

MACHINE LEARNING FOR DATA STREAMS

ENSEMBLE

- Ensemble methods can also be considered as blind approaches. In fact, the general technique applied by these methods is that the data stream is divided into sequential blocks of fixed size, and each of these blocks is used to train a classifier. The ensemble is continuously refined by adding a new classifier, removing the oldest or the weakest classifier, increasing or decreasing the classifier weights using some criteria usually based on current data block performance. (Paper “Classifying evolving data streams with partially labeled data (2011)”)

1. A Practical Approach to Classify Evolving Data Streams Training with Limited Amount of Labeled Data (2008): No aparece en los surveys (2), (3), (5) y (6)_NOT READ YET

- Reference in the paper “Classifying evolving data streams with partially labeled data (2011)”: To the best of our knowledge, only two relevant previous works have addressed the problem of scarceness of labeled instances in concept drifting data streams. ... The second work was recently proposed by Masud et al. [22]. It is based on an ensemble approach where each model in the ensemble is built as micro-clusters using a semi-supervised clustering technique. In fact, the learning step of each model starts by choosing k_c points from the labeled data of class C to initialize k_c centroids. Then the EM algorithm is applied by iterating the following two steps until convergence: The E-step assigns each unlabeled data point x to a cluster such that its contribution to a cluster-impurity function is minimized, and the M-step recomputes each cluster centroid by averaging all the points in that cluster. Finally, a summary of the statistics of the instances belonging to each built cluster is saved as a micro-cluster. These micro-clusters serve as a classification model.
- Reference in the paper “Classifying evolving data streams with partially labeled data (2011)”: To cope with stream evolution, Masud et al. [22] keep an ensemble of L models. Whenever a new model is built from a new data chunk, they update the ensemble by choosing the best L models from $L+1$ models (previous L models and the new model), based on their individual accuracies on the labeled instances of the new data chunk. Besides, they refine the existing models in the ensemble whenever a new class of data evolves in the stream.
- Reference in the paper “Classifying evolving data streams with partially labeled data (2011)”: Note finally that this approach is blind since it does not incorporate any drift detection method.

- Reference in the document “A Survey on Ensemble Learning for Data Stream Classification (2017)”: In [Masud et al. 2008] instances are grouped into microclusters, which are then used as input to a k-Nearest Neighbor ensemble to predict new instances class labels.
- Reference in the document “A Survey on Ensemble Learning for Data Stream Classification (2017)”: It uses clustering methods based on a radius measure, similar to the classic k-means algorithm, therefore they are unable to capture non-spherical clusters and often degrade to a single large cluster.

2. Mining recurring concepts in a dynamic feature space_MReC-DFS (2014):

RESUMEN MReC-DFS (RGBNC): They utilized the Naive Bayes (NB) algorithm with ensemble weighting mechanism to handle the recurring concept drift for data stream classification. In their method, the ensemble weight mechanism considered the accuracy and error values

Due to the dynamic nature of data, classes and data samples are not constant over the period of time. So, considering accuracy and error may affect the performance of the classification if one class attribute has bigger data samples. So, the multiple objective criteria like, sensitivity, specificity should be included to ensemble weighting.