CS-GY 6763/CS-UY 3943: Lecture 8 Linear programming and relaxations

NYU Tandon School of Engineering, R. Teal Witter

SET COVER PROBLEM

Given:

- *n* ground elements $[n] = \{1, 2, ..., n\}^{\leftarrow}$ water *m* sets $S_1, S_2, ..., S_m$ where $S_j \subseteq [n]^{\leftarrow}$ sensor non-negative weights $w_j \ge 0 \leftarrow$ writ

for
$$j \in [m]$$
.
 $\sum_{j \in C} w_j \leq k \quad max \quad |V_{j \in C} v_j|$

Find:

$$\min_{C \subseteq [m]} \sum_{j \in C} w_j \qquad \text{subject to} \qquad \cup_{j \in C} S_j = [n].$$

Given:

- ground elements are known viruses
- sets are three-byte code sequences that occur in viruses so

 $S_j = \{$ viruses that contain *j*th three-byte sequence $\}$

• non-negative weights $w_j \ge 0$

for $j \in [m]$.

Which sequences should we use to identify viruses?

Given:

- ground elements are edges
- sets are nodes so



 $S_j = \{ edges adjacent to jth node \}$

•
$$W_j = 1$$

for $j \in [m]$.

What vertices should we choose so that all edges are connected to at least one chosen vertex?

Let $\mathbf{x} \in \mathbb{R}^m$ be a vector of decision variables and $\mathbf{c} \in \mathbb{R}^n$ be a vector of constraints. Then the primal linear programs is:

Minimize $\mathbf{b}^{\mathsf{T}}\mathbf{x}$ subject to $\mathbf{A}\mathbf{x} \ge \mathbf{c}$, $\mathbf{x} \ge 0$ (Primal) $\sum_{\mathbf{x},\mathbf{m}} \mathbf{m} \times \mathbf{l}$

Question: What are the dimensions of A and b?

Let $x_j = 1$ iff $j \in C$.

The objective is to minimize the sum of weights in C:

$$\min_{C \subseteq [m]} \sum_{j \in C} W_j \iff \min_{\mathbf{x}} \sum_{j=1}^m W_j X_j \iff \min_{\mathbf{x}} \mathbf{b}^\mathsf{T} \mathbf{x}$$
Question: What is b?
$$\mathbf{b} = \int_{\mathbf{w}_j}^{\mathbf{w}_j} \int_{\mathbf{w}_m}^{\mathbf{w}_j} \mathbf{b}$$

LP FOR SET COVER: CONSTRAINT

$$C = \begin{bmatrix} i \\ i \end{bmatrix} \qquad A_{\chi} = \begin{bmatrix} -1 & -1 & -1 & -1 \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1 & -1 & -1 \end{bmatrix} \begin{bmatrix} i \\ -1$$

The constraint is that C covers the ground elements:

$$\texttt{(n)} \quad \textbf{:} \quad \cup_{j \in C} S_j \quad \Leftrightarrow \quad \sum_{j:i \in S_j}^m x_j \ge 1 \ \forall i \in [n] \quad \Leftrightarrow \quad \textbf{Ax} \ge \textbf{C}$$

Question: What are A and c?



We can solve linear program in polynomial time with e.g. Interior Point, Ellipsoid Method.

But there's a problem ...what is it?

Definition (Relaxation)

A linear program (where $\mathbf{x} \in \mathbb{R}^m$) is a *relaxation* of an integer program (where $\mathbf{x} \in \{0, 1\}^m$) if

- a feasible solution to the IP is a feasible solution to the LP and
- the value of the feasible solution in the IP has the same value in the LP.

Therefore $OPT_{LP} \leq OPT_{IP} = OPT_{SC}$.

Theorem

Let \mathbf{x}^* be optimal solution to LP. Define $f = \max_{i \in [n]} |\{j : i \in S_j\}|.$

Choose C so that $j \in C$ iff $x_j^* \ge 1/f$.

Then C is feasible and gives an f-approximation to set cover.

Question: What approximation do we get for vertex cover?

LP TO SET COVER: PROOF

Claim: *C* is feasible.

Fix *i*. We know

jec iff x = 1/p

Then
$$\exists j$$
 so that $x_{ij}^* \ge \frac{1}{f_i} \ge \frac{1}{f_i}$

 $\sum_{j:i\in S_j} x_j^* \ge 1.$

LP TO SET COVER: PROOF

Claim: *C* gives an *f*-approximation to set cover.

our solution
to set cover =
$$\sum_{j \in C} W_j \qquad \leq \sum_{j \in C} f_{w_j} x_j^{\sharp}$$

 $\leq f \sum_{j=1}^{\infty} w_j x_j^{\sharp} = f \cdot OPT_{2P} \leq f \cdot OPT_{5C}$

LINEAR PROGRAMMING: PRIMAL AND DUAL



Note: strong duality holds if primal and dual are bounded and feasible.

DUAL FOR SET COVER



Intuition: y_i represents how much we pay for ground element *i*.

Theorem

Let \mathbf{y}^* be optimal solution to dual. Choose C' so that $j \in C'$ iff

$$\sum_{i:i\in S_j} y_i^* = w_j.$$

Then C' is feasible and gives an f-approximation to set cover.

Claim: C' is feasible.

Suppose for contradiction there's an uncovered ground element *k*.

Then for all subsets S_j containing k, we have $\sum_{i:i \in S_j} y_i^* < w_j$.

Define $\epsilon = \min_{j:k \in S_j} (W_j - \sum_{i:i \in S_j y_i^*}).$

Now let \mathbf{y}' be \mathbf{y}^* except with $y'_k = y^*_k + \epsilon$.

Then

$$x'_{i} \qquad \underset{i \in S_{i}}{\overset{\times}{\sum}} y'_{i} \leq w_{i}$$

$$\sum_{i=1}^{n} y'_{i} = e + \underset{i=1}{\overset{\times}{\sum}} y^{*_{i}}$$

Claim: C' gives an *f*-approximation to set cover.

our soln =
$$\sum_{j \in C'} W_j = \sum_{j \in C} \sum_{\substack{i \in S_j \\ i \in S_j}} y_i^{\bigstar} = \sum_{\substack{j \in C' \\ i \in S_j}} y_i^{\bigstar} = \sum_{\substack{i \in I \\ i \in I}} y_i^{\bigstar} = fort_{dual} = fort_{primal}$$
$$\leq f \cdot ort_{sc}$$



We know we can use an LP solver for primal.

Can we do better for dual?