

# ORF 543: Homework 1

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## Problem A

Suppose that  $X \sim \mathcal{N}(\mu, \sigma^2)$  is a Gaussian. Show that

$$\kappa_k(X) = \begin{cases} \mu, & k = 1 \\ \sigma^2, & k = 2 \\ 0, & k \geq 3 \end{cases}$$

(5 points)

### Solution

**Proof.** For Gaussian  $X$ , we can explicitly compute the expectation. Using the substitution  $u := \frac{z-\mu}{\sigma\sqrt{2}}$ ,

$$\begin{aligned} \mathbb{E} [e^{itX}] &= \int_{-\infty}^{\infty} e^{itz} \frac{e^{-\frac{(z-\mu)^2}{2\sigma^2}}}{\sqrt{2\pi\sigma^2}} dz = \frac{\sigma\sqrt{2}}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{\infty} e^{it(\sigma\sqrt{2}u+\mu)-u^2} du \\ &= \frac{e^{it\mu}}{\sqrt{\pi}} \int_{-\infty}^{\infty} e^{-u^2+it\sigma\sqrt{2}u} du = \frac{e^{it\mu}}{\sqrt{\pi}} \left( \sqrt{\pi} e^{-\frac{t^2\sigma^2}{2}} \right) = e^{i\mu t - \frac{\sigma^2 t^2}{2}} \\ &\implies \log \mathbb{E} [e^{itX}] = i\mu t - \frac{\sigma^2 t^2}{2} \end{aligned}$$

We can compute

$$\begin{aligned} \kappa_1(X) &= \frac{1}{i} \frac{d}{dt} \left[ i\mu t - \frac{\sigma^2 t^2}{2} \right]_{t=0} = \frac{i\mu}{i} = \mu, \\ \kappa_2(X) &= \frac{1}{-1} \frac{d^2}{dt^2} \left[ i\mu t - \frac{\sigma^2 t^2}{2} \right]_{t=0} = \frac{-\sigma^2}{-1} = \sigma^2, \end{aligned}$$

and, since for  $k \geq 3$  the derivatives vanish,

$$\kappa_k(X) = \frac{1}{i^k} \frac{d^k}{dt^k} \left[ i\mu t - \frac{\sigma^2 t^2}{2} \right]_{t=0} = 0,$$

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## Problem B

Suppose  $X, Y$  are independent. Show that for all  $k \geq 0$

$$\kappa_k(X + Y) = \kappa_k(X) + \kappa_k(Y)$$

(5 points)

### Solution

**Proof.** Since  $X$  and  $Y$  are independent, we know that  $\mathbb{E}[e^{it(X+Y)}] = \mathbb{E}[e^{itX}e^{itY}] = \mathbb{E}[e^{itX}]\mathbb{E}[e^{itY}]$ . So,

$$\begin{aligned}\kappa_k(X + Y) &= \frac{1}{i^k} \frac{d^k}{dt^k} \Big|_{t=0} \log \mathbb{E}[e^{it(X+Y)}] = \frac{1}{i^k} \frac{d^k}{dt^k} \Big|_{t=0} \log (\mathbb{E}[e^{itX}]\mathbb{E}[e^{itY}]) \\ &= \frac{1}{i^k} \frac{d^k}{dt^k} \Big|_{t=0} (\log \mathbb{E}[e^{itX}] + \log \mathbb{E}[e^{itY}]) \\ &= \frac{1}{i^k} \frac{d^k}{dt^k} \Big|_{t=0} \log \mathbb{E}[e^{itX}] + \frac{1}{i^k} \frac{d^k}{dt^k} \Big|_{t=0} \log \mathbb{E}[e^{itY}] \\ &= \kappa_k(X) + \kappa_k(Y)\end{aligned}$$

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## Problem C

Suppose  $X_1, \dots, X_n$  are i.i.d random variables with the same distribution as a random variable  $X$ . Compute the cumulants of

$$S_n := \frac{1}{n} \sum_{i=1}^n X_i$$

in terms of the cumulants of  $X$  and of  $n$ . (10 points)

### Solution

**Proof.** We want to first investigate how the cumulant changes when we scale a random variable. Let  $Y$  be any random variable and let  $a \in \mathbb{R}$  be arbitrary. Define the cumulant generating function of  $Y$  as

$$K_Y(t) = \log \mathbb{E} [e^{itY}]$$

Then,

$$K_{aY}(t) = \log \mathbb{E} [e^{it(aY)}] = \log \mathbb{E} [e^{i(at)Y}] = K_Y(at)$$

So, we find that the  $k^{\text{th}}$  cumulant of a scaled variable can be found to be

$$\kappa_k(aY) = \frac{1}{i^k} \frac{d^k}{dt^k} \Big|_{t=0} K_{aY}(t) = \frac{1}{i^k} \frac{d^k}{dt^k} \Big|_{t=0} K_Y(at) = a^k \cdot \frac{1}{i^k} \frac{d^k}{dt^k} \Big|_{t=0} K_Y(t) = a^k \kappa_k(Y),$$

where the third equality comes from the chain rule and the fact that  $at$  and  $t$  look the same when evaluated at  $t = 0$  (we can think of this by imagining performing  $k$  derivatives on  $K_Y(at)$  and  $k$  derivatives on  $K_Y(t)$ ; when we evaluate at  $t = 0$ , they will only differ by a factor of  $a^k$ ). With this in mind, we see that scaling a random variable by a constant scales the  $k^{\text{th}}$  cumulant by the  $k^{\text{th}}$  power of that constant. This, along with the result from part (b) and the fact that all the  $X_i$  have the same cumulants as  $X$ , is enough to see that for all  $k \geq 0$ :

$$\kappa_k(S_n) = \frac{1}{n^k} \kappa_k \left( \sum_{i=1}^n X_i \right) = \frac{1}{n^k} \sum_{i=1}^n \kappa_k(X_i) = \frac{1}{n^k} \cdot n \cdot \kappa_k(X) = \frac{\kappa_k(X)}{n^{k-1}}$$

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## Problem D

Fix  $\vec{x} \in \mathbb{R}^{n_0}$ . Prove that

$$\kappa_k(z^{(2)}(\vec{x})) = \begin{cases} 0, & k \text{ odd} \\ O\left(n_1^{1-\frac{k}{2}}\right), & k \text{ even} \end{cases}$$

(10 points)

### Solution

**Proof.** We can write the output of the final layer of the network as

$$z^{(2)}(\vec{x}) = b^{(2)} + \sum_{j=1}^{n_1} W_j^{(2)} \sigma\left(z_j^{(1)}\right),$$

where  $W_j^{(2)} \sim \mathcal{N}\left(0, \frac{C_W}{n_1}\right)$ ,  $W_{ij}^{(1)} \sim \mathcal{N}\left(0, \frac{C_W}{n_0}\right)$ , and  $b_j^{(1)}, b^{(2)} \sim \mathcal{N}\left(0, C_b\right)$  are independent, and  $z_j^{(1)} = W_j^{(1)} \vec{x} + b_j^{(1)}$ . (A helpful thing to note here is that this means all the  $z_j^{(1)}$ 's are independent since they are functions of  $W_j^{(1)}$ 's and  $b_j^{(1)}$ 's, which are independent for different  $j$ 's; this is abused repeatedly here and in later parts). Now, we start small by observing that since  $W_j^{(2)} \sim \mathcal{N}\left(0, \frac{C_W}{n_1}\right)$

$$\mathbb{E} \left[ e^{itW_j^{(2)}\sigma(z_j^{(1)})} \right] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi \frac{C_W}{n_1}}} e^{itws} e^{-\frac{w^2}{2 \frac{C_W}{n_1}}} dw \cdot PDF(S),$$

where  $S$  denotes the random variable  $\sigma(z_j^{(1)})$  and  $PDF(S)$  is the differential probability density of the continuous variable  $s$  over all the values that  $S$  can take. Then, we can use the substitution  $w' = \frac{w}{\sqrt{2 \frac{C_W}{n_1}}}$  and some usual Gaussian integral magic to see

$$\begin{aligned} \mathbb{E} \left[ e^{itW_j^{(2)}\sigma(z_j^{(1)})} \right] &= \frac{1}{\sqrt{\pi}} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{it\sqrt{2 \frac{C_W}{n_1}} s w'} e^{-w'^2} dw' \cdot PDF(s) \\ &= \frac{1}{\sqrt{\pi}} \int_{-\infty}^{\infty} \sqrt{\pi} e^{-\frac{t^2}{2} \cdot \frac{C_W}{n_1} s^2} PDF(s) = \int_{-\infty}^{\infty} e^{-\frac{t^2}{2} \cdot \frac{C_W}{n_1} s^2} PDF(s) \\ &= \mathbb{E} \left[ e^{-\frac{t^2}{2} \cdot \frac{C_W}{n_1} \cdot \sigma^2(z_j^{(1)})} \right] \end{aligned}$$

where the last step comes from the definition of expectation. Therefore, we see that

$$\kappa_k \left( W_j^{(2)} \sigma \left( z_j^{(1)} \right) \right) = \frac{1}{i^k} \left. \frac{d^k}{dt^k} \right|_{t=0} \log \mathbb{E} \left[ e^{-\frac{t^2}{2} \cdot \frac{C_W}{n_1} \cdot \sigma^2(z_j^{(1)})} \right]$$

Note, however, that the function  $\log \mathbb{E} \left[ e^{-\frac{t^2}{2} \cdot \frac{C_W}{n_1} \cdot \sigma^2(z_j^{(1)})} \right]$  is an even function of  $t$ , and therefore the  $k^{\text{th}}$  derivative of this must vanish for odd  $k$ . This means that for odd  $k$ ,  $\kappa_k \left( W_j^{(2)} \sigma \left( z_j^{(1)} \right) \right) = 0$ , and so we find that by independence, for odd  $k$  it holds that

$$\kappa_k \left( z^{(2)} \right) = \kappa_k \left( b^{(2)} \right) + \sum_{j=1}^{n_1} \kappa_k \left( W_j^{(2)} \sigma \left( z_j^{(1)} \right) \right) = \kappa_k \left( b^{(2)} \right) = 0,$$

where we know that  $\kappa_k \left( b^{(2)} \right) = 0$  because the odd cumulants of a zero mean Gaussian are 0. Suppose now that  $k$  is even. Define  $W = \sqrt{n_1} \cdot W_j^{(2)}$  to be a rescaled version of the random variable  $W_j^{(2)}$ . Then,  $W \sim \mathcal{N}\left(0, C_W\right)$ . So, we can say that

$$\kappa_k \left( W \sigma \left( z_j^{(1)} \right) \right) = n_1^{\frac{k}{2}} \kappa_k \left( W_j^{(2)} \sigma \left( z_j^{(1)} \right) \right)$$

The cumulant in the left hand side of this equation is written in terms of variables that have nothing to do with  $n_1$ ; so we can say that  $\kappa_k \left( W_j^{(2)} \sigma \left( z_j^{(1)} \right) \right) = O \left( n_1^{-\frac{k}{2}} \right)$ . This yields that for even  $k$ ,

$$\kappa_k \left( z^{(2)} \right) = \kappa_k \left( b^{(2)} \right) + \sum_{j=1}^n \kappa_k \left( W_j^{(2)} \sigma \left( z_j^{(1)} \right) \right) = \kappa_k \left( b^{(2)} \right) + \sum_{j=1}^{n_1} O \left( n_1^{-\frac{k}{2}} \right) = O \left( n_1^{1-\frac{k}{2}} \right),$$

where we note that  $\kappa_k \left( b^{(2)} \right) = \begin{cases} C_b = O(1) = O \left( n_1^{1-\frac{k}{2}} \right), & k = 2 \\ 0, & k \neq 2 \end{cases}$ . We have arrived at the result that

$$\kappa_k \left( z^{(2)} \right) = \begin{cases} 0, & k \text{ odd} \\ O \left( n_1^{1-\frac{k}{2}} \right), & k \text{ even} \end{cases}$$

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## Problem E

Fix  $\vec{x} \in \mathbb{R}^{n_0}$  and define

$$\Sigma^{(2)} := C_b + \frac{C_W}{n_1} \sum_{i=1}^{n_1} \left( \sigma(z_i^{(1)}(\vec{x})) \right)^2$$

Show that

$$\mathbb{E} \left[ \Sigma^{(2)} \right] = K^{(2)}$$

Use this to show that for all  $t \in \mathbb{R}$

$$\log \mathbb{E} \left[ e^{it \Sigma^{(2)}(\vec{x})} \right] = -\frac{t^2}{2} K^{(2)} + \log \mathbb{E} \left[ e^{-\frac{t^2}{2} \Delta^{(2)}} \right]$$

where

$$\Delta^{(2)} := \Sigma^{(2)} - \mathbb{E} \left[ \Sigma^{(2)} \right]$$

(15 points)

## Solution

**Proof.** We have

$$\mathbb{E} \left[ \Sigma^{(2)} \right] = C_b + \frac{C_W}{n_1} \sum_{i=1}^{n_1} \mathbb{E} \left[ \left( \sigma(z_i^{(1)}(\vec{x})) \right)^2 \right]$$

Much of this proof will feel like repeating steps made in part **(d)**; that is because they are. Note that  $z_i^{(1)}$  is a random variable distributed as  $\mathcal{N} \left( 0, C_b + \frac{C_W}{n_0} \|\vec{x}\|^2 \right) = \mathcal{N} \left( 0, K^{(1)} \right)$ . So, we see that

$$\begin{aligned} \mathbb{E} \left[ \left( \sigma(z_i^{(1)}) \right)^2 \right] &= \langle \sigma^2 \rangle_{K^{(1)}} \\ \implies \mathbb{E} \left[ \Sigma^{(2)} \right] &= C_b + \frac{C_W}{n_1} \cdot n_1 \cdot \langle \sigma^2 \rangle_{K^{(1)}} = C_b + C_W \cdot \langle \sigma^2 \rangle_{K^{(1)}} = K^{(2)} \end{aligned}$$

Now, we start small by observing that since  $W_j^{(2)} \sim \mathcal{N} \left( 0, \frac{C_W}{n_1} \right)$

$$\mathbb{E} \left[ e^{it W_j^{(2)} \sigma(z_j^{(1)})} \right] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi \frac{C_W}{n_1}}} e^{itws} e^{-\frac{w^2}{2 \frac{C_W}{n_1}}} dw \cdot PDF(S),$$

where  $S$  denotes the random variable  $\sigma(z_j^{(1)})$  and  $PDF(S)$  is the differential probability density of the continuous variable  $s$  over all the values that  $S$  can take. Then, we can use the substitution  $w' = \frac{w}{\sqrt{2 \frac{C_W}{n_1}}}$  and some usual Gaussian integral magic to see

$$\begin{aligned} \mathbb{E} \left[ e^{it W_j^{(2)} \sigma(z_j^{(1)})} \right] &= \frac{1}{\sqrt{\pi}} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{it \sqrt{2 \frac{C_W}{n_1}} s w'} e^{-w'^2} dw' \cdot PDF(s) \\ &= \frac{1}{\sqrt{\pi}} \int_{-\infty}^{\infty} \sqrt{\pi} e^{-\frac{t^2}{2} \cdot \frac{C_W}{n_1} s^2} PDF(s) = \int_{-\infty}^{\infty} e^{-\frac{t^2}{2} \cdot \frac{C_W}{n_1} s^2} PDF(s) \\ &= \mathbb{E} \left[ e^{-\frac{t^2}{2} \cdot \frac{C_W}{n_1} \cdot \sigma^2(z_j^{(1)})} \right] \end{aligned}$$

where the last step comes from the definition of expectation. So, we see that since all our random variables are independent and  $b^{(2)}$  being Gaussian  $\implies \mathbb{E} \left[ e^{itb^{(2)}} \right] = e^{-\frac{t^2}{2} C_b}$ ,

$$\mathbb{E} \left[ e^{it W_j^{(2)} \sigma(z_j^{(1)})} \right] = \mathbb{E} \left[ e^{-\frac{t^2}{2} \cdot \frac{C_W}{n_1} \cdot \sigma^2(z_j^{(1)})} \right]$$

$$\begin{aligned}
&\implies \mathbb{E} \left[ e^{itb^{(2)}} \prod_{j=1}^{n_1} \mathbb{E} \left[ e^{itW_j^{(2)}\sigma(z_j^{(1)})} \right] \right] = e^{-\frac{t^2}{2}C_b} \prod_{j=1}^{n_1} \mathbb{E} \left[ e^{-\frac{t^2}{2} \cdot \frac{C_W}{n_1} \cdot \sigma^2(z_j^{(1)})} \right] \\
&\implies \mathbb{E} \left[ \exp \left\{ it \left( b^{(2)} + \sum_{j=1}^{n_1} W_j^{(2)} \sigma(z_j^{(1)}) \right) \right\} \right] = \mathbb{E} \left[ \exp \left\{ -\frac{t^2}{2} \left( C_b + \frac{C_W}{n_1} \sum_{j=1}^{n_1} \sigma^2(z_j^{(1)}) \right) \right\} \right] \\
&\implies \mathbb{E} \left[ e^{itz^{(2)}} \right] = \mathbb{E} \left[ e^{-\frac{t^2}{2}\Sigma^{(2)}} \right]
\end{aligned}$$

Since we can write  $\Sigma^{(2)} = \Delta^{(2)} + \mathbb{E}[\Sigma^{(2)}] = \Delta^{(2)} + K^{(2)}$ , we find that

$$\begin{aligned}
\mathbb{E} \left[ e^{itz^{(2)}} \right] &= \mathbb{E} \left[ e^{-\frac{t^2}{2}K^{(2)}} \cdot e^{-\frac{t^2}{2}\Delta^{(2)}} \right] = e^{-\frac{t^2}{2}K^{(2)}} \cdot \mathbb{E} \left[ e^{-\frac{t^2}{2}\Delta^{(2)}} \right] \\
&\implies \log \mathbb{E} \left[ e^{itz^{(2)}} \right] = -\frac{t^2}{2}K^{(2)} + \log \mathbb{E} \left[ e^{-\frac{t^2}{2}\Delta^{(2)}} \right]
\end{aligned}$$

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## Problem F

Show that

$$\mathbb{E} \left[ \Delta^{(2)} \right] = 0$$

and that for all  $q \geq 2$  we have

$$\mathbb{E} \left[ \left( \Delta^{(2)} \right)^q \right] = O \left( n_1^{-\lceil \frac{q}{2} \rceil} \right)$$

(15 points)

### Solution

**Proof.** Clearly, we have that since  $\mathbb{E} [\Sigma^{(2)}] = K^{(2)}$  is nonrandom,

$$\mathbb{E} \left[ \Delta^{(2)} \right] = \mathbb{E} \left[ \Sigma^{(2)} - K^{(2)} \right] = \mathbb{E} \left[ \Sigma^{(2)} \right] - K^{(2)} = 0$$

We will first show that we can define a moment of a random variable  $X$  in terms of its lower moments and cumulants. Observe that if we let the moment generating function of  $X$  be

$$M_X(t) = \mathbb{E} \left[ e^{itX} \right] = \sum_{j=0}^{\infty} \frac{(it)^j}{j!} \mathbb{E} \left[ X^j \right],$$

we can then relate the cumulant generating function to this with

$$K_X(t) = \log \mathbb{E} \left[ e^{itX} \right] = \log M_X(t) \implies M_X(t) = e^{K_X(t)}$$

We can take  $k$  derivatives of  $M_X(t)$  using the Leibniz Rule to find that

$$\begin{aligned} \frac{d^k}{dt^k} M_X(t) &= \frac{d^k}{dt^k} e^{K_X(t)} = \frac{d^{k-1}}{dt^{k-1}} \left[ \left( \frac{d}{dt} K_X(t) \right) M_X(t) \right] \\ &= \sum_{j=0}^{k-1} \binom{k-1}{j} \frac{d^{k-1-j}}{dt^{k-1-j}} \left[ \frac{d}{dt} K_X(t) \right] \frac{d^j}{dt^j} [M_X(t)] = \sum_{j=0}^{k-1} \binom{k-1}{j} \frac{d^{k-j}}{dt^{k-j}} K_X(t) \frac{d^j}{dt^j} M_X(t) \end{aligned}$$

We can evaluate this derivative at  $t = 0$ . Let  $\mu_j(X) = \frac{1}{i^j} \frac{d^j}{dt^j} \Big|_{t=0} M_X(t)$  be the  $j^{\text{th}}$  moment and  $\kappa_j(X) = \frac{1}{i^j} \frac{d^j}{dt^j} \Big|_{t=0} K_X(t)$  be the  $j^{\text{th}}$  cumulant. Then, we get that

$$i^k \mu_k(X) = \sum_{j=0}^{k-1} \binom{k-1}{j} i^{k-j} \kappa_{k-j}(X) \cdot i^j \mu_j(X) \implies \mu_k(X) = \sum_{j=0}^{k-1} \binom{k-1}{j} \kappa_{k-j}(X) \mu_j(X)$$

We are interested in investigating the order of growth of  $\mathbb{E} \left[ \left( \Delta^{(2)} \right)^q \right] = \mu_q \left( \Delta^{(2)} \right)$ . However, it will be necessary to first understand the order of growth of the cumulants  $\kappa_q \left( \Delta^{(2)} \right)$ . We know from the definition of the cumulant generating function as the power series of cumulants that

$$\sum_{j=0}^{\infty} \frac{\kappa_j \left( \Delta^{(2)} \right)}{j!} (iu)^j = \log \mathbb{E} \left[ e^{iu \Delta^{(2)}} \right]$$

With the substitution of  $u = i \frac{t^2}{2}$ , we find that

$$\sum_{j=0}^{\infty} \frac{\kappa_j \left( \Delta^{(2)} \right)}{(-2)^j j!} (t^2)^j = \log \mathbb{E} \left[ e^{-\frac{t^2}{2} \Delta^{(2)}} \right]$$

With the result from part (e), we know that

$$\log \mathbb{E} \left[ e^{-\frac{t^2}{2} \Delta^{(2)}} \right] = \log \mathbb{E} \left[ e^{itz^{(2)}} \right] + \frac{t^2}{2} K^{(2)},$$

yielding that for all  $k > 0$ ,

$$\begin{aligned} & \sum_{j=0}^{\infty} \frac{\kappa_j(\Delta^{(2)})}{(-2)^j j!} t^{2j} = \log \mathbb{E} \left[ e^{itz^{(2)}} \right] + \frac{t^2}{2} K^{(2)} \\ \implies & \left. \frac{d^{2k}}{dt^{2k}} \right|_{t=0} \left[ \sum_{j=0}^{\infty} \frac{\kappa_j(\Delta^{(2)})}{(-2)^j j!} t^{2j} \right] = \left. \frac{d^{2k}}{dt^{2k}} \right|_{t=0} \left[ \log \mathbb{E} \left[ e^{itz^{(2)}} \right] + \frac{t^2}{2} K^{(2)} \right] \\ \implies & \left[ \sum_{j=k}^{\infty} \frac{\kappa_j(\Delta^{(2)})}{(-2)^j j!} \frac{(2j)!}{(2j-2k)!} t^{2j-2k} \right]_{t=0} = (-1)^k \kappa_{2k}(z^{(2)}) + K^{(2)} \cdot \mathbb{1}_{k=1} \\ \implies & \frac{(2k)!}{(-2)^k k!} \kappa_k(\Delta^{(2)}) = (-1)^k \kappa_{2k}(z^{(2)}) + K^{(2)} \cdot \mathbb{1}_{k=1} \\ \implies & \kappa_k(\Delta^{(2)}) = \frac{2^k k!}{(2k)!} \kappa_{2k}(z^{(2)}) - K^{(2)} \cdot \mathbb{1}_{k=1}, \end{aligned}$$

where  $\mathbb{1}_{k=1}$  is an indicator that is 1 when  $k = 1$  and 0 otherwise. We can plug in the result from part (d) to find that  $\kappa_{2k}(z^{(2)}) = O(n_1^{1-k})$ , and so

$$\kappa_k(\Delta^{(2)}) = O(n_1^{1-k})$$

We now have all that we need. We will show the claim by strong induction on  $q$ . Clearly, the base case holds for  $q = 1$ , since  $\mathbb{E} \left[ (\Delta^{(2)})^1 \right] = 0 = O(1)$ . Suppose now that the claim holds for all moments  $k < q$ ; we want to show that the claim holds for the  $q^{\text{th}}$  moment. We can write out our recursive relation

$$\mu_q(\Delta^{(2)}) = \sum_{k=0}^{q-1} \binom{q-1}{k} \kappa_{q-k}(\Delta^{(2)}) \mu_k(\Delta^{(2)}) = \sum_{k=0}^{q-2} O(1) \cdot O(n_1^{1-(q-k)}) \cdot O\left(n_1^{-\lceil \frac{k}{2} \rceil}\right),$$

where the last equality comes from our previous result and the application of our inductive hypothesis. Note here that the final index of the sum decreased to  $q-2$ ; this is because element of the sum with  $k = q-1$  evaluates to 0 since  $\kappa_1(\Delta^{(2)}) = \mathbb{E}[\Delta^{(2)}] = 0$ . Using the identity that  $\lceil \frac{k}{2} \rceil + \lfloor \frac{k}{2} \rfloor = k$  for all integers  $k$ , we can write

$$\mu_q(\Delta^{(2)}) = \sum_{k=0}^{q-2} O\left(n_1^{1-q+\lfloor \frac{k}{2} \rfloor}\right)$$

Observe that the largest exponent occurs for the largest possible value of  $k$ , which is  $k = q-2$ . So, we find that the entire sum has an order of growth equal to  $O\left(n_1^{1-q+\lfloor \frac{q-2}{2} \rfloor}\right)$ . We can simplify this exponent: note that for all integers  $q$  we have  $\lfloor \frac{q-2}{2} \rfloor = \lfloor \frac{q}{2} \rfloor - 1 = q - \lceil \frac{q}{2} \rceil - 1$ . Applying this,

$$\mu_q(\Delta^{(2)}) = O\left(n_1^{1-q+q-\lceil \frac{q}{2} \rceil - 1}\right) = O\left(n_1^{-\lceil \frac{q}{2} \rceil}\right)$$

This is exactly our inductive claim for the  $q^{\text{th}}$  moment. So, we can say by induction that for all  $q > 1$ ,

$$\mathbb{E} \left[ (\Delta^{(2)})^q \right] = O\left(n_1^{-\lceil \frac{q}{2} \rceil}\right)$$

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## Problem G

Use (e) and (f) to prove that

$$\log \mathbb{E} \left[ e^{itz^{(2)}(\vec{x})} \right] = -\frac{t^2}{2} K^{(2)} + \frac{t^4}{8} \mathbb{E} \left[ \left( \Delta^{(2)} \right)^2 \right] + O(n_1^{-2})$$

Conclude that

$$\kappa_4 \left( z^{(2)}(\vec{x}) \right) = \frac{3C_W^2}{n_1} \left( \langle \sigma^4(z) \rangle_{K^{(1)}} - \langle \sigma^2(z) \rangle_{K^{(1)}}^2 \right)$$

(15 points)

### Solution

**Proof.** We start by examining

$$\log \mathbb{E} \left[ e^{-\frac{t^2}{2} \Delta^{(2)}} \right] = \log \mathbb{E} \left[ \sum_{k=0}^{\infty} \frac{\left( \frac{-t^2}{2} \right)^k}{k!} \left( \Delta^{(2)} \right)^k \right] = \log \sum_{k=0}^{\infty} \frac{\left( \frac{-t^2}{2} \right)^k}{k!} \mathbb{E} \left[ \left( \Delta^{(2)} \right)^k \right]$$

We have seen from part (f) that the expectation vanishes when  $k = 1$  and has order  $O\left(n_1^{-\lceil \frac{k}{2} \rceil}\right)$  when  $k \geq 3$ . So, we can break what we have into

$$\log \left( 1 + 0 + \frac{t^4}{8} \mathbb{E} \left[ \left( \Delta^{(2)} \right)^2 \right] + \sum_{k=3}^{\infty} \frac{\left( \frac{-t^2}{2} \right)^k}{k!} \mathbb{E} \left[ \left( \Delta^{(2)} \right)^k \right] \right) = \log \left( 1 + \frac{t^4}{8} \mathbb{E} \left[ \left( \Delta^{(2)} \right)^2 \right] + \beta \right),$$

where  $\beta = \sum_{k=3}^{\infty} \frac{\left( \frac{-t^2}{2} \right)^k}{k!} \mathbb{E} \left[ \left( \Delta^{(2)} \right)^k \right] = O(n_1^{-2})$ . We can expand the function  $\log(1+x)$  about  $\beta$ , and again about 0, to see that since  $\mathbb{E} \left[ \left( \Delta^{(2)} \right)^2 \right] = O(n_1^{-1})$

$$\log \left( 1 + \frac{t^4}{8} \mathbb{E} \left[ \left( \Delta^{(2)} \right)^2 \right] + \beta \right) = \log \left( 1 + \frac{t^4}{8} \mathbb{E} \left[ \left( \Delta^{(2)} \right)^2 \right] \right) + O(n_1^{-2}) = \frac{t^4}{8} \mathbb{E} \left[ \left( \Delta^{(2)} \right)^2 \right] + O(n_1^{-2})$$

We can plug this into the result from part (e) to see

$$\log \mathbb{E} \left[ e^{itz^{(2)}(\vec{x})} \right] = -\frac{t^2}{2} K^{(2)} + \frac{t^4}{8} \mathbb{E} \left[ \left( \Delta^{(2)} \right)^2 \right] + O(n_1^{-2})$$

So, we can find the fourth cumulant to be

$$\kappa_4 \left( z^{(2)} \right) = \frac{1}{i^4} \frac{d^4}{dt^4} \Big|_{t=0} \left[ -\frac{t^2}{2} K^{(2)} + \frac{t^4}{8} \mathbb{E} \left[ \left( \Delta^{(2)} \right)^2 \right] + O(n_1^{-2}) \right] = 3 \mathbb{E} \left[ \left( \Delta^{(2)} \right)^2 \right]$$

We can observe the cuteness of this expectation via

$$\mathbb{E} \left[ \left( \Delta^{(2)} \right)^2 \right] = \mathbb{E} \left[ \left( \Sigma^{(2)} \right)^2 - 2 \mathbb{E} \left[ \Sigma^{(2)} \right] \Sigma^{(2)} + \mathbb{E} \left[ \Sigma^{(2)} \right]^2 \right] = \mathbb{E} \left[ \left( \Sigma^{(2)} \right)^2 \right] - \mathbb{E} \left[ \Sigma^{(2)} \right]^2 = \text{Var} \left[ \Sigma^{(2)} \right]$$

Returning to the definition of  $\Sigma^{(2)}$ , since all the  $z_i^{(1)}$ 's are independent

$$\begin{aligned} \mathbb{E} \left[ \left( \Delta^{(2)} \right)^2 \right] &= \text{Var} \left[ \Sigma^{(2)} \right] = \text{Var} \left[ C_b + \frac{C_W}{n_1} \sum_{i=1}^{n_1} \left( \sigma(z_i^{(1)}) \right)^2 \right] = \frac{C_W^2}{n_1^2} \sum_{i=1}^{n_1} \text{Var} \left[ \left( \sigma(z_i^{(1)}) \right)^2 \right] \\ &= \frac{C_W^2}{n_1^2} \sum_{i=1}^{n_1} \left( \langle \sigma^4(z) \rangle_{K^{(1)}} - \langle \sigma^2(z) \rangle_{K^{(1)}}^2 \right) = \frac{C_W^2}{n_1} \left( \langle \sigma^4(z) \rangle_{K^{(1)}} - \langle \sigma^2(z) \rangle_{K^{(1)}}^2 \right) \end{aligned}$$

We then evaluate the fourth cumulant to be

$$\kappa_4(z^{(2)}) = 3\mathbb{E}\left[\left(\Delta^{(2)}\right)^2\right] = \frac{3C_W^2}{n_1} \left(\langle\sigma^4(z)\rangle_{K^{(1)}} - \langle\sigma^2(z)\rangle_{K^{(1)}}^2\right)$$

■

## Problem H

Assume that  $f : \mathbb{R} \rightarrow \mathbb{R}$  is a smooth function that grows no faster than a polynomial at infinity. Show the following width refinement

$$\mathbb{E} \left[ f(z^{(2)}(\bar{x})) \right] = \langle f(z) \rangle_{K^{(2)}} + \frac{C_W^2}{8n_1} (\langle \sigma^4(z) \rangle_{K^{(1)}} - \langle \sigma^2(z) \rangle_{K^{(1)}}^2) \langle D^4 f(z) \rangle_{K^{(2)}} + O(n_1^{-2}),$$

where  $D^4$  stands for the fourth derivative. (25 points)

### Solution

**Proof.** We can say from the first result in part (g) that the cumulant generating function takes the form

$$\log \mathbb{E} \left[ e^{itz^{(2)}} \right] = -\frac{t^2}{2!} K^{(2)} + \frac{t^4}{4!} \kappa_4(z^{(2)}) + O(n_1^{-2})$$

Exponentiating,

$$\mathbb{E} \left[ e^{itz^{(2)}} \right] = e^{-\frac{t^2}{2!} K^{(2)}} \cdot e^{\frac{t^4}{4!} \kappa_4(z^{(2)}) + O(n_1^{-2})}$$

Now, consider the Fourier Transform  $F(\cdot)$  of our nice and smooth arbitrary function  $f$  such that  $f(z) = \int_{-\infty}^{\infty} F(\omega) e^{i\omega z} d\omega$ . We can write

$$\mathbb{E} \left[ f(z^{(2)}) \right] = \mathbb{E} \left[ \int_{-\infty}^{\infty} F(\omega) e^{i\omega z^{(2)}} d\omega \right] = \int_{-\infty}^{\infty} F(\omega) \mathbb{E} \left[ e^{i\omega z^{(2)}} \right] d\omega,$$

where the expectation and integral play nice because  $f$  is smooth and poly-bounded, and we can take the  $F(\omega)$  out of the expectation because the expectation is over the random variable  $z^{(2)}$ . We can recognize the form of this expectation and substitute in our earlier approximation for it to get that

$$\int_{-\infty}^{\infty} F(\omega) \mathbb{E} \left[ e^{i\omega z^{(2)}} \right] d\omega = \int_{-\infty}^{\infty} F(\omega) \cdot e^{-\frac{\omega^2}{2!} K^{(2)}} \cdot e^{\frac{\omega^4}{4!} \kappa_4(z^{(2)}) + O(n_1^{-2})} d\omega$$

Recognizing from part (a) that  $e^{-\frac{\omega^2}{2} K^{(2)}}$  is the expectation  $\mathbb{E} \left[ e^{i\omega x} \right]$  over a random variable  $x \sim \mathcal{N}(0, K^{(2)})$ ,

$$= \int_{-\infty}^{\infty} F(\omega) \cdot \langle e^{i\omega z} \rangle_{K^{(2)}} \cdot e^{\frac{\omega^4}{4!} \kappa_4(z^{(2)}) + O(n_1^{-2})} d\omega$$

We can Taylor expand the exponential to see that

$$e^{\frac{\omega^4}{4!} \kappa_4(z^{(2)}) + O(n_1^{-2})} = 1 + \left( \frac{\omega^4}{4!} \kappa_4(z^{(2)}) + O(n_1^{-2}) \right) + \frac{1}{2!} \left( \frac{\omega^4}{4!} \kappa_4(z^{(2)}) + O(n_1^{-2}) \right)^2 + \dots$$

Now, we know that  $\kappa_4(z^{(2)})$  is of order  $O(n_1^{-1})$ , and so any power  $q > 1$  will have  $\left( \frac{\omega^4}{4!} \kappa_4(z^{(2)}) + O(n_1^{-2}) \right)^q$  on the order of  $O(n_1^{-2})$ . Therefore, the exponential reduces to  $1 + \frac{\omega^4}{4!} \kappa_4(z^{(2)}) + O(n_1^{-2})$ , and so

$$\begin{aligned} \mathbb{E} \left[ f(z^{(2)}) \right] &= \int_{-\infty}^{\infty} F(\omega) \cdot \langle e^{i\omega z} \rangle_{K^{(2)}} \cdot \left( 1 + \frac{\omega^4}{4!} \kappa_4(z^{(2)}) + O(n_1^{-2}) \right) d\omega \\ &= \int_{-\infty}^{\infty} F(\omega) \cdot \langle e^{i\omega z} \rangle_{K^{(2)}} d\omega + \int_{-\infty}^{\infty} F(\omega) \cdot \omega^4 \cdot \langle e^{i\omega z} \rangle_{K^{(2)}} \cdot \frac{\kappa_4(z^{(2)})}{4!} d\omega + O(n_1^{-2}) \\ &= \int_{-\infty}^{\infty} \langle F(\omega) e^{i\omega z} \rangle_{K^{(2)}} d\omega + \frac{\kappa_4(z^{(2)})}{4!} \int_{-\infty}^{\infty} \langle \omega^4 F(\omega) e^{i\omega z} \rangle_{K^{(2)}} d\omega + O(n_1^{-2}) \end{aligned}$$

We use the laws of Fourier land to see that the Fourier Transform of the fourth derivative  $D^4 f(z) = f^{(4)}(z)$  is precisely equal to  $i^4 \omega^4 F(\omega) = \omega^4 F(\omega)$ , where  $F(\omega)$  is the Fourier Transform of  $f$ . This allows us swap the integrals and expectations once again and undo the Fourier Transforms, yielding:

$$\mathbb{E} \left[ f(z^{(2)}) \right] = \langle f(z) \rangle_{K^{(2)}} + \frac{\kappa_4(z^{(2)})}{4!} \langle D^4 f(z) \rangle_{K^{(2)}} + O(n_1^{-2})$$

Substituting the second result from part (g), we get our final refinement

$$\mathbb{E} \left[ f(z^{(2)}) \right] = \langle f(z) \rangle_{K^{(2)}} + \frac{C_W^2}{8n_1} \left( \langle \sigma^4(z) \rangle_{K^{(1)}} - \langle \sigma^2(z) \rangle_{K^{(1)}}^2 \right) \langle D^4 f(z) \rangle_{K^{(2)}} + O(n_1^{-2})$$

■