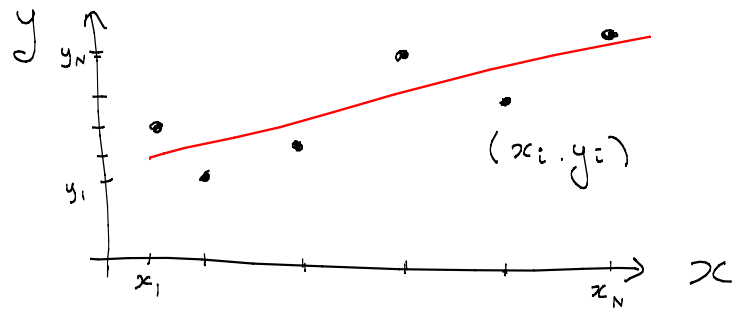


lecture 13

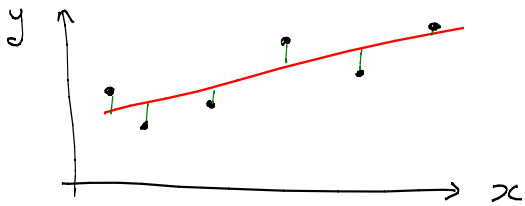
Segmented least squares

- least squares (introduction)
- segmentation
- dynamic programming solution

Least Squares



Fit a **line** to a set of points.



Model: $y_i = ax_i + b + \epsilon_i$

↑
error due to
e.g. - measurement
- wrong model
(ignoring non-linearity)

$$y_i = ax_i + b + \epsilon_i$$

"Least squares" - find the model parameters a and b that minimize the sum of squared errors:

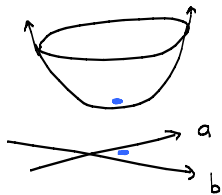
$$\sum_{i=1}^N \epsilon_i^2 \equiv \sum_{i=1}^N (y_i - ax_i - b)^2$$

why squared? why not absolute value?

$$\sum_{i=1}^N \epsilon_i^2 \equiv \sum_{i=1}^N (y_i - ax_i - b)^2$$

- a, b are the model parameters
- x_i, y_i are input data (fixed)

Claim: If we vary the parameters of the line over all (a, b) , there is a single **minimum**.



How to find the (a, b) that minimizes $\sum \epsilon_i^2$?

Calculus III

$$\begin{cases} \frac{\partial}{\partial a} \sum_i (y_i - ax_i - b)^2 = 0 \\ \frac{\partial}{\partial b} \sum_i (y_i - ax_i - b)^2 = 0 \end{cases}$$

$$\Rightarrow \begin{cases} \sum_i 2x_i(y_i - ax_i - b) = 0 \\ \sum_i 2(y_i - ax_i - b) = 0 \end{cases}$$

which we rewrite as two linear equations with variables (a, b) . See next slide.

$$\left(\sum_{i=1}^N x_i^2\right) a + \left(\sum_{i=1}^N x_i\right) b = \sum_{i=1}^N x_i y_i$$

$$\left(\sum_{i=1}^N x_i\right) a + Nb = \sum_{i=1}^N y_i$$

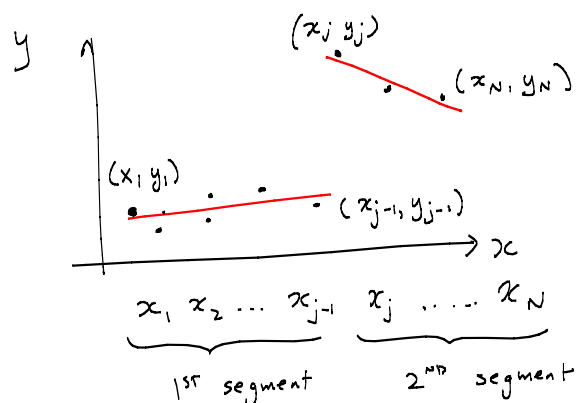
and solve :

$$a = \frac{\sum y_i \sum x_i - N \sum x_i y_i}{(\sum x_i)^2 - N \sum x_i^2}$$

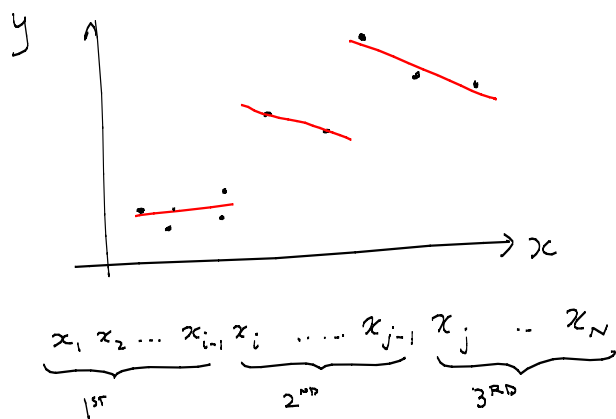
$$b = \frac{\sum x_i \sum x_i y_i - \sum x_i^2 \sum y_i}{(\sum x_i)^2 - N \sum x_i^2}$$

Segmented Least Squares

What if we allow ourselves to fit two lines ?



What if we allow ourselves to fit three lines (or k lines) ?



$x_1 \ x_2 \ x_3 \ \dots \ x_{N-1} \ x_N$

How many ways can we partition this sequence into k segments ?

e.g.

$(x_1 \ x_2 \ \dots \ x_N)$	1 segment
$(x_1 \ x_2 \ x_3)(x_4, \dots x_N)$	2 segments
$(x_1 \ x_2 \ x_3 \ x_4, \dots)(x_N)$	2 segments
\vdots	
$(x_1, x_2)(x_3, x_4)(x_5, \dots x_N)$	3 segments
\vdots	
$(x_1)(x_2)(x_3)(x_4) \dots (x_N)$	N segments

Claim: There are 2^{N-1} ways can we segment $x_1 \ x_2 \ \dots \ x_N$.

(I will return to this at end of lecture.)

Example ($N=6$)

[abcdef],
[a', 'bdef],
[ab', 'cdef],
[abc', 'def],
[abcd', 'ef],
[abcde', 'f],
[a', 'b', 'cdef],
[a', 'bc', 'def],
[a', 'bcd', 'ef],
[a', 'bcde', 'f],
[ab', 'c', 'def],
[ab', 'cd', 'ef],
[ab', 'cde', 'f],
[abc', 'd', 'ef],
[abc', 'de', 'f],
[abcd', 'e', 'f],
[a', 'b', 'c', 'def],
[a', 'b', 'cd', 'ef],
[a', 'b', 'cde', 'f],
[a', 'bc', 'd', 'ef],
[a', 'bcd', 'e', 'f],
[a', 'bcd', 'ef],
[ab', 'c', 'd', 'ef],
[ab', 'c', 'de', 'f],
[ab', 'cd', 'e', 'f],
[abc', 'd', 'e', 'f],
[a', 'b', 'c', 'd', 'ef],
[a', 'b', 'c', 'de', 'f],
[a', 'b', 'cd', 'e', 'f],
[a', 'bc', 'd', 'e', 'f],
[ab', 'c', 'd', 'e', 'f],
[a', 'b', 'c', 'd', 'e', 'f]

We would like to segment the data and fit lines such that

- the errors for each segment are small
 - use as few lines as we can (to avoid "over fitting")
- e.g. if segments are two points each is. $N/2$ segments, then we will have zero fitting error)

Note there is a trade off here !

Cost of a segmentation
 $(x_1 \dots x_{i-1}) (x_i \dots x_N)$

$\equiv \sum_{\text{segments}} \text{least squares fitting error for each segment}$

+ $C \cdot (\text{number of segments})$

↑
 cost for each segment
 (make this bigger if you want to guard against overfitting)

Approach

1.) $x_1 x_2 x_3 \dots (x_i \dots x_j) \dots x_N$
 ↑
 solve least squares fit for each (i, j) where $i < j$

2.) solve the combinatorial problem of choosing a segmentation - using dynamic programming

1) Suppose (x_i, \dots, x_j) is a segment.
 Let e_{ij} be the least squares fitting error for that segment.

Same as at beginning of today's lecture

Fit line to $\{(x_\ell, y_\ell) : i \leq \ell \leq j\}$

$$e_{ij} \equiv \sum_{\ell=i}^j \varepsilon_\ell^2 \equiv \sum_{\ell=i}^j (y_\ell - ax_\ell - b)^2$$

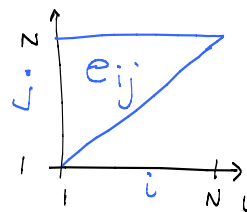
and solve for (a, b) using least squares.

Precompute e_{ij}

$$e_{ii} = 0$$

$$e_{i, i+1} = 0 \quad \text{since we can fit a line to two points}$$

for $i = 1$ to N
 for $j = i+2$ to N
 compute e_{ij}



[Total time is $O(N^3)$ if each "compute e_{ij} " is $O(N)$, but it's possible to do it in $O(N^2)$.]

Cost of a particular segmentation
 $\equiv \sum_{\text{segments } (i,j)} \text{fitting error } e_{ij} \text{ for segment } (x_i \dots x_j) + C \cdot (\text{number of segments})$

2) How to avoid the $O(2^N)$ possible segmentations?

Dynamic Programming: break problem into subproblems that share "sub-sub problems".
 Re-use the solutions of the sub-sub problems.

Let $Opt(i)$ be the minimum cost of segmentation for the problem with input $\{(x_1, y_1), (x_2, y_2), \dots, (x_j, y_j)\}$

i.e. how to segment $(x_1 \dots x_j)$?

$$Opt(0) = 0$$

$$Opt(1) = Opt(2) = C$$

$$Opt(j) = ?$$

$$Opt(N) = ?$$

Two Approaches

- Recursion
 - Iteration
- both will use memoization to avoid combinatorial explosion

Recursion

The **last segment** of the optimal solution is $(x_i, x_{i+1}, \dots, x_N)$ for some unknown i .

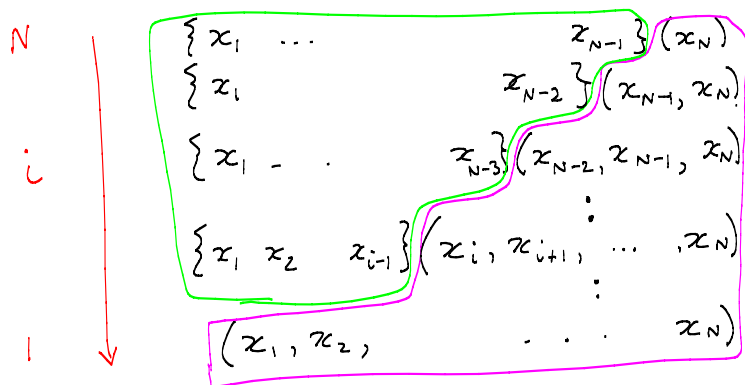
Thus,

$$Opt(N) = \boxed{Opt(i-1)} + \boxed{e_{iN} + C}$$

\uparrow Cost of segments that use $\{x_1, x_2, \dots, x_{i-1}\}$
 \uparrow Cost of last segment (x_i, \dots, x_N)

Thus, the **lowest cost** of segmentation is

$$Opt(N) = \min_{1 \leq i \leq N} \{ \boxed{Opt(i-1)} + \boxed{e_{iN} + C} \}$$



$$Opt(N) = \min_{1 \leq i \leq N} \{ \boxed{Opt(i-1)} + \boxed{e_{iN} + C} \}$$

recursion with memoization

$$= \sum_{\text{Segments } (i,j)} e_{ij} + C \cdot (\text{number of segments})$$

Iteration

Solve for $Opt(j)$, $j=1$ to N

$Opt[0] = 0$	$\{\}$
$Opt[1] = C$	$\{x_1\}$
$Opt[2] = C$	$\{x_1, x_2\}$
$Opt[3] = ?$	$\{x_1, x_2, x_3\}$
	\vdots
$Opt[j] = ?$	$\{x_1, x_2, x_3, \dots, x_j\}$
$Opt[N] = ?$	$\{x_1, x_2, x_3, \dots, x_j, \dots, x_N\}$

$$Opt[0] = 0$$

for $j=1$ to N

$$Opt[j] = \min_{1 \leq i \leq j} \{ Opt[i-1] + e_{ij} + C \}$$

Time required for above is $O(N^2)$.

The methods described above tell us how to compute the lowest total cost. But they don't keep track of the segmentation and models.

You could modify the pseudocode to do this. Or you could do afterwards (Similar to what we saw with weighted interval scheduling.)

```

findSegments(j) {
  if j > 0 { // find (x_i ... x_j)
    find i such that i ≤ j and
      Opt[j] == Opt[i-1] + e_ij + c
    print(i, j)
    findSegments(i-1)
  }
}

```

Note: if solution is not unique, then we might find a different segmentation here than we found before.

Recall from earlier in the lecture:

Example (N=6)

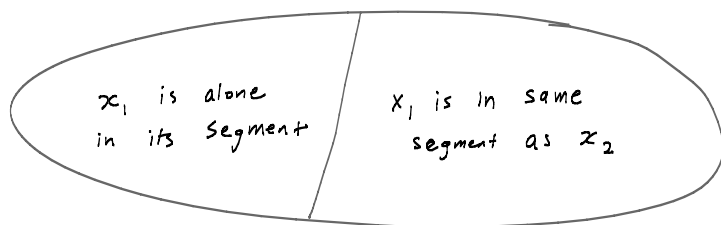
[abodef],
[a, 'bodef'],
[ab, 'cdef'],
[abc, 'def'],
[abod, 'ef'],
[abcde, 'f'],
[a, 'b', 'cdef'],
[a, 'bc', 'def'],
[a, 'bcd', 'ef'],
[a, 'bcde', 'f'],
[ab, 'c', 'def'],
[ab, 'cd', 'ef'],
[ab, 'cde', 'f'],
[abc, 'd', 'ef'],
[abc, 'de', 'f'],
[abcd, 'e', 'f'],
[a, 'b', 'c', 'def'],
[a, 'b', 'cd', 'ef'],
[a, 'b', 'cde', 'f'],
[a, 'bc', 'd', 'ef'],
[a, 'bcd', 'e', 'f'],
[ab, 'c', 'd', 'ef'],
[ab, 'cd', 'e', 'f'],
[ab, 'cde', 'f'],
[abc, 'd', 'e', 'f'],
[a, 'b', 'c', 'd', 'ef'],
[a, 'b', 'c', 'de', 'f'],
[a, 'b', 'cd', 'e', 'f'],
[a, 'bc', 'd', 'e', 'f'],
[ab, 'c', 'd', 'e', 'f'],
[a, 'b', 'c', 'd', 'e', 'f']

Claim: There are 2^{N-1} ways can we segment

$x_1 x_2 \dots x_N$.

$x_1 x_2 x_3 \dots x_{N-1} x_N$

How many ways can we partition this sequence into k segments of consecutive elements?



Let $f(N, k)$ be the number of ways we can partition $x_1 x_2 \dots x_N$ into k segments.

$$f(N, k) = f(N-1, k-1) + f(N-1, k)$$

\uparrow \uparrow
 x_1 is alone x_1 is in same
 in its segment segment as x_2

Q: How many segmentations are there in total for all $k = 1, \dots, N$?

A: $\sum_{k=1}^N f(N, k)$

Exercise:

Show $\sum_{k=1}^N f(N, k) = 2^{N-1}$