Using denoising autoencoders as the model of an estimation of distribution algorithm

1 Description

Estimation of Distribution Algorithms (EDAs, [1, 2, 3]) are optimization algorithms that use probabilistic models to capture the most relevant features of the solutions with higher values. EDAs have been applied to a variety of optimization problems from domains such as Bioinformatics [4], Energy [5, 6], vehicle [7] design, etc.

Recently, denoising autoencoders [8, 9] have been proposed as an alternative to classical probabilistic models in the context of EDAs [10] showing promising but not state of the art results. When used in EDAs, a denoising autoencoder is learned in each generation to model the probability distribution of the solutions which survived the selection process. The autoenconder is then sampled to generate new solutions.

2 Objectives

The goal of the project is to implement in Python an EDA that uses a denoising autoencoder as suggested in [10] and test it in the optimization of different functions (see [10] for examples of functions).

As in other projects, a report should describe the characteristics of the design, implementation, and results. A Jupyter notebook should include calls to the implemented function that illustrate the way it works.

3 Suggestions

- The *DEAP* library `https://code.google.com/p/deap/` could be used as a basis to create the EDA. One EDA (UMDA) is implemented as part of this library. Implementations of the denoising autoencoder in *tensorflow* `https://gist.github.com/blackecho/3a6e4d512d3aa8aa6cf9` and *keras* `https://wiseodd.github.io/techblog/2016/12/03/autoencoders/` are also available. Therefore it is possible to combine these implementations to complete the project.
- As part of the comparison other classes of autoencoders could also included as part of the EDAs.

References

[1] H. Mühlenbein. The equation for response to selection and its use for prediction. *Evolutionary Computation*, 5(3):303–346, 1997.

[2] P. Larrañaga and J. A. Lozano, editors. *Estimation of Distribution Algorithms. A New Tool for Evolutionary Computation*. Kluwer Academic Publishers, Boston/Dordrecht/London, 2002.

[3] J. A. Lozano, P. Larrañaga, I. Inza, and E. Bengoetxea, editors. *Towards a New Evolutionary Computation: Advances on Estimation of Distribution Algorithms*. Springer, 2006.

[4] R. Armañanzas, I. Inza, R. Santana, Y. Saeys, J. L. Flores, J. A. Lozano, Y. Van de Peer, R. Blanco, V. Robles, C. Bielza, and P. Larrañaga. A review of estimation of distribution algorithms in bioinformatics. *BioData Mining*, 1(6):doi:10.1186/1756–0381–1–6, 2008.

[5] Márcio Henrique da Silva and Roberto Schirru. A self-adaptive quantum PBIL method for the nuclear reload optimization. *Progress in Nuclear Energy*, 74:103–109, 2014.

[6] Komla Folly. Parallel PBIL applied to power system controller design. *Journal of Artificial Intelligence and Soft Computing Research*, 3(3):215–223, 2013.

[7] Wencong Su and Mo-Yuen Chow. Performance evaluation of an EDA-based large-scale plug-in hybrid electric vehicle charging algorithm. *Smart Grid, IEEE Transactions on*, 3(1):308–315, 2012.

[8] Pascal Vincent, Hugo Larochelle, Yoshua Bengio, and Pierre-Antoine Manzagol. Extracting and composing robust features with denoising autoencoders. In *Proceedings of the 25th international conference on Machine learning*, pages 1096–1103. ACM, 2008.

[9] Pascal Vincent, Hugo Larochelle, Isabelle Lajoie, Yoshua Bengio, and Pierre-Antoine Manzagol. Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion. *Journal of Machine Learning Research*, 11(Dec):3371–3408, 2010.

[10] Malte Probst. Denoising autoencoders for fast combinatorial black box optimization. In *Proceedings of the Companion Publication of the 2015 Annual Conference on Genetic and Evolutionary Computation*, pages 1459–1460. ACM, 2015.