

# Experimental Comparisons of Semi-Supervised and Supervised ART Classifiers (Invited Talk)

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## Abstract

We present a series of experimental results that reveal the merits of the semi-supervised learning when applied to two different types of ART architectures (Fuzzy ARTMAP and Ellipsoidal ARTMAP). The concept of semi-supervised learning (SSL) was first introduced in the Simplified Boosted ARTMAP architecture by Verzi, et al., 2002, and was extended to Boosted Ellipsoidal ARTMAP by Anagnostopoulos, et al., 2002.

Semi-supervised learning (SSL) refers to the semi-supervised manner, according to which exemplars are formed during training to identify clusters. According to the typical, fully supervised learning scheme of ART architectures, training patterns that are similar to an already formed category in the input space can be associated with or can influence the structure of this category only if both of them correspond to the same class label. Furthermore, training is considered incomplete, if there is at least one exemplar that does not correctly predict the class label of a training pattern. Therefore, while in fully supervised learning mode, a category is not allowed to commit a misclassification error. Eventually, after completion of the learning process, a typical supervised ART architecture will feature a zero post-training error.

The fact that, under fully supervised learning, ART neural network architectures trained to completion attain a zero post-training error may signify that these classifiers have been over-trained. For any classifier and/or pattern recognition problem the difference between test set performance and the post-training accuracy is minimized, in general, for any non-zero post-training error. Additionally it might be the case that for some classification tasks ART neural networks using a fully supervised learning mode are forced to employ a large number of exemplars in order to train to perfection. Instead, a learning scheme (like an SSL scheme) that would allow categories to occasionally misclassify training patterns and also allow training patterns, under certain circumstances, to modify categories

associated with not necessarily the same class, would increase the post-training error, but potentially increase the performance on the test set, and at the same time, reduce the amount of categories created by the classifier.

In our experiments with the aforementioned ART neural networks we are incorporating an error rate parameter referred to as *epsilon*. An *epsilon* value of 0 disallows any misclassification error in the training set, while an *epsilon* value of 1 allows high percentages of misclassification error in the training set. In our experiments we are searching for the value of *epsilon* that maximizes the network's generalization performance on an independently drawn (from the training set) set, referred to as cross-validation set. By doing so we show that the *epsilon*-optimized ART networks exhibit higher generalization performance than the fully supervised ART (*epsilon* = 0), while at the same time significantly reducing the number of categories that the fully supervised ART versions create. Experimental results were conducted for appropriately designed simulated data and for real databases as well.

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## References

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