Experiments with Lazy Evaluation of Classification Decision Trees Made with Genetic Programming

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Abstract: In this paper, we present a lazy evaluation approach of classification decision trees with genetic programming. We describe and experiment with the lazy evaluation that does not evaluate the whole population but evaluates only the individuals that are chosen to participate in the tournament selection method. Further on, we used dynamic weights for the classification instances, that are linked to the chance of that instance getting picked for the evaluation process. These weights change based on the misclassification rate of the instance. We test our lazy evaluation approach on 10 standard classification benchmark datasets and show that not only lazy evaluation approach uses less time to evolve the good solution, but can even produce better solution due to changing instance weights and thus preventing the overfitting of the solutions.

1 INTRODUCTION

Genetic algorithm (GA) is a metaheuristic process which uses the theory of evolution to generate the final solution to a problem with the gradual evolution of solutions inspired by natural selection process observed in nature. The basic evolution loop of all variations of GA is the following. The loop starts with the evaluation process of the solutions in the whole population, then continues with the selection process of evaluated solutions. Next, the mating process (crossover) between various solutions generates new offspring solutions, and then other evolutionary operators can be applied (such as mutation and elite selection) (Espejo et al., 2010). The whole process of the genetic algorithm is computationally intensive, and every speed up of the evolution without sacrificing the quality of the final solution is welcomed.

The processing time of every genetic operator during the evolution process is dependent on the type of problem we are solving. In this paper, we focus on classification problem, which is one of the supervised methods of machine learning field.

One way to solve classification problem with GA is by using genetic programming (GP), which is a variation of GA where solutions are programs represented in a hierarchical decision tree structure (Espejo et al., 2010). The classical techniques of building these decision trees used in the industry and academia are CART (Breiman et al., 1984), C4.5 (Quinlan, 2014), ID3 (Cheng et al., 1988) and ensembles of these methods (Liaw et al., 2002) (Ganjisaffar et al., 2011). With GP we can utilize the power of evolution to build these decision trees as has been used numerous times before. In the evolutionary process of construction classification decision trees, the computationally most intensive part is the evaluation of the decision trees (Zhang and Cho, 1998).

In this paper, we propose a lazy evaluation of the classification decision trees made with GP, where solutions from the population are evaluated only when needed and on the limited amount of classification instances. We extend our previous work on this field (Podgorelec and Zorman, 2015), (Podgorelec et al., 2013), and add the dynamic evaluation process – it can be expanded if the evaluation process does not differentiate between the quality of different solutions. The process of lazy dynamic evaluation also changes the importance of classification instances through the evolution, giving the more importance to the instances, that are more often misclassified and less importance to those that are more often correctly classified.

Not much similar work has been done before, but we definitely build on the ideas from the existing literature. The most notable impact to our work was introduced by Gathercole and Ross (Gathercole and Ross, 1994). In their paper, they proposed a dynamic training subset selection for the supervised problem (such as classification) where they proposed three dif-

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ferent subset selection processes where they heuristically change the testing classification set in each generation. Our proposed method of lazy and dynamic evaluation builds on their idea, where we weight instances through the evolution, but we expand this with the lazy evaluation, where an individual is tested only when it is needed and only on it's testing set. Zhang and Cho introduced the idea that incrementally selected testing subsets can reduce evaluation time without sacrificing generalization accuracy of evolved solutions (Zhang and Cho, 1998). Šprogar introduced the idea, that even excluding the fitness of the genetic solutions can improve the robustness of evolution process (Šprogar, 2005). His proposal eliminates the operator for evaluation and can also speed up the process of evolution.

The rest of the paper is organized as follows. We start with the section where we analyze the processing time of genetic programming method for classification purposes. Next is the section where we present the idea of the lazy evaluation method and describe it in detail. In the following section, we describe the layout of the experiment and present the results of the implemented method of lazy evaluation. We conclude with the final remarks, the interpretation of the results and present our plans for the future research.

2 PROCESSING TIME ANALYSIS OF GP FOR CLASSIFICATION

Let us analyze the individual processing times of each genetic operator in the GP process. Figure 1 shows the standard evolutionary process in the GP, where the evolution loop is highlighted with the gray rectangle.

As it is evident from the figure, most of the processing time is spent in the evolution loop – the amount of this time is mostly dependent on the stopping criteria. If there is a dynamic stopping criterion, such as an amount of stagnating generations (generations without improvement), the total processing time varies from run to run and is mostly due to chance. If we have fixed number of generations, then we can approximate the processing time more precisely.

If we use the big Omicron (big *O*) notation, the approximation of processing time goes as it is presented in the following. The big *O* notation is used to express the upper bound of the processing time growth rate of a process, or in other words, the time complexity of an algorithm.

The evolution loop starts with the selection of the individuals, that are chosen to go through the mating process. There are many different selection methods, but here we are only exploring the tournament selection method. *Tournament selection* chooses k random individuals from the populations and the best individual (fitness wise) wins the tournament and is selected to participate in the mating process. The order of growth for one generation is $O(mk)$, where m is the number of parents chosen (usually the same as the population size, when parents produce two offspring), and k is the tournament size (usually between 2 to 10).

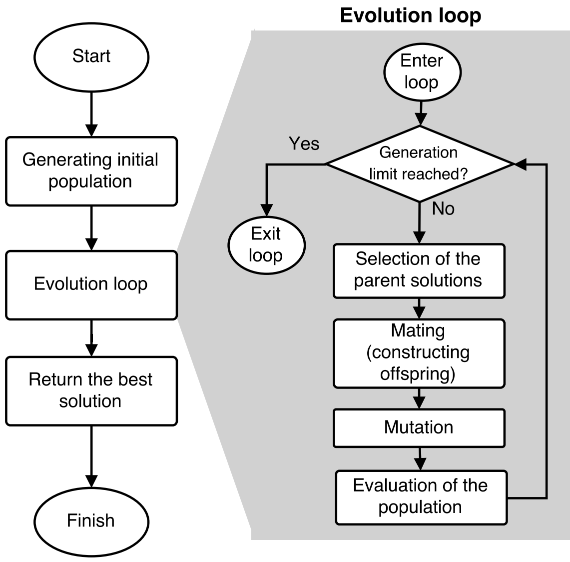


Figure 1: Flowchart of genetic programming with the evolution loop highlighted in the light gray background.

The mating process is heavily dependent on the genotype representation. In GP we present one individual in a form of a tree, or more specifically here one individual is a classification decision tree. So naturally, the processing time of the crossover process is also dependent on the representation. In our implementation, we set the chance of crossover happening to 100%. In the regular form GP (without heuristic crossover) the crossover process chooses a random node in the tree from the first parent, and the random node from the second parent and exchanges the subtrees, creating one or two offspring. The choosing of the nodes happens two times (two parent trees) and the loop of node choosing runs from minimal of 1 to maximum depth of the tree. The maximum depth of the tree is again a heavily dependent, this time on the classification problem – simpler classification problems permit shallower trees and more complex ones demand bigger decision trees. So the order of growth for the crossover process in one generation is $O(2d)$ (2 because of two parent trees), or simpler just $O(d)$, where d is the maximum depth of the tree.

After the crossover, the mutation process is next. Here we must consider the chance of the mutation happening. Standard chances vary from 1% and all the way to 50%. The time complexity of mutation operator is similar than in crossover. When the new child is created and it is determined that it was chosen by chance to go through the mutation, the node is chosen in a random fashion and is replaced by a random subtree or the node content (the decision rule) is changed. The node picking itself has the order of growth *O(d)* as does the creation of the random subtree *O(d)* (if the maximum depth of the tree is set to *d*). So the time complexity is *O(2d)*, or simpler just *O(d)*, but keep in mind, that this doesn't happen to every new individual.

Now for the most time-consuming process in GP loop – evaluation process. Here we take every individual and use every classification instance in the training set to classify that instance. From these classification results, the classification metrics can be calculated (accuracy, F-score, recall, precision, AUC, and others), which are then part of the fitness of that individual. The process of calculating the classification metrics is another time-consuming process. The calculation of accuracy is straightforward by just counting the correctly classified instances, but calculating the F-score is a more time-consuming process (as we have to calculate recall and precision for every class, and then calculate individual F-score for each class and then aggregate it to get the final F-score). Let's assume we have *n* number of new offspring individuals, the maximum depth of each individual tree is *d*, we have *t* number of training classification instances that are to be classified by each tree, and that we calculate only the accuracy for the fitness. The time complexity of evaluation for every individual in one generation is *O(ndt)*.

If we combine the time complexities of individual operators we get the following time complexity of an evolution loop for one generation:

$$O(mk) + O(d) + O(d) + O(ndt)$$

m =number of parents from selection

k =tournament size

d =maximum depth of the tree

n =number of offspring individuals

t =number of classification instances in the training set

It is evident, that all of the times are linear and thus the total time should be mostly dependent on the highest factor in the equation. We also ran the GP and timed each genetic operator in the evolution loop multiple times. In Figure 2 is the pie chart that shows the proportions of each processing times in one generation on average of 100 independent runs.

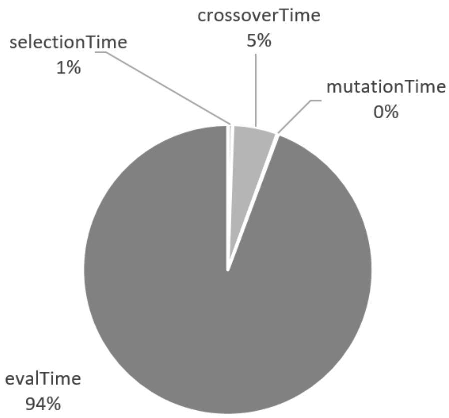


Figure 2: Pie chart showing the average processing times of genetic operators in one generation of GP for classification decision tree construction. The experiment was made on *car* dataset with 1382 instances in the training set, 150 solutions in the population, 2000 generations and 100 independent runs of GP.

As is evident from the pie chart in Figure 2, 94% of the total processing time in the evolution loop is spent the evaluation process. Note that this cannot be generalized to all GAs or even all GPs and is specific for GP construction classification decision trees. Even using different data set (we used the *car* data set) could produce slightly different results. Despite this, we see that shortening evaluation time should significantly impact the running time of the GP in general.

3 LAZY EVALUATION METHOD

As we found out in the previous section, the most time-consuming process in evolution loop is the evaluation process, thus we propose an approach which shortens this time.

In our proposed approach, which we named *lazy evaluation*, we do not evaluate the whole population on all of the classification instances. Instead, we evaluate only decision trees chosen to participate in the tournament of the selection operator and only some classification instances.

The Figure 3 shows two separated plots. On the top is the probability of one decision tree from the population to be chosen to be evaluated in one tournament, dependent on the size of the tournament and the population size. On the bottom, there is the number of evaluations (number of classification instances X population size) in one generation dependent on lazy evaluation tournament size (and standard GP) and population size.

As it is evident from the Figures 3, the number of evaluations per generation is drastically lower as

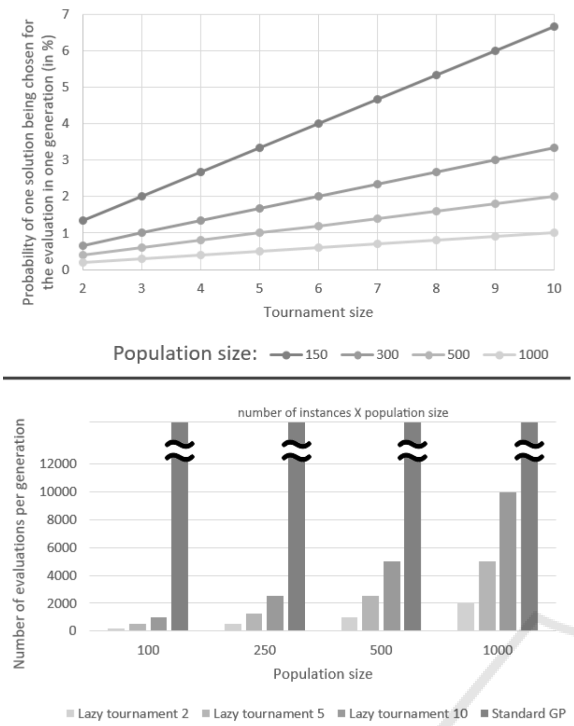


Figure 3: Exploring the number of evaluations.
Top: Line chart showing the probability of one decision tree being chosen for the evaluation, dependent on the tournament size and the population size.
Bottom: Number of evaluations in generation dependent on a number of classification instances and population size. *Standard GP* denotes the standard GP without extensions.

in traditional evaluation (all decision trees on all classification instances). Let us take the example where we have population size 100 and number of classification instances is 1000. If we use lazy evaluation with tournament size of 2, we have 400 evaluations $(2*100*2)$, for evaluation with tournament size of 5 we get 1000 evaluations $(5*100*2)$ and if we have the lazy evaluation with tournament size of 10, we have 2000 $(10*100*2)$. But the standard GP always has $100,000$ evaluations $(100*1000)$, much more than any of the lazy evaluations.

Of course, this is only in theory, so time saved with this approach would not be directly in the same proportion in practice. We will test the real time saved in the next section with the experiment.

3.1 Weighting the Classification Instances

Based on the proposition and results from the paper (Gathercole and Ross, 1994), we decided to include the weighting of classification instances through the evolution process. The weights of classification instances determine the probability of that instance getting chosen to be used for the evaluation process – the higher the weight, more chance of that instance getting picked. The weights change based on the difficulty of classifying of that particular instance – more times the instance is misclassified, the higher its weight becomes and more chance it has to be chosen again for the evaluation. This forces the GP to focus on more difficult instances and compensates for a few instances used in the evaluation.

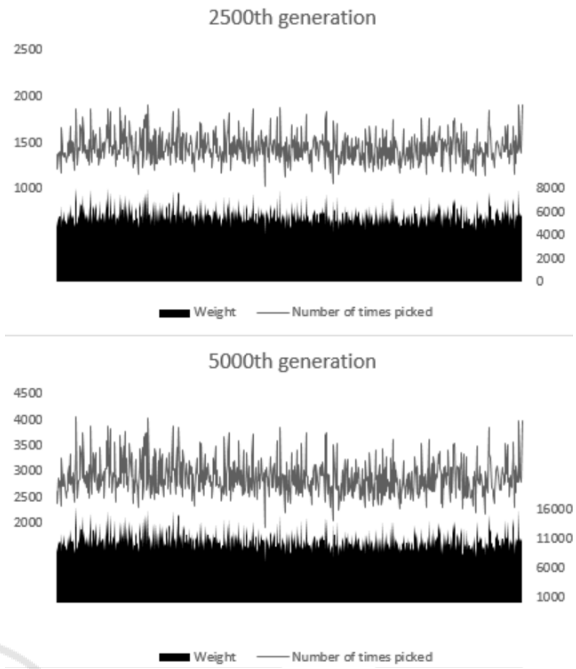
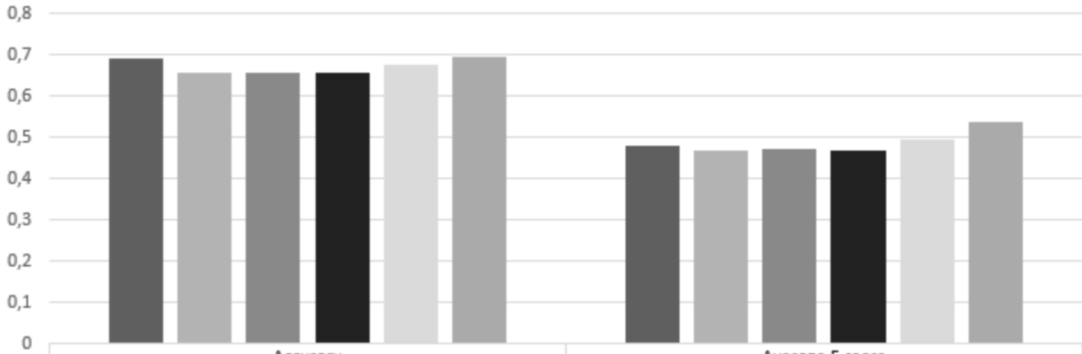


Figure 4: The line in the charts shows the number of times the particular instance was chosen for evaluation process in the 2500th generation (top) and 5000th generation (bottom). The area in the bottom part of charts shows the weight of that particular instance. Note that the number of picks of any particular instance for evaluation is linked to its weight.

In contrast to the paper by Gathercole and Ross (Gathercole and Ross, 1994), we choose different instances for every tournament in one generation and not the same instances for every evaluation in one generation. This raises the chance of one instance getting chosen for the evaluation and further diversifies the search space without raising the number of total evaluation in one generation.

Our weighting strategy is as follows. In the beginning, all of the instances have the same initial weight of 1. For every misclassification of that instance, its weight is increased by the amount $1/n$, where n is the number of classification instances in the test set.

The Figure 4 shows instance weights and number of picks, first chart in the middle of the evolution (2500th generation) and the last chart for the last



	Accuracy	Average F-score
Standard GP	0,691993695	0,478167031
LE (1 inst)	0,655908209	0,467599643
LE (2 inst)	0,657079612	0,470439188
LE (3 inst)	0,657122602	0,470371177
LE (5 inst)	0,675456711	0,493522465
LE (10 inst)	0,696038254	0,535906312

Figure 5: Classification metric of the resulting classification decision trees on all 10 datasets with 5 fold cross validation. *LE* = Lazy evaluation; *inst* = number of instances used in the evaluation process.

(5000th) generation. As we can see from the charts, some of the weights (and consequently a number of picks) stay the same through the evolution, but others increase throughout the evolution.

4 FIRST EXPERIMENTS WITH LAZY EVALUATION OF GP FOR CLASSIFICATION

We conducted first set of experiments with our proposed approach with lazy evaluation of evolutionary classification decision trees. We used 10 classification benchmark datasets from UCI repository (Lichman, 2013) and we measured following metrics: total accuracy, average F-score ($\beta = 1$) and total running time of the whole process from start to finish. All of the tests were done using 5 fold cross-validation.

Datasets used in te experiments were the following: *autos, balance-scale, breast-cancer, breast-w, car, credit-a, diabetes, heart-c, iris* and *vehicle*.

The GP settings were set to the following values:

- selection method: tournament
- fitness function: $(1 - accuracy) + (0.02 * numberOfNodes)$
- population size: 150
- elite size: 1
- number of generations: 2000
- crossover probability: 100%
- mutation probability: 10%
- number of runs: 10

Although some operators in GP can be parallelized, we compared non-parallelized version in our experiments, but parallelizing the lazy evaluation is one of our goals in the future.

4.1 Classification Results

Figure 5 shows two classification metrics: overall accuracy and average F-score for all of the 10 datasets. As it is evident from the number from the table in Figure 5, there are slight differences in both metrics between different settings. The best performing GP accuracy wise is GP with lazy evaluation (0.70) where we used 10 instances in the evaluation process, followed by the standard GP with no lazy evaluation. The same lead is shown in the F-score metric, where GP with lazy evaluation scored 0.54.

Kruskal-Wallis test for multiple groups returned that there are statistically significant differences between groups for accuracy ($\chi^2 = 370.465$, $p < 0.001$). Post-hoc test of pair-wise comparison for accuracy with Holm-Bonferroni correction for multiple comparisons shows, that there are no statistically significant differences between two of the best performing GPs (between Standard GP and GP with lazy evaluation with 10 instances. $p = 0.852$).

Similar are the results of Kruskal-Wallis test for average F-score metric, where there are statistically significant differences between different settings ($\chi^2 = 191.558$, $p < 0.001$). Here the post-hoc test with the correction shows that there are statistically significant differences between standard GP and GP with lazy evaluation with 10 instances ($p < 0.001$).

4.2 Evolution Time Analysis

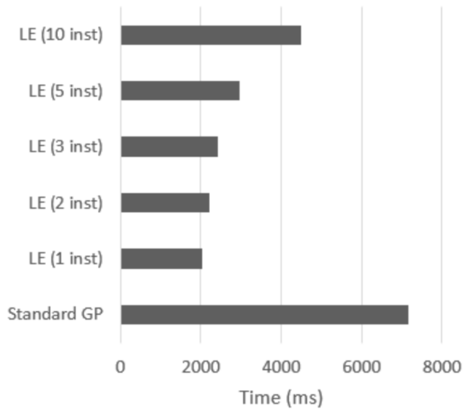


Figure 6: Average total running times of the whole evolution process in milliseconds for all settings.
LE = Lazy evaluation; *inst* = number of instances used in the evaluation process.

Looking at the running time shows a clear lead of the lazy evaluation GPs in comparison to standard GP. The slowest lazy evaluation GP is the one with 10 instances used in the evaluation process that used on average 4495.92 milliseconds, which is just 62.6% of the average total running time of the standard GP with the average total running time of 7182,97 milliseconds.

We see that the running times are not proportionally smaller in comparison to the theoretical saving due to fewer evaluations, but they are still smaller.

5 CONCLUSIONS

We proposed a lazy evaluation approach in genetic programming process of creating the classification decision trees that uses dynamic choosing of the instances.

Results of the first experiments show, that this approach has great potential and should be explored further on. Not only that all of the lazy evaluation GPs took less processing time to finish the whole evolution process in comparison to standard GP, some settings (with more instances in evaluation process) returned comparable results (in accuracy and average F-score). One of the lazy evaluation settings included (with 10 instances in evaluation) in the experiment even returned better results than the standard GP. This can be contributed to changing environment of the GP, thus preventing to overfit the solutions and to the weighting process that gives more importance (more chance to be involved in evaluation process) to harder to classify instances.

We are planning to research lazy evaluation further and to test the importance of the tournament size and explore the number of evaluation instances further on. Other than that, there is already an ongoing implementation of parallel lazy evaluation that should be directly comparable to parallel GP for decision tree creation.

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