

Beyond Classical Search

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Outline

1 Local Search

- Hill Climbing
- Random Hill Climbing
- Local Beam Search

2 Advanced Search

- Continuous Search Spaces
- Partial Information
- Online Search

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Local Search

Sometimes only the goal matters (not the path)

- 8-Queens
- Bag Generation
- Job Scheduling

Iterative Improvement

Single *current* state, explores neighbors

Stops when

Goal reached / usually not

Optimal / usually not

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Optimal? *Usually not*

Complete? *Usually not*

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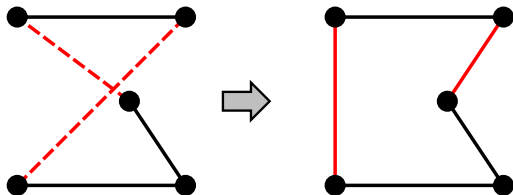
Example: Traveling Salesperson Problem

Problem

Visit all cities exactly once, minimum distance

Start A random complete tour

Move Swap a pair to reduce total distance



Achieves 1% of optimal with thousands of cities

Example: n -queens

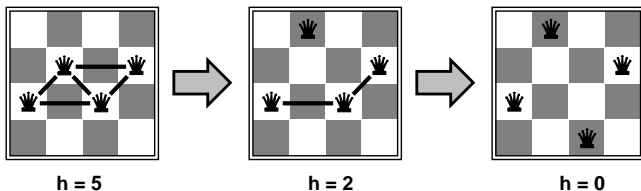
Problem

Put n queens on an $n \times n$ board

No two queens on the same row, column, or diagonal

Start All queens placed randomly

Move Move a queen to reduce conflicts

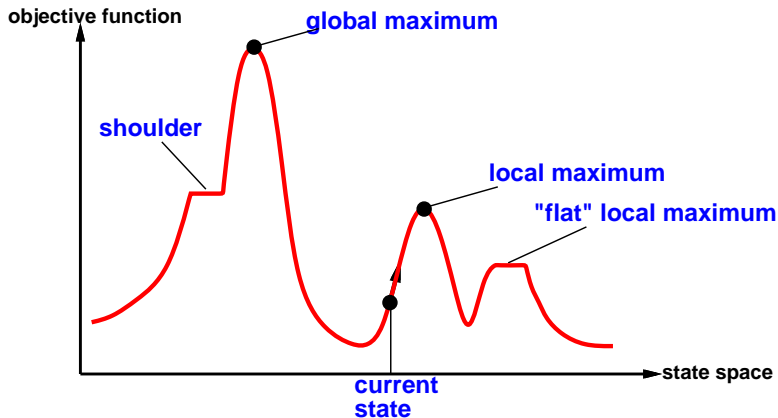


Can solve n -queens problems for, e.g. $n = 1$ million

Hill Climbing

```
def hill_climb(problem):  
  
    # start at the problem's initial state  
    current = Node(problem.get_random_complete_state())  
    while True:  
  
        # select the neighboring state with the best score  
        state_scores = []  
        for state, score in problem.get_neighbors(current.state):  
            state_scores.append((score, state))  
        best_score, best_state = max(state_scores)  
  
        # if no neighbors are better, return the current  
        if best_score <= current.score:  
            return current.state  
  
        # otherwise, move current to the best state  
        current = Node(best_state, best_score)
```

Hill Climbing



Un-Sticking Hill Climbing

Sideways Moves

Allow moving to neighbors as good as the current

Stochastic Hill Climbing

Choose randomly from *all* neighbors that improve score

Random Restart Hill Climbing

Generate a new initial state and try again *Complete*

Simulated Annealing

Some bad moves; gradually decrease size and frequency
of bad moves as temperature decreases

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Random Restart Hill Climbing

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Simulated Annealing

Some bad moves; gradually decrease size and frequency
Complete and Optimal if “gradual” enough

Simulated Annealing

```
def simulated_annealing(problem, get_temperature):
    current = Node(problem.get_random_complete_state())
    for time in itertools.count():

        # stop when the temperature reaches zero
        temperature = get_temperature(time)
        if temperature == 0:
            return current

        # select a random neighbor
        neighbors = problem.get_neighbors(current.state)
        state, score = random.choice(neighbors)

        # always move to the neighbor if it's better,
        # and sometimes if it's worse
        change = score - current.score
        prob = math.exp(change / temperature)
        if change > 0 or random.random() < prob:
            current = Node(state, score)
```

Local Beam Search

Idea

Keep k states instead of just one

vs. k Random Restarts

Local beam search goes deeper, where k random restarts goes shallow
Local beam search explores states more intelligently
Local beam search explores states more thoroughly

Variants

- Greedy k beam search
- Keep k random states, probabilities based on scores

Local Beam Search

Idea

Keep k states instead of just one

vs. k Random Restarts

One state has good neighbors, others have bad neighbors

Local Beam Search All searches share good neighbors

k Random Restarts Other searches use bad neighbors

Variants

1. Keep k best states

2. Keep k random states, probabilities based on scores

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Local Beam Search

```
def local_beam_search(problem, k):
    current = [Node(problem.get_random_complete_state())]
    while True:

        # get all neighbors of the current states
        state_scores = []
        for node in current:
            for state, score in problem.get_neighbors(node.state):

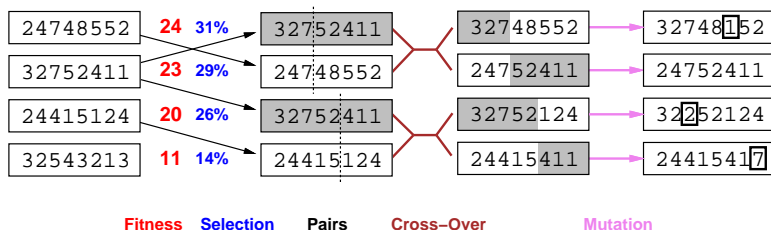
                # return the first goal state generated
                if problem.is_goal(state):
                    return state
                state_scores.append((score, state))

        # select the k best states to consider next time
        current = []
        for score, state in heapq.nlargest(k, state_scores):
            current.append(Node(state, score))
```

Genetic Algorithms

Idea

- Stochastic local beam search
- Successors generated from **pairs** of states

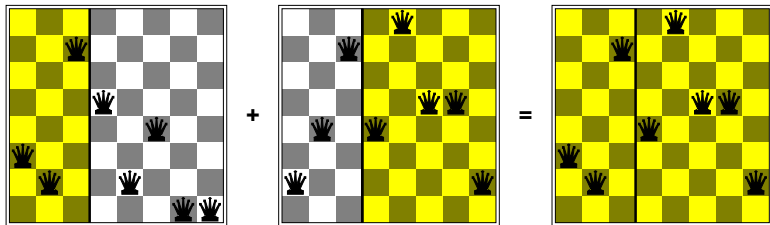


Genetic Algorithms

Requirements

- States must be encoded as strings
- Substrings must be meaningful components

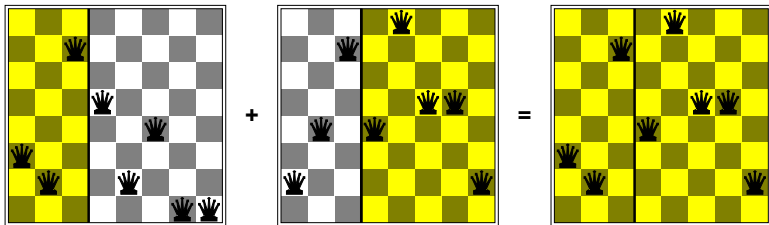
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Continuous Search Spaces

Problem

Place 3 airports in Romania, minimizing

$$\sum_{a \in \text{airports}} \sum_{c \in \text{cities}} (x_c - x_a)^2 + (y_c - y_a)^2$$

As a Search Problem?

Solutions

Discretize each action moves $\pm\delta$ in x or y direction

Gradient each action moves $\alpha \nabla f(x)$

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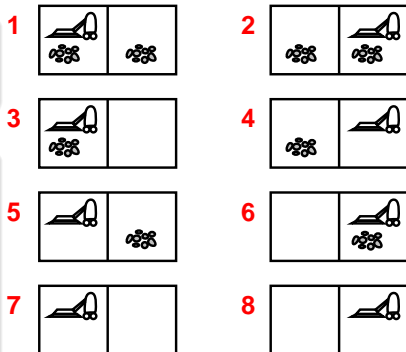
Searching with Partial Information

Problem

Start in **any state**

Solution?

Initial	(1, 2, 3, 4, 5, 6, 7, 8)
Right	(2, 4, 6, 8)
Suck	(4, 8)
Left	(3, 7)
Suck	(7)



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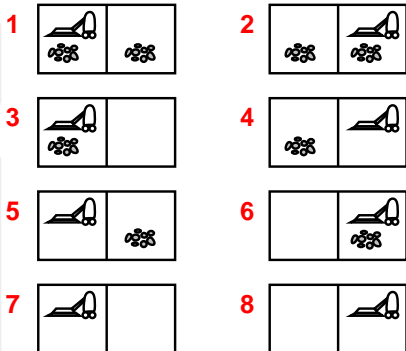
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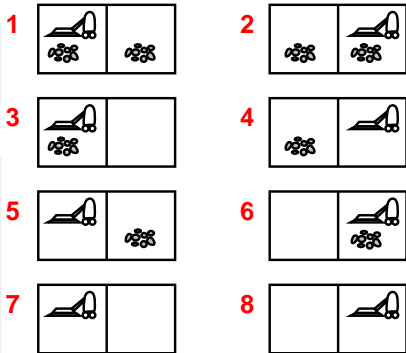
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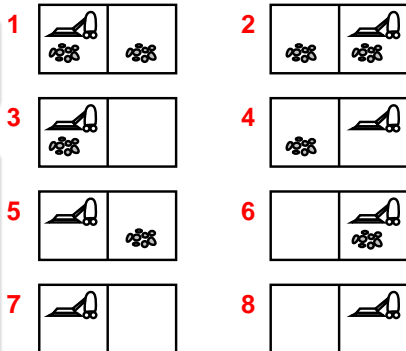
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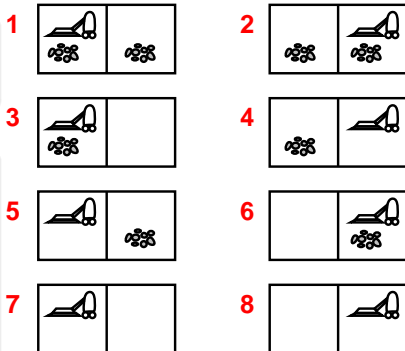
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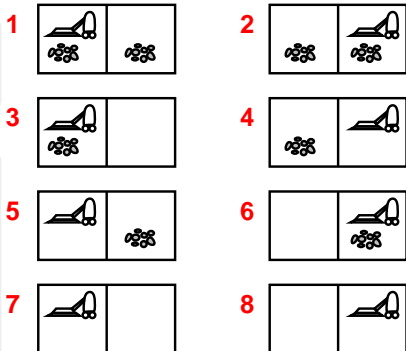
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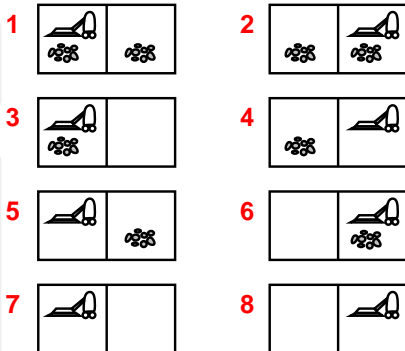
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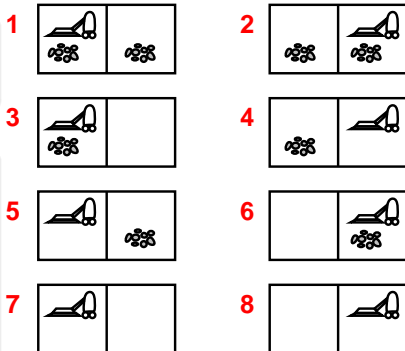
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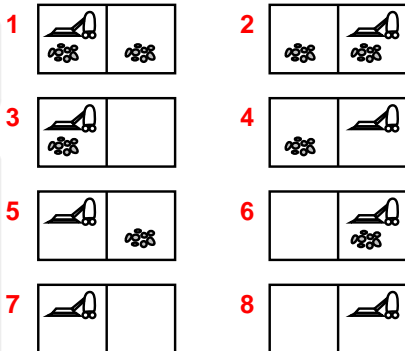
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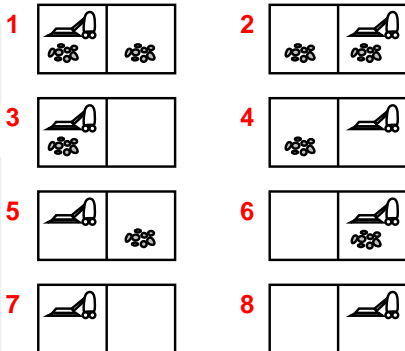
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Online Search

Problem

Successor function is not available until a state is visited,
e.g. robot exploration, maze problems

Solution: Learning Real-Time A*

Augment hill climbing with memory


$$h(x) = 2$$

Complete, efficient, safety-explores new states

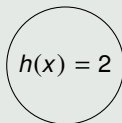
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Complete in finite, safely explorable environments

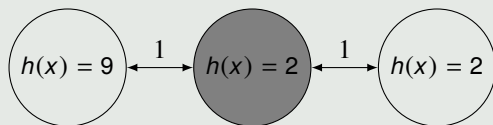
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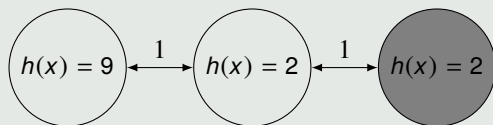
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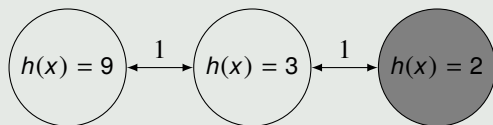
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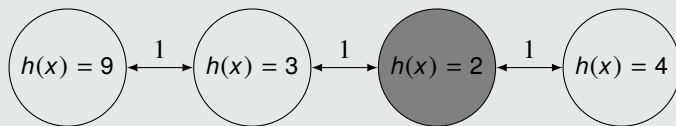
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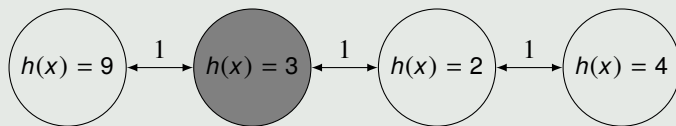
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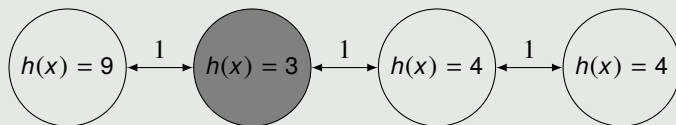
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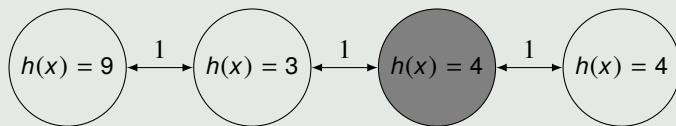
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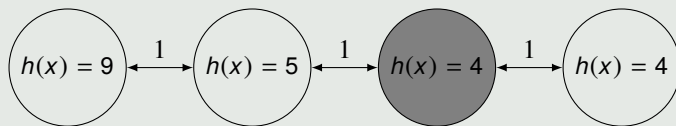
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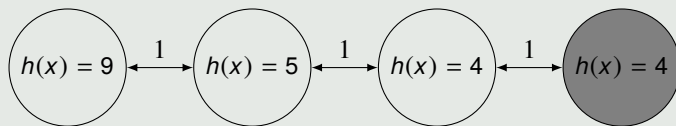
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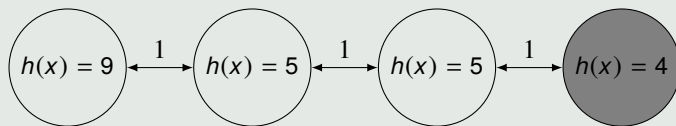
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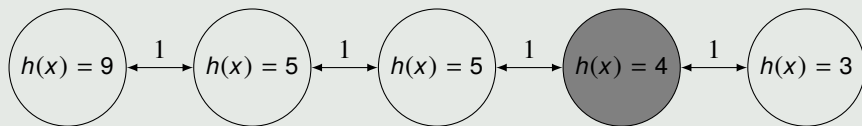
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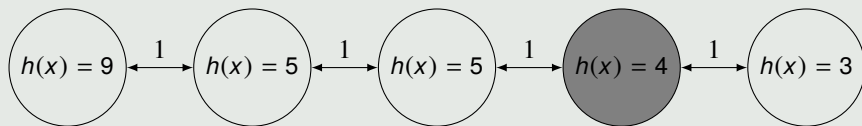
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Key Points

Search Algorithms

- Hill Climbing
- Simulated Annealing
- Local Beam Search
- Discretized Search
- Multiple-Belief State Search
- LRTA* Search