A Mentorship Approach to Crossover in Genetic Algorithms

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1 INTRODUCTION

Artificial Intelligence is predicated on the idea of creating something we consider intelligent. One good idea to create an intelligent model is to analyze a system or process we already consider to be so. One place we see this is in neural networks that take inspiration from the neural pathways of the brain. Another instance of this is in the process of evolution which has led to the concept of genetic algorithms. In this algorithm, hypotheses are typically categorized by bit strings to symbolize features and expressions. These hypotheses go through stages of selection, crossover, and mutation akin to biological evolution which leads to a new generation that repeats the process until a goal is reached. Selection can be thought of similarly to natural selection where agents that perform better are more likely to survive whereas weaker, less fit agents have a small chance to survive. The selection process typically involves using the fitness of each agent or hypothesis to decide how likely it is to move on to the next generation. Crossover in biological terms is similar to procreation between two "parents" which involves the crossing over of DNA. In genetic algorithms, this involves taking two hypotheses, crossing over or swapping sections of their bit strings creating two children that would be then added to the population for the next generation. The simplest method to choose parents is a random selection of pairs from the population but making a more informed selection of pairs for crossover could lead to convergence faster. In this paper, I am implementing a new method of selection as well as an additional method of parent selection for the crossover operator to improve convergence speed while keeping diversity.

2 RELATED WORK

Multiple methods have been considered and analyzed as viable selection methods. What we will consider as the generic version of the algorithm covered in the book Machine Learning by Tom Mitchel is known as the Roulette Wheel Selection (RWS). This gives the probability of each individual as a ratio of its fitness to the total fitness of the population. The Tournament Selection algorithm involves randomly pairing hypotheses and comparing their fitness values. The fitter individual moves on to the next 'round' while the other is disqualified. This process is repeated until the number of winners is equal to the desired number of parents.[3] Another method is Linear Rank Selection which is a variant of RWS. It is based on the rank of individuals rather than their fitness so the individual's probability of being chosen is increased given a higher rank.[2] Finally, Elitism assesses each individual's fitness and has a percentage of the best as parents. Then each member of the population is compared to the chosen parents one by one. If any member is fitter than a parent, it is swapped out. This continues until all members have been compared to the existing parents. Then the original members first selected to be parents are compared to the current set of parents to ensure the fittest individuals were chosen. [**?**]

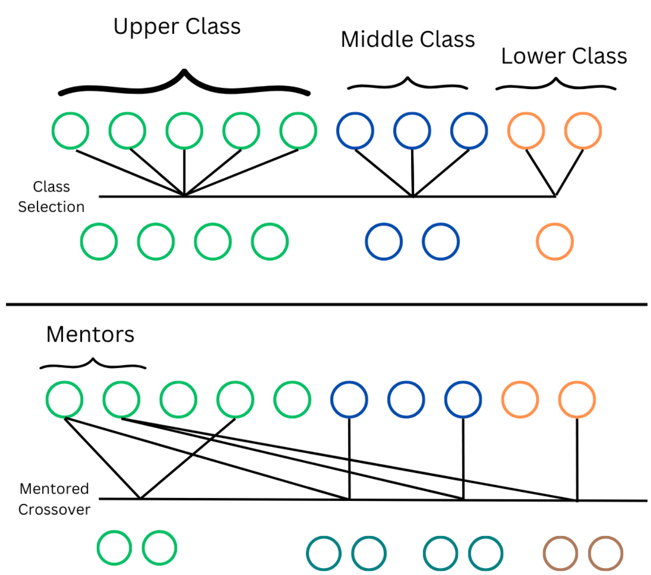

Figure 1: A diagram showing the class selection method and mentored crossover method. The long horizontal lines are only to point to the name of the operation/process being done

3 APPROACH

My proposed approach can be described as an Equity Mentored Selection which is based on RWS. The initial population is evaluated and separated into classes we can call the upper, middle, and

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lower classes. The sizing of each class is proportionally set where we prioritize giving larger size to the higher classes so an example proportional split for upper, middle, and lower class is 0.6, 0.3, 0.1 respectively. After this split is made, the selection is made within each group. In other words, given the 3 splits, we selected a group of individuals only from the upper class, then we select individuals only from the middle, and the same for the middle. This guarantees some measure of diversity as there will be a representative of each division of fitness but keeps the poorly performing individual size small in our population. The group of individuals will represent what we call classPop. The second group will be represented by the typical application of cross-over pairing individuals in the population called crossPop. A third and final group is made up of individuals that are a product of cross over but they are selected by crossing over the top k individuals randomly with the population. These 3 groups will make up the next generation.

4 EVALUATION

The proposed algorithm will be tested on the Travelling Salesman Problem(TSP) using data given by TSPLIB which is a collection of TSP datasets managed by Gerhard Reinelt. The evaluation metrics that will be observed are the number of generations before convergence and a score defined by the sum of the hamming distance from every individual in the final generation plus the fitness of that individual.

REFERENCES

[1]]Chudasama11 S. M. Shah Chetan Chudasama and Mahesh Panchal. [n. d.]. Comparison of Parents Selection Methods of Genetic Algorithm for TSP. ([n. d.]).
[2] Khalid Jebari and Mohammed Madiafi. 2013. Selection Methods for Genetic Algorithms. (Dec. 2013). https://www.researchgate.net/profile/Khalid-Jebari/publication/259461147_Selection_Methods_for_Genetic_Algorithms/links/5480d9100cf22525dcb60519/Selection-Methods-for-Genetic-Algorithms.pdf
[3] Noraini Mohd Razali and John Geraghty. 2011. Genetic Algorithm Performance with Different Selection Strategies in Solving TSP. (July 2011). https://www.iaeng.org/publication/WCE2011/WCE2011_pp1134-1139.pdf