



Kandinsky - Abstract Interpretation, 1925

Abstract Interpretation

and Applications in Security,
Data Science, and Machine Learning

OPLSS 2025

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Static Analysis of Safety Properties

The Art of Losing Precision

No Surprises, Please

What Could
Possibly Go Right?

It's Complicated

Trace Properties

$$T \in \mathcal{P}(\Sigma^\infty)$$

Safety Properties = “Nothing Bad Ever Happens”

Example

- Any State Property $S \in \mathcal{P}(\Sigma)$: $T \stackrel{\text{def}}{=} S^\infty$

Safety Property Verification

- T can be **verified** by **exhaustive testing**



$$\mathcal{T}_p(I) \subseteq T$$

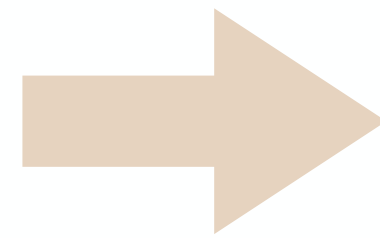
- T can be **falsified** by finding a **single finite execution not in T**

Machine Learning Safety

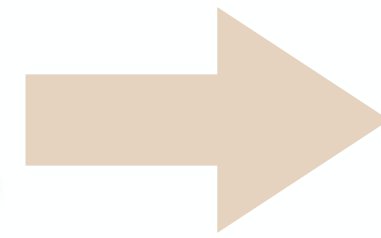
Machine Learning in High-Stakes Systems



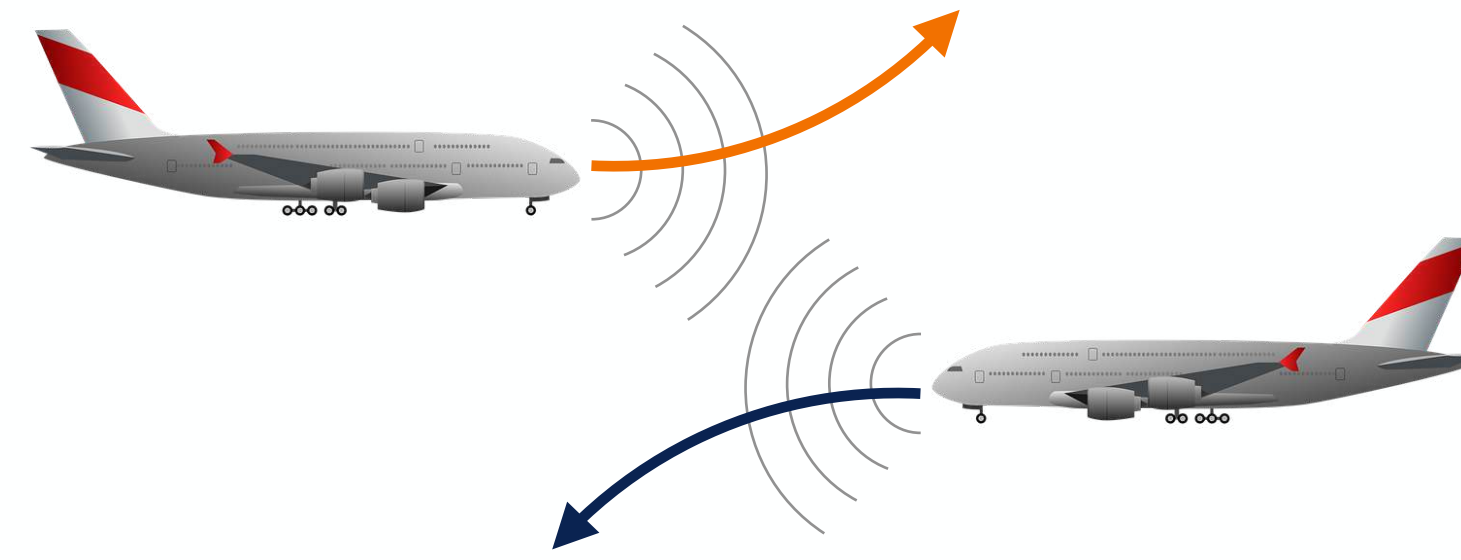
data



ML software



perform tasks that are impossible using explicit programming

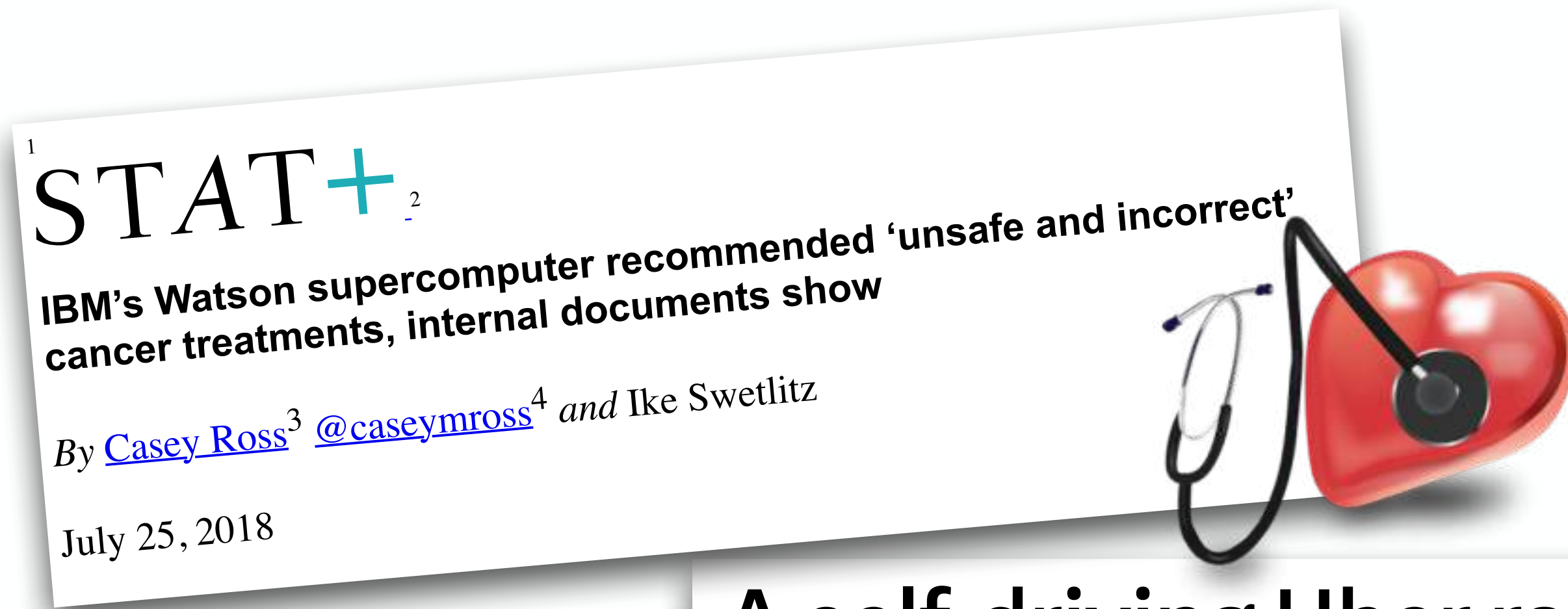


act as surrogate model



automate decision-making

Machine Learning in High-Stakes Systems

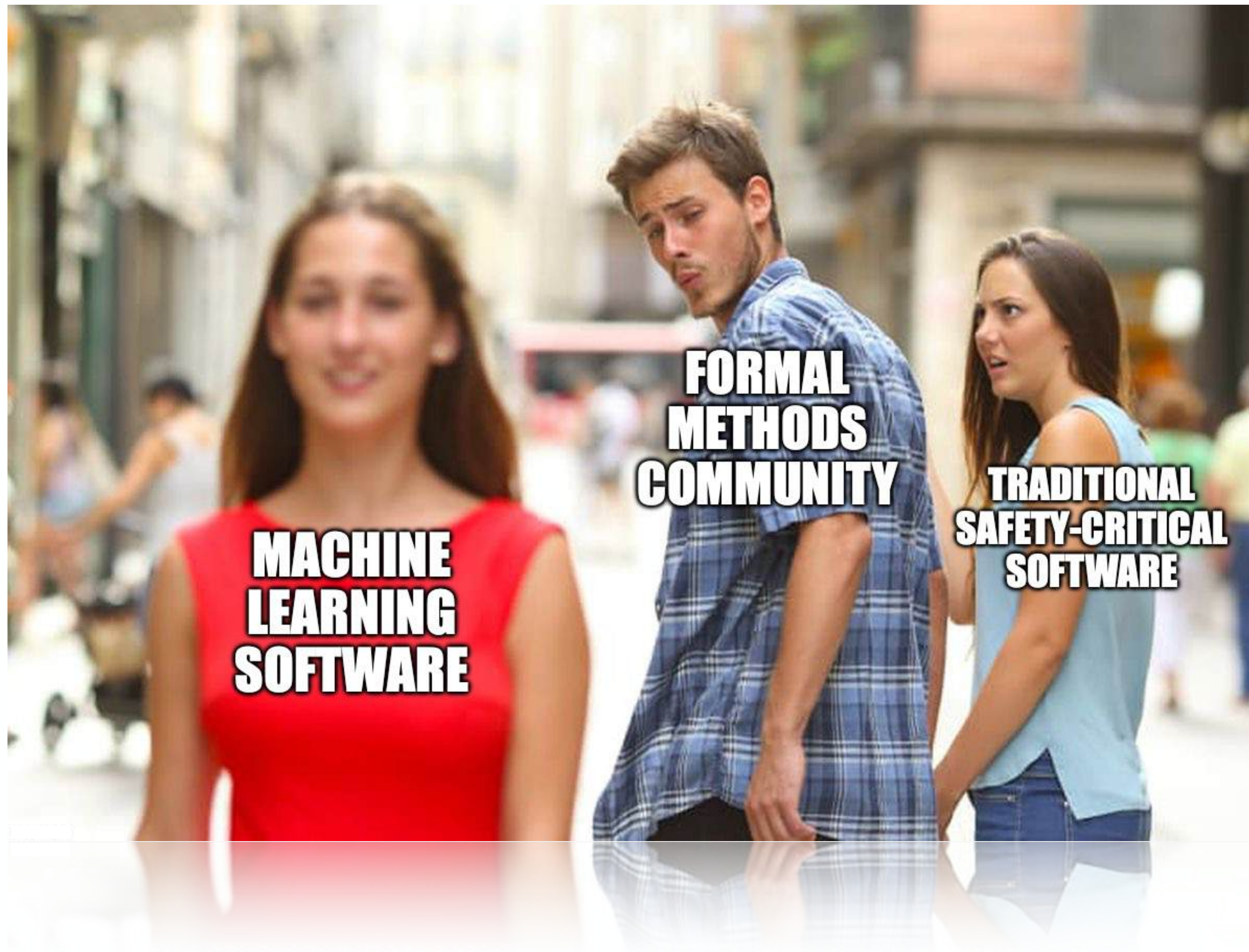


A self-driving Uber ran a red light last December, contrary to company claims

Feds Say Self-Driving Uber SUV Did Not Recognize Jaywalking Pedestrian In Fatal Crash

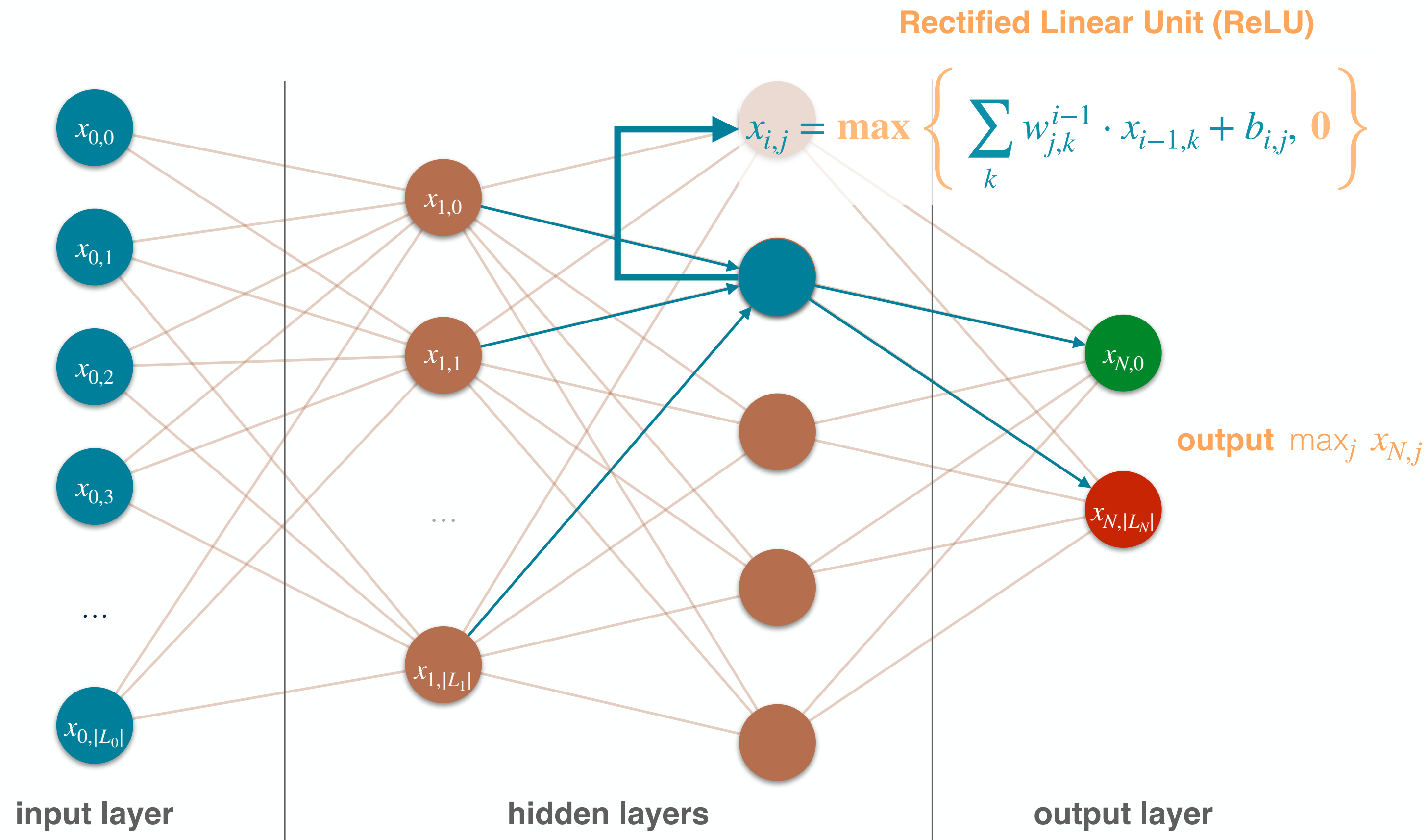
[Richard Gonzales](#) November 7, 2019 10:57 PM ET



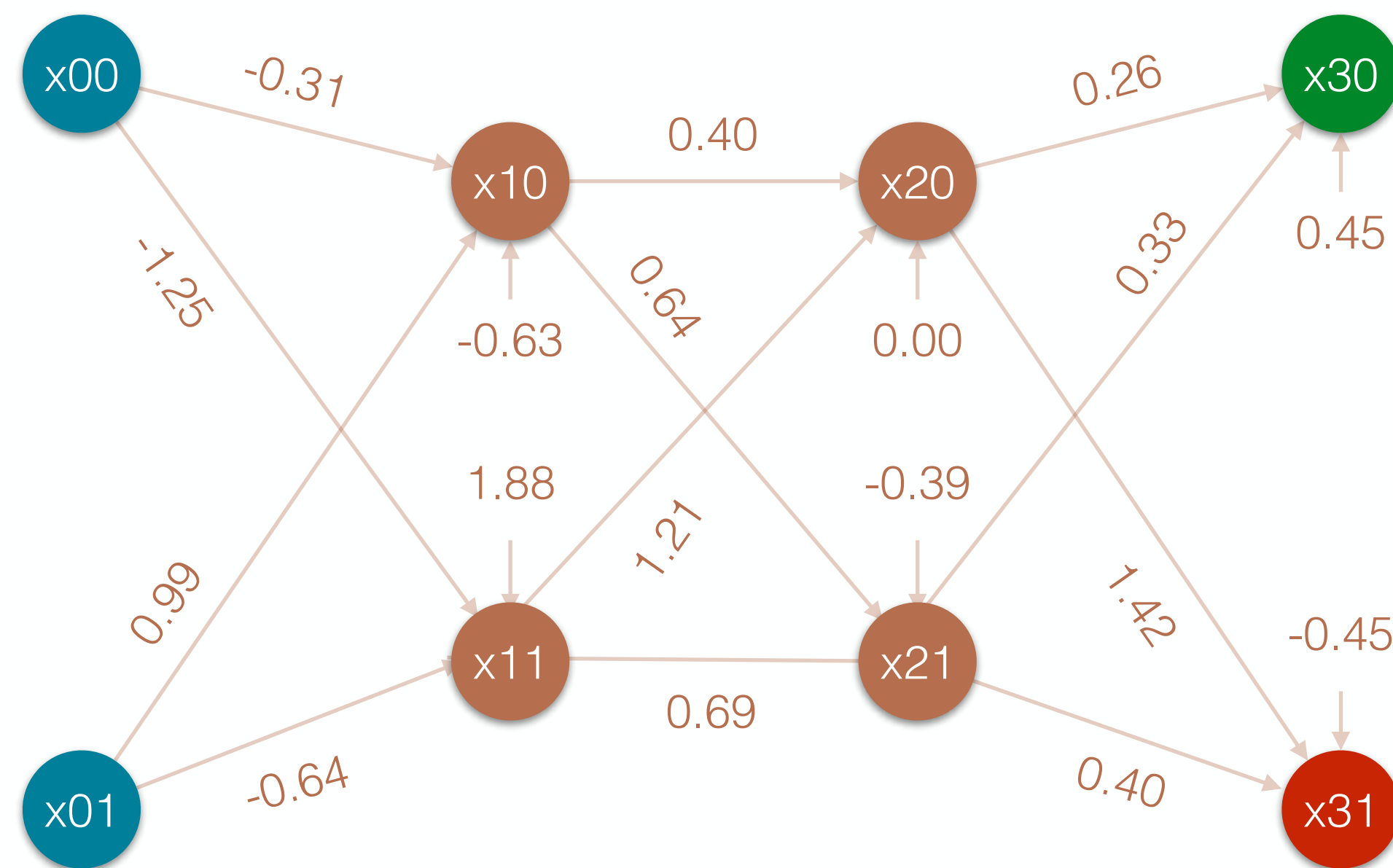


Neural Networks

Feed-Forward ReLU-Activated Neural Networks



Neural Networks as Programs



```
x00 = input()
x01 = input()
```

```
x10 = -0.31 * x00 + 0.99 * x01 + (-0.63)
x11 = -1.25 * x00 + (-0.64) * x01 + 1.88
```

```
x10 = 0 if x10 < 0 else x10
x11 = 0 if x11 < 0 else x11
```

```
x20 = 0.40 * x10 + 1.21 * x11 + 0.00
x21 = 0.64 * x10 + 0.69 * x11 + (-0.39)
```

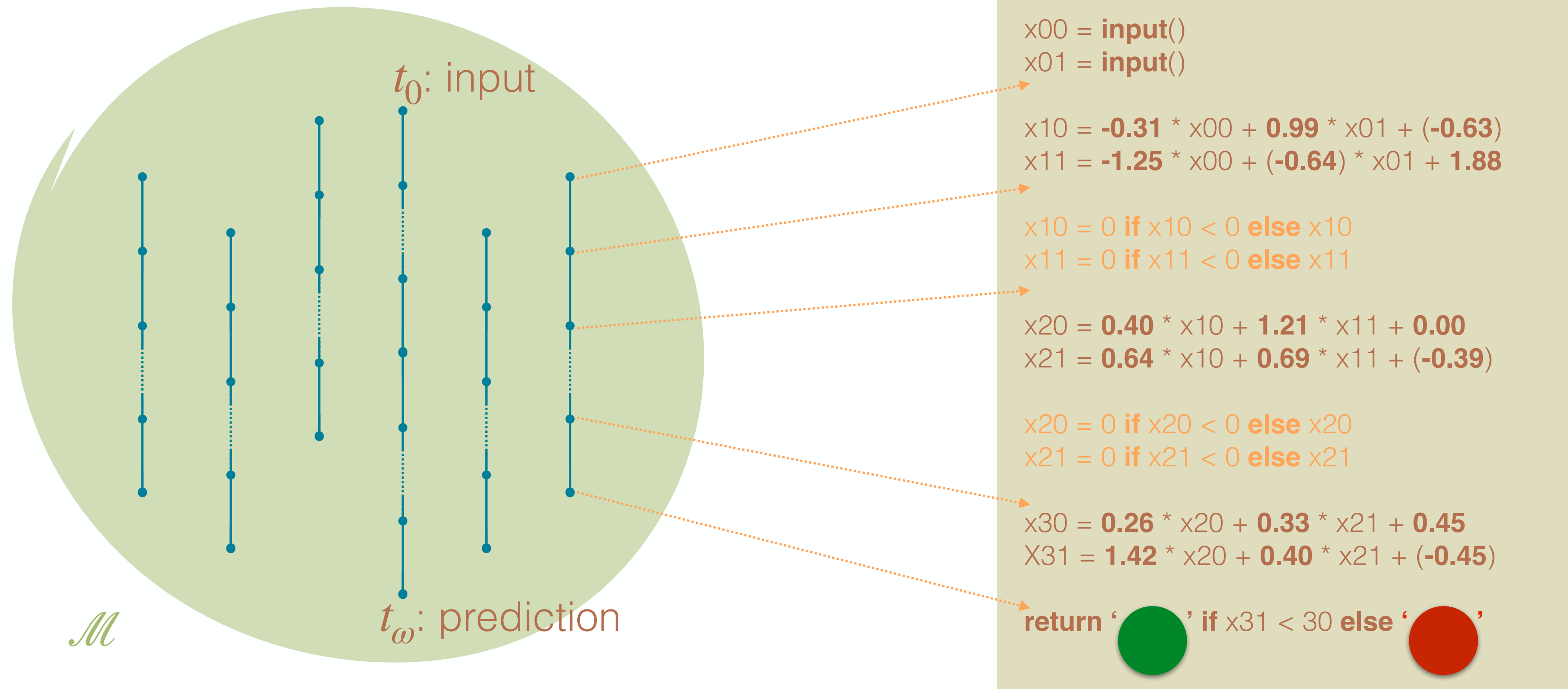
```
x20 = 0 if x20 < 0 else x20
x21 = 0 if x21 < 0 else x21
```

```
x30 = 0.26 * x20 + 0.33 * x21 + 0.45
x31 = 1.42 * x20 + 0.40 * x21 + (-0.45)
```

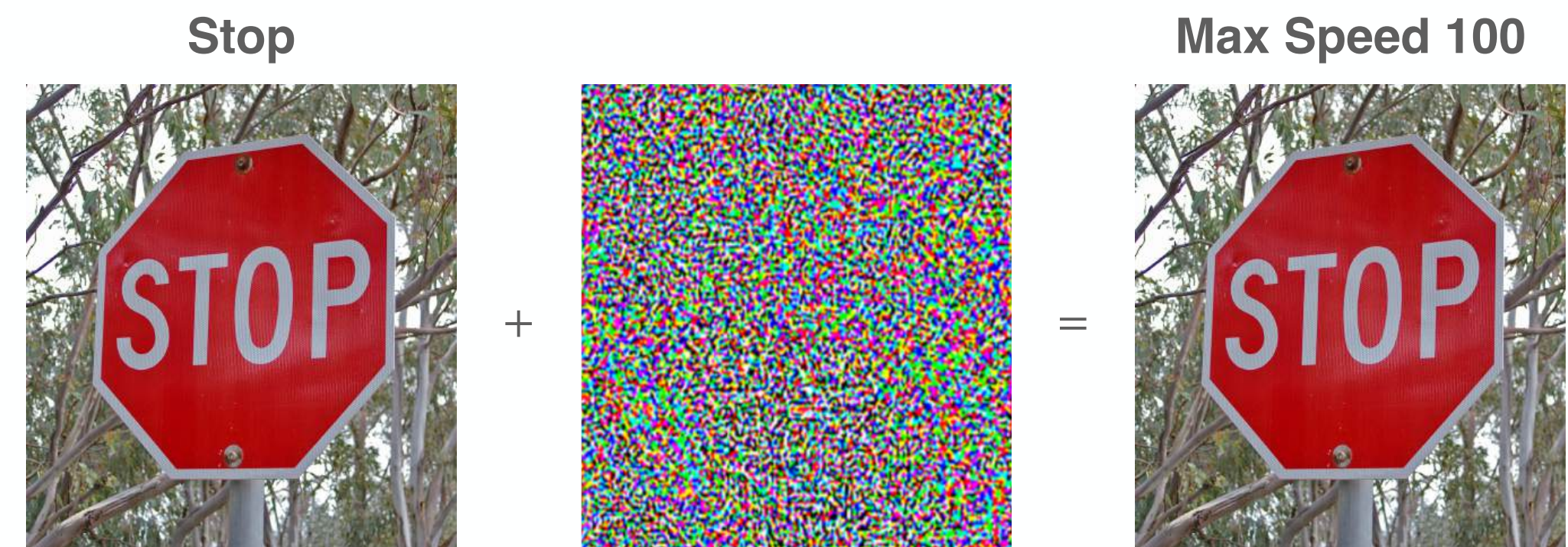
```
return '●' if x31 < 30 else '●'
```

Neural Networks as Programs

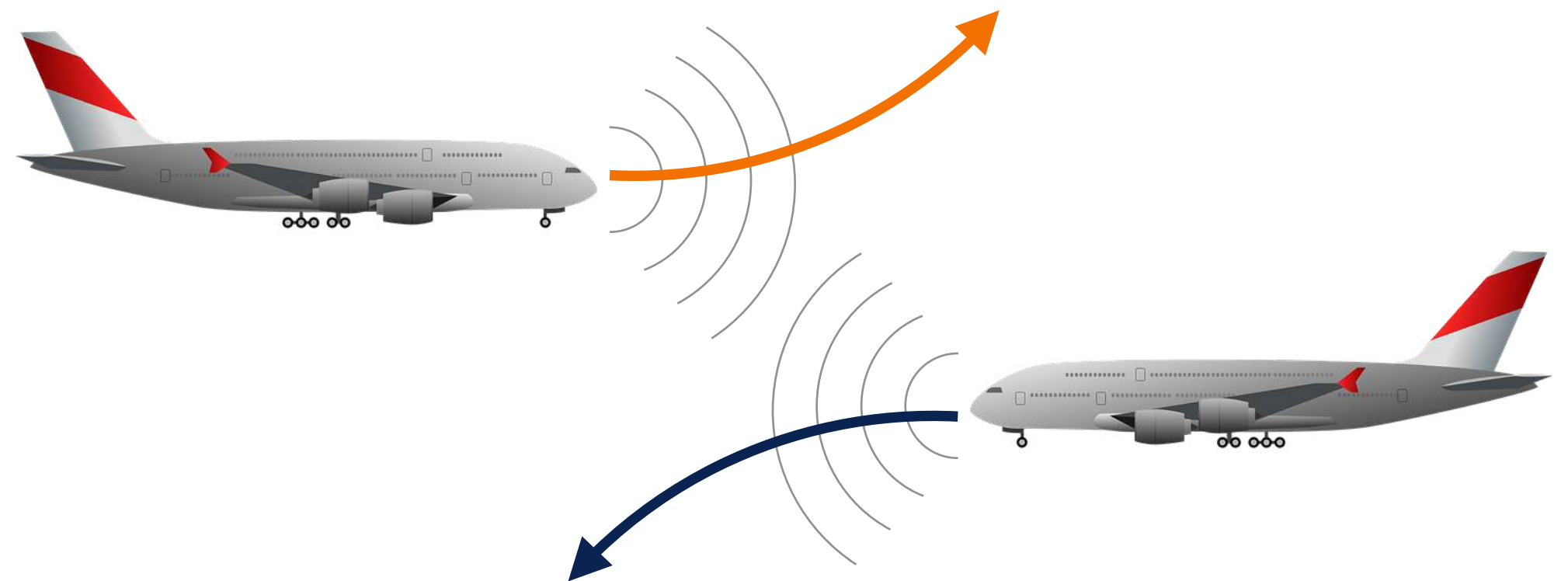
Maximal Trace Semantics



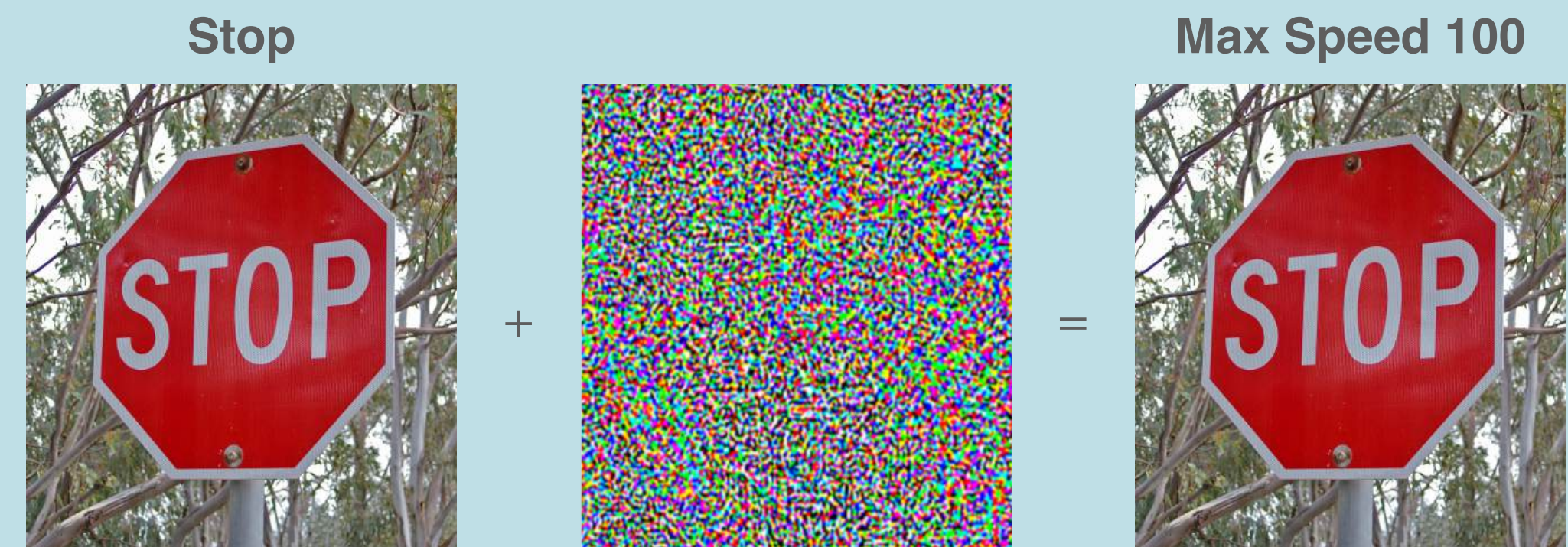
Stability



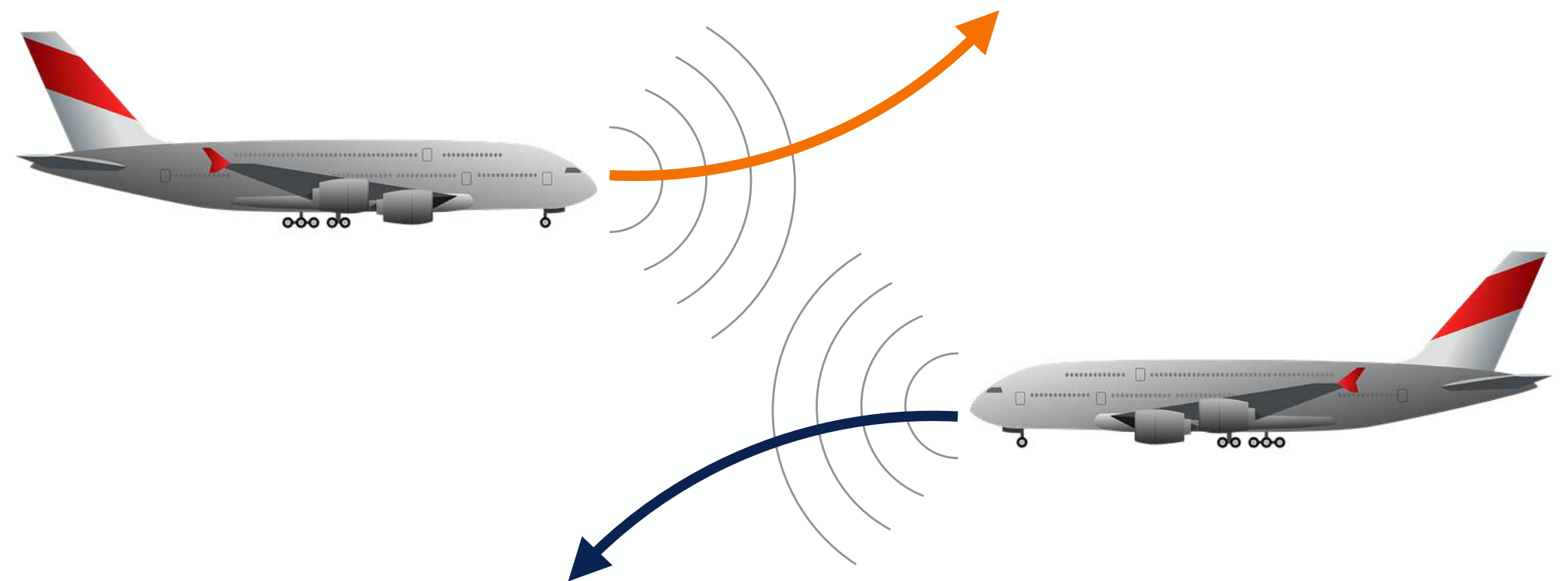
Safety



Stability



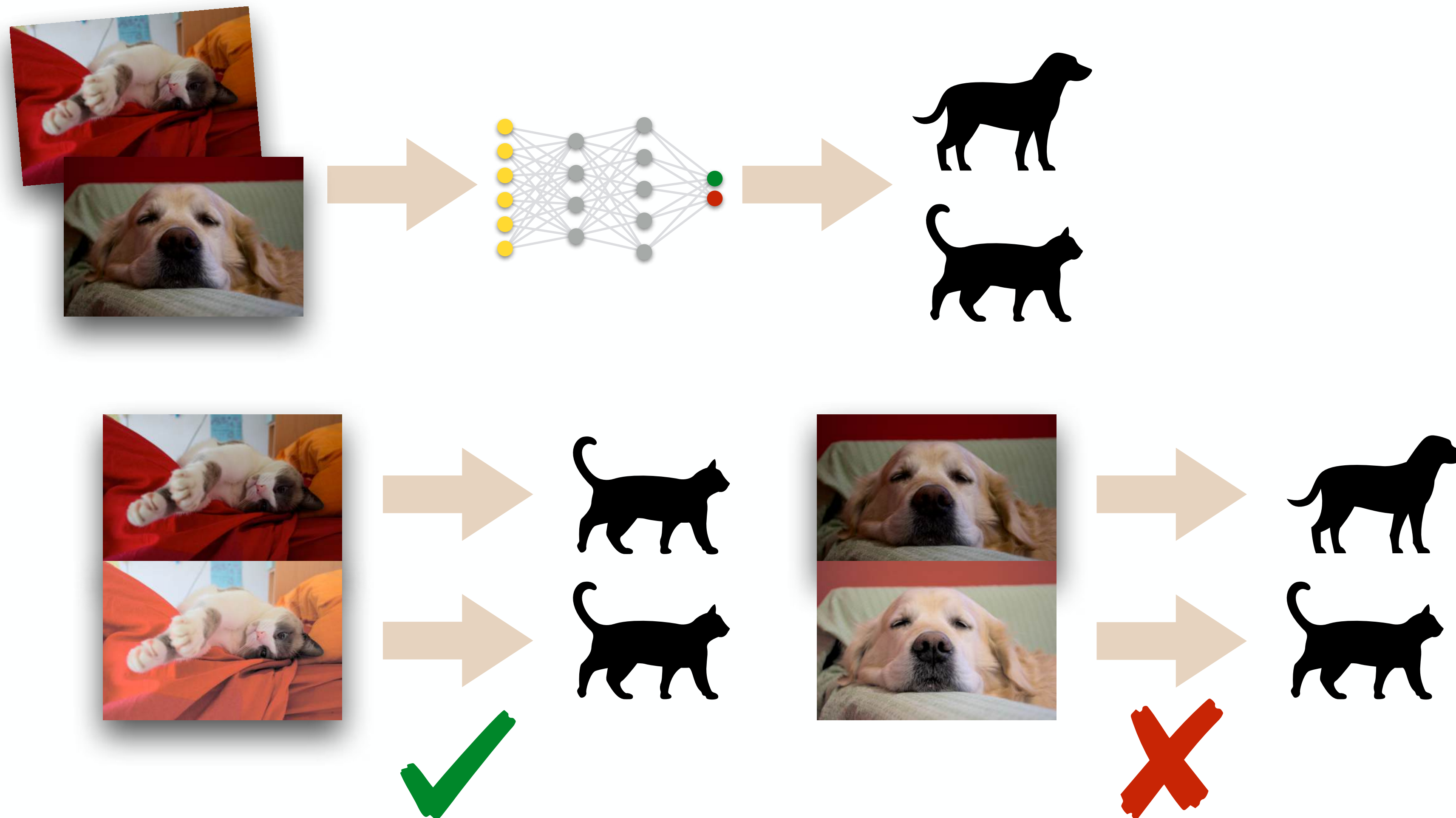
Safety



Prediction Stability

Local Prediction Stability

Prediction is Unaffected by Input Perturbations



Static Local Prediction Stability Analysis

3-Step Recipe

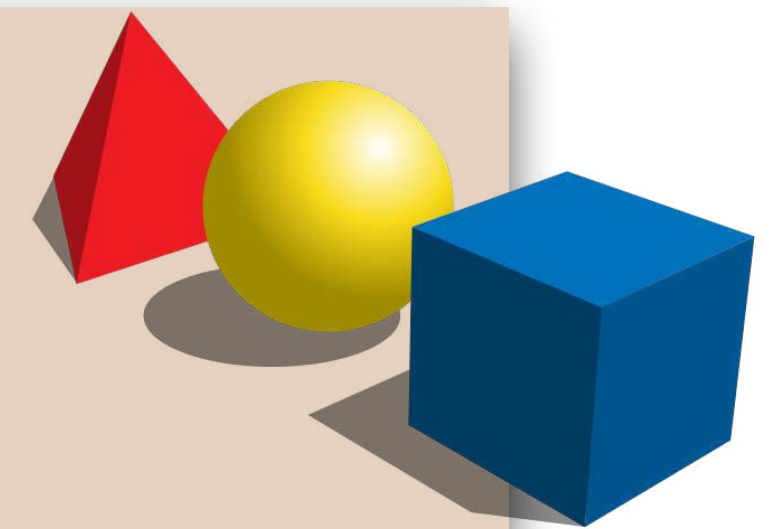
practical tools

targeting specific programs



abstract semantics, abstract domains

algorithmic approaches to decide program properties



concrete semantics

mathematical models of the program behavior



Local Prediction Stability

Distance-Based Perturbations

$$P_{\delta,\epsilon}(\mathbf{x}) \stackrel{\text{def}}{=} \{\mathbf{x}' \in \mathbb{R}^{|L_0|} \mid \delta(\mathbf{x}, \mathbf{x}') \leq \epsilon\}$$

Example (L_∞ distance): $P_{\infty,\epsilon}(\mathbf{x}) \stackrel{\text{def}}{=} \{\mathbf{x}' \in \mathbb{R}^{|L_0|} \mid \max_i |\mathbf{x}_i - \mathbf{x}'_i| \leq \epsilon\}$

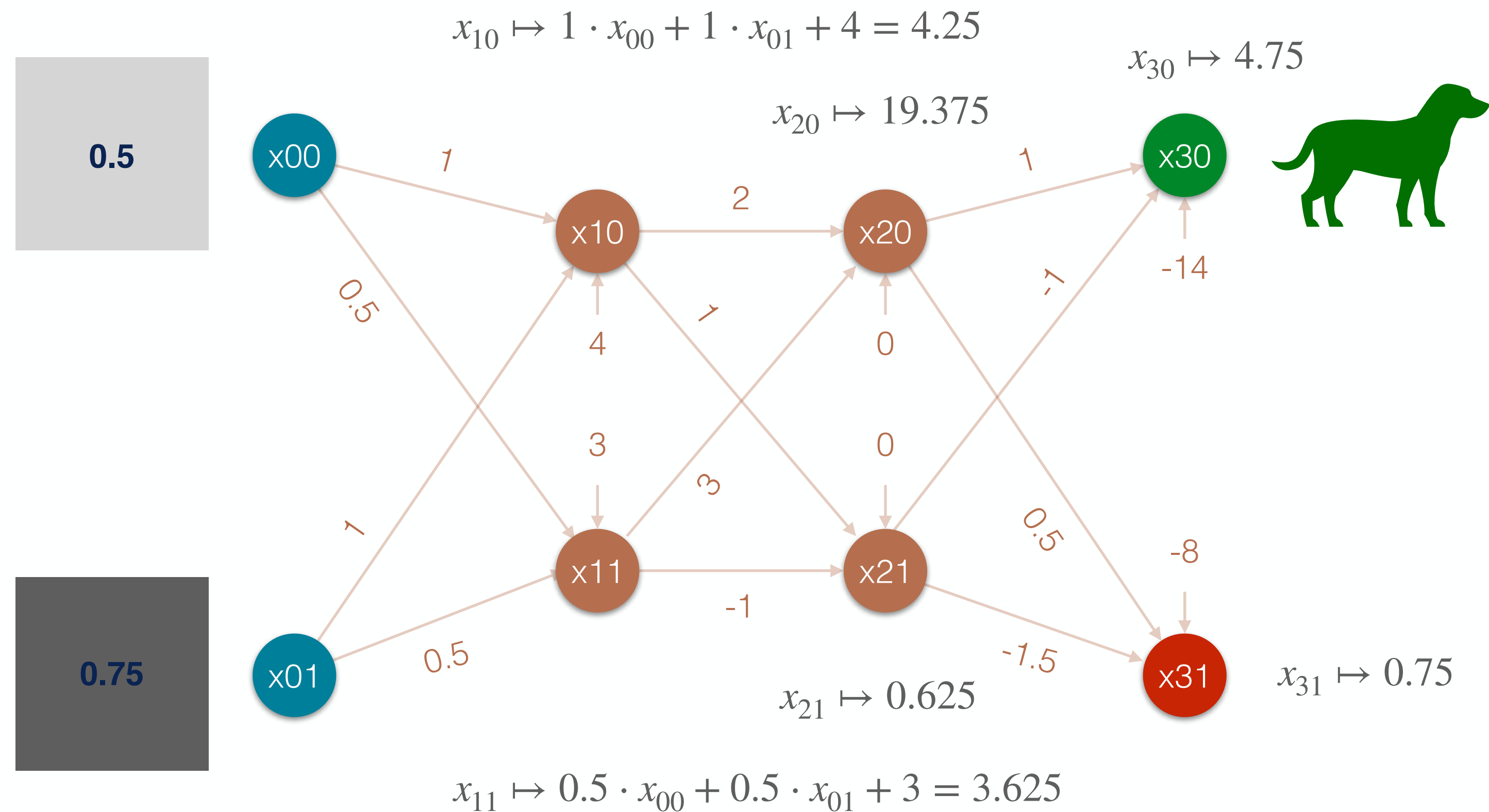
$$\mathcal{R}_{\mathbf{x}}^{\delta,\epsilon} \stackrel{\text{def}}{=} \{t \in \Sigma^* \mid t_0 \in P_{\delta,\epsilon}(\mathbf{x}) \Rightarrow t_\omega = C(\mathbf{x})\}$$

classification of $\mathbf{x}$

$\mathcal{R}_{\mathbf{x}}^{\delta,\epsilon}$ is the set of all traces that are **prediction stable** in the neighborhood $P_{\delta,\epsilon}(\mathbf{x})$ of a given input $\mathbf{x}$

Static Local Prediction Stability

Example



$$P(\langle 0.5, 0.75 \rangle) \stackrel{\text{def}}{=} \{ \mathbf{x} \in \mathcal{R} \times \mathcal{R} \mid 0 \leq \mathbf{x}_0 \leq 1 \wedge 0 \leq \mathbf{x}_1 \leq 1 \}$$

Static Local Prediction Stability Analysis

Concrete Semantics

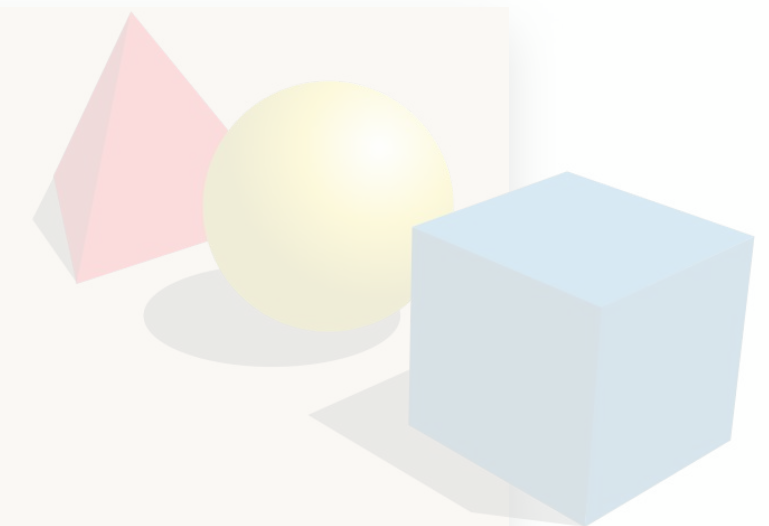
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abstract semantics, abstract domains

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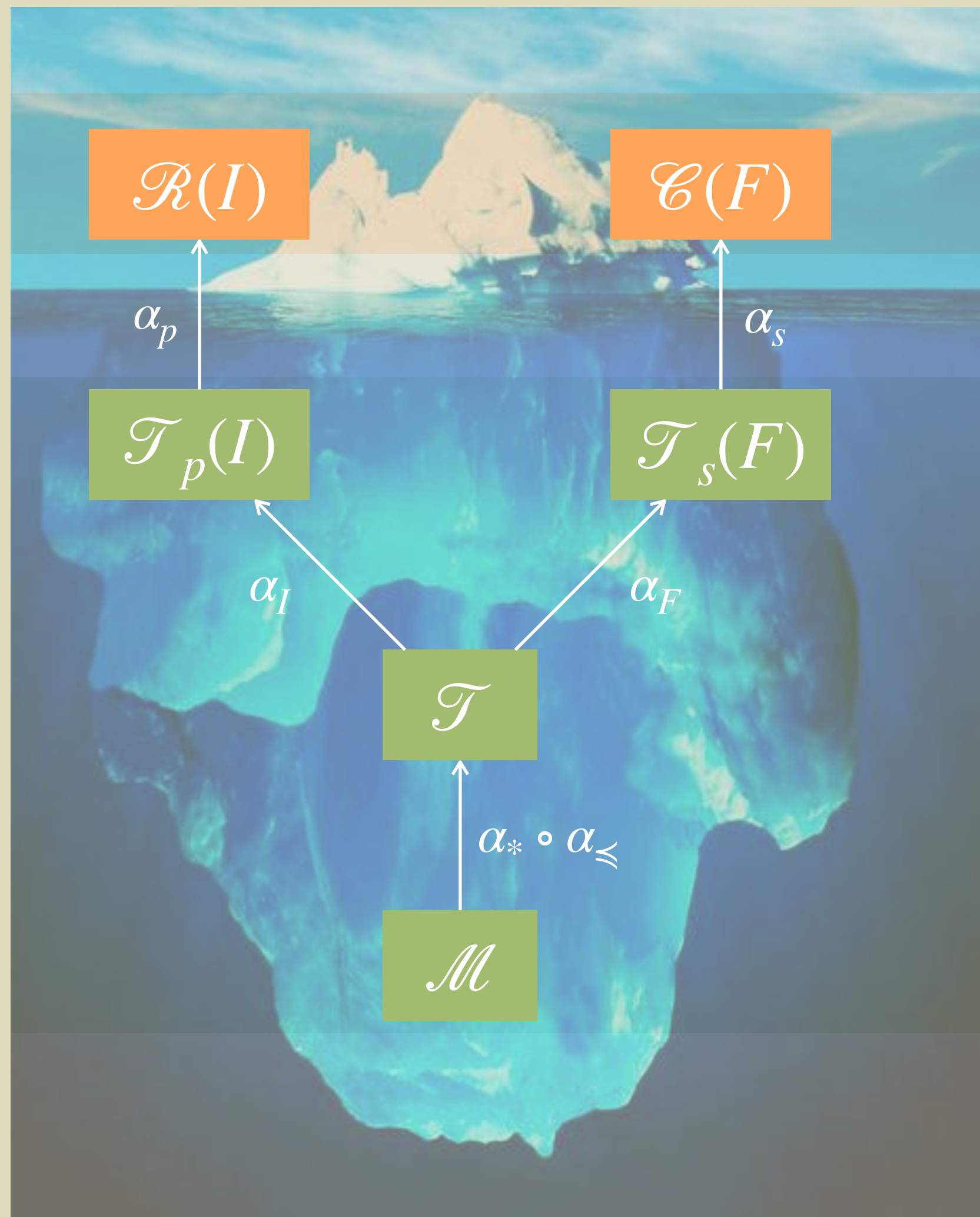


concrete semantics

mathematical models of the program behavior



Hierarchy of Semantics



Forward/Backward Reachability Semantics

Forward/Backward Reachable State Abstraction

Prefix/Suffix Trace Semantics

Prefix/Suffix Trace Abstraction

Partial Finite Trace Semantics

Partial Finite Trace Abstraction

Maximal Trace Semantics

Local Prediction Stability

Distance-Based Perturbations

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Example (L_∞ distance): $P_{\infty,\epsilon}(\mathbf{x}) \stackrel{\text{def}}{=} \{\mathbf{x}' \in \mathbb{R}^{|L_0|} \mid \max_i |\mathbf{x}_i - \mathbf{x}'_i| \leq \epsilon\}$

$$\mathcal{R}_{\mathbf{x}}^{\delta,\epsilon} \stackrel{\text{def}}{=} \{t \in \Sigma^* \mid t_0 \in P_{\delta,\epsilon}(\mathbf{x}) \Rightarrow t_\omega = C(\mathbf{x})\}$$

└────────────────── classification of $\mathbf{x}$

$\mathcal{R}_{\mathbf{x}}^{\delta,\epsilon}$ is the set of all traces that are **prediction stable** in the neighborhood $P_{\delta,\epsilon}(\mathbf{x})$ of a given input $\mathbf{x}$

Theorem

$$M \models \mathcal{R}_{\mathbf{x}}^{\delta,\epsilon} \Leftrightarrow \mathcal{M}[[M]] \subseteq \mathcal{R}_{\mathbf{x}}^{\delta,\epsilon} \Leftrightarrow \mathcal{T}_p(P_{\delta,\epsilon}(\mathbf{x}))[[M]] \subseteq \mathcal{R}_{\mathbf{x}}^{\delta,\epsilon}$$

Static Local Prediction Stability Analysis

Abstract Semantics

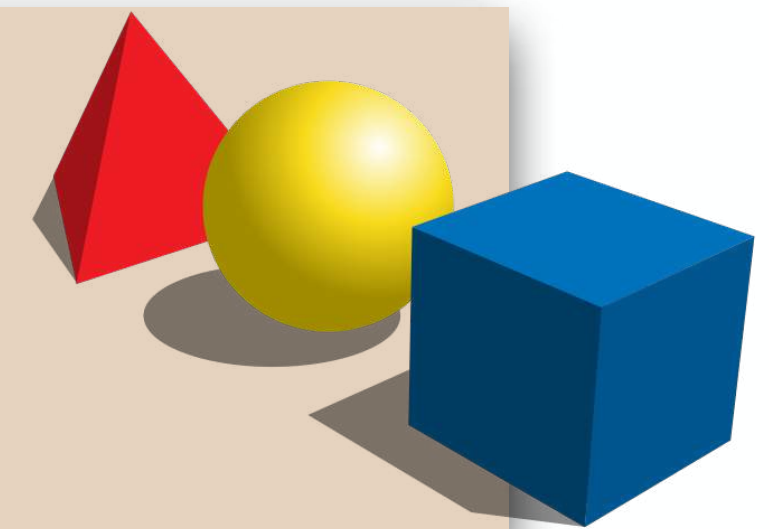
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abstract semantics, abstract domains

algorithmic approaches to decide program properties



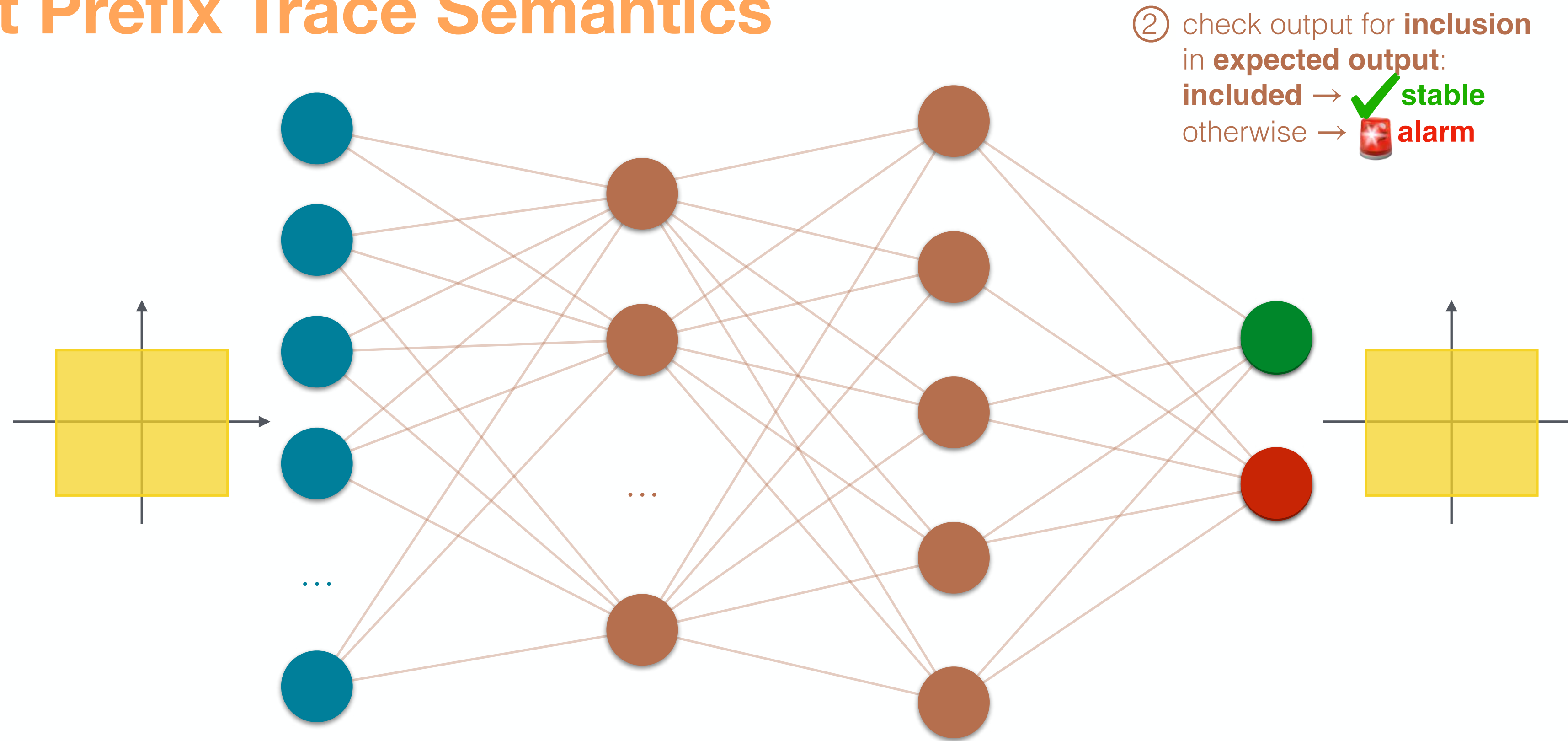
concrete semantics

mathematical models of the program behavior



Static Local Prediction Stability Analysis

Abstract Prefix Trace Semantics



① proceed **forwards** from an **abstraction** $P_{\delta,\epsilon}^\#$ of $P_{\delta,\epsilon}$

Theorem

$$\mathcal{T}_p(P_{\delta,\epsilon}(\mathbf{x}))[[M]] \subseteq \mathcal{T}_p^\#(P_{\delta,\epsilon}^\#(\mathbf{x}))[[M]] \subseteq \mathcal{R}_{\mathbf{x}}^{\delta,\epsilon} \Rightarrow M \models \mathcal{R}_{\mathbf{x}}^{\delta,\epsilon}$$

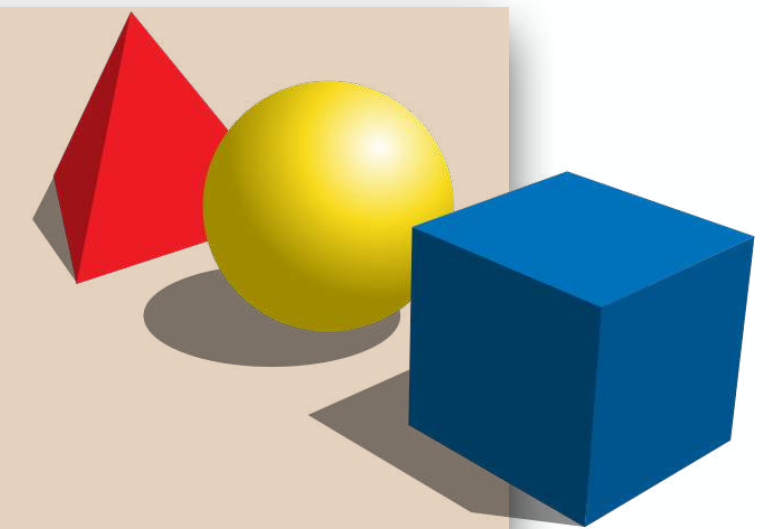
Static Local Prediction Stability Analysis

Abstract Domain #1: Interval Domain

practical tools
targeting specific programs



abstract semantics, abstract domains
algorithmic approaches to decide program properties



concrete semantics
mathematical models of the program behavior

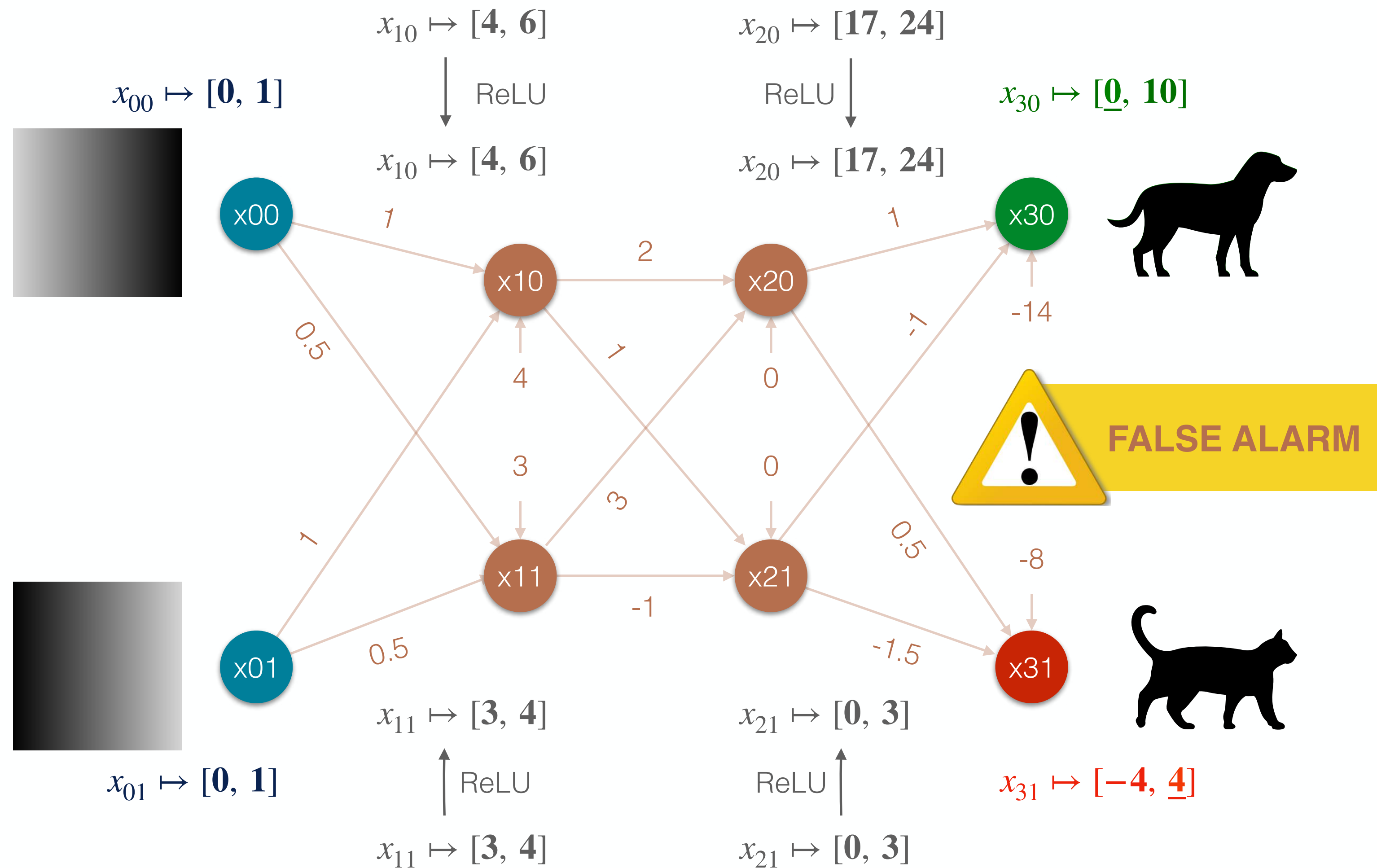


Interval Domain

Example

$$x_{i,j} \mapsto [a, b]$$

$$a, b \in \mathbb{R}$$



Static Analysis by Abstract Interpretation



€ 10 +
€ 40 +
€ 25 +
€ 5

€ 80



€ 9.95 +
€ 35.85 +
€ 24.95 +
€ 4.85

€ 75.60

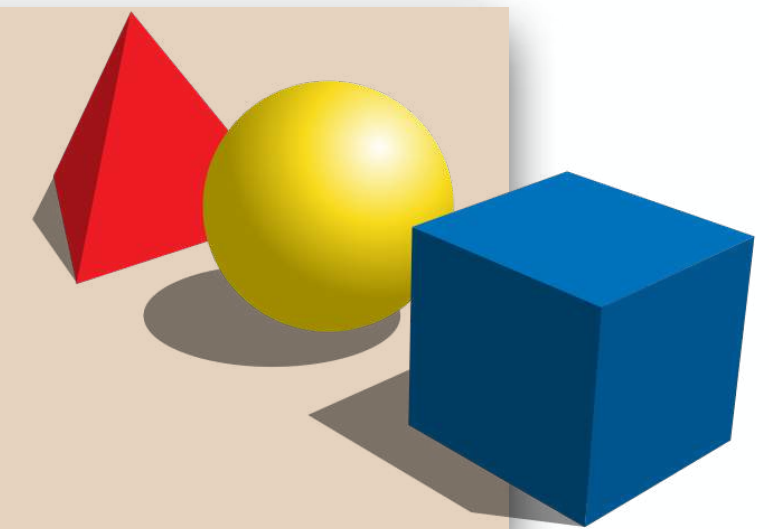
Static Local Prediction Stability Analysis

Abstract Domain #2: Symbolic Domain

practical tools
targeting specific programs



abstract semantics, abstract domains
algorithmic approaches to decide program properties



concrete semantics
mathematical models of the program behavior



Symbolic Domain [Li et al. @ SAS 2019]



represent each neuron as
a **linear combination** of the inputs
and the **previous ReLUs**

$$x_{i,j} \mapsto \begin{cases} \sum_{k=0}^{i-1} \mathbf{c}_k \cdot \mathbf{x}_k + \mathbf{c} & \mathbf{c}_k, \mathbf{c} \in \mathbb{R}^{|\mathbf{x}_k|} \\ [a, b] & a, b \in \mathbb{R} \end{cases}$$

$$\begin{aligned} x_{i-1,0} &\mapsto \mathbf{E}_{i-1,0} \\ \dots & \\ x_{i-1,j} &\mapsto \mathbf{E}_{i-1,j} \\ \dots & \end{aligned}$$

$$x_{i,j} = \sum_k w_{j,k}^{i-1} \cdot x_{i-1,k} + b_{i,j}$$

$$x_{i,j} \mapsto \sum_k w_{j,k}^{i-1} \cdot \mathbf{E}_{i-1,k} + b_{i,j}$$

$$x_{i,j} \mapsto \begin{cases} \mathbf{E}_{i,j} \\ [a, b] \end{cases}$$

ReLU

$$x_{i,j} \mapsto \begin{cases} \mathbf{E}_{i,j} \\ [a, b] \end{cases}$$

$$0 \leq a$$

$$x_{i,j} \mapsto \begin{cases} \mathbf{x}_{i,j} \\ [0, b] \end{cases}$$

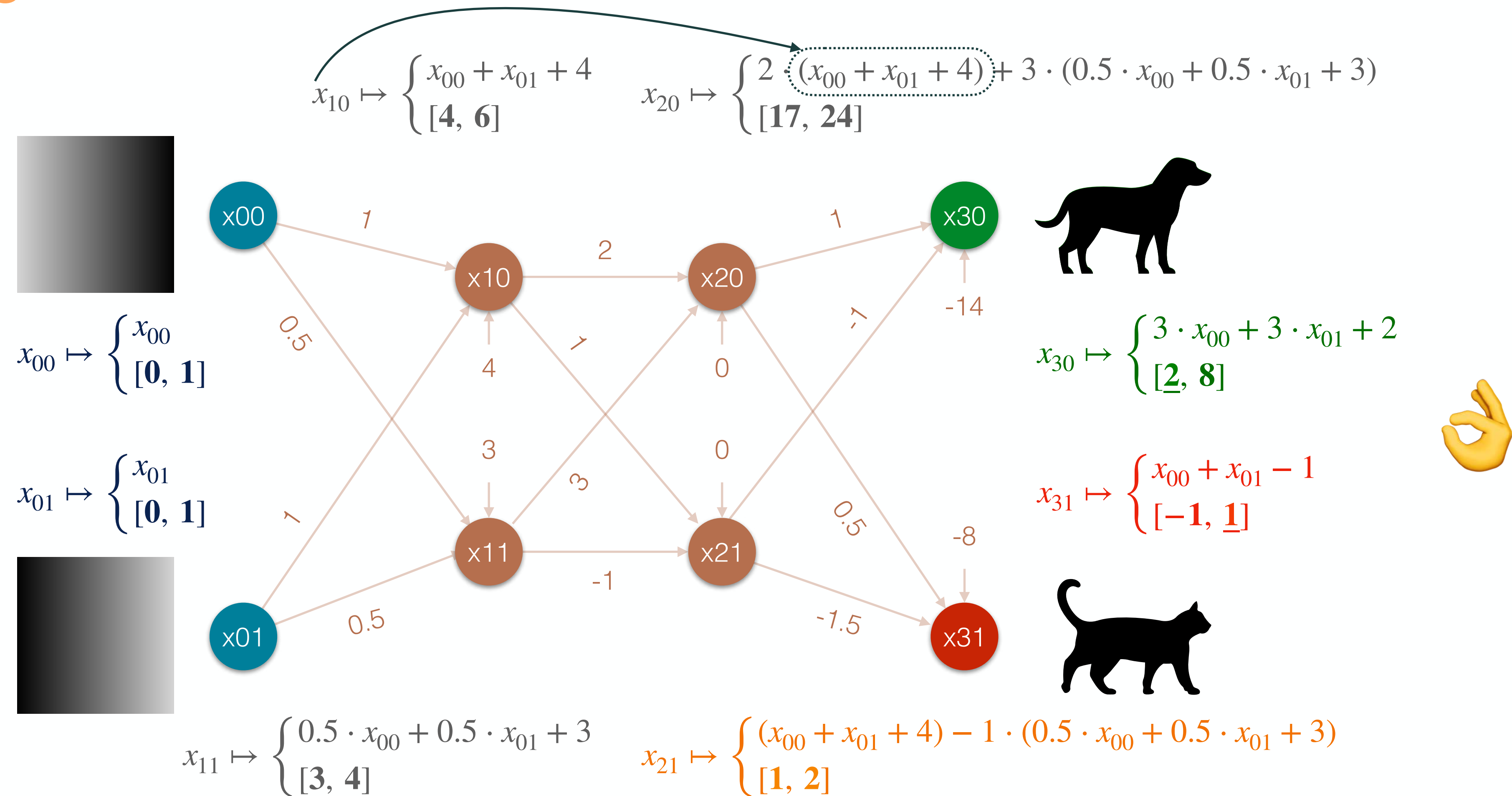
$$a < 0 \wedge 0 < b$$

$$x_{i,j} \mapsto \begin{cases} \mathbf{0} \\ [0, 0] \end{cases}$$

$$b \leq 0$$

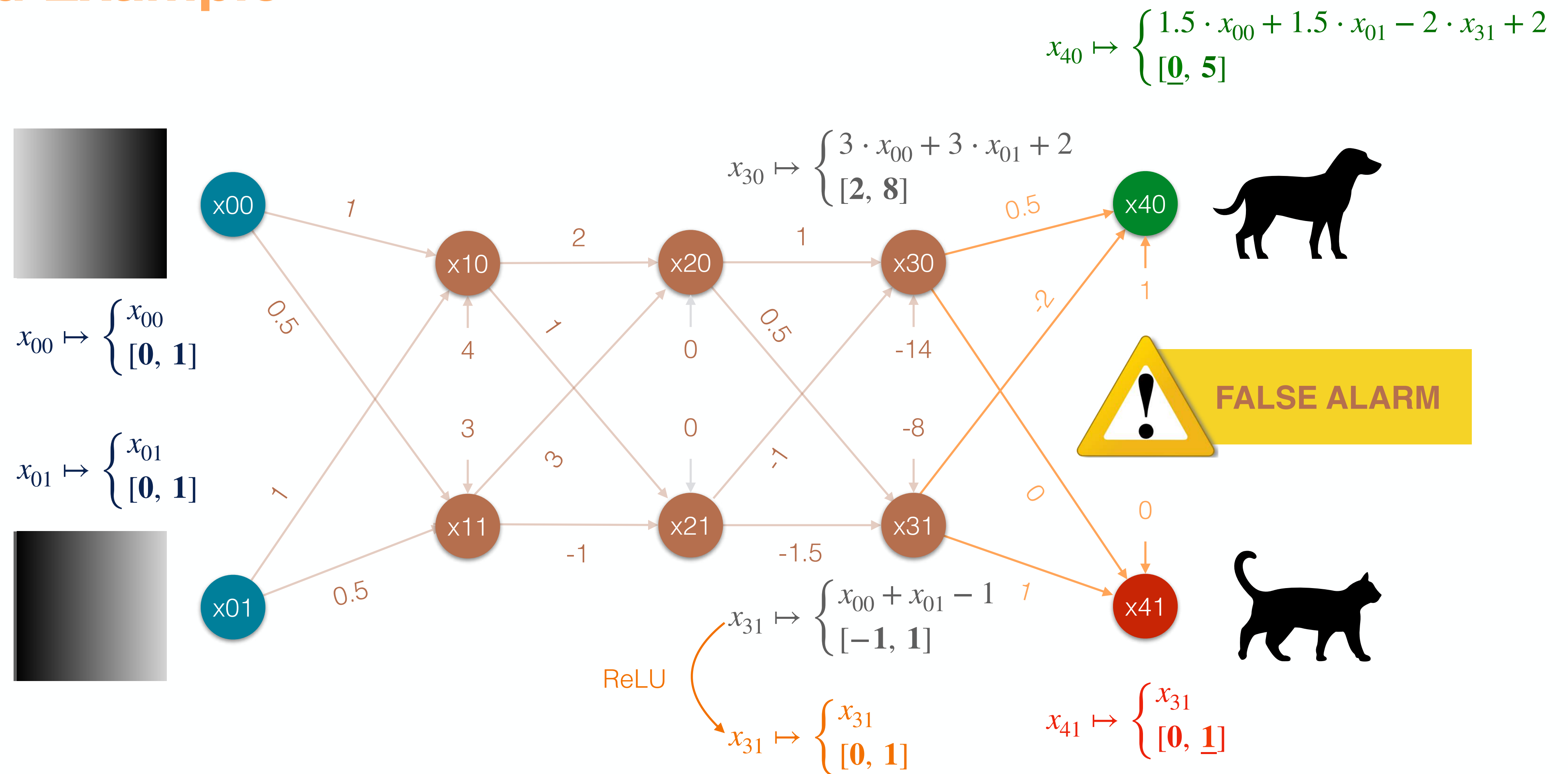
Symbolic Domain

Example



Symbolic Domain

Modified Example



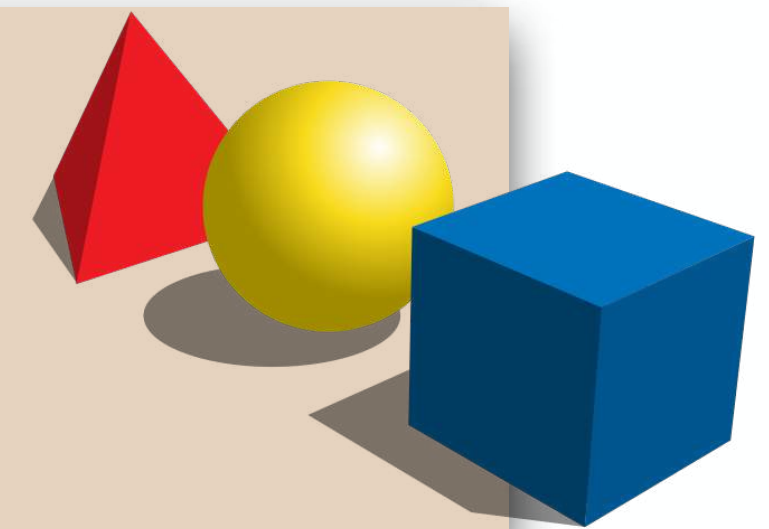
Static Local Prediction Stability Analysis

Abstract Domain #3: DeepPoly Domain

practical tools
targeting specific programs



abstract semantics, abstract domains
algorithmic approaches to decide program properties



concrete semantics
mathematical models of the program behavior

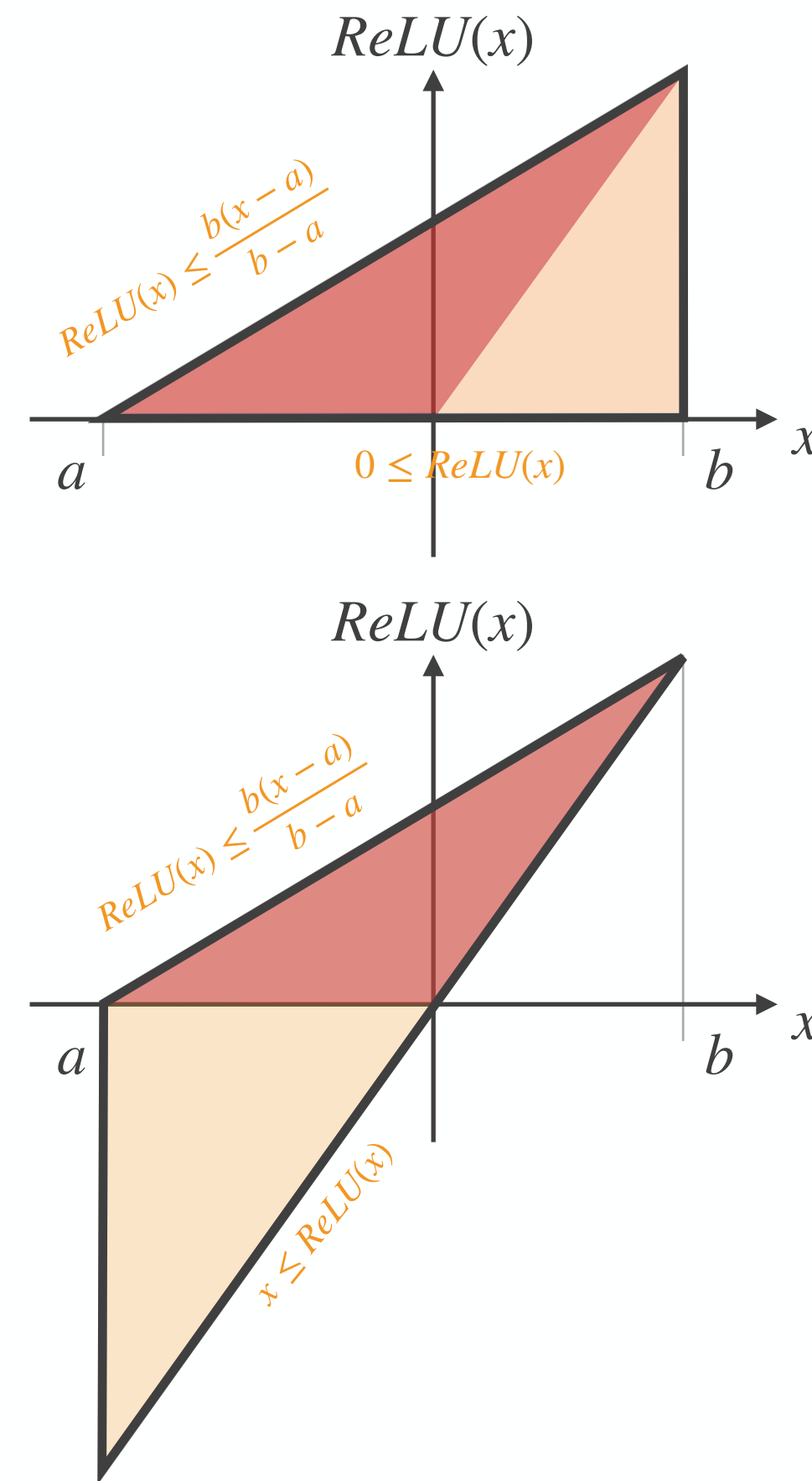
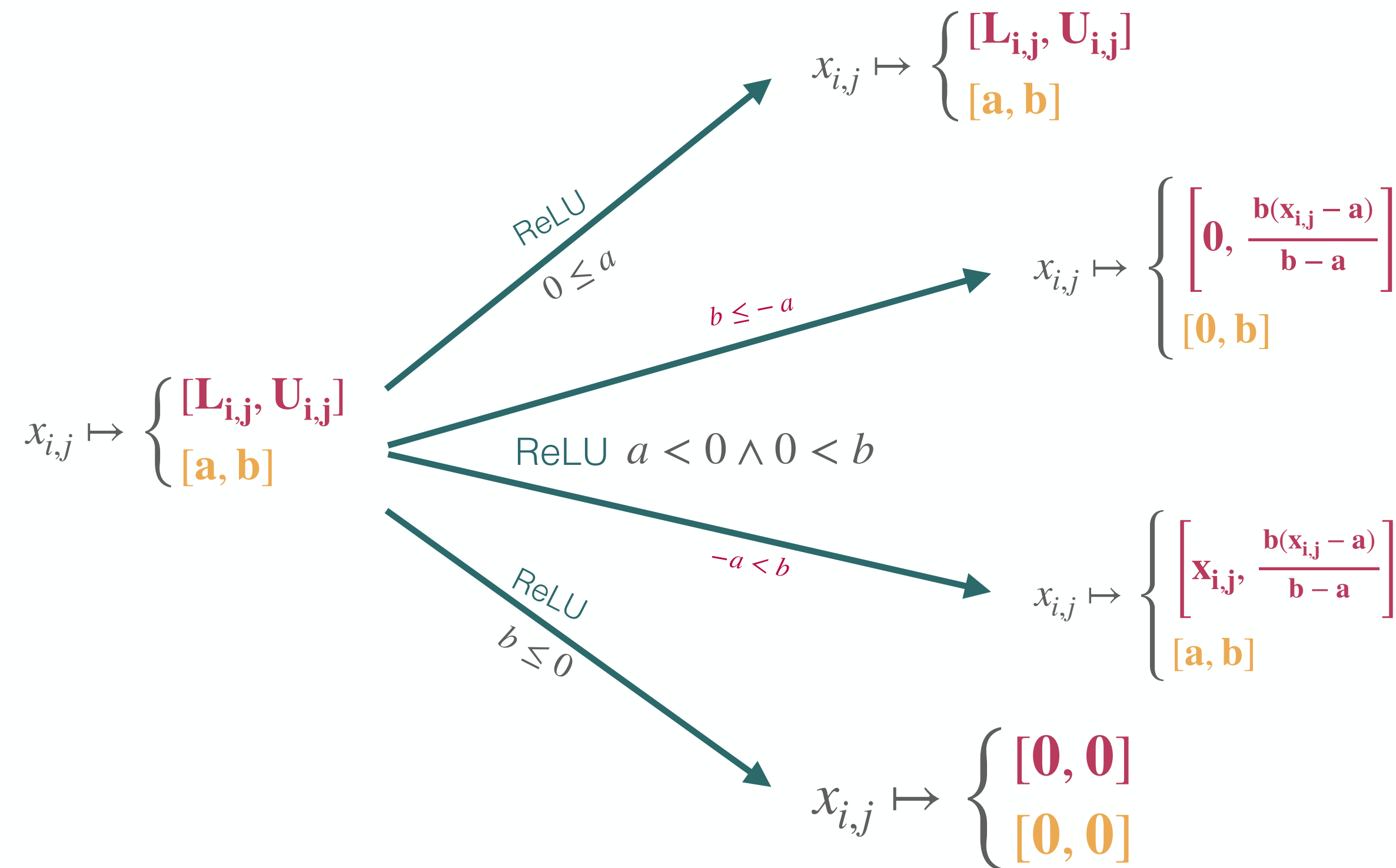


DeepPoly Domain [Singh et al. @ POPL 2019]



maintain **symbolic lower- and upper-bounds** for each neuron
+ **convex ReLU approximations**

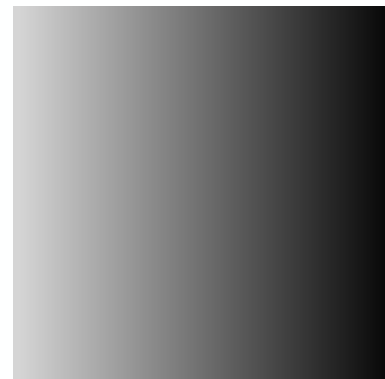
$$x_{i+1,j} \mapsto \begin{cases} [\sum_k c_{i,k} \cdot x_{i,k} + c, \sum_k d_{i,k} \cdot x_{i,k} + d] & c_{i,k}, c, d_{i,k}, d \in \mathbb{R} \\ [a, b] & a, b \in \mathbb{R} \end{cases}$$



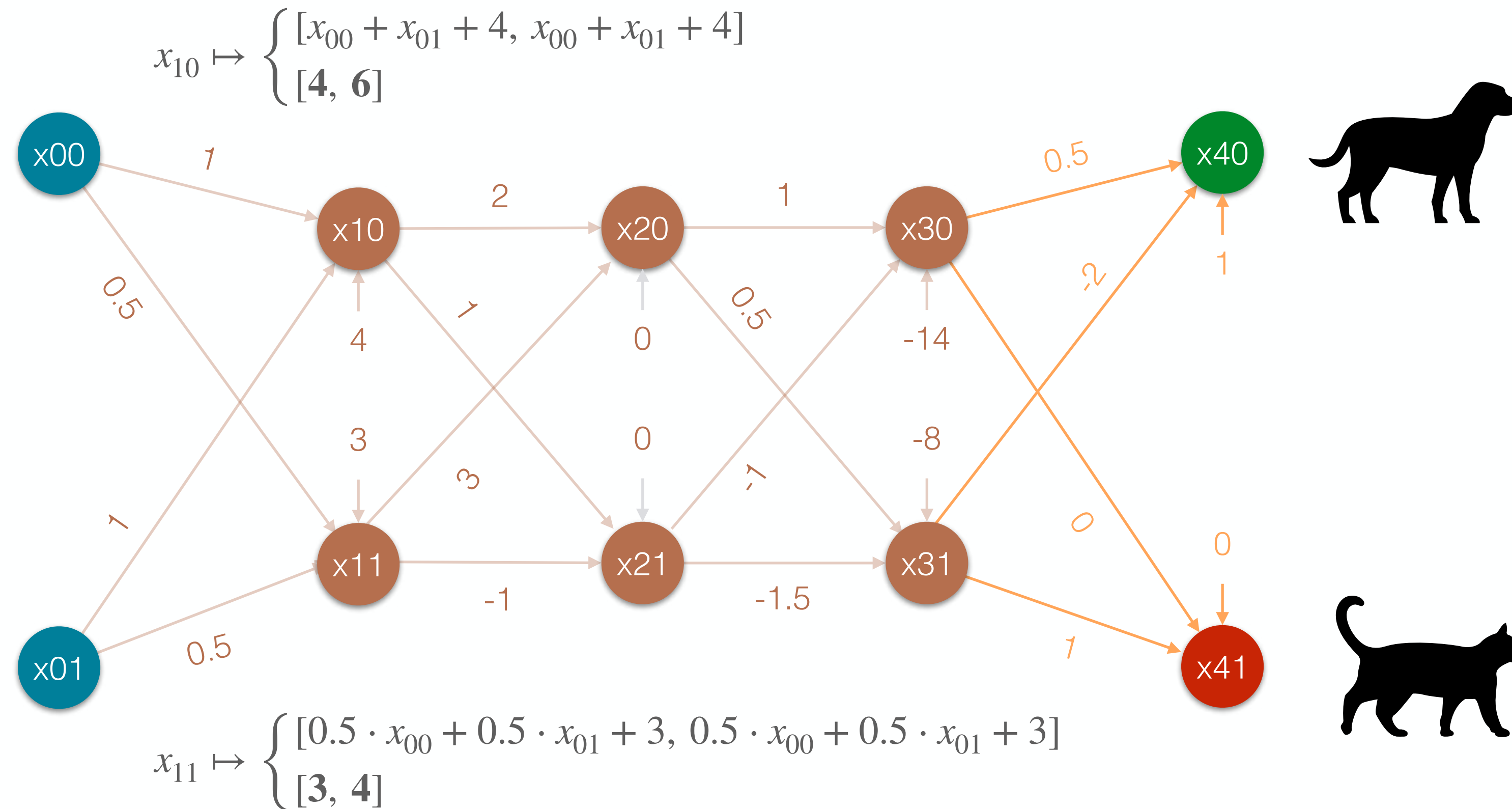
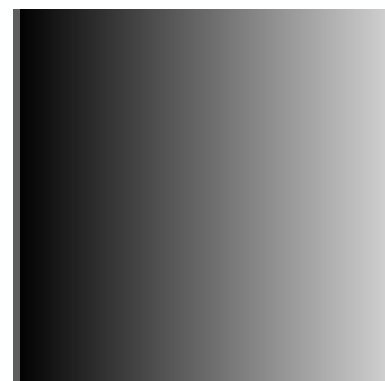
DeepPoly Domain

Example

$$x_{00} \mapsto \begin{cases} [x_{00}, x_{00}] \\ [0, 1] \end{cases}$$



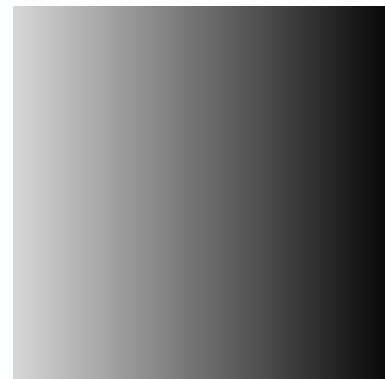
$$x_{01} \mapsto \begin{cases} [x_{01}, x_{01}] \\ [0, 1] \end{cases}$$



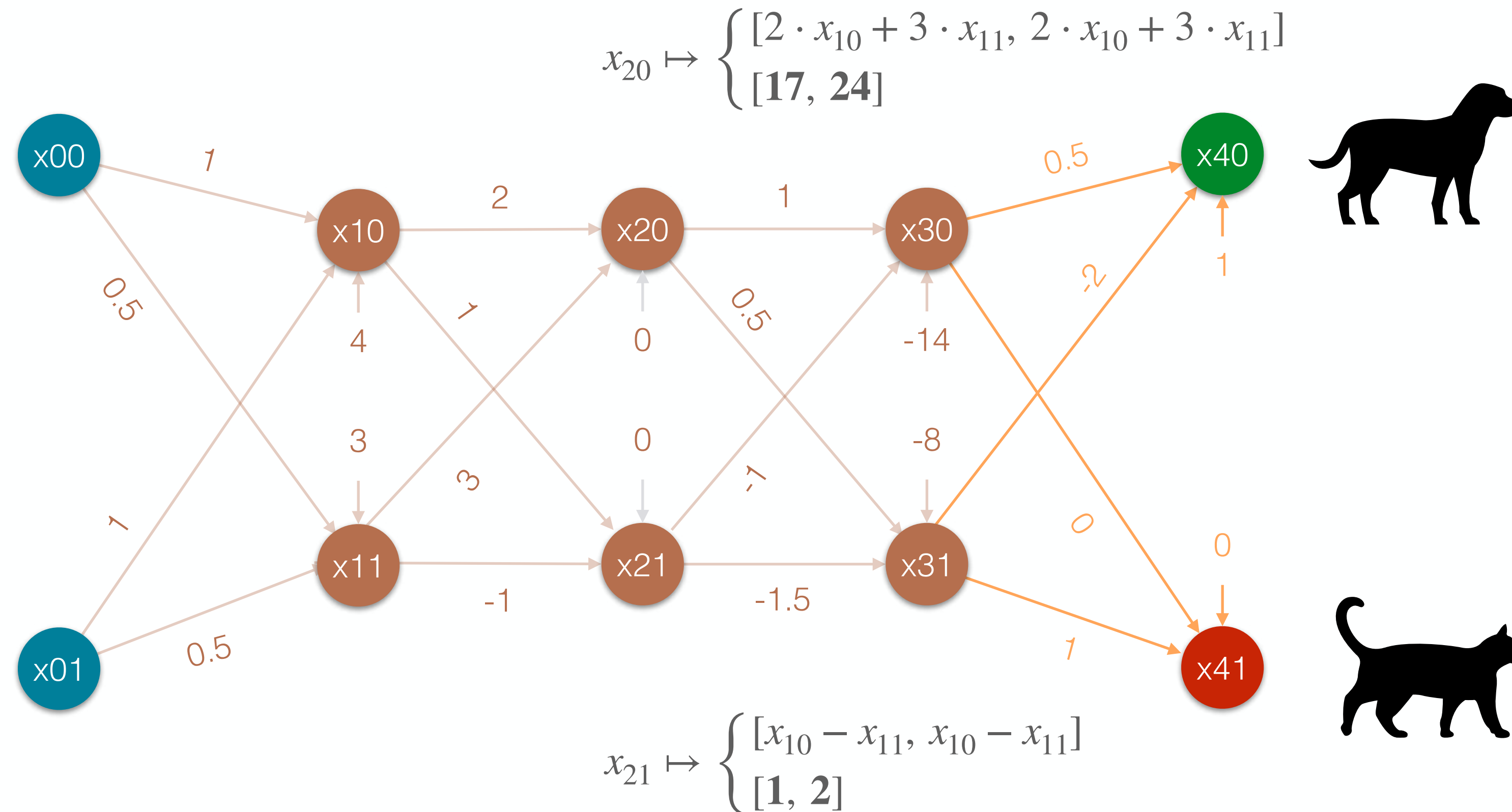
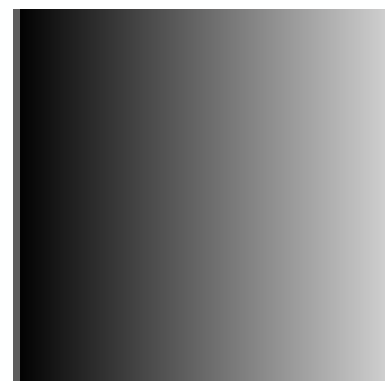
DeepPoly Domain

Example

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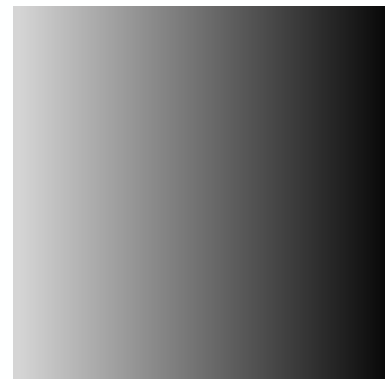
$$x_{01} \mapsto \begin{cases} [x_{01}, x_{01}] \\ [0, 1] \end{cases}$$



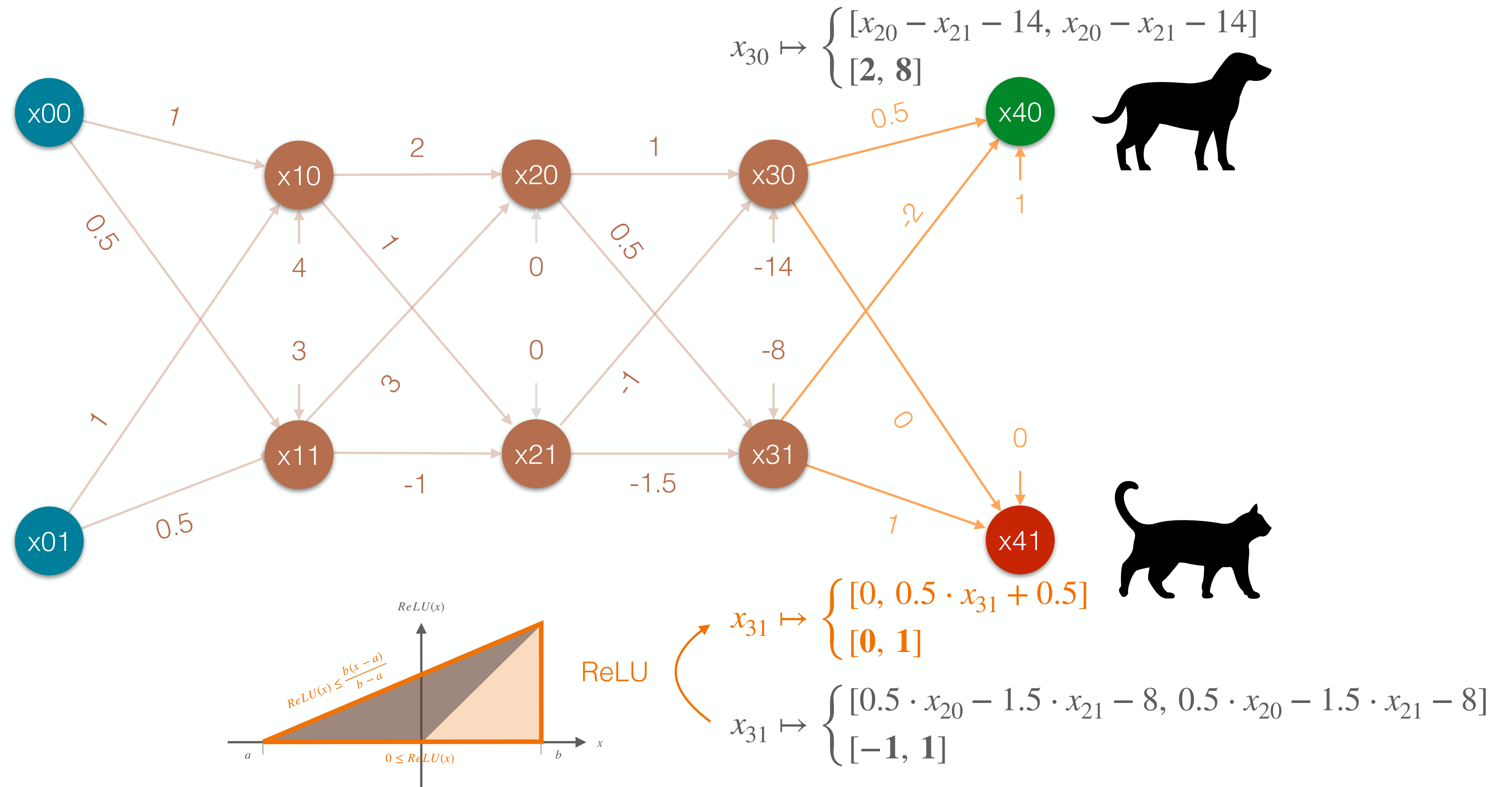
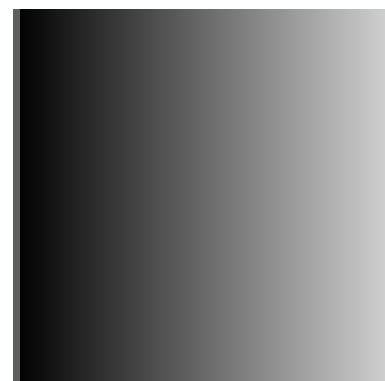
DeepPoly Domain

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$$x_{00} \mapsto \begin{cases} [x_{00}, x_{00}] \\ [0, 1] \end{cases}$$



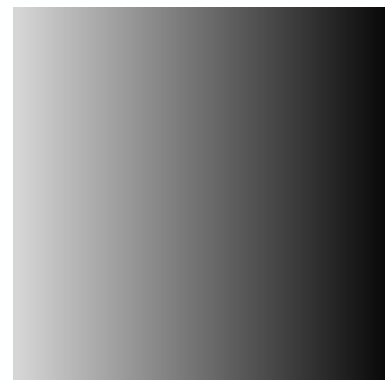
$$x_{01} \mapsto \begin{cases} [x_{01}, x_{01}] \\ [0, 1] \end{cases}$$



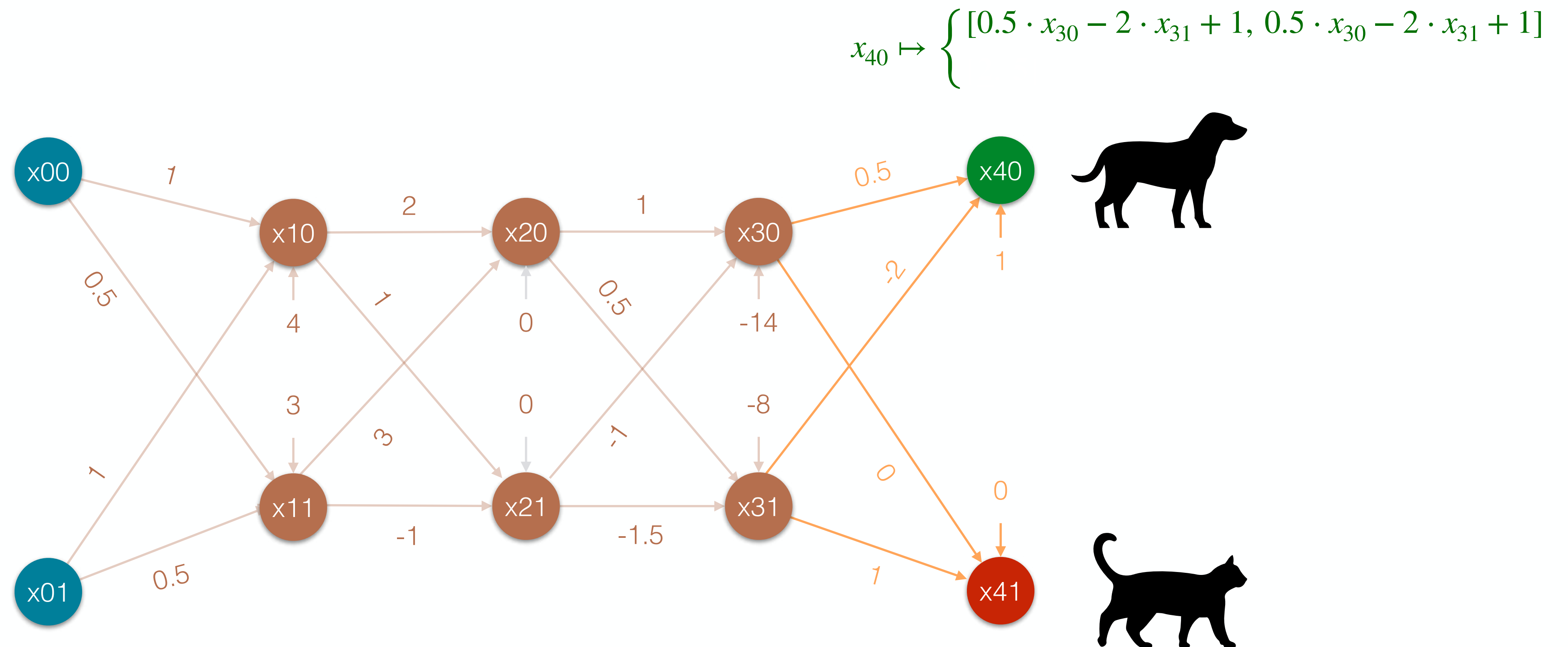
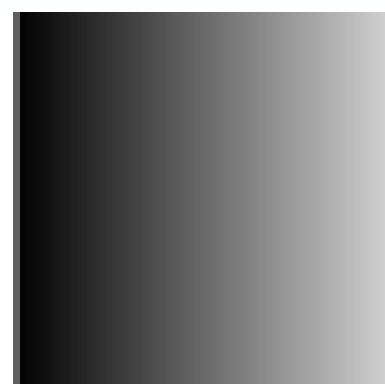
DeepPoly Domain

Example

$$x_{00} \mapsto \begin{cases} [x_{00}, x_{00}] \\ [0, 1] \end{cases}$$



$$x_{01} \mapsto \begin{cases} [x_{01}, x_{01}] \\ [0, 1] \end{cases}$$



DeepPoly Domain

Back-Substitution

$$x_{00} \mapsto [\mathbf{0}, \mathbf{1}]$$

$$x_{01} \mapsto [\mathbf{0}, \mathbf{1}]$$

$$x_{10} \mapsto \begin{cases} [x_{00} + x_{01} + 4, x_{00} + x_{01} + 4] \\ [\mathbf{4}, \mathbf{6}] \end{cases}$$

$$x_{11} \mapsto \begin{cases} [0.5 \cdot x_{00} + 0.5 \cdot x_{01} + 3, 0.5 \cdot x_{00} + 0.5 \cdot x_{01} + 3] \\ [\mathbf{3}, \mathbf{4}] \end{cases}$$

$$x_{20} \mapsto \begin{cases} [2 \cdot x_{10} + 3 \cdot x_{11}, 2 \cdot x_{10} + 3 \cdot x_{11}] \\ [\mathbf{17}, \mathbf{24}] \end{cases}$$

$$x_{21} \mapsto \begin{cases} [x_{10} - x_{11}, x_{10} - x_{11}] \\ [\mathbf{1}, \mathbf{2}] \end{cases}$$

$$x_{30} \mapsto \begin{cases} [x_{20} - x_{21} - 14, x_{20} - x_{21} - 14] \\ [\mathbf{2}, \mathbf{8}] \end{cases}$$

$$x_{31} \mapsto \begin{cases} [0, 0.5 \cdot (0.5 \cdot x_{20} - 1.5 \cdot x_{21} - 8) + 0.5] \\ [\mathbf{0}, \mathbf{1}] \end{cases}$$

$$x_{40} \mapsto \begin{cases} [0.5 \cdot x_{30} - 2 \cdot x_{31} + 1, 0.5 \cdot x_{30} - 2 \cdot x_{31} + 1] \end{cases}$$

DeepPoly Domain

Back-Substitution

$$x_{00} \mapsto [\mathbf{0}, \mathbf{1}]$$

$$x_{01} \mapsto [\mathbf{0}, \mathbf{1}]$$

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$$x_{40} \mapsto \begin{cases} [0.5 \cdot x_{30} - 2 \cdot x_{31} + 1, 0.5 \cdot x_{30} - 2 \cdot x_{31} + 1] \\ \end{cases}$$

$$\mapsto \begin{cases} [x_{21} + 1, 0.5 \cdot x_{20} - 0.5 \cdot x_{21} - 6] \end{cases}$$

DeepPoly Domain

Back-Substitution

$$x_{00} \mapsto [\mathbf{0}, \mathbf{1}]$$

$$x_{01} \mapsto [\mathbf{0}, \mathbf{1}]$$

$$x_{10} \mapsto \begin{cases} [x_{00} + x_{01} + 4, x_{00} + x_{01} + 4] \\ [\mathbf{4}, \mathbf{6}] \end{cases}$$

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$$\mapsto \begin{cases} [x_{21} + 1, 0.5 \cdot x_{20} - 0.5 \cdot x_{21} - 6] \\ \end{cases}$$

$$\mapsto \begin{cases} [x_{10} - x_{11} + 1, 0.5 \cdot x_{10} + 2 \cdot x_{11} - 6] \\ \end{cases}$$

DeepPoly Domain

Back-Substitution

$$x_{00} \mapsto [\mathbf{0}, \mathbf{1}]$$

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$$x_{11} \mapsto \begin{cases} [0.5 \cdot x_{00} + 0.5 \cdot x_{01} + 3, 0.5 \cdot x_{00} + 0.5 \cdot x_{01} + 3] \\ [\mathbf{3}, \mathbf{4}] \end{cases}$$

$$x_{20} \mapsto \begin{cases} [2 \cdot x_{10} + 3 \cdot x_{11}, 2 \cdot x_{10} + 3 \cdot x_{11}] \\ [\mathbf{17}, \mathbf{24}] \end{cases}$$

$$x_{21} \mapsto \begin{cases} [x_{10} - x_{11}, x_{10} - x_{11}] \\ [\mathbf{1}, \mathbf{2}] \end{cases}$$

$$x_{30} \mapsto \begin{cases} [x_{20} - x_{21} - 14, x_{20} - x_{21} - 14] \\ [\mathbf{2}, \mathbf{8}] \end{cases}$$

$$x_{31} \mapsto \begin{cases} [0, 0.5 \cdot (0.5 \cdot x_{20} - 1.5 \cdot x_{21} - 8) + 0.5] \\ [\mathbf{0}, \mathbf{1}] \end{cases}$$

$$x_{40} \mapsto \begin{cases} [0.5 \cdot x_{30} - 2 \cdot x_{31} + 1, 0.5 \cdot x_{30} - 2 \cdot x_{31} + 1] \end{cases}$$

$$\mapsto \begin{cases} [x_{21} + 1, 0.5 \cdot x_{20} - 0.5 \cdot x_{21} - 6] \end{cases}$$

$$\mapsto \begin{cases} [x_{10} - x_{11} + 1, 0.5 \cdot x_{10} + 2 \cdot x_{11} - 6] \end{cases}$$

$$\mapsto \begin{cases} [0.5 \cdot x_{00} + 0.5 \cdot x_{01} + 2, 1.5 \cdot x_{00} + 1.5 \cdot x_{11} + 2] \end{cases}$$

DeepPoly Domain

Partial Back-Substitution

$$x_{00} \mapsto [\mathbf{0}, \mathbf{1}]$$

$$x_{01} \mapsto [\mathbf{0}, \mathbf{1}]$$

$$x_{10} \mapsto \begin{cases} [x_{00} + x_{01} + 4, x_{00} + x_{01} + 4] \\ [\mathbf{4}, \mathbf{6}] \end{cases}$$

$$x_{11} \mapsto \begin{cases} [0.5 \cdot x_{00} + 0.5 \cdot x_{01} + 3, 0.5 \cdot x_{00} + 0.5 \cdot x_{01} + 3] \\ [\mathbf{3}, \mathbf{4}] \end{cases}$$

$$x_{20} \mapsto \begin{cases} [2 \cdot x_{10} + 3 \cdot x_{11}, 2 \cdot x_{10} + 3 \cdot x_{11}] \\ [\mathbf{17}, \mathbf{24}] \end{cases}$$

$$x_{21} \mapsto \begin{cases} [x_{10} - x_{11}, x_{10} - x_{11}] \\ [\mathbf{1}, \mathbf{2}] \end{cases}$$

$$x_{30} \mapsto \begin{cases} [x_{20} - x_{21} - 14, x_{20} - x_{21} - 14] \\ [\mathbf{2}, \mathbf{8}] \end{cases}$$

$$x_{31} \mapsto \begin{cases} [0, 0.5 \cdot (0.5 \cdot x_{20} - 1.5 \cdot x_{21} - 8) + 0.5] \\ [\mathbf{0}, \mathbf{1}] \end{cases}$$

$$x_{40} \mapsto \begin{cases} [0.5 \cdot x_{30} - 2 \cdot x_{31} + 1, 0.5 \cdot x_{30} - 2 \cdot x_{31} + 1] \\ [\mathbf{0}, \mathbf{5}] \end{cases}$$

$$\mapsto \begin{cases} [x_{21} + 1, 0.5 \cdot x_{20} - 0.5 \cdot x_{21} - 6] \\ [\mathbf{2}, \mathbf{5.5}] \end{cases}$$

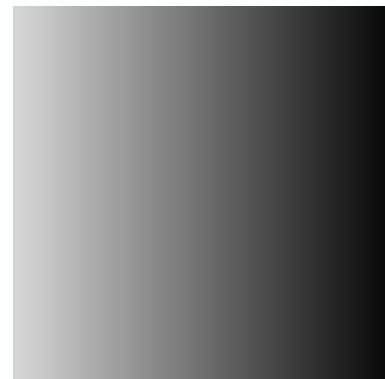
$$\mapsto \begin{cases} [x_{10} - x_{11} + 1, 0.5 \cdot x_{10} + 2 \cdot x_{11} - 6] \\ [\mathbf{1}, \mathbf{5}] \end{cases}$$

$$\mapsto \begin{cases} [0.5 \cdot x_{00} + 0.5 \cdot x_{01} + 2, 1.5 \cdot x_{00} + 1.5 \cdot x_{11} + 2] \\ [\mathbf{2}, \mathbf{5}] \end{cases}$$

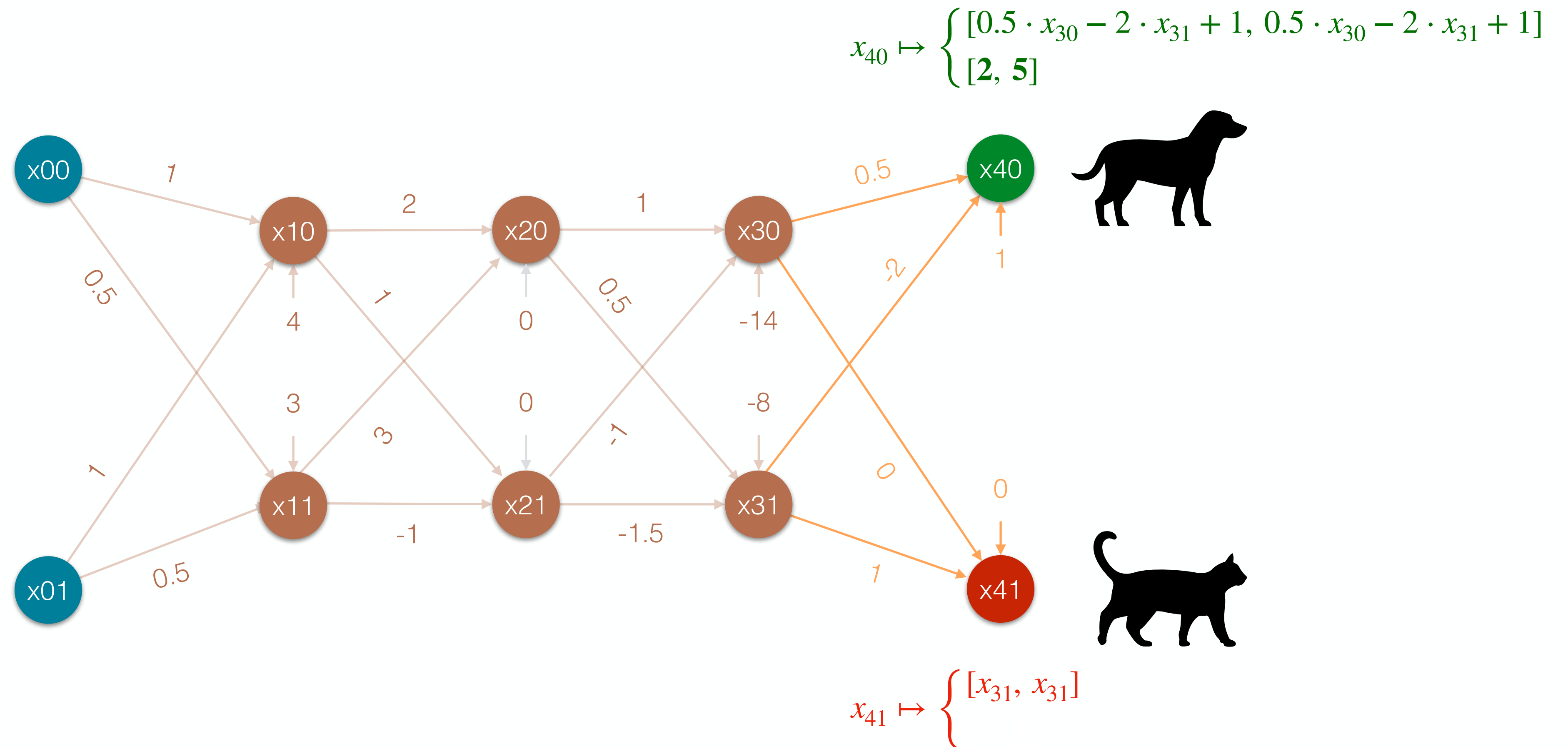
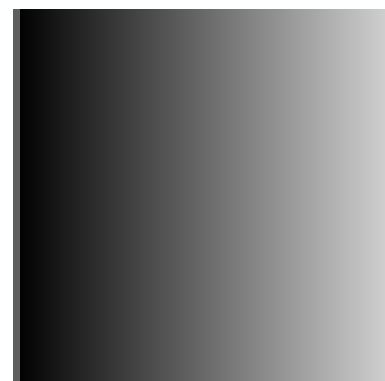
DeepPoly Domain

Example

$$x_{00} \mapsto \begin{cases} [x_{00}, x_{00}] \\ [0, 1] \end{cases}$$



$$x_{01} \mapsto \begin{cases} [x_{01}, x_{01}] \\ [0, 1] \end{cases}$$



DeepPoly Domain

Back-Substitution

$$x_{00} \mapsto [\mathbf{0}, \mathbf{1}]$$

$$x_{01} \mapsto [\mathbf{0}, \mathbf{1}]$$

$$x_{10} \mapsto \begin{cases} [x_{00} + x_{01} + 4, x_{00} + x_{01} + 4] \\ [\mathbf{4}, \mathbf{6}] \end{cases}$$

$$x_{11} \mapsto \begin{cases} [0.5 \cdot x_{00} + 0.5 \cdot x_{01} + 3, 0.5 \cdot x_{00} + 0.5 \cdot x_{01} + 3] \\ [\mathbf{3}, \mathbf{4}] \end{cases}$$

$$x_{20} \mapsto \begin{cases} [2 \cdot x_{10} + 3 \cdot x_{11}, 2 \cdot x_{10} + 3 \cdot x_{11}] \\ [\mathbf{17}, \mathbf{24}] \end{cases}$$

$$x_{21} \mapsto \begin{cases} [x_{10} - x_{11}, x_{10} - x_{11}] \\ [\mathbf{1}, \mathbf{2}] \end{cases}$$

$$x_{30} \mapsto \begin{cases} [x_{20} - x_{21} - 14, x_{20} - x_{21} - 14] \\ [\mathbf{2}, \mathbf{8}] \end{cases}$$

$$x_{31} \mapsto \begin{cases} [0, 0.5 \cdot (0.5 \cdot x_{20} - 1.5 \cdot x_{21} - 8) + 0.5] \\ [\mathbf{0}, \mathbf{1}] \end{cases}$$

$$x_{41} \mapsto \begin{cases} [x_{31}, x_{31}] \end{cases}$$

$$\mapsto \begin{cases} [0, 0.25 \cdot x_{20} - 0.75 \cdot x_{21} - 3.5] \end{cases}$$

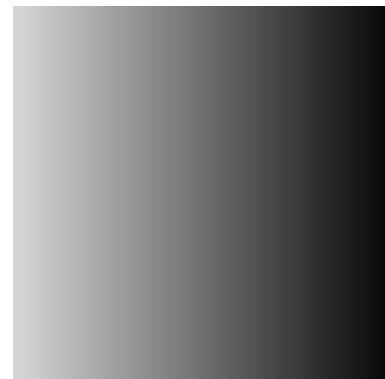
$$\mapsto \begin{cases} [0, -0.25 \cdot x_{10} + 1.5 \cdot x_{11} - 3.5] \end{cases}$$

$$\mapsto \begin{cases} [0, 0.5 \cdot x_{00} + 0.5 \cdot x_{01}] \\ [\mathbf{0}, \mathbf{1}] \end{cases}$$

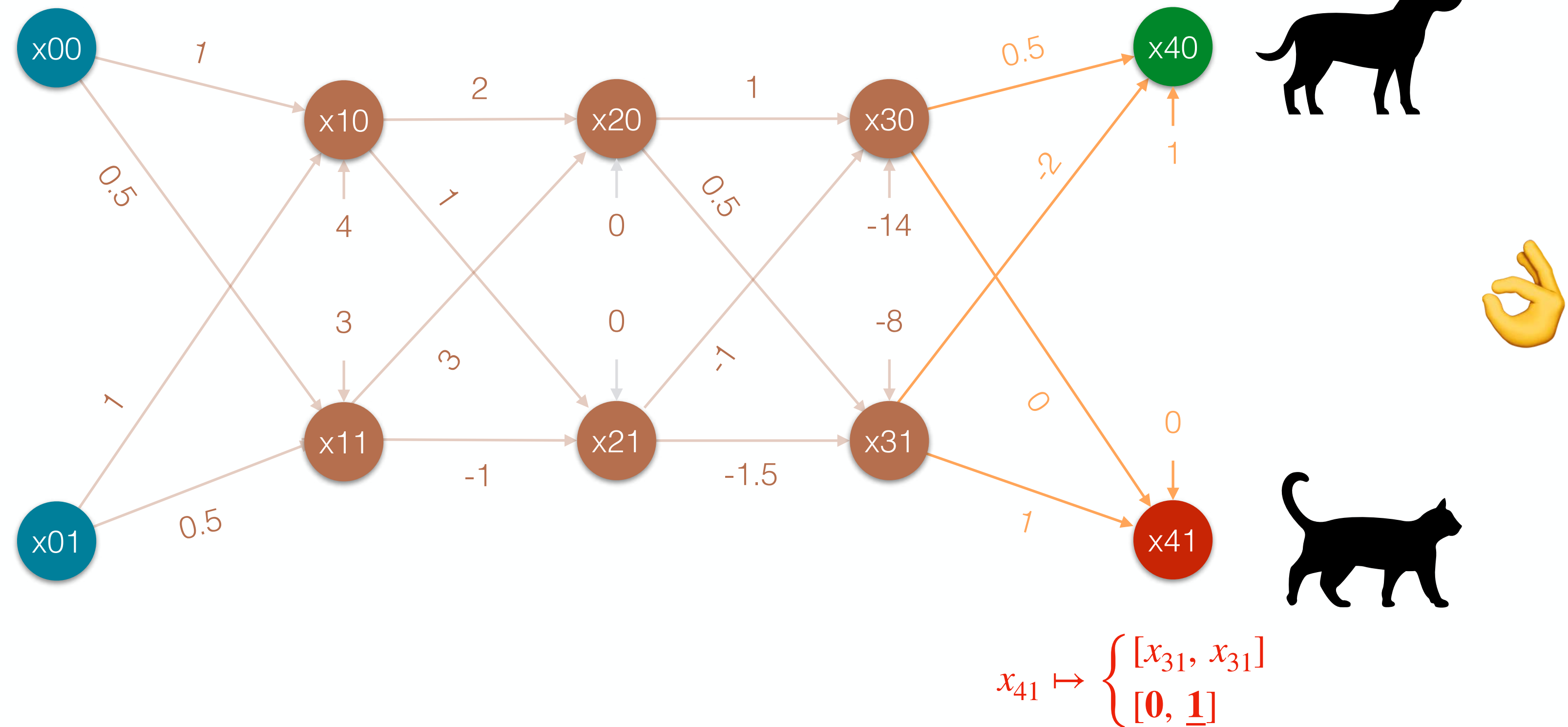
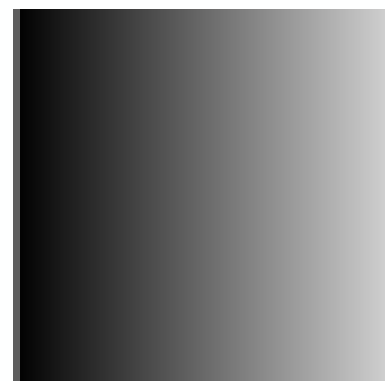
DeepPoly Domain

Example

$$x_{00} \mapsto \begin{cases} [x_{00}, x_{00}] \\ [0, 1] \end{cases}$$

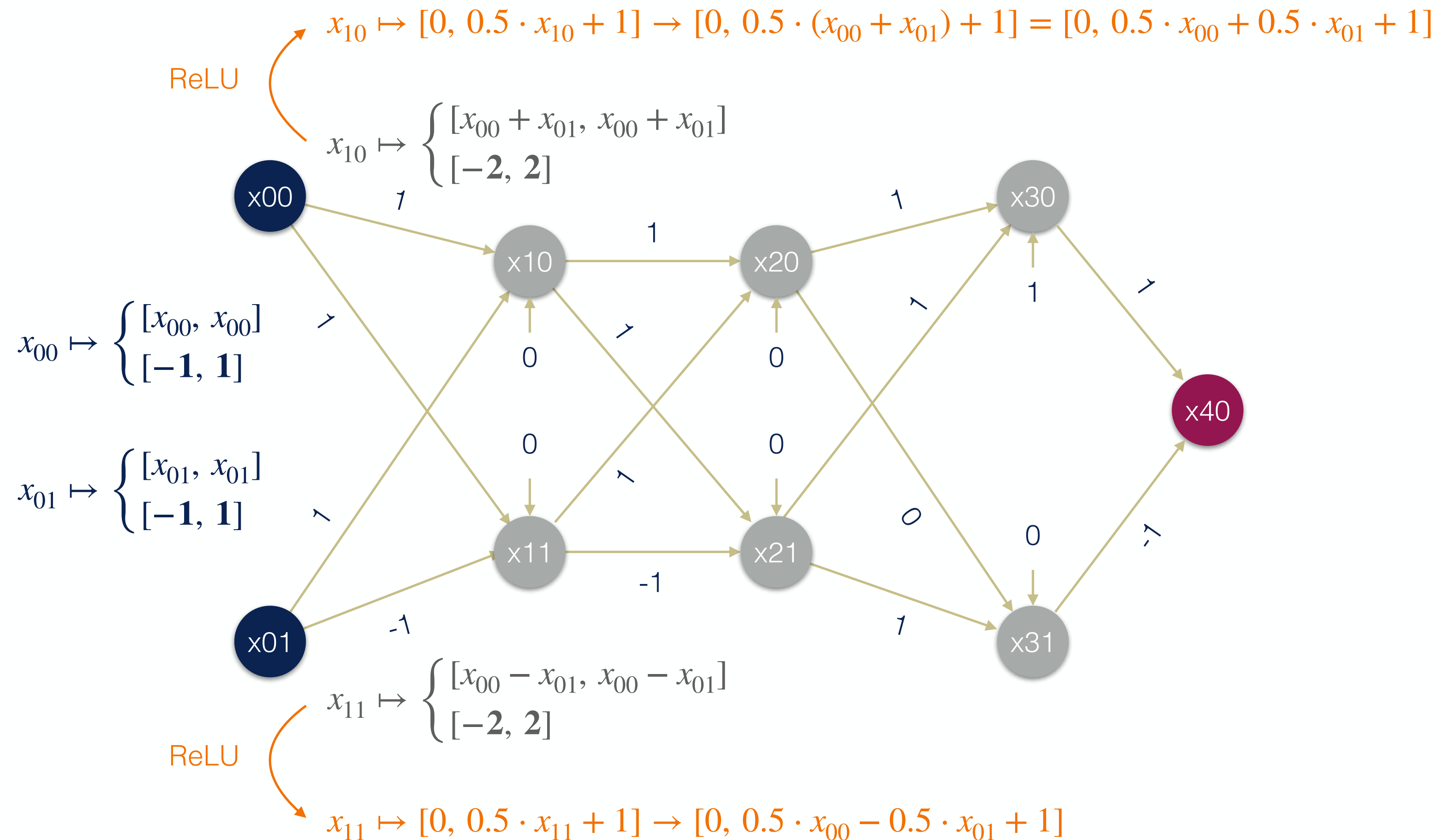


$$x_{01} \mapsto \begin{cases} [x_{01}, x_{01}] \\ [0, 1] \end{cases}$$



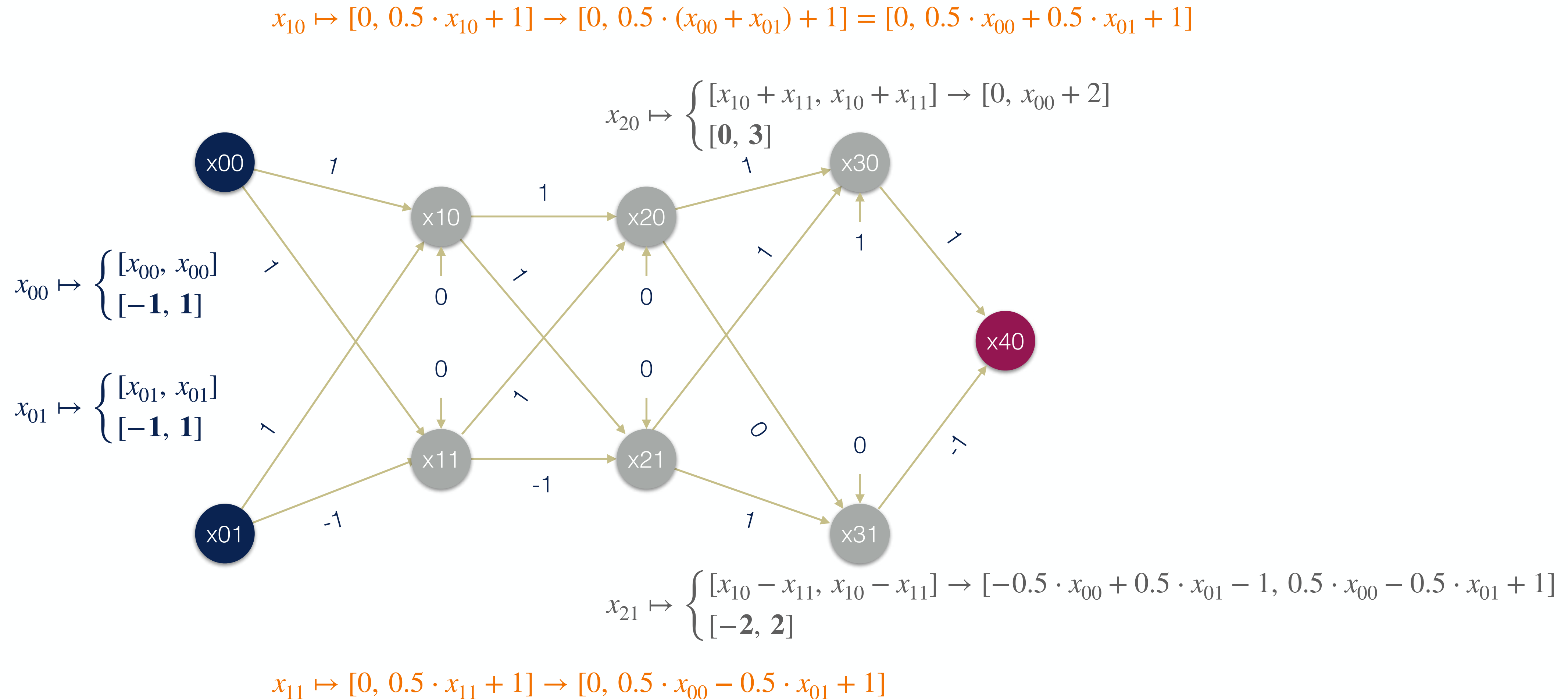
DeepPoly Domain

Maintaining Symbolic Bounds wrt the Inputs (“à la Symbolic”)



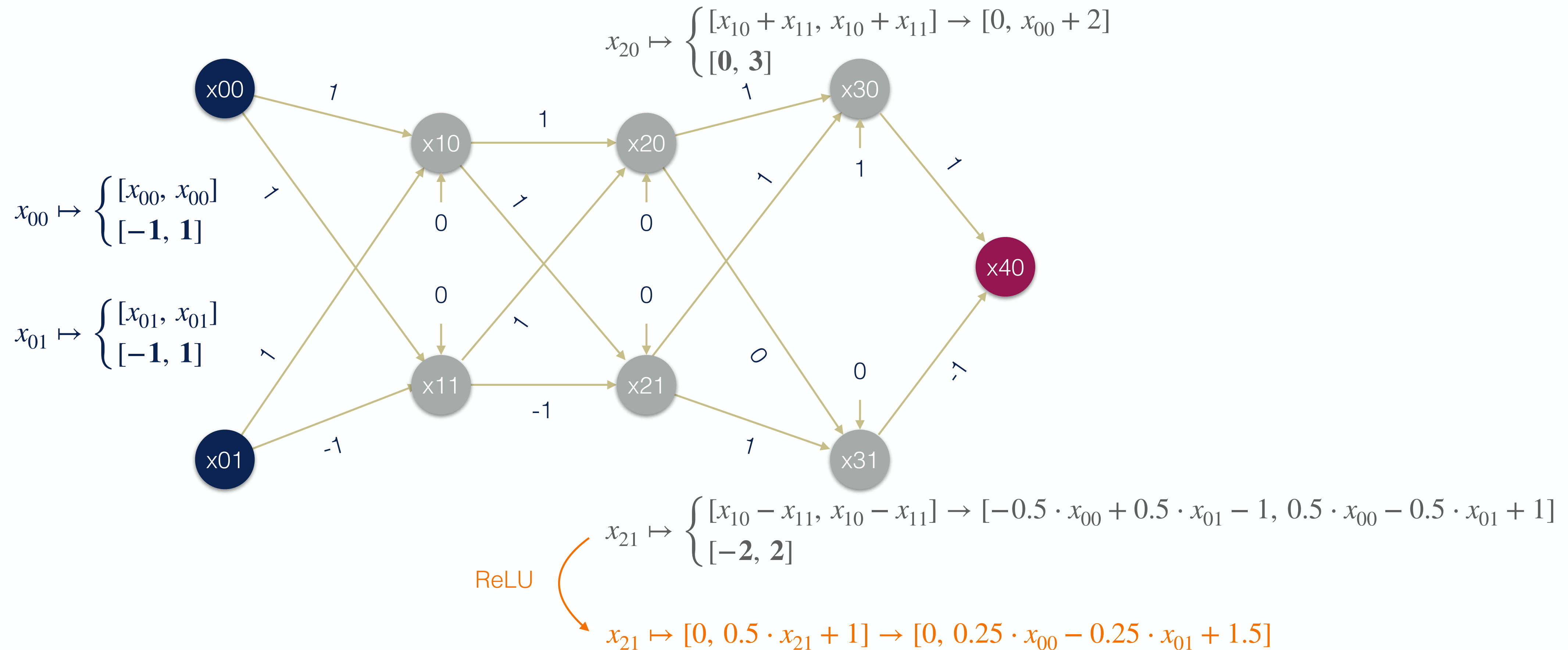
DeepPoly Domain

Maintaining Symbolic Bounds wrt the Inputs (“à la Symbolic”)



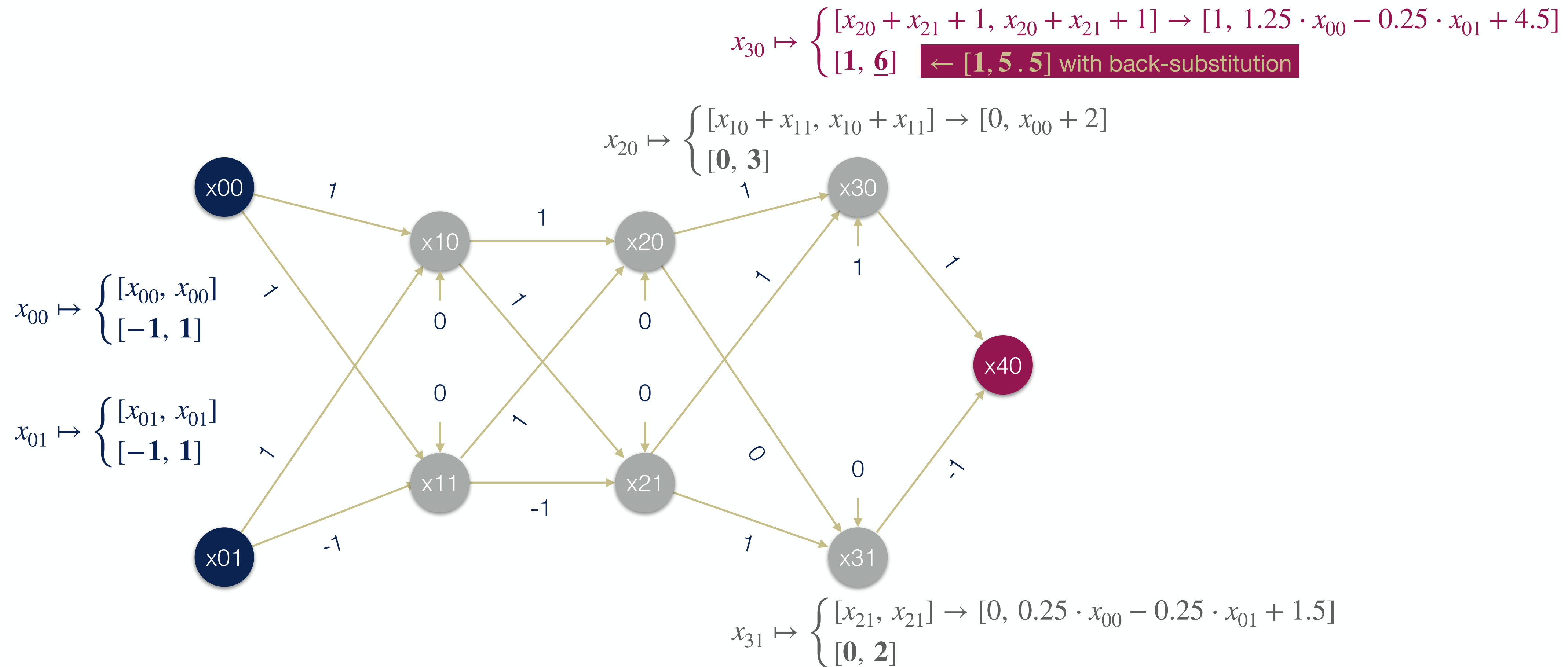
DeepPoly Domain

Maintaining Symbolic Bounds wrt the Inputs (“à la Symbolic”)



DeepPoly Domain

Maintaining Symbolic Bounds wrt the Inputs (“à la Symbolic”)

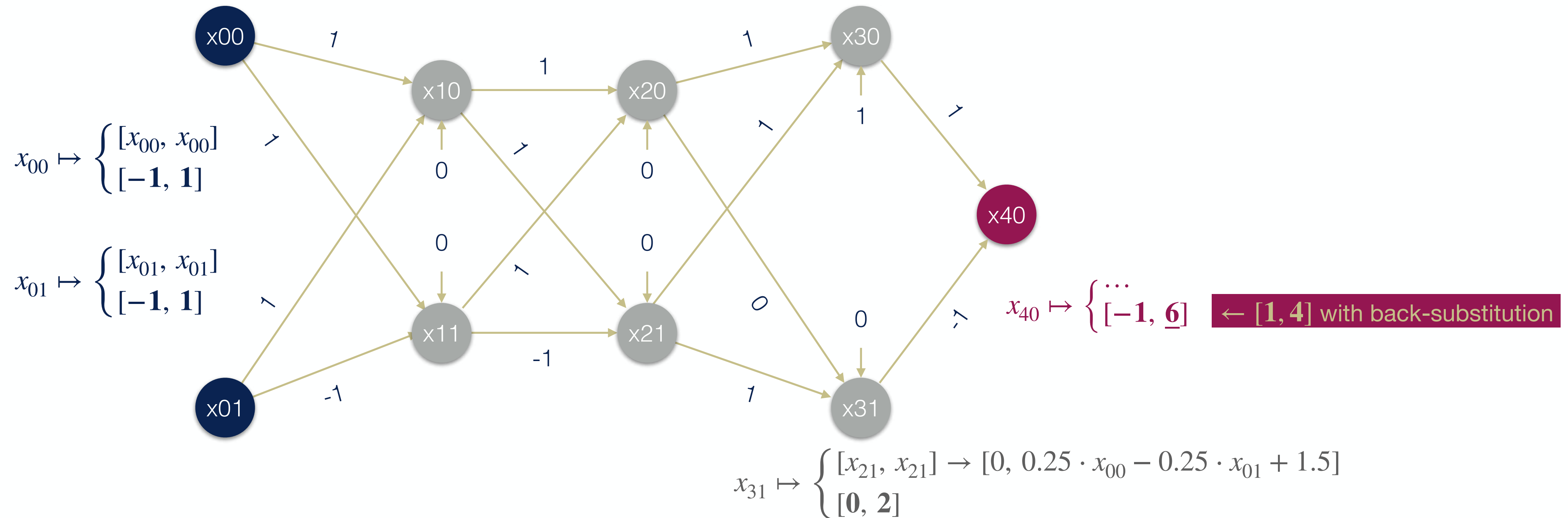


$$x_{21} \mapsto [0, 0.5 \cdot x_{21} + 1] \rightarrow [0, 0.25 \cdot x_{00} - 0.25 \cdot x_{01} + 1.5]$$

DeepPoly Domain

Maintaining Symbolic Bounds wrt the Inputs (“à la Symbolic”)

$$x_{30} \mapsto \begin{cases} [x_{20} + x_{21} + 1, x_{20} + x_{21} + 1] \rightarrow [1, 1.25 \cdot x_{00} - 0.25 \cdot x_{01} + 4.5] \\ [1, \underline{6}] \leftarrow [1, 5.5] \text{ with back-substitution} \end{cases}$$



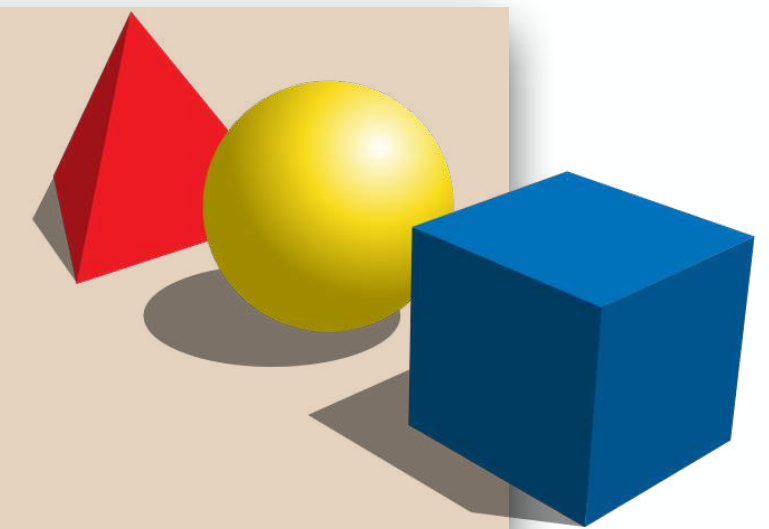
Static Local Prediction Stability Analysis

Going Farther: Multi-Neuron Abstractions

practical tools
targeting specific programs



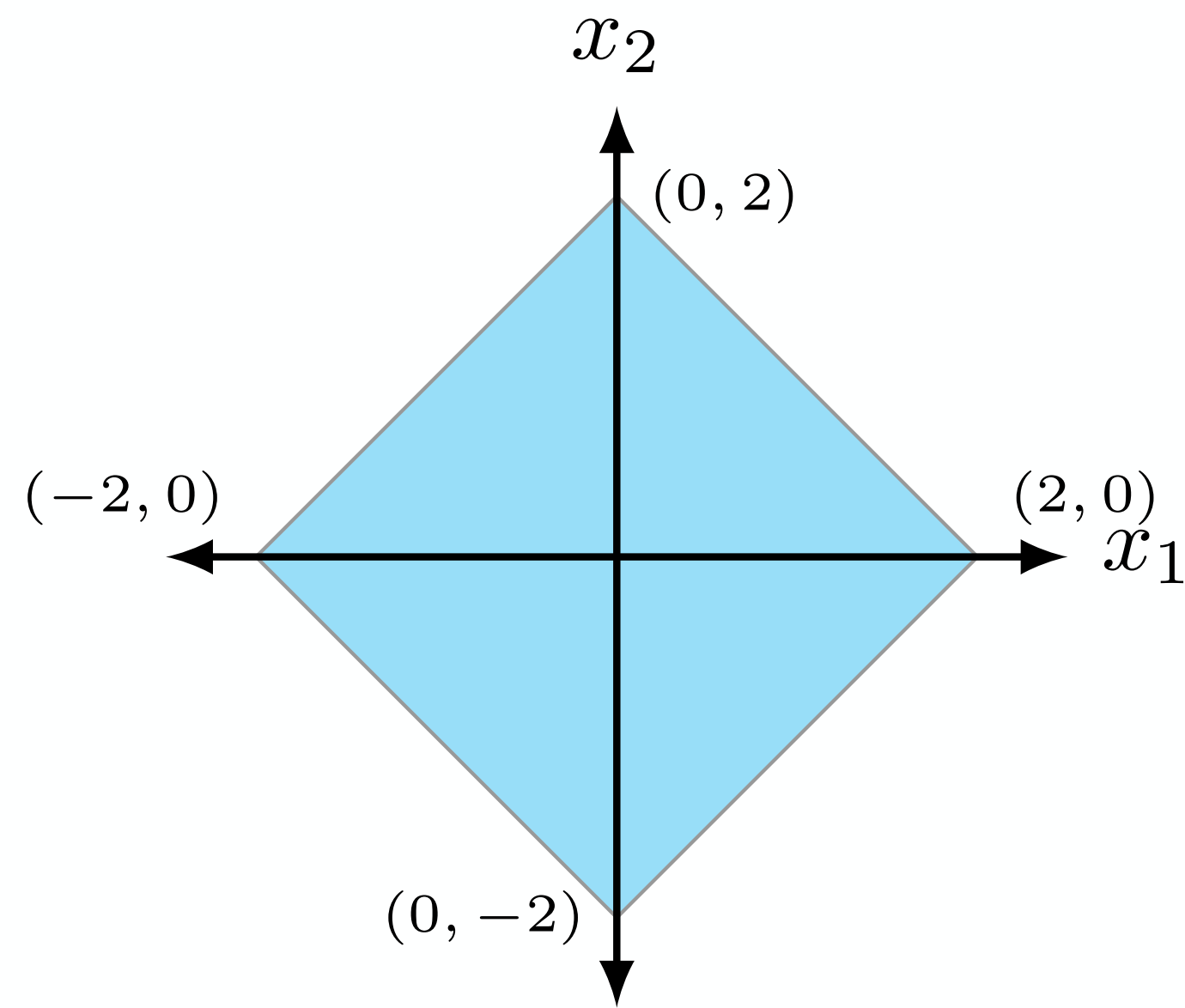
abstract semantics, abstract domains
algorithmic approaches to decide program properties



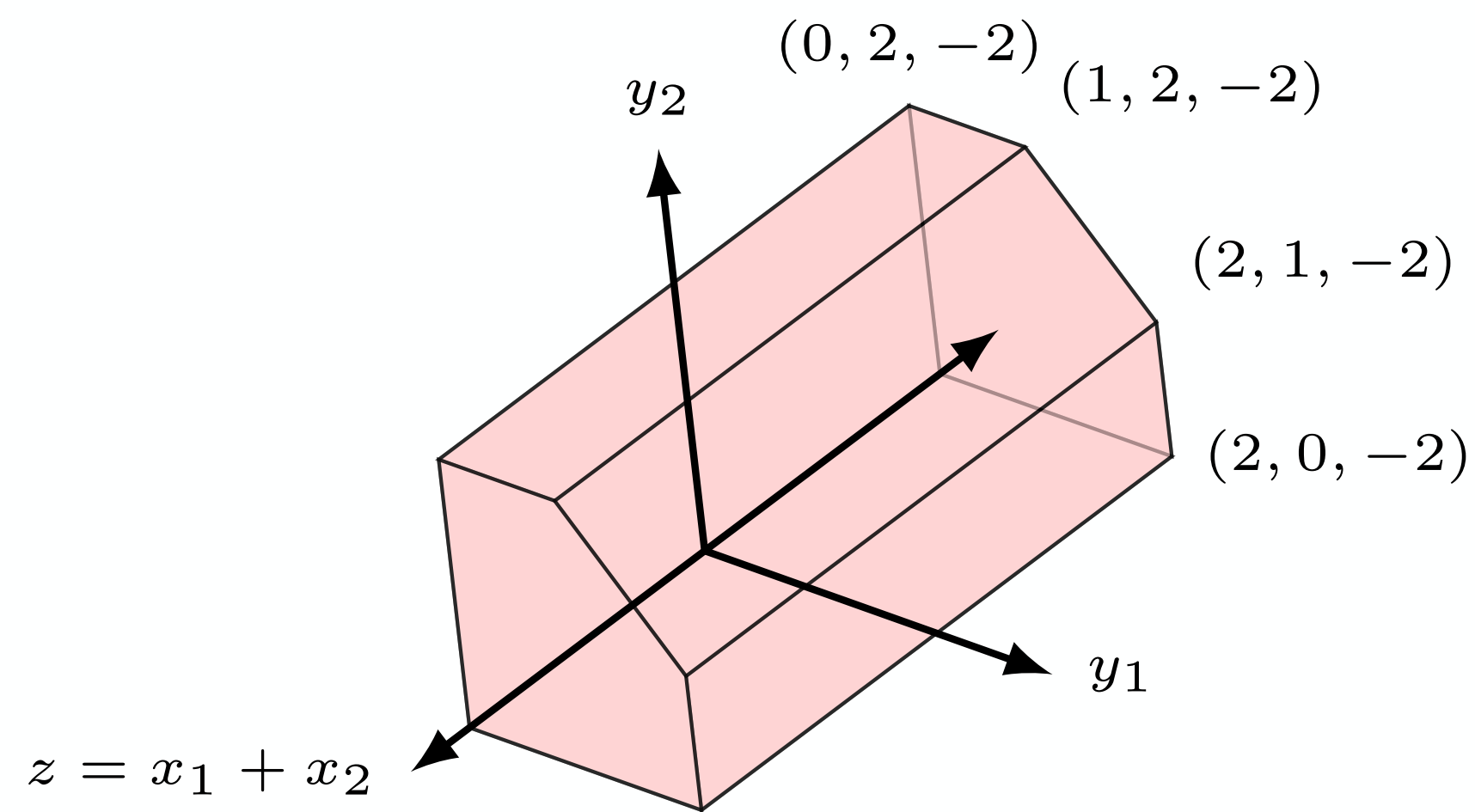
concrete semantics
mathematical models of the program behavior



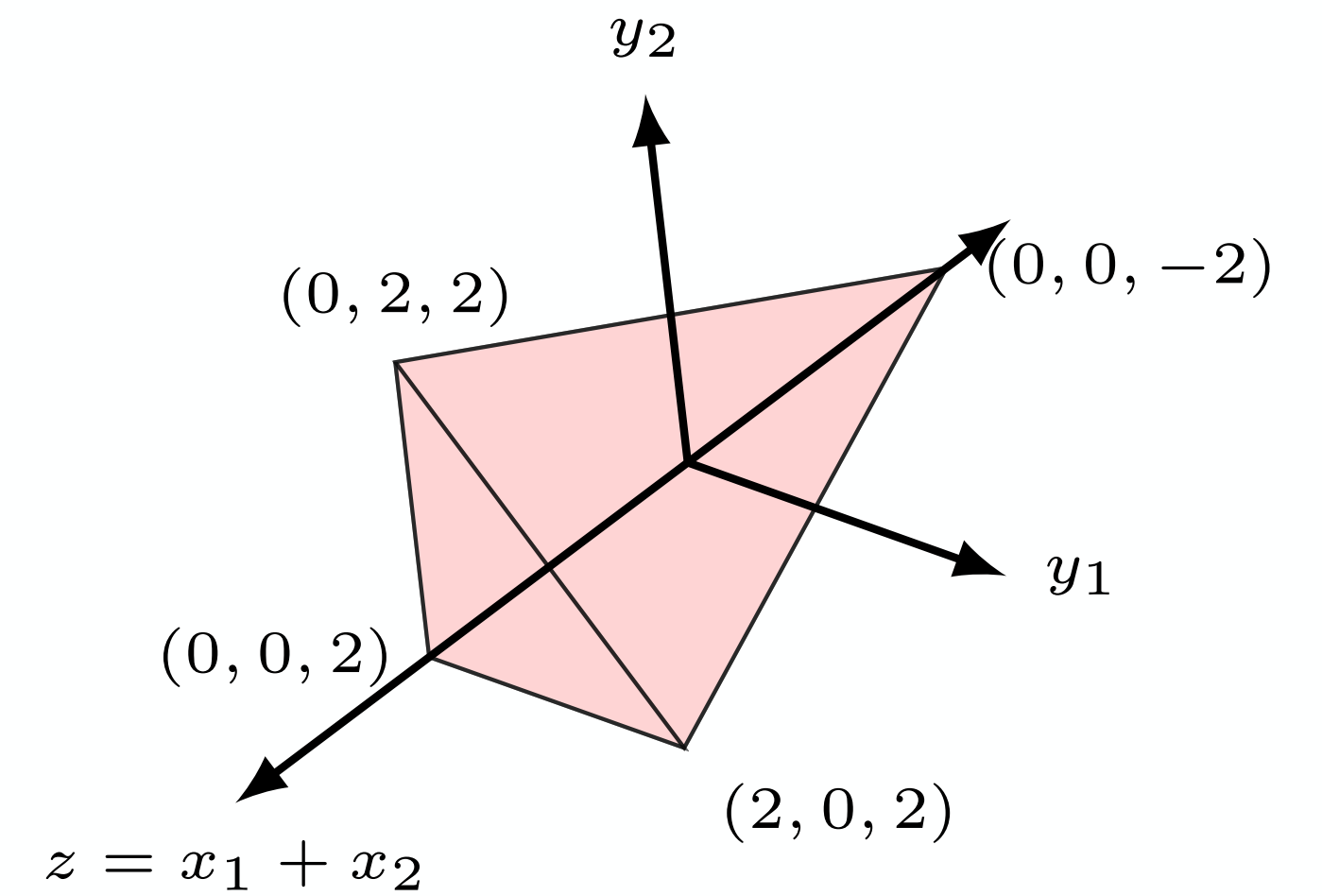
Multi-Neuron Abstractions [Singh et al. @ NeurIPS 2019]



(a) Input shape



(b) 1-ReLU



(c) 2-ReLU

Static Local Prediction Stability Analysis

An Exercise Worth Trying 😊

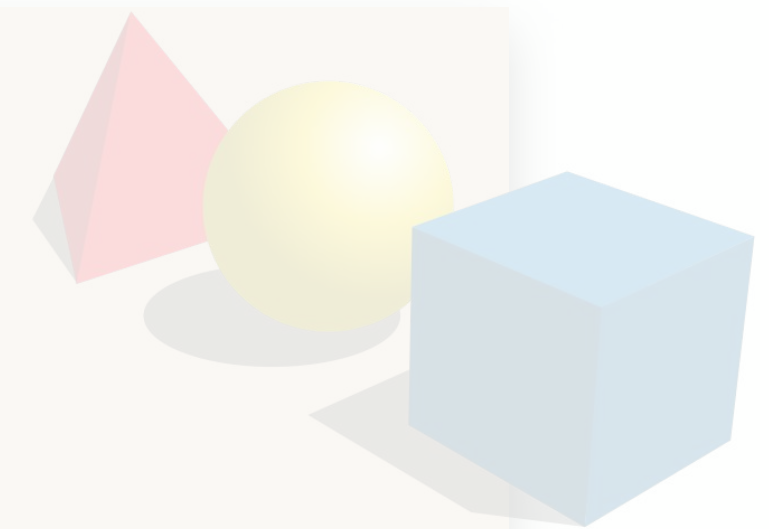
practical tools

targeting specific programs



abstract semantics, abstract domains

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concrete semantics

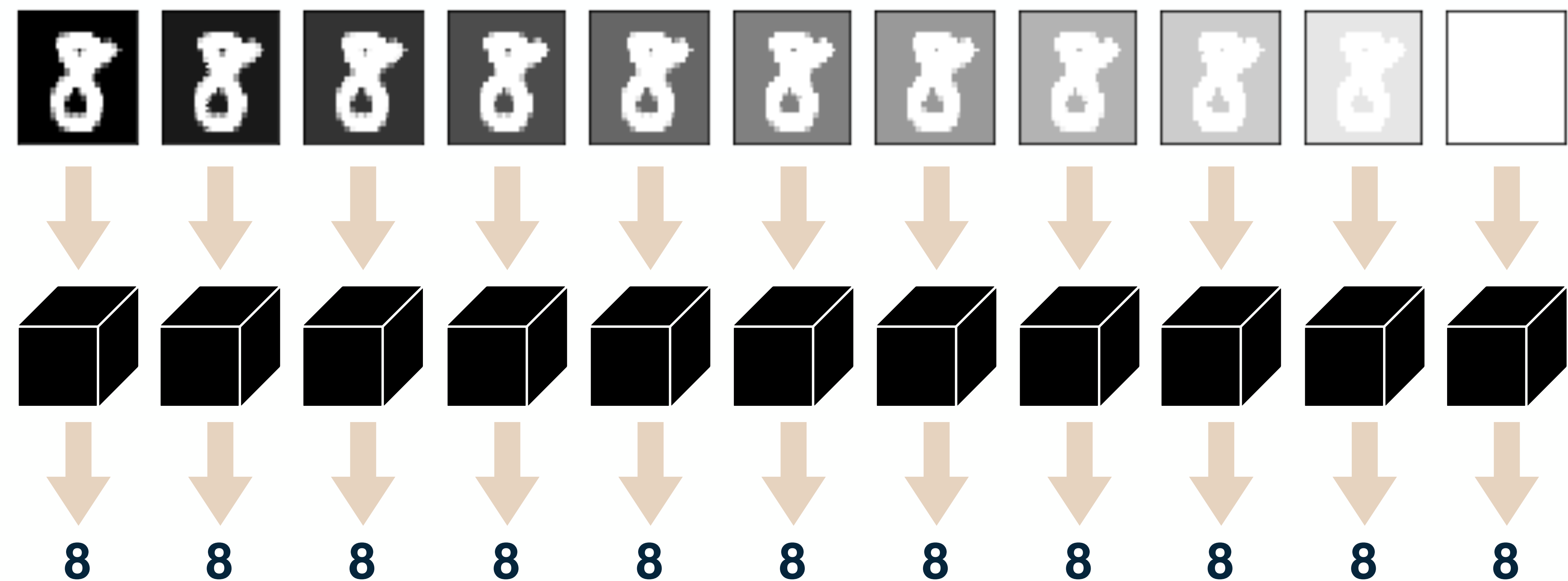
mathematical models of the program behavior



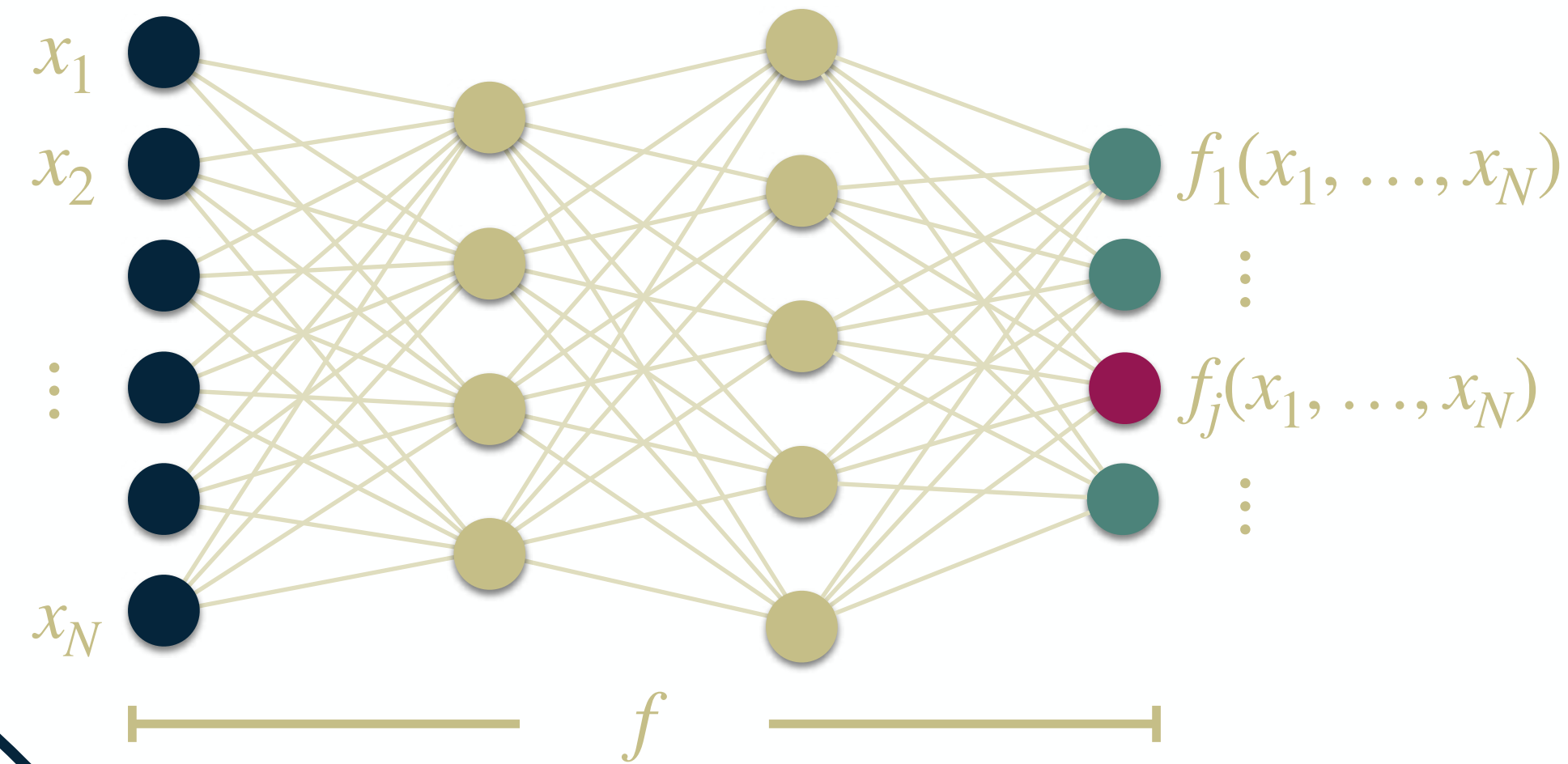
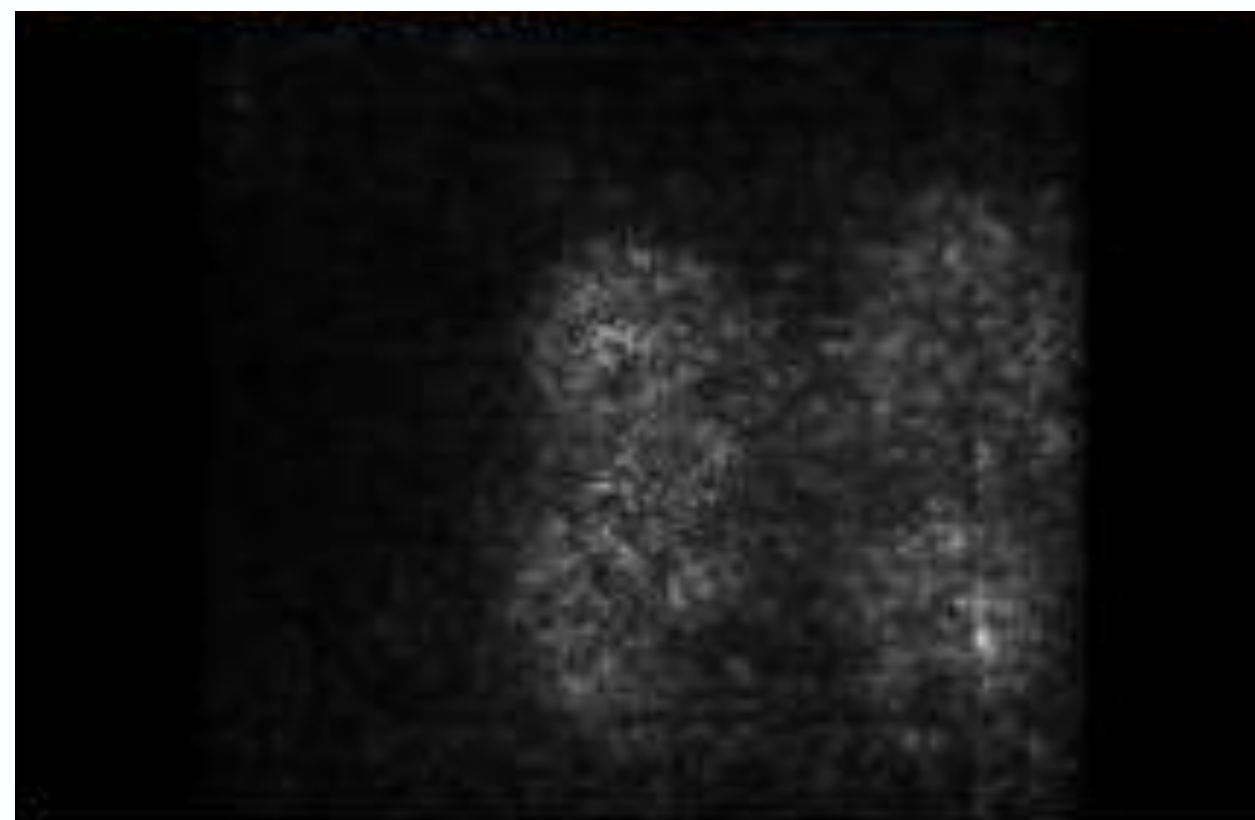
Saliency Map Stability

Local Prediction Stability

Not Enough!



Saliency Maps [Simonyan & al. @ ICLR 2014]



Dog

$$\text{map}_j(x) = \left| \frac{\partial f_j(x_1, \dots, x_N)}{\partial x_1} \right| \dots \left| \frac{\partial f_j(x_1, \dots, x_N)}{\partial x_N} \right|$$

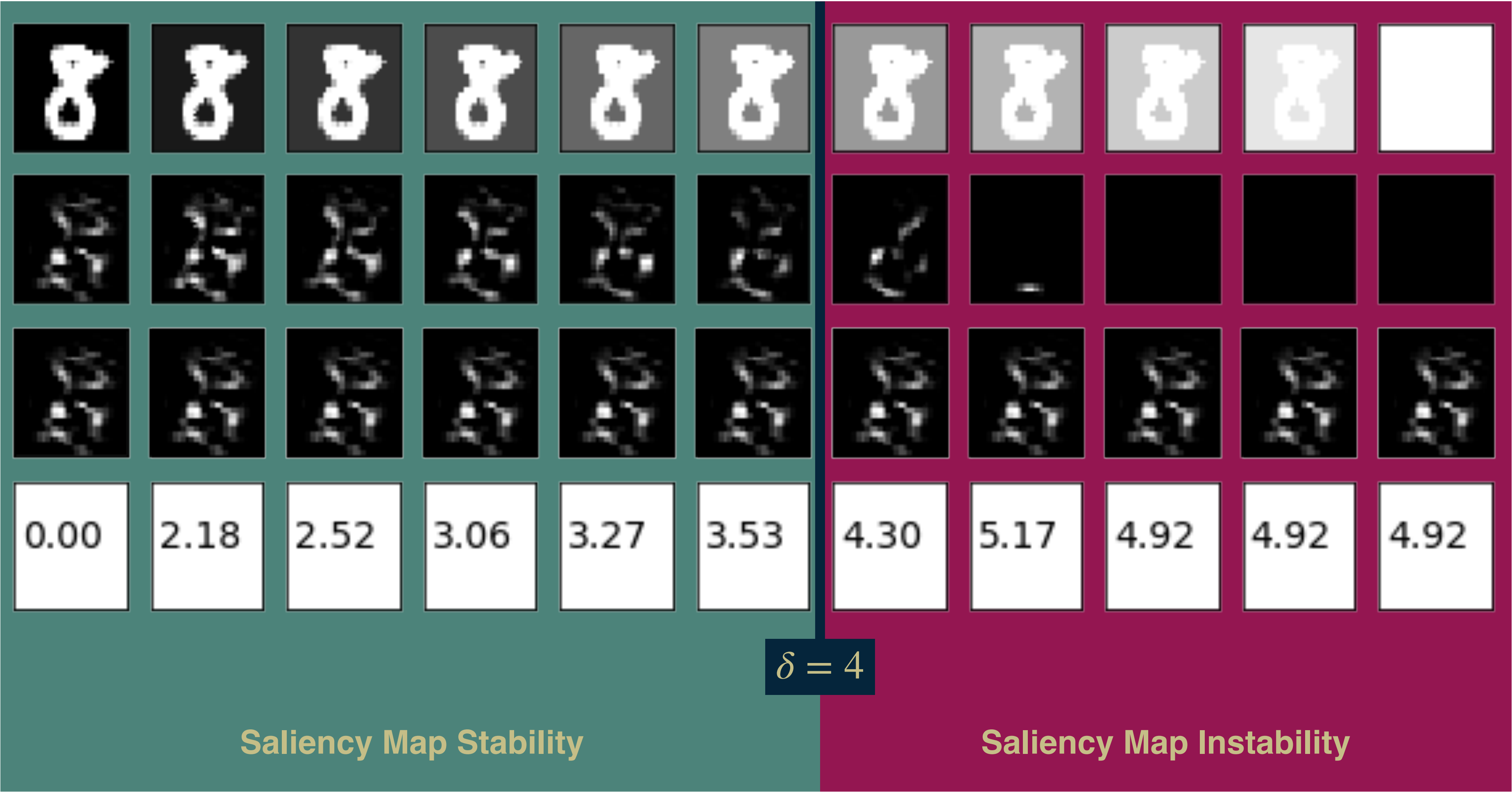
Local Saliency Map Stability

Input Image

Saliency Map

Expected Saliency Map

Distance



Reading Suggestion

Verifying Attention Robustness of Deep Neural Networks against Semantic Perturbations

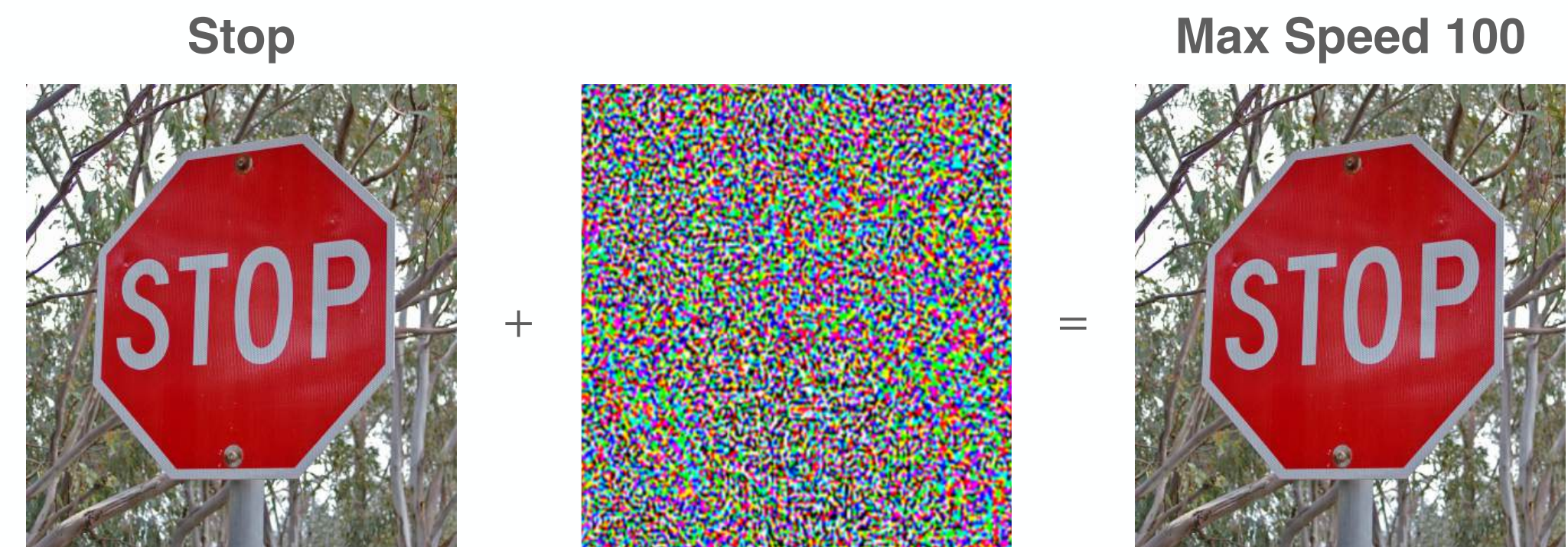
Satoshi Munakata¹, Caterina Urban², Haruki Yokoyama¹, Koji Yamamoto¹,
and Kazuki Munakata¹

¹ Fujitsu, Kanagawa, Japan

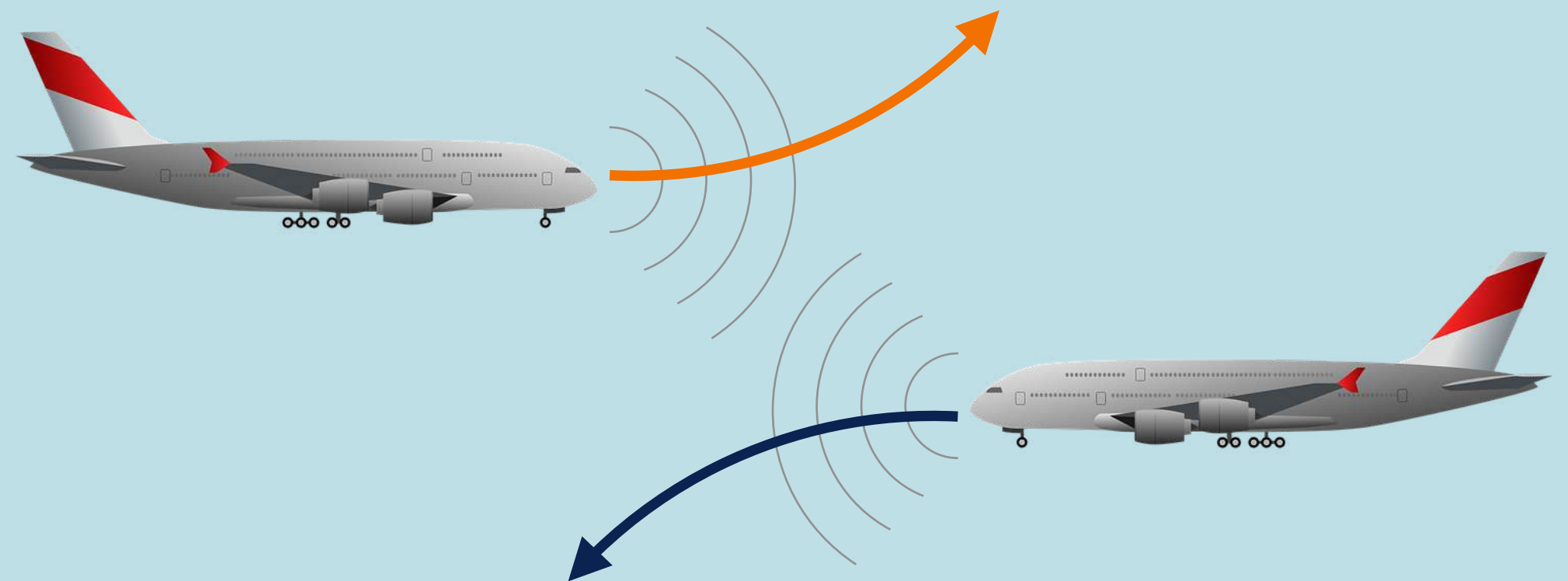
² Inria & ENS | PSL & CNRS, Paris, France

Abstract. It is known that deep neural networks (DNNs) classify an input image by paying particular attention to certain specific pixels; a graphical representation of the magnitude of attention to each pixel is called a *saliency-map*. Saliency-maps are used to check the validity of the classification decision basis, e.g., it is not a valid basis for classification if a DNN pays more attention to the background rather than the subject of an image. Semantic perturbations can significantly change the saliency-map. In this work, we propose the first verification method for *attention robustness*, i.e., the local robustness of the changes in the saliency-map against combinations of semantic perturbations. Specifically, our method determines the range of the perturbation parameters (e.g., the brightness change) that maintains the difference between the actual saliency-map change and the expected saliency-map change below a given threshold value. Our method is based on activation region traversals, focusing on the outermost robust boundary for scalability on larger DNNs. We empirically evaluate the effectiveness and performance of our method on DNNs trained on popular image classification datasets.

Stability



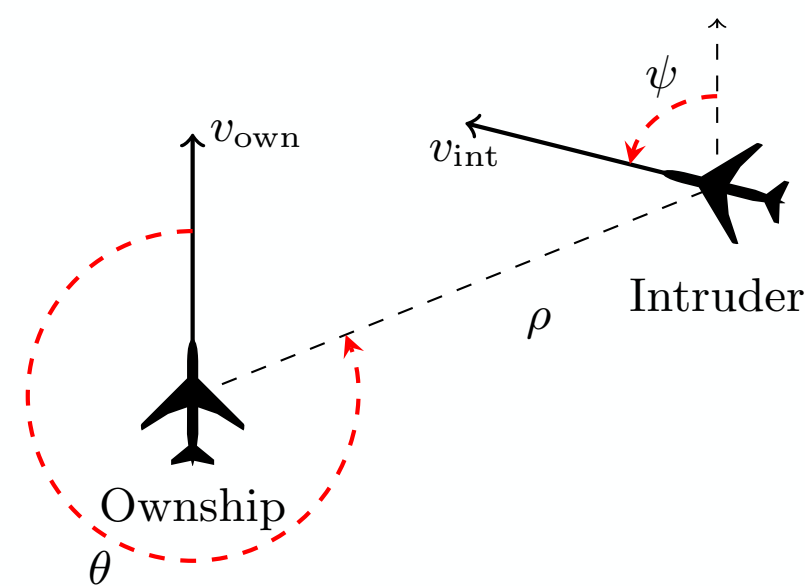
Safety



ACAS Xu

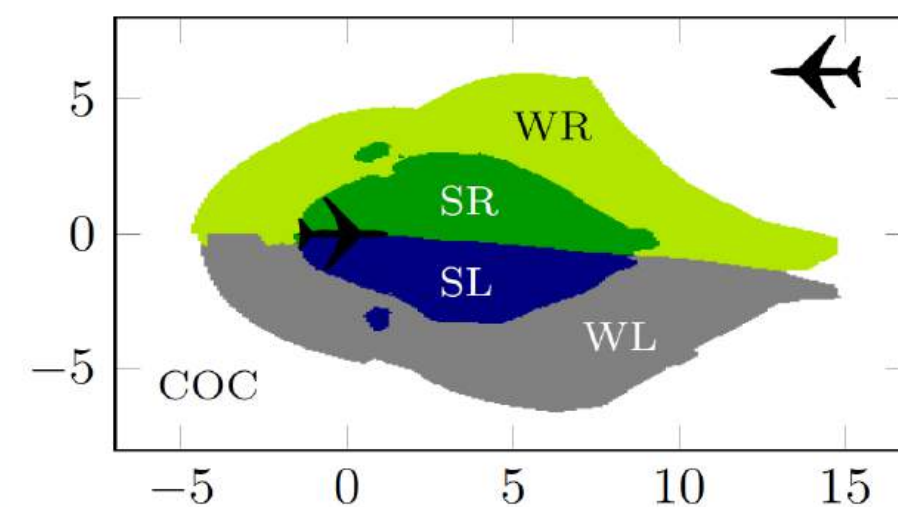
Airborne Collision Avoidance System for Unmanned Aircraft

implemented using **45 feed-forward fully-connected ReLU networks**



5 input sensor measurements

- ρ : distance from ownship to intruder
- θ : angle to intruder relative to ownship heading direction
- ψ : heading angle to intruder relative to ownship heading direction
- v_{own} : speed of ownship
- v_{int} : speed of intruder

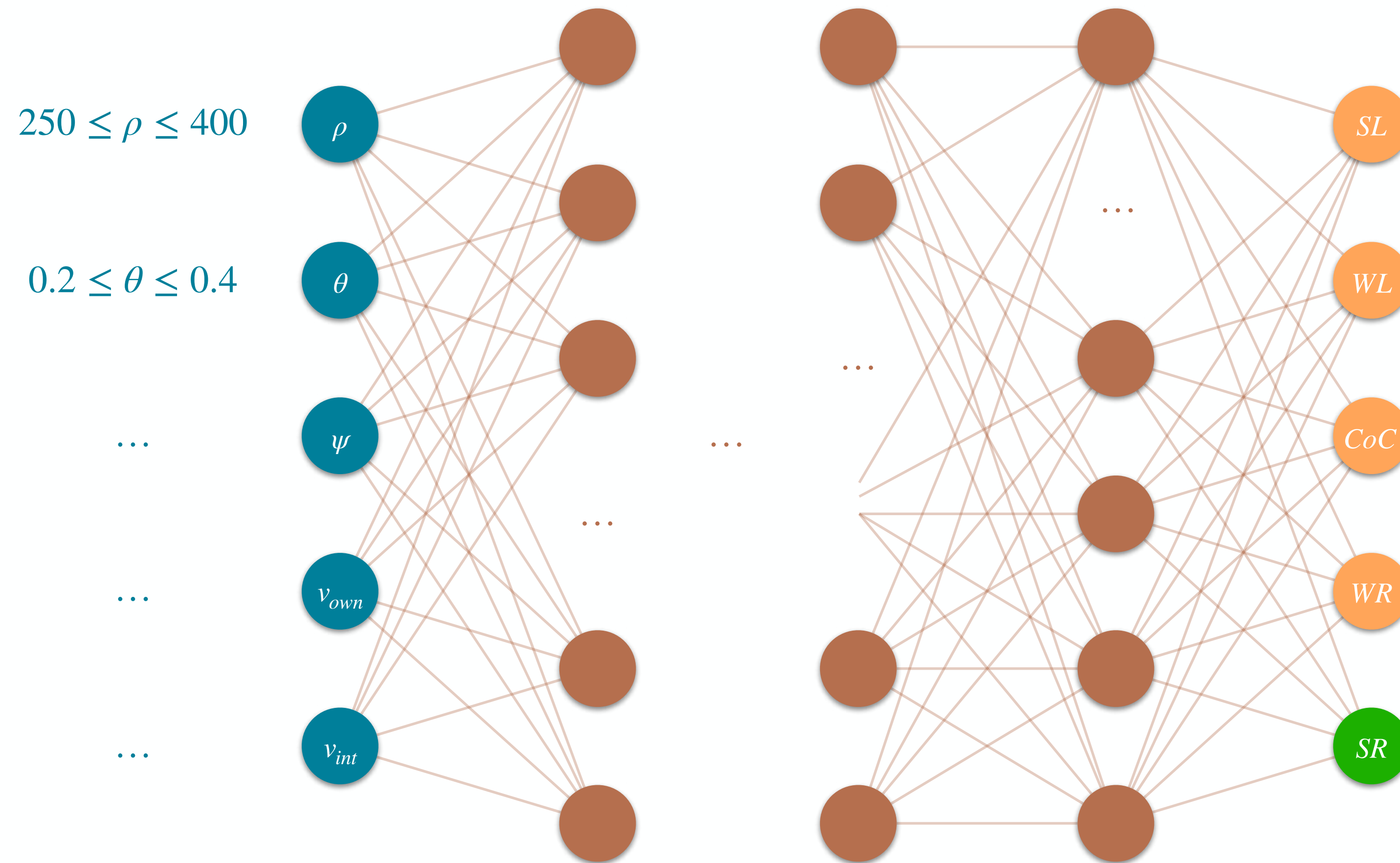


5 output horizontal advisories

- Strong Left
- Weak Left
- Clear of Conflict
- Weak Right
- Strong Right

ACAS Xu Safety Properties

Example: “if intruder is near and approaching from the left, go Strong Right”



Static Safety Analysis

3-Step Recipe

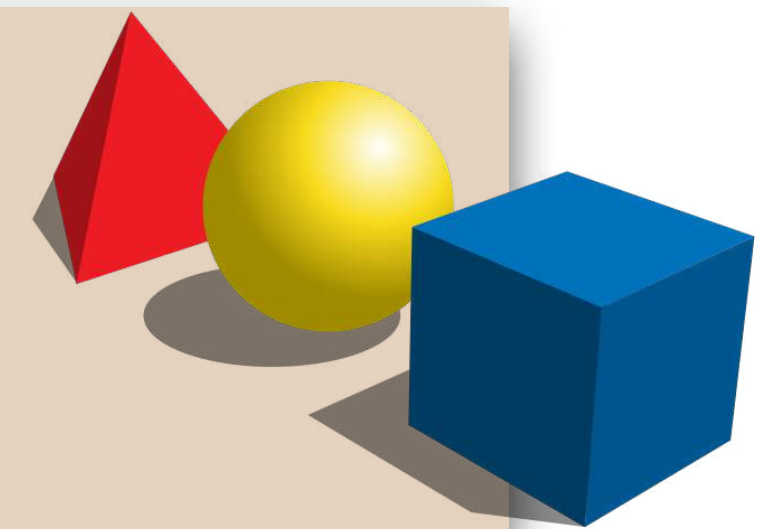
practical tools

targeting specific programs



abstract semantics, abstract domains

algorithmic approaches to decide program properties



concrete semantics

mathematical models of the program behavior



Safety

Input-Output Properties

I: input specification

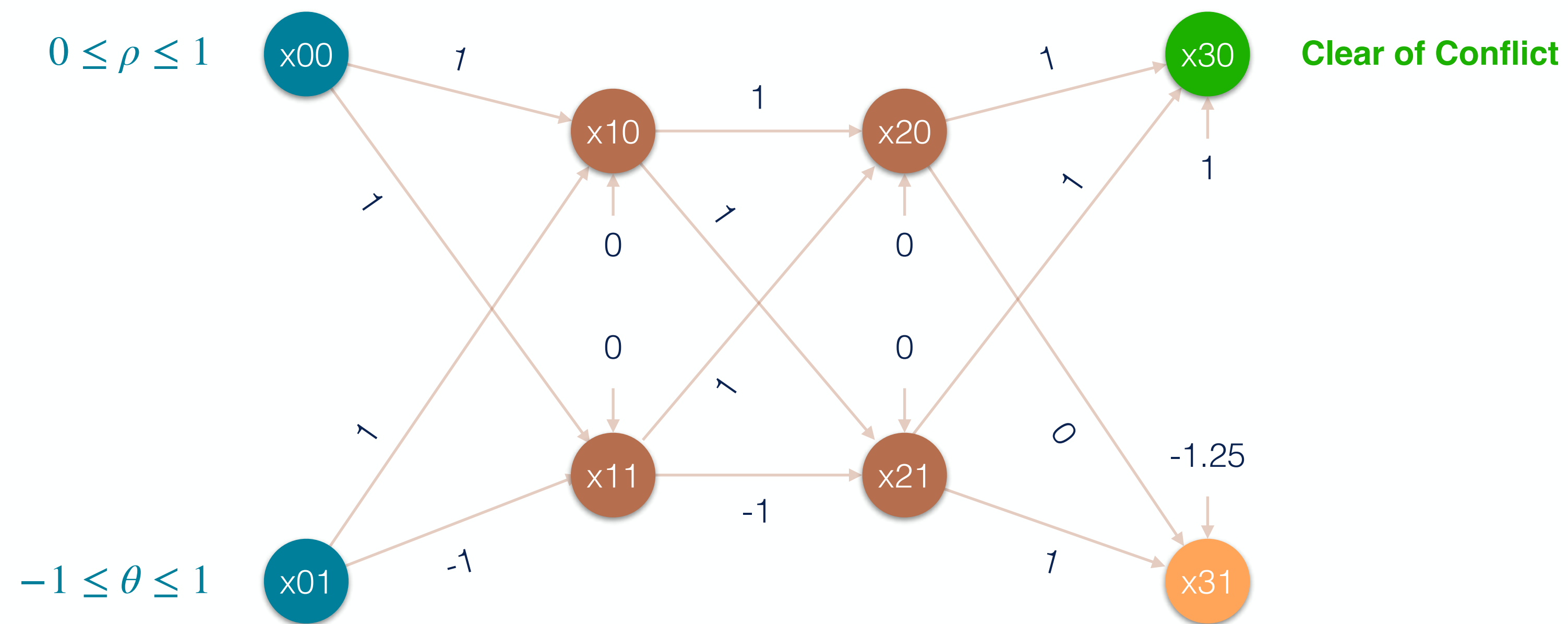
O: output specification

$$\mathcal{R}_{\mathbf{x}}^{\delta, \epsilon} \stackrel{\text{def}}{=} \{t \in \Sigma^* \mid t_0 \models \mathbf{I} \Rightarrow t_\omega \models \mathbf{O}\}$$

$\mathcal{S}_{\mathbf{O}}^{\mathbf{I}}$ is the set of all traces that are **satisfy** the input and output specifications **I** and **O**

Safety

Example



Static Safety Analysis

Concrete Semantics

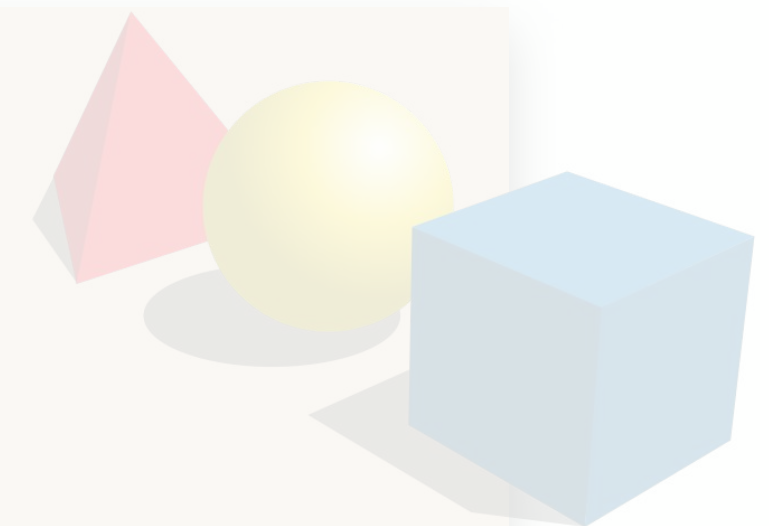
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algorithmic approaches to decide program properties

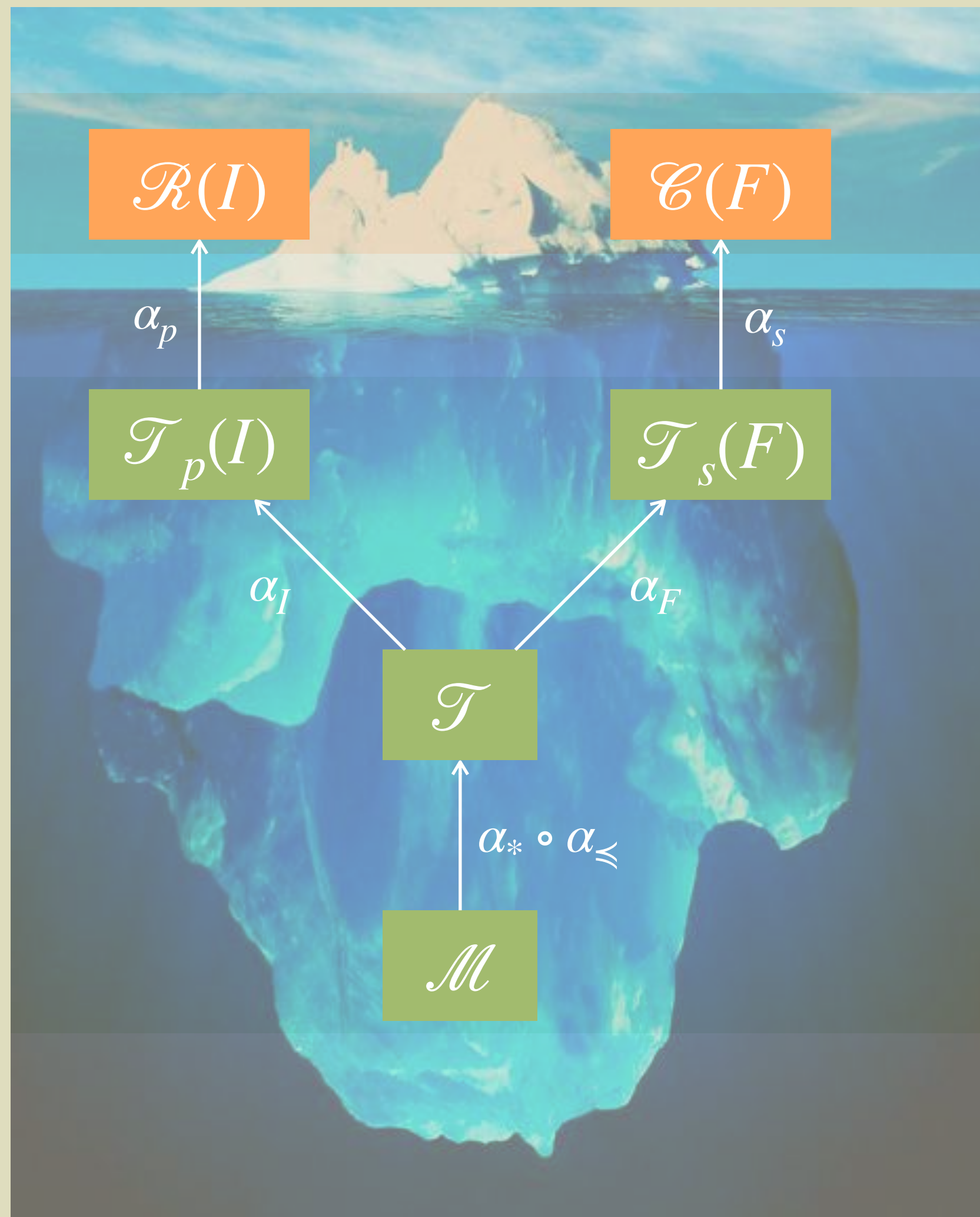


concrete semantics

mathematical models of the program behavior



Hierarchy of Semantics



Forward/Backward Reachability Semantics

Forward/Backward Reachable State Abstraction

Prefix/Suffix Trace Semantics

Prefix/Suffix Trace Abstraction

Partial Finite Trace Semantics

Partial Finite Trace Abstraction

Maximal Trace Semantics

Safety

Input-Output Properties

I: input specification

O: output specification

$$\mathcal{R}_{\mathbf{x}}^{\delta, \epsilon} \stackrel{\text{def}}{=} \{t \in \Sigma^* \mid t_0 \models \mathbf{I} \Rightarrow t_\omega \models \mathbf{O}\}$$

$\mathcal{S}_{\mathbf{O}}^{\mathbf{I}}$ is the set of all traces that **satisfy** the input and output specifications **I** and **O**

Theorem

$$M \models \mathcal{S}_{\mathbf{O}}^{\mathbf{I}} \Leftrightarrow \mathcal{M}[[M]] \subseteq \mathcal{S}_{\mathbf{O}}^{\mathbf{I}} \Leftrightarrow \mathcal{T}_p(\mathbf{I})[[M]] \subseteq \mathcal{S}_{\mathbf{O}}^{\mathbf{I}}$$

Static Safety Analysis

Abstract Semantics

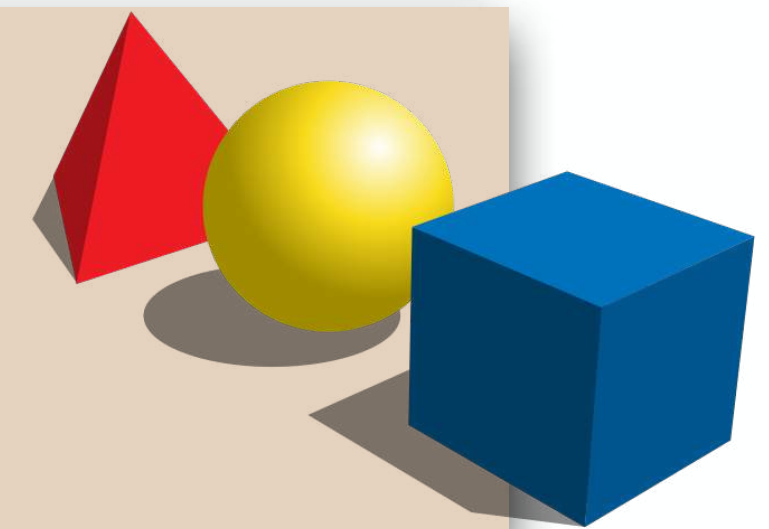
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abstract semantics, abstract domains

algorithmic approaches to decide program properties



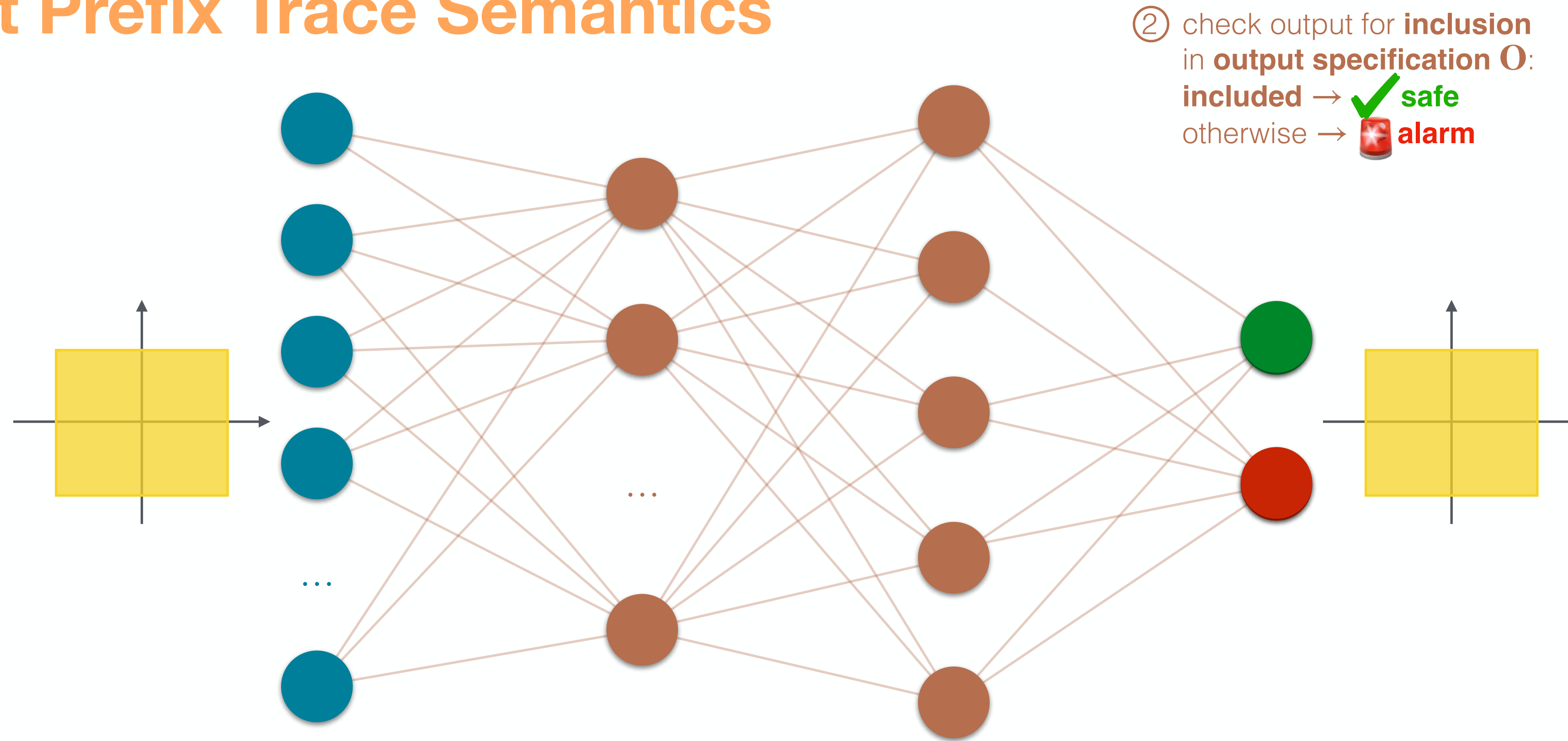
concrete semantics

mathematical models of the program behavior



Static Safety Analysis

Abstract Prefix Trace Semantics



① proceed **forwards** from an **abstraction $I^\#$** of **I**

Theorem

$$\mathcal{T}_p(I)[M] \subseteq \mathcal{T}_p^\#(I^\#)[M] \subseteq \mathcal{S}_O^I \Rightarrow M \models \mathcal{S}_O^I$$

Static Safety Analysis

Abstract Domain #3: DeepPoly Domain

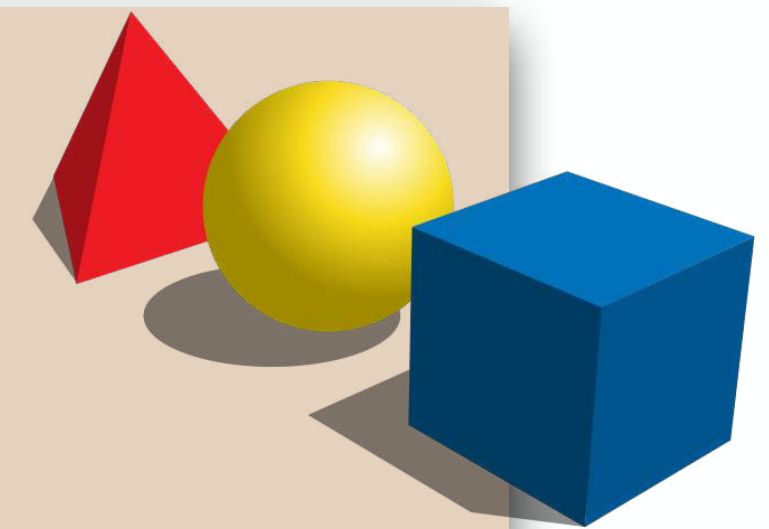
practical tools

targeting specific programs



abstract semantics, abstract domains

algorithmic approaches to decide program properties



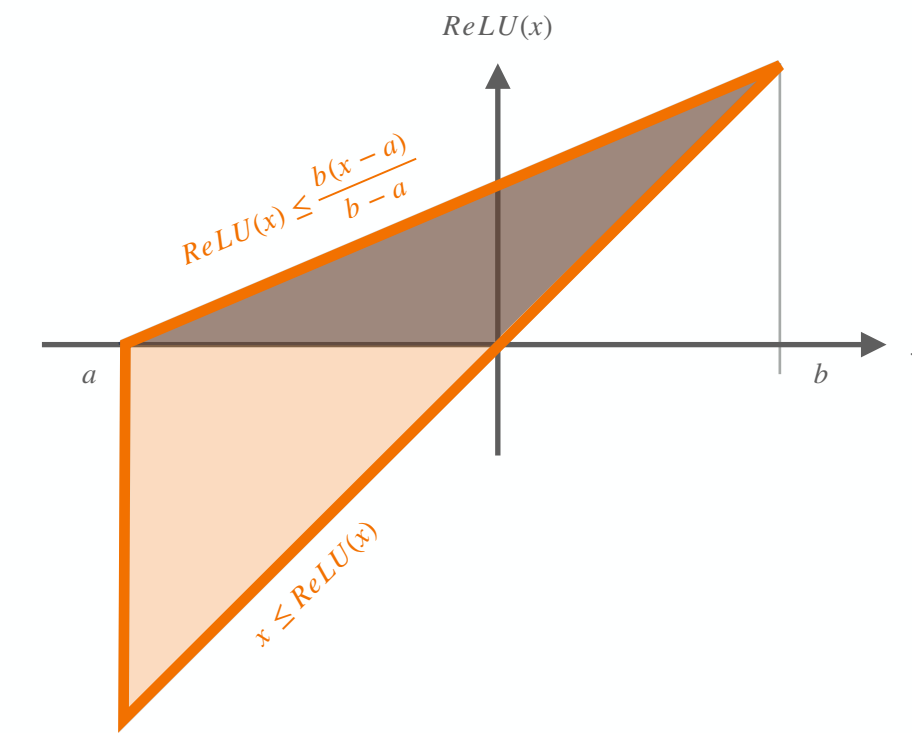
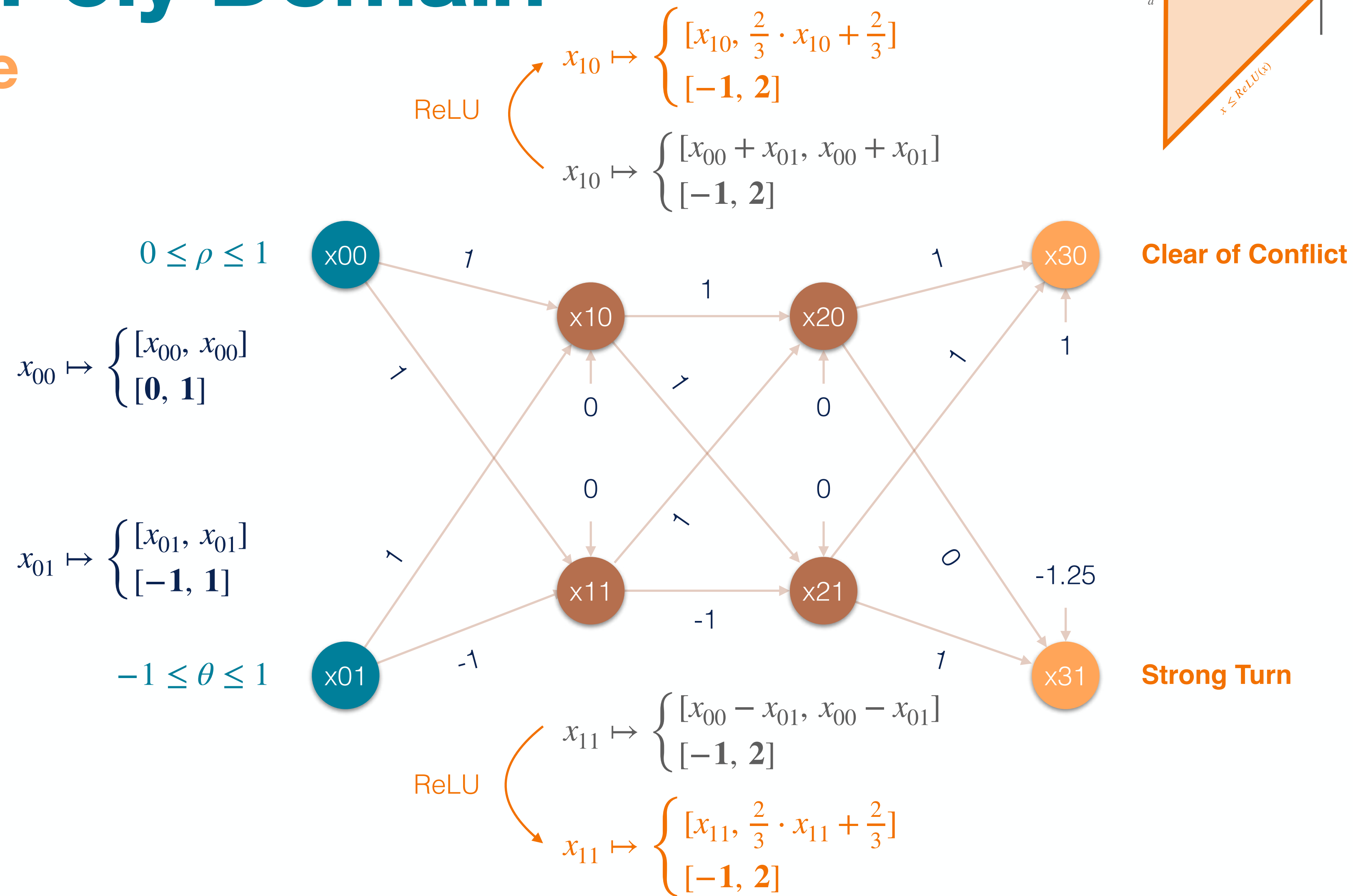
concrete semantics

mathematical models of the program behavior



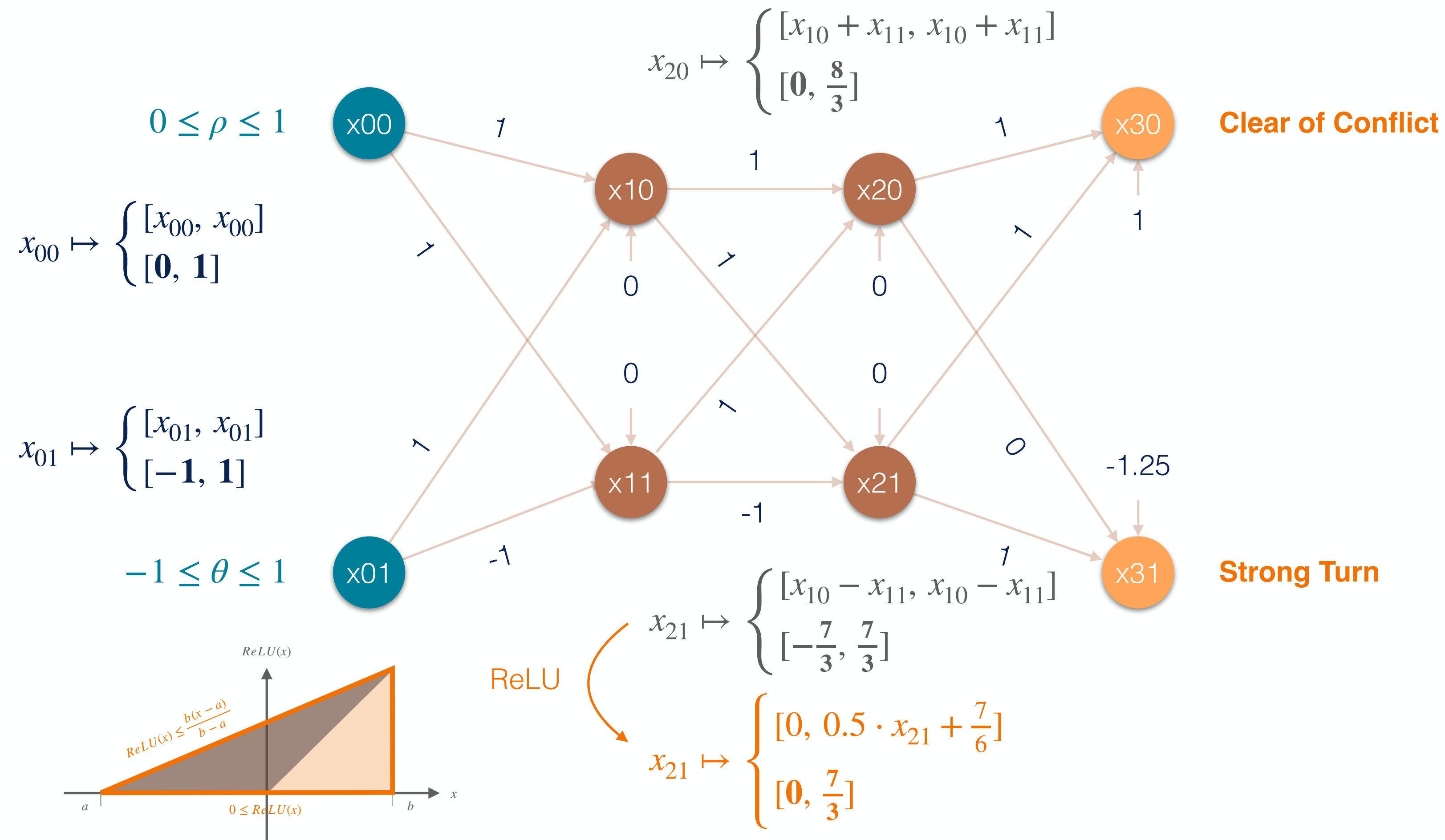
DeepPoly Domain

Example



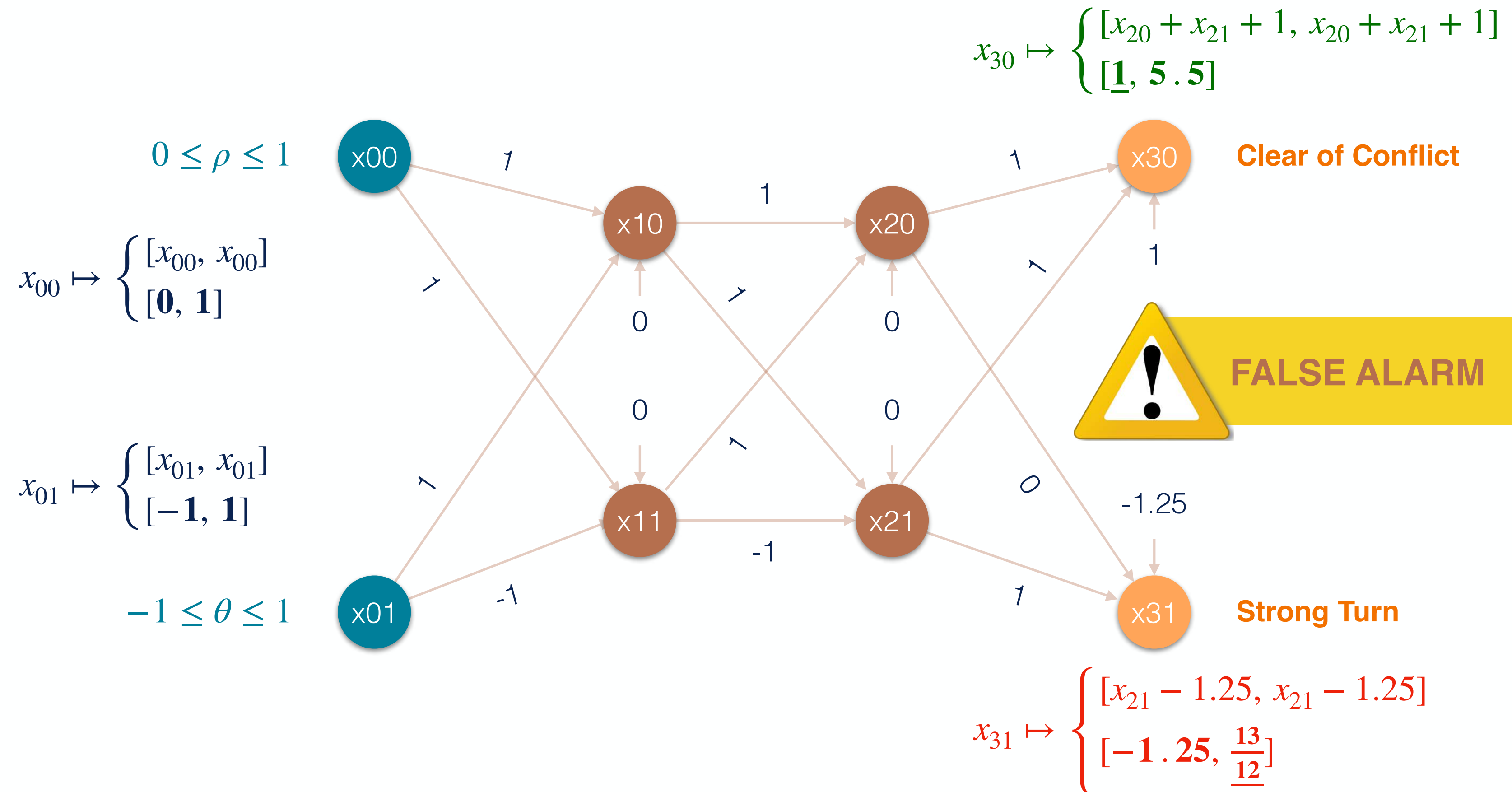
DeepPoly Domain

Example



DeepPoly Domain

Example



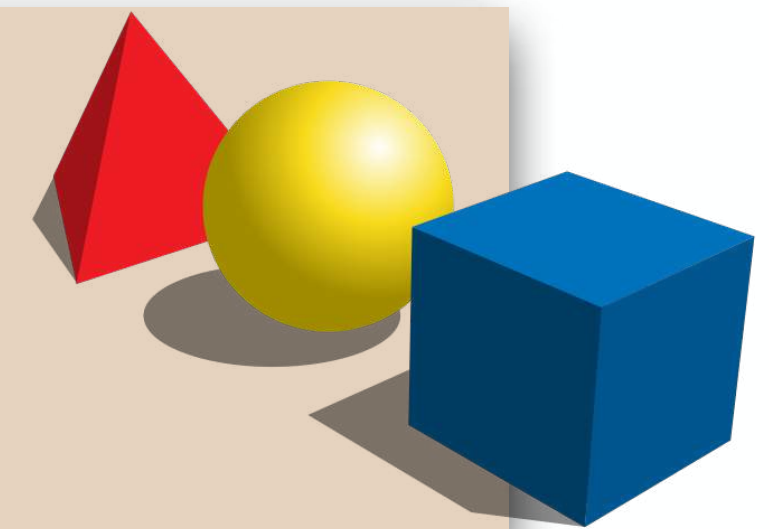
Static Safety Analysis

Abstract Domain #2: Symbolic Domain

practical tools
targeting specific programs



abstract semantics, abstract domains
algorithmic approaches to decide program properties

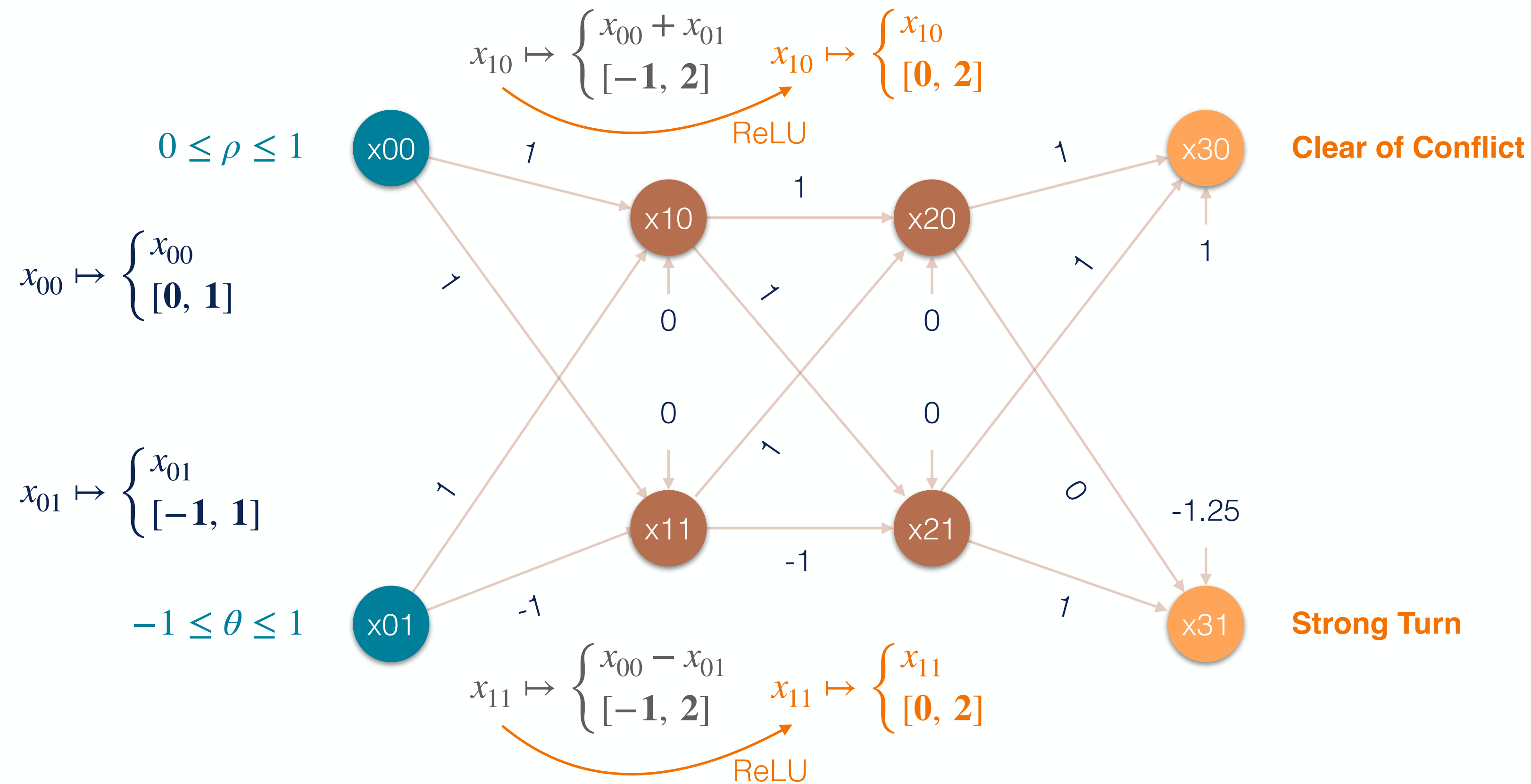


concrete semantics
mathematical models of the program behavior



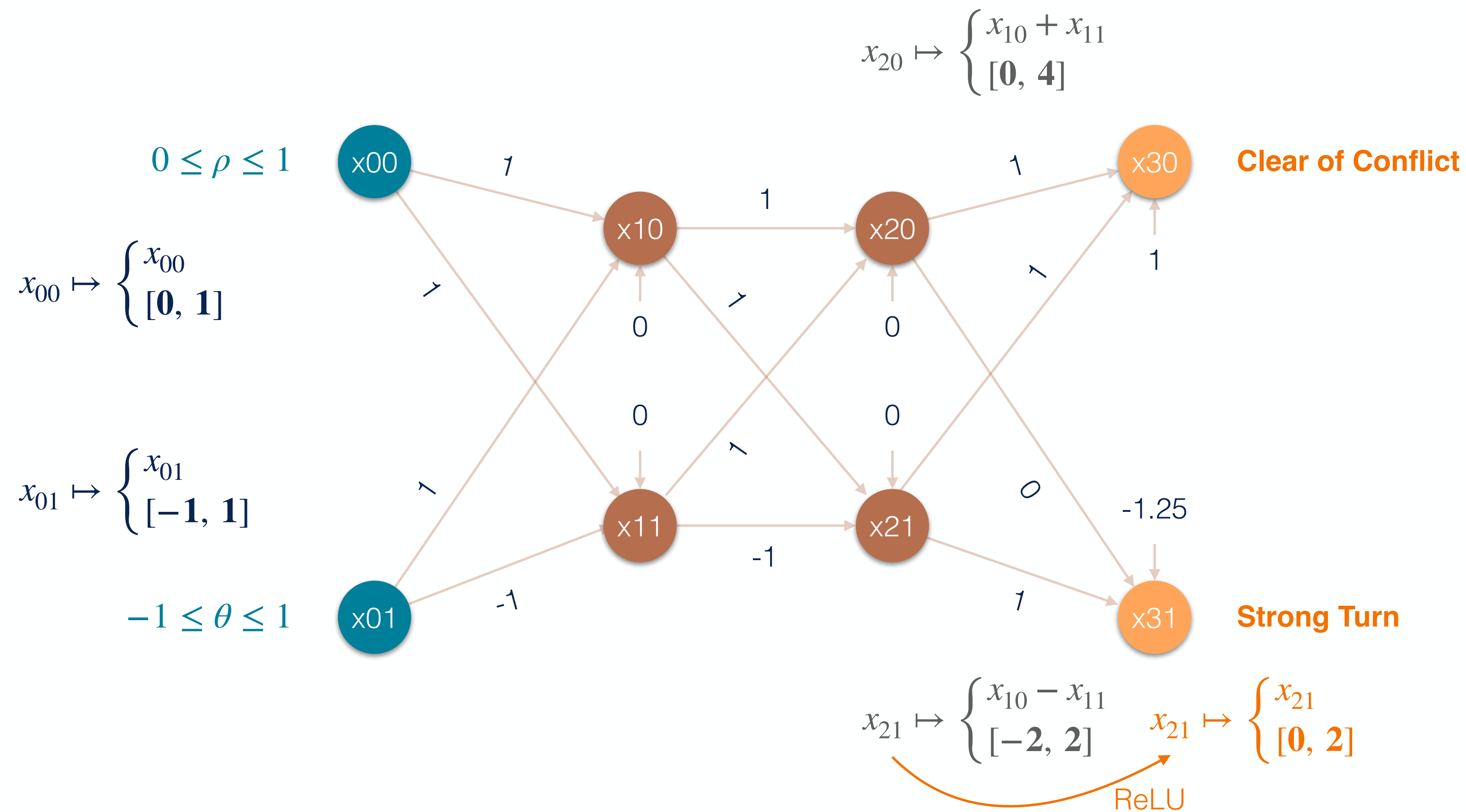
Symbolic Domain

Example



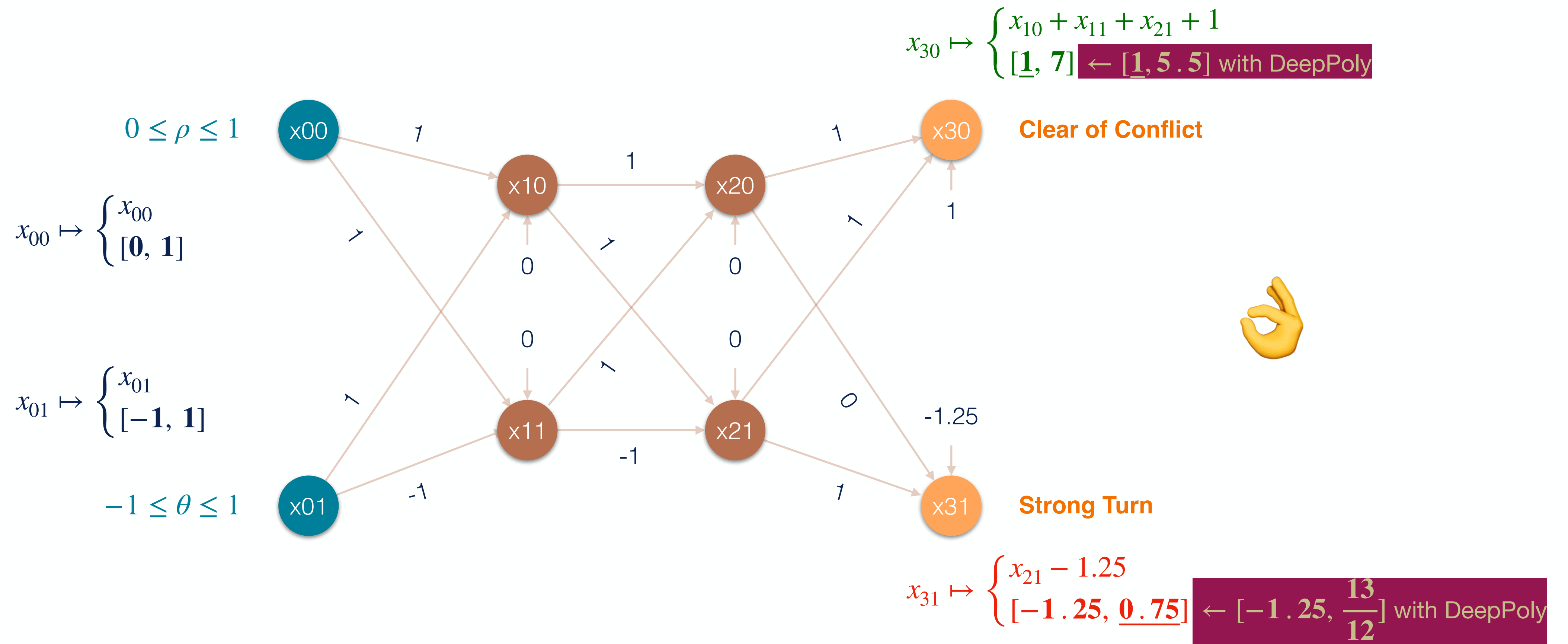
Symbolic Domain

Example



Symbolic Domain

Example



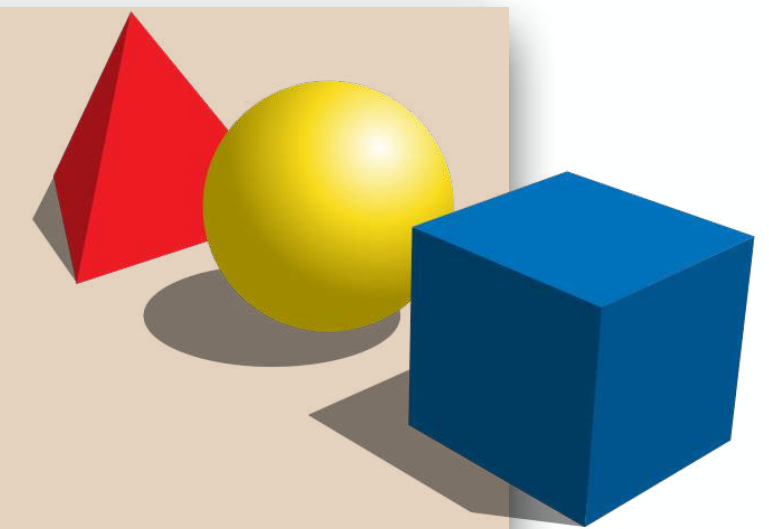
Static Safety Analysis

Abstract Domain #4: Reduced Product Domain

practical tools
targeting specific programs



abstract semantics, abstract domains
algorithmic approaches to decide program properties

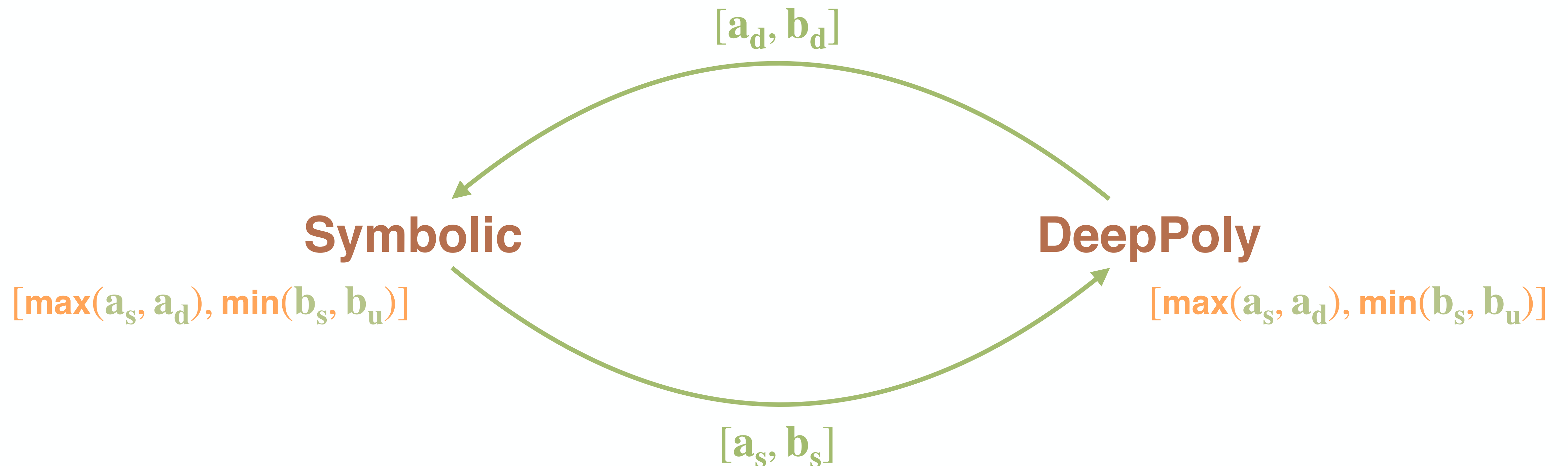


concrete semantics
mathematical models of the program behavior



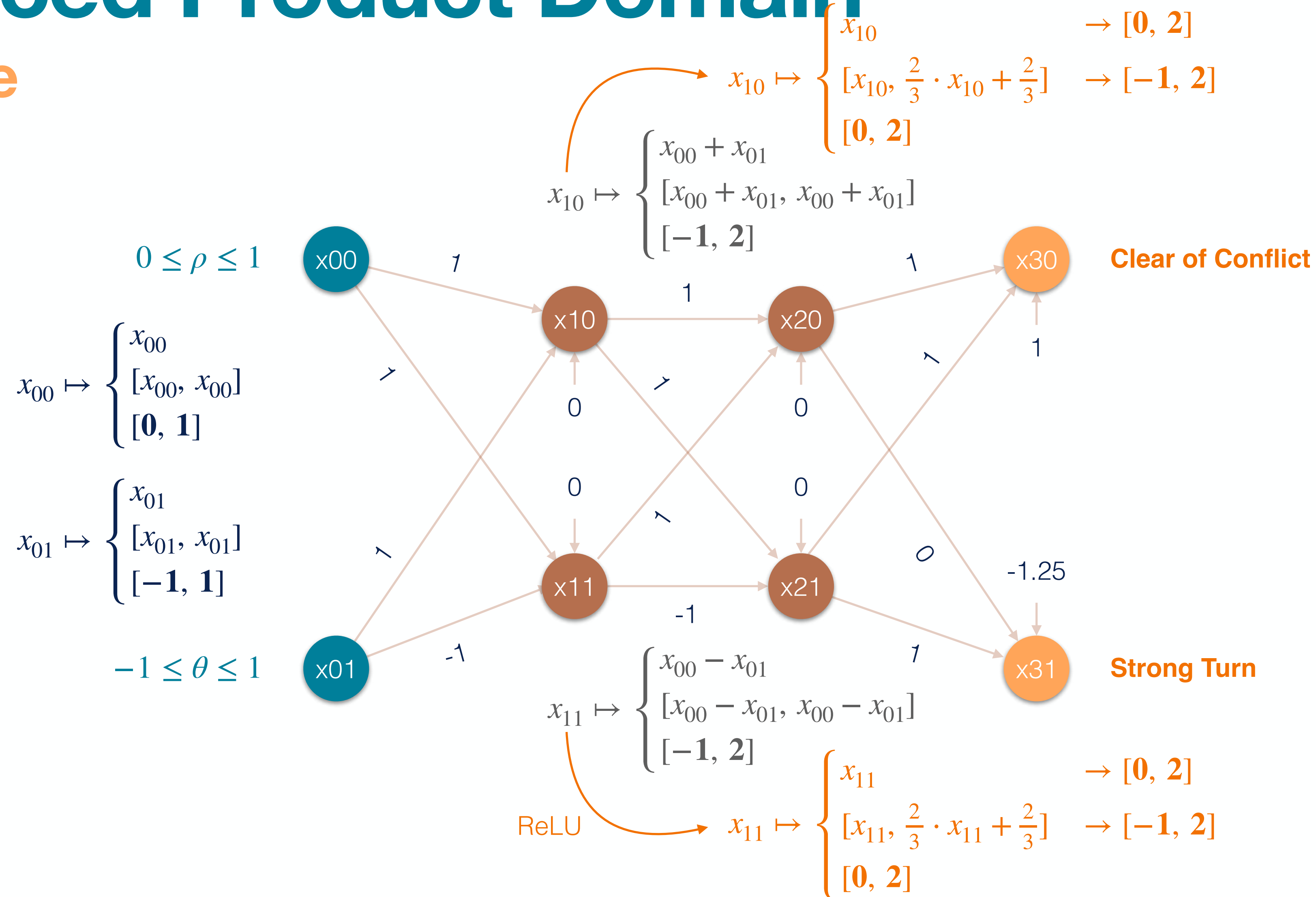
Reduced Product Domain

Symbolic Domain & DeepPoly Domain



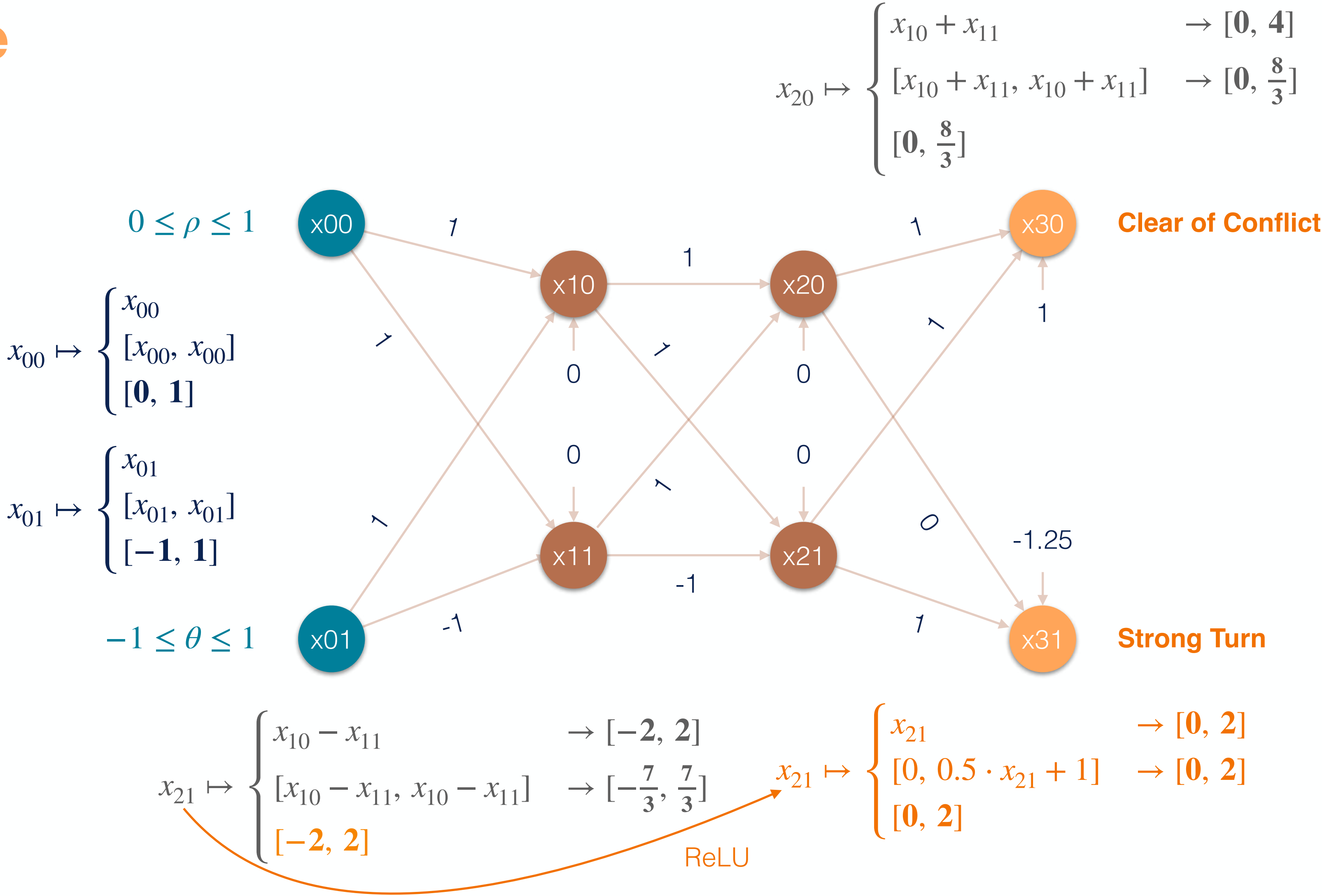
Reduced Product Domain

Example



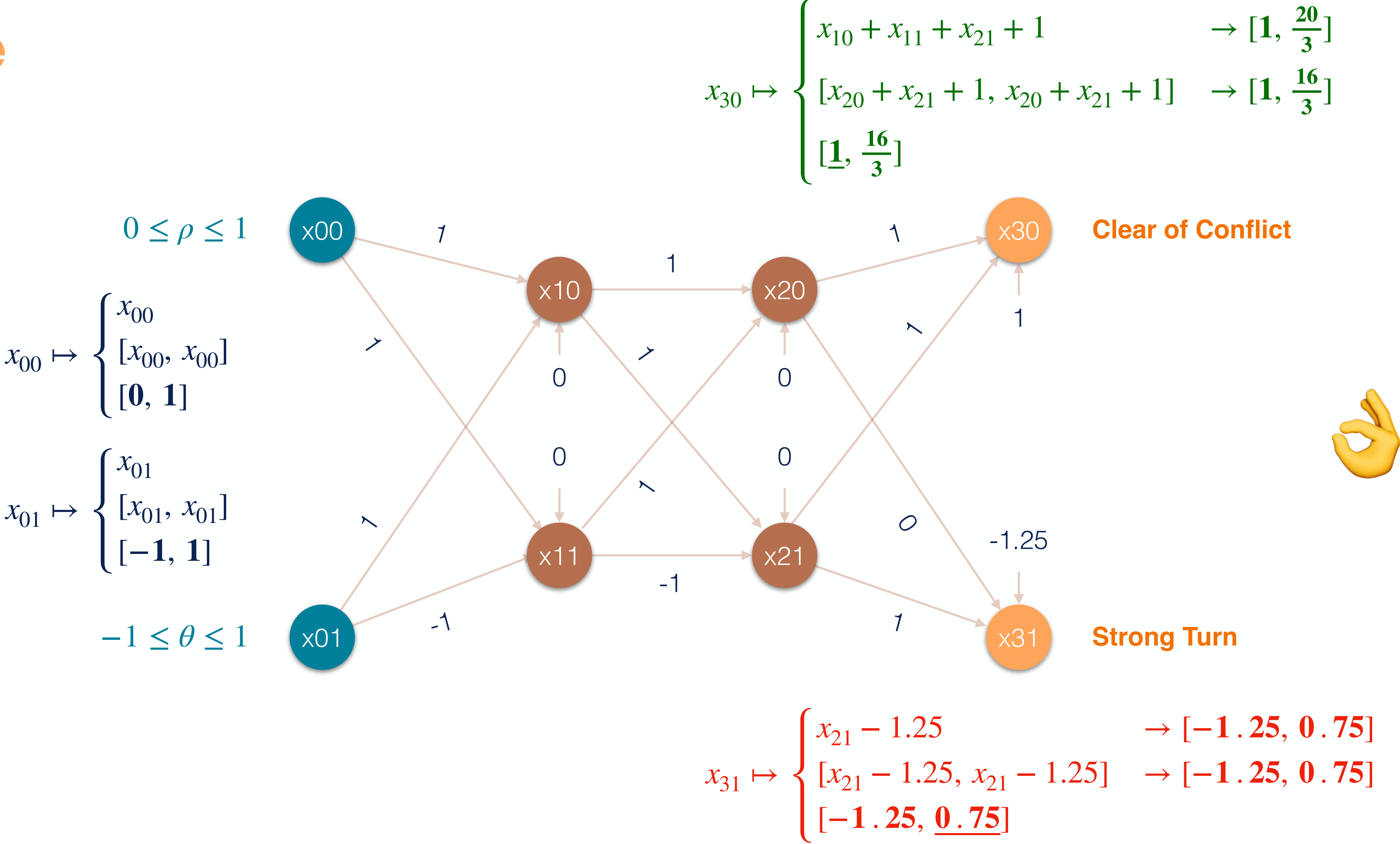
Reduced Product Domain

Example



Reduced Product Domain

Example



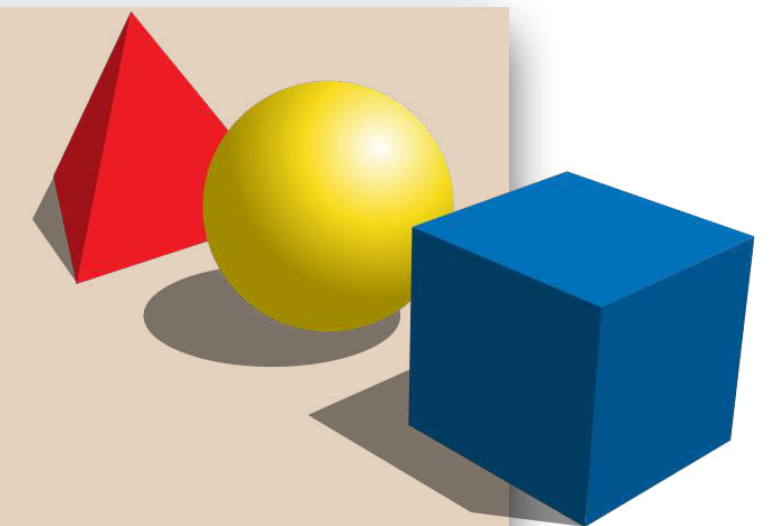
Static Safety Analysis

Going Farther: Complete Methods

practical tools
targeting specific programs



abstract semantics, abstract domains
algorithmic approaches to decide program properties



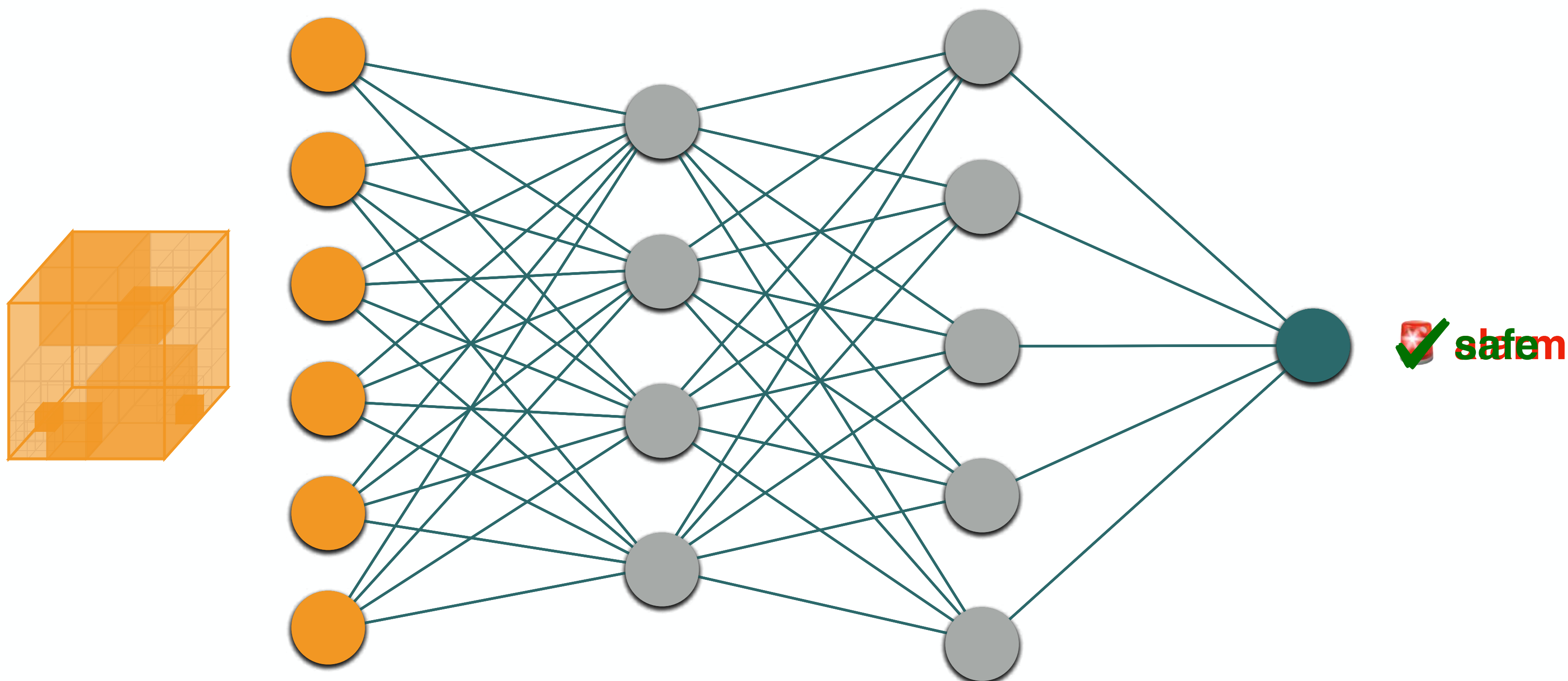
concrete semantics
mathematical models of the program behavior



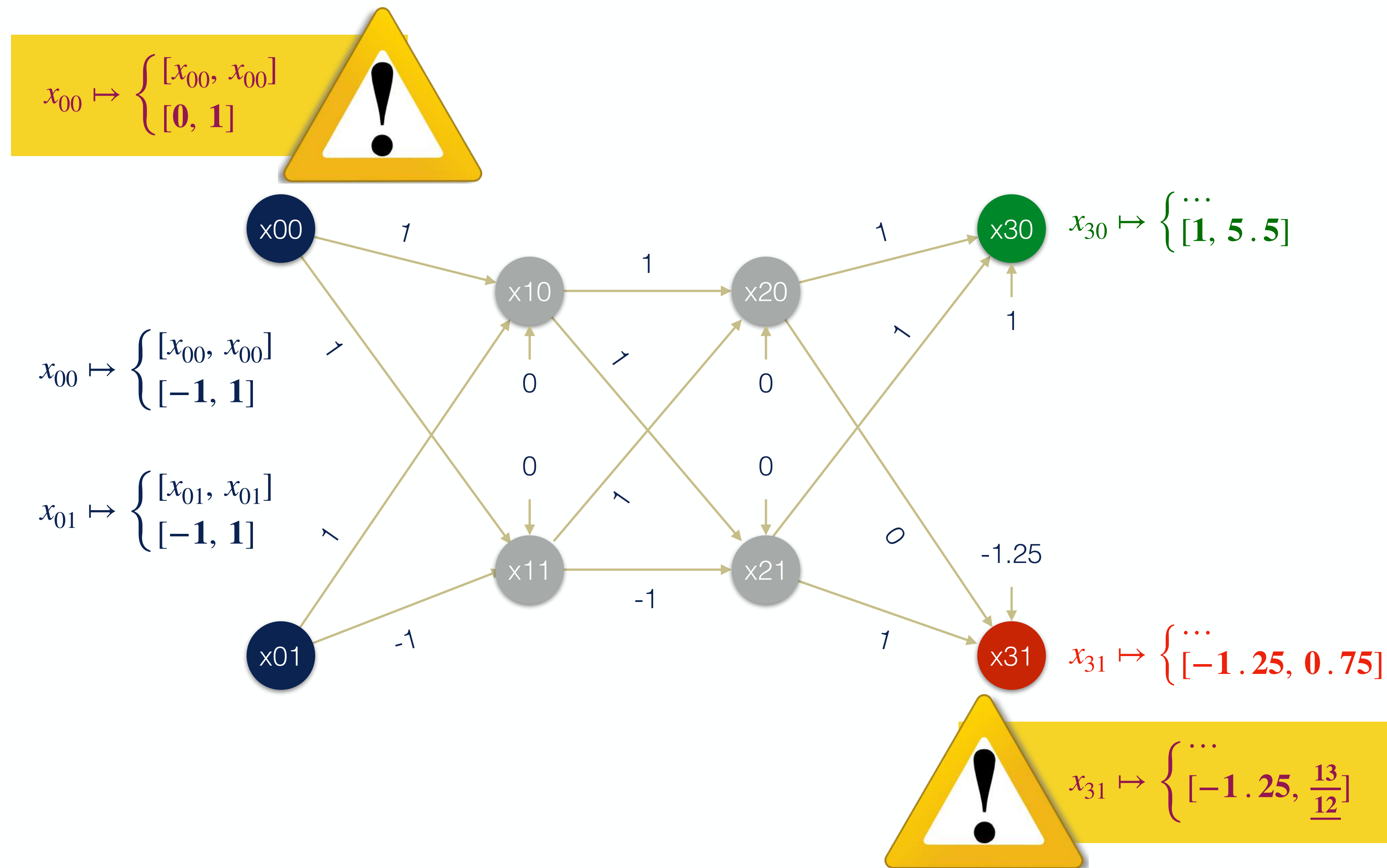


symbolic propagation
+ **iterative** input **refinement**

Asymptotically Complete Method



DeepPoly Domain+ Input Refinement



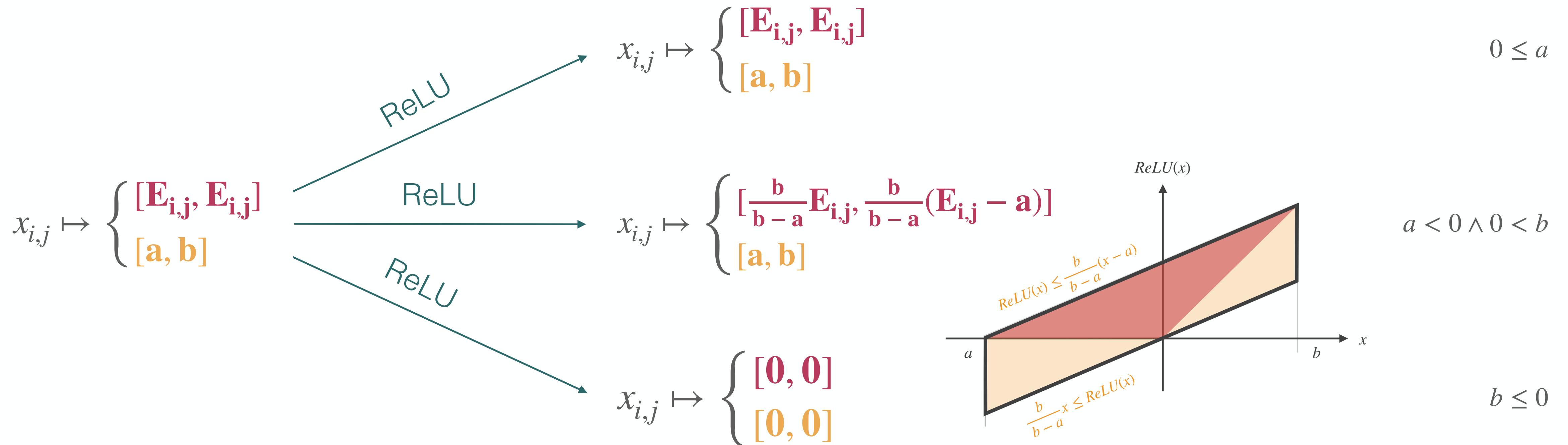
Neurify

Asymptotically Complete Method



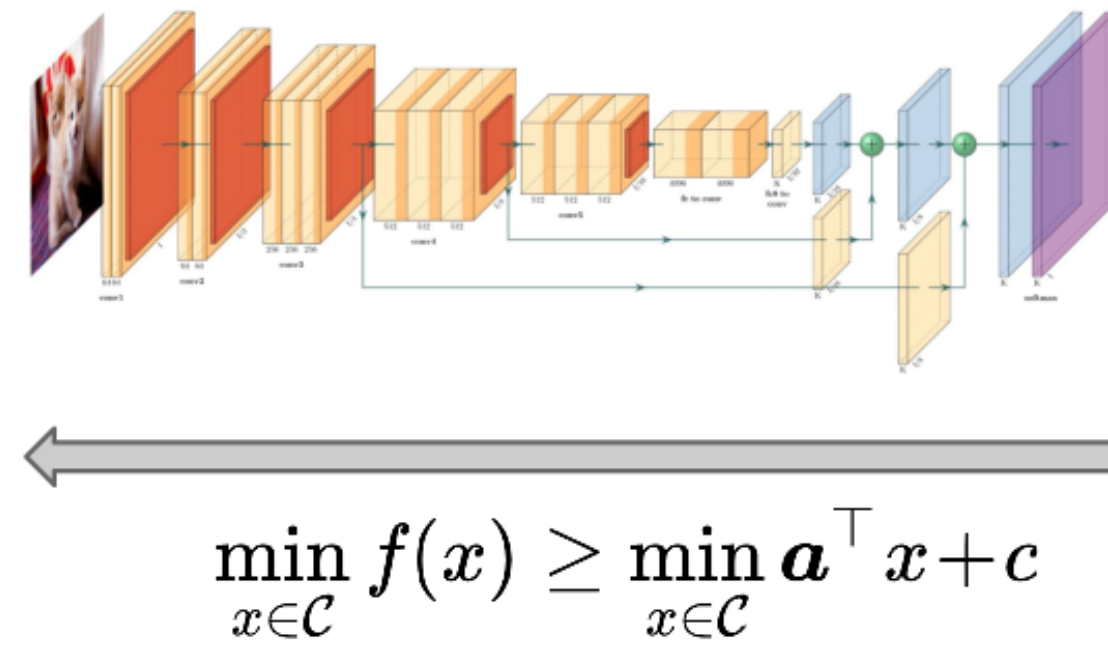
symbolic propagation
+ convex ReLU approximation +
iterative input/ReLU refinement

$$x_{i,j} \mapsto \begin{cases} [\sum_k c_{0,k} \cdot x_{0,k} + c, \sum_k d_{0,k} \cdot x_{0,k} + d] & c_{0,k}, c, d_{0,k}, d \in \mathbb{R} \\ [a, b] & a, b \in \mathbb{R} \end{cases}$$

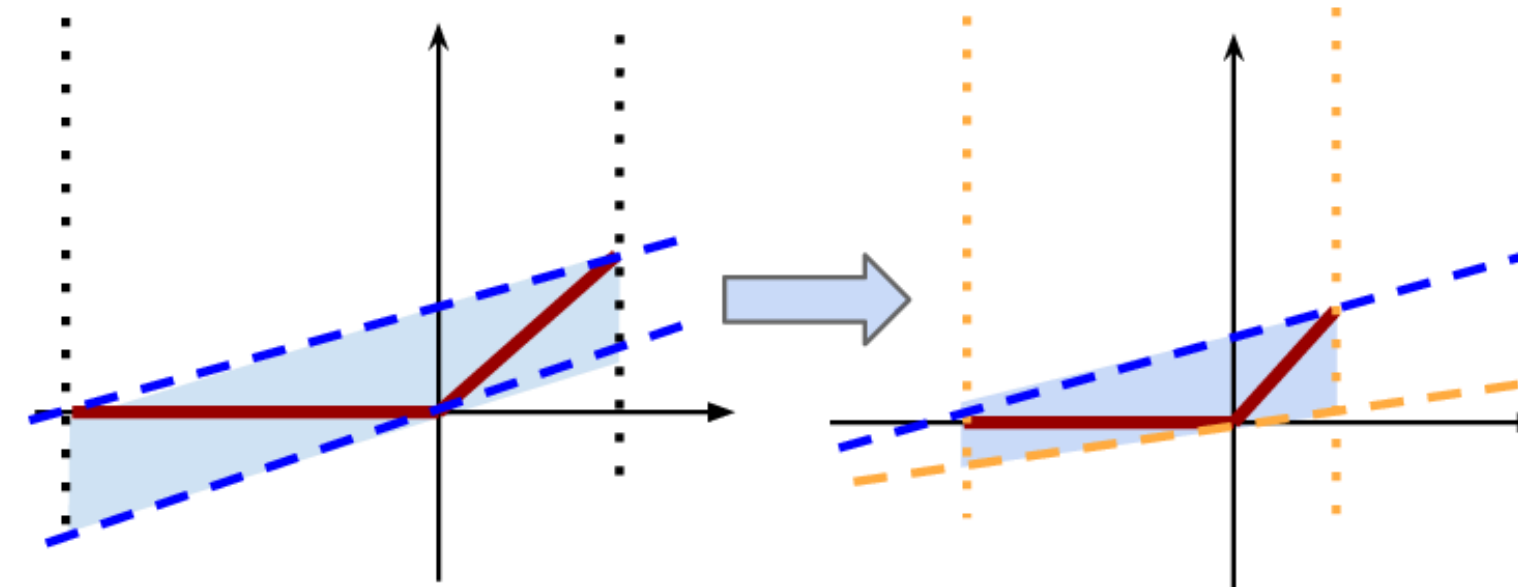


$\alpha\beta$ -CROWN

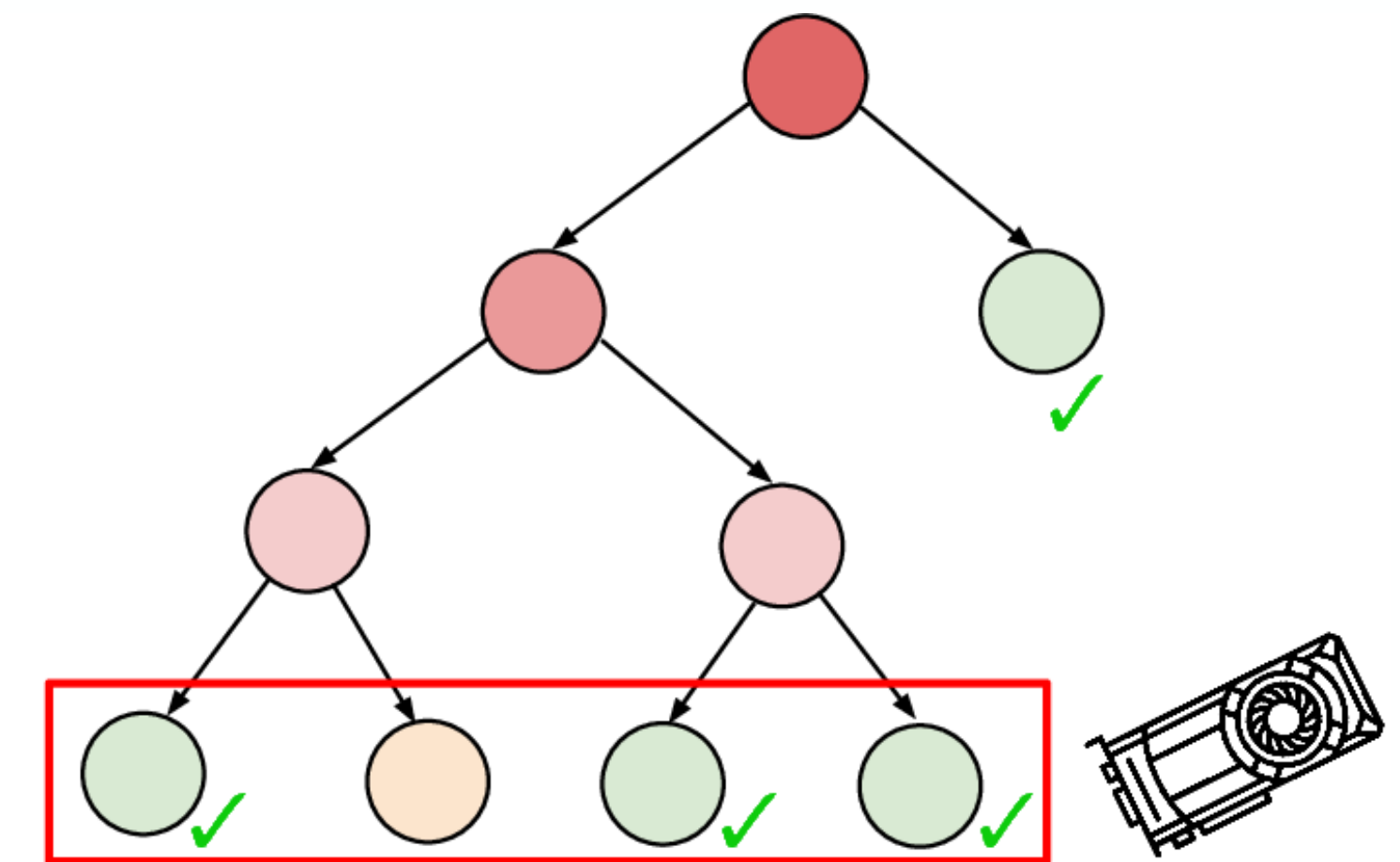
The State of the Art



Efficient bound propagation (**CROWN**)



GPU optimized relaxation (α -**CROWN**)



Parallel branch and bound (β -**CROWN**)



Winner of the International Verification of Neural Networks Competition since 2021

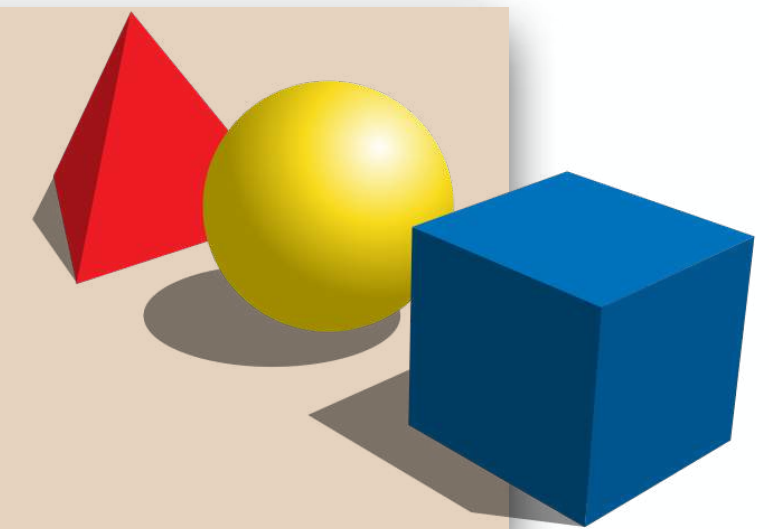
Static Safety Analysis

Going Farther: Other Abstractions

practical tools
targeting specific programs



abstract semantics, abstract domains
algorithmic approaches to decide program properties



concrete semantics
mathematical models of the program behavior

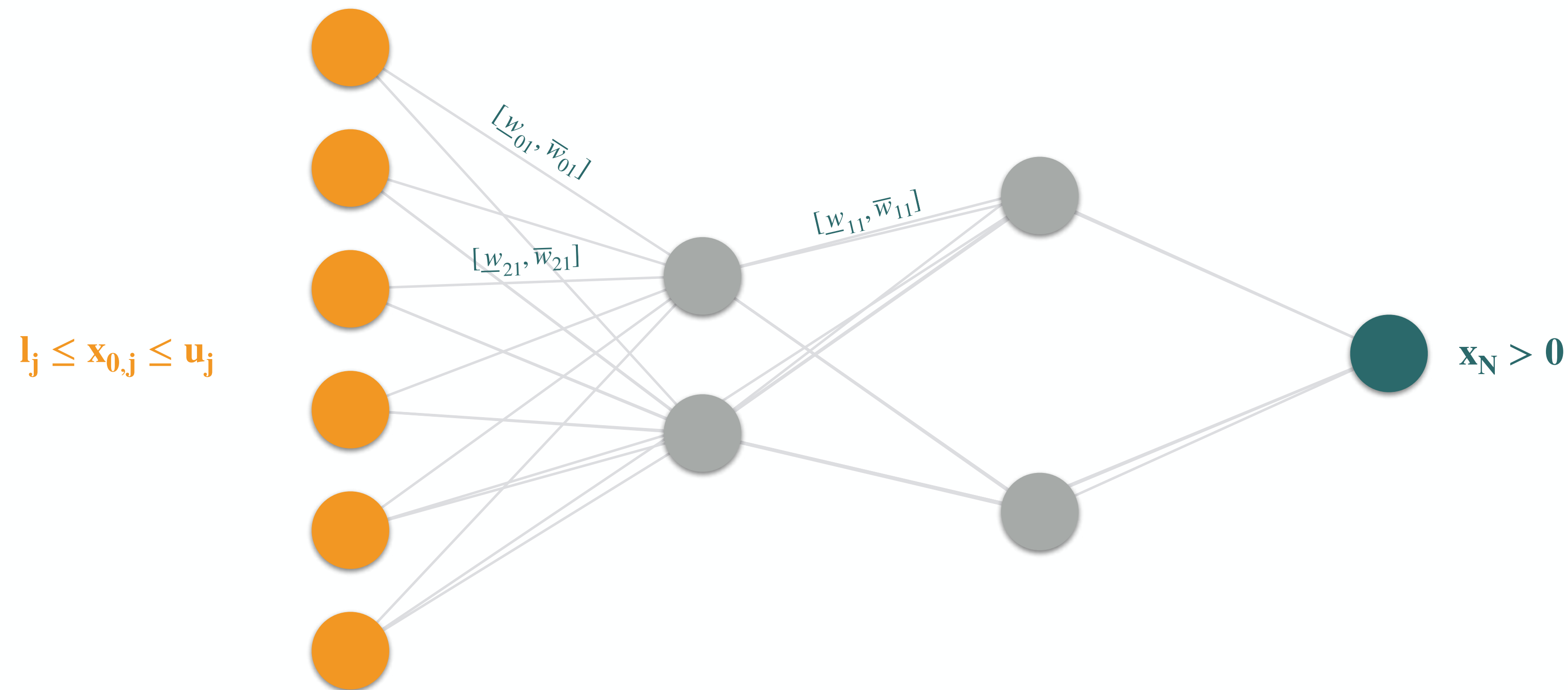


Interval Neural Networks

[Prabhakar and Afza @ NeurIPS 2019]

Related Work

Elboher et al. @ CAV 2020



merge neurons layer-wise
based on partitioning strategy +
replace weights with intervals