Automatically Choosing Selection Operator based on Semantic Information in Evolutionary Feature Construction

Hengzhe Zhang

Supervisor: Mengjie Zhang, Bing Xue, Qi Chen, Wolfgang Banzhaf (MSU)

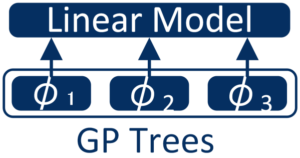
Victoria University of Wellington

15/09/2023

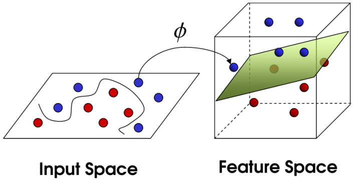
Table of Contents

Background

- The general idea of feature construction is to construct a set of new features $\{\phi_1, \ldots, \phi_m\}$ to enhance the learning performance on a given dataset $\{\{x_1, y_1\}, \ldots, \{x_n, y_n\}\}$ compared to learning on the original features $\{x^1, \ldots, x^p\}$.
- Genetic programming (GP) has been extensively employed to automatically construct features due to its flexible representation and gradient-free search mechanism.



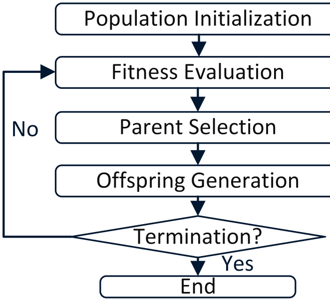
(a) Feature Construction on Linear Regression



(b) New Feature Space

Genetic Programming

- GP consists of four main stages: population initialization, fitness evaluation, parent selection, and offspring generation.
- Feature Construction: GP is used to transform features, followed by the training of a linear model to fit the data.[1]
- Ensemble Learning: GP is naturally suited for ensemble learning through the use of archived individuals.[2]



The evolutionary process of GP.

[1] Zhang H, Zhou A, Chen Q, et al. "SR-Forest: A Genetic Programming based Heterogeneous Ensemble Learning Method," in TEVC, 2023.

[2] Zhang H, Zhou A, Zhang H. "An evolutionary forest for regression," in TEVC, 2021.

Why Operator Selection:

- Many selection operators in GP: Lexicase, Tournament, etc.
- The most suitable operator is unknown in advance.
- During the evolution process, the most suitable operator may change.
- TR/LS: Use tournament selection in the first 10% of generations, then switch to lexicase selection.[1]

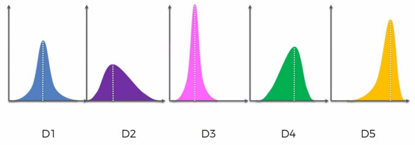
[1] Xu M, Mei Y, Zhang F, et al. "Genetic Programming with Lexicase Selection for Large-scale Dynamic Flexible Job Shop Scheduling," in IEEE TEVC, 2023.

- The Armed Bandit (Slot Machine) is a popular game in casinos.
- Multi-Armed Bandit means we need to select the machine with the highest expected reward to play, given a limited budget.
- The dilemma is whether to continue playing this machine (Exploitation) or try another one (Exploration).

Slot Machines

Multi-armed Bandit Algorithms:

- Random Selection: Best for Exploration, Worst for Exploitation.
- Greedy Algorithm: Best for Exploitation, Worst for Exploration.
- Epsilon-Greedy: α percent for Greedy, $1 - \alpha$ percent for Random.
- Thompson Sampling: Models the reward of each machine using a beta distribution.

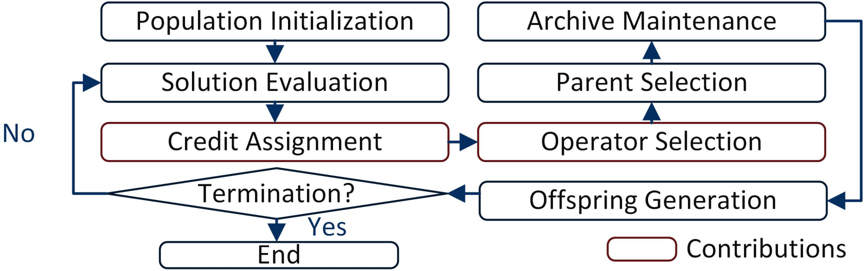


Thompson Sampling

Algorithm

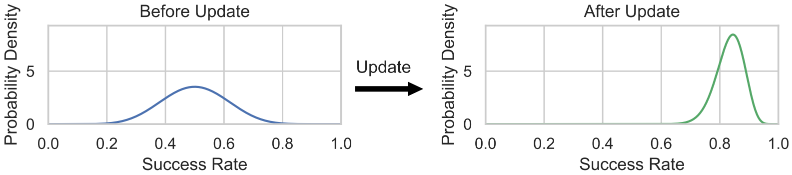
Two New Components:

- Credit Assignment: Define the rewards used to update the parameters of the beta distribution for each operator.
- Operator Selection: Sample several operators from beta distributions.



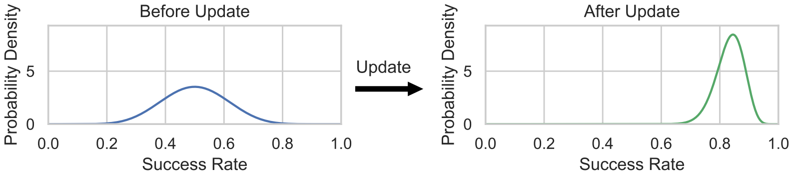
Workflow of the proposed algorithm.

- Successful Trial: For the historical best record of the loss vector (semantics) $(\mathcal{L}_{\Phi,1}, \ldots, \mathcal{L}_{\Phi,N})$, if an individual performs better in any case, the selection operator that led to the generation of this individual receives one reward.
- Failed Trial: The selection operator fails to select parents that lead to improved offspring.



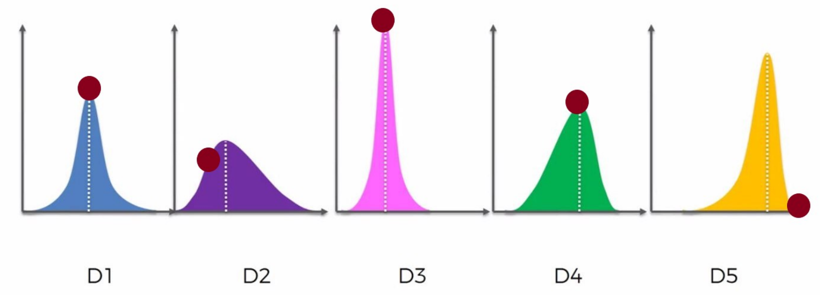
Credit assignment update in the beta distribution of one arm.

- Dynamic Multi-armed Bandit: Historical knowledge from earlier generations should be gradually forgotten because this information is less relevant to later generations.
- Decay is applied to the parameters of the beta distribution, scaled by γ in every generation.



Credit assignment update in the beta distribution of one arm.

- Sampling One Operator: Assuming K arms, first sample a number x from each beta distribution. Then, the sampled operator is $\arg\max_{k \in K} x_k$.
- Sampling Multiple Operators: In each round, we sample $\frac{n}{2}$ operators to select $\frac{n}{2}$ pairs of individuals for crossover and mutation.



In this case, D5 is selected.

Experimental Settings

Datasets

- We use 37 real-world regression datasets in the experiments. These datasets are all sourced from PMLB and have fewer than 5000 data items, after excluding those generated from synthetic functions.
- The number of instances in these datasets ranges from 47 to 3848, and the number of dimensions varies between 2 and 124.

Baseline Methods

Baseline selection operators:

- Tournament
- Lexicase
- TR/LS: Tournament for 10% of generations, Lexicase for 90% of generations.[1]

[1] Xu M, Mei Y, Zhang F, et al. "Genetic Programming with Lexicase Selection for Large-scale Dynamic Flexible Job Shop Scheduling," in IEEE TEVC, 2023.

The parameter settings are commonly used in GP.

Parameter settings for GP.

Parameter	Value
Maximum Population Size	30D (500)
Number of Generations	200
Ensemble Size	30
Crossover and Mutation Rates	0.9 and 0.1
Maximum Tree Depth	10
Initial Tree Depth	0-2
Number of Trees in An Individual	10
Elitism (Number of Individuals)	1
Functions	Add, Sub, Mul, AQ, Sin, Cos, Abs, Max, Min, Negative

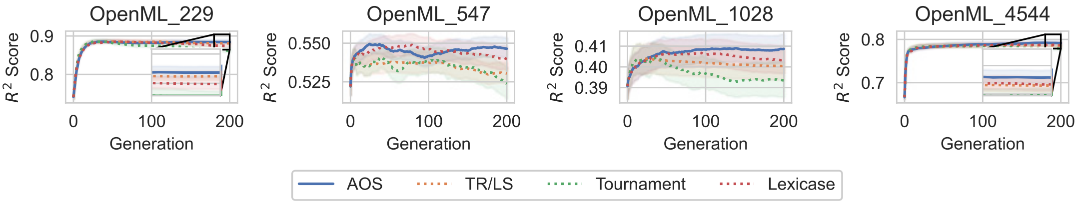
Experimental Results

- AOS outperforms the sole use of lexicase selection, tournament selection, and an expert-designed strategy (TR-LS).

Comparison of R^2 scores for different selection operators.

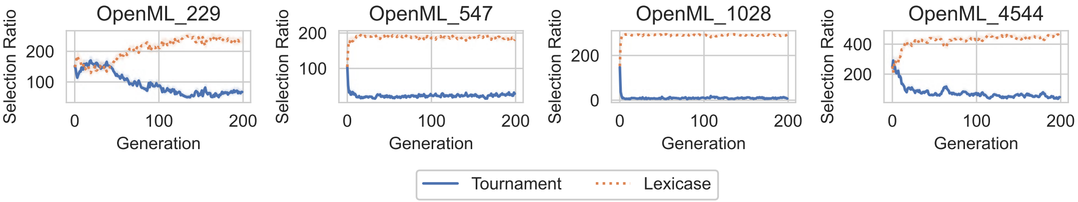
	TR/LS	**Tournament**	**Lexicase**
AOS	6(+)/30(∼)/1(-)	16(+)/21(∼)/0(-)	9(+)/28(∼)/0(-)
TR/LS	—	11(+)/25(∼)/1(-)	5(+)/30(∼)/2(-)
Tournament	—	—	0(+)/26(∼)/11(-)

- AOS exhibits strong performance in the final generations, particularly evident in the Social Workers Decisions (OpenML 1028) dataset.



Evolutionary plots of test R^2 scores using four different selection operators.

- AOS predominantly selects lexicase selection, but occasionally opts for tournament selection.
- A hybrid of tournament and lexicase selection could be an effective way to alleviate issues associated with hyper-selection.
- Hyper-selection: One individual can dominate up to 90% of the selections. [1]

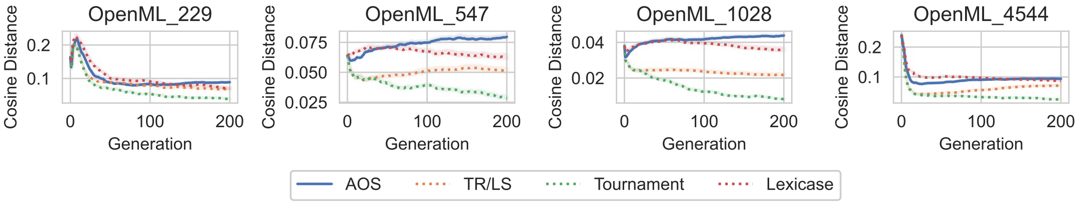


Selection ratios of different operators during the evolutionary process.

[1] Helmuth T, McPhee N F, Spector L. "The impact of hyperselection on lexicase selection," in GECCO, 2016.

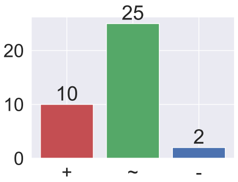
Cosine Distance

- Cosine distance measures the complementarity of GP individuals with respect to the regression target.
- AOS maintains a favorable cosine distance throughout the entire evolutionary process.

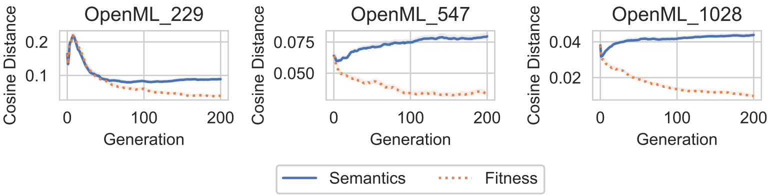


Cosine distance of archived individuals.

- Utilizing semantic information for credit assignment is beneficial, leading to improved performance on 10 datasets and worse performance on just 2 datasets.
- This advantage arises because semantic credit assignment helps maintain a higher level of diversity compared to using fitness-based credit assignment.



(a) Test R^2 scores.



(b) Cosine distance.

Conclusion

- Automatic operator selection can outperform traditional selection operators and expert-designed strategies.
- The use of semantic information in reward assignment is important for automatic operator selection in GP.

Open Source Project: Evolutionary Forest (100 GitHub Stars)

Thanks for listening!

Email: Hengzhe.zhang@ecs.vuw.ac.nz