



Department of Computer Science  
UNIVERSITY OF COLORADO **BOULDER**



## SVM

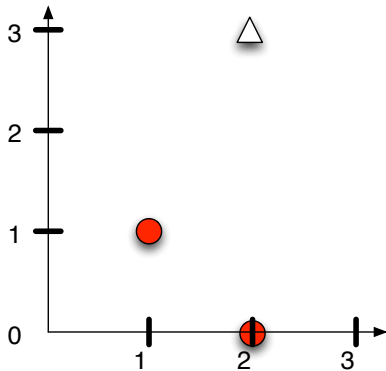
### Introduction to Data Science Algorithms

Jordan Boyd-Graber and Michael Paul

SLIDES ADAPTED FROM HINRICH SCHÜTZE

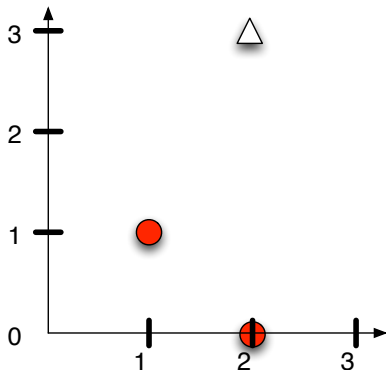
## Find the maximum margin hyperplane

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Which are the support vectors?

## Walkthrough example: building an SVM over the data shown

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Working geometrically:

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- If you got  $0 = .5x + y - 2.75$ , close!

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- If you got  $0 = .5x + y - 2.75$ , close!
- Set up system of equations

$$w_1 + w_2 + b = -1 \quad (1)$$

$$\frac{3}{2}w_1 + 2w_2 + b = 0 \quad (2)$$

$$2w_1 + 3w_2 + b = +1 \quad (3)$$

## Walkthrough example: building an SVM over the data shown

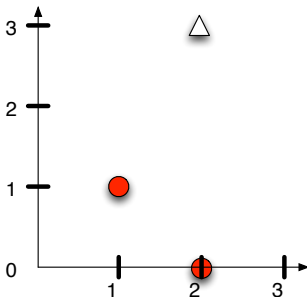
Working geometrically:

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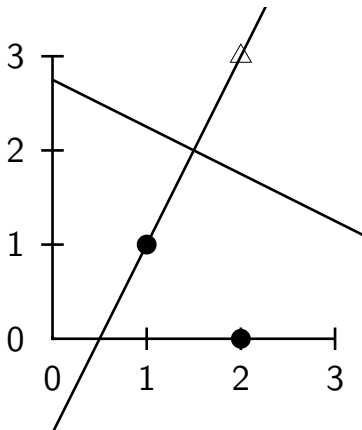


The SVM decision boundary is:

$$0 = \frac{2}{5}x + \frac{4}{5}y - \frac{11}{5}$$

## Canonical Form

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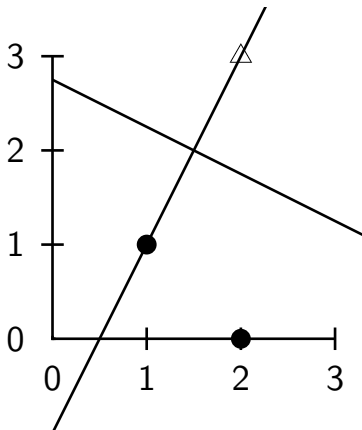


$$w_1x_1 + w_2x_2 + b$$



## Cannonical Form

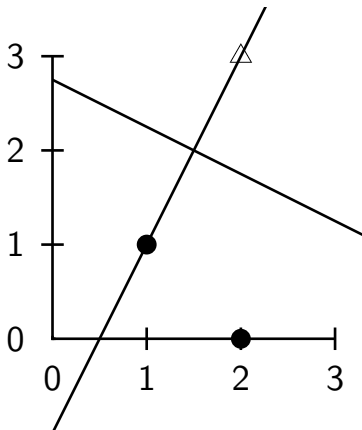
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$$.4x_1 + .8x_2 - 2.2$$

## Cannonical Form

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$$.4x_1 + .8x_2 - 2.2$$

- $.4 \cdot 1 + .8 \cdot 1 - 2.2 = -1$
- $.4 \cdot \frac{3}{2} + .8 \cdot 2 = 0$
- $.4 \cdot 2 + .8 \cdot 3 - 2.2 = +1$

## What's the margin?

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- Distance to closest point

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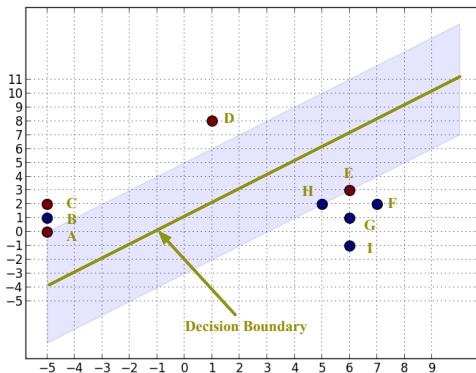
- Weight vector

$$\frac{1}{\|w\|} = \frac{1}{\sqrt{\left(\frac{2}{5}\right)^2 + \left(\frac{4}{5}\right)^2}} = \frac{1}{\sqrt{\frac{20}{25}}} = \frac{5}{\sqrt{5}\sqrt{4}} = \frac{\sqrt{5}}{2} \quad (5)$$

## Slack Example

Decision function:

$$w = \begin{bmatrix} -\frac{1}{4} \\ \frac{1}{4} \end{bmatrix}; b = -\frac{1}{4}$$

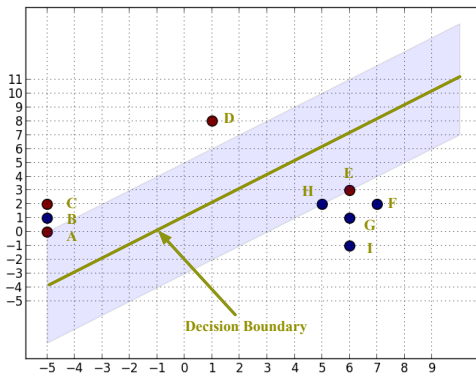


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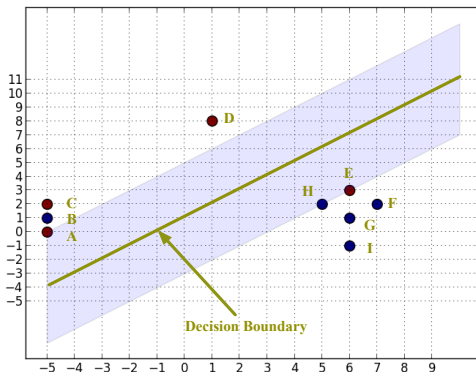


## Slack Example

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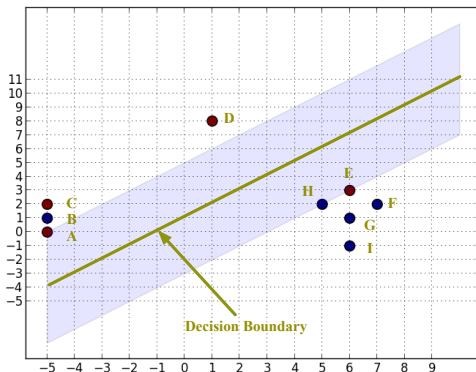


## Slack Example

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- Compute  $\xi_B, \xi_E$



## Computing slack

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$$y_i(\vec{w}_i \cdot x_i + b) \geq 1 - \xi_i \quad (6)$$

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### Point B

$$y_B(\vec{w}_B \cdot x_B + b) = \quad (7)$$

$$-1(-0.25 \cdot -5 + 0.25 \cdot 1 - 0.25) = -1.25 \quad (8)$$

Thus,  $\xi_B = 2.25$

## Computing slack

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### Point E

$$y_E(\vec{w}_E \cdot x_E + b) = \quad (9)$$

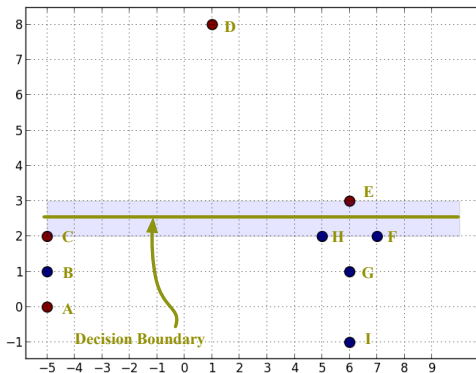
$$1(-0.25 \cdot 6 + 0.25 \cdot 3 + -0.25) = -1 \quad (10)$$

Thus,  $\xi_E = 2$

## Slack Example

Decision function:

$$w = \begin{bmatrix} 0 \\ 2 \end{bmatrix}; b = -5$$

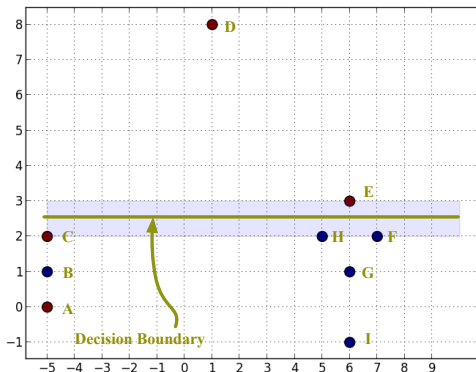


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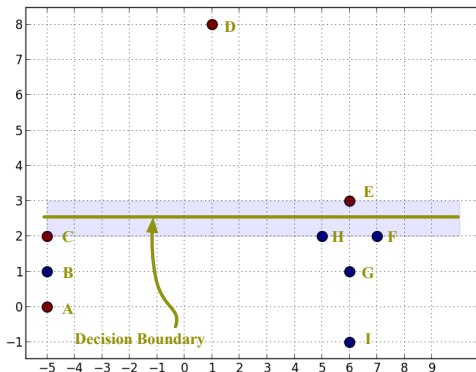


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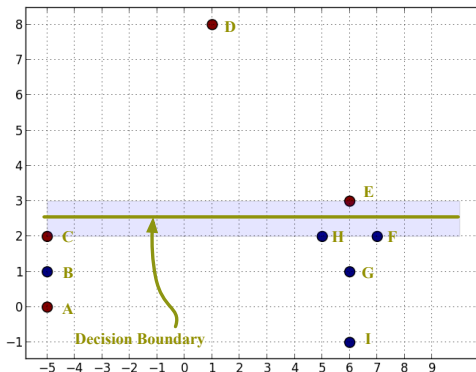


## Slack Example

Decision function:

$$w = \begin{bmatrix} 0 \\ 2 \end{bmatrix}; b = -5$$

- What are the support vectors?
- Which have non-zero slack?
- Compute  $\xi_A, \xi_C$



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$$y_i(\vec{w}_i \cdot x_i + b) \geq 1 - \xi_i \quad (11)$$

## Computing slack

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### Point A

$$y_A(\vec{w}_A \cdot x_A + b) = \quad (12)$$

$$1(0 \cdot -5 + 2 \cdot 0 + -5) = -5 \quad (13)$$

Thus,  $\xi_A = 6$

## Computing slack

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$$y_i(\vec{w}_i \cdot x_i + b) \geq 1 - \xi_i \quad (11)$$

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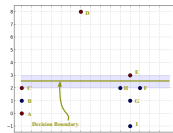
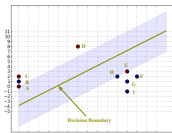
### Point C

$$y_C(\vec{w}_C \cdot x_C + b) = \quad (14)$$

$$1(0 \cdot -5 + 2 \cdot 2 + -5) = -1 \quad (15)$$

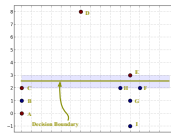
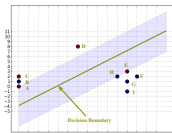
Thus,  $\xi_C = 2$

## Which one is better?



- Which decision boundary (wide / narrow) has the better objective?

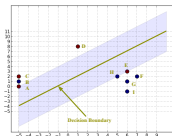
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- Which decision boundary (wide / narrow) has the better objective?

$$\min_w \frac{1}{2} \|w\|^2 + C \sum_i \xi_i \quad (16)$$

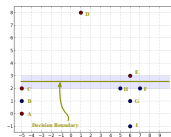
## Which one is better?



$$\frac{1}{2}||w||^2 = \frac{1}{2} \left( \frac{-1^2}{4} + \frac{1^2}{4} \right) = 0.0625 \quad (16)$$

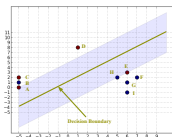
$$\sum_i \xi_i = 4.25 \quad (17)$$

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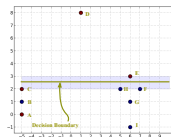
$$\min_w \frac{1}{2}||w||^2 + C \sum_i \xi_i \quad (18)$$

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$$\sum_i \xi_i = 4.25 \quad (17)$$



$$\frac{1}{2} \|w\|^2 = \frac{1}{2} (2^2) = 2 \quad (18)$$

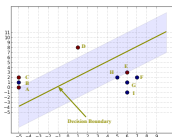
$$\sum_i \xi_i = 8 \quad (19)$$

- Which decision boundary (wide / narrow) has the better objective?

$$\min_w \frac{1}{2} \|w\|^2 + C \sum_i \xi_i \quad (20)$$

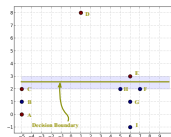


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$$\sum_i \xi_i = 8 \quad (19)$$

- Which decision boundary (wide / narrow) has the better objective?

$$\min_w \frac{1}{2}||w||^2 + C \sum_i \xi_i \quad (20)$$

- In this case it doesn't matter. Common  $C$  values:  $1.0$ ,  $\frac{1}{m}$

## Importance of $C$

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- Need to do cross-validation to select  $C$
- Don't trust default values
- Look at values with high  $\xi$ ; are they bad data?

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- Need to do cross-validation to select  $C$
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- Look at values with high  $\xi$ ; are they bad data?
- Next time: how to find  $w$