

The second moment method:

$$Y_{ij} = \sqrt{\frac{\lambda}{n}} x_i x_j + w_{ij}, \quad i < j$$

$$L = \frac{dP_\lambda}{dP_0} = \int e^{\sum_{i < j} \left( \sqrt{\frac{\lambda}{n}} Y_{ij} x_i x_j - \frac{\lambda}{2n} x_i^2 x_j^2 \right)} dP_0^n(x).$$

$$\mathbb{E}_0 [L^2] = \mathbb{E}_\lambda [L]$$

$$= \int \mathbb{E}_\lambda \left[ e^{\sum_{i < j} \left( \sqrt{\frac{\lambda}{n}} Y_{ij} x_i x_j - \frac{\lambda}{2n} x_i^2 x_j^2 \right)} \right] dP_0^n(x).$$

$$\left( Y_{ij} = \sqrt{\frac{\lambda}{n}} x_i x_j + w_{ij} \right)$$

$$= \int \mathbb{E} e^{\sum_{i < j} \left( \sqrt{\frac{\lambda}{n}} w_{ij} x_i x_j + \frac{\lambda}{n} x_i x_j x_i x_j - \frac{\lambda}{2n} x_i^2 x_j^2 \right)} dP_0^n(x).$$

$$= \iint e^{\sum_{i < j} \frac{\lambda}{n} x_i x_j x_i x_j} dP_0^n(x) dP_0^n(x')$$

$$= \mathbb{E}_{x, x' \sim P_0^n} \left[ e^{\frac{1}{2} \frac{\lambda}{n} \langle x, x' \rangle^2 - \frac{1}{2} \sum_{i=1}^n \frac{\lambda}{n} x_i^2 x_i'^2} \right].$$

Include diagonal terms:

$$Y_{ii} = \sqrt{\frac{\lambda}{n}} x_i^2 + w_{ii}, \quad w_{ii} \sim N(0, \sigma^2).$$

$$\Rightarrow \mathbb{E}_0 [L^2] = \mathbb{E}_{x, x' \sim P_0^n} \left[ e^{\frac{\lambda}{2n} \langle x, x' \rangle^2} \right].$$

$$= \mathbb{E}_{x, x'} \left[ e^{\frac{\lambda}{2} \left( \frac{\langle x, x' \rangle}{\sqrt{n}} \right)^2} \right].$$

$$\mathbb{E} \left( \frac{\langle x, x' \rangle}{\sqrt{n}} \right)^2 = \sigma^2$$

$$\rightarrow \mathbb{E}_g \left[ e^{\frac{\lambda}{2} \sigma^2 z^2} \right]$$

$$= \frac{1}{\sqrt{1 - \lambda \sigma^4}} \frac{1}{2}$$

•  $\langle x, x' \rangle$  to be of order  $\sqrt{n}$  whop.

• Assume  $\langle x, x' \rangle$  is  $\sigma\sqrt{n}$ -subgaussian.

$$\left( \mathbb{E} \left[ e^{\theta \langle x, x' \rangle} \right] \right) \leq e^{\frac{\sigma^2 \theta^2 n}{2}} \quad \forall \theta \in \mathbb{R}.$$

$$\begin{aligned} \text{Then } \mathbb{E} \left[ e^{\frac{\lambda}{2n} \langle x, x' \rangle^2} \right] &= \mathbb{E} \left[ e^{\sqrt{\frac{\lambda}{n}} \langle x, x' \rangle \cdot g} \right], \quad g \sim N(0, 1). \\ &\leq \mathbb{E} \left[ e^{\frac{\lambda}{2n} \sigma^2 \sigma^2 n} \right] \\ &= \mathbb{E} \left[ e^{\frac{\lambda}{2} \sigma^2} \right] \\ &= \frac{1}{\sqrt{1 - \lambda \sigma^2}}. \end{aligned}$$

$$\mathbb{E} \left[ e^{\sigma^2 g} \right] = e^{\sigma^2/2}.$$

$$\text{If } \lambda \sigma^2 < 1 \Rightarrow \mathbb{E} \left[ L^2 \right] < +\infty,$$

$$\Rightarrow \mathbb{P}_\lambda \triangleleft \mathbb{P}_0.$$

Simplify assumption to:  $\mathbb{P}_0$  is  $\sigma^2$ -subgaussian.

$$\text{If } \lambda \sigma^2 < 1 \Rightarrow \mathbb{P}_\lambda \triangleleft \mathbb{P}_0.$$

Proof relies on conditional second moment.

The event on which we condition:

Fix  $\delta > 0$ .

$$(x \sim P_0^n) \quad \mathcal{E} = \left\{ \|x\|_2 \leq \sqrt{n(1+\delta)} \right\}$$

$$P_\lambda(\mathcal{E}) \geq 1 - \varepsilon.$$

$$\mathbb{E} \left[ \|x\|_2^2 \right] = n.$$

$$P \left( \underbrace{\|x\|_2^2}_{\sum x_i^2} - n \geq \delta n \right)$$

$$\leq \frac{\mathbb{E} \left[ \left( \sum x_i^2 - n \right)^2 \right]}{\delta^2 n^2}$$

$$= \frac{\mathbb{E} \left[ \left( x_1^2 - 1 \right)^2 \right]}{\delta^2 n} \xrightarrow[n \rightarrow +\infty]{} 0.$$

$$\Rightarrow P(\mathcal{E}) \geq 1 - \frac{\varepsilon}{\delta^2 n}.$$

$$\tilde{P}_\lambda(\cdot) = P_\lambda(\cdot | \mathcal{E}).$$

$$\bullet \quad \mathbb{E}_{P_0} \left[ \tilde{L}_\lambda^2 \right] = \mathbb{E}_{\substack{x, x' \\ \sim (P_0^n)^2}} \left[ e^{\frac{\lambda}{2n} \langle x, x' \rangle^2} \mid \begin{array}{l} \|x\|_2^2 \leq (1+\delta)n \\ \|x'\|_2^2 \leq (1+\delta)n \end{array} \right]$$

$$\tilde{L}_\lambda = \frac{d\tilde{P}_\lambda}{dP_0}$$

$$\leq \mathbb{E}_{x, x'} \left[ e^{\frac{\lambda}{2n} \langle x, x' \rangle^2} \mid \|x\|_2^2 \leq (1+\delta)n \right]$$

$$= \mathbb{E}_{x, x', g} \left[ e^{\frac{\lambda}{n} \langle x, x' \rangle g} \mid \|x\|_2^2 \leq (1+\delta)n \right]$$

$$\leq \mathbb{E}_{x, g} \left[ e^{\frac{\lambda}{2n} \|x\|^2 g^2 \sigma^2} \mid \|x\|_2^2 \leq (1+\delta)n \right]$$

$$\leq \mathbb{E}_g \left[ e^{\frac{\lambda}{2n} (1+\delta)n \cdot g^2 \sigma^2} \right]$$

$$\leq \frac{1}{\sqrt{1 - (1+\delta)\lambda\sigma^2}} < +\infty$$

$\Rightarrow$  If  $(1+\delta)\lambda\sigma^2 < 1$  then  $\tilde{P}_\lambda \triangleleft P_0$ .

$$\begin{aligned} \Rightarrow P_n(A_n) &\leq \sqrt{\mathbb{E}_0[\tilde{L}_n^2] \cdot P_0(A_n)} + P_n(\mathcal{E}^c) \\ &\leq \sqrt{K \cdot P_0(A_n)} + \frac{a}{\delta n} \end{aligned}$$

$\rightarrow 0$  if  $P_0(A_n) \rightarrow 0$ .

If  $\lambda\sigma^2 < 1$  then  $IP_\lambda \triangleleft P_0$ .

$$\mathbb{E} \left[ f(\langle x, x' \rangle^2) \mid \|x\|_2^2 \leq n(1+\delta) \right]$$

$$\mathbb{E} \left[ \text{---} \mid \text{---}, \|x'\|_2^2 \leq n(1+\delta) \right]$$

$$\mathbb{P}(\|x'\|_2^2 \leq n(1+\delta))$$

$$+ \mathbb{E} \left[ \text{---} \mid \text{---}, \|x'\|_2^2 > n(1+\delta) \right]$$

$$\cdot \mathbb{P}(\|x'\|_2^2 > n(1+\delta))$$

$$\frac{a}{\delta^2 n}$$

$$\tilde{\mathbb{P}}_\lambda (y | \varepsilon) \quad \varepsilon = \left\{ \|\mathbf{x}\|_2^2 \leq n(1+\varepsilon) \right\} \\ y = \sqrt{\frac{n}{4}} \lambda \mathbf{x}^T + w$$

Second moment method implies contiguity for all  $\lambda < \frac{1}{\sigma^2}$ ,  $\sigma^2$ : subgaussian constant of the prior.

• For Rademacher:  $\sigma^2 = 1$

$\mathbb{P}_\lambda \ll \mathbb{P}_0$  for all  $\lambda < 1$ .

$\lambda > 1$ : detection is possible.

Second is tight for sharp subgaussian priors:

sharp subgaussian:  $\sigma^2 = \text{variance} = 1$ .  
 $\sigma^2 \geq \text{variance}$ .

• Sparse Rademacher:  $\mathbb{P}_0 = \frac{p}{2} \delta_{+\frac{1}{p}} + (1-p) \delta_0 + \frac{p}{2} \delta_{-\frac{1}{p}}$ .

Lemma (PBWM 2010):

If  $p \geq \frac{1}{13}$  then  $\sigma^2 = 1$

If  $p < \frac{1}{13}$  then  $\sigma^2 > 1$ .

$$\sigma^2 = \sup_{t \in \mathbb{R}} \left\{ \frac{2}{t^2} \log \left( 1 - p^2 + \frac{p^2}{2} e^{t/p} + \frac{p^2}{2} e^{-t/p} \right) \right\}$$

$\Rightarrow$  contiguity up to  $1/\sigma^2$ .

By simulation one sees  $\frac{1}{\sigma^2} < \lambda_c$  for  $\rho < \frac{1}{\sqrt{3}}$ .  
 sharper results?

- Fluctuations of likelihood ratio.

Le Cam's first lemma:

1. If  $\frac{dP_n}{dQ_n} \xrightarrow{d} e^{N(\mu, \sigma^2)}$  under  $Q_n$ ,  $\mu = -\frac{1}{2}\sigma^2$ .

then  $P_n \triangleleft\triangleleft Q_n$ .

2. If  $\frac{dP_n}{dQ_n} \xrightarrow{d} e^{N(\mu, \sigma^2)}$  under  $P_n$ ,  $\mu = \frac{1}{2}\sigma^2$ .

then  $P_n \triangleleft\triangleleft Q_n$ .

$U = e^Z$ ,  $Z \sim N(\mu, \sigma^2)$ .

$E U = e^{\mu + \frac{\sigma^2}{2}} = 1$  if  $\mu = -\frac{\sigma^2}{2}$ .

- Theorem: for  $\lambda < \lambda_c$ ,  $P_\lambda$ : centered, unit var, bounded.

$\log L \xrightarrow{d} N(\pm\mu, \sigma^2)$

$\mu = \frac{1}{4}(-\log(1-\lambda) - \lambda)$ .

$\sigma^2 = \frac{1}{2}(-\log(1-\lambda) - \lambda)$ .

"+" is under  $P_\lambda$ , "-" is under  $P_0$ .

$\Rightarrow$  Implies continuity up to  $\lambda_c$ .

• The characteristic function of  $\log L$ :

$$\phi_n(s) = \mathbb{E}_{P_\lambda} [e^{is \log L}]$$

Proposition:  $\forall \lambda < \lambda_c, \forall s \in \mathbb{R}, \exists K > 0,$

$$|\phi_n(s) - e^{(is - s^2)\mu}| \leq \frac{K}{\sqrt{n}}$$

$s \rightarrow e^{(is - s^2)\mu}$  is the characteristic fct of  $N(\mu, \sigma^2)$   
 $\mu = \frac{1}{2} \sigma^2$ .

• Corollaries of Proof: If  $\lambda < \lambda_c$

$$\left. \begin{array}{l} d_{KL}(P_\lambda, P_0) \xrightarrow{n \rightarrow +\infty} \mu \\ d_{TV}(P_\lambda, P_0) \longrightarrow 1 - \operatorname{erfc}(\sqrt{\mu}) \end{array} \right\}$$

$$\mu = \frac{1}{4} (-\log(1-\lambda) - \lambda)$$

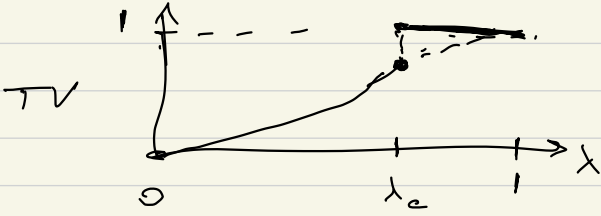
$$\frac{1}{n} d_{KL}(P_\lambda, P_0) \rightarrow \phi_{\mathbb{R}^2}(\lambda)$$

$$\left( \begin{array}{l} \text{If } \lambda > \lambda_c : d_{KL}(P_\lambda, P_0) = \Theta(n) \\ \text{If } \lambda < \lambda_c : d_{KL}(P_\lambda, P_0) = o(n) \end{array} \right)$$

$$\operatorname{erfc}(x) = \frac{2}{\sqrt{\pi}} \int_x^{+\infty} e^{-t^2} dt$$



if  $\lambda_c = 1$



if  $\lambda_c < 1$