# Partially Unbalanced Crossover Operators by Adaptive Bias

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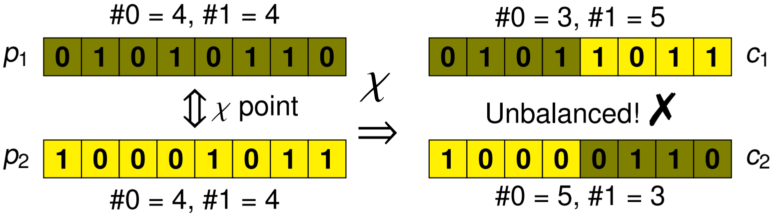
# Classic crossover and balancedness

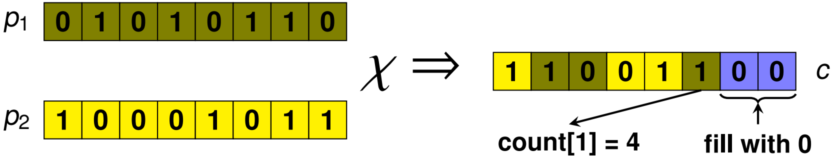
- In some optimization problems, feasible solutions are represented by *balanced* binary strings, composed of an equal number of zeros and ones




- In general, classic GA crossover operators in GA do not preserve balancedness

# Counter-based crossover

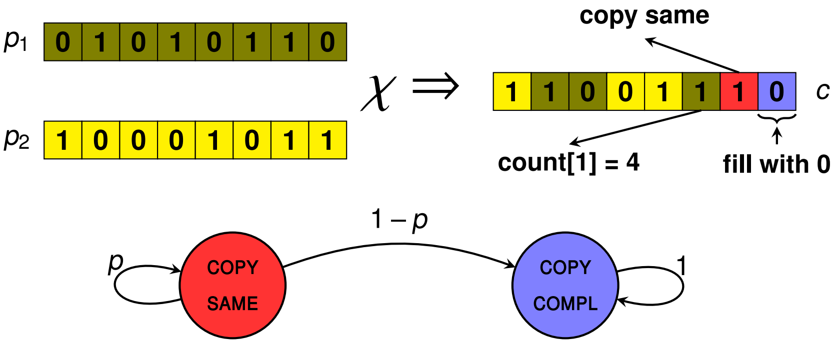
- Uniform crossover with *counters* to keep track of the multiplicities of zeros and ones [Millan98]
- copy the other value when the threshold is reached




- Gives an advantage over one-point crossover, but finds less optimal solutions as the problem size grows [Manzoni20]

# Partially unbalanced crossover

- **Tip the balance:** Slightly enlarge the search space by allowing some unbalancedness in the offspring
- Keep copying the wrong value with probability $p$, and switch to the correct one with probability $1 - p$



# Adaptive bias mechanism

- **Adaptive bias**: probability $p$ is updated with a *geometric cooling mechanism* similar to simulated annealing

$$p \leftarrow \alpha \cdot p \ , \ \ where \ \ \alpha \in (0,1)$$

- **Weighted penalty factor** added to the fitness function:

$$w_{pen}(x) = (1 - p) \cdot |w_H(x) - k| \ ,$$

where $w_H(x)$=number of 1s in $x$, and $k$ is the target weight

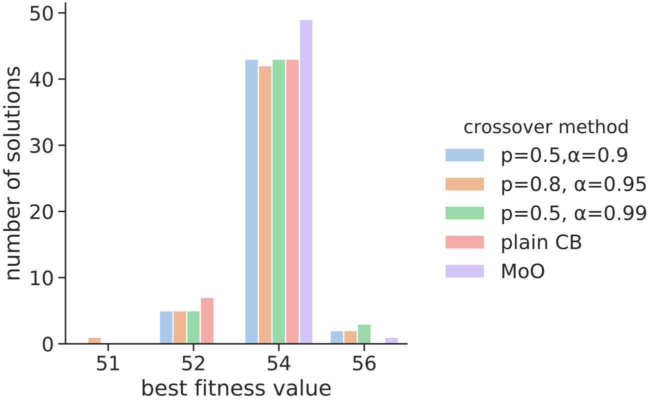
# Experimental validation

- **Problem**: balanced nonlinear Boolean functions [Carlet10]
- The truth table of a Boolean function $f : \{0,1\}^n \rightarrow \{0,1\}$ of $n$ variables is encoded by a $2^n$-bit string
- **Balancedness constraint**: the truth table must be composed of an equal number o 0s and 1s
- **Optimization goal**: maximize the *nonlinearity* $Nl(f)$ of $f$

$$fit(f) = Nl(f) - wpen(f) = Nl(f) - (1-p) \cdot |2^{n-1} - w_H(f)|$$

- Same experimental setting used in [Manzoni20] to compare with counter-based crossover and map-of-ones

# Results




Distribution of fitness values over 50 experimental runs for Boolean functions of $n = 7$ variables

# Conclusions and Future Research

**Conclusions:**

- The partially unbalanced crossover generated slightly more optimal solutions than other crossover methods
- However, there are no statistically significant differences in the best fitness distributions

**Future Directions:**

- Better analyze and tune the adaptive bias parameters to boost performances, as well as other GA parameters
- Apply the adaptive bias strategy to other problems where balanced solutions are required, e.g. orthogonal arrays [Mariot18] and orthogonal Latin squares [Mariot17]

# References


[Carlet10] Carlet, C., Boolean functions for cryptography and error correcting codes. Boolean models and methods in mathematics, computer science, and engineering, vol. 2, pp. 257–397 (2010)

[Manzoni20] Manzoni, L., Mariot, L., Tuba, E.: Balanced crossover operators in genetic algorithms. Swarm and Evolutionary Computation 54, 100646 (2020)

[Mariot18] Mariot, L., Picek, S., Jakobovic, D., Leporati, A.: Evolutionary Search of Binary Orthogonal Arrays. In: Auger, A., Fonseca, C.M., Lourenço, N., Machado, P., Paquete, L., Whitley, D. (eds.): PPSN 2018 (I). LNCS vol. 11101, pp. 121–133. Springer (2018)

[Mariot17] Mariot, L., Picek, S., Jakobovic, D., Leporati, A.: Evolutionary Algorithms for the Design of Orthogonal Latin Squares based on Cellular Automata. In: Proceedings of GECCO'17, pp. 306–313 (2017)

[Millan98] Millan, W., Clark, J., Dawson, E.: Heuristic Design of Cryptographically Strong Balanced Boolean Functions. EUROCRYPT 1998: pp. 489–499 (1998)