# CS540 Introduction to Artificial Intelligence Lecture 17

Young Wu
Based on lecture slides by Jerry Zhu, Yingyu Liang, and Charles

Dyer

July 10, 2020

## Traveling Salesperson Example

Motivation

### Search vs. Local Search

#### Motivation

- Some problems do not have an initial state and a goal state.
- Every state is a solution. Some states are better than others, defined by a cost function (sometimes called score function in this setting), f (s).
- The search strategy will go from state to state, but the path between states is not important.
- There are too many states to enumerate, so standard search through the state space methods are too expensive.

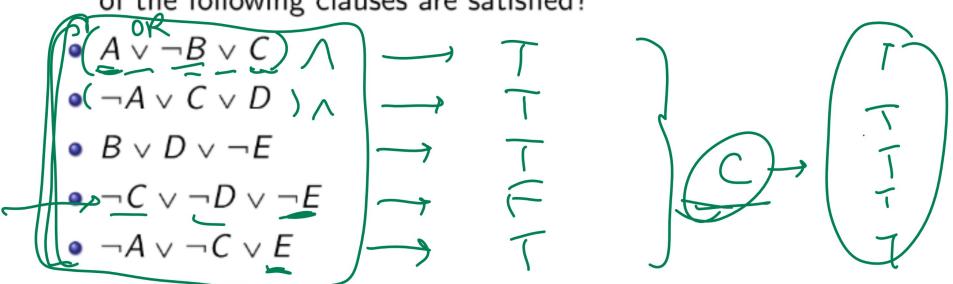
### Local Search

### Motivation

- Local search is about searching through a state space by iteratively improving the cost to find an optimal or near-optimal state.
- The successor states are called the neighbors (sometimes move set).
- The assumption is that similar (nearby) solutions have similar costs.

# Boolean Satisfiability Example 1

 Assume all variables A. B. C. D. E are set to True. How many of the following clauses are satisfied?



# Boolean Satisfiability Example 2

Assume all variables A, B, C, D, E are set to True. Which one
of the variables should changed to False to maximize the
number of clauses satisfied?

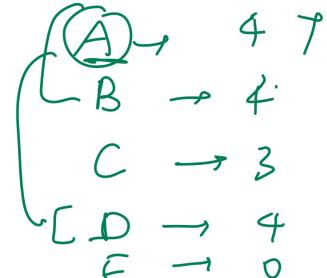
C 11.D

- $A \vee \neg B \vee C$
- $\bullet$   $\neg A \lor C \lor D$
- B ∨ D ∨ ¬E
- $\bullet$   $\neg C \lor \neg D \lor \neg E$
- $\bullet \neg A \lor \neg C \lor E$

# Boolean Satisfiability Example 3

Assume all variables A, B, C, D, E are set to True. Which one
of the variables should changed to False to maximize the
number of clauses satisfied?

•  $\neg A \lor \neg B \lor \neg C$ •  $\neg A \lor \neg B \lor \neg D$ •  $\neg A \lor \neg C \lor \neg D$ •  $\neg A \lor \neg B \lor \neg D$ •  $\neg A \lor \neg B \lor \neg D$ •  $\neg B \lor \neg C \lor \neg D$ 



# Hill Climbing (Valley Finding) Description

- Start at a random state.
- Move to the best neighbor state (one of the successors).
- Stop when all neighbors are worse than the current state.
- The idea is similar to gradient descent.

# Hill Climbing Algorithm

- Input: state space S and cost function f.
- Output:  $s^* \in S$  that minimizes f(s).
- Start at a random state s<sub>0</sub>.
- At iteration t, find the neighbor that minimizes f.

$$s_{t+1} = \arg\min_{s \in s'(s_t)} f(s)$$

Stop when none of the neighbors have a lower cost.

stop if 
$$f(s_{t+1}) \leq f(s_t)$$

### Random Restarts

Discussion

 A simple modification is picking random initial states multiple times and finding the best among the local minima.

## First Choice Hill Climbing

Discussion

- If there are too many neighbors, randomly generate neighbors until a better neighbor is found.
- This method is called first choice hill climbing.

## Simulated Annealing

### Description

- Each time, a random neighbor is generated.
- If the neighbor has a lower cost, move to the neighbor.
- If the neighbor has a higher cost, move to the neighbor with a small probability.
- Stop until bored.
- It is a version of Metropolis-Hastings Algorithm.

## Acceptance Probability

### Definition

- The probability of moving to a state with a higher cost should be small.
- Constant: p = 0.1
- ② Decreases with time:  $p = \frac{1}{t}$
- Oecreases with time and as the energy difference increases:

$$p = \exp\left(-\frac{|f(s') - f(s)|}{\text{Temp}(t)}\right)$$

 The algorithm corresponding to the third idea is called simulated annealing. Temp should be a decreasing in time (iteration number).

## **Temperature**

### Definition

 Temp represents temperature which decreases over time. For example, the temperature can change arithmetically or geometrically.

Temp 
$$(t + 1) = \max\{ \text{ Temp } (t) - 1, 1 \}$$
, Temp  $(0) = \text{ large}$   
Temp  $(t + 1) = 0.9$  Temp  $(t)$ , Temp  $(0) = \text{ large}$ 

- High temperature: almost always accept any s'.
- Low temperature: first choice hill climbing.

## Simulated Annealing

### Algorithm

- Input: state space S, temperature function Temp, and cost function f.
- Output:  $s^* \in S$  that minimizes f(s).
- Start at a random state s<sub>0</sub>.
- At iteration t, generate a random neighbor s', and update the state according to the following rule.

$$s_{t+1} = egin{cases} s' & ext{if } f\left(s'
ight) < f\left(s_{t}
ight) \\ s' & ext{with probability } \exp\left(-rac{\left|f\left(s'
ight) - f\left(s_{t}
ight)
ight|}{ ext{Temp }\left(t
ight)}
ight) \\ s_{t} & ext{otherwise} \end{cases}$$

## Simulated Annealing Performance

Discussion

- Use hill-climbing first.
- Neighborhood design is the most important.
- In theory, with infinitely slow cooling rate, SA finds global minimum with probability 1.

## Genetic Algorithm

### Description

- Start with a fixed population of initial states.
- Find the successors by:
- Cross over.
- Mutation.

## Reproduction Probability

### Definition

• Each state in the population has probability of reproduction proportional to the fitness. Fitness is the opposite of the cost: higher cost means lower fitness. Use F to denote the fitness function, for example,  $F(s) = \frac{1}{f(s)}$  is a valid fitness function.

$$p_i = \frac{F(s_i)}{\sum_{j=1}^{N} F(s_j)}, i = 1, 2, ..., N$$

 A pair of states are selected according to the reproduction probabilities (using CDF inversion).

# Cross Over

- The states need to be encoded by strings.
- Cross over means swapping substrings.
- For example, the children of 10101 and 01010 could be the same as the parents or one of the following variations.

```
(11010, 00101), (10010, 01101)
(10110, 01001), (10100, 01011)
```

# Mutation Definition

- The states need to be encoded by strings.
- Mutation means randomly updating substrings. Each character is changed with small probability q, called the mutation rate.
- For example, the mutated state from 000 could stay the same or be one of the following.

one of 001, 010, 100, with probability  $q (1-q)^2$  one of 011, 101, 110, with probability  $q^2 (1-q)$  and 111, with probability  $q^3$ 

# Cross Over, Modifications Definition

- The previous cross over method is called 1 point cross over.
- It is also possible to divide the string into N parts. The method is called N point cross over.
- It is also possible to choose each character from one of the parents randomly. The method is called uniform cross over.

# Mutation, Modifications Definition

- For specific problems, there are ways other than flipping bits to mutate a state.
- Two-swap: ABCDE to EBCDA
- Two-interchange: ABCDE to EDCBA

# Fitness Example 1

- Fall 1999 Final Q5
- Which ones (multiple) of the following states have the highest reproduction probability?
- The fitness function is  $f(x) = 5x_1 + 3x_2x_3 x_4 + 2x_5$ .

$$V$$
  $(1,1,0,1,1)$   $-1$   $(1,1,0,1,1)$   $-1$   $(1,1,0,1,1)$   $-1$   $(1,1,0,1,1)$   $-1$   $(1,1,0,1)$ 

- B: (0, 1, 1, 0, 1)
- C: (1, 1, 0, 0, 0)
- (1,0,1,1,1)
  - E: (1,0,0,0,0)

,0

## Fitness Example 2

 Which one of the following states have the highest reproduction probability? The fitness function is

$$f(x) = \min\{t \in \{1, 2, 3, 4, 5, 6\} : x_t = 1\} \text{ with } x_6 = 1.$$

• A: (0,0,1,0,0)

x3 and X1

- B: (0,1,0,0,1)
- B: (0,1,0,0,1)
  C: (0,0,1,1,0)
- D: (0,0,0,1,0)
- E: (0,0,0,0,0)

# Fitness Example 3

- Which one of the following states have the highest reproduction probability? The fitness function is
   f (x) = max{t ∈ {0,1,2,3,4,5} : x<sub>t</sub> = 1} with x<sub>0</sub> = 1.
- A: (0,0,1,0,0) -> 3
- B: (0,1,0,0,<u>1</u>)
- C: (0,0,1,1,0) ~ 4
- E:I(0,0,0,0,0)

## Genetic Algorithm, Part I

### Algorithm

- Input: state space S represented by strings s and cost function f or fitness function F.
- Output:  $s^* \in S$  that minimizes f(s).
- Randomly generate N solutions as the initial population.

$$s_1, s_2, ..., s_N$$

Compute the reproduction probability.

$$p_i = \frac{F(s_i)}{N}, i = 1, 2, ..., N$$
  
 $\sum_{j=1}^{N} F(s_j)$ 

## Genetic Algorithm, Part II

### Algorithm

• Randomly pick two states according to  $p_i$ , say  $s_a$ ,  $s_b$ . Randomly select a cross over point c, swap the strings.

$$s'_{a} = s_{a} [0...c) s_{b} [c...m]$$
  
 $s'_{b} = s_{b} [0...c) s_{a} [c...m]$ 

 Randomly mutate each position of each state s<sub>i</sub> with a small probability (mutation rate).

$$s_i'[k] = \begin{cases} s_i[k] & \text{with probability } 1-q \\ \text{random} & \text{with probability } q \end{cases}, k = 1, 2, ..., m$$

Repeat with population s'.



# Variations Discussion

- Parents can survive.
- Use ranking instead of F(s) to compute reproduction probabilities.
- Cross over random bits instead of chunks.

## Genetic Algorithm Performance

Discussion

- Use hill-climbing first.
- State design is the most important.
- In theory, cross over is much more efficient than mutation.