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Exercise 5-6. Let $M = (E, \mathcal{I})$ be a matroid. Let $k \in \mathbb{N}$ and define

$$\mathcal{I}_k = \{ X \in \mathcal{I} : |X| \le k \}.$$

Show that $M_k = (E, \mathcal{I}_k)$ is also a matroid. This is known as a truncated matroid.

Exercise 5-7. A family \mathcal{F} of sets is said to be *laminar* if, for any two sets $A, B \in \mathcal{F}$, we have that either (i) $A \subseteq B$, or (ii) $B \subseteq A$ or (iii) $A \cap B = \emptyset$. Suppose that we have a laminar family \mathcal{F} of subsets of E and an integer k(A) for every set $A \in \mathcal{F}$. Show that (E, \mathcal{I}) defines a matroid (a *laminar* matroid) where:

$$\mathcal{I} = \{ X \subseteq E : |X \cap A| \le k(A) \text{ for all } A \in \mathcal{F} \}.$$

5.2 Matroid Optimization

Given a matroid $M = (E, \mathcal{I})$ and a cost function $c : E \to \mathbb{R}$, we are interested in finding an independent set S of M of maximum total cost $c(S) = \sum_{e \in S} c(e)$. This is a fundamental problem.

If all $c(e) \ge 0$, the problem is equivalent to finding a maximum cost *base* in the matroid. If c(e) < 0 for some element e then, because of (I_1) , e will not be contained in any optimum solution, and thus we could eliminate such an element from the ground set. In the special case of a graphic matroid M(G) defined on a connected graph G, the problem is thus equivalent to the maximum spanning tree problem which can be solved by a simple greedy algorithm. This is actually the case for any matroid and this is the topic of this section.

The greedy algorithm we describe actually returns, for every k, a set S_k which maximizes c(S) over all independent sets of size k. The overall optimum can thus simply be obtained by outputting the best of these. The greedy algorithm is the following:

- \triangleright Sort the elements (and renumber them) such that $c(e_1) \ge c(e_2) \ge \cdots \ge c(e_{|E|})$
- $\begin{array}{ll} \triangleright & S_0 = \emptyset, \, \mathrm{k=0} \\ \triangleright & \mathrm{For} \, j = 1 \, \mathrm{to} \, |E| \\ & \triangleright & \mathrm{if} \, S_k + e_j \in \mathcal{I} \, \mathrm{then} \\ & & \triangleright \, k \leftarrow k+1 \\ & & \triangleright \, S_k \leftarrow S_{k-1} + e_j \\ & & \flat \, s_k \leftarrow e_j \\ & \triangleright & \mathrm{Output} \, S_1, \, S_2, \cdots, S_k \end{array}$

Theorem 5.2 For any matroid $M = (E, \mathcal{I})$, the greedy algorithm above finds, for every k, an independent set S_k of maximum cost among all independent sets of size k.

Proof: Suppose not. Let $S_k = \{s_1, s_2, \dots, s_k\}$ with $c(s_1) \ge c(s_2) \ge \dots \ge c(s_k)$, and suppose T_k has greater cost $(c(T_k) > c(S_k))$ where $T_k = \{t_1, t_2, \dots, t_k\}$ with $c(t_1) \ge c(t_2) \ge$ $\dots \ge c(t_k)$. Let p be the first index such that $c(t_p) > c(s_p)$. Let $A = \{t_1, t_2, \dots, t_p\}$ and $B = \{s_1, s_2, \dots, s_{p-1}\}$. Since |A| > |B|, there exists $t_i \notin B$ such that $B + t_i \in \mathcal{I}$. Since

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 $c(t_i) \geq c(t_p) > c(s_p)$, t_i should have been selected when it was considered. To be more precise and detailed, when t_i was considered, the greedy algorithm checked whether t_i could be added to the current set at the time, say S. But since $S \subseteq B$, adding t_i to S should have resulted in an independent set (by (I_1)) since its addition to B results in an independent set. This gives the contradiction and completes the proof. \triangle

Observe that, as long as $c(s_k) \ge 0$, we have that $c(S_k) \ge c(S_{k-1})$. Therefore, to find a maximum cost set over all independent sets, we can simply replace the loop

 \triangleright For j = 1 to |E|

by

 \triangleright For j = 1 to q

where q is such that $c(e_q) \ge 0 > c(e_{q+1})$, and output the last S_k .

For the maximum cost spanning tree problem, the greedy algorithm reduces to Kruskal's algorithm which considers the edges in non-increasing cost and add an edge to the previously selected edges if it does not form a cycle.

One can show that the greedy algorithm actually characterizes matroids. If M is an independence system, i.e. it satisfies (I_1) , then M is a matroid if and only if the greedy algorithm finds a maximum cost set of size k for every k and every cost function.

Exercise 5-8. We are given n jobs that each take one unit of processing time. All jobs are available at time 0, and job j has a profit of c_j and a deadline d_j . The profit for job j will only be earned if the job completes by time d_j . The problem is to find an ordering of the jobs that maximizes the total profit. First, prove that if a subset of the jobs can be completed on time, then they can also be completed on time if they are scheduled in the order of their deadlines. Now, let $E(M) = \{1, 2, \dots, n\}$ and let $\mathcal{I}(M) = \{J \subseteq E(M) : J$ can be completed on time $\}$. Prove that M is a matroid and describe how to find an optimal ordering for the jobs.

5.3 Rank Function of a Matroid

Similarly to the notion of rank for matrices, one can define a rank function for any matroid. The rank function of M, denoted by either $r(\cdot)$ or $r_M(\cdot)$, is defined by:

$$r_M: 2^E \to \mathbb{N}: r_M(X) = \max\{|Y|: Y \subseteq X, Y \in \mathcal{I}\}.$$

Here are a few specific rank functions:

- For a linear matroid, the rank of X is precisely the rank in the linear algebra sense of the matrix A_X corresponding to the columns of A in X.
- For a partition matroid $M = (E, \mathcal{I})$ where

$$\mathcal{I} = \{ X \subseteq E : |X \cap E_i| \le k_i \text{ for } i = 1, \cdots, l \}$$

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(the E_i 's forming a partition of E) its rank function is given by:

$$r(X) = \sum_{i=1}^{l} \min(|E_i \cap X|, k_i).$$

• For a graphic matroid M(G) defined on graph G = (V, E), the rank function is equal to:

$$r_{M(G)}(F) = n - \kappa(V, F),$$

where n = |V| and $\kappa(V, F)$ denotes the number of connected components (including isolated vertices) of the graph with edges F.

The rank function of any matroid $M = (E, \mathcal{I})$ has the following properties:

 $(R_1) \ 0 \le r(X) \le |X|$ and is integer valued for all $X \subseteq E$

$$(R_2) \ X \subseteq Y \Rightarrow r(X) \le r(Y),$$

 $(R_3) \ r(X) + r(Y) \ge r(X \cap Y) + r(X \cup Y).$

The last property is called *submodularity* and is a key concept in combinatorial optimization. It is clear that, as defined, any rank function satisfies (R_1) and (R_2) . Showing that the rank function satisfies submodularity needs a proof.

Lemma 5.3 The rank function of any matroid is submodular.

Proof: Consider any two sets $X, Y \subseteq E$. Let J be a maximal independent subset of $X \cap Y$; thus, $|J| = r(X \cap Y)$. By (I_2) , J can be extended to a maximal (thus maximum) independent subset of X, call it J_X . We have that $J \subseteq J_X \subseteq X$ and $|J_X| = r(X)$. Furthermore, by maximality of J within $X \cap Y$, we know

$$J_X \setminus Y = J_X \setminus J. \tag{1}$$

Now extend J_X to a maximal independent set J_{XY} of $X \cup Y$. Thus, $|J_{XY}| = r(X \cup Y)$.

In order to be able to prove that

$$r(X) + r(Y) \ge r(X \cap Y) + r(X \cup Y)$$

or equivalently

$$|J_X| + r(Y) \ge |J| + |J_{XY}|$$

we need to show that $r(Y) \ge |J| + |J_{XY}| - |J_X|$. Observe that $J_{XY} \cap Y$ is independent (by (I_1)) and a subset of Y, and thus $r(Y) \ge |J_{XY} \cap Y|$. Observe now that

$$J_{XY} \cap Y = J_{XY} \setminus (J_X \setminus Y) = J_{XY} \setminus (J_X \setminus J),$$

the first equality following from the fact that J_X is a maximal independent subset of X and the second equality by (1). Therefore,

$$r(Y) \ge |J_{XY} \cap Y| = |J_{XY} \setminus (J_X \setminus J)| = |J_{XY}| - |J_X| + |J|,$$

proving the lemma.

 \triangle