## CENTER FOR BIOSYSTEMS AND BIOTECH DATA SCIENCE Negin Harandi, Wesley De Neve, Arnout Van Messem, Joris Vankerschaver

# EXPLORING THE POWER OF EVOLUTIONARY COMPUTATION ALGORITHMS IN AUTOML

## **Automated Machine Learning (AutoML)**

Automated Machine Learning (AutoML) has emerged as a promising approach to designing machine learning (ML) pipelines that can select and tune models for a given dataset automatically. Despite its potential benefits, AutoML faces several challenges, including managing large and complex search spaces and finding optimal solutions efficiently. To address these issues, researchers have looked to evolutionary computation (EC) techniques to automatically search for the best ML models and their hyperparameters. These techniques have demonstrated success in achieving good performance across various tasks.



would require lot of manual steps for training and retraining ML models. "Piled Higher and Deeper" by Jorge Cham, PhD Comics.

Low-fidelity
Early-stopping
Surrogate Model
Weight-sharing

An overview of AutoML pipeline [1,2,3]

## **Evolutionary Computation (EC) Algorithm**



A subset of evolutionary computation (EC) algorithms

Evolutionary Computation (EC) is a sub-field of AI that uses computational models of biological and naturally-inspired processes to solve complex problems. This category of algorithms is populationbased and relies on rules of selection and other kinds of operators.



## **Hyperparameter Optimization (HPO) using EC**

Hyperparameter optimization (HPO) is another vital step in ML pipelines that can significantly affect model performance and requires selecting optimal model parameters to maximize performance.



### Evolutionary hyperparameter optimization pipeline

## Discussion

For the second secon

GA general working mechanism [5]



I am working on hyperparameter optimization of deep learning models using evolutionary computation algorithms, such as PSO, GWO, GOA, etc. The goal is to find optimal hyperparameters that can improve the performance of the models. Although these algorithms have better performance in comparison to the traditional optimization algorithms, some of these algorithms suffer from center-bias (or zero-bias) problem which has been identified recently [6]. This problem arises when the algorithm tends to converge towards the center of the search space and fail to explore the entire space. As a result, the algorithm may miss potentially good solutions that are located away from the origin. The center-bias problem can lead to local optima and reduce the effectiveness of the SI algorithms in hyperparameter optimization.





### Working mechanism of grey wolf optimization (GWO) [5]

### Contact

### Negin.Harandi@ugent.be

https://research.ugent.be/web/person/negin-harandi-0/en

in https://www.linkedin.com/in/Negin17h

## Conclusion

My research can show the potential of SI algorithms for hyperparameter optimization. These algorithms can

efficiently explore the vast hyperparameter space and find optimal solutions. However, the center-bias problem

## remains a significant obstacle that needs to be considered.

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[3] Zhan, Z.-H., Li, J.-Y., Zhang, J.: Evolutionary Deep Learning: A Survey. Neurocomputing 483, 42–58 (2022)

[4] xkcd: GA Recipes. https://xkcd.com/720/ Accessed 2023-05-08

[5] Nematzadeh, S., Kiani, F., Torkamanian-Afshar, M., Aydin, N.: Tuning hyperparameters of machine learning algorithms and deep neural networks using metaheuristics: A bioinformatics study on biomedical and biological cases. Computational Biology and Chemistry 97, 107619 (2022) [6] Kudela, J.: The Evolutionary Computation Methods No One Should Use. arXiv preprint arXiv:2301.01984 (2023)









**PSO vs. GWO** 

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