



→ AdaBoost / Gradient Boost

Ensemble Learning: Adaptive Boosting (AdaBoost)

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Boosting: AdaBoost

- AdaBoosting: Idea

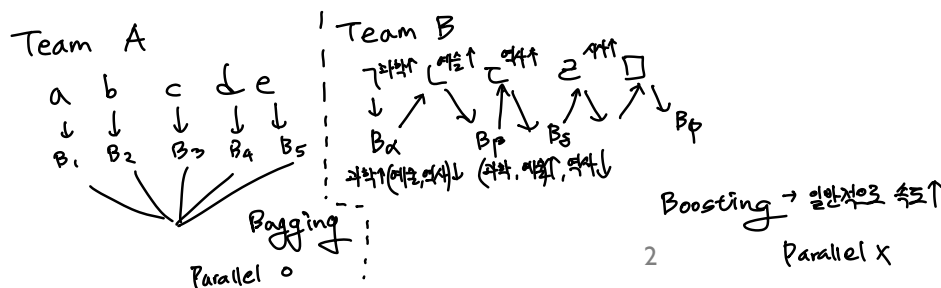
- ✓ Strong model vs. Weak model

→ better than random guessing

- A weak model, performing only slightly better than random guessing, could be boosted in to arbitrarily accurate strong model

- ✓ New classifiers should focus on difficult cases

- Examine the learning set
- Get some rule of thumb → Weak Model
- Reweight the examples of the training set, concentrate on hard cases for the previous rule
- Derive the next rule of thumb
- ...
- Build a single, accurate predictor by combining the rules of thumb



Boosting: AdaBoost

- AdaBoosting: Idea

≠ Classification Case

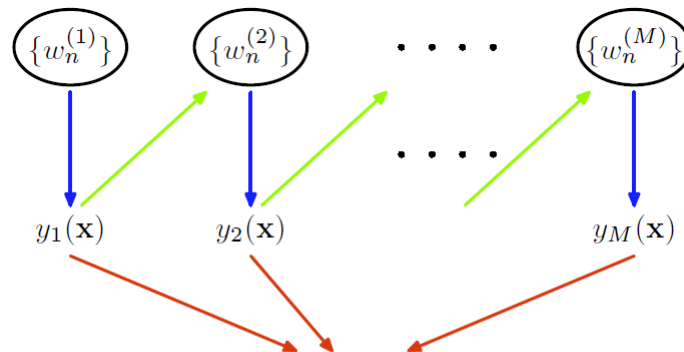
- ✓ Strong model vs. Weak model

- A weak model, performing only slightly better than random guessing, could be **boosted** in to arbitrarily accurate strong model

- ✓ Train models sequentially, with a new model training at each round

- ✓ At the end of each round, misclassified examples are identified and have their emphasis increased in a new training set which is then fed back into the next round

- ✓ Large errors made by earlier models can be compensated by the subsequent models



$$Y_M(\mathbf{x}) = \text{sign} \left(\sum_{m=1}^M \alpha_m y_m(\mathbf{x}) \right)$$

Boosting: AdaBoost

• AdaBoosting: Algorithm

Algorithm 2 Adaboost

Input: Required ensemble size T

Input: Training set $S = \{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$, where $y_i \in \{-1, +1\}$

Define a uniform distribution $D_1(i)$ over elements of S .

for $t = 1$ to T **do**

Train a model h_t using distribution D_t .

Calculate $\epsilon_t = P_{D_t}(h_t(x) \neq y)$

If $\epsilon_t \geq 0.5$ **break**

Set $\alpha_t = \frac{1}{2} \ln \left(\frac{1-\epsilon_t}{\epsilon_t} \right)$

Update $D_{t+1}(i) = \frac{D_t(i) \exp(-\alpha_t y_i h_t(x_i))}{Z_t}$

where Z_t is a normalization factor so that D_{t+1} is a valid distribution.

end for

For a new testing point (x', y') ,

$H(x') = \text{sign} \left(\sum_{t=1}^T \alpha_t h_t(x') \right)$

<Stump Tree>

한번에 그어서
분리
↓
Weak Model

첫번째 데이터셋에

example i 가 선택될 확률

오류율

random guessing 보다는 나아간다

$$\alpha_t \begin{cases} \epsilon_t \approx 0.5 = \frac{1}{2} \ln \left(\frac{0.5}{0.5} \right) = 0 \\ \epsilon_t = 0 = \frac{1}{2} \ln \left(\frac{1}{0} \right) \approx \infty \end{cases}$$

가중치 업데이트

$D_t(i) \rightarrow t$ 시점의 선택확률 기준점

$\alpha_t \rightarrow h_t$ 가 정확하면 Sampling Rate가 원동성↑

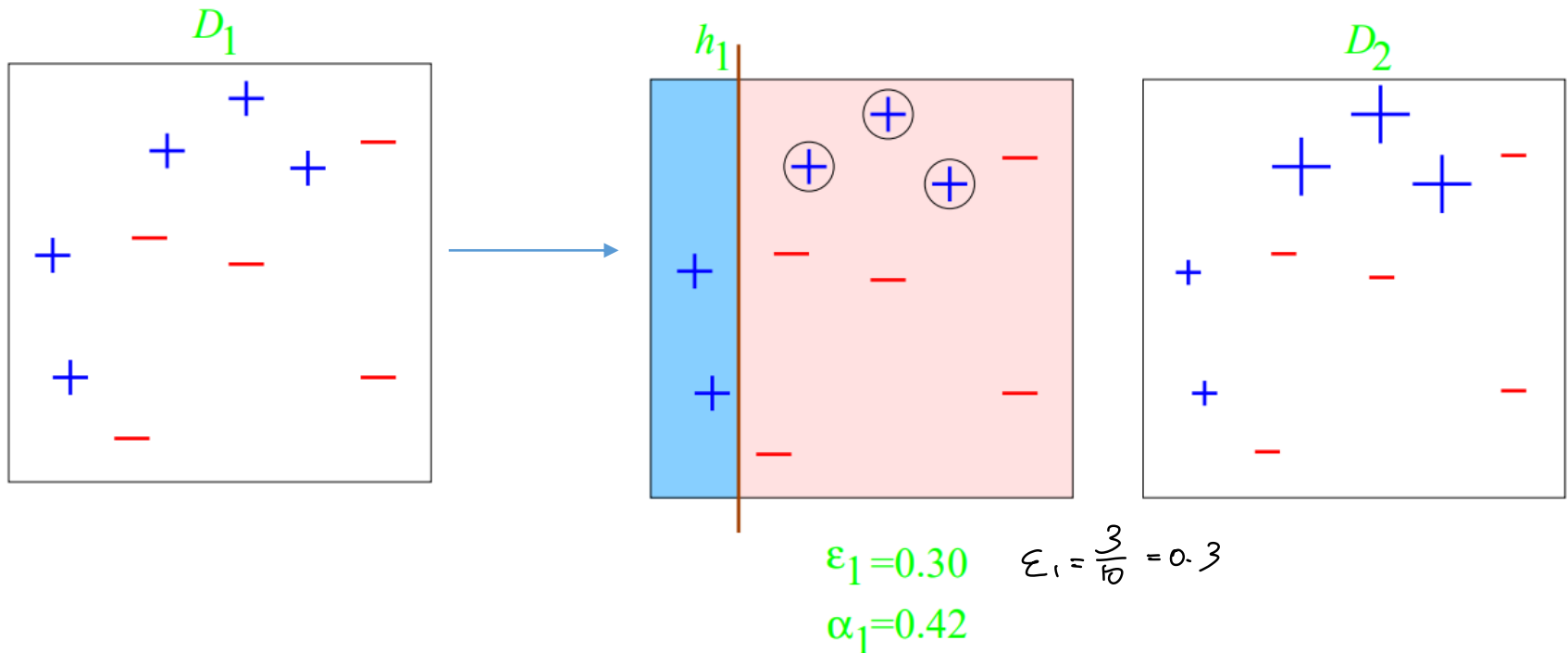
Test Data에 대한 가중치

$y_i = h_t(x_i) \Rightarrow +$
 $\begin{pmatrix} + & + \\ - & - \end{pmatrix}$
 $y_i \neq h_t(x_i) \Rightarrow -$
 $\begin{pmatrix} + & - \\ - & + \end{pmatrix}$
 +가 이의 정답
 $D_{t+1}(i) \downarrow$
 *가 이의 오답
 $D_{t+1}(i) \uparrow$

Boosting: AdaBoost

- Illustrative example I

✓ Round I



- 3 misclassifications out of 10: $\epsilon_i = 0.30$

- Model confidence: $\alpha_i = \frac{1}{2} \log \left(\frac{1 - \epsilon_i}{\epsilon_i} \right) = \frac{1}{2} \log \frac{1 - 0.3}{0.3} = 0.42$

Boosting: AdaBoost

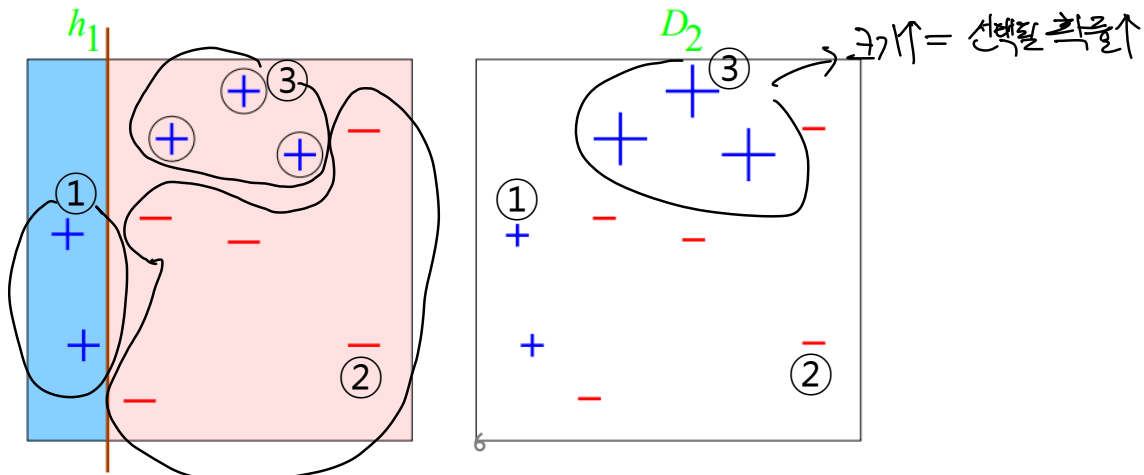
• AdaBoost Example

- ✓ The selection probability of x_i for the next training dataset

$$D_{t+1}(i) = \frac{D_t(i) \exp(-\alpha_t y_i h_t(x_i))}{Z_t}$$

점수 높은 데이터는
선택될 확률 ↑
오류율은 증가

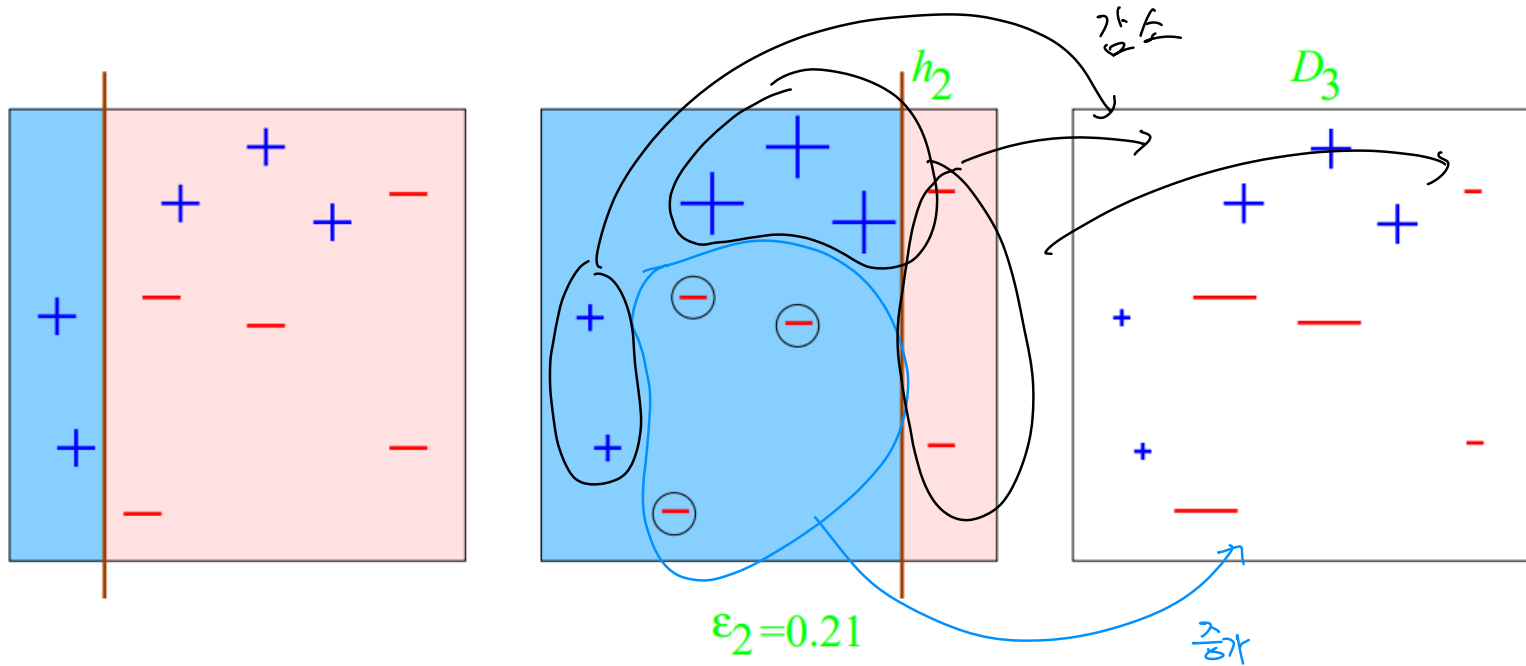
- ✓ Case 1: $y_i = 1, h_t(x_i) = 1 \rightarrow y_i h_t(x_i) = 1 \rightarrow -\alpha_t y_i h_t(x_i) < 0 \rightarrow$ decrease p
- ✓ Case 2: $y_i = -1, h_t(x_i) = -1 \rightarrow y_i h_t(x_i) = 1 \rightarrow -\alpha_t y_i h_t(x_i) < 0 \rightarrow$ decrease p
- ✓ Case 3: $y_i = 1, h_t(x_i) = -1 \rightarrow y_i h_t(x_i) = -1 \rightarrow -\alpha_t y_i h_t(x_i) > 0 \rightarrow$ increase p
- ✓ α_t is the confidence of the current model that controls the magnitude of change



Boosting: AdaBoost

- Illustrative example I

✓ Round 2



Bagging

B_1	0.3	0.3	0.3
B_2	0.3	0.3	0.3
B_3	0.3	0.3	0.3

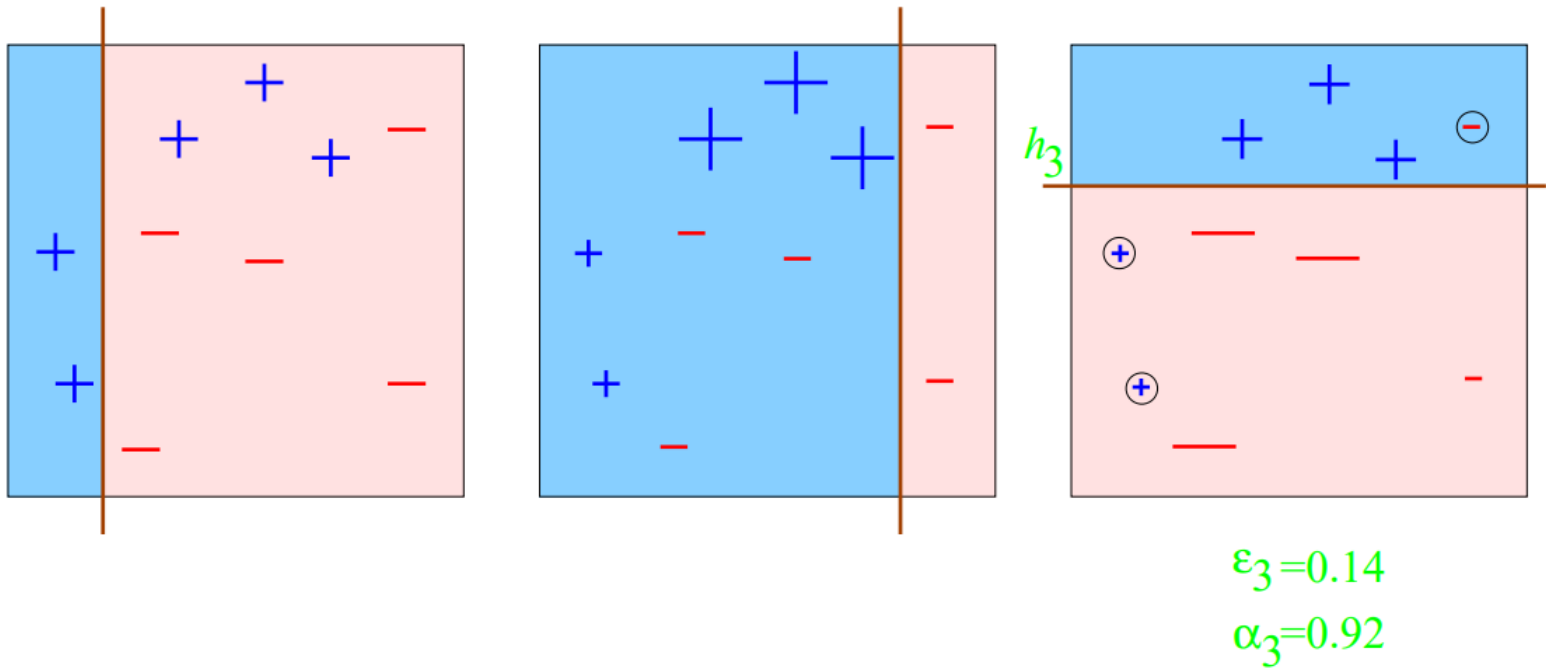
Boosting

0.3	0.3	0.3
0.5	0.3	0.2
0.4	0.4	0.2

Boosting: AdaBoost

- Illustrative example I

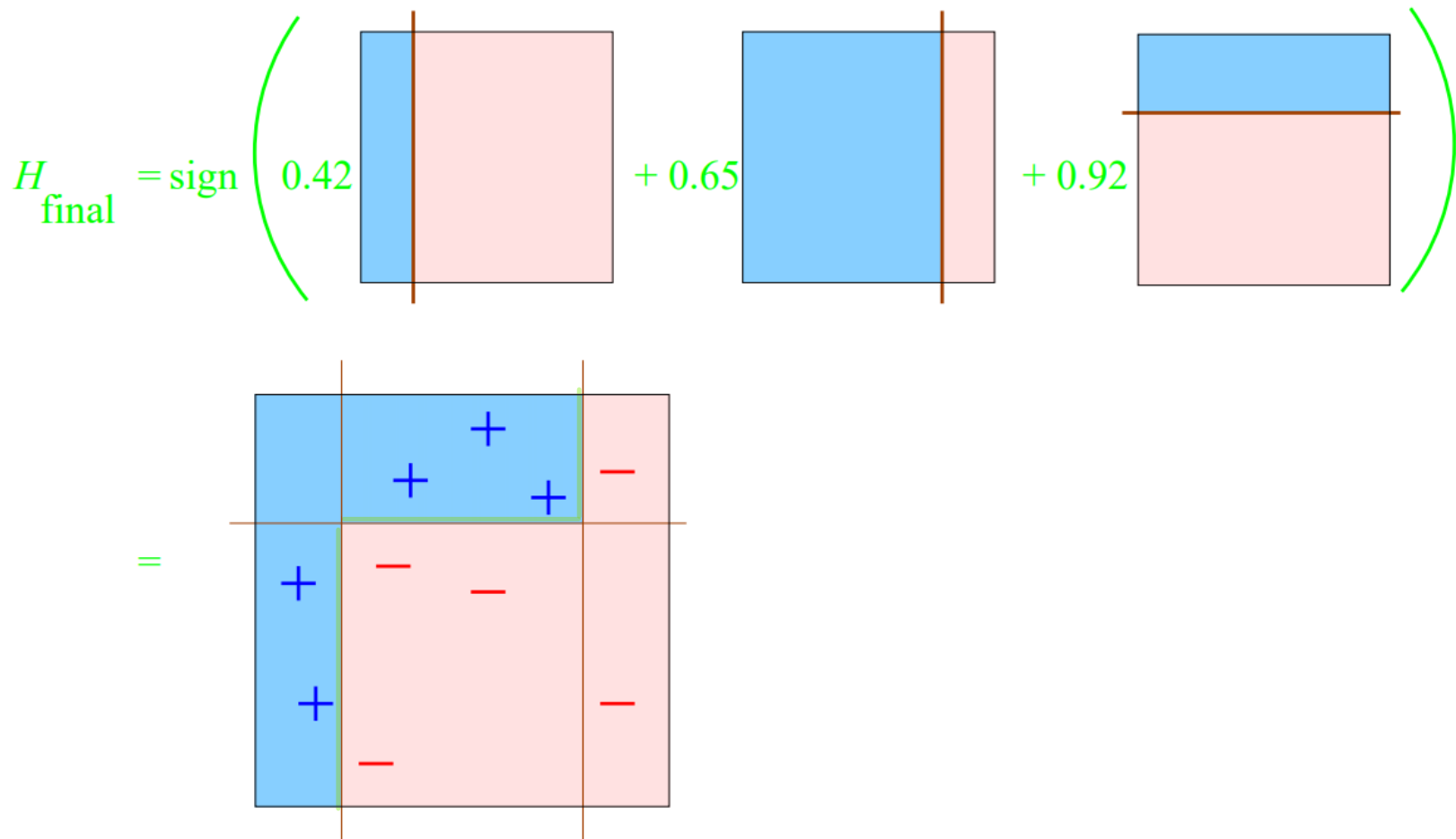
✓ Round 3



Boosting: AdaBoost

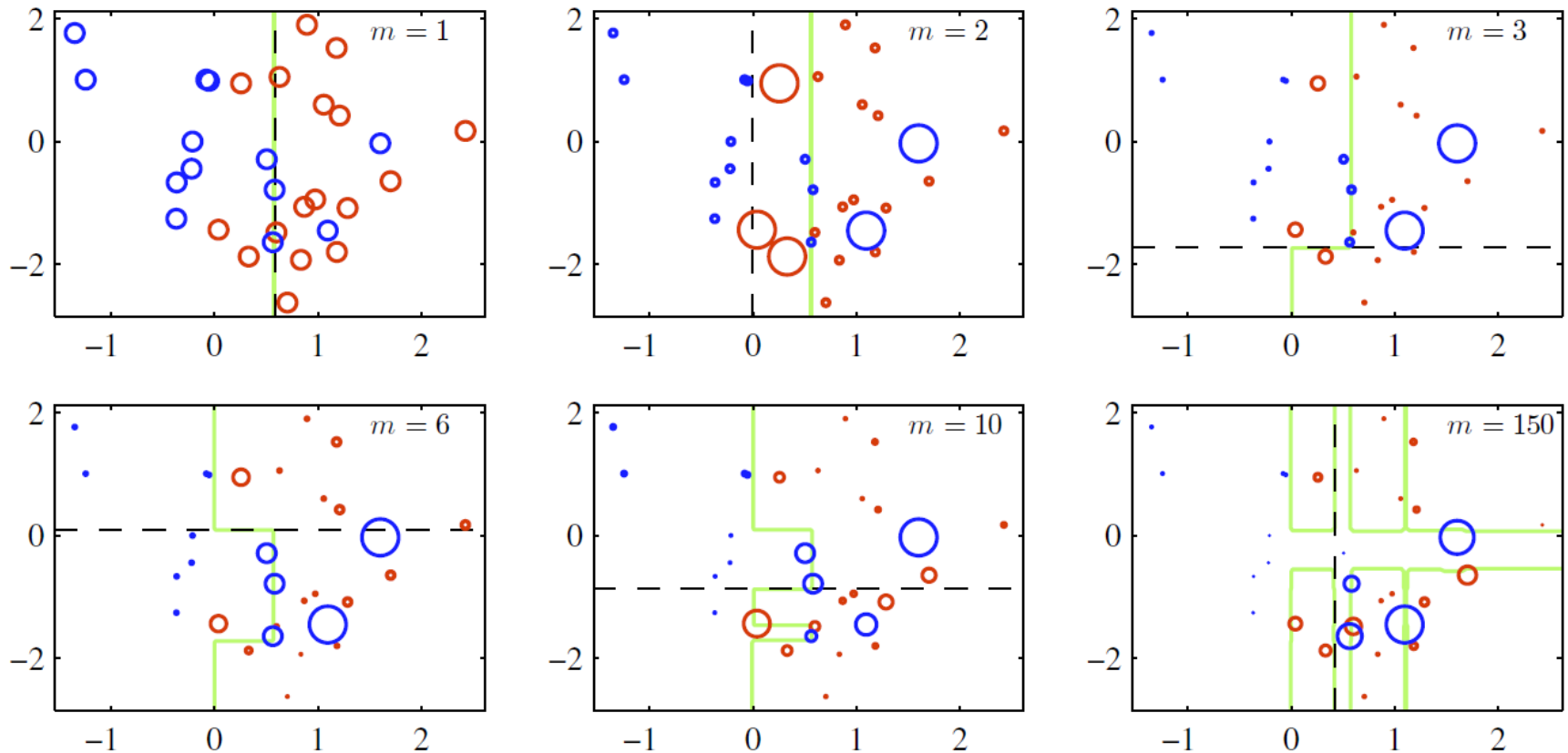
- Illustrative example I

✓ Final classifier



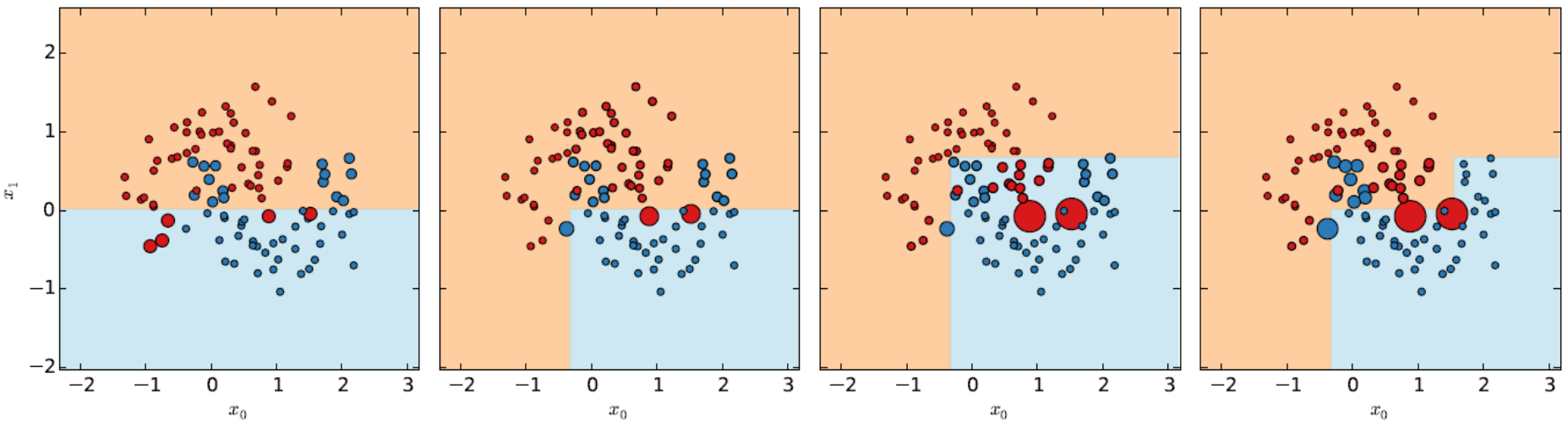
Boosting: AdaBoost

- Illustrative example 2



Boosting: AdaBoost

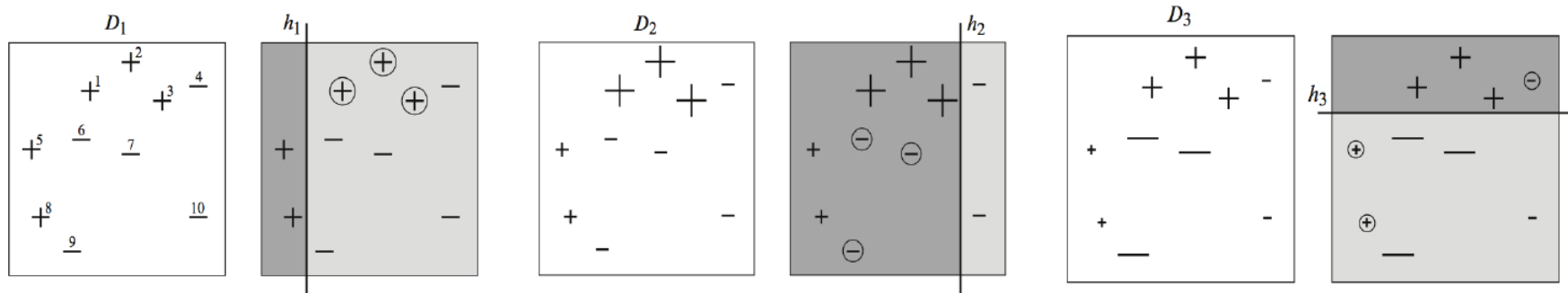
- Illustrative example 3



https://www.slideshare.net/DataRobot/gradient-boosted-regression-trees-in-scikitlearn?from_action=save

Boosting: AdaBoost

- Illustrative example 4



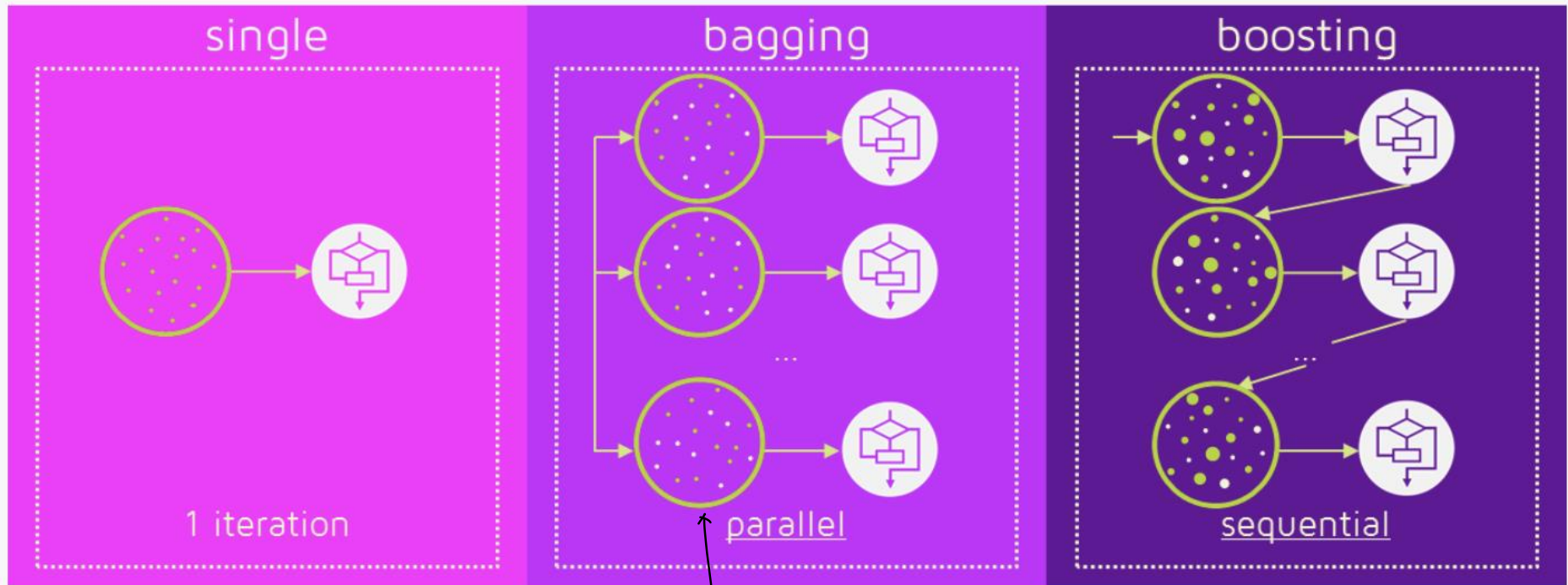
$$H(x') = \text{sign}\left(\sum_{t=1}^T \alpha_t h_t(x')\right)$$

$H = \text{sign}\left(0.42 \begin{array}{|c|} \hline \text{[Diagram of } h_1 \text{]} \\ \hline \end{array} + 0.65 \begin{array}{|c|} \hline \text{[Diagram of } h_2 \text{]} \\ \hline \end{array} + 0.92 \begin{array}{|c|} \hline \text{[Diagram of } h_3 \text{]} \\ \hline \end{array}\right)$

$= \begin{array}{|c|c|c|c|} \hline \text{[Diagram of } H \text{]} \\ \hline \end{array}$

Boosting: AdaBoost

- Single model vs. Bagging vs. Boosting



<https://quantdare.com/what-is-the-difference-between-bagging-and-boosting/>

Uniform distribution

복합 구조

Boosting: AdaBoost

- AdaBoost in Action

AdaBoost in Action

Kai O. Arras

Social Robotics Lab, University of Freiburg

Nov 2009  Social Robotics Laboratory

Boosting: AdaBoost

- Bagging vs. Boosting

- ✓ Selected instances in each training dataset

A sample of a single classifier on an imaginary set of data.	
(Original) Training Set	
Training-set-1:	1, 2, 3, 4, 5, 6, 7, 8

A sample of Bagging on the same data.	
(Resampled) Training Set	
Training-set-1:	2, 7, 8, 3, 7, 6, 3, 1
Training-set-2:	7, 8, 5, 6, 4, 2, 7, 1
Training-set-3:	3, 6, 2, 7, 5, 6, 2, 2
Training-set-4:	4, 5, 1, 4, 6, 4, 3, 8

→ random

A sample of Boosting on the same data.	
(Resampled) Training Set	
Training-set-1:	2, 7, 8, 3, 7, 6, 3, ①
Training-set-2:	①, 4, 5, 4, ①, 5, 6, 4
Training-set-3:	7, ①, 5, 8, ①, 8, ①, 4
Training-set-4:	1, ①, 6, 1, ①, 3, ①, 5

h_1, h_2, h_3, h_4 는 모두
1번 example 정확도를 실패하고 있다

Boosting: AdaBoost

- Face detection with AdaBoost



