Bridging Neural ODE and ResNet: A Formal Error Bound for Safety Verification

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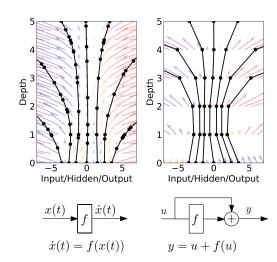


SAIV 2025

Motivations

Relations

- Continuous-depth generalization of ResNet
- Euler-discretization of neural ODE

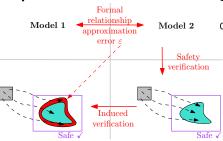


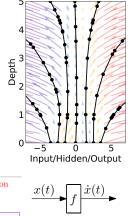
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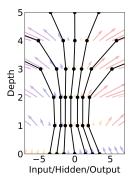
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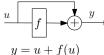
Proposed Framework











Problem Definition

- \mathcal{X}_{in} : input set
- neural ODE reachable set:

$$\mathcal{R}_{\mathsf{neural\ ODE}}(\mathcal{X}_{in}) = \{ y \in \mathbb{R}^n \mid y = \Phi(1, u) \ u \in \mathcal{X}_{in} \}$$

ResNet reachable set:

$$\mathcal{R}_{\mathsf{ResNet}}(\mathcal{X}_{in}) = \{ y \in \mathbb{R}^n \mid y = u + f(u) \ u \in \mathcal{X}_{in} \}$$

• Problem 1 (Error Bounding):

$$\mathcal{R}_{\varepsilon}(\mathcal{X}_{in}) = \{ \Phi(1, u) - (u + f(u)) \mid u \in \mathcal{X}_{in} \}$$

Proposed Approach

• Lagrange remainder:

$$x(t) = x(0) + t \frac{dx(0)}{dt} + \frac{t^2}{2!} \frac{d^2x(t^*)}{dt^2}$$
, for unkown $t^* \in [0, t]$

Numerical Example

Proposed Approach

Lagrange remainder:

$$x(1) = x(0) + \frac{dx(0)}{dt} + \frac{1}{2} \frac{d^2x(t^*)}{dt^2}$$
, for unkown $t^* \in [0, 1]$

• neural ODE based on ResNet:

$$\Phi(1, u) = (u + f(u)) + \varepsilon(u)$$

• Where ε :

$$\varepsilon(u) = \frac{1}{2}f'(x(t^*))f(x(t^*))$$

Proposed Approach

Lagrange remainder:

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• neural ODE based on ResNet:

$$\Phi(1, u) = (\underline{u} + f(u)) + \varepsilon(\underline{u})$$

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ResNet based on neural ODE:

$$\frac{\mathbf{u}}{\mathbf{u}} + f(\mathbf{u}) = \Phi(1, \mathbf{u}) - \varepsilon(\mathbf{u})$$

Numerical Example

Fixed-Point Attractor System

- 5 dimensional neural ODE
- $\dot{x} = f(x) = \tau x + W \tanh(x)$, where:
 - $\to \tau = -10^{-6}$
 - $\rightarrow W$ is a 5×5 matrix
 - $\rightarrow tanh$: hyperbolic tangent AF

Verification Proxy

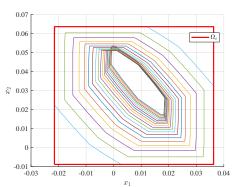
Bounding Ω_{ε}

neural ODE reachable tube:

$$\mathcal{R}_{\mathsf{neural\ ODE}}^{\mathsf{tube}}(\mathcal{X}_{in}) = \{ \Phi(t, u) \in \mathbb{R}^n \mid t \in [0, 1], \ u \in \mathcal{X}_{in} \}$$

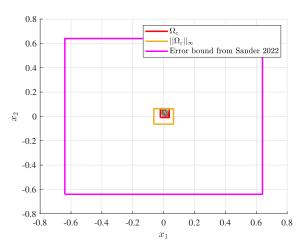
Bound the error term:

$$\varepsilon(u) = \frac{1}{2}f'(\Phi(t^*, u))f(\Phi(t^*, u))$$



Error Bound Comparison

• $\Omega_{\epsilon} < 16$ million times×Sander 2022



Verification Proxy

- \mathcal{X}_s : safe set
- Problem 2 (Safety Specification):

$$\mathcal{R}(\mathcal{X}_{in}) \subseteq \mathcal{X}_s$$

neural ODE based on ResNet:

$$\mathcal{R}_{\mathsf{neural\ ODE}}(\mathcal{X}_{in}) \subseteq \Omega_{\mathsf{ResNet}}(\mathcal{X}_{in}) + \Omega_{\varepsilon}(\mathcal{X}_{in})$$

Verification Proxy

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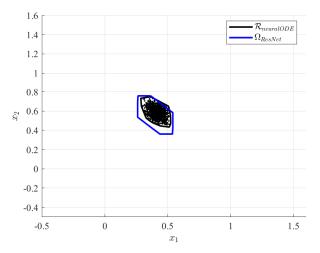
$$\mathcal{R}_{\mathsf{neural\ ODE}}(\mathcal{X}_{in}) \subseteq \Omega_{\mathsf{ResNet}}(\mathcal{X}_{in}) + \Omega_{\varepsilon}(\mathcal{X}_{in})$$

• ResNet based on neural ODE:

$$\mathcal{R}_{\mathsf{ResNet}}(\mathcal{X}_{in}) \subseteq \Omega_{\mathsf{neural ODE}}(\mathcal{X}_{in}) + \Omega_{-\varepsilon}(\mathcal{X}_{in})$$

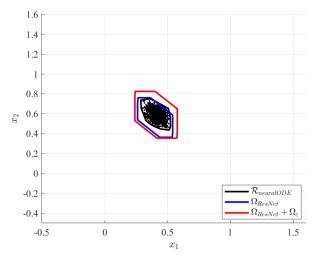
Verification of neural ODE based on ResNet

• $\mathcal{X}_s \supseteq \Omega_{\mathsf{ResNet}}(\mathcal{X}_{in}) + \Omega_{\varepsilon}(\mathcal{X}_{in}) \supseteq \mathcal{R}_{\mathsf{neural ODE}}$



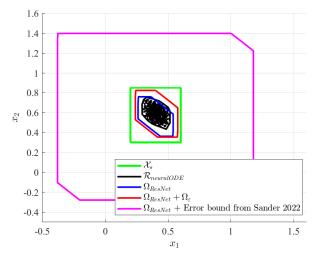
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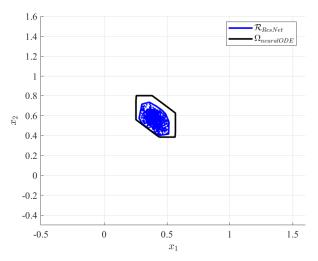
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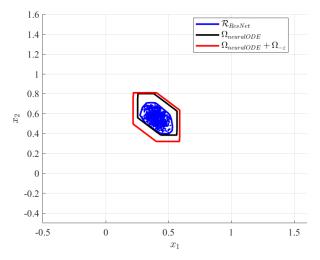
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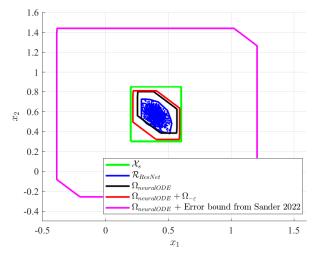
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Motivations Error Bounding Verification Proxy **Numerical Example**

Conclusions

Set-based method bounding neural ODE and ResNet approximation

- Tighter over-approximation than SOTA
- Use reachability/verification tools on one model to verify the other

Future Work

- Explore additional complexity sources
 - Handle non-smooth activation functions (e.g., ReLU)
- Study versatility of verification proxy approach
 - Apply to complex nonlinear dynamical systems
 - Extend to other neural network architectures (e.g., RNN or CNN)

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