Algorithms for the Minimax k-Ideal Problem

Toshio Nemoto

Faculty of Information and Communication
Bunkyo University
1100 Namegaya, Chigasaki 253, Japan
e-mail: nemoto@shonan.bunkyo.ac.jp

October, 1997

Abstract

Suppose we are given a poset(partially ordered set) $\mathcal{P}=(V,\preceq)$, a real-valued weight w(e) associated with each element $e\in V$ and a positive integer k. We consider the problem which asks to find an ideal of size k of \mathcal{P} such that the maximum element weight in the ideal is the minimum for all ideals that can be constructed from \mathcal{P} . We call this problem the minimax k-ideal problem. In this paper we propose two fast algorithms: a greedy algorithm and a threshold algorithm. Combining these algorithms, we accomplish the best available bound $O(\min\{n\log n+m,(m+n)\log^*n\})$ for this problem; the two bounds in this expression are, respectively, due to the greedy algorithm and the threshold algorithm, where |V|=n and m is the number of arcs of the Hasse diagram representing the given poset. This ruesult shows that this problem does not have an $\Omega(n\log n+m)$ lower bound in spite of the fact that the minimum-range k-ideal problem, which is a general problem of the minimax k-ideal problem, has an $\Omega(n\log n+m)$ lower bound.

1. Introduction

A binary relation \leq on a set V is called a partial order when it has the following properties:

• $\forall v \in V : v \leq v$. (Reflexivity)

• $v \leq w, w \leq v \Rightarrow v = w$. (Antisymmetry)

• $u \leq v, v \leq w \Rightarrow u \leq w$. (Transitivity)

We call the pair (V, \preceq) a partially ordered set or a poset for short. For a poset $\mathcal{P} = (V, \preceq)$ a subset I of V is called an *ideal* of \mathcal{P} if $u \preceq v \in I$ implies $u \in I$. Posets and ideals appear in numerous application settings and in many forms (see, e.g., [Ahuja+Magnanti+Orlin93], [Picard76], [Picard+Queyranne82]). In this paper we consider the minimax k-ideal problem defined as follows:

$$P_{k-\min\max}$$
: Minimize $\max_{e \in I} w(e)$ (1.1a)

subject to
$$I \in \mathcal{I}(\mathcal{P})$$
, (1.1b)

$$|I| = k, (1.1c)$$

where w is a weight function $w: V \to \mathbf{R}$ and assumed as $w(\emptyset) = -\infty$. When there is no possibility of confusion, an optimal ideal of Problem $P_{k\text{-minimax}}$ is called a *minimax ideal* (of size k) of \mathcal{P} .

In general, for the minimax combinatorial optimization problems there are three main strategies (cf. [Pferschy95] which classifies into three main strategies for solving the bottleneck assignment problem): The first is based on a "greedy" principle — that is, it makes the cheapest choice at each step; the second is based on a "threshold" method which needs an efficient search method to find an optimal solution (see [Lawler76]); the third is a combination of the above two strategies (see [Punnen+Nair94] which succeeded in constructing an efficient algorithm for the bottleneck assignment problem by this strategy).

According to the first and the second general approaches we propose a greedy algorithm and a threshold algorithm for the minimax k-ideal problem. To the author's knowledge, no one has ever considered the minimax k-ideal problem. The greedy algorithm runs in $O(n \log n + m)$ time and the threshold method can be implemented in $O((m+n) \log^* n)$ time, where \log^* is the iterated logarithm, defined by

$$\log^{(0)} x = x,\tag{1.2a}$$

$$\log^{(i+1)} x = \log\log^{(i)} x,\tag{1.2b}$$

$$\log^* x = \min\{i \mid \log^{(i)} x \le 1\}. \tag{1.2c}$$

Notice that $\log^* x$ is a very slowly growing function. For example, if $x=2^{65536}$, then $\log^* x=5$. Therefore, the required time of the threshold method is shorter than that of the greedy algorithm when $m<<(\frac{n}{2})^2$.

Combining these algorithms, we accomplish the best available bound $O(\min\{n \log n + m, (m + n) \log^* n\})$ for this problem; the two bounds in this expression are, respectively, due to the greedy algorithm and the threshold algorithm. This time complexity shows that the minimax k-ideal problem does not have an $\Omega(n \log n + m)$ lower bound in spite of the fact that the minimum-range k-ideal problem, which is a general problem of the minimax k-ideal problem, has an $\Omega(n \log n + m)$ lower bound[Nemoto95].

2. A Greedy Algorithm

We propose an $O(n \log n + m)$ algorithm for Problem $P_{k\text{-minimax}}$ based on the greedy principle. The algorithm enlarges an element set J from an evident ideal \emptyset with the property that J is an ideal of \mathcal{P} keeping. For the set J the algorithm maintains the set C of all the upper neighbors of each element in J, which are candidates for inclusion in J. In choosing an element from the set

C, we use a greedy principle on weights. This approach yields an $O(n \log n + m)$ time complexity. The algorithm is shown precisely in Figure 1.

Algorithm MINIMAX-GREEDY(\mathcal{P}, k)

Input: A poset $\mathcal{P} = (V, \preceq)$ and a positive integer k.

Output: A minimax ideal of size k of \mathcal{P} .

Step 1: Put $J := \emptyset$.

Step 2: Repeat the following (*) k times.

(*) Put $C:=\{v\mid v \text{ is a minimal element of } \mathcal{P}(V-J)\}$. If $C=\emptyset$, then stop (there is no feasible ideal of \mathcal{P}); otherwise find a minimum-weight element \hat{v} in C and put $J:=J\cup\{\hat{v}\}$.

Step 3: The current J is a minimax ideal of size k.

(End)

Figure 1: A greedy algorithm for Problem $P_{k-minimax}$.

The validity of this algorithm is shown below.

Lemma 2.1: The algorithm MINIMAX-GREEDY(\mathcal{P}, k) computes a minimax ideal of size k of a poset \mathcal{P} .

(Proof) For the ideal \hat{I} found by the algorithm MINIMAX-GREEDY (\mathcal{P},k) , let \hat{e} be a maximum-weight element in \hat{I} , and let C' and J' be the set C and J, respectively, in the algorithm MINIMAX-GREEDY (\mathcal{P},k) just before \hat{v} is chosen. Similarly, for a minimax ideal I^* of size k, let v^* be a maximum-weight element in I^* . Suppose $w(\hat{v}) > w(v^*)$. If $v^* \notin J'$, i.e., $v^* \in V - J'$, then $I^* \cap C' \neq \emptyset$ from the fact that C' is the set of all the minimal elements of $\mathcal{P}(V-J')$. Hence, I^* has an element $\tilde{v} \in I^* \cap C'$ such that $w(v^*) < (w(\hat{v}) \leq) w(\tilde{v})$, contradicting the fact that e^* is the maximum weight element in I^* . If $v^* \in J'$, then there exists an element $\tilde{v} \in C' \cap I^*$ such that $w(\tilde{v}) \leq w(v^*)(< w(\hat{v}))$ because $|I^*| > |J'|$ and e^* has the maximum weight in I^* . This contradicts the choice of \hat{v} . Consequently, we have $w(\hat{v}) = w(v^*)$.

We now turn to the time complexity analysis. In Step 2-(*), it is not difficult to renew the set C by making use of the list of all the lower neighbors of each element in $\mathcal{P}(V-J)$. Notice that the list of all the lower neighbors is controlled in the complete list representation of the given Hasse diagram $G(\mathcal{P})$. Suppose C_i is the set C at the *i*th iteration, we can get $C_{i+1} = (C_i - \{\hat{v}\}) \cup \{v \mid i\}$

the list of arcs δ^+v has just become empty by removing \hat{v} from $G(\mathcal{P}(V-J))$. Finding C_1 and identifying new elements added to C_{i+1} at the end of the *i*th iteration, require O(m+n) time in the whole of the algorithm. By having the heap data structure (see [Ahuja+Magnanti+Orlin93]) for C, finding a minimum-weight element \hat{v} in C, inserting new members to C and deleting \hat{v} from C are carried out in $O(\log n)$, respectively. Since each operation is done for an element at most once, it takes $O(n \log n)$ time. In total, this algorithm requires $O(n \log n + m)$ time. Consequently, we have the following theorem.

Theorem 2.2: The algorithm MINIMAX-GREEDY(\mathcal{P}, k) computes a minimax ideal of size k of \mathcal{P} in $O(n \log n + m)$.

Example: Consider Problem $P_{k\text{-minimax}}$ of k=5 on the poset \mathcal{P} represented by the Hasse diagram shown in Figure 2. The weight of each element is attached at the lower left of the element. The algorithm MINIMAX-GREEDY(\mathcal{P} , 5) might execute as indicated in Table 1. At termination, we have a minimax ideal $\{v_1, v_4, v_8, v_{13}, v_{14}\}$.

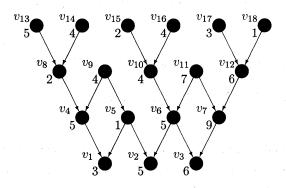


Figure 2: The Hasse diagram $G(\mathcal{P})$ representing a poset $\mathcal{P} = (V, \preceq)$ with the weights.

3. A Threshold Algorithm

Combining an efficient search method and a threshold method, we describe the other algorithm for the minimax cardinality-restricted ideal problem. Basically, the framework of the algorithm described here is the same as that of the algorithm proposed by Gabow and Tarjan [Gabow+Tarjan88] for the bottleneck spanning tree problem. However, to make use of the framework it is necessary to give some new ideas.

Table 1: The algorithm MINIMAX-GREEDY($\mathcal{P}, 5$) applied to the poset shown in Figure 2.

	Iter.	C	\hat{v}	$oldsymbol{J}$
Step 1				0
Step 2	1	$\{v_1, v_2, v_3\}$	v_1	$\{v_1\}$
	2	$\{v_2, v_3, v_4\}$	v_4	$\{v_1,v_4\}$
	3	$\{v_2, v_3, v_8\}$	v_8	$\{v_1,v_4,v_8\}$
	4	$\{v_2, v_3, v_{13}, v_{14}\}$	v_{14}	$\{v_1, v_4, v_8, v_{14}\}$
	5	$\{v_2, v_3, v_{13}\}$	v_{13}	$\{v_1, v_4, v_8, v_{14}, v_{13}\}$

First we show two lemmas which play a fundamental role in the threshold approach for the ideal problems.

Lemma 3.1: For a poset $\mathcal{P} = (V, \preceq)$ and a subset U of V let

$$W = V - \bigcup_{v \in U} F(v), \tag{3.1}$$

where $F(v) = \{w \mid w \in V, v \leq w\}$ which is called the principal filter generated by v. Then $W \subseteq V - U$ and W is an ideal of \mathcal{P} .

(Proof) It is clear that $W \subseteq V - U$. Suppose W is not an ideal of \mathcal{P} , that is, there exist two elements $w \in W$ and $u \notin W$ ($u \in \bigcup_{v \in U} F(v)$) such that $u \preceq w$ on \mathcal{P} . Since $w \in F(u) \subseteq \bigcup_{v \in U} F(v)$, we have $w \notin W$, contradicting the fact $w \in W$.

Lemma 3.2: For a poset $\mathcal{P} = (V, \preceq)$ let I be an ideal of \mathcal{P} . Then, for a subset $U \subseteq V$, U is an ideal of the subposet $\mathcal{P}(I)$ if and only if U is an ideal of \mathcal{P} and $U \subseteq I$.

(Proof) (\Rightarrow) Suppose U is not an ideal of \mathcal{P} . Hence, there exist two elements u and v such that $u \leq v$, $v \in U$ and $u \notin U$. If $u \in I - U$, then it contradicts the fact that U is an ideal of $\mathcal{P}(I)$. If $u \in V - I$, then it contradicts the fact that I is an ideal of \mathcal{P} . Therefore, U is an ideal of \mathcal{P} . (\Leftarrow) Suppose U is not an ideal of $\mathcal{P}(I)$, i.e., there exist two elements u and v such that $u \leq v$, $v \in U$ and $u \notin U$, i.e., $v \in U$ and $u \in I - U \subseteq V - U$. This contradicts that U is an ideal of \mathcal{P} . \square

For any real value β , let $H(\beta) = \{e \mid e \in E, w(e) > \beta\}$. Then, the set

$$E - \cup_{e \in H(\beta)} F(e) \tag{3.2}$$

is an ideal of \mathcal{P} due to Lemma 3.1. We abbreviate the subposet $\mathcal{P}(E - \cup_{e \in H(\beta)} F(e))$ induced by (3.2) to $\mathcal{P}(-\infty, \beta]$. Now, let

$$\beta^* = \min\{\beta \mid \text{ there is an ideal of size } k \text{ of } \mathcal{P}(-\infty, \beta]\}. \tag{3.3}$$

Then, we have the following lemma.

Lemma 3.3: Any ideal of size k of $\mathcal{P}(-\infty, \beta^*]$ is a minimax ideal of size k of \mathcal{P} .

(Proof) Suppose that there exists an ideal I' of size k of \mathcal{P} such that $\max\{w(e) \mid e \in I'\} < \beta^*$. Then, I' is also the ideal of $\mathcal{P}(-\infty, \beta^*]$ from the fact that $I' \subseteq E - \bigcup_{e \in H(\beta^*)} F(e)$ and Lemma 3. 2. This contradicts the minimality of β^* .

To find a minimax ideal of size k of \mathcal{P} it suffices to compute β^* since an ideal of size k of $\mathcal{P}(-\infty, \beta^*]$ can be found in O(m+n) time by the breath(depth)-first search method.

We find β^* by repeatedly splitting and narrowing the interval of possible values of β . The number of intervals which the current interval is split into is given by a function $A(2,i):\{1,2,\cdots\}\to \mathbb{Z}_+$ defined by

$$A(2,1) = 2, (3.4a)$$

$$A(2,i) = 2^{A(2,i-1)}. (3.4b)$$

This is the *Ackermann's function* with a slight change (see [Tarjan83] for Ackermann's function). See Figure 3 for the description of a threshold algorithm for Problem $P_{k-minimax}$.

Here, for any real number x, $\lfloor x \rfloor$ denotes the maximum integer less than or equal to x. and $\lceil x \rceil$ denotes the minimum integer larger than or equal to x. Though it is not necessary to construct the set $S_{A(2,i)+1}$ in Step 2-(a) of the algorithm MINIMAX-THRESHOLD(\mathcal{P}, k), we need it to implement this algorithm efficiently. The efficient implementation will be described later. The validity of the above algorithm is shown below.

Theorem 3.4: The algorithm MINIMAX-THRESHOLD(P, k) computes a minimax ideal correctly.

(Proof) This algorithm terminates in a finite number of iterations since the cardinality of the finite set U is strictly decreasing in Step 2-(d). It is clear $\beta^* = \lambda$ when $\lambda = \mu$. From the property that $\mathcal{P}(S_0 \cup \cdots \cup S_j)$ has an ideal of size k of \mathcal{P} in Step 2-(c), we have $\beta^* = \lambda (= \min\{w(v) \mid v \in U\} = \min\{w(v) \mid v \in U_1\})$ if j = 0.

We now consider an efficient implementation of this algorithm and the time complexity analysis. It is easy to implement Step 1, Step 2-(a) and Step 2-(d). Therefore the remaining part in this section is devoted to the implementation of Step 2-(b) and (c).

Algorithm MINIMAX-THRESHOLD(\mathcal{P}, k)

Input: A poset $\mathcal{P} = (V, \preceq)$ and a positive integer k.

Output: A minimax ideal of size k of \mathcal{P} .

Step 1: Put $\lambda := \min\{w(v) \mid v \in V\}$, $\mu := \max\{w(v) \mid v \in V\}$ and i := 1.

Step 2: Repeat the following (a),(b),(c) and (d).

- (a) Let $S_0 := \{v \mid v \in V, w(v) \le \lambda\}$ and $U := \{v \mid v \in V, \lambda < w(v) \le \mu\}$. (Let $S_{A(2,i)+1} := \{v \mid v \in V, \mu < w(v)\}$.)
- (b) Partition U into A(2,i) subsets $S_1,S_2,\cdots,S_{A(2,i)}$, each of size $\lfloor \frac{|U|}{A(2,i)} \rfloor$ or $\lceil \frac{|U|}{A(2,i)} \rceil$, such that if $v \in S_j$ and $u \in S_{j+1}$ $(j=1,\cdots,A(2,i)-1)$, then $w(v) \leq w(u)$.
- (c) Find $j^* = \min\{j \mid \mathcal{P}(S_0 \cup S_1 \cup \cdots \cup S_j) \text{ has an ideal of size } k \text{ of } \mathcal{P}\}.$
- (d) Put $\lambda:=\min\{w(v)\mid v\in S_{j^*}\}$, $\mu:=\max\{w(v)\mid v\in S_{j^*}\}$ and i:=i+1. If $j^*=0$ or $\lambda=\mu$, then put $\beta^*:=\lambda$ and stop.

Step 3: Find an ideal of size k of $\mathcal{P}(-\infty, \beta^*]$. It is a minimax ideal of size k of \mathcal{P} .

(End)

Figure 3: A threshold algorithm for Problem $P_{k-\min\max}$.

First, we consider the implementation of Step 2-(b). It can be carried out by finding the median: Split U into a lower half and an upper half, then split each half into halves and so on. See Figure 4 which precisely describes the procedure to implement Step 2-(b). The technique used in (b1) of the procedure PARTITION-A(2,i)-SUBSETS is known as the procedure select [Aho+Hopcroft+Ullman83].

Lemma 3.5: The procedure PARTITION-A(2, i)-SUBSETS implements the required work in Step 2-(b) in $O(|U| \log A(2, i))$ time.

(Proof) The correctness of this procedure is obvious. The time complexity is derived from the following three facts: (1) finding the median in S_j and partitioning into two sets take $O(|S_j|)$ time [Blum+Floyd+Pratt+Rivest+Tarjan73], (2) the total size of the sets S_j in each iteration of Step 2 is |U| and (3) the number of the repetition of Step 2 is $\log A(2,i)$.

Next, we consider the implementation of Step 2-(c). The following lemma demonstrates a good condition to test whether a given subposet has an ideal of size k.

Procedure PARTITION-A(2, i)-SUBSETS

Input: An element set U with weights w and a positive integer i.

Output: Sets $S_j (j=1,\cdots,A(2,i))$ satisfying the condition in Step2-(b).

Step 1: Put $S_1 := U$ and j := 1.

Step 2: Repeat the following (*1) and (*2) until $j = \log A(2, i)$.

(*1) Put t=1. Repeat the following (b1) and (b2) until t>A(2,i). (b1) If $|S_t|=1$ or 0, then put $S_{t+\frac{A(2,i)}{2^j}}:=\emptyset$; otherwise find the median ν in S_t , put

$$S^{<} := \{ v \mid v \in S_t, w(v) < \nu \}, S^{=} := \{ v \mid v \in S_t, w(v) = \nu \}, S^{>} := \{ v \mid v \in S_t, w(v) > \nu \}.$$

and partition $S^=$ into two subsets $S_-^=$ and $S_+^=$ such that $|S_-^=|=\lfloor \frac{S_t}{2} \rfloor - |S^<|$. Put $S_t:=S^<\cup S_-^=$ and $S_{t+\frac{A(2,i)}{2^j}}:=S_+^=\cup S^>$.

(b2) Put $t := t + \frac{A(2,i)}{2^{j-1}}$.

(*2) Put j := j + 1.

(End)

Figure 4: A procedure of MINIMAX-THRESHOLD(\mathcal{P}, k).

Lemma 3.6: For a poset $\mathcal{P} = (V, \preceq)$ and a subset U of V, there exists an ideal I of size k of \mathcal{P} such that $I \subseteq U$ if and only if the following inequality holds:

$$\left| \bigcup_{v \in V - U} F(v) \right| \le |V| - k. \tag{3.5}$$

(Proof) (\Rightarrow) Suppose there is an ideal $I \subseteq U$ of size k of \mathcal{P} . Let C be the set of all the upper neighbors of the elements of I on \mathcal{P} . Then

$$\bigcup_{v \in C} F(e) = \bigcup_{v \in V - I} F(e) \supseteq \bigcup_{v \in V - U} F(e). \tag{3.6}$$

Therefore,

$$V - \bigcup_{v \in V - U} F(e) \supseteq V - \bigcup_{v \in C} F(e) = I. \tag{3.7}$$

Hence, we have

$$\left| V - \bigcup_{v \in V - U} F(e) \right| \ge |I| = k. \tag{3.8}$$

This means (3.5).

(\Leftarrow) Let $W = V - \bigcup_{v \in V - U} F(v)$, then we have the facts that $W \subseteq U$ and W is an ideal of \mathcal{P} due to Lemma 3. 1, and that $|W| \ge k$ from the assumption. These imply that the subposet $\mathcal{P}(W)$ has an ideal I of size k. Thus, from Lemma 3. 2, I is an ideal of size k of \mathcal{P} such that $I \subseteq W \subseteq U$. \square

The following result is an immediate consequence of the preceding lemma.

Corollary 3.7: For sets S_j $(j = 1, \dots, A(2, i), A(2, i) + 1)$ obtained in Step 2-(a) and (b) of the algorithm MINIMAX-THRESHOLD and a positive integer k, we have

$$j^* = \min\{j \mid \mathcal{P}(S_0 \cup S_1 \cup \dots \cup S_j) \text{ has an ideal of size } k \text{ of } \mathcal{P}\}$$

$$= \max\left\{j \mid \left| \bigcup_{v \in S_j \cup S_{j+1} \cup \dots \cup S_{A(2,i)} \cup S_{A(2,i)+1}} F(v) \right| > |V| - k \right\}.$$

$$(3.9)$$

(Proof) From Lemma 3.6 and $V - (S_0 \cup S_1 \cup \cdots \cup S_j) = S_{j+1} \cup \cdots \cup S_{A(2,i)} \cup S_{A(2,i)+1}$,

$$(3.9) = \min \left\{ j \left| \left| \bigcup_{v \in S_{j+1} \cup S_{j+2} \cup \dots \cup S_{A(2,i)} \cup S_{A(2,i)+1}} F(v) \right| \le |V| - k \right\}$$

$$= (3.10).$$
(3.11)

Due to Corollary 3. 7 we propose a procedure for finding j^* (see Figure 5).

Procedure FIND-j*

Input: The sets S_i $(j = 1, \dots, A(2, i) + 1)$ and a positive integer k.

Output: The index j^* defined by (3.9).

Step 1: Put j := A(2,i) + 1 and $Q := \bigcup_{v \in S_{A(2,i)+1}} F(v)$.

Step 2: While $|Q| \leq |V| - k$ do the following (*).

(*) Put j := j-1 and $Q := Q \cup \bigcup_{v \in S_i} F(v)$.

Step 3: The current j is j^* .

(End)

Figure 5: A procedure of MINIMAX-THRESHOLD(\mathcal{P}, k).

Notice that all that we need in Step2-(*) is to identify the set $\bigcup_{v \in S_j} F(v) - Q = \bigcup_{v \in S_j} F(v) - \bigcup \{F(v) \mid v \in S_{j+1} \cup \cdots \cup S_{A(2,i)} \cup S_{A(2,i)+1}\}$ if we identify the set Q in the previous iteration. The depth(breath)-first search ([Ahuja+Magnanti+Orlin93]) works well for finding the set $\bigcup_{v \in S_j} F(v) - \bigcup_{v \in S_{j+1} \cup \cdots \cup S_{A(2,i)+1}} F(v)$ in Step 2-(*). To implement this search we attach each element label which have one of two states: unscanned or scanned. See Figure 6 and Figure 7 for an implementation of this search.

Procedure FIND-Q

Input: A set S_j and the set $Q(=\bigcup_{v\in S_{j+1}\cup\cdots\cup S_{A(2,i)+1}}F(v))$ identified by label: if label(v)=scanned, then $v\in Q$, otherwise $v\not\in Q$.

Output: The set $\bigcup_{v \in S_i} F(v) - Q$.

Step 1: Put $K := \emptyset$ and $L := S_j$.

Step 2: While $L \neq \emptyset$, do the following (*).

(*) Select an element $v \in L$. Call DFS(v) and put $K := K \cup \{u \mid u \in V, label(u) \text{ is changed in DFS}(v)\}$ and $L := L - \{v\}$.

Step 3: The current K is the set $\bigcup_{v \in S_j} F(v) - Q$. (End)

Figure 6: A procedure in the procedure FIND- j^* .

Lemma 3.8: The procedure FIND- j^* which uses the procedure FIND-Q with the procedure DFS(v) as a subroutine finds j^* in O(m+n) time.

(Proof) The procedure FIND- j^* computes $|\bigcup_{v \in S_{A(2,i)+1}} F(v)|$, $|\bigcup_{v \in S_{A(2,i)} \cup S_{A(2,i)+1}} F(v)|$, \cdots , in turn, and finds j satisfying (3.10). Due to Corollary 3. 7 this j is j^* . The time complexity O(m+n) is obtained from the following two facts: (1) if the procedure DFS(v) is executed for every element at most once, it requires O(m+n) time in total since the total number of times the procedure DFS(v) tests whether label(v) is scanned or unscanned is at most the number of arcs of the Hasse diagram, and (2) for each element the procedure DFS(v) is executed at most once since the sets S_t ($t=j,\ldots,A(2,i)+1$) are disjoint.

Theorem 3.9: The algorithm MINIMAX-THRESHOLD(\mathcal{P}, k) computes a minimax ideal of \mathcal{P} in $O((m+n)\log^* n)$ time.

Procedure DFS(v)

Input: A poset \mathcal{P} with label and an element v.

Output: The poset \mathcal{P} with label in which label(u) = scanned for all $u \in F(v)$.

Step 1: Put $W := \{v\}$.

Step 2: While $W \neq \emptyset$, do the following (*).

(*) Select an element $u \in W$. If label(u) = scanned, then put $W := W - \{u\}$. If label(u) = unscanned, then put label(u) := scanned and $W := W - \{u\} \cup \{\hat{u} \mid \hat{u} \text{ is an upper neighbor of } u\}$.

(End)

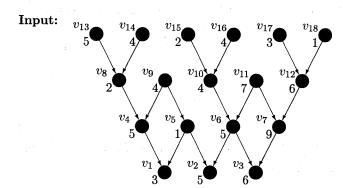
Figure 7: A procedure in the procedure FIND-Q.

(Proof) In Step 2 each of (a) and (d) takes O(n) time per iteration. From Lemma 3. 5 Step 2-(b) requires $O(|U|\log A(2,i))$ time per iteration and from Lemma 3. 8 Step 2-(c) needs O(m+n) time. Hence, it requires $O(|U|\log A(2,i)+m+n)$ time in the ith iteration of Step 2. Notice that $|U| \leq \lceil \frac{n}{A(2,i-1)} \rceil$ in the ith iteration. Thus, $O(|U|\log A(2,i)+m+n)=O(m+n)$ since

$$|U|\log A(2,i) \le \lceil \frac{n}{A(2,i-1)} \rceil \log A(2,i) \le 2 \frac{n}{A(2,i-1)} \log 2^{A(2,i-1)} = 2n. \tag{3.12}$$

The number of iterations of Step 2 is $O(\log^* n)$. Therefore the over all time bound is $O((m + n) \log^* n)$.

Example: Consider Problem $P_{k\text{-minimax}}$ of k=5 on the poset \mathcal{P} represented by the Hasse diagram which is the same as Figure 2. The algorithm MINIMAX-THRESHOLD($\mathcal{P}, 5$) might execute as indicated as follows. At termination, we have a minimax ideal.



Step 1: $\lambda = 1, \mu = 9.$

Step 2:

Iteration 1:

(a) $S_0 = \{v_5, v_{18}\}, U = \{v_1, v_2, v_3, v_4, v_6, v_7, v_8, v_9, v_{10}, v_{11}, v_{12}, v_{13}, v_{14}, v_{15}, v_{16}, v_{17}\}, S_3 = \emptyset.$

(b) $S_1 = \{v_1, v_8, v_9, v_{10}, v_{14}, v_{15}, v_{16}, v_{17}\}, S_2 = \{v_2, v_3, v_4, v_6, v_7, v_{11}, v_{12}, v_{13}\}.$

 $(c) \qquad \cup_{v \in S_2} F(v)$

$$|\cup_{v \in V} F(v)| = 17 \le |V| - k = 13 \Rightarrow j^* = 2.$$

(d) $\lambda = 5, \, \mu = 9.$

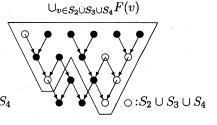
Iteration 2:

(a) $S_0 = \{v_1, v_5, v_8, v_9, v_{10}, v_{14}, v_{15}, v_{16}, v_{17}, v_{18}\}, U = \{v_2, v_3, v_4, v_6, v_7, v_{11}, v_{12}, v_{13}\}, S_5 = \emptyset.$

(b) $S_1 = \{v_2, v_6\}, S_2 = \{v_4, v_{13}\}, S_3 = \{v_3, v_{12}\}, S_4 = \{v_7, v_{11}\}.$

(c) $\bigcup_{v \in S_4} F(v)$ $\bigcirc : S_4$

 $\cup_{v \in S_3 \cup S_4} F(v)$ $\bigcirc \circ : S_3 \cup \cdots$

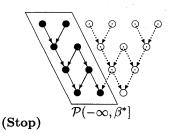


 $\begin{aligned} |\cup_{v \in S_4} F(v)| &< |V| - k \\ \Rightarrow j^* \neq 4. \\ \text{(d) } \lambda = \mu = 5 \Rightarrow \beta^* = \lambda = 5. \end{aligned}$

$$|\cup_{v \in S_3 \cup S_4} F(v)| < |V| - k \quad |\cup_{v \in S_2 \cup S_3 \cup S_4} F(v)| \ge |V| - k$$

$$\Rightarrow j^* \ne 3. \qquad \Rightarrow j^* = 2.$$

Step 3:



Any ideal of size 5 of $\mathcal{P}(-\infty, \beta^*]$ is a minimax ideal of \mathcal{P} .

References

[Aho+Hopcroft+Ullman83] A. V. Aho, J. E. Hopcroft and J. D. Ullman: *Data structures and algorithms* (Addison-Wesley, MA, 1983).

- [Ahuja+Magnanti+Orlin93] R. K. Ahuja, T. L. Magnanti and J. B. Orlin: *Network Flows: Theory, Algorithms, and Applications* (Prentice Hall, New York, 1993).
- [Blum+Floyd+Pratt+Rivest+Tarjan73] M. Blum, P. Floyd, V. Pratt, R. L. Rivest and R. E. Tarjan: Time bounds for selection. *Journal of Computer and System Sciences* 7 (1973) 448-461.
- [Gabow+Tarjan88] H. N. Gabow and R. T. Tarjan: Algorithms for two bottleneck optimization problems. *Journal of Algorithms* **9** (1988) 411-417.
- [Lawler76] E. L. Lawler: Combinatorial optimization: Networks and Matroids (Holt, Reinehart and Winston, New York, 1976).
- [Nemoto95] T. Nemoto: An efficient algorithm for the minimum-range ideal problem: In Optimization Modeling and Algorithm— 7, (The Institute of Statistical Mathematics Cooperative Research Report 77, Tokyo, 1995), pp.26-41.
- [Pferschy95] U. Pferschy: Solution methods and computational investigations for the linear bottleneck assignment problem. Technical Report 22-1995, Institute of Mathematics, University of Technology Graz, Austria, (1995).
- [Picard76] J. C. Picard: Maximal closure of a graph and applications to combinatorial problems. *Management Science* **22** (1976) 1268-1272.
- [Picard+Queyranne82] J. C. Picard and M. Queyranne: Selected applications on minimum cuts in networks. *Information Systems and Operational Research* **20** (1982) 394-422.
- [Punnen+Nair94] A. P. Punnen and K. P. K. Nair: Improved complexity bound for the maximum cardinality bottleneck bipartite matching problem. *Discrete Applied Mathematics* **55** (1994) 91-93.
- [Tarjan83] R. E. Tarjan: Data Structures and Network Algorithm (SIAM, Philadelphia, PA, 1983).