INFFC: An iterative class noise filter based on the fusion of classifiers with noise sensitivity control

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Abstract. This is a summary of our article published in Information Fusion [2] to be part of the MultiConference CAEPIA'15 KeyWorks.

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1 Summary

In classification, noise may deteriorate the system performance and increase the complexity of the models built. If the data used to train this model (formally known as a classifier) are corrupted, both the learning phase and the model obtained will be negatively affected. The former will require more time to find a solution but also more examples in order to be able to obtain an accurate classifier. As a consequence, the final model will probably be less accurate and more complex due to the presence of noise, since non-real patterns may be modeled.

Two different types of noise can be found in classification datasets: attribute and class noise [3]. Class noise is the most disruptive type of noise as incorrectly labeled examples cause a high impact in the classifier building step. On this account, many works in the literature, including our proposal, focus on its treatment. In order to mitigate consequences created by noise, two main approaches have been followed in the literature [1]: (a) *algorithm level approaches*, which comprise the adaptations of existing algorithms to properly handle the noise, and (b) *data level approaches*, which preprocess the datasets aiming at getting rid of the noisy examples. Data level approaches are the most popular choice, as they are independent of the classifier used and allow one to preprocess the datasets once for every classifier considered. Among them, noise filtering, which removes noisy examples from the training data, is one of the most used techniques.

The study of the noise filtering schemes that are proposed in the literature draws our attention on three main paradigms. *Ensemble-based filtering*, where the use of ensembles for filtering is based on the hypothesis that collecting predictions from different classifiers could provide a better class noise detection. *Iterative filtering*, in which an iterative elimination of noisy examples will help each step to be less influenced by the noise removed in previous steps. Finally, *Metric-based filtering* are based on the computation of measures over the training data, and those examples with an estimated noise level above a prefixed threshold are removed.

On this account, we propose a novel noise filtering technique called *Iterative Noise Filter based on the Fusion of Classifiers* (INFFC), by combining these three noise filtering paradigms: the usage of ensembles for filtering, the iterative filtering and the computation of noise measures. We use the first two strategies (use of multiple classifiers and iterative filtering) to improve the filtering accuracy, whereas the last one (the noisy score) controls the level of conservation of the filter removing potentially noisy examples.

The fusion of classifiers for filtering is a prominent approach in noise filtering, and successful proposals using this paradigm already exist. The main differences between our proposal and previous ensemble-based filters are: (a) the proposed method follows an iterative noise filtering scheme that allows us to avoid the usage of detected noisy examples in each new iteration of the filtering process, and (b) we introduce a noisy score to control the filtering sensitivity, in such a way that the amount of noisy examples removed in each iteration can be adapted to the necessities of the practitioner.

The validity of the proposed method is studied in an exhaustive experimental study, comparing several representative noise filters with our proposal. We compare the new filtering method against several state-of-the-art methods to deal with datasets with class noise. All of them will be used to preprocess several real-world datasets in which different class noise levels will be introduced, and to study their efficacy in three classifiers with different sensitivity to noise: C4.5, SVM and kNN. Their accuracy over the datasets preprocessed with our proposal and the other existing filters will be compared using the appropriate statistical tests. We also analyze whether our proposal is able to better detect and eliminate the corrupted examples than the other filters, and the influence of threshold value used to detect noisy examples.

References

1. B. Frenay and M. Verleysen. Classification in the presence of label noise: A survey. *Neural Networks and Learning Systems, IEEE Transactions on*, 25(5):845–869, 2014.
2. J. A. Sáez, M. Galar, J. Luengo, and F. Herrera. Inffc: An iterative class noise filter based on the fusion of classifiers with noise sensitivity control. *Information Fusion*, 27:19–32, 2016.
3. X. Zhu and X. Wu. Class Noise vs. Attribute Noise: A Quantitative Study. *Artificial Intelligence Review*, 22:177–210, 2004.