

# **4 Greedy, Dynamic Programming**

# Greedy

- heuristic algorithm for optimisation problems
- always picks local optimum
- *hope* to find global optimum

# Knapsack (Fractional)

w1, p1	w2, p2	w3, p3
w4, p4	w5, p5	w6, p6



maxWeight = 20

$w_i$  - weights,  $p_i$  - profits

Objective:

Maximise profit subject to maxWeight constraint.

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Can use a **fraction** of an object.

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- Knap-FR  $\Rightarrow$  subproblem is:
  - “Maximise profit for **one** unit of the backpack”
- The choice  $\Rightarrow$  item with *best value per unit*

# Local Optimum $\Rightarrow$ Global Optimum?

- **This must hold**
  - otherwise greedy solution not appropriate
- **Check**
  - Dantzig, George B. "Discrete-variable extremum problems."
  - *Combinatorial Optimization: Theory and Algorithms*, Algorithms and Combinatorics



# Algorithm

1. Sort the inputs based on value/weight
2. Pick best unused until backpack is full
3. Fill remaining with a fraction

# Intermezzo - Sorting in Java

```
class Item {double ratio, ...;}
```

```
List<Item> items = ...
```

```
Collections.sort(items);
```

How does Java know to sort Items?

# Intermezzo - Sorting in Java

1. *Natural* order:

```
class Item implements Comparable<Item> {  
    double ratio, ...;  
    public int compareTo(Item otherItem) {...}  
}
```

# Intermezzo - Sorting in Java

## 2. *Custom comparator:*

```
ItemComp comparator = new ItemComp();  
Collections.sort(items, comparator);
```

```
class ItemComp implements Comparator<Item>{  
    public int compare(Item i1, Item i2) {}  
}
```

# Intermezzo - Sorting in Java

2. *Custom comparator* (anonymous class):

```
Collections.sort(items,  
    new Comparator<Item>() {  
        public int compare(Item i1, Item i2) {}  
    }  
);
```

# Intermezzo - Sorting in Java

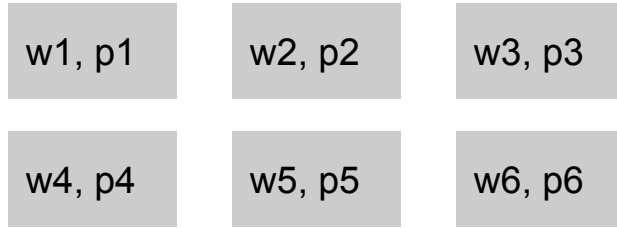
## 3. *Using lambdas* (JDK 1.8-ea):

```
Collections.sort(items,  
    (item1, item2) -> {return ...;}  
);
```

# Greedy Summary

- May not produce optimal results
  - Prove local optimum  $\Rightarrow$  global optimum
- Fast and not too hard to code
- Some more problems [12405](#), [10026](#), [10037](#)

# Knapsack (Discrete)



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  - Counter-example

$w = 4, p = 10, r = 2.5$
$w = 3, p = 7, r = 2.33$
$w = 2, p = 4, r = 2$

Greedy  
→

maxWeight = 5

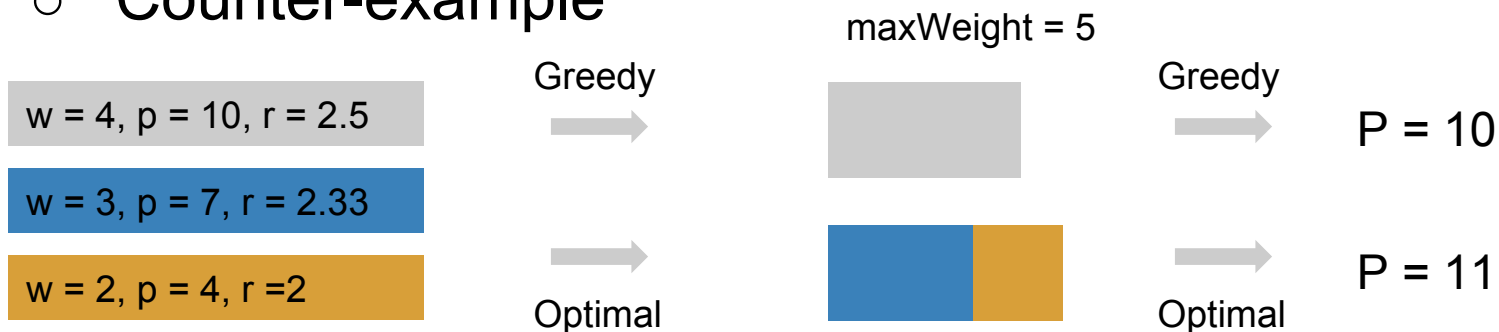


Greedy  
→

P = 10

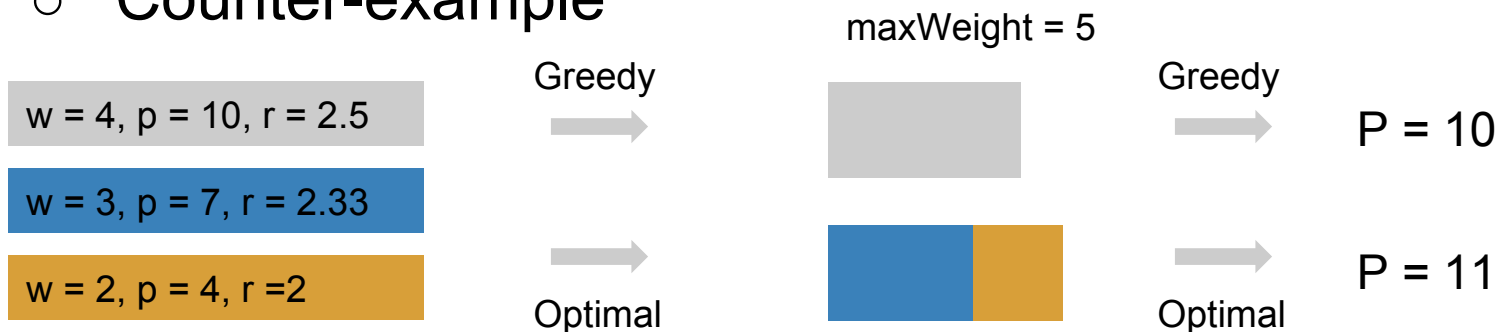
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- Seems like we have to use complete search

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- Recurrence relation
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# Knapsack (Discrete)

- Recurrence relation
    - $\text{best}(i, \text{max}W) = \text{best profit using the first } i \text{ items, up to a maximum weight of max}W$
- $\Rightarrow \text{best}(0, *) , \text{best}(*, 0) = 0$
- $\Rightarrow \text{best}(n - 1, \text{maxWeight})$  - the maximum profit

# Knapsack (Discrete)

$\text{best}(i, \text{max}W) =$

$$\max(\underbrace{\text{best}(i - 1, \text{max}W)}, \text{best}(i - 1, \text{max}W - w[i]) + p[i])$$

1. Don't pick item  $i$
2. Same weight limit
3. Same best profit



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1. Pick item  $i$
2. Update remaining capacity
3. Add its profit

Two options: use/don't use item  $i$   
Pick the best!

# Overlapping Subproblems

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- **Dynamic Programming**
  - solve each subproblem only once
  - store results to subproblems (*memoization*)
  - reuse results without recomputation

# Top Down vs Bottom Up

- Top Down approach
  - start with  $\text{best}(n - 1, \text{maxWeight})$
  - recurse to solve subproblems
- Bottom up
  - start with the smaller problems
  - build-up to solution

# Summary

When Complete Search is too slow:

- Greedy
  - when local optimum  $\Rightarrow$  global optimum
- Dynamic programming
  - remove repeating/overlapping subproblems



# Maximum Sum [UVA](#) [git](#)

Given a matrix of integers, find the sub-matrix with the maximum sum.

4				15
0	-2	-7	0	
9	2	-6	2	
-4	1	-4	1	
-1	8	0	-2	

# Maximum Sum - Complete Search

Complete search in  $O(n^6)$ :

- Iterate through every starting point  $O(n^2)$ 
  - Iterate through every possible length  $O(n^2)$ 
    - Sum up the numbers  $O(n^2)$
- This is too slow for  $n \sim 100$

# Maximum Sum - Faster

- Observation: there are quite a few redundant computations (e.g. sum of square in column 1 is recomputed in col 2 and again in col 3)

4	4	4
0 -2 -7 0	0 -2 -7 0	0 -2 -7 0
9 2 -6 2	9 2 -6 2	9 2 -6 2
-4 1 -4 1	-4 1 -4 1	-4 1 -4 1
-1 8 0 -2	-1 8 0 -2	-1 8 0 -2

# Maximum Sum - Faster

Could speed up by avoiding recomputation.  
Idea: Precompute sums of all submatrices  
starting from (0, 0)

0	-2	-7	0	0	-2	-9	-9
9	2	-6	2	9	9	-4	-2
-4	1	-4	1	5	6	-11	-8
-1	8	0	-2	4	13	-4	-3

# Maximum Sum - Faster

Can reconstruct sum of arbitrary sub-matrix:

0	-2	-9	-9
9	9	-4	-2
5	6	-11	-8
4	13	-4	-3

$\text{Sub\_Sum}(2,2,3,3) =$   
 $\text{Sum}(2, 2, 3, 3)$   
 $\text{Sum}(0, 0, 1, 3) +$   
 $\text{Sum}(0, 0, 3, 1) -$   
 $\text{Sum}(0, 0, 1, 1)$

Maximum Sum  
Precompute //  $O(n^2)$   
for (i, j) // starting positions  
for (k, l) // end position  
sub\_sum = sum[k][l] +  
sum[i-1][l] +  
sum[k][j-1] -  
sum[i-1][j-1]

Total Complexity =  $O(n^2 + n^4)$  - Much Faster!