Submodular Functions, Optimization, and Applications to Machine Learning

— Fall Quarter, Lecture 10 —

http://www.ee.washington.edu/people/faculty/bilmes/classes/ee563_spring_2018/

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Nov 2nd, 2020



$$f(A) + f(B) \ge f(A \cup B) + f(A \cap B)$$

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Announcements, Assignments, and Reminders

- Homework 2, due Nov 2nd, 11:59pm on our assignment dropbox (https://canvas.uw.edu/courses/1397085/assignments).
- Final problem on HW2 should now be first problem on HW3 (will be out soon).
- Reminder, all lectures are being recorded and posted to youtube. To get the links, see our announcements (https://canvas.uw.edu/courses/1397085/announcements).
- Office hours, Wed & Thur, 10:00pm at our class zoom link.

Class Road Map - EE563

- L1(9/30): Motivation, Applications, Definitions, Properties
- L2(10/5): Sums concave(modular), uses (diversity/costs, feature selection), information theory
- L3(10/7): Monge, More Definitions, Graph and Combinatorial Examples,
- L4(10/12): Graph & Combinatorial Examples, Matrix Rank, Properties, Other Defs, Independence
- L5(10/14): Properties, Defs of Submodularity, Independence
- L6(10/19): Matroids, Matroid Examples, Matroid Rank,
- L7(10/21): Matroid Rank, More on Partition Matroid, Laminar Matroids, System of Distinct Reps, Transversals
- L8(10/26): Transversal Matroid, Matroid and representation, Dual Matroid
- L9(10/28): Other Matroid Properties, Combinatorial Geometries, Matroid and Greedy, Polyhedra, Matroid Polytopes
- L10(11/2): Matroid Polytopes, Matroids
 → Polymatroids. Polymatroids

- L11(11/4):
- L12(11/9):
- L-(11/11): Veterans Day, Holiday
- L13(11/16):
- L14(11/18):
- L15(11/23):L16(11/25):
- L17(11/30):
- L18(12/2):
- L19(12/7):
- L20(12/9): maximization.

The greedy algorithm

- In combinatorial optimization, the greedy algorithm is often useful as a heuristic that can work quite well in practice.
- The goal is to choose a good subset of items, and the fundamental tenet of the greedy algorithm is to choose next whatever <u>currently</u> looks best, without the possibility of later recall or backtracking.
- Sometimes, this gives the optimal solution (we saw in Lecture 5 three greedy algorithms that can find the maximum weight spanning tree, namely Kruskal, Jarník/Prim/Dijkstra, and Borůvka's Algorithms).
- \bullet Greedy is good since it can be made to run very fast, e.g., $O(n\log n).$
- Often, however, greedy is heuristic (it might work well in practice, but worst-case performance can be unboundedly poor).
- We will next see that the greedy algorithm working optimally is a defining property of a matroid, and is also a defining property of a polymatroid function.

Matroid and the greedy algorithm

• Let (E,\mathcal{I}) be an independence system, and we are given a non-negative modular weight function $w:E\to\mathbb{R}_+$.

Algorithm 1: The Matroid Greedy Algorithm

```
 \begin{array}{ll} \textbf{1} \  \, \mathsf{Set} \  \, X \leftarrow \emptyset \ ; \\ \textbf{2} \  \, \mathsf{while} \  \, \exists v \in E \setminus X \  \, \mathsf{s.t.} \  \, X \cup \{v\} \in \mathcal{I} \  \, \mathsf{do} \\ \textbf{3} \  \, \Big| \  \, v \in \mathrm{argmax} \left\{ w(v) : v \in E \setminus X, \  \, X \cup \{v\} \in \mathcal{I} \right\} \ ; \\ \textbf{4} \  \, \Big| \  \, X \leftarrow X \cup \{v\} \ ; \\ \end{array}
```

• Same as sorting items by decreasing weight w, and then choosing items in that order that retain independence.

Theorem 10.2.4

Let (E,\mathcal{I}) be an independence system. Then the pair (E,\mathcal{I}) is a matroid if and only if for each weight function $w \in \mathcal{R}_+^E$, Algorithm ?? above leads to a set $I \in \mathcal{I}$ of maximum weight w(I).

Summary of Important (for us) Matroid Definitions

Given an independence system, matroids are defined equivalently by any of the following:

- All maximally independent sets have the same size.
- A normalized monotone non-decreasing submodular integral rank function with unit increments.
- The greedy algorithm achieves the maximum weight independent set for all weight functions.

Convex Polytope - key representation theorem

A polytope can be defined in a number of ways, two of which include

Theorem 10.2.6

A subset $P \subseteq \mathbb{R}^E$ is a polytope iff it can be described in either of the following (equivalent) ways:

- P is the convex hull of a finite set of points.
- If it is a bounded intersection of halfspaces, that is there exits matrix A and vector b such that

$$P = \{x : Ax \le b\} \tag{10.9}$$

 This result follows directly from results proven by Fourier, Motzkin, Farkas, and Carátheodory.

Linear Programming duality forms

There are many ways to construct the dual. For example,

$$\max\{c^{\mathsf{T}}x|x \ge 0, Ax \le b\} = \min\{y^{\mathsf{T}}b|y \ge 0, y^{\mathsf{T}}A \ge c^{\mathsf{T}}\}$$
 (10.11)

$$\max\{c^{\mathsf{T}}x|x \ge 0, Ax = b\} = \min\{y^{\mathsf{T}}b|y^{\mathsf{T}}A \ge c^{\mathsf{T}}\}$$
 (10.12)

$$\min\left\{c^\intercal x|x\geq 0, Ax\geq b\right\} = \max\left\{y^\intercal b|y\geq 0, y^\intercal A\leq c^\intercal\right\} \tag{10.13}$$

$$\min\{c^{\mathsf{T}}x|Ax \ge b\} = \max\{y^{\mathsf{T}}b|y \ge 0, y^{\mathsf{T}}A = c^{\mathsf{T}}\}$$
 (10.14)

• For each $I \in \mathcal{I}$ of a matroid $M = (E, \mathcal{I})$, we can form the incidence vector $\mathbf{1}_I \in \{0,1\}^E \subset [0,1]^E \subset \mathbb{R}_+^E$.

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- Taking the convex hull, we get the independent set polytope, that is

$$P_{\mathsf{ind. set}} = \operatorname{conv}\left\{\bigcup_{I \in \mathcal{I}} \{\mathbf{1}_I\}\right\} \subseteq [0, 1]^E$$
 (10.1)

Independence Polyhedra

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$$P_{\mathsf{ind. set}} = \mathsf{conv}\left\{\bigcup_{I \in \mathcal{I}} \{\mathbf{1}_I\}\right\} \subseteq [0, 1]^E$$
 (10.1)

• Now take the rank function r of M, and define the following polyhedron:

$$P_r^+ \triangleq \left\{ x \in \mathbb{R}^E : x \ge 0, x(A) \le r(A), \forall A \subseteq E \right\}$$
 (10.2)

Examples of P_r^+ are forthcoming.

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• Now, take any $x \in P_{\text{ind. set}}$, then we will show that that $x \in P_r^+$ (or $P_{\text{ind. set}} \subseteq P_r^+$). We show this after a few examples of P_r^+ .

$$P_r^+ = \{ x \in \mathbb{R}^E : x \ge 0, x(A) \le r(A), \forall A \subseteq E \}$$
 (10.3)

• Consider this in two dimensions. We have equations of the form:

$$x_1 > 0 \text{ and } x_2 > 0$$
 (10.4)

$$x_1 \le r(\{v_1\}) \in \{0, 1\} \tag{10.5}$$

$$x_2 \le r(\{v_2\}) \in \{0, 1\} \tag{10.6}$$

$$x_1 + x_2 \le r(\{v_1, v_2\}) \in \{0, 1, 2\}$$
 (10.7)

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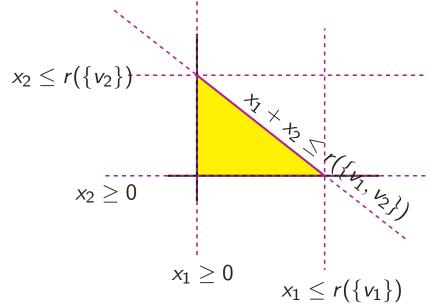
$$x_2 \le r(\{v_2\}) \in \{0, 1\} \tag{10.6}$$

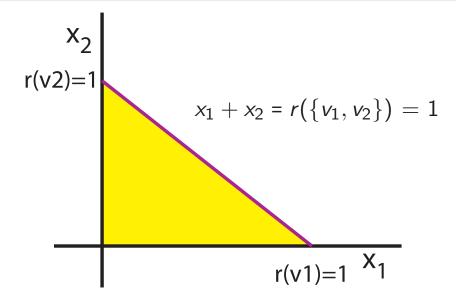
$$x_1 + x_2 \le r(\{v_1, v_2\}) \in \{0, 1, 2\}$$
 (10.7)

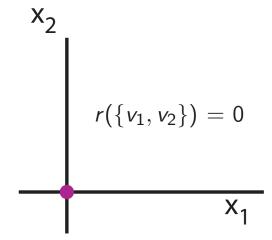
ullet Because r is submodular, we have

$$r(\{v_1\}) + r(\{v_2\}) \ge r(\{v_1, v_2\}) + r(\emptyset)$$
(10.8)

so since $r(\{v_1, v_2\}) \le r(\{v_1\}) + r(\{v_2\})$, the last inequality is either superfluous $(r(v_1, v_2) = r(v_1) + r(v_2)$, "inactive") or "active."

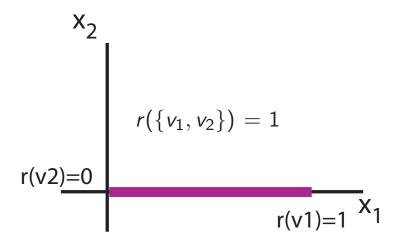






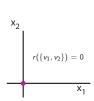
$$x_2$$
 $x_1 + x_2 = r(\{v_1, v_2\}) = 2$
 $r(v_1) = 1$
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And, if v2 is a loop ...

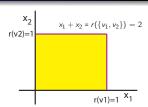


r(v1)=1 x_1

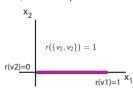
Matroid Polyhedron in 2D

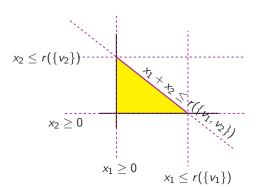


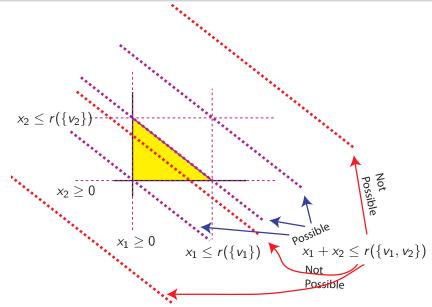




And, if v2 is a loop ...







$$P_r^+ = \left\{ x \in \mathbb{R}^E : x \ge 0, x(A) \le r(A), \forall A \subseteq E \right\}$$
 (10.9)

• Consider three dimensions, $E = \{1, 2, 3\}$. Get equations of the form:

$$x_1 \ge 0$$
 and $x_2 \ge 0$ and $x_3 \ge 0$ (10.10)
 $x_1 \le r(\{v_1\})$ (10.11)
 $x_2 \le r(\{v_2\})$ (10.12)

$$x_3 \le r(\{v_3\}) \tag{10.13}$$

$$x_1 + x_2 \le r(\{v_1, v_2\}) \tag{10.14}$$

$$x_2 + x_3 \le r(\{v_2, v_3\}) \tag{10.15}$$

$$x_1 + x_3 \le r(\{v_1, v_3\}) \tag{10.16}$$

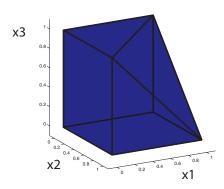
$$x_1 + x_2 + x_3 \le r(\{v_1, v_2, v_3\})$$
 (10.17)

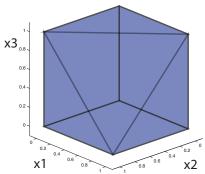
• Consider the simple cycle matroid on a graph consisting of a 3-cycle, G=(V,E) with matroid $M=(E,\mathcal{I})$ where $I\in\mathcal{I}$ is a forest.

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- So any set of either one or two edges is independent, and has rank equal to cardinality.

- Consider the simple cycle matroid on a graph consisting of a 3-cycle, G = (V, E) with matroid $M = (E, \mathcal{I})$ where $I \in \mathcal{I}$ is a forest.
- So any set of either one or two edges is independent, and has rank equal to cardinality.
- The set of three edges is dependent, and has rank 2.

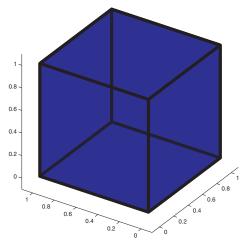
Two view of P_r^+ associated with a matroid $(\{e_1,e_2,e_3\},\{\emptyset,\{e_1\},\{e_2\},\{e_3\},\{e_1,e_2\},\{e_1,e_3\},\{e_2,e_3\}\}).$





 P_r^+ associated with the "free" matroid in 3D.

 P_r^{+} associated with the "free" matroid in 3D.



Review

• The next two slides are from the previous lecture.

- For each $I \in \mathcal{I}$ of a matroid $M = (E, \mathcal{I})$, we can form the incidence vector $\mathbf{1}_I \in \{0,1\}^E \subset [0,1]^E \subset \mathbb{R}_+^E$.
- Taking the convex hull, we get the independent set polytope, that is

$$P_{\mathsf{ind. set}} = \mathsf{conv}\left\{\bigcup_{I \in \mathcal{I}} \{\mathbf{1}_I\}\right\} \subseteq [0, 1]^E$$
 (10.1)

• Now take the rank function r of M, and define the following polyhedron:

$$P_r^+ \triangleq \left\{ x \in \mathbb{R}^E : x \ge 0, x(A) \le r(A), \forall A \subseteq E \right\}$$
 (10.2)

Examples of P_r^+ are forthcoming.

• Now, take any $x \in P_{\text{ind. set}}$, then we will show that that $x \in P_r^+$ (or $P_{\text{ind. set}} \subseteq P_r^+$). We show this after a few examples of P_r^+ .

• Recall, any vector $x \in \mathbb{R}^E$ can be seen as a normalized modular function, as for any $A \subseteq E$, we have

$$x(A) = \sum_{a \in A} x_a \tag{10.11}$$

• Given an $A \subseteq E$, define the incidence vector $\mathbf{1}_A \in \{0,1\}^E$ on the unit hypercube as follows:

$$\mathbf{1}_{A} \stackrel{\text{def}}{=} \left\{ x \in \{0, 1\}^{E} : x_{i} = 1 \text{ iff } i \in A \right\}$$
 (10.12)

equivalently,

$$\mathbf{1}_{A}(j) \stackrel{\text{def}}{=} \begin{cases} 1 & \text{if } j \in A \\ 0 & \text{if } j \notin A \end{cases}$$
 (10.13)

Matroid Polytopes

Lemma 10.3.1 $(P_{\mathsf{ind. set}} \subseteq P_r^+)$

• If $x \in P_{ind}$ set, then

$$x = \sum_{i} \lambda_i \mathbf{1}_{I_i} \tag{10.18}$$

Lemma 10.3.1 ($P_{\mathsf{ind. set}} \subseteq P_r^+$)

• If $x \in P_{ind. set}$, then

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for some appropriate vector $\lambda = (\lambda_1, \lambda_2, \dots, \lambda_n)$.

• Clearly, for such x, $x \ge 0$.

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• If $x \in P_{ind}$ set, then

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- Clearly, for such x, x > 0.
- Now, for any $A \subseteq E$,

$$x(A) = x^{\mathsf{T}} \mathbf{1}_A = \sum_{i} \lambda_i \mathbf{1}_{I_i}^{\mathsf{T}} \mathbf{1}_A \tag{10.19}$$

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$$\leq \sum_{i} \lambda_{i} \max_{j:I_{j} \subseteq A} \mathbf{1}_{I_{j}}(E) \tag{10.20}$$

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for some appropriate vector $\lambda = (\lambda_1, \lambda_2, \dots, \lambda_n)$.

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 (10.21)

$$= r(A) \tag{10.22}$$

Lemma 10.3.1 ($P_{\mathsf{ind. set}} \subseteq P_r^+$)

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- Clearly, for such x, $x \ge 0$.
- Now, for any $A \subseteq E$,

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 (10.21)

$$= r(A) \tag{10.22}$$

• Thus, $x \in P_r^+$ and hence $P_{ind. set} \subseteq P_r^+$.

• Thus, we have that:

$$P_{\text{ind. set}} = \operatorname{conv} \left\{ \bigcup_{I \in \mathcal{I}} \{ \mathbf{1}_I \} \right\}$$

$$\subseteq P_r^+ = \left\{ x \in \mathbb{R}^E : x \ge 0, x(A) \le r(A), \forall A \subseteq E \right\}$$
 (10.23)

Thus, we have that:

$$P_{\text{ind. set}} = \operatorname{conv} \left\{ \bigcup_{I \in \mathcal{I}} \left\{ \mathbf{1}_I \right\} \right\}$$

$$\subseteq P_r^+ = \left\{ x \in \mathbb{R}^E : x \ge 0, x(A) \le r(A), \forall A \subseteq E \right\} \quad (10.23)$$

• Therefore, since $\{\mathbf{1}_I: I \in \mathcal{I}\} \subseteq \operatorname{conv}\left\{\bigcup_{I \in \mathcal{I}} \{\mathbf{1}_I\}\right\} = P_{\operatorname{ind. set}} \subseteq P_r^+$, we have that

$$\max \{w(I): I \in \mathcal{I}\} \le \max \{w^{\mathsf{T}}x: x \in P_{\mathsf{ind. set}}\}$$
 (10.24)

$$\leq \max\{w^{\mathsf{T}}x : x \in P_r^+\}$$
 (10.25)

Containment: Matroid Independence Polyhedron

Thus, we have that:

$$P_{\text{ind. set}} = \operatorname{conv} \left\{ \bigcup_{I \in \mathcal{I}} \left\{ \mathbf{1}_I \right\} \right\}$$

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• Therefore, since $\{\mathbf{1}_I: I \in \mathcal{I}\} \subseteq \operatorname{conv}\{\bigcup_{I \in \mathcal{I}} \{\mathbf{1}_I\}\} = P_{\text{ind. set}} \subseteq P_r^+$, we have that

$$\max \left\{ w(I) : I \in \mathcal{I} \right\} \le \max \left\{ w^{\mathsf{T}} x : x \in P_{\mathsf{ind. set}} \right\} \tag{10.24}$$

$$\leq \max\left\{w^{\mathsf{T}}x : x \in P_r^+\right\} \tag{10.25}$$

• In fact, the two polyhedra $P_{\text{ind. set}}$ and P_r^+ are identical (and thus both are polytopes). We'll show this in the next few theorems.

Theorem 10.3.2

Let $M = (V, \mathcal{I})$ be a matroid, with rank function r, then for any weight function $w \in \mathbb{R}^V_+$, there exists a chain of sets $U_1 \subset U_2 \subset \cdots \subset U_n \subset V$ such that

$$\max \{w(I)|I \in \mathcal{I}\} = \sum_{i=1}^{n} \lambda_i r(U_i)$$
(10.26)

where $\lambda_i > 0$ satisfy

$$w = \sum_{i=1}^{n} \lambda_i \mathbf{1}_{U_i} \tag{10.27}$$

Proof.

• Firstly, note that for any such $w \in \mathbb{R}^E$, we have

$$\begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{pmatrix} = (w_1 - w_2) \begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix} + (w_2 - w_3) \begin{pmatrix} 1 \\ 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix} +$$

$$\cdots + (w_{n-1} - w_n) \begin{pmatrix} 1 \\ 1 \\ \vdots \\ 1 \\ 0 \end{pmatrix} + (w_n) \begin{pmatrix} 1 \\ 1 \\ \vdots \\ 1 \\ 1 \end{pmatrix}$$

$$(10.28)$$

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$$(10.28)$$

• If we can take w in non-increasing order $(w_1 \ge w_2 \ge \cdots \ge w_n)$, then each coefficient of the vectors is non-negative (except possibly the last one, w_n).

• Again assuming $w \in \mathbb{R}_+^E$, w.l.o.g. order elements of V non-increasing by w so (v_1,v_2,\ldots,v_n) such that $w(v_1) \geq w(v_2) \geq \cdots \geq w(v_n)$

- Again assuming $w \in \mathbb{R}_+^E$, w.l.o.g. order elements of V non-increasing by w so (v_1, v_2, \ldots, v_n) such that $w(v_1) \geq w(v_2) \geq \cdots \geq w(v_n)$
- Define the sets U_i based on this order as follows, for $i = 0, \ldots, n$

$$U_i \stackrel{\text{def}}{=} \{v_1, v_2, \dots, v_i\}$$
 (10.29)

Note that $U_0 = \emptyset$ and

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$$U_0=\emptyset$$
 and
$$\mathbf{1}_{U_0}=\begin{pmatrix}0\\0\\\vdots\\0\end{pmatrix},\mathbf{1}_{U_1}=\begin{pmatrix}1\\0\\0\\\vdots\\0\end{pmatrix},\ldots,\mathbf{1}_{U_\ell}=\begin{pmatrix}1\\1\\\vdots\\1\\0\\0\\\vdots\\0\end{pmatrix}\{(n-\ell)\times$$

- Again assuming $w \in \mathbb{R}_+^E$, w.l.o.g. order elements of V non-increasing by w so (v_1, v_2, \ldots, v_n) such that $w(v_1) \geq w(v_2) \geq \cdots \geq w(v_n)$
- Define the sets U_i based on this order as follows, for $i=0,\ldots,n$

$$U_i \stackrel{\text{def}}{=} \{v_1, v_2, \dots, v_i\}$$
 (10.29)

• Define the set I as those elements where the rank increases, i.e.:

$$I \stackrel{\text{def}}{=} \{ v_i | r(U_i) > r(U_{i-1}) \}.$$
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Hence, given an i with $v_i \notin I$, $r(U_i) = r(U_{i-1})$.

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• Therefore, I is the output of the greedy algorithm for $\max\{w(I)|I\in\mathcal{I}\}$. since items v_i are ordered decreasing by $w(v_i)$, and we only choose the ones that increase the rank, which means they don't violate independence.

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- Therefore, I is the output of the greedy algorithm for $\max\{w(I)|I\in\mathcal{I}\}.$
- And therefore, I is a maximum weight independent set (can even be a base, actually).

Proof.

• Now, we define λ_i as follows

$$0 \le \lambda_i \stackrel{\text{def}}{=} w(v_i) - w(v_{i+1}) \text{ for } i = 1, \dots, n-1$$
 (10.31)

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• Since we ordered v_1, v_2, \ldots non-increasing by w, for all i, and since $w \in \mathbb{R}^E_+$, we have $\lambda_i \geq 0$



Linear Program LP

Consider the linear programming primal problem

maximize
$$w^{\mathsf{T}}x$$
 subject to $x_v \geq 0$ $(v \in V)$ (10.35)
$$x(U) \leq r(U) \quad (\forall U \subseteq V)$$

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And its convex dual (note $y \in \mathbb{R}^{2^n}_+$, y_U is a scalar element within this exponentially big vector):

$$\begin{array}{ll} \text{minimize} & \sum_{U\subseteq V} y_U r(U), \\ \text{subject to} & y_U \geq 0 \\ & \sum_{U\subseteq V} y_U \mathbf{1}_U \geq w \end{array} \tag{10.36}$$

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Thanks to strong duality, the solutions to these are equal to each other.

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 s.t. $x_v \ge 0$ $(v \in V)$ (10.37) $x(U) \le r(U)$ $(\forall U \subseteq V)$

This is identical to the problem

$$\max w^{\mathsf{T}} x \text{ such that } x \in P_r^+ \tag{10.38}$$

where, again,
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where, again,
$$P_r^+ = \left\{x \in \mathbb{R}^E : x \geq 0, x(A) \leq r(A), \forall A \subseteq E \right\}.$$

• Therefore, since $P_{\text{ind. set}} \subseteq P_r^+$, the above problem can only have a larger solution. I.e.,

$$\max w^{\mathsf{T}} x \text{ s.t. } x \in P_{\mathsf{ind. set}} \le \max w^{\mathsf{T}} x \text{ s.t. } x \in P_r^+.$$
 (10.39)

Hence, we have the following relations:

$$\max \{w(I) : I \in \mathcal{I}\} \leq \max \{w^{\mathsf{T}}x : x \in P_{\mathsf{ind. set}}\}$$

$$\leq \max \{w^{\mathsf{T}}x : x \in P_r^+\}$$

$$\stackrel{\text{def}}{=} \alpha_{\mathsf{min}} = \min \left\{ \sum_{U \subseteq V} y_U r(U) : \forall U, y_U \geq 0; \sum_{U \subseteq V} y_U \mathbf{1}_U \geq w \right\}$$

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for the chain of U_i 's and $\lambda_i \geq 0$ that satisfies $w = \sum_{i=1}^n \lambda_i \mathbf{1}_{U_i}$ (i.e., the r.h.s. of Eq. 10.43 is feasible w.r.t. the dual LP).

• Hence, we have the following relations:

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• Therefore, we also have $\max \{w(I): I \in \mathcal{I}\} \leq \alpha_{\min}$ and

$$\max\{w(I): I \in \mathcal{I}\} = \sum_{i=1}^{n} \lambda_i r(U_i) \ge \alpha_{\min}$$
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Polytope equivalence

Hence, we have the following relations:

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- Therefore, all the inequalities above are equalities.
- And since $w \in \mathbb{R}_+^E$ is an arbitrary direction into the positive orthant, we see that $P_r^+ = P_{\text{ind. set}}$

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- That is, we have just proven:

Theorem 10.3.3

$$P_r^+ = P_{\textit{ind. set}} \tag{10.45}$$

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Theorem 10.3.4

$$P_r^+ = P_{ind. set} \tag{10.48}$$

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 So we can describe the independence polytope of a matroid using the set of inequalities (an exponential number of them).

Greedy solves a linear programming problem

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The LP problem $\max \{w^\intercal x : x \in P_r^+\}$ can be solved exactly using the greedy algorithm.

Note that this LP problem has an exponential number of constraints (since P_r^+ is described as the intersection of an exponential number of half spaces).

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• This means that if LP problems have certain structure, they can be solved much easier than immediately implied by the equations.

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- By essentially the same argument as above (Exercise:), we can shown that the convex hull of the incidence vectors of the bases of a matroid is a polytope that can be described by Eq. 10.49- 10.51 above.
- What does this look like? The base polytope.

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- $\bullet \ \ \text{Recall, a set A is spanning in a matroid $M=(E,\mathcal{I})$ if $r(A)=r(E)$.}$
- Consider convex hull of incidence vectors of spanning sets of a matroid M, and call this $P_{\text{spanning}}(M)$.

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Theorem 10.3.6

The spanning set polytope is determined by the following equations:

$$0 \le x_e \le 1 \qquad \text{for } e \in E \tag{10.52}$$

$$x(A) \ge r(E) - r(E \setminus A)$$
 for $A \subseteq E$ (10.53)

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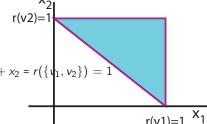
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 Example of spanning set polytope in 2D.



Spanning set polytope

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- ullet For any $x \in \mathbb{R}^E$, we have that

$$x \in P_{\mathsf{spanning}}(M) \Leftrightarrow 1 - x \in P_{\mathsf{ind. set}}(M^*)$$
 (10.54)

as we show next ...

. .

. . proof continued.

• This follows since if $x \in P_{\text{spanning}}(M)$, we can represent x as a convex combination:

$$x = \sum_{i} \lambda_i \mathbf{1}_{A_i} \tag{10.55}$$

where A_i is spanning in M.

.. proof continued.

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Consider

$$\mathbf{1} - x = \mathbf{1}_E - x = \mathbf{1}_E - \sum_i \lambda_i \mathbf{1}_{A_i} = \sum_i \lambda_i \mathbf{1}_{E \setminus A_i}, \qquad (10.56)$$

which follows since $\sum_{i} \lambda_{i} \mathbf{1} = \mathbf{1}_{E}$, so $\mathbf{1} - x$ is a convex combination of independent sets in M^* and so $1 - x \in P_{\text{ind set}}(M^*)$.

... proof continued.

• which means, from the definition of $P_{\text{ind. set}}(M^*)$, that

$$1 - x \ge 0 \tag{10.57}$$

$$\mathbf{1}_A - x(A) = |A| - x(A) \le r_{M^*}(A) \text{ for } A \subseteq E$$
 (10.58)

And we know the dual rank function is

$$r_{M^*}(A) = |A| + r_M(E \setminus A) - r_M(E)$$
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giving

$$x(A) \ge r_M(E) - r_M(E \setminus A)$$
 for all $A \subseteq E$ (10.60)



Matroids

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- We've been discussing results about matroids (independence polytope, etc.).
- By now, it is clear that matroid rank functions are special cases of submodular functions. We ultimately will be reviewing submodular function minimization procedures, but in some cases it it worth showing a result for a general submodular function first.
- Henceforth, we will skip between submodular functions and matroids, each lecture talking less about matroids specifically and taking more about submodular functions more generally ...

• Regarding sets, a subset X of S is a maximal subset of S possessing a given property $\mathfrak P$ if X possesses property $\mathfrak P$ and no set properly containing X (i.e., any $X' \supset X$ with $X' \setminus X \subseteq V \setminus X$) possesses $\mathfrak P$.

Maximal points in a set

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- Given any compact (essentially closed & bounded) set $P \subseteq \mathbb{R}^E$, we say that a vector x is maximal within P if it is the case that for any $\epsilon > 0$, and for all directions $e \in E$, we have that

$$x + \epsilon \mathbf{1}_e \notin P \tag{10.61}$$

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• Examples of maximal regions (in red)











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Examples of non-maximal regions (in green)











Review from Lecture 6

The next slide comes from Lecture 6.

- Independent sets: Given a matroid $M = (E, \mathcal{I})$, a subset $A \subseteq E$ is called independent if $A \in \mathcal{I}$ and otherwise A is called dependent.
- A base of $U \subseteq E$: For $U \subseteq E$, a subset $B \subseteq U$ is called a base of U if B is inclusionwise maximally independent subset of U. That is, $B \in \mathcal{I}$ and there is no $Z \in \mathcal{I}$ with $B \subset Z \subseteq U$.
- A base of a matroid: If U=E, then a "base of E" is just called a base of the matroid M (this corresponds to a basis in a linear space, or a spanning forest in a graph, or a spanning tree in a connected graph).

P-basis of x given compact set $P \subseteq \mathbb{R}_+^E$

Definition 10.4.1 (subvector)

Matroid Polytopes

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Definition 10.4.2 (P-basis)

Given a compact set $P \subseteq \mathcal{R}_+^E$, for any $x \in \mathbb{R}_+^E$, a subvector y of x is called a P-basis of x if y maximal in P.

In other words, y is a P-basis of x if y is a maximal P-contained subvector of x.

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Here, by y being "maximal", we mean that there exists no z>y (more precisely, no $z\geq y+\epsilon \mathbf{1}_e$ for some $e\in E$ and $\epsilon>0$) having the properties of y (the properties of y being: in P, and a subvector of x).

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In still other words: y is a P-basis of x if:

- $y \le x$ (y is a subvector of x); and
- ② $y \in P$ and $y + \epsilon \mathbf{1}_e \notin P$ for all $e \in E$ where y(e) < x(e) and $\forall \epsilon > 0$ (y is maximal P-contained).

A vector form of rank

ullet Recall the definition of rank from a matroid $M=(E,\mathcal{I}).$

$$\operatorname{rank}(A) = \max\left\{|I| : I \subseteq A, I \in \mathcal{I}\right\} = \max_{I \in \mathcal{I}} |A \cap I| \tag{10.62}$$

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• vector rank: Given a compact set $P \subseteq \mathbb{R}_+^E$, define a form of "vector rank" relative to P: Given an $x \in \mathbb{R}^E$:

$${\sf rank}(x) = \max{(y(E): y \le x, y \in P)} = \max_{y \in P}{(x \land y)(E)} \tag{10.63}$$

where $y \leq x$ is componentwise inequality $(y_i \leq x_i, \forall i)$, and where $(x \wedge y) \in \mathbb{R}_+^E$ has $(x \wedge y)(i) = \min(x(i), y(i))$.

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• Sometimes use $rank_P(x)$ to make P explicit.

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A vector form of rank

• Recall the definition of rank from a matroid $M = (E, \mathcal{I})$.

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- If \mathcal{B}_x is the set of P-bases of x, than $\operatorname{rank}(x) = \max_{y \in \mathcal{B}_x} y(E)$.
- If $x \in P$, then rank(x) = x(E) (x is its own unique self P-basis).
- If $x_{\min} \in \operatorname{argmin}_{x \in P} x(E)$, and $x \leq x_{\min}$ what then? Then $\operatorname{rank}(x)$ is either x(E) (if $x = x_{min}$) or otherwise $rank(x) = -\infty$.
- In general, might be hard to compute and/or have ill-defined properties. Next, we look at an object that restrains and cultivates this form of rank.

- $0 \in P$
- ② If $y \le x \in P$ then $y \in P$ (called down monotone).
- § For every $x \in \mathbb{R}_+^E$, any maximal vector $y \in P$ with $y \leq x$ (i.e., any P-basis of x), has the same component sum y(E)

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 - Condition 3 restated: That is for any two distinct $\underline{\text{maximal}}$ vectors $y^1, y^2 \in P$, with $y^1 \leq x \ \& \ y^2 \leq x$, with $y^1 \neq y^2$, we must have $y^1(E) = y^2(E)$.

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 - Condition 3 restated (again): For every vector $x \in \mathbb{R}_+^E$, every maximal independent (i.e., $\in P$) subvector y of x has the same component sum $y(E) = \operatorname{rank}(x)$.
 - Condition 3 restated (yet again): All P-bases of x have the same component sum.

- $0 \in P$
- ② If $y \le x \in P$ then $y \in P$ (called down monotone).
- **3** For every $x \in \mathbb{R}_+^E$, any maximal vector $y \in P$ with $y \leq x$ (i.e., any P-basis of x), has the same component sum y(E)
 - Vectors within P (i.e., any $y \in P$) are called independent, and any vector outside of P is called dependent.

Polymatroidal polyhedron (or a "polymatroid")

Definition 10.4.3 (polymatroid)

- $0 \in P$
- ② If $y \le x \in P$ then $y \in P$ (called down monotone).
- § For every $x \in \mathbb{R}_+^E$, any maximal vector $y \in P$ with $y \leq x$ (i.e., any P-basis of x), has the same component sum y(E)
 - Vectors within P (i.e., any $y \in P$) are called independent, and any vector outside of P is called dependent.
 - Since all P-bases of x have the same component sum, if \mathcal{B}_x is the set of P-bases of x, than $\operatorname{rank}(x) = y(E)$ for any $y \in \mathcal{B}_x$.

A Matroid is:

A Matroid is:

A Polymatroid is:

 $\ \, \textbf{ a compact set} \,\, P \subseteq \mathbb{R}_+^E$

Matroid and Polymatroid: side-by-side

A Matroid is:

- lacksquare a set system (E,\mathcal{I})
- $\textbf{2} \ \text{empty-set containing} \ \emptyset \in \mathcal{I}$

- lacktriangle a compact set $P \subseteq \mathbb{R}_+^E$
- 2 zero containing, $0 \in P$

A Matroid is:

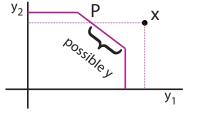
- lacksquare a set system (E,\mathcal{I})
- 2 empty-set containing $\emptyset \in \mathcal{I}$

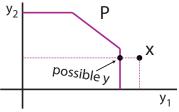
- lacktriangle a compact set $P \subseteq \mathbb{R}_+^E$
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A Matroid is:

- lacktriangledown a set system (E,\mathcal{I})
- 2 empty-set containing $\emptyset \in \mathcal{I}$
- $\textbf{3} \ \, \mathsf{down} \ \, \mathsf{closed}, \, \emptyset \subseteq I' \subseteq I \in \mathcal{I} \Rightarrow I' \in \mathcal{I}.$
- **•** any maximal set I in \mathcal{I} , bounded by another set A, has the same matroid rank (any maximal independent subset $I \subseteq A$ has same size |I|).

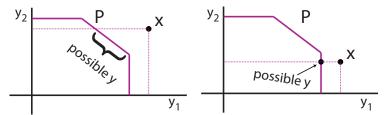
- $oldsymbol{2}$ zero containing, $oldsymbol{0} \in P$
- **3** down monotone, $0 \le y \le x \in P \Rightarrow y \in P$
- **1** any maximal vector y in P, bounded by another vector x, has the same vector rank (any maximal independent subvector $y \le x$ has same sum y(E)).





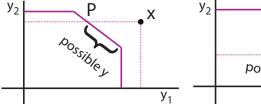
Left: \exists multiple maximal $y \le x$ Right: \exists only one maximal $y \le x$,

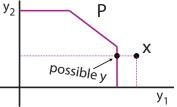
• Polymatroid condition here: \forall maximal $y \in P$, with $y \le x$ (which here means $y_1 \le x_1$ and $y_2 \le x_2$), we just have $y(E) = y_1 + y_2 = \text{const.}$



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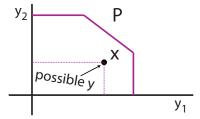
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- ullet On the left, we see there are multiple possible maximal $y\in P$ such that $y\leq x.$ Each such y must have the same value y(E).



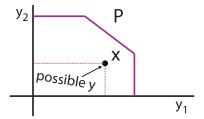


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- On the left, we see there are multiple possible maximal $y \in P$ such that $y \leq x$. Each such y must have the same value y(E).
- On the right, there is only one maximal $y \in P$. Since there is only one, the condition on the same value of $y(E), \forall y$ is vacuous.



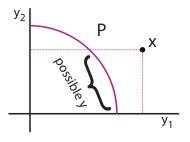
- \exists only one maximal $y \leq x$.
 - If $x \in P$ already, then x is its own P-basis, i.e., it is a self P-basis.

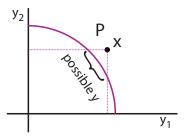


 \exists only one maximal $y \leq x$.

- If $x \in P$ already, then x is its own P-basis, i.e., it is a self P-basis.
- In a matroid, a base of A is the maximally contained independent set. If A is already independent, then A is a self-base of A (as we saw in previous Lectures)

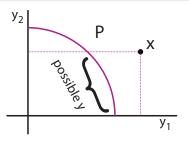
Polymatroid as well?

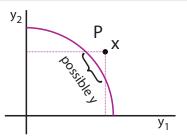




Left and right: \exists multiple maximal $y \le x$ as indicated.

• On the left, we see there are multiple possible maximal such $y \in P$ that are $y \leq x$. Each such y must have the same value y(E), but since the equation for the curve is $y_1^2 + y_2^2 = \text{const.} \neq y_1 + y_2$, we see this is not a polymatroid.



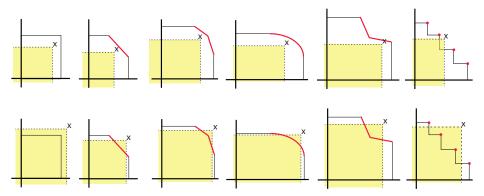


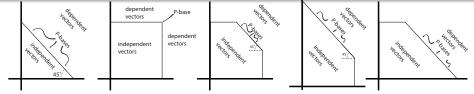
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- On the right, we have a similar situation, just the set of potential values that must have the y(E) condition changes, but the values of course are still not constant.

troid Polytopes Matroids Polymatroids Polymatroids

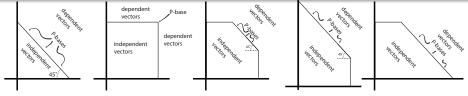
Other examples: Polymatroid or not?



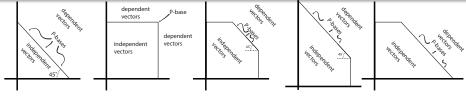


It appears that we have five possible forms of polymatroid in 2D, when neither of the elements $\{v_1, v_2\}$ are self-dependent.

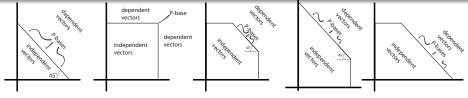
lacktriangle On the left: full dependence between v_1 and v_2



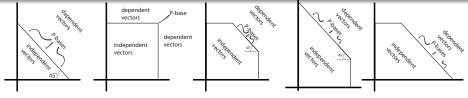
- lacktriangledown On the left: full dependence between v_1 and v_2
- 2 Next: full independence between v_1 and v_2



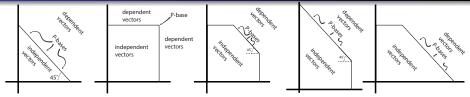
- lacktriangledown On the left: full dependence between v_1 and v_2
- 2 Next: full independence between v_1 and v_2
- lacktriangle Next: partial independence between v_1 and v_2



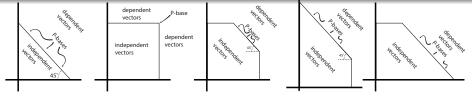
- lacktriangledown On the left: full dependence between v_1 and v_2
- 2 Next: full independence between v_1 and v_2
- lacktriangle Next: partial independence between v_1 and v_2
- lacktriangle Right two: other forms of partial independence between v_1 and v_2



- lacksquare On the left: full dependence between v_1 and v_2
- 2 Next: full independence between v_1 and v_2
- lacktriangle Next: partial independence between v_1 and v_2
- f 0 Right two: other forms of partial independence between v_1 and v_2
 - The P-bases (or single P-base in the middle case) are as indicated.



- On the left: full dependence between v_1 and v_2
- 2 Next: full independence between v_1 and v_2
- **1** Next: partial independence between v_1 and v_2
- **a** Right two: other forms of partial independence between v_1 and v_2
 - The P-bases (or single P-base in the middle case) are as indicated.
- Independent vectors are those within or on the boundary of the polytope. Dependent vectors are exterior to the polytope.



It appears that we have five possible forms of polymatroid in 2D, when neither of the elements $\{v_1, v_2\}$ are self-dependent.

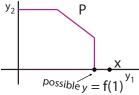
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 - The P-bases (or single P-base in the middle case) are as indicated.
- Independent vectors are those within or on the boundary of the polytope. Dependent vectors are exterior to the polytope.
- The set of *P*-bases for a polytope is called the base polytope.

Matroid Polytopes

• Note that if x contains any zeros (i.e., suppose that $x \in \mathbb{R}_+^E$ has $E \setminus S$ s.t. $x(E \setminus S) = 0$, so S indicates the non-zero elements, or $S = \operatorname{supp}(x)$), then this also forces $y(E \setminus S) = 0$, so that y(E) = y(S). This is true either for $x \in P$ or $x \notin P$.

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- Therefore, in this case, it is the non-zero elements of x, corresponding to elements S (i.e., the support $\mathrm{supp}(x)$ of x), determine the common component sum.

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- Therefore, in this case, it is the non-zero elements of x, corresponding to elements S (i.e., the support $\mathrm{supp}(x)$ of x), determine the common component sum.
- For the case of either $x \notin P$ or right at the boundary of P, we might give a "name" to this component sum, lets say f(S) for any given set S of non-zero elements of x. We could name $\operatorname{rank}(\frac{1}{\epsilon}\mathbf{1}_S) \triangleq f(S)$ for ϵ small enough. What kind of function might f be?



Definition 10.4.4

A polymatroid function is a real-valued function f defined on subsets of E which is normalized, non-decreasing, and submodular. That is we have

- ② $f(A) \le f(B)$ for any $A \subseteq B \subseteq E$ (monotone non-decreasing)

We can define the polyhedron P_f^{+} associated with a polymatroid function as follows

$$P_f^+ = \left\{ y \in \mathbb{R}_+^E : y(A) \le f(A) \text{ for all } A \subseteq E \right\}$$

$$= \left\{ y \in \mathbb{R}^E : y \ge 0, y(A) \le f(A) \text{ for all } A \subseteq E \right\}$$

$$(10.64)$$

$$P_f^+ = \left\{ x \in \mathbb{R}^E : x \ge 0, x(A) \le f(A), \forall A \subseteq E \right\}$$
 (10.66)

 $x_2 + x_3 < f(\{v_2, v_3\})$

• Consider this in three dimensions. We have equations of the form:

$$x_1 \ge 0 \text{ and } x_2 \ge 0 \text{ and } x_3 \ge 0$$
 (10.67)
 $x_1 \le f(\{v_1\})$ (10.68)
 $x_2 \le f(\{v_2\})$ (10.69)
 $x_3 \le f(\{v_3\})$ (10.70)
 $x_1 + x_2 \le f(\{v_1, v_2\})$ (10.71)

$$x_1 + x_3 \le f(\{v_1, v_3\}) \tag{10.73}$$

$$x_1 + x_2 + x_3 \le f(\{v_1, v_2, v_3\})$$
 (10.74)

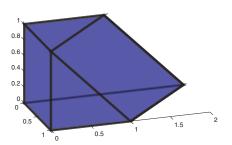
Prof. Jeff Bilmes

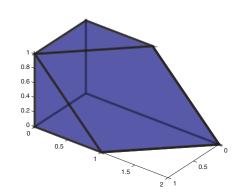
(10.71)

(10.72)

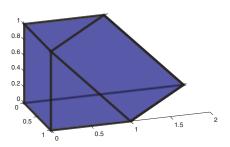
• Consider the asymmetric graph cut function on the simple chain graph $v_1-v_2-v_3$. That is, $f(S)=|\{(v,s)\in E(G):v\in V,s\in S\}|$ is count of any edges within S or between S and $V\setminus S$, so that $\delta(S)=f(S)+f(V\setminus S)-f(V)$ is the standard graph cut.

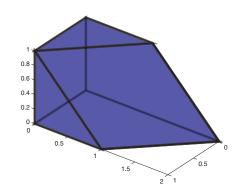
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- Observe: P_f^+ (at two views):





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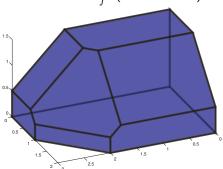


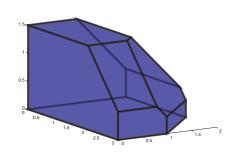


which axis is which?

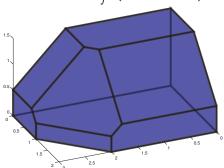
• Consider: $f(\emptyset) = 0$, $f(\{v_1\}) = 1.5$, $f(\{v_2\}) = 2$, $f(\{v_1, v_2\}) = 2.5$, $f(\{v_3\}) = 3$, $f(\{v_3, v_1\}) = 3.5$, $f(\{v_3, v_2\}) = 4$, $f(\{v_3, v_2, v_1\}) = 4.3$.

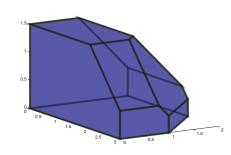
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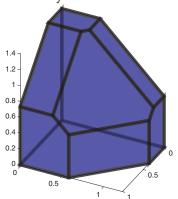


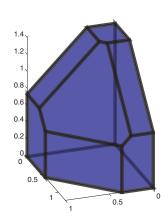
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• Consider modular function $w:V\to\mathbb{R}_+$ as $w=(1,1.5,2)^{\mathsf{T}}$, and then the submodular function $f(S)=\sqrt{w(S)}$.

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• Observe: P_f^+ (at two views):

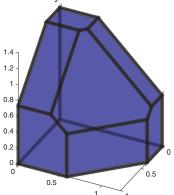


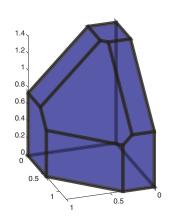


Associated polyhedron with a polymatroid function

• Consider modular function $w: V \to \mathbb{R}_+$ as $w = (1, 1.5, 2)^\mathsf{T}$, and then the submodular function $f(S) = \sqrt{w(S)}$.

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which axis is which?

• Consider function on integers: g(0) = 0, g(1) = 3, g(2) = 4, and g(3) = 5.5.

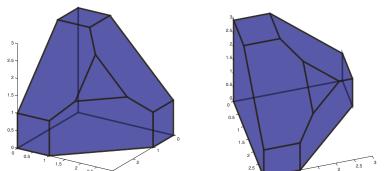
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Associated polytope with a non-submodular function

- Consider function on integers: g(0) = 0, g(1) = 3, g(2) = 4, and g(3) = 5.5. Is f(S) = g(|S|) submodular? f(S) = g(|S|) is not submodular since $f(\{e_1, e_3\}) + f(\{e_1, e_2\}) = 4 + 4 = 8$ but $f(\{e_1, e_2, e_3\}) + f(\{e_1\}) = 5.5 + 3 = 8.5$. Alternatively, consider concavity violation, 1 = g(1+1) g(1) < g(2+1) g(2) = 1.5.
- Observe: P_f^+ (at two views), maximal independent subvectors not constant rank, hence **not** a polymatroid.



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 - \bullet Given a polymatroid function f, its associated polytope is given as

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- Is there any relationship between these two polytopes?
- In the next theorem, we show that any P_f^+ -basis has the same component sum, when f is a polymatroid function, and P_f^+ satisfies the other properties so that P_f^+ is a polymatroid.

Theorem 10.5.1

Let f be a polymatroid function defined on subsets of E. For any $x \in \mathbb{R}_+^E$, and any P_f^+ -basis $y^x \in \mathbb{R}_+^E$ of x, the component sum of y^x is

$$y^{x}(E) = \operatorname{rank}(x) \triangleq \max \left(y(E) : y \le x, y \in P_{f}^{+} \right)$$
$$= \min \left(x(A) + f(E \setminus A) : A \subseteq E \right) \tag{10.76}$$

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Taking $E \setminus B = \operatorname{supp}(x)$ (so elements B are all zeros in x), and for $b \notin B$ we make x(b) is big enough, the r.h.s. min has solution $A^* = B$. We recover submodular function from the polymatroid polyhedron via the following:

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In fact, we will ultimately see a number of important consequences of this theorem (other than just that P_f^+ is a polymatroid)

Proof.

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- Now suppose that we are given an $x \in \mathbb{R}_+^E$, and maximal $y^x \in P_f^+$ with $y^x \leq x$ (i.e., y^x is a P_f^+ -basis of x).

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- Goal is to show that any such y^x has $y^x(E) = \text{const}$, dependent only on x and also f (which defines the polytope) but not dependent on y^x , the particular P_f^+ -basis.

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- Doing so will thus establish that P_f^+ is a polymatroid.

... proof continued.

• First trivial case: could have $y^x = x$, which happens if $x(A) \leq f(A), \forall A \subseteq E$ (i.e., $x \in P_f^+$ strictly). In such case,

$$\min (x(A) + f(E \setminus A) : A \subseteq E)$$

$$= x(E) + \min (f(E \setminus A) - x(E \setminus A) : A \subseteq E)$$

$$= x(E) + \min (f(A) - x(A) : A \subseteq E)$$

$$(10.78)$$

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$$(10.80)$$

$$=x(E) \tag{10.81}$$

(=0:0=)

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 $\bullet \ \mbox{When } x \in P_f^+ \mbox{, } y = x \mbox{ is clearly the solution to} \\ \max \Big(y(E) : y \leq x, y \in P_f^+ \Big) \mbox{, so this is tight, and } \mathrm{rank}(x) = x(E).$

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- When $x \in P_f^+$, y = x is clearly the solution to $\max\left(y(E): y \leq x, y \in P_f^+\right)$, so this is tight, and $\mathrm{rank}(x) = x(E)$.
- This is a value dependent only on x, a self basis, unique P_f^+ -base.

... proof continued.

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... proof continued.

- 2nd trivial case: $x(A) > f(A), \forall A \subseteq E$ (i.e., $x \notin P_f^+$ every direction),
- Then for any order (a_1, a_2, \dots) of the elements and $A_i \triangleq (a_1, a_2, \dots, a_i)$, we have $x(a_i) \geq f(a_i) \geq f(a_i|A_{i-1})$, the second inequality by submodularity.

... proof continued.

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$$\min (x(A) + f(E \setminus A) : A \subseteq E) \tag{10.82}$$

$$= x(E) + \min(f(A) - x(A) : A \subseteq E)$$
 (10.83)

$$= x(E) + \min \left(\sum_{i} f(a_i|A_{i-1}) - \sum_{i} x(a_i) : A \subseteq E \right)$$
 (10.84)

$$= x(E) + \min \left(\sum_{i} \underbrace{\left(f(a_i | A_{i-1}) - x(a_i) \right)}_{\leq 0} : A \subseteq E \right) \quad (10.85)$$

$$= x(E) + f(E) - x(E) = f(E) = \max(y(E) : y \in P_f^+).$$

... proof continued.

ullet Assume neither trivial case. Because $y^x \in P_f^+$, we have that $y^x(A) \leq f(A)$ for all $A \subseteq E$.

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• For any P_f^+ -basis y^x of x, and any $A \subseteq E$, we have weak relationship:

$$y^{x}(E) = y^{x}(A) + y^{x}(E \setminus A)$$
(10.88)

$$\leq x(A) + f(E \setminus A). \tag{10.89}$$

This follows since $y^x \leq x$ and since $y^x \in P_f^+$.

... proof continued.

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This follows since $y^x \leq x$ and since $y^x \in P_f^+$.

This ensures

$$\max\left(y(E):y\leq x,y\in P_f^+\right)\leq \min\left(x(A)+f(E\setminus A):A\subseteq E\right) \quad \text{(10.90)}$$

٠.

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$$y^{x}(E) = \min(x(A) + f(E \setminus A) : A \subseteq E)$$
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• For any P_f^+ -basis y^x of x, and any $A \subseteq E$, we have weak relationship:

$$y^{x}(E) = y^{x}(A) + y^{x}(E \setminus A)$$
(10.88)

$$\leq x(A) + f(E \setminus A). \tag{10.89}$$

This follows since $y^x \leq x$ and since $y^x \in P_f^+$.

- This ensures
 - $\max\left(y(E):y\leq x,y\in P_f^+\right)\leq \min\left(x(A)+f(E\setminus A):A\subseteq E\right) \ \ \textbf{(10.90)}$
- \bullet Given an A where equality in Eqn. (10.89) holds, above min result follows.

..proof continued.

$$f(B) + f(C)$$

.. proof continued.

$$f(B) + f(C) = y(B) + y(C)$$
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$$= y(B \cap C) + y(B \cup C) \tag{10.92}$$

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• For any $y \in P_f^+$, call a set $B \subseteq E$ tight if y(B) = f(B). The union (and intersection) of tight sets B, C is again tight, since

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$$= y(B \cap C) + y(B \cup C) \tag{10.92}$$

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• Because $y(A) \leq f(A), \forall A$, this means $y(B \cap C) = f(B \cap C)$ and $y(B \cup C) = f(B \cup C)$, so both also are tight.

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- Because $y(A) \leq f(A), \forall A$, this means $y(B \cap C) = f(B \cap C)$ and $y(B \cup C) = f(B \cup C)$, so both also are tight.
- For $y \in P_f^+$, it will be ultimately useful to define this lattice family of tight sets: $\mathcal{D}(y) \triangleq \{A : A \subseteq E, \ y(A) = f(A)\}.$

... proof continued.

• Also, we define $\operatorname{sat}(y) \stackrel{\text{def}}{=} \bigcup \{T : T \in \mathcal{D}(y)\}$, so $y(\operatorname{sat}(y)) = f(\operatorname{sat}(y))$.



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- Given a $e \in E$, either $y^x(e)$ is cut off due to x (so $y^x(e) = x(e)$) or e is saturated by f, meaning it is an element of some tight set and $e \in \operatorname{sat}(y^x)$ (since if $e \in T \in \mathcal{D}(y^x)$, then $e \in \operatorname{sat}(y^x)$).

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- Let $E \setminus A = \operatorname{sat}(y^x)$ be the union of all such tight sets (which is also tight, so $y^x(E \setminus A) = f(E \setminus A)$).



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$$y^{x}(E) = y^{x}(A) + y^{x}(E \setminus A) = x(A) + f(E \setminus A)$$
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ullet So we identified the A to be the elements that are non-tight, and achieved the min, as desired.



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Theorem 10.5.2

For any polymatroid P (compact subset of \mathbb{R}_+^E , zero containing, down-monotone, and $\forall x \in \mathbb{R}_+^E$ any maximal independent subvector $y \leq x$ has same component sum $y(E) = \operatorname{rank}(x)$), there is a polymatroid function $f: 2^E \to \mathbb{R}$ (normalized, monotone non-decreasing, submodular) such that $P = P_f^+$ where $P_f^+ = \{x \in \mathbb{R}^E: x \geq 0, x(A) \leq f(A), \forall A \subseteq E\}$.

Recall the definition of the set of tight sets at $y \in P_f^+$:

$$\mathcal{D}(y) \triangleq \{A : A \subseteq E, \ y(A) = f(A)\}$$
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Theorem 10.5.3

For any $y \in P_f^+$, with f a polymatroid function, then $\mathcal{D}(y)$ is closed under union and intersection.

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Theorem 10.5.3

For any $y \in P_f^+$, with f a polymatroid function, then $\mathcal{D}(y)$ is closed under union and intersection.

Proof.

We have already proven this as part of Theorem 10.5.1



Tight sets $\mathcal{D}(y)$ are closed, and max tight set $\operatorname{sat}(y)$

Recall the definition of the set of tight sets at $y \in P_f^+$:

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Theorem 10.5.3

For any $y \in P_f^+$, with f a polymatroid function, then $\mathcal{D}(y)$ is closed under union and intersection.

Proof.

We have already proven this as part of Theorem 10.5.1



Also recall the definition of sat(y), the maximal set of tight elements relative to $y \in \mathbb{R}^E_+$.

$$\operatorname{sat}(y) \stackrel{\text{def}}{=} \bigcup \{T : T \in \mathcal{D}(y)\}$$
 (10.97)

Join \vee and meet \wedge for $x,y \in \mathbb{R}_+^E$

• For $x,y\in\mathbb{R}_+^E$, define vectors $x\wedge y\in\mathbb{R}_+^E$ and $x\vee y\in\mathbb{R}_+^E$ such that, for all $e\in E$

$$(x \lor y)(e) = \max(x(e), y(e))$$
 (10.98)

$$(x \wedge y)(e) = \min(x(e), y(e))$$
 (10.99)

Hence,

$$x \vee y \triangleq \left(\max(x(e_1), y(e_1)), \max(x(e_2), y(e_2)), \dots, \max(x(e_n), y(e_n)) \right)$$

and similarly

$$x \wedge y \triangleq \left(\min\left(x(e_1), y(e_1)\right), \min\left(x(e_2), y(e_2)\right), \dots, \min\left(x(e_n), y(e_n)\right)\right)$$

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• From this, we can define things like an lattices, and other constructs.