

1) (a) Arbitrary Gaussian:

$$N(w | \mu_N, \Sigma_N) = (2\pi)^d \cdot |\Sigma_N|^{-\frac{1}{2}} \cdot \exp\left(-\frac{1}{2} \cdot (w - \mu_N)^T \Sigma_N^{-1} \cdot (w - \mu_N)\right)$$

$$\Rightarrow \text{exp. term} = -\frac{1}{2} \cdot (w - \mu_N)^T \Sigma_N^{-1} \cdot (w - \mu_N)$$

$$= \underbrace{-\frac{1}{2} \cdot w^T \Sigma_N^{-1} \cdot w}_{\text{"quadratic term in } w"} - \underbrace{\mu_N^T \Sigma_N^{-1} \cdot w}_{\text{"linear term in } w"} + \text{const}$$

(2) Posterior Distribution:

$$\bullet p(z | X, w, \beta) = \prod_{n=1}^N N(z_n | w^T \phi(x_n), \beta^{-1}) \quad (\text{Likelihood})$$

$$\bullet p(w | \alpha) = N(w | 0, \alpha^{-1} I) \quad (\text{Prior})$$

$$\Rightarrow \text{exp. term (of posterior)} = \sum_{n=1}^N -\frac{1}{2} \cdot (z_n - w^T \phi(x_n))^T \cdot \beta \cdot (z_n - w^T \phi(x_n)) - \frac{1}{2} \cdot (w - 0)^T \cdot \alpha \cdot I \cdot (w - 0)$$

$$= -\frac{\beta}{2} \cdot \sum_{n=1}^N (z_n - w^T \phi(x_n))^2 - \frac{\alpha}{2} \cdot w^T \cdot w$$

$$= -\frac{\beta}{2} \cdot \sum_{n=1}^N (z_n^2 - 2z_n w^T \phi(x_n) + w^T \phi(x_n) \cdot \phi(x_n)^T w) - \frac{\alpha}{2} w^T \cdot w$$

$$= -\frac{1}{2} w^T \cdot \left(\sum_{n=1}^N \beta \cdot \phi(x_n) \cdot \phi(x_n)^T + \alpha \cdot I \right) \cdot w$$

$$- \sum_{n=1}^N \beta \cdot z_n \cdot \phi(x_n)^T \cdot w + \text{const}$$

Compare quadratic and linear terms of (1) and (2):

$$\bullet \Sigma_N^{-1} \stackrel{!!}{=} \sum_{n=1}^N \beta \cdot \phi(x_n) \cdot \phi(x_n)^T + \alpha \cdot I = \beta \cdot \Phi^T \cdot \Phi + \alpha \cdot I$$

$$\bullet \mu_N^T \cdot \Sigma_N^{-1} \stackrel{!!}{=} \sum_{n=1}^N \beta \cdot z_n \cdot \phi(x_n)^T = \beta \cdot z^T \cdot \Phi$$

$$\Rightarrow \mu_N = \beta \cdot \Sigma_N^{-1} \cdot \Phi^T \cdot z$$

$$(b) \cdot p(t_{n+1} | x_{n+1}, w, \beta) = \mathcal{N}(t_{n+1} | w^T \cdot \phi(x_{n+1}), \beta^{-1}) \quad (\text{Likelihood})$$

$$\cdot p(w | X, t, \beta, \alpha) = \mathcal{N}(w | \mu_N, \Sigma_N) \quad (\text{Prior})$$

$$\Rightarrow \text{exp. term (of posterior)} = -\frac{1}{2} \cdot \beta \cdot (t_{n+1} - w^T \cdot \phi(x_{n+1}))^2 - \frac{1}{2} \cdot (w - \mu_N)^T \cdot \Sigma_N^{-1} \cdot (w - \mu_N)$$

$$= -\frac{1}{2} \cdot w^T \cdot \underbrace{\left[\Sigma_N^{-1} + \beta \cdot \phi(x_{n+1}) \cdot \phi(x_{n+1})^T \right]}_{= \Sigma_{N+1}^{-1}} \cdot w$$

$$- \underbrace{\left[\beta \cdot \phi(x_{n+1}) \cdot t_{n+1} + \mu_N^T \cdot \Sigma_N^{-1} \right]}_{(1)} \cdot w + \text{const}$$

$$\stackrel{(1)}{=} \mu_{N+1}^T \cdot \Sigma_{N+1}^{-1} \Rightarrow \mu_{N+1} = \beta \cdot \Sigma_{N+1}^{-1} \cdot \Phi^T \cdot t$$

$$2) \mathbb{E}[L_q] = \int_{\mathbb{R}^d} \int_{\mathbb{R}} |y(x) - z|^{1/q} \cdot p(x, z) dz dx$$

$$= \int_{\mathbb{R}^d} p(x) \cdot \left[\int_{\mathbb{R}} |y(x) - z|^{1/q} \cdot p(z|x) dz \right] dx$$

\Rightarrow For every $x \in \mathbb{R}^d$, choose $\hat{y} := y(x) \in \mathbb{R}$, such that

$$F_q(\hat{y}|x) := \int_{\mathbb{R}} |\hat{y} - z|^{1/q} \cdot p(z|x) dz \rightarrow \min$$

(a) For $q=1$, this gives

$$y(x) := \operatorname{argmin}_{\hat{y} \in \mathbb{R}} (F_q(\hat{y}|x))$$

(b) Assumption: $p(\cdot|x)$ is uniformly continuous:

• Fix $0 < \varepsilon < 1$:

$$\Rightarrow \exists 0 < \delta = \delta(\varepsilon) < 1 : \forall \hat{y} \in \mathbb{R}, z \in U_\delta(0) : |p(\hat{y}+z|x) - p(\hat{y}|x)| < \varepsilon$$

• Consider

$$\begin{aligned} F_q(\hat{y}|x) &= \int_{\mathbb{R}} |\hat{y} - z|^{1/q} \cdot p(z|x) dz = \int_{\mathbb{R}} |z|^{1/q} \cdot p(\hat{y}+z|x) dz \\ &= \underbrace{\int_{\mathbb{R} \setminus U_\delta(0)} |z|^{1/q} \cdot p(\hat{y}+z|x) dz}_{\downarrow} + \int_{U_\delta(0)} |z|^{1/q} \cdot p(\hat{y}+z|x) dz \end{aligned}$$

Choose $0 < q = q(\delta) < 1$:

$$\left| \int_{\mathbb{R} \setminus U_\delta(0)} |z|^{1/q} \cdot p(\hat{y}+z|x) dz - \int_{\mathbb{R} \setminus U_\delta(0)} p(\hat{y}+z|x) dz \right| < \varepsilon$$

$$\Rightarrow \int_{\mathbb{R} \setminus U_\delta(0)} |z|^{1/q} \cdot p(\hat{y}+z|x) dz = \int_{\mathbb{R} \setminus U_\delta(0)} p(\hat{y}+z|x) dz + O(\varepsilon)$$

$$= \int_{\mathbb{R} \setminus \mathcal{U}_\delta(0)} p(\hat{y} + \varepsilon | x) d\varepsilon + \int_{\mathcal{U}_\delta(0)} \varepsilon^{1^q} \cdot p(\hat{y} + \varepsilon | x) d\varepsilon + \mathcal{O}(\varepsilon)$$

$$= \underbrace{\int_{\mathbb{R}} p(\hat{y} + \varepsilon | x) d\varepsilon}_{=1} - \underbrace{\int_{\mathcal{U}_\delta(0)} (1 - \varepsilon^{1^q}) \cdot p(\hat{y} + \varepsilon | x) d\varepsilon}_{\downarrow} + \mathcal{O}(\varepsilon)$$

$$\left| \int_{\mathcal{U}_\delta(0)} (1 - \varepsilon^{1^q}) \cdot p(\hat{y} + \varepsilon | x) d\varepsilon - \int_{\mathcal{U}_\delta(0)} (1 - \varepsilon^{1^q}) \cdot p(\hat{y} | x) d\varepsilon \right|$$

$$= \left| \int_{\mathcal{U}_\delta(0)} (1 - \varepsilon^{1^q}) \cdot [p(\hat{y} + \varepsilon | x) - p(\hat{y} | x)] d\varepsilon \right|$$

$$\leq \int_{\mathcal{U}_\delta(0)} (1 - \varepsilon^{1^q}) \cdot \underbrace{|p(\hat{y} + \varepsilon | x) - p(\hat{y} | x)|}_{< \varepsilon \text{ by uniform continuity}} d\varepsilon$$

$$< \varepsilon \cdot \int_{\mathcal{U}_\delta(0)} 1 - \varepsilon^{1^q} d\varepsilon = \mathcal{O}(\varepsilon)$$

$$\Rightarrow \int_{\mathcal{U}_\delta(0)} (1 - \varepsilon^{1^q}) \cdot p(\hat{y} + \varepsilon | x) d\varepsilon = \int_{\mathcal{U}_\delta(0)} (1 - \varepsilon^{1^q}) \cdot p(\hat{y} | x) d\varepsilon + \mathcal{O}(\varepsilon)$$

$$= \left(\int_{\mathcal{U}_\delta(0)} 1 - \varepsilon^{1^q} d\varepsilon \right) \cdot p(\hat{y} | x) + \mathcal{O}(\varepsilon)$$

$$= 1 - \underbrace{\left(\int_{\mathcal{U}_\delta(0)} 1 - \varepsilon^{1^q} d\varepsilon \right)}_{>0} \cdot p(\hat{y} | x) + \mathcal{O}(\varepsilon)$$

$$\Rightarrow \arg \min_{\hat{y} \in \mathbb{R}} (F_q(\hat{y} | x)) = \arg \max_{\hat{y} \in \mathbb{R}} (p(\hat{y} | x)) =: y(x)$$