

Neural Probabilistic Logic Programming in Discrete-Continuous Domains

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Neural-Symbolic AI (NeSy)

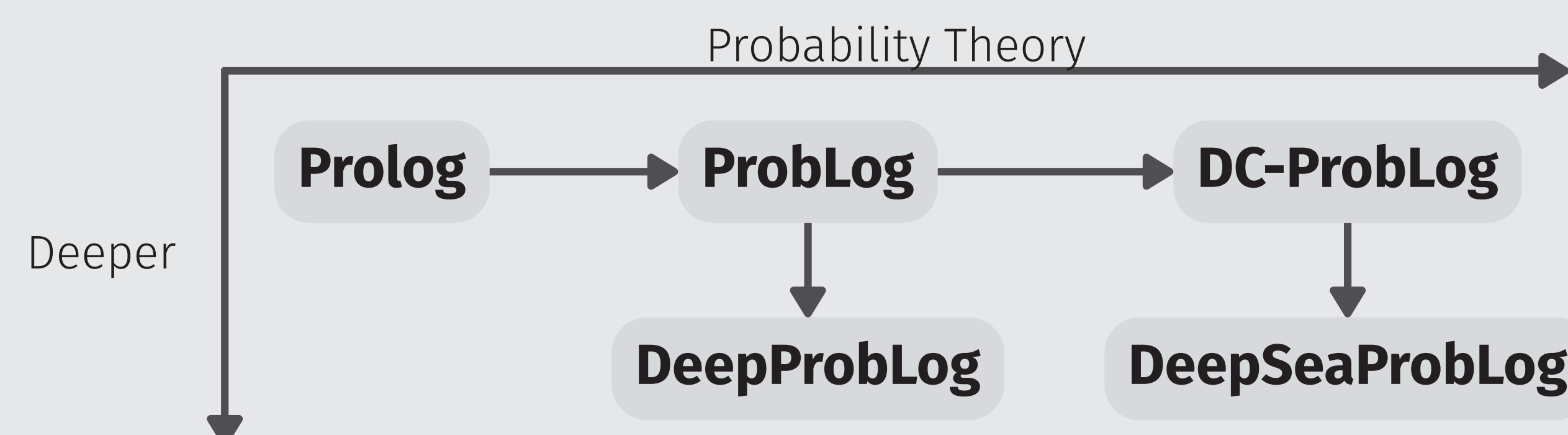
Neural Networks
Backpropagation

Discrete-Continuous
Probability theory

Symbolic Methods
Logic

Probabilistic NeSy

Declarative Family



Building Blocks

```
% Declaring Neural Distributional Facts (NDFs)
humid ~ bernoulli(0.5).
cloudy(🌍) ~ categorical(cloudy_net(🌍)).
temp(🌍) ~ normal(temp_net(🌍)).
```

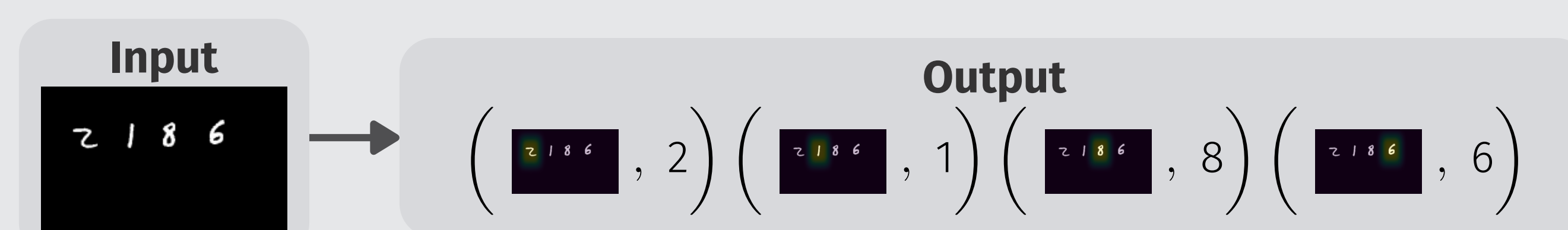
```
% Reasoning with Probabilistic Comparison Formulas (PCFs)
rainy(🌍) :- humid, cloudy(🌍) =\= 0.
```

```
good_weather(🌍) :- temp(🌍) < 0, rainy(🌍).
good_weather(🌍) :- temp(🌍) > 20, not rainy(🌍).
```

```
% Querying probabilities of logical statements
query(good_weather(image_020823))
```

NeSy Attention

Predict + localise digits **without** bounding box supervision



Neural-Symbolic Architecture



```
box(X) ~
generalisednormal(X).
```

```
left_right(👤, 👤, 👤, 👤) :-
box(👤) < box(👤),
box(👤) < box(👤),
box(👤) < box(👤).
```

Box ordering

```
class(Mask) ~
categorical(class_net(Mask)).
```

```
supervise(👤, 👤, 👤, 👤) :-
class(👤) =:= 1, class(👤) =:= 2,
class(👤) =:= 5, class(👤) =:= 3.
```

Supervision

Method	Results	
	acc.	IoU
DeepSeaProbLog	93.77 ± 0.57	17.69 ± 0.23
LTN	76.50 ± 12.10	10.73 ± 1.69
Neural Baseline	54.71 ± 14.33	6.26 ± 1.77

Inference

Logic represented by tractable **probabilistic circuit** **Neural distributions** as weighing functions

$$P(q) = \int \sum \prod \mathbb{1}(c(\mathbf{x})) p_{\Lambda}(\mathbf{x}) d\mathbf{x}$$

$$P(\text{temp}(\text{🌍}) < 0) = \int \mathbb{1}(x < 0) \frac{\exp\left(-\frac{(x - \mu(\text{🌍}))^2}{2\sigma^2(\text{🌍})}\right)}{\sqrt{2\pi}\sigma(\text{🌍})} dx$$

Learning

Obstacles

- Indicator functions are not differentiable

$$\mathbb{1}(c(\mathbf{x})) p_{\Lambda}(\mathbf{x}) \xrightarrow{\text{relaxation}} \sigma(\tau \cdot c(\mathbf{x})) p_{\Lambda}(\mathbf{x})$$

- Sampling approximation blocks gradient

$$\sigma(\tau \cdot c(\mathbf{x})) p_{\Lambda}(\mathbf{x}) \xrightarrow{\text{reparametrisation}} \sigma(\tau \cdot c(r_{\Lambda}(\mathbf{u}))) p(\mathbf{u})$$

Result

Convergence to **unbiased gradients** for $\tau \rightarrow +\infty$. **Efficient backpropagation** through the deep probabilistic-logical model

$$\partial_{\lambda} P(q) \approx \int \partial_{\lambda} \sum \prod \sigma(\tau \cdot c(r_{\Lambda}(\mathbf{u}))) p(\mathbf{u}) d\mathbf{u}$$

NeSy Generation

Task 1: Distant Learning

Learn to fill in $?\text{--}?\text{--}5$

$$\begin{array}{cc} 5 & - & 0 & = & 5 \\ 8 & - & 3 & = & 5 \\ 9 & - & 4 & = & 5 \end{array}$$

Task 2: Conditional Generation

Zero-shot completion of $4\text{--}?\text{--}5$ in **same style**.

$$\begin{array}{cc} 4 & - & 3 & = & 1 \\ 4 & - & 1 & = & 3 \\ 4 & - & 9 & = & -5 \end{array}$$

Links



Personal



Twitter



Code