# Testing $\mathcal{M P}(G)$ 

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## Definition (matching polytope) <br> $\mathcal{M P}(G)=\operatorname{conv}\left\{\chi_{M}: M\right.$ is a matching in $\left.G\right\}$.

## Reminder

## Definition (matching polytope)

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$$

## Edmonds Polytope Theorem)

$\mathcal{M P}(G)$ consists exactly of the vectors $\left(x_{e}\right)_{e \in E} \in \mathbb{R}^{E(G)}$ that satisfy the following three types of inequalities:

$$
\begin{aligned}
\left(E_{e}\right): & x_{e} \geq 0 \quad \forall e \in E(G) \\
\left(E_{v}\right): & \sum_{e: v l e} x_{e} \leq 1 \quad \forall v \in V(G) \\
\left(E_{S}\right): & \sum_{e \subseteq S} x_{e} \leq \frac{|S|-1}{2} \quad \forall S \in \mathcal{O}
\end{aligned}
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Some of these may be redundant (we saw that for bipartite $G$ this can lead to significant simplification), but the polytope is generally complicated (the number of required inequalities is exponential in the number of vertices and edges of the graph).

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Find an efficient algorithm that, given a $x \in \mathbb{Q}^{E(G)}$, outputs either the true information that $x$ is an element of $\mathcal{M P}(\mathcal{G})$, or a defining inequality violated by the $x$ vector.

By efficient we mean polynomial time in the size of $G$. So the naive algorithm (substitute $x$ coordinates into every inequality and after checks announce the result) won't do.

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So for the rest, we can assume that the $\left(E_{v}\right)$ and $\left(E_{e}\right)$ inequalities hold for the vector $x$ to be tested.

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So $\left(x_{e}\right)_{e \in E} \in \mathbb{R}^{E(G)}$ is an edge-weighted graph.
We assumed the weights to be non-negative. At every vertex, the sum of weights of incident edges is at most 1 .

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Edge weighting can also be naturally thought of as a function $x: E(G) \rightarrow \mathbb{R}_{+}$(we know that $x$ satisfies the $\left(E_{e}\right)$ inequalities). So $x(e)=x_{e}$ will denote the weight of edge $e$.

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x(F)=\sum_{e: e \in F} x_{e}=\sum_{e: e \in F} x(e)
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If $R \subset V(G)$, then

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x(R)=\sum_{e: e=x y \in E(G), x, y \in R} x_{e}=\sum_{e: e=x y \in E(G), x, y \in R} x(e)
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At first glance, these conventions may be confusing. The meaning of $x(\cdot)$ depends on whether the parentheses contain an edge, an edge set, or a vertex set. Let's take the time and effort to get used to it.

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$2^{|V|}$ inequalities

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x(R):=\sum_{e \subseteq R} x_{e} \leq \frac{|R|}{2} \quad \forall R \in \mathcal{P}(V)
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Summarizing, the $\left(E_{S}\right)$ conditions only mean that the above estimate (which holds for every vertex set) can be sharpened by $1 / 2$ for subsets with odd cardinality.

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In the following,
$\partial R:=\{e=u v \in E: u \in R, v \notin R\}, \quad x(\partial R):=$ $\sum_{e=u v \in E: u \in R, v \notin R} x_{e}$
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notations are used.
Since the components of $x$ are non-negative, for any vertex set $R$

$$
2 \cdot x(R) \leq x(\partial R)+2 \cdot x(R) \leq|R|, \quad \text { thus } \quad x(R) \leq \frac{|R|}{2}
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We show that if this problem is solved for non-negative vectors where all $\left(E_{v}\right)$ conditions are satisfied with equality, then the general problem can be solved.

Given a non-negative edge weighting, assuming that for every vertex the sum of weights of incident edges is at most 1.
From a $(G, x)$ construct a $\widetilde{G}, \widetilde{x}$ pair, which already satisfies the $\left(E_{v}\right)$ inequalities with equality (the sum of weights of incident edges at each vertex is exactly 1 ).

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## Claim supporting the 1st Goal

For $(G, x)$, then all $\left(E_{S}\right)$ conditions hold if and only if they hold for $(\widetilde{G}, \widetilde{x})$.

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If for $(G, x)$ any $\left(E_{S}\right)$ condition is false, then the same $S$ set (which is also a subset of $V(\widetilde{G})$ ) will violate the conditions in $\widetilde{G}$.

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We only need to prove that if for $(G, x)$ all $\left(E_{S}\right)$ conditions are true, then these also hold for $\widetilde{G}$.

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## Notation

Let $S \subset V(\widetilde{G})$ be arbitrary. $R=S \cap V(G)$ and $T^{\prime}=S \cap V\left(G^{\prime}\right)$ are the two parts of set $S$. Think of $T^{\prime}$ as a twin of a vertex set $T \subset V(G)$.

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If $S$ has an odd cardinality, then one of $S$ and $T$ is odd, and the other has an even cardinality.

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This is a straightforward case. Then the set of edges $E(R)$ inside $R$ and the set of edges $E\left(T^{\prime}\right)$ inside $T^{\prime}$ together give the set of edges $E(S)$ inside $S$. Specifically, $x(S)=x(R)+x\left(T^{\prime}\right)=x(R)+x(T)$.

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We can estimate $x(R)$ and $x(T)$ by $|R| / 2$ and $|T| / 2$, respectively, and even the upper bound sharpened by $1 / 2$ for the set with an odd cardinality.

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We can assume that $D \subset V(G)$ is a set with an odd number of elements:

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x(D) \leq \frac{|D|-1}{2}
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We will be more cautious when estimating $x\left(M \cup M^{\prime} \cup K^{\prime}\right)$.

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inequality is used, which we derived from the $\left(E_{v}\right)$ and $\left(E_{e}\right)$ inequalities.

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inequality is used, which we derived from the $\left(E_{v}\right)$ and $\left(E_{e}\right)$ inequalities.

Regarding the previously neglected, halved term, it is obvious that

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x(E(D, M)) \leq \frac{1}{2}\left(x\left(\partial_{G}(M)+\partial_{G^{\prime}}\left(M^{\prime} \cup K^{\prime}\right)\right)\right.
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where $E(D, M)$ is the number of edges crossing between $D$ and $M$.

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where $E(D, M)$ is the number of edges crossing between $D$ and $M$.
Combining these two inequalities yields the desired result straightforwardly.

We have thus obtained that testing the $\left(E_{S}\right)$ inequalities is equivalent for $(G, x)$ and $(\widetilde{G}, \widetilde{x})$.

Break


## Cuts

- In what follows, we only deal with edge-weighted ( $G, x$ ) graphs where the $\left(E_{v}\right)$ inequalities hold with equality, that is, for every $v \in V(G)$ vertex

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\sum_{e \in E: v l e} x_{e}=1
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and the vertex set has an even cardinality.

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- Our previous derivation can be repeated (now with equalities):

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2 \sum_{e=x y \in E: x, y, \in S} x_{e}+\sum_{e \in \partial S} x_{e}=|S| .
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- We change the language slightly: $\partial S$ is the boundary of set $S$. However, this can be regarded as the edge set $E(\mathcal{V})$ of the cut $\mathcal{V}=(S, \bar{S})$. Let $x(\mathcal{V})=x(E(\mathcal{V}))$. The $\mathcal{V}$ cut is odd if both its sides are sets with an odd cardinality (we already assume $G$ has an even number of vertices).


## Reformulation

- We obtained that for every odd $\mathcal{V}$ cut

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Given an edge-weighted, non-negative, and even-sized graph $(G, x)$. Determine efficiently the minimum weight odd cut.

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- We obtained that for every odd $\mathcal{V}$ cut

$$
x(\mathcal{V})=|S|-2 x(S)=2\left(\frac{|S|-1}{2}-x(S)\right)+1
$$

That is

$$
\frac{|S|-1}{2}-x(S)=\frac{x(\mathcal{V})-1}{2}
$$

- Accordingly, all $\left(E_{S}\right)$ inequalities hold if and only if the weight of every edge set of an odd cut $\mathcal{V}$ is at least 1.


## Goal 2

Given an edge-weighted, non-negative, and even-sized graph $(G, x)$. Determine efficiently the minimum weight odd cut.

- If Goal 2 is achievable, then it implies solving the Edmonds' polytope testing problem.


## Related Cut Problems

- If we seek $\min _{\mathcal{V} \text { cut }} x(\mathcal{V})$, this can be easily done using flow theory.


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- Thus, if we impose oddness on $\mathcal{V}$, the complexity of our question is not clear.
- If our vertex set has an odd cardinality, then one side of every cut would be odd. Thus, determining the minimum weight among odd sets would be equivalent to searching among all subsets.


## The New Problem

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- The initial LP formulation made the use of $x$ natural for weighting. However, $w$ is the most common notation for weight. We switch to it now.
- Solving this efficiently requires introducing a new concept.


## Gomory-Hu Tree

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Consider a tree $F$ on $V(G)$. Then $F$ has $n-1$ edges, and note that deleting any edge of $F$ separates $F$ into two components. If $e$ was the deleted edge, let the vertex sets be $S_{e}$ and $T_{e}$. Then $\mathcal{V}_{e}=\left(S_{e}, T_{e}\right)$ is a cut.

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## Definition

The tree $F$ is a Gomory-Hu tree if for every $e=x y \in E(F)$ the cut $\left(S_{e}, T_{e}\right)$ is w-optimal as an $x y$ cut in $G$, meaning

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The $T$ tree is a graph on the vertex set of $G$. However, its edges have nothing to do with $G$. It is not necessarily a subgraph.

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Beyond explicit optimality in the definition, additional information can be extracted from a Gomory-Hu tree.

## Actually, We Have $\binom{n}{2}$ Optimal Cuts

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Given a Gomory-Hu tree $F$, then for every pair of vertices $x, y \in V$, among the $n-1$ cuts determined by $F$, there is a minimum $x y$ cut.

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Let $x, y \in V$ be arbitrary. There exists a unique $x y$ path in $F$. Let the edges on this path be $e_{1}, e_{2}, \ldots, e_{\ell}$, and the cuts associated with these edges be $\mathcal{V}_{1}, \mathcal{V}_{2}, \ldots, \mathcal{V}_{\ell}$.

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## Stronger Lemma

$\mathcal{V}$ is an optimal $x y$ cut.

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Assume (for contradiction) that $\mathcal{V}_{\text {opt }}$ is a minimum weight $x y$ cut, and

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But since $F$ is a Gomory-Hu tree, $\mathcal{V}_{i}$ is an optimal cut separating the endpoints of $e_{i}$.

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This establishes the claim and hence the lemma.

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Let $(G, w)$ and $F$ be given as a Gomory-Hu tree. This defines $n-1$ cuts, each pair has an optimal separator.

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## Remark

Among the $n-1$ cuts determined by $F$, there must be an odd-odd cut. Indeed, an edge adjacent to a leaf corresponds to a cut where one side has 1 vertex and the other has $n-1$.

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Among the $n-1$ cuts determined by $F$, there must be an odd-odd cut. Indeed, an edge adjacent to a leaf corresponds to a cut where one side has 1 vertex and the other has $n-1$.

## Theorem

Among the $n-1$ cuts implied by $F$, the smallest weight odd-odd cut exists.

## Proof of the Theorem

Let $O$ be an optimal odd set.


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$V(G)=V(F)$. For every $e \in \partial_{F} O$, consider the cut $\mathcal{V}_{e}=\left(S_{e}, T_{e}\right)$ determined by $F$, where $S_{e}$ contains the endpoint of e outside $O$.

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## Proof of the Stronger Theorem

$$
\begin{aligned}
\sum_{e \in \partial_{F} O}\left|S_{\vec{e}}\right| & \underset{(\bmod 2)}{\equiv} \sum_{\substack{x \in O, \vec{e} \in E(F), \vec{e} \text { points out of } x}}\left|S_{\vec{e}}\right|= \\
= & \sum_{x \in O} \sum_{\substack{e \in E(F) \\
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The second congruence holds because an odd number of odd numbers is being summed up.

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## 3rd Goal $\equiv$ Gomory-Hu Theorem

For every $G, w$, there exists a Gomory-Hu tree $F$, and one can be computed in polynomial time.

## Consequence

Given a graph $G$ and $w \in \mathbb{Q}^{\mathrm{E}(G)}$, there exists a polynomial-time algorithm to decide whether $w$ is an element of $\mathcal{M P}(G)$; if not, it provides an Edmonds condition violated by w.

Break Time


## Lemma

The mapping $f=w \circ \partial: \mathcal{P}(V) \rightarrow \mathbb{R}_{+}$
(i) is symmetric, i.e., $f(S)=f(\bar{S}) \quad \forall S \subseteq V$,
(ii) is submodular, i.e.,

$$
f(S)+f(T) \geq f(S \cap T)+f(S \cup T) \quad \forall S, T \subseteq V
$$

(iii) is posimodular, i.e., $f(S)+f(T) \geq f(S \backslash T)+f(T \backslash S) \quad \forall S, T \subseteq V$.
(i): Symmetry is clear since $\partial S=\partial \bar{S}$.

## Proof

(i): Symmetry is clear since $\partial S=\partial \bar{S}$.
(ii): Submodularity holds: Summing weights on both sides. In the left expression, each edge is counted at least as many times as in the right expression (by case analysis). Since weights are nonnegative, the inequality holds.
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(ii): Submodularity holds: Summing weights on both sides. In the left expression, each edge is counted at least as many times as in the right expression (by case analysis). Since weights are nonnegative, the inequality holds.
(iii): Posimodularity follows from the previous two properties:

$$
\begin{gathered}
f(S)+f(T)=f(S)+f(\bar{T}) \geq f(S \cap \bar{T})+f(S \cup \bar{T})=f(S \backslash T)+f(\overline{T \backslash S})= \\
=f(S \backslash T)+f(T \backslash S)
\end{gathered}
$$

## The Main Lemma

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Let $\mathcal{V}$ be an $x y$ optimal cut and $x^{\prime}, y^{\prime}$ vertices. Then there exists a $\mathcal{V}^{\prime} x^{\prime} y^{\prime}$ cut, which is $x^{\prime} y^{\prime}$ optimal, and $\mathcal{V}$ and $\mathcal{V}^{\prime}$ are non-crossing cuts.

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## Definition

The cuts $(S, T)$ and $\left(S^{\prime}, T^{\prime}\right)$ are crossing cuts if $S \cap S^{\prime}, S \cap T^{\prime}, T \cap S^{\prime}, T \cap T^{\prime} \neq \emptyset$.

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This is equivalent to saying that cuts $(S, T)$ and $\left(S^{\prime}, T^{\prime}\right)$ are non-crossing cuts if $S \subseteq S^{\prime}$ or $S^{\prime} \subseteq S$ or $S \cap S^{\prime}=\emptyset$.

Let $\mathcal{V}^{\prime}$ be any $x^{\prime} y^{\prime}$ optimal cut. Suppose $\mathcal{V}$ and $\mathcal{V}^{\prime}$ are crossing cuts. Two cases arise.

## Proof of the Main Lemma

Let $\mathcal{V}^{\prime}$ be any $x^{\prime} y^{\prime}$ optimal cut. Suppose $\mathcal{V}$ and $\mathcal{V}^{\prime}$ are crossing cuts. Two cases arise.

Case 1: $x^{\prime}, y^{\prime}$ are on the same side of $\mathcal{V}$ (suppose this is the $x$ side). Let $x^{\prime}$ and $y^{\prime}$ be renamed such that $x^{\prime}$ falls on the same side of $x$ as $x^{\prime}$.

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Case 2: $x^{\prime}, y^{\prime}$ are on different sides of $\mathcal{V}$ (suppose $x^{\prime}$ falls on the side of $x$ ).

## Proof of the Main Lemma: Case 1

Two more subcases are possible here (diagrams above) depending on whether $\mathcal{V}^{\prime}$ cuts $x$ and $y$ or not.

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Among the cuts marked in red on the figure, one is an $x y$ cut (let this be $\mathcal{V}^{*}$ ), and the other is an $x^{\prime} y^{\prime}$ cut (let this be $\mathcal{V}^{* *}$ ).

Then by submodularity, or posimodularity (depending on which case we are in and how we label the $S$ sides), we have

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f(\mathcal{V})+f\left(\mathcal{V}^{\prime}\right) \geq f\left(\mathcal{V}^{*}\right)+f\left(\mathcal{V}^{* *}\right)
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$$

However, equality must hold, since $\mathcal{V}$ and $\mathcal{V}^{\prime}$ were optimal/minimal cuts and "performing their task" $\mathcal{V}^{*}$ and $\mathcal{V}^{* *}$ also do. So,

$$
f\left(\mathcal{V}^{\prime}\right)=f\left(\mathcal{V}^{* *}\right)
$$

and $\mathcal{V}^{* *}$ does not cross $\mathcal{V}$, thus $\mathcal{V}^{* *}$ fulfills the desired property.

## Proof of the Main Lemma: Case 2

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If $\mathcal{V}^{\prime}$ does not separate $x$ and $y$, then similarly as in the Case 1 , another $x^{\prime} y^{\prime}$ optimal cut can be found that does not cross $\mathcal{V}$ :


Figure

## Start of Our Algorithm: Bisection

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Let's arbitrarily choose two vertices, let them be $x$ and $y$. Determine the optimal $x y$ cut. Let this be $(S, T)$ such that $x \in S$ and $y \in T$.

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We bisect $G$ : Let $G / T$ be the graph whose vertices are the vertices in $S$ plus one meta-vertex $m_{T}$, representing $T$, and edges are the edges within $S$ plus the edges incident to $\partial S$, where each edge from $\partial S$ is connected to $m_{T}$ instead of its original endpoint in $T$.

## Start of Our Algorithm: Bisection

Let's arbitrarily choose two vertices, let them be $x$ and $y$. Determine the optimal $x y$ cut. Let this be $(S, T)$ such that $x \in S$ and $y \in T$.

We bisect $G$ : Let $G / T$ be the graph whose vertices are the vertices in $S$ plus one meta-vertex $m_{T}$, representing $T$, and edges are the edges within $S$ plus the edges incident to $\partial S$, where each edge from $\partial S$ is connected to $m_{T}$ instead of its original endpoint in $T$.

The definition of $G / S$ is similar, except here $m_{S}$ is the new meta-vertex.

## Bisection on a picture



Figure: The initial bisection

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## Gomory-Hu Algorithm: Recursive Bisection Algorithm

Perform the initial bisection.
While each part contains at least 2 original vertices, repeat the bisection (the vertices $x$ and $y$ defining the bisection are always original vertices).

## The Gomory-Hu Algorithm in a Figure



Figure: The meta-vertices are circled in red, and the edges passing through them are the meta-edges. $x$ and $y$ define the original $\mathcal{V}$ cut. Only one edge from the computed tree passes through this cut. This edge is not necessarily the $x y$ edge.

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- The meta-edges connect different parts corresponding to different vertices.
- So, the meta-edges can be viewed as the edges between the original vertices.
- These meta-edges constitute the computed graph (on the vertex set of $G$ ).


## Where's the Tree? ... Found It!

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Indeed:

- We compute an $n-1$ edge graph on $n$ vertices.
- It is clear from the recursion (and can be formally proved by induction) that the output is a connected graph.


## Correctness of the Gomory-Hu Algorithm

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Theorem
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The assertion is to show that each cut defined by a meta-edge is an optimal separation of its endpoints. That is, we need to prove $n-1$ statements.

## Cuts of Our Graph Compared to the Base Cut

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Let $\mathcal{V}$ be the cut corresponding to the initial bisection. The cuts of $G$ can be grouped as follows:

1. Crossing cuts with $\mathcal{V}$,
2. Non-crossing cuts with $\mathcal{V}^{\prime}$ :
a) $\mathcal{V}^{\prime}=\mathcal{V}$
b) $\mathcal{V}^{\prime}=\left(S^{\prime}, T^{\prime}\right), S^{\prime} \subsetneq S$
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## Observation

The cuts of $G / T$ can be paired with $\mathcal{V}$ and cuts of type 2.b), while cuts of $G / S$ can be paired with $\mathcal{V}$ and cuts of type 2.c). All cuts in $G / T$ and $G / S$ are present in either $G \backslash T$ or $G \backslash S$ (and nowhere else).

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Észrevételből optimális $\mathcal{V}$-t nem keresztező $\mathrm{x}^{\prime} \mathrm{y}^{\prime}$ vágás

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The meta-vertices are circled in red, and the edges passing through them are the meta-edges. $x$ and $y$ define the original $\mathcal{V}$ cut. Only one edge

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We prove this by contradiction. Assume there exists a $\mathcal{V}^{\prime}$ $w$-optimal $x^{\prime} y^{\prime}$ cut such that $w\left(\mathcal{V}^{\prime}\right)<w(\mathcal{V})$.

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We prove this by contradiction. Assume there exists a $\mathcal{V}^{\prime}$ $w$-optimal $x^{\prime} y^{\prime}$ cut such that $w\left(\mathcal{V}^{\prime}\right)<w(\mathcal{V})$.
From the main lemma, we know that $\mathcal{V}^{\prime}=\left(S^{\prime}, T^{\prime}\right)$ can be chosen such that $S^{\prime} \subset S$ or $T^{\prime} \subset T$. We may assume $S^{\prime} \subsetneq S$.

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That is, it cannot be that $x$ and $x^{\prime}$ are on the same side while the entire $T$ is on the other side, including $y$.
In this case, $\mathcal{V}^{\prime}$ would be an $x y$ cut, which is a contradiction. $\mathcal{V}^{\prime}$ separates $x$ and $x^{\prime}$.

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The $\mathcal{V}^{\prime \prime}$ cut has $x$ on one side, $x^{\prime}$ and $m_{T}$ on the other side (where $x^{\prime}$ and $m_{T}$ stick together after bisections, hence the $F$ crosscut fits onto $x^{\prime}$ ).

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By our initial observation, $\mathcal{V}^{\prime \prime}$ corresponds to a cut $\widetilde{\mathcal{V}^{\prime \prime}}$ in $G$. From the above, this is an $x y$ cut, with weight smaller than $\mathcal{V}$ 's weight, which contradicts.

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The contradiction proves the assertion, the only missing piece in proving the correctness of the Gomory-Hu algorithm.

## Summary

## Gomory-Hu Theorem

For every $(G, w)$, there exists a Gomory-Hu tree $F$, which can be computed by determining $n-1$ minimal st cuts, achievable by applying the flow algorithm $n-1$ times. Specifically, the Gomory-Hu algorithm is polynomial.

## This is the End!

## Thnak you for your attention!

