Chapter 3
Making an Electronic Nose Versatile: The Role of Incremental Learning Algorithms

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ABSTRACT

Development of a pattern recognition system in the area of machine olfaction is a complex and challenging task due to the following reasons: (1) It is practically very difficult to get adequate data required to train the computation model, compared to the other applications of pattern recognition like image processing; (2) In many applications, the samples arrive in batches or are available over multiple seasons or even over multiple years; (3) The user industry, in general, shows reluctance when approached for samples and wants immediate result; (4) Data availability in batches makes the training process difficult, and requires storage of data for all the samples.

Because of these factors, it is necessary to make the system flexible in such a way that the system is able to update an existing classifier without affecting the classification performance on old data, and such classifiers should have the property

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as being both stable and plastic. Conventional pattern classification algorithms require the entire dataset during training, and thereby fail to meet the criteria of being plastic and stable at the same time. The incremental learning algorithms possess these features, and thus, the electronic nose systems become extremely versatile when equipped with these classifiers. In this chapter, the authors describe different incremental learning algorithms for machine olfaction.

INTRODUCTION TO INCREMENTAL LEARNING

In conventional supervised classifiers, the entire dataset is required during training and thus their role is severely limited in some applications of machine olfaction systems. In such applications, it may not be possible to collect the entire dataset within a short time and assembling of data may spread over multiple seasons or even years. Hence, the pattern classifier should have the following two important features:

1. Plasticity: the property to incorporate new knowledge without accessing the old dataset
2. Stability: the property to retain the old and acquired knowledge.

Plasticity and stability are two contradictory requirements for machine learning algorithms and this is commonly known as the stability – plasticity dilemma (Giraud-Carrier, 2000). Conventional training algorithms fail to meet both these requirements, as the models require the entire dataset before the commencement of the training session. Augmentation of new knowledge requires the old as well as new dataset, and after training with the augmented dataset, there may be some loss of knowledge. This is indeed a severe limitation while introducing a new technology employing a machine olfaction system. The situation may change significantly if the user industry starts getting some results with a few data, even though the classification may not be accurate enough initially. In such a situation, incremental learning algorithms can play a very important role. These incremental learning procedures can learn perpetually without forgetting the learned knowledge and can start classifying with very few data as well. For example, when an electronic nose is equipped with a computational model that has the feature of incremental learning, the instrument may be sent from one field or plant to another and trained with the new samples. It will try to classify the signature when subjected to a sample and at the same time, learn the new patterns without forgetting previous knowledge. Since this instrument once trained with some samples will give a result of classification, the user industry would either be satisfied with the result or, if they desire, may retrain the instrument.