Dynamic Programming III: Segmented Least Squares

The Problem

We are given a set of points $\{p_1 = (x_1, y_2), p_2 = (x_2, y_2), \dots, p_n = (x_n, y_n)\}$ sorted by x-coordinate. Our goal is to fit a (segmented) line to P with least squares error.

What is "error" here? We use square error (SSE) from any line we use. That is, if our line is determined by slope a and y-intercept b, then our SSE would be

$$SSE = \sum_{i=1}^{n} (y_i - ax_i - b)^2.$$

Using calculus, we can derive that this is minimized when we set

$$a = \frac{n\sum_{i} x_i y_i - (\sum_{i} x_i)(\sum_{i} y_i)}{n\sum_{i} x_i^2 - (\sum_{i} x_i)^2} \quad \text{and} \quad b = \frac{\sum_{i} y_i - a\sum_{i} x_i}{n}.$$

But what if we can use as many segments as we want, just with a penalty c for each additional segment? How should we decide on the number of segments, and on what the segments should look like?

Our goal is to partition P into some C contiguous segments with minimal least squares error when there is a penalty c for each segment.

Making the Key Observation

The last point p_n belongs to a single segment which must begin somewhere. Where does it begin? In each case, what does the optimal solution look like?

Step 1: The Subproblem

Let OPT(i) denote the optimum solution for the points p_1, \ldots, p_i , and OPT(0) = 0. Let $e_{i,j}$ denote the minimum error of any line with respect to points p_i, \ldots, p_j (i.e., find the line using the calculus solution up above).

Step 2: The Recurrence

If the last segment of the optimal partition is p_i, \ldots, p_n , then: $OPT(n) = e_{i,n} + C + OPT(i-1)$. Hence

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

where we use the segment p_i, \ldots, p_j if and only if $i \in \operatorname{argmax}$ of the above.

Step 3: Prove that your recurrence is correct. In the optimal solution on j points, j must be in a segment that starts at the $i \in \operatorname{argmax}$ of the above. $\operatorname{OPT}(i-1)$ gives the optimal segmented SSE for the first i-1 points and $e_{i,j}$ gives the optimal SSE for the segment from i to j, so adding these two error terms plus the penalty of C for using the one additional segment from i to j is the valid cost of this solution. If j instead was in a different segment that started at a different i', then for the same reasons, the cost of this solution would be $\operatorname{OPT}(i'-1) + C + e_{i',j}$, but this term did not minimize the above which is why it was not selected, hence it cannot have optimal (minimal) error. Hence the above recurrence is correct.

Step 4: State and prove your base cases. OPT(0) = 0 is enough to get us off the ground. Notice that OPT(1) is then well-defined.

Step 5: State how to solve the original problem. This is once again OPT(n).

Step 6: The Algorithm

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Algorithm 1 SegmentedLeastSquares(p_1, \ldots, p_n)
Input: Set of n points p_1, \ldots p_n.
Initialize memo array M of length n+1 with M[0]=0.

for all pairs i \leq j do

Compute e_{i,j} for the segment p_i, \ldots, p_j
end for

for j = 1, \ldots, n do

M[j] = \min_{1 \leq i \leq j} \{e_{i,j} + C + M[i-1]\}
end for
return M[n]
```

Step 7: Running Time

The recurrence optimizes over n things, and we loop over n entries, so filling the memo takes $O(n^2)$ time. Solving for $e_{i,j}$ takes O(n) time and there are $O(n^2)$ pairs of (i,j), so this takes $O(n^3)$ time, which is the dominant term for the algorithm.

Algorithm 2 FindSegments(j)

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Input: Number of points n.

Initialize memo array M of length n+1 with M[0]=0.

if j=0 then

return Null

else

Find an i that minimizes e_{ij}+C+M[i-1]

return the segment \{p_i,\ldots,p_j\} and FindSegments(i-1)

end if
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