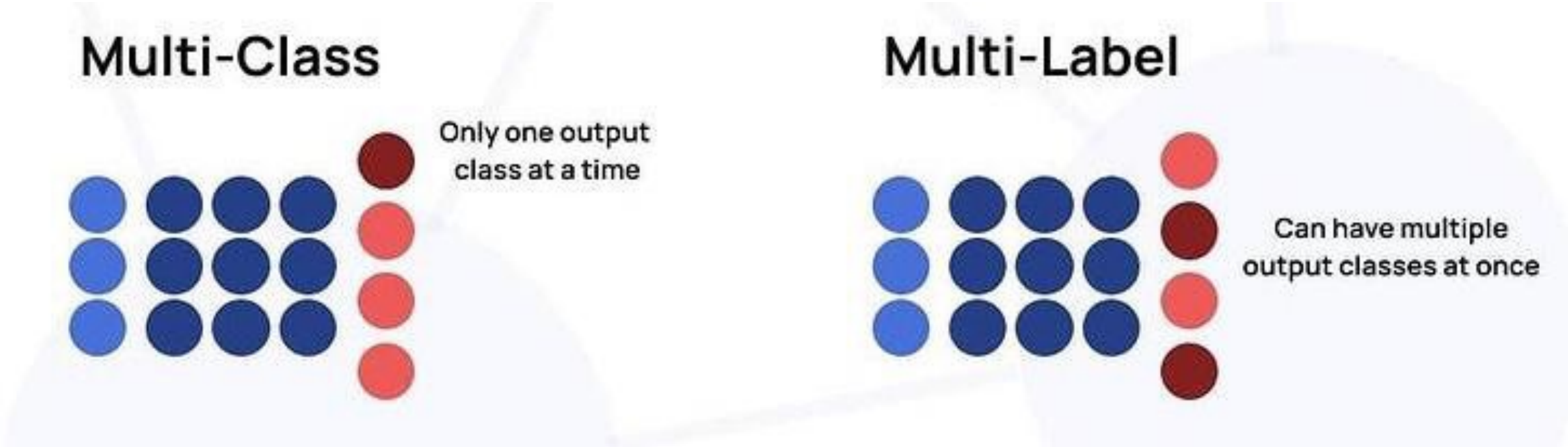
Mì Ai

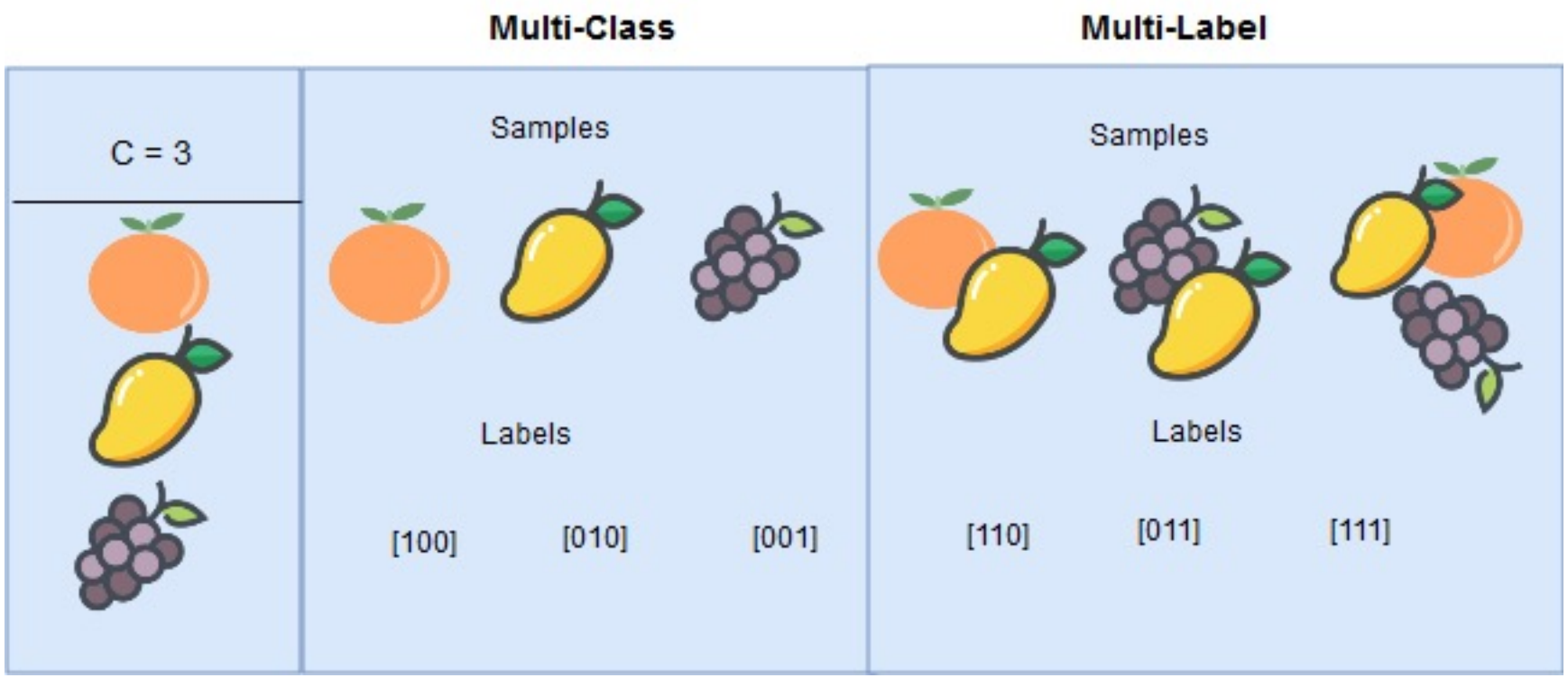
Multi-label Classification

Multi-labels vs Multi-classes

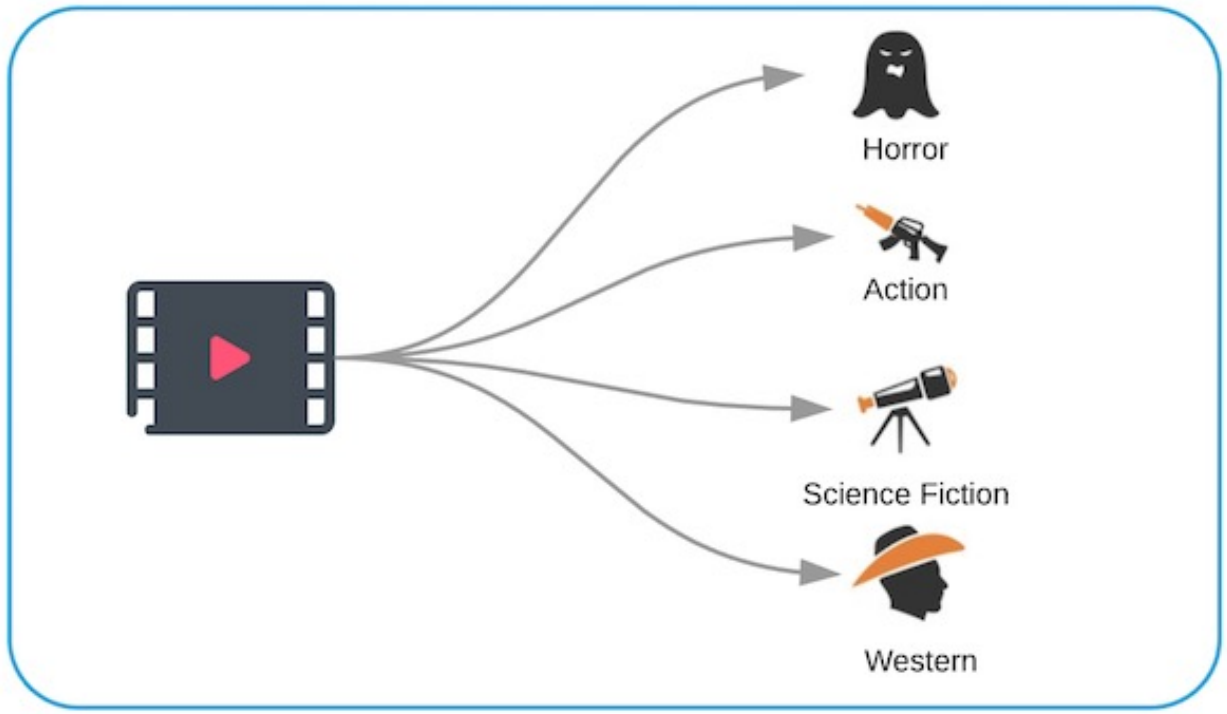
Multi-labels vs Multi-classes



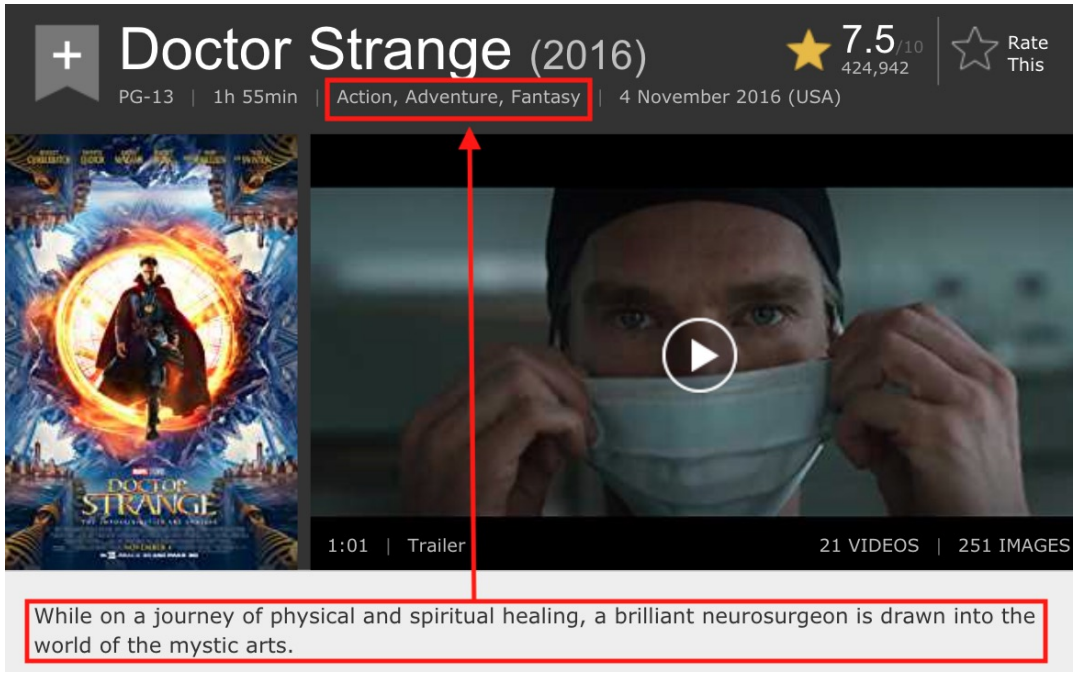
Multi-labels vs Multi-classes



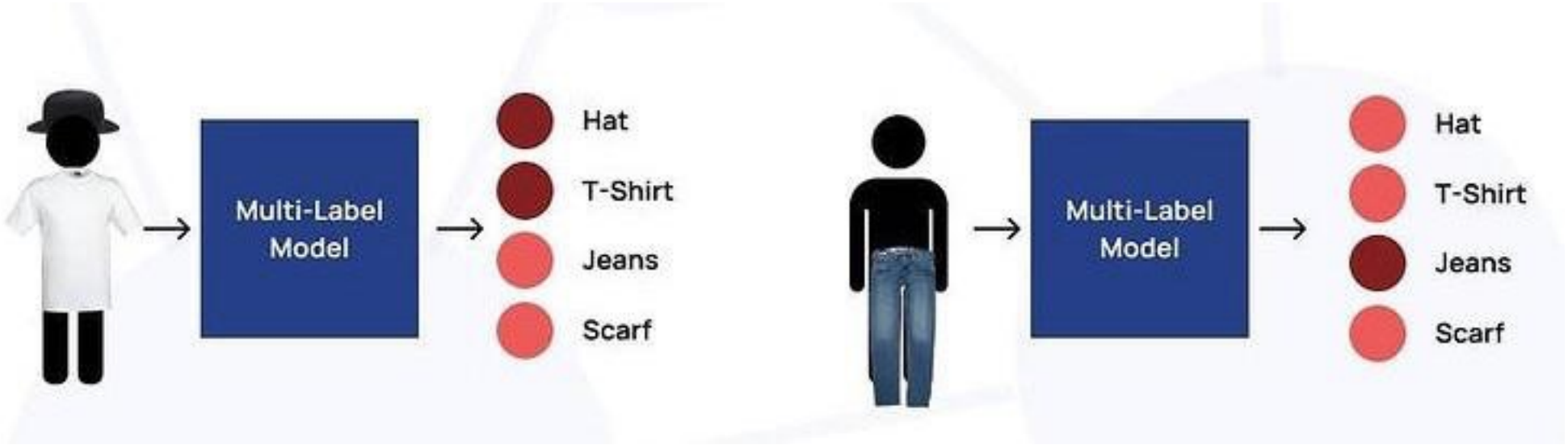
Multi-labels



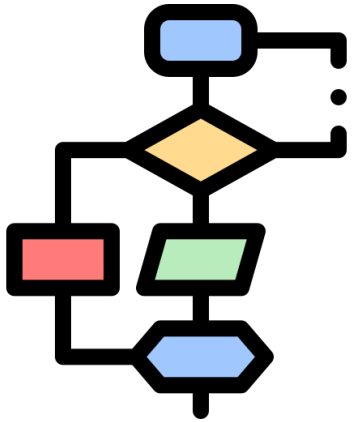
Multi-class classification



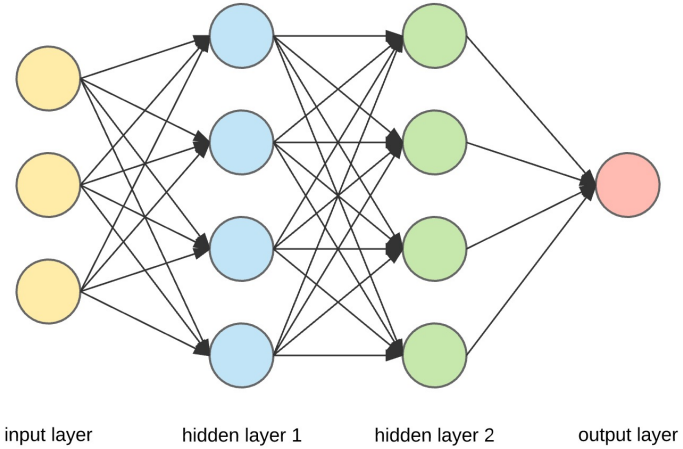
Multi-labels



Techniques



Traditional ML Algorithm



Neural Network

Traditional ML Algorithm

1. Problem Transformation
2. Adapted Algorithm

Traditional ML Algorithm

Problem Transformation

- Binary Relevance
- Classifier Chains
- Label Powerset

Adapted Algorithm

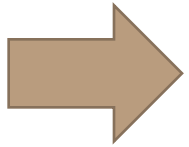
- MLkNN
- Others: http://scikit.ml/modelselection.html

Traditional ML Algorithm

Problem Transformation

- Binary Relevance

X	Y_1	Y_2	Y_3	Y_4
$x^{(1)}$	0	1	1	0
$x^{(2)}$	1	0	0	0
$x^{(3)}$	0	1	0	0
$x^{(4)}$	1	0	0	1
$x^{(5)}$	0	0	0	1



X	Y_1
$x^{(1)}$	0
$x^{(2)}$	1
$x^{(3)}$	0
$x^{(4)}$	1
$x^{(5)}$	0

X	Y_2
$x^{(1)}$	1
$x^{(2)}$	0
$x^{(3)}$	1
$x^{(4)}$	0
$x^{(5)}$	0

X	Y_3
$x^{(1)}$	1
$x^{(2)}$	0
$x^{(3)}$	0
$x^{(4)}$	0
$x^{(5)}$	0

X	Y_4
$x^{(1)}$	0
$x^{(2)}$	0
$x^{(3)}$	0
$x^{(4)}$	1
$x^{(5)}$	1

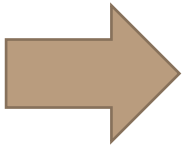
Nguồn: https://www.analyticsvidhya.com/blog/2017/08/introduction-to-multi-label-classification/

Traditional ML Algorithm

Problem Transformation

- Classifier Chains

X	y1	y2	y3	y4
x1	0	1	1	0
x2	1	0	0	0
x3	0	1	0	0



X	y1
x1	0
x2	1
x3	0

Classifier 1

X	y1	y2
x1	0	1
x2	1	0
x3	0	1

Classifier 2

X	y1	y2	y3
x1	0	1	1
x2	1	0	0
x3	0	1	0

Classifier 3

X	y1	y2	y3	y4
x1	0	1	1	0
x2	1	0	0	0
x3	0	1	0	0

Classifier 4

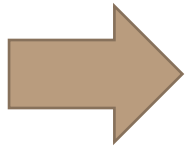
Nguồn: https://www.analyticsvidhya.com/blog/2017/08/introduction-to-multi-label-classification/

Traditional ML Algorithm

Problem Transformation

- Label Powerset

X	y1	y2	y3	y4
x1	0	1	1	0
x2	1	0	0	0
x3	0	1	0	0
x4	0	1	1	0
x5	1	1	1	1
x6	0	1	0	0



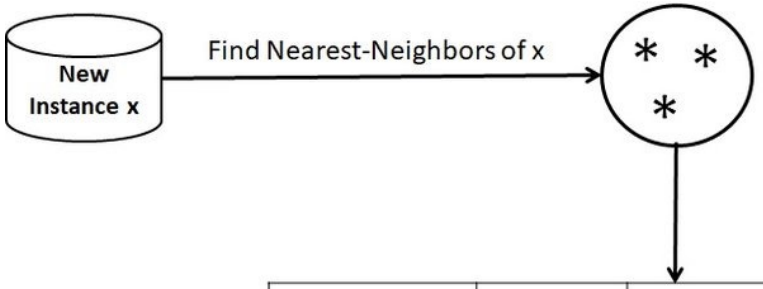
X	y1
x1	1
x2	2
x3	3
x4	1
x5	4
x6	3

Nguồn: https://www.analyticsvidhya.com/blog/2017/08/introduction-to-multi-label-classification/

Traditional ML Algorithm

Adapted Algorithm

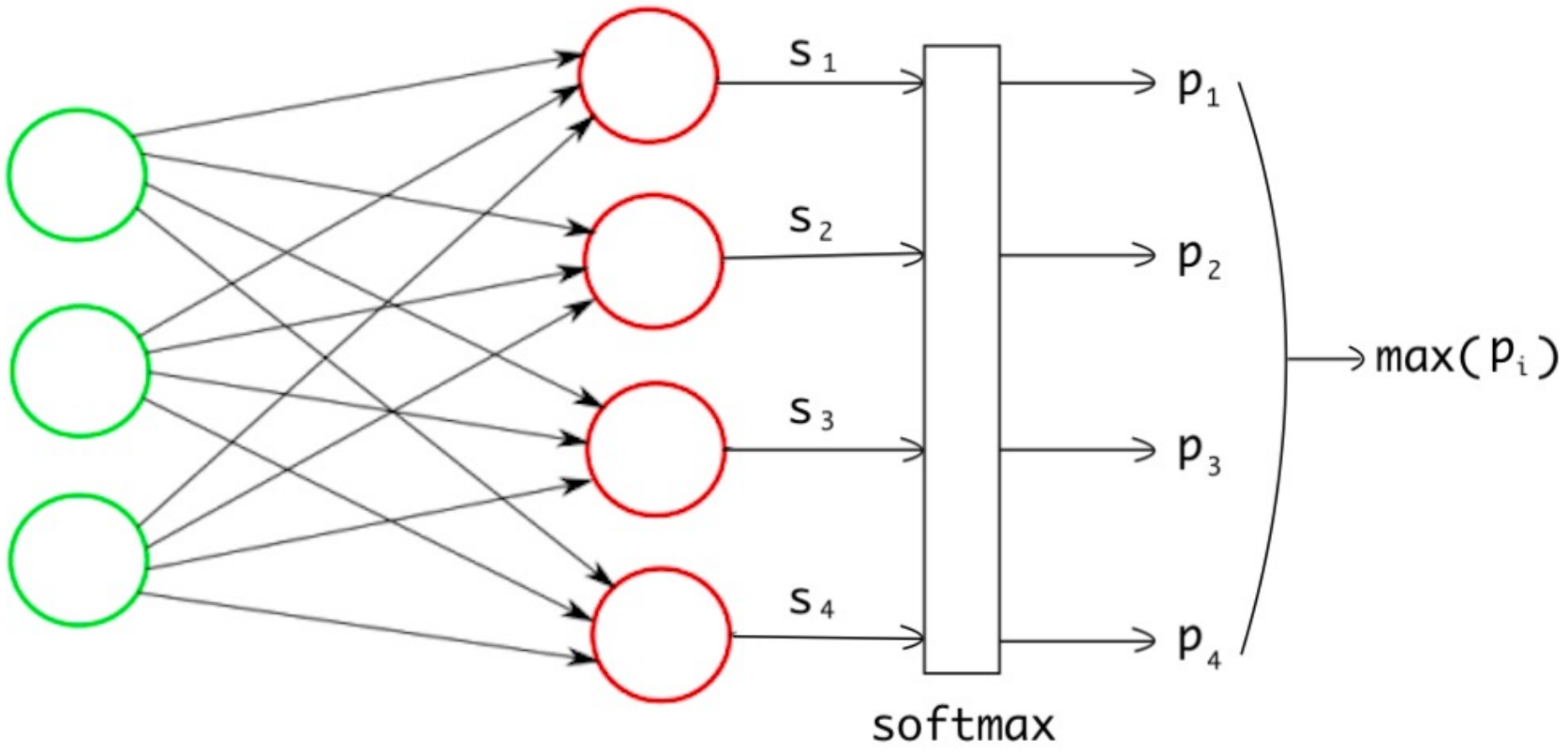
- MLkNN



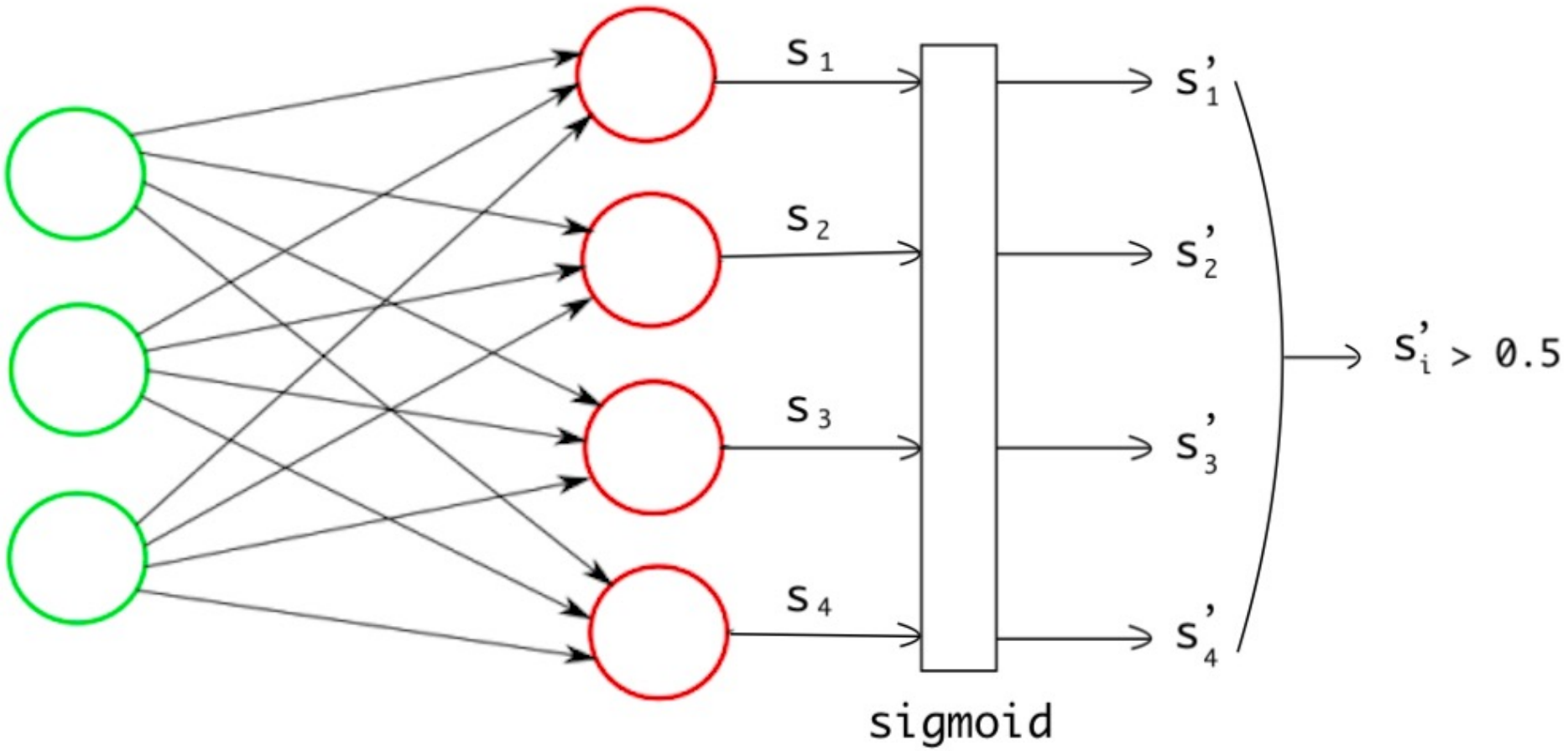
Labels	Label 1	Label 2	Label 3	Label 4
1st Neighbor	1	0	1	0
2nd Neighbor	0	0	1	1
3rd Neighbor	1	1	0	0
Probabilities	P(l=1)=0,66	P(l=1)=0,33	P(l=1)=0,66	P(l=1)=0,33
	P(l=0)=0,33	P(l=0)=0,66	P(l=0)=0,33	P(l=0)=0,66
MAP Probabilities Threshold=0,5	0,6	0,6	0,6	0,6
Final label of x	1	0	1	0

Nguồn: https://www.researchgate.net/figure/MLKNN-principle-example-to-classify-a-new-instance_fig1_336522781/

Neural Network



Neural Network



Evaluation

- **Exact Match Ratio**

  One trivial way around would just to ignore partially correct (consider them incorrect) and extend the *accuracy* used in single label case for multi-label prediction.

$$\text{Exact Match Ratio, MR} = \frac{1}{n}\sum_{i=1}^{n} I(y_i = \hat{y}_i)$$

  where I is the indicator function. Clearly, a disadvantage of this measure is that it does not distinguish between complete incorrect and partially correct which might be considered harsh.

Evaluation

- **Accuracy**

  Accuracy for each instance is defined as the proportion of the predicted correct labels to the total number (predicted and actual) of labels for that instance. Overall accuracy is the average across all instances. It is less ambiguously referred to as the *Hamming score*.

$$\text{Accuracy} = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i \cap \hat{y}_i|}{|y_i \cup \hat{y}_i|}$$

Hands-on