

MpBP: Verifying Robustness of Neural Networks with Multi-path Bound Propagation

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Neural Network Verification

- Verifies whether a **region input** results in unsafe outputs
- Difficulty: the composition of non-linear activations (e.g. ReLU)

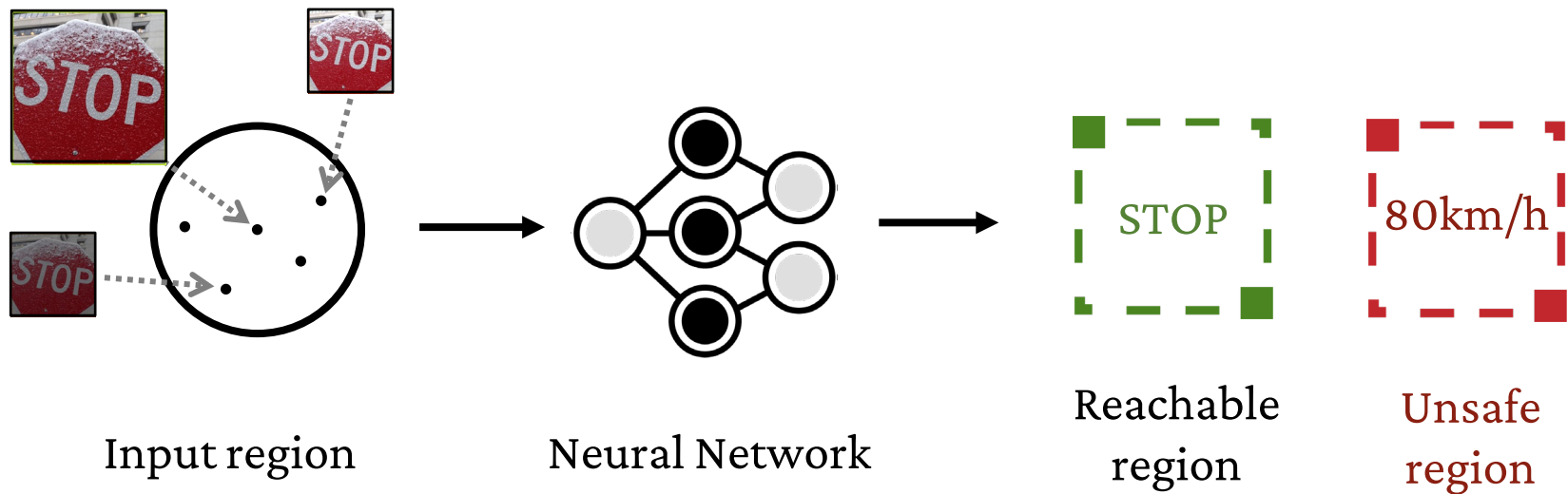
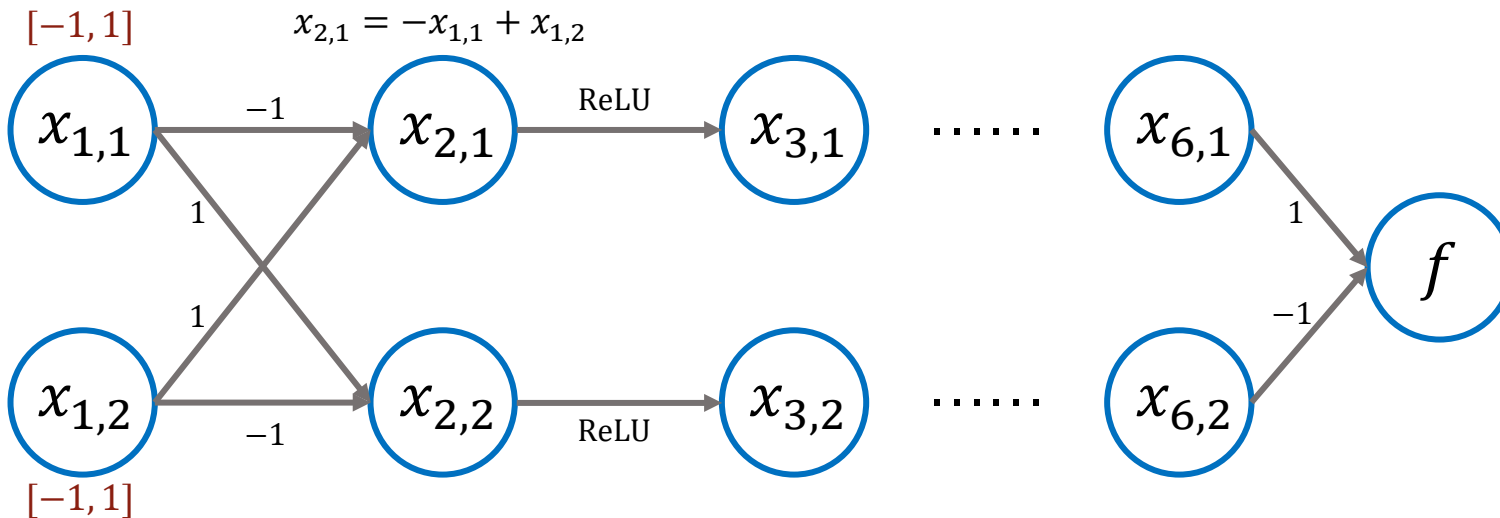


Image source: <https://www.businessinsider.com/why-are-stop-signs-red>

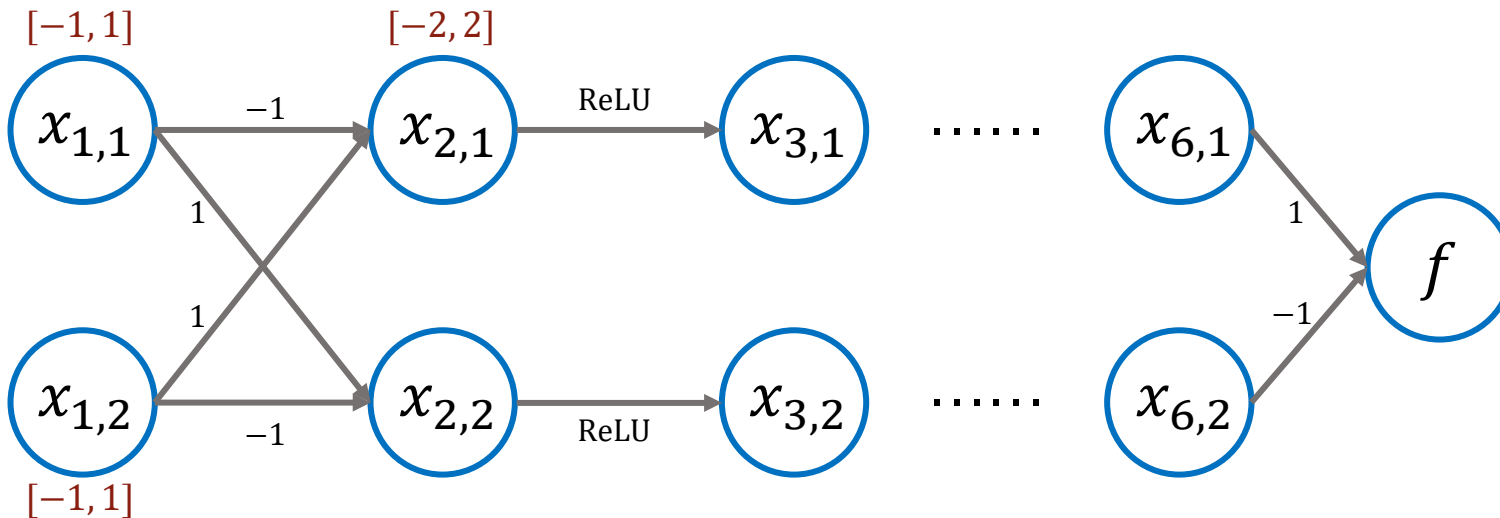
Bound Propagation

- Propagates **bound functions** along the neural network
- Widely-used because of its efficiency



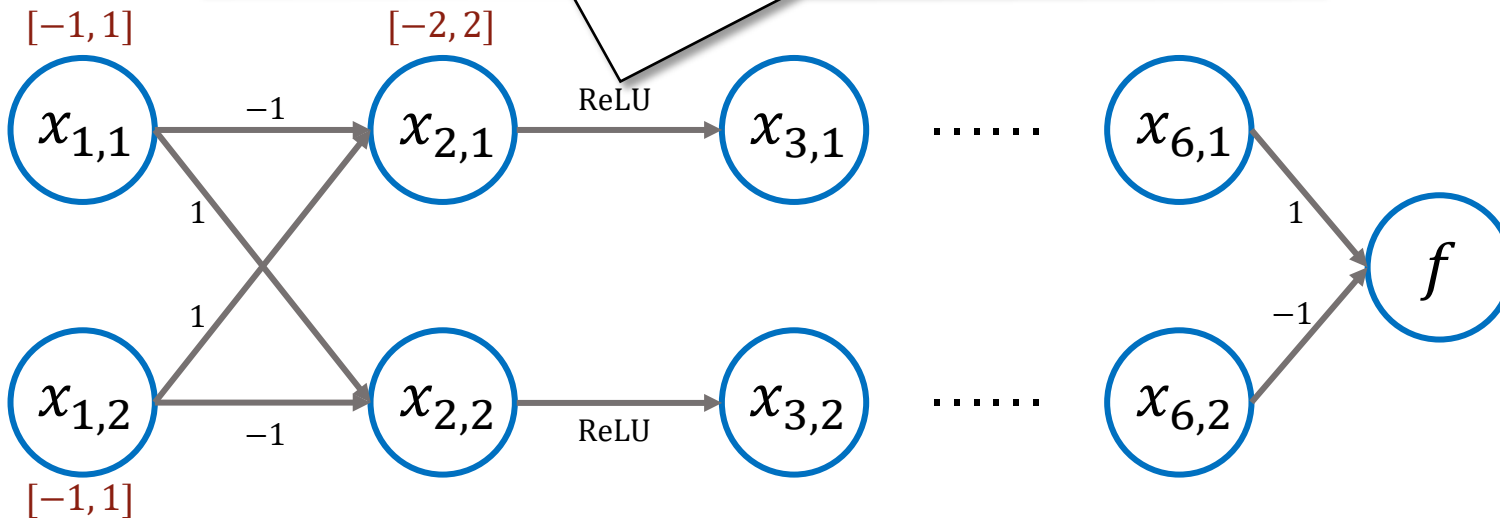
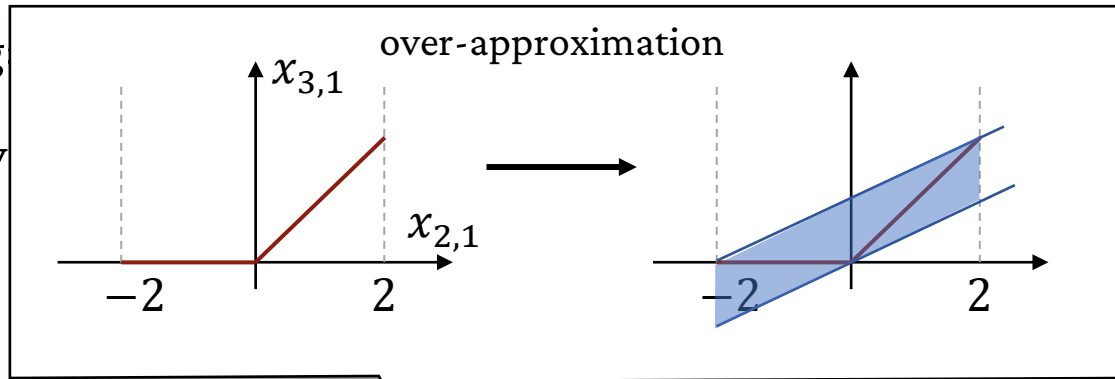
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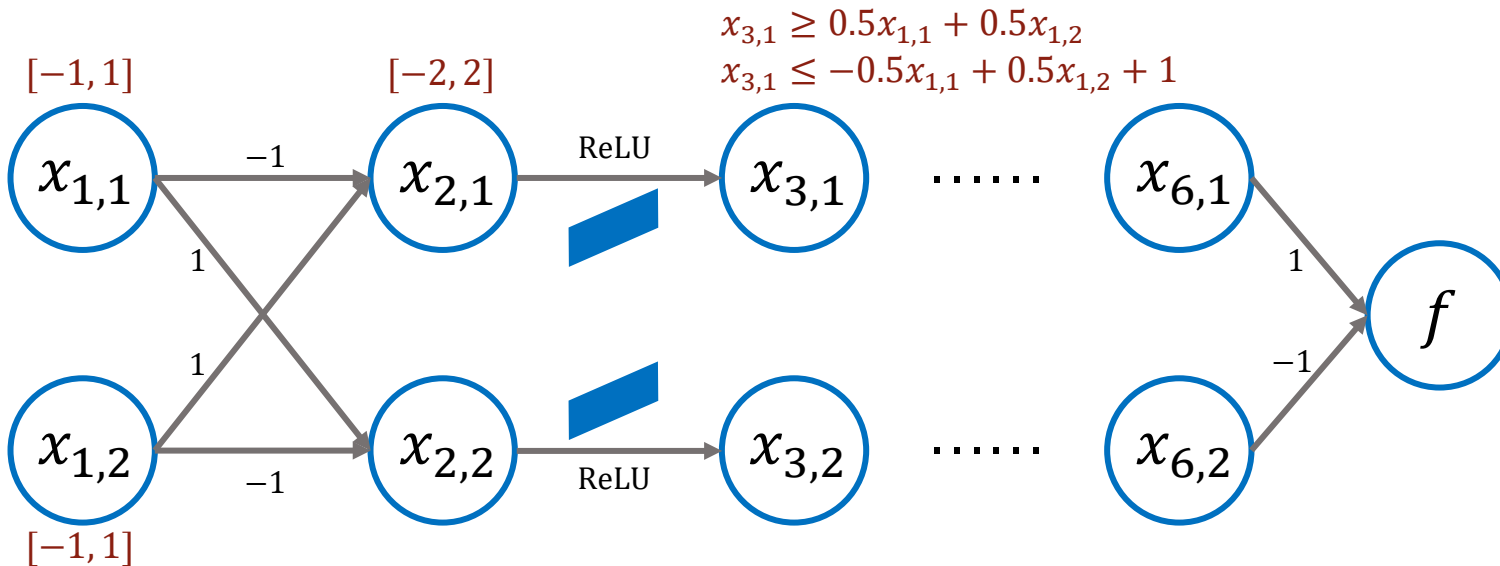
Bound Propagation

- Propag
- Widely



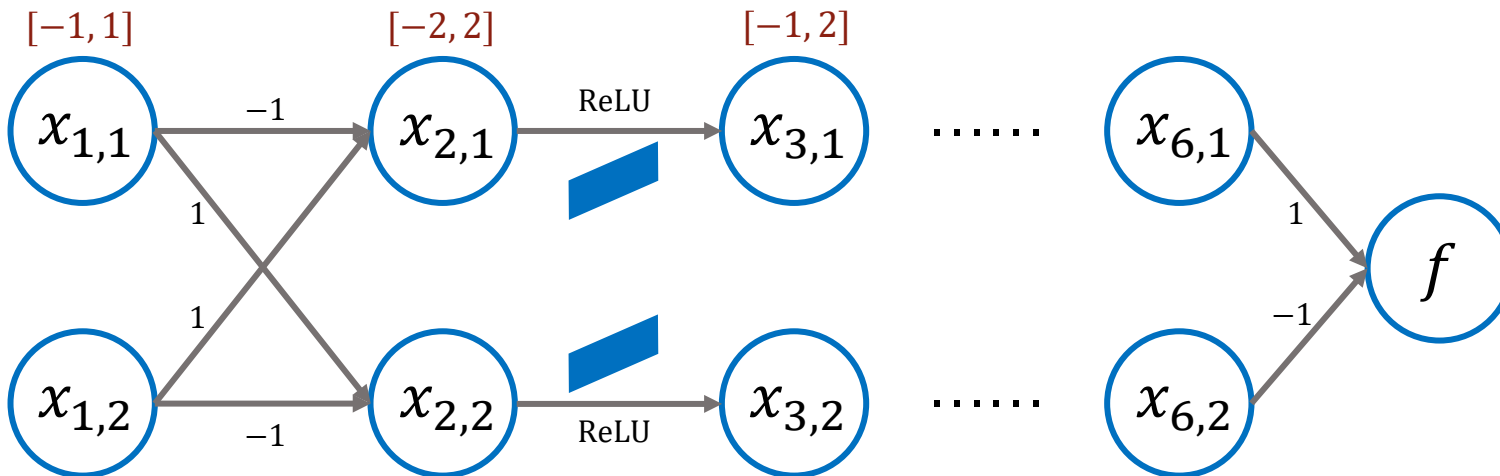
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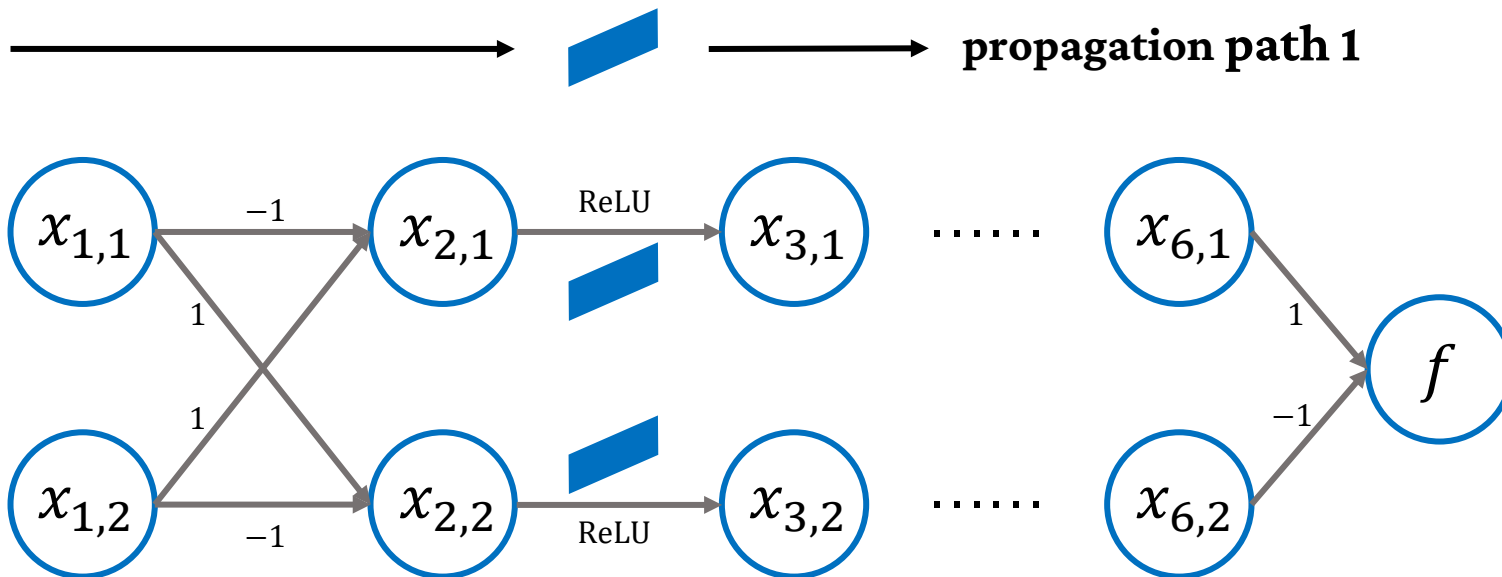


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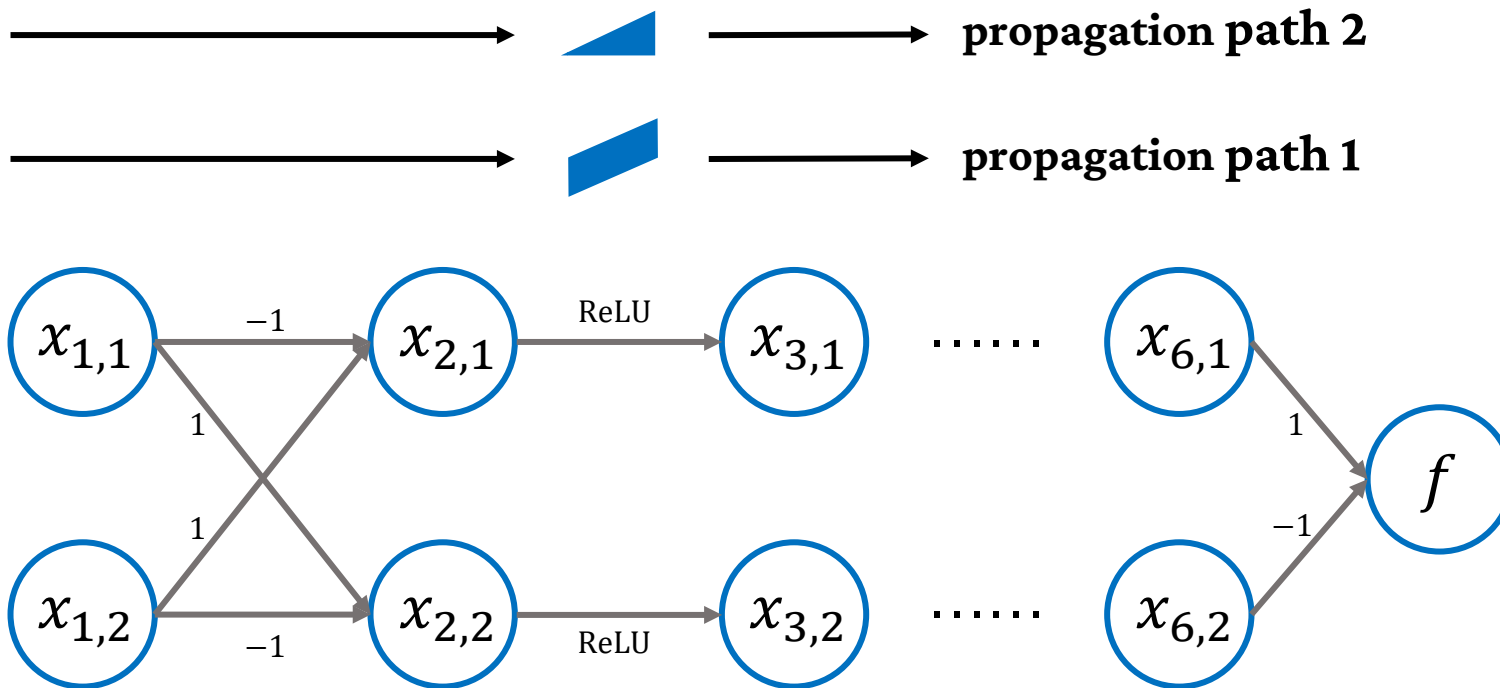
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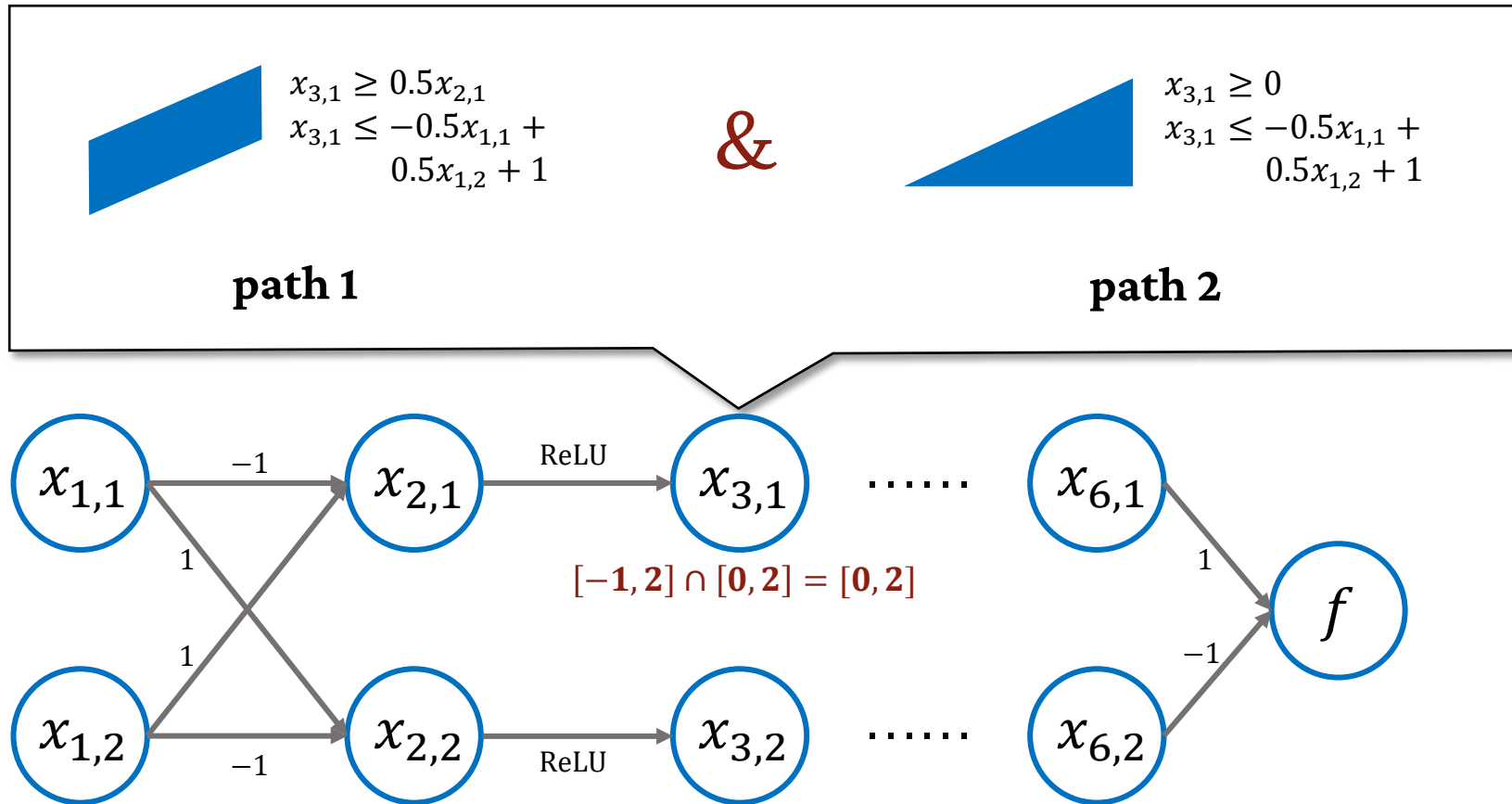
Our: Bound Propagation Path



Our: Two-path Bound Propagation



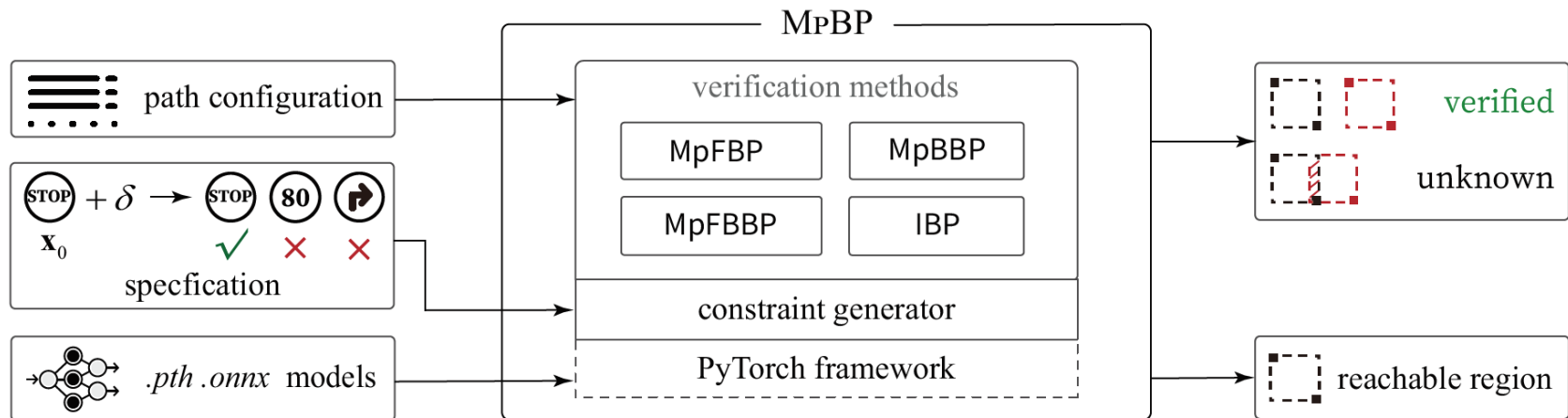
Our: Two-path Bound Propagation



- Extends bound propagation methods to their **multi-path** counterparts
 - Multi-path backward bound propagation (MpBBP)*
 - Multi-path forward (MpFBP), MpFBBP, etc.
- Uses the PyTorch framework to **parallelize** BP along multiple paths
 - Reduces the time cost to the level of classical BP on GPUs

This Paper

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Multi-path Back-propagation for Neural Network Verification (in Chinese). Ye ZHENG, Xiaomu SHI, Jiexiang LIU.

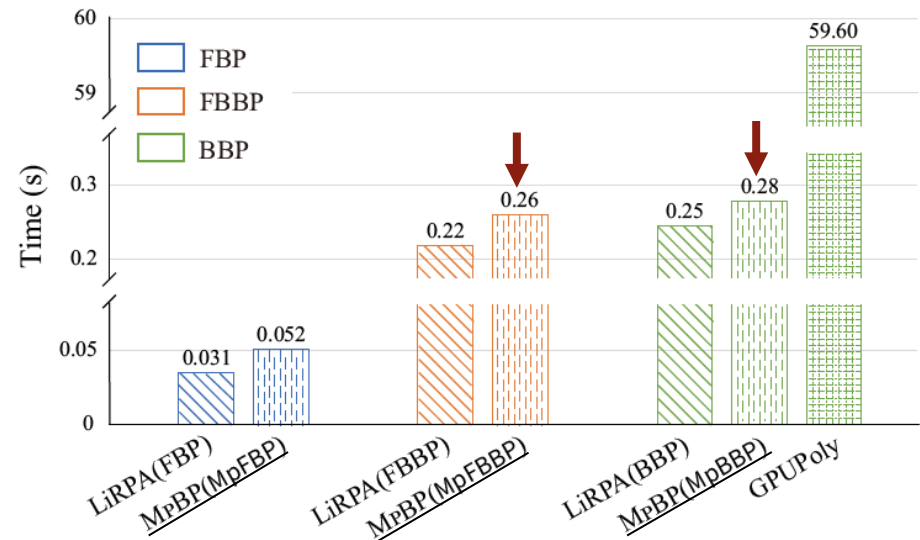
Experiments – vs. the SOTA

- Comparison w.r.t. effectiveness and efficiency

Table 1: Effectiveness Evaluation: Numbers of verified problems are shown. Larger number means more effective.

Tools		Models and Perturbation Thresholds δ			
		MNIST FFNN			
		0.0014	0.0018	0.0022	0.0026
FBP \rightarrow	MpBP	73	62	51	40
	LiRPA	69	59	48	33
FBBP \rightarrow	MpBP	86	78	69	58
	LiRPA	83	77	66	56
		CIFAR-10 CNN		Tiny ImgNet CNN	
		0.0010	0.0014	0.0010	0.0014
BBP \rightarrow	MpBP	61	38	27	22
	LiRPA	56	36	25	19
	GPUPoly	56	36	-	-

Figure 3: Efficiency: Comparison of Verification Time



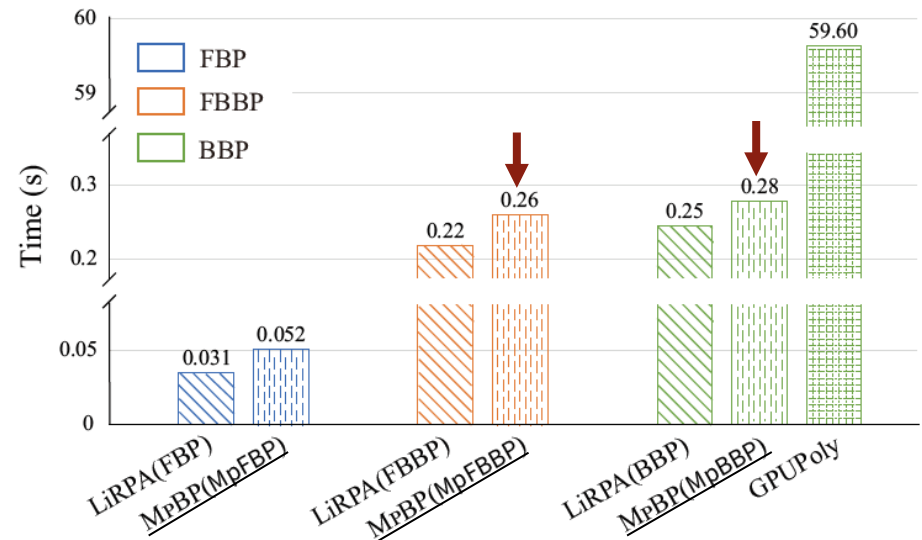
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Thank you!

