



## 1 Zoo Tycoon

**Algorithm:** Construct a source  $s$  and a sink  $t$ . For each food  $j$ , create a vertex  $x_j$ , and add an edge from  $s$  to  $x_j$  with capacity  $T_j$ . For each animal  $i$ , add a vertex  $y_i$ , and for each food  $j$  not in  $S_i$ , add an edge from  $x_j$  to  $y_i$  with infinite capacity. Finally, for each animal  $i$ , add a vertex  $z_i$ . For each food  $j \in S_i$ , add an edge from  $x_j$  to  $z_i$  with infinite capacity. Additionally, add an edge from  $y_i$  to  $z_i$  with capacity  $D_i$ , and from  $z_i$  to  $t$  with capacity  $F_i$ . Now run a network flow algorithm on this flow network, and return true if and only if there is a flow of size  $F = \sum_i F_i$ .

**Correctness:** We will show that our algorithm returns true if and only if a feasible feeding plan exists.

First, assume there is a feasible feeding plan. Define  $p_j$  to be the amount of food  $j$  used by the plan, and  $p_{ij}$  to be the amount of food  $j$  fed to animal  $i$ . We will construct a flow of size  $F$ . To do so, for each food, route  $p_j$  units of flow on the edge  $(s, x_j)$ . For each animal  $i$ , for each food not in  $S_i$ , route  $p_{ij}$  units of flow from  $x_j$  to  $y_i$ . Then, for each animal, route  $\sum_{j \notin S_i} p_{ij}$  units of flow from  $y_i$  to  $z_i$ . For each  $j \in S_i$ , route  $p_{ij}$  unit of flow from  $x_j$  to  $z_i$ . Finally, for each animal  $i$ , route  $F_i$  units of flow from  $z_i$  to  $t$ . We now verify that this is a flow of size  $F$ :

- Conservation constraints are satisfied: by construction. For any node other than  $s$  and  $t$ , it is easy to check that we routed exactly as much flow out as we routed in.
- Capacity constraints are satisfied:
  - Because the feeding plan didn't use more than  $T_j$  of any food  $j$ , the capacity constraints are satisfied on all edges from  $s$  to each  $x_j$ .
  - Because the feeding plan didn't feed any animal more than  $D_i$  total units of food not in  $S_i$ , the capacity constraints on each edge  $(y_i, z_i)$  are satisfied.
  - Because each animal consumes exactly  $F_i$  units of food, the capacity constraints are satisfied on all edges from each  $z_i$  to  $t$ .
- The size of the flow is  $F$ : this follows from the fact that each animal eats exactly  $F_i$  units of food, so the amount of flow going into  $t$  will be exactly  $F$ .

Conversely, assume there is a flow  $f$  of size  $F$  in our network (that is, assume our algorithm returns T). For each edge  $e$  from  $x_j$  to  $z_i$  or  $y_i$ , feed animal  $i$   $f_e$  tons of food  $j$ . We now check that this is a feasible feeding plan:

- No more than  $T_j$  tons of each food  $j$  are used: the amount of food  $j$  used is the total flow out of  $x_j$ . By the conservation constraint, this is exactly the amount of flow routed on  $(t, x_j)$ . By the capacity constraint on that edge, this is at most  $T_j$ .
- No animal  $i$  is fed more than  $D_i$  total tons of food not in  $S_i$ : the amount of food not in  $S_i$  being fed to animal  $i$  is the total flow into  $y_i$ . By the conservation constraint, this is equal to the total flow on  $(y_i, z_i)$ . By the capacity constraints, this is at most  $D_i$ .

- Each animal  $i$  is being fed exactly  $F_i$  tons of food: the amount of food being fed to animal  $i$  is the total flow into  $y_i$  plus the total flow into  $z_i$ . By the conservation constraints, this is equal to the flow leaving  $z_i$ . By the capacity constraints, this is at most  $F_i$ . Consider the  $s - t$  cut where the source side is just  $t$ . The capacity of this cut is  $F$ . Since the size of our flow is  $F$ , this cut must be saturated. But then every edge from a  $z_i$  to  $t$  must have flow  $F_i$ , implying that each animal is fed exactly  $F_i$  tons of food.

**Runtime:** The graph constructed by this algorithm has  $O(n + m)$  vertices and  $O(nm)$  edges - it therefore takes  $O(nm)$  time to construct. We then call a network flow algorithm on this graph. The runtime will be  $O(F(n + m, nm))$ , where  $F(x, y)$  is the runtime of your favorite network flow algorithm on a graph with  $x$  vertices and  $y$  edges.

## 2 Disrupting Shipping

**Algorithm:** Find the min cut in  $G$ . Destroy  $d$  edges crossing this cut, or all the edges, if there are fewer than  $d$ .

**Correctness:** If the algorithm completely disconnects  $s$  and  $t$ , we've clearly done the best we can. Otherwise, we delete  $d$  edges, and the graph is still connected.

Note that by the duality of Max Flow and Min Cut, the Max Flow of a graph can only be reduced by as much as you can reduce the size of the min cut. By cutting  $d$  edges with unit capacity, you can only decrease the weight of the min cut by  $d$ .

Our algorithm does exactly this. Let  $C$  be the cut computed by our algorithm. After cutting  $d$  edges from  $C$ ,  $C$  must remain the min cut - other cuts have had their capacity reduced by at most  $d$ , and  $C$ 's capacity has been reduced by exactly  $d$ . It follows that the max flow is reduced by  $d$  as well. By the previous paragraph, this is optimal.

**Runtime:** The runtime of our algorithm is just the time required to compute a max flow on the input graph.

## 3 No Child Left Behind

- Algorithm:** Construct a flow graph from the matching graph in the standard way. [We will think of putting orphans on the source side, and mentors on the sink side.] On this graph, construct a flow corresponding to  $M$ , and let  $G_M$  be the residual graph from such a flow. Run the Ford-Fulkerson algorithm, starting from residual graph  $G_M$  (rather than the usual starting residual graph, which is just  $G$ ). Once you have obtained the max flow  $f$  in this way, return the matching implied by  $f$ .

**Correctness:** We have already shown in class that there is a one-to-one correspondence between max flows and max matchings in the network used by our algorithm. In particular, the flow at the end of each iteration of Ford-Fulkerson can be thought of as a matching. We will show that none of these successive matchings un-matches orphans who are matched in  $M$ . We argue by induction on the number of iterations.

**Base Case:** Before we run the first iteration of Ford-Fulkerson, we have  $M$ .

**Inductive Hypothesis:** Let  $M_k$  be the matching after  $k$  iterations of the algorithm, and let  $G_k$  be the residual graph for that matching. Assume that all the matched orphans for  $M$  are still matched in  $M_k$ .

**Inductive Case:** Consider the  $k + 1$ st iteration of Ford-Fulkerson. The algorithm finds an augmenting path in  $G_k$ . This path must start at  $s$ , and go to an orphan node. Because there are no edges between orphans, it must then go to a mentor node via a forward edge. It then either continues on to  $t$ , or goes back to the orphan size via a back edge. It then goes back to the mentors, and so on. In other words, an augmenting path starts at  $s$ , goes to an orphan, alternates orphan-mentor-orphan-mentor etc. before finally ending up at  $t$ . Every orphan-mentor edge in this path is a forward edge, and every mentor-orphan edge is a back edge.

We now show that every orphan  $i$  who was assigned after step  $k$  will remain assigned.

- \* If  $i$  is not in the augmenting path, their mentorship relationship doesn't change - in particular, they stay assigned if they were assigned before.
- \* Now assume  $i$  is in the augmenting path. Note that after the flow is augmented according to this path,  $i$  has one unit of out-flow, and one unit of in-flow. It follows that every orphan in the augmenting path is assigned.

Now note that the proof of correctness, which argues by finding a matching min-cut, holds regardless of the starting residual graph used. It follows that our algorithm in fact finds a max flow, and thus a maximum matching. This answers part (b) as well.

- b. See the end of the previous part. Note: given a bipartite graph with sets  $A$  and  $B$ , the sets of elements of  $A$  which can be simultaneously matched form a matroid, called a *transversal matroid*. The subset property is obvious, and the augmentation property follows from a similar argument to the one in part (a).