Towards a Quantum-Inspired Multi-Gene Linear Genetic Programming Model

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ABSTRACT

This paper presents a new model for regression problems based on Multi-Gene and Quantum Inspired Linear Genetic Programming. We discuss theoretical aspects, operators, representation, and experimental results.

1. INTRODUCTION

The development of new GP regression models is relevant to provide more accurate results through fewer evaluations, and two distinct approaches are possible: (i) modify the GP basic structure: finding new ways to codify and solve this problem by providing some new recombinators. There is some work in this area, such as Linear GP [1,2]; (ii) allowing more outputs per individual: a simple approach is to enable more functions per individual and to combine their outputs, like Multi-Gene (or Multi-Tree) GP (MGGP) [3]. Thus, new GP based models that can operate in both senses could generate better results within fewer evaluations. This paper proposes a Quantum-Inspired Multi-Gene Linear GP model (QIMuLGP) for regression tasks, a generalization of Quantum-Inspired Linear GP (QILGP) [2]. QIMuLGP modifies canonical GP structures, explores new recombinators and function nodes, and enables several outputs per individual that can be combined applying the least squares method. We evaluated this approach on 11 datasets, comparing its results with GP, MGGP and QILGP.

2. QUANTUM-INSPIRED MULTI-GENE GP

We propose a novel GP model in this paper: Quantum-Inspired Multi-Gene Linear GP (QIMuLGP). The main difference from the original QILGP [2] and this generalization is that each individual has more than one chromosome. Therefore, the fitness of an individual results from a linear combination of each chromosome output, where the weights are adjusted using least squares method – like MGGP. Figure 1 illustrates QIMuLGP structure and its basic operation. It has a quantum population with $N$ quantum indivi-duals (QIs) with $M$ chromosomes each (e.g., $N = 3$ and $M = 4$ in Figure 1). QIMuLGP has two classical individu-als: (i) one to observe an individual and other for the best individual found. Through CIs, X86 machine code programs are generated. Figure 1 also enumerates four basic types of X times to complete a generation: (i) $4^1$: a QI is observed creating a CI (Observed Individual); (ii) $4^2$: the $M$ chromosomes of Observed Individual are linearly combined to calculate its fitness; (ii) $4^3$: if it is better, it is copied to Best Classical Individual; (iv) $4^4$: an operator $P$ is applied to the QI observed in step 1, taking as reference Best Classical Individual, increasing the probability that future observations of the QI results in CI more similar to the best found.

The observation of a QI comprises observing each of its chromosomes, which defines the chromosomes of the resulting CI. The Figure 2 shows the observation process. The evolution continues the same way as QILGP.

3. RESULTS AND DISCUSSIONS

Tables 1 and 2 present the main results (RMSE and standard deviation) for the best set as well as the time spent for performing an evaluation (milliseconds). We varied the number of evaluations according to the number of variables of each dataset (parenthesis in the first columns) multiplied by some default values (3,000, 5,000, 7,000, 11,000). In general, two patterns can be identified: (i) performing more evaluations can benefit almost all evolutionary algorithms; (ii) Multi-Gene approaches (MGGP and QIMuLGP) compare favorably with their canonical counterparts.

QIMuLGP enhanced the average RMSE of QILGP about 54%, with a dispersion reduction of 10%, but the computa-tional cost was 24 times higher. The comparison with MGGP shows that QIMuLGP RMSE values were 19% higher on average. However, the proposed model had an speedup factor of 8.

4. CONCLUSIONS

We applied QIMuLGP in set of 11 regression benchmarks, and it was found that QIMuLGP greatly improve the accuracy when comparing to its simplified version (QILGP).

Table 1: Main results of GP and MGGP for test set.

<table>
<thead>
<tr>
<th>Function</th>
<th>Evals/vars</th>
<th>GP</th>
<th>MGGP</th>
<th>RMSE</th>
<th>Time</th>
<th>GP</th>
<th>MGGP</th>
<th>RMSE</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>qudit (FQ)</td>
<td>3,000</td>
<td>5,000</td>
<td>7,000</td>
<td>11,000</td>
<td>5</td>
<td>0.9848</td>
<td>0.9675</td>
<td>0.9632</td>
<td>0.9544</td>
</tr>
<tr>
<td>Terminal qudits (TQ)</td>
<td>3,000</td>
<td>5,000</td>
<td>7,000</td>
<td>11,000</td>
<td>5</td>
<td>0.9848</td>
<td>0.9675</td>
<td>0.9632</td>
<td>0.9544</td>
</tr>
</tbody>
</table>
| Figure 1: Basic diagram of QIMuLGP model.

and MGGP obtained slightly better results than QILMuGP, however using twice the computational effort.

5. ACKNOWLEDGMENTS

The authors would like to thank CNPD, CAPES, FAPERJ and PUC-Rio for supporting this work.

6. REFERENCES


Table 2: Main results of QILGP and QIMuLGP for test set.

<table>
<thead>
<tr>
<th>Function</th>
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<th>QIMuLGP</th>
<th>RMSE</th>
<th>Time</th>
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<th>QIMuLGP</th>
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<td>0.9632</td>
<td>0.9544</td>
</tr>
</tbody>
</table>
| Figure 2: Creation of a gene by the observation of a quantum gene.

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