# Non-universal Suffrage Selection Operators Favor Population Diversity in Genetic Algorithms

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State-of-the-art concept learning systems based on genetic algorithms evolve a redundant population of individuals, where an individual is a partial solution that covers some instances of the learning set. In this context, it is fundamental that the population be diverse and that as many instances as possible be covered. The universal suffrage selection (US) operator is a powerful selection mechanism that addresses these two requirements. In this paper we compare experimentally the US operator with two variants, called Weighted US (WUS) and Exponentially Weighted US (EWUS), of this operator in the system ECL [1]. The US selection operator operates in two steps:

1. randomly select $n$ examples from the positive examples set;
2. for each selected positive example $e_i$, $1 \leq i \leq n$, let $Cov(e_i)$ be the set of individuals covering $e_i$. If $Cov(e_i) = \emptyset$ then call a seed procedure for creating an individual that covers $e_i$. If $Cov(e_i) \neq \emptyset$, choose one individual from $Cov(e_i)$ with a roulette wheel mechanism, where the sector associated to an individual $x \in Cov(e_i)$ is proportional to the ratio between the fitness of $x$ and the sum of the fitness of all individuals occurring in $Cov(e_i)$.

The basic idea behind this operator is that individuals are candidates to be elected, and positive examples are the voters. In this way, each positive example has the same voting power, i.e. has the same probability of being selected in the first step of the US selection operator. The WUS and EWUS operators modify the first step of the US operator. Within these operators, each example is assigned a weight, and then in the first step of the selection examples are chosen with a roulette wheel mechanism, where the probability of choosing an example depends on the weight of the example. The weights used by the WUS and the EWUS operators are respectively: $w_i = \frac{|Cov(e_i)|}{|Pop|}$ and $w_i = \frac{e^{-|Cov(e_i)|}}{\sum_{j=1}^{P} e^{-|Cov(e_j)|}}$. Weights are adjusted at each iteration of the GA. In this way examples harder to cover will be selected with higher probabilities. The validity of each selection operator is tested on three datasets. The first is an artificially generated dataset, the other two are well known datasets: the mutagenesis and the vote datasets. The first dataset consists of five hundred positive examples and five hundred negative examples. Each example can be described by three attributes $q, p$ and

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$r$, that can assume respectively the values $\{a, b\}$, $\{c, d, e\}$ and $\{f, g\}$. Results are shown in Tables 1 and 2, where *Unc* stands for the average number of positive examples uncovered at the end of the evolution, *Cov* for the average number of individuals covering a positive example, *Div* for the average number of different clauses in the final population and *Acc* for the average accuracy.

**Table 1.** Table 1.1 shows the diversity in the final populations obtained by using the three selection operators. The first column shows the kind of clause, e.g. f means a clause of the form $z(X) \leftarrow r(X, f)$. For each kind of clause the percentage of individuals in the final population representing it is given in the table for each variant of the selection operator

| Clause | US | WUS | EWUS |
|---|---|---|---|
| f | 0.35 (0.16) | 0.26 (0.16) | 0.09 (0.02) |
| a | 0.24 (0.05) | 0.28 (0.02) | 0.08 (0.02) |
| c | 0.30 (0.10) | 0.22 (0.16) | 0.13 (0.03) |
| a,d | 0.03 (0.05) | 0.03 (0.00) | 0.02 (0.02) |
| a,f | 0.05 (0.02) | 0.03 (0.00) | 0.01 (0.02) |
| a,c | 0.03 (0.05) | 0.15 (0.07) | 0.06 (0.02) |
| d | 0 | 0 | 0.1 (0.07) |
| a,f,d | 0 | 0 | 0.01 (0.02) |
| f,c | 0 | 0 | 0.01 (0.02) |
| others | 0 | 0.03 (0.04) | 0.49 (0.02) |

Table 1.1

| Clause | US | WUS | EWUS |
|---|---|---|---|
| Unc | 13.5 (3.53) | 13 (0.01) | 0.67 (0.58) |
| Cov | 19.80 (0.24) | 17.20 (3.11) | 9.00 (0.23) |

Table 1.2

**Table 2.** Results for the mutagenesis and the vote dataset. Standard deviation is given between brackets

Mutagenesis

| | US | WUS | EWUS |
|---|---|---|---|
| Div | 8 (0.82) | 9.34 (3.2) | 21 (1.63) |
| Unc | 10 (2.45) | 7.67 (3.09) | 0.33 (0.47) |
| Cov | 17.36 (7.85) | 15.33 (7.35) | 6.97 (2.81) |
| Acc | 0.85 (0.08) | 0.86 (0.08) | 0.89 (0.06) |

Vote

| | US | WUS | EWUS |
|---|---|---|---|
| Div | 8.67 (1.47) | 13.5 (1.50) | 13 (1.12) |
| Unc | 2.33 (0.47) | 0.80 (0.75) | 0 (0) |
| Cov | 21.13 (7.42) | 20.50 (8.38) | 22.87 (5.16) |
| Acc | 0.92 (0.05) | 0.93 (0.06) | 0.94 (0.04) |

The results suggest that 'less' universal selection schemes are more effective for promoting diversity while maintaining the key property of the US selection operator of covering many positive examples.

## References

1. F. Divina and E. Marchiori, *Evolutionary concept learning*, in GECCO 2002: Proceedings of the Genetic and Evolutionary Computation Conference, New York, 9–13 July 2002, Morgan Kaufmann Publishers, pp. 343–350.