

# CSE 421

# Algorithms

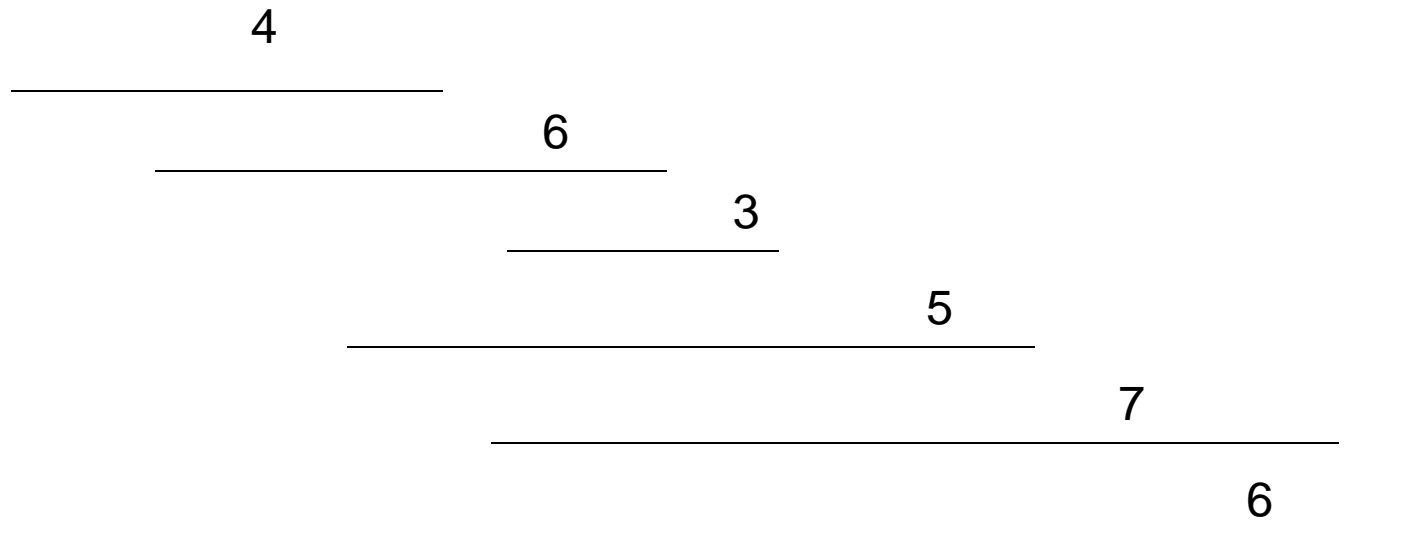
Richard Anderson

Lecture 17

Dynamic Programming

# 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



# 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

# 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 Algorithm

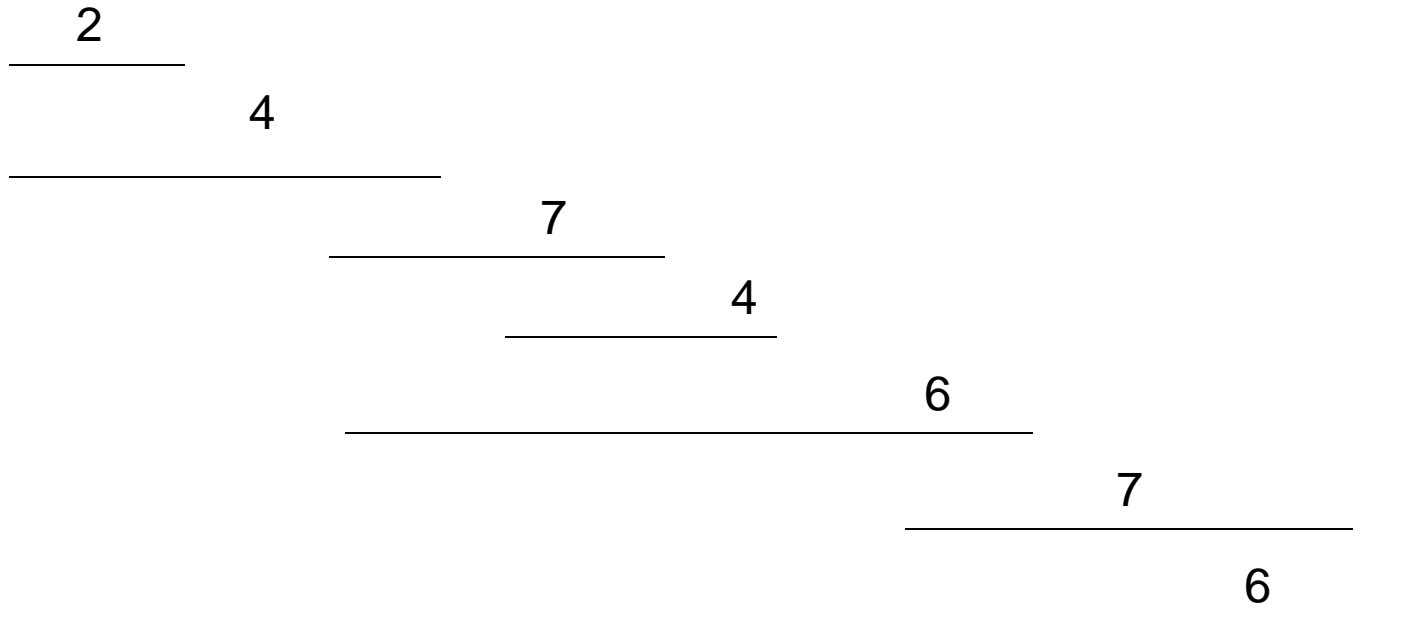
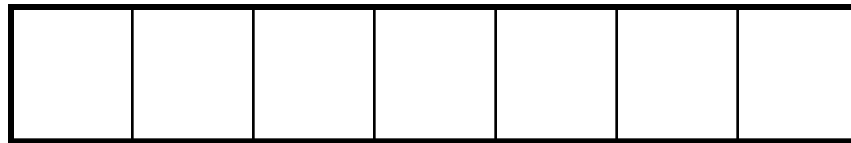
Express the MaxValue algorithm as an iterative algorithm

MaxValue {

}

# Fill in the array with the Opt values

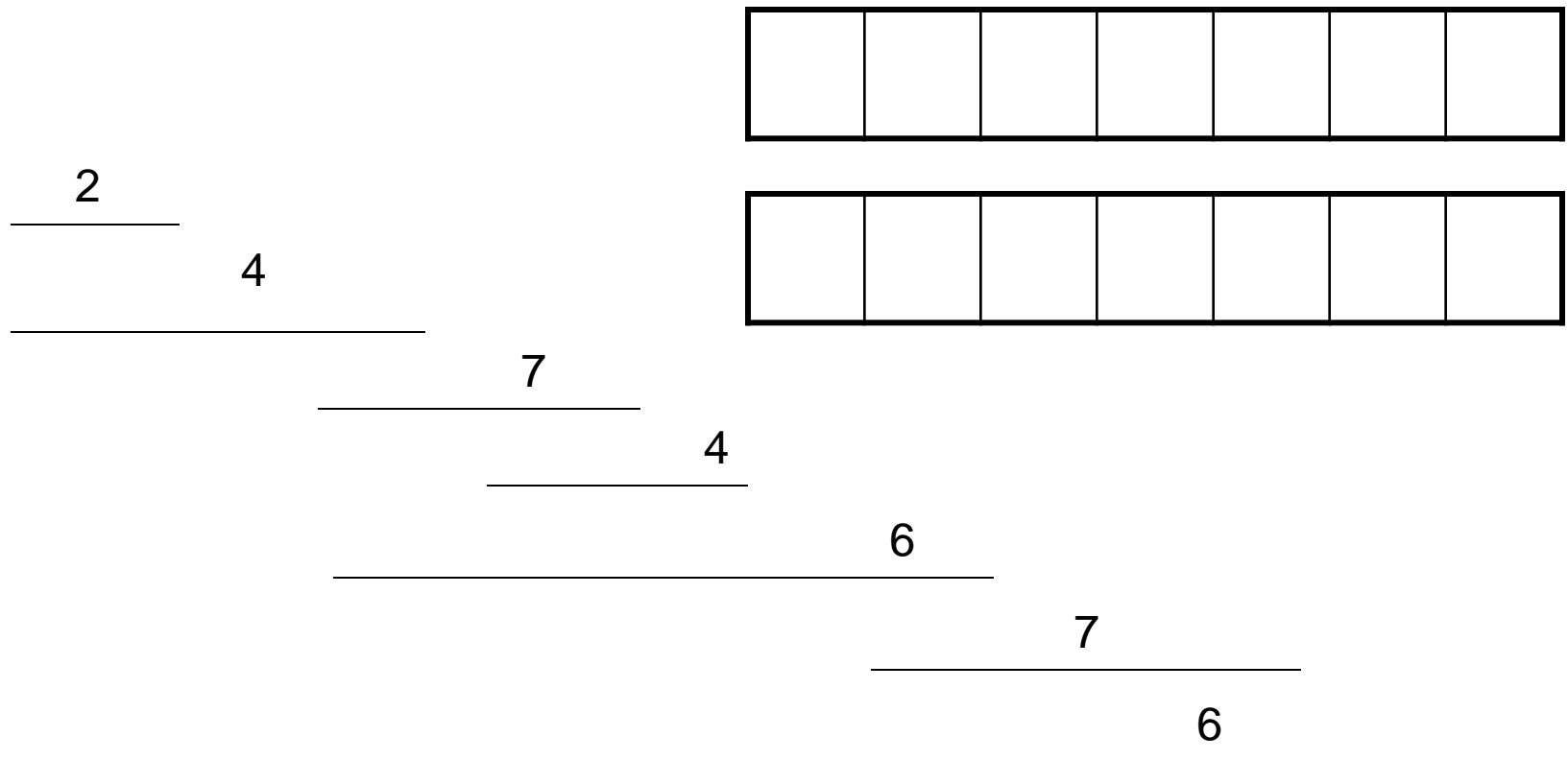
$$\text{Opt}[j] = \max(\text{Opt}[j - 1], w_j + \text{Opt}[p[j]])$$



# 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

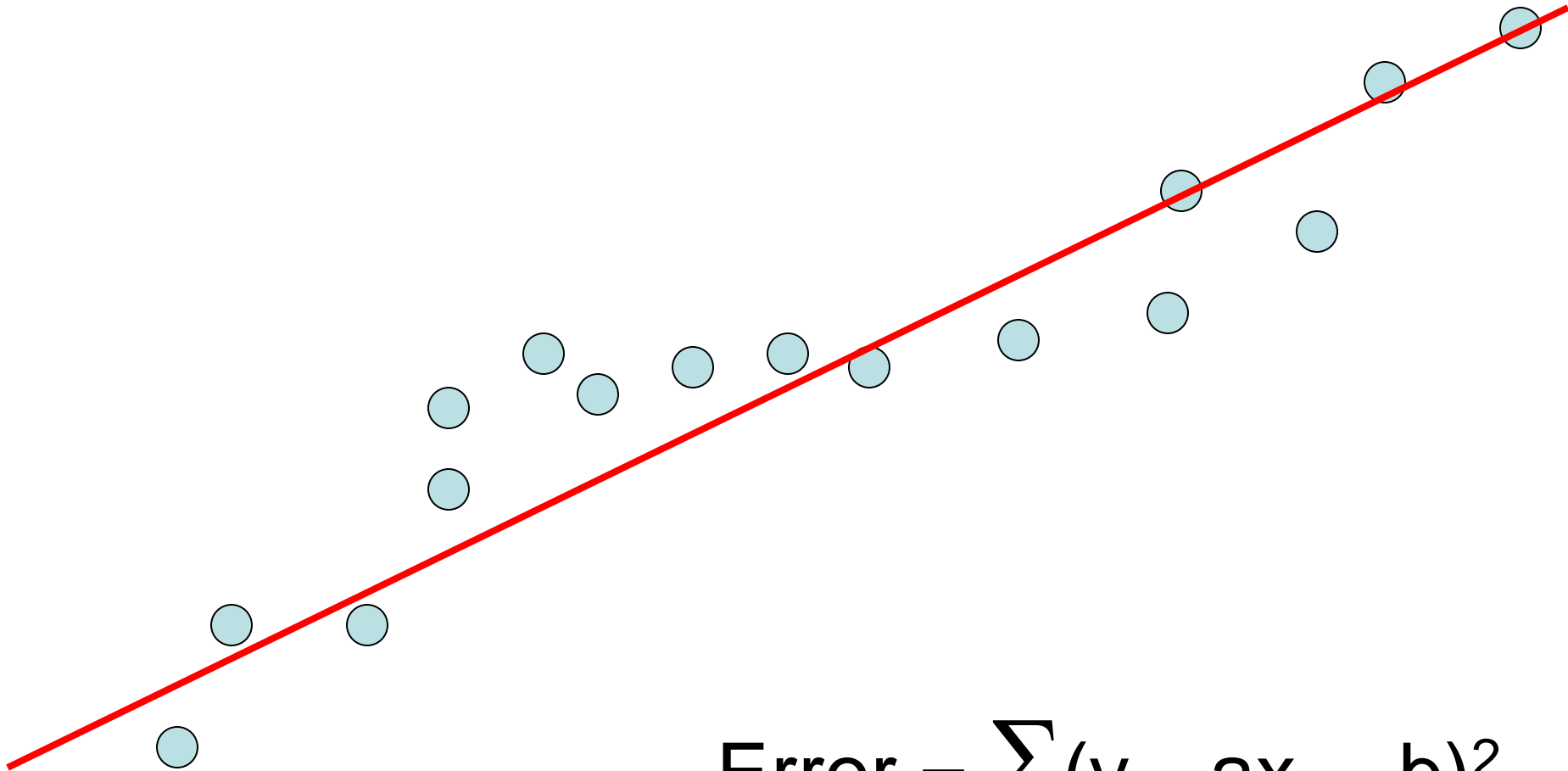




# Dynamic Programming

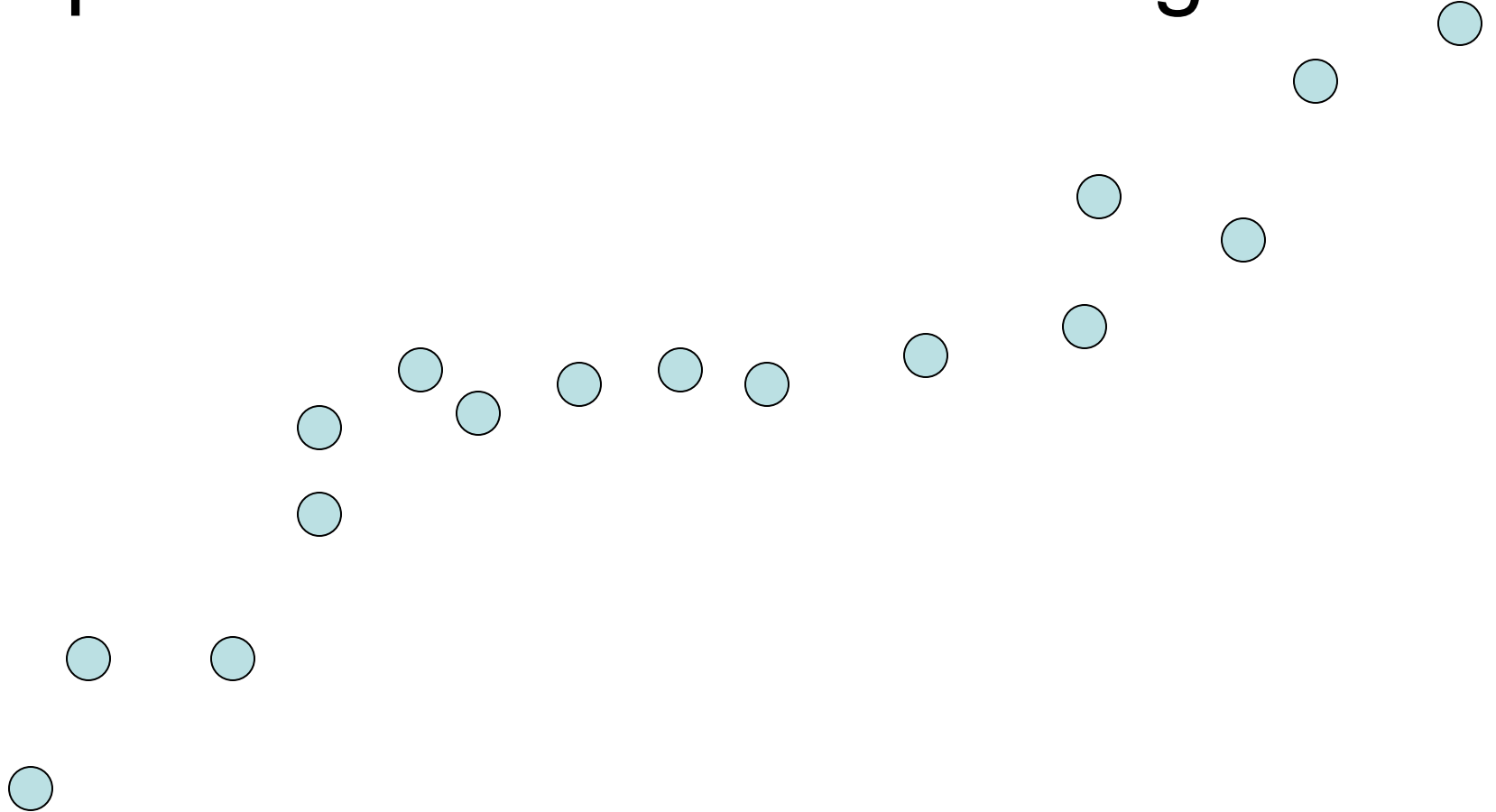
- The most important algorithmic technique covered in CSE 421
- Key ideas
  - Express solution in terms of a polynomial number of sub problems
  - Order sub problems to avoid recomputation

# Optimal linear interpolation

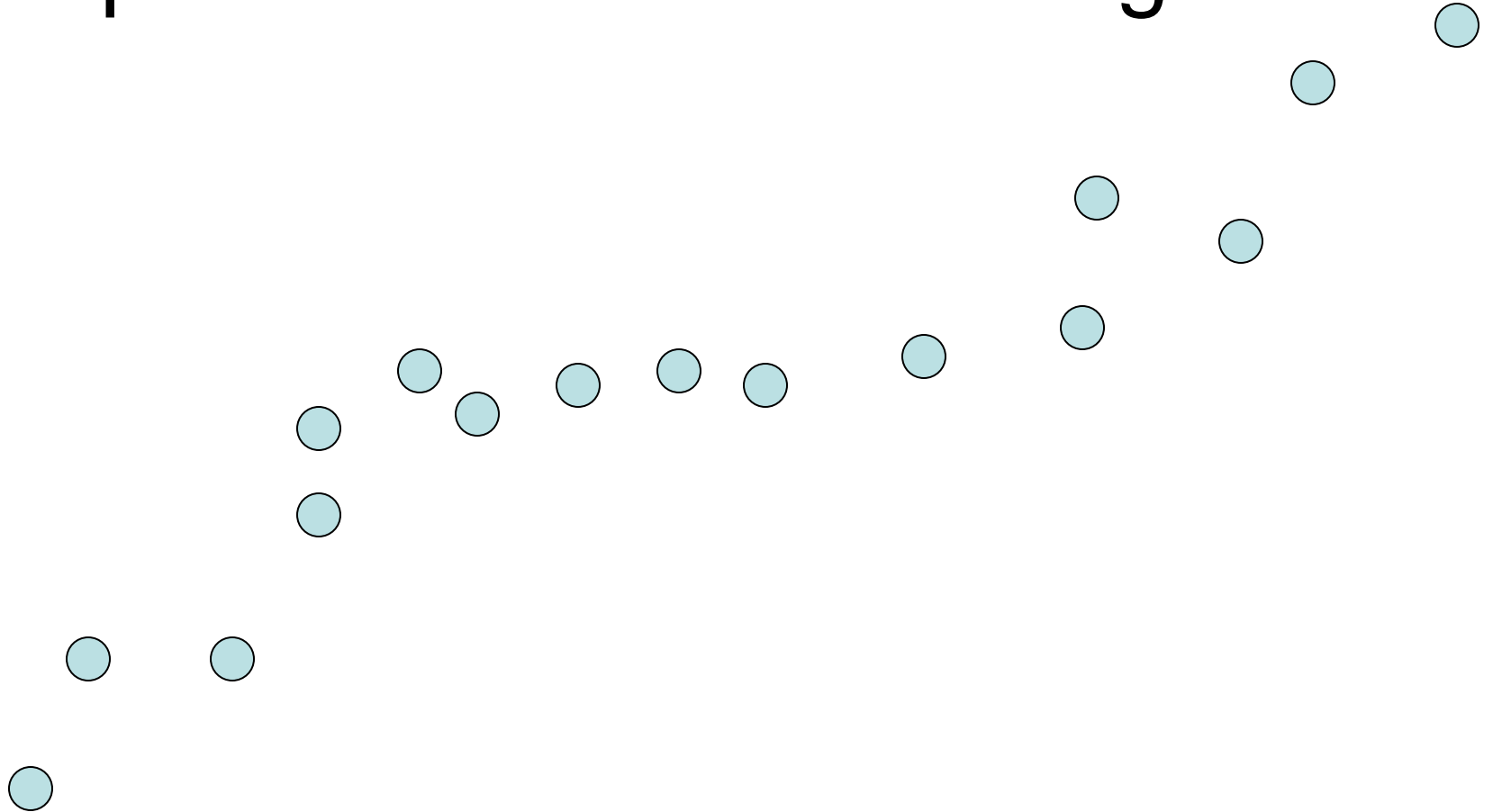


$$\text{Error} = \sum (y_i - ax_i - b)^2$$

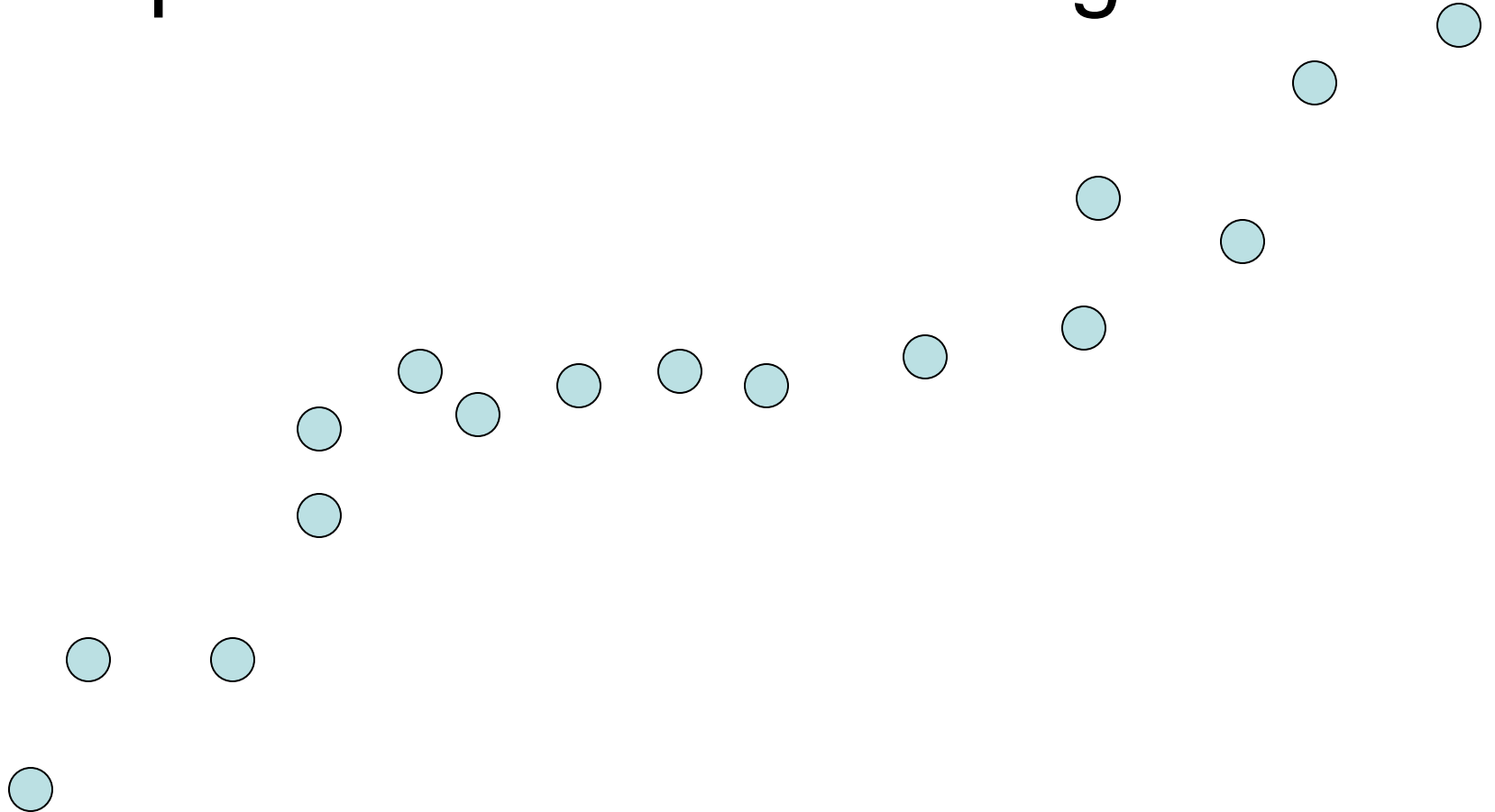
What is the optimal linear interpolation with three line segments



What is the optimal linear interpolation with two line segments

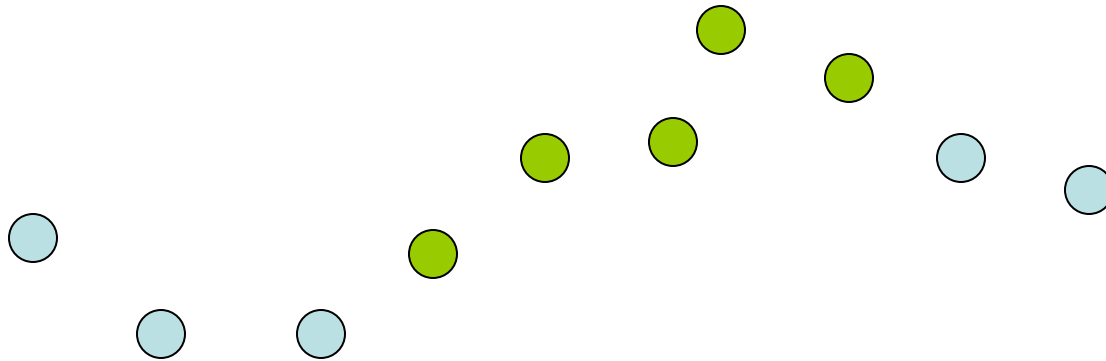


What is the optimal linear interpolation with  $n$  line segments



# Notation

- 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 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

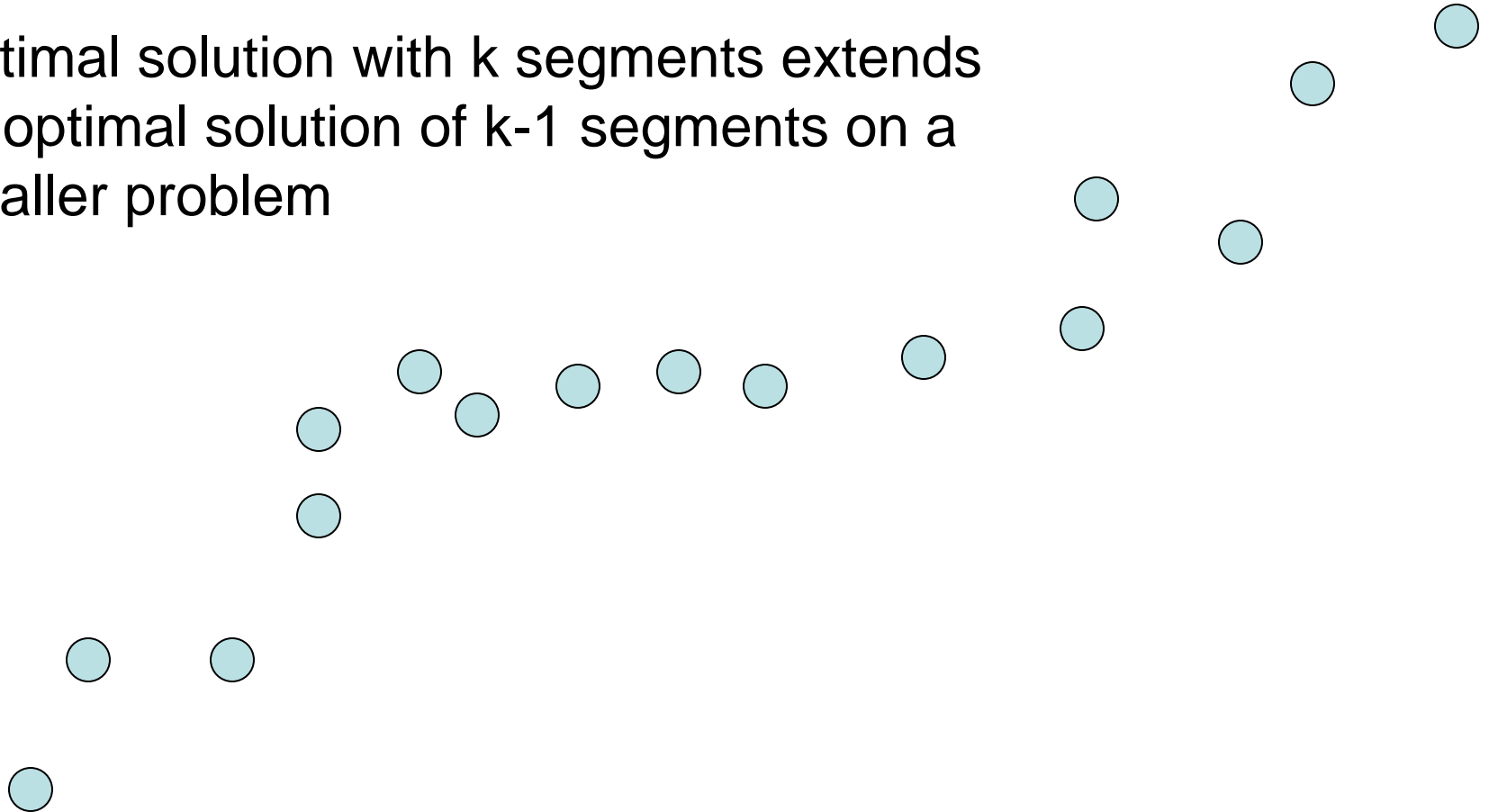


$\text{Opt}_k[j]$  : Minimum error approximating  
 $p_1 \dots p_j$  with  $k$  segments

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  $j - 1$

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

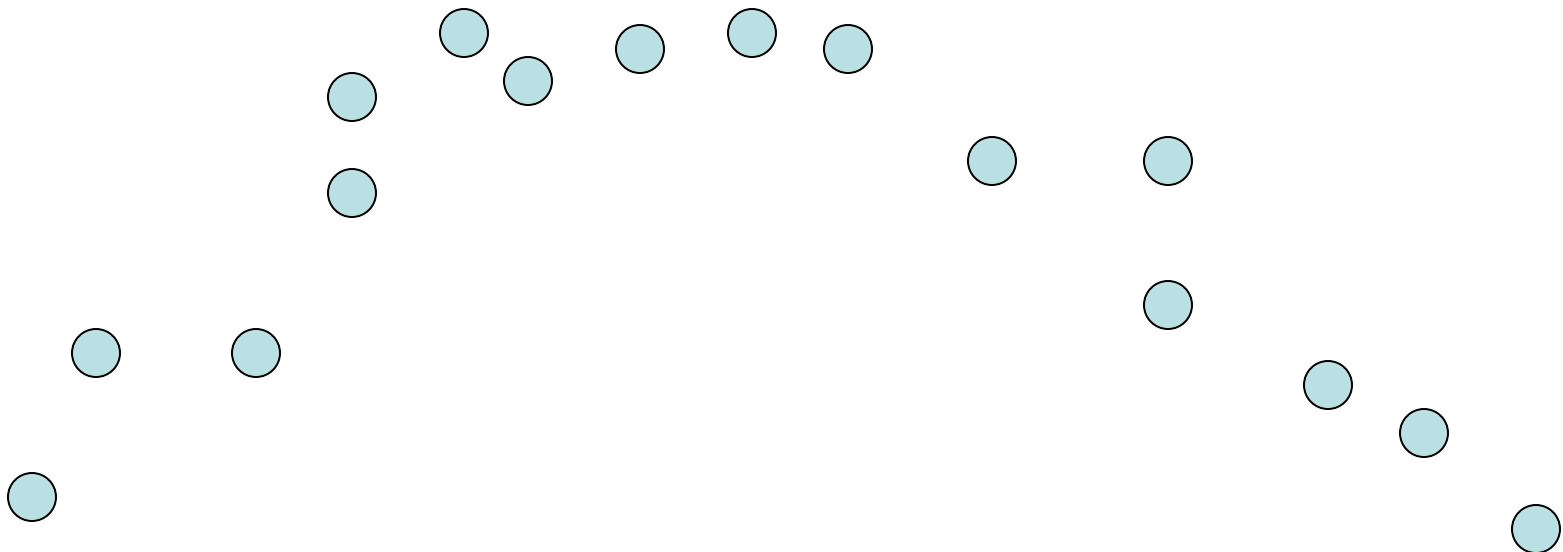
$\text{Opt}[k, j] = t$

# 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

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