

# Approximating Tame functions (NNs) by piecewise polynomials: Theoretical bound & Numerical results

## Piecewise Polynomial Regression of Tame Functions via Integer Programming

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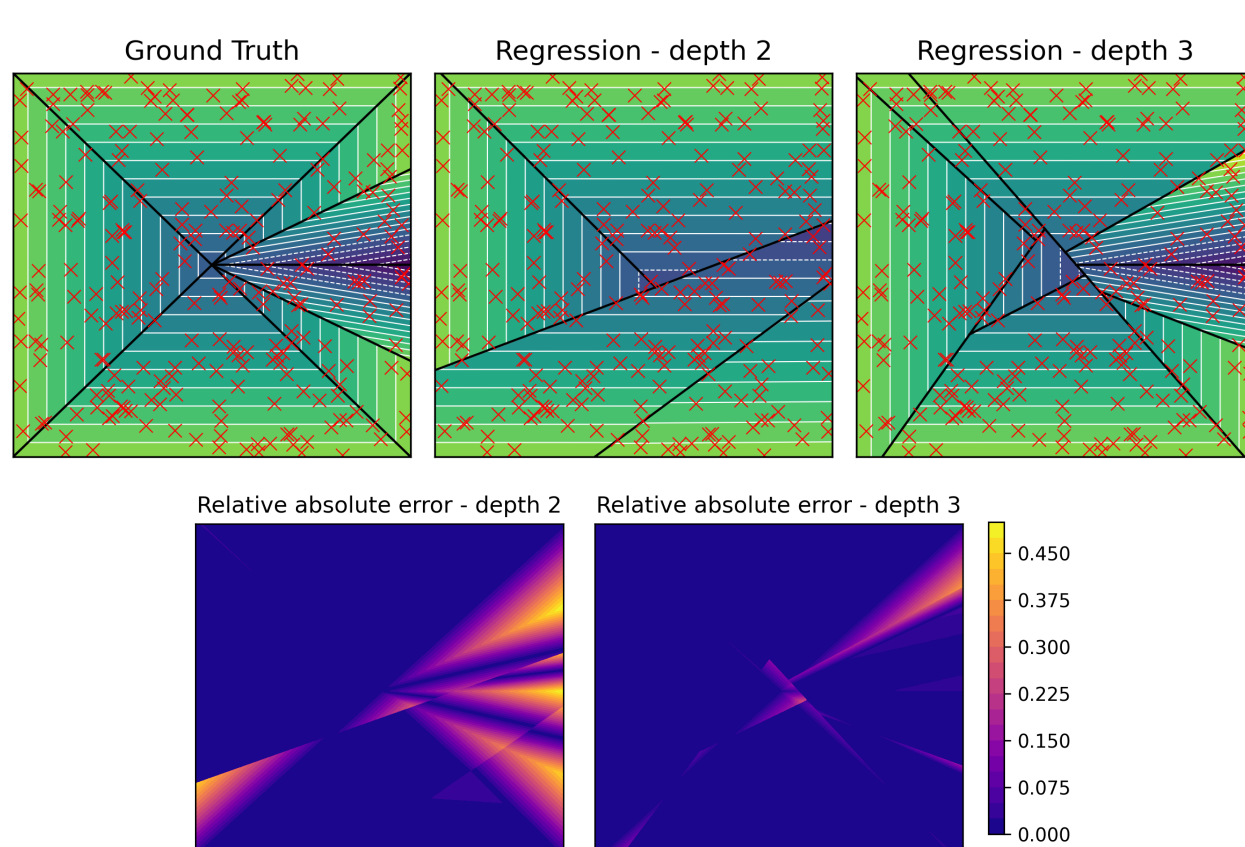
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### Tame Functions

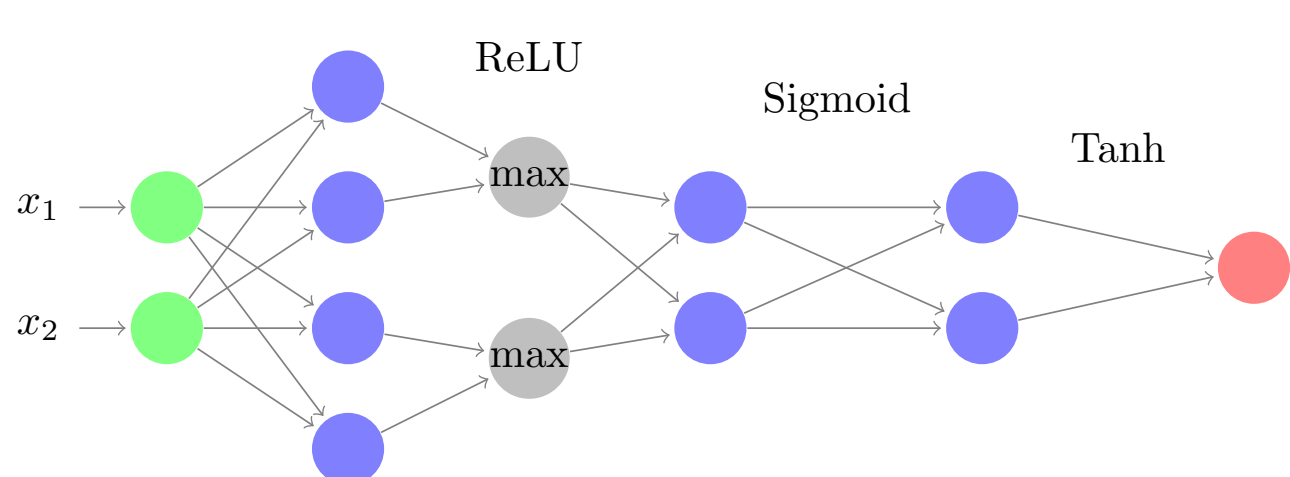
Tame functions are a general class of nonsmooth and nonconvex functions. They appear in a broad range of useful and difficult applications, such as:

- common deep learning architectures [8, 6],
- empirical risk minimization frameworks [9],
- in mixed-integer optimization, with the value function and the solution to the so-called subadditive dual [2],
- in quantum information theory, with approximations of the matrix exponential for a k-local Hamiltonian [7, 1],
- and in quantum chemistry, with functions describing the electronic structure of molecules.

An example tame function ("cone") with seven strata (left) and its approximation and error



A Neural Network example of a tame function:



### Approximation bound

When approximating a  $m$ -times continuously differentiable function  $f$ , the best degree  $N$  polynomial incurs an  $\mathcal{O}(1/N^m)$  error [3].

For nonsmooth functions, the rate is notably worse. For example, approximating the absolute value over the interval  $[-1, 1]$  incurs exactly the slow rate  $1/N$  [4]:

$$\inf_{p \in \mathcal{P}_N} \|\cdot - p\|_{\infty, [-1, 1]} = \frac{\beta}{N} + o\left(\frac{1}{N}\right).$$

Thus, to approximate **Tame functions**, polynomials are not efficient. Denote  $\tilde{\mathcal{P}}_N^l(A)$  a set of piecewise polynomials on  $A$ , such that

1. each piece is a polyhedron defined as the intersection of  $l$  halfspaces, represented as a leaf of a complete binary tree of depth  $l$ ,
2. the restriction of the function to each piece is a polynomial of degree at most  $N$ .

**Theorem 1.** Consider a function  $f : A \rightarrow \mathbb{R}$ , a qualified (Asm. 1 in the paper)  $\mathcal{C}^m$ -stratification of  $f$  for some  $m \geq 2$  such that:

- $f$  is a **tame** function,
- $A$  is a connected compact subset of  $[0, 1]^n$ ,
- $f$  is continuous over  $A$ .

Then  $f$  can be approximated by **piecewise polynomial functions**:

$$\inf_{p \in \tilde{\mathcal{P}}_N^l(A)} \|f - p\|_{\infty, A} \leq C_1 N^{-m} + C_2 l^{-\frac{2}{n-1}}.$$

where  $C_1 = c_1(n, m, A, f)$  and  $C_2 = c_2(n, m, f)$ .

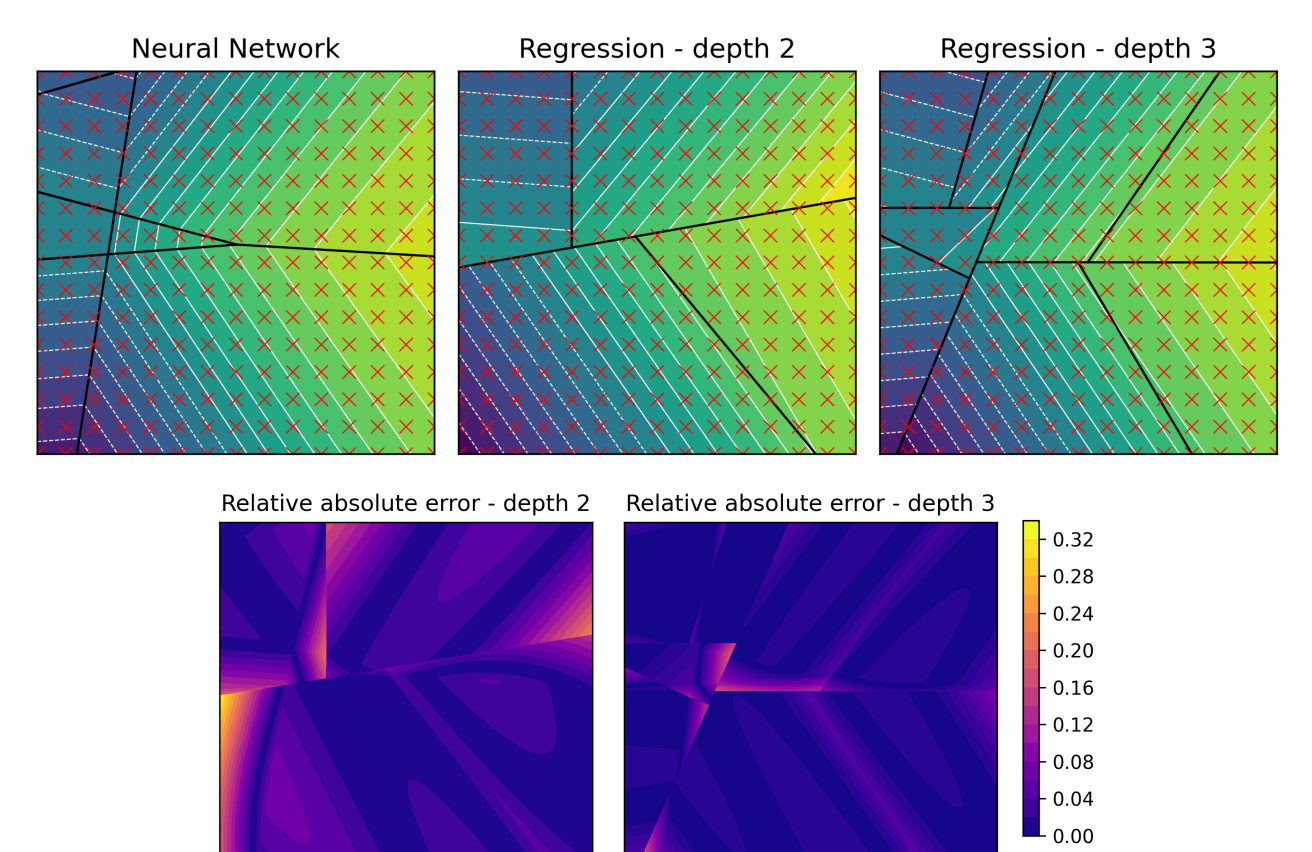
### Stratification

We say that  $f$  admits a definable  $\mathcal{C}^m$ -stratification if there exists a finite partition of  $\mathbb{R}^n$  such that

- each stratum is a definable connected  $\mathcal{C}^m$ -manifold,
- $f$  is  $\mathcal{C}^m$ -smooth on each stratum,
- any two strata  $\mathcal{M}$  and  $\mathcal{M}'$  satisfy the frontier condition:  $\mathcal{M} \cap \text{cl } \mathcal{M}' \neq \emptyset \Rightarrow \mathcal{M} \subset \text{cl } \mathcal{M}'$ .

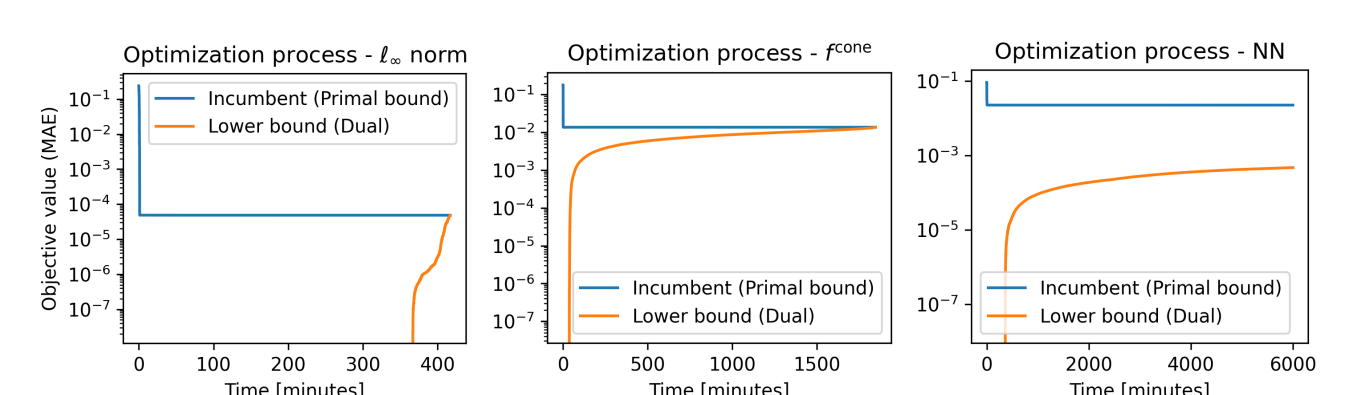
### Mixed-Integer Formulation

We slightly modify the affine-hyperplane tree Mixed-Integer Linear formulation (OCT-H, [5]) to separate the input space into  $2^l$  polyhedral regions and fit a polynomial to each region.



### Solving process

The primal objective value converges quickly; most of the computation time is spent on improving lower bound.



### References

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