



Computer Vision, Speech Communication & Signal Processing Group,  
Intelligent Robotics and Automation Laboratory  
National Technical University of Athens, Greece (NTUA)

# Multivariate Tropical Regression and Piecewise-Linear Surface Fitting

Petros Maragos<sup>1</sup> and Emmanouil Theodosis<sup>2</sup>

<sup>1</sup>:School of ECE, National Technical University of Athens, Greece

<sup>2</sup>:School of Engineering & Applied Sciences, Harvard University, USA



# Optimal Regression for Fitting Euclidean vs Tropical Lines

**Problem:** Fit a curve to data  $(x_i, y_i)$ ,  $i = 1, \dots, m$

**Euclidean:**

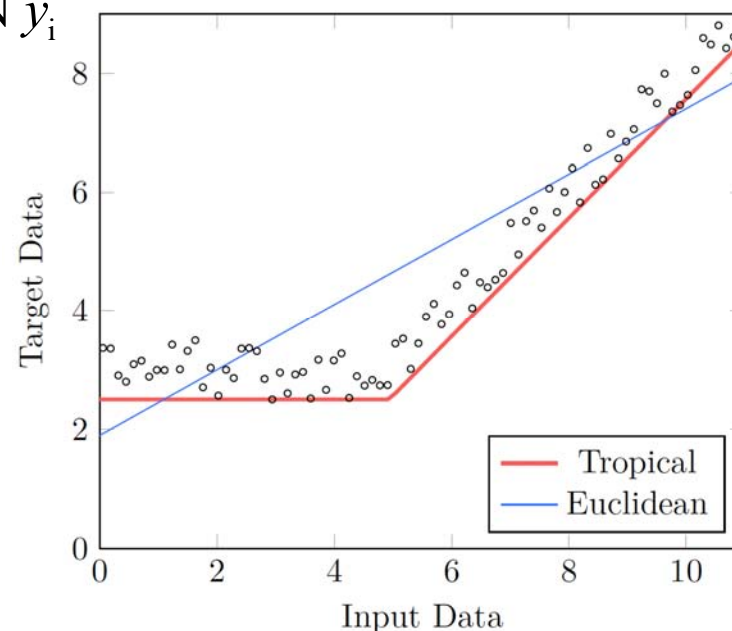
Fit a straight line  $y = ax + b$  by minimizing  $\ell_2$ -norm of error:

$$a = \frac{\sum x_i y_i - (\sum x_i)(\sum y_i) / m}{\sum (x_i)^2 - (\sum x_i)^2 / m}, \quad b = \frac{1}{m} \sum y_i - ax_i$$

**Tropical:**

Fit a tropical line  $y = \max(a + x, b)$  by minimizing some  $\ell_p$ -norm of error:

Greatest Subsolution:  $a = \min_i y_i - x_i$ ,  $b = \min_i y_i$



# Outline

## 1. Elements of Tropical Geometry

- “a marriage between algebraic geometry and polyhedral geometry”  
[Maclagan & Sturmfels 2015]
- Tropical semirings: Max-plus & Min-plus Arithmetic
- Tropical Polynomials
- Geometrical objects: tropical lines, tropical polynomial curves/surfaces, tropical half-spaces & polyhedra

## 2. Elements of Max-plus Algebra for Vectors/Matrices:

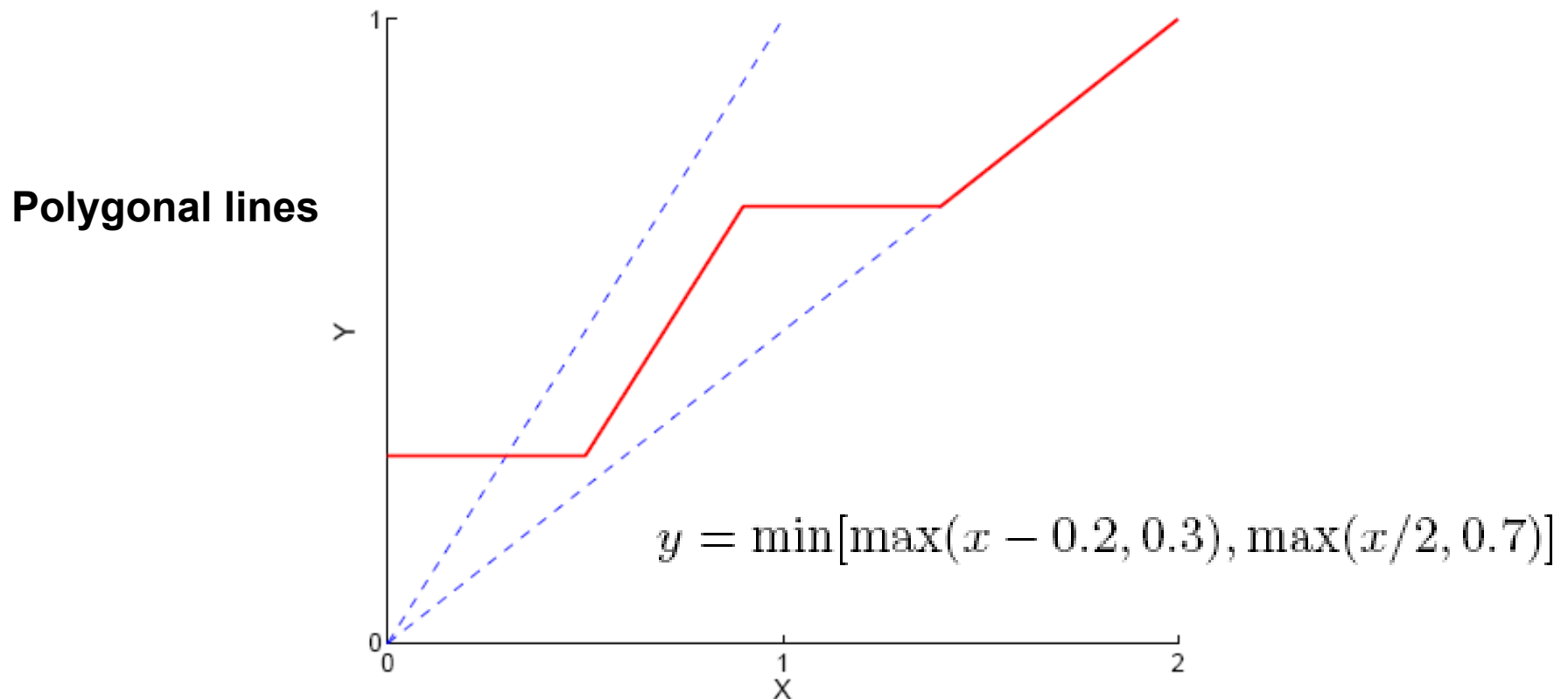
- Max-plus Matrix algebra
- Max-plus systems (Nonlinear Control) and
- Signal Processing: Max-plus convolutions (weighted dilations/erosions)

## 3. Optimization and Tropical Regression:

- Optimal solutions of max-plus matrix equations
- Tropical Regression: fitting tropical polynomials to data
- Algorithm and Complexity

# What does TROPICAL mean?

- The adjective “**tropical**” was coined by French mathematicians Dominique Perrin and Jean-Eric Pin, to honor their Brazilian colleague Imre Simon, a pioneer of min-plus algebra as applied to finite automata in computer science.
- Tropical (**Τροπικός** in Greek) comes from the greek word «**Τροπή**» which means “turning” or “changing the way/direction”.



# Tropical Semirings

## Scalar Arithmetic Rings

Integer/Real Addition-Multiplication Ring:  $(\mathbb{R}, +, \times)$ ,  $(\mathbb{Z}, +, \times)$

## Tropical Semirings

$$\mathbb{R}_{\max} = \mathbb{R} \cup \{-\infty\}, \quad \mathbb{R}_{\min} = \mathbb{R} \cup \{+\infty\}$$

$$\vee = \max, \quad \wedge = \min$$

**Max-plus semiring:**  $(\mathbb{R}_{\max}, \vee, +)$

**Min-plus semiring:**  $(\mathbb{R}_{\min}, \wedge, +)$

## Log-Sum-Exp (LSE) approximation

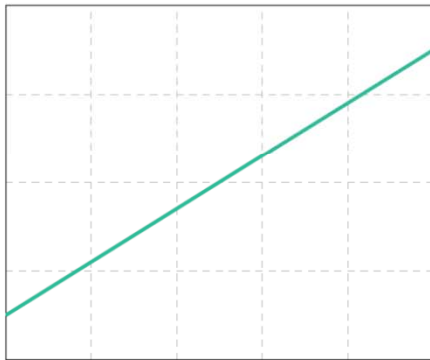
(Maslov "Dequantization" in idempotent mathematics [Maslov 1987, Litvinov 2007])

$$\lim_{T \downarrow 0} T \cdot \log(e^{a/T} + e^{b/T}) = \max(a, b)$$

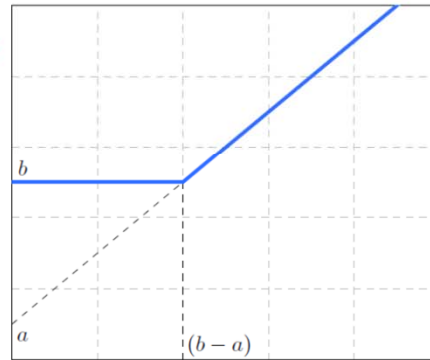
$$\lim_{T \downarrow 0} (-T) \log(e^{-a/T} + e^{-b/T}) = \min(a, b)$$

# Graphs of Max-plus Tropical 1D Polynomials

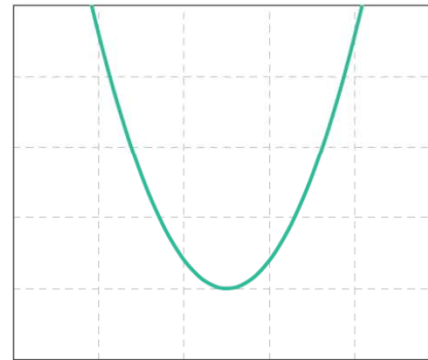
$$y_{\text{t-line}} = \max(a + x, b), \quad y_{\text{t-parab}} = \max(a + 2x, b + x, c)$$



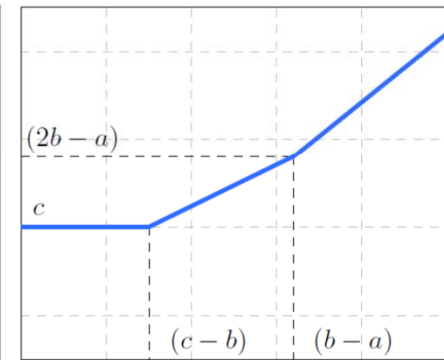
(a) Euclidean line



(b) Tropical line

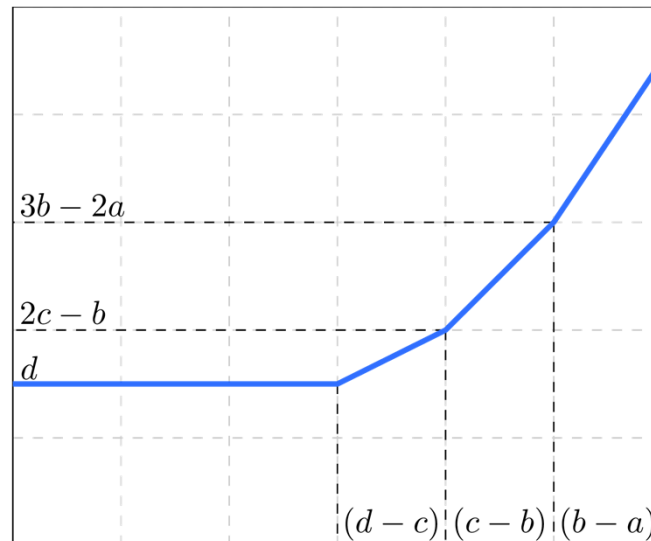
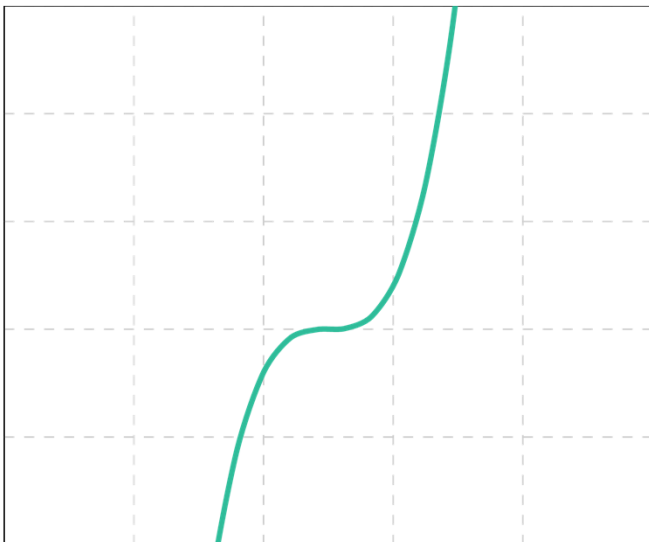


(c) Euclid parabola



(d) Tropic parabola

Cubic polynomial



# Graph and Trop Curve of a tropical “Conic” polynomial

## Tropical Polynomial of degree 2 in two variables

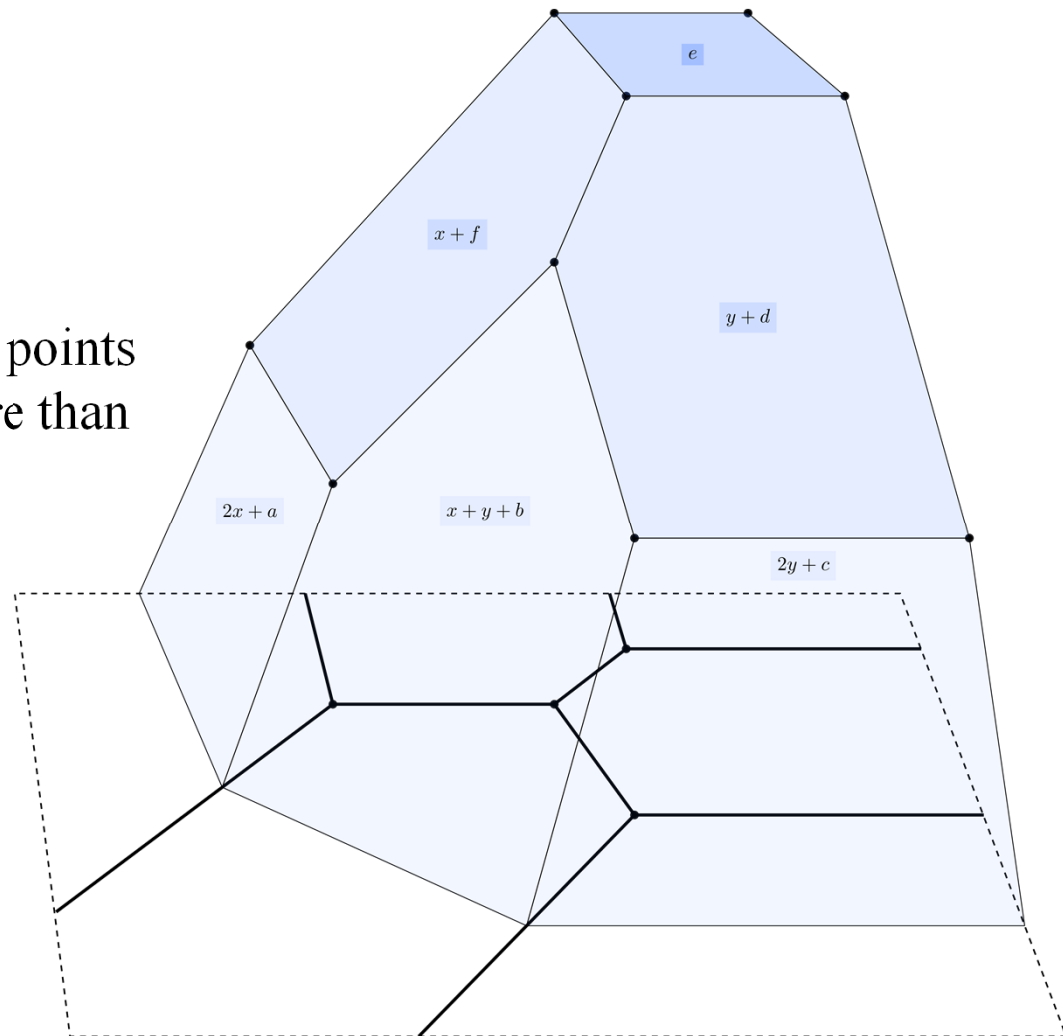
classical: " $ax^2 + bxy + cy^2 + dy + e + fx$ "

tropical:  $p(x, y) = \min(a + 2x, b + x + y, c + 2y, d + y, e, f + x)$

**Graph of  $p(x, y)$**

and

its **Tropical Curve** = set of  $(x, y)$  points where the min is attained by more than one terms.



# Obtain Tropical Polynomials via Dequantization

**Classic polynomial:**  $f(\mathbf{u}) = \sum_{k=1}^K c_k u_1^{a_{k1}} u_2^{a_{k2}} \cdots u_n^{a_{kn}}, \quad \mathbf{u} = (u_1, u_2, \dots, u_n)$

Posynomial if  $c_k > 0$ ,  $\mathbf{a}_k = (a_{k1}, \dots, a_{kn}) \in \mathbb{R}^n$ ,  $\mathbf{u} > 0$ ;

**Log-Sum-Exp** (Viro's "logarithmic paper" [Viro 2001]):

$$\mathbf{x} = \log(\mathbf{u}), \quad b_k = \log(c_k)$$

$$\lim_{T \downarrow 0} T \cdot \log f(e^{\mathbf{x}/T}) = \lim_{T \downarrow 0} T \cdot \sum_{k=1}^K \exp(\langle \mathbf{a}_k, \mathbf{x} / T \rangle + b_k / T) \rightarrow$$

**Tropical (max-plus) Polynomial = Piecewise-Linear Function**

$$p(\mathbf{x}) = \text{MAX}_{k=1}^K \{ \langle \mathbf{a}_k, \mathbf{x} \rangle + b_k \} = \text{MAX}_{k=1}^K \{ a_{k1}x_1 + \cdots + a_{kn}x_n + b_k \}$$

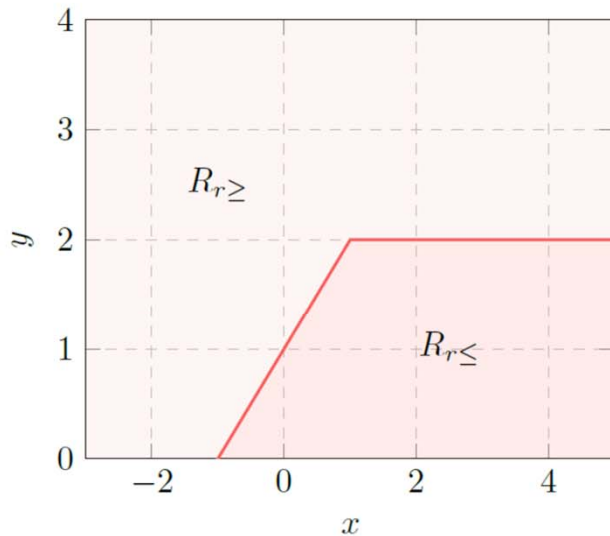


# Tropical Half-spaces and Polytopes in 2D

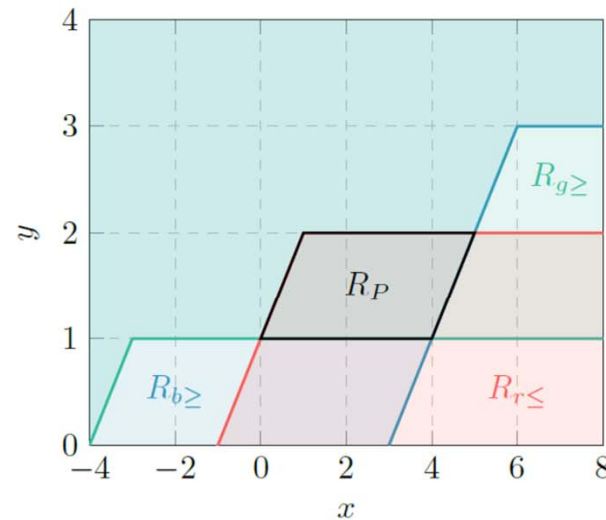
Tropical (affine) Half-space of  $\mathbb{R}_{\max}^n$

[ Gaubert & Katz 2011]

$$\mathcal{T}(\mathbf{a}, \mathbf{b}) \triangleq \left\{ \mathbf{x} \in \mathbb{R}_{\max}^n : \max(a_{n+1}, \bigvee_{i=1}^n a_i + x_i) \leq \max(b_{n+1}, \bigvee_{i=1}^n b_i + x_i) \right\}$$



(a) Single region

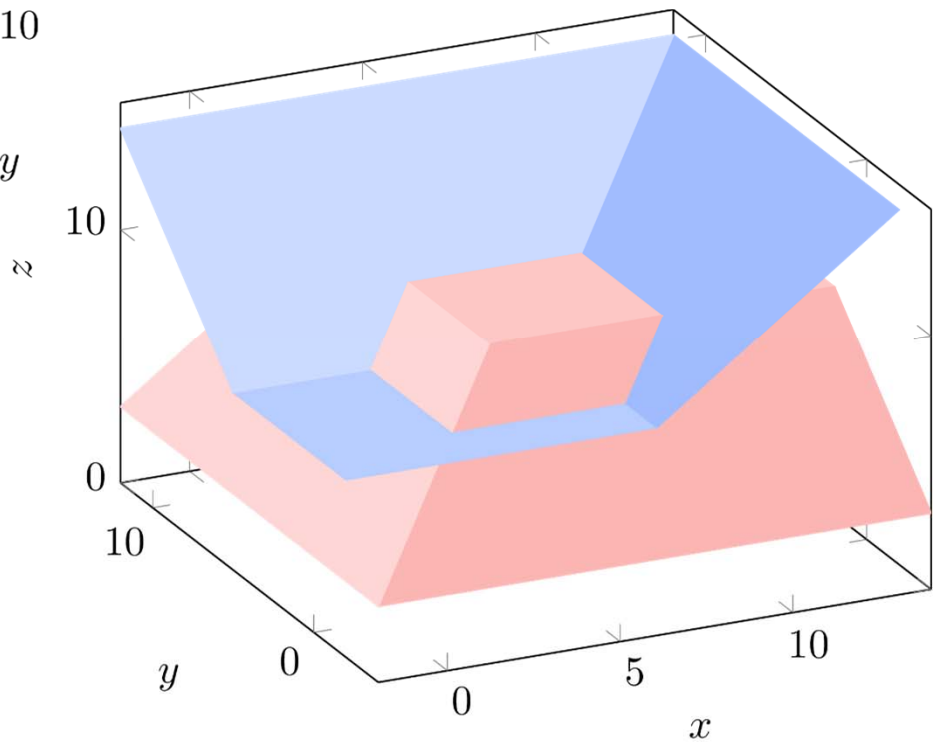
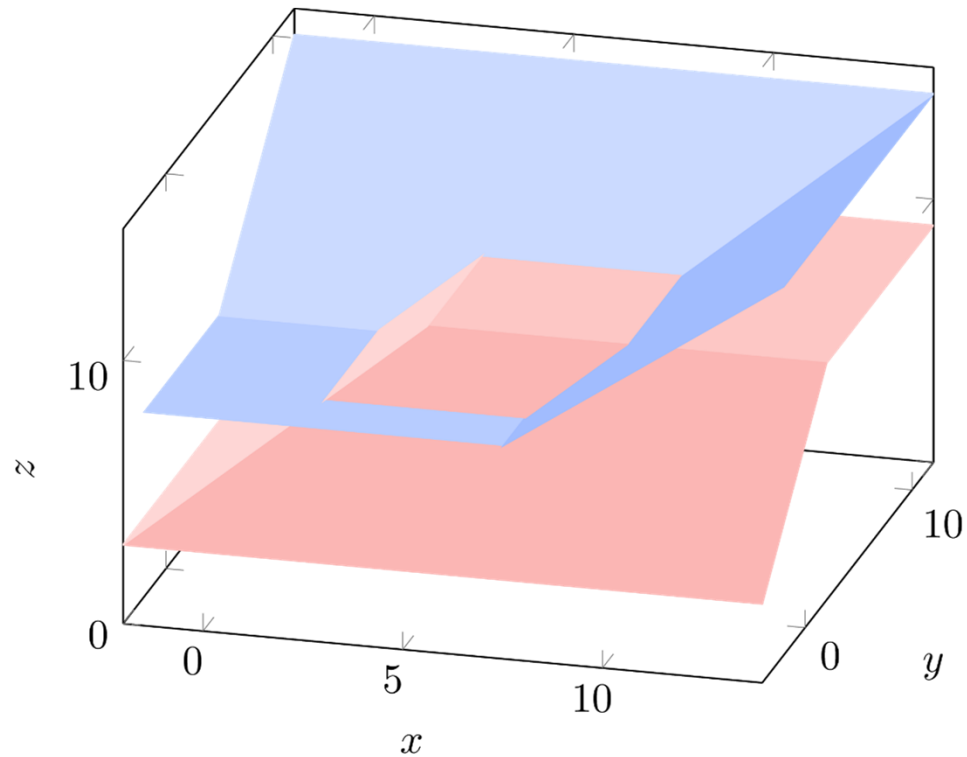


(b) Multiple regions

The region separating boundaries are tropical lines (or hyper-planes).

Tropical **Polyhedra** are formed from finite intersections of tropical half-spaces. **Polytopes** are compact polyhedra.

# Tropical Halfspaces and Polyhedra in 3D



# Max- plus Matrix Algebra

- vector/matrix **‘addition’** = pointwise max

$$\begin{aligned}\mathbf{x} \vee \mathbf{y} &= [x_1 \vee y_1, \dots, x_n \vee y_n]^T \\ \mathbf{A} \vee \mathbf{B} &= [a_{ij} \vee b_{ij}]\end{aligned}$$

- vector/matrix **‘dual addition’** = pointwise min

$$\begin{aligned}\mathbf{x} \wedge \mathbf{y} &= [x_1 \wedge y_1, \dots, x_n \wedge y_n]^T \\ \mathbf{A} \wedge \mathbf{B} &= [a_{ij} \wedge b_{ij}]\end{aligned}$$

- vector/matrix **‘multiplication by scalar’**

$$\begin{aligned}c + \mathbf{x} &= [c + x_1, \dots, c + x_n]^T \\ c + \mathbf{A} &= [c + a_{ij}]\end{aligned}$$

- $(\max, +)$  **‘matrix multiplication’**

$$[\mathbf{A} \boxplus \mathbf{B}]_{ij} = \bigvee_{k=1}^n a_{ik} + b_{kj}$$

- $(\min, +)$  **‘matrix dual multiplication’**

$$[\mathbf{A} \boxplus' \mathbf{B}]_{ij} = \bigwedge_{k=1}^n a_{ik} + b_{kj}$$

# Linear versus Max-Plus Systems

- **State-space representation:** linear vs. max-plus

$$x(k) = Ax(k-1) + Bu(k)$$

$$y(k) = Cx(k) + Du(k)$$

$$x(k) = A \boxplus x(k-1) \vee B \boxplus u(k)$$

$$y(k) = C \boxplus x(k) \vee D \boxplus u(k)$$

- **Matrix products**

- **Linear:**  $[AB]_{ij} = \sum_{k=1}^n a_{ik}b_{kj}$

- **Max-plus:**  $[A \boxplus B]_{ij} = \bigvee_{k=1}^n a_{ik} + b_{kj}$

- **Example**

$$\begin{bmatrix} 4 & -1 \\ 2 & -\infty \end{bmatrix} \boxplus \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 3 \\ 1 \end{bmatrix}, \left\{ \begin{array}{l} \max(x+4, y-1) = 3 \\ x+2 = 1 \end{array} \right\} \Rightarrow \begin{array}{l} x = -1 \\ y \leq 4 \end{array}$$

- **What can we model with max-plus systems?**

Discrete Event Systems/Control, Scheduling, Shortest Paths on Graphs, Dynamic Programming, WFSTs for Speech recognition, Morphological Filters for Image Processing

Ref: [P. Maragos, "Dynamical Systems on Weighted Lattices: General Theory", Math. Control, Signals and Systems, 2017.]

# Morphological Operators on Lattices

( $\leq$  = partial ordering,  $\vee$  = supremum,  $\wedge$  = infimum)

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- $\psi$  is **increasing** iff  $f \leq g \Rightarrow \psi(f) \leq \psi(g)$ .
- $\delta$  is **dilation** iff  $\delta(\vee_i f_i) = \vee_i \delta(f_i)$ .
- $\varepsilon$  is **erosion** iff  $\varepsilon(\wedge_i f_i) = \wedge_i \varepsilon(f_i)$ .
- $\alpha$  is **opening** iff increasing and antiextensive ( $\alpha(f) \leq f$ ),  
and idempotent ( $\alpha = \alpha^2$ ).
- $\beta$  is **closing** iff increasing and extensive ( $\beta(f) \geq f$ ),  
and idempotent ( $\beta = \beta^2$ ).
- $(\varepsilon, \delta)$  is **adjunction** iff  $\delta(g) \leq f \Leftrightarrow g \leq \varepsilon(f)$ .

(Galois connection)  
Residuation pair  
("Tropical Adjoints")

Then:  $\varepsilon$  is erosion,  $\delta$  is dilation,

$\delta\varepsilon$  is opening (projection),  $\varepsilon\delta$  is closing (projection).

# Solve Max-plus Equations

- **Problems:**

- (1) Exact problem: Solve  $\delta_A(\mathbf{x}) = \mathbf{A} \boxplus \mathbf{x} = \mathbf{b}$ ,  $\mathbf{A} \in \overline{\mathbb{R}}^{m \times n}$ ,  $\mathbf{b} \in \overline{\mathbb{R}}^m$
- (2) Approximate Constrained: Min  $\|\mathbf{A} \boxplus \mathbf{x} - \mathbf{b}\|_{p=1 \dots \infty}$  s.t.  $\mathbf{A} \boxplus \mathbf{x} \leq \mathbf{b}$

- **Theorem:** (a) The **greatest (sub)solution** of (1) and unique solution of (2) is

$$\hat{\mathbf{x}} = \varepsilon_A(\mathbf{b}) = \mathbf{A}^* \boxplus' \mathbf{b} = [\bigwedge_i b_i - a_{ij}], \quad \mathbf{A}^* \triangleq -\mathbf{A}^T$$

and yields the **Greatest Lower Estimate (GLE)** of data  $\mathbf{b}$ :

$$\delta_A(\varepsilon_A(\mathbf{b})) = \mathbf{A} \boxplus (\mathbf{A}^* \boxplus' \mathbf{b}) \leq \mathbf{b}$$

- (b) **Min Max Absolute Error (MMAE) unconstrained unique solution:**

$$\tilde{\mathbf{x}} = \hat{\mathbf{x}} + \mu, \quad \mu = \|\mathbf{A} \boxplus \hat{\mathbf{x}} - \mathbf{b}\|_{\infty}/2$$

- **Geometry:** Operators  $\delta, \varepsilon$  are vector dilation and erosion, and the **GLE**  $\mathbf{b} \mapsto \delta\varepsilon(\mathbf{b})$  is an opening (**lattice projection**).
- **Complexity:**  $O(mn)$

# Optimally Fitting Tropical Lines to Data

**Problem:** Fit a tropical line  $y = \max(a + x, b)$  to noisy data  $(x_i, f_i)$ ,  $i = 1, \dots, m$ , where  $f_i = y_i + \text{error}$  by minimizing  $\ell_{1, \dots, \infty}$  norm of error:

**Greatest Subsolution (GLE):**  $\hat{w} = (\hat{a}, \hat{b})$ ,  $\hat{a} = \min_i f_i - x_i$ ,  $\hat{b} = \min_i f_i$

**Min Max Abs. Error (MMAE) Solution:**  $\tilde{w} = \hat{w} + \mu$ ,  $\mu = \|\text{GLE error}\|_{\infty} / 2$

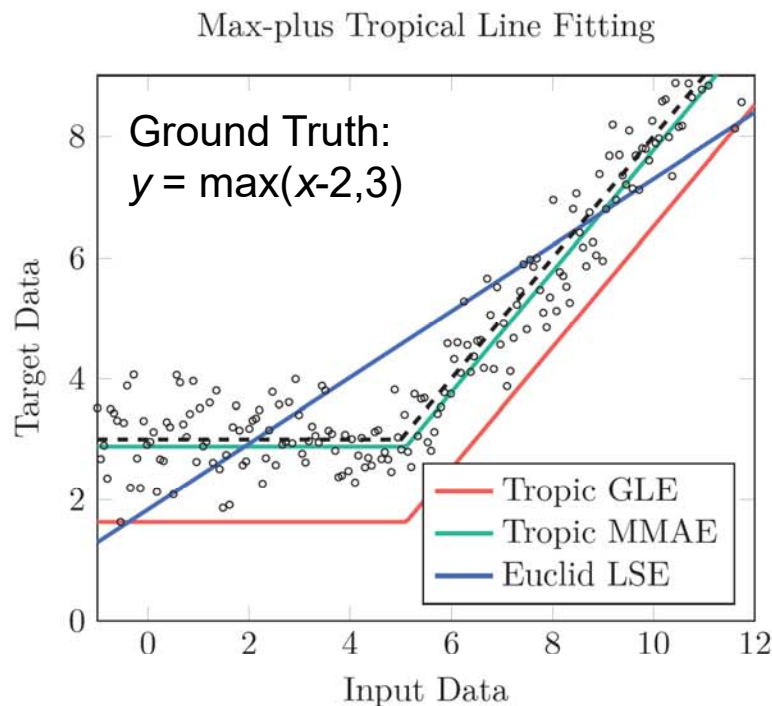
$$\underbrace{\begin{bmatrix} x_1 & 0 \\ \vdots & \vdots \\ x_m & 0 \end{bmatrix}}_{\mathbf{X}} \boxplus \underbrace{\begin{bmatrix} a \\ b \end{bmatrix}}_{\mathbf{w}} = \underbrace{\begin{bmatrix} f_1 \\ \vdots \\ f_m \end{bmatrix}}_{\mathbf{f}} \Rightarrow \underbrace{\begin{bmatrix} \hat{a} \\ \hat{b} \end{bmatrix}}_{\hat{\mathbf{w}}} = \underbrace{\begin{bmatrix} \bigwedge_i f_i - x_i \\ \bigwedge_i f_i \end{bmatrix}}_{\mathbf{X}^* \boxplus' \mathbf{f}}$$

# Numerical Examples of Optimally Fitting Tropical Lines to Data

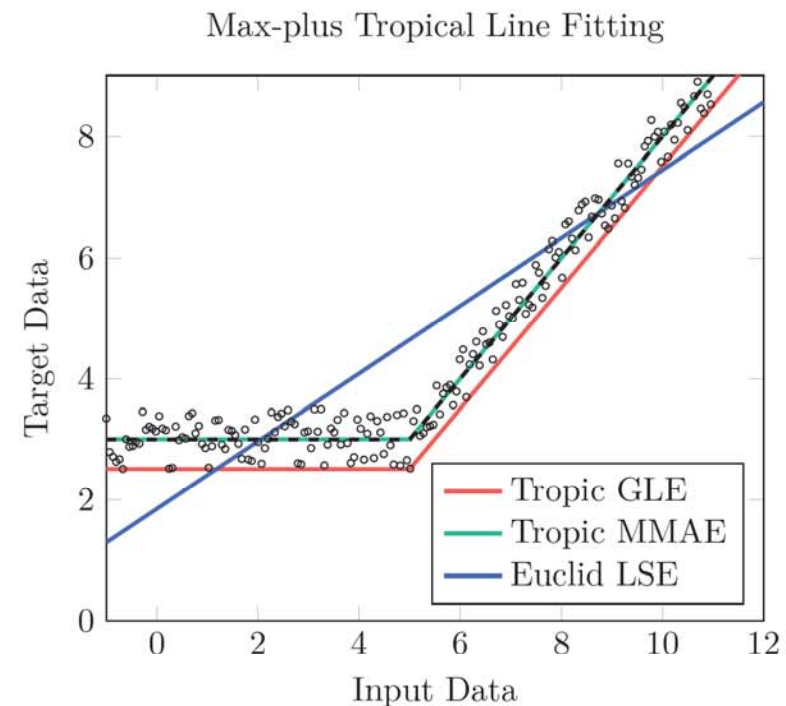
**Problem:** Fit a tropical line  $y = \max(a + x, b)$  to noisy data  $(x_i, f_i)$ ,  $i = 1, \dots, m = 200$ , where  $f_i = y_i + \text{error}$  by minimizing  $\ell_{1, \dots, \infty}$  of error:

**Greatest Subsolution (GLE):**  $\hat{w} = (\hat{a}, \hat{b})$ ,  $\hat{a} = \min_i f_i - x_i$ ,  $\hat{b} = \min_i f_i$

**Min Max Abs. Error (MMAE) Solution:**  $\tilde{w} = \hat{w} + \mu$ ,  $\mu = \|\text{GLE error}\|_{\infty} / 2$



(a) T-line with Gaussian Noise



(b) T-line with Uniform Noise



# Optimal Fitting Max-Plus Tropical Planes to Data

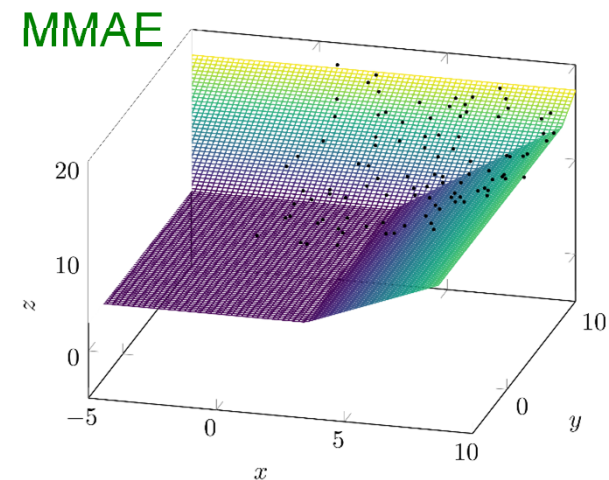
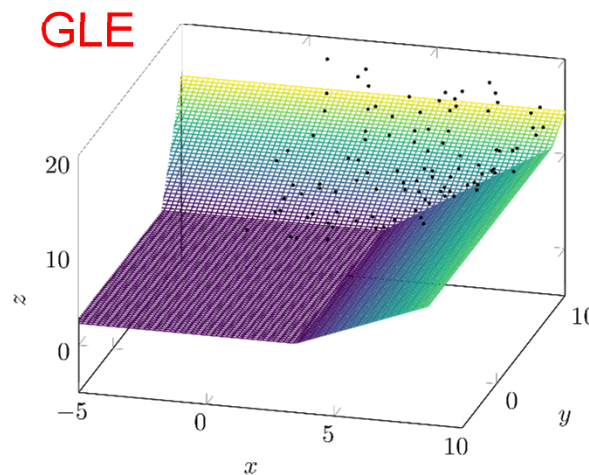
**Problem:** Fit a **tropical plane**  $z = \max(a + x, b + y, c)$  to noisy **data**  $(x_i, y_i, f_i)$ , where  $f_i = z_i + \text{error}$ ,  $i = 1, \dots, m = 100$ , by minimizing  $\ell_{1, \dots, \infty}$  norm of error:

**Greatest Subsolution (GLE):**  $\hat{w} = (\hat{a}, \hat{b}, \hat{c})$

**Min Max Abs. Error (MMAE) Solution:**  $\tilde{w} = \hat{w} + \mu$ ,  $\mu = \|\text{GLE error}\|_{\infty} / 2$

$$\underbrace{\begin{bmatrix} x_1 & y_1 & 0 \\ \vdots & \vdots & \vdots \\ x_m & y_m & 0 \end{bmatrix}}_{\mathbf{X}} \boxplus \underbrace{\begin{bmatrix} a \\ b \\ c \end{bmatrix}}_{\mathbf{w}} = \underbrace{\begin{bmatrix} f_1 \\ \vdots \\ f_m \end{bmatrix}}_{\mathbf{f}} \Rightarrow \underbrace{\begin{bmatrix} \hat{a} \\ \hat{b} \\ \hat{c} \end{bmatrix}}_{\hat{\mathbf{w}}} = \underbrace{\begin{bmatrix} \bigwedge_i f_i - x_i \\ \bigwedge_i f_i - y_i \\ \bigwedge_i f_i \end{bmatrix}}_{\mathbf{X}^* \boxplus' \mathbf{f}}$$

Ground Truth:  
 $z = \max(x + 5, y + 7, 9)$   
 Noise:  $N(0, 1)$



# Optimal Fitting 2D Higher-degree Tropical Polynomials to Data

**Data** (noisy paraboloid):

3D tuples  $(x_i, y_i, f_i) \in \mathbb{R}^3$

$$f_i = x_i^2 + y_i^2 + \varepsilon_i,$$

$(x_i, y_i) \sim \text{Unif}[-1, 1]$

$\varepsilon_i \sim \mathcal{N}(0, 0.25^2)$

**Model:**

Fit  $K$ -rank 2D trop. polynomial

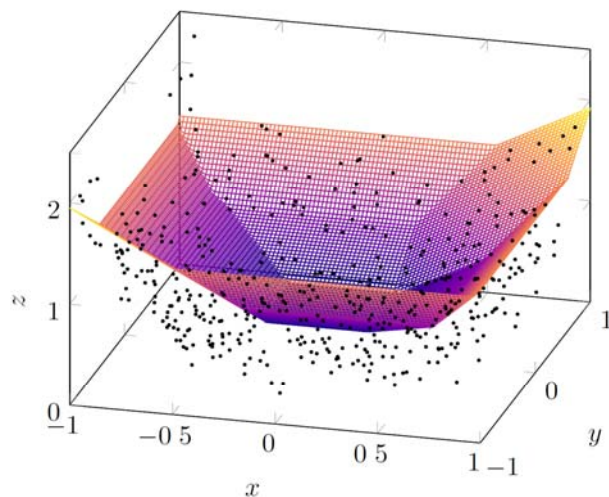
$$p(x, y) = \text{MAX}_{k=1}^K \{a_k x + b_k y + c_k\}$$

by minimizing error  $\|f_i - p(x_i, y_i)\|_0$ .

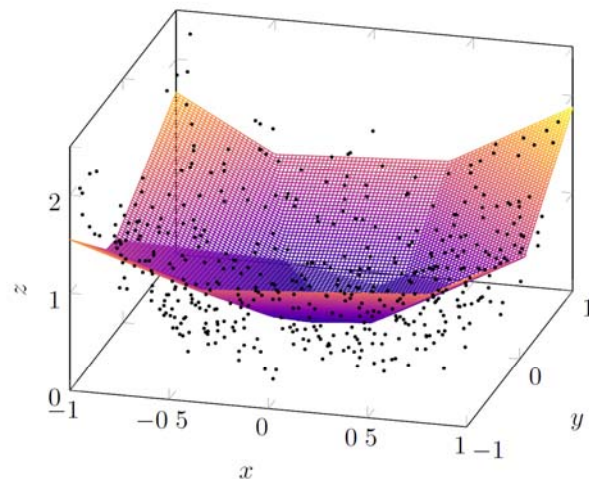
**Estimation algorithm:**

$K$  – means on data gradients  $\rightarrow a_k, b_k$

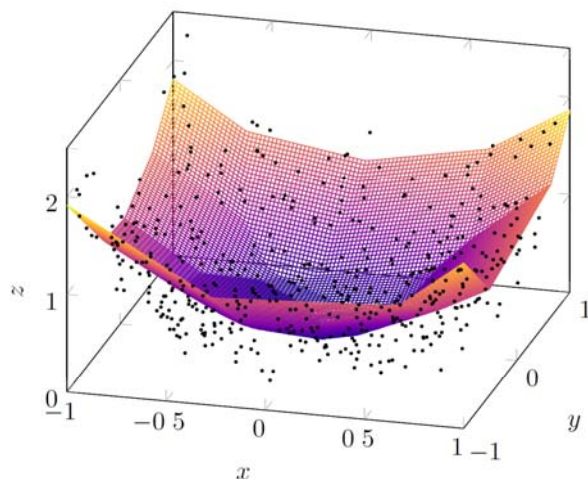
solve max-plus eqns  $\rightarrow c_k$



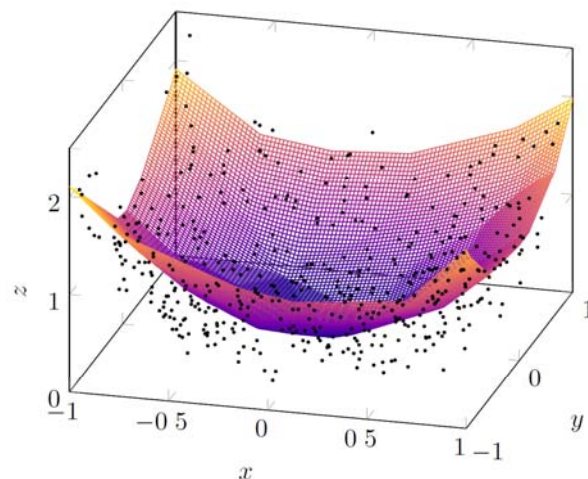
(a) 2D conic ( $K=11$ )



(b)  $K=10$



(c)  $K=25$



(d)  $K=100$

# Computational Complexity of Tropical Regression

**Data size:**  $m$  data in  $\mathbb{R}^{n+1}$

**Model:** MAX of  $K$  hyperplanes  $\mathbf{a}_k^T \cdot \mathbf{x} + b_k$ ,  $k = 1, \dots, K$ ,  $\mathbf{x} \in \mathbb{R}^n$

**# of Parameters:**  $K(n+1)$

Traditional Least-Squares Estimator:  $O((n+1)^3 m^3)$

(Quadratic Programming with Constraints)

Iterative  $K$ -means Partition and LSE:  $O((n+1)^2 mi)$

[Magnani & Boyd 2009],  $i = \#$  iterations until convergence

Convex Adaptive Partitioning:  $O(n(n+1)^2 m \log(m) \log(\log(m)))$

[Hannah & Dunson 2011]

**Our algorithm:**  $O(Kmni)$

$i = \# K$ -means iterations

if  $iK \ll m \Rightarrow O(mn)$

# Conclusions

- Tropical Geometry, max-plus matrix algebra, and morphological signal operators share a common idempotent semiring arithmetic.
- Introduced Tropical Polynomials for multidimensional data fitting using Piecewise-Linear Functions.
- Developed algorithm of low-complexity ( $\sim$ linear) for tropical regression based on optimal solutions of systems of max-plus equations.
- **Future work:** extensions to more general regression functions using max- $^*$  algebra on weighted lattices.

## References

- P. Maragos and E. Theodosis, “*Tropical Geometry and Piecewise-Linear Approximation of Curves and Surfaces on Weighted Lattices*”, arXiv, 2019.
- P. Maragos, “*Dynamical Systems on Weighted Lattices: General Theory*”, Math. Control, Signals and Systems, 2017.

Thank you for your attention!

We wish everyone courage and health  
during the COVID19 pandemic.

For more information, demos, and current results:

<http://cvsp.cs.ntua.gr> and <http://robotics.ntua.gr>