Language Model Programming: Lecture 2

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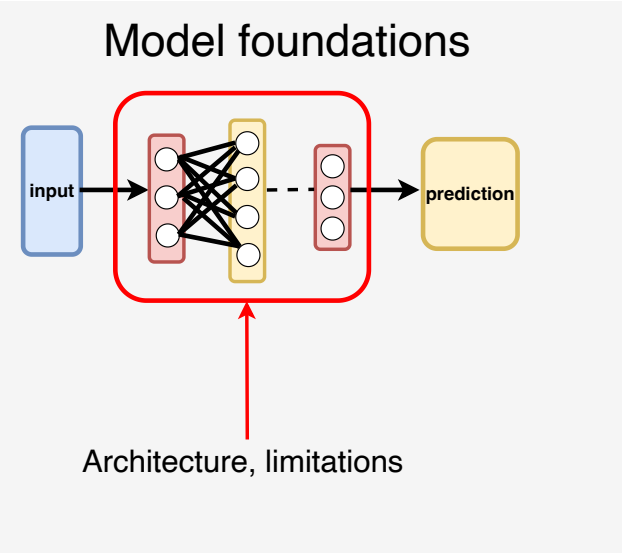
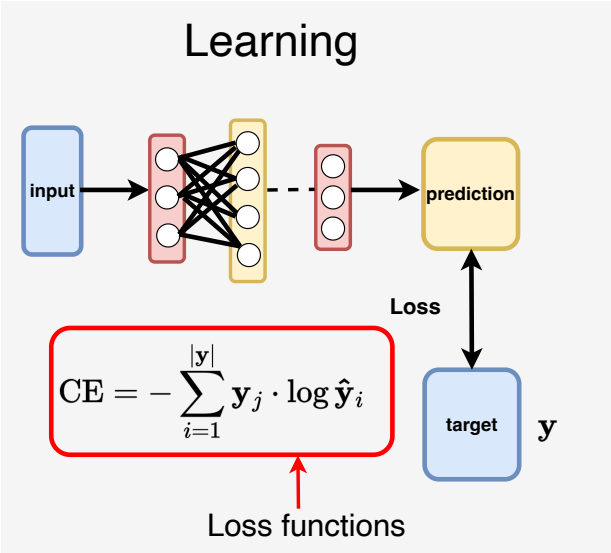
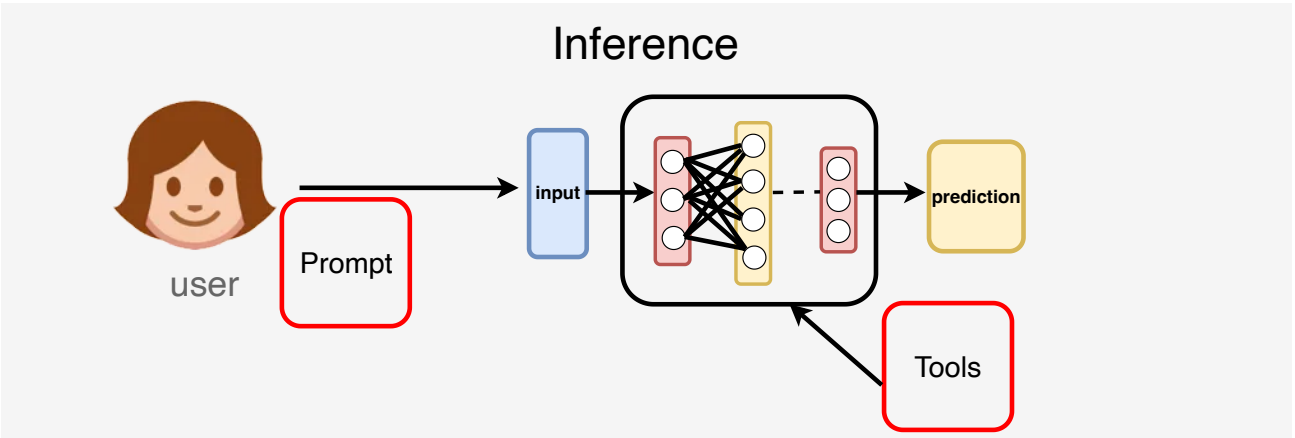
Reminder of bigger picture







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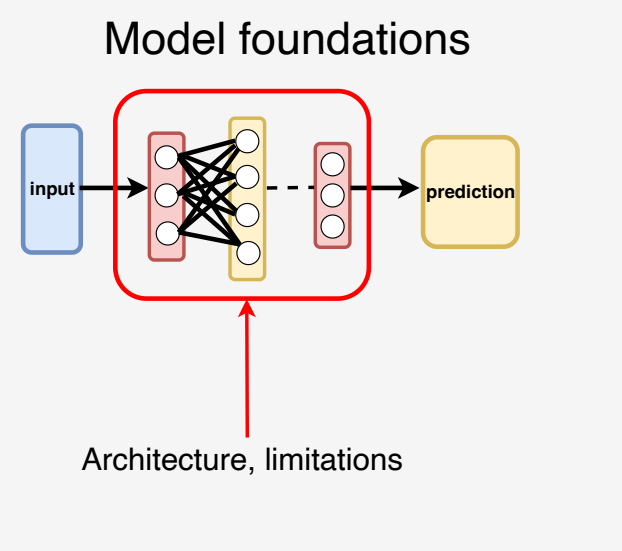
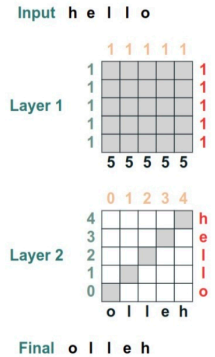
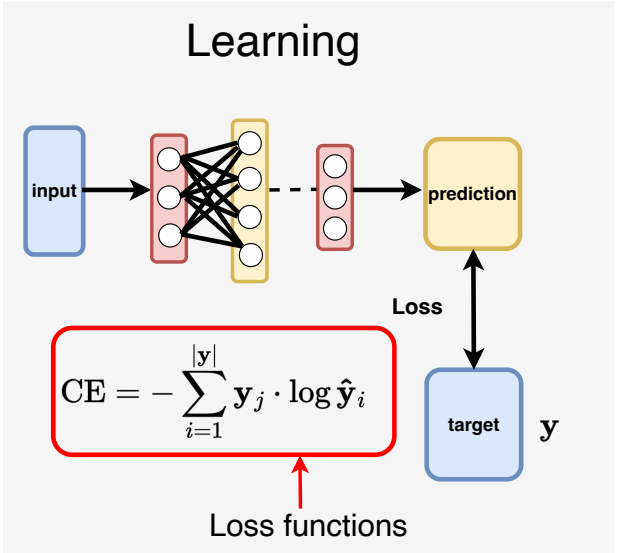


RASPy

```
def flip():
    length = (key(1) == query(1)).value(1)
    flip = (key(length - indices - 1) == query(indices)).value(tokens)
    return flip
flip()
```



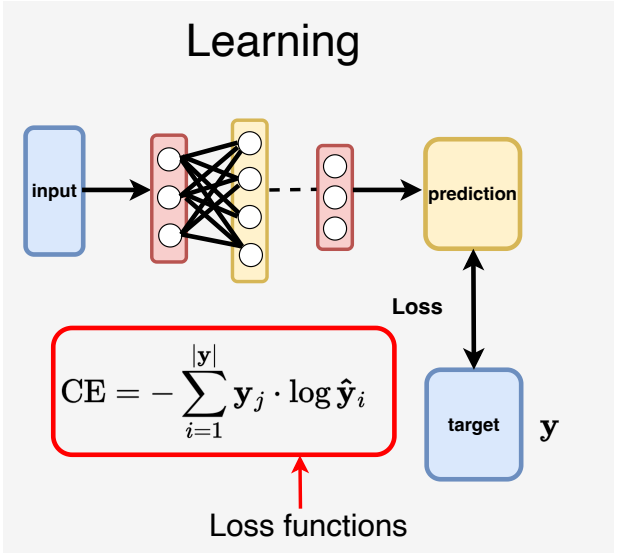
Goals for lecture today




```
1  // File path_planner.scl
2  type actor(x: i32, y: i32), goal(x: i32, y: i32), enemy(x: i32, y: i32)
3
4  const UP = 0, DOWN = 1, RIGHT = 2, LEFT = 3
5  rel safe_cell(x, y) = range(0, 5, x), range(0, 5, y), not enemy(x, y)
6  rel edge(x, y, x, yp, UP) = safe_cell(x, y), safe_cell(x, yp), yp == y + 1
7  // Rules for DOWN, RIGHT, and LEFT edges are omitted...
8
9  rel next_pos(p, q, a) = actor(x, y), edge(x, y, p, q, a)
10 rel path(x, y, x, y) = next_pos(x, y, _)
11 rel path(x1, y1, x3, y3) = path(x1, y1, x2, y2), edge(x2, y2, x3, y3, _)
12 rel next_action(a) = next_pos(p, q, a), path(p, q, r, s), goal(r, s)
```

Fig. 3. The logic program of the PacMan-Maze application in Scallop.

Goals for lecture today



Declarative Programming

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Fig. 3. The logic program of the PacMan-Maze application in Scallop.

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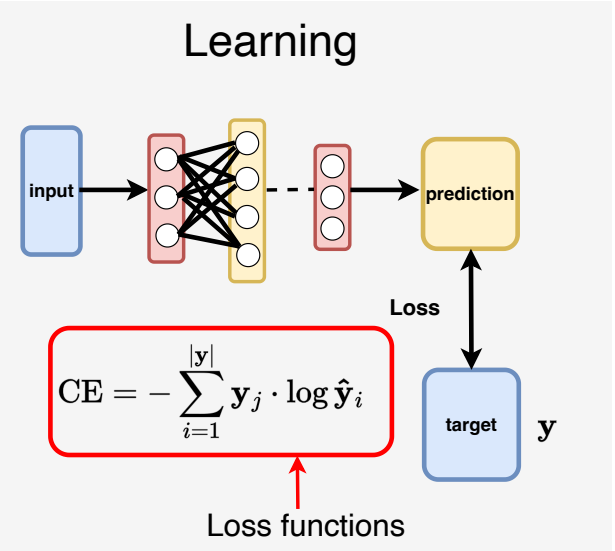
```

Fig. 3. The logic program of the PacMan-Maze application in Scallop.



- Describe a probabilistic approach to **modeling with declarative knowledge**
- Introduce **semantic loss**, a type of loss function based on this semantics.
- **next lecture**: logical and probabilistic programming for model inference.

Questions about last lecture?

Basic properties of declarative programming

```
import problog as p                    ## pip install problog
PROGRAM = p.program.PrologString("""
0.8::stress(ann).
0.4::stress(bob).
0.6::influences(ann,bob).
0.2::influences(bob,carl).

smokes(X) :- stress(X).
smokes(X) :- influences(Y,X), smokes(Y).

query(smokes(carl))."""")
p.get_evaluatable().create_from(PROGRAM).evaluate()
```

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1. We say what we want to do without saying how to do it.

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```

1. We say what we want to do without saying how to do it.
2. What we say can be made to be formally precise.

Basic properties of declarative programming

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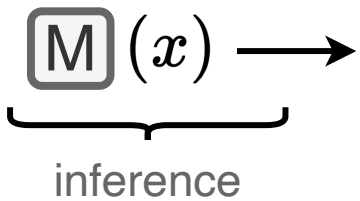
```

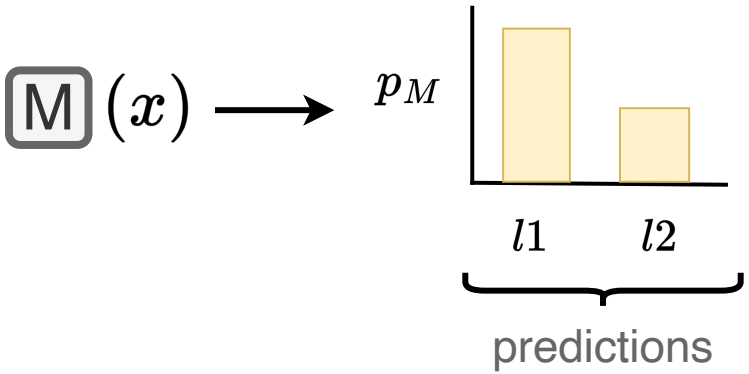
- **Logic programming**: Framework for programming based on (a subset of) logic, will revisit more tomorrow.

Thinking declaratively about model behavior

Declarative Modeling: Predictions as Propositions



Declarative Modeling: Predictions as Propositions



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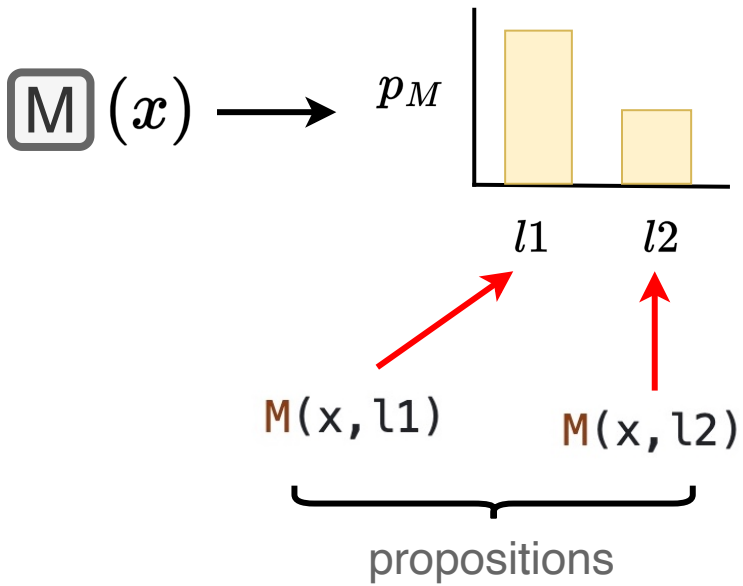

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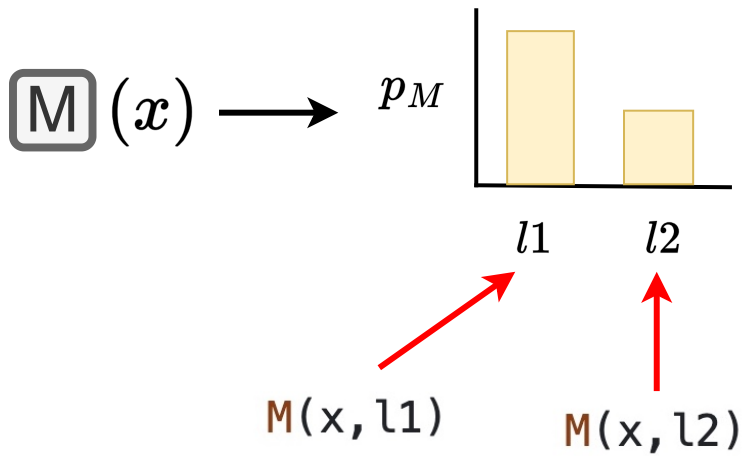
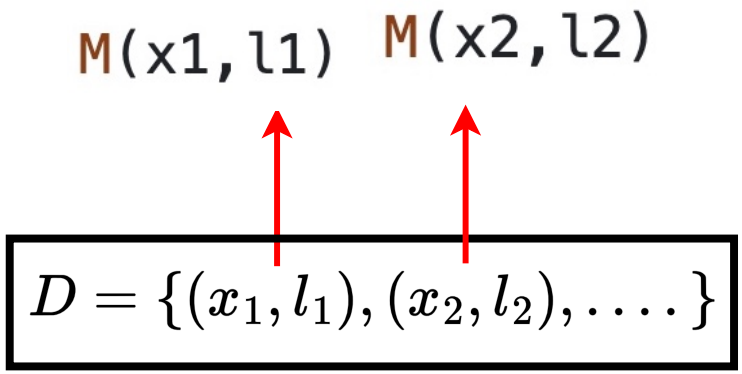
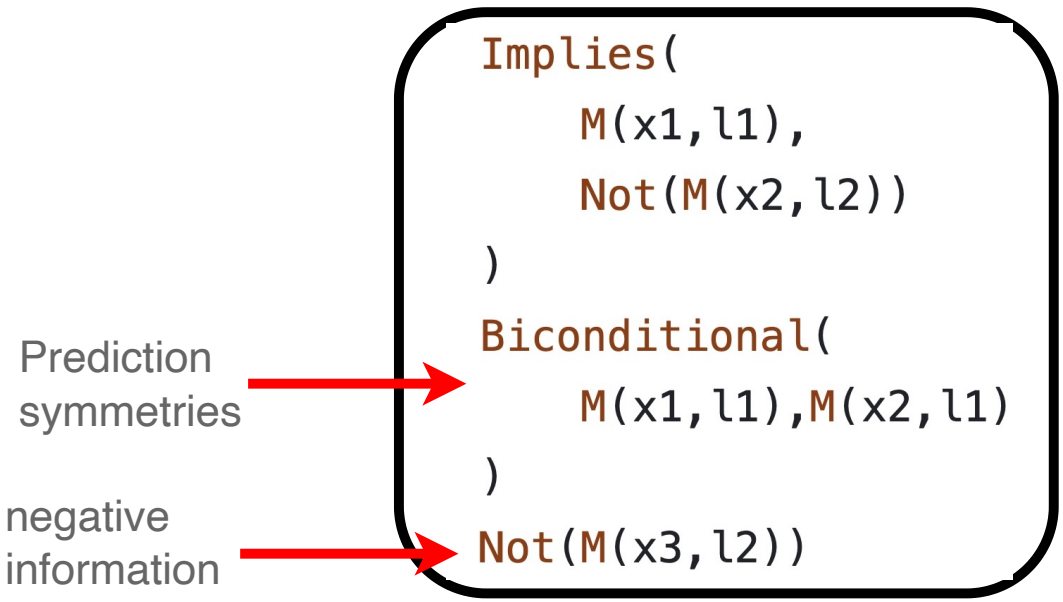


$$\underbrace{\theta(\ \texttt{M(x,l)}\ )}_{\text{proposition weight}} = p_M(l \mid x)$$

Declarative Modeling: Predictions as Propositions



Declarative Modeling: Programs as constraints on predictions



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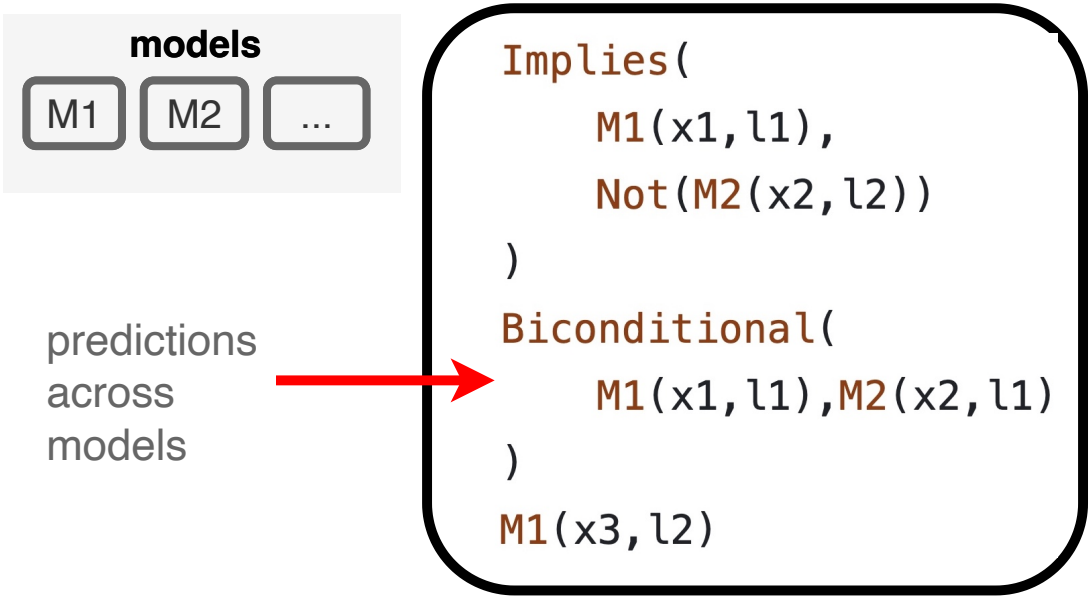
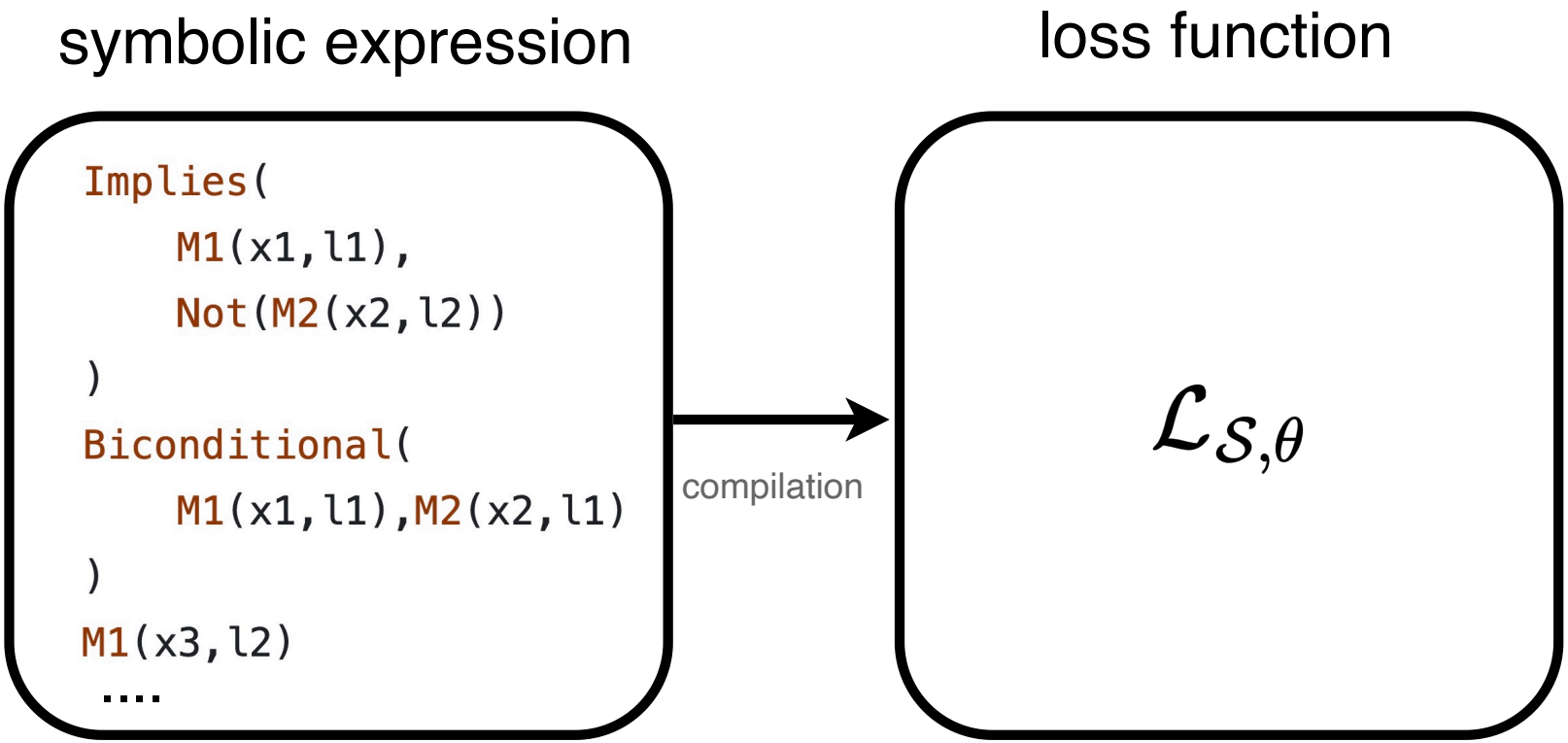
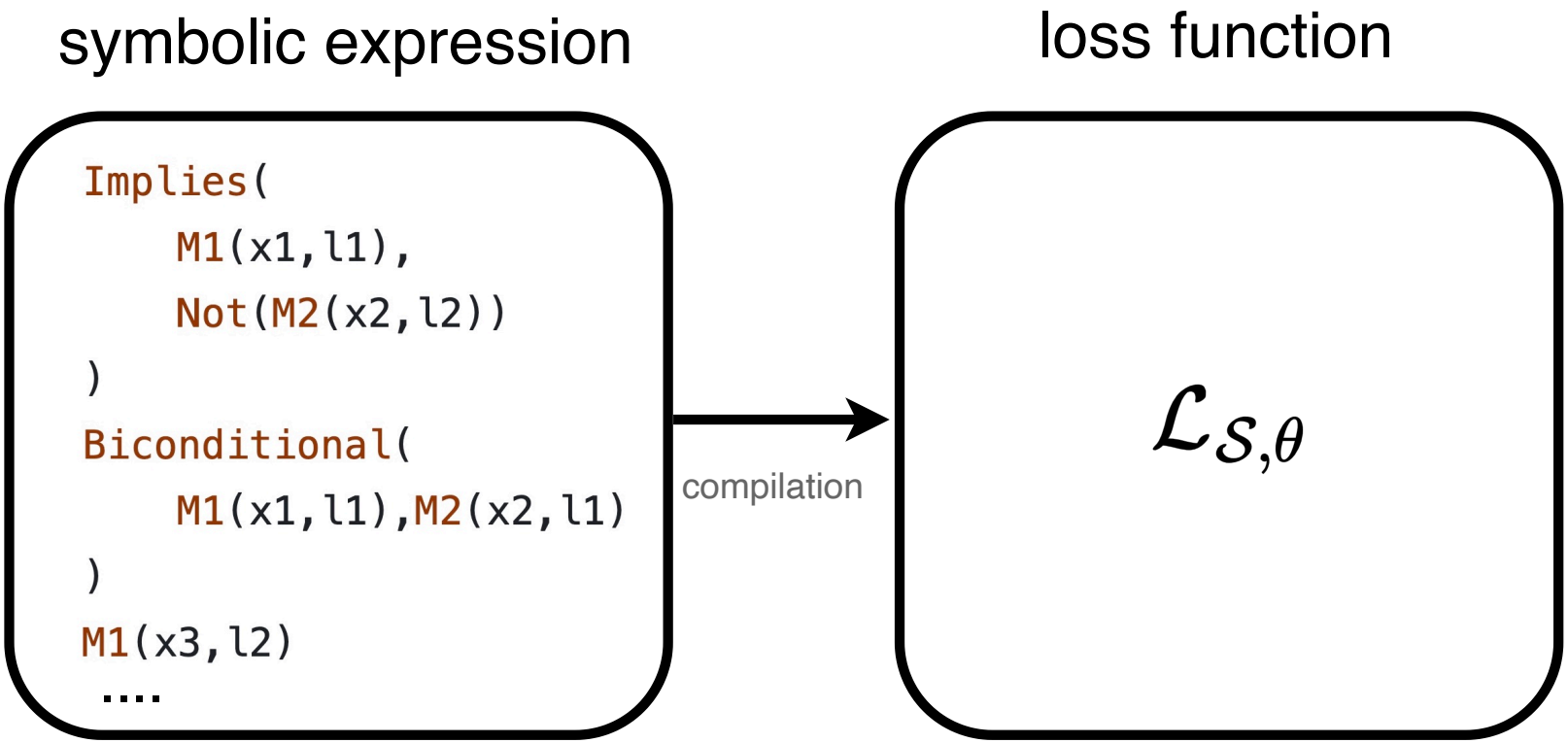


Declarative Model Programming



Declarative Model Programming



- Say what we want models to do (without saying how), compilation into a learning or (inference) algorithm.

A motivating example

Classifying inferential relations between texts

USER	Imagining the situation: "A man was on his bike" would it be reasonable to conclude (answer yes/no) that "A person moved"?
ASSISTANT	Yes

- **Natural Language Inference** (**NLI**): Given a **premise** *(first)*, is it reasonable to conclude that the **hypothesis** *(second)* is likely to be true?

Classifying inferential relations between texts

USER	Imagining the situation: "A man was on his bike" would it be reasonable to conclude (answer yes/no) that "A person moved"?
ASSISTANT	Yes
USER	Why do you think this?
ASSISTANT	I reached this conclusion because the statement implies that the man was actively using his bike, suggesting movement. Riding a bike typically involves pedaling and propelling oneself forward, which would involve movement on the part of the person.

Datasets for NLI

```
### "pip install install  datasets"
from datasets import load_dataset

## Stanford Natural Language Inference dataset
snli_dataset= load_dataset("snli")
## Multi-genre NLI datasets
mnli_dataset = load_dataset("multi_nli")

## first few training instances
snli_dataset["train"][3]
#{
#  "premise": "Children smiling and waving at camera",
#  "hypothesis": "They are smiling at their parents",
#  "label": 1 ## =neutral
#}
```

- **Labels**: `entailment` (**E**), `contradiction` (**C**) and `neutral` (**N**).

Model sketch in Pytorch and Huggingface Transformers

```
import torch
from transformers import \
     AutoModelForSequenceClassification as hf_model

class NLIModel(torch.nn.Module):
    def __init__(self,model_name):
        super().__init__()
        self.model = hf_model.from_pretrained(
           model_name,  ## base transformer
           num_labels=3 ## 3 labels for NLI
        )
    def forward(self,features): ### forward pass
        output = self.model(**features)
        prob = output.logits.softmax(dim=-1)
        return (output.loss,prob)
```

- A task-specific classification model with a special *classification head*.

Model sketch in Pytorch and Huggingface Transformers

```
from transformers import AutoTokenizer as hf_tok
### pre-trained encoder model
nli_model = NLIModel("roberta-base")
tokenizer = hf_tok.from_pretrained("roberta-base")

### prepare data and labels
p = "Children smiling and waving at camera"
h = "They are smiling at their parents"
batch_data = tokenizer([(p,h)],return_tensors="pt")
labels = torch.tensor([[1]])

## run forward pass
output = nli_model({
    "input_ids": batch_data.input_ids,
    "labels"   : labels,
})
print(output[1])
###tensor([[0.3339, 0.3034, 0.3627]], ....)
```

Model Development Process: Classification

```
### pre-trained encoder model
nli_model = NLIModel("roberta-base")
```

1. Define a custom model with a base **pre-trained** transformer model and a set of additional classification parameters; couple with a dataset.

2. **Fine-tune** the new parameters and the full transformer using this dataset.

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   The idea: We can leverage the pre-trained knowledge of the model and apply it to new tasks; introduce new task format.

Model Development Process: Classification

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1. Define a custom model with a base **pre-trained** transformer model and a set of additional classification parameters; couple with a dataset.

2. **Fine-tune** the new parameters and the full transformer using this dataset.

   Variations: parameter efficient tuning, adapters; **Alternatives**: Zero/few-shot modeling, prompting. *discussed later*

What we want a model to do (semantics)

What rules should an ideal NLI model follow?

- **Predictions as propositions** We can symbolically represent NLI predictions as follows:

$$\mathbf{E}(p, h), \mathbf{C}(p, h), \mathbf{N}(p, h)$$

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Denoting an *entailment* (**E**), *neutral* (**N**) or *contradict* (**C**) between any premise/hypothesis pair (p, h).

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Example rules on predictions:

$$\forall(p, h).\, \mathbf{C}(p, h) \leftrightarrow \mathbf{C}(h, p)$$
$$\forall(p, h).\, \mathbf{E}(p, h) \rightarrow \neg\mathbf{C}(h, p)$$
$$\forall(p, h).\, \mathbf{N}(p, h) \rightarrow \neg\mathbf{C}(h, p)$$

(example rules taken from Li et al. (2019); Minervini and Riedel (2018))

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- **Example rules**

$$\forall(p, h).\, \mathbf{C}(p, h) \leftrightarrow \mathbf{C}(h, p)$$
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For the pair

p :John is wearing a green shirt

h :John is wearing a yellow shirt,

contradiction is a symmetric relation, flipping the order yields the same prediction.

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For the pair

p :A man is wearing a **big** green shirt

h :A man is wearing a green shirt.

there shouldn't be a contradiction if I flip the order for an entailment or a neutral prediction.

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- **Example rules**

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For the pair

p :A man is wearing a **big** green shirt

h :A man is wearing a green shirt.

Li et al. (2019) found such constraints to be routinely violated, e.g., BERT violates contradiction symmetry around 20% of time.

What rules should an ideal NLI model follow?

- **More rules**

  Transitivity relations Given the triple (p, h, z)

$$\forall(p, h, z).$$
$$((\mathbf{E}(p, h) \wedge \mathbf{E}(h, z) \rightarrow \mathbf{E}(p, z)) \wedge$$
$$(\mathbf{E}(p, h) \wedge \mathbf{C}(h, z) \rightarrow \mathbf{C}(p, z)) \wedge$$
$$(\mathbf{N}(p, h) \wedge \mathbf{E}(h, z) \rightarrow \neg\mathbf{C}(p, z)) \wedge$$
$$(\mathbf{N}(p, h) \wedge \mathbf{C}(h, z) \rightarrow \neg\mathbf{E}(p, z)))$$

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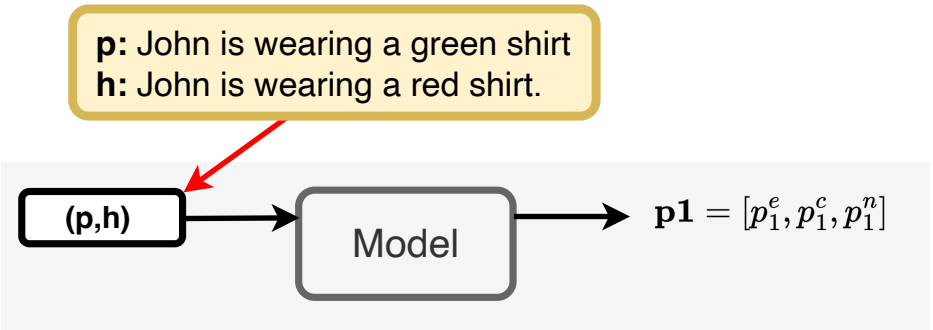
$$(\mathbf{N}(p,h) \wedge \mathbf{E}(h,z) \rightarrow \neg\mathbf{C}(p,z)) \wedge$$
$$(\mathbf{N}(p,h) \wedge \mathbf{C}(h,z) \rightarrow \neg\mathbf{E}(p,z)))$$

  Uniqueness constraints: there should be only one prediction.

$$\forall(p,h).$$
$$(\mathbf{E}(p,h) \vee \mathbf{C}(p,h) \vee \mathbf{N}(p,h)) \wedge$$
$$(\neg\mathbf{E}(p,h) \vee \neg\mathbf{C}(p,h)) \wedge$$
$$(\neg\mathbf{E}(p,h) \vee \neg\mathbf{N}(p,h)) \wedge$$
$$(\neg\mathbf{N}(p,h) \vee \neg\mathbf{C}(p,h))$$

Modeling with declarative knowledge: Semantics



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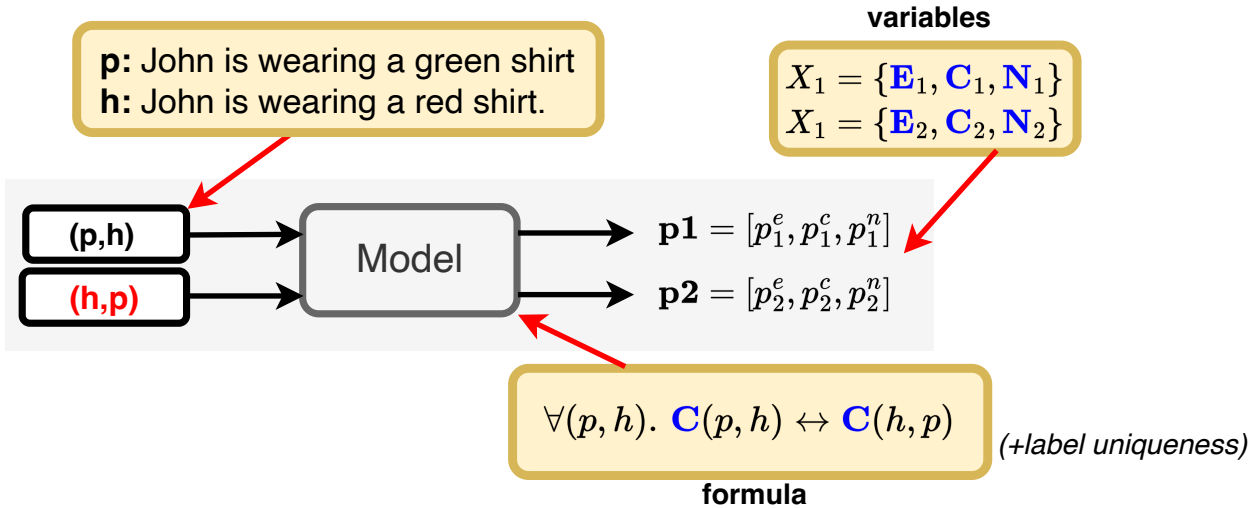

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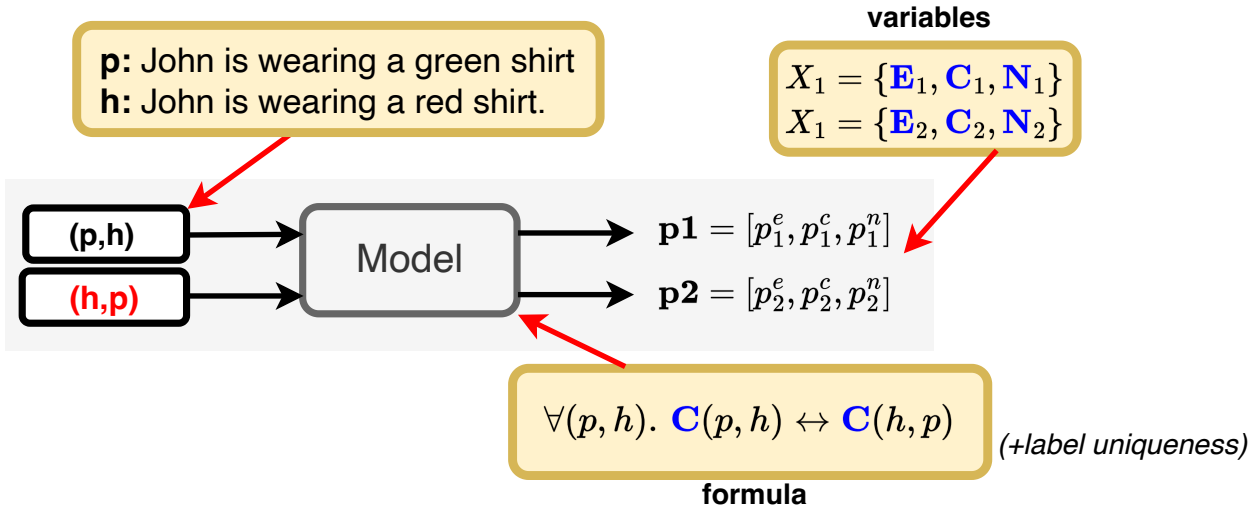

Thinking about our formula K in conventional semantic terms.

	Worlds	Satisfies K?	Correct?
w_1	$\neg\mathbf{E}_1, \mathbf{C}_1, \neg\mathbf{N}_1, \neg\mathbf{E}_2, \mathbf{C}_2, \neg\mathbf{N}_2$	yes	yes
w_2	$\neg\mathbf{E}_1, \mathbf{C}_1, \neg\mathbf{N}_1, \neg\mathbf{E}_2, \neg\mathbf{C}_2, \mathbf{N}_2$	no	no
w_3	$\neg\mathbf{E}_1, \mathbf{C}_1, \neg\mathbf{N}_1, \mathbf{E}_2, \neg\mathbf{C}_2, \neg\mathbf{N}_2$	no	no
w_4	$\neg\mathbf{E}_1, \neg\mathbf{C}_1, \mathbf{N}_1, \neg\mathbf{E}_2, \mathbf{C}_2, \neg\mathbf{N}_2$	no	no
w_5	$\neg\mathbf{E}_1, \neg\mathbf{C}_1, \mathbf{N}_1, \neg\mathbf{E}_2, \neg\mathbf{C}_2, \mathbf{N}_2$	yes	no
w_6	$\neg\mathbf{E}_1, \neg\mathbf{C}_1, \mathbf{N}_1, \mathbf{E}_2, \neg\mathbf{C}_2, \neg\mathbf{N}_2$	yes	no
w_7	$\mathbf{E}_1, \neg\mathbf{C}_1, \neg\mathbf{N}_1, \neg\mathbf{E}_2, \mathbf{C}_2, \neg\mathbf{N}_2$	no	no
w_8	$\mathbf{E}_1, \neg\mathbf{C}_1, \neg\mathbf{N}_1, \neg\mathbf{E}_2, \neg\mathbf{C}_2, \mathbf{N}_2$	yes	no
w_9	$\mathbf{E}_1, \neg\mathbf{C}_1, \neg\mathbf{N}_1, \mathbf{E}_2, \neg\mathbf{C}_2, \neg\mathbf{N}_2$	yes	no

count: 5

Modeling with declarative knowledge: Semantics

Thinking about our formula K in conventional semantic terms.

	Worlds	Satisfies K?	Correct?
w_1	$\neg E_1, C_1, \neg N_1, \neg E_2, C_2, \neg N_2$	yes	yes
w_2	$\neg E_1, C_1, \neg N_1, \neg E_2, \neg C_2, N_2$	no	no
w_3	$\neg E_1, C_1, \neg N_1, E_2, \neg C_2, \neg N_2$	no	no
w_4	$\neg E_1, \neg C_1, N_1, \neg E_2, C_2, \neg N_2$	no	no
w_5	$\neg E_1, \neg C_1, N_1, \neg E_2, \neg C_2, N_2$	yes	no
w_6	$\neg E_1, \neg C_1, N_1, E_2, \neg C_2, \neg N_2$	yes	no
w_7	$E_1, \neg C_1, \neg N_1, \neg E_2, C_2, \neg N_2$	no	no
w_8	$E_1, \neg C_1, \neg N_1, \neg E_2, \neg C_2, N_2$	yes	no
w_9	$E_1, \neg C_1, \neg N_1, E_2, \neg C_2, \neg N_2$	yes	no

count: 5

Modeling with declarative knowledge: Semantics

Thinking about our formula K in conventional semantic terms.

	Worlds	Satisfies K?	Correct?
w_1	$\neg E_1, C_1, \neg N_1, \neg E_2, C_2, \neg N_2$	yes	yes
w_2	$\neg E_1, C_1, \neg N_1, \neg E_2, \neg C_2, N_2$	no	no
w_3	$\neg E_1, C_1, \neg N_1, E_2, \neg C_2, \neg N_2$	no	no
w_4	$\neg E_1, \neg C_1, N_1, \neg E_2, C_2, \neg N_2$	no	no
w_5	$\neg E_1, \neg C_1, N_1, \neg E_2, \neg C_2, N_2$	yes	no
w_6	$\neg E_1, \neg C_1, N_1, E_2, \neg C_2, \neg N_2$	yes	no
w_7	$E_1, \neg C_1, \neg N_1, \neg E_2, C_2, \neg N_2$	no	no
w_8	$E_1, \neg C_1, \neg N_1, \neg E_2, \neg C_2, N_2$	yes	no
w_9	$E_1, \neg C_1, \neg N_1, E_2, \neg C_2, \neg N_2$	yes	no

count: 5

What we care about: worlds **w** where our target formula K is true (denoted as $\mathbf{w} \models K$)

Modeling with declarative knowledge: Semantics

Thinking about our formula K in conventional semantic terms.

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w_1	$\neg E_1, C_1, \neg N_1, \neg E_2, C_2, \neg N_2$	yes	yes
w_2	$\neg E_1, C_1, \neg N_1, \neg E_2, \neg C_2, N_2$	no	no
w_3	$\neg E_1, C_1, \neg N_1, E_2, \neg C_2, \neg N_2$	no	no
w_4	$\neg E_1, \neg C_1, N_1, \neg E_2, C_2, \neg N_2$	no	no
w_5	$\neg E_1, \neg C_1, N_1, \neg E_2, \neg C_2, N_2$	yes	no
w_6	$\neg E_1, \neg C_1, N_1, E_2, \neg C_2, \neg N_2$	yes	no
w_7	$E_1, \neg C_1, \neg N_1, \neg E_2, C_2, \neg N_2$	no	no
w_8	$E_1, \neg C_1, \neg N_1, \neg E_2, \neg C_2, N_2$	yes	no
w_9	$E_1, \neg C_1, \neg N_1, E_2, \neg C_2, \neg N_2$	yes	no
		count: 5	

What we care about: worlds **w** where our target formula K is true (denoted as $\mathbf{w} \models K$)

$$\textsc{count}(K) := \sum_{\mathbf{w} \models K} 1$$

Modeling with declarative knowledge: Semantics

Thinking about our formula K in conventional semantic terms.

	Worlds	Satisfies K?	Correct?
w_1	$\neg E_1, C_1, \neg N_1, \neg E_2, C_2, \neg N_2$	yes	yes
w_2	$\neg E_1, C_1, \neg N_1, \neg E_2, \neg C_2, N_2$	no	no
w_3	$\neg E_1, C_1, \neg N_1, E_2, \neg C_2, \neg N_2$	no	no
w_4	$\neg E_1, \neg C_1, N_1, \neg E_2, C_2, \neg N_2$	no	no
w_5	$\neg E_1, \neg C_1, N_1, \neg E_2, \neg C_2, N_2$	yes	no
w_6	$\neg E_1, \neg C_1, N_1, E_2, \neg C_2, \neg N_2$	yes	no
w_7	$E_1, \neg C_1, \neg N_1, \neg E_2, C_2, \neg N_2$	no	no
w_8	$E_1, \neg C_1, \neg N_1, \neg E_2, \neg C_2, N_2$	yes	no
w_9	$E_1, \neg C_1, \neg N_1, E_2, \neg C_2, \neg N_2$	yes	no
		count: 5	

When predictions scores are considered: weights the rows based on these prediction scores.

$$\mathrm{WMC}(\mathsf{K}, \theta) := \sum_{\mathbf{w} \models \mathsf{K}} \underbrace{\prod_{\mathbf{w} \models X_i} P_\theta(X_i) \cdot \prod_{\mathbf{w} \models \neg X_i} (1 - P_\theta(X_i))}_{\text{score of row}}$$

Modeling with declarative knowledge: Semantics

Thinking about our formula K in conventional semantic terms.

	Worlds	Satisfies K?	Correct?
w_1	$\neg E_1, C_1, \neg N_1, \neg E_2, C_2, \neg N_2$	yes	yes
w_2	$\neg E_1, C_1, \neg N_1, \neg E_2, \neg C_2, N_2$	no	no
w_3	$\neg E_1, C_1, \neg N_1, E_2, \neg C_2, \neg N_2$	no	no
w_4	$\neg E_1, \neg C_1, N_1, \neg E_2, C_2, \neg N_2$	no	no
w_5	$\neg E_1, \neg C_1, N_1, \neg E_2, \neg C_2, N_2$	yes	no
w_6	$\neg E_1, \neg C_1, N_1, E_2, \neg C_2, \neg N_2$	yes	no
w_7	$E_1, \neg C_1, \neg N_1, \neg E_2, C_2, \neg N_2$	no	no
w_8	$E_1, \neg C_1, \neg N_1, \neg E_2, \neg C_2, N_2$	yes	no
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$$\mathrm{WMC}(\mathsf{K}, \theta) := \underbrace{\sum_{\mathbf{w} \models \mathsf{K}} \prod_{\mathbf{w} \models X_i} P_\theta(X_i) \cdot \prod_{\mathbf{w} \models \neg X_i} (1 - P_\theta(X_i))}_{\text{weighted model counting (WMC)}}$$

Modeling with declarative knowledge: Semantics

- Suppose for K that we have weights θ:

  $P_\theta(E_1), (C_1), P_\theta(N_1), P(E_2), P_\theta(C_2), P_\theta(N_2) = [0.3, 0.2, 0.5, 0.1, 0.8, 0.1]$

  then

	Worlds	Satisfies K?	Score
$\mathbf{w}_1$	$\neg E_1, C_1, \neg N_1, \neg E_2, C_2, \neg N_2$	True	0.0454
$\mathbf{w}_2$	$\neg E_1, C_1, \neg N_1, \neg E_2, \neg C_2, N_2$	False	0.0013
$\mathbf{w}_3$	$\neg E_1, C_1, \neg N_1, E_2, \neg C_2, \neg N_2$	False	0.0013
$\mathbf{w}_4$	$\neg E_1, \neg C_1, N_1, \neg E_2, C_2, \neg N_2$	False	0.1814
$\mathbf{w}_5$	$\neg E_1, \neg C_1, N_1, \neg E_2, \neg C_2, N_2$	True	0.005
$\mathbf{w}_6$	$\neg E_1, \neg C_1, N_1, E_2, \neg C_2, \neg N_2$	True	0.005
$\mathbf{w}_7$	$E_1, \neg C_1, \neg N_1, \neg E_2, C_2, \neg N_2$	False	0.0778
$\mathbf{w}_8$	$E_1, \neg C_1, \neg N_1, \neg E_2, \neg C_2, N_2$	True	0.0022
$\mathbf{w}_9$	$E_1, \neg C_1, \neg N_1, E_2, \neg C_2, \neg N_2$	True	0.0022

WMC: $\approx$0.05976

e.g., score of $\mathbf{w}_1 = (1 - 0.3) * 0.2 * (1 - 0.5) * (1 - 0.1) * 0.8 * (1 - 0.1)$

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- Suppose for K that we have weights θ:

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  Total count $\mathrm{WMC}(\mathrm{K}) = 0.05976$

Modeling with declarative knowledge: Semantics

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WMC: $\approx$0.05976

Intuitively: the higher the count, the more our rule is satisfied.

Modeling with declarative knowledge: Semantics

- Suppose for K that we have weights θ:

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w_9	$E_1, \neg C_1, \neg N_1, E_2, \neg C_2, \neg N_2$	True	0.0022

WMC: ≈ 0.05976

Note: Counting is intractable. Variation of Boolean satisfiability (SAT).

Questions?

Compiling to Loss

Semantic loss

- **Probabilistic logic**, based on the semantics of weighted model counting, for a formula K, we want to compute the following probability:

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$$P_\theta(\mathsf{K} = 1)$$

$$\text{where } P_\theta(\mathsf{K} = 1) = \frac{\mathrm{WMC}(\mathsf{K}, \theta)}{\mathrm{WMC}(\mathsf{K}, \theta) + \mathrm{WMC}(\neg\mathsf{K}, \theta)}$$

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$$\mathcal{L}_{\mathsf{sl}}(\mathsf{K}, \theta) := -\log P_\theta(\mathsf{K} = 1)$$

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Has a natural probabilistic semantics:

> The semantic loss is ... [equal]... to a negative logarithm of the probability of generating a state that satisfies the constraint when sampling values according to p. Hence, it is the self-information (or 'surprise') of obtaining an assignment that satisfies the constraint... (Xu et al., 2018)

Semantic loss

- Unpacking $P_\theta(\mathrm{K} = 1)$, we see that:

$$P_\theta(\mathrm{K} = 1) \propto \sum_{\mathbf{w} \models \mathrm{K}} \prod_{\mathbf{w} \models X_i} P_\theta(X_i) \cdot \prod_{\mathbf{w} \models \neg X_i} (1 - P_\theta(X_i))$$

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we can express as a binary probability distribution involving $\mathbf{w}$, or $p_\theta(X_1 = \mathbf{w}_1, ..., X_n = \mathbf{w}_n)$, computed as

$$p_\theta(X_1 = \mathbf{w}_1, ..., X_n = \mathbf{w}_n) = \prod_i^n P_\theta(X_i = \mathbf{w}_i).$$

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we can express as a binary probability distribution involving $\mathbf{w}$, or $p_\theta(X_1 = \mathbf{w}_1, ..., X_n = \mathbf{w}_n)$, computed as

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makes a common independence assumption, interesting properties studied in van Krieken et al. (2024). This makes $P_\theta(\mathrm{K}=1) = \mathrm{WMC}(\mathrm{K}, \theta)$.

Special cases

Semantic loss: special cases

- Suppose we have unlabeled (p, h) pairs that we want to learn from, how? via **uniqueness constraints** or for each instance (simpl. $P(p, h)$ to P):

$$\mathrm{K} := \big(\mathbf{E} \wedge \neg \mathbf{C} \wedge \neg \mathbf{N}\big) \vee \big(\neg \mathbf{E} \wedge \mathbf{C} \wedge \neg \mathbf{N}\big) \vee \big(\neg \mathbf{E} \wedge \neg \mathbf{C} \wedge \mathbf{N}\big)$$

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Intuition: A model must confidently assign a consistent class, even to unlabeled examples (Xu et al., 2018), **semi-supervised** learning.

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Intuition: A model must confidently assign a consistent class, even to unlabeled examples (Xu et al., 2018), **semi-supervised** learning.

We can compute this directly:

$$\mathcal{L}_{\text{uniq}}(\theta, \mathsf{K}) = -\log \underbrace{\sum_{i=1}^{3} P_\theta(X_i) \cdot \prod_{j=1, j\neq i} (1 - P_\theta(X_i))}_{\text{direct } n^2}$$

Semantic loss: special cases

$$\mathsf{K} := (\mathbf{E} \wedge \neg \mathbf{C} \wedge \neg \mathbf{N}) \vee (\neg \mathbf{E} \wedge \mathbf{C} \wedge \neg \mathbf{N}) \vee (\neg \mathbf{E} \wedge \neg \mathbf{C} \wedge \mathbf{N})$$

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$$\mathcal{L}_{\text{uniq}}(\theta, \mathsf{K}) = -\log \sum_{i=1}^{3} P_\theta(X_i) \cdot \prod_{j=1, j \neq i} (1 - P_\theta(X_i))$$

- Suppose for K that we have weights θ:

$$P_\theta(E), (C), P_\theta(N) = [0.3, 0.2, 0.5]$$

then the loss is equal to

$$-\log \left(\underbrace{(0.3 * 0.8 * 0.5)}_{\mathbf{E} \wedge \neg \mathbf{C} \wedge \neg \mathbf{N}} + (0.2 * 0.7 * 0.5) + (0.5 * 0.7 * 0.8)) \right)$$

Model sketch in Pytorch: semi-supervised learning

```
unlabel_p = "John is weearing a red shirt"
unlabel_h = "John is wearing a yellow shirt"
batch_data = tokenizer([(p,h),(unlabel_p,unlabel_h)],
        return_tensors="pt",padding=True)
labels = torch.tensor([[1],[-100]])

label_loss,probs = NLIModel({
    "input_ids": batch_data.input_ids,
    "labels"   : labels,
})
unlab_probs = probs[1:]
wmc = torch.zeros_like(unlab_probs)
for i in range(3):
    negate      = 1 - unlab_probs
    negate[:,i] = unlab_probs[:,i]
    wmc[:,i]    = negate.prod(dim=-1)

wmc_loss = -1*torch.log(wmc.sum(dim=-1)).squeeze(-1)
```

original implementation, pytorch version version (version above)

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```
unlab_probs = probs[1:]
wmc = torch.zeros_like(unlab_probs)
for i in range(3):
    negate       = 1 - unlab_probs
    negate[:,i] = unlab_probs[:,i]
    wmc[:,i]     = negate.prod(dim=-1)

wmc_loss = -1*torch.log(wmc.sum(dim=-1)).mean()

print(wmc.requires_grad)
## => True
print(wmc_loss)
## tensor(0.8082, grad_fn=<MulBackward0>)
```

some notes on autodiff, more notes.

Semantic loss: other special cases

- **Supervised learning**: suppose we have two gold annotations $\mathbf{E}_1(p_1, h_1)$ and $\mathbf{C}_2(p_2, h_2)$ *(no additional variables)* and the formula:

$$\mathrm{K} := \mathbf{E}_1(p_1, h_1) \wedge \mathbf{C}_2(p_2, h_2).$$

Semantic loss: other special cases

- **Supervised learning**: suppose we have two gold annotations $\mathbf{E}_1(p_1, h_1)$ and $\mathbf{C}_2(p_2, h_2)$ *(no additional variables)* and the formula:

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Performing counting of this gives the following:

	Worlds	**Satisfies K?**
$\mathbf{w}_1$	$\mathbf{E}_1, \mathbf{C}_2$	True
$\mathbf{w}_2$	$\neg\mathbf{E}_1, \mathbf{C}_2$	False
$\mathbf{w}_3$	$\mathbf{E}_1, \neg\mathbf{C}_2$	False
$\mathbf{w}_4$	$\neg\mathbf{E}_1, \neg\mathbf{C}_2$	False

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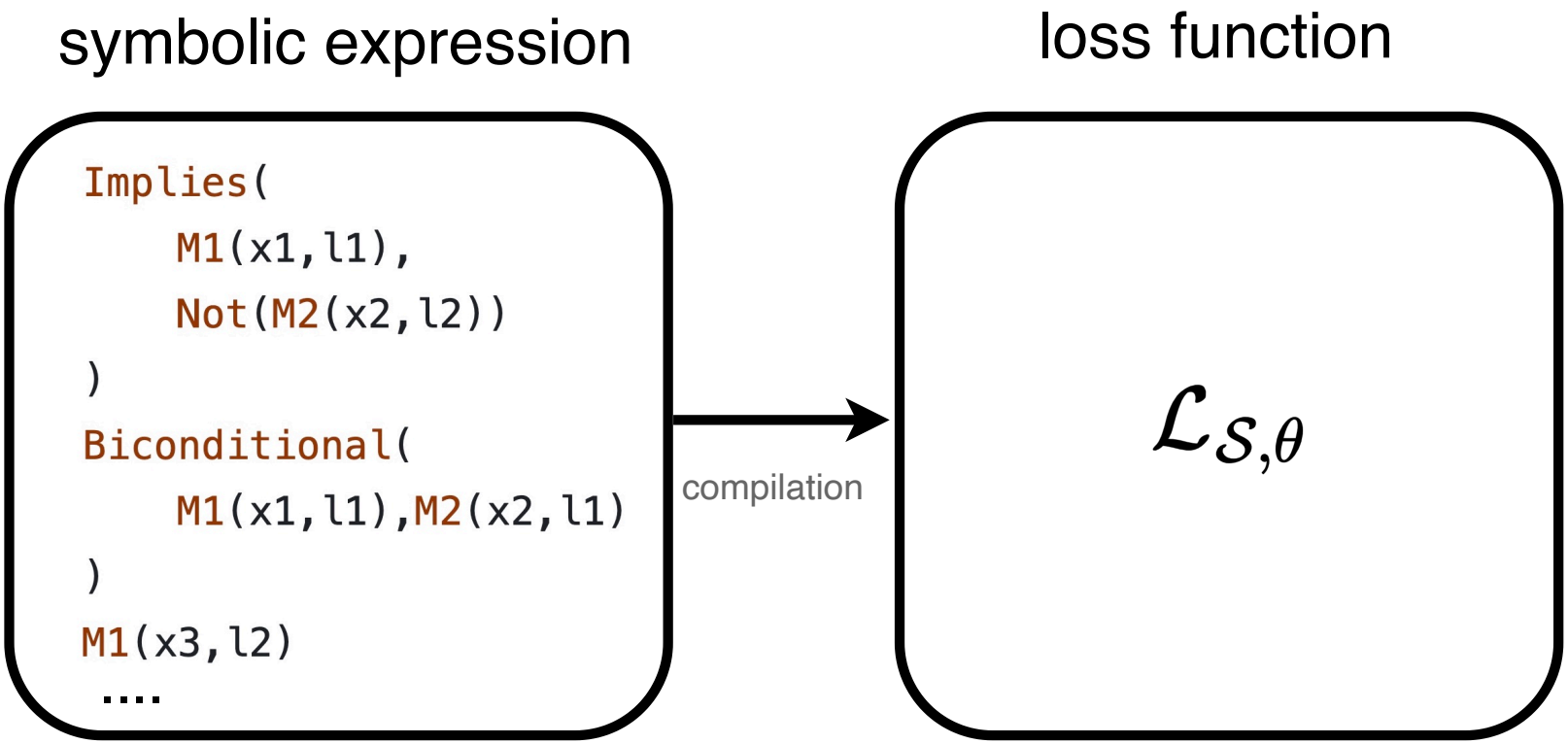
where only a single model gets counted, yielding a semantic loss of $-\log(\mathbf{p}_1 * \mathbf{p}_2)$ equal to the **cross-entropy loss**.

Going in the reverse direction



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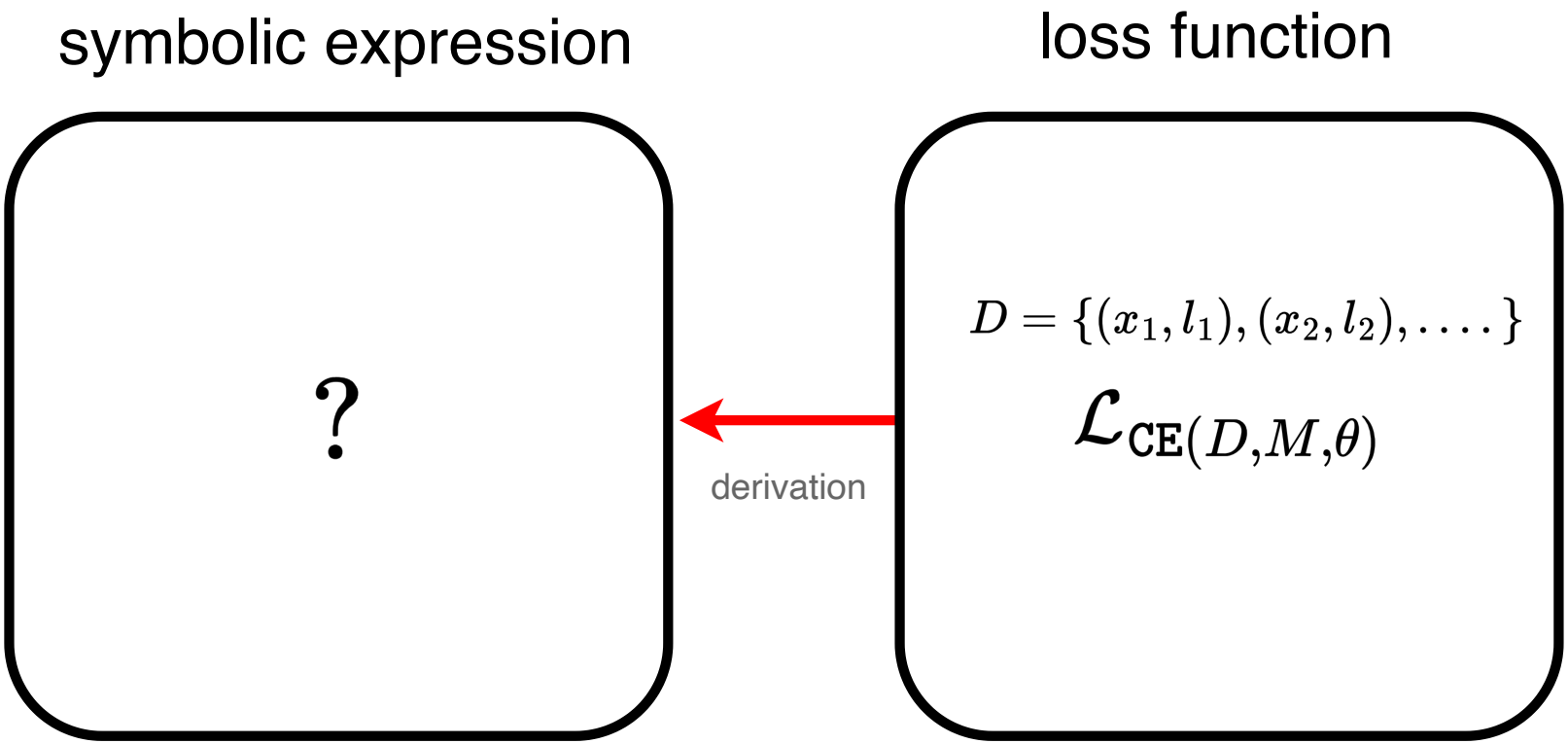
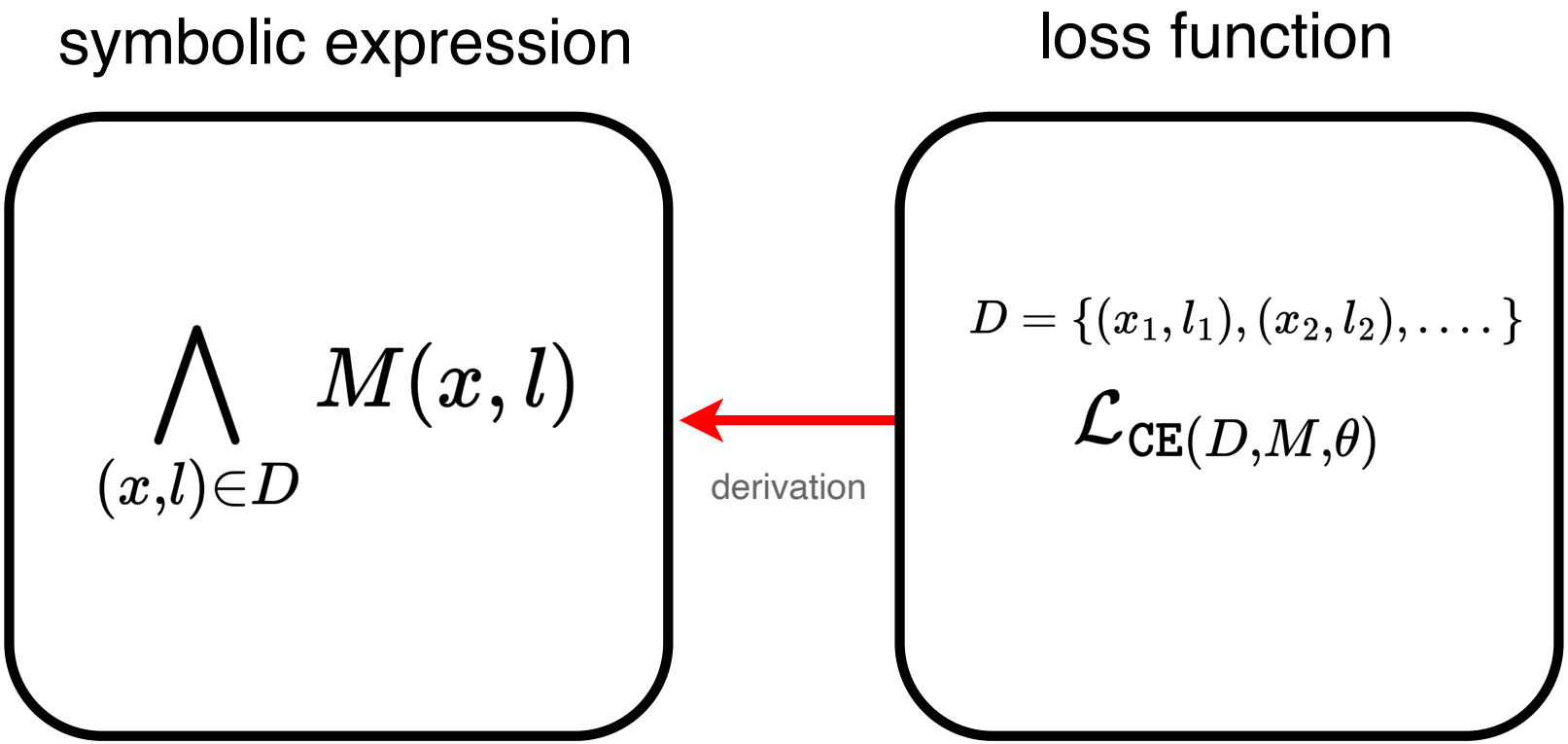


- We can also try to decompile from a known loss function to a symbolic expression, help to understand the semantics of known loss functions.

Going in the reverse direction



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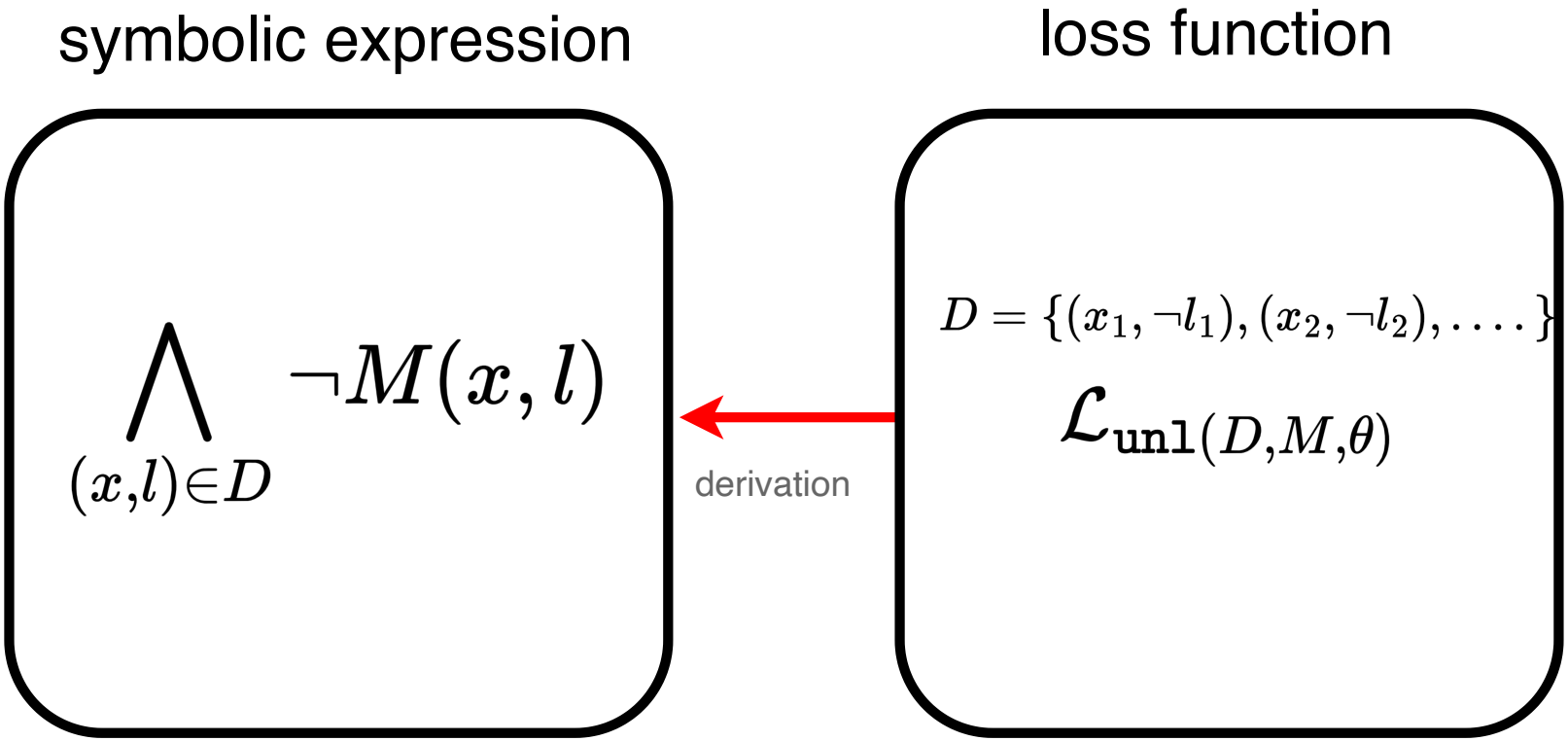

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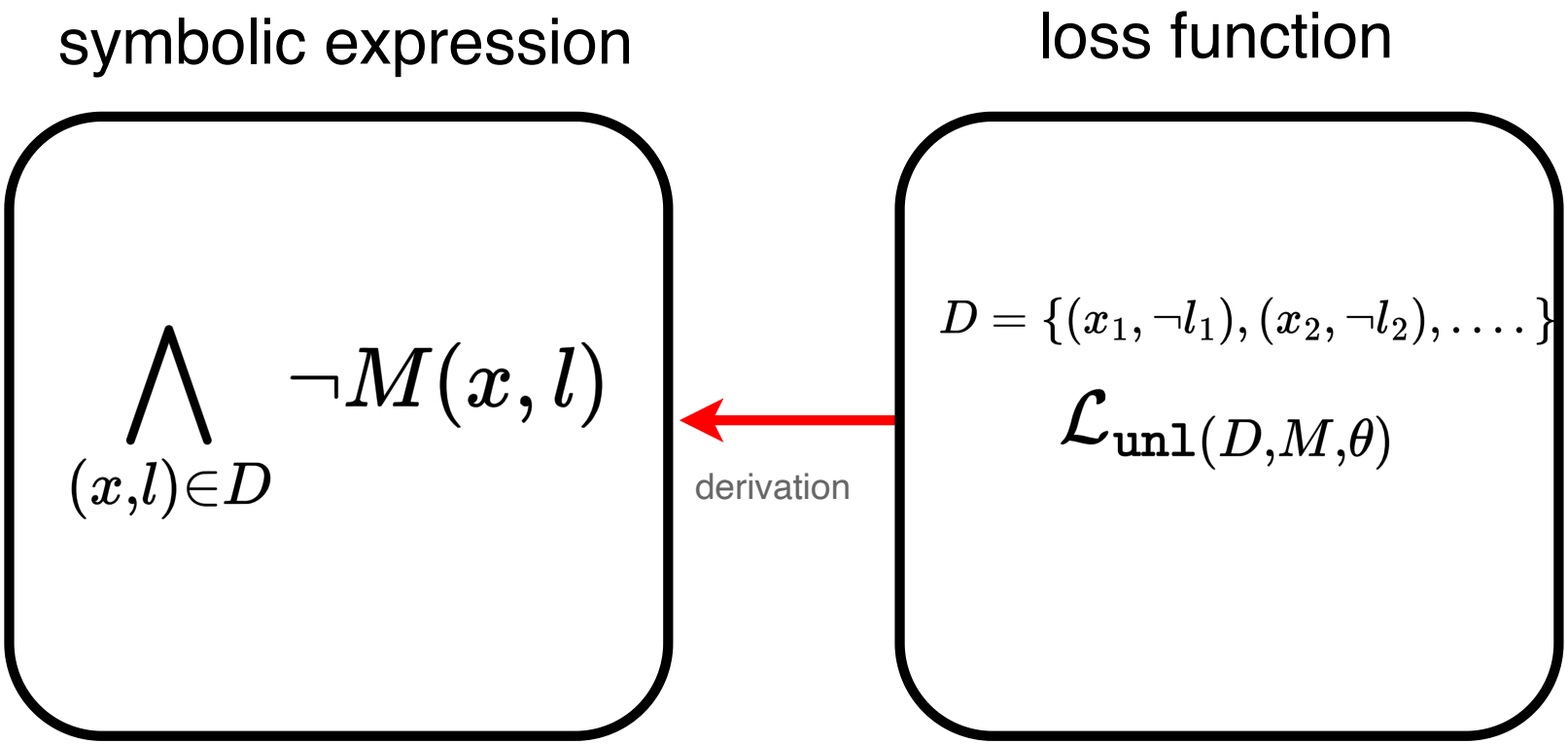

observation: standard loss (e.g., cross entropy) functions have a fairly simple logical semantics (Li et al., 2019; Giannini et al., 2023).

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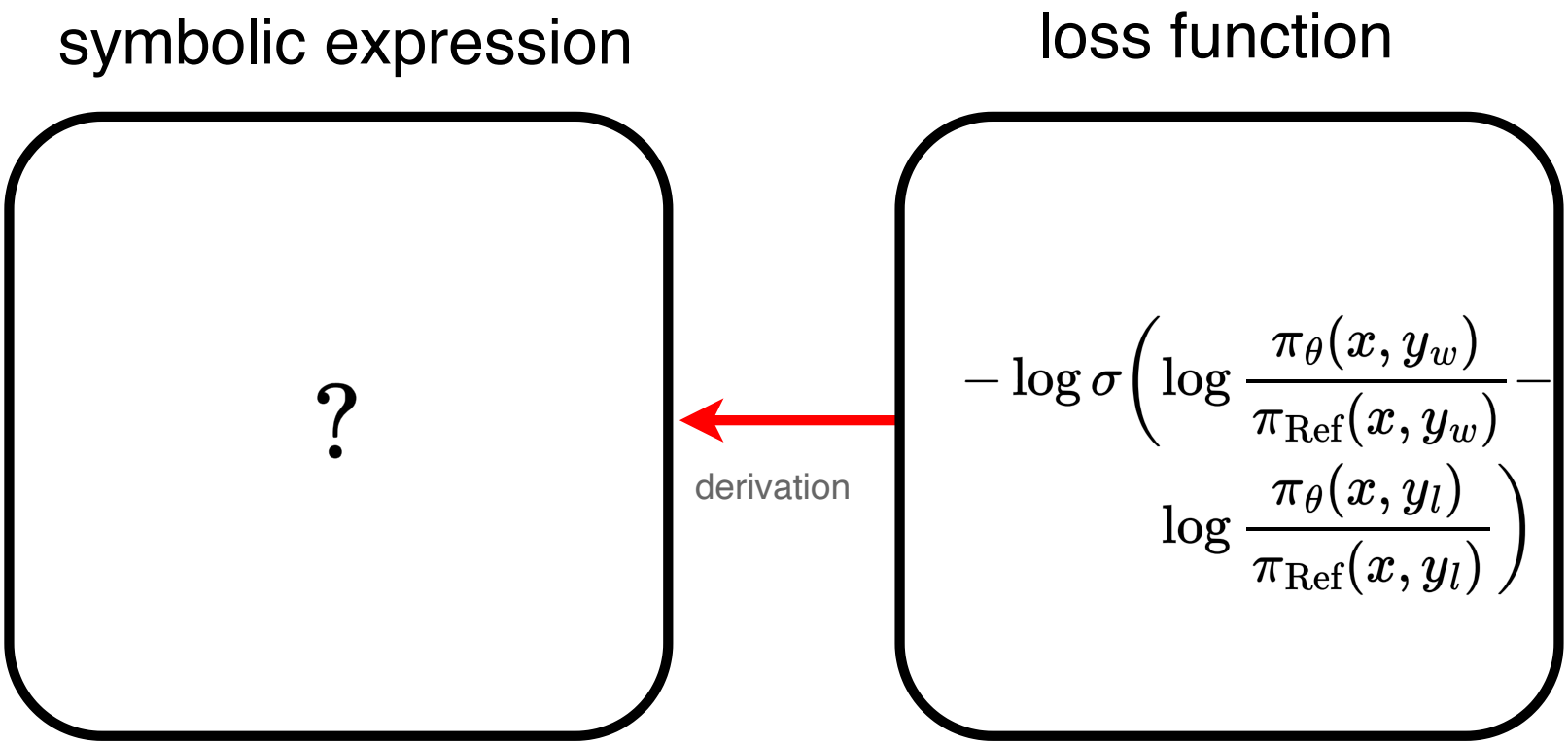

Formal properties of semantic loss

- The **semantic loss** $\mathcal{L}_{\mathsf{sl}}$ for K is:

$$\mathcal{L}_{\mathsf{sl}}(\mathsf{K}, \theta) := -\log P_\theta(\mathsf{K} = 1)$$

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Can be useful for reasoning about the relationship between different losses, both semantically and in terms of their relative loss behavior.

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$$\forall (t, P) \in D_{\text{neg}} \quad \bigwedge \neg P(t) \qquad (\textit{unlikelihood loss})$$

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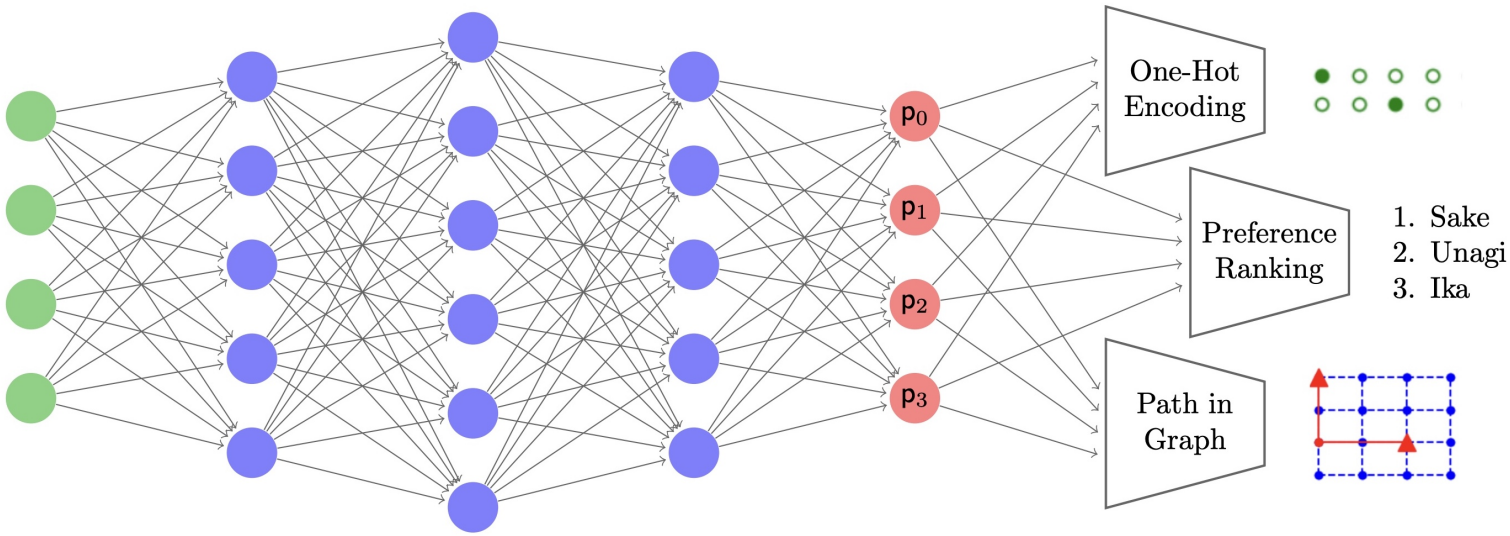
Whatever we can express in (propositional) logic can now be a loss function, many new possibilities for programming models.

Questions?

Other uses of semantic loss



from Xu et al. (2018)

- Can be used for *structured prediction*, jointly predicting many output variables for building structured objects (Ahmed et al., 2022b).

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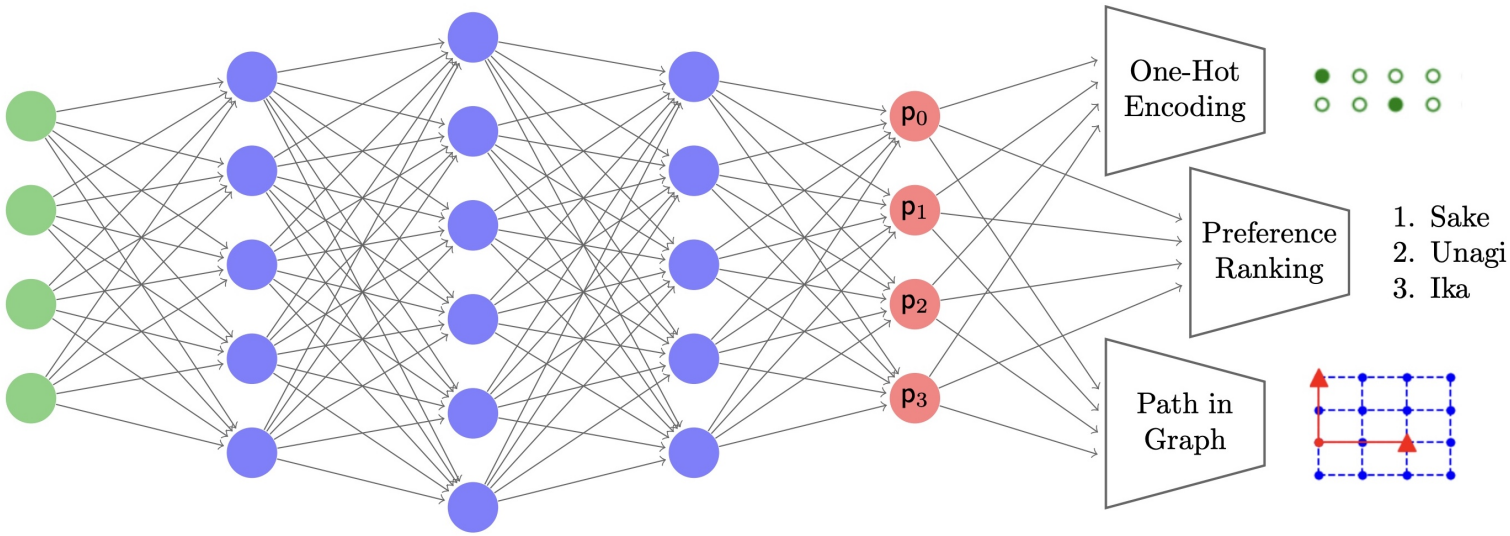

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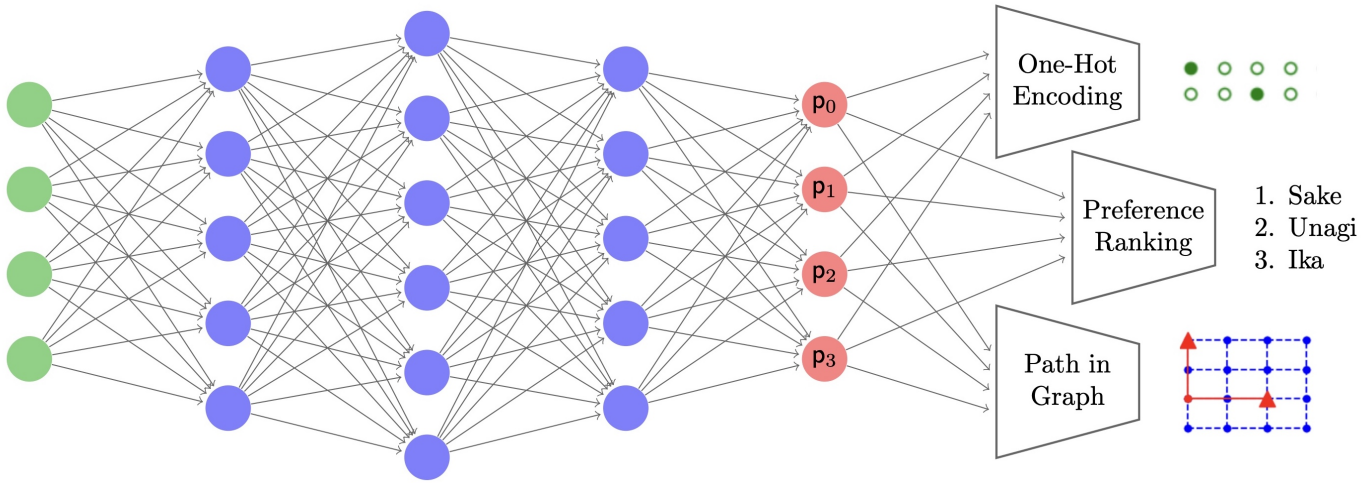

- **Preference learning**: Ranking preferences, e.g., (Choi et al., 2015) given variables P_1, P_2, P_3, binary matrix $P_{i,j}$ $(i, j \in \{1, ..., 3\})$ and a total order:

$$\forall i.((P_{i,1} \wedge \neg P_{i,2}, \wedge \neg P_{i,3}) \vee$$
$$(\neg P_{i,1} \wedge P_{i,2}, \wedge \neg P_{i,3}) \vee$$
$$(\neg P_{i,1} \wedge \neg P_{i,2}, \wedge P_{i,3}))$$

$$\forall j.((P_{1,j} \wedge \neg P_{2,j} \wedge \neg P_{3,j}) \vee$$
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How the semantic loss is used

```
loss_weight = 0.3
wmc_loss = -1*torch.log(wmc.sum(dim=-1)).mean()
loss = label_loss + loss_weight*wmc_loss
```

- Usually coupled with ordinary loss, or as a *regularizer*

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From Marra et al. (2021)

> [This] class of NeSy is model-based. They use logic to define a loss function (usually a regularization term) for neural networks. The networks compute scores for a set of atoms... At each training step the logic-based loss function checks whether the assigned scores satisfy the logical theory and computes a corresponding penalty. **Logical inference is therefore turned into a learning problem** (i.e. **"learning to satisfy"**)

When "learning to satisfy" can go wrong

- Suppose that consider $\mathbf{C}_1$ and $\mathbf{C}_2$ are the correct analyses and we optimize our model for:

$$\forall(p, h).\, \mathbf{C}(p, h) \leftrightarrow \mathbf{C}(h, p)$$

with semantics:

	Worlds	Satisfies F?	Correct?
w_1	$\neg\mathbf{E}_1, \mathbf{C}_1, \neg\mathbf{N}_1, \neg\mathbf{E}_2, \mathbf{C}_2, \neg\mathbf{N}_2$	yes	yes
w_2	$\neg\mathbf{E}_1, \mathbf{C}_1, \neg\mathbf{N}_1, \neg\mathbf{E}_2, \neg\mathbf{C}_2, \mathbf{N}_2$	no	no
w_3	$\neg\mathbf{E}_1, \mathbf{C}_1, \neg\mathbf{N}_1, \mathbf{E}_2, \neg\mathbf{C}_2, \neg\mathbf{N}_2$	no	no
w_4	$\neg\mathbf{E}_1, \neg\mathbf{C}_1, \mathbf{N}_1, \neg\mathbf{E}_2, \mathbf{C}_2, \neg\mathbf{N}_2$	no	no
w_5	$\neg\mathbf{E}_1, \neg\mathbf{C}_1, \mathbf{N}_1, \neg\mathbf{E}_2, \neg\mathbf{C}_2, \mathbf{N}_2$	yes	no
w_6	$\neg\mathbf{E}_1, \neg\mathbf{C}_1, \mathbf{N}_1, \mathbf{E}_2, \neg\mathbf{C}_2, \neg\mathbf{N}_2$	yes	no
w_7	$\mathbf{E}_1, \neg\mathbf{C}_1, \neg\mathbf{N}_1, \neg\mathbf{E}_2, \mathbf{C}_2, \neg\mathbf{N}_2$	no	no
w_8	$\mathbf{E}_1, \neg\mathbf{C}_1, \neg\mathbf{N}_1, \neg\mathbf{E}_2, \neg\mathbf{C}_2, \mathbf{N}_2$	yes	no
w_9	$\mathbf{E}_1, \neg\mathbf{C}_1, \neg\mathbf{N}_1, \mathbf{E}_2, \neg\mathbf{C}_2, \neg\mathbf{N}_2$	yes	no
		count: 5	

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notice: Most satisfying models are models where both are false; will nudge model towards this analysis.

Shortcut learning

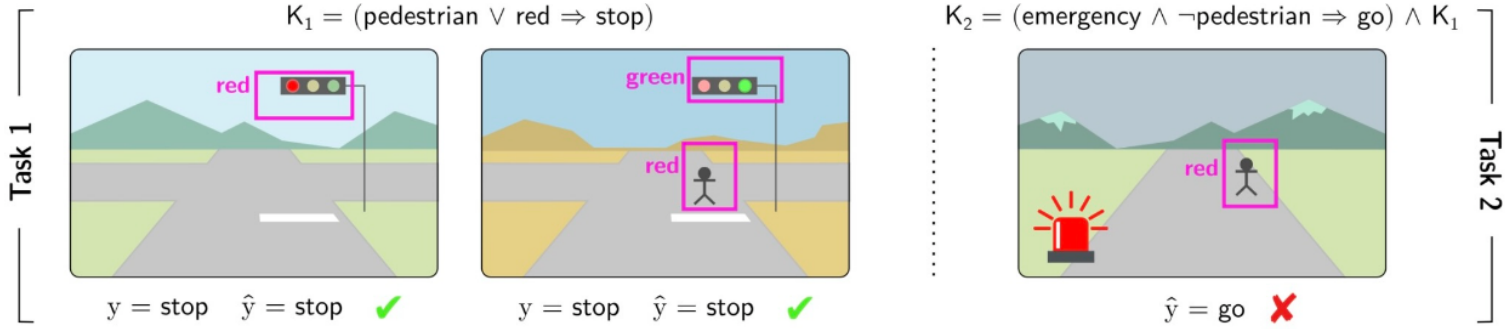

Figure 1: **Reasoning shortcuts undermine trustworthiness**. An autonomous vehicle has to decide whether to $Y =$ `stop` or $Y =$ `go` based on three binary concepts extracted from an image $\mathbf{x}$, namely $C_1 =$ `red` light, $C_2 =$ `green` light and $C_3 =$ presence of `pedestrians` (shown in **pink**). **Left**: In Task 1, the prior knowledge $\mathsf{K} = (\texttt{pedestrian} \vee \texttt{red} \Rightarrow \texttt{stop})$ instructs the vehicle to stop whenever the light is red or there are pedestrians on the road. The model can perfectly classify an (even exhaustive) training set by acquiring a *reasoning shortcut that classifies pedestrians as red lights*. **Right**: The learned concepts are then reused to guide an autonomous ambulance with the additional rule that in emergency situations red lights can be ignored, with potentially dire consequences. Our work identifies the causes of RSs (Section 4) and several mitigation strategies (Section 5).

From Marconato et al. (2024)

Why does this happen?

- Related to its independence assumption, makes the model prefer *deterministic* solutions (van Krieken et al., 2024).

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  $$\neg(p(g) \wedge p(r))$$

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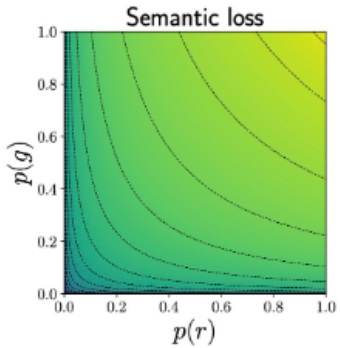


Figure 2. The loss landscape of the semantic loss for the traffic light problem – brighter (resp. darker) regions correspond to higher (resp. lower) semantic loss values.

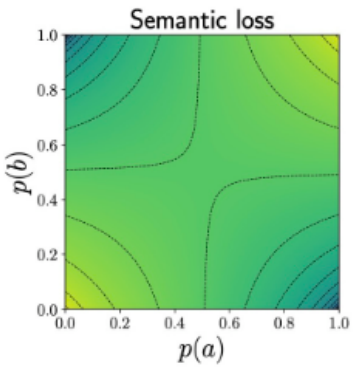
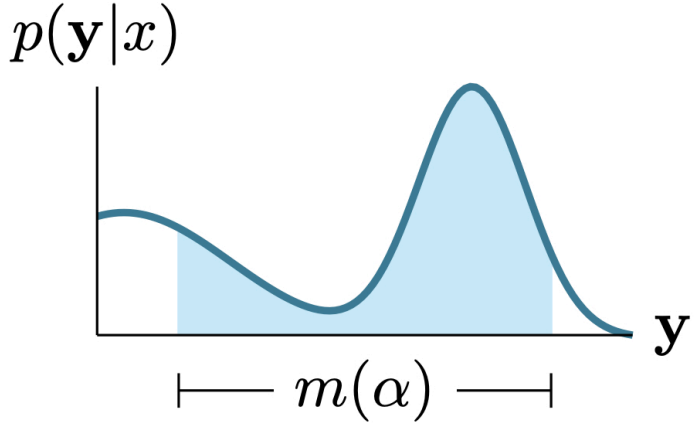


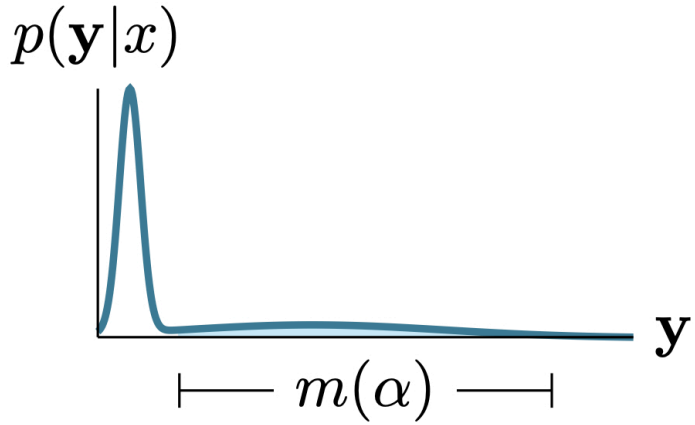
Figure 6. The loss landscape of the semantic loss under the independence assumption for the XOR formula $\varphi = (a \wedge \neg b) \vee (\neg a \wedge b)$.

Theorem 3.1 (Implicants determine minima, informal)**.** *An independent distribution $p_{\boldsymbol{\theta}}(\mathbf{w})$ minimises the semantic loss if and only if it is deterministic for some variables, and those variables form an implicant of φ.*

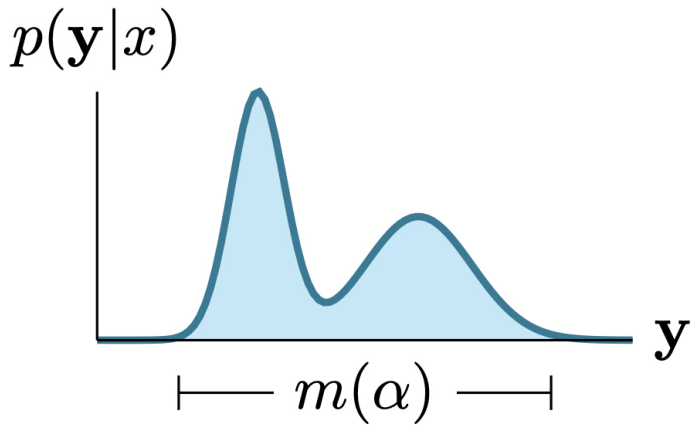
Another view

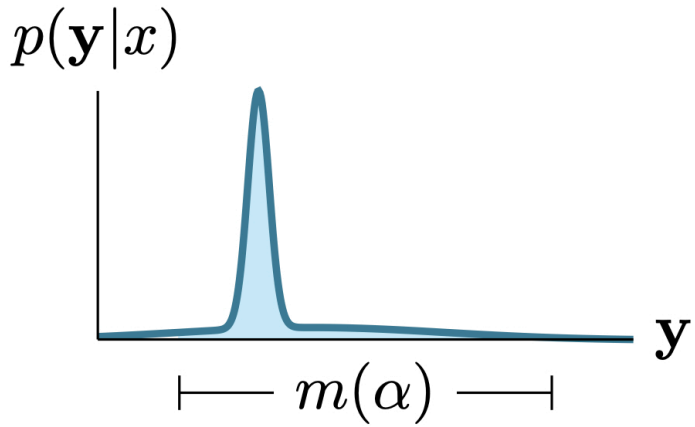


(a) Network uncertain over both valid and invalid predictions



(b) Network allocating most mass to one invalid prediction



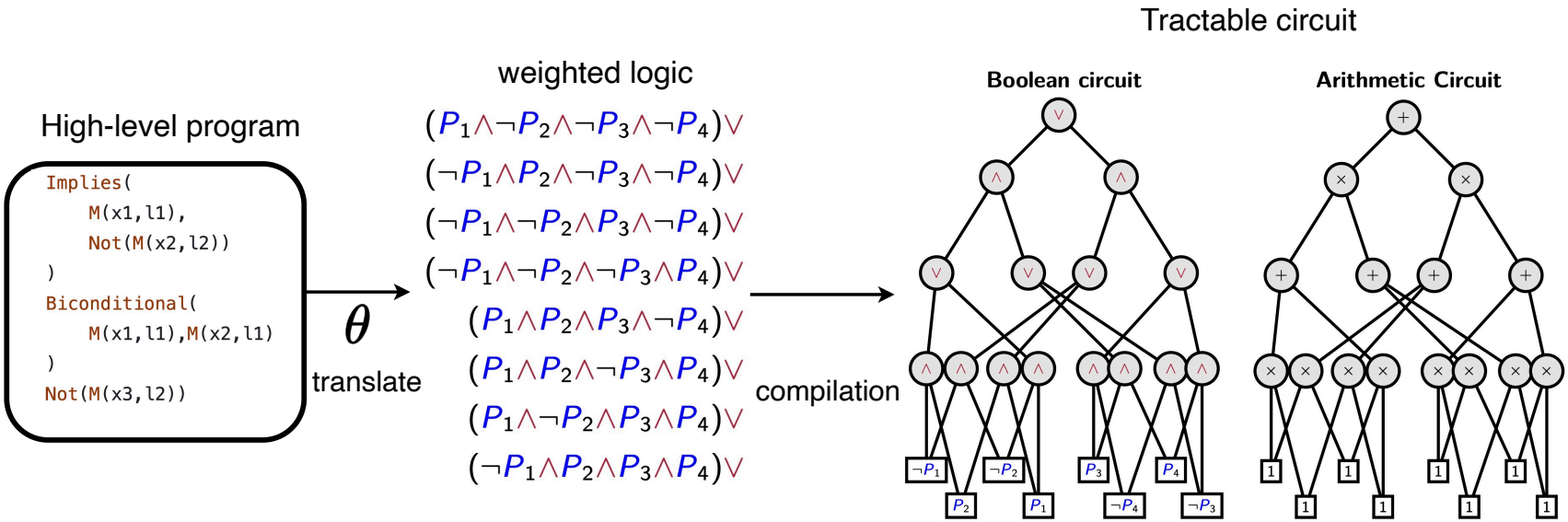


From Ahmed et al. (2022b)

practical bottleneck: computing

$\mathrm{WMC}(\mathsf{K}, \theta)$

How this works in practice



- **Knowledge compilation**: tractable representations for efficient logical and probabilistic inference (Darwiche and Marquis, 2002; Marquis, 2008).

Problog

```
import problog as p                    ## pip install problog
P = p.program.PrologString("""
0.8::stress(ann).
0.4::stress(bob).
0.6::influences(ann,bob).
0.2::influences(bob,carl).

smokes(X) :- stress(X).
smokes(X) :- influences(Y,X), smokes(Y).

query(smokes(carl))."""")

lf = p.formula.LogicFormula.create_from(P)#ground
dag = f.formula.LogicDAG.create_from(lf)# break cycles
cnf = p.cnf_formula.CNF.create_from(dag)# convert CNF
ddnnf = p.ddnf.DDNNF.create_from(cnf)# compile circuit

ddnnf.evaluate()
```

Creating tractable representations

- **Uniqueness constraint** would be commonly written in *conjunctive normal form* (CNF):

$$\underbrace{(\mathbf{E} \vee \mathbf{N} \vee \mathbf{C})}_{\text{clause}} \wedge (\neg \mathbf{E} \vee \neg \mathbf{N}) \wedge (\neg \mathbf{N} \vee \neg \mathbf{C}) \wedge (\neg \mathbf{E} \vee \neg \mathbf{N})$$

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We could also write it in the following form:

$$\big(\mathbf{E} \wedge \neg \mathbf{N} \wedge \neg \mathbf{C}\big) \vee \big(\neg \mathbf{E} \wedge \mathbf{C} \wedge \neg \mathbf{N}\big) \vee \big(\neg \mathbf{E} \wedge \neg \mathbf{C} \wedge \mathbf{N}\big)$$

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$$\underbrace{(\mathbf{E} \vee \mathbf{N} \vee \mathbf{C})}_{\text{clause}} \wedge (\neg\mathbf{E} \vee \neg\mathbf{N}) \wedge (\neg\mathbf{N} \vee \neg\mathbf{C}) \wedge (\neg\mathbf{E} \vee \neg\mathbf{N})$$

We could also write it in the following form:

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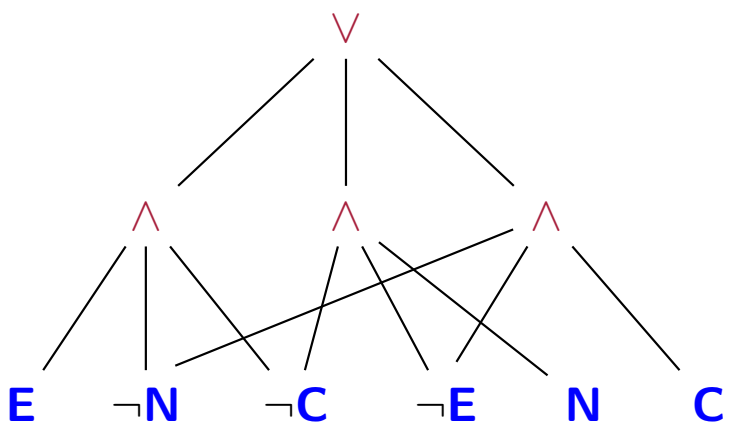

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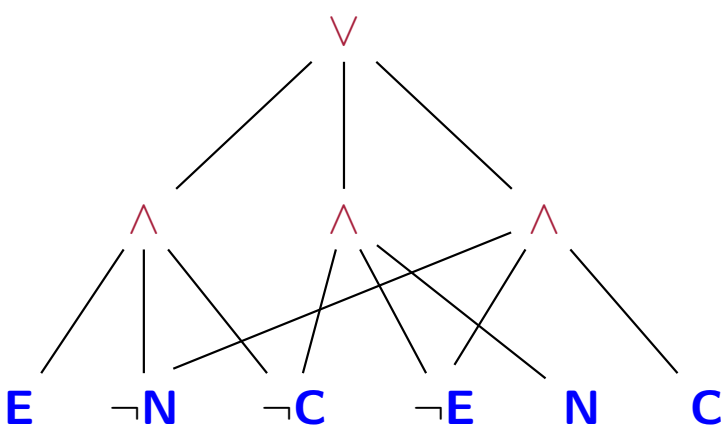

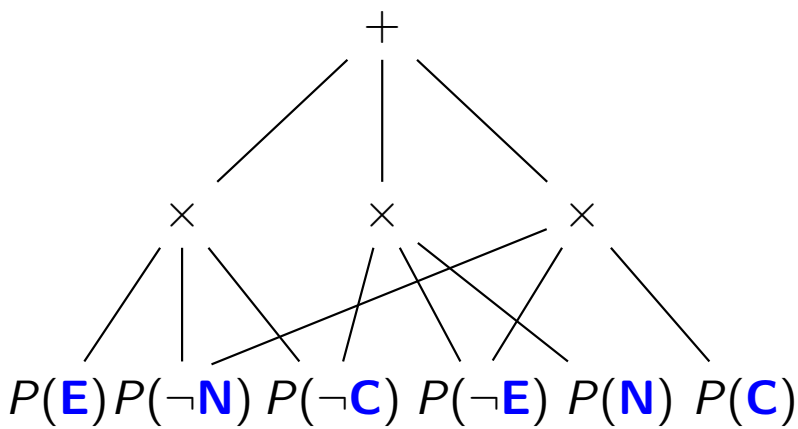

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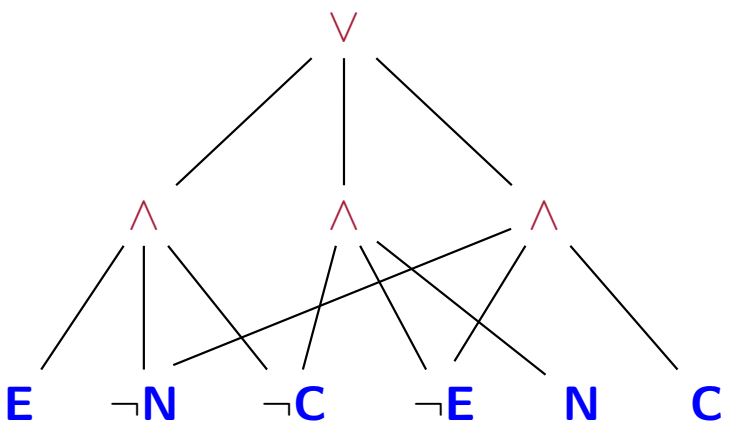
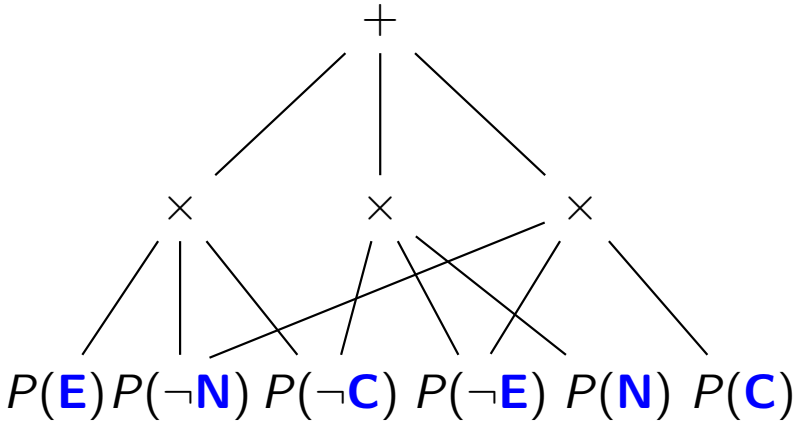


Boolean circuit



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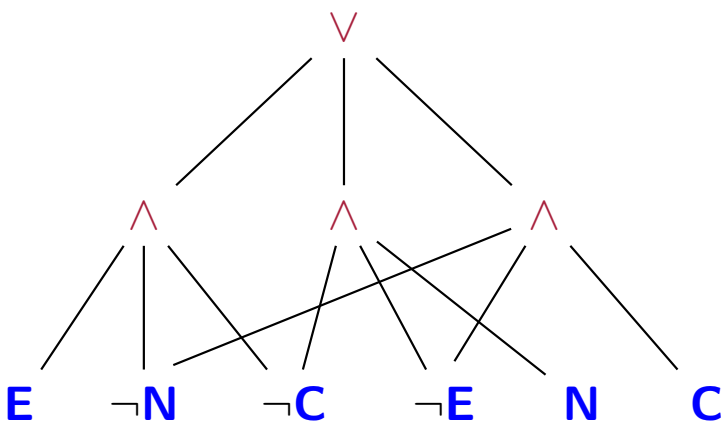

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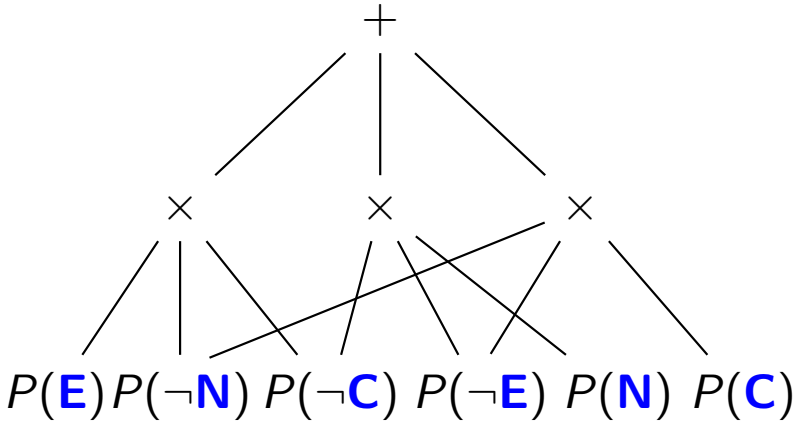

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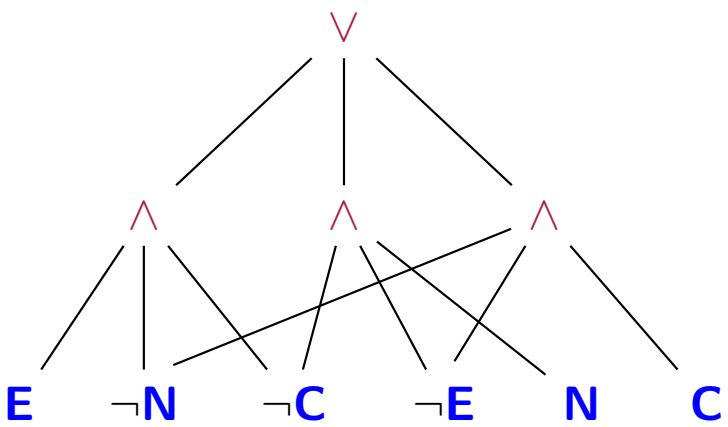

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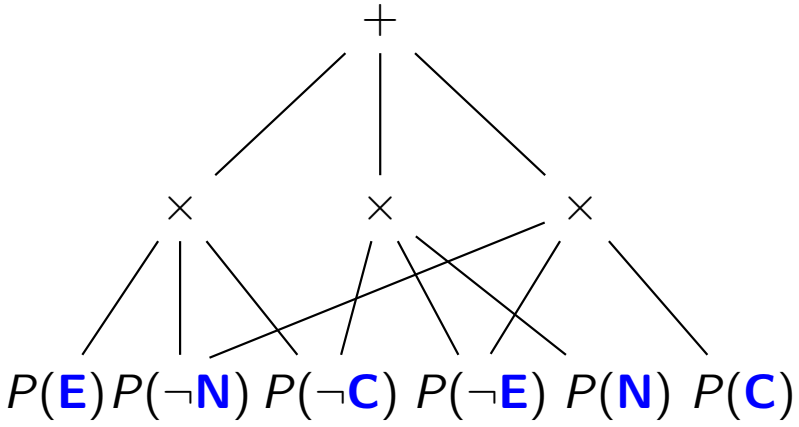

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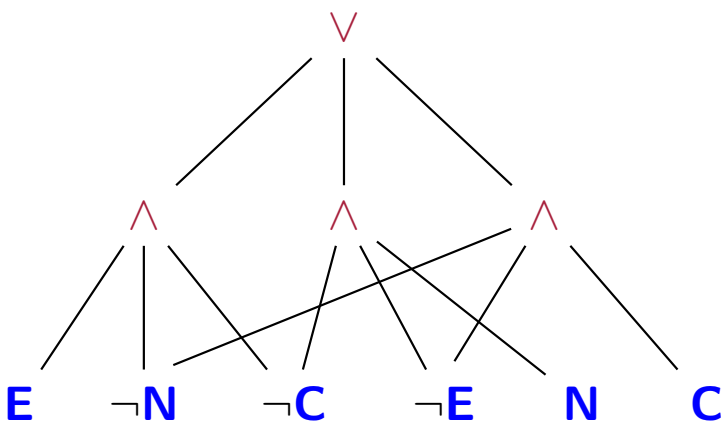

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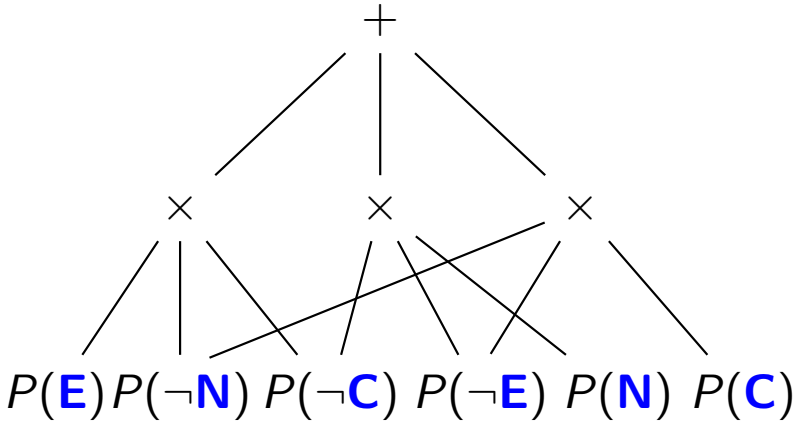

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  decomposability: For conjunction nodes $\wedge$, children never share the same variables.

  determinism: For each disjunction node $\vee$, the children are logically inconsistent.

Compilation Software: example

```
from pysdd.sdd import SddManager

sdd = SddManager(var_count=3)
p1, p2, p3 = sdd.vars
uniqueness = (p1 & -p2 & -p3) | (-p1 & p2 & -p3) \
        | (-p1 & -p2 & p3)

count = uniqueness.wmc(log_mode=False)
print(f"model count: {count.propagate()}")
```

https://github.com/wannesm/PySDD, see Darwiche (2011)

- Can extract underlying circuits, mix with Pytorch.

Avoiding the bottleneck

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- Allows for truth values to be **real-valued**, implements Boolean operators as real-valued functions (t-norms). For example:

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Can define the loss to be

$$-\log\left(P_\theta(\mathbf{E}(p_1, h_1)) \cdot P_\theta(\mathbf{C}_2(p_2, h_2)\right)$$

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T-norm	$A \wedge B$	ab	$\min(a,b)$	$\max(0, a+b-1)$
T-conorm	$A \vee B$	$a+b-ab$	$\max(a,b)$	$\min(1, a+b)$
Residuum	$A \rightarrow B$	$\min\left(1, \frac{b}{a}\right)$	$\begin{cases} 1, & \text{if b} \geq \text{a}, \\ b, & \text{else} \end{cases}$	$\min(1, 1-a+b)$

Table 1: Mapping discrete statements to differentiable functions using t-norms. Literals are upper-cased (e.g. A) while real-valued probabilities are lower-cased (e.g. a). Here, differentiable forms are from a mixture of R-fuzzy logic and S-fuzzy logic. In this paper, we focus on the product t-norm.

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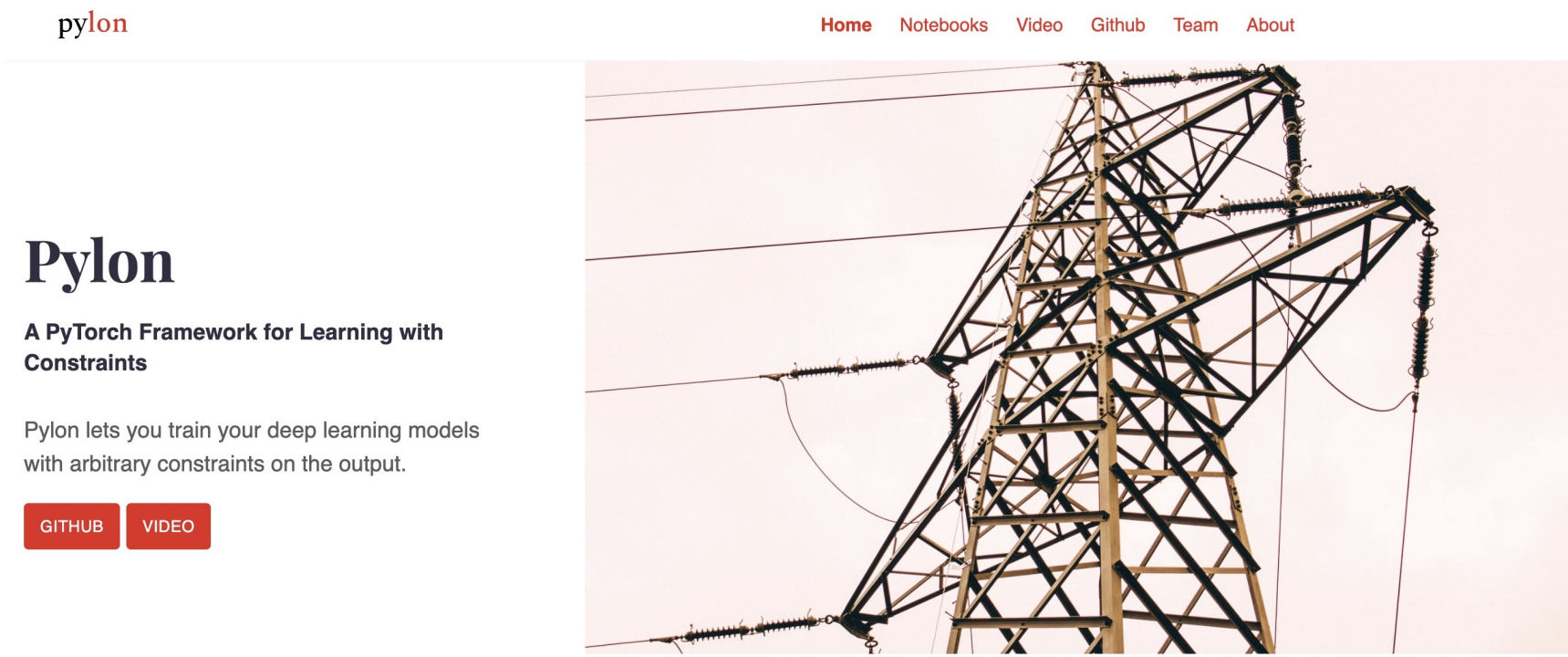
  trouble: Loses virtually all the nice semantic properties we discussed.

Pylon



https://pylon-lib.github.io/, see Ahmed et al. (2022a)

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- **Semantic loss**: A loss function based on this semantics, based on probabilistic logic and WMC.

  Logic as a loss function, learning to satisfy, regularizer.
- **Next time**: A bit more about tractable representations of logic and probabilistic inference, language mode inference.

Thank you.

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