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Moving Away from Error-Based Learning in Multi-Objective Estimation of Distribution Algorithms

Luis Martí   Jesús García   Antonio Berlanga
José M. Molina
GIAA, Dept. of Informatics, Universidad Carlos III de Madrid
{lmarti,jgherrer}@inf.uc3m.es;
{aberlan,molina}@ia.uc3m.es

ABSTRACT

In this work we analyze the model–building issue and the requirements it imposes on the learning paradigm being used. We argue that error–based learning, the class of learning most commonly used in MOEDAs, is responsible for current MOEDA underachievement. We present ART as a viable alternative and present a novel algorithm called multi-objective ART-based EDA (MARTEDA) that uses a Gaussian ART neural network for model-building and an hypervolume based selector as described for the HypE algorithm. We experimentally show that thanks to MARTEDA's novel model-building approach and an indicator-based population ranking the algorithm it is able to outperform similar MOEDAs and MOEAs.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods and Search; I.2.m [**Artificial Intelligence**]: Evolutionary Computing and Genetic Algorithms—*Multiobjective Evolutionary Algorithms*

General Terms

Algorithms, Experimentation, Performance

Keywords

Multi–objective Optimization, Estimation of Distribution Algorithms, Adaptive Resonance Theory

1. INTRODUCTION

Multi–objective optimization has received lot of attention by the evolutionary computation community leading to multi–objective evolutionary algorithms (MOEAs) (cf. [2]). The solution to this problem is a set of trade–off points. There is a class of MOPs that are particularly appealing because of their inherent complexity: the so–called many–objective problems.

Estimation of distribution algorithms (EDAs) [4] constitute good candidates for dealing with those problems. Nevertheless, the so called multi–objective EDAs (MOEDAs) have not live up to their expectations. This underachievement can be attributed to the incorrect application of off–the–shelf machine learning algorithms for the model–building problem [5]. When analyzing this issue the authors distinguish a number of inconveniences, in particular, the incorrect treatment of population outliers and the loss of population diversity.

Adaptive resonance theory (ART) [3] is a theory of human cognition that has seen a realization as a family of neural networks. It relies on a learning scheme denominated match–based learning and topology self–organization that makes it interesting as a case study in model–building. Match–based learning equally weights isolated and clustered data, and, therefore, the algorithm does not disregard outliers.

In this work we analyze the model–building issue and the requirements it imposes on the learning paradigm. We present ART as a viable alternative and present a novel algorithm called multi–objective ART–based EDA (MARTEDA) that uses a Gaussian ART neural network [6] for model–building and an hypervolume–based selector as described for the HypE algorithm [1].

2. MULTI–OBJECTIVE ART–BASED EDA

Adaptive Resonance Theory (ART) neural networks are capable of fast, stable, on-line, unsupervised or supervised, incremental learning, classification, and prediction following a match–based learning scheme [3]. Match–based learning is complementary to error-based learning. During training, ART networks adjust previously–learned categories in response to familiar inputs, and creates new categories dynamically in response to inputs different enough from those previously seen. It has been pointed out that ART networks are not suitable for some classes of classical machine–learning applications, however, what is an inconvenience in that area is a feature in our case.

The Gaussian ART [6] is most suitable for model–building since it capable of handling continuous data. The result of applying Gaussian ART is a set of nodes each representing a local Gaussian density. These nodes can be combined as a Gaussian mixture that can be used to synthesize new individuals.

The multi–objective ART–based EDA (MARTEDA) is a MOEDA that uses the previously described Gaussian ART network as its model–building algorithm. Although it intends to deal with the issues raised by the previous discussion, it was also designed with scalability in mind, since it is expected to cope with many–objective problems. It also exhibits an elitist behavior, as its has proved itself a very advantageous property. Finally, thanks to the combination of

Table 1: Mean hypervolume indicator values measured with respect to the Pareto–optimal front obtained when solving the WFG4–WFG9 problems.

Algorithm	$M=3$	$M=6$	$M=9$	$M=3$	$M=6$	$M=9$	$M=3$	$M=6$	$M=9$
		WFG4			**WFG5**			**WFG6**	
n. MIDEA	0.011420	0.007677	7.812410	0.006476	4.394012	11.070481	0.008215	0.713190	10.319707
MrBOA	0.007650	0.826774	6.369398	0.005478	1.148575	9.255472	0.007652	1.009668	7.852777
MONEDA	0.008805	1.140457	3.042990	0.006681	1.541551	4.308926	0.007490	1.388210	3.933372
SMS–EMOA	0.004632	0.786933	1.622598	0.005336	0.962102	2.808043	0.007183	0.758274	3.078716
HypE	0.004713	0.680543	1.824288	0.005818	1.086601	1.937923	0.007240	0.786465	2.225838
SPEA2	0.008257	7.642719	12.210563	0.007617	10.353490	15.768681	0.006699	8.921045	14.262868
MARTEDA	0.004876	0.673998	1.697777	0.005697	0.855696	1.656922	0.006867	0.769621	2.313733
		WFG7			**WFG8**			**WFG9**	
n. MIDEA	0.012461	0.008097	8.374176	0.007100	4.812899	12.143185	0.009004	0.774026	10.975159
MrBOA	0.008277	0.881532	6.947678	0.005959	1.245781	10.042999	0.008120	1.072959	8.360360
MONEDA	0.009660	1.227789	3.256424	0.007331	1.660554	4.729832	0.007900	1.526314	4.173037
SMS–EMOA	0.004974	0.829736	1.760524	0.005751	1.053422	3.017884	0.007709	0.832265	3.342257
HypE	0.005105	0.745058	1.994483	0.006396	1.141182	2.057936	0.007925	0.838846	2.371348
SPEA2	0.009010	8.122091	13.301820	0.008037	11.216923	16.847992	0.007092	9.543971	15.292170
MARTEDA	0.005313	0.716586	1.791584	0.006211	0.928543	1.815167	0.007437	0.826339	2.499234

fitness assignment and model–building it promotes diversity preservation.

3. EXPERIMENTS

The results of the experiments involving MARTEDA and a selection of the WFG problems are reported in this section. WFG4 to WFG9 were selected because of the simplicity of their Pareto–optimal front, that lies on the first orthant of a unit hypersphere. Each problem was configured with 3, 6 and 9 objective functions. For all cases the decision space dimension was fixed to 15.

Besides applying MARTEDA to the aforementioned problems some other MOEDAs and MOEAs are also assessed in order to provide a comparative ground for the tests. The algorithms applied are naïve MIDEA, MrBOA, MONEDA, SMS–EMOA, HypE and SPEA2. The hypervolume indicator was used for performance assessment.

Table 1 summarize the results of applying each of the algorithms involved to the six problems. In the three dimensional configurations our approach performed similarly to the rest of the algorithms. This result is consistent with previously obtained ones. This was an expected result since MARTEDA uses an already existent fitness function and its model–building algorithm is meant to provide a significant advantage in more extreme situations. This might lead us to hypothesize that thanks to the treatment of the outliers in the model–building data–set, the MARTEDA approach manages to overcome the difficulties that hampers the rest of the methods.

4. FINAL REMARKS

We presented adaptive resonance theory as a viable alternative paradigm and introduced a novel algorithm called multi–objective ART–based EDA (MARTEDA) that uses a Gaussian ART neural network for model–building and an hypervolume–based selector as described for the HypE algorithm. We showed that by using this novel model–building approach and an indicator–based population ranking the algorithm is able to outperform similar MOEDAs and MOEAs.

Still, the main conclusion of this work is that we provide strong evidences that further research must be dedicated to the model–building issue in order to make current MOEDAs capable of dealing with complex multi–objective problems with many objectives. In spite of the fact that obviously further studies are necessary, these extensive experiments have provided solid ground for the use of MARTEDA in a real–world application context.

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