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

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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.
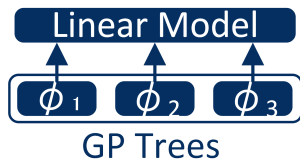

(a) Feature Construction on Linear Regression
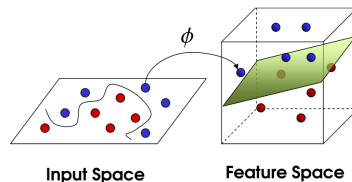
(b) New Feature Space

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]
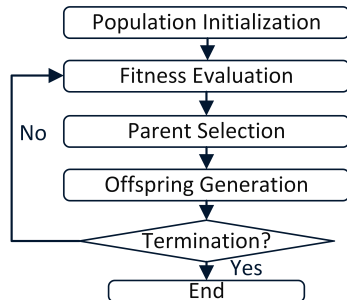
The evolutionary process of GP.

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[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]

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[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.
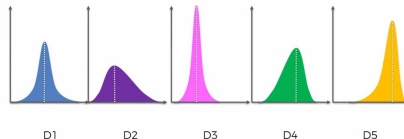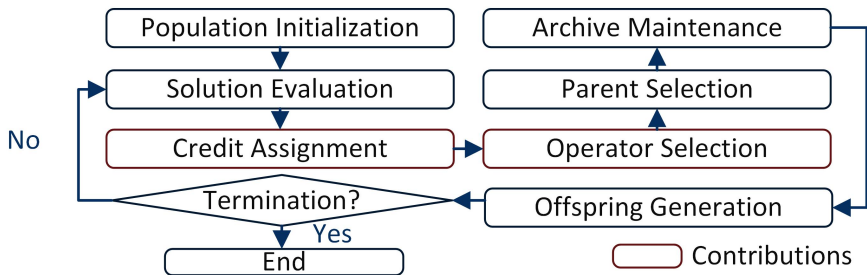
Thompson Sampling

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.
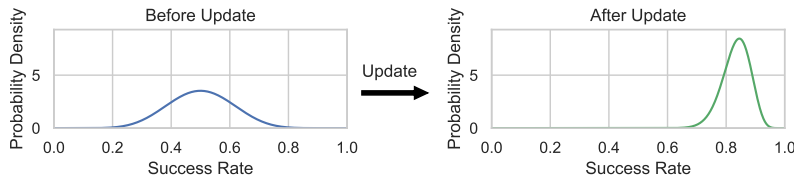

Credit assignment update in the beta distribution of one arm.

- 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.
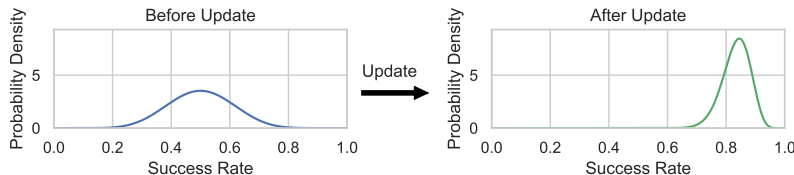
Credit assignment update in the beta distribution of one arm.

- 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.
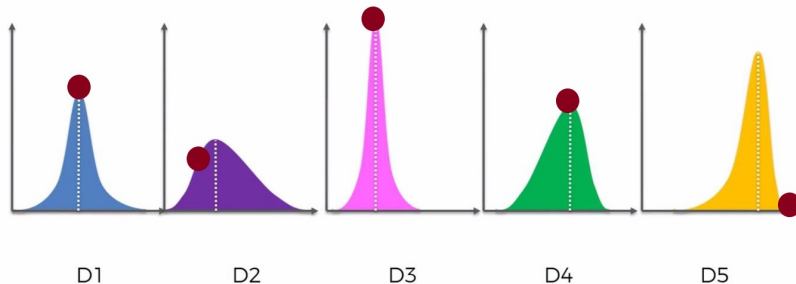
In this case, D5 is selected.

Experimental Settings

- 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 selection operators:

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

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[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($\sim$)/1(-)	16(+)/21($\sim$)/0(-)	9(+)/28($\sim$)/0(-)
TR/LS	—	11(+)/25($\sim$)/1(-)	5(+)/30($\sim$)/2(-)
Tournament	—	—	0(+)/26($\sim$)/11(-)

- AOS exhibits strong performance in the final generations, particularly evident in the Social Workers Decisions (OpenML 1028) dataset.
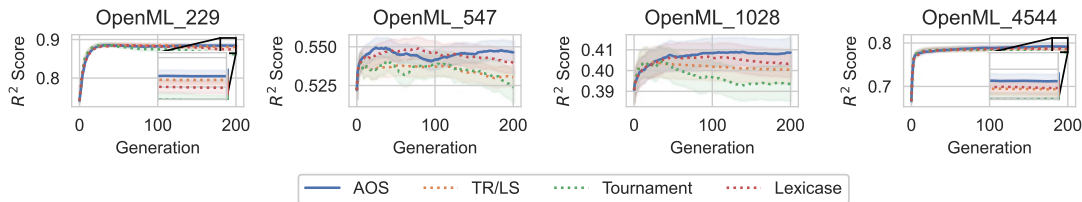
Evolutionary plots of test R^2 scores using four different selection operators.

- 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]
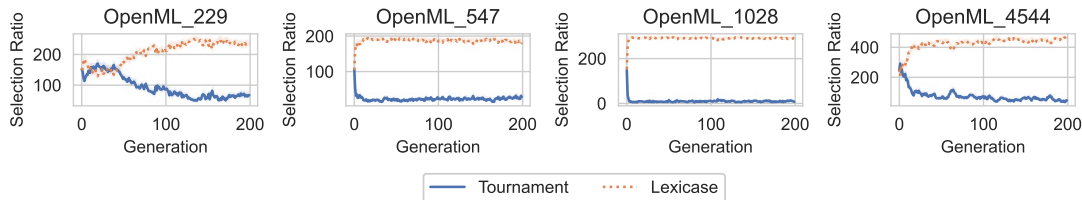
Selection ratios of different operators during the evolutionary process.

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

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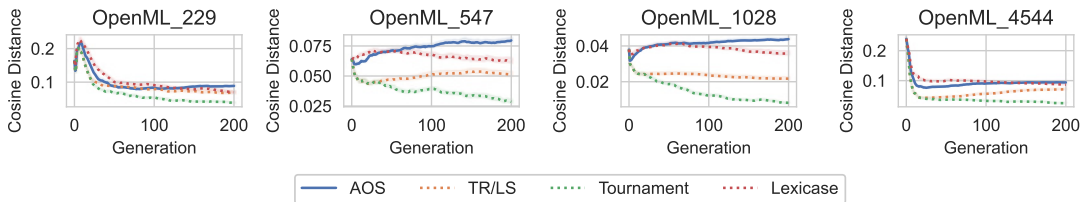
Cosine distance of archived individuals.

- 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.
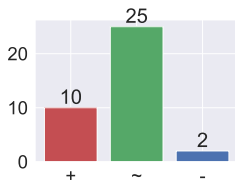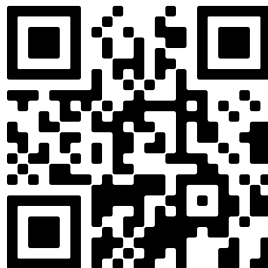

(a) Test R^2 scores.
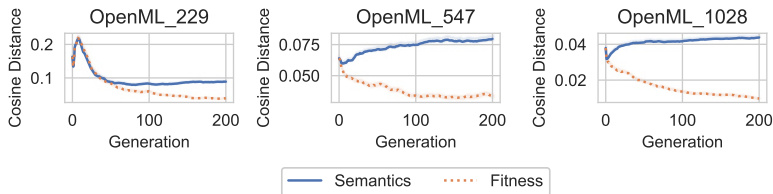
(b) Cosine distance.

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!

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