pdi-Bagging / pdi-Boosting

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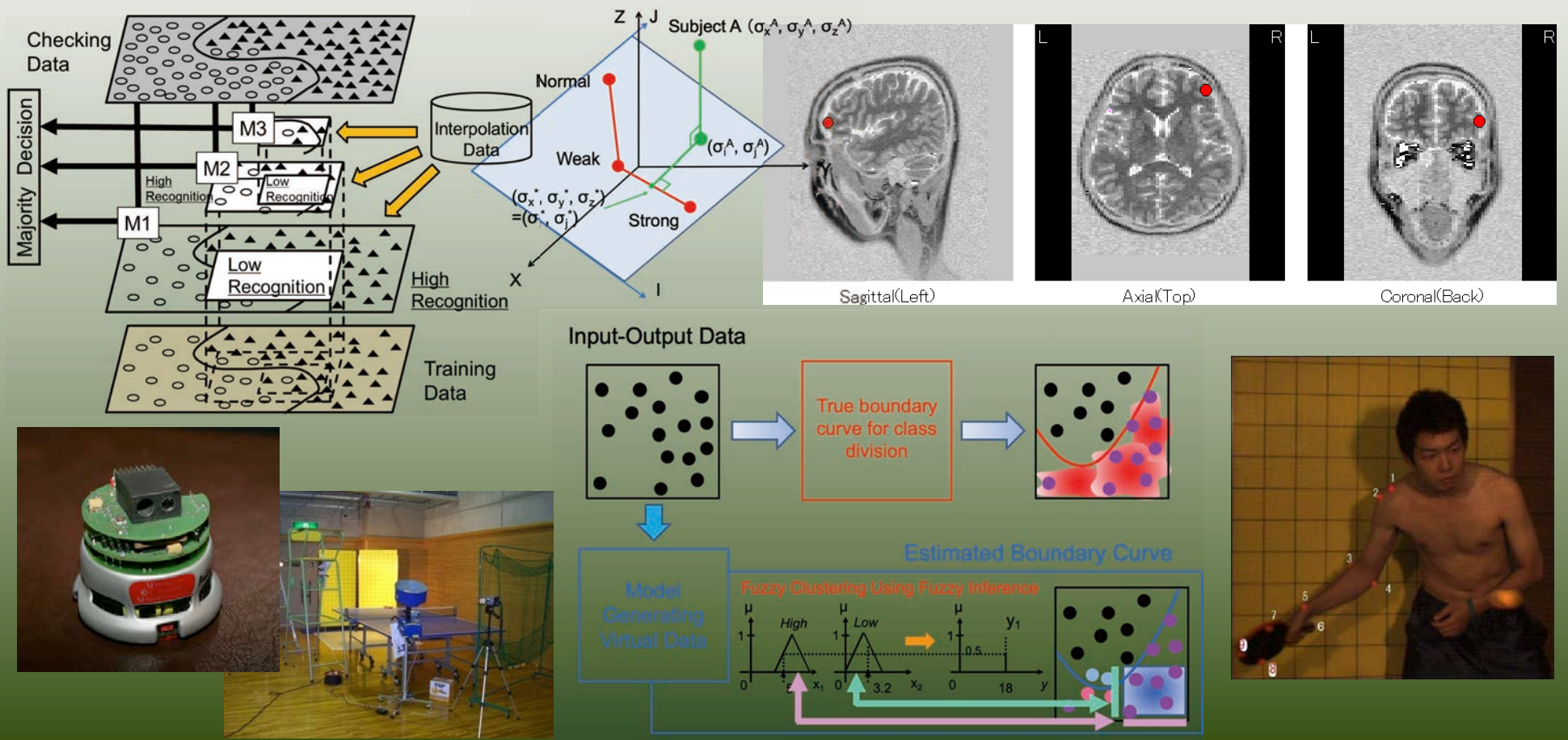


Introduction

Introduction

- Professor, Faculty of Informatics
  Kansai University (Dr.Eng.)
  - Doctor's Degree, Graduate School of Engineering, Osaka Prefecture University
  - Sharp Corporation
  - Central Research Laboratories, Matsushita Electric Industrial (Panasonic) Co. Ltd.
  - Neuro-Fuzzy System
  - Visiting Professor, Department of Cognitive and Neural Systems, Boston University
  - Associate Dean, Graduate School of Informatics, Kansai University
  - President, Japan Society for Fuzzy Theory and Intelligent Informatics
  - Vice President, International Fuzzy Systems Association (IFSA)
  - General Manager, Table Tennis Club, Kansai University
  - Executive Board Member, Osaka Table Tennis Association
  - Japan Sport Association official table tennis senior instructor

Data Science in Our Laboratory

Principle of Data Science in Our Laboratory

We propose a model to be identified from observed data sets with high accuracy.

Not like that,

We propose a structure of data how to let model be highly accuracy.

Purpose of Data Science in Our Laboratory

1. We form the detected data distribution as knowledge.

2. We extract expert skill as knowledge.

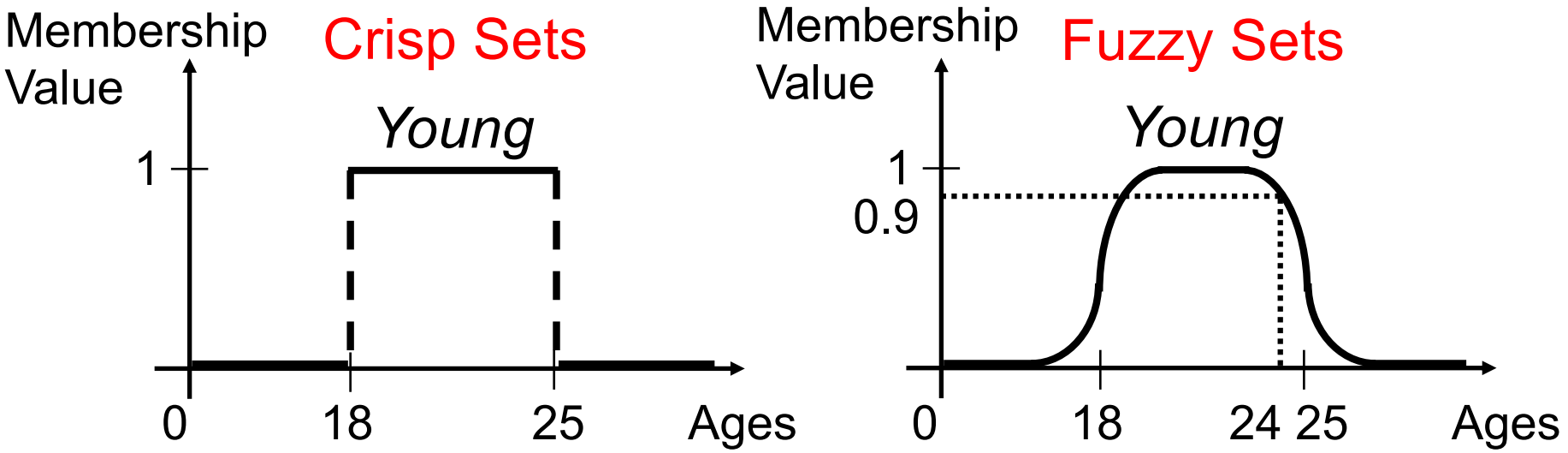
3. We improve the skill of beginners by the comparison with the expert skill.

Methods of Data Science in Our Laboratory

To achieve our purpose,

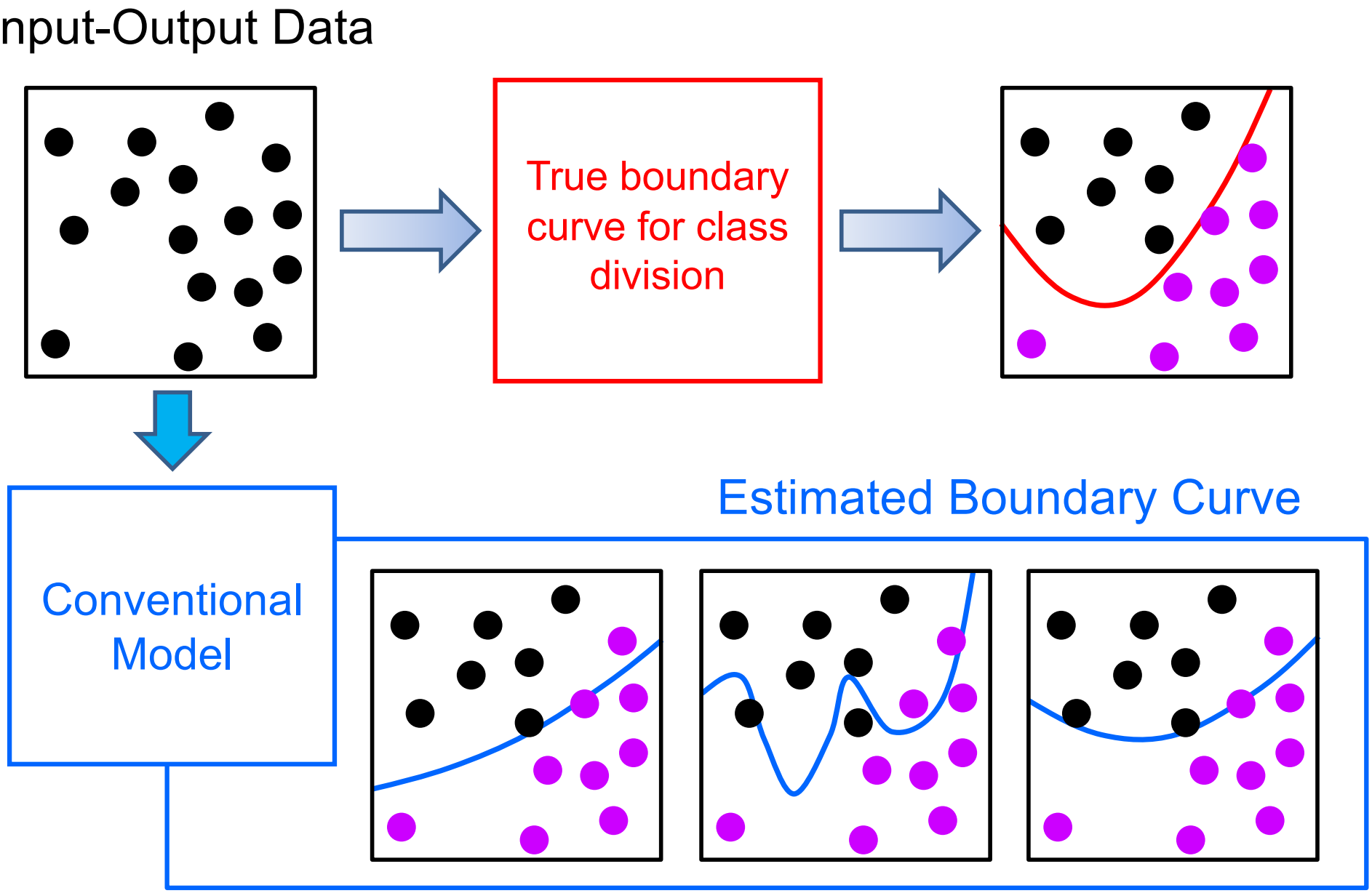
1. Estimating degree of the existence of data.
2. Estimating location of the existence of data.
3. Estimating distribution of the existence of data.

Fuzzy Sets (Estimating degree of the existence of data.)

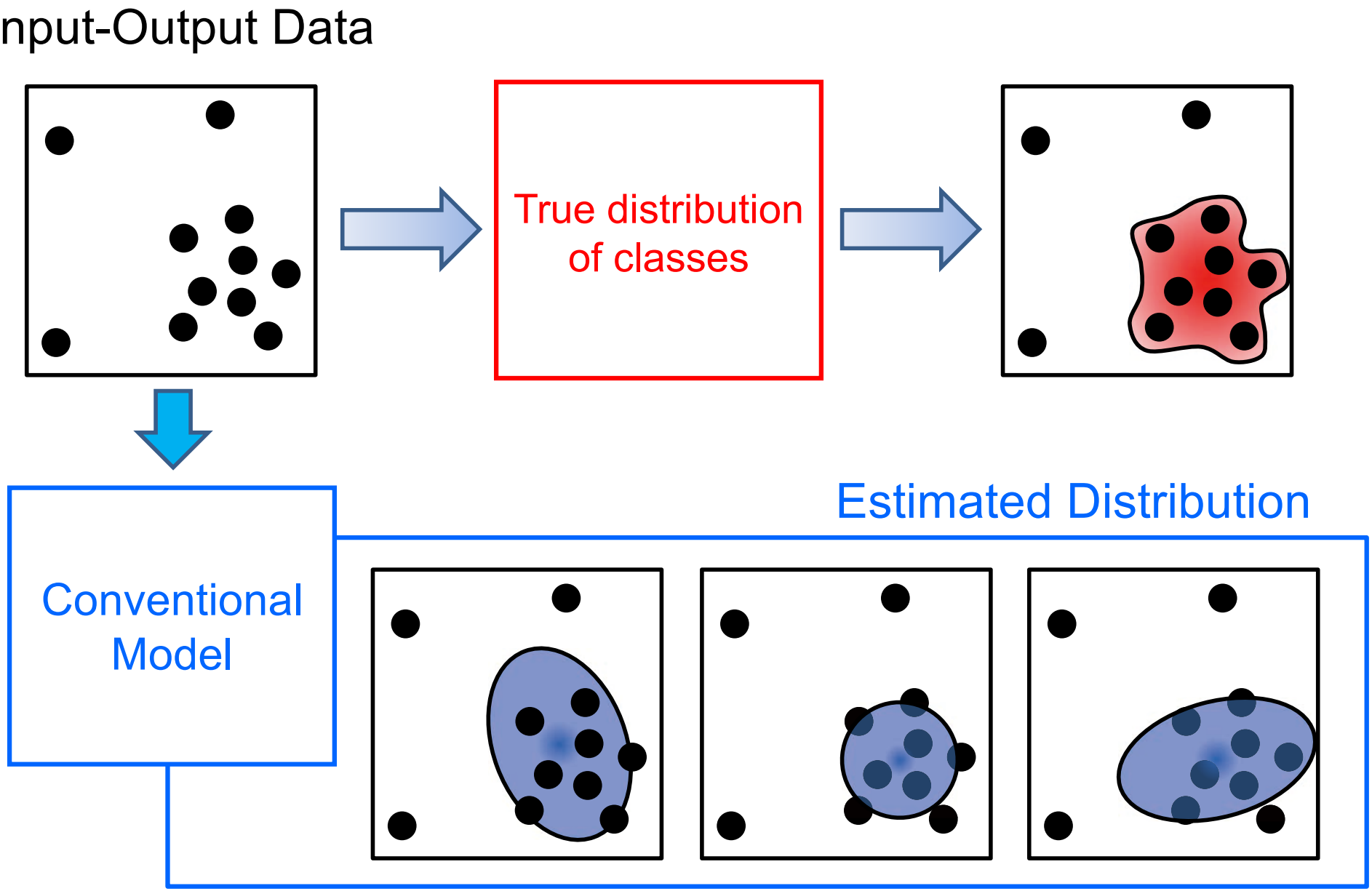


- Crisp Sets
  - Represents conventional sets.
  - In the case of a set of "*Young*", the value is 1.0 if you are satisfied with the "*Young*" between the ages of 18 and 25, and 0.0 if you are not satisfied.
  - However, the value of the "*Young*" is 1.0 when 18 years and 1 day, but the value of "*Young*" is 0.0 when 17 years, 11 months, 30 days, 23 hours, 59 minutes, and 59 seconds. → It is not common sense.
- Fuzzy Sets
  - The fuzzy set "*Young*" is figured with membership function.
  - The degree of "*Young*" is expressed as membership value in $[0, 1]$ interval.

Estimating location of the existence of data.

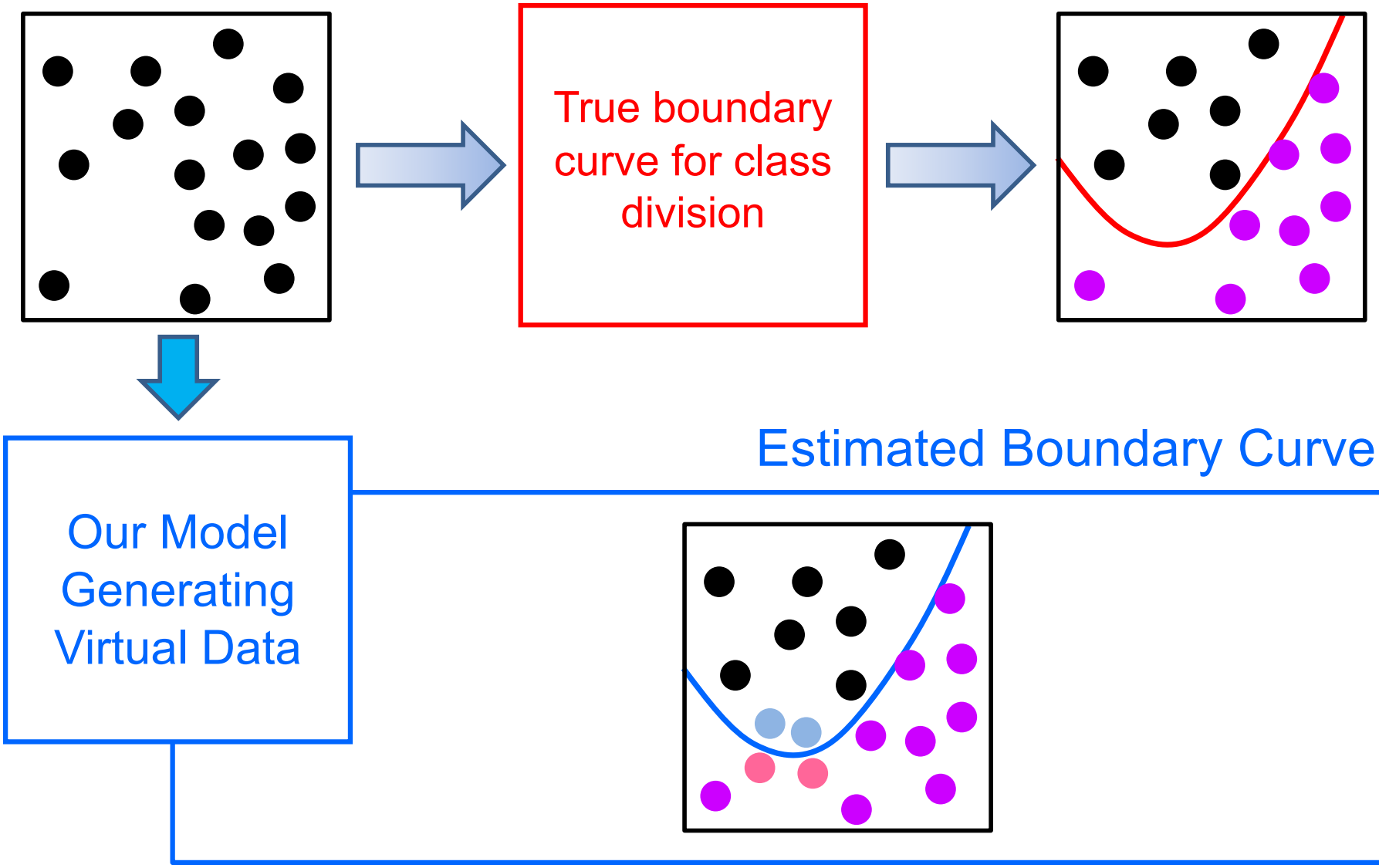


Estimating distribution of the existence of data.



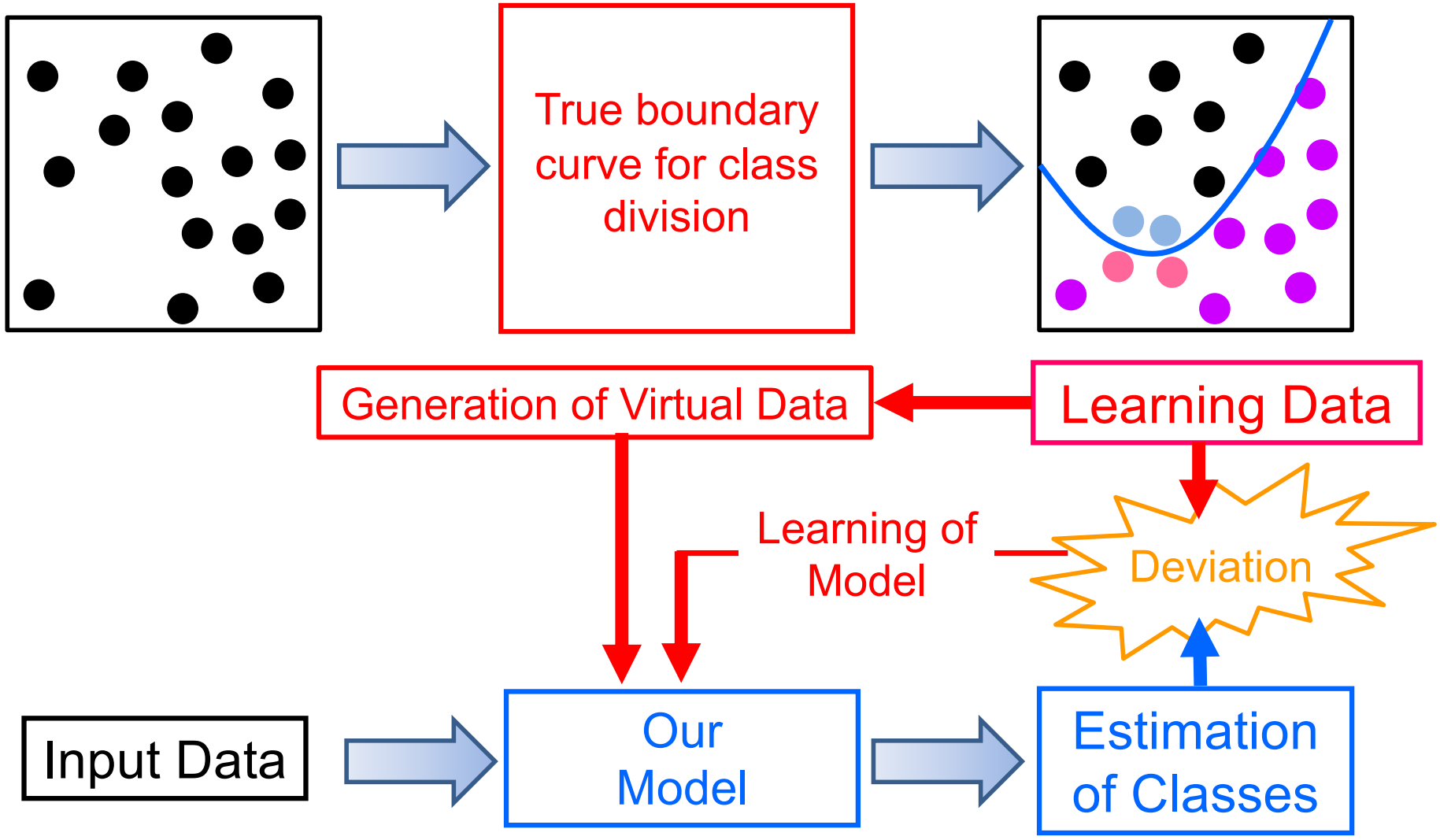
Our model

Input-Output Data



Data and Our Model

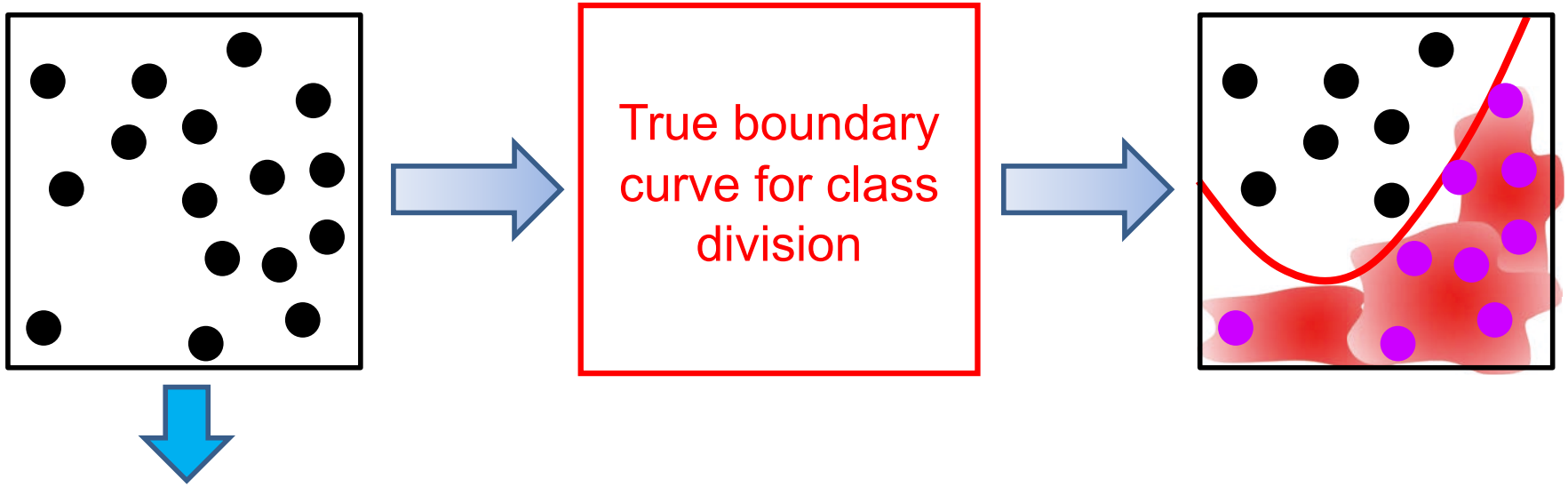
Input-Output Data



- Deviation γ depends on the modification of model M and the generation of virtual data v. $\gamma = modify(M,\ v)$

Our model Using Fuzzy Inference

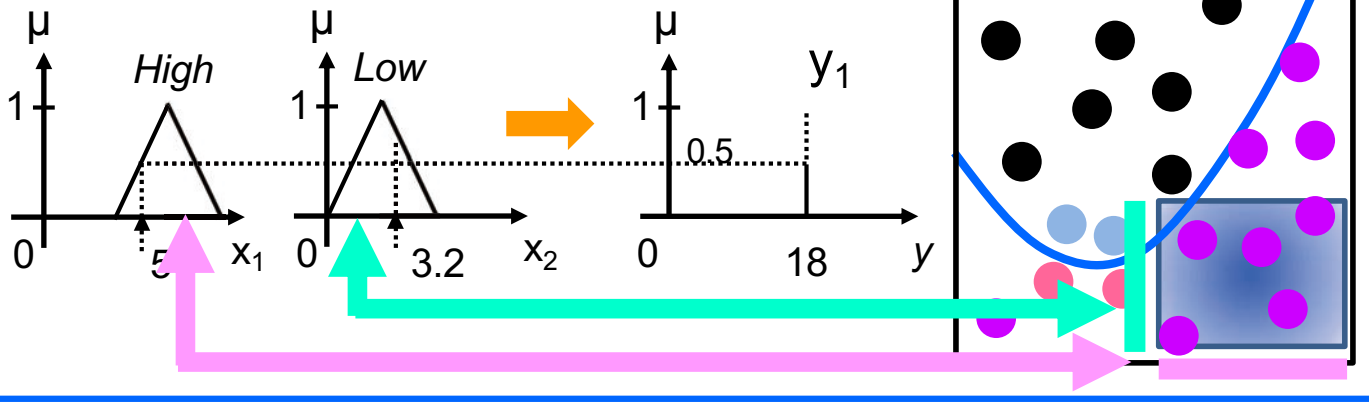
Input-Output Data



Model Generating Virtual Data

Estimated Boundary Curve

Fuzzy Clustering Using Fuzzy Inference

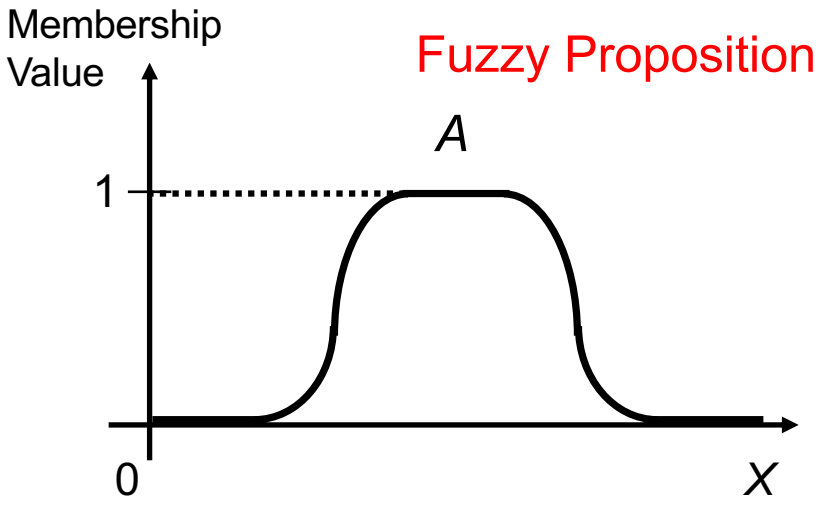


Fuzzy Clustering Using Fuzzy Inference

Fuzzy Inference

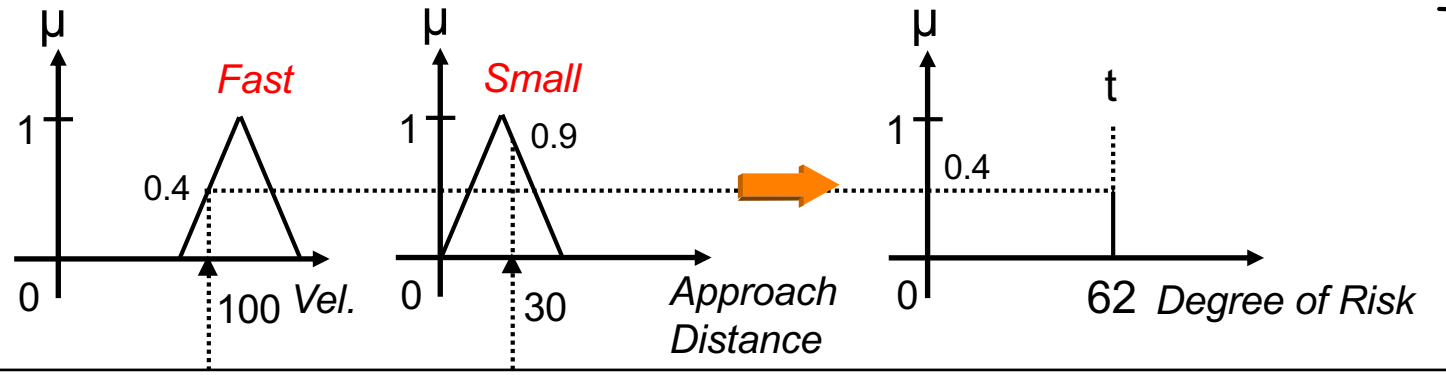
- Fuzzy inference is a method that realizes "approximate inference that allows ambiguity" based on fuzzy logic, and is also called approximate reasoning.

- The properties of fuzzy inference are summarized in the following three items, where, A and τ are fuzzy sets.
  - Fuzzy Proposition : $X\ is\ A$ (ex. : John is YOUNG)
  - Linguistic Truth Value : $Truth(X\ is\ A) = \tau$ (Almost TRUE)
  - Approximate reasoning is performed, allowing approximate validity of the inference rules.

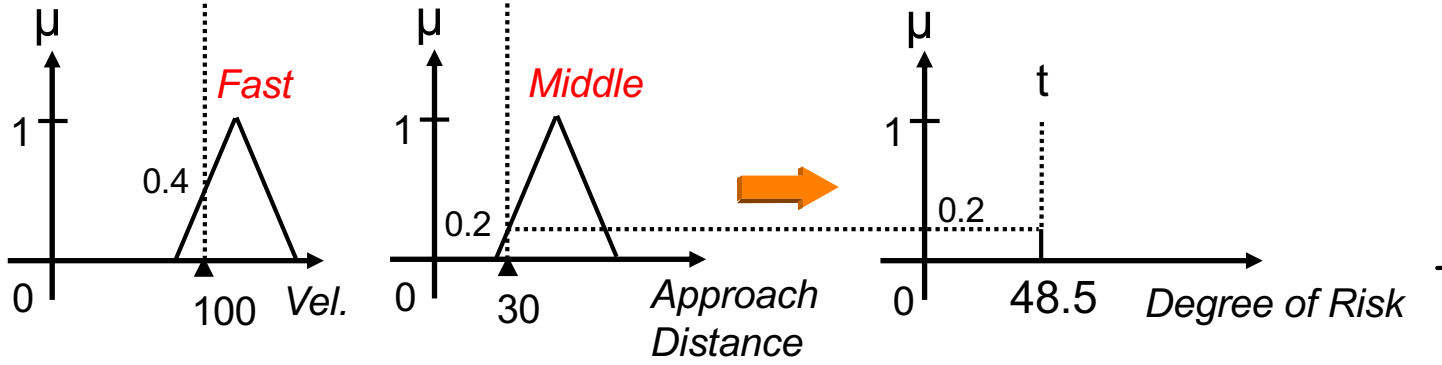


Fuzzy Clustering (Hazard recognition in automated driving)

If Velocity is ***Fast*** and Approach Distance is ***Small*** then Degree of Risk t_1 = **62**

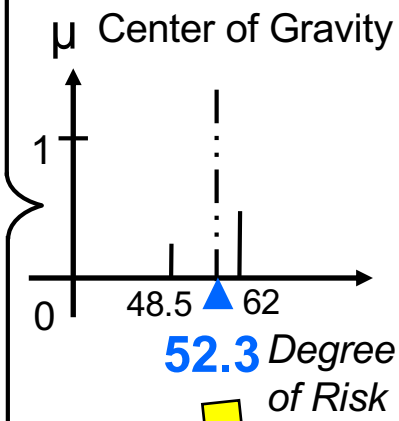


If Velocity is ***Fast*** and Approach Distance is ***Middle*** then Degree of Risk t_2 = **48.5**



x_1 : Velocity

x_2 : Approach Distance



Output = 52.3

Detection

100 km/h →

30 m →

Fuzzy Inference s : Rule Number, i : Number of Variables

$$y^* = \frac{\sum_s \min_i \mu_F(x_i) \times t_s}{\sum_s \min_i \mu_F(x_i)} \quad or \quad y^* = \frac{\sum_s \prod_i \mu_F(x_i) \times t_s}{\sum_s \prod_i \mu_F(x_i)}$$

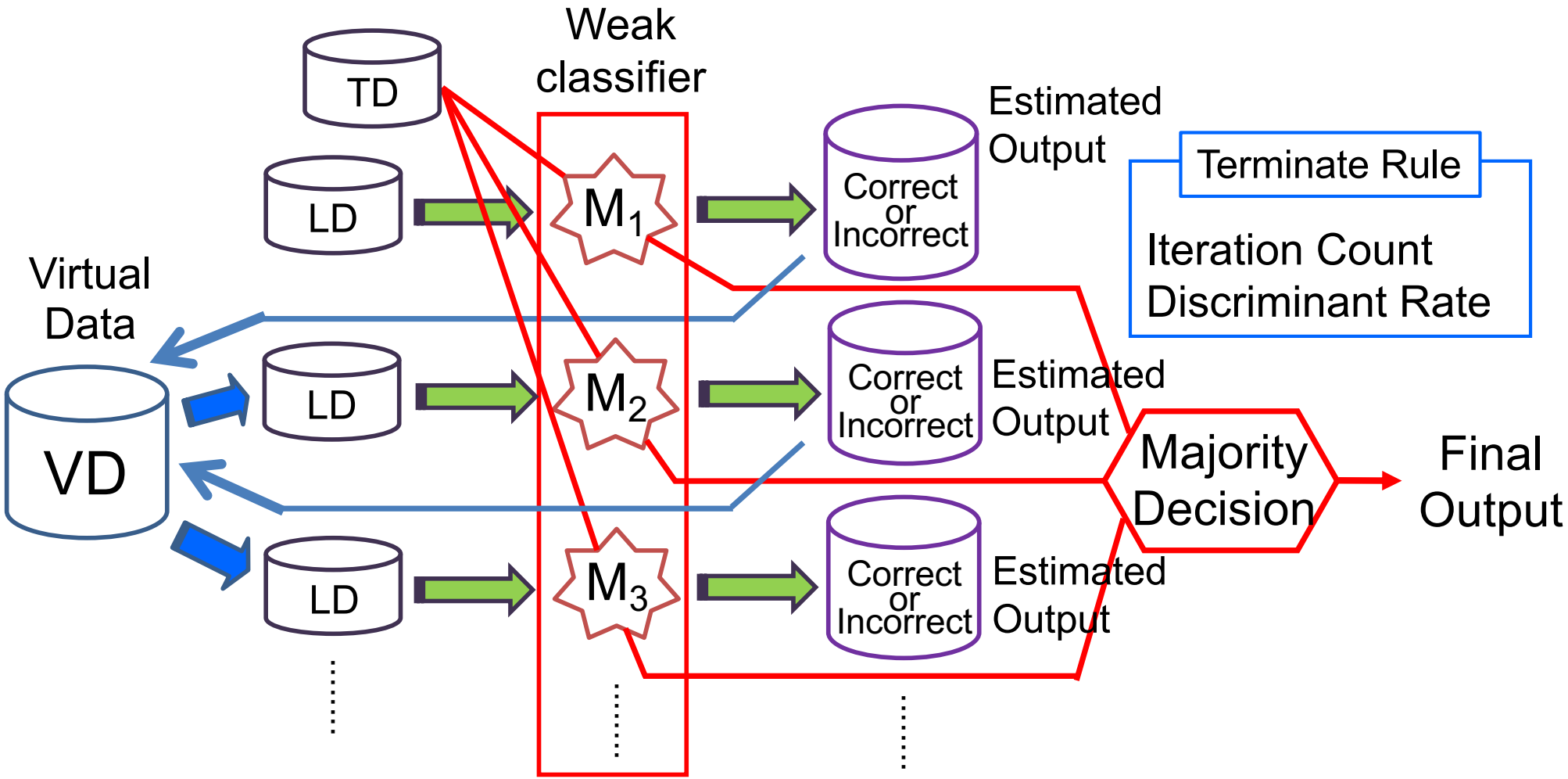
→ Danger

Estimated Output (52.3) > θ (Risk Threshold 50.0) → Danger

pdi-Bagging / pdi-Boosting Using Fuzzy Clustering

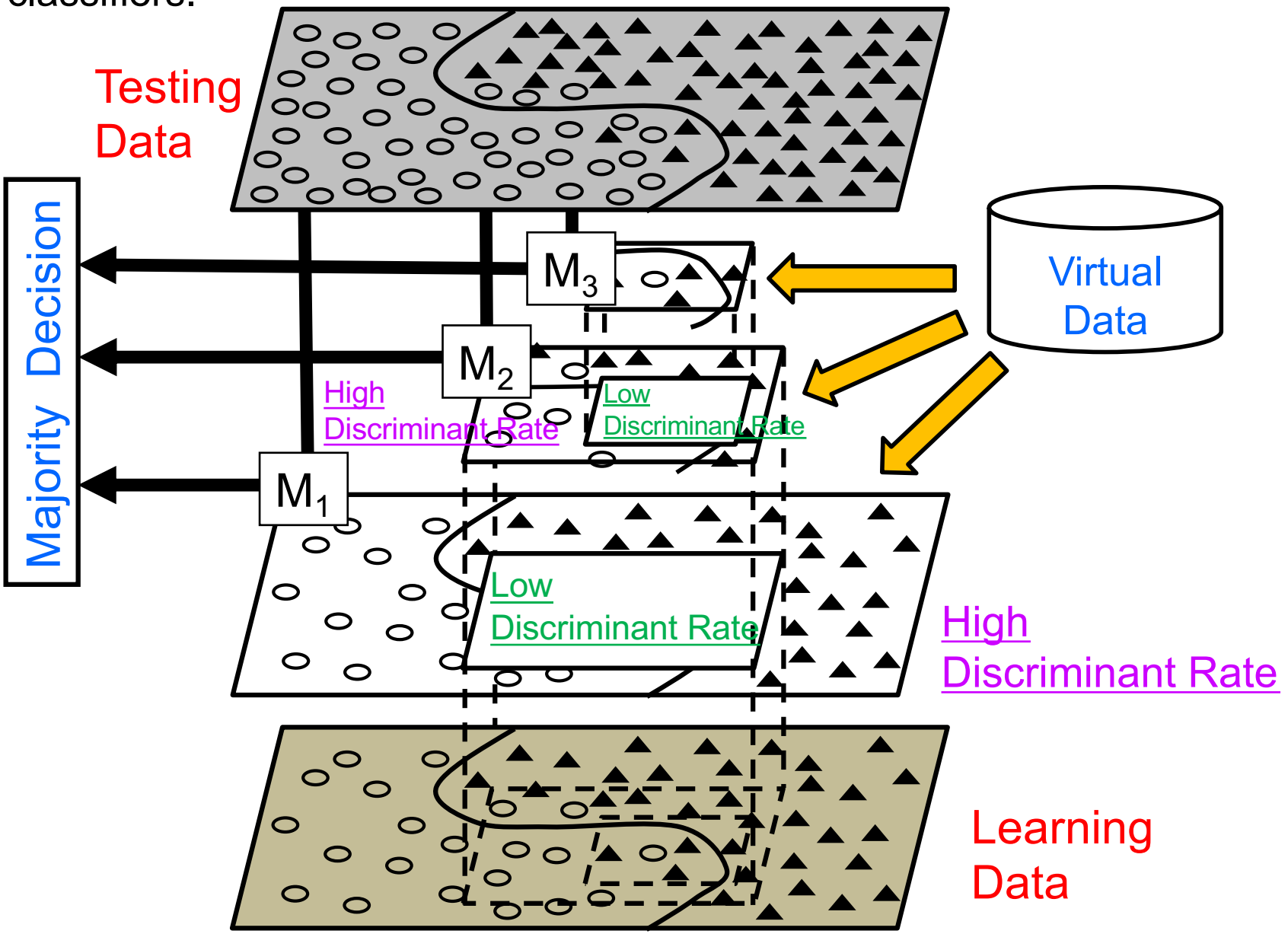
Ensemble Learning (pdi-Bagging / pdi-Boosting)

- In pdi-Bagging / pdi-Boosting, instead of updating the weight of AdaBoost, virtual data is generated around misclassified data and added to the learning data of the next layer.
- The final output for the testing data is determined by majority decision rule using multiple weak classifiers.

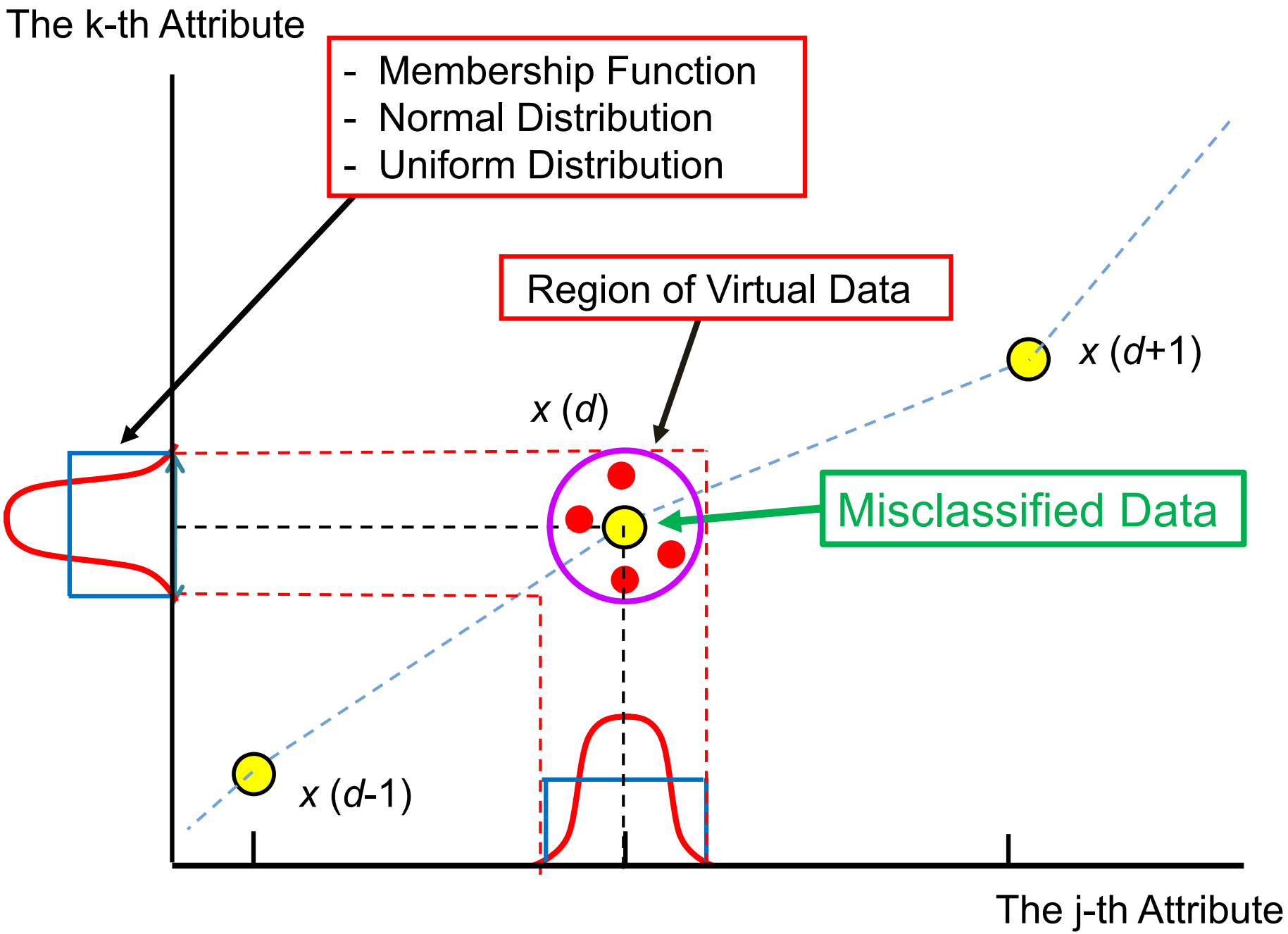


pdi-Bagging/pdi-Boosting (pdi : possibility data interpolation)

The pdi-Bagging / pdi-Boosting can realize a deep inference using the multiple weak classifiers.

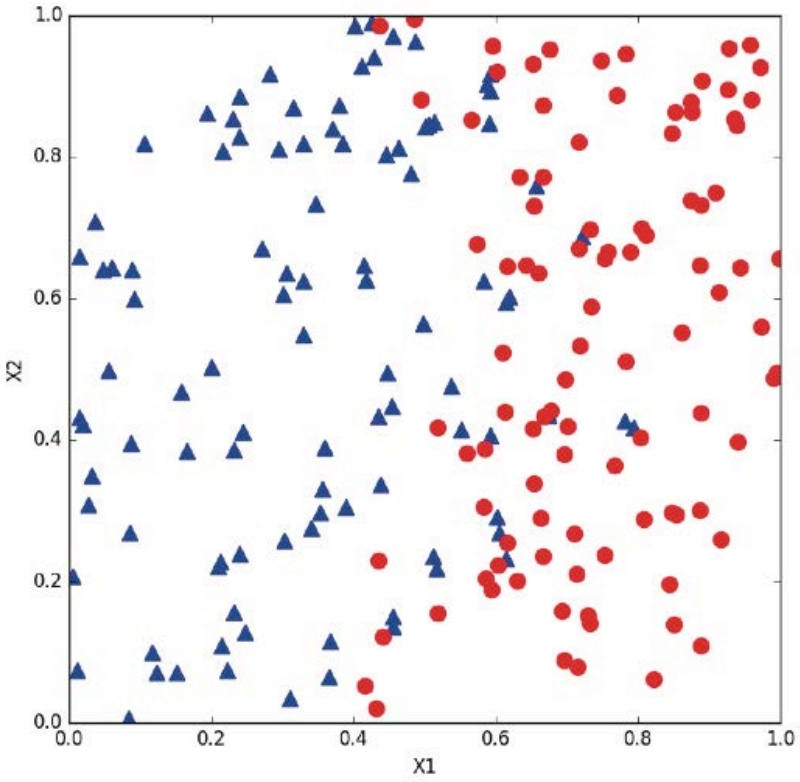


Generation of virtual data to add to learning data



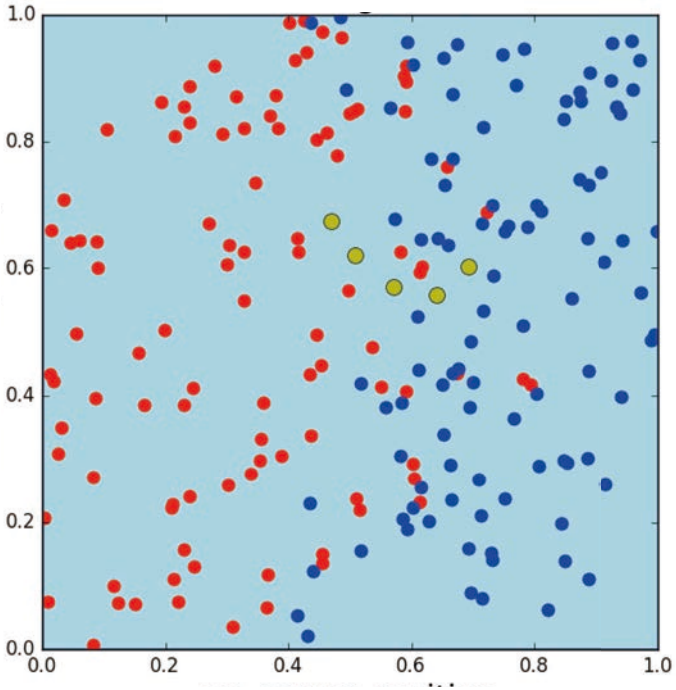
Numerical Example of pdi-Bagging / pdi-Boosting

- Number of Data : 200 (Learning Data : 100, Testing Data : 100)
- Classes : 2 (2 inputs and 1 output)
- Membership Function : five
- Number of Rules : 25 (Total N. of Learning Coefficients : 225)
- Learning Coefficient $(K_b, K_\alpha, K_c, K_\beta)$: 0.01
- Learning Coefficient (K_p) : 0.4, 0.6
- Number of Learning :
  10 (Consequent Part)
  10, 20, 30
  (Alternating Learning of Antecedent Part and Consequent Part)
- Trials : 10 (30 to 70 learning per trial)
- Weights of Evaluations for Changing Class :
  $w_1=w_2=w_3=1/3$
- N. of Layers for termination of algorithm : K=3

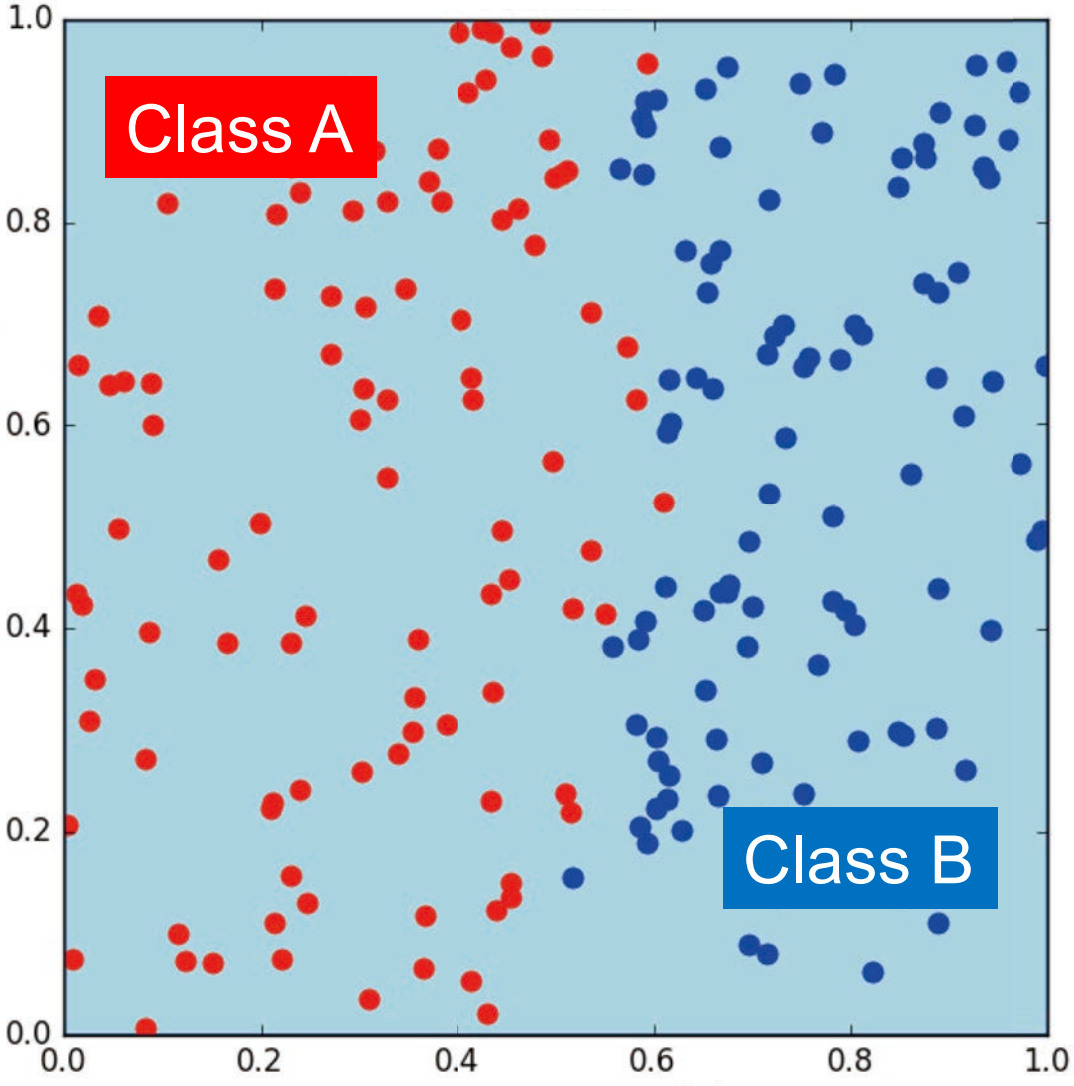


pdi-Bagging Using Fuzzy Clustering

Learning Data



Estimated Output of pdi-Bagging



Demonstration

Thank you for your attention!

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