

CSE 421

Algorithms

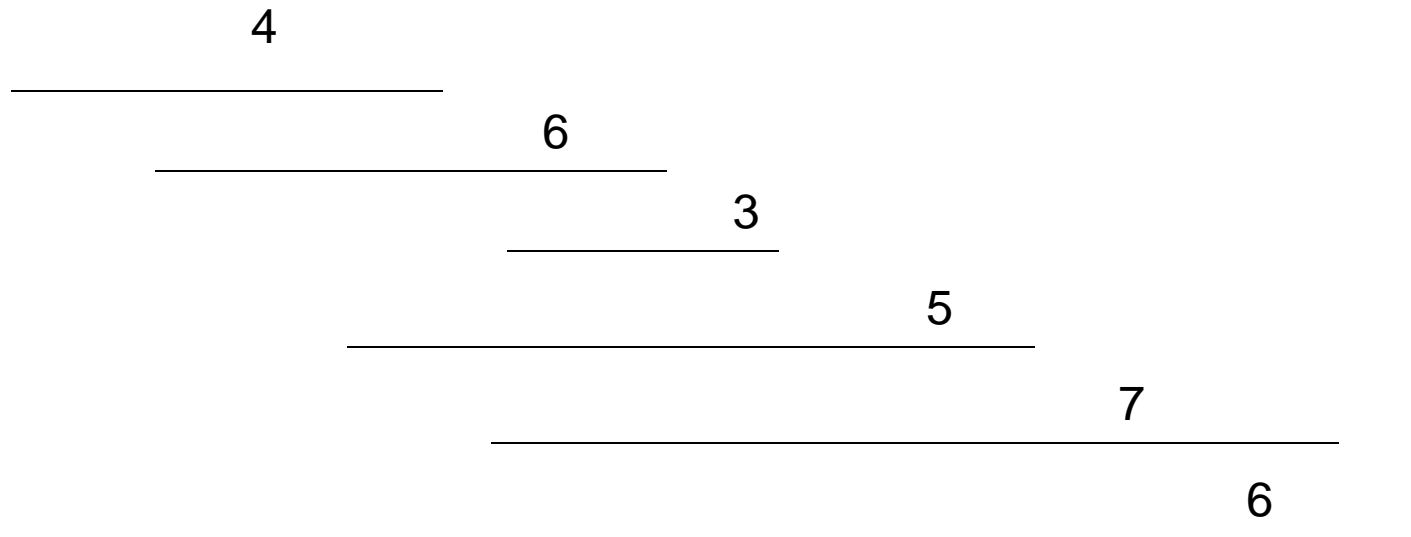
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Lecture 16

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_j + 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

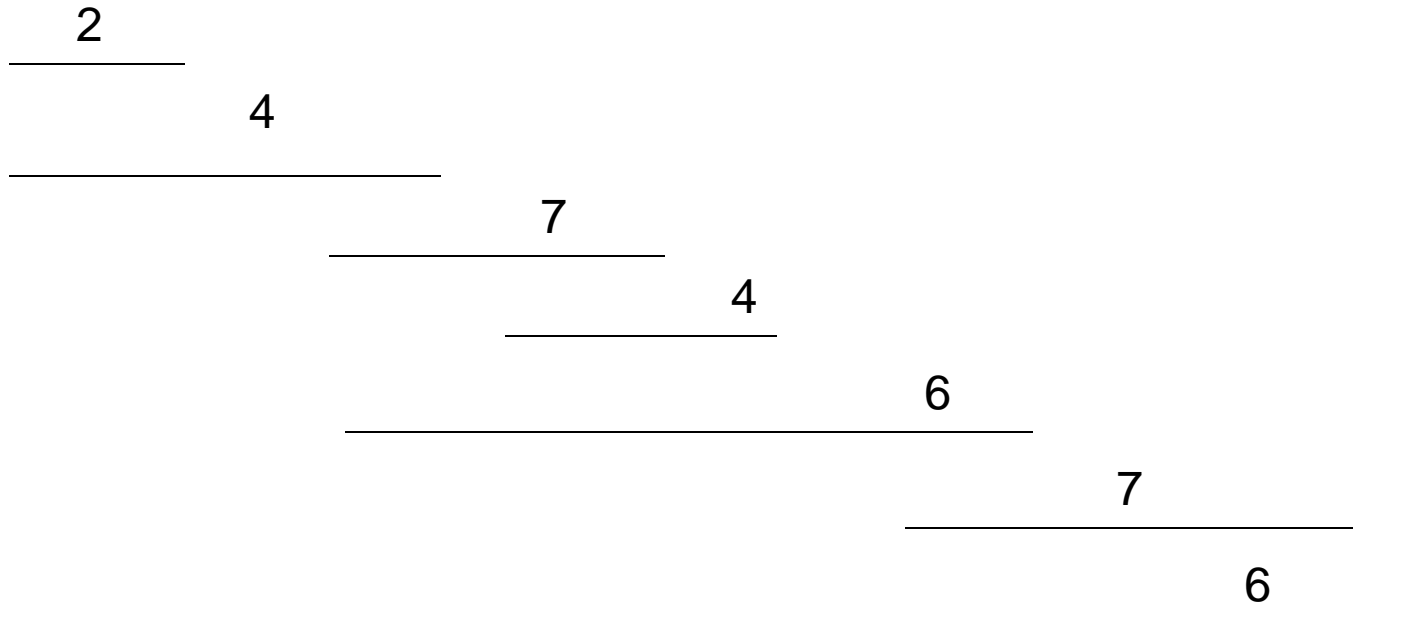
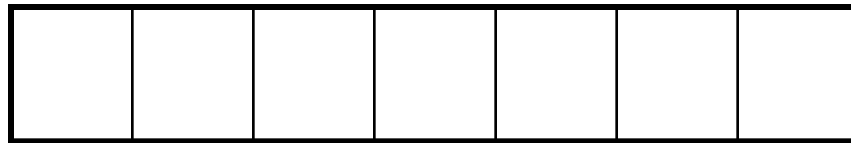
Express the MaxValue algorithm as an iterative algorithm

MaxValue {

}

Fill in the array with the Opt values

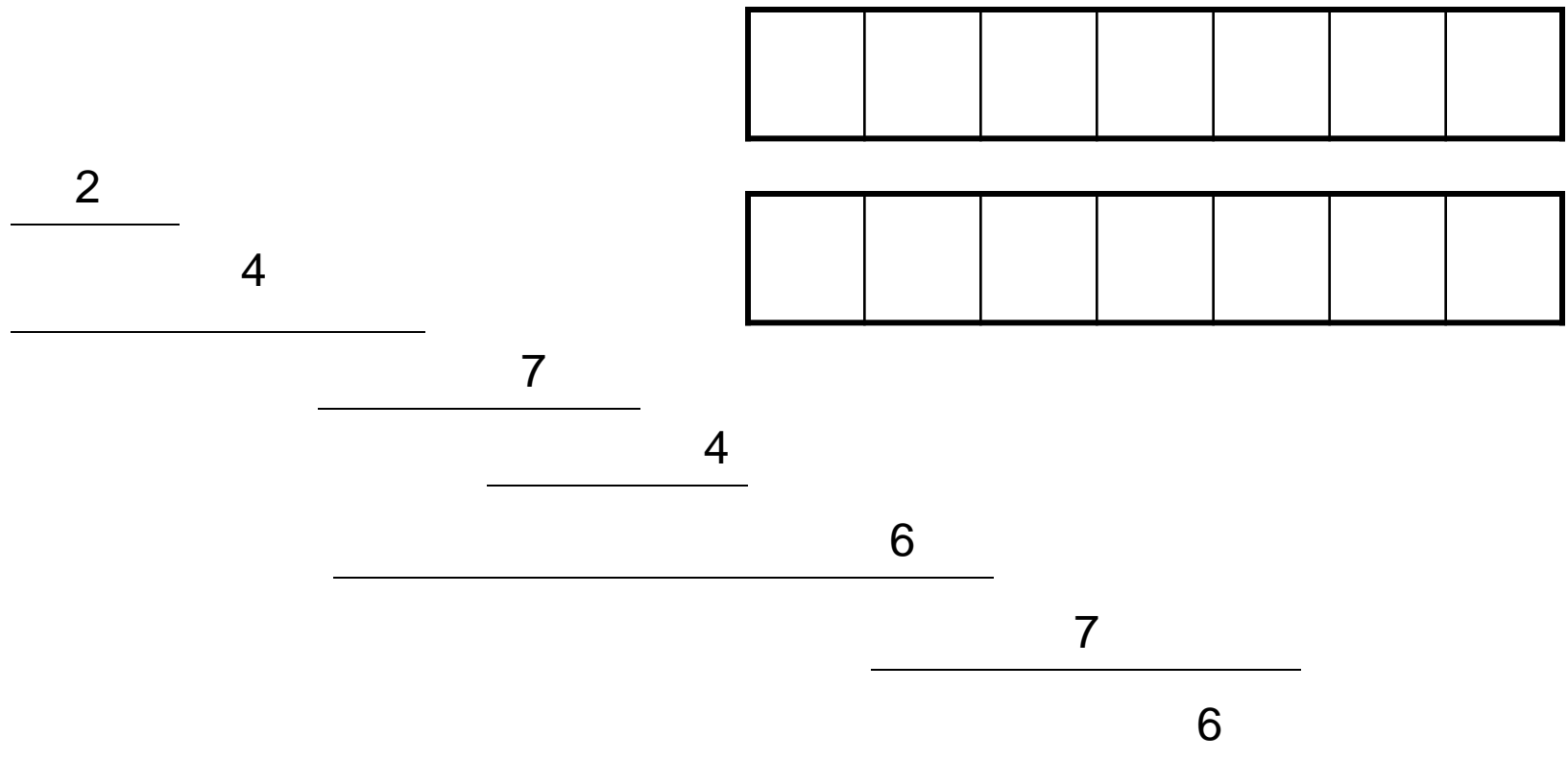
$$\text{Opt}[j] = \max(\text{Opt}[j - 1], w_j + \text{Opt}[p[j]])$$



Computing the solution

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

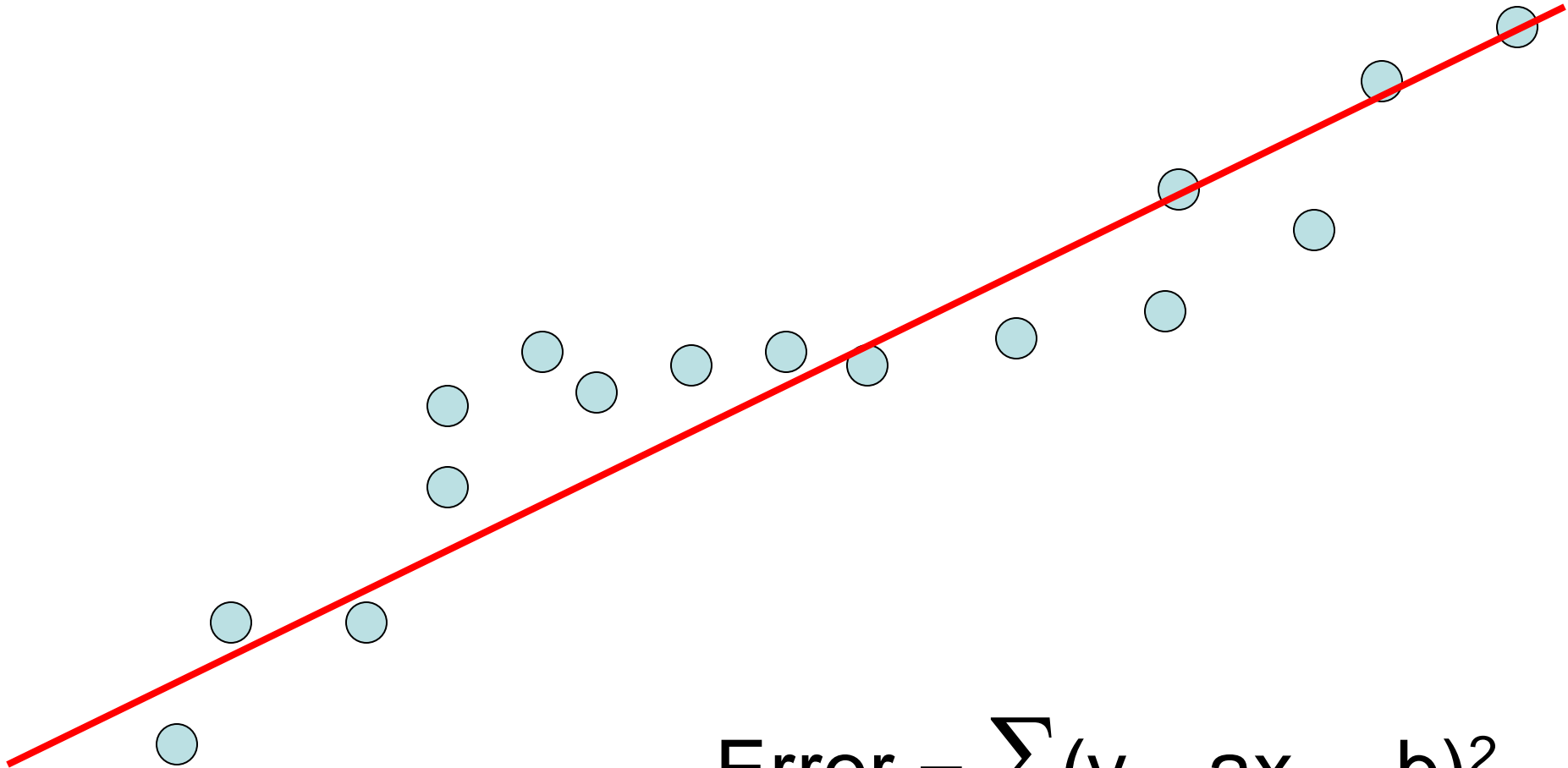
Record which case is used in Opt computation



Dynamic Programming

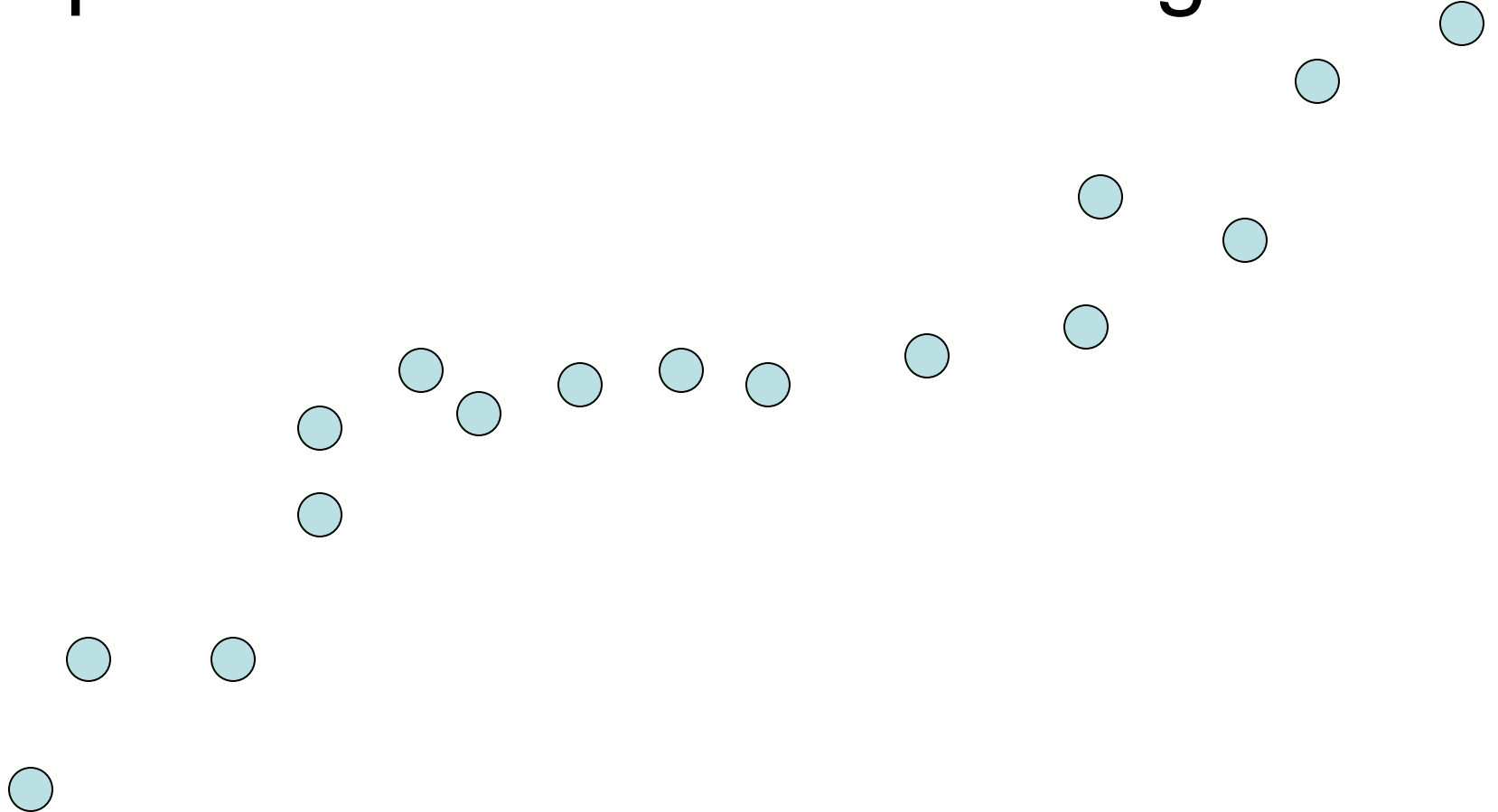
- The most important algorithmic technique covered in CSE 421
- Key ideas
 - Express solution in terms of a polynomial number of sub problems
 - Order sub problems to avoid recomputation

Optimal linear interpolation

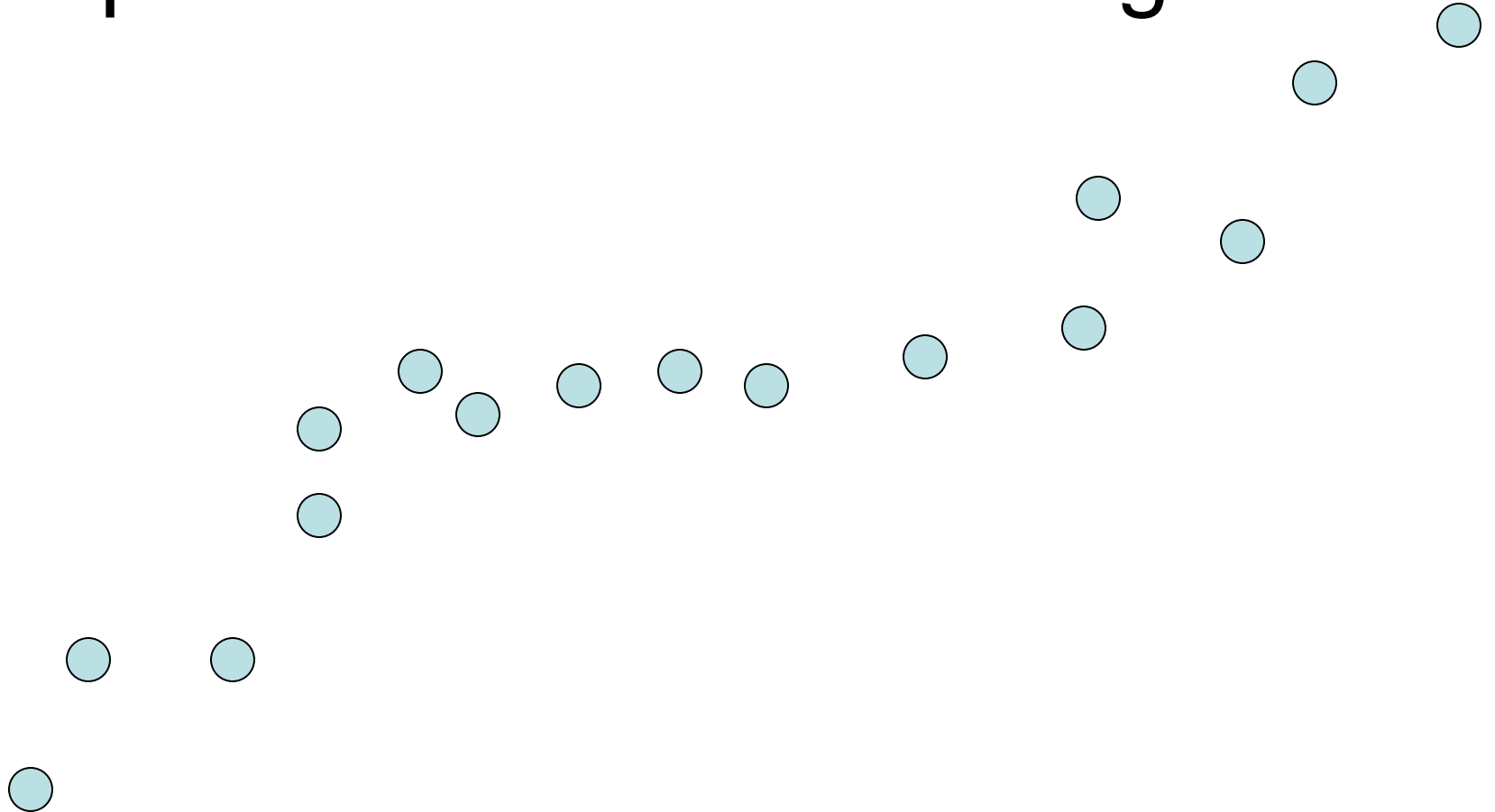


$$\text{Error} = \sum (y_i - ax_i - b)^2$$

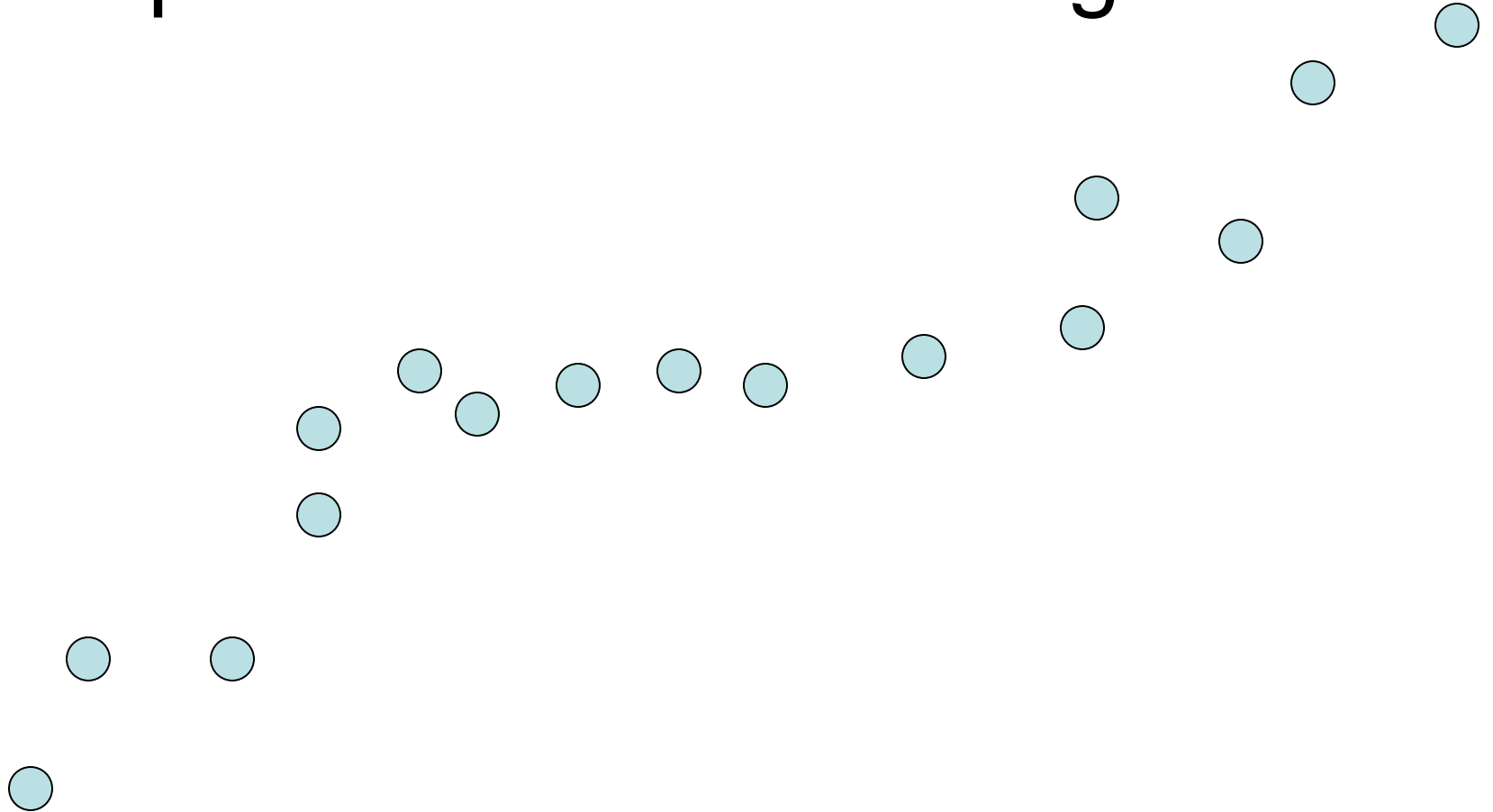
What is the optimal linear interpolation with three line segments



What is the optimal linear interpolation with two line segments

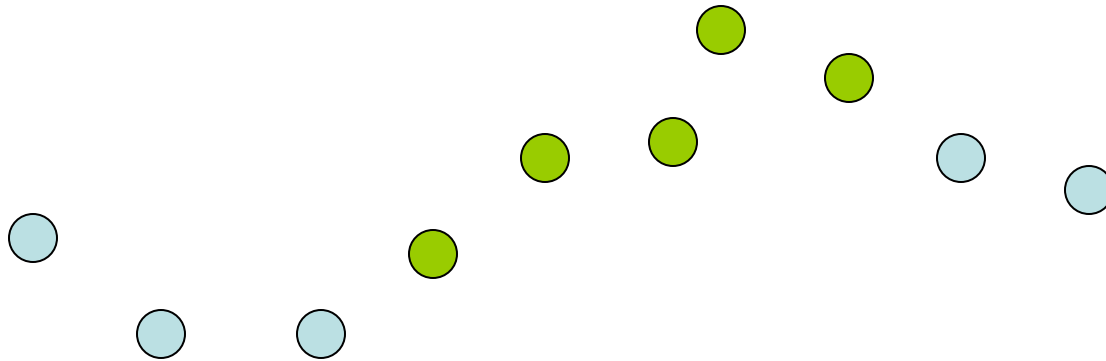


What is the optimal linear interpolation with n line segments



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

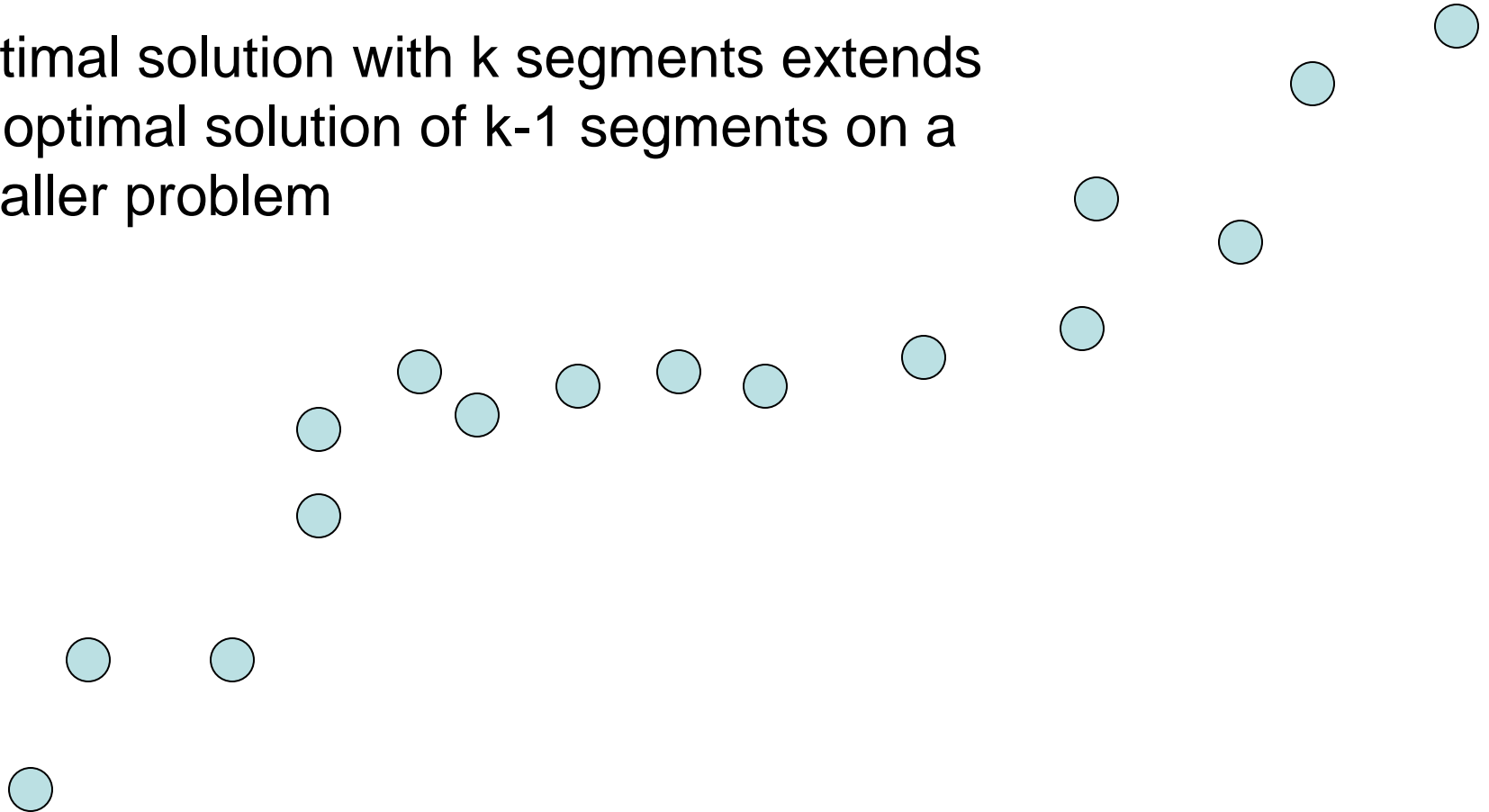
- Optimal segmentation with three segments
 - $\text{Min}_{i,j}\{E_{1,i} + E_{i,j} + E_{j,n}\}$
 - $O(n^2)$ combinations considered
- Generalization to k segments leads to considering $O(n^{k-1})$ combinations

$\text{Opt}_k[j]$: 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 $j - 1$

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

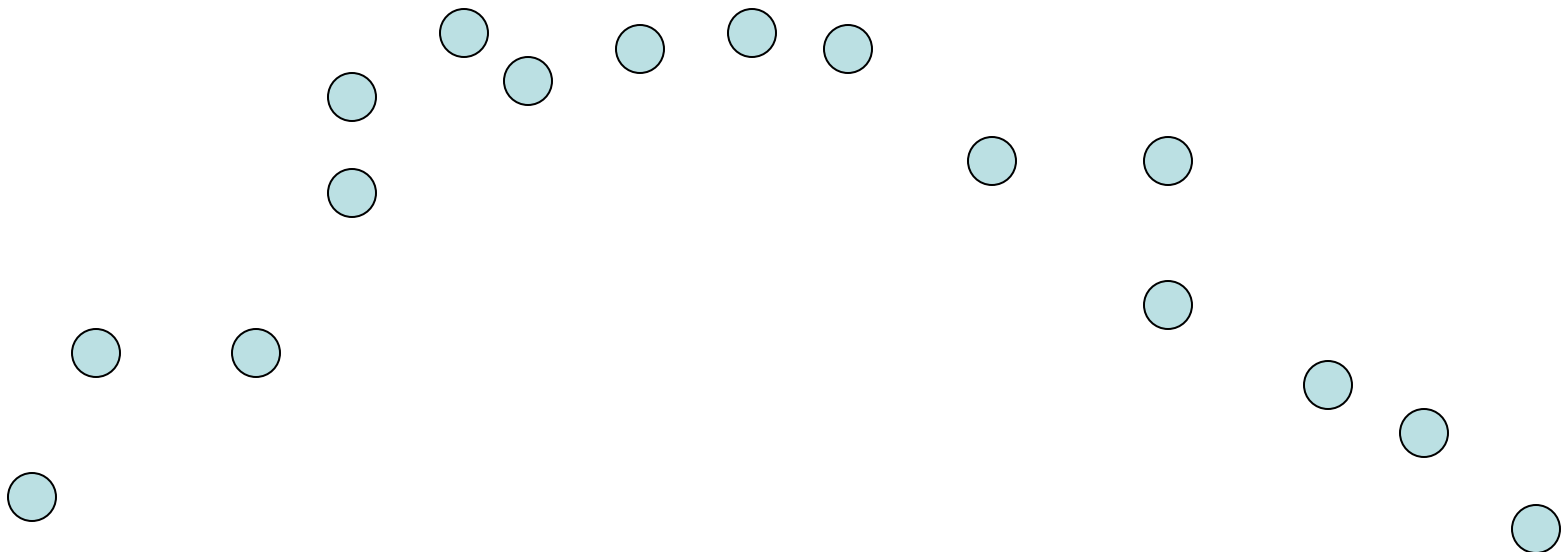
$\text{Opt}[k, j] = t$

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

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