

$$z^T z = \sum_i z_i^2$$

$$X\theta - \bar{y} = \uparrow$$

$$\downarrow$$

	x	$x\theta$	$x\theta$
	1 2 3	9	$\begin{pmatrix} h(x_1) \\ h(x_2) \end{pmatrix}$
	4 5 6	10	
		11	

$$(X\theta - \bar{y}) \quad \begin{pmatrix} 5 \\ 6 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} = \begin{pmatrix} 5 \\ 6 \end{pmatrix}$$

$$\begin{pmatrix} 5 & 6 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} = \begin{pmatrix} 5 & 6 \end{pmatrix}$$

$$\frac{1}{2} \sum_{i=1}^m \frac{1}{2} w_i (\theta^T x^{(i)} - y^{(i)})^2 = \sum_{i=1}^m (h_\theta(x^{(i)}) - y^{(i)}) \times \frac{1}{2} w_i (h_\theta(x^{(i)}) - y^{(i)})$$

$$\uparrow$$

$$h_\theta(x^{(i)}) - y^{(i)}$$

\nearrow

$$A = \theta^T \quad B = X^T$$

$$C = 0$$

$$(\theta^T X - \bar{y})^T (\theta^T X - \bar{y}) = \sum_{i=1}^m (\theta^T x^{(i)} - y^{(i)})^2$$

$$\begin{pmatrix} 1 & 2 \\ 3 & 4 \\ 5 & 6 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} =$$

$$X\theta\theta$$

\Rightarrow

$$\text{and } \sum a_i x_i x_i =$$

$$= \begin{pmatrix} a_1 & a_2 \end{pmatrix} X^T X$$

$$(X\theta - \bar{y})^T \times W \times (X\theta - \bar{y})$$

$$W = \begin{pmatrix} \frac{w_1}{2} & & \\ & \frac{w_2}{2} & \\ & & \ddots \\ & & & \frac{w_m}{2} \end{pmatrix}$$

$$((h(x_1) - y_1) \times w_1, (h(x_2) - y_2) \times w_2, \dots)$$

$$\nabla_{\theta} \text{tr } \theta^T X^T X \theta^T I =$$

$$\nabla_A \text{tr } AB = B^T$$

$$X^T X \theta + X^T X \theta$$

2b)

$$\nabla_{\theta} (X\theta - \bar{y})^T W (X\theta - \bar{y}) =$$

$$= (\theta^T X^T W - \bar{y}^T W) (X\theta - \bar{y})$$

$$= \theta^T X^T W X \theta - \theta^T X^T W \bar{y} - \bar{y}^T W X \theta + \bar{y}^T W \bar{y}$$

$$= \nabla_{\theta} \text{tr} (\theta^T X^T W X \theta - \theta^T X^T W \bar{y} - \bar{y}^T W X \theta + \bar{y}^T W \bar{y}) (X\theta^T)$$

$$= \nabla_{\theta} \text{tr} \theta^T X^T W X \theta - 2 \text{tr} \bar{y}^T W X \theta$$

$$- 2 X^T W \bar{y}$$

$$\text{tr } \theta^T X^T W \bar{y}$$

$$\text{tr } \bar{y}^T W X \theta$$

$$= (\theta^T X^T W \bar{y})^T$$

$$= \bar{y}^T W^T X \theta$$

$W = W^T$
(W = diagonal
and quadratic)

$$A^T = \theta$$

$$B = X^T W X$$

$$A = \theta^T$$

$$C = I$$

$$\Rightarrow X^T W^T X \theta + X^T W X \theta - 2 X^T W \bar{y}$$

$$= 2 X^T W X \theta - 2 X^T W \bar{y}$$

$$\Rightarrow X^T W X \theta = X^T W \bar{y}$$

$$\Rightarrow \theta = (X^T W X)^{-1} X^T W \bar{y}$$

$$\nabla_A \text{tr } AB = B^T$$

2c)

$$L(\theta) = L(\theta; X, \bar{y}) = p(\bar{y} | X, \theta)$$

$$L(\theta) = \prod_{i=1}^m p(y^{(i)} | x^{(i)}; \theta, \sigma^2)$$

$$= \prod_{i=1}^m \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(y^{(i)} - \theta^T x^{(i)})^2}{2\sigma^2}\right)$$

\Rightarrow

$$\ell(\theta) = \log L(\theta)$$

$$= \log \prod_{i=1}^m \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(y^{(i)} - \theta^T x^{(i)})^2}{2\sigma^2}\right)$$

$$= \sum_{i=1}^m \left(\log \frac{1}{\sqrt{2\pi}\sigma} - \frac{(y^{(i)} - \theta^T x^{(i)})^2}{2\sigma^2} \right)$$

$$= \cancel{m \log} \sum_{i=1}^m \log \frac{1}{\sqrt{2\pi}\sigma} - \sum_{i=1}^m \frac{(y^{(i)} - \theta^T x^{(i)})^2}{2\sigma^2}$$

\nearrow max: likelihood

Const \Rightarrow doesn't matter to minimize

$$\Rightarrow \min \frac{1}{2} \sum_{i=1}^m \frac{(y^{(i)} - \theta^T x^{(i)})^2}{\sigma^2}$$

Weighted (in reg) $\sum_{i=1}^m w^{(i)} (y^{(i)} - \theta^T x^{(i)})^2$
(from lecture notes)

$$\Rightarrow w_i = \frac{1}{\sigma^2} \quad \forall i \in \{1, \dots, m\}$$