## Chapter 7

## Lowest Point Above a Set of Lines

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Here, we investigate some cool algorithms for solving problems in linear time. All these algorithms use the **search & prune** technique – the idea is that you repeatedly reduce the input size, till it is small enough that you can solve the problem using brute force.

## 7.1. The lowest point above a set of lines

Let L be a set of n lines in the plane. To simplify the exposition, assume the lines are in general position:

- (A) No two lines of L are parallel.
- (B) No line of L is vertical or horizontal.
- (C) No three lines of L meet in a point.

We are interested in the problem of computing the point with the minimum y coordinate that is above all the lines of L. We consider a point on a line to be above it.

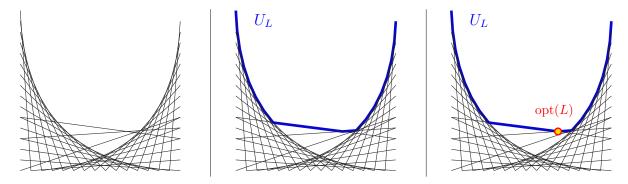


Figure 7.1.1: An input to the problem, the critical curve  $U_L$ , and the optimal solution – the point opt(L).

For a line  $\ell \in L$ , and a value  $\alpha \in \mathbb{R}$ , let  $\ell(\alpha)$  be the value of  $\ell$  at  $\alpha$ . Formally, consider the intersection point of  $p = \ell \cap (x = \alpha)$  (here,  $x = \alpha$  is the vertical line passing through  $(\alpha, 0)$ ). Then  $\ell(x) = y(p)$ .

Let  $U_L(\alpha) = \max_{\ell \in L} \ell(\alpha)$  be the **upper envelope** of L. The function  $U_L(\cdot)$  is convex, as one can easily verify. The problem asks to compute  $y^* = \min_{x \in \mathbb{R}} U_L(x)$ . Let  $x^*$  be the coordinate such that  $y^* = U_L(x^*)$ .

Definition 7.1.1. Let opt(L) =  $(x^*, y^*)$  denote the optimal solution – that is, lowest point on  $U_L(x)$ .

Remark 7.1.2. There are some uninteresting cases of this problem. For example, if all the lines of L have negative slope, then the solution is at  $x^* = +\infty$ . Similarly, if all the slopes are positive, then the solution is  $x^* = -\infty$ . We can easily check these cases in linear time. In the following, we assume that at least one line of L has positive slope, and at least one line has a negative slope.

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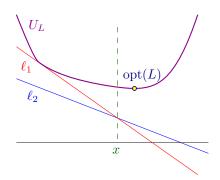


Figure 7.1.2: Illustration of the proof of Lemma 7.1.4.

**Lemma 7.1.3.** Given a value x, and a set L of n lines, one can in linear time do the following:

- (A) Compute the value of  $U_L(x)$ .
- (B) Decide which one of the following happens: (I)  $x = x^*$ , (II)  $x < x^*$ , or (III)  $x > x^*$ .

*Proof:* (A) Computing  $\ell(x)$ , for  $x \in \mathbb{R}$ , takes O(1) time. Thus computing this value for all the lines of L takes O(n) time, and the maximum can be computed in O(n) time.

(B) For case (I) to happen, there must be two lines that realizes  $U_L(x)$  – one of them has a positive slope, the other has negative slope. This clearly can be checked in linear time.

Otherwise, consider  $U_L(x)$ . If there is a single line that realizes the maximum for x, then its slope is the slope of  $U_L(x)$  at x. If this slope is positive than  $x^* < x$ . If the slope is negative then  $x < x^*$ .

The slightly more challenging case is when two lines realizes the value of  $U_L(x)$ . That is  $(x, U_L(x))$  is an intersection point of two lines of L (i.e., a **vertex**) on the upper envelope of the lines of L). Let  $\ell_1, \ell_2$  be these two lines, and assume that  $\text{slope}(\ell_1) < \text{slope}(\ell_2)$ .

If  $\operatorname{slope}(\ell_2) < 0$ , then both lines have negative slope, and  $x^* > x$ . If  $\operatorname{slope}(\ell_1) > 0$ , then both lines have positive slope, and  $x^* < x$ . If  $\operatorname{slope}(\ell_1) < 0$ , and  $\operatorname{slope}(\ell_1) > 0$ , then this is case (I), and we are done.

**Lemma 7.1.4.** Let (x, y) be the intersection point of two lines  $\ell_1, \ell_2 \in L$ , such that  $slope(\ell_1) < slope(\ell_2)$ , and  $x < x^*$ . Then  $opt(L) = opt(L - \ell_1)$ , where  $L - \ell_1 = L \setminus \{\ell_1\}$ 

Proof: See Figure 7.1.2. Since  $x < x^*$ , it must be that  $U_L(\cdot)$  has a negative slope at x (and also immediately to its right). In particular, for any  $\alpha > x$ , we have that  $U_L(\alpha) \ge \ell_2(x) > \ell_1(x)$ . That is, the line  $\ell_1(x)$  is "buried" below  $\ell_2$ , and can not touch  $U_L(\cdot)$  to the right of x. In particular, removing  $\ell_1$  from L can not change  $U_L(\cdot)$  to the right of x. Furthermore, since  $U_L(\cdot)$  has negative slope immediately after x, it implies that minimum point can not move by the deletion of  $\ell_1$ . Thus implying the claim.

**Lemma 7.1.5.** Let (x, y) be the intersection point of two lines  $\ell_1, \ell_2 \in L$ , such that  $slope(\ell_1) < slope(\ell_2)$ , and  $x^* < x$ . Then  $opt(L) = opt(L - \ell_2)$ .

*Proof:* Symmetric argument to the one used in the proof of Lemma 7.1.4.

**Observation 7.1.6.** The point p = opt(L) is a vertex formed by the intersection of two lines of L. Indeed, since none of the lines of L are horizontal, if p was in the middle of a line, then we could move it and improve the value of the solution.

**Lemma 7.1.7** (Prune). Given a set L of n lines, one can compute, in linear time, either:

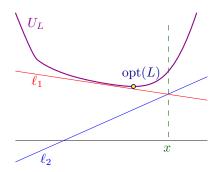


Figure 7.1.3: Illustration of the proof of Lemma 7.1.5.

- (A) A set  $L' \subseteq L$  such that opt(L) = opt(L'), and  $|L'| \le (7/8) |L|$ .
- (B) A value x such that x(opt(L)) = x.

*Proof:* If |L| = n = O(1) then one can compute opt(L) by brute force. Indeed, compute all the  $\binom{n}{2}$  vertices induced by L, and for each one of them check if they define the optimal solution using the algorithm of Lemma 7.1.3. This takes O(1) time, as desired.

Otherwise, pair the lines of L in  $N = \lfloor n/2 \rfloor$  pairs  $\ell_i, \ell'_i$ . For each pair, let  $x_i$  be the x-coordinate of the vertex  $\ell_i \cap \ell'_i$ . Compute, in linear time, using median selection, the median value z of  $x_1, \ldots, x_N$ . For the sake of simplicity of exposition assume that  $x_i < z$ , for  $i = 1, \ldots, N/2 - 1$ , and  $x_i > z$ , for  $i = N/2 + 1, \ldots, N$  (otherwise, reorder the lines and the values so that it happens).

Using the algorithm of Lemma 7.1.3 decide which of the following happens:

- (I)  $z = x^*$ : we found the optimal solution, and we are done.
- (II)  $z < x^*$ . But then  $x_i < z < x^*$ , for i = 1, ..., N/2 1, By Lemma 7.1.4, either  $\ell_i$  or  $\ell'_i$  can be dropped without effecting the optimal solution, and which one can be dropped can be decided in O(1) time. In particular, let L' be the set of lines after we drop a line from each such pair. We have that  $\operatorname{opt}(L') = \operatorname{opt}(L)$ , and  $|L'| = n (N/2 1) \le (7/8)n$ .
- (III)  $z > x^*$ . This case is handled symmetrically, using Lemma 7.1.5.

**Theorem 7.1.8.** Given a set L of n lines in the plane, one can compute the lowest point that is above all the lines of L (i.e., opt(L)) in linear time.

*Proof:* The algorithm repeatedly apply the pruning algorithm of Lemma 7.1.7. Clearly, by the above, this algorithm computes opt(L) as desired.

In the *i*th iteration of this algorithm, if the set of lines has  $n_i$  lines, then this iteration takes  $O(n_i)$  time. However,  $n_i \leq (7/8)^i n$ . In particular, the overall running time of the algorithm is

$$O\left(\sum_{i=0}^{\infty} (7/8)^i n\right) = O(n).$$

## 7.2. Bibliographical notes

The algorithm presented in Section 7.1 is a simplification of the work of Megiddo [m-lpltw-84]. Megiddo solved the much harder problem of solving linear programming in constant dimension in linear time, The algorithm presented is essentially the core of his basic algorithm.