**CONCLUSION**

The majority of works addressing the fraud-detection problem in credit card transactions unrealistically assume that the class of each transaction is immediately provided for training the classifier. Here we analyze in detail the real-world working conditions of FDS and provide a formal description of the articulated classification problem involved. In particular, we have described the alert–feedback interaction, which are the mechanism providing recent supervised samples to train/update the classifier. We also claim that, in contrast to traditional performance measures used in the literature, in a real-world FDS, the precision of the reported alerts is probably the most meaningful one, since investigators can check only few alerts. Our experiments on two vast data sets of real-world transactions show that, in order to get precise alerts, it is mandatory to assign larger importance to feedbacks during the learning problem. Not surprisingly, feedbacks play a central role in the proposed learning strategy, which consists in separately training a classifier on feedbacks and a classifier on delayed supervised samples, and then aggregating their posteriors to identify alerts. Our experiments also show that solutions that lower the influence of feedbacks in the learning process (e.g., classifiers that mix feedbacks and delayed supervised samples or that implement instance weighting schemes) are often returning less precise alerts. Future work concerns the study of adaptive and possibly nonlinear aggregation methods for the classifiers trained on feedbacks and delayed supervised samples. We also expect to further increase the alert precision by implementing a learning to rank approach that would be specifically designed to replace the linear aggregation of the posterior probabilities. Finally, a very promising research direction concerns semi-supervised learning methods for exploiting in the learning process also few recent unlabeled transactions.