Lecture 16

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1 Vertex Cover

Input: An undirected G = (V, E), and a weight function $w : V \to \mathbb{R}^+$ **Output:** A subset $S^* \subset V$ that contains all the edges of the graph, with a minimal weight for the subset:

$$w\left(S^{*}\right) = \sum_{x \in S^{*}} w\left(x\right)$$

What is the relative approximation between this problem, and the algorithm from the unweighted version? Unconstrained. For example, on a graph with two nodes, one of weight ε , and one of weight 1, the above algorithm will choose both nodes, when the optimal solution is just the node ε .

1.0.1 Strategy to create an approximate solution through linear programming

- 1. We will formalise the problem as a linear programming problem, with integer requirements (ILP)
- 2. We will remove the requirements of integer on the variables and switch them to linear. We have got a problem of linear programming, which we can solve in polynomial time.
- 3. We will find the optimal solution to the problem from 2
- 4. We will build a correct approximate solution to the problem through the partial solution that we found in step 3.

ILP:

• For every node $v \in V$ we will define a variable

$$x(v) = \begin{cases} 1, & \text{if } v \in S \\ 0, & \text{if } v \notin S \end{cases}$$

• We will check that every edge $e = (u, v) \in E$ is contained within the requirement:

$$x(u) + x(v) \ge 1$$

• We want to minimise the weight of the chosen solution:

$$w(S) = \sum_{v \in S} w(v) = \sum_{v \in V} x(v) \cdot w(v)$$

Let us formally represent the requirements for the ILP:

$$\min_{v \in V: x(u) + x(v) \geq 1 \land x(v) \in \{0,1\}} \left\{ x\left(v\right) \cdot w\left(v\right) \right\}$$

Note this is not the standard form, since we are not maximising, but rather minimising. Remove the integer requirements:

$$\min_{v \in V: x(u) + x(v) \ge 1 \land 0 \le x(v) \le 1} \left\{ x\left(v\right) \cdot w\left(v\right) \right\}$$

Find optimal solution to step 2:

The ellipsoid algorithm find the optimal solution (if there is one) in polynomial time.

Theorem 1. There always exists an optimal solution.

 Proof . There are a finite number of nodes

1.0.2 Connection between the optimal solution to LP and ILP

Let x_{LP}^* be the optimal solution to the linear programming problem, and x_{ILP}^* be the optimal solution to the integer linear programming problem. So

$$\sum_{v \in V} x_{LP}^*\left(v\right) \cdot w\left(v\right) \leq \sum_{v \in V} x_{ILP}^*\left(v\right) \cdot w\left(v\right)$$

Let there be S_{ILP} the set of correct solutions to the ILP problem, and S_{LP} the set of correct solutions to the LP problem. We shall note that for every integer solution it is also a solution to LP, and therefore $S_{ILP} \subset S_{LP}$. From here:

$$\begin{split} w\left(x_{LP}^{*}\right) &= \sum_{v \in V} x_{LP}^{*}\left(v\right) \cdot w\left(v\right) \\ &= \min_{x \in S_{LP}} \left\{ \sum_{v \in V} x\left(v\right) \cdot w\left(v\right) \right\} \\ &\leq \min_{x \in S_{ILP}} \left\{ \sum_{v \in V} x\left(v\right) \cdot w\left(v\right) \right\} \\ &= \sum_{v \in V} x_{ILP}^{*}\left(v\right) \cdot w\left(v\right) \\ &= w\left(x_{ILP}^{*}\right) \end{split}$$

1.0.3 We will build an approximate solution from the partial solution in step 3

Let there be x_{LP}^* the optimal solution to the linear programming problem. For all $v \in V$ we will define

$$x(v) = \begin{cases} 1, & \text{if } x_{LP}^* \ge \frac{1}{2} \\ 0, & \text{if } x_{LP}^* < \frac{1}{2} \end{cases}$$

Theorem 2 (Lemma). The rounded solution is a correct solution to the problem.

Proof . Let there be $(u,v) \in E$ an edge in the graph. Since X_{LP}^* is a correct solution $x_{LP}^*(u) + x_{LP}^*(v) \ge 1$, from here $x_{LP}^*(u) \ge \frac{1}{2} \vee x_{LP}^*(v) \ge \frac{1}{2}$. This implies that $x(u) = 1 \vee x(v) = 1$. Therefore (u,v) is covered, and x must be a covering.

Theorem 3. The algorithm is a 2-approximation algorithm to the weighted vertex cover problem.

Proof. Let there be x_{LP}^* the optimal partial solution, and x the rounded solution. Let $v \in V$, if $x_{LP}^*(v) < \frac{1}{2}$ then $x(v) = 0 \le x_{LP}^*(v) \le 2x_{LP}^*(v)$. If $x_{LP}^*(v) \ge \frac{1}{2}$ then $x(v) = 1 \le 2x_{LP}^*(v)$, and therefore, for all $v \in V$, $x(v) \le 2x_{LP}^*(v)$.

$$\begin{split} \sum_{v \in V} x\left(v\right) \cdot w\left(v\right) &\leq \sum_{v \in V} 2x_{LP}^{*}\left(v\right) \cdot w\left(v\right) \\ &= 2\sum_{v \in V} x_{LP}^{*}\left(v\right) \cdot w\left(v\right) \\ &\leq 2\sum_{v \in V} x_{LP}^{*}\left(v\right) \cdot w\left(v\right) \\ &= 2w\left(S^{*}\right) \end{split}$$

2 Flow

2.0.1 Informal network flow

Input: A directed graph, the amounts that each edge can have pass through it, the origin node s, and destination node t Legal flow:

1. Conservation of flow: What enters is what leaves

2. Capacity limit: What flows on an edge is not more than its capacity

Flux: The amount of flow that leaves the origin node s.

Objective: Find the flow with the maximised flux.

2.0.2 Formal network flow

Definition 2.1 (Network flow). N = (V, E, c, s, t) where

- G = (V, E) the directed graph
- $c: E \to \mathbb{R}^+$, the capacity function on the edges
- $s \in V$, the origin node
- $t \in V$, the destination node

A correct flow in a flow network N is the function $f: E \to \mathbb{R}^+$ that satisfies:

- Capacity limit: $\forall e \in E \ 0 \le f(e) \le c(e)$
- Conservation of flow: $\forall v \in V \setminus \{s,t\} \sum_{(u,v) \in E} f(u,v) = \sum_{(v,u) \in E} f(v,u)$

The flux for a given flow f, which is written |f| is the amount of flow that leaves the end node t:

$$\sum_{x \in V \land (s,x) \in E} f(s,x)$$

The objective: Given a network flow N, find the flow with the maximised flux. We may solve this problem in polynomial time using Linear Programming. The Ford-Fulkerson algorithm solves this problem in **less time**, and ensures that integer flow in the case that there are integer capacities on the edges.

There is always a feasible solution to the problem, since the flow can be zero.

If we look at two correct flows f, g, then $q = \frac{f+g}{2}$ is also a correct flow. Since the set is closed, and convex, and there exists a feasible solution, then there is an optimal solution.