Assignment #2

Due: July 17, 2021, 11:59 pm (EDT) SIWEI TANG(tangsiw3) Yuewei Wang (wangyuew)

Q1:

- a) Define a flow network where $u_1...u_n$ are all n days and $v_1...v_k$ are all doctors. We fix the network by adding s and t as source and sink respectively. Edges in the network are:
 - $(s, u_i):c(s, u_i) = a_i \text{ for } i \in \{1, 2, ..., n\}$
 - (v_j, t) : $c(v_j, t) = |A_j|$ for $j \in \{1, 2, ..., k\}$
 - (u_i, v_j) : $c(u_i, v_j) = 1$ if $u_i \in A_j$

1:procedure HospitalSchedule $(a_1...a_n, A_1...A_k)$

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2: sum := a_1 + a_2 + ... + a_n
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3: Define a flow network (G) with $u_1...u_n$, $v_1...v_k$, s, t and all edges.

4:
$$f := \mathbf{Edmonds\text{-}Karp}(G, s, t)$$
 # to obtain the max-flow

5: **if** |f| < sum then

return "no schedule is possible given the doctors' availabilities"

7: else

6:

8: **for**
$$j = 1:k$$
 do

9:
$$S_i := \{\}$$

10: **for**
$$i=1:n$$
 do

11:
$$if f(u_i, v_j) = 1 then$$

$$S_{i} = S_{i} \cup \{v_{i}\}$$

13:
$$\operatorname{return} S_1, \dots, S_k$$

- **b)** Correctness: In G we defined, for the number of doctors that can be scheduled on each day, $0 \le f(s, u_i) \le c(s, u_i) = a_i$ for $i \in \{1, 2, ..., n\}$ due to the capacity constraint. Similar to the number of days that each doctor is scheduled, $0 \le f(v_j, t) \le c(v_j, t) = |A_j|$ for $j \in \{1, 2, ..., k\}$. Each flow between u_i to v_j will be $0 \le f(u_i, v_j) \le c(u_i, v_j) = 1$. There are two cases:
 - $f(u_i, v_j) = 0$: The doctor j is not scheduled on day i.
 - $f(u_i, v_i) = 1$: The doctor j is scheduled on day i.

Since exactly a_i doctors should work on day i, a valid flow f in G must satisfy |f| = 1

 $\sum_{i=1}^{n} a_i$ so that generating a valid schedule S_1 ,..., S_k . Edmonds-Karp algorithm gives the max-flow, line 5 checks the criteria: if the value of flow is less than the sum, then no valid schedule exists.

 S_j will only schedule available days for each doctor (i.e. $f(u_i, v_j) = 1$ for $j \in \{1, 2, ..., k\}$). Line 8 to 12 iteratively checks the flow value for each doctor, which satisfies the criteria.

Runtime: Finding the sum takes O(n). Defining all vertices in the network takes O(n+k+2). All edges take $O(n+k+\sum_{i=1}^k |A_i|)$, which is O(nk+n+k) since $\sum_{i=1}^k |A_i|$ will no more than nk. Calling Edmonds-Karp algorithm takes $O((n+k+2)(nk+n+k)^2)$. The nested loop in line 8 to 12 takes O(nk). Therefore, the total complexity is $O((n+k+2)(nk+n+k)^2)$.

- Modify the flow network by adding vertices of v'_1 ...' v_k for c days such that:
 - (v'_{j}, t) : $c(v'_{j}, t) = c$ for $j \in \{1, 2, \dots, k\}$
 - (u_i, v'_j) : $c(u_i, v'_j) = 1$ if $u_i \notin A_j$

1:procedure ScheduleDays(c, a_1 ... a_n , A_1 ... A_k)

- 2: $sum := a_1 + a_2 + ... + a_n$
- 3: Define a flow network (*G*) with $u_1...u_n$, $v_1...v_k$, $v_1'...v_k'$, s, t and all edges.
- 4: $f := \mathbf{Edmonds\text{-}Karp}(G, s, t)$ # to obtain the max-flow
- 5: **if** |f| < sum then
- 6: **return** "no schedule is possible given the doctors' availabilities"
- 7: else
- 8: **for** j = 1:k **do**
- 9: $S_i := \{\}$
- 10: **for** i=1:n **do**
- 11: $\mathbf{if} f(u_i, v_j) = 1 \mathbf{then}$
- $S_j = S_j \cup \{v_j\}$
- 13: else if $f(u_i, v'_j) = 1$ then
- $S_j = S_j \cup \{v'_j\}$
- 15: $\operatorname{return} S_1, \dots, S_k$
- **d)** Correctness: Similar as the proof in b), but there are additional flows associated with $v'_1...'v_k$. $f(v'_j, t)$ represents the number of days that are not in A_j but doctor j is scheduled. Since at most c days could be not in A_j , $0 \le f(v'_j, t) \le c(v'_j, t) = c$ for $j \in \{1, 2, ..., k\}$. Similar as $f(u_i, v_j)$, each flow between u_i to v'_j is that $0 \le f(u_i, v'_j) \le c(u_i, v'_j) = 1$. There are also two cases such that 1 means the doctor j is scheduled on day i and 0 is not. Similar as b), we check |f| with $\sum_{i=1}^{n} a_i$ since exactly a_i doctors work on day i. For $j \in \{1, 2, ..., k\}$, S_j will schedule when $f(u_i, v_j) = 1$ but also when $f(u_i, v'_j) = 1$ since at most c days not in A_j can be scheduled. Both conditions are checked in line 11 to 14.

Runtime: The algorithm is modified from a) with difference in line 13 to 14, which takes constant steps to check the condition. Therefore, the total complexity is still $O((n + k + 2)(nk + n + k)^2)$.

By Max-Flow-Min-Cut Theorem, if f^* is a maximum flow and (S, T) is the minimum cut, then |f| = c(S, T). Also, we can find that for the minimum cut (S, T), the edge (u, v) where $u \in S$ and $v \in T$ is a critical edge. So we can transfer the problem into finding the edge that crosses the minimum cut (S, T).

Algorithm:

1:procedure FindCriticalEdge(G, s, t)

2:
$$(f_m, G_{f_m}) := \mathbf{Edmonds\text{-}Karp}(G, s, t)$$
 # slightly modify to obtain the max-flow and the residual graph from Edmonds-Karp

3: Find the minimum cut (S, T): $S = \{v \in V \mid \text{there is a path from } s \text{ to } v \text{ in } G_f \}$

$$T = V \backslash S$$

4: **for** each edge $(u, v) \in E$ **do**

5: **if** $u \in S$ and $v \in T$ **then**

6:
$$e_{c} := (u, v)$$

7: **if** e_e exists **then**

8: return e_{c}

9: else

10: **return** "no critical edge exists"

Proof of Correctness:

Since Edmonds-Karp algorithm gives the max-flow, it finds the augmenting paths by a breadth-first search in G, so it chooses a shortest path in G from s o t where each edge has weight 1.

By definition of cut, there exists at least one edge between cut S and T. For every vertice $x \in S$, there is a path from S to T including x. By trace this path, we can find an edge (u, v) such that $u \in S$ and $v \in T$.

Running time:

For line 2, by Edmonds-Karp Algorithm, the complexity is $O(|V||E|^2)$.

For line 3, use breadth first search, so it takes O(|E|).

For line 4 to 6, check every edge if $u \in S$ and $v \in T$, if it satisfies these two requirements, then return the result. It takes O(|E|).

So in total $O(|V||E|^2) + O(|E|) + O(|E|) = O(|V||E|^2)$

a)

In directed graph G(V, E), for two different vertices s and t that in G, the pseudo-flow is the flow function such that all vertices u in G that is not s and t,

$$\sum_{x \in V} f(x, u) = \sum_{x \in V} f(u, x).$$

By question, if a pseudo-flow f from s to t such that |f| = 1, it means that the inflow and outflow of vertice s is 1, since all edges is positive integer, so that means that only one edge that connects to s with f(s, u) = 1, for all other vertices u' that directly connect to s, f(s, u') = 0. By that logic, we can find list of connected vertices $s, u_1, u_2, u_3, \ldots, t$ such that $f(s, u_1) = f(u_1, u_2) = \ldots$, for all other edges, f is 0.

So every path s, s, u_1 , u_2 , u_3 ,...,t is pseudo-flow with |f| = 1 for every edge in the path and |f| = 0 for every edge out of the edge. In such a case, finding the shortest path is equivalent to finding the pseudo-flow.

b)

Let f(u, v) be the variables that edge $(u, v) \in E$ in graph G, which represents the pseudo-flow. Then we will solve in LPP as:

minimize:
$$\sum_{(u,v)\in E} f_{(u,v)} l_{(u,v)}$$
 subject to:
$$\sum_{(u,v)\in E} f_{(u,v)} = \sum_{(v,u)\in E} f_{(v,u)} \text{ for } v\in V\backslash\{s,t\}$$

$$\sum_{(s,v)\in E} f_{(s,v)} = 1$$

$$f_{(s,v)} \geq 0$$

Justification:

For the three constraints, $\sum_{(u,v)\in E} f_{(u,v)} = \sum_{(v,u)\in E} f_{(v,u)}$ since the pseudo-flow is

conserved. $\sum_{(s,v)\in E} f_{(s,v)} = 1$ since pseudo-flow with |f| = 1 is the target looking for. Also, $f_{(s,v)} \ge 0$ since the pseudo-flow value is non-negative.

By part a), finding paths from s to t in G is equivalent to pseudo-flow from s to t with |f| = 1. The possible solutions are the same as finding the pseudo-flow f from s to t with |f| = 1. In such a case, the solutions is the same as finding paths from s to t such that

 $\sum_{(u,v)\in E} f_{(u,v)} l_{(u,v)}$ is equivalent to the total weight of the path. So in order to minimize

 $\sum_{(u,v)\in E} f_{(u,v)} l_{(u,v)}$. It is the same as minimizing the weight of the path. Therefore, we need to

find the shortest path so that it has the minimum weight.

a)

Let e_i represents the new variable that l_1 error of data point $((x_i, y_i)$ for i = 1, 2, ..., n. Let a and b also be variables of LPP, then we will solve e_i as:

minimize:
$$\sum_{i=1}^{n} e_{i}$$
subject to: $e_{i} = |y_{i} - ax_{i} - b|$ for $i = 1, 2, ..., n$

By the equivalent relationship, let e_i in terms of inequalities that

$$\begin{aligned} e_i &= |y_i - ax_i - b| \Leftrightarrow e_i \geq (y_i - ax_i - b) \text{ and } e_i \geq -(y_i - ax_i - b) \\ \text{Then } e_i &= max\{(y_i - ax_i - b), -(y_i - ax_i - b)\} \\ e_i &\geq max\{(y_i - ax_i - b), -(y_i - ax_i - b)\} \end{aligned}$$

By the definition of optimal solution in LPP, e_i has the minimum objective value that satisfies the optimal solution in minimization LPP.

b)

By the requirements of the separating line maximizes the gap δ , $e_1 \leq |y_i - ax_i - b|$ for i=1,2,..., m in type 1 points and $e_2 \leq |y_j - ax_j - b|$ for j=1,2,..., n in type 2 points.

Since
$$y_i < ax_i + b$$
 for type 1, $ax_i + b - y_i > 0$, then
$$|y_i - ax_i - b| = ax_i + b - y_i$$
. Similarly, $|y_j - ax_j - b| = y_j - ax_j - b$ since $y_i > ax_i + b$ for type 2. Then:
$$e_1 \le ax_i + b - y_i$$
 for $i = 1, 2, ..., m$ and $e_2 \le y_i - ax_j - b$ for $j = 1, 2, ..., n$

Since the gap $\delta = min\{e_1, e_2\}$, in terms of inequalities:

$$\delta \le ax_i + b - y_i$$
 for $i = 1, 2, ..., m$ and $\delta \le y_j - ax_j - b$ for $j = 1, 2, ..., n$.

Then we will solve the LPP as:

maximize:
$$\delta$$
 subject to: $\delta \le ax_i + b - y_i$ for $i = 1, 2, ..., m$ in type 1 points $\delta \le y_j - ax_j - b$ for $j = 1, 2, ..., n$ in type 2 points

By the definition of optimal solution in LPP, δ has the maximum objective value that satisfies the optimal solution in maximization LPP. Note that the optimal δ is positive since

 $ax_i + b - y_i > 0$ for all type 1 points and $y_j - ax_j - b > 0$ for all type 2 points. There are two cases if the separating line y = ax + b exists:

case 1: y = ax + b is a vertical line

then a = 0 and x = b is the line.b will be in the middle of the barrier of type 1 and type 2 points (i.e. x_1 is the largest x-coordinate among all type 1 points and x_2 is the smallest x-coordinate among all type 2 points, b is in between two values). Then the gap δ will be the difference to each x-coordinate.

case 2: y = ax + b is not vertical

subcase 1: the line satisfy that $y_i > ax_j + b$ for all type 1 points and $y_i < ax_j + b$ for all type 2 points, which is the goal we want.

subcase 2: the line separates both types but with $y_i < ax_j + b$ for all type 1 points and $y_i > ax_j + b$ for all type 2 points, the optimal δ exist. Then, the original type 1 will be type 2 and vice versa.