Evolutionary Bayesian Classifier-Based Optimization in Continuous Domains

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Abstract. In this work, we present a generalisation to continuous domains of an optimization method based on evolutionary computation that applies Bayesian classifiers in the learning process. The main difference between other estimation of distribution algorithms (EDAs) and this new method –known as Evolutionary Bayesian Classifier-based Optimization Algorithms (EBCOAs)– is the way the fitness function is taken into account, as a new variable, to generate the probabilistic graphical model that will be applied for sampling the next population.

We also present experimental results to compare performance of this new method with other methods of the evolutionary computation field like evolution strategies, and EDAs. Results obtained show that this new approach can at least obtain similar performance as these other paradigms[1].

1 Introduction

Evolutionary computation techniques have undergo a great development with the extensive use of paradigms such as Genetic Algorithms (GAs) [5,8], Evolution Strategies (ES) [6], and Estimation of Distribution Algorithms (EDAs) [10,13,17,18,20]. Many other evolutionary computation paradigms have also been recently proposed such as Learnable Evolution Model (LEM) [14], and Evolutionary Bayesian Classifier-based Optimization Algorithms (EBCOAs) [16].

The main difference between them is the way of improving the population of individuals, in order to obtain fitter solutions to a concrete optimization problem. In GAs and ES the evolution is based on using crossover and mutation operators, without expressing explicitly the characteristics of the selected individuals within a population. EDAs

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take into account these explicit characteristics by considering the interdependencies between the different variables that form an individual, learning a probabilistic graphical model to represent them. The approach of LEM, EBCOAs, and other similar proposals in this direction [12] is different in the sense of applying classification techniques to build models that represent the main characteristics for which an individual in the population appears in the group of the best (or worst) individuals within the population of a generation. In that sense, these paradigms also take into consideration less fit individuals of the population in order to enhance and estimate the differences between the best and worst cases. This knowledge is later used for instantiating new individuals for a new population.

This paper introduces EBCOAs (Evolutionary Bayesian Classifier-based Optimization Algorithms) for continuous domains, which are motivated as an improvement of EDAs for the need to avoid them to fall into local optima in very complex optimization problems. EBCOAs evolve to a fitter generation by constructing models that take into account more differences than simply a subset of the fittest individuals. Continuous EBCOAs generalize the ideas presented in [16] by supervised classification paradigms in the form of conditional Gaussian networks to improve the generation of individuals every generation.

2 Bayesian Classifiers for Continuous Domains

In EBCOAs for continuous domains, the classifiers are based on the learning of probabilistic graphical models, more concretely Bayesian classifiers based on conditional Gaussian networks [11]. The literature contains several examples of classifiers combined with evolutionary computation techniques. One of the first examples is the LEM algorithm [14] which makes use of rules to build a classifiers that records the main differences between the groups of best and worst individuals of each population.

The *supervised classification* problem with n continuous predictor variables consists in assigning any vector $\boldsymbol{x} = (x_1, \ldots, x_n) \in \mathcal{R}^n$ to one of the $|C|$ classes of a class variable C that is known. The class value is denoted by c and therefore we have that $c \in \{1, 2, \ldots, |C|\}$. As a result, a classifier in supervised classification is defined as a function $\gamma : (x_1, \ldots, x_n) \rightarrow \{1, 2, \ldots, |C|\}$ that assigns class labels to observations.

Next, we provide some examples of the classifiers from the ones considering less interdependencies to the ones considering most of them.

2.1 Naive Bayes

The Bayesian classifier that considers all the variables $X_1, \ldots, X_n$ to be conditionally independent given the class value C is known as naive Bayes [15]. In this case, the probabilistic graphical model can be considered to be a fixed structure as illustrated in Figure 1(a). In continuous domains it is usual to assume that the joint density function follows a n–dimensional normal distribution, and since independence between the variables –given the class variable C– is assumed, this is factorized by a product of unidimensional and conditionally independent normal densities. Therefore, when classifying a new individual using the naive Bayes classifier we have that: