

Solution for Stats 369, HW2

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Exercise 1.6.

(a)

For any matrix M by change of variables we get

$$f_M(1) = \frac{1}{2} \int_{\mathcal{S}^{n-1}} \frac{(\det(nM))^{1/2}}{(2\pi)^{n/2}} \exp\left(-\frac{n\sigma^\top M\sigma}{2}\right) \nu_0(d\sigma),$$

then we have for $z > \lambda_1(W)$,

$$\begin{aligned} \frac{f_{\beta(zI-W)}(1)}{f_I(1)} &= \det(\beta(zI-W))^{1/2} \cdot \frac{\int_{\mathcal{S}^{n-1}} \exp\left(-\frac{n\beta\sigma^\top(zI-W)\sigma}{2}\right) \nu_0(d\sigma)}{\int_{\mathcal{S}^{n-1}} \exp\left(-\frac{n\sigma^\top\sigma}{2}\right) \nu_0(d\sigma)} \\ &= \beta^{n/2} \cdot \det(zI-W)^{1/2} \cdot \frac{\exp\left(-\frac{nz\beta}{2}\right) \cdot \int_{\mathcal{S}^{n-1}} \exp\left(\frac{n\beta\sigma^\top W\sigma}{2}\right) \nu_0(d\sigma)}{\exp\left(-\frac{n}{2}\right)} \\ &= \beta^{n/2} \cdot \exp\left(-\frac{n(z\beta-1)}{2}\right) \cdot \det(zI-W)^{1/2} \cdot Z_n(\beta; W). \end{aligned}$$

Rearranging terms concludes the proof of part (a).

(b)

By the explicit formula for $Z_n(\beta; W)$ in (1.7.13) we can write

$$\frac{1}{n} \log Z_n(\beta; W) = -\frac{1}{2} \log \beta + \frac{1}{2} (z\beta - 1) - \frac{1}{2n} \sum_{i=1}^n \log(z - \lambda_i(W)) + \frac{1}{n} \log \frac{f_{\beta(zI-W)}(1)}{f_I(1)}$$

for any $z > \lambda_1(W)$. Since $\lambda_1(W) \rightarrow 2$ the above equation holds eventually for any $z > 2$. Note that by direct calculations

$$\begin{aligned} \int \log(z - \lambda) s_\infty(d\lambda) &= \frac{z^2}{4} - \frac{1}{2} - \frac{z\sqrt{z^2-4}}{4} + \log\left(\frac{z + \sqrt{z^2-4}}{2}\right) \\ \int \frac{1}{z - \lambda} s_\infty(d\lambda) &= \frac{z - \sqrt{z^2-4}}{2}. \end{aligned}$$

For any $z > 2$ we have $\int \frac{1}{z-\lambda} s_\infty(d\lambda)$ is increasing in z and takes values in $(0, 1)$. The equation

$$\beta = \int \frac{1}{z - \beta} s_\infty(d\lambda) = \frac{z - \sqrt{z^2 - 4}}{2}$$

indeed has a unique solution $z = \beta + \frac{1}{\beta} > 2$ for any chosen $\beta < 1$. For this z , since $\lambda_1(W) \rightarrow 2$ we have $\log(z - \lambda_i(W))$ will eventually be bounded, and $\log(z - \lambda)$ is a continuous function, we can deduce from

weak convergence $s_n \xrightarrow{w} s_\infty$ that

$$\frac{1}{2n} \sum_{i=1}^n \log(z - \lambda_i(W)) = \frac{1}{2} \int \log(z - \lambda) s_n(d\lambda) \rightarrow \frac{1}{2} \int \log(z - \lambda) s_\infty(d\lambda).$$

Now it only remains to show with probability 1 that

$$\frac{1}{n} \log \frac{f_{\beta(zI-W)}(1)}{f_I(1)} \rightarrow 0.$$

In fact we have $|\log f_{\beta(zI-W)}(1)| = o(n)$ and $|\log f_I(1)| = o(n)$. For $x \sim \mathbf{N}(0, n\beta(zI - W)^{-1})$, we have

$$\|x\|^2 = \frac{1}{n\beta} \sum_{j=1}^n \lambda_j^{-1} v_j^2, \quad v_j \stackrel{i.i.d.}{\sim} \mathbf{N}(0, 1),$$

where we use the shorthand $\lambda_j = \lambda_j(zI - W)$. Let $X_j = \frac{1}{\beta\lambda_j}(v_j^2 - 1)$, then $\{X_j\}$ are independent random variables with zero mean and

$$\|x\|^2 = \frac{1}{n} \sum_{j=1}^n X_j + \frac{1}{n\beta} \sum_{j=1}^n \lambda_j^{-1}.$$

Denote by

$$\sigma_n^2 = \sum_{j=1}^n \mathbb{E}[X_j^2] = \frac{2}{\beta^2} \sum_{j=1}^n \lambda_j^{-2} = \Theta(n),$$

we can deduce from local central limit theorem that

$$f_{\beta(zI-W)}(1) = \frac{n}{\sigma_n} \cdot \left\{ \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1 - \frac{1}{n\beta} \sum_{j=1}^n \lambda_j^{-1}}{2\sigma_n^2/n^2}\right) + O\left(\frac{1}{\sigma_n}\right) \right\}.$$

Using the fact that $\frac{1}{n\beta} \sum_{j=1}^n \lambda_j^{-1} \rightarrow \frac{1}{\beta} \int \frac{1}{z-\lambda} s_\infty(d\lambda) = 1$ yields $f_{\beta(zI-W)}(1) = \exp(o(n))$. Similarly we have $f_I(1) = \exp(o(1))$.

(c)

Since

$$\begin{aligned} \lim_{n \rightarrow \infty} \frac{1}{n} \log Z_n(\beta; W) &= -\frac{1}{2} \log \beta + \frac{1}{2} \beta z - \frac{1}{2} - \frac{1}{2} \int \log(z - \lambda) s_\infty(d\lambda) \\ &= -\frac{1}{2} \log \beta + \frac{1}{2} \beta z - \frac{1}{2} - \frac{1}{2} \left\{ \frac{z^2}{4} - \frac{1}{2} - \frac{z\sqrt{z^4-4}}{4} + \log\left(\frac{z + \sqrt{z^2-4}}{2}\right) \right\}, \end{aligned}$$

we can substitute in $z = \beta + \frac{1}{\beta}$ and obtain

$$\phi(\beta) = -\frac{1}{2} \log \beta + \frac{1}{2} \beta^2 - \frac{1}{2} \left\{ \frac{1}{4} \left(\beta^2 + \frac{1}{\beta^2} \right) + \frac{1}{4} \left(\beta^2 - \frac{1}{\beta^2} \right) - \log \beta \right\} = \frac{\beta^2}{4}.$$

For $k = 2$ and $\lambda = 0$ we have

$$\Psi_{\text{RS}}(q, \beta) = \frac{\beta^2}{4} (1 - q^2) + \frac{q}{2(1-q)} + \frac{1}{2} \log(1 - q).$$

Note that $\Psi_{\text{RS}}(q, \beta)$ is increasing in $q \in [0, 1]$ and thus

$$\phi(\beta) = \inf_{\beta \in [0, 1]} \Psi_{\text{RS}}(q, \beta) = \Psi_{\text{RS}}(0, \beta) = \frac{\beta^2}{4}.$$

The two solutions coincide.

Exercise 1.7.

We copy here the free energy density for 1RSB,

$$\begin{aligned} \Psi_{1\text{RSB}}(b, q_0, q_1, m) = & \frac{\beta\lambda}{\sqrt{2(k!)}} b^k + \frac{\beta^2}{4} [1 - (1-m)q_1^k - mq_0^k] + \frac{1}{2} \frac{q_0 - b^2}{1 - (1-m)q_1 - mq_0} \\ & + \frac{1}{2m} \log(1 - (1-m)q_1 - mq_0) - \frac{1-m}{2m} \log(1 - q_1). \end{aligned} \quad (1)$$

Taking $\lambda = 0$, $b = 0$, and $q_0 = 0$, we have

$$\Psi_{1\text{RSB}}(q_1, m; \beta) = \frac{\beta^2}{4} [1 - (1-m)q_1^k] + \frac{1}{2m} \log(1 - (1-m)q_1) - \frac{1-m}{2m} \log(1 - q_1). \quad (2)$$

(a)

See the matlab program below.

```

1  clc
2  clear
3  close all
4
5  kset = [3,4,5];
6  for iterk = 1:length(kset)
7      k = kset(iterk);
8
9      mset = [0.01:0.01:1.99]';
10     m = 1;
11     fq0 = @(q1) q1.^(k-2).*(1-q1).*(1-(1-m)*q1);
12     q1 = 0.0001:0.0001:0.9999;
13     [fstar, qid] = max(fq0(q1));
14     Tdm1 = sqrt(fstar*k/2)
15     Tdm1value(iterk) = Tdm1;
16     Tset = [1.5*Tdm1:-0.01:0.01];
17     Tsetvalue{iterk} = Tset;
18
19     mstar = 1;
20     for iterT = 1:length(Tset)
21         T = Tset(iterT)
22         beta = 1/T;
23         Psi = @(q1,m) beta^2/4 * (1 - (1-m).*(q1.^k) + 1./(2*m).*(log(1-(1-m).*(q1)
24             - (1-m)./(2.*m).*(log(1-q1));
25         for iterm = 1:length(mset)
26             m = mset(iterm);
27             fq0 = @(q1) q1.^(k-2).*(1-q1).*(1-(1-m)*q1);
28             q1 = 0.001:0.001:0.999;
29             [fstar, qid] = max(fq0(q1));
30             Tdm = sqrt(fstar*k/2);
31             Tdmvalue{iterk} = Tdm;
32
33             if beta <= 1/Tdm
34                 qlstarm = 0;
35             else
36                 fq = @(q1) q1.^(k-2).*(1-q1).*(1-(1-m)*q1) - 2/(k*beta^2);
37                 q1 = 0.001:0.001:0.999;
38                 qid = max(find((fq(q1) > 0) == 1));

```

```

38         qlstarm = q1(qid);
39     end
40     Psistarm(iterm) = Psi(qlstarm,m);
41 end
42
43 %plot(mset,Psistarm-beta^2/4);
44 [Psimin, iterm] = min(Psistarm);
45 mstar = mset(iterm);
46 if mset(iterm) > 1
47     Psimin = beta^2/4;
48     Ts = T;
49     mstar = 1;
50     qlstarm = 0;
51 end
52 if min(Psistarm-beta^2/4) > -1e-6
53     mstar = 1;
54 end
55 Psivalue(iterk,iterT) = Psimin;
56 mvalue(iterk,iterT) = mstar;
57 qlvalue(iterk,iterT) = qlstarm;
58 end
59 end
60 save('result.mat');

```

(b)

See Figure 1,2,3.

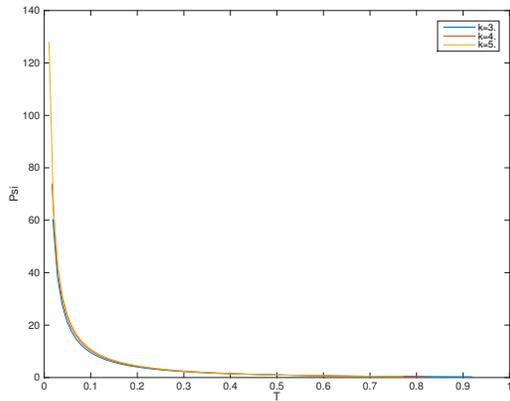


Figure 1: $\psi_{1RSB}(T)$.

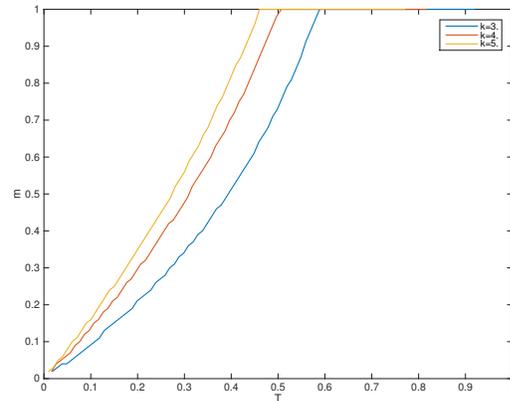


Figure 2: $m(T)$

(c)

k	3	4	5	6	7	8	9	10
T_s	0.5885	0.5064	0.4602	0.4436	0.4162	0.4040	0.3949	0.3879

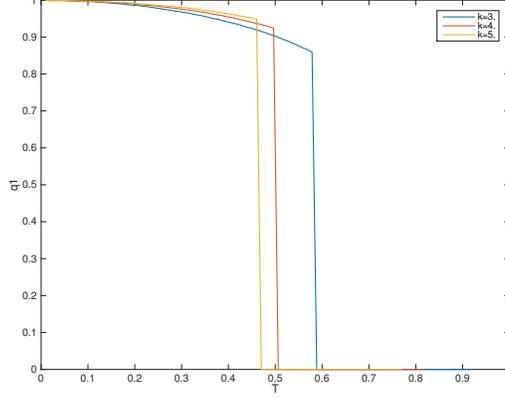


Figure 3: $q_1(T)$.

Exercise 1.8.

(a)

Since we have

$$\begin{aligned}
& \Psi_{\text{1RSB}}(1 - c(\mu)T + o(T), \mu T; T) \\
&= \frac{1}{4T^2} [1 - (1 - \mu T)(1 - c(\mu)T + o(T))^k] + \frac{1}{2\mu T} \log(1 - (1 - \mu T)(1 - c(\mu)T + o(T))) - \frac{1 - \mu T}{2\mu T} \log(c(\mu)T + o(T)) \\
&= \frac{1}{4T^2} [(kc(\mu) + \mu)T + o(T)] + \frac{1}{2\mu T} \log((\mu + c(\mu))T + o(T)) - \frac{1 - \mu T}{2\mu T} \log(c(\mu)T + o(T)).
\end{aligned} \tag{3}$$

The coefficient of $O(1/T)$ term (which is the leading order term as $T \rightarrow 0$) gives

$$e(\mu) = \frac{1}{4}kc(\mu) + \mu + \frac{1}{2\mu} \log(\mu + c(\mu)) - \frac{1}{2\mu} \log(c(\mu)). \tag{4}$$

We have

$$\frac{d}{d\mu} e(c(\mu)) = \frac{1}{4}k + \frac{1}{2\mu} \frac{1}{\mu + c(\mu)} - \frac{1}{2\mu} \frac{1}{c(\mu)} = 0, \tag{5}$$

which gives

$$c^2 + c\mu - \frac{2}{k} = 0. \tag{6}$$

Thus, we have

$$c(\mu) = \frac{\sqrt{\mu^2 + 8/k} - \mu}{2}. \tag{7}$$

(b)

We have

$$\Psi_{\text{1RSB}}(q_{1,*}(\beta, \mu T), \mu T; \beta) = \beta e_{\text{1RSB}} + o(\beta). \tag{8}$$

Substituting $c(\mu)$ into the $e(\mu)$, we have

$$e_{\text{1RSB}}(\mu) = \frac{1}{\sqrt{\mu^2 + 8/k} + \mu} + \frac{1}{4}\mu + \frac{1}{2\mu} \log\left(1 + \frac{2\mu}{\sqrt{\mu^2 + 8/k} - \mu}\right). \tag{9}$$

(c)

$e_{1\text{RSB}}^*$ is the ground state energy of the k -spin glass model. That is,

$$e_{1\text{RSB}}^* = \lim_{n \rightarrow \infty} \mathbb{E} \left[\max_{\sigma \in \mathcal{S}^{n-1}} \frac{1}{\sqrt{2(k!)}} \langle J, \sigma^{\otimes k} \rangle \right]. \quad (10)$$

The value for $e_{1\text{RSB}}^*$ for different k gives

k	2	3	4	5	6	7	8	9	10
$e_{1\text{RSB}}^*$	1.0000	1.1717	1.2686	1.3350	1.3850	1.4248	1.4577	1.4857	1.5099