

# Linear Classifiers (Part 2)

CS114B Lab 3

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- ▶ A dot product of two vectors produces a scalar, but in general, we don't just want an arbitrary real number
  - ▶ Sometimes, we want a probability (logistic regression)
  - ▶ Sometimes, we just want the decision itself (perceptron)

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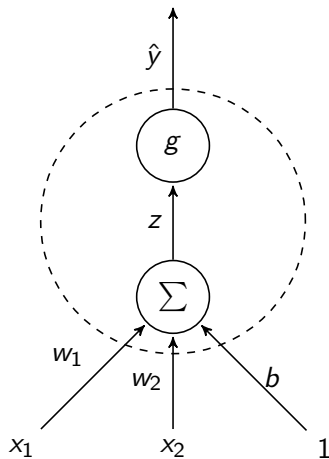
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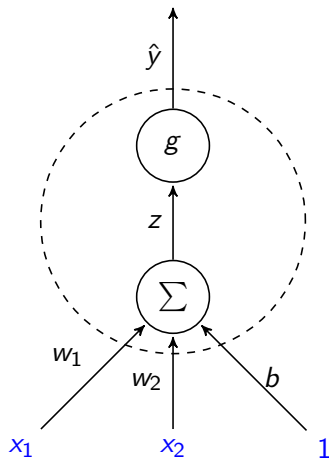
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  - ▶ What if  $z = 0$ ?
    - ▶ Set by convention (1, 0, or 1/2)

# Graphical Representation of a Linear Classifier (1)



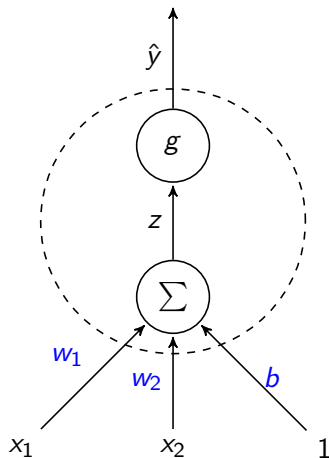
# Graphical Representation of a Linear Classifier (1)

- Input (including dummy feature 1)



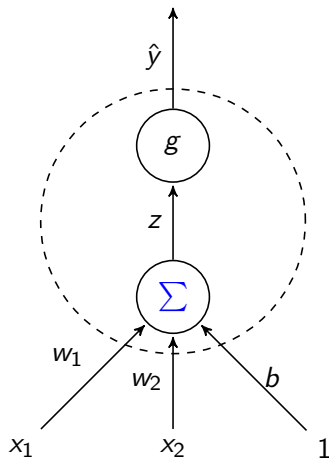
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- Parameters (weights and bias term)



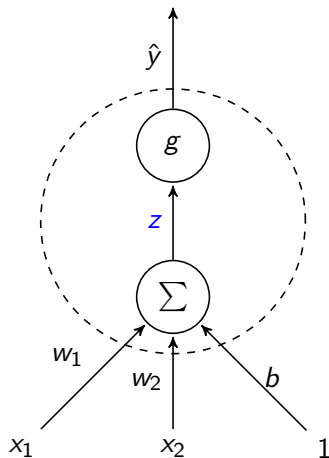
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► Sum function  $\Sigma$



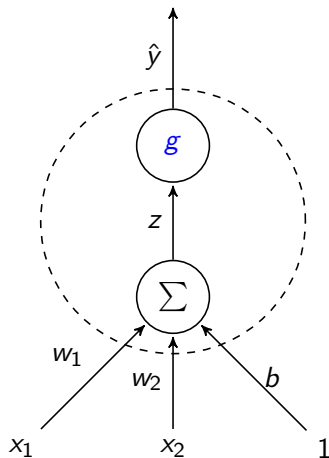
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► “Score”



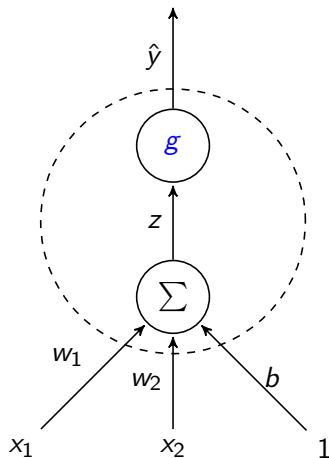
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► Activation function  $g$





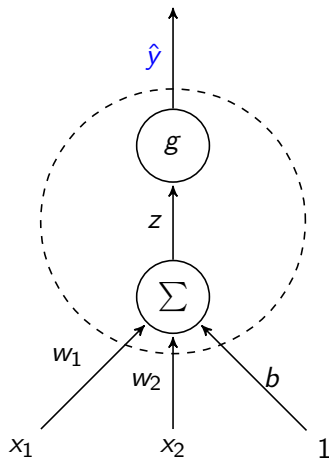
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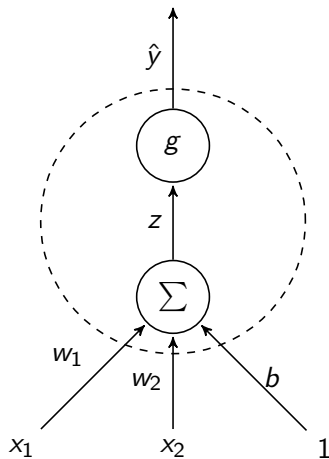
- Activation function  $g$ 
  - Logistic, step, etc.

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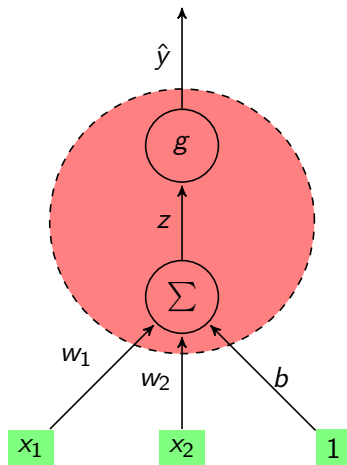
► Output



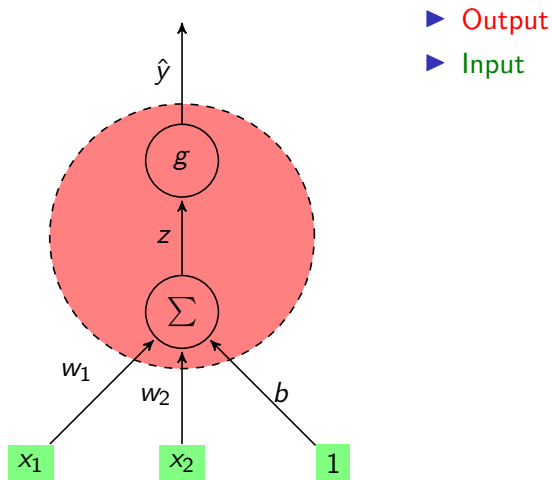
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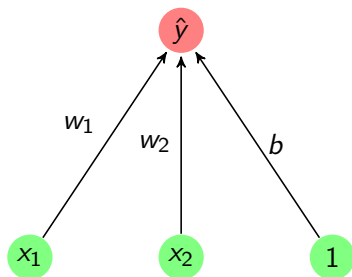
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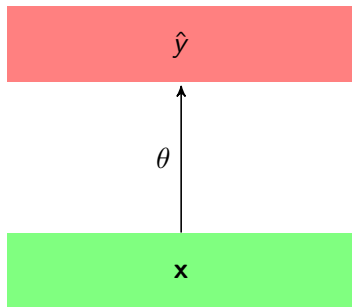
► Input



## Graphical Representation of a Linear Classifier (2)

► Output

► Input



## Graphical Representation of a Linear Classifier (2)

- ▶ Output
- ▶ Input
- ▶  $\hat{y} = g(\theta \cdot \mathbf{x})$ 
  - ▶ We will assume that the dummy feature 1 is part of  $\mathbf{x}$

