CS580 Algorithm Design, Analysis, and Implementation

Lecture notes, Jan 27, 2022 Wufei Ma

1 Dynamic Programming

Weighted interval scheduling. The dynamic programming algorithms compute the optimal value. We can use post-processing to find the exact solution.

```
1
      Function Find-Solution(j):
2
          if j == 0 then:
3
             return null
4
          else if v[j] + M[p(j)] > M[j-1]:
5
              print j
6
              Find-Solution(p(j))
7
          else:
8
              Find-Solution(j-1)
9
          endif
```

The number of recursive calls is less than or equal to *n* so the complexity is O(n).

We can also implement the dynamic programming algorithm in a bottom-up manner by computing $OPT(\cdot)$ from 1 to *n*.

Least squares. Given *n* points in the plane, $(x_1, y_1), \ldots, (x_n, y_n)$. Find a line y = ax + b that minimizes the sum of the squared error.

We can solve this problem with calculus:

$$a = \frac{n\sum_{i} x_{i}y_{i} - (\sum_{i} x_{i})(\sum_{i} y_{i})}{n\sum_{i} x_{i}^{2} - (\sum_{i} x_{i})^{2}}, \quad b = \frac{\sum_{i} y_{i} - a\sum_{i} x_{i}}{n}$$

Segmented least squares. Points lie roughly on a sequence of several line segments. Given *n* points in the plane $(x_1, y_1), \ldots, (x_n, y_n)$ with $x_1 < \cdots < x_n$, find a sequence of lines that minimizes the sum of the sums of the squared errors *E* in each segment and the number of lines *L*:

$$E + c \cdot L$$
, $c > 0$

Let OPT(j) be the minimum cost for points p_1, \ldots, p_j . Let e(i, j) be the minimum sum of squares for points p_1, \ldots, p_j . To compute OPT(j), the last line segment uses points p_i, \ldots, p_j for some *i* and the cost is e(i, j) + c + OPT(i - 1).

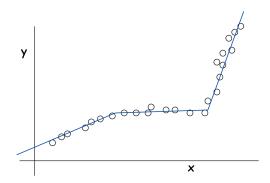


Figure 1: Segmented least squares.

```
1
      Function Segmented-Least-Squares():
2
          M[0] = 0
3
          for j = 1 to n:
4
              for i = 1 to j:
5
                  compute e(i, j)
6
          for j = 1 to n:
7
              M[j] = min(e(i,j) + c + M[i-1]) for 1 <= i <= j</pre>
8
          return M[n]
```

Since we compute e(i, j), which takes O(n) time, for $O(n^2)$ pairs, the running time of this algorithm is $O(n^3)$.

How do we find the optimal solution to this problem?

In fact, we can solve this problem in $O(n^2)$ time by pre-computing various statistics.

Knapsack problem. Given *n* objects and a knapsack. Item *i* weights $w_i > 0$ kilograms and has value $v_i > 0$. Knapsack has capacity of *W* kilograms. The goal is to fill knapsack so as to maximize the total value.

Let OPT(i, w) be the max profit from items 1, ..., *i* with weight limit *w*. We have

$$OPT(i) = \begin{cases} 0 & \text{if } i = 0\\ OPT(i-1,w) & \text{if } w_i > w\\ max\{OPT(i-1,w), v_i + OPT(i-1,w-w_i)\} & \text{otherwise} \end{cases}$$

This algorithm basically fills up an *n*-by-W matrix, and the running time is O(nW), which is pseudo-polynomial. The decision version of Knapsack is NP-complete.

Knapsack approximation algorithm. There exists a poly-time algorithm that produces a feasible solution that has a value within 0.01% of optimum.