



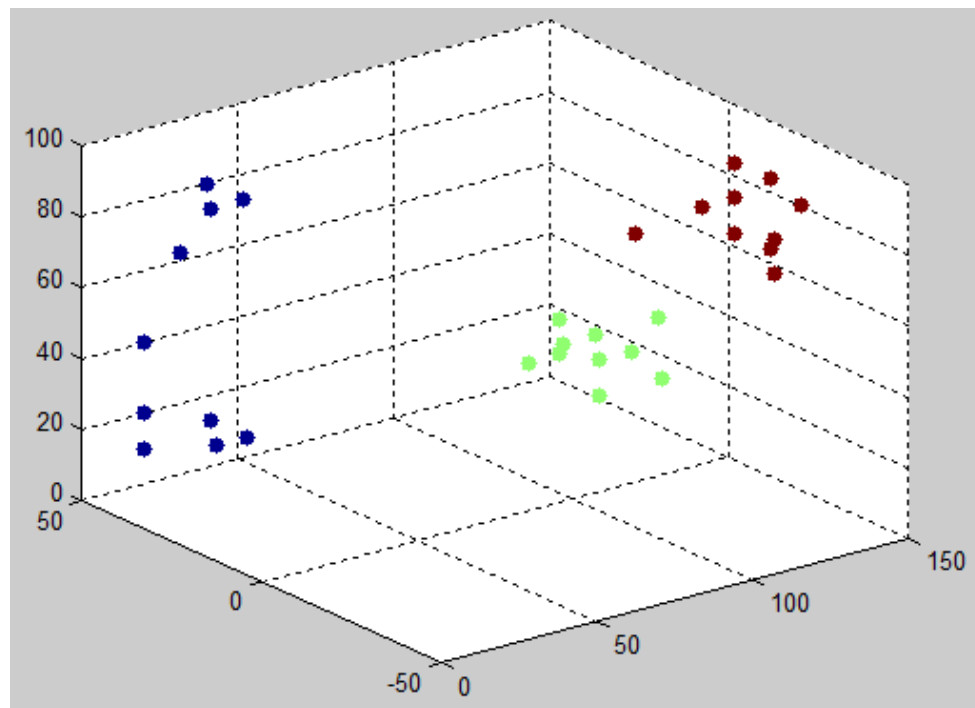
# **Machine Learning (IS ZC464) Session 3: Classification**

# Classification

- The goal of classification is to take an input vector  $x$  and to assign it to one of  $K$  discrete classes  $C_k$  where  $k = 1, 2, 3, \dots, K$
- Examples
  - Email: Spam / Not Spam?
  - Online Transactions: Fraudulent (Yes / No)?
  - Tumor: Malignant / Benign ?

# Decision Regions

- Training data is viewed to be plotted in a d-dimensional space where  $d$  is the number of features used.
- A test data is also viewed to be mapped in the same space.
- Similarity (or closeness) of the test data from the cluster of training classes is obtained.
- The nearest class is assigned to the test data



# Binary Classification

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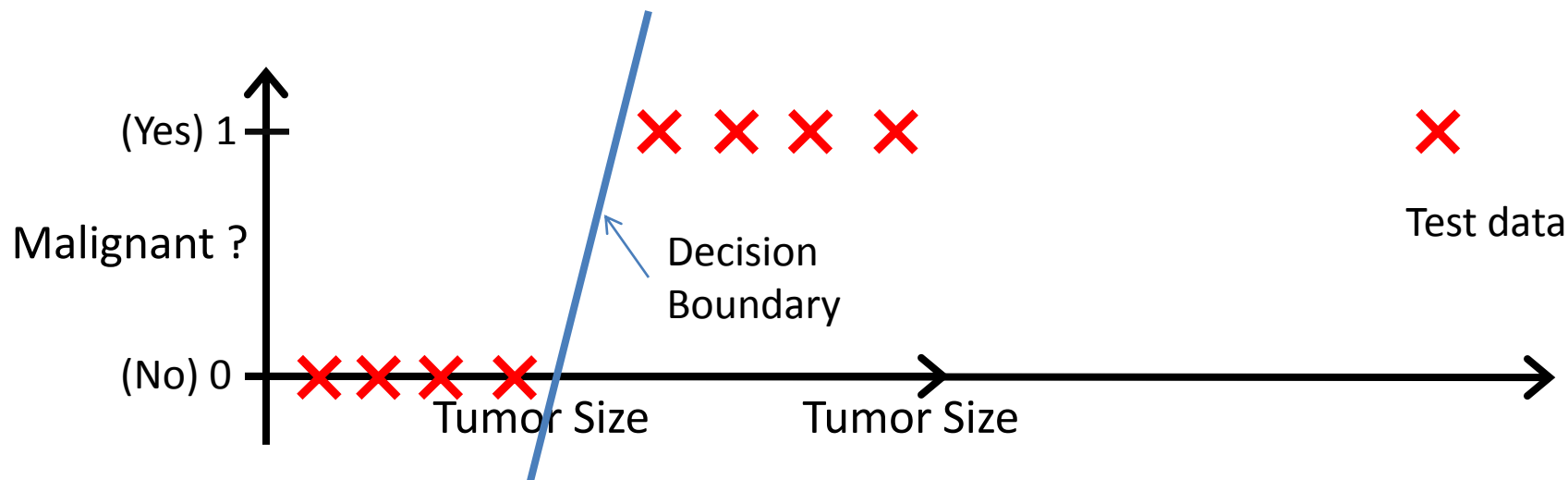
- Only two classes

$$y \in \{0, 1\}$$

0: “Negative Class” (e.g., benign tumor)

1: “Positive Class” (e.g., malignant tumor)

# Example of a Decision Boundary



Threshold classifier output  $h_{\theta}(x)$  at 0.5:

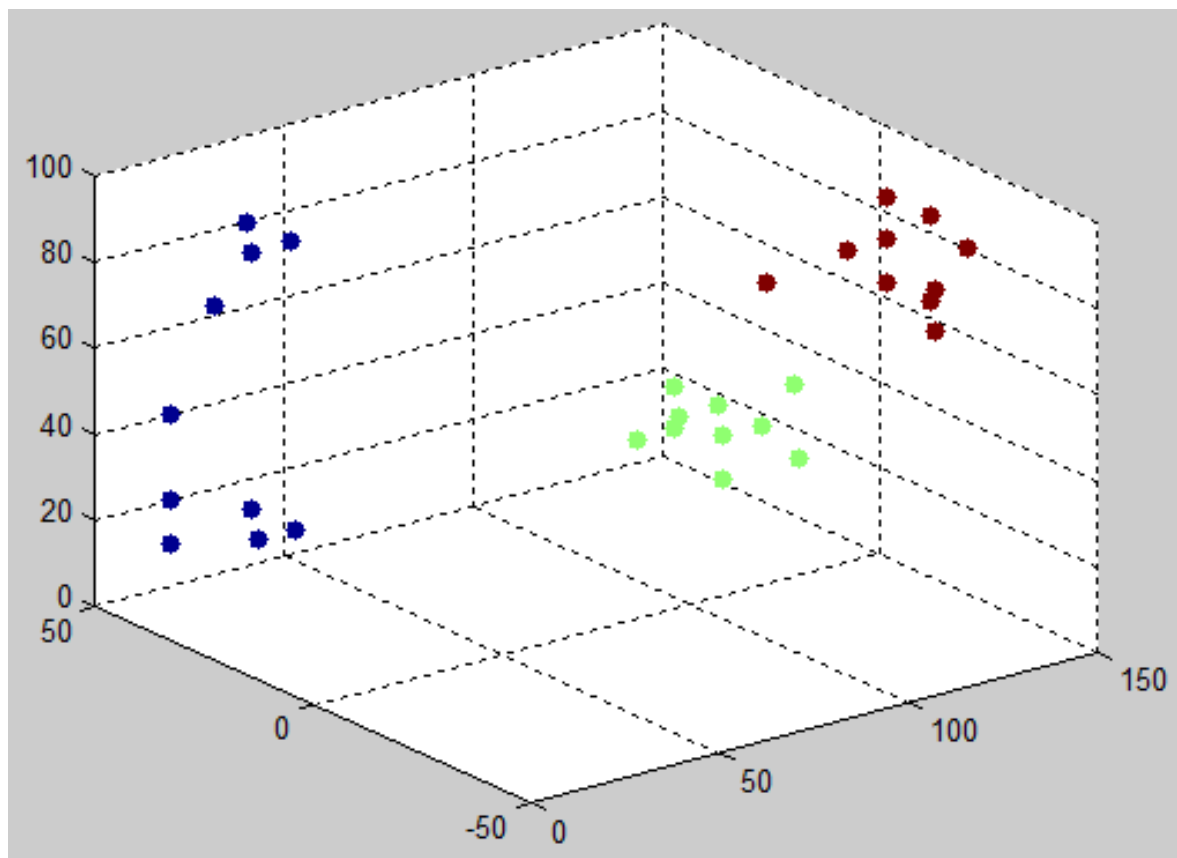
If  $h_{\theta}(x) \geq 0.5$ , predict “y = 1”

If  $h_{\theta}(x) < 0.5$ , predict “y = 0”

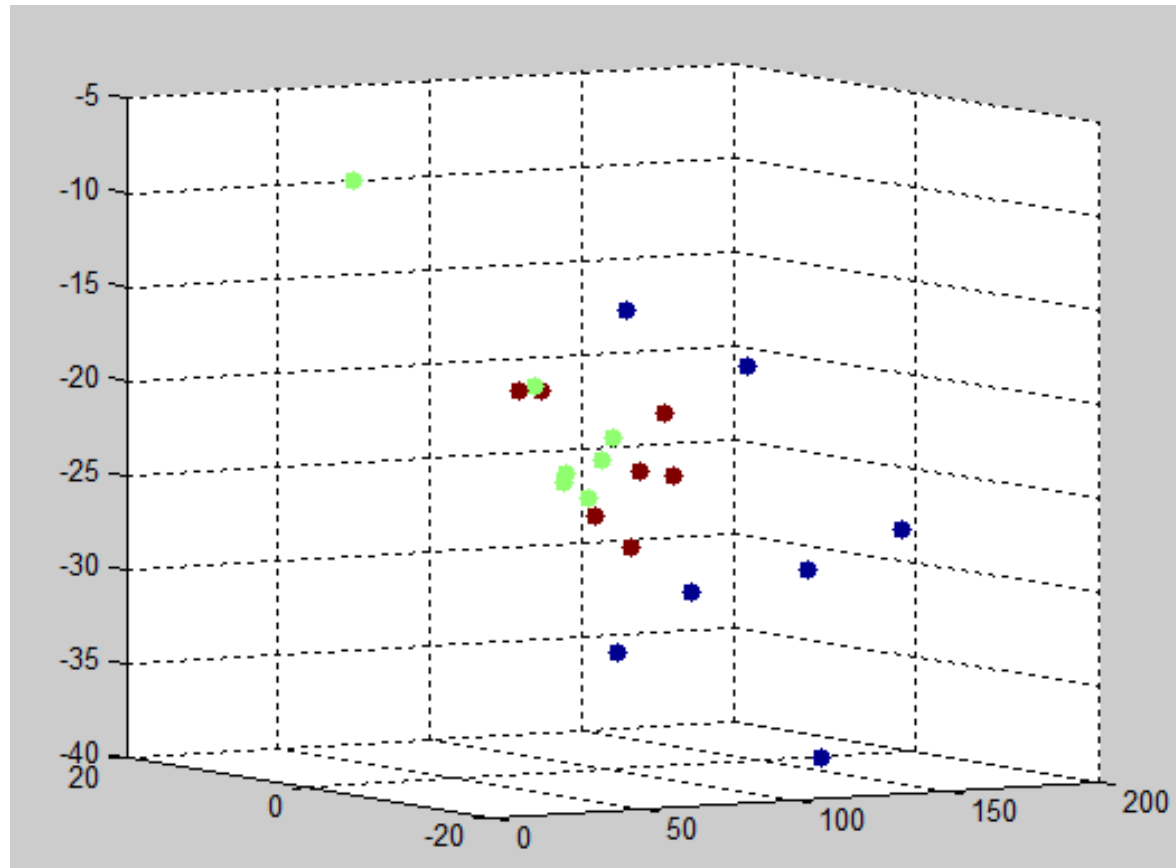
# Solving Classification Problems

- Require the decision boundaries (or surfaces in hyper dimensional space) to be identified based on the training data.
- The decision boundary may be a line, a polynomial curve or a surface.
- The decision boundary can be represented as a hypothesis  $h_{\theta}(x)$

# Linearly Separable Non-Face Data

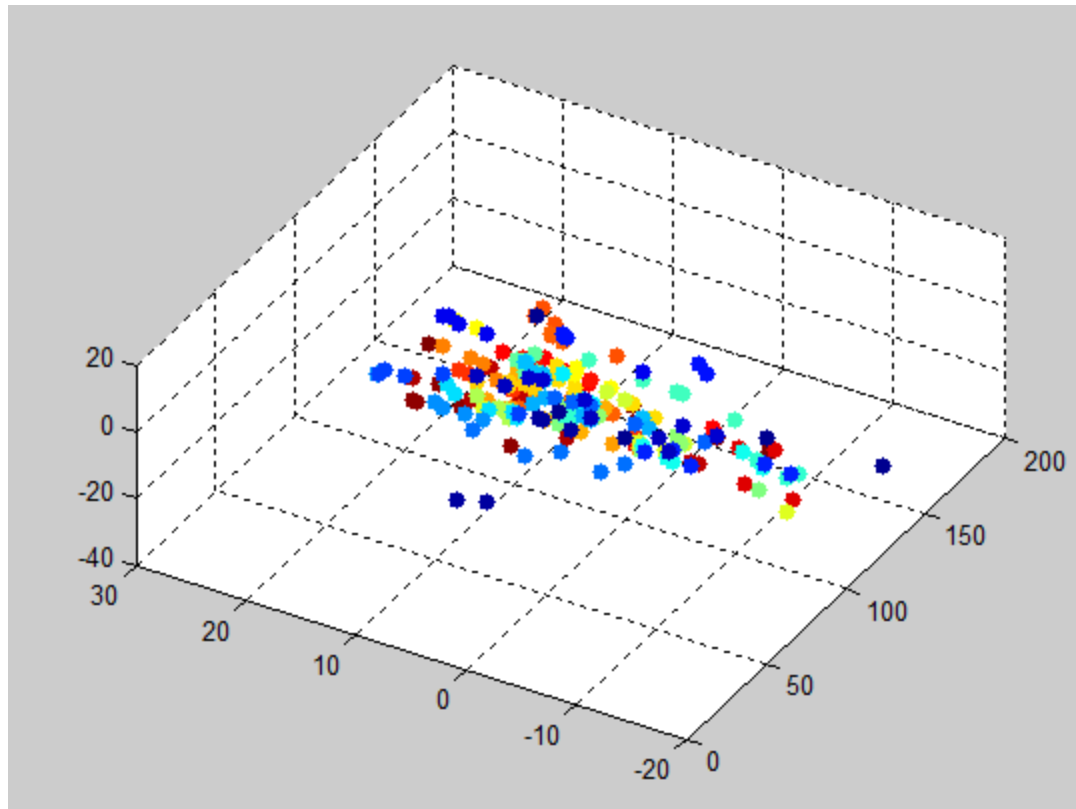


# Each face is a point in the n-dimensional space. (ORL face data for three persons)





The points in the  $n$ -dimensional space cannot be clustered (colorwise) by hyperplanes.



# Discriminant Functions

- Represent the decision boundary
- Discriminant functions are obtained by taking a linear function of the input vector (feature vector).
- Define  $y(x) = w_0 + w_1x + w_2x + \dots w_Dx$
- Take a simple case
 
$$y(x) = w_0 + w_1x$$
- This is the equation of line.
- How does this behave as a decision boundary

# Example

- Consider the following training data
- Class 1:  $\langle 1, 2 \rangle$ ,  $\langle 1, 1 \rangle$ ,  $\langle 2, 1 \rangle$
- Class 2:  $\langle 3, 3 \rangle$ ,  $\langle 3, 4 \rangle$ ,  $\langle 4, 3 \rangle$
- Can view a decision boundary as a line separating two classes
- The equation of the line is

$$x_2 = -x_1 + 1$$

(not using  $y$  deliberately as used for target)

