

Neural Power Units

Arithmetic extrapolation with fractional powers

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<https://github.com/nmheim/NeuralArithmetic.jl>

Arithmetic extrapolation

→ Neural Networks are great at **interpolation**, but they poorly **extrapolate**.

→ Neural arithmetic assumes that the problem is composed of arithmetic operations.

Examples

Function approximation

$$f(x, y) = (x + y, xy, \frac{x}{y}, \sqrt{x})^T$$

Differential equations in physical / financial modelling

$$\begin{bmatrix} \dot{S} \\ \dot{I} \\ \dot{R} \end{bmatrix} = \begin{bmatrix} -\beta & 0 & \eta \\ \beta & -\alpha & 0 \\ 0 & \alpha & \eta \end{bmatrix} \begin{bmatrix} I^\gamma S^\kappa \\ I \\ R \end{bmatrix}$$

Definition: Neural Arithmetic Logic Unit (NALU)

$$\text{Addition: } \mathbf{a} = \hat{\mathbf{W}}\mathbf{x} \qquad \hat{\mathbf{W}} = \tanh(\mathbf{W}) \odot \sigma(\mathbf{M})$$

$$\text{Multiplication: } \mathbf{m} = \exp(\hat{\mathbf{W}} \log(|\mathbf{x}| + \epsilon))$$

$$\text{Output: } \mathbf{y} = \mathbf{a} \odot \mathbf{g} + \mathbf{m} \odot (1 - \mathbf{g}) \quad \mathbf{g} = \sigma(\mathbf{G}\mathbf{x})$$

NALU has **constrained weights**, and is gating between an **addition** (+) and **multiplication/division** (\times, \div) path.

Inconsistent convergence, negative numbers not handled correctly.

Definition: Neural Multiplication & Addition Units

$$\text{NMU: } y_j = \prod_i \hat{M}_{ij} x_i + 1 - \hat{M}_{ij} \quad \hat{M}_{ij} = \min(\max(M_{ij}, 0), 1) \quad (1)$$

$$\text{NAU: } \mathbf{y} = \hat{\mathbf{A}}\mathbf{x} \quad \hat{A}_{ij} = \min(\max(A_{ij}, -1), 1) \quad (2)$$

NMU & NAU have **constrained weights**, and are learning (+) and (\times) by **stacking**.

No division (\div).

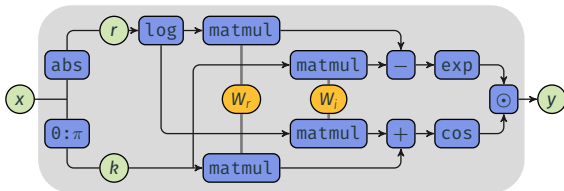
We improved NALU's multiplication path

$$m = \exp(W \log_{\text{real}}(|\mathbf{x}|))$$

by lifting it into **complex space** ($\log := \log_{\text{complex}}$)

$$\mathbf{z} = \text{Re}(\exp(W_{\mathbb{C}} \log \mathbf{x})) = \text{Re}(\exp((W_r + iW_i) \log \mathbf{x})).$$

Naive Neural Power Unit (NaiveNPU)

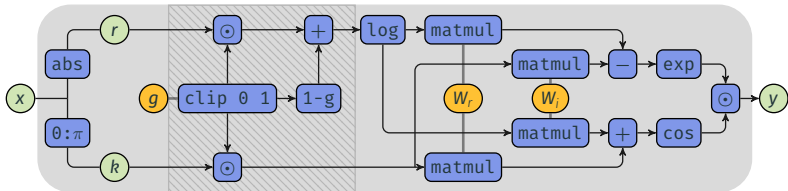


Definition: Naive Neural Power Unit

$$y = \exp(W_r \log r - \pi W_j k) \odot \cos(W_j \log r + \pi W_r k), \text{ where}$$

$$r = |\mathbf{x}| + \epsilon, \quad k_i = \begin{cases} 0 & x_i \geq 0 \\ 1 & x_i < 0 \end{cases},$$

Neural Power Unit (NPU) & Relevance Gate



Definition: Neural Power Unit

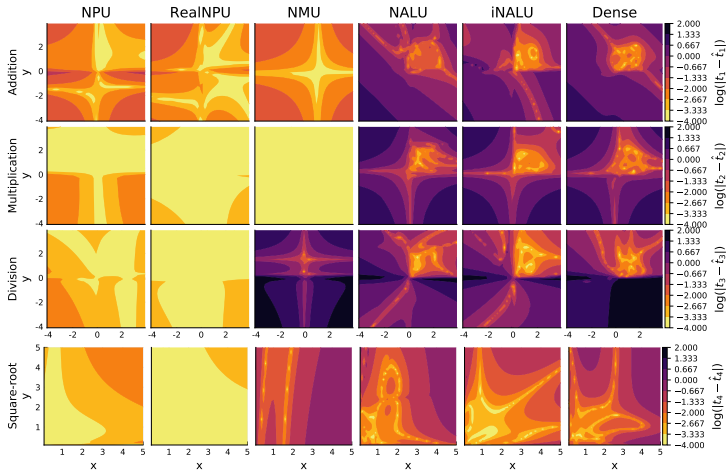
$y = \exp(W_r \log \hat{r} - \pi W_i \hat{k}) \odot \cos(W_i \log \hat{r} + \pi W_r \hat{k})$, where

$$\hat{r} = \hat{g} \odot (|x| + \epsilon) + (1 - \hat{g}),$$

$$k_i = \begin{cases} 0 & x_i \geq 0 \\ \hat{g}_i & x_i < 0 \end{cases}, \quad \hat{g}_i = \min(\max(g_i, 0), 1),$$

Learning Simple Arithmetic

$$f(x, y) = (x + y, xy, \frac{x}{y}, \sqrt{x})^T$$

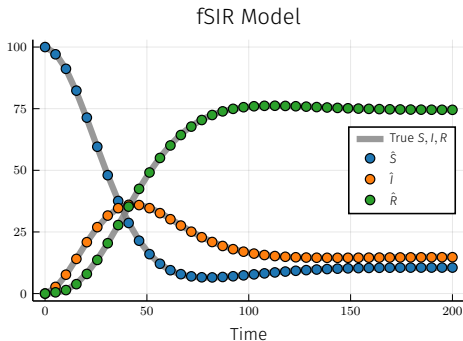


RealNPU denotes the NPU with $W_i = 0$.

Towards Equation Discovery

The fractional SIR model (fSIR, Taghvaei et al. [2020])

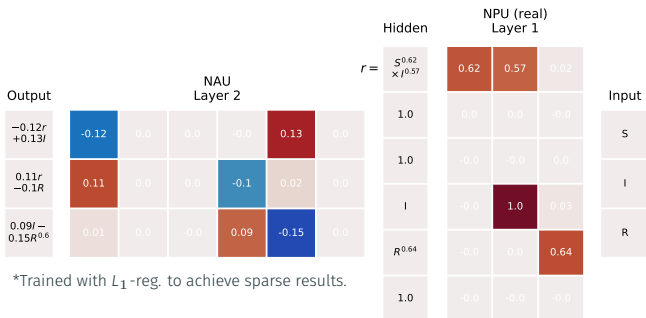
$$\begin{bmatrix} \dot{S} \\ \dot{I} \\ \dot{R} \end{bmatrix} = \begin{bmatrix} -\beta & 0 & \eta \\ \beta & -\alpha & 0 \\ 0 & \alpha & \eta \end{bmatrix} \begin{bmatrix} I^\gamma S^\kappa \\ I \\ R \end{bmatrix}, \quad \begin{aligned} \alpha &= 0.05 \\ \beta &= 0.05 \\ \eta &= 0.01 \\ \gamma &= \kappa = 0.5 \end{aligned}$$



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