




egobox, a Rust toolbox for efficient global optimization

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Summary

Efficient global optimization (EGO) algorithms are used to tackle design optimization problems that involve computationally costly models ([Jones et al., 1998](#)). Basically, the idea is to use Gaussian process regression to approximate the objective function and use probabilistic information to select the promising next point where the optimum could be located.

Starting from that, one still has to tackle numerous challenges regarding the dimensionality, multi-modality and computation time. Different algorithms have been developed to overcome these hurdles ([Bartoli et al., 2019](#); [Dubreuil et al., 2020](#)). A key component of such surrogate-based algorithms is the existence of an implementation of Gaussian process regression also known as kriging method ([Bouhlel et al., 2016](#)).

The Surrogate Modeling Toolbox ([Bouhlel et al., 2019](#); [smtorg, 2018](#)) library addresses such concerns using the Python programming language. The egobox library provides such key component to the Rust machine-learning community while focusing on adaptative global optimization.

Statement of need

Started by porting relevant parts from the SMT library in Rust, the egobox library aims at providing building blocks useful to implement EGO-like algorithms. This open source library will be used by research engineers needing to tackle design optimization problems using a surrogate-based adaptative approach while taking advantage of the Rust programming language.

Indeed research scientists reach for prototyping programming language such as Python to develop new methods. Thanks to performant easy-to-use libraries like numpy, scipy, scikit-learn the Python language has become popular in science computing. The ability of Python to glue together different codes explains Python ecosystem is now a de-facto open source standard for scientific software. Nevertheless, one might notice that the performances of above Python libraries relies extensively on C/Fortran compiled code.

Thus, in the long run, a language like Python well-suited for prototyping may not be suitable for maintainability or performance even with a strong software development discipline. Performance issues may arise as new algorithms are built on top of the others which at some point may not be tractable with such interpreted programming language. As stated above, it is common to resort to compiled languages like C/C++ or Fortran to implement computation-intensive methods or for embedding them in more constrained environments where a Python runtime does not fit.

Library features

With the above need in mind, the Rust programming language appears to be of interest with its selling points being performance, reliability, and productivity. The language is meant to challenge C as a system language but also supporting strong typing, and high level features such as functional programming, algebraic data types, and module management. It has a strict approach regarding memory-safety management and benefits from a state of the art tooling for software development.

The Rust community has developed scientific libraries like `ndarray`, `ndarray-linalg` which can be seen as the `numpy` and `scipy` Rust counterparts. Last but not least, the `linfa` project addresses the machine-learning domain with the purpose of being the Rust equivalent of `scikit-learn`.

The `egobox` library relies on the above thriving Rust machine learning ecosystem and focuses on providing some building blocks to implement efficient global optimization algorithms. The library is organized in four sub-packages as follows:

- `doe`: sampling methods implementing Latin Hypercube sampling, popular sampling method used to create design of experiments,
- `gp`: Gaussian process regression also known as kriging algorithm used as surrogate models for computationally costly black-box functions,
- `moe`: mixture of experts which aims at increasing the accuracy of a surrogate approximation by clustering the design space, training and selecting the best surrogate models on each cluster,
- `ego`: an efficient global optimization implementation with handling of inequality constraints and mixed integer optimization through continuous relaxation.

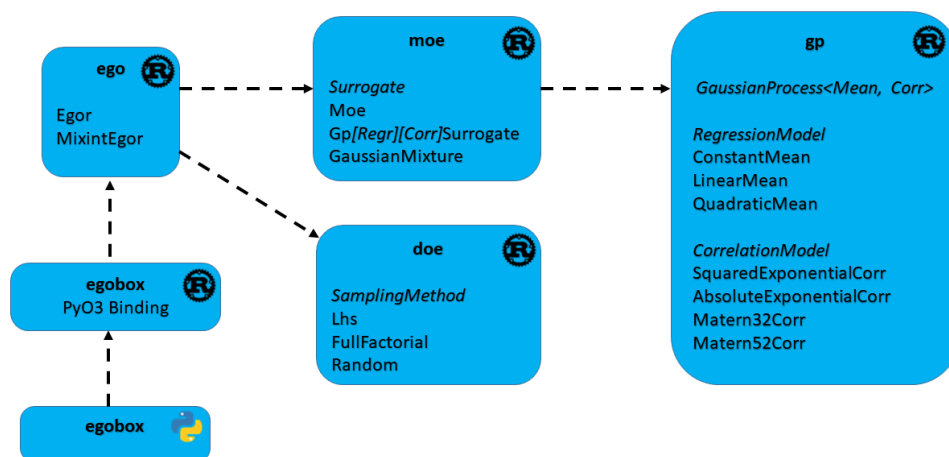


Figure 1: Architecture of the library

Finally thanks to the `PyO3` project, the Rust language is well-suited to create Python extensions which benefits from Rust strengths while being integrated in the Python ecosystem.

In order to increase the dissemination among the scientific community and demonstrate actual optimization capabilities based on the library, we implemented a Python module `egobox` as the binding of the implemented EGO-like Rust optimizer, namely `Egor`.

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