

# Hinge Loss for Binary Classifiers

# Objectives

- introduce disadvantage of squared error for classification
- introduce hinge loss cost function
- characteristics of hinge loss

Squared error "loss" can be problematic 2

Classifier design

$$\min_{\underline{w}} l(\underline{w}; \underline{A}, \underline{d}) + \lambda r(\underline{w}) \leftarrow \begin{array}{l} \text{regularizer} \\ \text{loss function} \end{array}$$

Squared error loss  $ll(\underline{w}; \underline{A}, \underline{d}) = \|\underline{A}\underline{w} - \underline{d}\|_2^2$

Example: dwarf planet vs. planet

object	Ceres	Eris	Pluto	Mercury	Earth	Jupiter
$x_i$ radius ( $\times 10^6$ m)	1.0	2.3	2.4	4.9	12.8	143.0
$d_i$ label	-1	-1	-1	1	1	1

$$\underline{A} = \begin{bmatrix} 1 & 1 \\ 2.3 & 1 \\ 2.4 & 1 \\ 4.9 & 1 \\ 12.8 & 1 \\ 143 & 1 \end{bmatrix}, \underline{d} = \begin{bmatrix} -1 \\ -1 \\ -1 \\ -1 \\ 1 \\ 1 \end{bmatrix}$$

$$\underline{w}_{LS} = (\underline{A}^T \underline{A})^{-1} \underline{A}^T \underline{d}$$

$$\approx 0.01 \begin{bmatrix} 1 \\ -28 \end{bmatrix}$$

dwarf:  $x_i < 28$  (earth!)  
planet:  $x_i \geq 28$

squared error  $\rightarrow$  poor classification

# Avoid loss due to "easy-to-classify" data

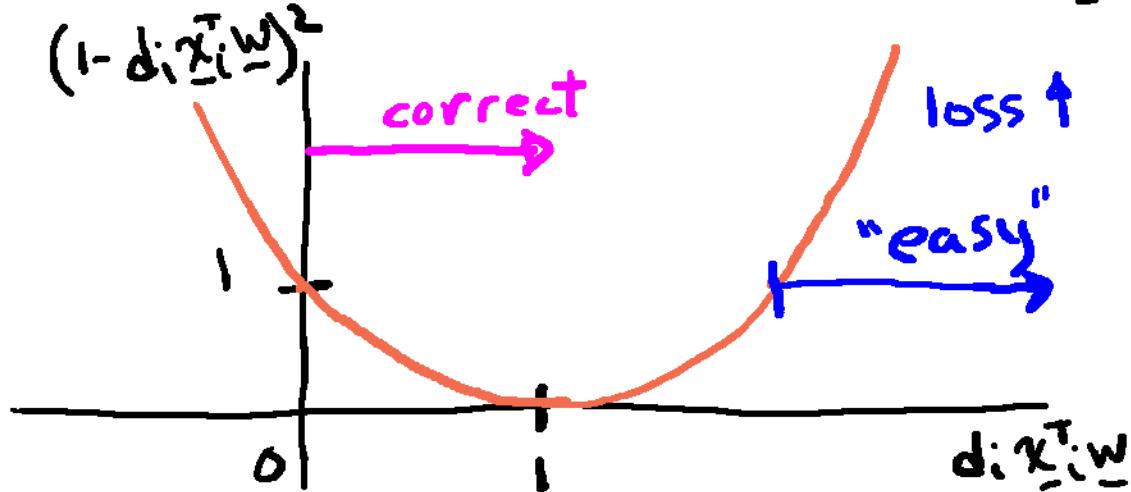
3



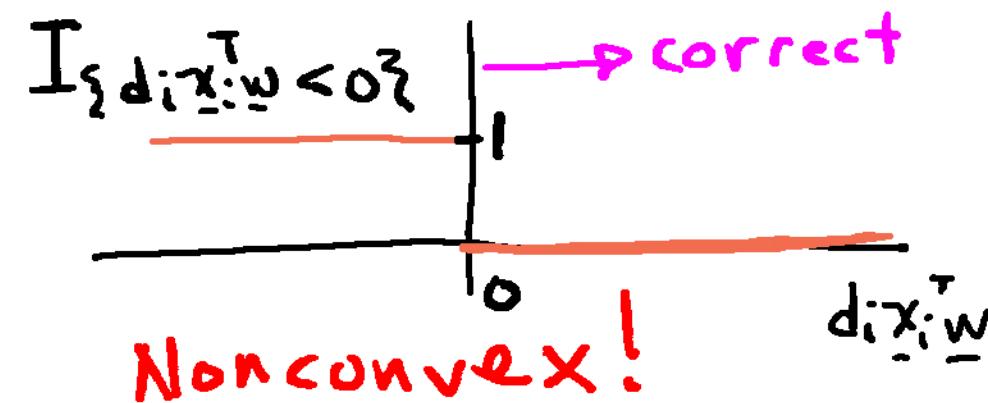
max margin classifier: midpoint  $\hat{d} = \text{sign}(x - 3.65)$   
 Margin  $4.9 - 2.4 = 2.5$  (class separation)

Squared error loss:  $\|\underline{A}\underline{w} - \underline{d}\|_2^2 = \sum_{i=1}^N (d_i - \underline{x}_i^\top \underline{w})^2 = \sum_i (1 - d_i \underline{x}_i^\top \underline{w})^2$   
 (d<sub>i</sub> = ±1)

correct classification:  $d_i \underline{x}_i^\top \underline{w} > 0$

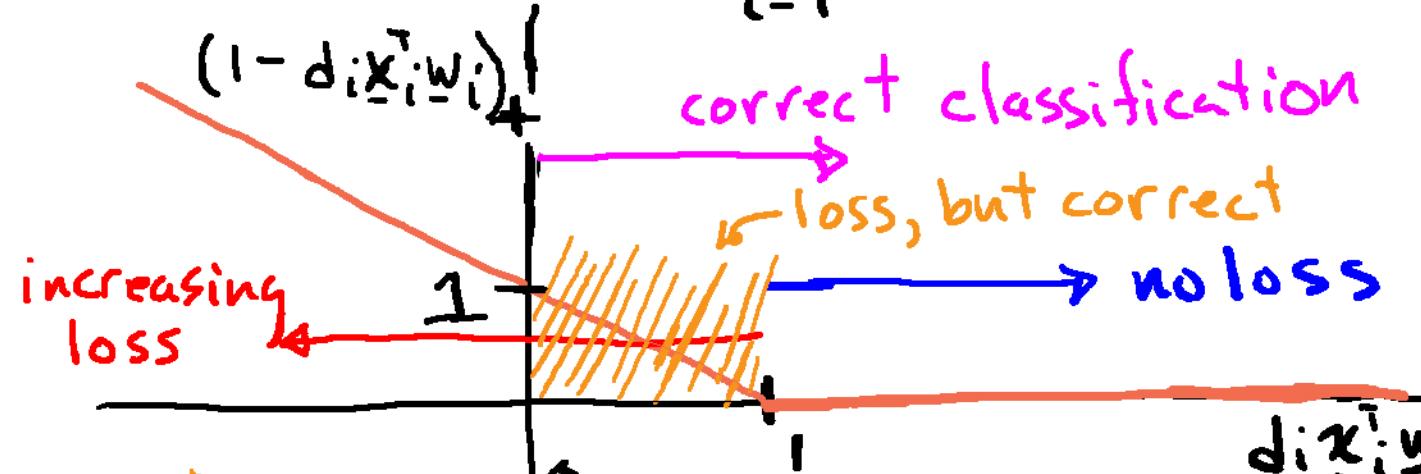


Ideal loss

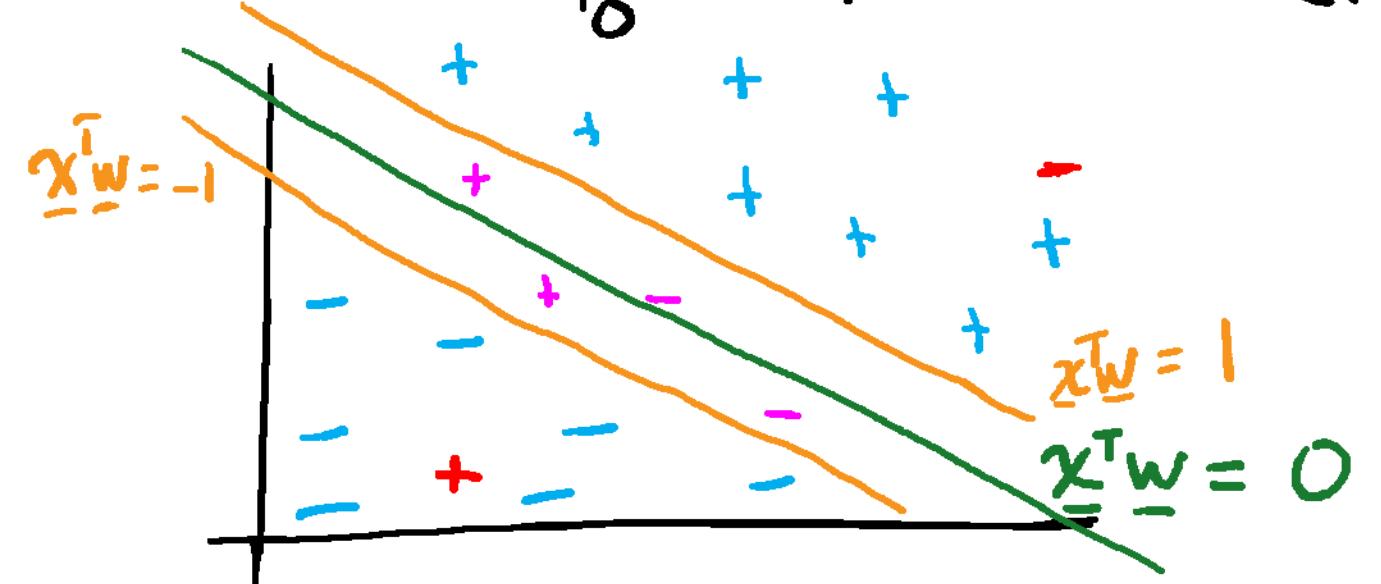
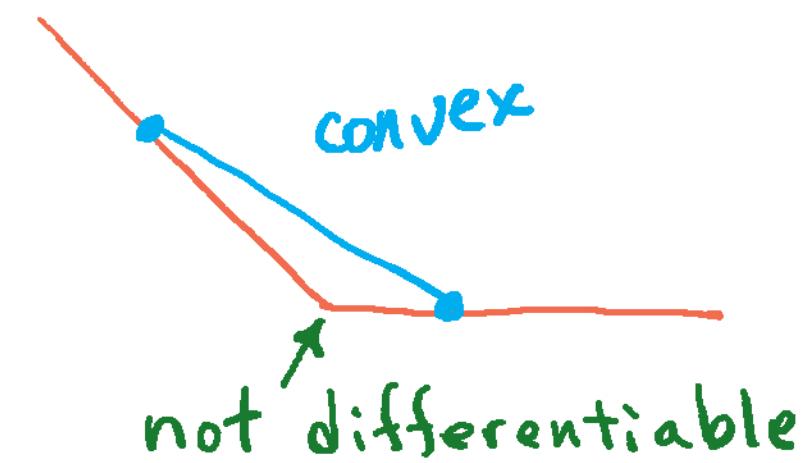


Hinge loss is convex and has no loss for easy  
to classify data 4

$$\ell(\underline{w}; \underline{A}, \underline{d}) = \sum_{i=1}^n (1 - d_i \underline{x}_i^\top \underline{w})_+$$



$$(\alpha)_+ = \begin{cases} \alpha & \alpha > 0 \\ 0 & \alpha \leq 0 \end{cases}$$



$+, -$  no hinge loss

$+, -$  small hinge loss

$+, -$  large hinge loss

Hinge loss better approximates ideal:  
number of misclassifications

Iterative algorithms required for  
finding minimum hinge loss classifier

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