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Bi-objective memetic GP with dispersion-keeping Pareto evaluation for real-world regression. (English) Zbl 1474.90406

Summary: Regression tasks aim to determine accurate and simple relationship expressions between variables, which can be regarded as bi-objective optimization problems. As GP (genetic programming) can use expression trees as representation, it is popularly-used for regression. Introducing multi-objective techniques into GP enables it to solve bi-objective tasks, and the success of memetic algorithms show the importance of local search in improving GP. However, existing memetic GP methods are mainly single-objective, in which the local search operators cannot be applied in multi-objective optimization. Moreover, the popularly-used solution evaluation mechanism (Pareto local search) in existing multi-objective memetic methods cannot assure solution dispersion. To handle these problems, a dispersion-keeping Pareto evaluation (DkPE) mechanism is proposed, based on which new crossover and mutation operators adaptive to bi-objective GP are designed. In addition, two base bi-objective GP methods (NSGP (non-dominated sorting GP) and SPGP (strength Pareto GP)) are developed. Applying the new operators in them respectively forms two bi-objective memetic GP methods (MNSGP (memetic NSGP) and MSPGP (memetic SPGP)). Results show that MNSGP and MSPGP outperform NSGP and SPGP respectively, which reflects that DkPE based crossover/mutation increase the performance of NSGP and SPGP. Moreover, solutions evolved by MNSGP outperform reference GP and non-GP based methods.

MSC:
90C29 Multi-objective and goal programming

Keywords:
memetic algorithm; bi-objective GP; local search; real-world regression

Software:
SPEA2; PAES; UCI-ml

Full Text: DOI

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