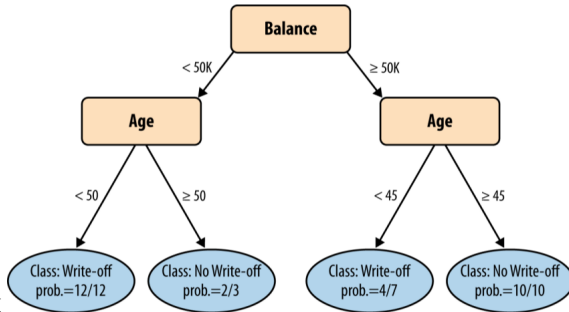


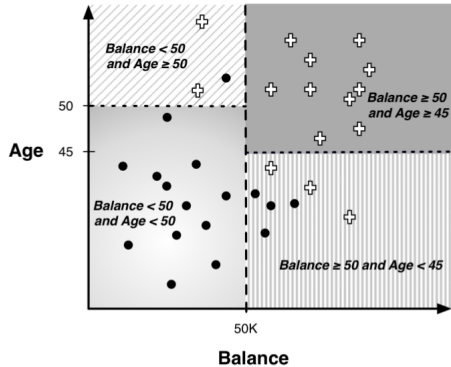
# Fundamental Methods of Data Science

Class 7

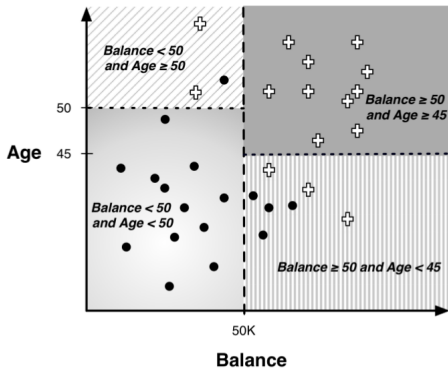
# Tree Classification



# Tree Classification

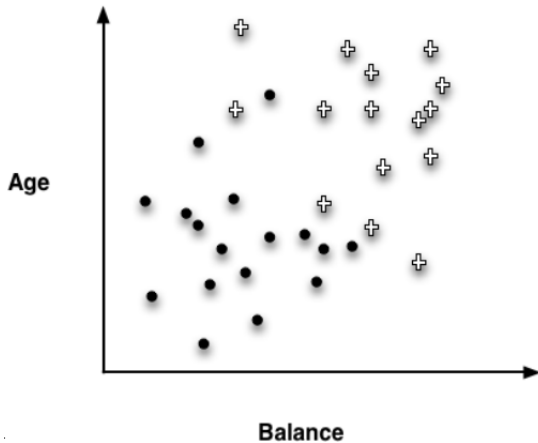


# Tree Classification



- ▶ We can continue classification
  - ▶ What is the problem with that?

## Classification



- Can we do better?

# Linear Classifiers



# Linear Classifiers



- ▶ Line is denoted by the linear equation
  - ▶  $Age = (-1.5) \times Balance + 60$

# Linear Classifiers



- ▶ Line is denoted by the linear equation
  - ▶  $Age = (-1.5) \times Balance + 60$
- ▶ How can we use it for classification?



# Linear Discriminant Functions



- Linear discriminant

$$class(x) = \begin{cases} + & \text{if } 1.0 \times Age - 1.5 \times Balance + 60 > 0 \\ \bullet & \text{if } 1.0 \times Age - 1.5 \times Balance + 60 \leq 0 \end{cases}$$

# Linear Discriminant Functions

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- How can we obtain such a model?

# Linear Discriminant Functions

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- ▶ How can we obtain such a model?
- ▶  $A \times Age + B \times Balance + C$ 
  - ▶ Use data to learn the values of A, B and C

# Linear Discriminant Functions

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- ▶ Can you see another advantage over Classification Trees?

# Linear Discriminant Functions

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- ▶ How can we obtain such a model?
- ▶  $A \times Age + B \times Balance + C$ 
  - ▶ Use data to learn the values of A, B and C
- ▶ Can you see another advantage over Classification Trees?
  - ▶ We get an actual value for free!
  - ▶  $f(x) = x['Age'] - 1.5 * x['Balance'] + 60$

# Linear Discriminant Functions vs Classification Trees

- ▶ Classification Trees

- ▶ Classification models
- ▶ Use IG to choose features
- ▶ Induct a model

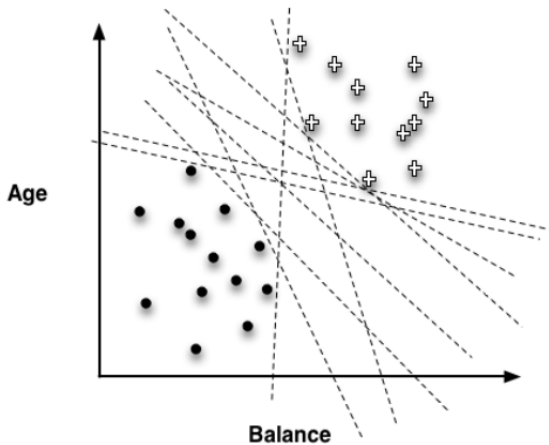
- ▶ Discriminant Functions

- ▶ Mathematical formulae
- ▶ Build a model (still need to know which features to use)
- ▶ Tune it according to data

# Linear Discriminant Functions and Classification

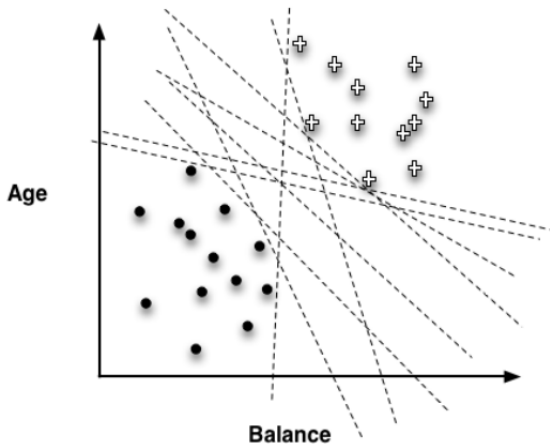
- ▶ Given such a function
  - ▶  $f(x) = x['Age'] - 1.5 * x['Balance'] + 60$
- ▶ Use the line for classification
  - ▶ Positive (Above the line)
  - ▶ Negative (Below the line)
- ▶ Can be extended to more than two features

## Possible Models





## Possible Models



- Which one to choose?

# Objective Functions

- ▶ “Best” line depends on the objective function
  - ▶ Objective function should represent our goal

# Objective Functions

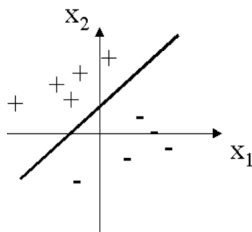
- ▶ “Best” line depends on the objective function
  - ▶ Objective function should represent our goal
- ▶ What about instances misclassified by the model?

# Objective Functions

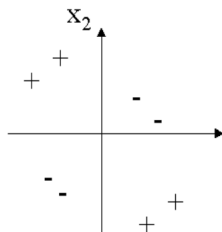
- ▶ “Best” line depends on the objective function
  - ▶ Objective function should represent our goal
- ▶ What about instances misclassified by the model?
  - ▶ We can penalize those

# Perceptron - A Simple Linear Discriminant Function Learner

- ▶ We will see an algorithm for computing such a function in case the data is linearly separable



**Linearly Separable**



**Not Linearly Separable**

# Perceptron

- ▶ We want to learn a function
  - ▶  $w_1 \cdot x + w_2 \cdot y + w_0 \cdot 1 = 0$
- ▶ By using an instance vector
  - ▶  $[(x_1, y_1), \dots, (x_n, y_n)]$

# Perceptron

- ▶ We want to learn a function
  - ▶  $w_1 \cdot x + w_2 \cdot y + w_0 \cdot 1 = 0$
- ▶ By using an instance vector
  - ▶  $[(x_1, y_1), \dots, (x_n, y_n)]$
- ▶ We start by arbitrary weights  $w_0, w_1, w_2$
- ▶ We adjust them each time they fail to properly classify a point

# Perceptron Learning Algorithm

$$\text{Desired output} \quad d(n) = \begin{cases} +1 & \text{if } x(n) \in \text{set } A \\ -1 & \text{if } x(n) \in \text{set } B \end{cases}$$

1. Select a random instance  $n$
2. If  $d(n)$  is correct, do nothing
3. Else, modify the weights
  - ▶  $w_i = w_i + \mu d(n) x_i(n)$
  - ▶  $\mu$  is the learning rate which must be small in order to avoid misplacing the classifier
4. Repeat until all instances are classified correctly



## Example

Initial Values:

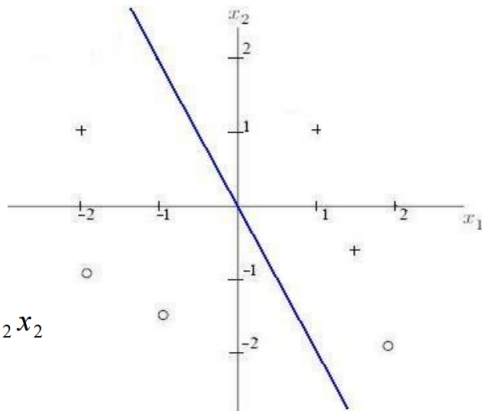
$$\eta = 0.2$$

$$w = \begin{pmatrix} 0 \\ 1 \\ 0.5 \end{pmatrix}$$

$$0 = w_0 + w_1 x_1 + w_2 x_2$$

$$= 0 + x_1 + 0.5x_2$$

$$\Rightarrow x_2 = -2x_1$$



## Example

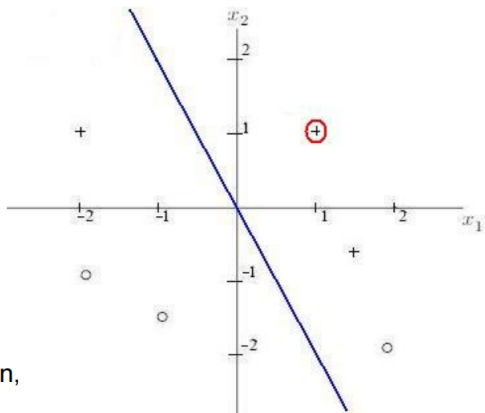
$$\eta = 0.2$$

$$w = \begin{pmatrix} 0 \\ 1 \\ 0.5 \end{pmatrix}$$

$$x_1 = 1, x_2 = 1$$

$$w^T x > 0$$

Correct classification,  
no action



## Example

$$\eta = 0.2$$

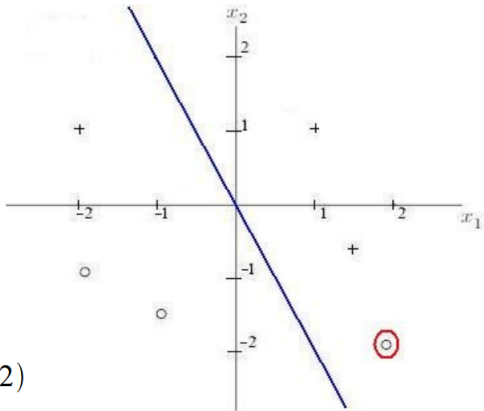
$$w = \begin{pmatrix} 0 \\ 1 \\ 0.5 \end{pmatrix}$$

$$x_1 = 2, x_2 = -2$$

$$w_0 = w_0 - 0.2 * 1$$

$$w_1 = w_1 - 0.2 * 2$$

$$w_2 = w_2 - 0.2 * (-2)$$



## Example

$$\eta = 0.2$$

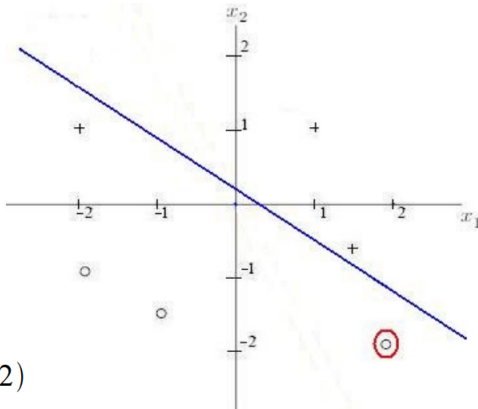
$$w = \begin{pmatrix} -0.2 \\ 0.6 \\ 0.9 \end{pmatrix}$$

$$x_1 = 2, x_2 = -2$$

$$w_0 = w_0 - 0.2 * 1$$

$$w_1 = w_1 - 0.2 * 2$$

$$w_2 = w_2 - 0.2 * (-2)$$



## Example

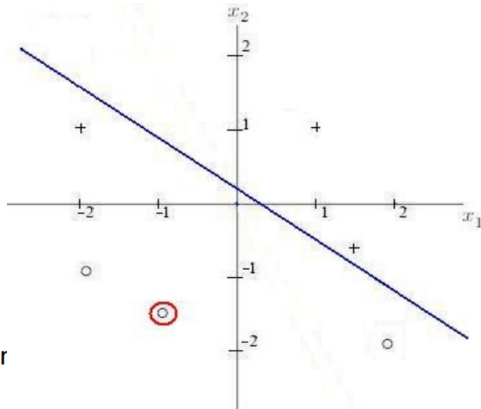
$$\eta = 0.2$$

$$w = \begin{pmatrix} -0.2 \\ 0.6 \\ 0.9 \end{pmatrix}$$

$$x_1 = -1, x_2 = -1.5$$

$$w^T x < 0$$

Correct classification  
no action



## Example

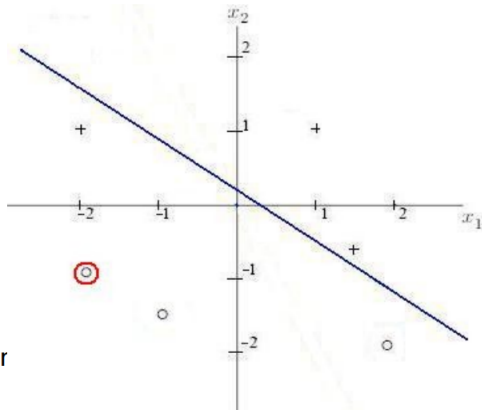
$$\eta = 0.2$$

$$w = \begin{pmatrix} -0.2 \\ 0.6 \\ 0.9 \end{pmatrix}$$

$$x_1 = -2, x_2 = -1$$

$$w^T x < 0$$

Correct classification  
no action



## Example

$$\eta = 0.2$$

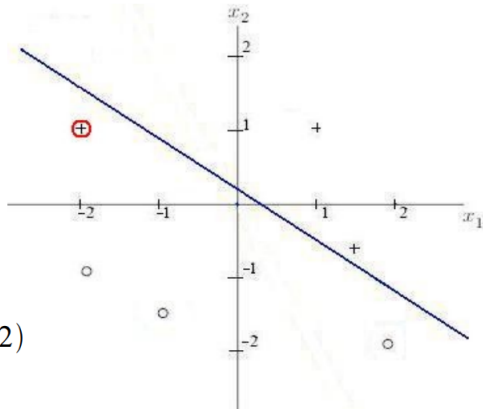
$$w = \begin{pmatrix} -0.2 \\ 0.6 \\ 0.9 \end{pmatrix}$$

$$x_1 = -2, x_2 = 1$$

$$w_0 = w_0 + 0.2 * 1$$

$$w_1 = w_1 + 0.2 * (-2)$$

$$w_2 = w_2 + 0.2 * 1$$



## Example

$$\eta = 0.2$$

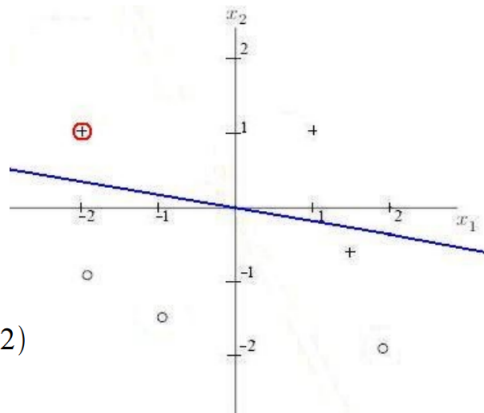
$$w = \begin{pmatrix} 0 \\ 0.2 \\ 1.1 \end{pmatrix}$$

$$x_1 = -2, x_2 = 1$$

$$w_0 = w_0 + 0.2 * 1$$

$$w_1 = w_1 + 0.2 * (-2)$$

$$w_2 = w_2 + 0.2 * 1$$





## Example

$$\eta = 0.2$$

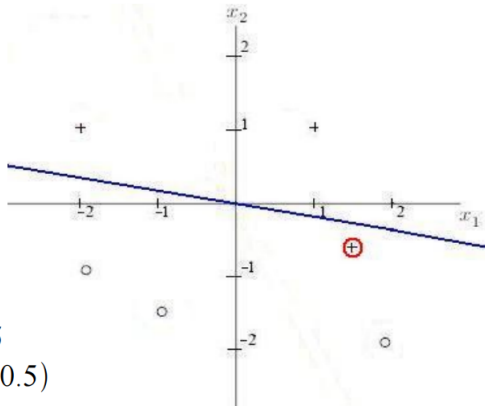
$$w = \begin{pmatrix} 0 \\ 0.2 \\ 1.1 \end{pmatrix}$$

$$x_1 = 1.5, x_2 = -0.5$$

$$w_0 = w_0 + 0.2 * 1$$

$$w_1 = w_1 + 0.2 * 1.5$$

$$w_2 = w_2 + 0.2 * (-0.5)$$



## Example

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$$w = \begin{pmatrix} 0.2 \\ 0.5 \\ 1 \end{pmatrix}$$

$$x_1 = 1.5, x_2 = -0.5$$

$$w_0 = w_0 + 0.2 * 1$$

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$$w_2 = w_2 + 0.2 * (-0.5)$$

