

$$\sum_{n=1}^N (y_n - \bar{w}^T \bar{x}_n)^2 + \frac{\lambda}{2} \|\bar{w}\|_2^2 \xrightarrow{\bar{w}} \min$$

regularizer

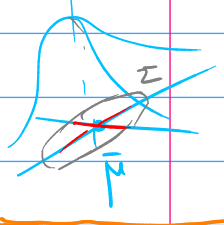
$$(\bar{y} - X\bar{w})^T (\bar{y} - X\bar{w}) + \frac{\lambda}{2} \bar{w}^T \bar{w} \rightarrow \min$$

$$-X^T \bar{y} + (X^T X + \lambda I) \bar{w} = 0 \stackrel{\lambda \bar{w}}{=} \bar{w}$$

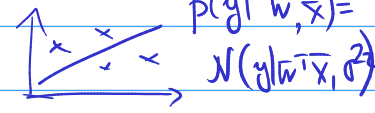
$$\bar{w}^* = (X^T X + \lambda I)^{-1} X^T \bar{y}$$

$$-\frac{1}{2} (\bar{w} - \bar{\mu})^T \Sigma^{-1} (\bar{w} - \bar{\mu})$$

$$= \text{const} - \ln e^{-\frac{\lambda}{2} \bar{w}^T \bar{w}} = \text{const} + \ln \mathcal{N}(\bar{w} | \bar{0}, \frac{1}{\lambda} I)$$



$$p(\bar{w} | D) \propto p(\bar{w}) p(D | \bar{w}) = \prod_{n=1}^N \mathcal{N}(y_n | \bar{w}^T \bar{x}_n, \sigma^2)$$



$$p(\bar{x} | \bar{\mu}, \Sigma) = \frac{1}{(2\pi)^{d/2} \cdot \sqrt{\det \Sigma}} e^{-\frac{1}{2} (\bar{x} - \bar{\mu})^T \Sigma^{-1} (\bar{x} - \bar{\mu})}$$

$$y \sim \bar{w}^T \bar{x}$$

$$p(D | \bar{w}) \xrightarrow{\bar{w}} \max \quad \bar{w}_{ML} = (X^T X)^{-1} X^T \bar{y}$$

$$\ln p(\bar{w} | D) = \text{const} + \ln p(D | \bar{w}) + \ln p(\bar{w}) =$$

$$= \text{const} - \frac{N}{2} \ln(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{n=1}^N (y_n - \bar{w}^T \bar{x}_n)^2 - \frac{d}{2} \ln 2\pi - \frac{1}{2} \ln \det \Sigma -$$

$$- \frac{1}{2} (\bar{w} - \bar{\mu})^T \Sigma^{-1} (\bar{w} - \bar{\mu})$$

$$= \text{const} - \frac{1}{2\sigma^2} (\bar{y} - X\bar{w})^T (\bar{y} - X\bar{w}) - \frac{1}{2} (\bar{w} - \bar{\mu})^T \Sigma^{-1} (\bar{w} - \bar{\mu}) =$$

$$= \text{const} - \frac{1}{2\sigma^2} (\bar{y}^T \bar{y} - 2\bar{w}^T (X^T \bar{y}) + \bar{w}^T X^T X \bar{w}) - \frac{1}{2} (\bar{w}^T \Sigma^{-1} \bar{w} - 2\bar{w}^T (\Sigma^{-1} \bar{\mu}) + \bar{\mu}^T \Sigma^{-1} \bar{\mu})$$

$$= \text{const} - \frac{1}{2} \bar{w}^T \left(\frac{1}{\sigma^2} X^T X + \Sigma^{-1} \right) \bar{w} + \bar{w}^T \left(\frac{1}{\sigma^2} X^T \bar{y} + \Sigma^{-1} \bar{\mu} \right)$$

$$\mu', \Sigma'$$

$$\ln p(\bar{w} | D) = \text{const} - \frac{1}{2} (\bar{w} - \bar{\mu}')^T \Sigma'^{-1} (\bar{w} - \bar{\mu}') = \text{const} - \frac{1}{2} \bar{w}^T \Sigma'^{-1} \bar{w} + \bar{w}^T (\Sigma'^{-1} \bar{\mu}')$$

$$\left\{ \begin{aligned} \Sigma'^{-1} &= \Sigma^{-1} + \frac{1}{\sigma^2} X^T X \\ \bar{\mu}' &= \Sigma' \cdot \left(\Sigma^{-1} \bar{\mu} + \frac{1}{\sigma^2} X^T \bar{y} \right) \end{aligned} \right.$$

$$p(\bar{w} | D) = \mathcal{N}(\bar{w} | \bar{\mu}', \Sigma')$$

$$p(\bar{w}) = \mathcal{N}(\bar{w} | \bar{0}, \sigma_0^2 I)$$

$$\Sigma' = \frac{1}{\sigma_0^2} I + \frac{1}{\sigma^2} X^T X$$

$$\bar{\mu}' = \left(\lambda I + \frac{1}{\sigma^2} X^T X \right)^{-1} \frac{1}{\sigma^2} X^T \bar{y}$$

$$= \left(\frac{\lambda}{\sigma_0^2} I + X^T X \right)^{-1} \cdot X^T \bar{y}$$

$$D = \{X, \bar{y}\}$$

$$D' = \{X', \bar{y}'\}$$

$$\bar{w}_{MAP} = \text{argmax} p(\bar{w} | D) = \bar{\mu}'$$

$$\phi(\bar{w} | D) \propto p(\bar{w}) p(D | \bar{w})$$

$\leftarrow N(\bar{w} | 0, \sigma^2 I)$

ridge

$$\sum (-)^2 + \frac{\lambda}{2} \|w\|_2^2 \rightarrow \min$$

lasso

$$\sum_n (y_n - \bar{w}^T \bar{x}_n)^2 + \frac{\lambda}{2} \|\bar{w}\|_2^2 \rightarrow \min$$

$$\sum_n (y_n - \bar{w}^T \bar{x}_n)^2 \xrightarrow{\bar{w}} \min, \quad \|\bar{w}\|_2^2 \leq a$$

$$\sum (-)^2 + \frac{\lambda}{2} \sum |w_i| \rightarrow \min$$

$$p(\bar{w}) \propto e^{-\alpha \sum |w_i|}$$

$$\sum |w_i| \leq a$$

