

12 – Dynamic Programming (2)

Matrix-chain Multiplication

Segmented Least Squares

Optimal substructure

Dynamic programming is typically applied to
optimization problems.

An optimal solution to the original problem contains
optimal solutions to smaller subproblems.

Matrix-chain multiplication

Given: Sequence (chain) $\langle A_1, A_2, \dots, A_n \rangle$ of matrices

Goal: Compute the product $A_1 \cdot A_2 \cdot \dots \cdot A_n$.

Problem: Parenthesize the product in a way that minimizes the number of scalar multiplications.

Definition: A product of matrices is *fully parenthesized* if it is either a single matrix or the product of two fully parenthesized matrix products, surrounded by parentheses.

Multiplying two matrices

$$A = (a_{ij})_{p \times q}, B = (b_{ij})_{q \times r}, A \cdot B = C = (c_{ij})_{p \times r},$$

$$c_{ij} = \sum_{k=1}^q a_{ik} b_{kj}.$$

Algorithm Matrix-Mult

Input: $(p \times q)$ matrix A , $(q \times r)$ matrix B

Output: $(p \times r)$ matrix $C = A \cdot B$

```
1 for i := 1 to p do
2   for j := 1 to r do
3     C[i, j] := 0
4     for k := 1 to q do
5       C[i, j] := C[i, j] + A[i, k] · B[k, j]
```

Number of multiplications and additions: $p \cdot q \cdot r$

Remark: Using this algorithm, multiplying two $(n \times n)$ matrices requires n^3 multiplications. This can also be done using $O(n^{2.376})$ multiplications.

Matrix-chain multiplication: Example

Computation of the product $A_1 A_2 A_3$, where

A_1 : (10×100) matrix

A_2 : (100×5) matrix

A_3 : (5×50) matrix

Parenthesization $((A_1 A_2) A_3)$ requires

$$A' = (A_1 A_2): 10 \cdot 100 \cdot 5 = 5000$$

$$A' A_3: 10 \cdot 5 \cdot 50 = 2500$$

Sum: 7500

Matrix-chain multiplication: Example

A_1 : (10×100) matrix

A_2 : (100×5) matrix

A_3 : (5×50) matrix

Parenthesization $(A_1 (A_2 A_3))$ requires

$$A'' = (A_2 A_3): 100 \cdot 5 \cdot 50 = 25000$$

$$A_1 A'': 10 \cdot 100 \cdot 50 = 50000$$

Sum: 75000

Fully parenthesized matrix products

All possible fully parenthesized matrix products
of the chain $\langle A_1, A_2, A_3, A_4 \rangle$ are:

$$(A_1(A_2(A_3A_4)))$$

$$(A_1((A_2A_3)A_4))$$

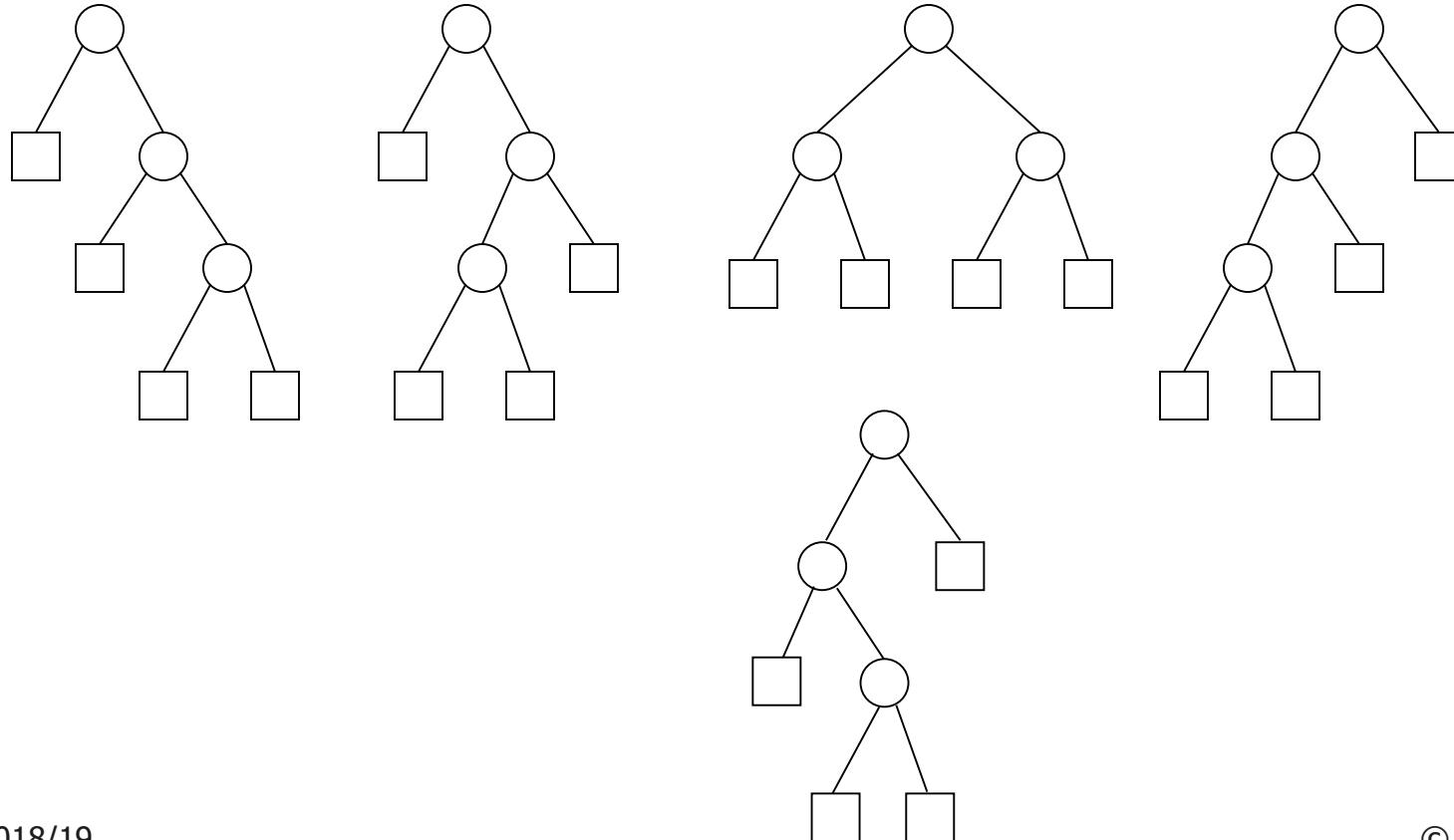
$$((A_1A_2)(A_3A_4))$$

$$((A_1(A_2A_3))A_4)$$

$$(((A_1A_2)A_3)A_4)$$

Number of different parenthesizations

Different parenthesizations correspond to different trees (selection).



Number of different parenthesizations

Let $P(n)$ be the number of alternative parenthesizations of the product $A_1 \dots A_k A_{k+1} \dots A_n$.

$$P(1) = 1$$

$$P(n) = \sum_{k=1}^{n-1} P(k)P(n-k) \quad \text{for } n \geq 2$$

$$P(n) = C_{n-1} \quad (n-1)\text{-st Catalan number}$$

$$C(n) = \frac{1}{n+1} \binom{2n}{n} \approx \frac{4^n}{n\sqrt{\pi n}} + O\left(\frac{4^n}{\sqrt{n^5}}\right)$$

Remark: Determining the optimal parenthesization by exhaustive search is not reasonable.

Matrix-chain multiplication

Given: Sequence $\langle A_1, A_2, \dots, A_n \rangle$ of matrices

Matrix A_i has dimension $p_{i-1} \times p_i$, for $i = 1, \dots, n$.

Goal: Parenthesize the product in a way that minimizes the number of scalar multiplications.

Structure of an optimal parenthesization

Subproblems $A_{i \dots j}$ $1 \leq i \leq j \leq n$

$$A_{i \dots i} = A_i \quad A_{i \dots j} = (A_{i \dots k})(A_{k+1 \dots j}) \quad i \leq k < j$$

Any optimal solution to the matrix-chain multiplication problem contains optimal solutions to subproblems. Determine an optimal solution recursively.

Let $m[i,j]$ be the **minimum number of operations** needed to compute the product $A_{i \dots j}$.

$$m[i,j] = 0 \quad \text{if } i = j$$

$$m[i,j] = \min_{i \leq k < j} \{m[i,k] + m[k+1,j] + p_{i-1}p_kp_j\} \quad \text{otherwise}$$

$s[i,j]$ = **optimal split value k** , i.e. the optimal parenthesization of $A_{i \dots j}$ splits the product between A_k and A_{k+1}

Recursive matrix-chain multiplication

Algorithm *RecMatChain*(p, i, j)

Input: Sequence $p = \langle p_0, p_1, \dots, p_n \rangle$,

where $(p_{i-1} \times p_i)$ is the dimensionen of matrix A_i

Invariant: $\text{RecMatChain}(p, i, j)$ returns $m[i, j]$

```
1 if  $i = j$  then return 0;  
2  $m[i, j] := \infty$ ;  
3 for  $k := i$  to  $j - 1$  do  
4    $m[i, j] := \min( m[i, j], p_{i-1} p_k p_j +$   
      $\text{RecMatChain}(p, i, k) +$   
      $\text{RecMatChain}(p, k+1, j) )$ ;  
5 return  $m[i, j]$ ;
```

Initial call: $\text{RecMatChain}(p, 1, n)$

Recursive matrix-chain multiplication

Let $T(n)$ be the time taken by `rec-mat-chain($p, 1, n$)`.

$$T(1) \geq 1$$

$$\begin{aligned} T(n) &\geq 1 + \sum_{k=1}^{n-1} (T(k) + T(n-k) + 1) \\ &\geq n + 2 \sum_{i=1}^{n-1} T(i) \\ \Rightarrow T(n) &\geq 3^{n-1} \quad (\text{induction}) \end{aligned}$$

Exponential running time!

Solution using dynamic programming

Algorithm *DynMatChain*

Input: Sequence $p = \langle p_0, p_1, \dots, p_n \rangle$ ($p_{i-1} \times p_i$) the dimension of matrix A_i ,

Output: $m[1, n]$

```
1  $n := \text{length}(p) - 1;$ 
2 for  $i := 1$  to  $n$  do  $m[i, i] := 0;$ 
3 for  $l := 2$  to  $n$  do /*  $l$  = length of the subproblem */
4   for  $i := 1$  to  $n - l + 1$  do /*  $i$  is the left index */
5      $j := i + l - 1;$  /*  $j$  is the right index */
6      $m[i, j] := \infty;$ 
7     for  $k := i$  to  $j - 1$  do
8        $m[i, j] := \min( m[i, j], p_{i-1} p_k p_j + m[i, k] + m[k + 1, j] );$ 
9 return  $m[1, n];$ 
```

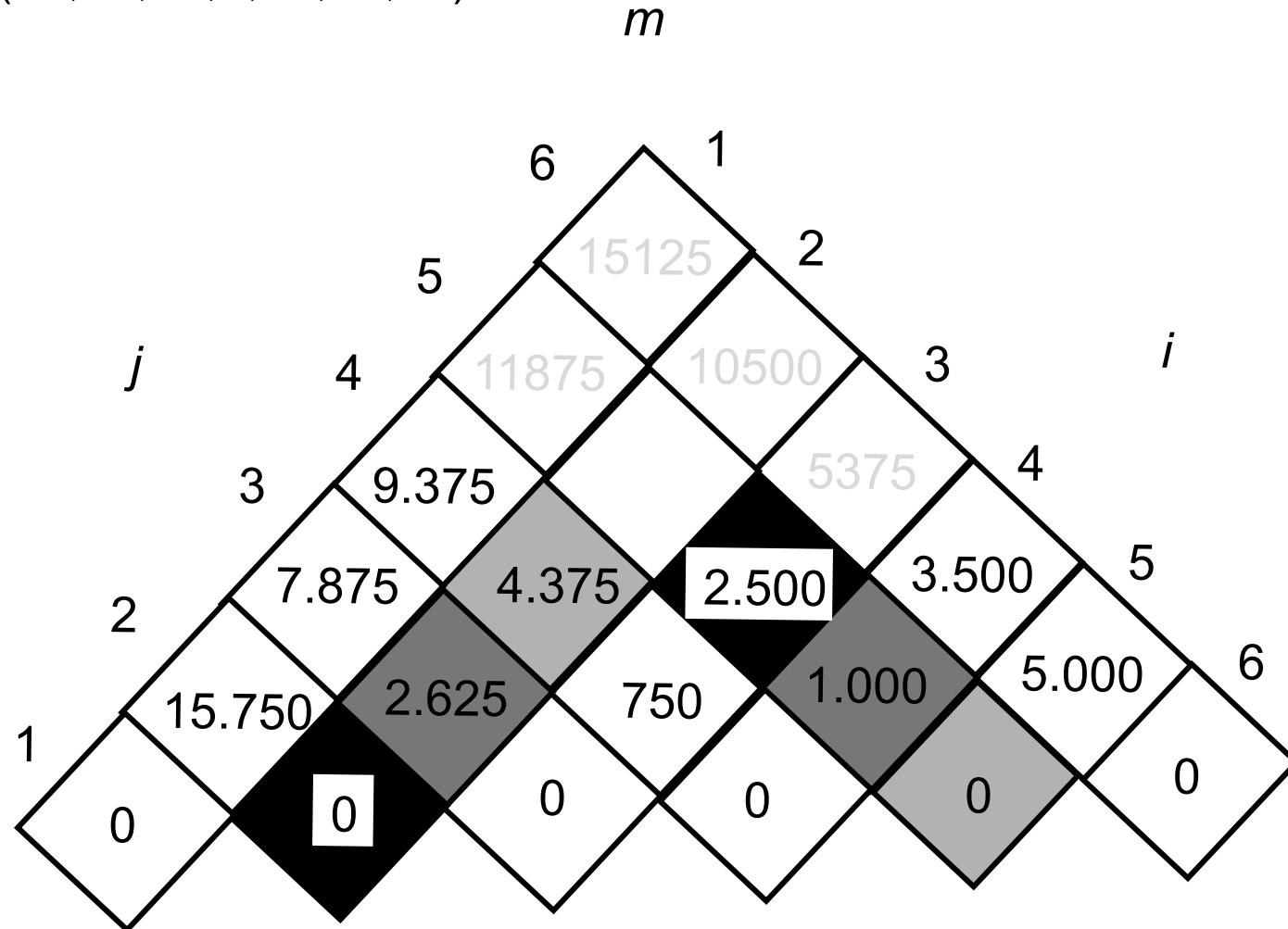
Example

A_1 (30×35)	A_4 (5×10)
A_2 (35×15)	A_5 (10×20)
A_3 (15×5)	A_6 (20×25)

$$p = (30, 35, 15, 5, 10, 20, 25)$$

Example

$$p = (30, 35, 15, 5, 10, 20, 25)$$



Example

$$m[2,5] = \min_{2 \leq k < 5} (m[2,k] + m[k+1,5] + p_1 p_k p_5)$$

$$= \min \begin{cases} m[2,2] + m[3,5] + p_1 p_2 p_5 \\ m[2,3] + m[4,5] + p_1 p_3 p_5 \\ m[2,4] + m[5,5] + p_1 p_4 p_5 \end{cases}$$

$$= \min \begin{cases} 0 + 2500 + 35 \cdot 15 \cdot 20 = 13000 \\ 2625 + 1000 + 35 \cdot 5 \cdot 20 = 7125 \\ 4375 + 0 + 35 \cdot 10 \cdot 20 = 11375 \end{cases}$$

$$= 7125$$

Including optimal split values

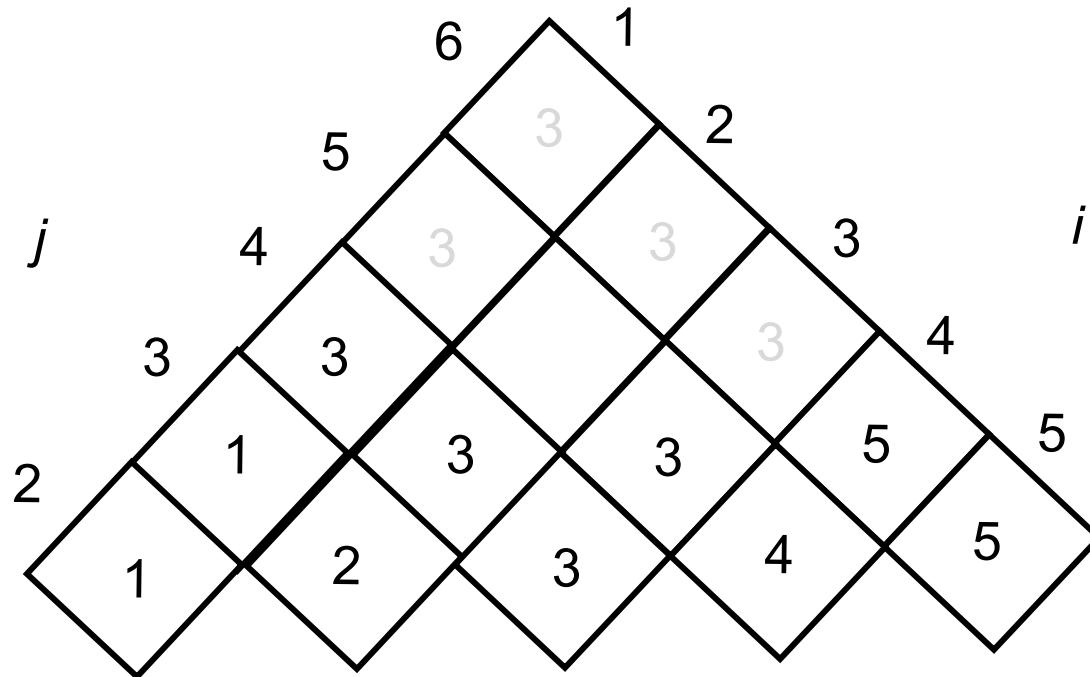
Algorithm *DynMatChain(p)*

Input: Sequence $p = \langle p_0, p_1, \dots, p_n \rangle$, $(p_{i-1} \times p_i)$ the dimension of matrix A_i

Output: $m[1, n]$ and a matrix $s[i, j]$ containing the optimal split values

```
1   $n := \text{length}(p) - 1;$ 
2  for  $i := 1$  to  $n$  do  $m[i, i] := 0$ 
3  for  $l := 2$  to  $n$  do
4    for  $i := 1$  to  $n - l + 1$  do
5       $j := i + l - 1;$ 
6       $m[i, j] := \infty;$ 
7      for  $k := i$  to  $j - 1$  do
8         $q := m[i, j];$ 
9         $m[i, j] := \min( m[i, j], p_{i-1} p_k p_j + m[i, k] + m[k + 1, j] );$ 
10       if  $m[i, j] < q$  then  $s[i, j] := k;$ 
11  return  $(m[1, n], s);$ 
```

Example of splitting values



Computation of an optimal parenthesization

Algorithm *OptParenthesization*

Input: Chain A of matrices, matrix s containing the optimal split values, two indices i and j

Output: An optimal parenthesization of $A_{i\dots j}$

```
1  if  $i < j$ 
2    then  $X := \text{OptParenthesization}(A, s, i, s[i, j]);$ 
3     $Y := \text{OptParenthesization}(A, s, s[i, j] + 1, j);$ 
4    return  $(X \cdot Y);$ 
5  else return  $A_i;$ 
```

Initial call: $\text{OptParenthesization}(A, s, 1, n)$

Dynamic programming; top-down approach



„*Memoization*“ for increasing the efficiency of a recursive solution:

Only the *first time* a subproblem is encountered, its **solution is computed** and then stored in a table. Each subsequent time that the subproblem is encountered, the value stored in the table is simply looked up and returned (without repeated computation!).

Memoized matrix-chain multiplication

Algorithm *MemMatChain*(p , i , j)

Invariant: MemMatChain(p , i , j) returns $m[i, j]$;
the value is correct if $m[i, j] < \infty$

```
1 if  $i = j$  then return 0;
2 if  $m[i, j] < \infty$  then return  $m[i, j]$ ;
3 for  $k := i$  to  $j - 1$  do
4    $m[i, j] := \min( m[i, j], p_{i-1} p_k p_j +$ 
     MemMatChain( $p$ ,  $i$ ,  $k$ ) +
     MemMatChain( $p$ ,  $k + 1$ ,  $j$  );
5 return  $m[i, j]$ ;
```

Memoized matrix-chain multiplication

Call:

```
1  $n := \text{length}(p) - 1;$ 
2 for  $i := 1$  to  $n$  do
3   for  $j := 1$  to  $n$  do
4      $m[i, j] := \infty;$ 
5 MemMatChain( $p, 1, n$ );
```

The computation of all entries $m[i, j]$ using *MemMatChain* takes $O(n^3)$ time.

$O(n^2)$ entries.

Each entry $m[i, j]$ is computed once.

Each entry $m[i, j]$ is looked up during the computation of $m[i', j']$ if $i' = i$ and $j' > j$ or $j' = j$ and $i' < i$.

Thus $m[i, j]$ is looked up during the computation of at most $2n$ entries.

Remarks about matrix-chain multiplication



1. There is an algorithm that determines an optimal parenthesization in time $O(n \log n)$.
2. There is a linear time algorithm that determines a parenthesization using at most $1.155 \cdot M_{opt}$ multiplications.

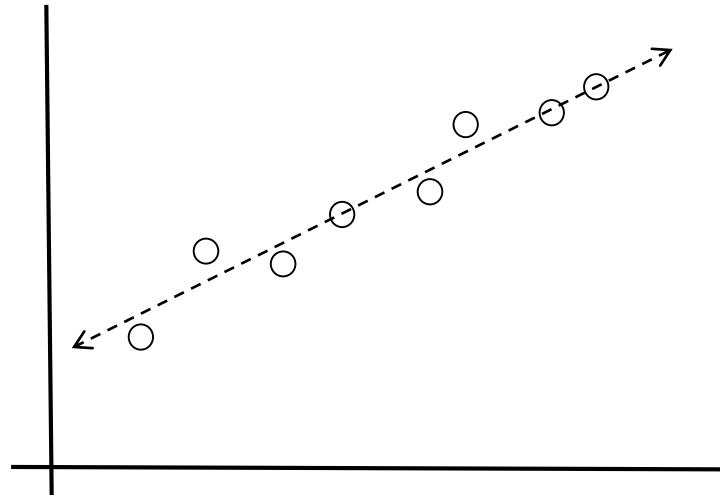
Segmented Least Squares

Problem in statistics and numerical analysis

$$P = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\} \quad x_1 < x_2 < \dots < x_n$$

Find $L = ax+b$ that minimizes the error of L w.r.t. P .

$$\text{Error}(L, P) = \sum_{1 \leq i \leq n} (y_i - ax_i - b)^2$$



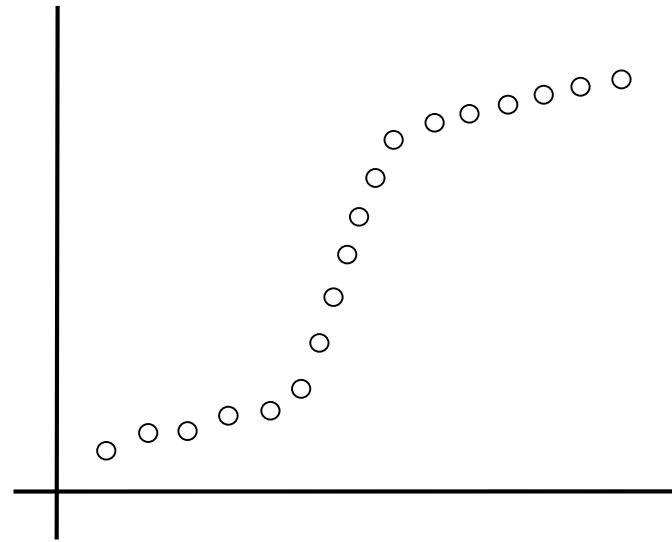
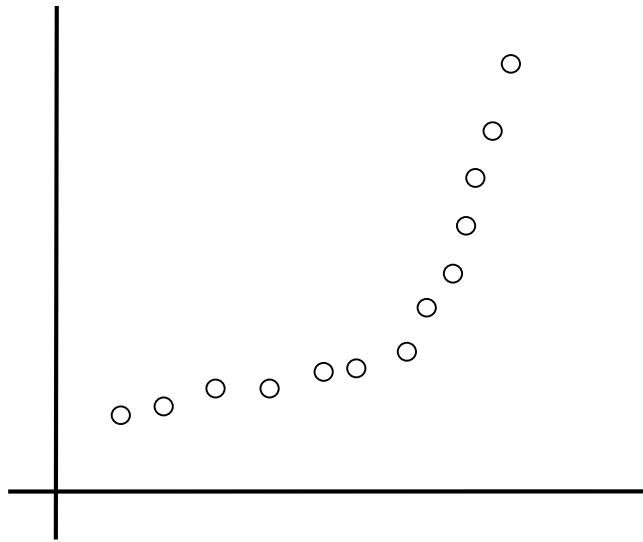
Solution

Line $L = ax+b$ where

$$a = \frac{n \sum_i x_i y_i - (\sum_i x_i)(\sum_i y_i)}{n \sum_i x_i^2 - (\sum_i x_i)^2}$$

$$b = \frac{\sum_i y_i - a \sum_i x_i}{n}$$

One line might not suffice



Segmented Least Squares

Problem: $P = \{p_1, p_2, \dots, p_n\}$ where

$$p_i = (x_i, y_i) \quad \text{for } i = 1, \dots, n \quad x_1 < x_2 < \dots < x_n$$

A **segment** is a subset $\{p_i, \dots, p_j\}$ where $i \leq j$

Partition P into segments. **Penalty** is the sum of

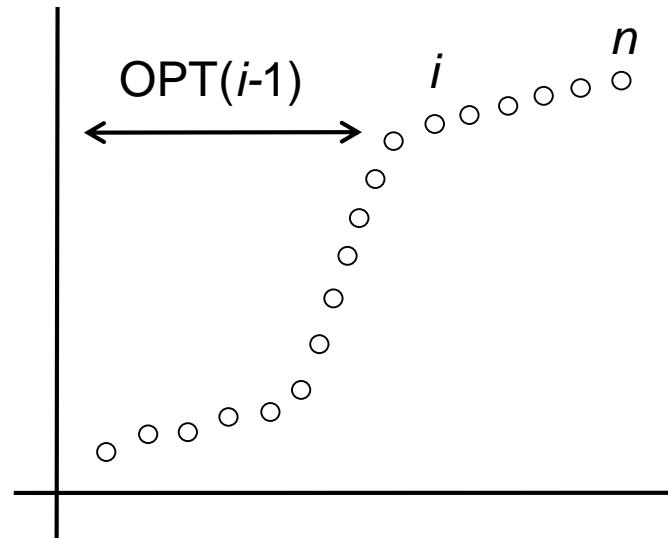
- $C \cdot \# \text{ segments}$ where $C > 0$
- For each segment, the error of the optimum line through it.

Goal: Find partition of minimum penalty.

Dynamic programming approach

Last segment is $\{p_i, \dots, p_n\}$ for some $1 \leq i \leq n$.

The remaining segments are an optimal solution for $\{p_1, \dots, p_{i-1}\}$.



Dynamic programming approach

$\text{OPT}(j)$ = value of an optimal solution for $\{p_1, \dots, p_j\}$ $1 \leq j \leq n$

$\text{OPT}(0) := 0$

$e_{i,j}$ = minimum error of any line through $\{p_i, \dots, p_j\}$ $1 \leq i \leq j \leq n$

$$\text{OPT}(n) = \min_{1 \leq i \leq n} (e_{i,n} + C + \text{OPT}(i-1))$$

$$\text{OPT}(j) = \min_{1 \leq i \leq j} (e_{i,j} + C + \text{OPT}(i-1))$$

Dynamic programming algorithm

Array $m[0..n]$ contains the values of the optimal solutions.

Algorithm SegmentedLeastSquares(n)

```
1   $m[0] := 0;$ 
2  for all pairs  $i \leq j$  do
3      Compute  $e_{i,j}$  for segment  $\{p_i, \dots, p_j\}$ ;
4  for  $j := 1$  to  $n$  do
5       $m[j] := \min_{1 \leq i \leq j} (e_{i,j} + C + m[i-1]);$ 
```

Running time: $O(n^2)$

Computing a solution

Algorithm FindSegments(j)

```
1 if  $j = 0$  then
2   Output nothing;
3 else
4   Find an  $i$  that minimizes  $e_{i,j} + C + m[i-1]$ ;
5   Output segment  $\{p_i, \dots, p_j\}$  and the result of FindSegments( $i-1$ );
6 endif;
```