



# **SEPARATING POINTS BY PIECEWISE-LINEAR FUNCTIONS POLYHEDRAL AND REAL TROPICAL GEOMETRY OF NEURAL NETWORKS**

**DISCRETE GEOMETRY WORKSHOP**

Oberwolfach

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\*work in progress

# LINEAR CLASSIFIERS AND HYPERPLANE ARRANGEMENTS

## Setup

Given data points  $D = \{p_1, \dots, p_M\} \in \mathbb{R}^d$  in **input space**

- a **linear classifier** is a linear function  $f: \mathbb{R}^d \rightarrow \mathbb{R}$
- $f$  defines a hyperplane  $\{x \in \mathbb{R}^d \mid f(x) = 0\}$  in input space separating  $\{p_i \mid f(p_i) > 0\}$  from  $\{p_i \mid f(p_i) < 0\}$
- $f$  can be parametrized as  $f(x) = \langle s, x \rangle + a$  for some fixed  $s \in \mathbb{R}^d, a \in \mathbb{R}$ .
- **parameter space of linear classifiers** is  $\{(s, a) \mid s \in \mathbb{R}^d, a \in \mathbb{R}\} \cong \mathbb{R}^{d+1}$ .

## Classification by $f$ :

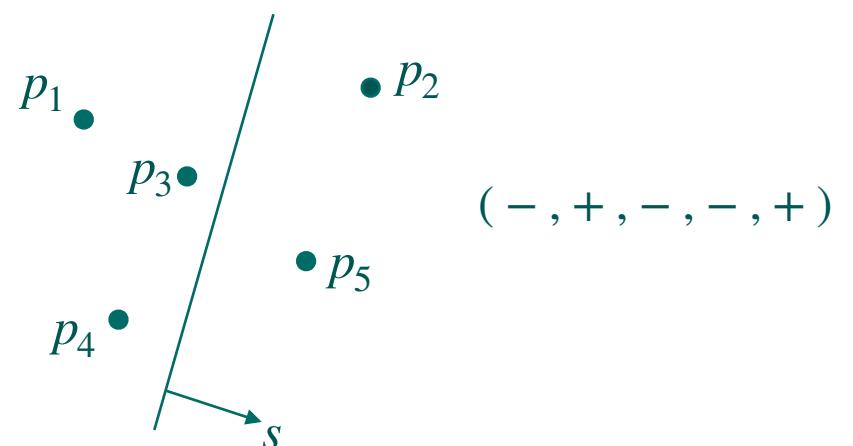
$$(\text{sgn}(f(p_1)), \dots, \text{sgn}(f(p_M))) \in \{-, 0, +\}^d$$

## Goal

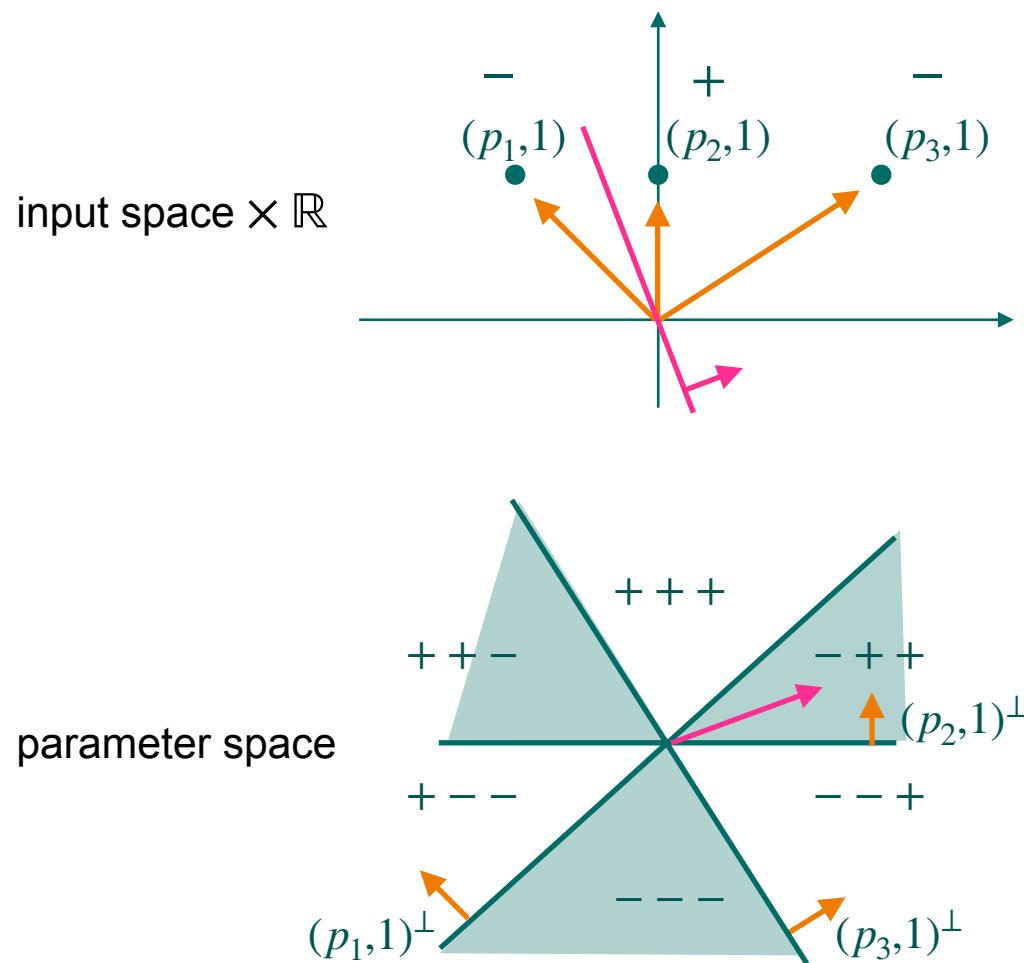
Subdivide parameter space into cells, in which classifiers have the same classification

## Theorem (Cover '64, ...)

These cells are chambers in the hyperplane arrangement  $\bigcup_{p \in D} (p, 1)^\perp \subseteq \mathbb{R}^{d+1}$  in parameter space



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$\{ +++, ++-, +--\}, \{ ---, --+\}, \{ -+-\}$   
are the **dichotomies** of the data set

Fix a labelling  $D = D^+ \sqcup D^-$

$f$  makes a mistake at  $p \in D^+$  if  $f(p) < 0$   
 $f$  makes a mistake at  $p \in D^-$  if  $f(p) > 0$

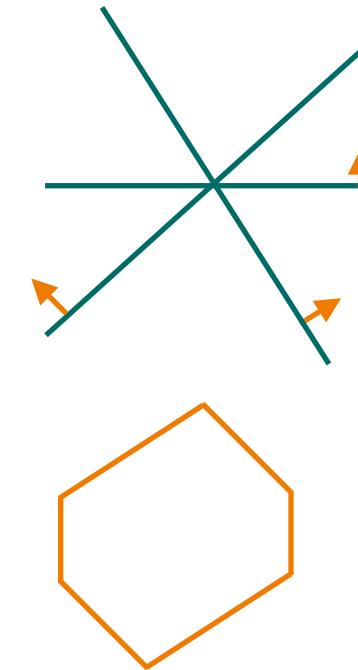
0/1-loss function counts number of mistakes of  $f$

# LINEAR CLASSIFIERS AKA HYPERPLANE ARRANGEMENTS

## THEOREM

Let  $D \subset \mathbb{R}^d$  be a finite data set. Then

- (i) the hyperplane arrangement  $\mathcal{H}_D = \bigcup_{p \in D} (1, p)^\perp$  subdivides the parameter space into regions according to the represented dichotomies,
- (ii)  $\mathcal{H}_D$  induces the normal fan of the zonotope  $P_D = \sum_{p \in D} \text{conv}(\mathbf{0}, (1, p))$ ,
- (iii) the dichotomies are the maximal covectors of the underlying realizable oriented matroid.



$$\{ +++, ++-, +-- , --- , --+ , -+- \}$$

*What happens for piecewise-linear functions?*



# FROM LINEAR TO PIECEWISE LINEAR CLASSIFICATION

Linear function	Tropical rational functions	
Separation by hyperplane	Signed tropical hypersurface	{ input space
Covectors of oriented matroids	Activation patterns	{ parameter space $\Theta(d, N)$
Zonotope	Activation polytope	{ parameter space $\Theta(d, N)$
Normal fan of zonotope	Activation fan	{ parameter space $\Theta(d, n, m)$
Arrangement of hyperplanes	Arrangement of indecision surfaces	{ parameter space $\Theta(d, n, m)$
Polyhedral cone of perfect classifiers	Perfect classification fan	{ parameter space $\Theta(d, n, m)$



## TROPICAL INTERMEZZO AND ReLU NEURAL NETWORKS

$$a \oplus b = \max(a, b), \quad a \odot b = a + b, \quad a \oslash b = a - b, \quad x^{\odot a} = a \cdot x$$

classical rational function  $\tilde{r}(x) = \left( \sum_{i=1}^n a_i x_1^{s_{i1}} \cdots x_d^{s_{id}} \right) / \left( \sum_{j=1}^m b_j x_1^{t_{j1}} \cdots x_d^{t_{jd}} \right)$

tropical rational function  $r(x) = \left( \bigoplus_{i=1}^n a_i \odot x_1^{\odot s_{i1}} \odot \cdots \odot x_d^{\odot s_{id}} \right) \oslash \left( \bigoplus_{j=1}^m b_j \odot x_1^{\odot t_{j1}} \odot \cdots \odot x_d^{\odot t_{jd}} \right)$   
 $= \max_{i=1, \dots, n} (a_i + s_{i1}x_1 + \cdots + s_{id}x_d) - \max_{j=1, \dots, m} (b_j + t_{j1}x_1 + \cdots + t_{jd}x_d)$   
 $= \max_{i=1, \dots, n} (a_i + \langle s_i, x \rangle) - \max_{j=1, \dots, m} (b_j + \langle t_j, x \rangle), \quad a_i, b_j \in \mathbb{R}, s_i, t_j \in \mathbb{R}^d$   
= difference of two convex piecewise linear functions

$(n, m) = (1, 1)$  recovers linear classifiers

**THEOREM (ARORA-BASU-MIANJY-MUKHERJEE, ZHANG-NAITZAT-LIM, '18)**

A function  $f: \mathbb{R}^d \rightarrow \mathbb{R}$  is a tropical rational function if and only if  $f$  can be represented by a ReLU neural network. The values  $d, n, m$  are related to the depth of the network.



# FROM LINEAR TO PIECEWISE LINEAR CLASSIFICATION

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## DECISION BOUNDARIES

$$\begin{aligned} g \oslash h &= \left( \bigoplus_{i=1}^n a_i \odot x^{\odot s_i} \right) \oslash \left( \bigoplus_{j=1}^m b_j \odot x^{\odot t_j} \right) \\ &= \max_{i=1,\dots,n} (a_i + \langle s_i, x \rangle) - \max_{j=1,\dots,m} (b_j + \langle t_j, x \rangle) \end{aligned}$$

### Decision boundary

$\mathcal{B}(g \oslash h) = \{x \in \mathbb{R}^d \mid g(x) \oslash h(x) = 0\}$   
 → Polyhedral complex with  $\leq n \cdot m$  linear pieces

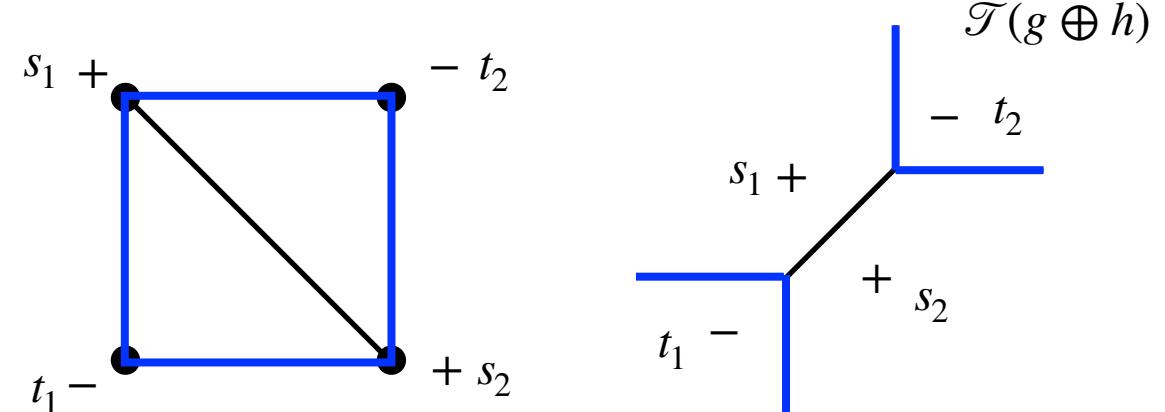
$$g \oslash h : \mathbb{R}^2 \rightarrow \mathbb{R}$$

$$\begin{aligned} g(x) \oslash h(x) &= \max (a_1 + \langle s_1, x \rangle, a_2 + \langle s_2, x \rangle) \\ &\quad - \max (b_1 + \langle t_1, x \rangle, b_2 + \langle t_2, x \rangle), \end{aligned}$$

Regular subdivision is given by  $a_1, a_2, b_1, b_2 \in \mathbb{R}$

### HOW TO CONSTRUCT THE DECISION BOUNDARY

- $g \oplus h = \max_{i \in [n], j \in [m]} (a_i + \langle s_i, x \rangle, b_j + \langle t_j, x \rangle)$
- Regular subdivision of signed Newton polytope  $\mathcal{N}(g \oplus h)$
- Tropical hypersurface  $\mathcal{T}(g \oplus h)$  is the codimension-1 skeleton of the dual complex
- Decision Boundary  $\mathcal{B}(g \oslash h)$  is the sign-mixed subcomplex of  $\mathcal{T}(g \oplus h)$



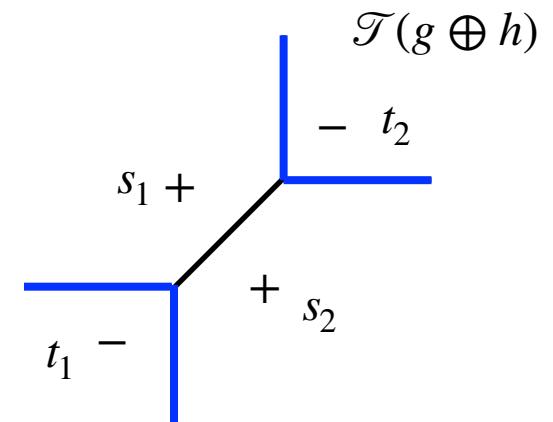
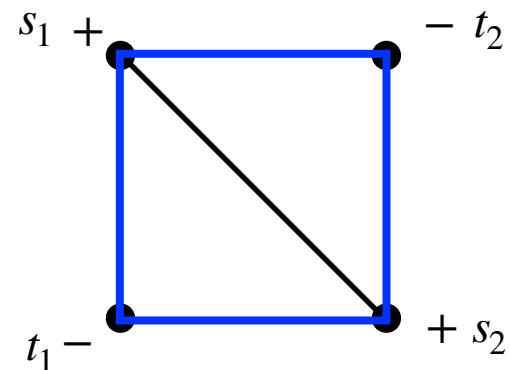
## DECISION BOUNDARIES

→ We can first consider tropical polynomials and later assign signs to terms

Fix number of terms  $N$  of tropical polynomial  $f : \mathbb{R}^d \rightarrow \mathbb{R}, f(x) = \max_{i \in [N]} a_i + \langle s_i, x \rangle$

$f = f_\theta$  is defined through its parameters  $\theta = (a_1, s_1, \dots, a_N, s_N)$

Parameter space  $\Theta(d, N) = \{(a_1, s_1, \dots, a_N, s_N) \mid a_i \in \mathbb{R}, s_i \in \mathbb{R}^d\} \cong \mathbb{R}^{N(d+1)}$





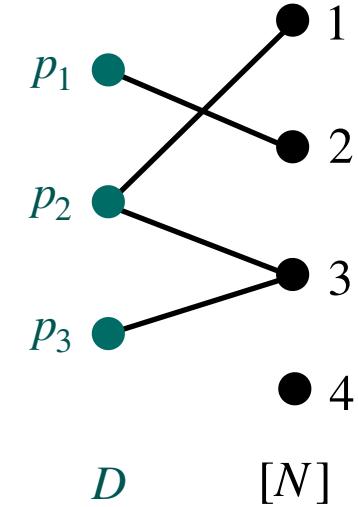
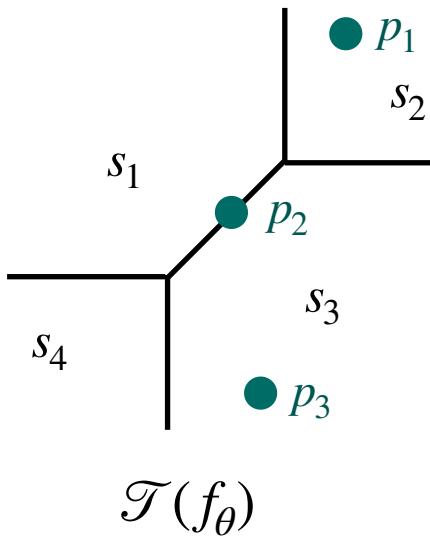
# FROM LINEAR TO PIECEWISE LINEAR CLASSIFICATION

Linear function	Tropical rational functions	
Separation by hyperplane	Signed tropical hypersurface	input space
Covectors of oriented matroids	Activation patterns	parameter space $\Theta(d, N)$
Zonotope	Activation polytope	
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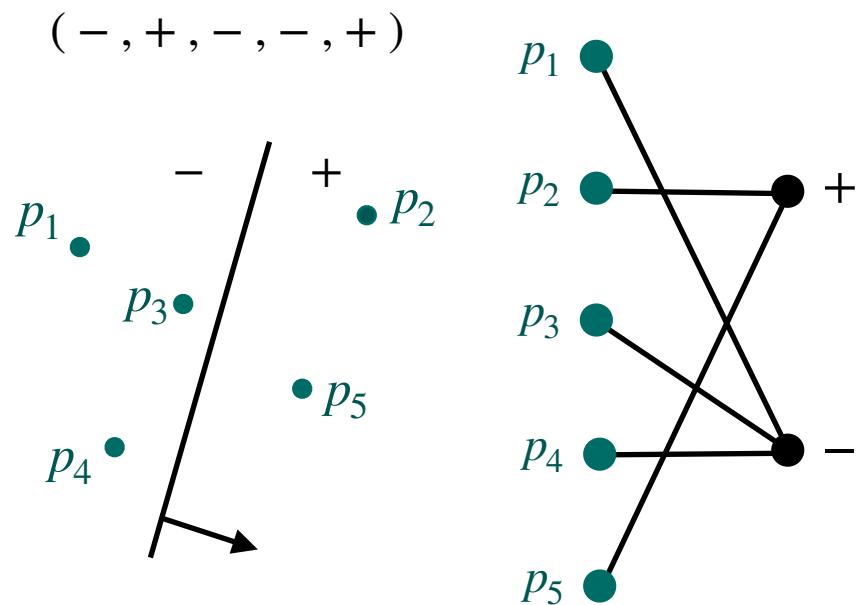
## CLASSIFICATION BY TROPICAL POLYNOMIALS

Given data points  $D = \{p_1, \dots, p_M\} \in \mathbb{R}^d$   
 tropical polynomial  $f_\theta(x) = \max_{i \in [N]} a_i + \langle s_i, x \rangle$ ,  
 parameter  $\theta \in \Theta(d, N)$ .

$p$  lies in the region  $s_k$  of  $\mathcal{T}(f_\theta)$   
 $\iff f_\theta(p) = a_k + \langle s_k, p \rangle$   
 $\iff p$  activates the  $k^{\text{th}}$  term



activation pattern: bipartite graph  $G_\theta = (V, E)$   
 $V = D \sqcup [N]$   
 $E = \{pk \mid p \text{ activates } k^{\text{th}} \text{ term of } f_\theta\}$   
 $\rightarrow$  generalization of covectors of oriented matroids





## CLASSIFICATION BY TROPICAL POLYNOMIALS

activation cone of a bipartite graph  $G$ :  $C(G) = \{\theta \mid G = G_\theta \text{ is activation pattern}\}$

activation fan = collection of all nonempty activation cones (over all bipartite graphs)  
→ complete fan in  $\Theta(d, N)$

A data point  $p \in \mathbb{R}^d$  defines a  $(N - 1)$ -dimensional simplex

$$\begin{aligned}\Delta(p) &= \text{conv}\left((1,p,0,\mathbf{0}, \dots, 0, \mathbf{0}), (0,\mathbf{0},1,p, \dots, 0, \mathbf{0}), \dots, (0,\mathbf{0},0,\mathbf{0}, \dots, 1, p)\right) \\ &\subseteq \Theta(d, N) \cong \mathbb{R}^{(d+1)N}\end{aligned}$$

activation polytope  $= \sum_{p \in D} \Delta(p)$  → generalization of zonotope

### THEOREM

The activation fan is the normal fan of the activation polytope.

*What are the properties of the activation patterns appearing in an activation fan?*



# ACTIVATION PATTERNS

## THEOREM (ACTIVATION PATTERNS)

Let  $\mathcal{G}$  be the set of activation patterns of the activation fan. Then  $\mathcal{G}$  satisfies

- **(Zero)**  $K_{N,D} \in \mathcal{G}$
- **(Symmetry)**  $G \in \mathcal{G} \implies$  any graph isomorphic to  $G$  under the action of  $S_N$  is contained in  $\mathcal{G}$
- **(Elimination)** If  $G, H \in \mathcal{G}, p \in D$  then there exists a graph  $F \in \mathcal{G}$  with  $N(p; F) = N(p; G) \cup N(p; H)$
- **(Boundary)** For each  $i \in [N]$  and  $G$  the bipartite graph with edges  $E(G) = \{pi \mid p \in D\}$  holds  $G \in \mathcal{G}$
- **(Comparability)** For any point  $p \in D$  the comparability graph  $CG_{G,H}^p$  of any two patterns  $G, H \in \mathcal{G}$  is acyclic

## DEFINITION (TROPICAL ORIENTED MATROID)

A tropical oriented matroid is a pair  $([M], \mathcal{T})$ , where  $\mathcal{T} \subseteq \{(A_1, \dots, A_M) \mid A_i \subseteq [N], i \in [M]\}$  are tropical covectors satisfying

- • **(Elimination)** If  $A, B \in T$  and  $j \in [D]$  then there exists a type  $C \in T$  with  $C_j = A_j \cup B_j$  and  $C_k \in \{A_k, B_k, A_k \cup B_k\}$  for all  $k \in [D]$ .
- • **(Boundary)** For each  $j \in [N]$  holds  $(\{j\}, \dots, \{j\}) \in T$
- • **(Comparability)** The comparability graph  $CG_{A,B}$  of any two types  $A$  and  $B$  in  $T$  is acyclic.
- **(Surrounding)** If  $A \in T$  the any refinement is also in  $T$ .

## DEFINITION (ORIENTED MATROID)

An oriented matroid is a pair  $([M], \mathcal{C})$ , where  $\mathcal{C} \subseteq \{-, 0, +\}^{[M]}$  are covectors satisfying

- • **(Zero)**  $(0, \dots, 0) \in \mathcal{C}$
- • **(Symmetry)**  $C \in \mathcal{C} \implies -C \in \mathcal{C}$

- **(Composition)** if  $C, D \in \mathcal{C}$  then  $(C \circ D) \in \mathcal{C}$
- • **(Elimination)** if  $C, D \in \mathcal{C}$  and  $i \in S(C, D)$  then there exists some  $Z \in \mathcal{C}$  such that  $Z_i = 0$  and  $Z_j = (C \circ D)_j \forall j \in [M] \setminus S(C, D)$ .



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## DIVIDING THE PARAMETER SPACE

Fix a partition  $n + m = N$ . This induces

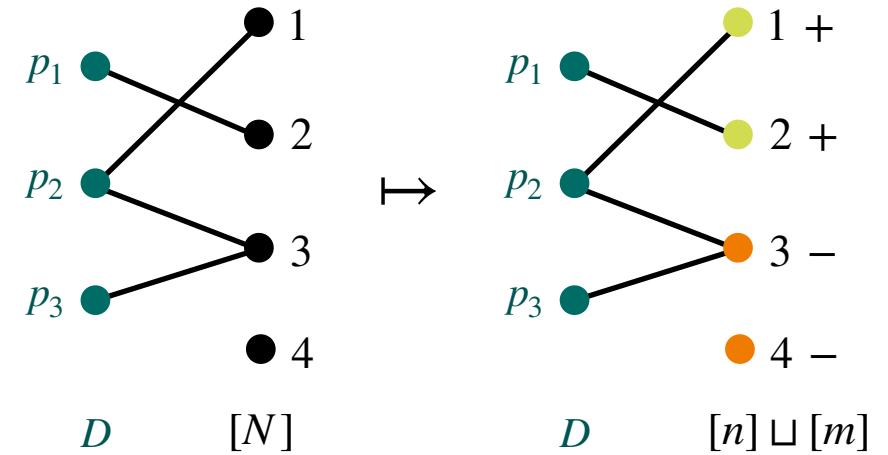
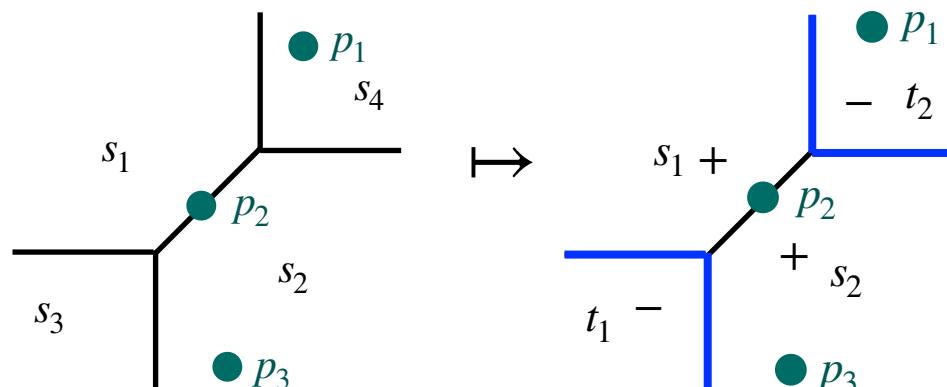
- a partition of the parameters  $\Theta(d, N) \rightarrow \Theta(d, n, m)$

$$(a_1, s_1, \dots, a_n, s_n, a_{n+1}, s_{n+1}, \dots, a_N, s_N) \mapsto (a_1, s_1, \dots, a_n, s_n, b_1, t_1, \dots, b_m, t_m)$$

- a partition into numerator and denominator

$$f(x) = \max_{i \in [N]} a_i + \langle s_i, x \rangle \mapsto g(x) \oslash h(x) = \max_{i=1, \dots, n} (a_i + \langle s_i, x \rangle) - \max_{j=1, \dots, m} (b_j + \langle t_j, x \rangle)$$

- signs on regions in input space
- a coloring of nodes in activation patterns





## INDECISION SURFACES

*What is the analogue of a hyperplane  $(1,p)^\perp = \{(a,s) \mid a + \langle s, p \rangle = 0\}$  from the hyperplane arrangement?*

The **indecision surface** of a data point  $p \in D$  is  $\mathcal{S}(p) = \{\theta \in \Theta(d, n, m) \mid (g_\theta \oslash h_\theta)(p) = 0\}$ .

### THEOREM

The indecision surface is the sign-mixed subcomplex of the normal fan of  $\Delta(p)$  with signs

$$\Delta(p) = \text{conv}\left((1,p,\mathbf{0},\mathbf{0},\dots,\mathbf{0},\mathbf{0}), \dots, (0,\mathbf{0},\dots,1,p,\mathbf{0},\mathbf{0},\dots,\mathbf{0},\mathbf{0}), (0,\mathbf{0},\dots,\mathbf{0},\mathbf{0},1,p,\dots,\mathbf{0},\mathbf{0}), \dots, (0,\mathbf{0},\mathbf{0},\mathbf{0},\dots,1,p)\right).$$

$$\underbrace{+}_{n \text{ times}} \quad \underbrace{+}_{m \text{ times}} \quad \underbrace{-}_{m \text{ times}} \quad \underbrace{-}_{m \text{ times}}$$

$\mathcal{S}(p)$  subdivides the parameter space into  $\mathcal{S}^+(p) = \{\theta \mid (g_\theta \oslash h_\theta)(p) > 0\}$  and  $\mathcal{S}^-(p)$ .



## THE PERFECT CLASSIFICATION FAN

Fix a target labelling  $D = D^+ \sqcup D^-$

$\text{label}(p) = +$  if  $p \in D^+$ ,

$\text{label}(p) = -$  if  $p \in D^-$

### THEOREM

The **perfect classification fan** w.r.t  $D^+ \sqcup D^-$  is

- $\bigcap_{p \in D} \mathcal{S}^{\text{label}(p)}(p)$
- the collection of all cones of the activation fan s.t. the activation pattern (bipartite graph) is compatible with the target labelling
- the set of solutions of a system of tropical polynomial inequalities (tropical semialgebraic set)

→ noncomplete fan with many bad properties

### WHAT I WOULD HAVE TOLD YOU AT A DIFFERENT CONFERENCE...

- connectivity of the perfect classification fan (through walls of codimension 1)
- local and global minima of the 0/1-loss function (counts the number of mistakes in a classification)
- sublevel sets of the 0/1-loss function as subfans of the activation fan
- ...



# THANK YOU

