

# Decomposition Polyhedra of Piecewise Linear Functions

DISCOGA Seminar

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Joint work with



Marie-Charlotte Brandenburg (RUB) and Christoph Hertrich (UTN)

# CPWL Functions

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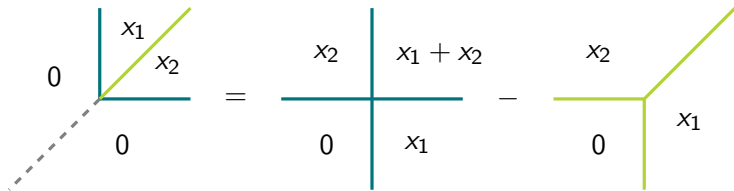
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- ▶ CPWL functions are the functions representable by ReLU neural networks
- ▶ Nonconvexity complicates optimization and neural network representations.
- ▶ Every CPWL function  $f$  can be written as difference of two convex CPWL functions  $g - h$  [Melzer, 1986; Kripfganz and Schulze, 1987].



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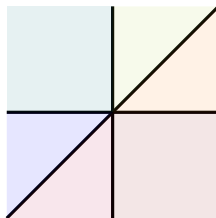
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3. Submodular functions

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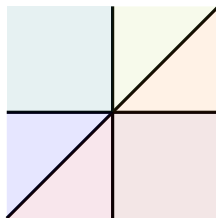
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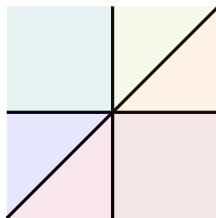
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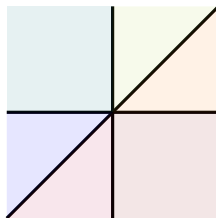
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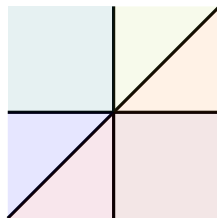
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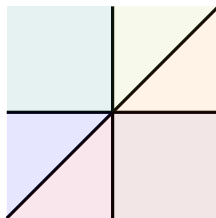


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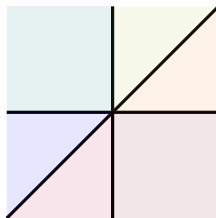




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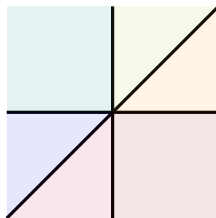
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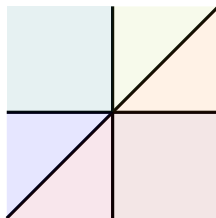
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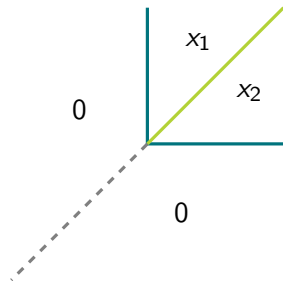


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- ▶  $\mathcal{P}^d$  = **regions** of  $\mathcal{P}$ .
- ▶ If all polyhedra are cones, then we call  $\mathcal{P}$  a **polyhedral fan**.

# CPWL function

## Definition

A function  $f: \mathbb{R}^d \rightarrow \mathbb{R}$  is **continuous and piecewise linear (CPWL)**, if there exists a polyhedral complex  $\mathcal{P}$  such that  $f$  is affine linear on all  $P \in \mathcal{P}$ .

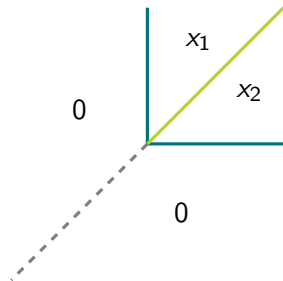


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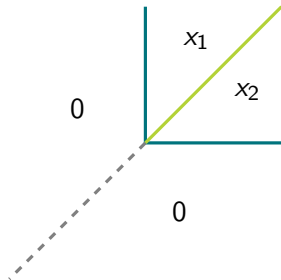
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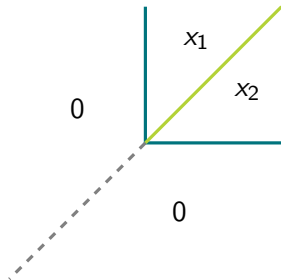
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- ▶  $f|_P$  is a **linear component** of  $f$ .
- ▶ The **number of pieces**  $q$  of  $f$  is the smallest possible number of regions  $|\mathcal{P}^d|$  of a compatible polyhedral complex  $\mathcal{P}$ .



## Convexity

- If  $f$  is a **convex** CPWL function, then

$$f(x) = \max_{i \in [k]} \{ \langle a_i, x \rangle + b_i \}$$

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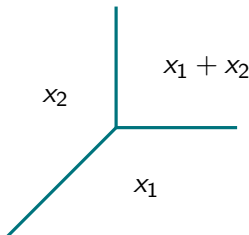
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- ▶ Example:  $\max\{x_1, x_2, x_1 + x_2\}$



## Existing Decompositions

Hyperplane extension

Kripfganz and Schulze '87  
Zalgaller '00  
Schlüter and Darup '21  
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Local maxima decomposition

Kripfganz and Schulze '87  
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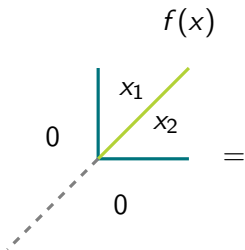
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- ▶ Local maxima decomposition is refinement of the hyperplane extension in the worst case

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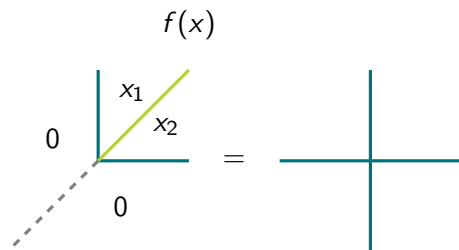
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$$g_{P,Q}(x) = \max\{\langle a_P, x \rangle + b_P, \langle a_Q, x \rangle + b_Q\}$$





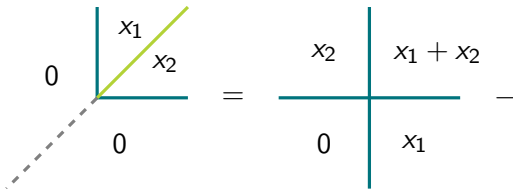
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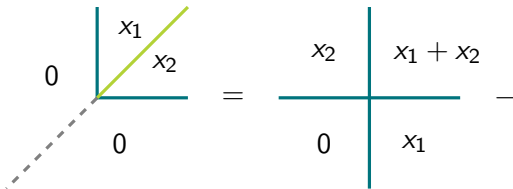
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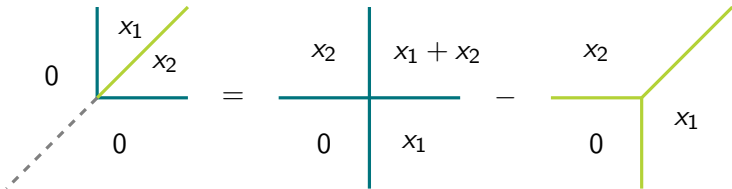
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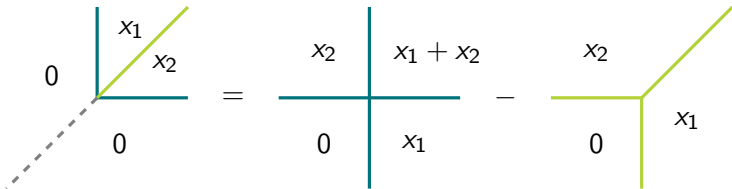
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- But: If  $f$  has  $q$  pieces,  $g$  and  $h$  can have  $O(q^d)$  many pieces

# Minimal Decompositions

Is this construction optimal?

The diagram illustrates the minimal decomposition of a wedge product. On the left, a blue L-shaped line with a green diagonal line (representing  $x_1 \wedge x_2$ ) is shown. The blue line has a vertical segment labeled  $x_2$  and a horizontal segment labeled  $x_1$ . The green line is labeled  $x_1$  and  $x_2$ . The origin is labeled 0. A dashed line extends from the origin. This is equal to the difference of two terms. The first term is a blue cross with  $x_2$  on the top vertical line,  $x_1$  on the bottom vertical line,  $x_1 + x_2$  on the top horizontal line, and 0 on the bottom horizontal line. The second term is a green cross with  $x_2$  on the top horizontal line,  $x_1$  on the bottom horizontal line, 0 on the top vertical line, and  $x_1$  on the bottom vertical line.

$$\begin{array}{|c|} \hline x_2 \\ \hline 0 \\ \hline \end{array} \begin{array}{|c|} \hline x_1 + x_2 \\ \hline x_1 \\ \hline \end{array} - \begin{array}{|c|} \hline x_2 \\ \hline 0 \\ \hline \end{array} \begin{array}{|c|} \hline x_1 \\ \hline x_1 \\ \hline \end{array}$$

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# Minimal Decompositions

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The diagram illustrates a non-optimal minimal decomposition. On the left, a function is represented by a blue L-shaped line with segments labeled  $x_1$  and  $x_2$ , and a green diagonal line labeled  $x_1 + x_2$ . The origin is marked with a 0. A dashed line extends from the origin. This is set equal to the difference of two functions. The first function is a blue L-shaped line with segments labeled  $x_2$  and  $x_1 + x_2$ , and a green diagonal line labeled  $x_1 + x_2$ . The second function is a green L-shaped line with segments labeled  $x_2$  and  $x_1$ , and a green diagonal line labeled  $x_1 + x_2$ .

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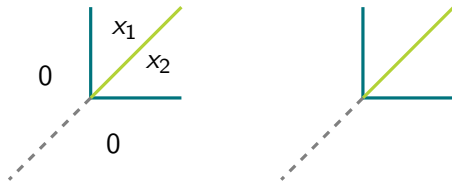
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- ▶ For  $\sigma \in \mathcal{P}^{d-1}$ , let  $P$  and  $Q$  be the unique polyhedra such that  $P \cap Q = \sigma$
- ▶ Define  $w_f(\sigma) = \begin{cases} \|a_P - a_Q\|_2 & \text{f locally convex around } \sigma \\ -\|a_P - a_Q\|_2 & \text{f locally concave around } \sigma \end{cases}$

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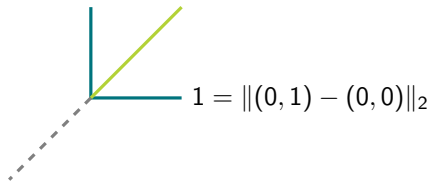
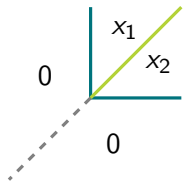
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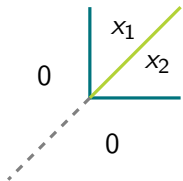
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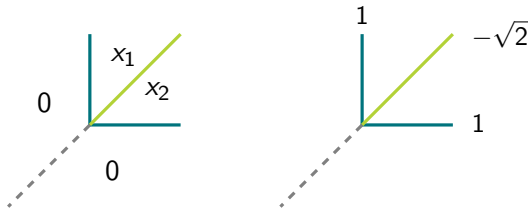




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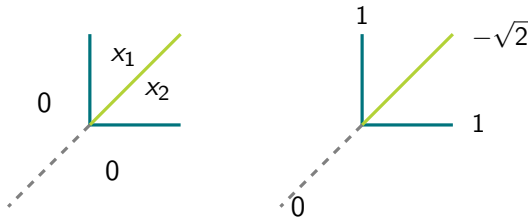
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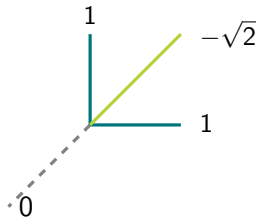
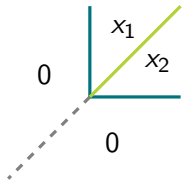
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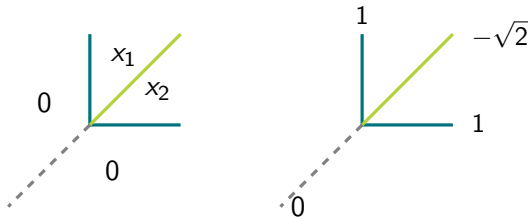
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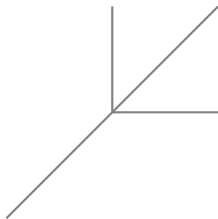
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- ▶ Then  $(\mathcal{P}, w_f)$  is a *balanced complex*.

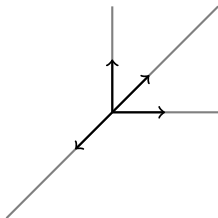
## Balanced polyhedral complexes

- Let  $\mathcal{P}$  be polyhedral fan in  $\mathbb{R}^2$



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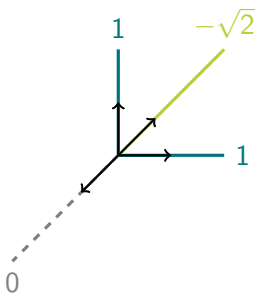
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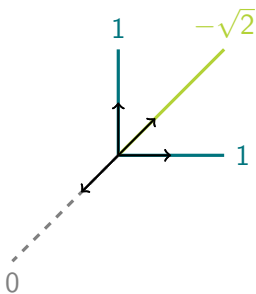
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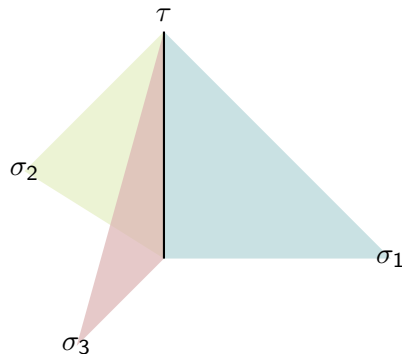
$$\sum_{\sigma \in \mathcal{P}^1} w(\sigma) r_\sigma = 1 \cdot (1, 0) - \sqrt{2} \cdot \left( \frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}} \right) + 1 \cdot (0, 1) = (0, 0)$$



## Balancing condition in higher dimension

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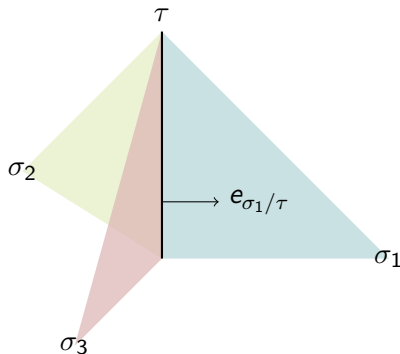


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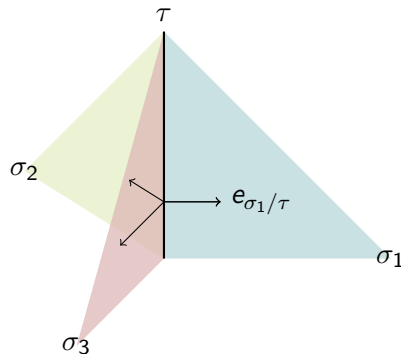


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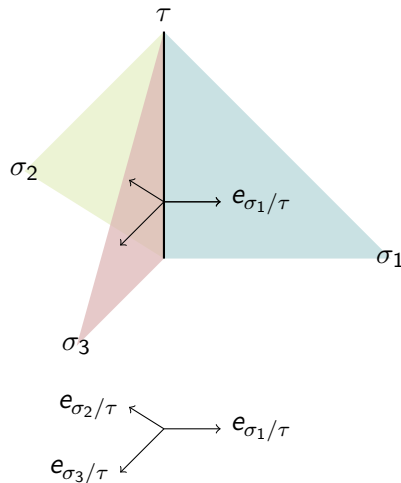


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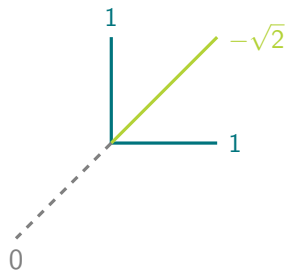


# Tropical Geometry

## Structure Theorem

- $w_f$  is balanced.

## Proof sketch

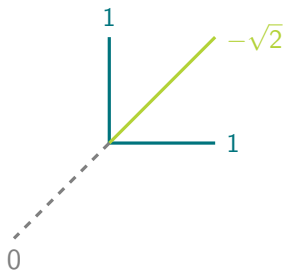


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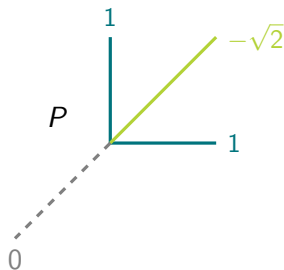
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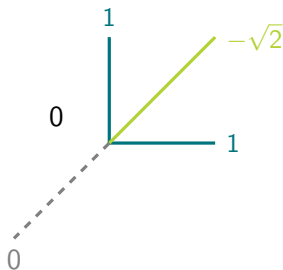
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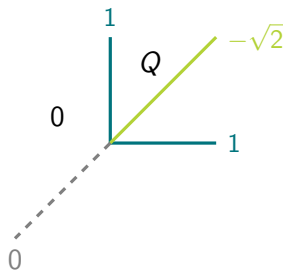
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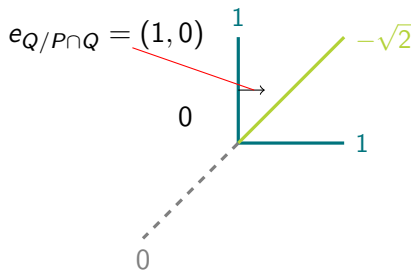
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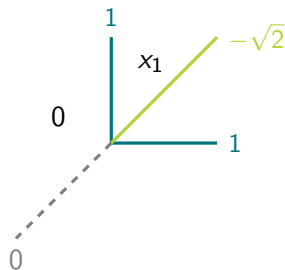
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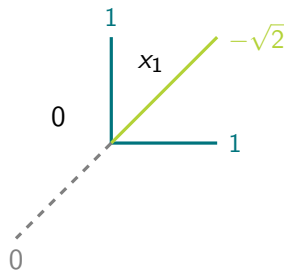
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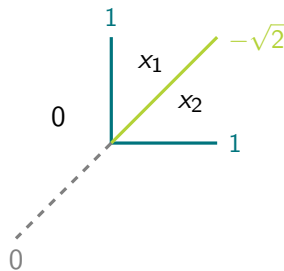
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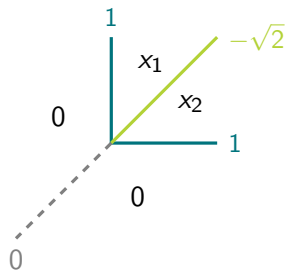
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# Newton Polytopes

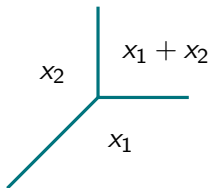
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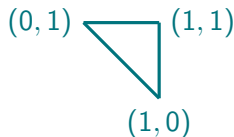
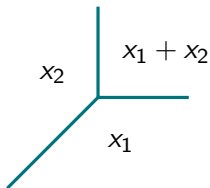




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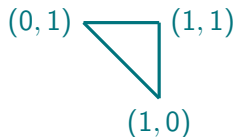
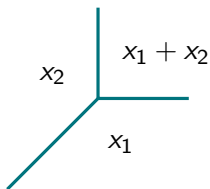
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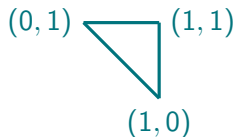
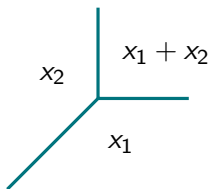
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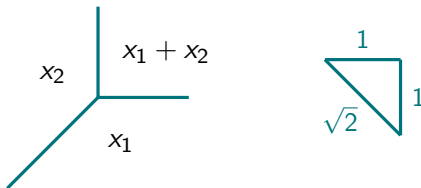
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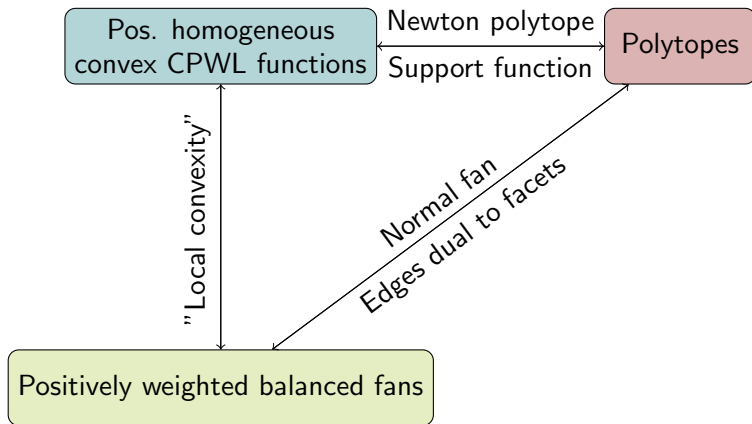
# Newton Polytopes

## Bijection between convex CPWL functions and polytopes

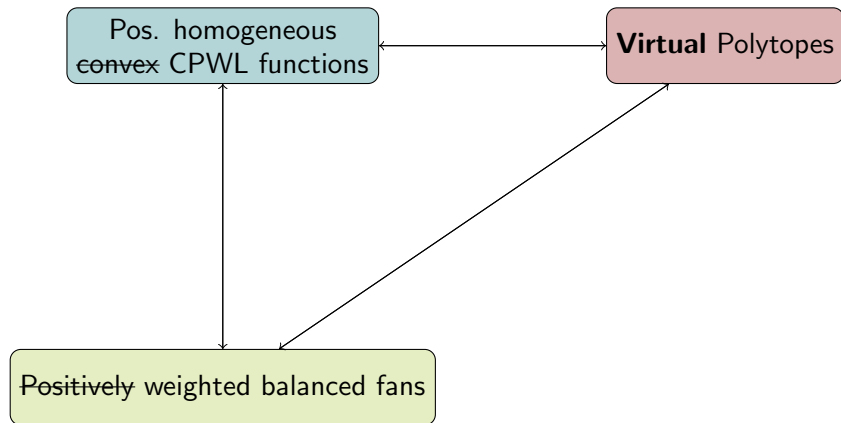
- ▶ A **positively homogeneous** convex CPWL function is a function  $f$  such that  $f(0) = 0$ , and  $\mathcal{P}_f$  is a polyhedral fan.
- ▶ Convex function  $f(x) = \max_{i \in [k]} \langle x, a_i \rangle$ , where  $a_i \in \mathbb{R}^d$ .
- ▶  $\text{Newt}(f) = \text{conv}(a_1, \dots, a_k)$ .
- ▶ Number of linear pieces = number of vertices
- ▶  $\mathcal{P}_f$  is normal fan of  $\text{Newt}(f)$ .
- ▶ edge length = weights on facets



# Summary



## Allowing Subtraction



## Dimension 2

Theorem (Tran and Wang, 2024)

*For every positively homogeneous CPWL-function  $f: \mathbb{R}^2 \rightarrow \mathbb{R}$  exists a **unique minimal representation** as difference of two convex functions  $g, h$ .*

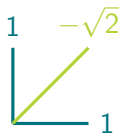


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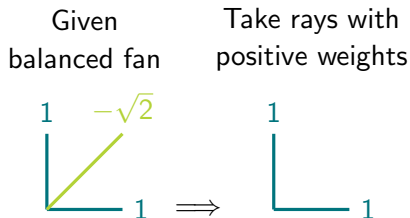
Given  
balanced fan



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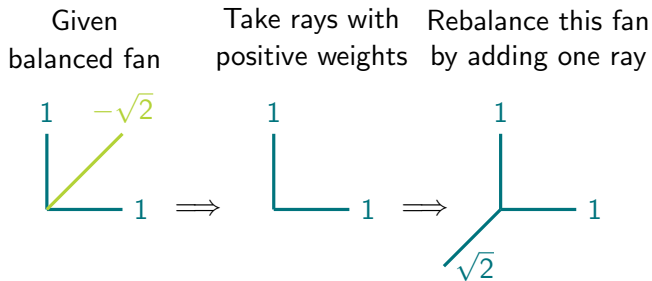
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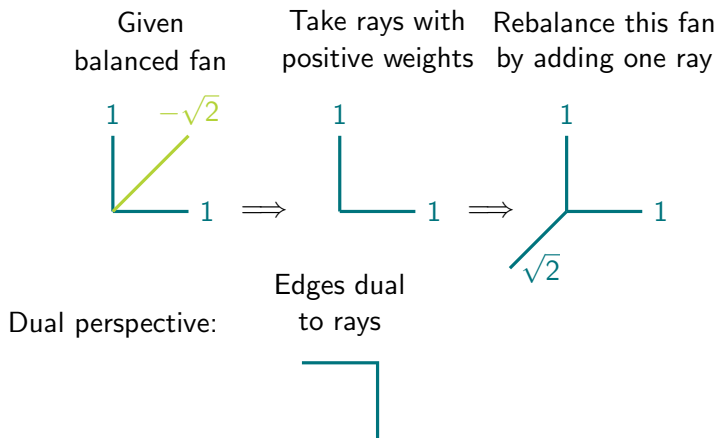
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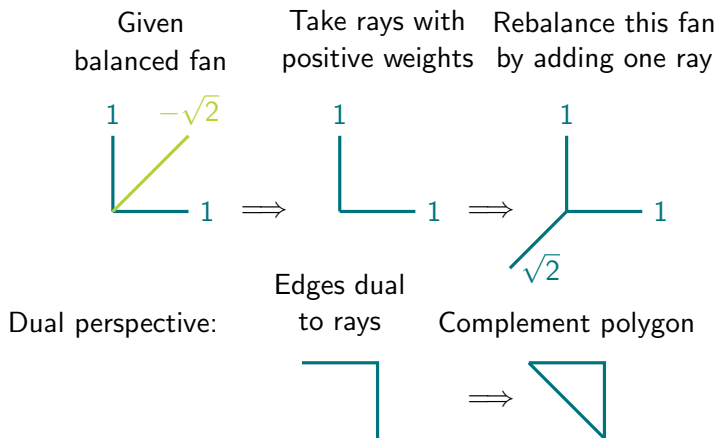
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## Conjecture for higher dimension

- For every  $\tau \in \mathcal{P}^{d-2}$ , let  $\sigma_1, \dots, \sigma_k \in \mathcal{P}^{d-1}$  be the facets containing  $\tau$  with  $w_f(\sigma_i) > 0$

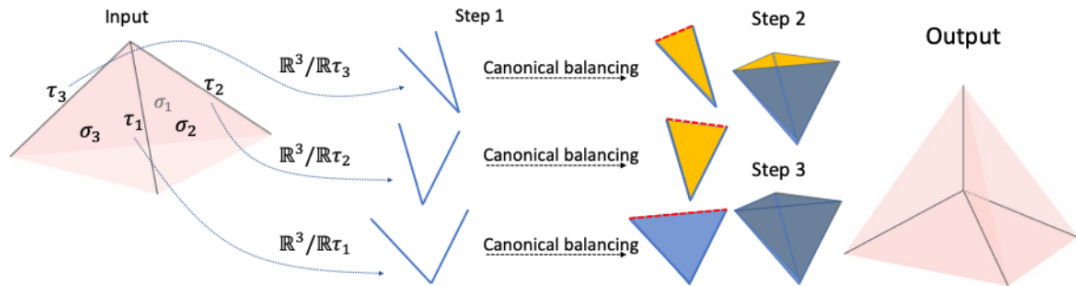


Figure: Figure from [Tran and Wang]

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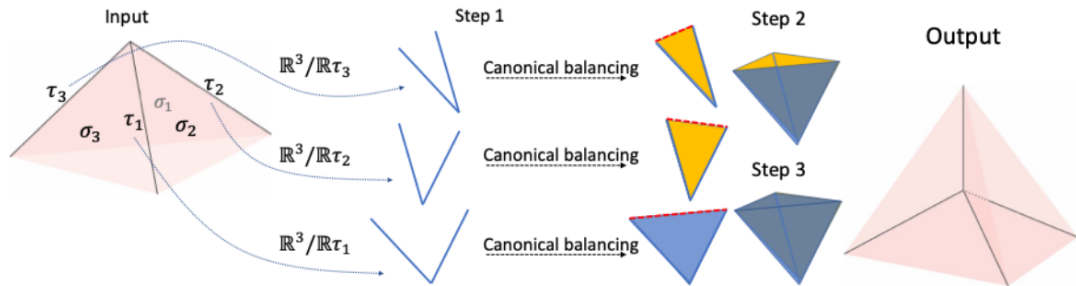


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- ▶ Construct the polygon  $P_\tau$  dual to  $\sigma_1/\tau, \dots, \sigma_k/\tau$  in the 2-dimensional space orthogonal to  $\text{span}(\tau)$
- ▶ Glue the polygons  $P_\tau$  together along edges corresponding to the same facets  $\sigma$  and take the convex hull

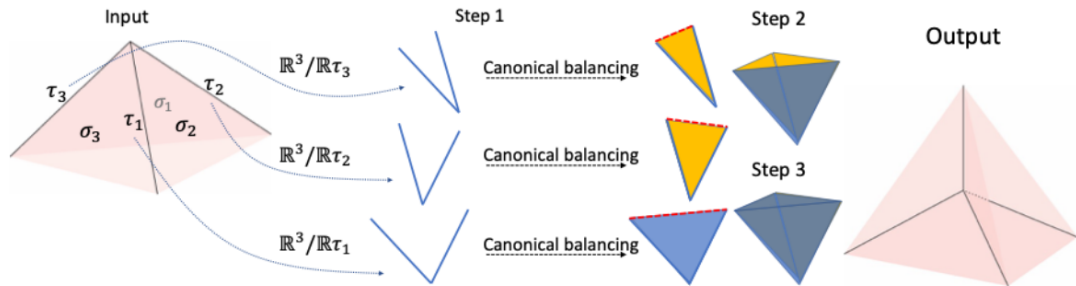
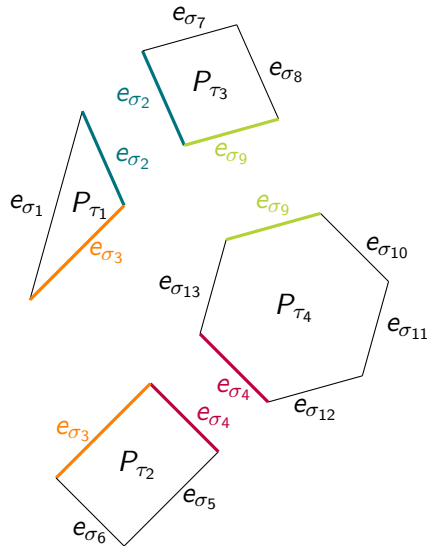


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## Counterexample to Conjecture



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What is the current state?

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- ▶ Describe the space of all decompositions. But this space lies in a infinite-dimensional vector space....
- ▶ To make the problem more tractable: Fix the possible breakpoints of the decompositions

# Fix the possible locus of nonlinearity

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- ▶  $\overline{\mathcal{V}_{\mathcal{P}}}$  is finite dimensional and the set of all convex functions

$$\overline{\mathcal{V}_{\mathcal{P}}}^+ \cong \mathcal{W}_{\mathcal{P}}^+ := \bigcap_{\sigma \in \mathcal{P}^{d-1}} \{w \in \mathcal{W}_{\mathcal{P}} \mid w(\sigma) \geq 0\}$$

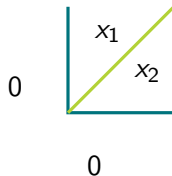
is a polyhedral cone.

# Decomposition Polyhedra

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$$\mathcal{D}_{\mathcal{P}}(f) = \{(g, h) \in \overline{\mathcal{V}_{\mathcal{P}}}^+ \times \overline{\mathcal{V}_{\mathcal{P}}}^+ \mid f = g - h\}.$$

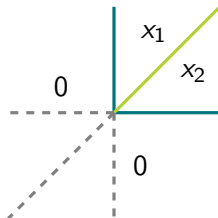


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  - ▶ where  $g'$  has at most as many pieces as  $g$ ,  $h'$  has at most as many pieces as  $h$ ,
  - ▶ and one of the two has strictly fewer pieces.

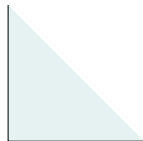


# Structure of the Decomposition Polyhedra

Theorem (Brandenburg, G., Hertrich, 2025)

- $\mathcal{D}_{\mathcal{P}}(f)$  is a polyhedron that arises as the intersection of two shifted cones.

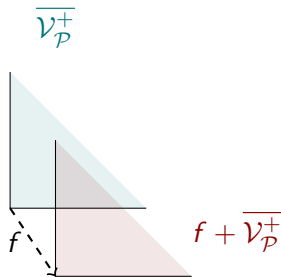
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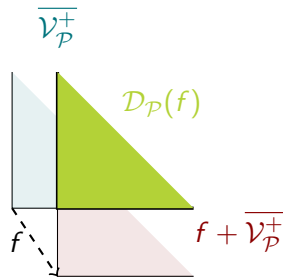
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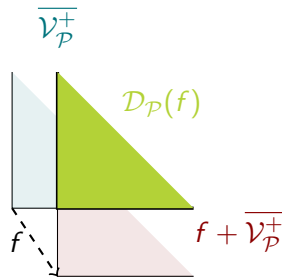
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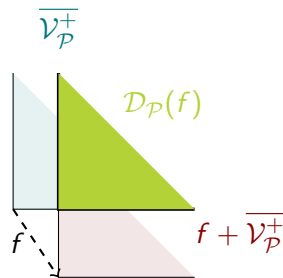
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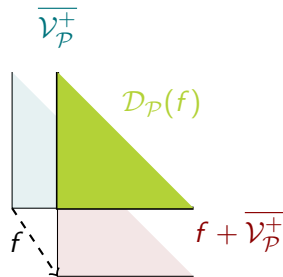
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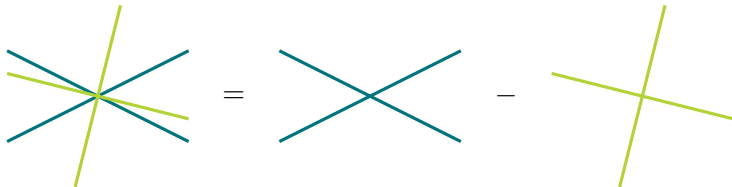
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- ▶ **Finite procedure** to find minimal decomposition among decompositions in  $\mathcal{D}_{\mathcal{P}}(f)$ .

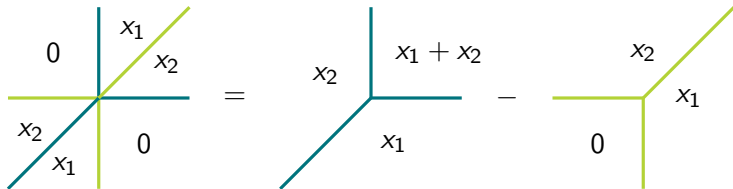


## Cases with a unique vertex

- Hyperplane functions  $f(x) = \sum_{i \in [k]} \lambda_i \cdot \max\{\langle x, a_i \rangle, \langle x, b_i \rangle\}$



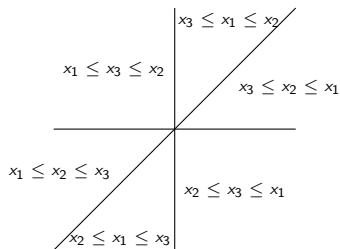
- The function  $f: \mathbb{R}^n \rightarrow \mathbb{R}$  that returns the  $k$ -th largest entry of an input vector  $x \in \mathbb{R}^n$ .



# Braid arrangement

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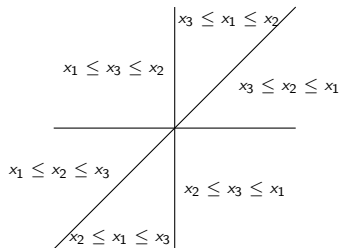




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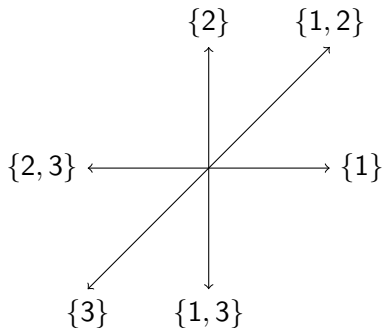
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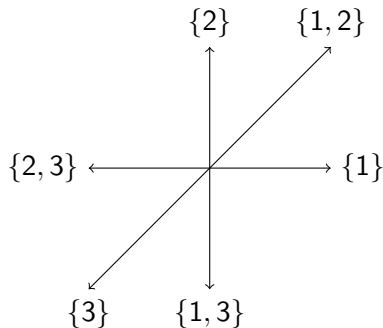
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## Lemma

The mapping  $\Phi$  that maps  $f \in \mathcal{V}_{\mathcal{B}}$  to the set function  $F(S) = f(\mathbb{1}_S)$  is a vector space isomorphism, where  $\mathbb{1}_S = \sum_{i \in S} e_i$ .

## Submodular function

A set function  $F: 2^{[d]} \rightarrow \mathbb{R}$  is called **submodular** if

$$F(A) + F(B) \geq F(A \cup B) + F(A \cap B)$$

for all  $A, B \subseteq [d]$  and  $F(\emptyset) = 0$ .

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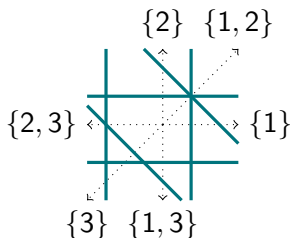
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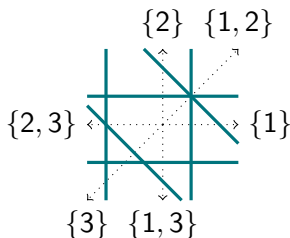
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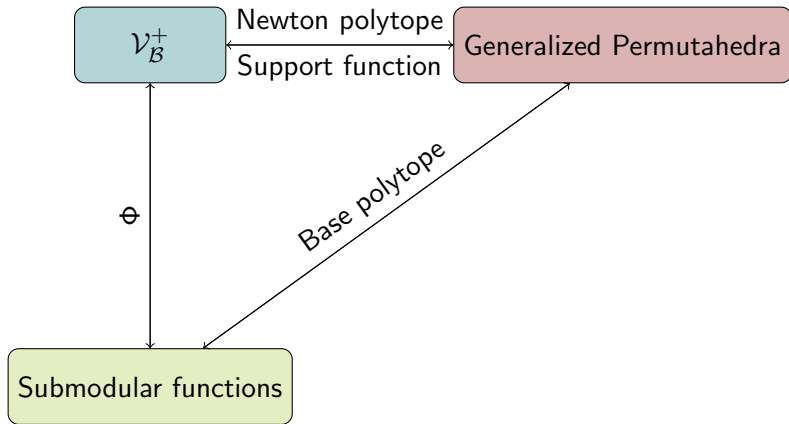
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A function  $f$  is convex if and only if  $\Phi(f)$  is submodular.

## Decomposing Set Functions

How to decompose a set function into a difference of submodular functions such that their base polytopes have as few vertices as possible?





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The decomposition polyhedra can be very complex

We do not even know the number of rays of the submodular cone for  $d > 5$ ....

## Open Problems (almost everything)

- ▶ Given a CPWL function  $f$  in dimension  $d$  with  $q$  pieces, does there always exist a decomposition  $f = g - h$  such that the number of pieces of  $g$  and  $h$  is **polynomial** in  $d$  and  $q$ ?

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*Thank you for your attention!*