moment restricted to the replica symmetric region. For diluted models, there is a non-rigorous approach by Mézard, Parisi, Montanari for the BP equations in the 1RSB case, but I don't know if it could be adapted to TAP equations (even non-rigorously).

Happy (After) Birthday, Anton!