



# CIS 678 - Machine Learning

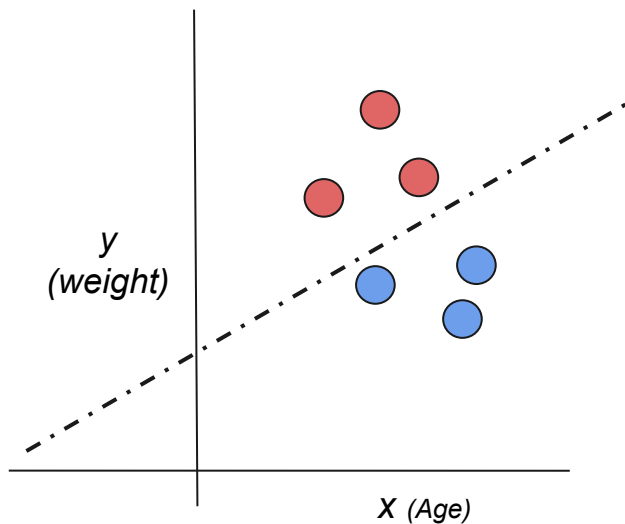
Classification Models: Logistic Regression



# Classification Models

- *k*-NN
- *Decision Tree*
- **Logistic Regression**
  - Random Forest Classifier
  - Support Vector Machines (SVMs)
  - Boosting Classifiers
  - Naive Bayes

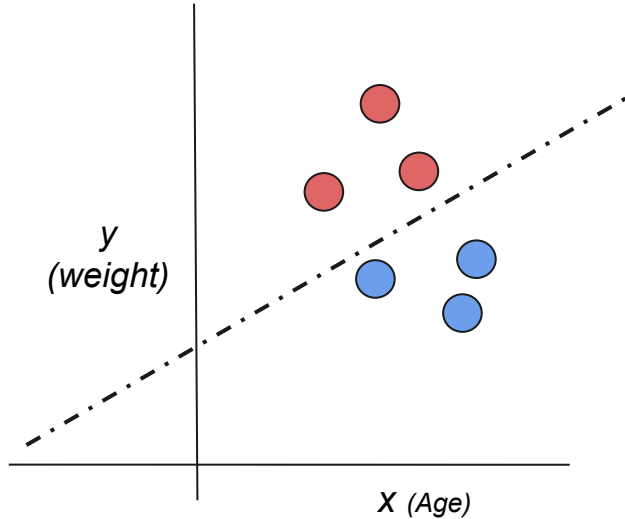
# Linear Line as a Threshold



Straight Line as the Separator

$$y \in \{\text{underweight}(\text{0}), \text{overweight}(\text{1})\}$$

# Linear Line as a Threshold



Straight Line as the Separator

$$y = \beta_0 + \beta_1 x$$

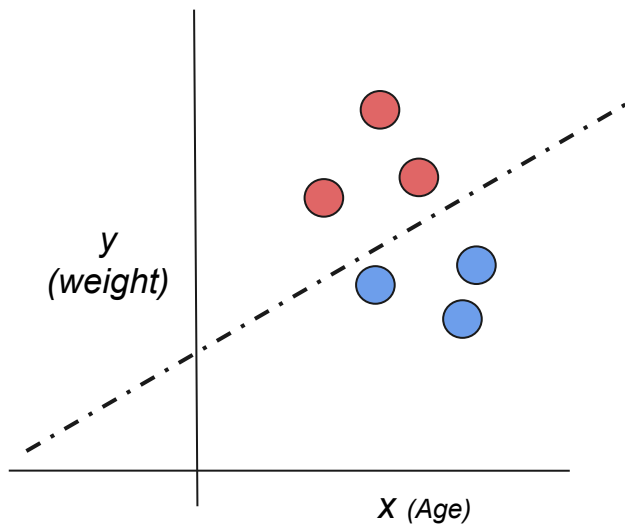
$$y - (\beta_0 + \beta_1 x) = 0$$

Classification Rule

$$\hat{y} = \begin{cases} 1, & \text{if } y - (\beta_0 + \beta_1 x) > 0 \\ 0, & \text{otherwise} \end{cases}$$

# Logistic Regression

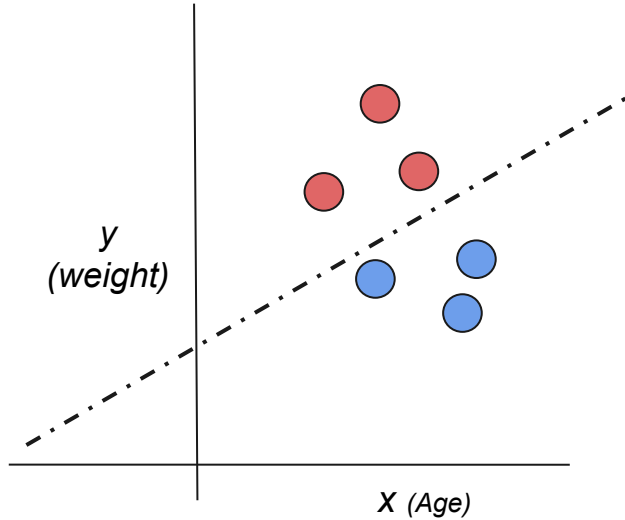
From Regression to Classification



$$p(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}}$$

# Logistic Regression

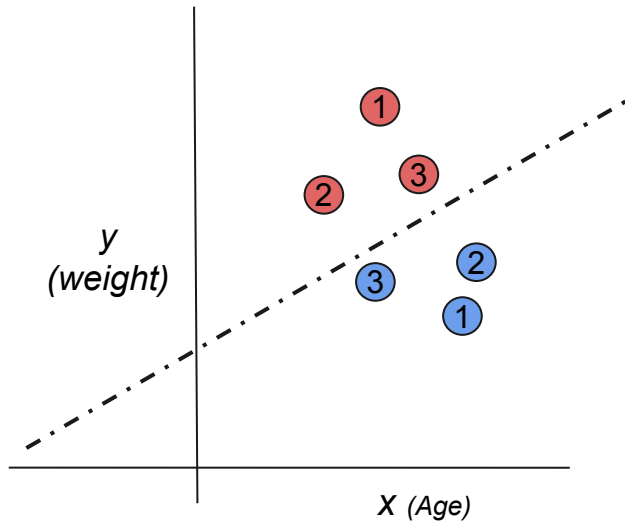
From Regression to Classification



- Relationship to Decision Boundary  
(The dotted line in this case)

# Logistic Regression

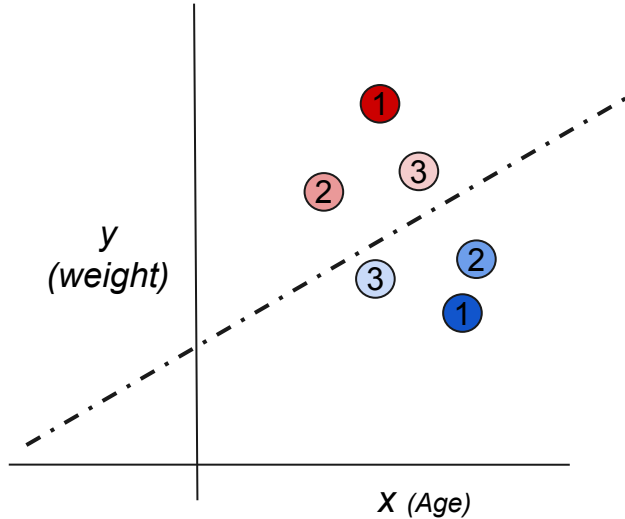
From Regression to Classification



- Relationship to Decision Boundary  
(The dotted line in this case)
- We index based on their distance

# Logistic Regression

From Regression to Classification

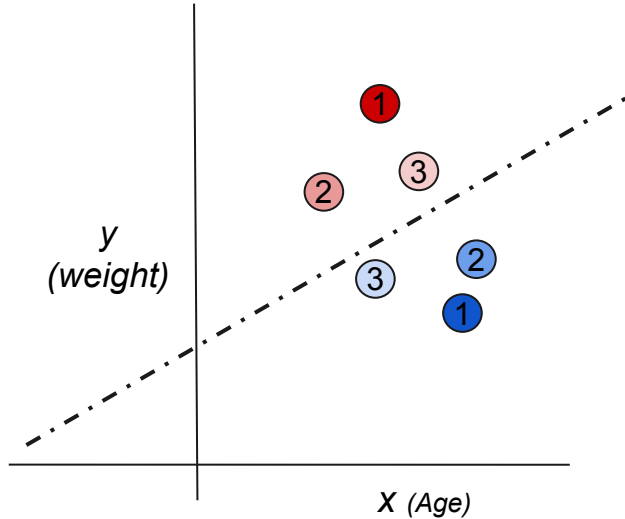


- Relationship to Decision Boundary (The dotted line in this case)
- We index based on their distance
- Also add color code for better understanding



# Logistic Regression

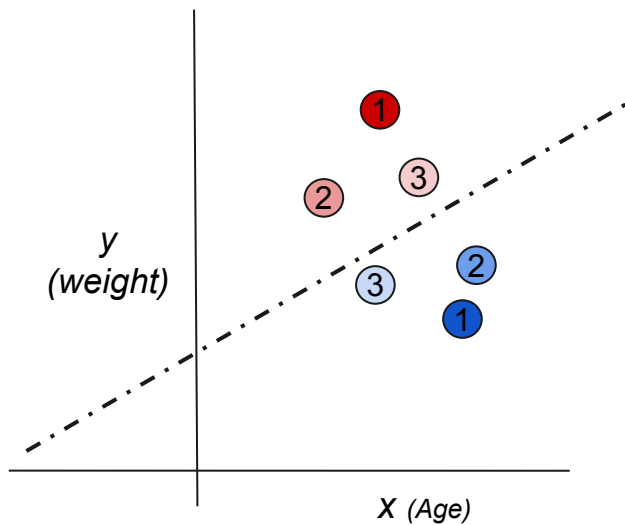
From Regression to Classification



- Relationship to Decision Boundary (The dotted line in this case)
- We index based on their distance
- Also add color code for better understanding
- Let's do feature encoding

# Logistic Regression

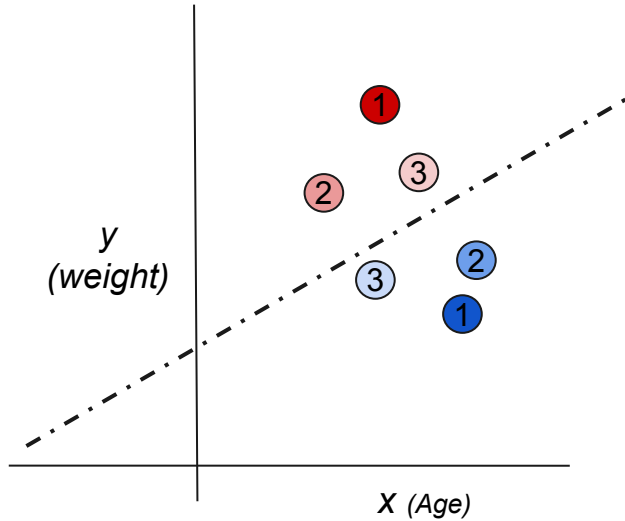
From Regression to Classification



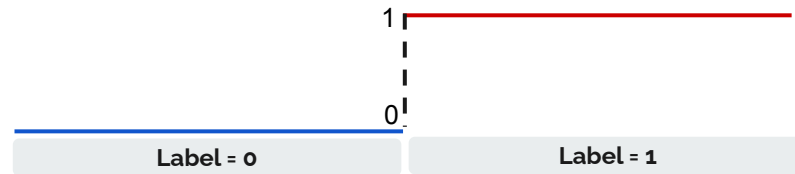
- Let's do feature encoding: **Binary** {0, 1}

# Logistic Regression

From Regression to Classification

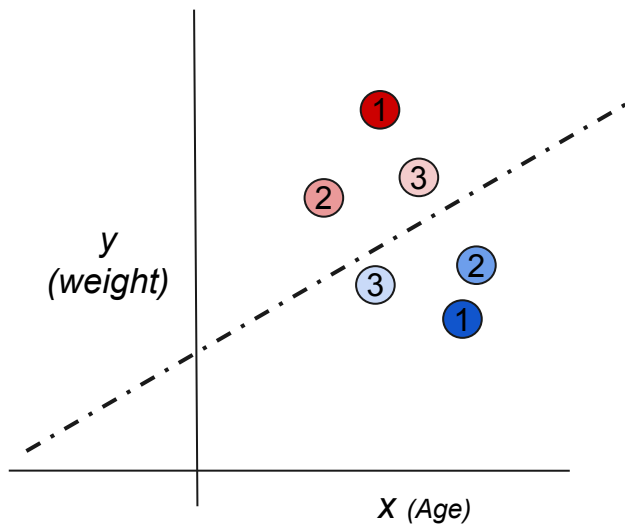


- Let's do feature encoding: **Binary {0, 1}**

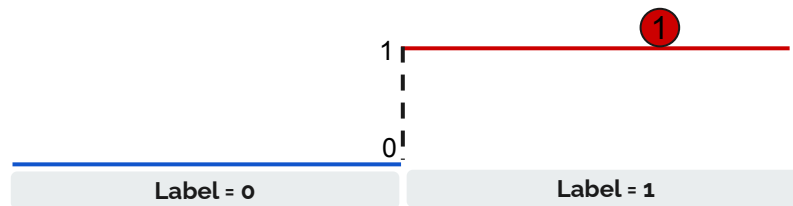


# Logistic Regression

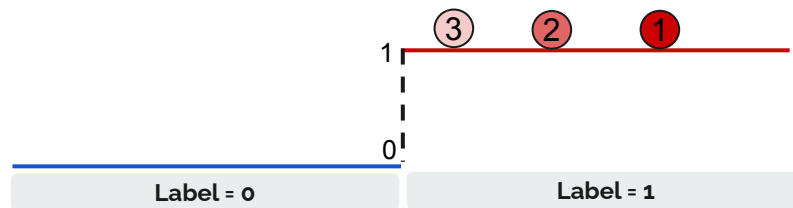
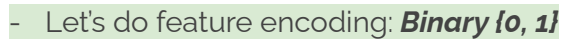
From Regression to Classification



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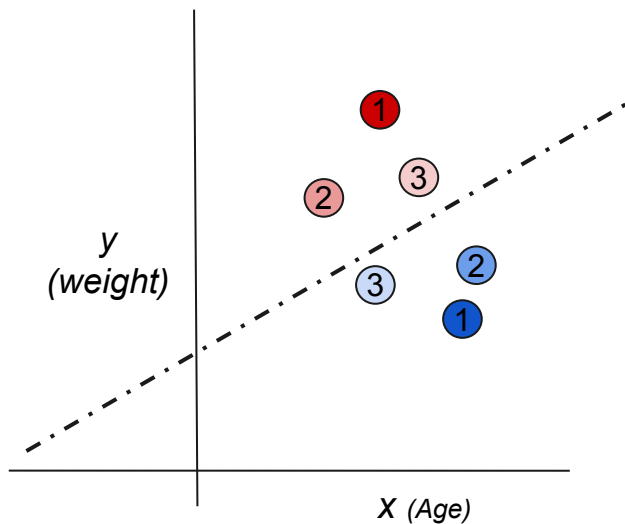


## From Regression to Classification

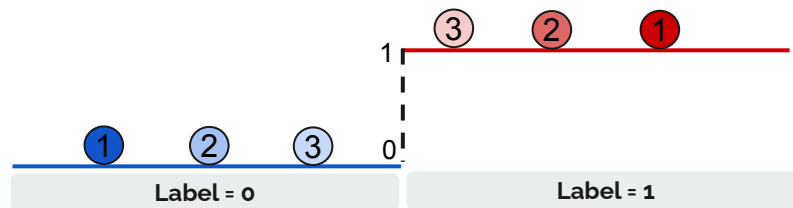


# Logistic Regression

From Regression to Classification

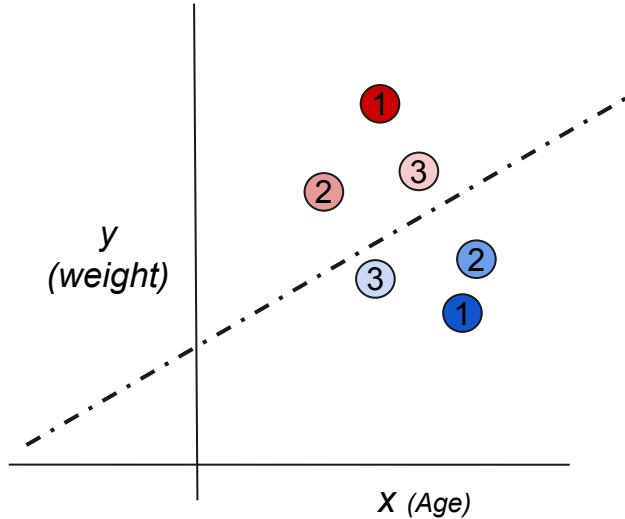


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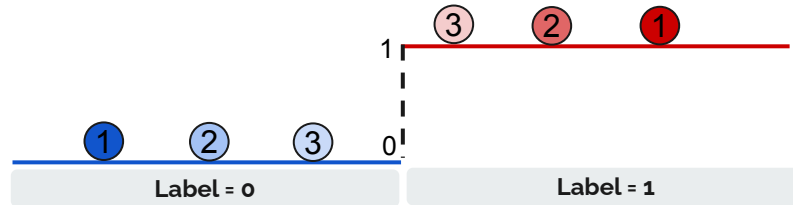


# Logistic Regression

From Regression to Classification

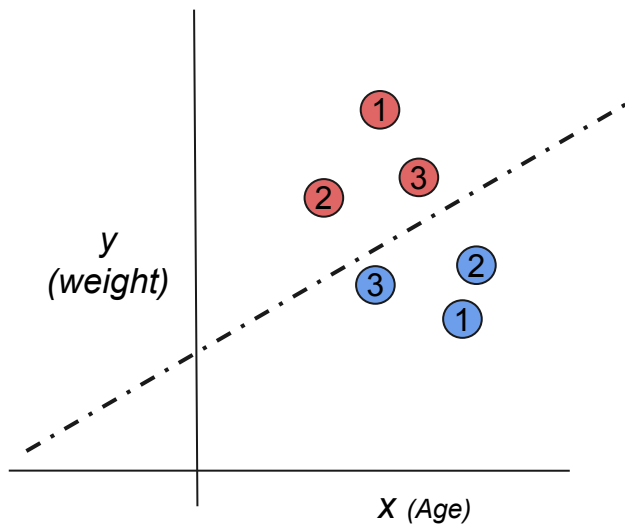


- Let's do feature encoding: **Binary {0, 1}**
- We have to sacrifice color density (all from the same class have the same label, either 0/1)

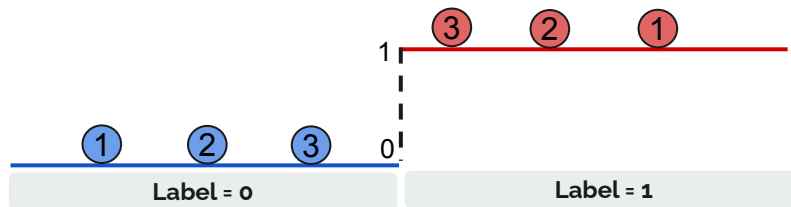


# Logistic Regression

From Regression to Classification



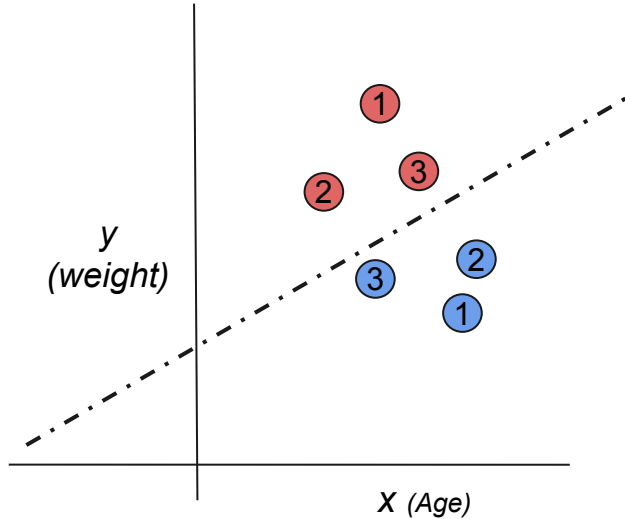
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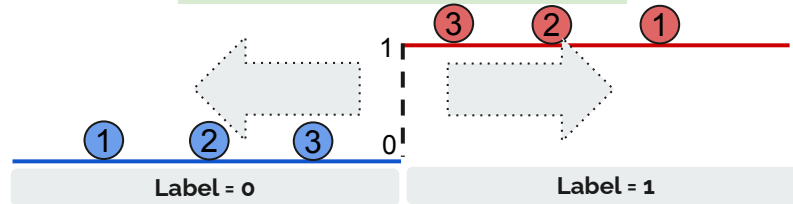


# Logistic Regression

From Regression to Classification

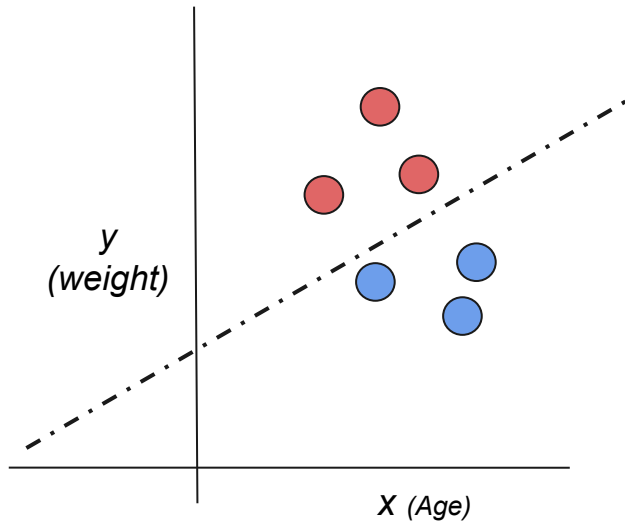


- Let's do feature encoding: **Binary {0, 1}**
- We have to sacrifice color density (all from the same class have the same label, either 0/1)
- We capture the indexing relationship with the distance from the 0-axis.



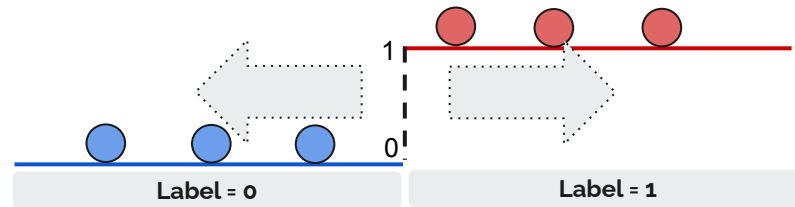
# Logistic Regression

From Regression to Classification



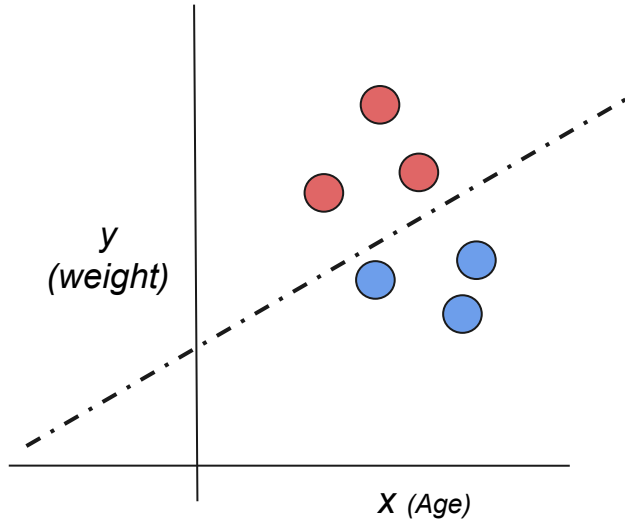
$$p(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}}$$

- All we have discussed so far are captured through the above function; how?



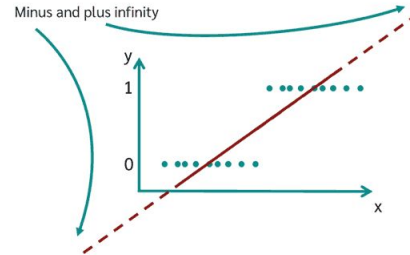
# Logistic Regression

From Regression to Classification



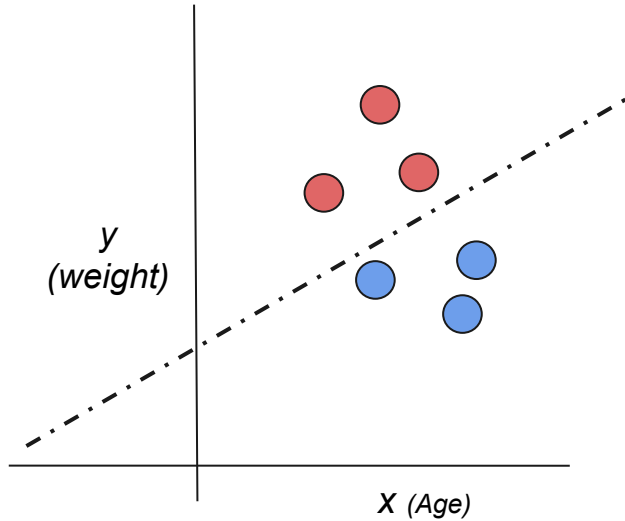
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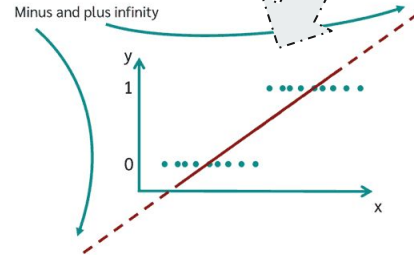
# Logistic Regression

From Regression to Classification



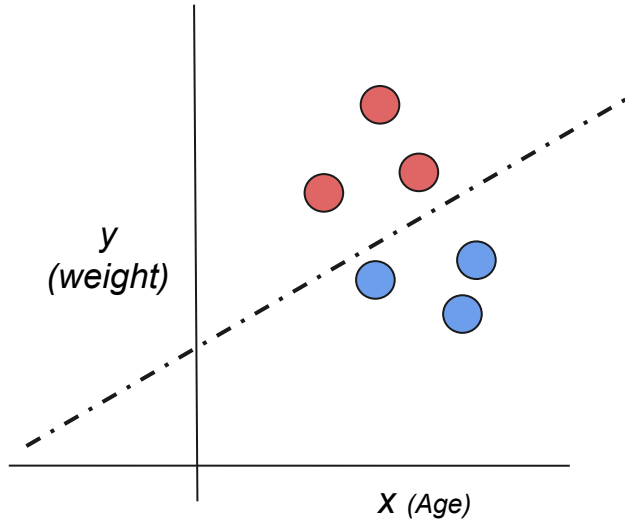
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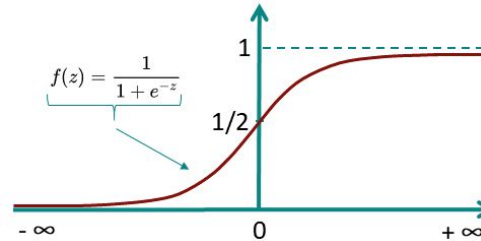
# Logistic Regression

From Regression to Classification



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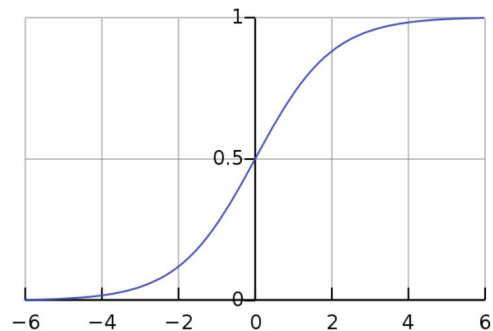
# Logistic Regression

- Probabilistic classifier

Sigmoid function characteristic

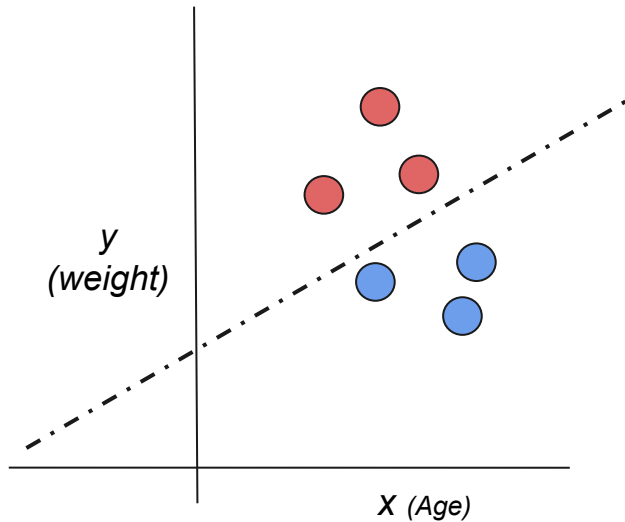
$$p(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}}$$

- Sigmoid function



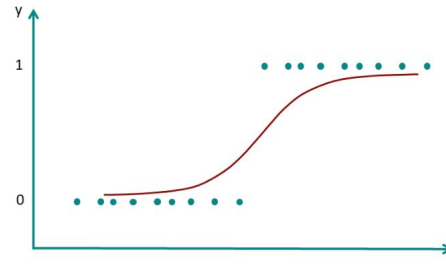
# Logistic Regression

From Regression to Classification

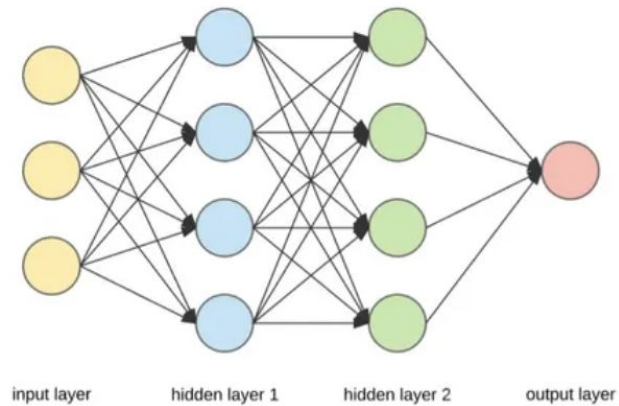


$$p(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}}$$

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# What's its connection to Neural Networks



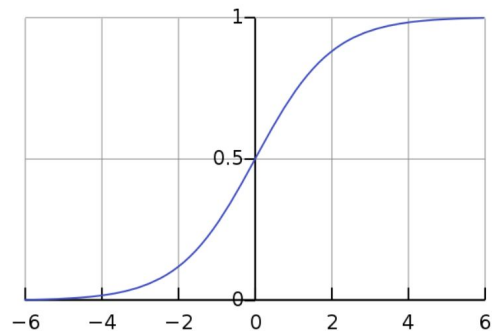


# Logistic Regression

- Probabilistic classifier

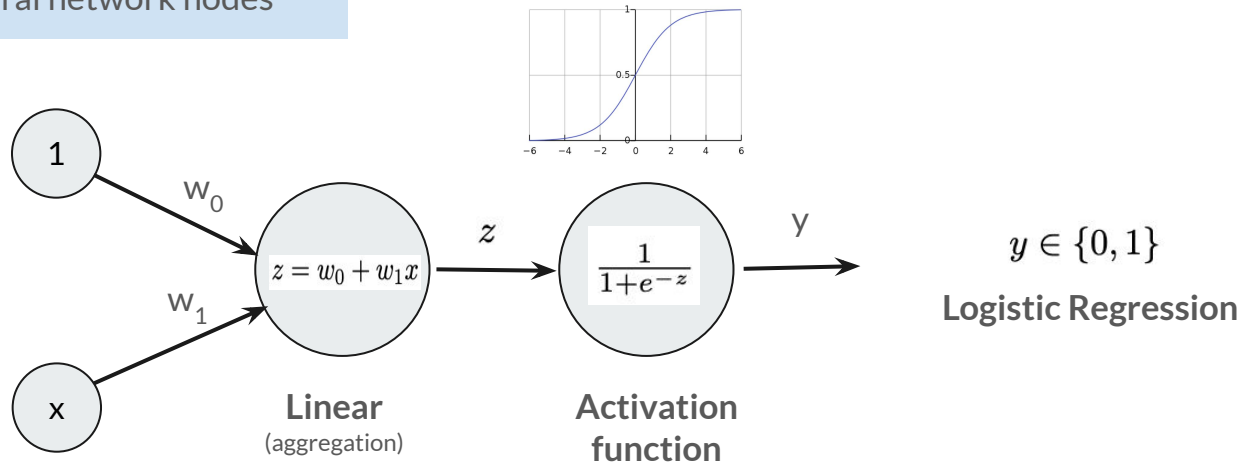
$$p(x) = \frac{1}{1 + e^{-(w_0 + w_1 x)}}$$

- Sigmoid function



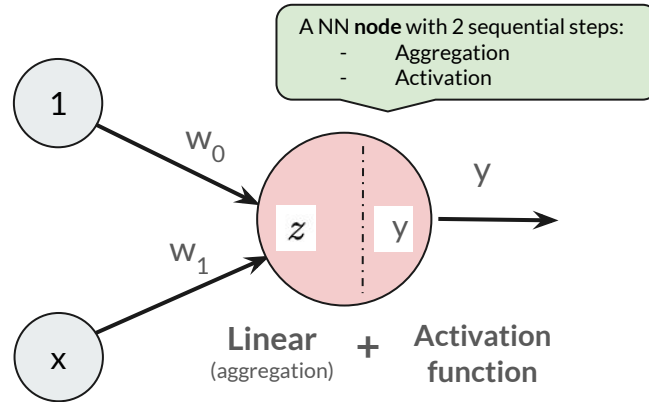
# Logistic Regression to Neural Networks (NNs)

Concept of neural network nodes



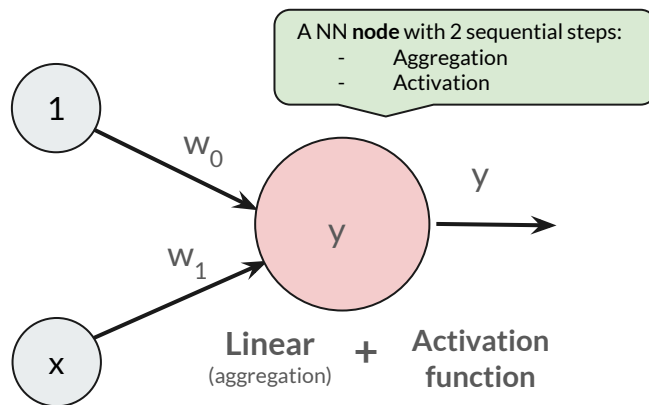
# Neural Networks (Node)

Concept of neural network nodes



# Neural Networks (Node)

Concept of neural network nodes





**QA**