

Set-based Search Example: Genetic Algorithms

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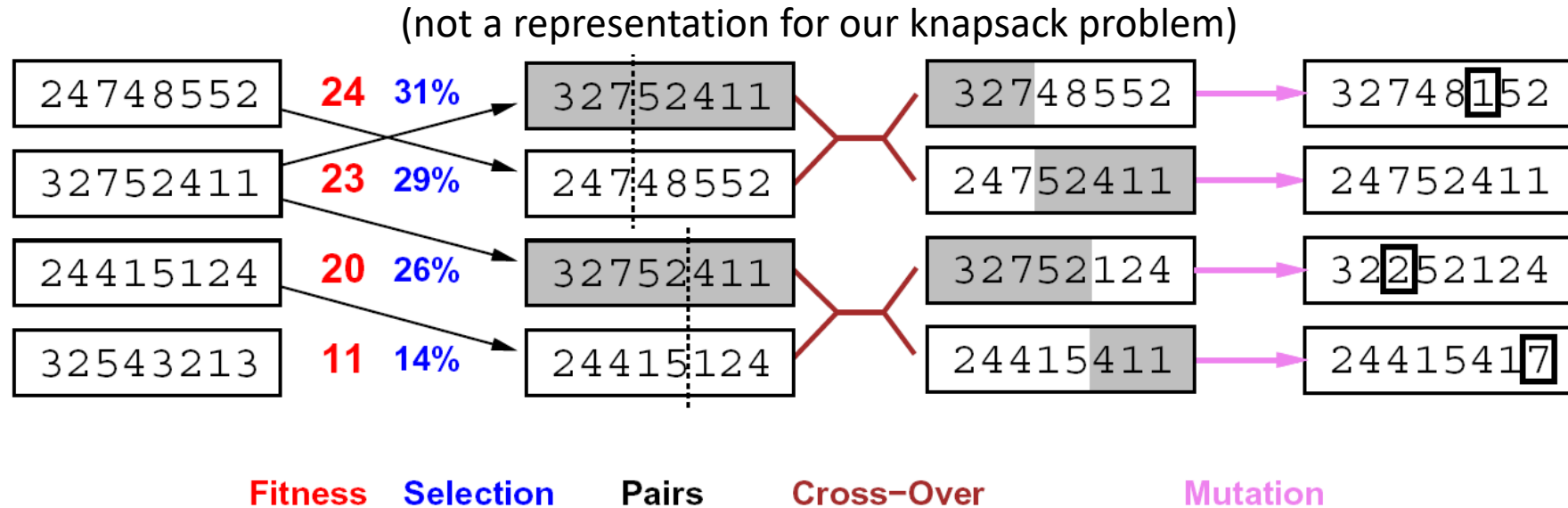
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Genetic Algorithms

Genetic Algorithms



- Genetic algorithms use a natural selection metaphor
 - Keep best N hypotheses at each step (selection) based on a fitness function
 - Also have pairwise crossover operators, with optional mutation to give variety
- Possibly the most misunderstood, misapplied (and even maligned) technique around

Encoding

- (could be used for knapsack as alternatives to our Extension rules)
GA Operators Brief Introduction

Mutation

Randomly chosen positions
↓ ↓ ↓
Parent: 1010001110
Offspring: 1000011010

Crossover

Randomly chosen position
↓ ↓
Parents: 1010001110 0011010010
Offspring: 0101010010 0011001110

Knapsack Problem

Knapsack Problem

- Problem: Filling a knapsack with fixed capacity with items. Each item has a given weight and value to you. (0/1 Knapsack Problem)
- We have items I we will index from 1 to n
 - We have associated weights W and values V
 - $W = (w_1, \dots, w_n), w_i > 0$
 - $V = (v_1, \dots, v_n), v_i > 0$
 - To simplify each $item_i \in I$ can be considered as a pair $item_i = (w_i, v_i)$
 - We have a max capacity of C
- What ways can we do this?
 - Hill climbing? Dynamic programming? Set-based search?

Knapsack Solutions

- Hill climbing
 - Estimation (just add best ratio of value to weight of things until you run out of space), quick, low memory, simple
 - Greedy algorithm (*413*)
 - Could be done via a set-based search
- Dynamic Programming (DP):
 - ***413***, Exact algorithm (optimal solution for sure), Long running time as problem grows, lots of memory to store sub-problem expansions, very simple to design, $O(n^2)$ time and $O(n)$ space if we treat every item as unique

Knapsack Solutions

- Genetic Algorithm (GA):
 - Estimation, never know if you found the best solution
 - Runs quickly as the problem explodes in complexity
 - memory usage rather small with basic implementation
 - quality can be highly variable with no guarantees
 - harder to design unless you know GAs

Examples

Example problem with hill climb

- We have a 1-0 knapsack with maximum capacity of 7. We have the set of items $I = \{(3,4), (4,5), (5,7)\}$ where every item is a pair such that $i = (\text{weight}, \text{value})$.
- Hill climb – get a ratio of each item, sort by descending ratio, add each item that you can.

Ratio (w/v)	Weight (w)	Value (v)	Knapsack W	Include?
0.8	4	5	$0 + 4 = 4$	Yes (val=5)
0.75	3	4	$4 + 3 = 7$	Yes (val=9)
0.72~	5	7	$7 + 5 = 12$	No, max reached

- This is best solution....for this instance of problem.
- Hill-climbing uses flawed heuristic.

Example problem with hill climb

- Estimation can cause problems.
- Add item (1,1).
- We have a 1-0 knapsack with maximum capacity of 7. We have the set of items $I = \{(1,1), (3,4), (4,5), (5,7)\}$

Ratio (w/v)	Weight (w)	Value (v)	Knapsack W	Include?
1	1	1	$0 + 1 = 1$	Yes (val=1)
0.8	4	5	$1 + 4 = 5$	Yes (val=6)
0.75	3	4	$5 + 3 = 8$	No, max reached

- $\{(1,1), \{4,5\}\}$ has value 6 but there is a solution value 9 with $\{(3,4), (4,5)\}$!

Example problem with hill climb

- We have a 1-0 knapsack with maximum capacity of 7. We have the set of items $I = \{(3,4), (4,5), (5,7)\}$ where every item is a pair such that $i = (\text{weight}, \text{value})$.
- Is the problem the ratio direction?

Ratio (v/w)	Weight (w)	Value (v)	Knapsack W	Include?
1.4	5	7	$0 + 5 = 5$	Yes (val=5)
1.333...	3	4	$5 + 3 = 8$	No, max reached

- No.
- An inverted ratio would also lead to sub-optimal solution $\{(5,7)\}$ which has value 5 but there is a solution value 9 with $\{(3,4), (4,5)\}$!

Example problem with dynamic programming

- We have a 1-0 knapsack with maximum capacity of 7 and a set of items $I = \{(1,1), (3,4), (4,5), (5,7)\}$, s.t. item = (weight, value)

Item value	Item weight	0	1	2	3	4	5	6	7
1	1	0	1	1	1	1	1	1	1
4	3	0	1	1	4	5	5	5	5
5	4	0	1	1	4	5	6	6	9
7	5	0	1	1	4	5	7	8	9

i

j

- ▶ Start from 0 and fill in the table, for each row in order add column first. Knapsack limit (top row) will be called i , current item will be j .
 - ▶ If $\text{weight}(j)$ is bigger than i , write value at $T[j-1][i]$,
 - ▶ Else select the maximum($\text{value}(j) + \text{value at } T[j-1][i - \text{weight}(j)]$, $T[j-1][i]$)
- ▶ Maximum value will be at the lowest row, on the last index. (9 in this case)

GA Solution

What do we need to design set-based solution?

- Facts
- Extension Rules
- Search Control Direction (the choice of extension rules)
- Search Instance

What do we need to design set-based solution?

Want Model A_{set}

- Facts
 - Parts that will fill our state set
 1. Parts of a single solution (like in resolution)
 2. Different possible full solutions (like in genetic/evolutionary algorithms)
 - We get for free $S_{set} \subseteq 2^F$ (also know as the power set of F -> all subsets of F)
- Extension Rules

What do we need to design set-based solution?

Want Model A_{set}

- Facts (S_{set})
- Extension Rules
 - How we move between subsets of facts
 - If we are in some state s and moving to s' , both are subsets of F
 - We take some subset A of facts from s and replace with another subset of facts B
 - Extension rules are how the B is determined based on which A is used
 - $Ext \subseteq \{A \rightarrow B \mid A, B \subseteq F\}$
 - We get for free $T_{set} = \{(s, s') \mid \exists A \rightarrow B \text{ with } A \subseteq s \text{ and } s' = (s - A) \cup B\}$

What do we need to design set-based solution?

Have $A_{set} = (S_{set}, T_{set})$

- Facts (S_{set})
- Extension Rules (T_{set})

Want K_{set} to complete $P_{set} = (A_{set}, Env, K_{set})$

- Search Control Direction (the choice of extension rules)
 - $K_{set}(s, e) = (s - A) \cup B$
 - f_{wert}, f_{select} deal with choosing the $A \rightarrow B \in Ext$
 - f_{wert} gives a value to each extension rule in current state
 - f_{select} chooses between ties
- Search Instance

What do we need to design set-based solution?

Have $A_{set} = (S_{set}, T_{set})$

- Facts (S_{set})
- Extension Rules (T_{set})

Have K_{set} to complete $P_{set} = (A_{set}, Env, K_{set})$

- Search Control Direction (the choice of extension rules) (K_{set})

Want where to start

- Search Instance
 - Some initial set of facts $s_0 \in S_{set}$, and a goal G to decide when done (ex. time passing, quality of set of facts stops improving, no more extension rules apply [i.e. resolution])

Facts

What do we need to design evolutionary algorithm solution to 0/1 knapsack?

- Facts

- We will deal with facts that are possible full solutions to the problem
 - That is each fact is some selection of items below the capacity C
 - (this is our choice, we could allow invalid solutions (too high capacity) as an alternative)
- $F = \{(x_1, \dots, x_m) \mid x_i \in \{0,1\} \text{ and } \sum_{i=1..m} w_i * x_i \leq C\}$
 - We have chosen to presume some consistent ordering of the available items in set I

What do we need to design evolutionary algorithm solution to 0/1 knapsack?

- Facts

- If $I = \{item_1, item_2, item_3\} = \{(3,4), (4,5), (5,7)\}$
- Then a $f \in F$ could be $f = (1,1,0)$ which would mean choosing $item_1 = (3,4)$ and $item_2 = (4,5)$ but not the first item $f = (0,1,1)$ would not be valid fact as it is over capacity

Extension Rules

What do we need to design evolutionary algorithm solution to 0/1 knapsack?

- Extension Rules

- Extension rules create new solutions from some subset of solutions
- We use two biologically inspired rules (mutation, crossover)
- $Ext = \{A \rightarrow B \mid A, B \subseteq F \text{ and } (Mutation(A, B) \text{ or } Crossover(A, B))\}$

Mutation

Mutation

- $Mutation(A, B)$
 - $A = \{(x_1, \dots, x_m)\}$
 - $B = \{(x_1, \dots, x_m), (y_1, \dots, y_m)\}$
 - where
 - $x_1 = y_1$ except for some $1 \leq i \leq m$ we will make $y_i = \neg x_i$
 - We will flip one 0 to 1, or vice versa to add or remove an item from new knapsack solution
- Also known as single-point mutation

Mutation Example

- $Mutation(A, B)$
- If $I = \{item_1, item_2, item_3\} = \{(3,4), (4,5), (5,7)\}$
 $C = 7$

$$A = \{(0,1,0)\}$$
$$B = \{(0,1,0), (1,1,0)\}$$

Or even

$$B = \{(0,1,0), (0,0,0)\}$$

Crossover

Crossover

- *Crossover*(A, B)
 - $A = \{(x_1, \dots, x_m), (y_1, \dots, y_m)\}$
 - $B = \{(x_1, \dots, x_m), (y_1, \dots, y_m), (z_1, \dots, z_m)\}$
 - where
 - Each z_i is selected by flipping a coin and selecting either x_i or y_i

Crossover Example

- $Crossover(A, B)$

- If $I = \{item_1, item_2, item_3\} = \{(3,4), (4,5), (5,7)\}$
 $C = 7$

$$A = \{(0,1,0), (1,0,0)\}$$
$$B = \{(0,1,0), (1,0,0), (1,1,0)\}$$

Or even one of the following

$$B = \{(0,1,0), (1,0,0), (0,0,0)\}$$
$$B = \{(0,1,0), (1,0,0), (1,0,0)\}$$
$$B = \{(0,1,0), (1,0,0), (0,1,0)\}$$

Search Control

What do we need to design evolutionary algorithm solution to 0/1 knapsack?

- Search Control Direction (the choice of extension rules)
 - RNG function to produce values
 - f_{wert} set to constant
 - f_{select} technically has all rules possible
 - We will choose to define it procedurally
 - f_{select} will pick mutation $x\%$ of time, mutation $y\%$ of time
 - $x+y = 100\%$
 - f_{select} also picks which individuals A are used by Mut/Cross to produce B
 - Fitness-based (value individuals by quality of solution (i.e. total value of items) and bias selection of A towards more fit individuals)

Search Instance

What do we need to design evolutionary algorithm solution to 0/1 knapsack?

- Search Instance
 - A generated set of random individuals (valid knapsack solutions) of some chosen population size (size of s_0)
 - For each random individual
 - select random knapsack items to add until capacity is reached
- Goal function
 - Time-based?
 - Run for x minutes of real-world time
 - Counter-based?
 - Make x new solutions
 - Improvement-based?
 - Run until we aren't finding better solutions often enough
 - Often involves predicting a log curve of improvement and stopping when it flattens too much

Remarks

Considerations

- Do you always select the single top fittest individual?
 - Rank-based selection (odds based on fitness order)
 - Roulette wheel selection (odds based on fitness portion of total)
- How do you manage the growing population?
 - Do you delete one/multiple each time
 - Who do you delete
- What about diversity?
 - What if population stagnates, can you enforce valuable diversity?
- What about invalid solutions?
 - Do you define F to allow invalid facts (can move through invalid fact to better valid ones), or do you disallow valid facts but possibly make it harder to move around search space

Onward to ... and-tree-based search

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