Week 3

Wednesday, June 24, 2020 6:05 PM

Optimization

Def:

Choosing the best option from a set of options

Local Search :

Search algorithms that maintain a single node and searches by moving to a neighboring node

Usage :

when we don't care about the path but what is the solution

- Think about the problem as a state-space landscape :
 - In which we try to find :
 - Global MAX using objective function
 - Global MIN using cost function
 - o Examples:
 - Hill climbing

Function Hill_Climb(problem):

- Current = initial state of the problem
- □ Repeat:
 - Neighbor = (lowest-highest) value of a neighbor of current
 - If neighbor not better than my current :
 - Return current
 - ◆ Current = neighbor
- In hill climbing we can get stuck at a local max or local min or a flat local max or shoulder That why we have variants

Hill Climbing Variants:

Steepest- ascent	choose the highest value neighbor
stochastic	choose randomly from higher value neighbors
First-choice	choose the first higher value neighbor
Random- restart	Conduct Hill Climbing multiple times
Local beam search	Choose k highest-valued neighbors

^{**} all these Variants does not move ever to a worse state from its current state

If you want that use simulated Annealing

Simulated Annealing

- Early on, higher "temperature" :
 - o More likely to accept neighbors that are worse than the current state
- Later on, lower "temperature" :
 - o Less likely to accept neighbors that are worse than the current state

Sude Code :

- Function Simulated_annealing(problem, max):
 - Current = initial state of problem
 - From t = 1 to max:
 - T = temperature(t)
 - Neighbor = random neighbor of current
 - ΔE = how much better neighbor is than current
 - If ΔE > :
 - Current = neighbor
 - Else:
 □ With probability of e^{ΔE/T} set current = neighbor
 - Return current

Linear Programming

Goal :

Minimize a cost function c₁x₁ + c₂x₂ + ...
 With constrains of form a₁x_{1+...} <= b
 Or of the form a₁x_{1+...} = b
 With bounds for each variable I_i <= X_i <= u_i

** we deal with < or = constrains so if we have > : We just use (-)

Examples for linear Programming Algorithms:

- Simplex
- Interior-Point

Constraint Satisfaction

We have some number of variables and every variable have a Value from a set of values And that value satisfy all the constrains

- Constraint Satisfaction Problem has : Set of variables {X₁, X₂,} Set of values for each variable {D₁, D₂,} Set of constraints C - Types of Constraints : Hard constraint : Constraint that must be satisfied in a correct solution Soft Constraints: • Constraint that express some notion of which solution is preferred over others - Classes of Constrains Unary Constraints : Constraint that only involve one variable o Binary Constraints: Constraint that involve two variables - Node Consistency: o All the values in a variable's domain satisfy all the variable **Unary Constraints** - Arc Consistency: AC-3 o All the values in a variable's domain satisfy all the variable binary Constraints Force Arc consistency over all the nodes o To make X arc-consistent with respect to Y: Sudo Code: Remove elements from X domain until: ☐ EVERY choice for X has a possible choice in Y - Function AC-3(cps): Queue = all arcs in csp O Sudo Code: While queue is not empty: (X, Y) = dequeue(queue) ■ Function Revise(csp, X, Y): If revise(csp, X, Y): Revised = false □ If X.domain == 0: □ For x in X.domain : • Return false

☐ For each Z in X.neighbors - {Y}:

Return true

■ Try least constraining value first

◆ Enqueue(queue, (Z, X))

Csp as a Search Problem

◆ If no y in Y.domsin satisfy Constants for(X, Y):

♦ Delete x from X.domain

♦ Revised = true

Consist of :

- Initial state:
 - empty assignment (no variable)

□ Return revised

- Action :
 - o add a (variable = value) to the assignment
- Transition Model
 - show how adding an action change the assignment
- Goal test:
- Check if all the variables are assigned and all the constraints are satisfied
 Path cost function :

Every time we make a new assignment

- Path cost function :
 - o All paths have some cost !! (doesn't really matter)
- * The search Algorithm used in **CSP is** : **BACKTRACIKNG**

Backtracking Search:

- SUDO CODE :
- Heuristics to use to improve the efficiency of the search - Function Backtrack(assignment, csp): process: if assignment is complete: Return assignment >- Select_unsigned_variable(assignment, csp): Var = Select_Unassigned_Var(assignment, csp) We can use: For value in Domain_values(var, assignment, csp)
 If value is consistent with assignment: Minimum remaining values (MRV) heuristic: ☐ Choose the variable with the smallest Add {var = value} to the assignment domain Result = Backtrack(assignment, csp) degree heuristic: If result is not failure: Choose the variable that has the highest • Return result degree Remove {var = value} from assignment Return failure - Domain values(var, assignment, csp): o Least constraining value heuristic: We can improve this by: Return values order by: - USING Maintaining arc-consistency WHICH IS: □ The number of choice that are removed from the neighbors domains by it Algorithm for enforcing arc-consistency

- USING Maintaining arc-consistency WHICH IS:
 - Algorithm for enforcing arc-consistency Every time we make a new assignment

 - **When we make a new assignment to X :
 Call AC-3 with a queue of all arc (Y, X)
 Y: is a neighbor of X

 - □ SUDO CODE SAME AS BACKTRACK WITH:
 - ◆ AFTER: add {var = value} to assignment
 - Inference = inference(assignment, csp)
 - ◆ If inference != failure :
 - ♦ ADD INFERENCE TO ASSIGNMENT
 - ◆ AND CONTINE BAACKTRACK CODE ...

- $\hfill\Box$ The number of choice that are removed from the neighbors domains by it
- Try least constraining value first