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Editorial

Classification refers to the process of mapping an assignment of values to some random variables **F**, the features, into a value for a distinguished random variable *C*, the class. Learning a system, the classifier, from a collection of assignments to (**F**, *C*) such that it performs accurate classification is a classical area of research in machine learning. A proof of the interest of the research community in classification is the large number of different approaches to solving the problem that exist in the literature. This special issue is devoted to a particular approach, the probabilistic approach, where learning a classifier reduces to learning a probability distribution for (**F**, *C*). Among the different approaches to estimating this probability distribution, this special issue focuses on the so-called probabilistic graphical models, which model the conditional independencies in the probability distribution by means of a graph. Exploiting the conditional independencies encoded in the graph leads to a robust estimate of the probability distribution. Since the publication of Pearl (1988), probabilistic graphical models have been applied to a wide range of problems, including classification. See Friedman, Geiger, and Goldszmidt (1997) for a seminal work on probabilistic graphical models for classification. This special issue reports new advances in probabilistic graphical models for classification. It includes five high-quality research papers that address three important questions.

How to search for the best graph? Acid et al. propose a new algorithm for learning Bayesian network classifiers. The strongest point of the algorithm is its search space, which consists of the classes of graphs that are equivalent not only in terms of conditional independencies but also in terms of classification. Langseth and Nielsen propose relaxing the assumptions of conditional independence made by the naive Bayes classifier by searching for a graph with latent nodes. One of the strongest point of this proposal is that it applies to classification in continuous domains.

How to search for the best probability estimates for a given graph? Roos et al. study the problem of seeking the parameters that maximize the conditional likelihood of the class given the features. The strongest point of the study is a graphical condition for Bayesian network classifiers that, if satisfied, guarantees that the globally optimal parameters can be easily obtained. Greiner et al. study the same problem as Roos et al. and propose an algorithm for parameter learning that works even in the presence of missing data.

How to average over all the graphs and probability estimates? Cerquides and López de Màntaras propose a Bayesian model averaging approach to learning tree augmented naive Bayes classifiers. Two of the strongest points of the proposal are that it averages over both graphs and parameters, and that it runs in polynomial time.

We are proud to present to the machine learning community this collection of papers which, in our humble opinion, will be a reference for future research on classification. We

would like to express our gratitude to Machine Learning for giving us the opportunity to edit this special issue, and in particular to Robert C. Holte, Foster Provost and Melissa Fearon for assisting us in the editing process. We would also like to thank all the 25 referees for their high-quality reviews of the papers submitted, which helped us to make the final decisions. Last but not least, we are grateful to all the authors who submitted their work for publication in this special issue.

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