Advanced Algorithm: Note #1

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Algorithm

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input \rightarrow Algorithm \rightarrow output (optimal solution) algorithm: fixed amount of resource requirement.
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Approximation Algorithm

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input \to Approximation Algorithm \to output (near-optimal solution) if cost(OPT) \le cost(alg. output) \le k \times cost(OPT) \Rightarrow k-approx. algorithm
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Randomized Algorithm

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input \rightarrow Randomized Algorithm (random bit string 0001101 ...) \rightarrow output
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1. Las Vegas Alg.

Always produces desired (optimal) output. $\,$

Different resource requirement.

ex: Quicksort

2. Monte Carlo Alg.

Deterministic time/memory . . . Output may be incorrect/not optimal.

Online Algorithm

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input \rightarrow Online Algorithm \rightarrow output (arriving one by one)
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Streaming Algorithm

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10, \rightarrow Streaming Alg.
```

2,

6,

8,

. . .

Knapsack Problem

n items, weight w_i , value v_i

Weight limit W

Goal: Select set of items S,

s.t.
$$\sum_{S} v_i$$
 is maximized, subject to $\sum_{S} w_i \leq W$

1. fractional Knapsack

(items can be split)

Algorithm for fractional Knapsack Sort items s.t.

$$\frac{v_1}{w_1} \geq \frac{v_2}{w_2} \geq \ldots \geq \frac{v_n}{w_n}$$
 Choose items 1,2,3, ..., i until i+1 doesn't fit. Total value = OPT = $v_1 + v_2 + \ldots v_i + c \cdot v_{i+1}$

2. 0-1 Knapsack

(items cannot be split)

2-Approx. Alg. for 0-1 Knapsack

Sort items s.t.
$$\frac{v_1}{w_1} \ge \frac{v_2}{w_2} \ge \ldots \ge \frac{v_n}{w_n}$$
 Choose items 1,2,3, ..., i until i+1 doesn't fit.

Pick
$$\max(v_1 + v_2 + \ldots + v_i, v_{i+1})$$
 (Assume $w_i \leq W, \forall i$)

$$\geq \frac{(v_1 + v_2 + \ldots + v_i) + (v_{i+1})}{2}$$

Pick
$$\max(v_1 + v_2 + \dots + v_i, v_{i+1})$$
 (Assume $w_i \leq W, \forall i$)
$$\geq \frac{(v_1 + v_2 + \dots + v_i) + (v_{i+1})}{2}$$

$$\geq \frac{v_1 + v_2 + \dots + v_i + c \cdot v_{i+1}}{2} = \frac{OPTforfractioinalKnapsack}{2}$$

$$\geq \frac{OPT}{2}$$

Recap: Complexity classes

(decision problems only.)

A problem is in P iff exists polynomial-time alg. which solves it.

A problem is in NP iff exists polynomial-time verifier.

A problem is in NP-hard iff
$$\begin{cases} \forall \ Y \in NP, \\ Y(poly-time\ reduction) \to X \end{cases}$$

 $\mbox{NP-complete} = \mbox{NP} \cap \mbox{NP-hard}$

If we know:
$$\begin{cases} ZisNP-hard\\ Z(poly-time\ reduction)\to X \end{cases}$$
 , then X is NP-hard.

Exact Set Cover (NP-hard)

Given $S=x_1,\ldots,x_n$

m subsets S_1, S_2, \ldots, S_m

Q: Is there a collection of subsets $S_{i_1}, S_{i_2}, \ldots, S_{i_k}$, s.t. every element $x_i \in S$ is contained in exactly one subset.

0-1 Knapsack

Given n items with weights w_i , value v_i and W, V. Is there a set of items S s.t. $\sum_{S} w_i \leq W$, $\sum_{S} v_i \geq V$

Reduction

 $S_i \to \text{item i}, v_i = w_i = \text{n digit number (base m+1)}$ $x_j \in S_i \Leftrightarrow \text{the j-th digit}=1$ ex: $x_1, x_2, x_4 \to 110100 \dots 0$

 $W=V = 11 \dots 1$ (n digits)

Dynamic Programming Algorithm for 0-1 Knapsack

A[i,v]: min weight set chosen from items 1,2, ..., i s.t. $\sum value \ge v$

$$A[0,v] = \begin{cases} 0, if \ v \le 0 \\ \infty, if \ v > 0 \end{cases}$$
for i=1 to n
for v=0 to $\sum_{A[i,v]=\min(A[i-1,v], A[i-1,v-v_i] + w_i)} v_i$

Find v^* s.t. $A[n, v^*] \leq W$ $A[n, v^* + 1] \ge W$ \Rightarrow total time: $\Theta(nv^*)$

input: v_i, w_i, W v_i : 5,8,10

binary: 101, 1000, 1010 unary: 11111, 1111111, 1 ... 1

Pseudo-polynomial time algorithm

Running is polynomial in the input size under unary representation (but not binary)

Strongly NP-hard

NP-hard even when all numerical values are poly(size of input)

0-1 Knapsack

Alg. Given any $\epsilon > 0$

Want: Find $(1+\epsilon)$ -approx. alg. Let $b = \frac{\epsilon}{2n} max_i v_i$

Consider 0-1 Knapsack

$$\hat{w_i} = w_i, \, \hat{W} = W$$

$$\hat{v_i} = \lceil \frac{v_i}{h} \rceil \times b$$

Run dynamic programming on Knapsack

Running time =
$$\Theta(n \times \frac{v^*}{b})$$

 $\frac{v^*}{b} \le \frac{n \cdot max_i v_i}{\frac{\epsilon}{2n} max_i v_i} = \frac{2n^2}{\epsilon}$
Time = $O(n^3 \cdot \epsilon^{-1})$

OPT: original 0-1 Knapsack
$$O\hat{P}T$$
: algorithm output. value(OPT) in 0-1 Knapsack \leq value(OPT) in $Knapsack$ \leq value($O\hat{P}T$) in $Knapsack$ \leq value($O\hat{P}T$) in $Knapsack$ \leq value($O\hat{P}T$) in $Knapsack$ + nb

In the original 0-1 Knapsack
$$\begin{aligned} & \operatorname{value}(\operatorname{OPT}) \leq \operatorname{value}(\hat{OPT}) + \operatorname{nb} \\ &= \operatorname{value}(\hat{OPT}) + n \cdot \frac{\epsilon}{2n} \max v_i \\ &\leq \operatorname{value}(\hat{OPT}) + \frac{\epsilon}{2} \operatorname{value}(\operatorname{OPT}) \\ &\Rightarrow \operatorname{value}(\hat{OPT}) \geq (1 - \frac{\epsilon}{2}) \operatorname{value}(\operatorname{OPT}) \\ &\Rightarrow \operatorname{value}(\hat{OPT}) \geq \frac{1}{1 + \epsilon} \operatorname{value}(\operatorname{OPT}) \end{aligned}$$

Def: PTAS polynomial-time approximation scheme

Def: FPTAS Given any $\epsilon > 0$ can approximate within a factor of $1 + \epsilon$ in time poly $(n, \frac{1}{\epsilon})$