Implementation and comparison of local search algorithms applied to the eight queens puzzle

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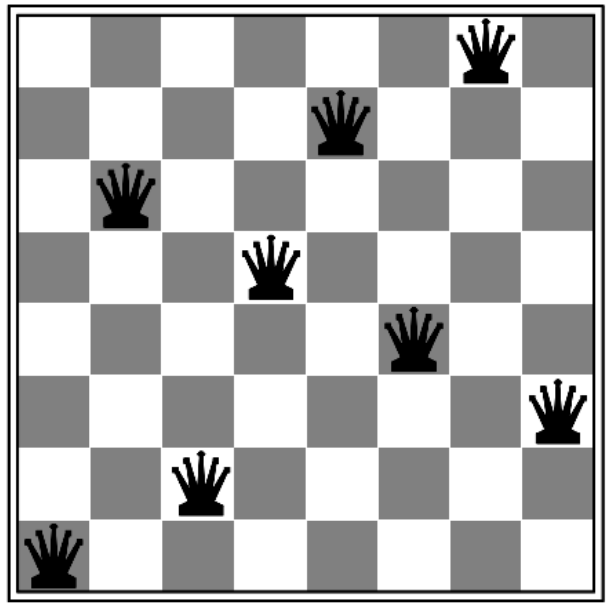
- How? Using Python for the implementation and "Artificial Intelligent: A Modern approach (third edition)" as a reference.
  - Code will be available on Github (on francespos account) after the exam.

The eight queens puzzle



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- We will use PEAS approach to describe the problem.

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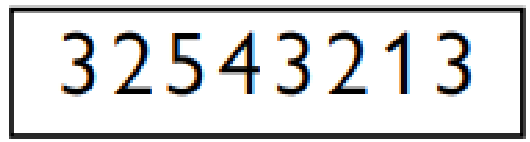

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- For each column c (i.e. position in the list), for each row r (i.e. value of an element in that position):
  - if queen in the column c is not in position r, an adjacent state is represent by the same list with the new element r in position c.

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  - Otherwise, a new iteration starts with the pair (state, value).

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- If temperature decreases slowly, for the Boltzmann distribution propriety, all probability is centered on global minimum with a limit value of 1.

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- The recombination procedure occurs by randomly selecting a crossover point, at which the parents are divided to form their children.

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- Space? $O(m)$. The current population is stored.