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Computer Science

Not-Sampled Issue and Round-Replacement Tournament Selection

Huayang Xie, Mengjie Zhang and Peter Andreae

Technical Report CS-TR-07/02
November 2007

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Abstract

The standard tournament selection samples individuals with replacement. The sampling-with-replacement strategy has its advantages but also has issues. One of the commonly recognised issues is that it is possible to have some individuals not sampled at all during the selection phase. The not-sampled issue aggravates the loss of diversity. However, it is not clear how the issue affects GP search. This paper uses a round-replacement tournament selection to investigate the importance of the issue. The theoretical and experimental results show that although the issue can be solved and the loss of diversity can be minimised for small tournament sizes, the different selection behaviour in the round-replacement tournament selection cannot significantly improve the GP performance. The not-sampled issue does not seriously affect the selection performance in the standard tournament selection.

Keywords Genetic Programming; tournament selection; standard tournament selection; round-replacement tournament selection.

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Not-Sampled Issue and Round-Replacement Tournament Selection

Abstract. The standard tournament selection samples individuals with replacement. The sampling-with-replacement strategy has its advantages but also has issues. One of the commonly recognised issues is that it is possible to have some individuals not sampled at all during the selection phase. The not-sampled issue aggravates the loss of diversity. However, it is not clear how the issue affects GP search. This paper uses a round-replacement tournament selection to investigate the importance of the issue. The theoretical and experimental results show that although the issue can be solved and the loss of diversity can be minimised for small tournament sizes, the different selection behaviour in the round-replacement tournament selection cannot significantly improve the GP performance. The not-sampled issue does not seriously affect the selection performance in the standard tournament selection.

1 Introduction

Tournament selection is one of the commonly used parent selection schemes in Evolutionary Algorithms (EAs) and becomes more popular in Genetic Programming (GP). According to the description given by Goldberg and Deb [1], the initial study of tournament selection can be traced back to the earlier 1980s [2]. One form of the conventional tournament selections introduced in [2] becomes the *standard* nowadays. The standard tournament selection repeatedly randomly samples k individuals uniformly with replacement from the current population of size N and selects the one with the best fitness. Because individuals in a tournament are sampled from the population with replacement, the standard tournament selection is simple to code and efficient for both non-parallel and parallel architectures [3]. The standard tournament selection has been widely studied theoretically since the 1990s [3–6], while many alternative implementations have been developed [7–11].

One commonly recognised issue in the standard tournament selection is that it is possible to have some individuals not sampled at all during the selection phase when using small tournament sizes [4]. We think the not-sampled issue aggravates the loss of diversity [5, 6, 12], which is a well recognised issue in EAs. However, it is not clear how seriously the aggravation affects GP search.

We split the loss of diversity into two parts. One contribution is from the fraction of the population that are not sampled at all during the selection phase. The other contribution is from the fraction of population that never win any tournament. An obvious way to tackle the not-sampled issue is to increase the tournament size because larger tournament sizes provide more sampling chances.

However, increasing tournament size will increase the tournament competition level. The loss of diversity contributed by not-selected individuals will increase, resulting in worse total loss of diversity.

The not-sampled issue will only be completely solved if every individual in a population is guaranteed to be sampled at least once during the selection phase. However, the sampling-*with*-replacement method in the standard tournament selection cannot guarantee this no matter how other aspects of selection will be changed. Therefore, a sampling-*without*-replacement strategy must be used. One strategy is that individuals are sampled without replacement into a tournament, then after the winner is selected all individuals in the tournament are returned back to the population. According to [1], the tournament selection using this sampling-without-replacement strategy is one of the conventional tournament selection methods. Unfortunately, it still cannot solve the not-sampled issue. The status of the not-sampled issue remains open.

The goal of this paper is to investigate whether the not-sampled issue seriously affects the selection performance in the standard tournament selection. To achieve this, we will firstly develop an approach that satisfies the following requirements: (1) can minimise the number of not-sampled individuals, (2) can maintain the same tournament competition level as in the standard tournament selection, and (3) can preserve selection pressure across the population, then compare the approach with the standard tournament selection. In particular, this paper addresses the following questions:

- How should individuals be sampled to minimise the loss of diversity contributed by not-sampled individuals?
- Can significant improvement in GP be obtained after the not-sampled problem is solved?

2 Sampling Without Replacement Strategies

We propose an alternative sampling-without-replacement strategy that is to only return the losers instead of all sampled individuals back to the population after choosing a winner. We term this strategy as *loser-replacement*. By using this strategy, the size of the population gradually decreases along the way to form the next generation. At the end, the population may be smaller than the tournament size so that a tournament may not be filled. If we simply accept such cases and run tournaments as usual, then the loser-replacement tournament selection will not have any selection pressure across the population. It will be very similar to a *random sequential selection* where every individual in the population can be randomly selected as a parent to mate but just once. The only difference between the outcomes of the loser-replacement tournament selection and the random sequential selection is the mating order. In the random sequential selection, the mating order is completely random, while in the loser-replacement tournament selection it is possible that better parents mate together and worse parents mate together with some stochastic elements. Although the loser-replacement strategy can ensure zero loss of diversity, it cannot preserve any selection pressure across population. Therefore, it is not very useful.

To satisfy all the essential requirements, we propose another sampling-without-replacement strategy. It is that after choosing a winner, all sampled individuals are kept in a temporary pool instead of being immediately returned back to the population. For this strategy, as long as the tournament size is greater than one, after a number of tournaments, the population will be empty. If there is a need to conduct more tournaments for selecting parents, the population must be refilled using the temporary pool. More precisely, for a population P of size N and tournaments of size k, the algorithm is:

Initialise an empty population T
while need to generate more offspring **do**
    if population size $< k$ **then**
        Refill: move all individuals from the temporary population T to the population P
    end if
    Sampling k individuals without replacement from the population P
    Select the winner from the tournament
    Move the k sampled individuals into the temporary population T
    return the winner
end while

We term a tournament selection using this strategy as *round-replacement* tournament selection. The remainder of the paper theoretically and experimentally analyses this strategy to further investigate the research questions.

3 Assumptions and Definitions

In general, a population consists of a set of bags of programs with distinct fitness where the sizes of these bags may be different. Let the population be S and the size of the population be $|S|$. Let the bag of programs with the fitness rank j be S_j and let its size be $|S_j|$. Let the tournament size be k. Let the program with the worst fitness be ranked 1st. We follow the standard breeding process, that is, one parent produces one offspring after mutation and two parents produce two offspring via crossover. Therefore the total number of tournaments is $|S|$ at the end of generating individuals in the next generation.

To analyse the selection behaviour, this paper uses the loss of *program* diversity and the selection probability distribution on three populations with different fitness distributions, namely *uniform*, *random*, and *quadratic* fitness distributions (see Figure 1).

The loss of program diversity is calculated based on the refined definition given in [12]. It is the ratio of the sum of the probabilities that each individual in the population has never been selected during the selection phase to the population size.

The selection probability distribution of a population is defined to consist of the probabilities of each individual in the population being selected at least once

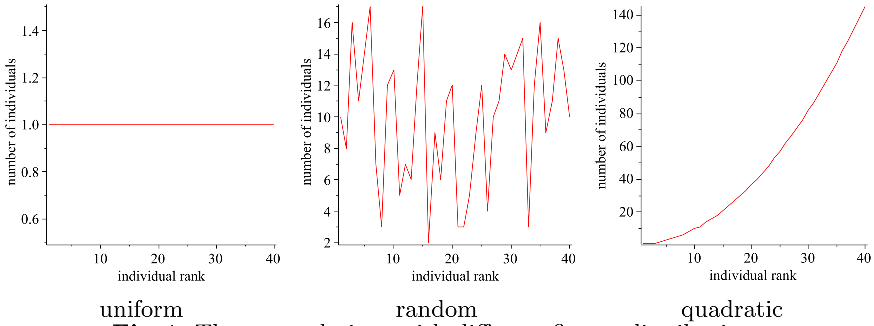


Fig. 1. Three populations with different fitness distributions.

in the selection phase. It gives a thorough picture about the selection behaviour over the population.

The three fitness distributions are designed to simulate the three stages of evolution. The uniform fitness distribution represents the initialisation stage, which is the only place that users can easily manipulate the fitness distribution of the population. Its population size is set to 40. The random fitness distribution represents the middle stage of evolution, where better and worse individuals are possibly randomly distributed. Its population size is set to 400. The quadratic like fitness distribution represents the later stage of evolution, where a large number of individuals converge to better fitness values. Its population size is set to 2000. Note that although these three populations have different sizes, the distinct number of fitness ranks are designed to be the same value 40 for easy visualisation and comparison purposes.

4 Modelling Standard Tournament Selection

The sampling probability and the selection probability models in the standard tournament selection are referenced below with some adaptions to meet the context in this paper.

For any program p, let I_y be the event that p is drawn or sampled at least once in y tournaments. The probability of the event I_y is:

$$P(I_y) = 1 - \left(\left(\frac{|S| - 1}{|S|} \right)^{|S|} \right)^{\frac{y}{|S|} k} \tag{1}$$

Let $E_{j,y}$ be the event that $p \in S_j$ is selected at least once in y tournaments. The probability of the event $E_{j,y}$ is:

$$P(E_{j,y}) = 1 - \left(1 - \frac{1}{|S_j|} \left(\frac{\sum_{i=1}^{j} |S_i|}{|S|} \right)^k - \left(\frac{\sum_{i=1}^{j-1} |S_i|}{|S|} \right)^k \right)^y \tag{2}$$

5 Modelling Round-Replacement Tournament Selection

After $|S|/k$ tournaments, the round-replacement algorithm will refill the population to start another round of tournaments and will conduct k rounds in total in order to form the entire next generation provided that the remainder of $|S|$ divided by k is zero. It is obvious that any program will be sampled exactly k times during the selection phase.

Lemma 1 *For a particular program $p \in S_j$, let W_j be the event that p wins or is selected in a tournament. The probability of the event W_j is:*

$$P(W_j) = \frac{\sum_{n=1}^{k} \frac{1}{n} \binom{|S_j|-1}{n-1} \binom{\sum_{i=1}^{j-1} |S_i|}{k-n}}{\binom{|S|}{k}} \tag{3}$$

Proof. The characteristic of the round-replacement tournament selection is that it guarantees p will be sampled in just one of the $|S|/k$ tournaments in a round. According to this, the effect of a full round of tournaments is to partition S into $|S|/k$ disjoint subsets. The program p is a member of precisely one of these $|S|/k$ subsets. Therefore the probability of it being *selected* in the first tournament is exactly the same as that in any other tournament in the round. Further, the probability of it being selected in the first round is exactly the same as that in any other rounds since all k rounds of tournaments are independent. Therefore we only need to model the selection probability of p in the first tournament of a round. Note that p will only be selected if no better ranked programs are sampled in the same tournament.

As it is possible that more than one program have the same rank, the probability of $p \in S_j$ being selected depends on the number of other programs having the same rank that are sampled in the same tournament. Assuming within the rest $k-1$ samples in the tournament, they are all from programs having the rank j and no programs with worse ranks are sampled, the number of possible sampling events is:

$$\binom{|S_j|-1}{k-1} \binom{\sum_{i=1}^{j-1} |S_i|}{0} \tag{4}$$

If within the rest $k-1$ samples in the tournament, there are n programs ($0 \leq n \leq k-1$) from the rank j and $k-1-n$ programs from worse ranks, then the number of sampling events is:

$$\binom{|S_j|-1}{n} \binom{\sum_{i=1}^{j-1} |S_i|}{k-1-n} \tag{5}$$

Therefore, the total number of sampling events where $p \in S_j$ can be selected as the winner is:

$$\sum_{n=0}^{k-1} \binom{|S_j|-1}{n} \binom{\sum_{i=1}^{j-1} |S_i|}{k-1-n} \tag{6}$$

As each of the $n+1$ programs has an equal probability to be chosen as the winner. Therefore, after a simple manipulation, we obtain Equation (3). $\square$

Let E_j be the event that p is selected in a round of tournaments. As there are $|S|/k$ times in total that p can be selected in a round, the probability of the event E_j is:

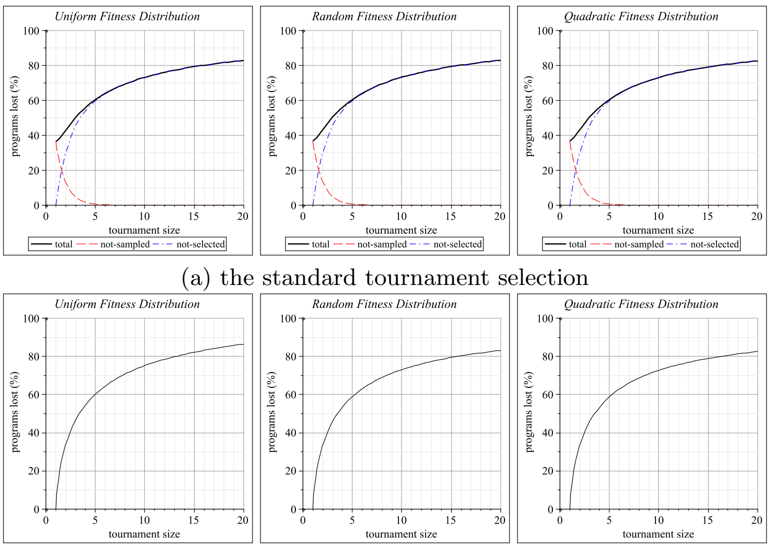
$$P(E_j) = P(W_j)\frac{|S|}{k} = \frac{\sum_{n=1}^{k} \frac{1}{n} \binom{|S_j|-1}{n-1} \binom{\sum_{i=1}^{j-1}|S_i|}{k-n}}{\binom{|S|-1}{k-1}} \tag{7}$$

Let $T_{j,c}$ be the event that p is selected at least once by the cth round. As the selection behaviour in any two rounds are independent and identical, the probability that the event $T_{j,c}$ is:

$$P(T_{j,c}) = 1 - (\overline{P(E_j)})^c \tag{8}$$

6 Selection Behaviour Comparison and Analysis

Based on the sampling probability models and the selection probability models presented in Sections 4 and 5, we calculated three loss of program diversity measures, namely the *total* loss of program diversity and the contributions from *not-sampled* and *not-selected* individuals, for the standard and the round-replacement tournament selections on each of the three populations with different fitness distributions (see Figure 2).



(a) the standard tournament selection

(b) the round-replacement tournament selection

Fig. 2. Loss of program diversity comparison. Note that tournament size is discrete but the plots show curves to aid interpretation only.

In Figure 2 (a), when the tournament size is 1, the total loss of program diversity is contributed by the not-sampled individuals only. This is because once an individual is sampled, it must be selected as a parent as there is no other competitors in the tournament. However, the contribution from not-sampled individuals becomes smaller and close to zero when the tournament size increases, while the contribution from not-selected individuals becomes larger and dominates the total loss of program diversity when the tournament size is greater than five. There is no noticeable differences between the loss of program diversity measures on different sized populations with different fitness distributions. The loss of program diversity is mainly controlled by the tournament size. Extra visualisations on other sized populations with the three given fitness distributions support the finding (figures are omitted due to the space limit).

In Figure 2 (b), there is only one trend visible in each sub-chart. This is because there is no contribution from the not-sampled individuals at all in the round-replacement tournament selection. Individuals are guaranteed to be sampled, precisely sampled once in a round and k times in total. The trends of the total loss of diversity and the contribution from the not-selected individuals completely overlap each other. Therefore, the round-replacement tournament selection minimises the loss of program diversity for the small tournament sizes (approximately less than five) while maintains the same competition level. Again there is no noticeable differences between the loss of program diversity measures on different sized populations with different fitness distributions.

With closer inspection in the total loss of diversity, when larger tournament sizes are used, a slight difference occurs in the round-replacement tournament selection on the smaller sized population. Apart from that, there is no noticeable changes in the two tournament selection schemes.

Figures 3 and 4 illustrate the selection probability distributions of the two tournament selection schemes on the three populations with different fitness distributions. Three different tournament sizes, namely 2, 4, and 7, are used to demonstrate the influences from different tournament sizes to the impacts of the round-replacement strategy. Tournament size 2 is chosen as it was used when the tournament selection was first introduced [1]. Tournament size 4 is chosen as it is a common setting from the literature. Tournament size 7 is chosen as it is recently recommended by the international GP research community.

Instead of plotting the selection probabilities for each individual, we only plot them for each of the 40 unique fitness ranks so that plots in different sized populations are in the same scale.

The two figures show that the round-replacement tournament selection has some different behaviour from the standard one, especially when the tournament size is 2. However, the differences are mainly related to the best individuals, whose selection probabilities reach 100% very quickly.

To further investigate whether the different selection behaviour in the round-replacement tournament selection can improve a GP system significantly, the next section presents an experimental analysis on some common problems.

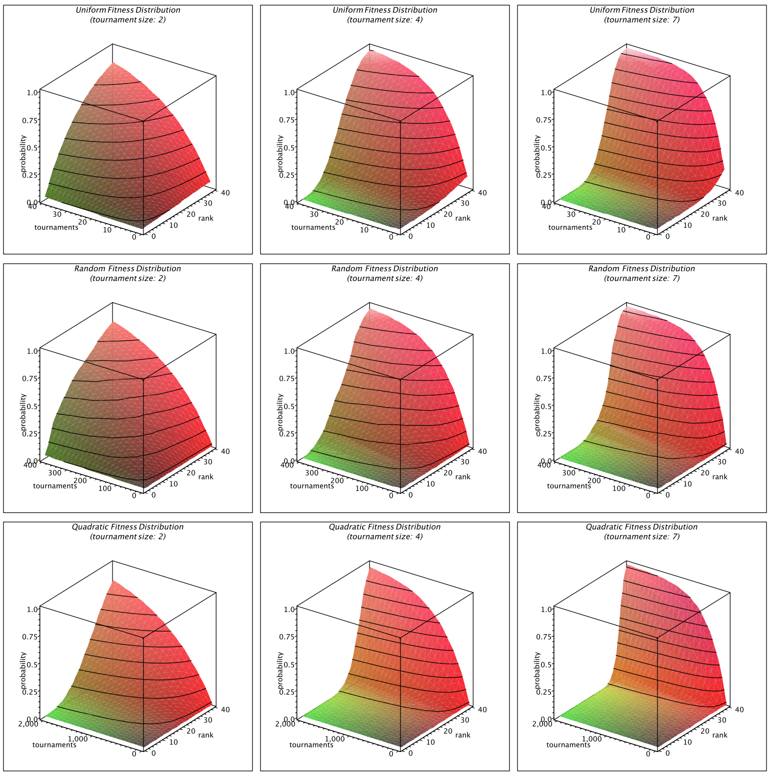


Fig. 3. Selection probability distribution in the standard tournament selection scheme with tournament size 2, 4 and 7 on three different fitness distributions.

7 Experiment Design

7.1 Data Sets

The experiments involve three different problem domains: an Even-n-Parity problem (EvePar), a Symbolic Regression problem (SymReg), and a Binary Classification problem (BinCla).

EvePar takes an input of a string of n boolean values and outputs *true* if there are an even number of true's, and otherwise *false*. In this study, the case of $n = 6$ is considered. Therefore, there are 2^6 combinations of unique 6-bit length strings as fitness cases.

SymReg is shown in Equation (9). We generated 100 fitness cases by choosing 100 values for x from [-5,5] with equal steps.

$$f(x) = \exp(1 - x) \times \sin(2\pi x) + 50 \sin(x) \tag{9}$$

BinCla involves determining whether examples represent a *malignant* or a *benign* breast cancer. The dataset is the Wisconsin Diagnostic Breast Cancer dataset chosen from the UCI Machine Learning repository [13]. The BinCla consists of 569 data examples, where 357 are benign and 212 are malignant.

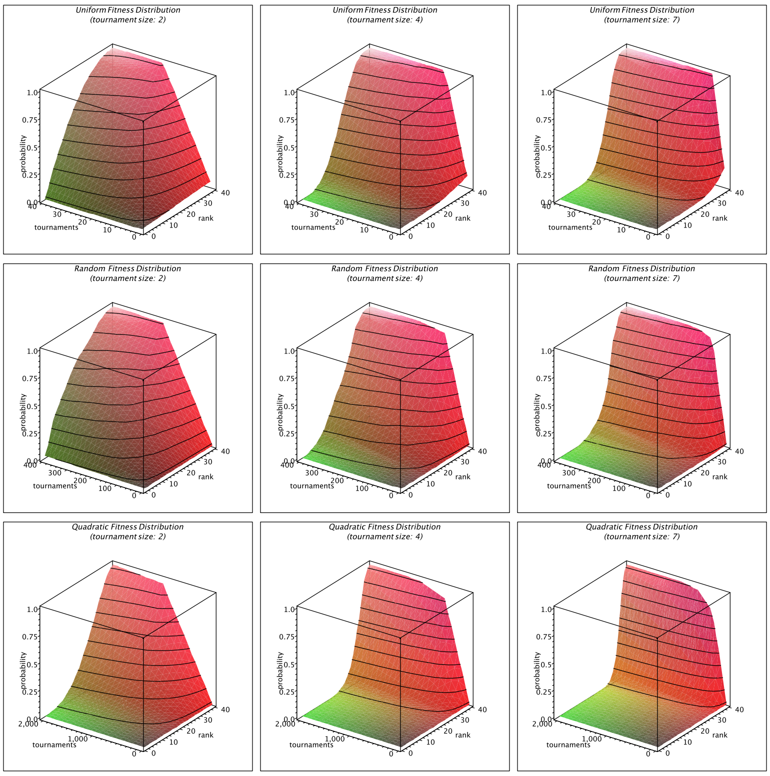


Fig. 4. Selection probability distribution in the round-replacement tournament selection scheme with tournament size 2, 4 and 7 on three different fitness distributions.

7.2 Function Sets and Fitness Functions

The function set used for EvePar consists of the standard Boolean operators { *and*, *or*, *not* } and *if* function. The function set used for SymReg includes the four standard arithmetic binary operators and unary operators { *abs*, *exp* *sin*,}. The function set used for BinCla includes the four standard arithmetic binary operators, unary operators { *abs*, *sqrt*, *sin* } and *if* function. The *if* function takes three arguments and returns its second argument if the first argument is positive, and its third argument otherwise.

The fitness function in EvePar is the number of wrong outputs (misses) for the 64 combinations of 6-bit length strings. The fitness function in SymReg is the root-mean-square (RMS) error of the outputs of a program relative to the expected outputs. The fitness function in BinCla is the classification error rate on the training data set. A program classifies the fitness case as *benign* if the output of the program is positive, and *malignant* otherwise.

7.3 Genetic Parameters and Configuration

The genetic parameters are the same for all three problems. The ramped half and half method is used to create new programs and the minimum depth of creation is three and the maximum is five. The maximum size of a program is 50 nodes. The crossover rate, the mutation rate, and the reproduction rate are 85%, 10% and 5% respectively. A run is terminated when the number of generations reaches the pre-defined maximum of 101 (including the initial generation), or the problem has been solved. As tournament sizes 2, 4, and 7 are used, the population size is set to 504 in order to have zero remainder at the end of a round of tournaments in the round-replacement tournament selection.

We ran experiments comparing the two GP systems using the standard and the round-replacement tournament selections respectively for each of the three problems. In each experiment, we repeated the whole evolutionary process 500 times independently. In each pair of the 500 runs, an initial population is generated randomly and is provided to both GP systems in order to reduce the performance variance caused by different initial populations.

Because of the nature of the tasks, EvePar and SymReg did not need a separate test set. For BinCla, we split the whole original data set randomly and equally into a training data set, a validation data set, and a test data set, ensuring that the class labellings were evenly split into the three data sets. It is possible that GP runs on BinCla subject to overfitting. Therefore, we let runs terminate according to the predefined termination criteria, then the performance of each run is the test fitness value of the recorded program with the best validation fitness.

8 Experimental Results and Analysis

Table 1 compares the performances of GP systems using the two tournament selection schemes. The measure for EvePar is the completion rate, measuring the fraction of runs that successfully returned the ideal solution. The best value is 100%. The measures for SymReg and BinCla are the averages of the RMS error and the classification error rate on test data over 500 runs respectively, thus the smaller the value, the better the performance. Note that the standard deviation follows the ± sign.

Table 1. Performance comparison.

Tournament Selection		EvePar	SymReg	BinCla
Scheme	Size	Completion (%)	RMS Error	Test Error Rate (%)
standard	2	0	48.2 ± 5.2	9.3 ± 2.9
	4	19.4	37.6 ± 8.3	8.8 ± 2.8
	7	17.6	40.9 ± 11.3	8.9 ± 2.8
round-replacement	2	0.4	47.4 ± 5.3	8.6 ± 2.8
	4	20.6	38.3 ± 8.0	8.8 ± 2.7
	7	22.4	40.6 ± 11.4	8.9 ± 2.8

The results demonstrate that the round-replacement tournament selection has some advantages. In order to provide statistically sound comparison results, we calculated the confidence intervals at 95% and 99% levels (two-sided) for the differences in completion rates, in RMS errors, and in error rates for EvePar, SymReg and BinCla respectively. For EvePar, we used the formula $\hat{P}_1 - \hat{P}_2 \pm Z\sqrt{\hat{P}_1(1-\hat{P}_1)/500 + \hat{P}_2(1-\hat{P}_2)/500}$, where $\hat{P}_1$ is the completion rate using the round-replacement tournament selection, $\hat{P}_2$ is the completion rate using the standard tournament selection, and Z is 1.96 for 95% confidence and 2.58 for 99% confidence. For SymReg and BinCla, we firstly calculated the difference of the measures between a pair of runs using the same initial population for each of the 500 pairs of runs, then used the formula $\bar{x} \pm Z\frac{s}{\sqrt{500}}$ to calculate the confidence interval, where $\bar{x}$ is the average difference over 500 values and s is the standard deviation. If zero is not included in the confidence interval, then the difference is statistically significant.

Table 2 only shows the confidence intervals at 95% level as the statistical analysis results from the two levels are consistent.

Table 2. Confidence intervals at 95% level.

Tournament size	EvePar	SymReg	BinCla
2	(-0.15, 0.95)	**(-1.48, -0.24)**	**(-0.99, -0.36)**
4	(-3.76, 6.16)	(-0.22, 1.57)	(-0.34, 0.24)
7	(-0.15, 9.75)	(-1.47, 0.85)	(-0.21, 0.37)

From the table, the round-replacement tournament selection is only statistically significantly better than the standard tournament selection (shown in bold) when the tournament size is 2 for SymReg and BinCla. However, practically the differences are small. For BinCla, when the tournament size is 2, although the mean test error rate 8.6% in the round-replacement tournament selection is better than 9.3% in the standard one, such a performance is still insignificantly different from 8.8%, which is obtained by using the standard tournament selection with tournament size 4 (the 95% confidence interval of the difference is from -0.52% to 0.10%).

The insignificant differences observed for tournament sizes 4 and 7 are not surprising because there is no observable reduction on the loss of program diversity correspondingly. The results show that there exists little impact from the slight differences on the selection probability of the top ranked programs.

Therefore, the theoretical and experimental analyses results show that although the not-sampled issue is solved, overall the different selection behaviour in the round-replacement tournament selection appears not to be able to significantly improve a GP system for the given tasks.

9 Conclusions and Future Work

The standard tournament selection samples individuals with replacement. It has the not-sampled issue when using smaller tournament sizes. The not-sampled issue aggravates the loss of program diversity. This paper proposed the round-replacement tournament selection that solved the issue and effectively minimised the loss of program diversity for smaller tournament sizes. Theoretical analyses illustrated some different selection behaviour in the selection scheme. However, the experimental results showed that when common tournament sizes are used for the given tasks, the different parent selection behaviour in the round-replacement tournament selection did not usually significantly improve the performance of a GP system. The results suggested that the not-sampled issue does not seriously affect the selection performance in the standard tournament selection. Instead, the not-sampled programs can be utilised to save the computational cost [4].

The reduced loss of program diversity through the round-replacement tournament selection appears not to be able to significantly improve the GP performance. Other mechanisms need to be investigated to further reduce the loss of program diversity. Further, in order to significantly improve the standard tournament selection scheme, making it be able to well understand the dynamics along evolution, other more important aspects, including the impacts of the fitness distribution, should be considered in the future.

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