The SMOTE algorithm generates an arbitrary number of synthetic minority examples to shift the classifier learning bias toward the minority class. 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 [1].

In random oversampling, data in the minority class is replicated randomly to a specific rate. In other words, according to the size of data and the rate of oversampling data from the minority class is randomly replicated.

ADASYN can adaptively generate synthetic data samples for the minority class to reduce the bias introduced by the imbalanced data distribution. ADASYN can also autonomously shift the classifier decision boundary to be more focused on those difficult to learn examples, therefore improving learning performance. These two objectives are accomplished by a dynamic adjustment of weights and an adaptive learning procedure according to data distributions. ADASYN can be generalized to multiple-class imbalanced learning problems as well. Further more, the ADASYN algorithm can also be modified to facilitate incremental learning applications. Most current imbalanced learning algorithms assume that representative data samples are available during the training process. However, in many real-world applications such as mobile sensor networks, Web mining, surveillance, and communication networks, training data may continuously become available in small chunks over a period of time. In this situation, a learning algorithm should have the capability to accumulate previous experience and use this knowledge to learn additional new information to aid prediction and future decision-making processes. The ADASYN algorithm can potentially be adapted to such an incremental learning scenario. To do this, one will need to dynamically update whenever a new chunk of data samples is received. This can be accomplished by an online learning and evaluation process.

One paper [2] compares SMOTE with random oversampling that tests the two oversampling techniques against Fisher classifier and k-NN classifier and compares F-measure and Recall scores. It uses 8 datasets from the UCI repository, each dataset having different class ratios. The paper also does an ANOVA analysis. From the results of this paper, it can be noted that SMOTE performs better in almost every dataset against random oversampling.

A paper that introduces ADASYN as a new sampling technique [3], compares ADASYN with SMOTE. This paper uses 5 datasets from the UCI repository, each dataset having different class ratios. This paper uses overall accuracy, precision, recall, F-measure and G-mean as measures of performance. ADASYN outperforms SMOTE in majority of the cases.

**References**

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