

# CSEP 521

# Applied Algorithms

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Lecture 6

Dynamic Programming

# Announcements

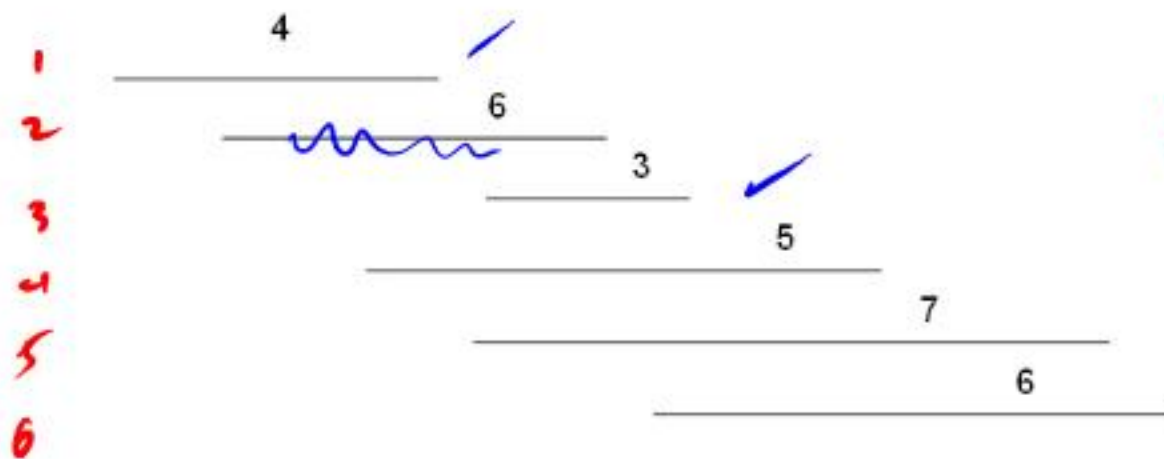
- Midterm today!
  - 60 minutes, start of class, closed book
- Reading for this week
  - 6.1, 6.2, 6.3., 6.4
- Makeup lecture
  - February 19, 6:30 pm.
    - Still waiting on confirmation on MS room.

*Tuesday  
JW, Microsoft*

# Dynamic Programming



- Weighted Interval Scheduling
- Given a collection of intervals  $I_1, \dots, I_n$  with weights  $w_1, \dots, w_n$ , choose a maximum weight set of non-overlapping intervals



$P[1] = 0$   
 $P[2] = 0$   
 $P[3] = 1$

Opt

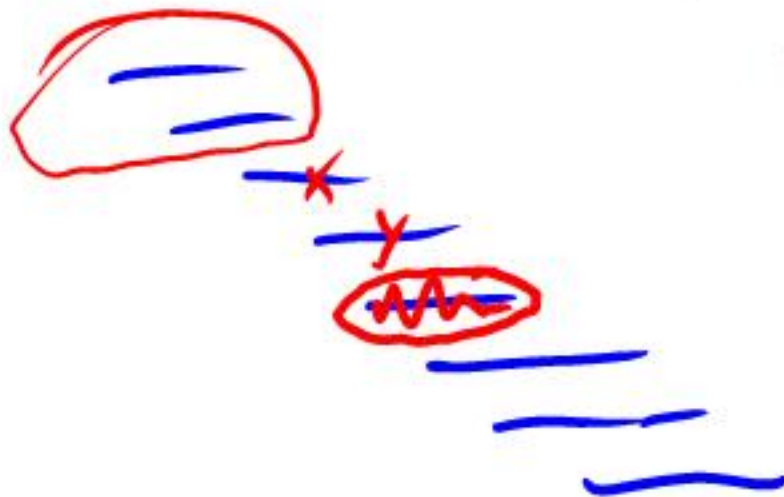
$Opt_j$       $I_1, I_2, \dots, I_j$

$Opt_j$  - function (

$Opt_{j-1}, Opt_{j-2}, \dots, Opt_1$ )

# Optimality Condition

- $\text{Opt}[j]$  is the maximum weight independent set of intervals  $I_1, I_2, \dots, I_j$
- $\text{Opt}[j] = \max(\text{Opt}[j-1], w_j + \text{Opt}[p[j]])$ 
  - Where  $p[j]$  is the index of the last interval which finishes before  $I_j$  starts



$\text{Opt}[j]$  - Include  $I_j$   
- Exclude  $I_j$

# Algorithm

MaxValue(j) =

if j = 0 return 0

else

return max( MaxValue(j-1),  
w<sub>j</sub> + MaxValue(p[ j ]))

Worst case run time:  $2^n$

# A better algorithm

$M[j]$  initialized to -1 before the first recursive call for all  $j$

MaxValue( $j$ ) =

if  $j = 0$  return 0;

else if  $M[j] \neq -1$  return  $M[j]$ ;

else

$M[j] = \max(\text{MaxValue}(j-1), w_j + \text{MaxValue}(p[j]));$

return  $M[j]$ ;

# Iterative version

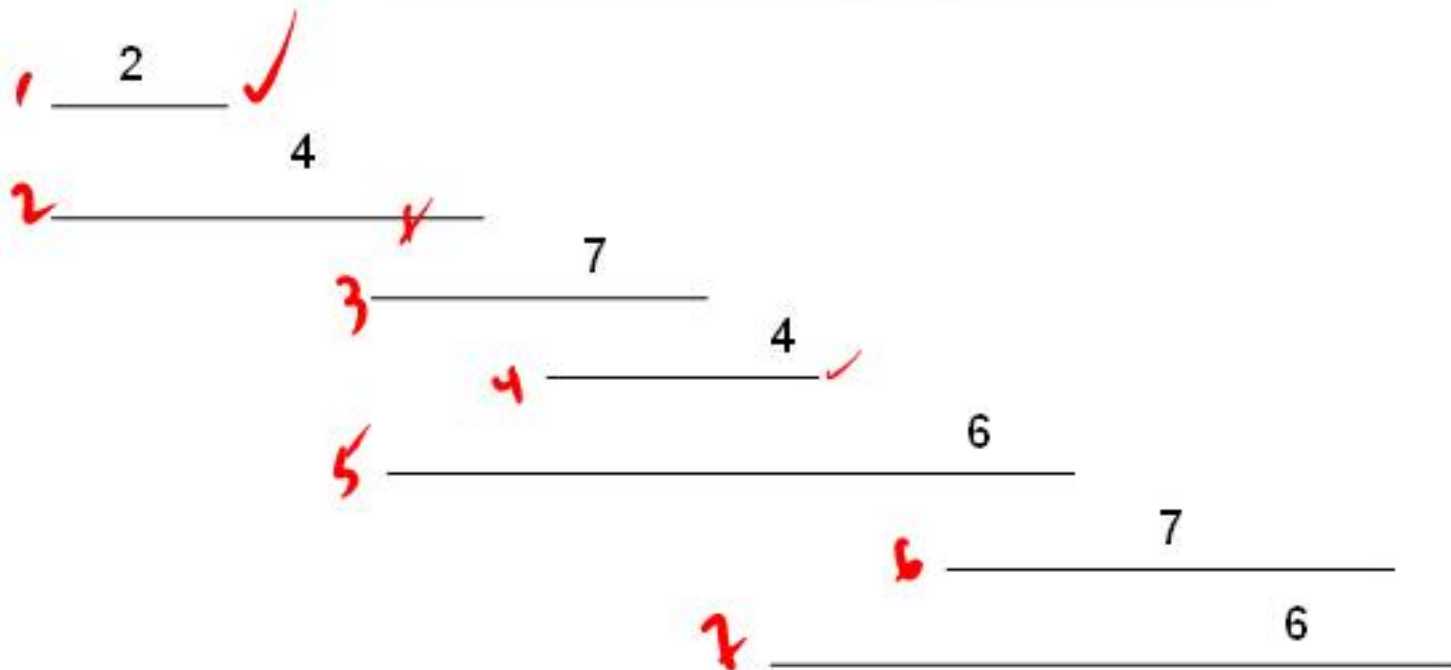
```
MaxValue (j) {  
    M[ 0 ] = 0;  
    for (k = 1; k <= j; k++){  
        M[ k ] = max(M[ k-1 ], wk + M[ P[ k ] ]);  
    }  
    return M[ j ];  
}
```

# Fill in the array with the Opt values

$$\text{Opt}[j] = \max(\text{Opt}[j - 1], w_j + \text{Opt}[p[j]])$$

1 2 3 4 5 6 7

2	4	9	9	9	16	16
---	---	---	---	---	----	----





# Computing the solution

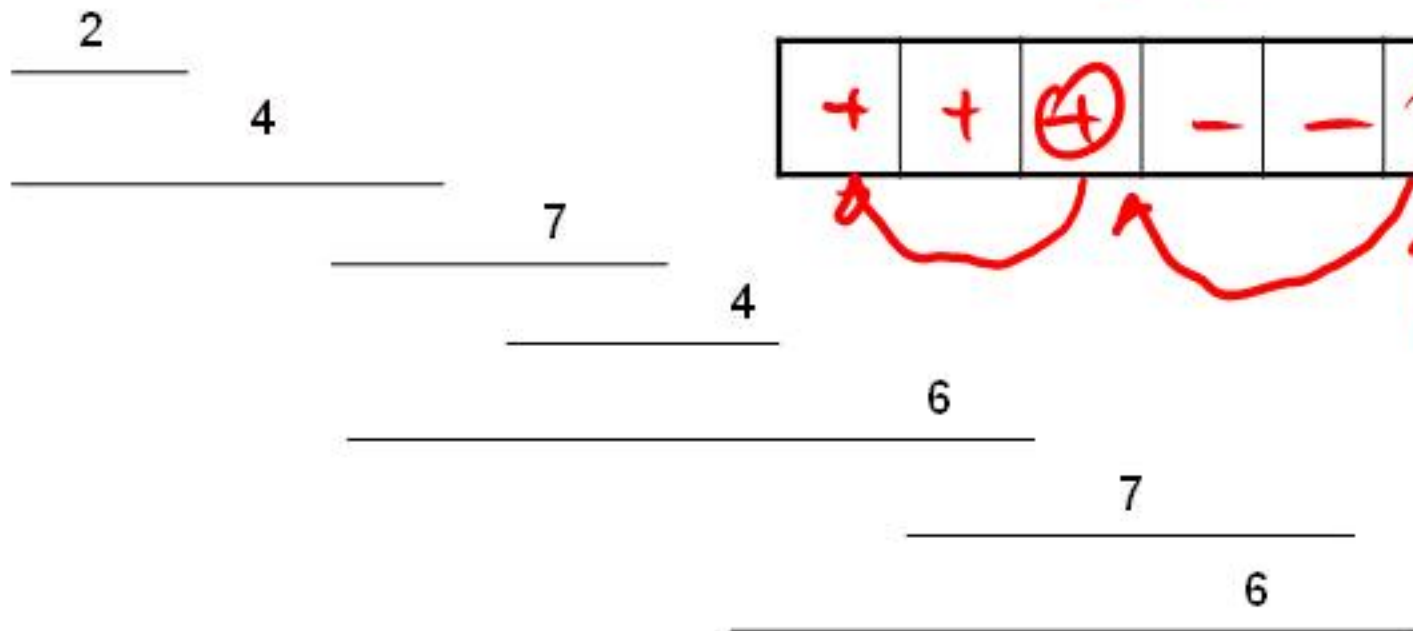
$$\text{Opt}[j] = \max(\text{Opt}[j-1], w_j + \text{Opt}[p[j]])$$

Record which case is used in Opt computation



2	4	1	9	9	16	16
---	---	---	---	---	----	----

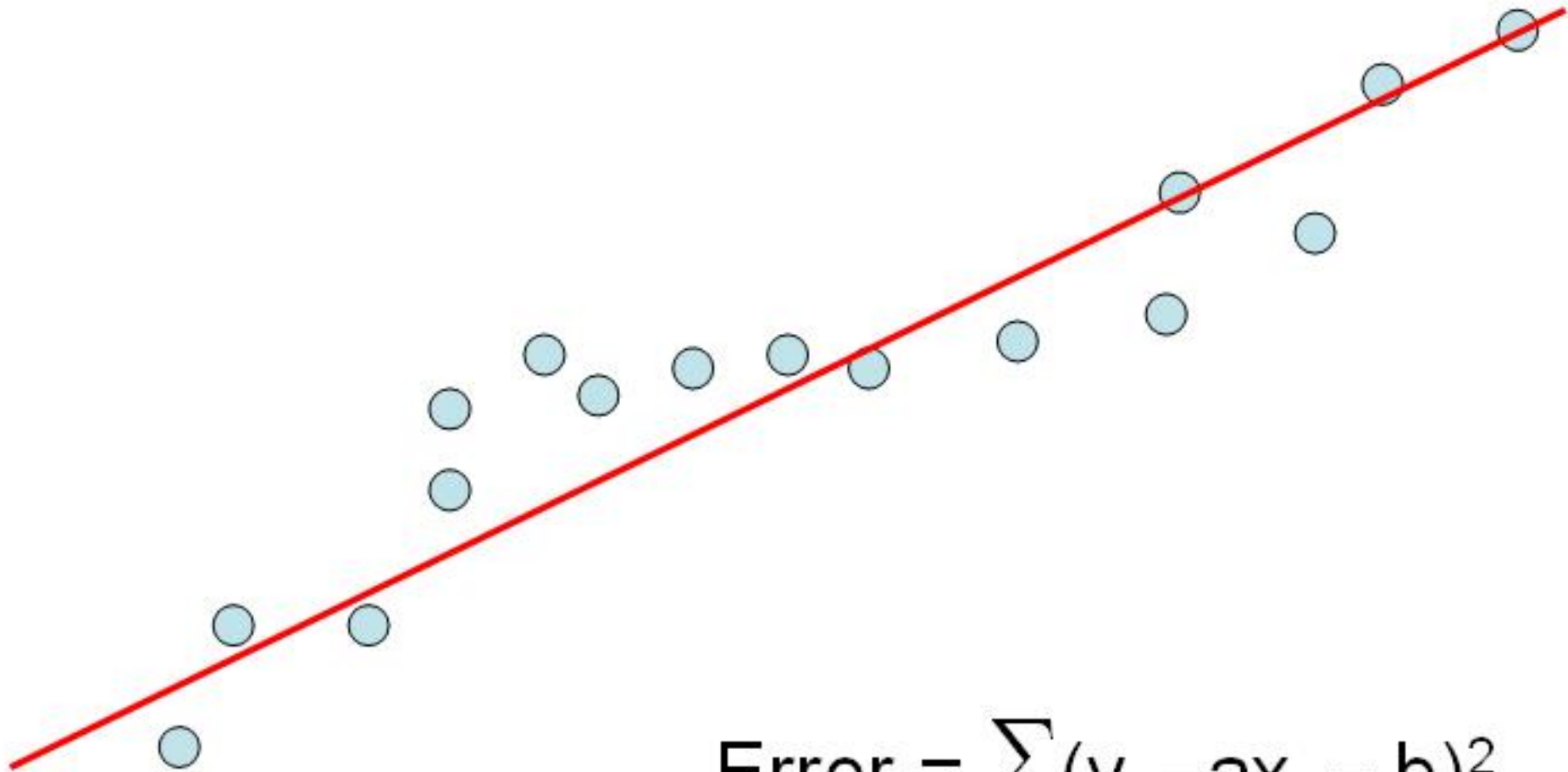
+	+	+	-	-	+	-
---	---	---	---	---	---	---



# Dynamic Programming

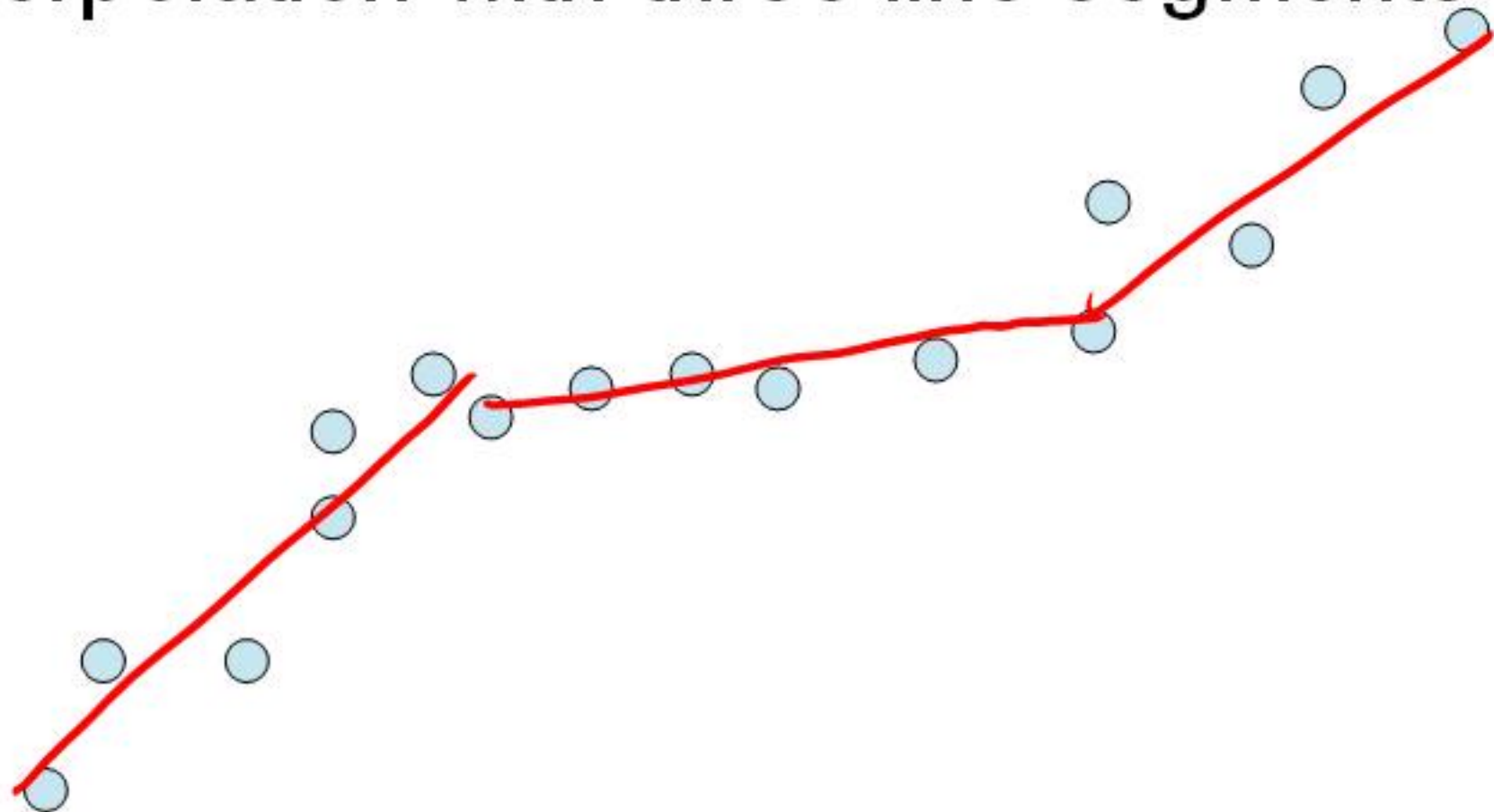
- The most important algorithmic technique covered in CSEP 521
- Key ideas
  - Express solution in terms of a polynomial number of sub problems
  - Order sub problems to avoid recomputation

# Optimal linear interpolation

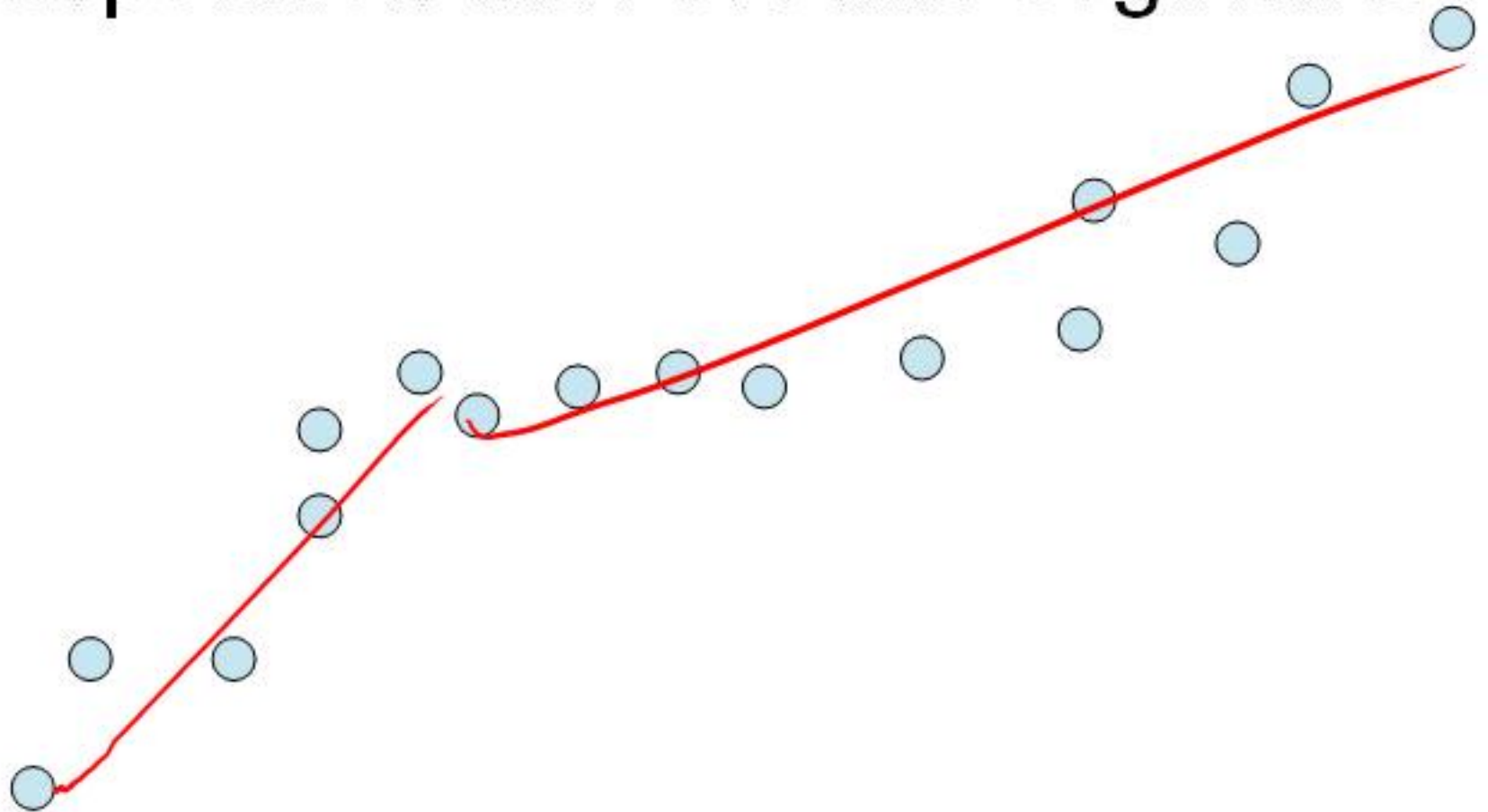


$$\text{Error} = \sum (y_i - ax_i - b)^2$$

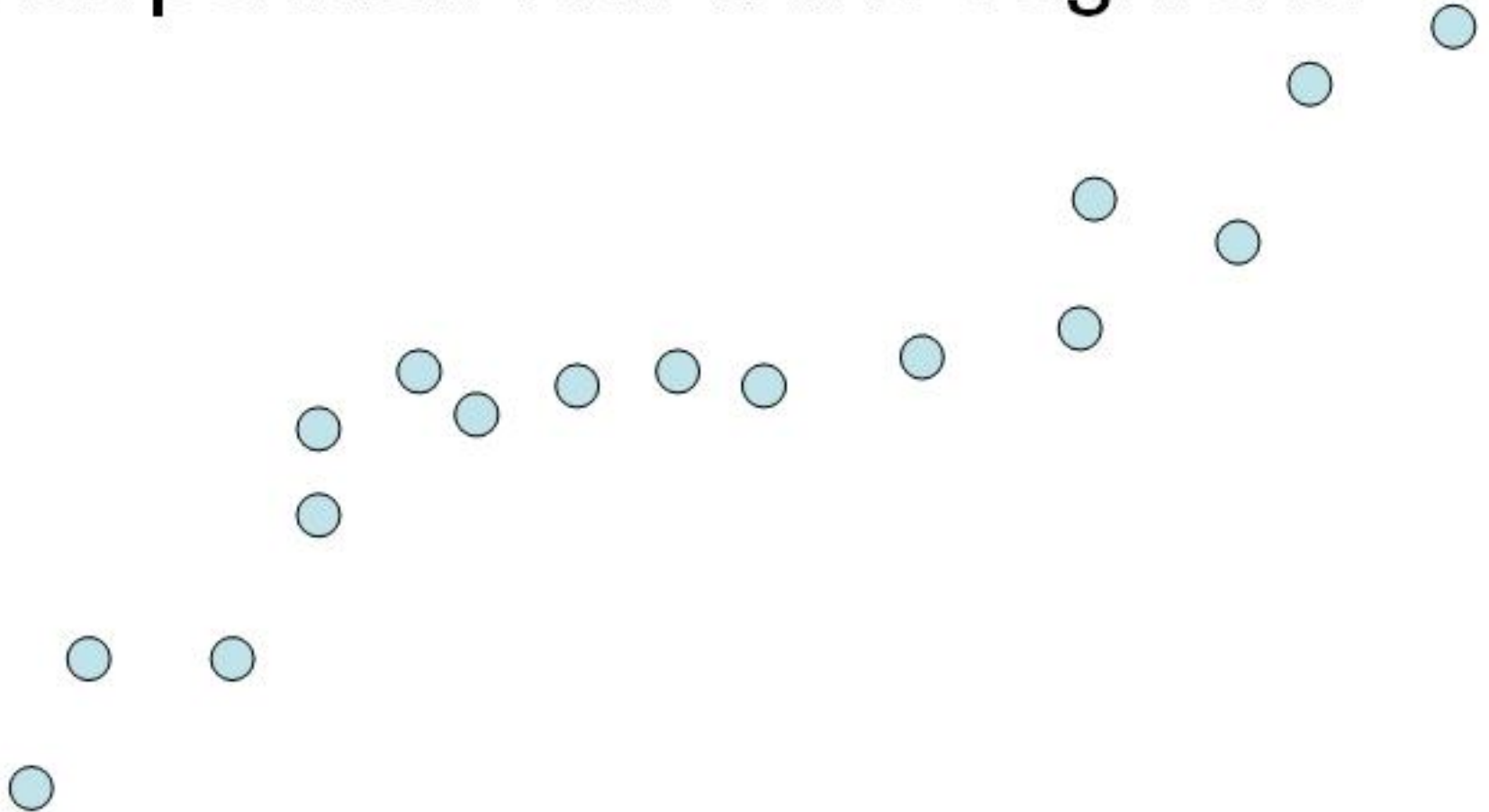
What is the optimal linear interpolation with three line segments



What is the optimal linear interpolation with two line segments



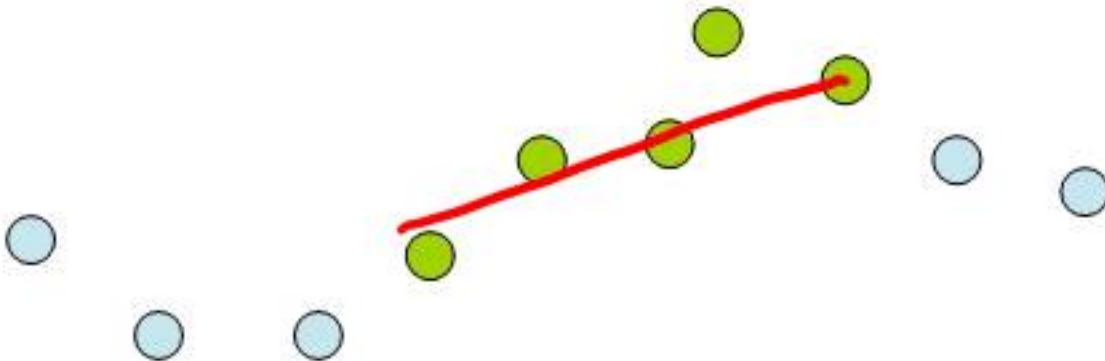
What is the optimal linear interpolation with  $n$  line segments



# Notation

$E_{i,j}$

- Points  $p_1, p_2, \dots, p_n$  ordered by  $x$ -coordinate ( $p_i = (x_i, y_i)$ )
- $E_{i,j}$  is the least squares error for the optimal line interpolating  $p_i, \dots, p_j$



# Optimal interpolation with two segments

- Give an equation for the optimal interpolation of  $p_1, \dots, p_n$  with two line segments

$$O_{pt_2} = \min_k \{ E_{1k} + E_{kn} \}$$

- $E_{i,j}$  is the least squares error for the optimal line interpolating  $p_i, \dots, p_j$



# Optimal interpolation with $k$ segments

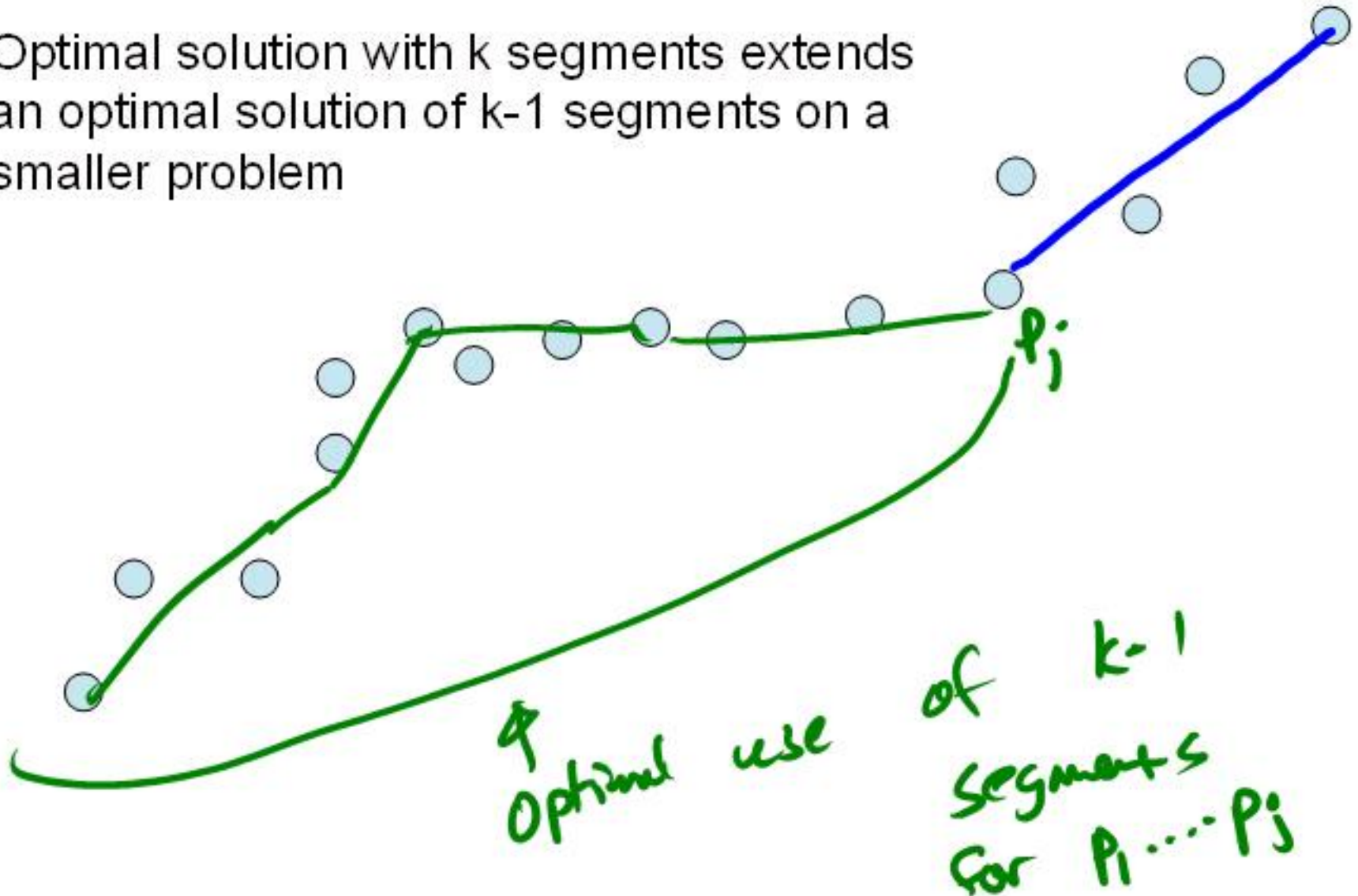
- Optimal segmentation with three segments
  - $\text{Min}_{i,j}\{E_{1,i} + E_{i,j} + E_{j,n}\}$
  - $O(n^2)$  combinations considered
- Generalization to  $k$  segments leads to considering  $O(n^{k-1})$  combinations

$\text{Opt}_k[j]$  : Minimum error  
approximating  $p_1 \dots p_j$  with  $k$  segments

How do you express  $\text{Opt}_k[j]$  in terms of  
 $\text{Opt}_{k-1}[1], \dots, \text{Opt}_{k-1}[j]$ ?

# Optimal sub-solution property

Optimal solution with  $k$  segments extends an optimal solution of  $k-1$  segments on a smaller problem



# Optimal multi-segment interpolation

Compute  $\text{Opt}[k, j]$  for  $0 < k < j < n$

for  $j := 1$  to  $n$

$\text{Opt}[1, j] = E_{1,j}$

for  $k := 2$  to  $n-1$

    for  $j := 2$  to  $n$

$t := E_{1,j}$

        for  $i := 1$  to  $j-1$

$t = \min(t, \text{Opt}[k-1, i] + E_{i,j})$

$\text{Opt}[k, j] = t$

$P_1 P_2$

$P_1 P_3$

$P_1 \dots P_4$

$\vdots$

$P_1 \dots P_n$

$\uparrow$

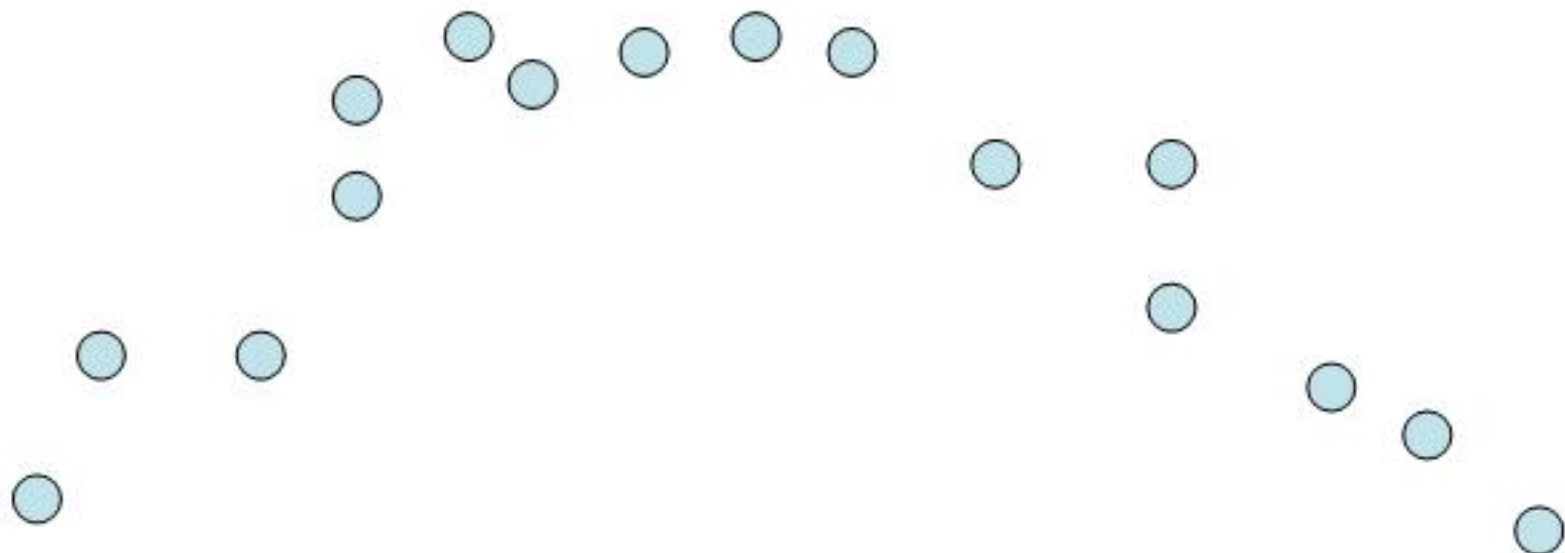
$k-1$

# Determining the solution

- When  $\text{Opt}[k,j]$  is computed, record the value of  $i$  that minimized the sum
- Store this value in a auxiliary array
- Use to reconstruct solution

# Variable number of segments

- Segments not specified in advance
- Penalty function associated with segments
- Cost = Interpolation error +  $C \times \text{\#Segments}$



# Penalty cost measure

- $\text{Opt}[j] = \min(E_{1,j}, \min_i(\text{Opt}[i] + E_{i,j} + P))$

# Subset Sum Problem

- Let  $w_1, \dots, w_n = \{6, 8, 9, 11, 13, 16, 18, 24\}$
- Find a subset that has as large a sum as possible, without exceeding 50



# Adding a variable for Weight

- $\text{Opt}[j, K]$  the largest subset of  $\{w_1, \dots, w_j\}$  that sums to at most  $K$
- $\{2, 4, 7, 10\}$ 
  - $\text{Opt}[2, 7] = 6$       $\{2, 4\}$
  - $\text{Opt}[3, 7] = 7$       $\{7\}$
  - $\text{Opt}[3, 12] = 11$       $\{4, 7\}$
  - $\text{Opt}[4, 12] = 12$       $\{2, 10\}$

# Subset Sum Recurrence

- $\text{Opt}[j, K]$  the largest subset of  $\{w_1, \dots, w_j\}$  that sums to at most  $K$

$$\text{Opt}[j, K] = \max [ \text{Opt}[j-1, K], w_j + \text{Opt}[j-1, K - w_j] ]$$

Runtime  $O(\log K)$

# Subset Sum Grid

$$\text{Opt}[j, K] = \max(\text{Opt}[j - 1, K], \text{Opt}[j - 1, K - w_j] + w_j)$$

4	0	2	2	4	4	6	7	7	9	10	11	12	13	14	14	16	17
3	0	2	2	4	4	6	7	7	9	9	11	11	13	13	13	13	13
2	0	2	2	4	4	6	6	6	6	6	6	6	6	6	6	6	6
1	0	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17

{2, 4, 7, 10}

# Knapsack Problem

- Items have weights and values
- The problem is to maximize total value subject to a bound on weight
- Items  $\{I_1, I_2, \dots, I_n\}$ 
  - Weights  $\{w_1, w_2, \dots, w_n\}$
  - Values  $\{v_1, v_2, \dots, v_n\}$
  - Bound  $K$
- Find set  $S$  of indices to:
  - Maximize  $\sum_{i \in S} v_i$  such that  $\sum_{i \in S} w_i \leq K$

$v_1, v_2, \dots, v_n$

# Knapsack Recurrence

Subset Sum Recurrence:

$$\text{Opt}[j, K] = \max(\text{Opt}[j - 1, K], \text{Opt}[j - 1, K - w_j] + w_j)$$

Knapsack Recurrence:

$$\text{Opt}^*[i, K] = \max(\text{Opt}^*[i - 1, K], \text{Opt}^*[i - 1, K - w_i] + v_i)$$

$$K = \sum w_i$$

# Knapsack Grid

$$\text{Opt}[j, K] = \max(\underbrace{\text{Opt}[j-1, K]}, \underbrace{\text{Opt}[j-1, K-w_j] + v_j})$$

4																	
3	0	3	3	5	5	8	9	9	12	-	-	-	-	-			
2	0	3	3	5	5	8	8	8	8	8	8	8	8	8	8	8	8
1	0	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16

Weights {2, 4, 7, 10} Values: {3, 5, 9, 16}