

$$\text{loss}(y, \hat{y}) = (y - \hat{y})^T (y - \hat{y})$$

ℓ_2 -regularization

$$= (y - X \cdot w)^T (y - X \cdot w) + \underline{\lambda w^T \cdot w}$$

$$\frac{\partial \text{loss}}{\partial w} = -2 \cdot X^T \cdot (y - X \cdot w) + 2 \cdot \lambda \cdot w$$

$$-2 X^T \cdot y + \cancel{2 X^T X} \cdot w + \cancel{2 \cdot \lambda} w = 0$$

$$(X^T X + \lambda I)^{-1} (X^T X + \lambda I) \cdot w = \overset{\uparrow}{X^T \cdot y}$$

$(X^T X + \lambda I)^{-1}$

No Regularization

$$w^* = (X^T X)^{-1} X^T y$$

$$X = \begin{bmatrix} | & | \end{bmatrix}$$

l_2 -regularization with λ parameter.

ridge or
Tikhonov
regularization.

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

$\lambda \uparrow \quad w \downarrow$

$$\begin{bmatrix} \\ \\ \end{bmatrix}_{D \times D} + \begin{bmatrix} \lambda & & 0 \\ & \lambda & \\ 0 & & \ddots & \lambda \end{bmatrix}_{D \times D}$$

$$\text{loss}(y, \hat{y}) + \underbrace{\lambda \sum_{d=1}^D |w_d|}_{L_1 \text{- regularization}}$$

L_1 -regularization.

$$l_{\textcircled{p}\text{-norm}} = \left[\sum_{d=1}^D (|w_d|)^p \right]^{1/p}$$

$\downarrow 4/3$

$$\underline{\underline{p=2}}$$

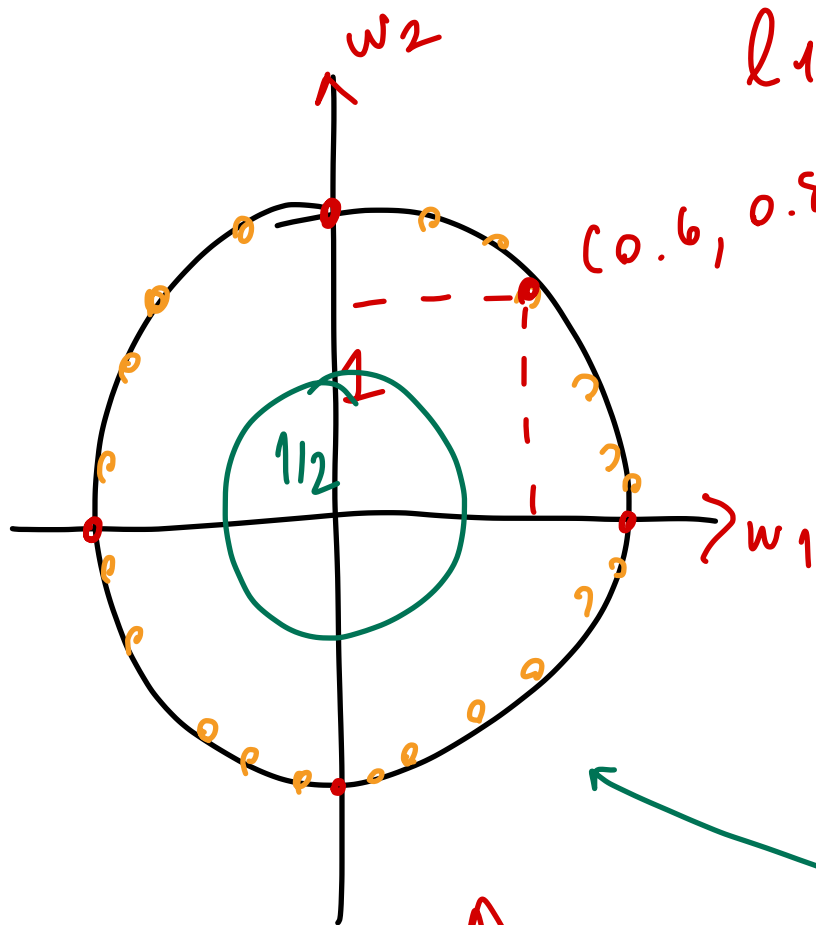
\Rightarrow

$$\sqrt{w_1^2 + w_2^2 + \dots + w_D^2}$$

$$p=1$$

\Rightarrow

$$|w_1| + |w_2| + \dots + |w_D|$$

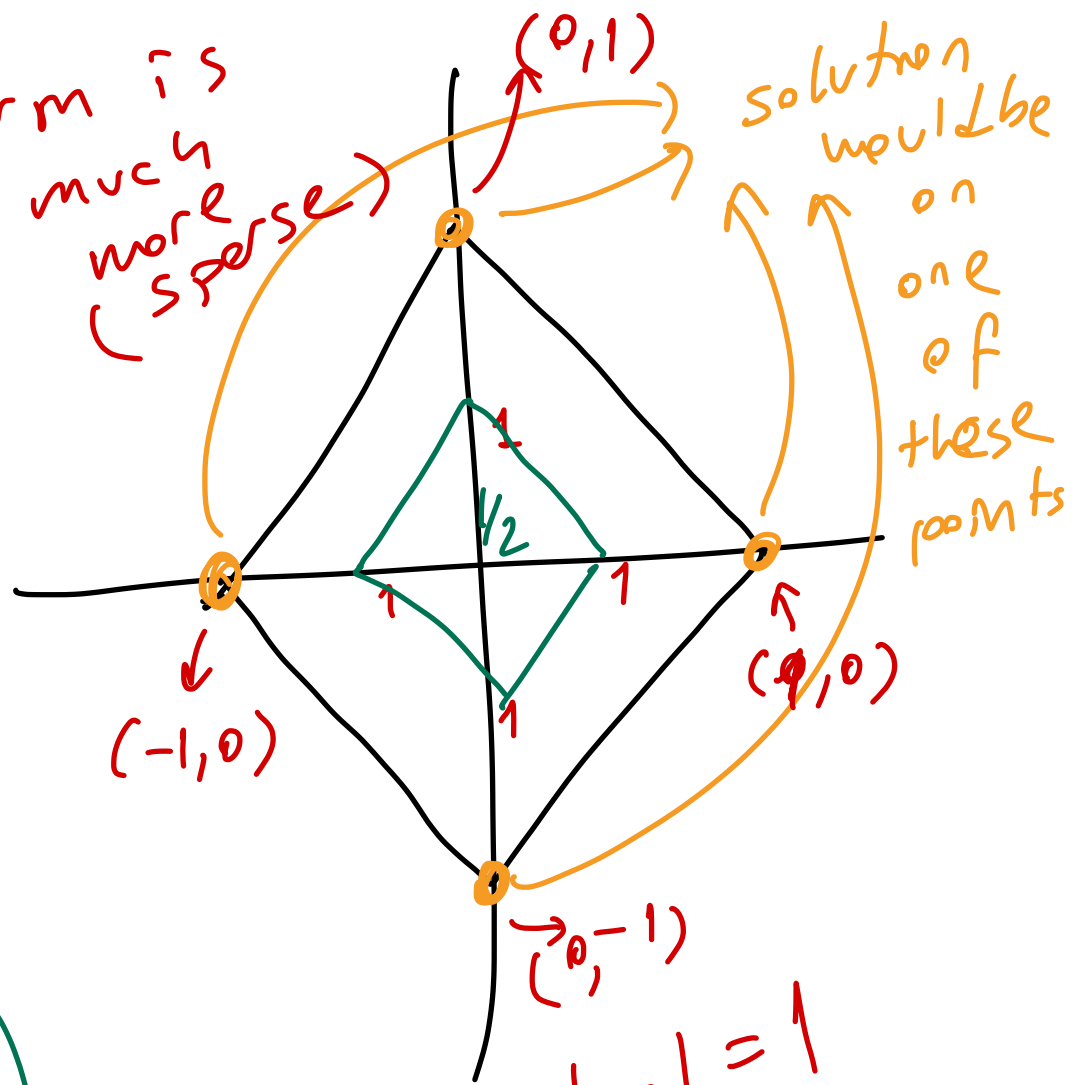


$$w_1^2 + w_2^2 = 1$$

$$w_1^2 + w_2^2 = 1/4$$

$(0.6, 0.8)$

l_1 norm is much more sparse



$$|w_1| + |w_2| = 1$$

$$|w_1| + |w_2| = 1/2$$

solution would be on one of these points