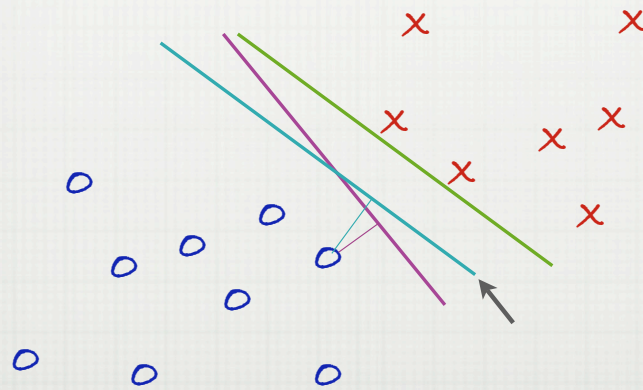


Support Vector Machines

SUE ANN HONG

10/18/2007

THE MOST FAMOUS SLIDE *EVER*



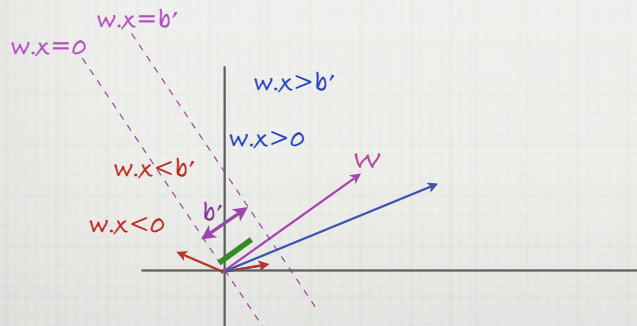
PRIMAL: THE "INTUITIVE" VERSION

$$\begin{aligned} \min \quad & \|w\|^2 + c \sum \xi \\ \text{s.t.} \quad & (w \cdot x + b)y \geq 1 - \xi \\ & \xi \geq 0 \end{aligned}$$

PRIMAL: THE "INTUITIVE" VERSION

$$\begin{aligned} \min \quad & \|w\|^2 + c \sum \xi \\ \text{s.t.} \quad & (w \cdot x + b)y \geq 1 - \xi \\ & \xi \geq 0 \end{aligned}$$

□ Linear classifier: $h(x) = \text{sign}(w \cdot x + b)$



□ $|w \cdot x + b|$ big if far away from the boundary "confidence"

PRIMAL: THE "INTUITIVE" VERSION

1. regularizer
2. $\sim 1/\text{margin}$

$$\begin{aligned} \min \quad & \|w\|^2 + c \sum \xi \\ \text{s.t.} \quad & (w \cdot x + b)y \geq 1 - \xi \\ & \xi \geq 0 \end{aligned}$$

"slack variable"

- $(w \cdot x + b)y > 0$ iff $w \cdot x + b$ and y same sign
- so want $(w \cdot x + b)y$ to be as large as possible
- could set ξ 's to anything big... no constraint?!
- need ξ 's to be small... but set $\xi_i < 0$ for a confident point, ξ_j can be big for some other point
- $\xi \geq 0$ means no love shared

PRIMAL: THE "INTUITIVE" VERSION

$$\begin{aligned} \min \quad & \|w\|^2 + c \sum \xi \\ \text{s.t.} \quad & (w \cdot x + b)y \geq 1 - \xi \\ & \xi \geq 0 \end{aligned}$$

- How do we find w ?
 - Quadratic programming
- how do we find c ?
 - Cross-validation!
- HW3! :) **get your libsvm today!**

DUAL: THE "SUPPORT VECTOR" VERSION

$$\begin{aligned} \max \sum \alpha - 1/2 \sum \alpha_i \alpha_j y_i y_j x_i x_j \\ \text{s.t. } \sum \alpha_i y_i = 0 \\ c \geq \alpha_i \geq 0 \end{aligned}$$

- Where did this come from?
- Remember Lagrange Multipliers
 - Let us "incorporate" constraints into objective
 - Then solve the problem in the "dual" space of lagrange multipliers

PRIMAL FEAR

$$\begin{aligned} \min \|w\|^2 + c \sum \xi \\ \text{s.t. } (w \cdot x + b)y \geq 1 - \xi \\ \xi \geq 0 \end{aligned}$$

$$\begin{aligned} \max \sum \alpha - 1/2 \sum \alpha_i \alpha_j y_i y_j x_i x_j \\ \text{s.t. } \sum \alpha_i y_i = 0 \\ c \geq \alpha_i \geq 0 \end{aligned}$$

- Number of parameters?
 - large # features?
 - large # examples?
 - for large # features, DUAL preferred
 - many α_i can go to zero!

DUAL: THE "SUPPORT VECTOR" VERSION

$$\begin{aligned} \max \sum \alpha - 1/2 \sum \alpha_i \alpha_j y_i y_j x_i x_j \\ \text{s.t. } \sum \alpha_i y_i = 0 \\ c \geq \alpha_i \geq 0 \end{aligned}$$

- How do we find α ?
- Quadratic programming
- How do we find c ?
- Cross-validation!

- Wait... how do we predict y for a new point x ??

$$y = \text{sign}(w \cdot x + b)$$

- How do we find w ?

$$w = \sum_i \alpha_i y_i x_i$$

- b ? "intersection" (algebra 1),

$$y = \text{sign}(\sum_i \alpha_i y_i x_i x_j + b)$$

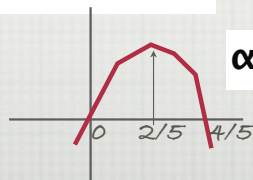
"SUPPORT VECTOR"'S?

$$\begin{aligned} \max \sum \alpha - 1/2 \sum \alpha_i \alpha_j y_i y_j x_i x_j \\ \text{s.t. } \sum \alpha_i y_i = 0 \\ c \geq \alpha_i \geq 0 \end{aligned}$$

$$\begin{aligned} \max \sum \alpha - \alpha_1 \alpha_2 (-1)(0+2) \\ - 1/2 \alpha_1^2 (1)(0+1) \\ - 1/2 \alpha_2^2 (1)(4+4) \end{aligned}$$

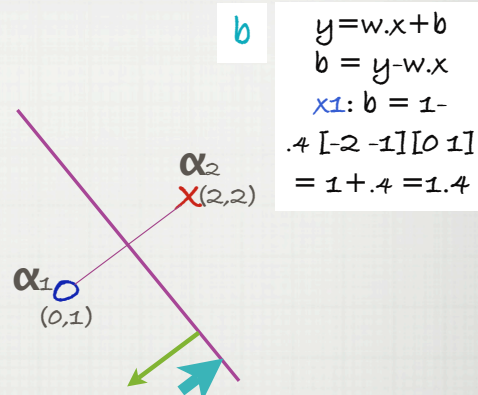
$$\begin{aligned} \max \alpha_1 + \alpha_2 + 2\alpha_1 \alpha_2 - \alpha_1^2/2 - 4\alpha_2^2 \\ \text{s.t. } \alpha_1 - \alpha_2 = 0 \\ c \geq \alpha_i \geq 0 \end{aligned}$$

$$\begin{aligned} \alpha_1 = \alpha_2 = \alpha \\ \max 2\alpha - 5/2\alpha^2 \\ \max 5/2\alpha(4/5 - \alpha) \end{aligned}$$



$$\alpha_1 = \alpha_2 = 2/5$$

$$\begin{aligned} w = \sum_i \alpha_i y_i x_i \\ w = .4([0 \ 1] - [2 \ 2]) \\ = .4[-2 \ -1] \end{aligned}$$



"SUPPORT VECTOR"'S?

$$\begin{aligned} \max \sum \alpha - 1/2 \sum \alpha_i \alpha_j y_i y_j x_i x_j \\ \text{s.t. } \sum \alpha_i y_i = 0 \\ c \geq \alpha_i \geq 0 \end{aligned}$$

$$b \quad b = y \cdot w \cdot x \dots$$

$$\begin{aligned} \max \sum \alpha - \alpha_1 \alpha_2 (-2) - \alpha_2 \alpha_3 (-2) - \alpha_3 \alpha_1 0 \\ - 1/2 \alpha_1^2 (1) - 1/2 \alpha_2^2 (8) - 1/2 \alpha_3^2 (1) \end{aligned}$$

$$\begin{aligned} \max \alpha_1 + \alpha_2 + \alpha_3 + 2\alpha_1 \alpha_2 + 2\alpha_2 \alpha_3 \\ - \alpha_1^2/2 - 4\alpha_2^2 - \alpha_3^2/2 \\ \text{s.t. } \alpha_1 - \alpha_2 + \alpha_3 = 0 \end{aligned}$$

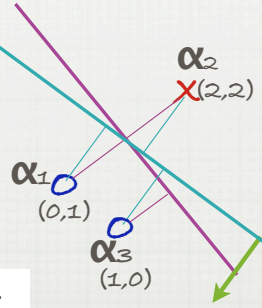
$$\alpha_2 = \alpha_1 + \alpha_3 \quad \text{let } \alpha_2 = k \quad \alpha_1 + \alpha_3 = k$$

$$\max (\alpha_1 + \alpha_3) + \alpha_2 + 2\alpha_2(\alpha_1 + \alpha_3) - \alpha_1^2/2 - 4\alpha_2^2 - \alpha_3^2/2$$

$$\max 2k + 4k^2 - \alpha_1^2/2 - 4k^2 - \alpha_3^2/2$$

$$\max (\alpha_1^2 - \alpha_3^2)/2$$

$$\max \alpha_1^2 - (k - \alpha_1)^2$$



$$\alpha_1 = k/2$$

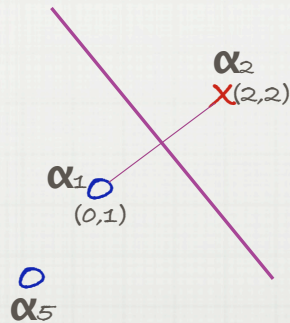
$$\alpha_3 = k/2$$

$$\begin{aligned} w &= \sum_i \alpha_i y_i x_i \\ w &= k (.5[0 \ 1] - [2 \ 2] + .5[1 \ 0]) \\ &= k[-1.5 \ -1.5] \end{aligned}$$

"SUPPORT VECTOR"'S?

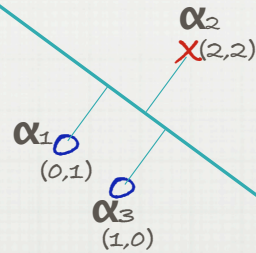
$$\begin{aligned} \max \sum \alpha - 1/2 \sum \alpha_i \alpha_j y_i y_j x_i x_j \\ \text{s.t. } \sum \alpha_i y_i = 0 \\ c \geq \alpha_i \geq 0 \end{aligned}$$

What is α_5 ?
Try this at home



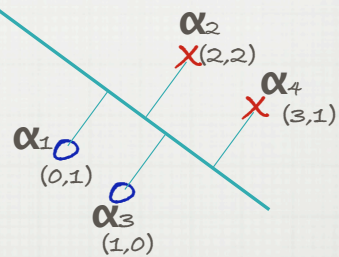
“SUPPORT VECTOR”’S?

$$\begin{aligned} \max \sum \alpha - 1/2 \sum \alpha_i \alpha_j y_i y_j x_i x_j \\ \text{s.t. } \sum \alpha_i y_i = 0 \\ c \geq \alpha_i \geq 0 \end{aligned}$$



“SUPPORT VECTOR”’S?

$$\begin{aligned} \max \sum \alpha - 1/2 \sum \alpha_i \alpha_j y_i y_j x_i x_j \\ \text{s.t. } \sum \alpha_i y_i = 0 \\ c \geq \alpha_i \geq 0 \end{aligned}$$



Which ones are support vectors?

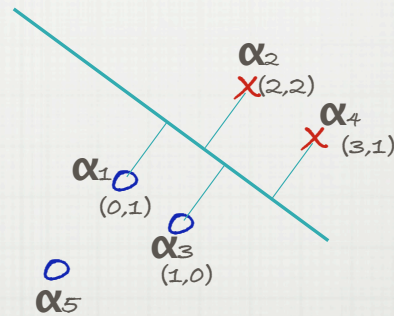
Why?

intuition: how many points “define” a line in 2D?

HW3

"SUPPORT VECTOR"'S?

$$\begin{aligned} \max \sum \alpha_i - \frac{1}{2} \sum \alpha_i \alpha_j y_i y_j x_i x_j \\ \text{s.t. } \sum \alpha_i y_i = 0 \\ c \geq \alpha_i \geq 0 \end{aligned}$$



HINGE LOSS YOUR LOSS

$$\begin{aligned} \min ||w||^2 + c \sum \xi \\ \text{s.t. } (w \cdot x + b)y \geq 1 - \xi \\ \xi \geq 0 \end{aligned}$$

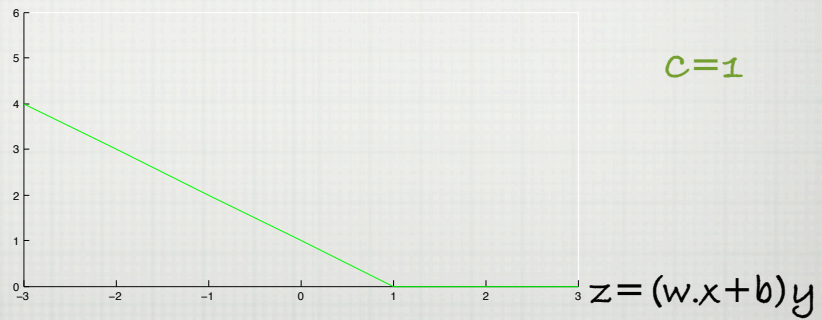
"Loss part": $c \sum \xi$ $||w||^2 \sim \text{regularization}$

- $\xi \geq 0$ only if $(w \cdot x + b)y < 1$
- we want: $\xi \geq 1 - (w \cdot x + b)y$ & minimize ξ
 $\Rightarrow \xi = 1 - (w \cdot x + b)y$

$\Rightarrow \text{loss} = c(1 - (w \cdot x + b)y)$ only if $(w \cdot x + b)y < 1$

HINGE LOSS YOUR LOSS

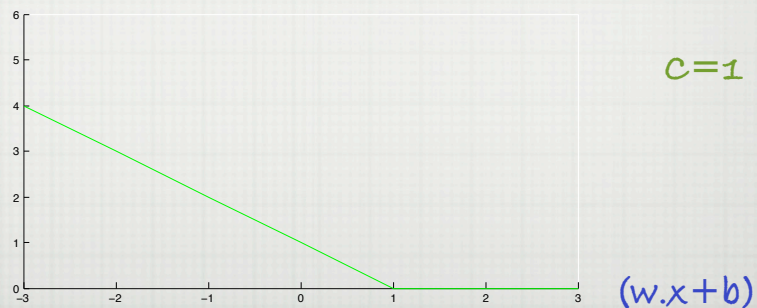
□ hinge loss $L = 1 - z$ only if $(w \cdot x + b)y < 1$



HINGE LOSS YOUR LOSS

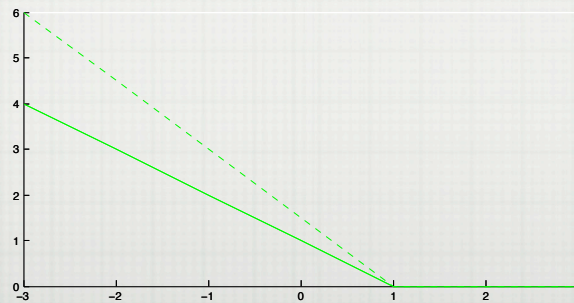
□ hinge loss $L = 1 - (w \cdot x + b)y$ only if $(w \cdot x + b)y < 1$

LOSS FOR POSITIVE CLASS



HINGE LOSS YOUR LOSS

□ hinge loss $L = 1 - (w \cdot x + b)y$ only if $(w \cdot x + b)y < 1$



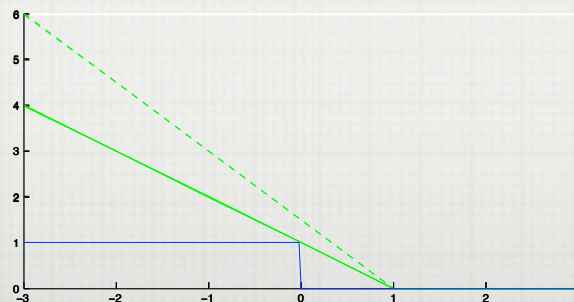
$C=1$

$C=1.5$

HINGE LOSS YOUR LOSS

□ hinge loss $L = 1 - (w \cdot x + b)y$ only if $(w \cdot x + b)y < 1$

□ 0/1 loss $L = 1$ if $(w \cdot x + b)y < 0$, 0 otherwise

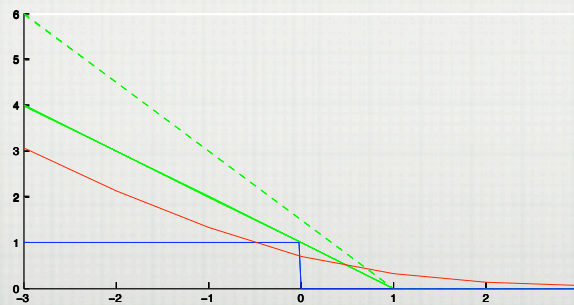


$C=1$

$C=1.5$

HINGE LOSS YOUR LOSS

- hinge loss $L = 1 - (w \cdot x + b)y$ only if $(w \cdot x + b)y < 1$
- 0/1 loss $L = 1$ if $(w \cdot x + b)y < 0$, 0 otherwise
- logistic loss $L = ||w||^2 + \sum \ln P(Y=1|x,w) = \dots \ln(1 + e^{-(w \cdot x + b)})$



$C=1$

$C=1.5$

SVM

- Decision boundary: plain SVM is quite simple
- Why is the dual form useful? interesting?
- Support vectors are neat! (computationally, kernel trick, ...)
- SVM, LR, Boosting, ... all a family (diff loss)
- Which letters didn't we see? C b ξ α γ μ x y z w t f ?

LAST REMARKS

- I <3 Burges' tutorial -- READ IT!!!
 - first part (VC-dim, etc) might not make sense until learning theory lectures, but charge on

- MIDTERM REVIEW ON TUESDAY
 - 5-6:30, tentatively, somewhere