

## Wizards

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### Main Idea:

For our algorithm, we implemented a Simulated Annealing algorithm to conduct a partially-randomized local search of the solution space (orderings of wizards) for this problem. Simulated annealing is derived originally from the process of annealing in metallurgy, which is a technique involving heating and controlled cooling of materials to maximize the size of its crystals and reduce the amount of defects. Similarly, in Simulated Annealing we set a temperature variable  $T$  and slowly decrease it by a factor of  $\alpha$  (typically between 0.9 and 0.99) until we find an optimal solution. We chose this algorithm because it is a relatively efficient method of optimization that avoids the deceit of local optima. Each time the main function *anneal()* is called, the program first shuffles the ordering of the wizards. It then continuously samples *neighbor* orderings (possible solutions) that are neighbors of the current ordering, calculates the cost of each sample using the *cost(solution, constraints)* function, then accepts the sample (using it as the current potential solution) with probability given by *acceptance\_probability(old\_cost, new\_cost, T)*.

We define a *neighbor* of an ordering as the result produced by randomly moving one wizard in the ordering to a random position, we define the *cost* of a sample ordering as the number of constraints that it fails to satisfy, and we define the *acceptance\_probability* of an ordering as 1 if its cost is more optimal than the current ordering cost or as  $\text{math.exp}((\text{old\_cost} - \text{new\_cost}) / T)$ , where  $T$  is an exponentially-decreasing “temperature” value. Briefly, we move from one ordering to another random solution if it is more optimal, but also move to a less-optimal solution with exponentially-diminishing probability. Because our “temperature” strictly decreases, we will eventually accept fewer and fewer “worse” orderings and converge on an optimum (which is hopefully a global optimum). This allows the algorithm to both explore and exploit, with a slow convergence towards exploitation. Accuracy and runtime were most greatly affected by altering the values for  $\alpha$  and the number of iterations for the while loop. When  $\alpha$  approaches 1, the runtime increases significantly. Similarly, when the number of while loop iterations is increased, the runtime also increases greatly. When  $\alpha$  is closer to 0 and/or the number of while loop iterations is decreased, we observed that the runtime was faster but significantly less constraints were satisfied.

### Sources

1. The Simulated Annealing Algorithm by Katrina Ellison Geltman:  
<http://katrinaeg.com/simulated-annealing.html>
2. Simulated Annealing: <http://mathworld.wolfram.com/SimulatedAnnealing.html>
3. What is Simulated Annealing?:  
<https://www.mathworks.com/help/gads/what-is-simulated-annealing.html?requestedDomain=www.mathworks.com>
4. Simulated annealing: [https://en.wikipedia.org/wiki/Simulated\\_annealing](https://en.wikipedia.org/wiki/Simulated_annealing)