

Analyzing the influence of Selection on Genetic Programming's Generalization ability in Symbolic Regression

**A comparison of epsilon-lexicase Selection and
Tournament Selection**

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Introduction

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Limitations and open Questions

Introduction

Research Question

- ▶ Does the usage of ϵ -lexicase parent selection influence the generalization behaviour of genetic programming in symbolic regression if compared to tournament selection?

Genetic Programming

- ▶ A metaheuristic that searches for computer programs that solve a given problem
- ▶ Inventor: John R. Koza ¹
- ▶ Evolutionary algorithm that simulates the process of Darwinian evolution:
 1. Population based
 2. The quality of solutions is evaluated by a fitness function
 3. Selection: Solutions are selected based on their individual fitness
 4. Variation: Mutation and recombination of solutions
- ▶ Unique Features:
 - ▶ Evolve solutions of variable length and structure
 - ▶ Solutions are typically represented by recursive tree structures

¹Koza (1992)

Parent Selection

- ▶ Operator that selects individual solutions from the population for reproduction and mutation
- ▶ Most commonly used selection operator in Genetic Programming (GP): Tournament selection²
- ▶ Intuition: High chance for “generalist” solutions to be selected since it is based on aggregated fitness scores

²Fang and Li (2010), p.181

epsilon-Lexicase Selection

- ▶ Recent alternative: Lexicase Selection and its variation ϵ -lexicase selection
- ▶ Idea: Selection method for uncompromising, continuous-valued symbolic regression problems ³
- ▶ Increases genetic diversity inside the population⁴
- ▶ Higher chance for “specialist” solutions to be selected since it is decided on a per case basis
- ▶ Performance increases have been demonstrated in many benchmarking problems ⁵

³Helmuth, Spector and Matheson (2015), p.12

⁴Helmuth, Spector and Matheson (2015), p.1

⁵La Cava, Spector and Danai (2016), p.744-745

Symbolic Regression

- ▶ Task: Find a mathematical model that fits a given set of datapoints
- ▶ One of the first applications of GP described by Koza (1992)
- ▶ High relevance: GP can outperform state-of-the-art machine learning algorithms like gradient boosting ⁶

⁶Orzechowski, Cava and Moore (2018)

Generalization

- ▶ The ability of a model to perform well on previously unseen fitness cases
- ▶ Main objective in most supervised machine learning problems
- ▶ Challenge: Avoid overfitting to training data

Motivation

- ▶ Little attention has been paid to generalization in GP ⁷
- ▶ High practical relevance of symbolic regression in many fields, e.g. financial forecasting

⁷O'Neill *et al.* (2010), Kushchu (2002)

Experimental Study

Benchmark problem

UC Irvine Machine Learning Repository: Prediction of energy efficiency in buildings ⁸

Table 1: Overview - Energy Heating data set

Variable	Description
X1	Relative Compactness
X2	Surface Area
X3	Wall Area
X4	Roof Area
X5	Overall Height
X6	Orientation
X7	Glazing Area
X8	Glazing Area Distribution
y1	Heating Load
y2	Cooling Load

⁸Dua and Graff (2017)

Experiment

Single run

- ▶ Total dataset ($N = 768$) is randomly split into a training and testing dataset (50:50)
- ▶ Train two models using GP with the training dataset only, one using tournament selection and the other ϵ -lexicase selection
- ▶ For each generation: Select elite model and compute its fitness for the testing dataset

Full experiment

- ▶ Stochastic algorithm: Repeat the basic experiment for 50 total runs
- ▶ Collect stats for: min_training_error, testing_error,

Genetic Programming Configuration

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Results

Descriptive Statistics

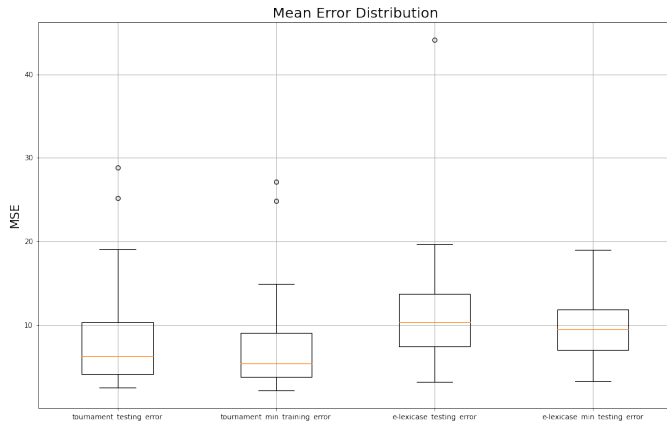


Figure 1: Distribution of Errors

Conclusions

Conclusions

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Limitations and open Questions

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