Handling imbalanced datasets

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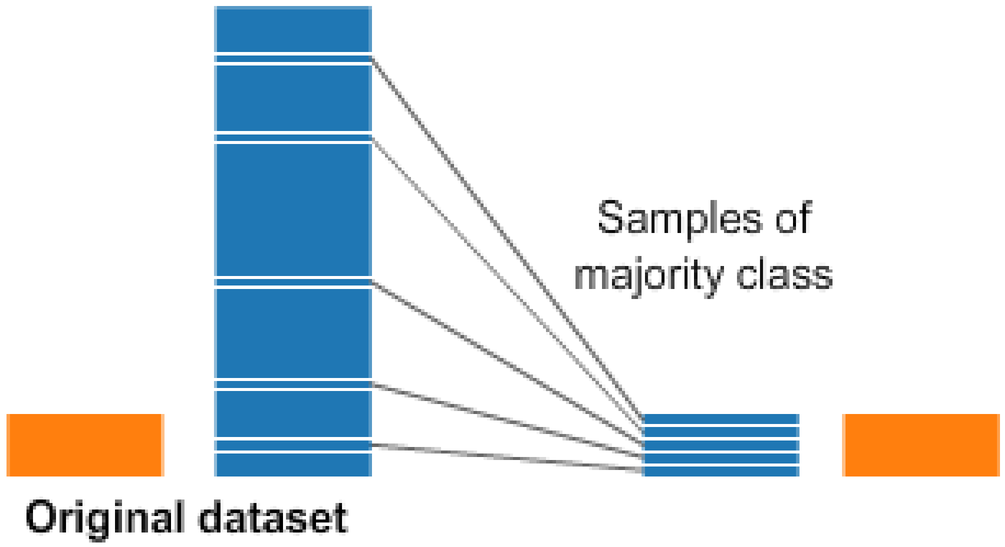
1. Statistical undersampling of the dataset



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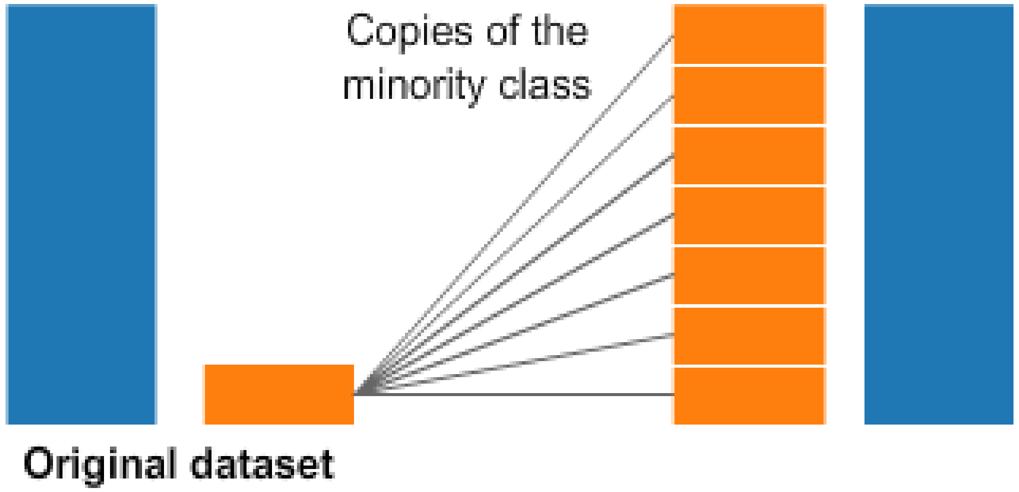
2. Statistical oversampling of the dataset



3. Synthetic oversampling of the dataset

Synthetic Minority Oversampling Technique (SMOTE)

“The minority class is over-sampled by taking each minority class sample and introducing synthetic examples along the line segments joining any/all of the k minority class nearest neighbors. Depending upon the amount of over-sampling required, neighbors from the k nearest neighbors are randomly chosen

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SMOTE: Synthetic Minority Over-sampling Technique

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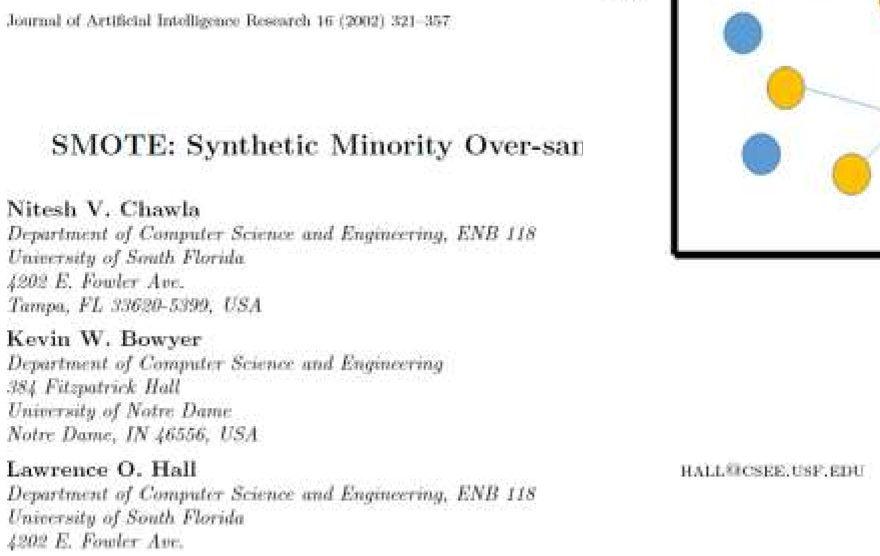
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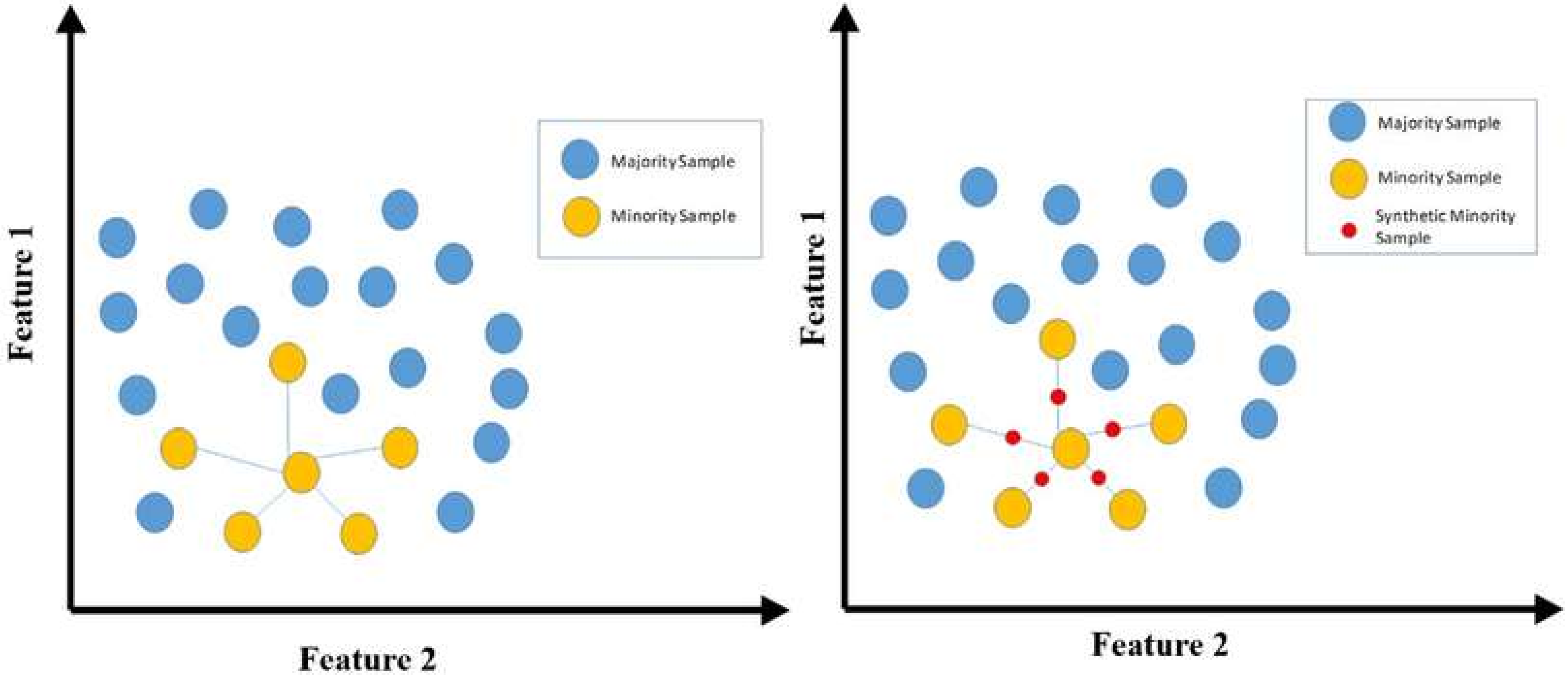

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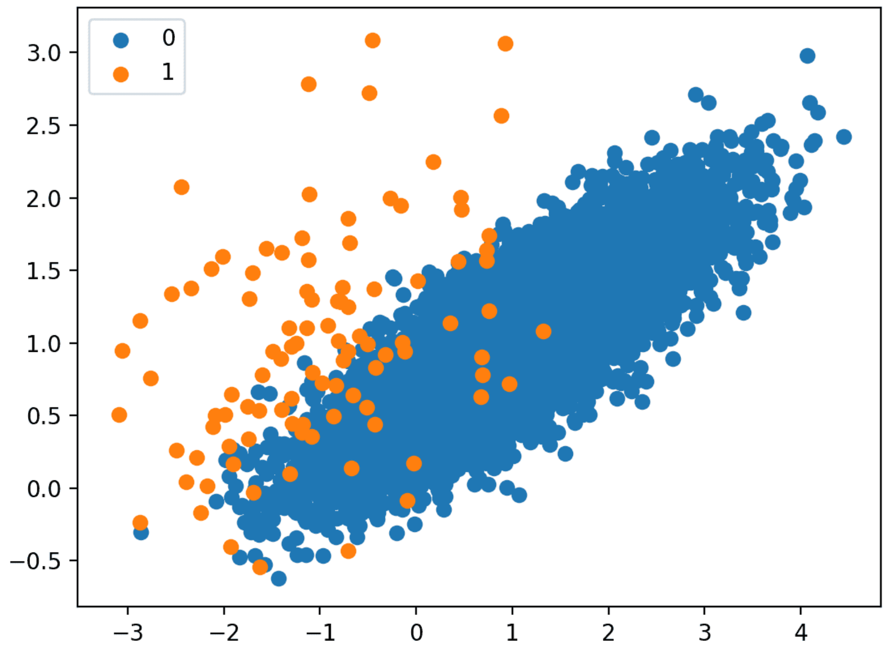

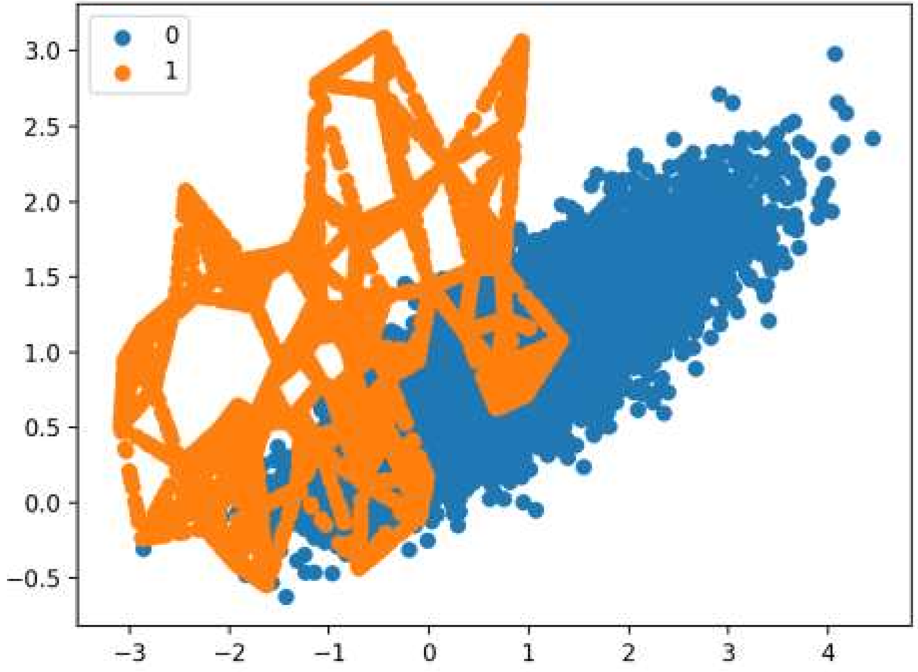

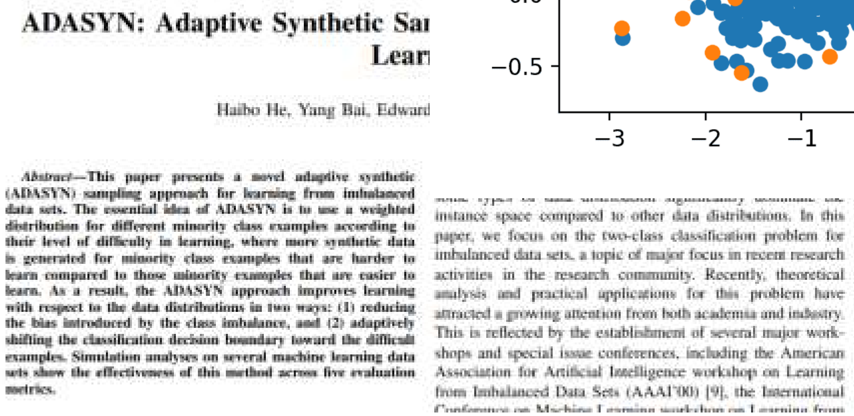

ADASYN: Adaptive Synthetic Sa
Lear

Haibo He, Yang Bai, Edward

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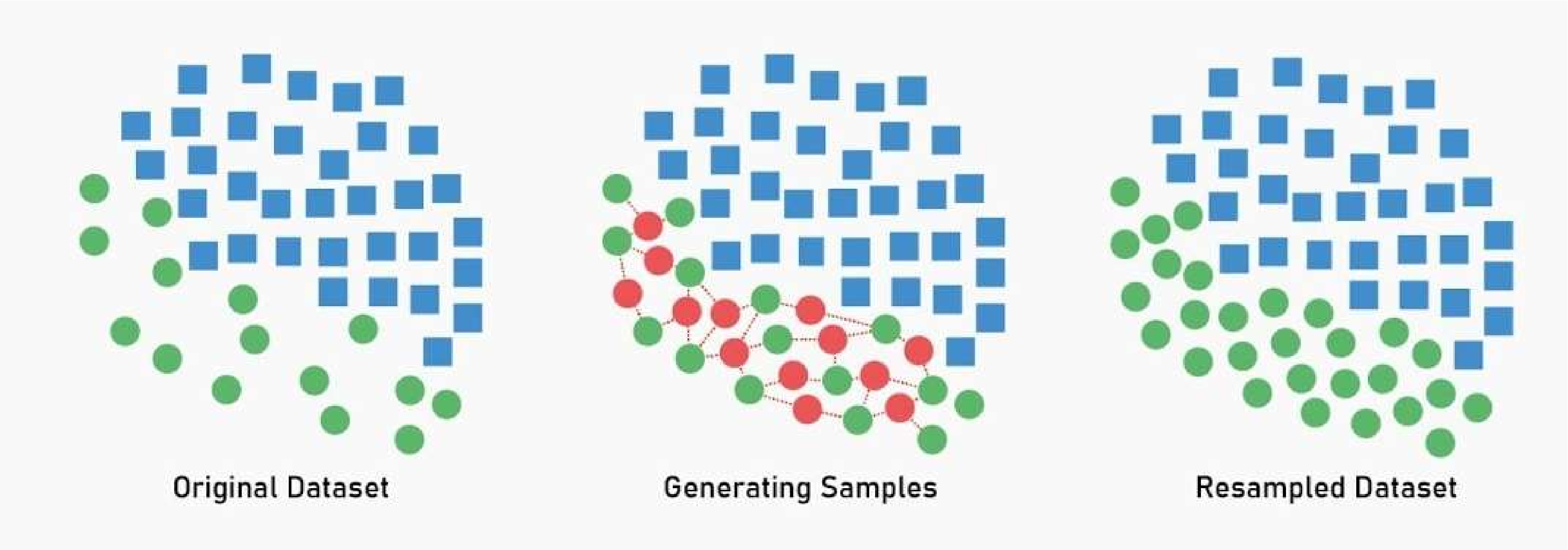

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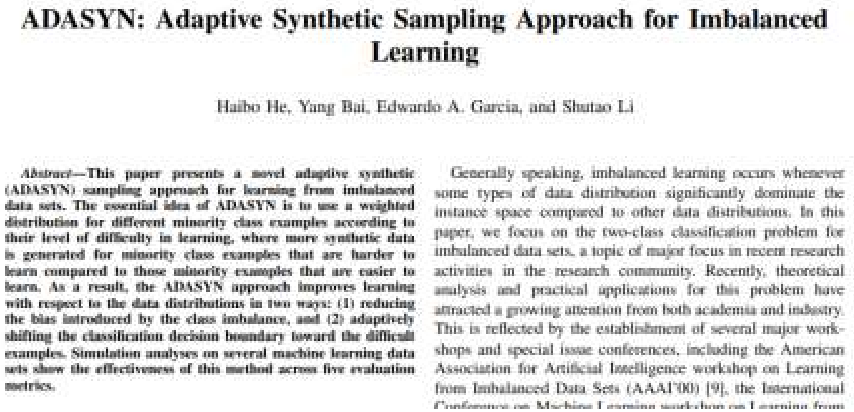
ADAptive SYNthetic oversampling
(Adasyn)

The same as SMOTE, but synthetic oversampling depends on the class distribution
-> it creates more synthetic samples near the boundary between the two classes (than within the distribution of the minority class)



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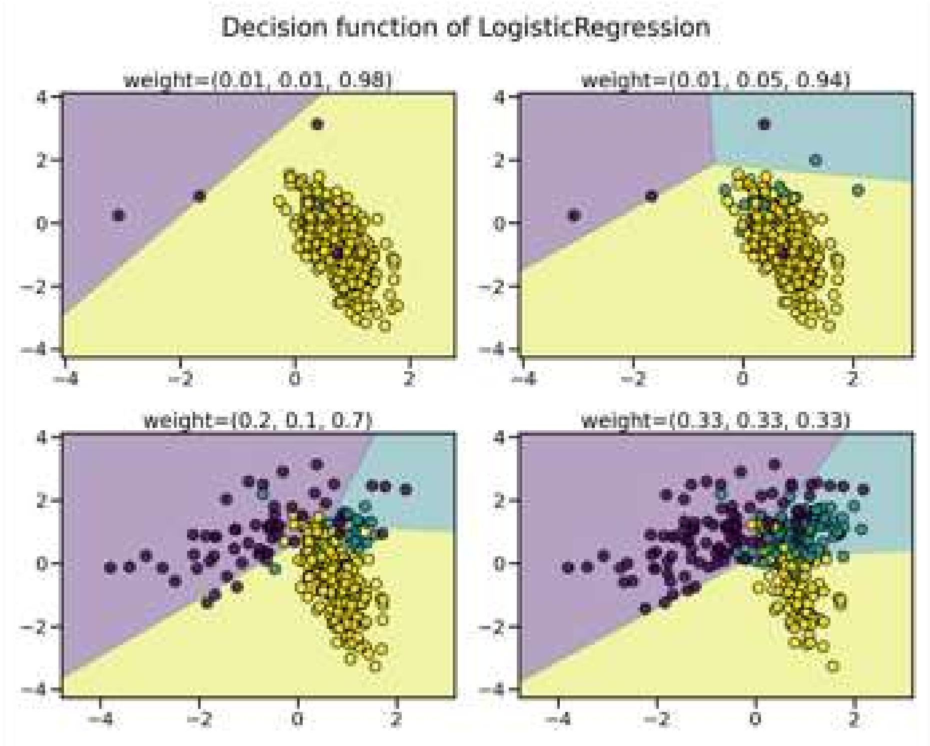

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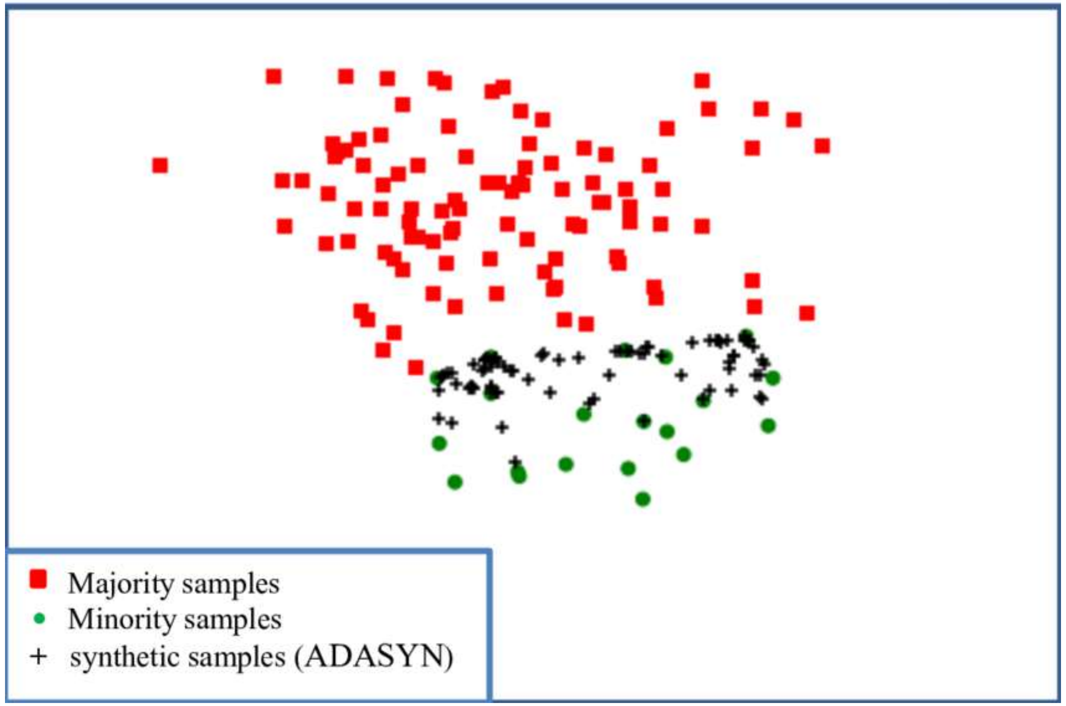

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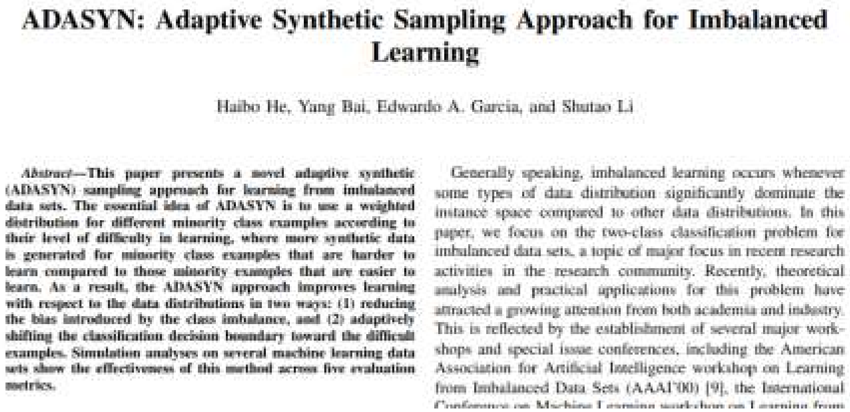

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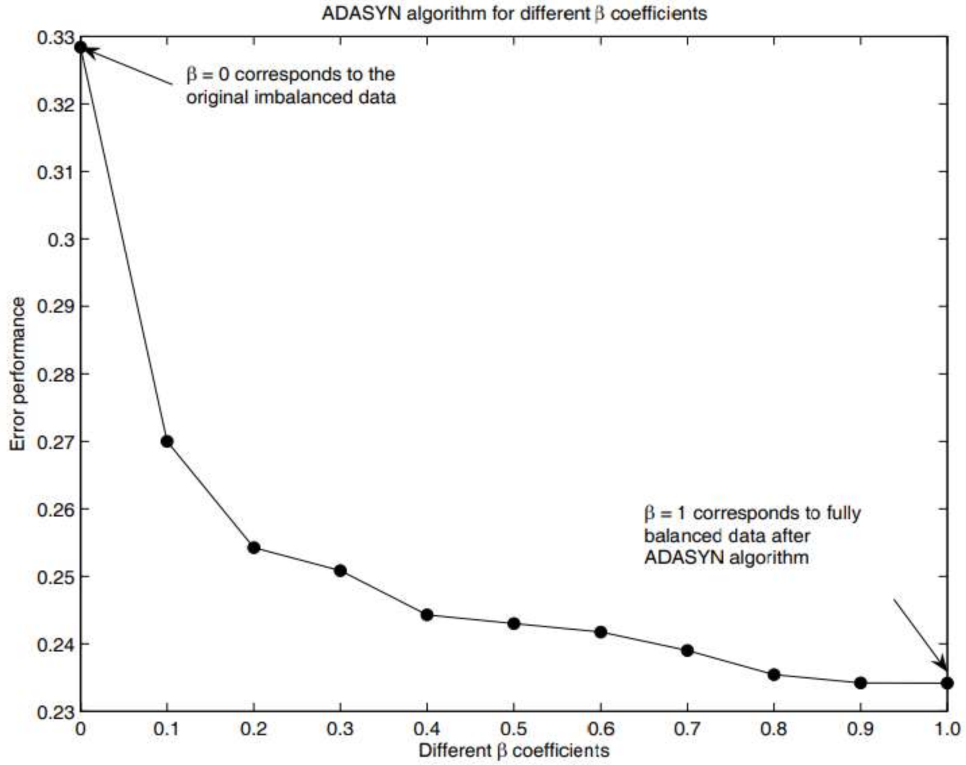

Fig. 1. ADASYN algorithm for imbalanced learning

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4. "Forcing" the behaviour of the ML model

i.e. cost-sensitive SVM

Specifically, each example in the training dataset has its own penalty term (*C* value) used in the calculation for the margin when fitting the SVM model. The value of an example's *C*-value can be calculated as a weighting of the global *C*-value, where the weight is defined proportional to the class distribution.

- C_i = weight_i * C

A larger weighting can be used for the minority class, allowing the margin to be softer, whereas a smaller weighting can be used for the majority class, forcing the margin to be harder and preventing misclassified examples.

- **Small Weight**: Smaller *C* value, larger penalty for misclassified examples.
- **Larger Weight**: Larger *C* value, smaller penalty for misclassified examples.

This has the effect of encouraging the margin to contain the majority class with less flexibility, but allow the minority class to be flexible with misclassification of majority class examples onto the minority class side if needed.

> *That is, the modified SVM algorithm would not tend to skew the separating hyperplane toward the minority class examples to reduce the total misclassifications, as the minority class examples are now assigned with a higher misclassification cost.*

— Page 89, Imbalanced Learning: Foundations, Algorithms, and Applications, 2013.