Using Generative Adversarial Networks 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, Generative Adversarial Networks (GANs) [8] have been proposed as an alternative to classical probabilistic models in the context of EDAs [9]. The reported results show that GAN-EDA is not competitive, neither in the number of fitness evaluations required, nor in the computational effort. However, the application of GAN as suggested in [8] does not exhaust the possibilities of GAN as models.

2 Objectives

The goal of the project is to implement in Python an estimation of distribution algorithm that uses a generative adversarial network. The work presented in [9] can be take as a reference of how to insert GAN in EDAs. The project should test the implemented algorithm it in the optimization of different functions (see [9] 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. Different implementations of GANs in *tensorflow* are available `https://github.com/carpedm20/DCGAN-tensorflow`, `https://github.com/ckmarkoh/GAN-tensorflow`. Implementations in *keras* `https://github.com/bstriner/keras-adversarial` are also available. Therefore it is possible to combine these implementations to complete the project.
- As part of the comparison other classes of models based on DNNs could also be included as models of the EDAs.

References

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