**This lecture notes is based on the following paper:
H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009**

# Learning from Imbalanced Data

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Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Learning from Imbalanced Data

1. The problem: Imbalanced Learning
2. The solutions: State-of-the-art
3. The evaluation: Assessment Metrics
4. The future: Opportunities and Challenges

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# *The Nature of* Imbalanced Learning Problem

Source: H. He and E. A. Garcia, “Learning from Imbalanced Data,” IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# The Problem

- ✓ Explosive availability of raw data
- ✓ Well-developed algorithms for data analysis

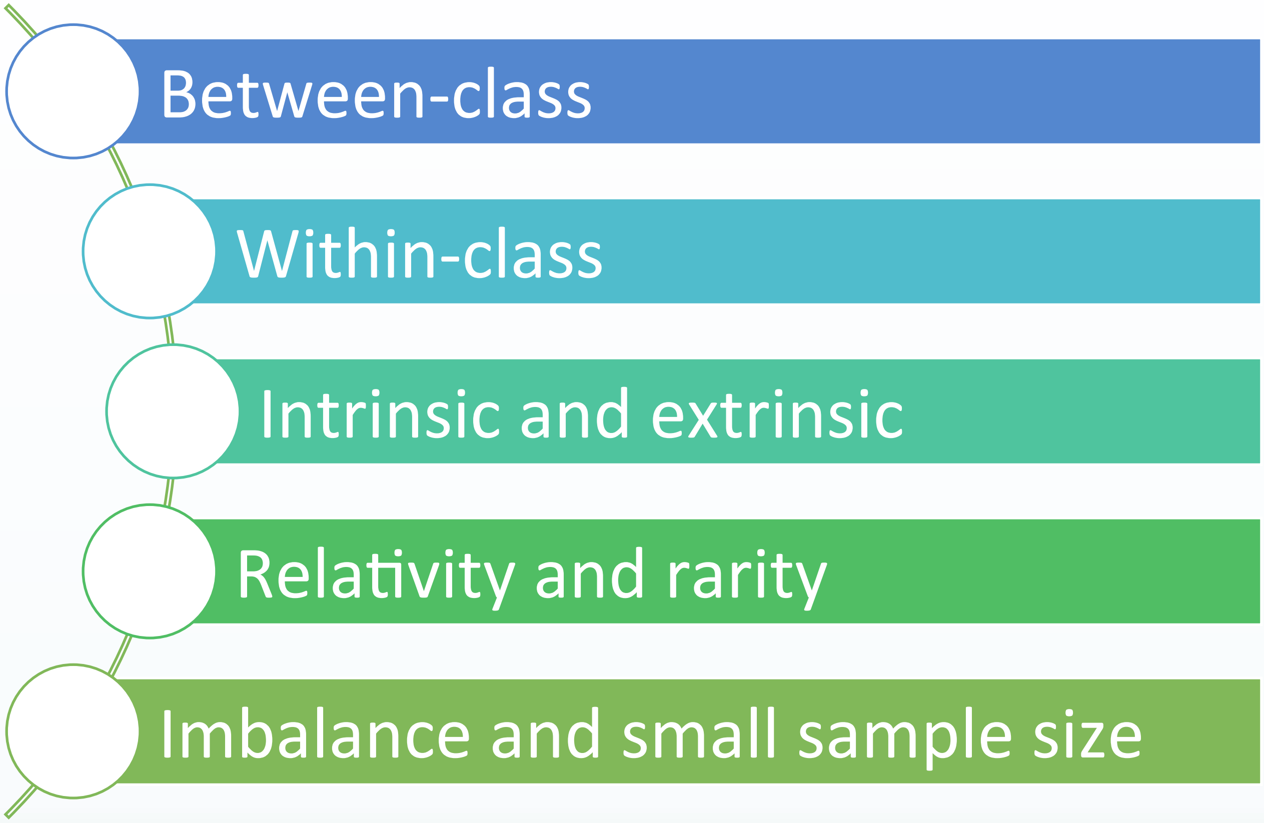
## Requirement?

- ***Balanced*** *distribution* of data
- ***Equal*** *costs* of misclassification

## What about data in reality?

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Imbalance is Everywhere



- Between-class
- Within-class
- Intrinsic and extrinsic
- Relativity and rarity
- Imbalance and small sample size

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Growing interest

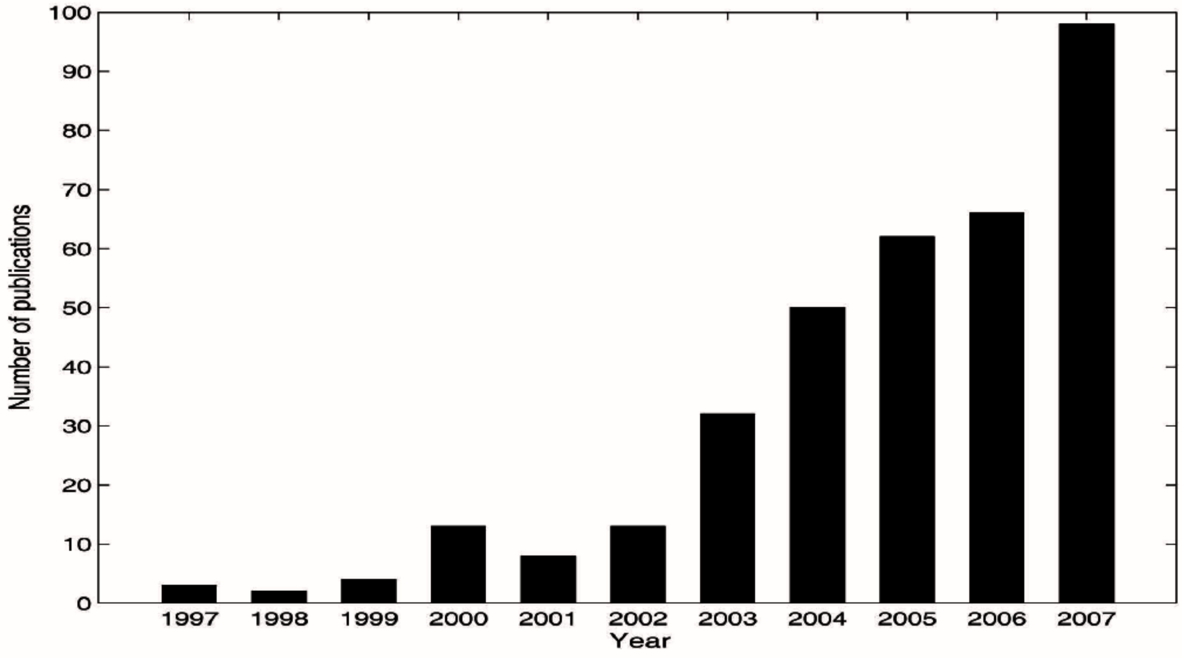


Fig. 1. Number of publications on imbalanced learning.

Source: H. He and E. A. Garcia, “Learning from Imbalanced Data,” IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# The Nature of Imbalance Learning

## Mammography Data Set:
## An example of ***between-class*** *imbalance*

| | Negative/healthy | Positive/cancerous |
|---|---|---|
| Number of cases | 10,923 | 260 |
| Category | Majority | Minority |
| **Imbalanced accuracy** | ≈ 100% | 0-10 % |

**Imbalance can be on the order of 100 : 1 up to 10,000 : 1!**

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# *Intrinsic* and *extrinsic* imbalance

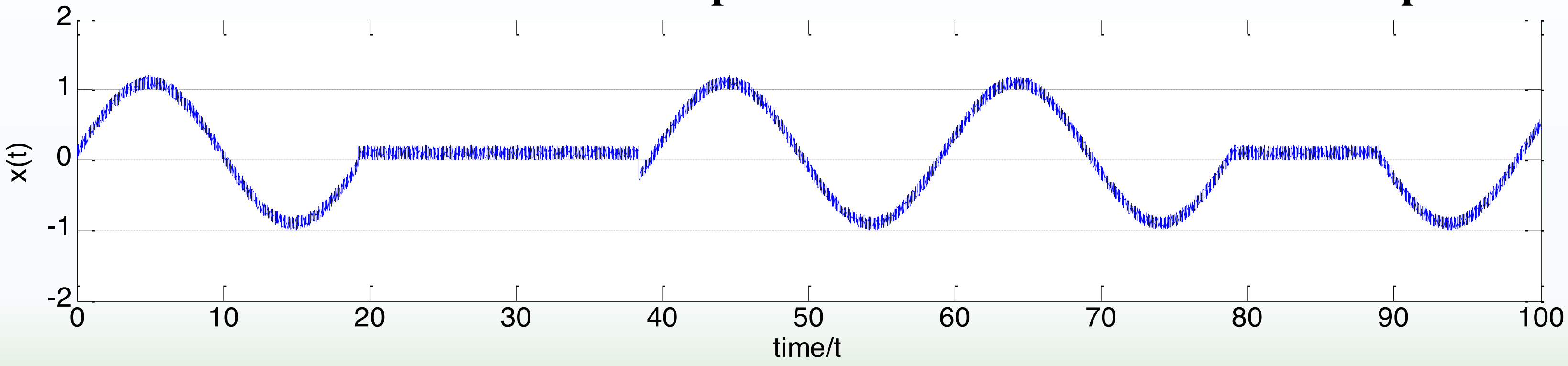
**Intrinsic:**

- Imbalance due to the nature of the dataspace

**Extrinsic:**

- Imbalance due to time, storage, and other factors
- **Example:**

**Data transmission over a specific interval of time with interruption**



Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# The Nature of Imbalance Learning

## *Data Complexity*

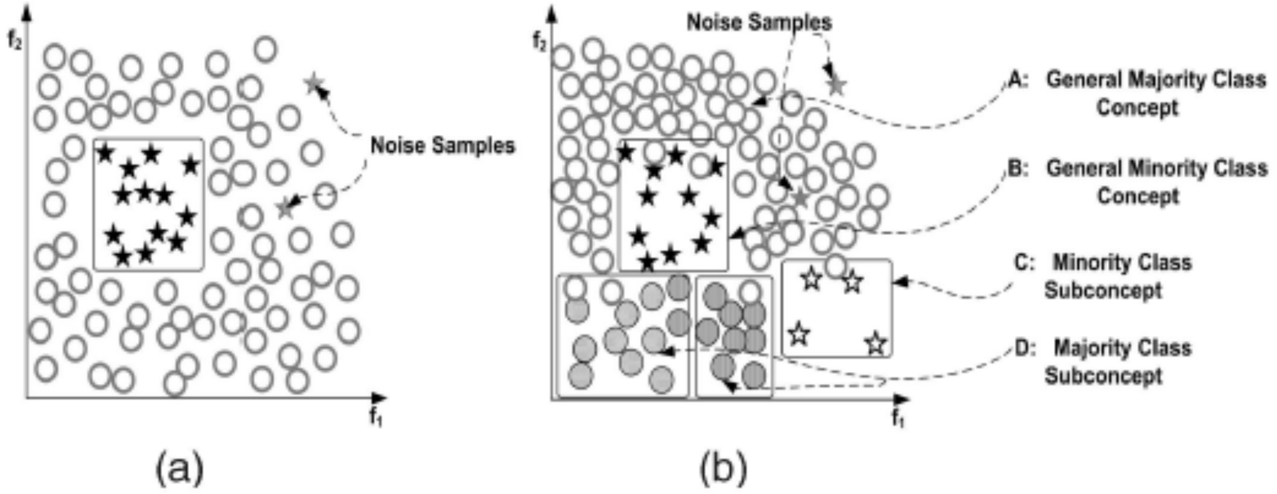

f2
f1
Noise Samples
(a)
f2
f1
Noise Samples
A: General Majority Class Concept
B: General Minority Class Concept
C: Minority Class Subconcept
D: Majority Class Subconcept
(b)

Fig. 2. (a) A data set with a between-class imbalance. (b) A high-complexity data set with both between-class and within-class imbalances, multiple concepts, overlapping, noise, and lack of representative data.

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# *Relative imbalance* and *absolute rarity*

$$\boldsymbol{Q}\text{: } 1{,}000{,}000 : 1{,}000 = 1{,}000 : 1 \quad ?$$

- The minority class may be outnumbered, but not necessarily rare
- Therefore they can be accurately learned with little disturbance

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# ***Imbalanced data*** with ***small sample size***

- Data with high dimensionality and small sample size
  - Face recognition, gene expression

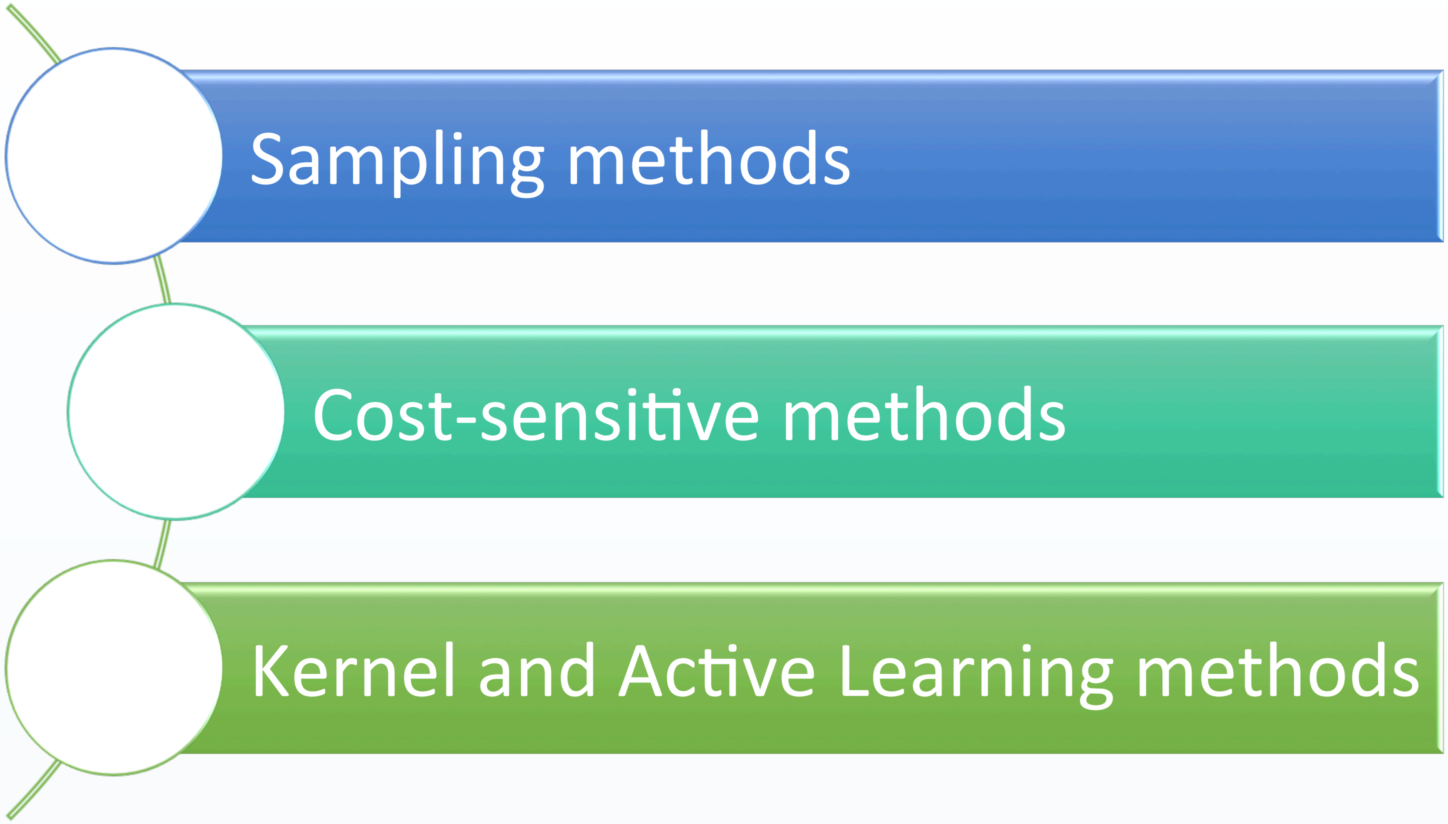
- Challenges with small sample size:
  1. Embedded absolute rarity and within-class imbalances
  2. Failure of generalizing inductive rules by learning algorithms
     - Difficulty in forming good classification decision boundary over *more* features but *less* samples
     - Risk of overfitting

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# *The Solutions to* Imbalanced Learning Problem

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Solutions to imbalanced learning

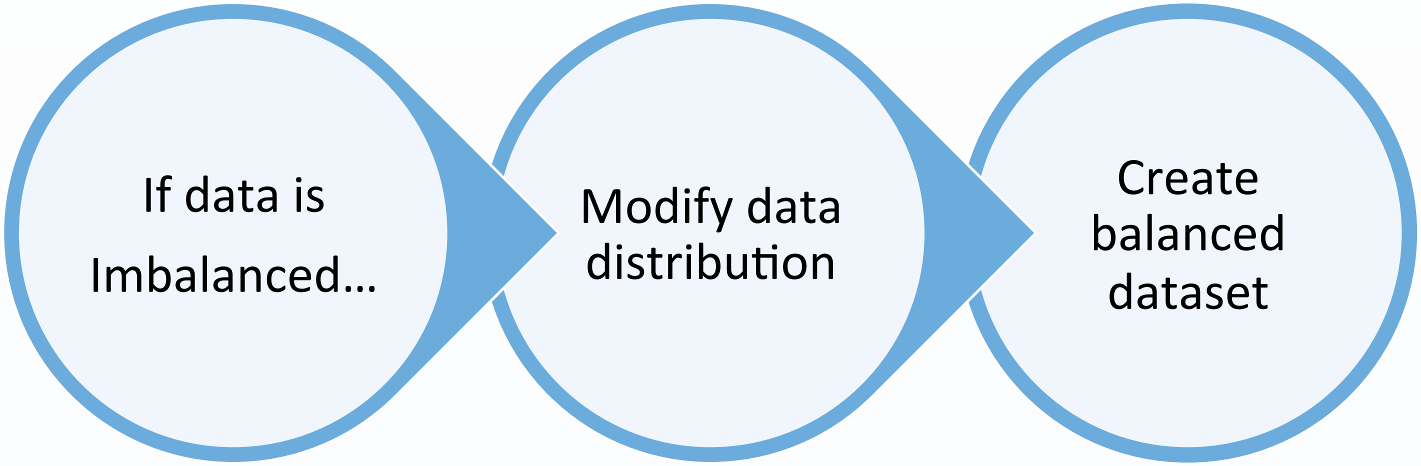


- Sampling methods
- Cost-sensitive methods
- Kernel and Active Learning methods

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Sampling methods

## Sampling methods



If data is Imbalanced…

Modify data distribution

Create balanced dataset

Create balance though sampling

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Sampling methods

## Random Sampling

***S***: training data set; ***S**$_{min}$*: set of minority class samples, ***S**$_{maj}$*: set of majority class samples; ***E***: generated samples

### *Random oversampling*

- Expand the minority
- $|S'_{min}| \leftarrow |S_{min}| + |E|$
- $|S'| \leftarrow |S_{min}| + |S_{maj}| + |E|$
- Overfitting due to multiple “tied” instances

### *Random undersampling*

- Shrink the majority
- $|S'_{maj}| \leftarrow |S_{maj}| - |E|$
- $|S'| \leftarrow |S_{min}| + |S_{maj}| - |E|$
- Loss of important concepts

Source: H. He and E. A. Garcia, “Learning from Imbalanced Data,” IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Sampling methods

## Informed Undersampling

- *EasyEnsemble*
    - ***Unsupervised***: *use random subsets of the majority class to create balance and form multiple classifiers*
- *BalanceCascade*
    - ***Supervised***: *iteratively create balance and pull out redundant samples in majority class to form a final classifier*

1. Generate $E \subset S_{maj}$ $(s.t. |E| = |S_{\min}|)$, and $N = \{E \cup S_{\min}\}$
2. Induce $H(n)$
3. Identify $N_{maj}^{*}$ as samples from $N$ that are correctly classified
4. Remove $N_{maj}^{*}$ from $S_{maj}$
5. Repeat (1) and induce $H(n+1)$ until stopping criteria is met

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Sampling methods

## Informed Undersampling

- ***Undersampling using K-nearest neighbor (KNN) classifier***
  - NearMiss-1, NearMiss-2, NearMiss-3, and the “most distant” method
  - NearMiss-2 provides competitive results for imbalanced learning
- ***One-sided selection (OSS)***
  - Selects representative subset $E$ from the majority class
  - Combine with the minority class $N = \{E \cup S_{\text{min}}\}$
  - Refine $N$ with data cleaning techniques

Source: H. He and E. A. Garcia, “Learning from Imbalanced Data,” IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Sampling methods

## Synthetic Sampling with Data Generation

- Synthetic minority oversampling technique (SMOTE)
  - Creates artificial minority class data using feature space similarities
  - For $\forall x_i \in S_{\min}$
    1. Randomly choose one of the $k$ nearest neighbor $\hat{x}_i$;
    2. Create a new sample $x_{new} = x_i + (\hat{x}_i - x_i) \times \delta$ , where $\delta$ is a uniformly distributed random variable.

Source: H. He and E. A. Garcia, “Learning from Imbalanced Data,” IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Sampling methods

## Synthetic Sampling with Data Generation

- Synthetic minority oversampling technique (SMOTE)

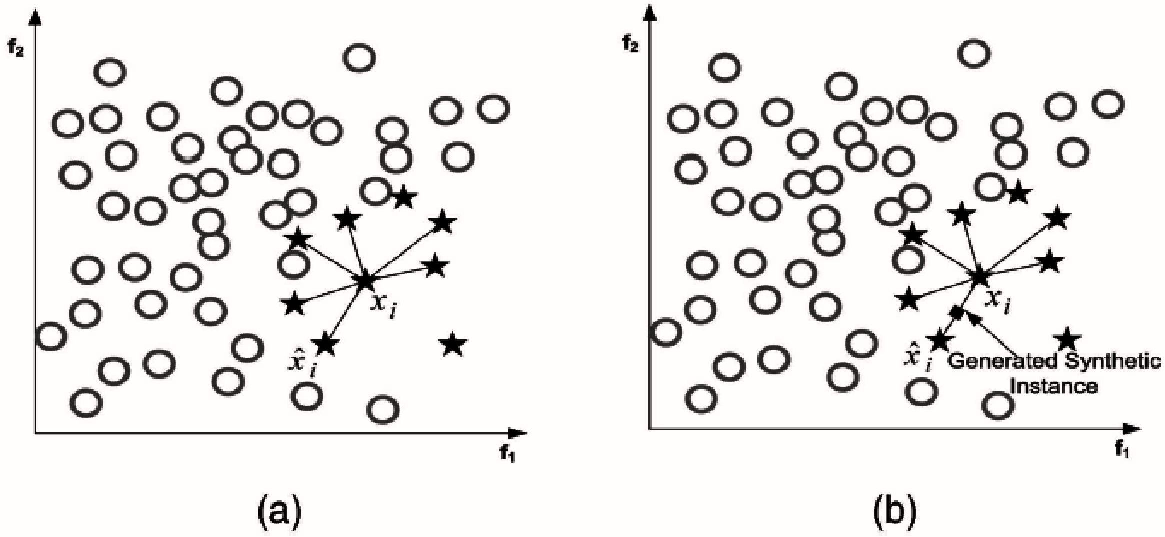


Fig. 3. (a) Example of the K-nearest neighbors for the $x_i$ example under consideration ($K = 6$). (b) Data creation based on euclidian distance.

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Sampling methods

## Adaptive Synthetic Sampling

- Overcomes over generalization in SMOTE algorithm
  - Border-line-SMOTE:
    1. Determine the set of $m$-nearest neighbors for each $x_i \in S_{min}$, call it $S_{i:m-NN}$
    2. Identify the number of nearest neighbors in majority class, i.e., $|S_{i:m-NN} \cap S_{maj}|$
    3. Select $x_i$ that satisfies: $\frac{m}{2} \leq |S_{i:m-NN} \cap S_{maj}| < m$

Source: H. He and E. A. Garcia, “Learning from Imbalanced Data,” IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Sampling methods

## Adaptive Synthetic Sampling

- Overcomes over generalization in SMOTE algorithm
  - Border-line-SMOTE

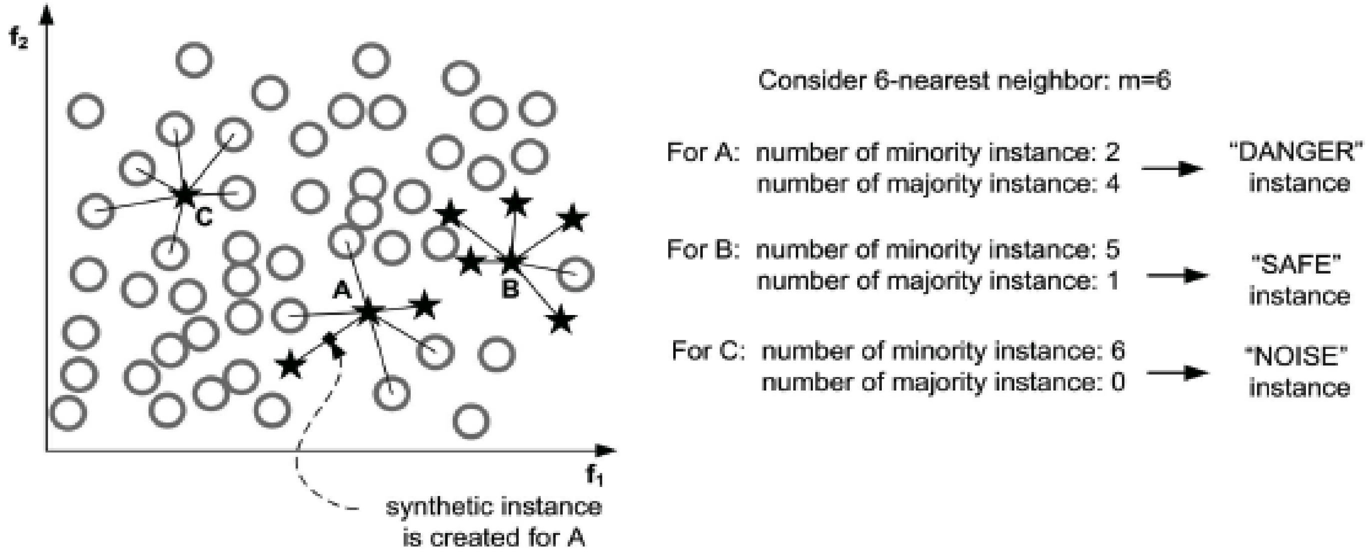
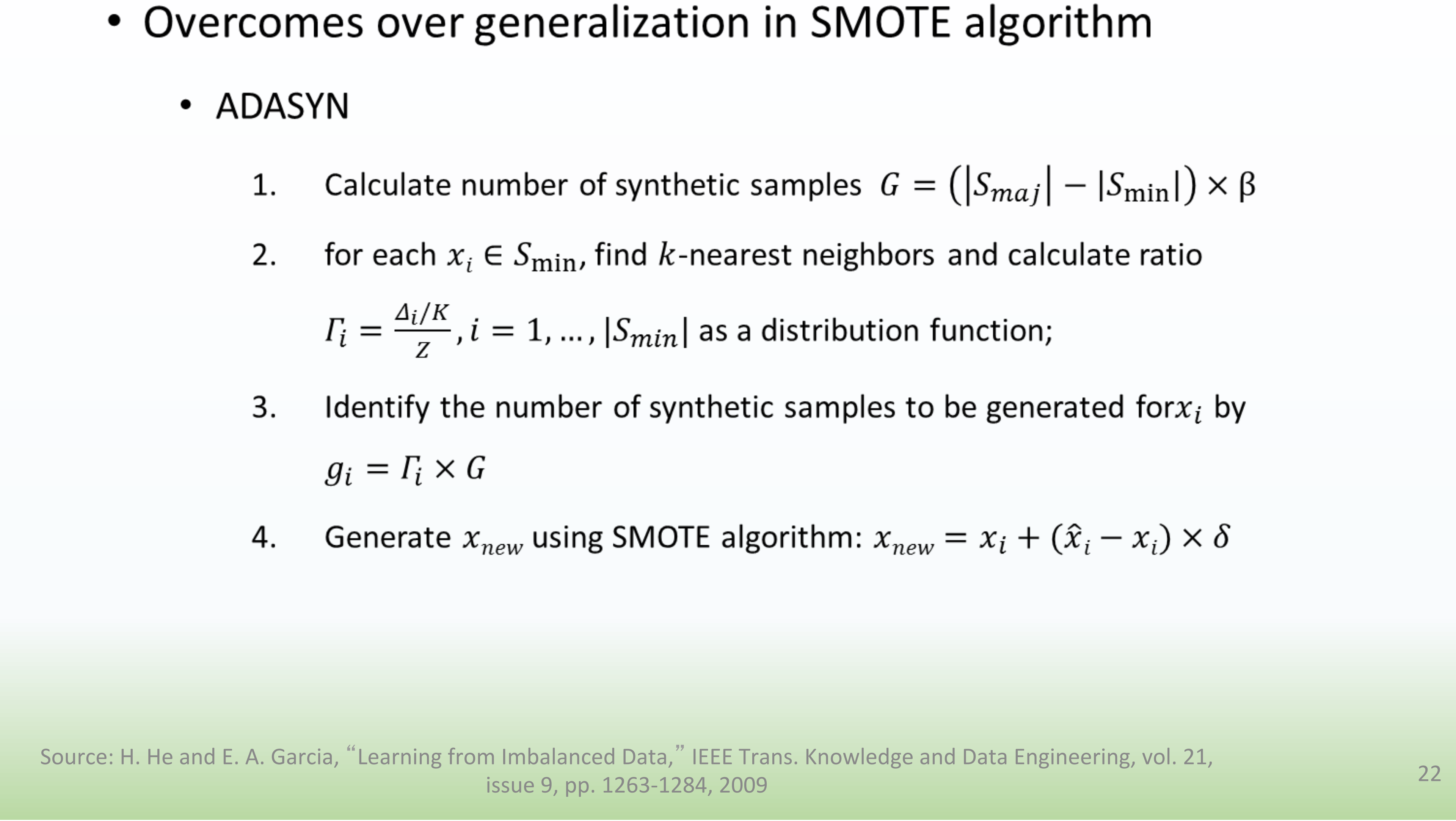

f2
f1
C
A
B
synthetic instance is created for A
Consider 6-nearest neighbor: m=6
For A: number of minority instance: 2
number of majority instance: 4
"DANGER" instance
For B: number of minority instance: 5
number of majority instance: 1
"SAFE" instance
For C: number of minority instance: 6
number of majority instance: 0
"NOISE" instance

Fig. 4. Data creation based on Borderline instance.

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Sampling methods

## Adaptive Synthetic Sampling



- Overcomes over generalization in SMOTE algorithm
  - ADASYN

1. Calculate number of synthetic samples $G = \left(\left|S_{maj}\right| - |S_{\min}|\right) \times \beta$
2. for each $x_i \in S_{\min}$, find $k$-nearest neighbors and calculate ratio

   $\Gamma_i = \frac{\Delta_i/K}{Z}, i = 1, \ldots, |S_{min}|$ as a distribution function;
3. Identify the number of synthetic samples to be generated for$x_i$ by

   $g_i = \Gamma_i \times G$
4. Generate $x_{new}$ using SMOTE algorithm: $x_{new} = x_i + (\hat{x}_i - x_i) \times \delta$

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Sampling methods

## Sampling with Data Cleaning

- Tomek links

  1. Given a pair $(x_i,\ x_j)$ where $x_i \in S_{\min}$, $x_j \in S_{maj}$, and the distance between them as $d(x_i, x_j)$
  2. If there is no instance $x_k\ s.t. d(x_i, x_k) <. d(x_i, x_j)$ or $d(x_j, x_k) < d(x_i, x_j)$, then $(x_i,\ x_j)$ is called a Tomek link

- Clean up unwanted inter-class overlapping after synthetic sampling

- Examples:
  - OSS, condensed nearest neighbor and Tomek links (CNN + Tomek links), neighborhood cleaning rule (NCL) based on edited nearest neighbor (ENN), SMOTE+ENN, and SMOTE+Tomek

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# Sampling methods

## Sampling with Data Cleaning

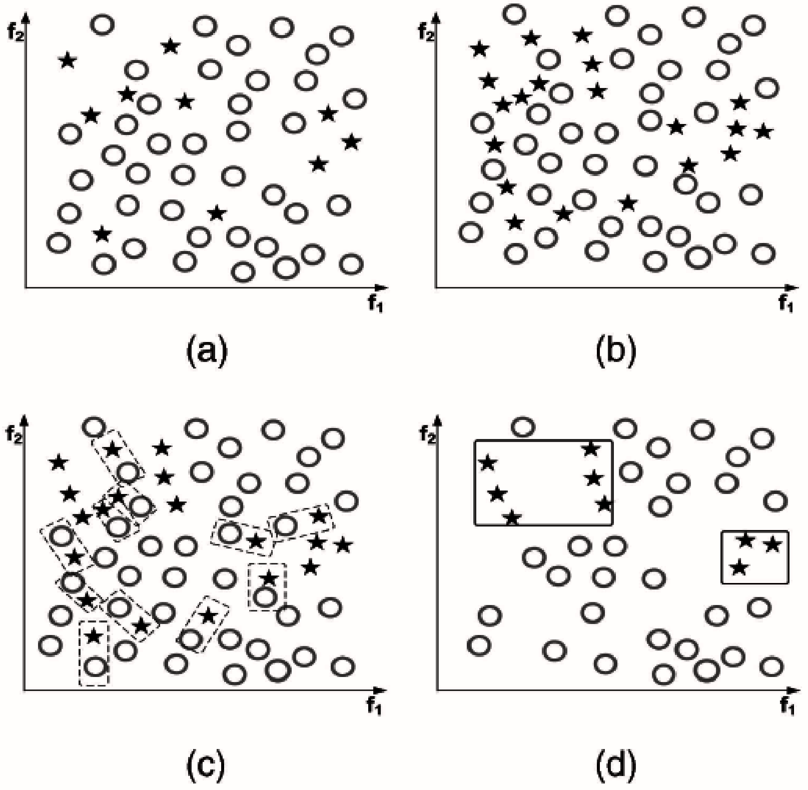


Fig. 5. (a) Original data set distribution. (b) Post-SMOTE data set. (c) The identified Tomek Links. (d) The data set after removing Tomek links.

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Cluster-based oversampling (CBO) method

1. For the majority class $S_{maj}$ with $m_{maj}$ clusters

   I. Oversample each cluster $C_{maj:j} \subset S_{maj}, j = 1, \ldots, m_{maj}$ except the largest $C_{maj:\max}$, so that for $\forall j, |C_{maj:j}| = |C_{maj:\max}|$

   II. Calculate the number of majority class examples after oversampling as $N_{CBO}$

2. For the minority class $S_{min}$ with $m_{min}$ clusters

   I. Oversample each cluster $C_{min:i} \subset S_{min}, i = 1, \ldots, m_{\min}$ to be of the same size $N_{CBO}/m_{\min}$ , so that for $\forall i, |C_{min:i}| = N_{CBO}/m_{\min}$

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Sampling methods

## CBO Method

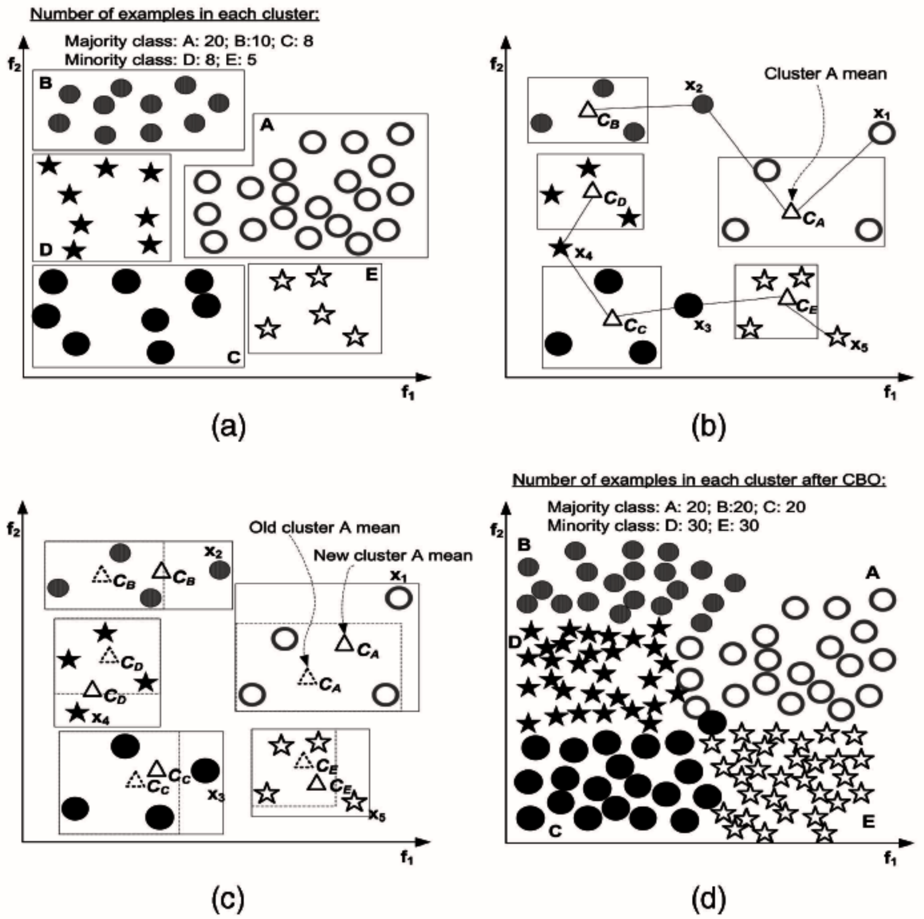
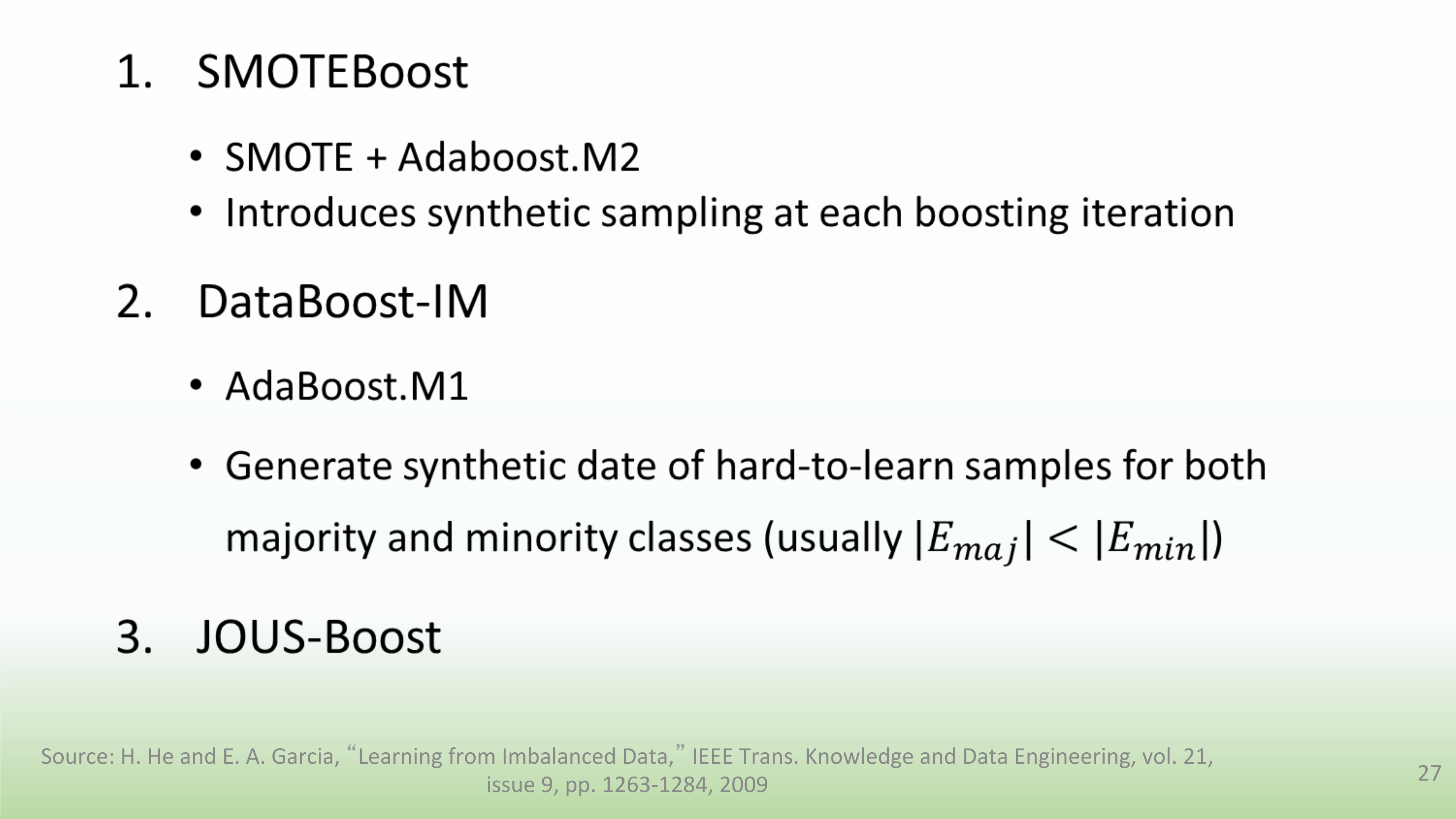

Number of examples in each cluster:
Majority class: A: 20; B:10; C: 8
Minority class: D: 8; E: 5
f₂
f₁
B
A
D
C
E
(a)
Cluster A mean
$x_2$
$x_1$
$x_4$
$x_3$
$x_5$
$C_B$
$C_D$
$C_A$
$C_C$
$C_E$
(b)
Old cluster A mean
New cluster A mean
(c)
Number of examples in each cluster after CBO:
Majority class: A: 20; B:20; C: 20
Minority class: D: 30; E: 30
(d)

Fig. 6. (a) Original data set distribution. (b) Distance vectors of examples and cluster means. (c) Newly defined cluster means and cluster borders. (d) The data set after cluster-based oversampling method.

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Integration of Sampling and Boosting

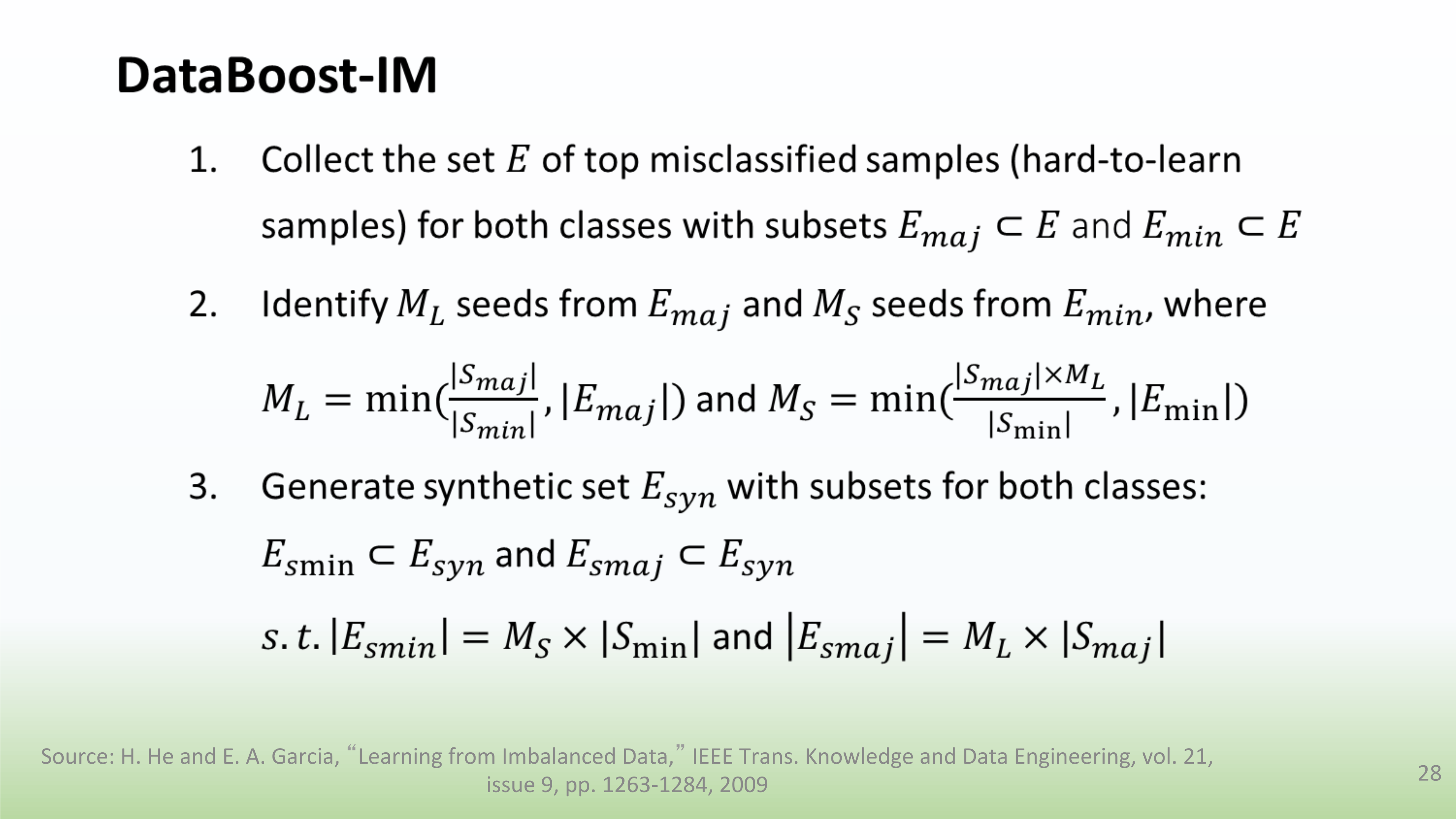


1. SMOTEBoost
   - SMOTE + Adaboost.M2
   - Introduces synthetic sampling at each boosting iteration
2. DataBoost-IM
   - AdaBoost.M1
   - Generate synthetic date of hard-to-learn samples for both majority and minority classes (usually $|E_{maj}| < |E_{min}|$)
3. JOUS-Boost

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Sampling methods

## Integration of Sampling and Boosting



### DataBoost-IM

1. Collect the set $E$ of top misclassified samples (hard-to-learn samples) for both classes with subsets $E_{maj} \subset E$ and $E_{min} \subset E$

2. Identify $M_L$ seeds from $E_{maj}$ and $M_S$ seeds from $E_{min}$, where

   $M_L = \min(\frac{|S_{maj}|}{|S_{min}|}, |E_{maj}|)$ and $M_S = \min(\frac{|S_{maj}| \times M_L}{|S_{\min}|}, |E_{\min}|)$

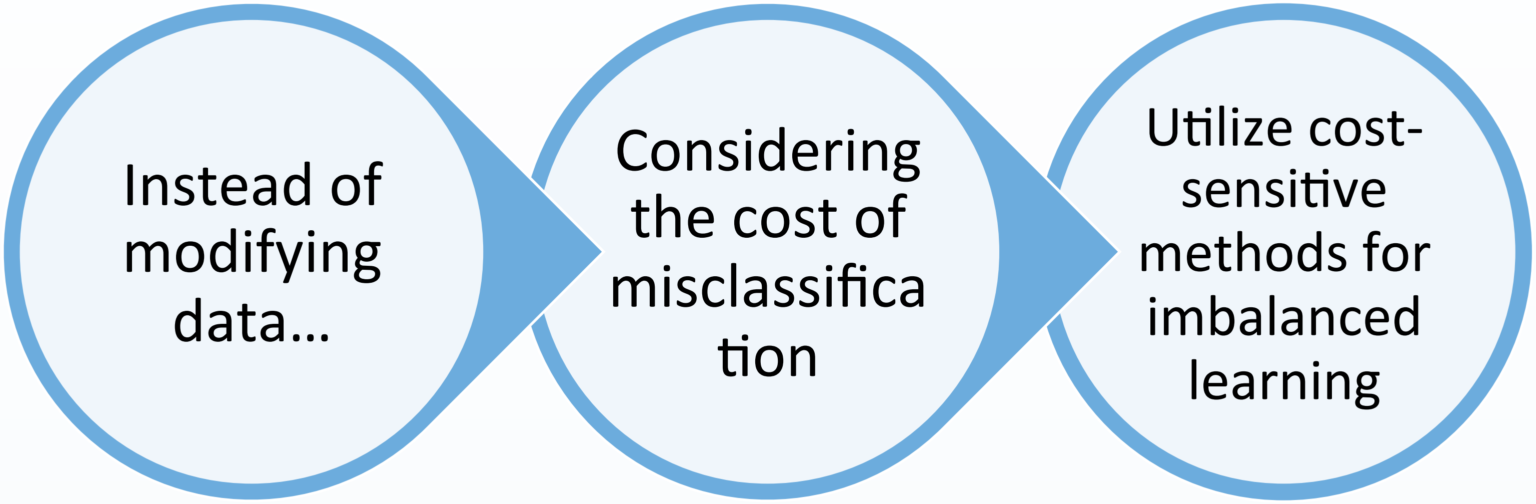
3. Generate synthetic set $E_{syn}$ with subsets for both classes:

   $E_{s\min} \subset E_{syn}$ and $E_{smaj} \subset E_{syn}$

   $s.t. |E_{smin}| = M_S \times |S_{\min}|$ and $\left|E_{smaj}\right| = M_L \times |S_{maj}|$

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Cost-Sensitive Methods



Instead of modifying data…

Considering the cost of misclassification

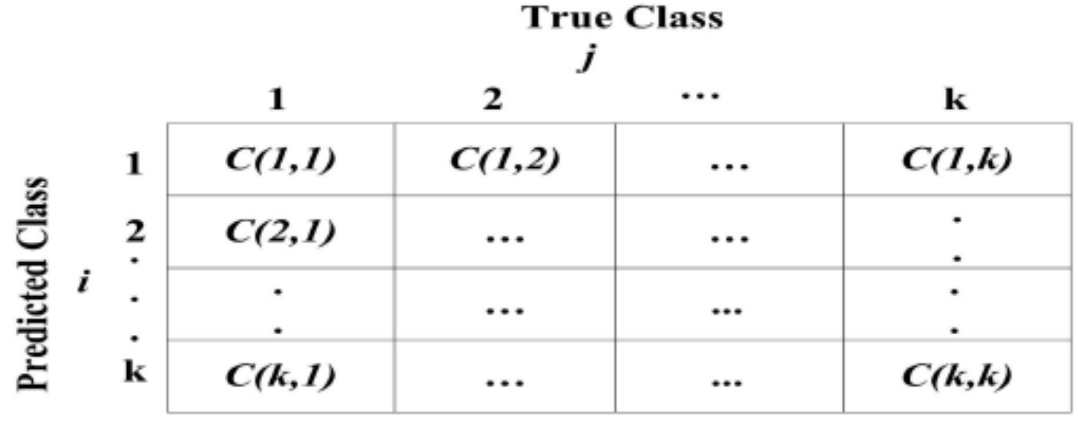
Utilize cost-sensitive methods for imbalanced learning

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Cost-Sensitive Learning Framework

- Define the cost of misclassifying a majority to a minority as $C(Min, Maj)$
- Typically $C(Maj, Min) > C(Min, Maj)$
- Minimize the overall cost - usually the *Bayes conditional risk* - on the training data set

$$R(i|x) = \sum_j P(j|x)C(i,j)$$



| | | True Class *j* | | | |
|---|---|---|---|---|---|
| | | 1 | 2 | ... | k |
| Predicted Class *i* | 1 | *C(1,1)* | *C(1,2)* | ... | *C(1,k)* |
| | 2 | *C(2,1)* | ... | ... | ⋮ |
| | ⋮ | ⋮ | ... | ... | ⋮ |
| | k | *C(k,1)* | ... | ... | *C(k,k)* |

Fig. 7. Multiclass cost matrix.

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Cost-Sensitive methods

## Cost-Sensitive Dataspace Weighting with Adaptive Boosting

- Iteratively update the distribution function $D_t$ of the training data according to error of current hypothesis $h_t$ and cost factor $C_i$
  - Weight updating parameter $\alpha_t = \frac{1}{2}\ln(\frac{1-\varepsilon_t}{\varepsilon_t})$
  - Error of hypothesis $h_t$: $\varepsilon_t = \sum_{i:h_t(x_i)\neq y_i} D_t(i)$

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Cost-Sensitive methods

## Cost-Sensitive Dataspace Weighting with Adaptive Boosting

- Given $D_t, h_t, C_i, \alpha_t$, and $\varepsilon_t$

1. AdaC1: $D_{t+1}(i) = \frac{D_t(i)\ exp(-\alpha_t C_i h_t(x_i) y_i)}{Z_t}$

2. AdaC2: $D_{t+1}(i) = \frac{C_i D_t(i)\ exp(-\alpha_t h_t(x_i) y_i)}{Z_t}$

3. AdaC3: $D_{t+1}(i) = \frac{C_i D_t(i)\ exp(-\alpha_t C_i h_t(x_i) y_i)}{Z_t}$

4. AdaCost: $D_{t+1}(i) = \frac{D_t(i)\ exp(-\alpha_t h_t(x_i) y_i \beta_i)}{Z_t}$,

   $\beta_i = \beta(sign(y_i, h_t(x_i)), C_i)$

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Cost-Sensitive Decision Trees

1. Cost-sensitive adjustments for the decision threshold
   - The final decision threshold shall yield the most dominant point on the ROC curve
2. Cost-sensitive considerations for split criteria
   - The impurity function shall be insensitive to unequal costs
3. Cost-sensitive pruning schemes
   - The probability estimate at each node needs improvement to reduce removal of leaves describing the minority concept
   - Laplace smoothing method and Laplace pruning techniques

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Cost-Sensitive Neural Network

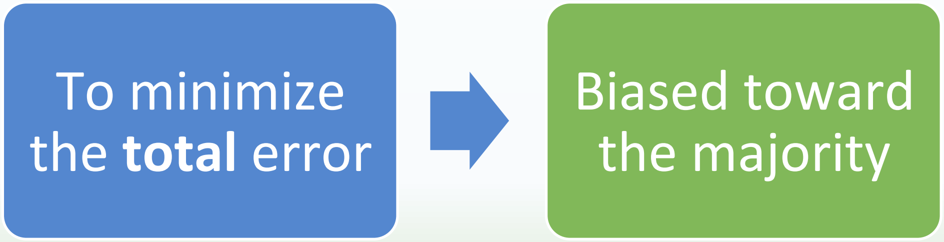
## Four ways of applying cost sensitivity in neural networks

| Modifying probability estimate of outputs | Altering outputs directly | Modify learning rate | Replacing error-minimizing function |
|---|---|---|---|
| • *Applied only at testing stage*<br>• *Maintain original neural networks* | • *Bias neural networks during training to focus on expensive class* | • *Set η higher for costly examples and lower for low-cost examples* | • *Use expected cost minimization function instead* |

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Kernel-based learning framework

- Based on statistical learning and Vapnik-Chervonenkis (VC) dimensions
- Problems with Kernel-based support vector machines (SVMs)
    1. Support vectors from the minority concept may contribute less to the final hypothesis
    2. Optimal hyperplane is also biased toward the majority class


To minimize the **total** error

Biased toward the majority

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Integration of Kernel Methods with Sampling Methods

1. SMOTE with Different Costs (SDCs) method
2. Ensembles of over/under-sampled SVMs
3. SVM with asymmetric misclassification cost
4. Granular Support Vector Machines—Repetitive Undersampling (GSVM-RU) algorithm

Source: H. He and E. A. Garcia, “Learning from Imbalanced Data,” IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Kernel-Based Methods

## Kernel Modification Methods

1. Kernel classifier construction
   - Orthogonal forward selection (OFS) and Regularized orthogonal weighted least squares (ROWLSs) estimator
2. SVM class boundary adjustment
   - Boundary movement (BM), biased penalties (BP), class-boundary alignment(CBA), kernel-boundary alignment (KBA)
3. Integrated approach
   - Total margin-based adaptive fuzzy SVM (TAF-SVM)
4. K-category proximal SVM (PSVM) with Newton refinement
5. Support cluster machines (SCMs), Kernel neural gas (KNG), P2PKNNC algorithm, hybrid kernel machine ensemble (HKME) algorithm, Adaboost relevance vector machine (RVM), …

Source: H. He and E. A. Garcia, “Learning from Imbalanced Data,” IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Active Learning Methods

- SVM-based active learning

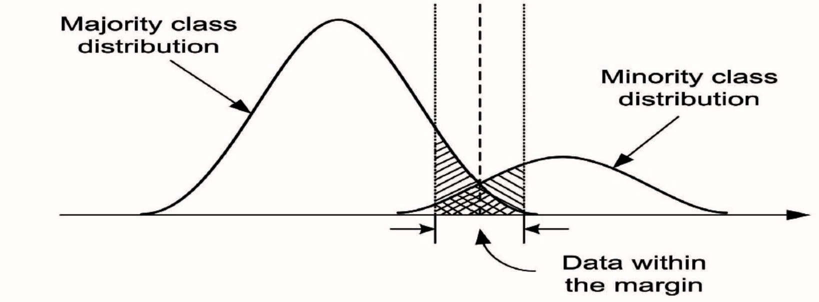


Fig. 8. Data imbalance ratio within and outside the margin [98].

- Active learning with sampling techniques
  - Undersampling and oversampling with active learning for the word sense disambiguation (WSD) imbalanced learning
  - New stopping mechanisms based on maximum confidence and minimal error
  - Simple active learning heuristic (SALH) approach

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Additional methods

## One-class learning/novelty detection methods

## Mahalanobis-Taguchi System

## Rank metrics and multitask learning

- Combination of imbalanced data and the small sample size problem

## Multiclass imbalanced learning

- AdaC2.M1
- Rescaling approach for multiclass cost-sensitive neural networks
- the ensemble knowledge for imbalance sample sets (eKISS) method

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# *The Evaluation of* **Imbalanced Learning Problem**

Source: H. He and E. A. Garcia, “Learning from Imbalanced Data,” IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Assessment Metrics

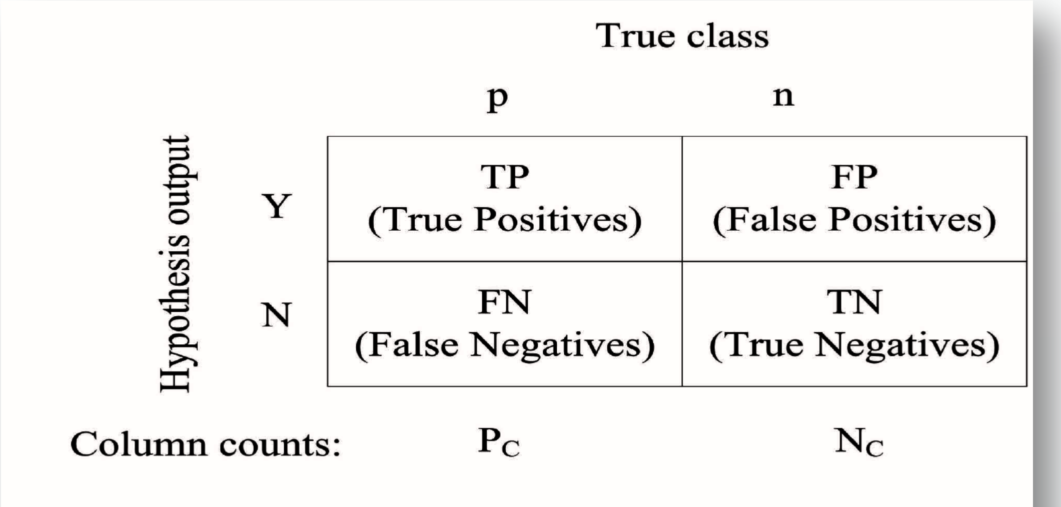
How to evaluate the performance of imbalanced learning algorithms ?

1. Singular assessment metrics
2. Receiver operating characteristics (ROC) curves
3. Precision-Recall (PR) Curves
4. Cost Curves
5. Assessment Metrics for Multiclass Imbalanced Learning

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Assessment Metrics

## Singular assessment metrics



| | | True class | |
|---|---|---|---|
| | | p | n |
| Hypothesis output | Y | TP<br>(True Positives) | FP<br>(False Positives) |
| | N | FN<br>(False Negatives) | TN<br>(True Negatives) |
| Column counts: | | $P_C$ | $N_C$ |

Fig. 9. Confusion matrix for performance evaluation.

$$Accuracy = \frac{TP + TN}{P_C + N_C}$$

$$ErrorRate = 1 - accuracy$$

- Limitations of accuracy – sensitivity to data distributions

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Assessment Metrics

## Singular assessment metrics

$$Precision = \frac{TP}{TP + FP},$$

$$Recall = \frac{TP}{TP + FN},$$

- Insensitive to data distributions

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Assessment Metrics

## Singular assessment metrics

### More comprehensive metrics

$$F\text{-}Measure = \frac{(1+\beta)^2 \cdot Recall \cdot Precision}{\beta^2 \cdot Recall + Precision}$$

$\beta = 1$, usually

$$G\text{-}mean = \sqrt{\frac{TP}{TP+FN} \times \frac{TN}{TN+FP}}$$

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

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# Assessment Metrics

## Receive Operating Characteristics (ROC) curves

- $TP_{rate} = \frac{TP}{P_C}$
- $FP_{rate} = \frac{FP}{N_C}$
- Area under the curve (AUC)

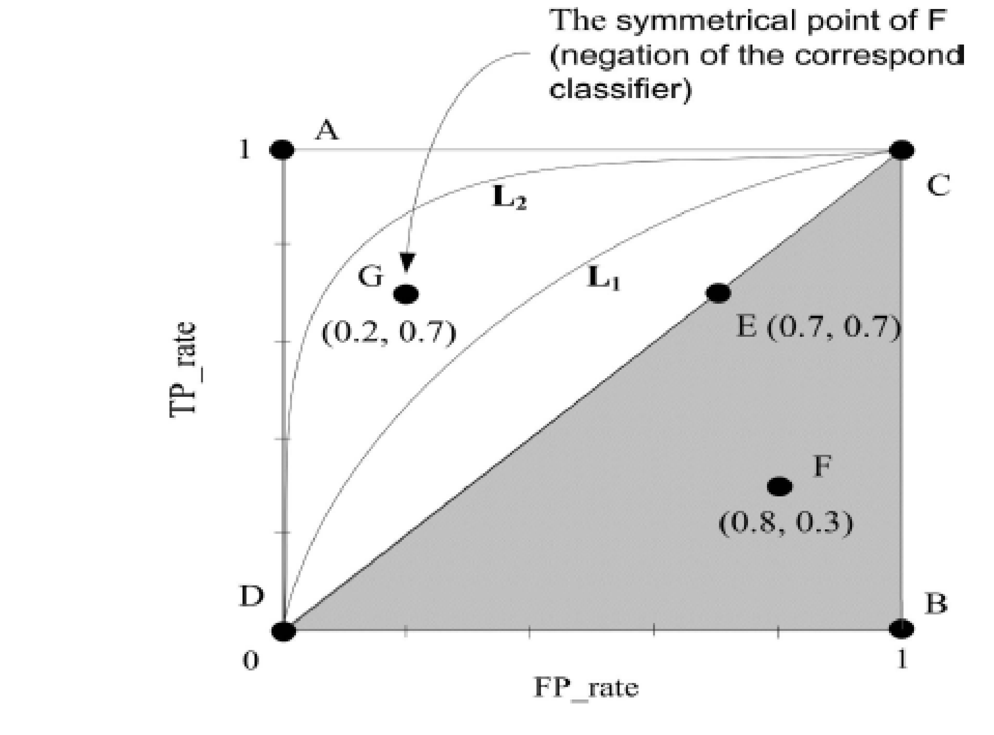
The symmetrical point of F (negation of the correspond classifier)
A
1
L₂
C
G
L₁
(0.2, 0.7)
E (0.7, 0.7)
TP_rate
F
(0.8, 0.3)
D
B
0
1
FP_rate

Fig. 10. ROC curve representation.

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Assessment Metrics

## Precision-Recall (PR) curves

- Plotting the precision rate over the recall rate
- A curve dominates in ROC space (resides in the upper-left hand) ***if and only if*** it dominates (resides in the upper-right hand) in PR space
- PR space has all the analogous benefits of ROC space
- Provide more informative representations of performance assessment under highly imbalanced data

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Cost Curves

- $PCF(+)$: the probability of an example being from the positive class
- Expected cost: $E[C] = (1 - TP - FP) \times PCF(+) + FP$

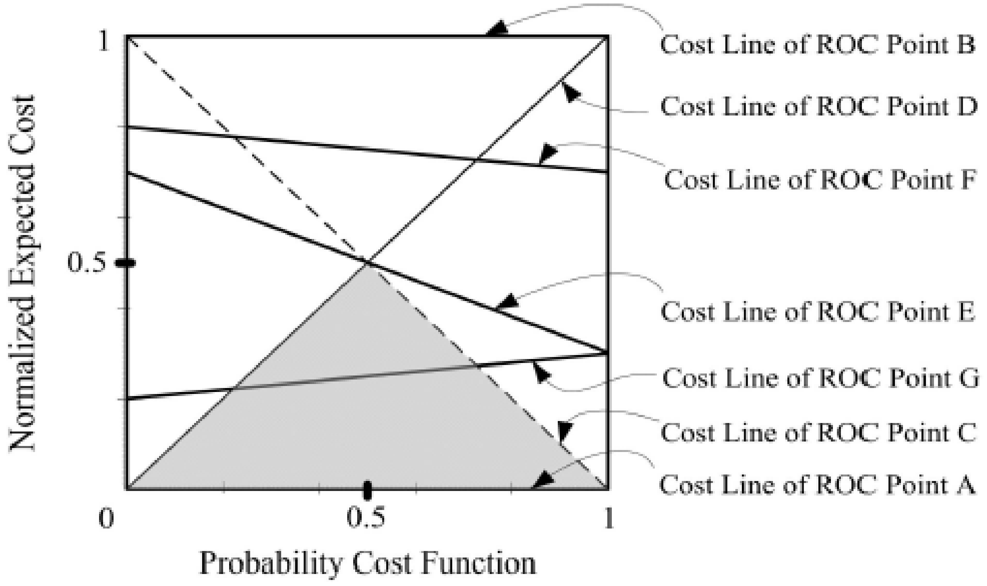

Fig. 11. Cost curve representation.

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# *The Future of* Imbalanced Learning Problem

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Opportunities and Challenges

Understanding the Fundamental Problem

Need of a Uniform Benchmark Platform

Need of Standardized Evaluation Practices

Semi-supervised Learning from Imbalanced data

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Opportunities and Challenges

## Understanding the Fundamental Problem

1. What kind of assumptions will make imbalanced learning algorithms work better compared to learning from the original distributions?
2. To what degree should one balance the original data set?
3. How do imbalanced data distributions affect the computational complexity of learning algorithms?
4. What is the general error bound given an imbalanced data distribution?

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Opportunities and Challenges

## Need of a Uniform Benchmark Platform

1. Lack of a uniform benchmark for standardized performance assessments
2. Lack of data sharing and data interoperability across different disciplinary domains;
3. Increased procurement costs, such as time and labor, for the research community as a whole group since each research group is required to collect and prepare their own data sets.

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Opportunities and Challenges

## Need of Standardized Evaluation Practices

- Establish the practice of using the curve-based evaluation techniques
- A standardized set of evaluation practices for proper comparisons

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Opportunities and Challenges

## Incremental Learning from Imbalanced Data Streams

1. How can we autonomously adjust the learning algorithm if an imbalance is introduced in the middle of the learning period?

2. Should we consider rebalancing the data set during the incremental learning period? If so, how can we accomplish this?

3. How can we accumulate previous experience and use this knowledge to adaptively improve learning from new data?

4. How do we handle the situation when newly introduced concepts are also imbalanced (i.e., the imbalanced concept drifting issue)?

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Opportunities and Challenges

## Semi-supervised Learning from Imbalanced Data

1. How can we identify whether an unlabeled data example came from a balanced or imbalanced underlying distribution?

2. Given an imbalanced training data with labels, what are the effective and efficient methods for recovering the unlabeled data examples?

3. What kind of biases may be introduced in the recovery process (through the conventional semi-supervised learning techniques) given imbalanced, labeled data?

Source: H. He and E. A. Garcia, "Learning from Imbalanced Data," IEEE Trans. Knowledge and Data Engineering, vol. 21, issue 9, pp. 1263-1284, 2009

# Reference:

**This lecture notes is based on the following paper:**

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Should you have any comments or suggestions regarding this lecture note, please feel free to contact Dr. Haibo He at he@ele.uri.edu

Web: http://www.ele.uri.edu/faculty/he/

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