

CSCI-SHU 220: Algorithms Subset Sum and Knapsack

NYU Shanghai
Spring 2025

Subset sum problems

Problem (subset sum)

Given a set $A = \{a_1, \dots, a_n\}$ of integers and an integer s , we want to check whether there exists a subset $A' \subseteq A$ such that $s = \sum_{a \in A'} a$.

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- Finding a **smallest** subset A' satisfying $s = \sum_{a \in A'} a$.
- Finding a **largest** subset A' satisfying $s = \sum_{a \in A'} a$.
- The variants where A' can contain **multiple copies** of each a_i .
(call it **infinite subset sum** for convenience)

Subset sum problems

- How are these problems related to knapsack?

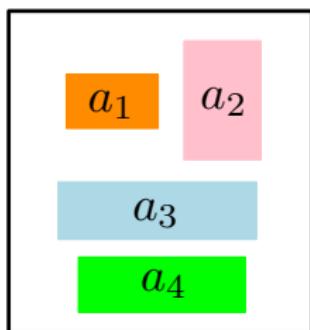
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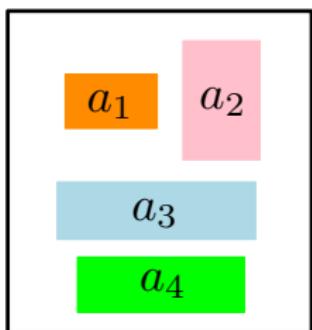


Can we fill the knapsack?

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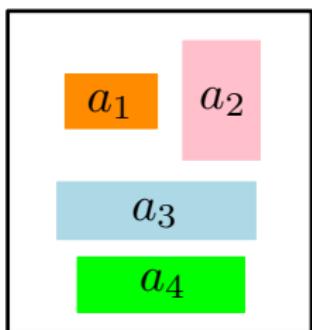


Fill the knapsack
using fewest items?

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Knapsack problems

Problem (0-1 knapsack)

Given a knapsack of weight capacity W and n items where the i -th item has weight $w_i \in \mathbb{N}$ and value $v_i \in \mathbb{R}$, include in the knapsack items of total weight at most W with **maximum total value**.

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- **Example**

$$W = 9$$

$$\text{Item 1: } w_1 = 4, v_1 = 6$$

$$\text{Item 2: } w_2 = 3, v_2 = 4$$

$$\text{Item 3: } w_3 = 5, v_3 = 5$$

The optimal solution chooses **Item 1** and **Item 3**.

Knapsack problems

- Any relation between **subset sum** and **0-1 knapsack**?

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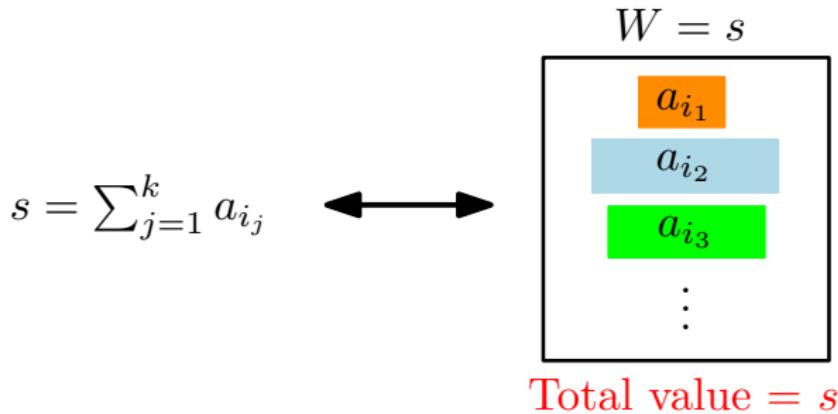
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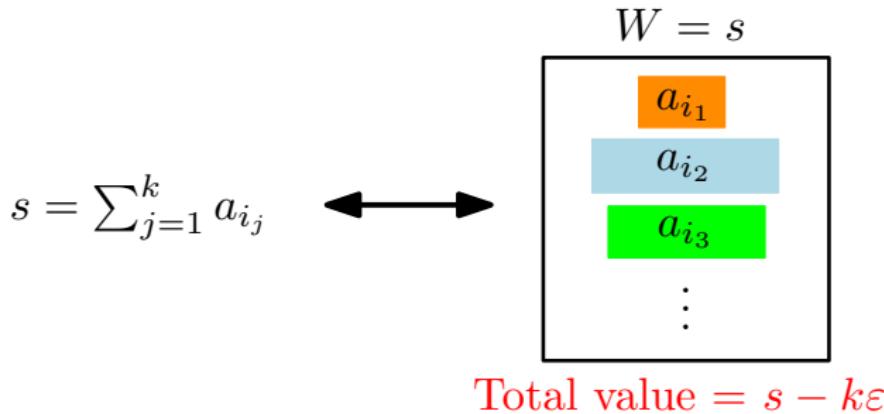
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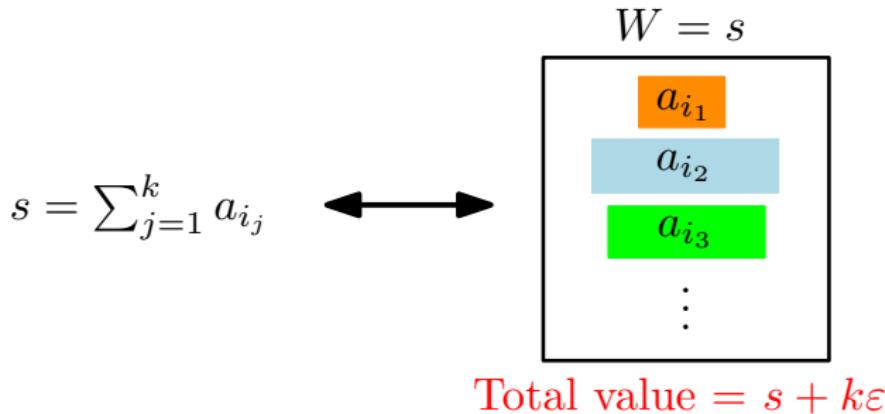
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Given a knapsack of weight capacity W and n types of (**infinite**) items where the i -th type has weight $w_i \in \mathbb{N}$ and value $v_i \in \mathbb{R}$, include in the knapsack items of total weight at most W with **maximum total value**.

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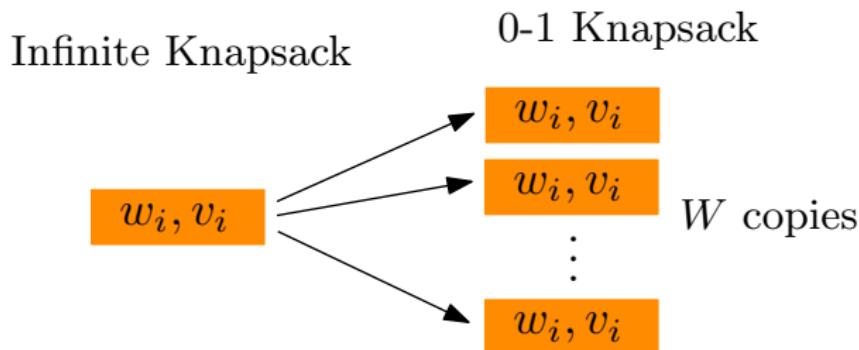
The optimal solution chooses **3 copies of Item 2**.

Knapsack problems

- We can reduce infinite knapsack to 0-1 knapsack.

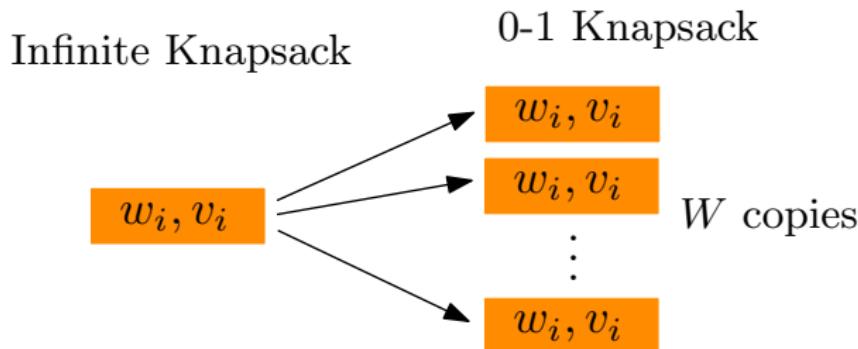
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- We usually don't use this reduction, since it increases the number of items significantly **from n to $O(nW)$** .

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- **Exercise**

Improve the time cost to $O(nw^*)$, where $w^* = \max_{j \in \{1, \dots, n\}} w_j^2$.

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$P_{w,A} = \text{getting maximum value using items in } A \text{ with total weight } w$
for $w \in \{1, \dots, W\}$ and $A \subseteq \{1, \dots, n\}$.

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- Suppose we want to solve the subproblem $P_{w,\{1,\dots,n\}}$, i.e., achieve the maximum value with total weight w when all items are available.
- What if we choose the j -th item as the one in our solution with the largest index? Then the remaining problem is $P_{w-w_j,\{1,\dots,j-1\}}$.

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- **Standard implementation**
 - $\text{KNAPSACK}(W, w_1, \dots, w_n, v_1, \dots, v_n)$
 - (assume $\text{opt}[w, k] = -\infty$ for all w and k initially)
 - $\text{opt}[0, k] \leftarrow 0$ for all $k \in \{1, \dots, n\}$
 - for** $k = 1, \dots, n$ **do**
 - for** $w = 1, \dots, W$ **do**
 - $\text{opt}[w, k] \leftarrow \max\{\text{opt}[w, k-1], \text{opt}[w - w_k, k-1] + v_k\}$
 - return** $\max_{w \in \{1, \dots, W\}} \text{opt}[w, n]$

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- **A better implementation**

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Given a knapsack of weight capacity W and n items where the i -th item has weight $w_i \in \mathbb{R}^+$ and value v_i , compute numbers $\rho_1, \dots, \rho_n \in [0, 1]$ satisfying $\sum_{i=1}^n \rho_i w_i \leq W$ such that $\sum_{i=1}^n \rho_i v_i$ is maximized.

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- **Example**

$$W = 6$$

Item 1: $w_1 = 4, v_1 = 5$

Item 2: $w_2 = 3, v_2 = 4$

Item 3: $w_3 = 5, v_3 = 5$

The optimal solution is $\rho_1 = 75\%$, $\rho_2 = 100\%$, $\rho_3 = 0\%$.

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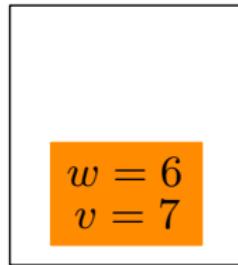
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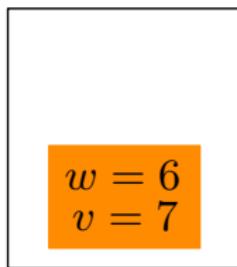
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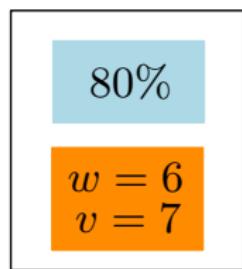
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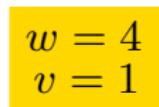
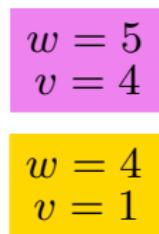
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- $\rho_i = 1$ for all $i \in \{1, \dots, k\}$
 $\rho_{k+1} = (W - \sum_{i=1}^k w_i) / w_{k+1}$
 $\rho_i = 0$ for all $i \in \{k + 2, \dots, n\}$

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 $\rho_i = 0$ for all $i \in \{k + 2, \dots, n\}$
- **Proof of correctness**
Assume there exists an optimal solution whose ρ_i is the same as the greedy solution for all $i < t$, and show the existence of an optimal solution whose ρ_i is the same as the greedy solution for all $i \leq t$.

Another problem related to subset sum

Problem (Fibonacci sum)

Given a positive integer s ...

- ① Check whether s is the sum of several **distinct** Fibonacci numbers.
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• Example

$$s = 31$$

- ① Yes
- ② $s = 2 + 8 + 21$
- ③ $s = 5 + 13 + 13$

Another problem related to subset sum

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 $i =$ the largest index such that $F_i \leq s$
 $\implies s = F_i + s'$ where $s' < F_i$
By our hypothesis, $s' = F_{j_1} + \dots + F_{j_r}$ where j_1, \dots, j_r are distinct.
 $\implies s = F_i + F_{j_1} + \dots + F_{j_r}$ and $i \notin \{j_1, \dots, j_r\}$ as $s' < F_i$

Another problem related to subset sum

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- ① Reduce to the **minimization** version of **subset sum**.
 A = set of Fibonacci numbers smaller than or equal to s
- ② Further reduce to the **0-1 knapsack** problem.
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- The first observation can be proved by **contradiction**, and the second one can be proved by **induction on i** .

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- Thus, we have $i = j$. Now try to further prove the optimality of the greedy solution by induction.

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 - $68 = 34 + 34$, $165 = 55 + 55 + 55$, $84 = 21 + 21 + 21 + 21$
 - $68 = 55 + 13$, $165 = 144 + 21$, $84 = 55 + 21 + 8$
- Now we should suspect that the greedy algorithm **might be correct**.

Another problem related to subset sum

- The greedy algorithm is **correct**.



There's always an optimal solution **with distinct numbers**.

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- General case?

We can keep modifying S using the equality $2F_i = F_{i+1} + F_{i-2}$.

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- Keep doing the following until the numbers in S are distinct:
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⇒ The modification procedure can have at most s^2 rounds.
- Now we see there's always an optimal solution with distinct numbers.