

Q2.1

$$J(\theta) = \frac{1}{2} \sum_{i=1}^m w^{(i)} (\theta^T x^{(i)} - y^{(i)})^2$$

$$= \frac{1}{2} \sum_{i=1}^m (\sqrt{w^{(i)}} \cdot \theta^T x^{(i)} - \sqrt{w^{(i)}} y^{(i)})^2$$

Because $\sum_i A_i^2 = A^T A$

$$= \frac{1}{2} (W^{\frac{1}{2}} X \theta - W^{\frac{1}{2}} y)^T (W^{\frac{1}{2}} X \theta - W^{\frac{1}{2}} y)$$

$$= \frac{1}{2} (\theta^T X^T W^{\frac{1}{2}T} - y^T W^{\frac{1}{2}T}) (W^{\frac{1}{2}} X \theta - W^{\frac{1}{2}} y)$$

Because $W^{\frac{1}{2}T} W^{\frac{1}{2}} = W$

$$= \frac{1}{2} (\theta^T X^T W X \theta - \theta^T X^T W y - y^T W X \theta + y^T W y)$$

$$= \frac{1}{2} [\theta^T X^T W (X \theta - y) - y^T W (X \theta - y)]$$

$$= \frac{1}{2} (\theta^T X^T - y^T) W (X \theta - y)$$

$$= \frac{1}{2} (X \theta - y)^T W (X \theta - y)$$

W is a $m \times m$ diagonal matrix $\begin{bmatrix} w_1 & & 0 \\ & w_2 & \\ 0 & & \ddots \\ & & & w_m \end{bmatrix}$ with m diagonal terms that represent weighting terms for (non-negative) least square error of each training data.