

Supplemental lecture 3

Greedy AlgorithmsEx. Continuous Knapsack

As before

$$(1) \text{ maximize } \sum_{i=1}^n x_i v_i$$

$$(2) \text{ Subject to } \sum_{i=1}^n x_i w_i \leq W$$

where $W > 0$, $v_i > 0$, $w_i > 0$ ($1 \leq i \leq n$)However, instead of $x_i \in \{0, 1\}$ we allow

$$0 \leq x_i \leq 1 \text{ for } 1 \leq i \leq n.$$

we call a vector $x = (x_1, \dots, x_n)$ a feasible solution iff (2) is satisfied.

A Greedy strategy consists of making some 'locally optimal' choice for an object, then solving resulting subproblem.

This means 'steal the best object', then the 'next best', etc.

see pseudo-code

Knapsack (v, w, W)

1.) $n \leftarrow \text{length}[v]$

2.) for $i \leftarrow 1$ to n

3.) $x[i] \leftarrow 0$

4.) $\text{weight} \leftarrow 0$

5.) while $\text{weight} < W$

* 6.) $i \leftarrow$ the "BEST" REMAINING OBJECT

7.) if $\text{weight} + w[i] \leq W$

8.) $x[i] \leftarrow 1$

9.) $\text{weight} \leftarrow \text{weight} + w[i]$

10.) mark i as included.

11.) else

12.) $x[i] \leftarrow \frac{W - \text{weight}}{w[i]}$

13.) $\text{weight} \leftarrow W$

14.) return x

GREEDY
LOOP

THE "BEST" OBJECT IN (6) CAN BE INTERPRETED IN SEVERAL WAYS.

IN GENERAL WE DEFINE A SELECTION FUNCTION $f(i)$ WHICH ENCODES THE DESIRABILITY OF OBJECT i . LINE (6) THEN MAXIMIZES f OVER ALL REMAINING (UNMARKED) OBJECTS.

To define the 'best' object,
we choose a selection function
 $f(i)$, and maximize it.

Possible choices for $f(i)$:

- $f(i) = v_i$: Process objects in order of decreasing v_i .
- $f(i) = \frac{1}{w_i}$: Process obj in order of increasing weight.
- $f(i) = \frac{v_i}{w_i}$: Process objects in order of decreasing value to weight ratio.

Ex. $n = 5, W = 10$

i	1	2	3	4	5
v_i	2	3	6.6	4	5
w_i	1	2	3	4	5
$\frac{v_i}{w_i}$	2	1.5	2.2	1	1.2

$f(i)$	x					val
v_i	0	0	1	.5	1	14.6
$\frac{1}{w_i}$	1	1	1	1	0	15.6
$\frac{v_i}{w_i}$	1	1	1	0	.8	16.4

Theorem

If we maximize $\frac{v_i}{w_i}$ on line (6), then Knapsack(1) returns an optimal solution.

Proof.

without loss of generality, Assume the objects are already sorted

$$\frac{v_1}{w_1} \geq \frac{v_2}{w_2} \geq \frac{v_3}{w_3} \geq \dots \geq \frac{v_n}{w_n}$$

Let $x = (x_1, x_2, \dots, x_n)$ be the solution returned by Knapsack(1).

If all $x_i = 1$, then x is clearly optimal.

Assume not all $x_i = 1$.

□

Let j be the first index for which $x_j < 1$. Inspecting the algorithm, we see that

$$x_i = 1 \quad \text{for } 1 \leq i < j$$

$$x_j < 1$$

$$x_i = 0 \quad \text{for } j < i \leq n$$

Also

$$\sum_{i=1}^n x_i w_i = W.$$

Let $\gamma = (\gamma_1, \gamma_2, \dots, \gamma_n)$ be any feasible solution, i.e.

$$\sum_{i=1}^n \gamma_i w_i \leq W.$$

Define

$$V(y) = \sum_{i=1}^n y_i v_i$$

and $V(x) = \sum_{i=0}^n x_i v_i$

we must show that $V(x) \geq V(y)$.

note:

$$\begin{aligned} \sum_{i=1}^n (x_i - y_i) w_i &= \sum_{i=1}^n x_i w_i - \sum_{i=1}^n y_i w_i \\ &= W - \sum_{i=1}^n y_i w_i \geq 0 \end{aligned}$$

$\Rightarrow$

$$\begin{aligned} V(x) - V(y) &= \sum_{i=1}^n (x_i - y_i) v_i \\ &= \sum_{i=1}^n (x_i - y_i) w_i \cdot \left(\frac{v_i}{w_i} \right) \end{aligned}$$

observe that

$$\bullet \quad i < j \Rightarrow x_i = 1 \Rightarrow x_i - y_i \geq 0 \quad \& \quad \frac{v_i}{w_i} \geq \frac{v_j}{w_j}$$

$$\therefore (x_i - y_i) \frac{v_i}{w_i} \geq (x_i - y_i) \frac{v_j}{w_j}$$

$$\bullet \quad i > j \Rightarrow x_i = 0 \Rightarrow x_i - y_i \leq 0 \quad \& \quad \frac{v_i}{w_i} \leq \frac{v_j}{w_j}$$

$$\therefore (x_i - y_i) \frac{v_i}{w_i} \geq (x_i - y_i) \frac{v_j}{w_j}$$

$$\bullet \quad i = j \Rightarrow (x_i - y_i) \frac{v_i}{w_i} = (x_i - y_i) \frac{v_j}{w_j}$$

In all cases therefore :

$$(x_i - y_i) \frac{v_i}{w_i} \geq (x_i - y_i) \frac{v_j}{w_j}$$

Hence

$$V(x) - V(y) = \sum_{i=1}^n (x_i - y_i) w_i \cdot \frac{v_i}{w_i}$$

$$\geq \sum_{i=1}^n (x_i - y_i) w_i \cdot \left(\frac{v_j}{w_j} \right)$$

$$= \left(\frac{v_j}{w_j} \right) \cdot \sum_{i=1}^n (x_i - y_i) w_i$$

$$\geq 0$$

$\therefore V(x) \geq V(y)$, as required. ~~■~~

Examining algorithm, we see its runtime is $\Theta(n \log n)$.

The Dynamic Programming Soln to 0-1 Knapsack cost $\Theta(n \cdot W)$, if $W = \Theta(n)$, then this is $\Theta(n^2)$

Idea: modify Knapsack() to work on the discrete version. If you can't steal all of next best object, skip it and go to the next one.

Ex. Same weights & value, But 0-1 Problem.

$$n=5, W=10$$

i	1	2	3	4	5
v_i	2	3	6.6	4	6
w_i	1	2	3	4	5
$\frac{v_i}{w_i}$	2	1.5	2.2	1	1.2

modified greedy solution

$$x = (1, 1, 1, 1, 0) \quad \left\{ \begin{array}{l} \text{Value} = 15.6 \\ \text{Weight} = 10 \end{array} \right.$$

Exercise Check that dynamic programming gives same solution.

Ex. $n=5, W=11$

i	1	2	3	4	5
v_i	1	6	18	22	28
w_i	1	2	5	6	7
$\frac{v_i}{w_i}$	1	3	3.6	3.67	4

modified greedy solution :

$$x = (1, 1, 0, 0, 1) \left\{ \begin{array}{l} \text{Value} = 35 \\ \text{Weight} = 10 \end{array} \right.$$

Exercise

check that dynamic programming yields

$$x = (0, 0, 1, 1, 0) \left\{ \begin{array}{l} \text{Value} = 40 \\ \text{Weight} = 11 \end{array} \right.$$

Coin Changing Problem

As before have denominations

$$d = (d_1, d_2, \dots, d_n)$$

and an amount N to be paid.

Goal: use fewest # of coins.

Greedy strategy:

- from amongst all denominations whose addition to the sum to exceed N , choose the largest.
- stop when sum is N .

Assume $d_1 = 1$ so we can pay any amount N .

Exercise (hard) :

show that for $d = (1, 5, 10, 25, 100)$,
the g -greedy strategy yields an optimal
solution for any $N \geq 0$.

Exercise (easy) :

show that for $d = (1, 10, 25, 100)$
the g -greedy strategy does not
always yield an opt. soln.

(Hint: $N = 30$).

Exercise.

let $b \in \mathbb{Z}^+$, $b \geq 2$, $d_i = b^{i-1}$ ($1 \leq i \leq n$),
so that $d = (1, b, b^2, \dots, b^{n-1})$.

show that the greedy strategy
does give an opt soln for all $N \geq 0$.

Exercise (very hard)

characterize all denomination sets $d = (d_1, d_2, \dots, d_n)$ for which the greedy strategy always yields an optimal solution, for all $N \geq 0$.

In general: the ingredients to look for in an opt. problem to determine if a greedy strategy works are:

- optimal substructure:
optimal solutions contain optimal sub-instance solutions.
- greedy choice Property:
a globally optimal soln. can be constructed by making a seq. of locally optimal choices.