



Universiteit  
Leiden  
The Netherlands

# Practical Assignment Part I

Evolutionary Algorithms Course, LIACS, 2025-2026



Solving the F18 and F23 problems from the *Pseudo-Boolean Optimization* (PBO) problem set using Genetic Algorithms

# F18: Low Autocorrelation Binary Sequences (LABS)

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The Low Autocorrelation Binary Sequences (LABS) problem poses a non-linear objective function over a binary sequence space, with the goal to maximize the reciprocal of the sequence's autocorrelation:  $x \in \{0,1\}^n$

$$\text{LABS : } x \mapsto \frac{n^2}{2 \sum_{k=1}^{n-1} \left( \sum_{i=1}^{n-k} s_i s_{i+k} \right)^2}, \text{ where } s_i = 2x_i - 1.$$

1. Doerr, C., Ye, F., Horesh, N., Wang, H., Shir, O. M., & Bäck, T. (2019, July). Benchmarking discrete optimization heuristics with IOHprofiler. In *Proceedings of the Genetic and Evolutionary Computation Conference Companion* (pp. 1798-1806).
2. <https://iohprofiler.github.io/IOHproblem/PBO>

# Example Problem: LABS

- ▶ Low Autocorrelation of Binary Sequences
- ▶ Autocorrelation function on  $\{-1,1\}^n$
- ▶ Important applications
  - ▶ Telecommunications
  - ▶ Radar
  - ▶ Sonar
- ▶ Transformation of variables:
  - ▶  $\{0,1\} \rightarrow \{-1,1\}$

# The Objective Function

- ▶ Search space:  $\{0,1\}^n$
- ▶ Goal: Find  $\mathbf{x} \in \{0, 1\}^n$  such that

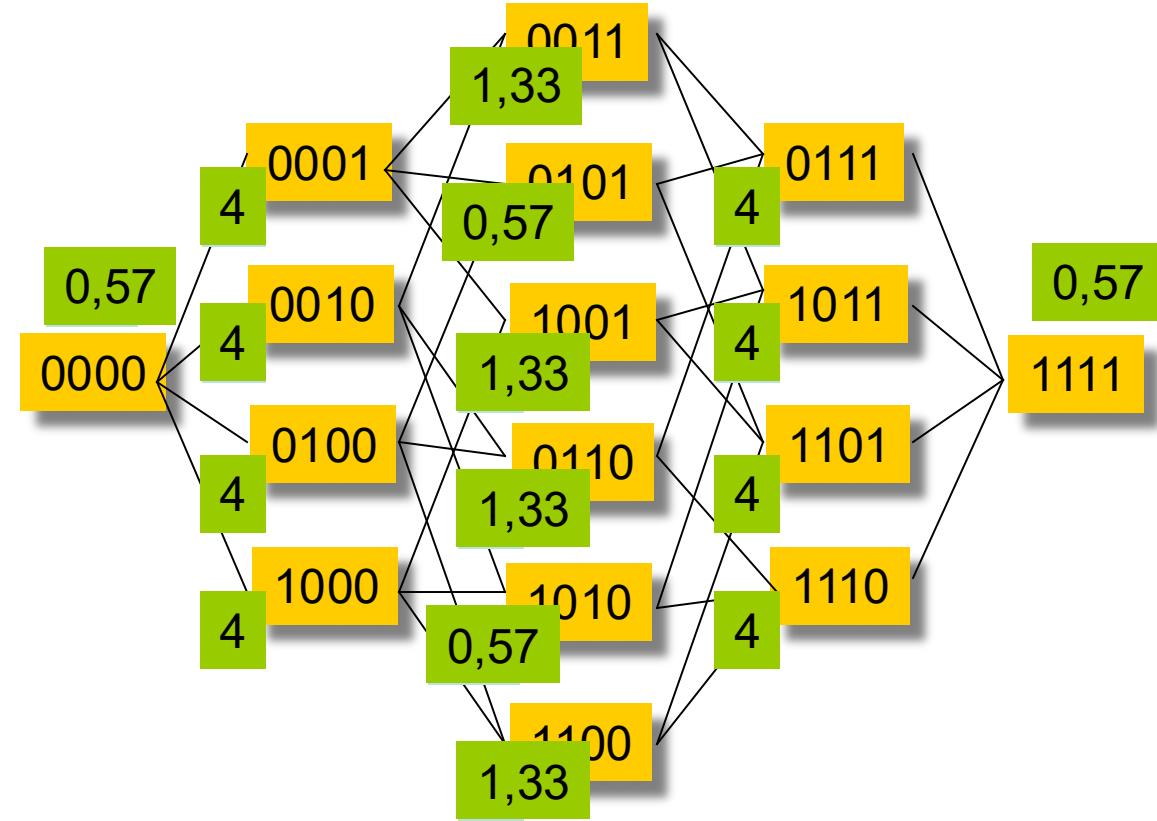
$$E(\mathbf{x}) = \sum_{k=1}^{n-1} \left( \sum_{i=1}^{n-k} y_i \cdot y_{i+k} \right)^2 \rightarrow \min$$

$$y_i = 2x_i - 1$$

- ▶ Alternative formulation (merit factor):

$$F(\mathbf{x}) = \frac{n^2}{2E(\mathbf{x})} \rightarrow \max$$

## Example: $n=4$



$$E(\mathbf{x}) = (y_1y_2 + y_2y_3 + y_3y_4)^2 + (y_1y_3 + y_2y_4)^2 + (y_1y_4)^2$$

# Some Values

- ▶ Theory indicates that

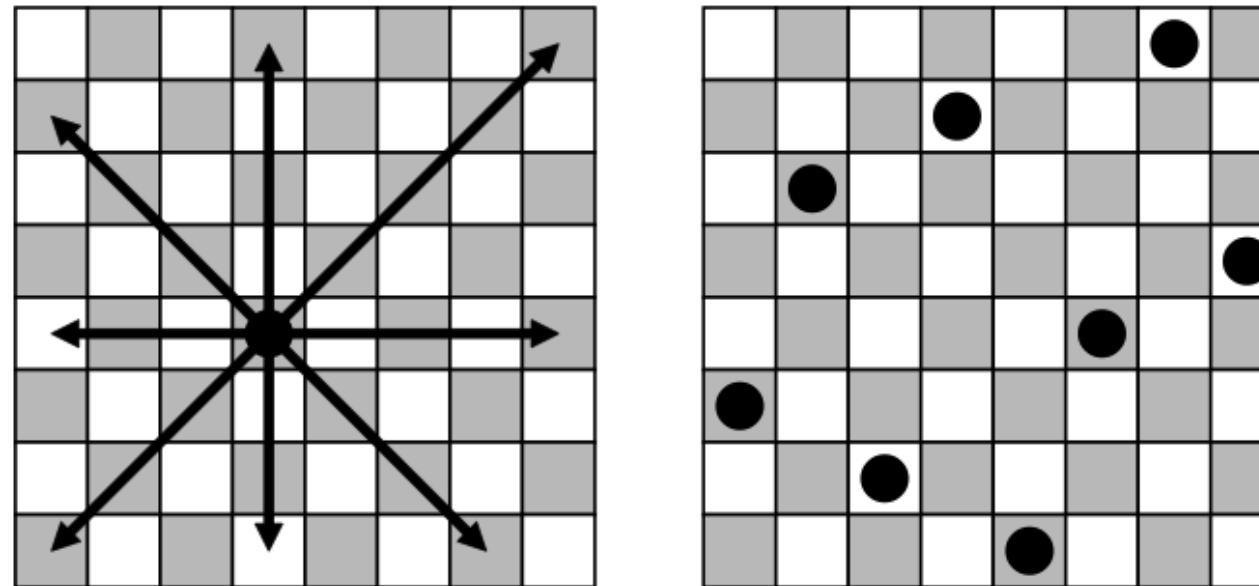
$$\lim_{n \rightarrow \infty} \arg \max F(\mathbf{x}) \approx 12.32$$

- ▶ See table for some known records
  - ▶ Values in bold are not confirmed to be best possible
  - ▶ Most optimizers get stuck around 7

n	Best value of f
20	7.6923
50	8.1699
100	<b>8.6505</b>
199	<b>7.5835</b>
200	<b>7.4738</b>
201	<b>7.5263</b>
202	<b>7.3787</b>
203	<b>7.5613</b>
219	<b>7.2122</b>
220	<b>7.0145</b>
221	<b>7.2207</b>
222	<b>7.0426</b>

# F23: N-Queens Problem

The N-queens problem (NQP) is defined as the task to place  $N$  queens on an  $N \times N$  chessboard in such a way that they cannot attack each other. The figure below provides an illustration for the 8-queens problem. Notably, the NQP is actually an instance of the MIVS problem- when considering a graph on which all possible queen-attacks are defined as edge.



1. Doerr, C., Ye, F., Horesh, N., Wang, H., Shir, O. M., & Bäck, T. (2019, July). Benchmarking discrete optimization heuristics with IOHprofiler. In *Proceedings of the Genetic and Evolutionary Computation Conference Companion* (pp. 1798-1806).
2. <https://iohprofiler.github.io/IOHproblem/PBO>

# Assignment Task

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- ▶ Work in a team of up to 2.
- ▶ Enrol in the same group with your teammate on Brightspace.
  
- ▶ You need to submit
  - ▶ Source code (Python) with the required format
    - Python template will be provided
    - We will run your code, so please make sure your program meets the requirements.
    - Please submit the version that is consistent with the result in your report.
  - ▶ A Scientific report
    - We provide the template.
    - Exercise for writing scientific articles.
  
- ▶ Practical Assignment:
  - ▶ PA deadline: Dec. 11, 23:59
  - ▶ Every week late: 0.5 pts grade degradation



## Requirements and Details

# Requirements

- ▶ Implement a Genetic Algorithm (GA) to solve the F18 and F23 problems.
- ▶ Tune the hyper-parameters of your own implementation with **100,000 function evaluations on both problems**
  - ▶ The hyperparameter setting determined by your tuning procedure has to work on both problems
  - ▶ Using different hyperparameter setting on each problem is NOT allowed
  - ▶ You can use ANY tuning methods for the hyperparameters; think about it
- ▶ Submit the code of GA, ‘*studentnumber1\_studentnumber2\_GA.py*’. For a group of three, ‘*studentnumber1\_studentnumber2\_studentnumber3\_GA.py*’.
- ▶ Submit the code for the tuning procedure, ‘*studentnumber1\_studentnumber2\_tuning.py*’. For a group of three, ‘*studentnumber1\_studentnumber2\_studentnumber3\_tuning.py*’.
  - ▶ The tuning code should make a function call to the GA implementation.

# Requirements

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- ▶ Additional files of other functions are allowed. However, we will only execute the GA and the tuning codes.
- ▶ Submit a report introducing your algorithms and presenting the experimental results. We will upload an example.
- ▶ Set a fixed random seed in the implementation to obtain the same results as those in the report by running the submitted codes.

# Tuning Hyperparameters

- ▶ Goal: we want to get good performance upon **5,000 function evaluations on each problem**.
- ▶ How we evaluate your algorithm: we will execute it for **20** independent runs and take an aggregated performance value.
- ▶ Now, I give you a much larger tuning budget, **100,000** function evaluations.
- ▶ You can use any tuning method you can find or come up with.
- ▶ The tuning method consumes maximally **100,000** function evaluations and outputs a hyperparameter setting, which makes the GA perform well on both problems with a budget of 5,000 function evaluations.

# Think about..

- ▶ Which variations (i.e., mutation and crossover) and selection operators will you use?
- ▶ How to encode/decode the phenotype of the N-Queens problem?
- ▶ How to tune the hyper-parameters (e.g., population size, mutation rate, etc.)?
- ▶ How do you allocate the tuning budget?
  - ▶ Remember we want to make the GA work well at a fixed budget of **5,000 function evaluations**.
  - ▶ GA is random... meaning one single run is not representative of the quality of a hyperparameter setting
  - ▶ How do I tune for two different problems at the same time?

# General Info

- ▶ How to evaluate your PA?
  - ▶ Following the guidelines (10%)
    - ▶ You will get a full score if you follow all the guidelines
  - ▶ Experimental Results (45%)
    - ▶ If your code reproduces the results in the report.
  - ▶ Report (45%)
    - ▶ Based on the presentation of the design of algorithms, experimental settings, and discussion about the results.
- ▶ Other:
  - ▶ Plagiarism check: if the report copies more than 30%, the PA grade is 0.
  - ▶ If the results in your report do not match the results we obtain from using your codes, the PA grade is 0.
  - ▶ If the results of your algorithms rank top 2 among all teams, you will get a 0.5 bonus for the **final grade**.