

# L101: Machine Learning for Language Processing

## Lecture 4

Guy Emerson

# Today's Lecture

- Decision boundaries
- Non-probabilistic classifiers
  - Support Vector Machine
  - Kernels
- Linguistic kernels

# Decision Boundaries

$$\operatorname{argmax}_y P(y|x)$$

# Decision Boundaries

$$\begin{aligned} & \operatorname{argmax}_y P(y|x) \\ &= \operatorname{argmax}_y \exp\left(\theta_y + \sum_i \theta_{y,i} x_i\right) \end{aligned}$$

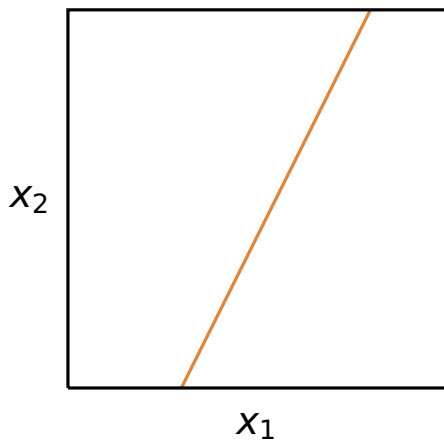
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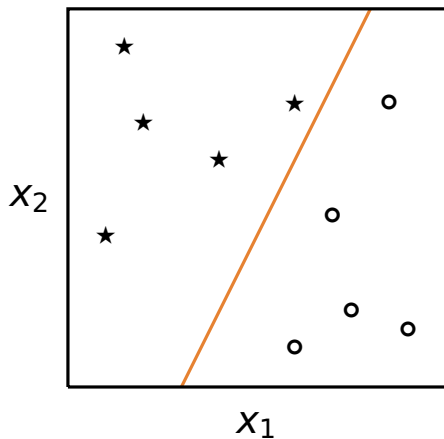
For two classes:

$$b + \sum_i a_i x_i > 0 ?$$

# Decision Boundaries



# Decision Boundaries



# Support Vector Machines

- Non-probabilistic
- $\operatorname{argmax}_y (\theta_y + \sum_i \theta_{y,i} x_i)$



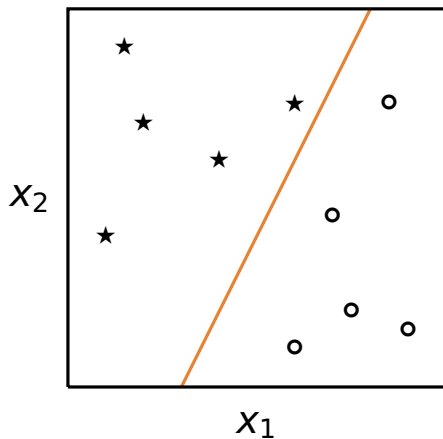
# Support Vector Machines

- Non-probabilistic
- $\operatorname{argmax}_y (\theta_y + \sum_i \theta_{y,i} x_i)$
- Linear: hyperplane boundary

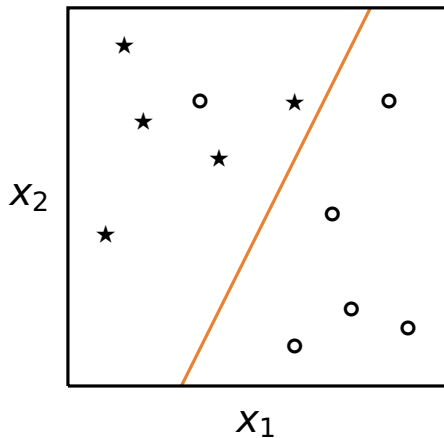
# Perceptron Algorithm

- Iterate through training data
- If correct, do nothing
- If incorrect, update:
  - Correct class  $y$ :  $\theta_{y,i} \leftarrow \theta_{y,i} + x_i$
  - Incorrect class  $y'$ :  $\theta_{y',i} \leftarrow \theta_{y',i} - x_i$

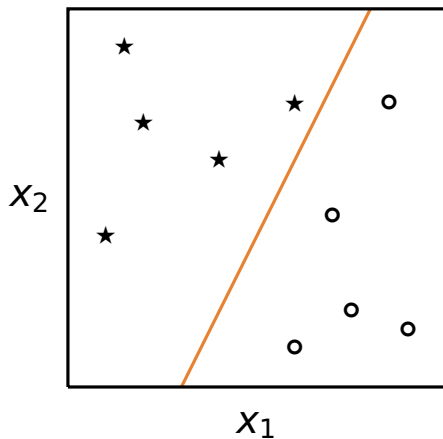
# Linear Separability



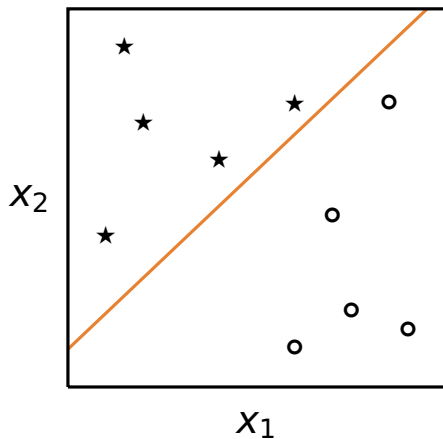
# Linear Separability



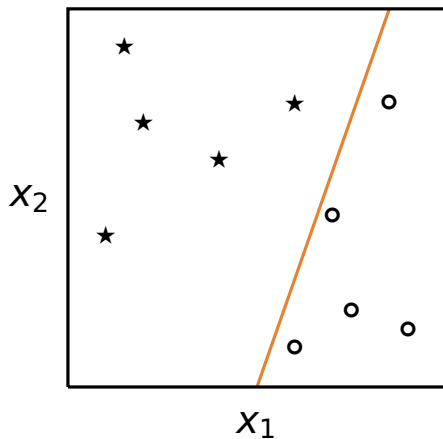
# Linear Separability



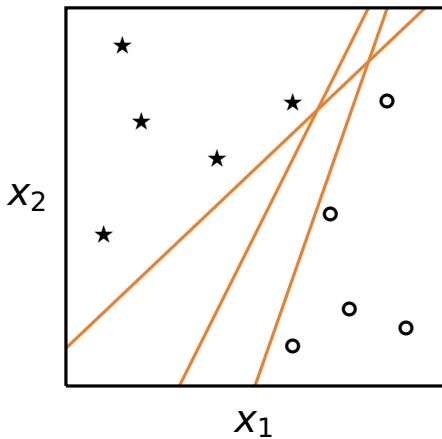
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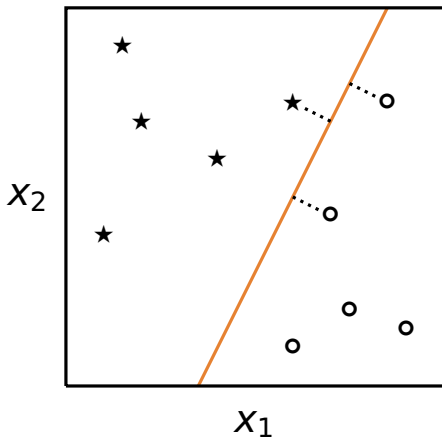


# Linear Separability

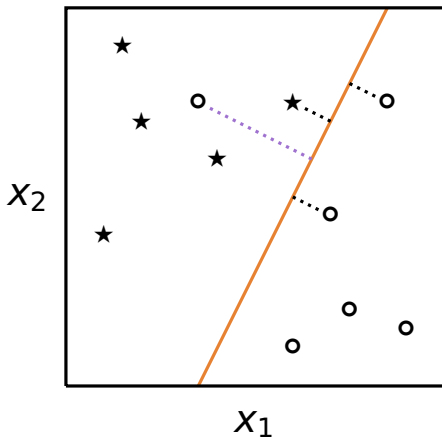




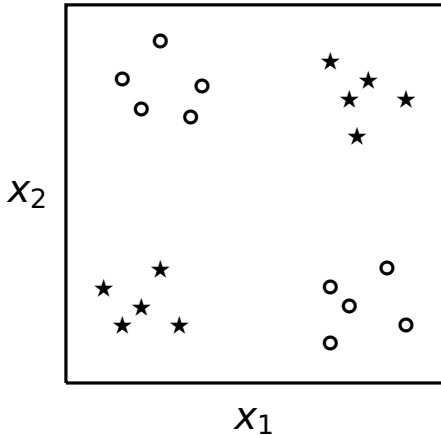
# Maximum Margin



# Maximum Margin



# Nonlinear Decision Boundaries



# Kernel Methods

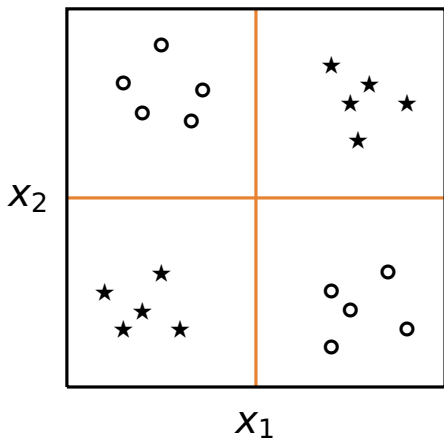
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- Input space  $\rightarrow$  Feature space
- Linear boundary in feature space

# Kernel Methods

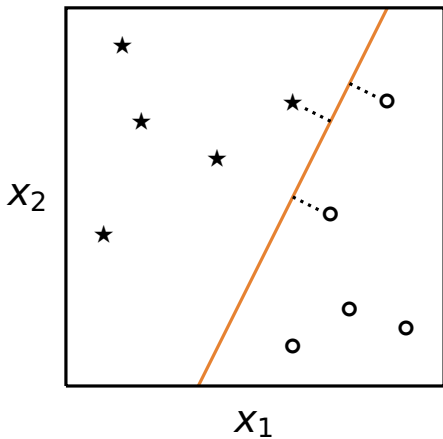
- Input space  $\rightarrow$  Feature space
- Linear boundary in feature space
- e.g.  $(x_1, x_2) \mapsto (x_1, x_2, x_1x_2)$

# Kernel Methods

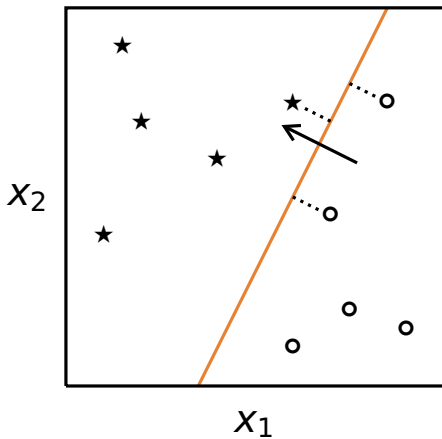


$$xy - x - y + 1 = 0$$

# Maximum Margin



# Maximum Margin





# Kernel Methods

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- Can represent and train an SVM only using dot products in feature space

# Kernel Methods

- Can represent and train an SVM only using dot products in feature space
- Kernel function in input space = dot product in feature space

# String Kernel

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Number of shared substrings

# String Kernel

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Number of shared substrings

The dog barked

The dog slept

# String Kernel

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Number of shared substrings

The dog barked

The dog slept

# String Kernel

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Number of shared substrings

The **dog** barked

The **dog** slept

# String Kernel

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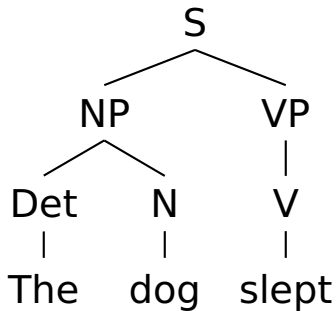
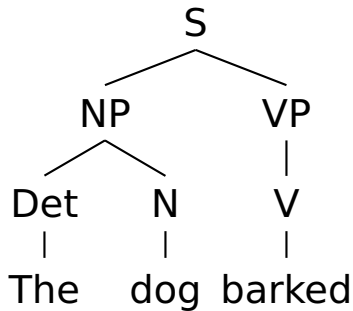
Number of shared substrings

The dog barked

The dog slept

# Tree Kernel

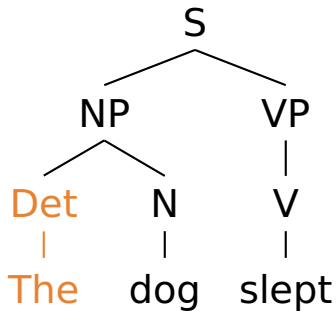
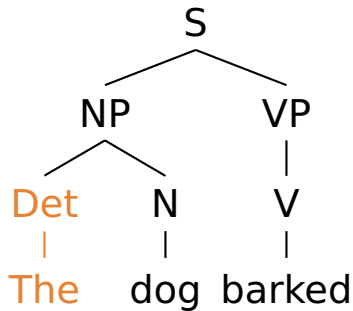
Number of shared subtrees





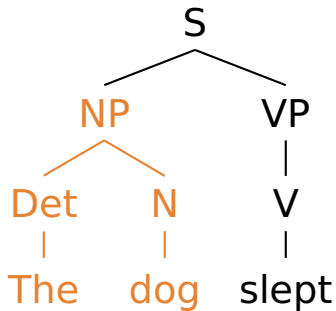
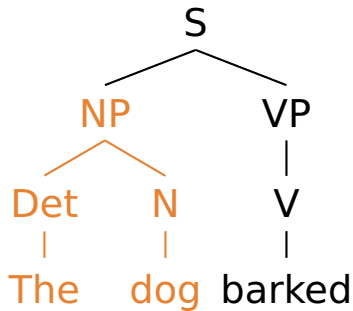
# Tree Kernel

Number of shared subtrees



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# Tree Kernel

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