

Tightening Convex Relaxations of Trained Neural Networks

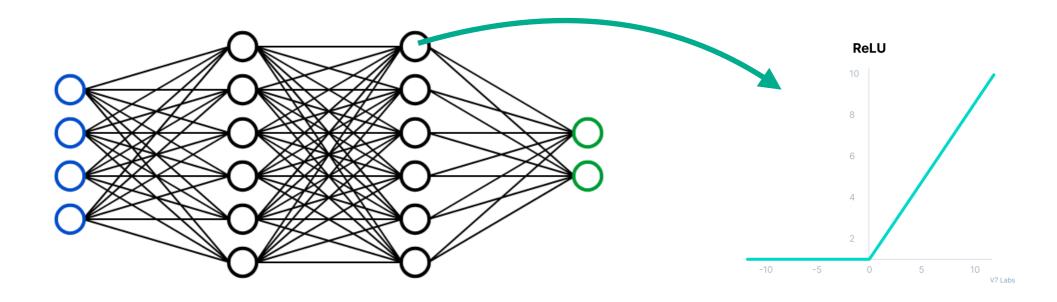
A unified approach for convex and S-shaped activations

Pablo Carrasco (Universidad de O'Higgins) Gonzalo Muñoz (Universidad de Chile)

Mixed-Integer Programming Workshop 2025

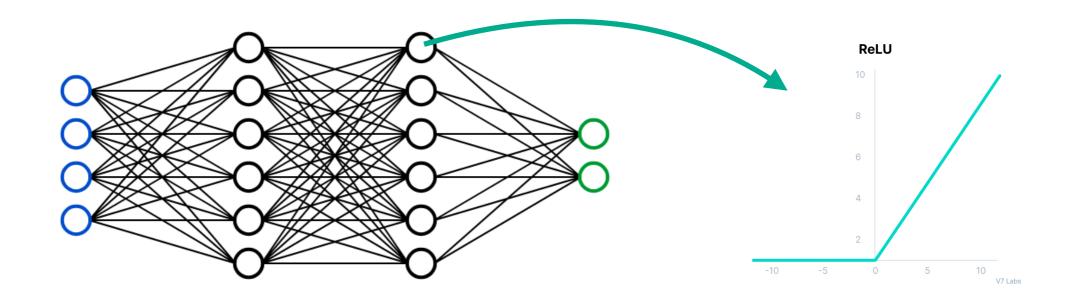
Optimization using trained neural networks

High level goal: to convexity y = NN(x)

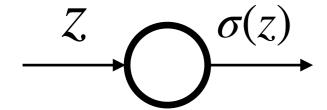


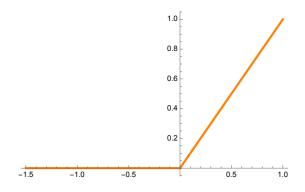
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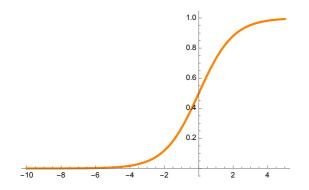
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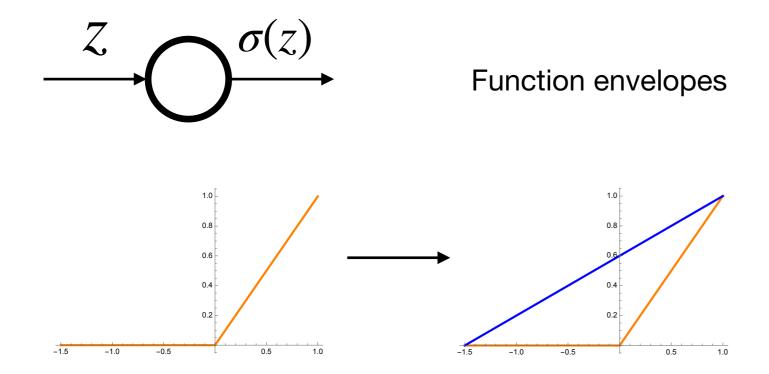


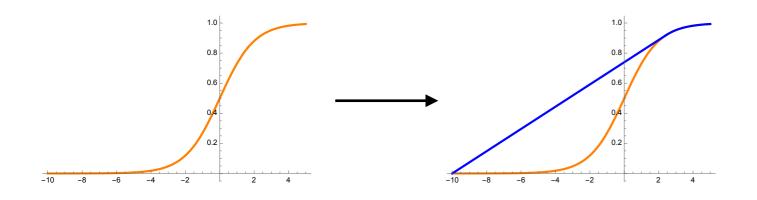
This can be useful in either using or evaluating a trained neural network via an optimization model

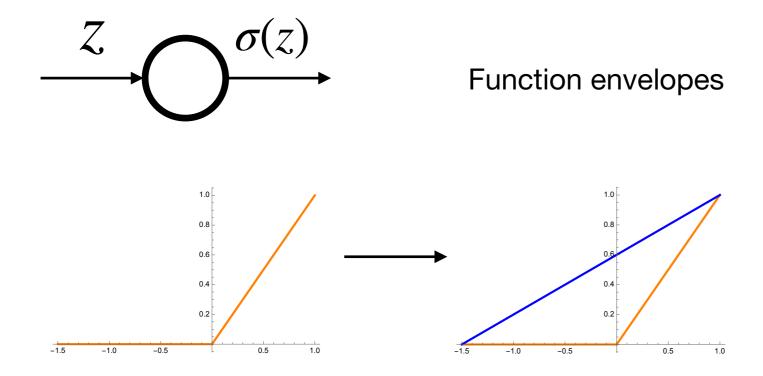


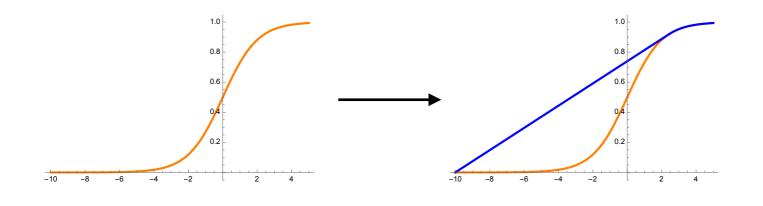




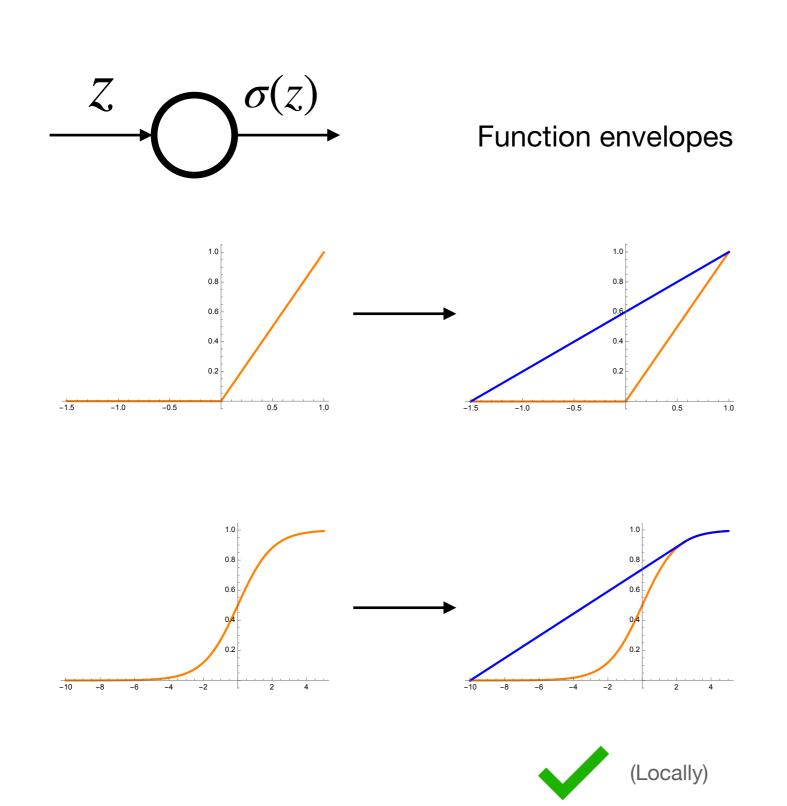


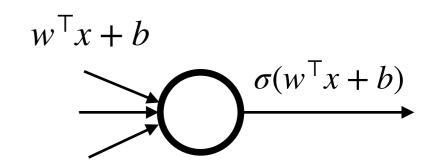


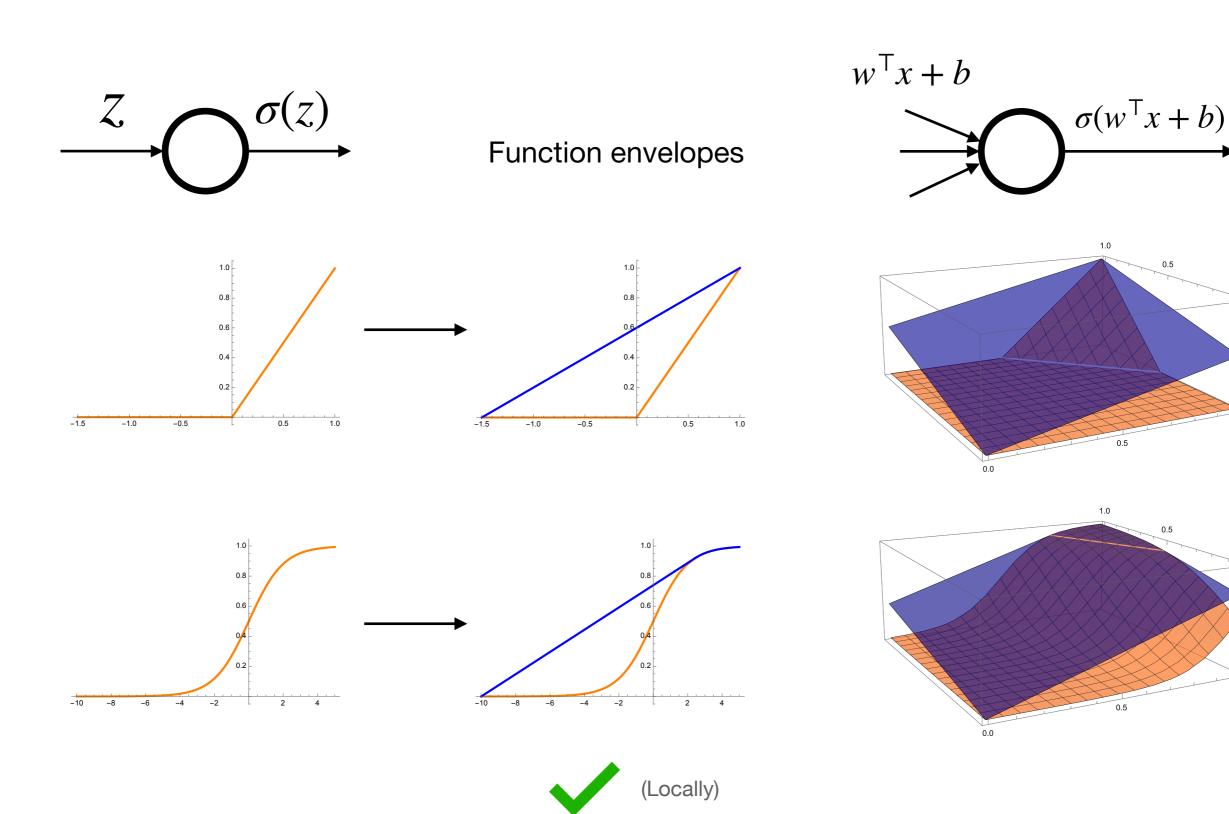


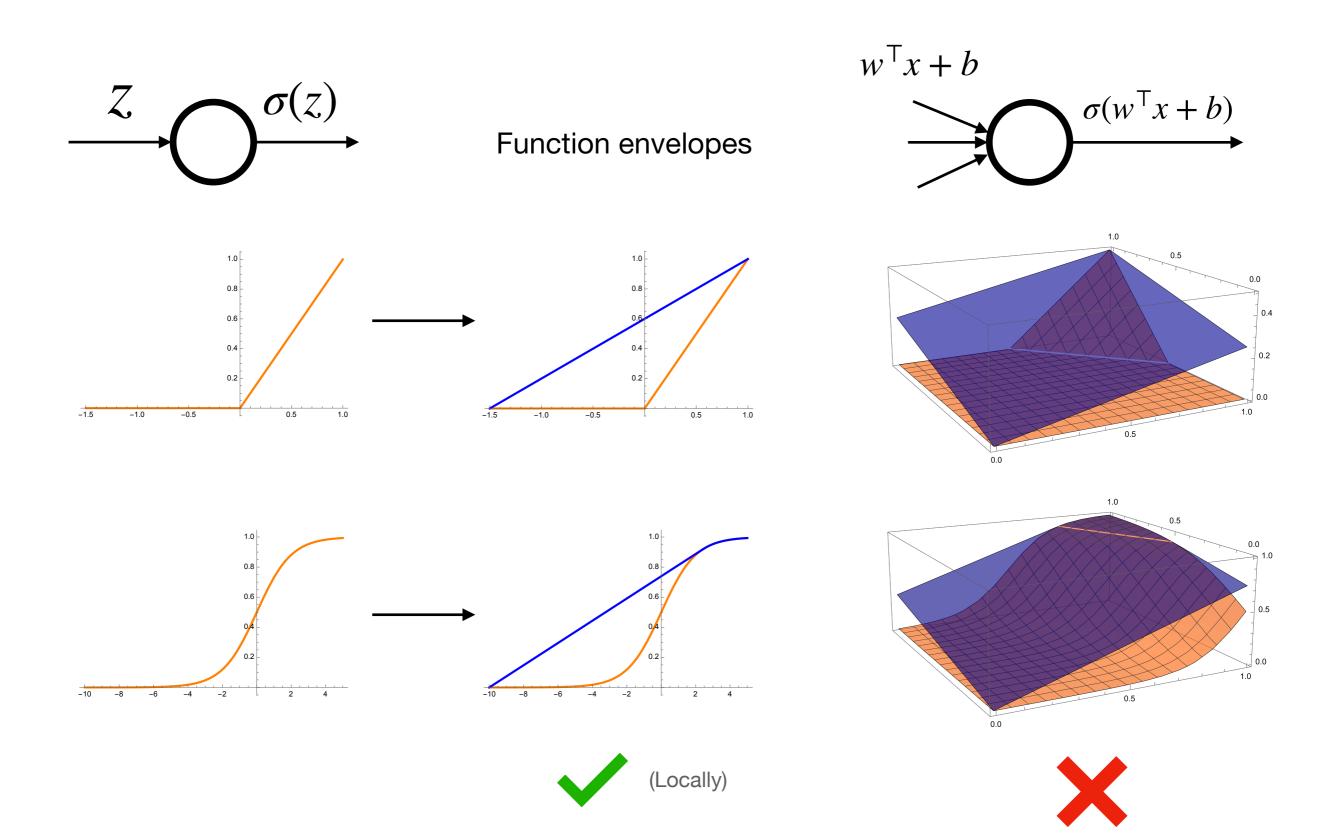








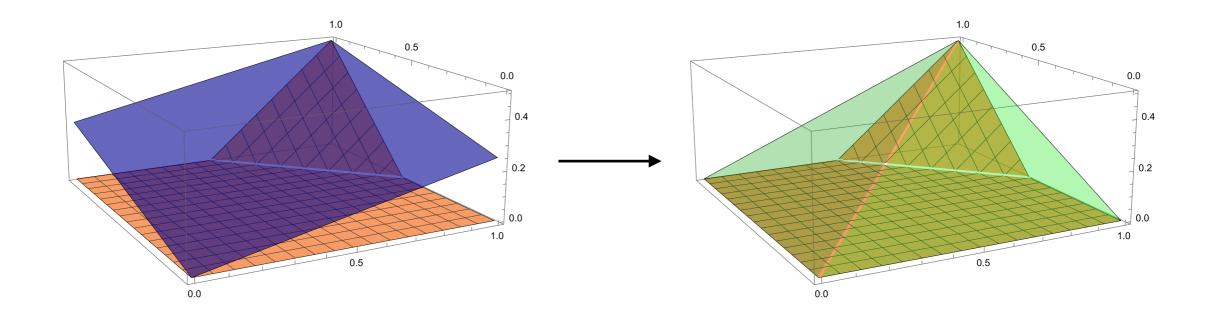




A path forward for the ReLU

Anderson et al. (2020) and Tjandraatmadja et al. (2020) showed how to tightly convexify

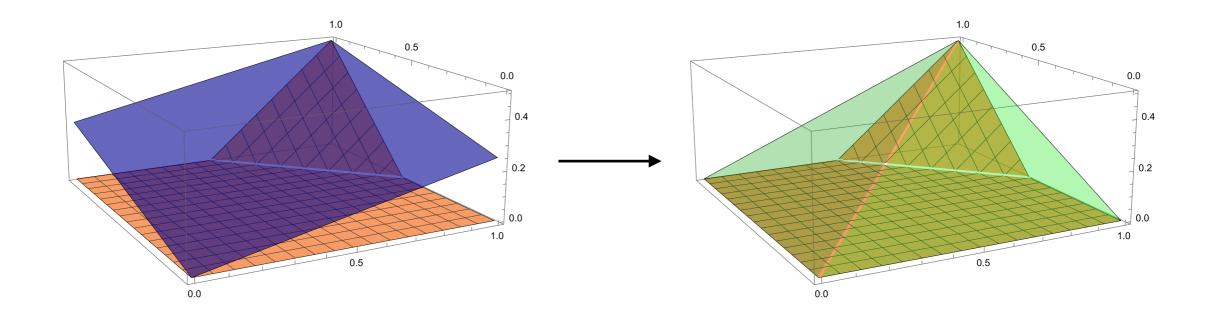
$$y = \sigma(w^{\mathsf{T}}x + b)$$



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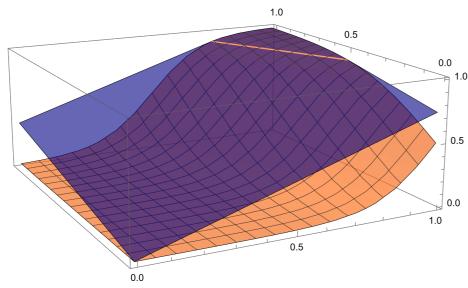
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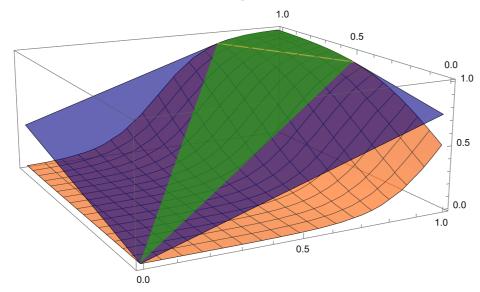


Their approach can handle polyhedral domains, piecewise linear convex activations, and they develop a polynomial time separation



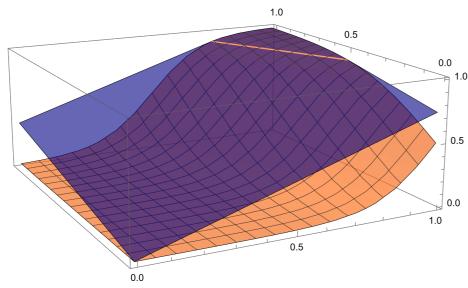


How to improve this?

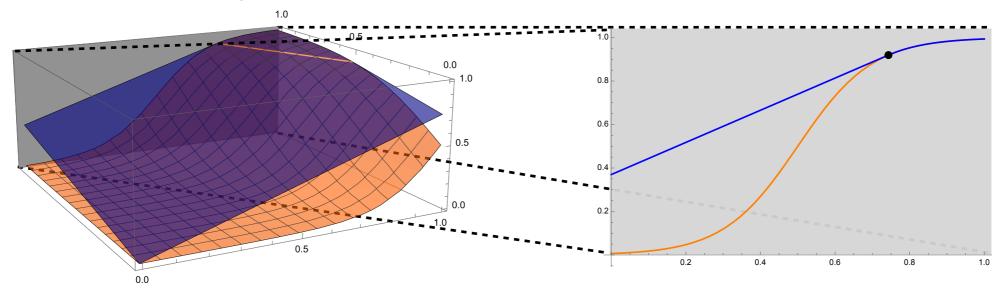


The green part is OK

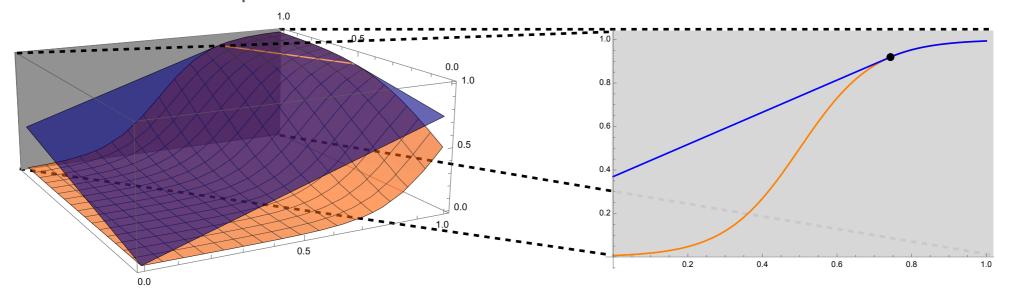




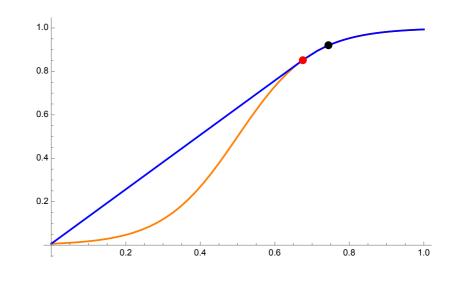
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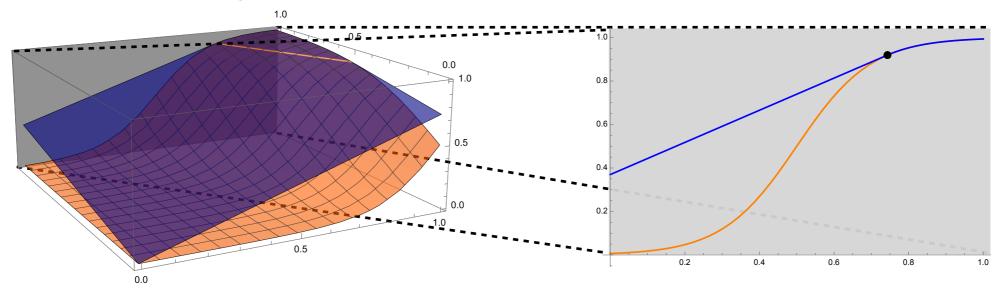
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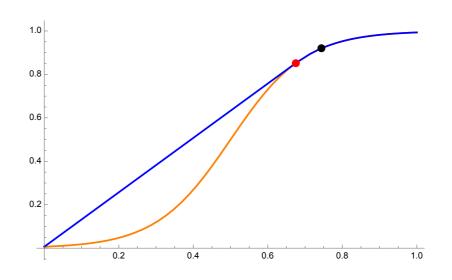
Tawarmalani and Sahinidis (2002) showed that, on the boundary, the envelope should look like this



How to improve this?

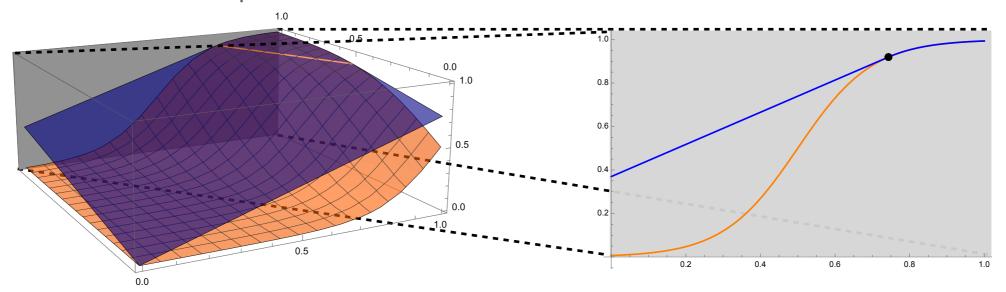


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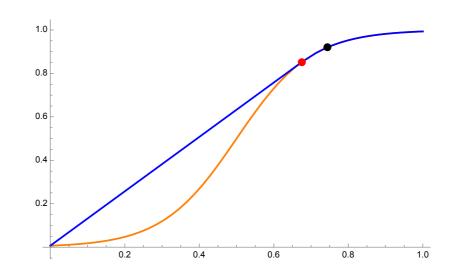


How to build from this?

How to improve this?



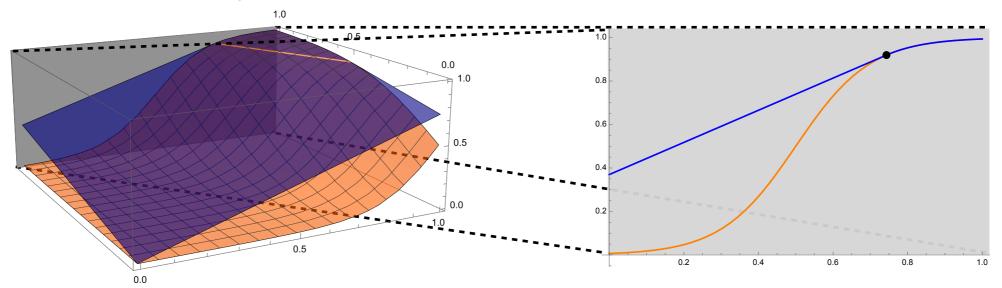
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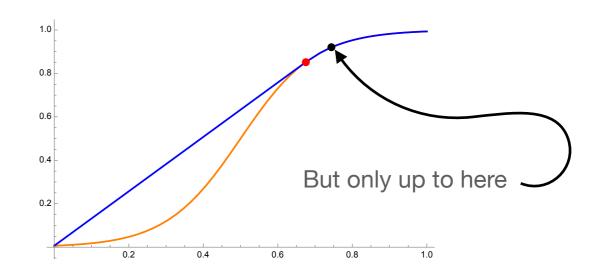
How to build from this?

Taking perspective from the boundary!

How to improve this?

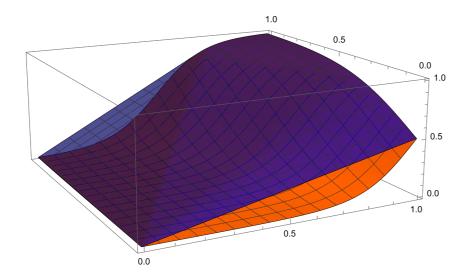


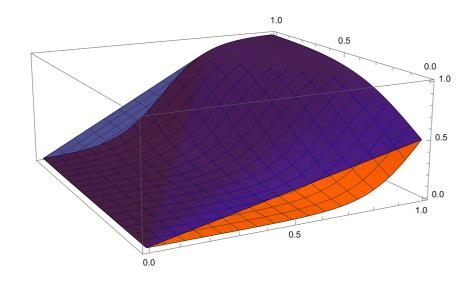
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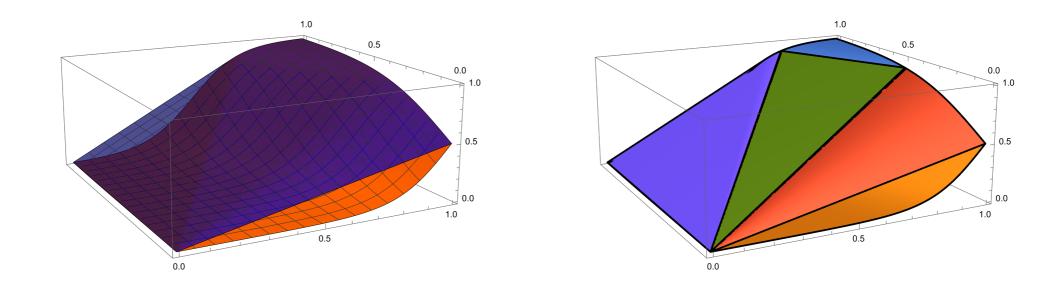
Taking perspective from the boundary!





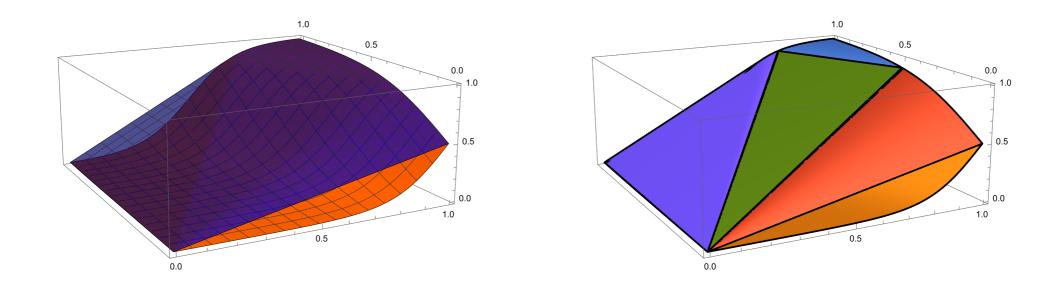
Theorem 1 Consider $w \in \mathbb{R}^n_+$, $b \in \mathbb{R}$ and let $f : [0,1]^n \to \mathbb{R}$ be a function of the form $f(x) = \sigma(w^\top x + b)$ where σ satisfies the STFE property. Then,

$$conc(f, [0, 1]^n)(x) = \begin{cases} f(x) & \text{if } x \in R_f \\ \sigma(b) + \frac{\sigma(\hat{z}) - \sigma(b)}{\hat{z} - b}(w^\top x) & \text{if } x \in R_l \\ \sigma(b) + x_i conc(f_{-i} - \sigma(b), [0, 1]^{n-1}) \left(\frac{x_{-i}}{x_i}\right) & \text{if } x \in R_i \end{cases}$$



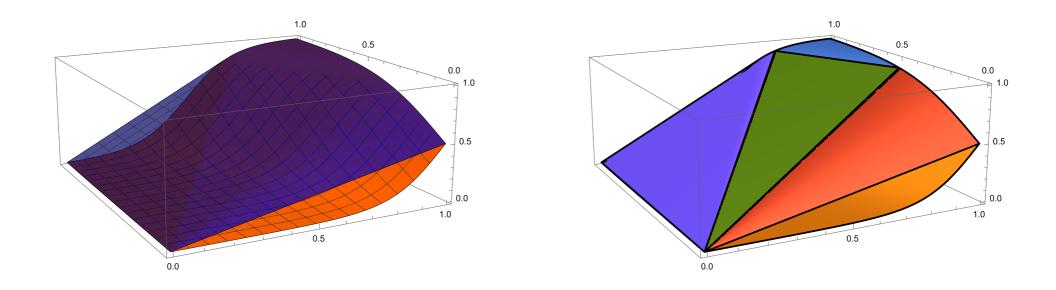
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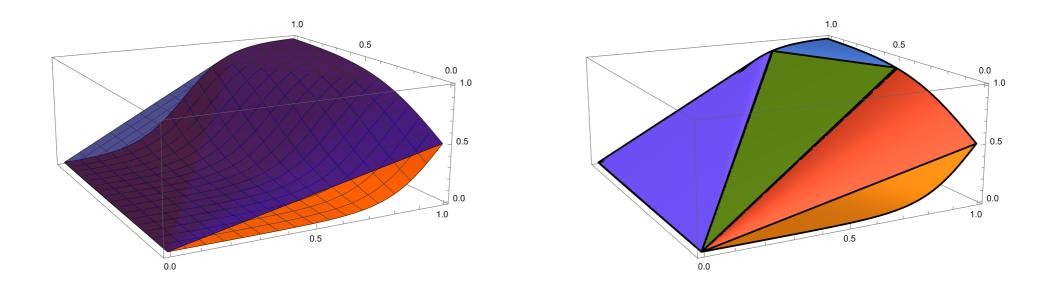
The envelope evaluation is either the joint f(x) = o(w + v) where o successives the STPD property. Then,

$$conc(f, [0, 1]^n)(x) = \begin{cases} f(x) & \text{if } x \in R_f \\ \sigma(b) + \frac{\sigma(\hat{z}) - \sigma(b)}{\hat{z} - b}(w^\top x) & \text{if } x \in R_l \\ \sigma(b) + x_i conc(f_{-i} - \sigma(b), [0, 1]^{n-1}) \left(\frac{x_{-i}}{x_i}\right) & \text{if } x \in R_i \end{cases}$$



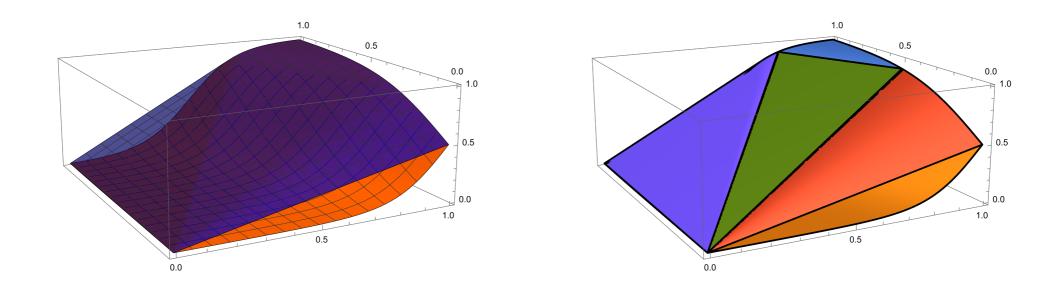
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 where $f(x) = f(x)$ are strictly property. Then,

$$conc(f,[0,1]^n)(x) = \begin{cases} \frac{\text{The function itself}}{\sigma(b) + \frac{\sigma(z) - \sigma(b)}{\hat{z} - b}}(w^\top x) & \text{if } x \in R_l \\ \sigma(b) + x_i conc(f_{-i} - \sigma(b),[0,1]^{n-1}) \left(\frac{x_{-i}}{x_i}\right) & \text{if } x \in R_i \end{cases}$$



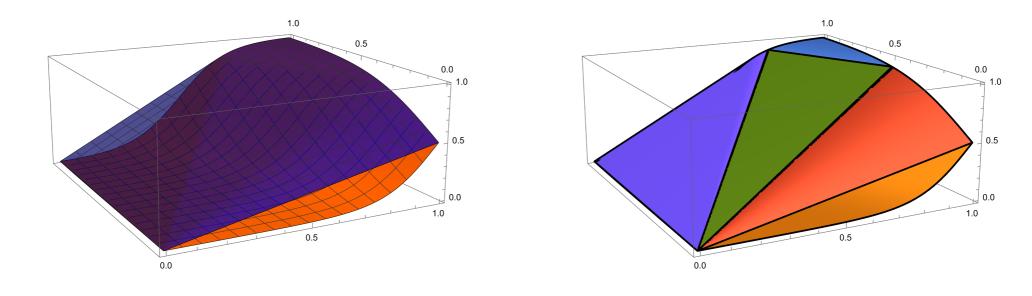
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$$conc(f,[0,1]^n)(x) = \begin{cases} \frac{\text{The function itself}}{\text{A linear function}} & f(a) = f(b) \\ \sigma(b) + x_i conc(f_{-i} - \sigma(b),[0,1]^{n-1}) \left(\frac{x_{-i}}{x_i}\right) & \text{if } x \in R_i \end{cases}$$





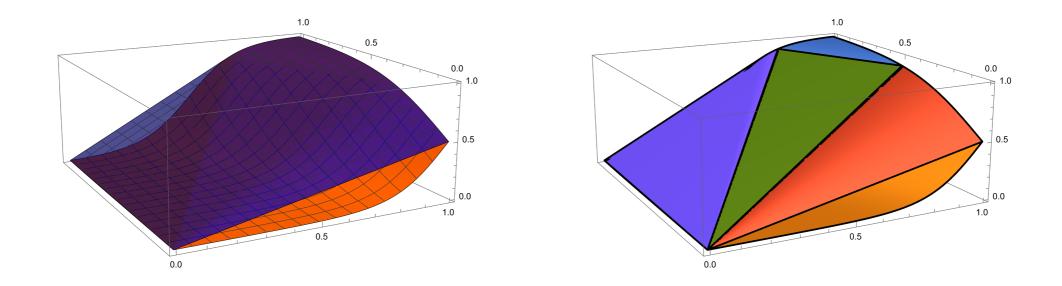
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 The perspective of an envelope of 1 dimension less i



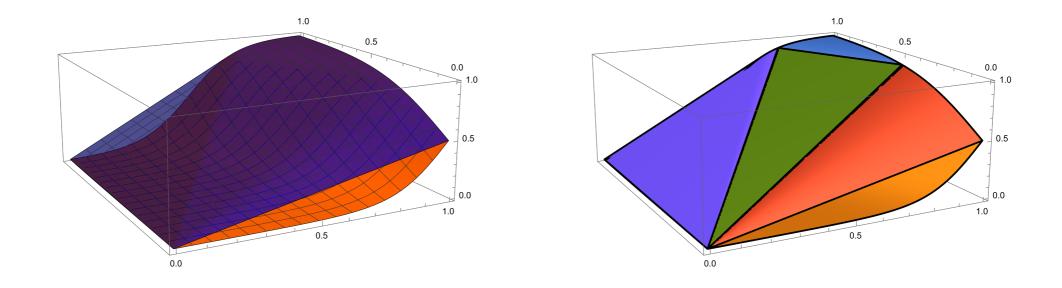


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 The perspective of an envelope of 1 dimension less i

This works for any convex or S-shaped activation function on a box, can construct supporting hyperplanes of the convex hull of the graph, and requires at most n 1-dimensional convexifications

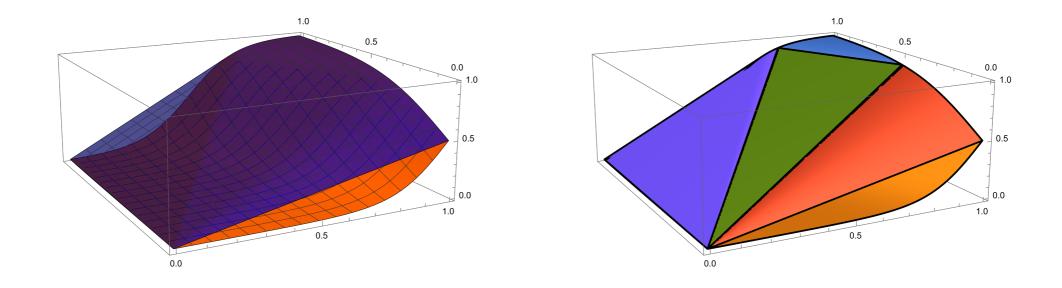


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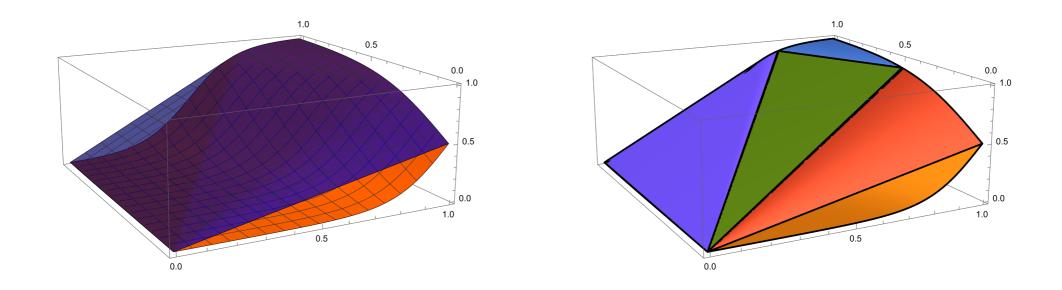
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On the faces, the global structure repeats itself

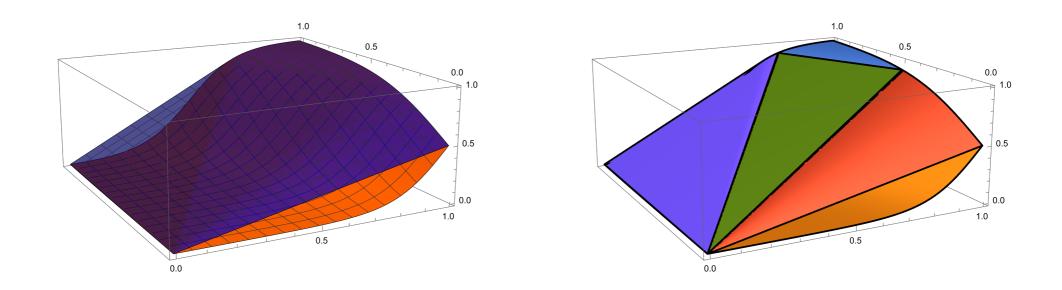


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Thank you!