Simulated annealing

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- n-queens heuristics function
  - Also known-as the fast heuristic algo
  - Place queen in random position on the first row
    - For each subsequent row, place queen in.the column that minimizes the number of conflicts with existing queens
    - repeat until all N queens are on the board
  - Goal is zero attacks
  - Minimizing v. Maximizing the objective function
    - If you want to minimize f(x) and your optimizer program seeks to maximize the objective function then define g(x) = - f(x) and find max(g(x)) = max(-f(x) = min(f(x))
    - If your optimization problem needs to maximize f(x) and your optimizer program seeks to minimize the objective function, de fine g (x) = - f(x) and find min (g(x)) = max(f(x))
  - Do lots of random restarts, hill climb until we reach the local peak, teen take the max of allthe iterations
  - How do ya know it you have done enough examples?
    - Keep track of all the places on the graph you've been before and restart the sample whenever you see you've gotten to the same place - taboo search - its taboo to go to where you have been before
    - Keep list of all local maxima and try to predict where a new maximum might be given areas not yet explored - stage algorithm
  - With a large step size can miss hills entirely
    - The algorithm could get into an infinite loop and never terminate - algorithm can oscillate and not converge on an answer
    - If you see oscillation, do smaller steps
    - Can start with a large size step and decrease overtime to better ensure that we reach the global maximum - can get same result with simulated annealing

- Use idea of cooling and heating to help us get out of local minima and find global minimum
- High temperature equates to more randomness and gradual cooling will decrease randomness

- Simulated annealing
    - Select point near us randomly
    - If new position is better, we take it
    - However if the new position isn't better, we are still going to take it with a probability of-
    - When T → infinity (high), delta E over T goes to O
        - No matter what E is - even negative. Eo = 1
    - Local beam search:
        - Use particle-to represent a position - k-particles - at each time frame look at randomly generated neighbors of each of these particles and keep K- best ones for the next iteration
        - If any particles reach a goal you terminate
        - Different than random restart because we-are comparing all the neighbors of all the particles to each other. There is information being passed to each position -normal random restart doesn't share information between iterations.
        - Stochastic beam search - similar but successor particles are chosen not just based on their fitness but with some randomness that ensures we don't get stuck in a local maximum - related to simulated kneeling
        - This is a heuristic search algorithms that explores a graph by expanding the most optimistic nodein a limited set - optimization of best-first search that reduces its memory requirements
        - Builds a search tree
        - At each level of the tree it generates all successors of the states at the current level, sorting them in increasing order of heuristic cost.
        - Only stores a predetermined number of best states at each level called beam width- only these states are expanded next
    - Genetic algorithms:
        - Analogy to natural selection in biology-uses breeding and mutation to find the optimal answer to a problem