1 "Cut-free" Proof

Problem 1 (b-free knapsack) *Consider a set of elements E and two weights $w : E \to \mathbb{Z}_+$ and $c : E \to Z_+$ and a budget $b \in \mathbb{Z}_+$. Given a feasible set $\mathcal{F} \subseteq 2^E$, find $\min_{X \in \mathcal{F}, F \subseteq E} w(X \setminus F)$ such that $c(F) \le b$.*

Always remember that $\mathcal{F}$ is usually not explicitly given.

Problem 2 (Normalized knapsack) *Given the same input as Problem 1, find $\min\limits_{X \in \mathcal{F}, F \subseteq E} \frac{w(X \setminus F)}{b+1-c(F)}$ such that $c(F) \le b$.*

Denote by τ the optimum of Problem 2. Define a new weight $w_\tau : \mathrm{E} \to \mathbb{R}$,

$$w_\tau(e) = \begin{cases} w(e) & \text{if } w(e) < \tau \cdot c(e) \text{ (light elem)} \\ \tau \cdot c(e) & \text{otherwise (heavy elem)} \end{cases}$$

Lemma 1.1 *Let (X^N, F^N) be the optimal solution to Problem 2. Every element in F^N is heavy.*

proof is exactly the same as lemma 1 in [2].

Lemma 1.2 *For any $X \in \mathcal{F}$, $w_\tau(X) \ge \tau(1+b)$.*

proof is the same.

Lemma 1.3 $X^N \in \arg\min\limits_{X \in \mathcal{F}} w_\tau(X)$.

Proof:

$$\begin{aligned} w_\tau(X^N) &\le w(X^N \setminus F^N) + w_\tau(F^N) \\ &= \tau \cdot (b + 1 - c(F^N)) + \tau \cdot c(F^N) \\ &= \tau(b+1) \end{aligned}$$

Thus by Lemma 1.2, X^N gets the minimum. □

Let (X^*, F^*) be the optimal solution to Problem 1.

Lemma 1.4 *X^* is either an α-approximate solution to $\min_{X \in \mathcal{F}} w_\tau(X)$ for some $\alpha > 1$, or $w(X^* \setminus F^*) \ge \tau(\alpha + (\alpha - 1)b)$.*

The proof is the same.

In fact, corollary 1 and theorem 5 are also the same as those in [2]. Finally we get a knapsack version of Theorem 4:

Theorem 1.5 (Theorem 4 in [2]) *Let $X^{\min}$ be the optimal solution to $\min_{X \in \mathcal{F}} w_\tau(X)$. The optimal set X^* in Problem 1 is a 2-approximation to $X^{\min}$.*

Thus to obtain a FPTAS for Problem 1, one need to design a FPTAS for Problem 2 and a polynomial time alg for finding all 2-approximations to $\min_{X \in \mathcal{F}} w_\tau(X)$.

FPTAS for Problem 2 in [2] (The name "FPTAS" here is not precise since we do not have a approximation scheme but an enumeration algorithm. But I will use this term anyway.) In their settings, $\mathcal{F}$ is the collection of all cuts in some graph. Let OPT^N be the optimum of Problem 2. We can assume that there is no $X \in \mathcal{F}$ s.t. $c(X) \leq b$ since this is polynomially detectable (through min-cut on $c(\cdot)$) and the optimum is 0. Thus we have $\frac{1}{b+1} \leq \mathrm{OPT}^N \leq |E| \cdot \max_e w(e)$. Then we enumerate $\frac{(1+\varepsilon)^i}{b+1}$ where $i \in \left\{0, 1, \ldots, \left\lfloor \log_{1+\varepsilon}(|E| w_{\max}(b+1)) \right\rfloor\right\}$. There is a feasible i s.t. $(1-\varepsilon)\mathrm{OPT}^N \leq \frac{(1+\varepsilon)^i}{b+1} \leq \mathrm{OPT}^N$ since $\frac{(1+\varepsilon)^i}{b+1} \leq \mathrm{OPT}^N \leq \frac{(1+\varepsilon)^{i+1}}{b+1}$ holds for some i.

Note that this enumeration scheme also holds for arbitrary $\mathcal{F}$ if we have a non-zero lowerbound on OPT^N.

Conjecture 1.6 *Let (C, F) be the optimal solution to connectivity interdiction. The optimum cut C can be computed in polynomial time. In other words, connectivity interdiction is almost as easy as knapsack.*

2 Connections

For unit costs, connectivity interdiction with budget $b = k - 1$ is the same problem as finding the minimum weighted edge set whose removal breaks k-edge connectivity.

It turns out that Problem 2 is just a necessary ingredient for MWU. Authors of [2] $\subseteq$ authors of [1].

How to derive normalized min cut for connectivity interdiction?

$$
\begin{aligned}
\max \quad & z \\
s.t. \quad & \sum_e y_e c(e) \leq B && \text{(budget for } F\text{)} \\
& \sum_{e \in T} x_e \geq 1 && \forall T \quad (x \text{ forms a cut}) \\
& \sum_e \min(0, x_e - y_e) w(e) \geq z \\
& y_e, x_e \in \{0, 1\} && \forall e
\end{aligned}
$$

we can assume that $y_e \leq x_e$.

$$
\begin{aligned}
\min \quad & \sum_e (x_e - y_e) w(e) \\
s.t. \quad & \sum_{e \in T} x_e \geq 1 && \forall T \quad (x \text{ forms a cut}) \\
& \sum_e y_e c(e) \leq B && \text{(budget for } F\text{)} \\
& x_e \geq y_e && \forall e \quad (F \subseteq C) \\
& y_e, x_e \in \{0, 1\} && \forall e
\end{aligned}
$$

Now this LP looks similar to the normalized min-cut problem.

A further reformulation (the new x is $x - y$) gives us the following,

$$\begin{aligned}
\min \quad & \sum_e x_e w(e) \\
s.t. \quad & \sum_{e\in T} x_e + y_e \ge 1 && \forall T \quad (x \text{ forms a cut}) \\
& \sum_e y_e c(e) \le B && (\text{budget for } F) \\
& y_e, x_e \in \{0,1\} \quad \forall e
\end{aligned}$$

Note that now this is almost a positive covering LP. Let $L(\lambda) = \min\{w(C \setminus F) - \lambda(b - c(F)) | \forall \text{cut } C\ \forall F \subseteq C\}$ Consider the Lagrangian dual,

$$\max_{\lambda\ge 0} L(\lambda) = \max_{\lambda \ge 0} \min \{w(C\setminus F) - \lambda(b - c(F)), \forall \text{cut } C\ \forall F \subseteq C\}$$

At this point, it becomes clear how the normalized min-cut is implicated in [2]. The optimum of normalized min-cut is exactly the value of λ when $L(\lambda)$ is 0.

3 Random Stuff

3.1 remove box constraints

Given a positive covering LP,

$$\begin{aligned}
LP1 = \min \quad & \sum_e w(e) x_e \\
s.t. \quad & \sum_{e\in T} c(e) x_e \ge k \quad \forall T \\
& c(e) \ge x_e \ge 0 \quad \forall e,
\end{aligned}$$

we want to remove constraints $c(e) \ge x_e$. Consider the following LP,

$$\begin{aligned}
LP2 = \min \quad & \sum_e w(e) x_e \\
s.t. \quad & \sum_{e\in T} c(e) x_e \ge k && \forall T \\
& \sum_{e\in T\setminus f} c(e) x_e \ge k - c(f) && \forall T\ \forall f \in T \\
& x_e \ge 0 && \forall e,
\end{aligned}$$

These two LPs have the same optimum. One can see that any feasible solution to LP1 is feasible in LP2. Thus $\text{OPT}(LP1) \ge \text{OPT}(LP2)$. Next we show that any x_e in the optimum solution to LP2 is always in $[0, c(e)]$. Let x^* be the optimum and suppose that $c(f) < x_f \in x^*$. Consider all constraints $\sum_{e\in T\setminus f} c(e) x_e \ge k - c(f)$ on $T \ni f$. For any such constraint, we have $\sum_{e\in T} c(e) x_e > k$ since we assume $x_f > c(f)$, which means we can decrease x_f without violating any constraint. Thus it contradicts the assumption that x^* is optimal. Then we can add redundant constraints $x_e \le c(e)\ \forall e$ to LP2 and see that LP1 and LP2 have the same optimum.

This applies to [1] but cannot get an improvement on their algorithm.(MWU does not care the number of constraints.) So does this trick apply to connectivity interdiction?

$$\min_{\text{cut C},f\in C}\frac{\sum_{e\in C\setminus\{f\}}w(e)x_e}{k-c(f)}$$

References

[1] Parinya Chalermsook, Chien-Chung Huang, Danupon Nanongkai, Thatchaphol Saranurak, Pattara Sukprasert, and Sorrachai Yingchareonthawornchai. Approximating k-Edge-Connected Spanning Subgraphs via a Near-Linear Time LP Solver. *LIPIcs, Volume 229, ICALP 2022*, 229:37:1–37:20, 2022.

[2] Chien-Chung Huang, Nidia Obscura Acosta, and Sorrachai Yingchareonthawornchai. An FPTAS for Connectivity Interdiction. In Jens Vygen and Jarosław Byrka, editors, *Integer Programming and Combinatorial Optimization*, volume 14679, pages 210–223, Cham, 2024. Springer Nature Switzerland.