CSC373H1 Summer 2014 Assignment 3

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Q1. Construction:

To construct a family of graphs where G(V, E) has exponential number of minimum cuts between source and terminal, we being with n being the number of vertices that appear between the source and the terminal, we will also assume that the capacity on each edge is 1. If n = 0 then there are no vertices between the source and the terminal and thus V = {s, t} and E = $\emptyset$, Clearly, a single minimum-cut exists since we can only s $\in$ S and t $\in$ T, no edges exist to place a capacity on, so indeed $2^{|V|-2} = 2^0 = 1$.

For arbitrary n, n $\geqslant$ 1, and n = |V| - 2, then G(V, E) would be constructed such that V = {s, t, v_1, v_2, ..., v_n} and E = {(s, v_1), (v_1, t), (s, v_2), (v_2, t), ..., (s, v_n), (v_n, t)} (i.e. the only edges connected to a vertex are those that have s as their startpoint, or t as their endpoint). This arrangement is chosen because every cut in G(V, E) will be a minimum cut. By the arrangement of G(V, E), and since all capacities are the same. Whether a vertex v is or is not in the set S will not affect the summation of outgoing edge capacities, either the capacity from (v, t) or from (s, v), respectively, will be used in computing the minimum cut. Therefore we have a maximum number of minimum cuts in G.

Proof of exponential minimum cuts:

From the description above, in our construction of G(V, E), for any $v_i \in$ V the vertex can be contained within or outside the set that describes a cut in G and the cut is still a minimum cut. If we think of each minimum-cut as being described by a binary string for n = i, i $\geqslant$ 1, (q_{v_1}, q_{v_2}, ..., q_{v_n}), such that:

$$q_{v_i} = \begin{cases} 1 & \text{if } v_i \in \text{minimum cut set} \\ 0 & \text{if } v_i \notin \text{minimum cut set} \end{cases}$$

Base: Let n = 1, and let the B_1 be the set of binary strings describing the minimum cuts in G(V, E). Then B_1 contains two binary strings such that B_1 = {0, 1}. Indeed, $|B_1| = 2 = 2^n = 2^{|V|-2}$.

IH: Let n = i, i > 1, and let B_i be the set of binary strings describing the minimum cuts in G(V, E), such that V = {s, t, v_1, v_2, ..., v_i} and E = {(s, v_1), (v_1, t), (s, v_2), (v_2, t), ..., (s, v_i), (v_i, t)}. Suppose that $|B_i| = 2^i = 2^{|V|-2}$.

IS: Let n = i + 1, it follows from the construction description that V' = {s, t, v_1, v_2, ..., v_i, v_{i+1}} and E' = {(s, v_1), (v_1, t), (s, v_2), (v_2, t), ..., (s, v_i), (v_i, t), (s, v_{i+1}), (v_{i+1}, t)}. Clearly, the addition of v_{i+1} extends G(V, E) to G(V', E'). The minimum cuts in G(V', E') are composed from the minimum cuts in G(V, E) except that v_{i+1} is either inside or outside these previous cuts. Thus, to compute the set of minimum cuts as binary strings, B_{i+1}, simply take each binary string in B_i and append a 0 to be a minimum cut where v_{i+1} is outside the set, and then again take each binary string in B_i and append a 1 to be a minimum cut where v_{i+1} is inside the set. Thus, $|B_{i+1}| = 2 * (|B_i|) = 2 * 2^i = 2^{i+1}$.

By proof of induction this construction will have exponential minimum cuts between the source and the terminal. ■

Q2. Claim:

Function f, such that f(S) is the number of edges (u, v) with u $\in$ S, v $\in$ V\S, is submodular.

Proof:

Using the fact provided in the question, all that is necessary to show that f is submodular is to show that for any two subsets A, B $\subseteq$ V, f(A) + f(B) $\geqslant$ f(A $\cup$ B) + f(A $\cap$ B).

Consider the set of edges in G(V, E), E = {e_1, e_2, ..., e_n}. If we think of f(S) as an iterative algorithm that goes through each $e_i \in$ E and checks whether the startpoint of $e_i \in$ S and whether the endpoint of $e_i \in$ V\S. Then we have f_{e_i}(S):

$$f_{e_i}(S) = \begin{cases} 1 & \text{if startpoint of } e_i \text{ in S and endpoint of } e_i \text{ in V}\backslash\text{S} \\ 0 & \text{otherwise} \end{cases}$$

And so, f(S) = $\sum_{i=1}^{n} f_{e_i}$(S). Suppose (u, v) is an arbitrary edge in E, also suppose A, B are some arbitrary subsets of V. We wish to show in all cases, however vertices u and v appear or do not appear in A and/or B, that $f_{(u,v)}$(A) + $f_{(u,v)}$(B) $\geqslant$ $f_{(u,v)}$(A $\cup$ B) + $f_{(u,v)}$(A $\cap$ B):

Case 1: u $\notin$ A and u $\notin$ B: Clearly, u $\notin$ (A $\cup$ B) and u $\notin$ (A $\cap$ B), thus, $f_{(u,v)}$(A) = $f_{(u,v)}$(B) = $f_{(u,v)}$(A $\cup$ B) = $f_{(u,v)}$(A $\cap$ B) = 0. So, $f_{(u,v)}$(A) + $f_{(u,v)}$(B) $\geqslant$ $f_{(u,v)}$(A $\cup$ B) + $f_{(u,v)}$(A $\cap$ B) holds.

Case 2: u $\in$ A and u $\notin$ B (W.L.O.G. swtiching B for A in this case and all subcases the claim holds):

Case 2.1: v $\in$ A: Clearly, u, v $\in$ (A $\cup$ B) and u $\notin$ (A $\cap$ B), it follows that $f_{(u,v)}$(A) = $f_{(u,v)}$(B) = $f_{(u,v)}$(A $\cup$ B) = $f_{(u,v)}$(A $\cap$ B) = 0. So, $f_{(u,v)}$(A) + $f_{(u,v)}$(B) $\geqslant$ $f_{(u,v)}$(A $\cup$ B) + $f_{(u,v)}$(A $\cap$ B) holds.

Case 2.2: v $\notin$ A and v $\in$ B: So, $f_{(u,v)}$(A) = 1 and $f_{(u,v)}$(B) = 0, but since u, v $\in$ (A $\cup$ B) and u $\notin$ (A $\cap$ B), then $f_{(u,v)}$(A $\cup$ B) = $f_{(u,v)}$(A $\cap$ B) = 0. So, $f_{(u,v)}$(A) + $f_{(u,v)}$(B) $\geqslant$ $f_{(u,v)}$(A $\cup$ B) + $f_{(u,v)}$(A $\cap$ B) holds.

Case 2.3: v $\notin$ A and v $\notin$ B: Again, $f_{(u,v)}$(A) = 1 and $f_{(u,v)}$(B) = 0. Also, u $\in$ (A $\cup$ B) and v $\notin$ (A $\cup$ B), then $f_{(u,v)}$(A $\cup$ B) = 1. Again, u $\notin$ (A $\cap$ B), then $f_{(u,v)}$(A $\cap$ B) = 0. So, $f_{(u,v)}$(A) + $f_{(u,v)}$(B) $\geqslant$ $f_{(u,v)}$(A $\cup$ B) + $f_{(u,v)}$(A $\cap$ B) holds.

Case 3: u $\in$ A and u $\in$ B (W.L.O.G. swtiching B for A in this case and all subcases the claim holds):

Case 3.1: v $\in$ A and v $\in$ B: Since u, v $\in$ A and B, then $f_{(u,v)}$(A) = $f_{(u,v)}$(B) = 0. Also, u, v $\in$ (A $\cup$ B) and (A $\cap$ B), then $f_{(u,v)}$(A $\cup$ B) = $f_{(u,v)}$(A $\cap$ B) = 0. So, $f_{(u,v)}$(A) + $f_{(u,v)}$(B) $\geqslant$ $f_{(u,v)}$(A $\cup$ B) + $f_{(u,v)}$(A $\cap$ B) holds.

Case 3.2: v $\notin$ A and v $\in$ B: It follows that $f_{(u,v)}$(A) = 1 and $f_{(u,v)}$(B) = 0. Since u, v $\in$ (A $\cup$ B) then $f_{(u,v)}$(A $\cup$ B) = 0, but u $\in$ (A $\cap$ B) and v $\notin$ (A $\cap$ B), thus $f_{(u,v)}$(A $\cap$ B) = 1. Again, $f_{(u,v)}$(A) + $f_{(u,v)}$(B) $\geqslant$ $f_{(u,v)}$(A $\cup$ B) + $f_{(u,v)}$(A $\cap$ B) holds.

Case 3.3: v $\notin$ A and v $\notin$ B: Clearly, $f_{(u,v)}$(A) = 1 and $f_{(u,v)}$(B) = 1. Also, u $\in$ (A $\cup$ B) and (A $\cap$ B), but v $\notin$ (A $\cup$ B) and (A $\cap$ B), then $f_{(u,v)}$(A $\cup$ B) = $f_{(u,v)}$(A $\cap$ B) = 1. Then, $f_{(u,v)}$(A) + $f_{(u,v)}$(B) $\geqslant$ $f_{(u,v)}$(A $\cup$ B) + $f_{(u,v)}$(A $\cap$ B) holds.

In all cases in which the vertices of some edge (u, v) $\in$ E might appear in A, B $\subseteq$ V it has been shown that $f_{(u,v)}$(A) + $f_{(u,v)}$(B) $\geqslant$ $f_{(u,v)}$(A $\cup$ B) + $f_{(u,v)}$(A $\cap$ B) holds. It must follow then that $\sum_{i=1}^{n} f_{e_i}$(A) + $\sum_{i=1}^{n} f_{e_i}$(B) $\geqslant$ $\sum_{i=1}^{n} f_{e_i}$(A $\cup$ B) + $\sum_{i=1}^{n} f_{e_i}$(A $\cap$ B) $\rightarrow$ f(A) + f(B) $\geqslant$ f(A $\cup$ B) + f(A $\cap$ B). Clearly, function f is submodular by the equivalence of submodular functions. ■

Q3. Consider the restructuring of LP formulation of maximum flow into standard form:

maximize: $\vec{c} \cdot \vec{x}$

subject to: $A\vec{x} \leqslant \vec{b}$, $\vec{x} \geqslant 0$.

Suppose this LP operates on G(V, E) such that paths P = $\{p_1, ..., p_n\}$ and E = $\{e_1, ..., e_m\}$.

Let $\vec{c} = [1, ..., 1]$, such that $|\vec{c}| = n$.

Let $\vec{x} = [x_1, ..., x_n]$, such that $x_i = f_{p_i}$, maximum flow along path p_i.

Let A be and m x n matrix and let A be defined as follows:

$$A[i, j] = \begin{cases} 1 & \text{edge } e_i \text{ appears on path } p_j \\ 0 & \text{edge } e_i \text{ does not appears on path } p_j \end{cases}$$

Let $\vec{b} = [c(e_1), ..., c(e_m)]$, such that $|\vec{b}| = m$.

Using the restructured LP, we construct the dual as follows:

minimize: $\vec{b} \cdot \vec{y}$

subject to: $A^t\vec{y} \geqslant \vec{c}$, $\vec{y} \geqslant 0$.

Let $\vec{y} = [y_1, ..., y_m]$, y_i is a value associated with e_i.

Again, we define $\vec{c}$ and $\vec{b}$ as the same in the original construction.

Now, A^t is an n x m matrix, and so A^t is defined as follows:

$$A^t[i, j] = \begin{cases} 1 & \text{in path } p_i \text{ the edge } e_j \text{ appears} \\ 0 & \text{in path } p_i \text{ the edge } e_j \text{ does not appear} \end{cases}$$

The conclusion for the dual LP is that the objective function and constraints represent a construction of a max-flow min-cut, such that when the dual LP is complete its solution will equal the max-flow calculated by the original LP. It can now be stated:

$$y_i = \begin{cases} 1 & \text{edge } e_i \text{ connects sets S and T*} \\ 0 & \text{edge } e_i \text{ does not connect sets S and T*} \end{cases}$$

*clearly S and T represent the set of vertices separated by the minimum cut of G(V, E).

Then the objective function represents the summation of the capacity of those edges where $y_i = 1$, and the summation will be the maximum flow in the network G(V, E). The n path constraints, $A^t\vec{y} \geqslant \vec{c}$, represent the fact that on each path at least one edge connects S to T. Thus, for path p_i, $\sum_{j=1}^{m} a_{ij}y_j \geqslant 1$.

Q4. Polytope P is represented by Ax $\leqslant$ b. Let x $\in \mathbb{R}^n$, so x is a point within P if Ax $\leqslant$ b holds. More specifically, let A be an m x n matrix, and b a series of m constants, such that $a_{i1}x_1 + ... + a_{in}x_n \leqslant b_i$ represents a closed half-space for each facet of the polytope, so that when all constraints are combined they represent all internal and boundary points of P.*

The LP must be designed so that we find a centre point y of a ball in P, such that all points on the surface of the ball that intersect in the plane where P exists are also in P. Suppose some point x exists at the border of P, then for some i, specifically the i that represents the facet on which x exists, $a_{i1}x_1 + ... + a_{in}x_n = b_i$. So, if the ball is the largest possible ball to fit in P the surface points must be as close to the boundaries as possible.

Suppose that $\vec{a}_i = [a_{i1}, ..., a_{in}]$ is a unit vector for some i, such that $\|\vec{a}_i\| = 1$. Indeed, $\vec{a}_i$ is the gradient unit vector to the facet represented by $a_{i1}x_1 + ... + a_{in}x_n = b_i$, it is also perpendicular to the facet. Also, as a gradient vector, $\vec{a}_i$ points in the direction outside the closed half-space defined by $a_{i1}x_1 + ... + a_{in}x_n \leqslant b_i$. To discover if the ball at center y with radius r $\in \mathbb{R}$ can fit in P we check for each facet i if the surface point $z_i = (\vec{a}_i$*r + y), perpendicular to the facet i, is within P. To do this we use the constraint $a_{i1}z_{i1} + ... + a_{in}z_{in} \leqslant b_i$. To explain z_i further, $\vec{a}_i$*r is an r length vector that when added to y, projects a point to the surface or boundary of the ball and is perpendicular to facet i. In order to find the largest such ball, the LP must be designed to calculate both the ball's maximum radius r and its centre point y. This is done by establishing z_i's such that for all i, given constraints $a_{i1}z_{i1} + ... + a_{in}z_{in} \leqslant b_i$, we want $a_{i1}z_{i1} + ... + a_{in}z_{in}$ to be as close as possible to b_i for some maximum r and centre point y.

Thus, the LP is:

maximize:

r

subject to:

$\vec{a}_i \cdot (\vec{a}_i{*}r + y) \leqslant b_i, \forall\ i, 1 \leqslant i \leqslant m$

$r \geqslant 0$.

*explanation of polotope taken from wikipedia, http:\\en.wikipedia.org\wiki\Convex_polytope.

Q5. Suppose we have primal LP's for P_1 and P_2 respectively, with constraints that place x within the specific polyhedron:
maximize: c_1x
subject to: $A_1x \leqslant b_1$

maximize: c_2x
subject to: $A_2x \leqslant b_2$

Separately, their dual LP's are:
minimize: sb_1
subject to: $sA_1 = c_1$, $s \geqslant 0$.

minimize: tb_2
subject to: $tA_2 = c_2$, $t \geqslant 0$.

Suppose that P_1 and P_2 were to intersect and $c_1 + c_2 = c$, a primal LP that would represent this would be a combination of the two previous primal LP's:
maximize: cx
subject to: $A_1x + A_2x \leqslant b_1 + b_2$

Clearly the dual LP is a combination of the two previous dual LP's:
minimize: $sb_1 + tb_2$
subject to: $sA_1 + tA_2 = c$, $s, t \geqslant 0$.

However, we know that P_1 and P_2 do not intersect, so in the primal LP no x will be found with the provided constraint. The primal LP is infeasible. In the dual LP suppose we let c be the zero vector, then clearly there exists an s and t such that $sA_1 + tA_2 = \vec{0}$. By the theorem of duality, where the primal LP has an optimal solution if and only if the dual has an optimal solution, it follows that our dual LP cannot have an optimal solution. If the dual had a feasible solution it would contradict the infeasibility of the primal LP.

If both LP's had optimal solutions then by weak duality we would have, $(sA_1 + tA_2)x = cx \leqslant sb_1 + tb_2$, implying that, when $sA_1 + tA_2 = \vec{0}$ then $sb_1 + tb_2 \geqslant 0$. Indeed, in the feasible case, the result of the dual LP would be an upperbound to the result of the primal LP. It should be noted that the inequality $sb_1 + tb_2 \geqslant 0$ suggests that the dual has a minimum value, which if it did, then the result of the dual LP would be feasible, but this cannot be. In the situation where P_1 and P_2 do not intersect, the objective function of the dual, $sb_1 + tb_2$, is unbounded. It follows that there exists some $s, t \geqslant 0$ where $sA_1 + tA_2 = \vec{0}$ but $sb_1 + tb_2 < 0$. ■

Q6. Claim: Indeed the objective function, $\sum$c(u, v)f(u,v), when minimized will produce the mean of the minimum mean cycle C(V', E') in G(V, E, c), which will equal $\frac{\sum_{e \in E'} c(e)}{|E'|}$.

Once the LP is complete the minimum mean cycle can be identified by the series of edges (u, v) where f(u, v) > 0.

By the first constraint, any vertex i in G, which has only outward pointing edges (i, j), then f(i, j) must equal 0. This is also the same for a vertex i' that has only inward pointing edges, so for any edge (j, i'), then f(j, i') must equal 0. Indeed, if there were no cycles in G then for all edges (u, v), f(u, v) = 0. However, if a cycle exists in G any edge (u', v') in the cycle is such that f(u', v') $\geqslant$ 0, and for any two edges in the same cycle, say, (u'$_1$, v'$_1$) and (u'$_2$, v'$_2$), then f(u'$_1$, v'$_1$) = f(u'$_2$, v'$_2$), and this maintains the first constraint.

The second constraint, gives away the real meaning of what the f values represent. It was established that only with edges from a cycle will the f value be greater than or equal to zero. Also, all edges in the same cycle have the same f values. Thus, $\sum$ f(u, v) = 1, such that when the LP is complete and that f(u, v) > 0 represent an edge in cycle C(V', E'), then f(u, v) = $\frac{1}{|E'|}$. Indeed, since f(u, v) = $\frac{1}{|E'|}$ and all other (u, v) not in C(V', E'), f(u, v) = 0, then the objective function indeed returns the mean of the minimum mean cycle, $\frac{\sum_{e \in E'} c(e)}{|E'|}$.

Converting the primal LP into standard form:

minimize: c · x

subject to: Ax = b, x $\geqslant$ 0.

Where |V| = n, and |E| = m. Then c and x are m length vectors where c = [c(e$_1$), ..., c(e$_m$)] and x = [f(e$_1$), ..., f(e$_m$)]. A is an n + 1 x m matrix, such that:

$$A[i,j] = \begin{cases} 1 & \text{vertex i is a startpoint in } e_j \\ -1 & \text{vertex i is a endpoint in } e_j \\ 1 & \text{i = n + 1} \end{cases}$$

Also, b is an n length vector such that the first n entries are zero and the entry n + 1 is 1. The final clause in A and the final element in b deal with the second constraint, $\sum$ f(u, v) = 1.

Converting to the dual LP:

maximize: y · b

subject to: yA $\leqslant$ c, y $\geqslant$ 0.

We do not know what y represents other than the fact that it is an n + 1 length vector. Indeed the first n elements in y must represent some function on each of the n vertices in G(V, E), we will take y$_i$ to represent some value associated with vector i. Additionally, let q be the last element of y. There are m constraints given that A is an n + 1 x m matrix. Such that each constraint is based on each edge in E. It would follow that for each (u, v) the constraint would be y$_u$ - y$_v$ + q $\leqslant$ c(u, v). As defined in A, y$_u$ - y$_v$, because u is a startpoint and v an endpoint, and the addition of q due to the row of 1's in the $(n+1)^{th}$ row. Additionally, the objective function y · b = q. Rewriting the dual:

maximize: q

subject to: y$_u$ - y$_v$ + q $\leqslant$ c(u, v), $\forall$ (u, v).

By the duality theorem, when the dual LP is complete, q should represent the mean of the minimum mean cycle. Suppose we rearrange the constraints such that c(u, v) + y$_v$ - y$_u$ $\geqslant$ q, $\forall$ (u, v). Also, suppose we know

some cycle C*(V*, E*) in G(V, E, c). Now if we take only the constraints of that cycle and sum them together we have:
$\sum_{(u,v)\in E^*}$ (c(u, v) + y_v - y_u) $\geqslant \sum_{(u,v)\in E^*}$ q $\rightarrow$
$\sum_{(u,v)\in E^*}$ c(u, v) + $\sum_{(u,v)\in E^*}$ (y_v - y_u) $\geqslant$ |E*| * q $\rightarrow$
($\sum_{(u,v)\in E^*}$ c(u, v) + $\sum_{(u,v)\in E^*}$ (y_v - y_u))/|E*| $\geqslant$ q $\rightarrow$
As stated previously, the optimal value of q is the mean of the minimum mean cycle, a tight bound only occurs when q = $\frac{\sum_{e\in E'} c(e)}{|E'|}$, for the minimum mean cycle C(V', E'). In order to establish a tight bound on q, it follows for the edges of any arbitrary cycle that $\sum_{(u,v)\in E^*}$ (y_v - y_u) = 0, then we have q $\leqslant \frac{\sum_{e\in E^*} c(e)}{|E^*|}$. Indeed if C*(V*, E*) is the minimum mean cycle then q = $\frac{\sum_{e\in E^*} c(e)}{|E^*|}$.

Q7. Let conventional milk be x_1, Let organic milk be x_2

Profit from selling x_1 = selling price - buying price = \$2 - \$1 = \$1

Profit from selling x_2 = seliing price - buying price = \$3 - \$1.50 = \$1.50

Max Profit Function: Max $P = x_1 + 1.5\, x_2$

Constraints:

$x_1 + x_2 \leqslant 3000$

$x_2 \leqslant 2x_1 \rightarrow x_2 - 2x_1 \leqslant 0$

$x_1, x_2 \geqslant 0$

Q8.