Logical and statistical approaches to Explainable AI (XAI)

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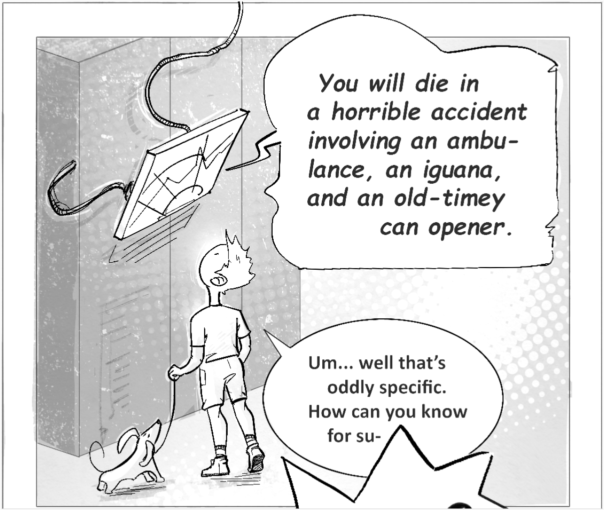
Motivation

Transparency is paramount to ensuring that AI is not biased. The AI guidelines introduce a number of measures to ensure transparency in the AI industry. For instance, the data sets and processes that are used in building AI systems should be documented and traceable.

(European Parliament)

Motivation


You will die in a horrible accident involving an ambu-lance, an iguana, and an old-timey can opener.
Um... well that's oddly specific. How can you know for su-

Motivation

▸ https://miro.medium.com/max/2250/1*y04opolhQJawO0SxzBZ9MA.png

Overview

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XAI is complex...

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And intertwined...

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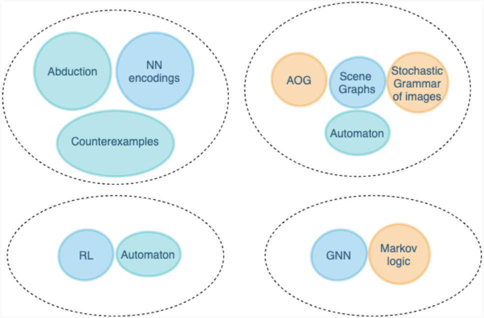

Overview – our focus

Overview

Computer vision (CV) & formal methods (FM)

Neural networks (NNs) in general & FM

Reinforcement learning (RL) & FM

Methods that try to generalize & FM

Computer vision (CV) & formal methods (FM)

CV – Neural State Machine (NSM) – build the machine

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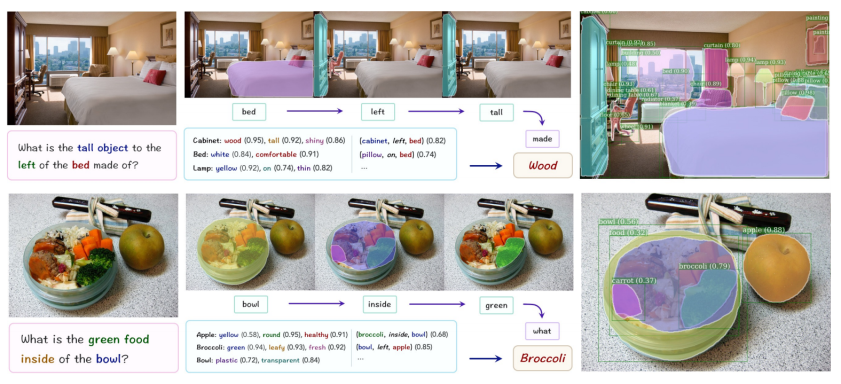

D. Hudson et al. "Learning by Abstraction: The Neural State Machine". NeurIPS, 2019

CV – Neural State Machine (NSM)

A: Use NSM!

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- model's *concept vocabulary* C,
- states via *object nodes* from the image,
- directed *relation edges* – transitions between the states,

$$(C, S, E, \{r_i\}_{i=0}^{N}, p_0, \delta) \tag{1}$$

- sequence of *instructions* in terms of C from the question,
- $p_0 : S \to [0, 1]$ is a (discrete, from now on) probability distribution of the initial state,
- $\delta_{S,E} : p_i \times r_i \to p_{i+1}$ is a *state transition function*.

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CV – Neural State Machine (NSM) – use the machine

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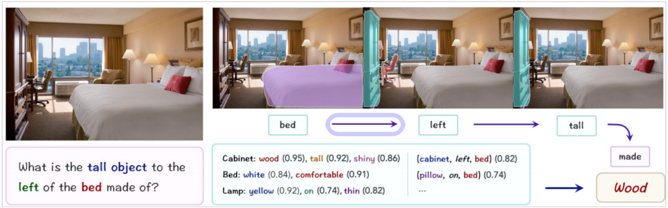

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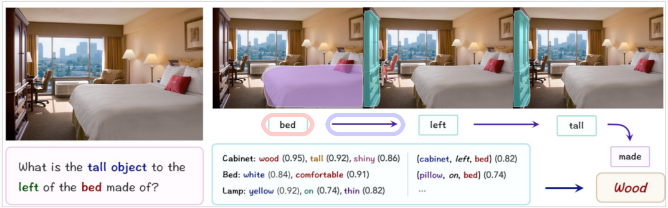
$$\delta_{S,E} : p_i \tag{2}$$



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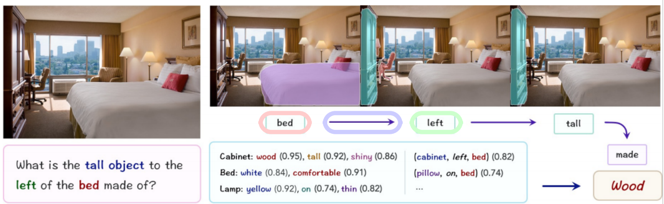
$$\delta_{S,E} : p_i \times r_i \tag{2}$$



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$$\delta_{S,E} : p_i \times r_i \rightarrow p_{i+1} \tag{2}$$

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CV – NSM – summary

1. Embed scene graph and question parts using the same concept vocabulary C,
2. make an automaton out of the object nodes and transitions,
3. traverse automaton to answer the question – track the progress!

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Neural networks (NNs) in general & FM

NNs in general

Q: Can FM help to make NNs in general explainable?

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A: Yes!

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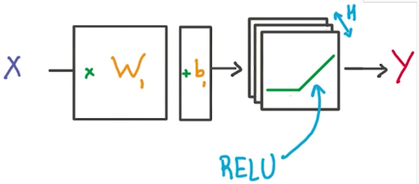
We focus on 2 methods:

- NN encoding,
- differentiable inductive logic programming (∂ILP).

NNs in general – NN encoding

Mixed-Integer Linear Programming (MILP) encoding.



- ReLU block from NN,
- encode and solve via MILP or SMT solver or use Abduction,
- do *not* use for training of NNs, but for their explanations.

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https://images.app.goo.gl/8TS2xkkthSTysjAJ6

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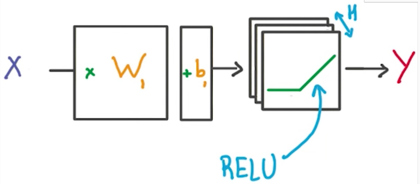

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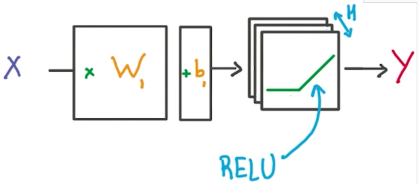

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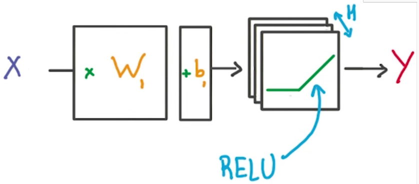

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NNs in general – ∂ILP

Q: How to combine noisy data with the explainable program generation?

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A: Convert ILP to the binary classification!

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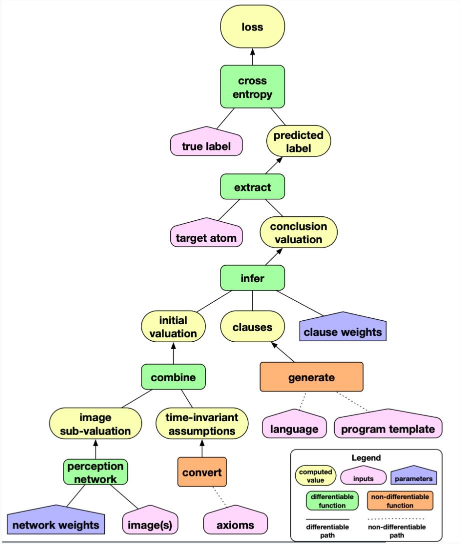
Concrete example: Recognize even digits from MNIST pictures

NNs in general – ∂ILP – an example



- R. Evans et al. "Learning Explanatory Rules from Noisy Data". JAIR, 2018.

- Make initial valuation – from the images and axioms,
- use the language from the predicates $\{zero/1, succesor/2, image/1, target/0, pred1/1, pred2/2\}$ and constants,
- use program template – generate all possible predicates,
- assign weights to the predicates,
- backpropagate to predict the right labels $\in \{0, 1\}$.

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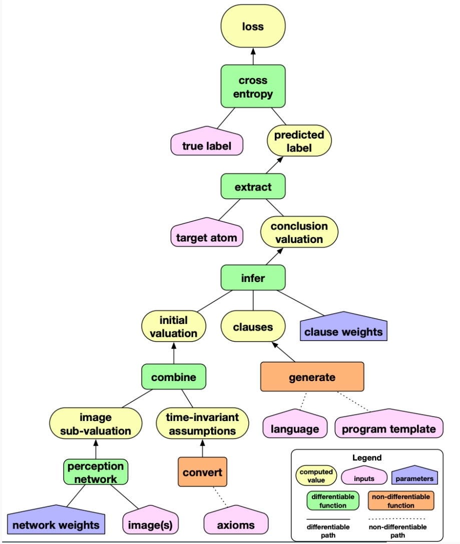

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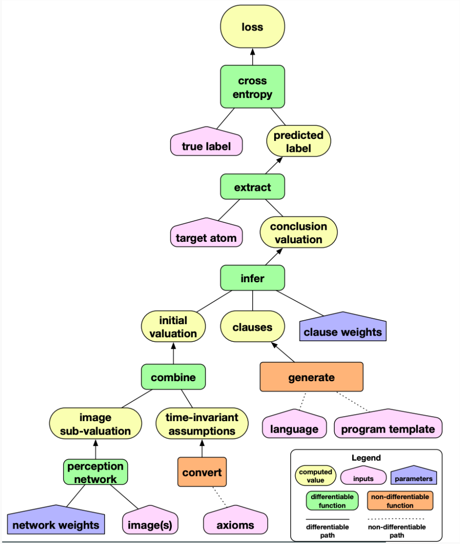

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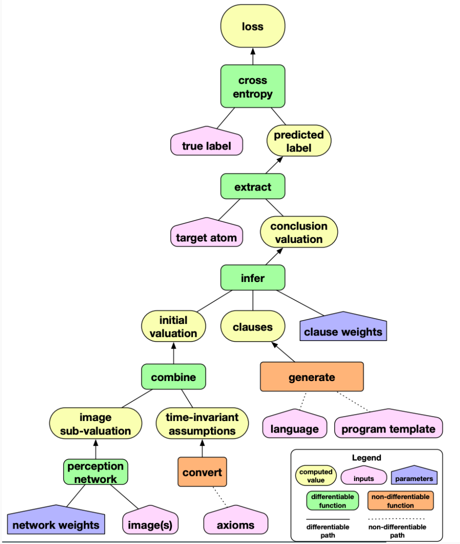

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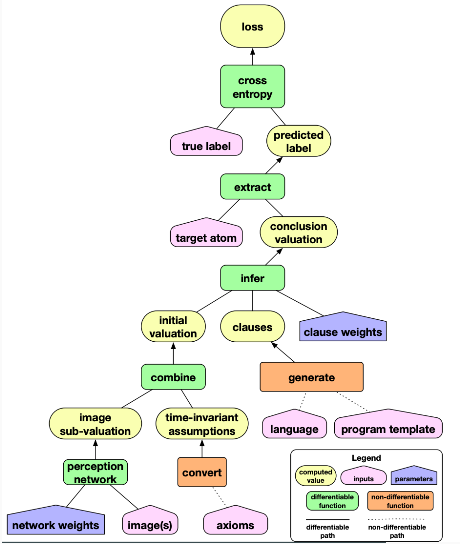

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Solution:

$$target() \leftarrow image(X), pred1(X)$$
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NNs in general – summary

1. (MILP) encoding of NN helps to explain but not to train,
2. use MILP, SMT solver or Abduction with encoding,
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Reinforcement learning (RL) & FM

RL – finite-state predicate automaton (FSPA)

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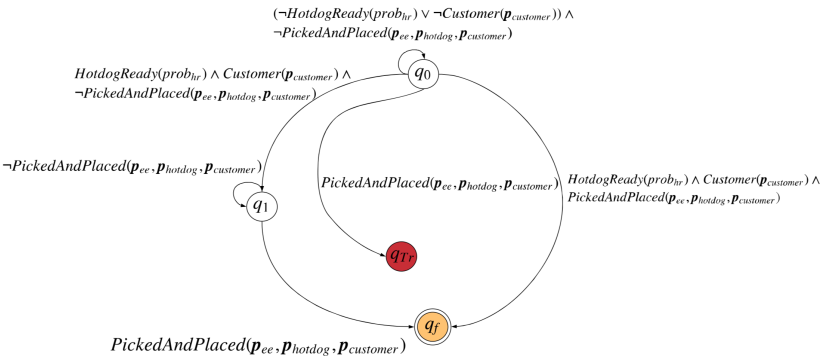

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A: Use an FSPA-augmented MDP!

$$ \tag{3} $$

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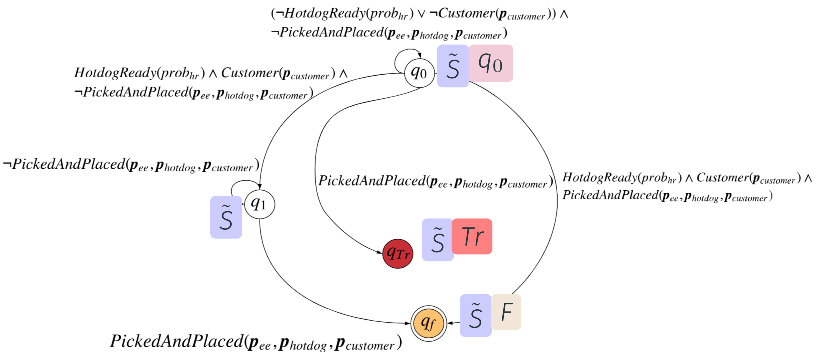
$$(\tilde{S}, q_0, F, Tr) \tag{3}$$



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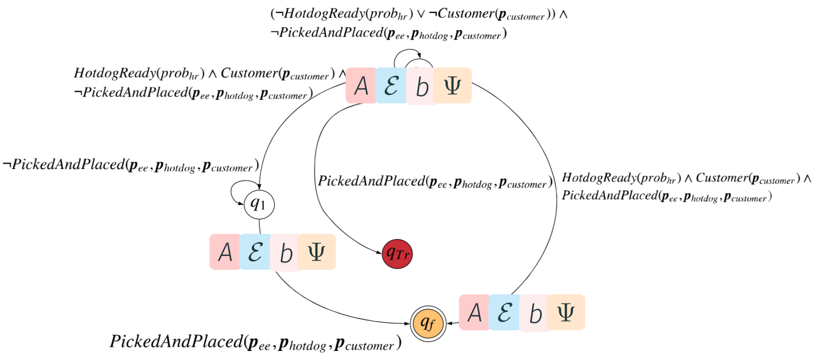

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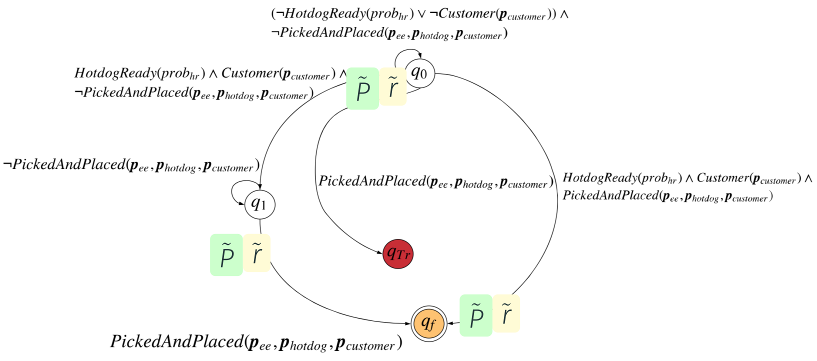

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RL – FSPA – problem statement

Input:

- robotic system with states S and actions A,
- TLTL task ϕ_{task} over S,
- safety requirements,
- knowledge base K.

Output:

- trajectory $s_{0:T}$ that satisfies ϕ_{task} and K.

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RL – FSPA – an example

Q: How to serve a hotdog?

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$$
\begin{gathered}
\mathit{HotdogServed}(s) = \mathcal{F}\mathit{PickedAndPlaced}(p_{endPose}, p_{hotdog}, p_{customer}) \wedge \\
(\neg \mathit{PickedAndPlaced}(p_{endPose}, p_{hotdog}, p_{customer}) \mathcal{U} \\
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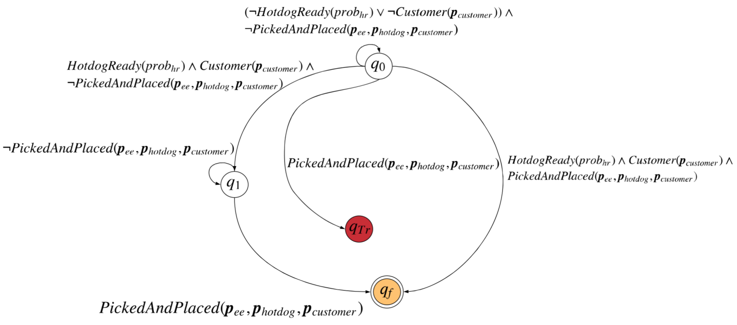

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Methods that try to generalize & FM

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Q: Can FM generalize across ML methods in explainability?

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We focus on 2 methods:

- Abduction and counterexamples,
- Markov logic networks (MLN)

Methods that try to generalize – Abduction

Compute an explanation with guarantee.

$$
\begin{array}{l}
\textbf{foreach } l \in C \textbf{ do} \\
\quad \textbf{if } \mathcal{M}, \mathcal{C} \backslash \{l\} \models (\mathcal{F} \rightarrow \mathcal{E}) \textbf{ then} \\
\quad \quad C \leftarrow C \backslash \{l\} \\
\quad \textbf{end} \\
\textbf{end}
\end{array}
$$

- Encode ML model with prediction $\mathcal{E}$ into formula $\mathcal{F}$,
- take initial data C for the prediction $\mathcal{E}$,
- get the minimal subset C_m s.t. $\mathcal{F} \wedge C_m \models \mathcal{E}$.

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Methods that try to generalize – Counterexamples

Same principle,

Methods that try to generalize – Counterexamples

Same principle,

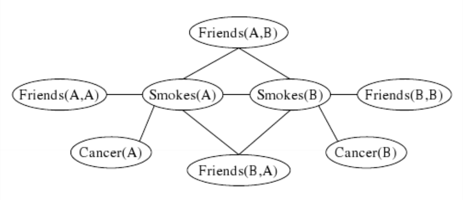
generate counterexamples and explanations simultaneously.

Methods that try to generalize – MLN

Relational reasoning is a central component of generally intelligent behavior, but has proven difficult for neural networks to learn.

("A simple neural network module for relational reasoning". NeurIPS, 20

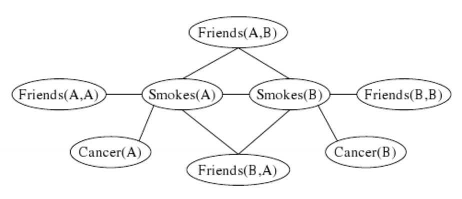
Methods that try to generalize – MLN and graph neural networks (GNN)



- Take Markov network,
- over first-order knowledge base,
- learn the weights via GNN.

▸ https://images.app.goo.gl/KCkz3jFqPVePAp298

Methods that try to generalize – MLN and graph neural networks (GNN)



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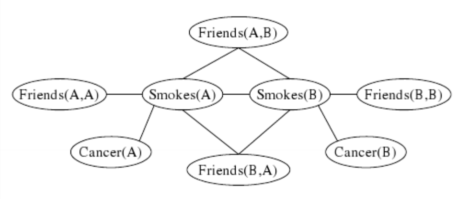

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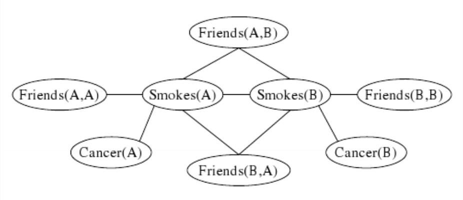

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2. use counterexample-based method – get counterexamples and explanations,
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