Symbolic Transfer Learning through Knowledge Manipulation Methods

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8th ECOOP — 1994

1st AAMAS — 2002

8th DALT School — 2011

5th CompleNet — 2014

18th PRIMA — 2015

28th ECAI — 2025

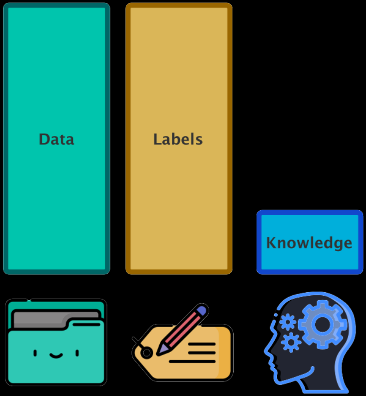
Next in Line. . .

Context

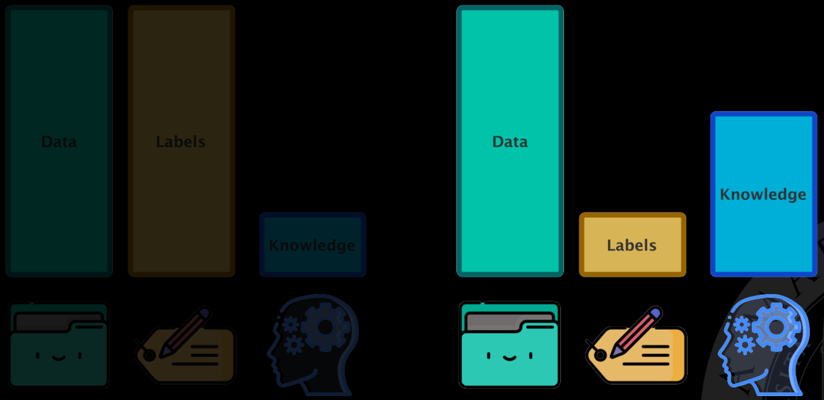
Players involved in a Machine Learning workflow:

- Data
  - ! require labels
- Knowledge
  - human experts
  - common sense
  - extracted from data/models
- Model
  - trained on data
  - sometimes also trained with prior knowledge

Utopy and Reality I



Utopy and Reality II



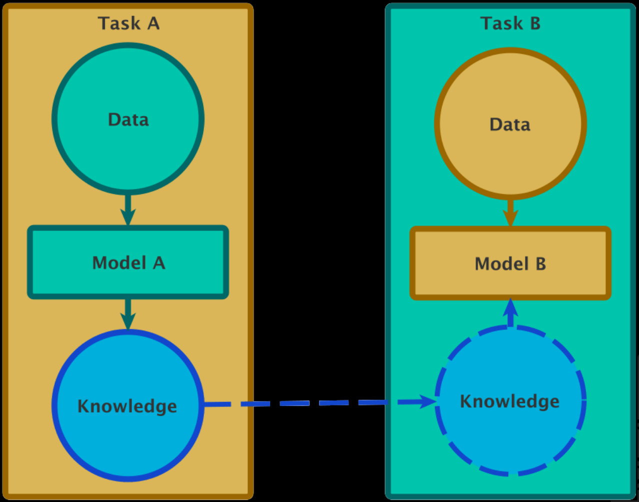
Utopy and Reality III

But in some scenarios we deal with both low data/labels and knowledge. . .

Transfer Learning I

Reuse the knowledge acquired in a similar task! [Tan et al., 2018]

Transfer Learning II



Transfer Learning III

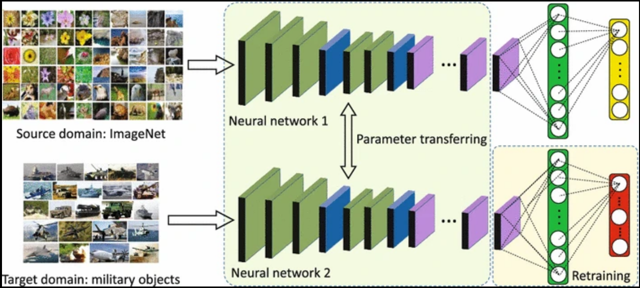
What kind of knowledge?

Transfer Learning IV

What kind of knowledge?

Typically model parameters (NN weights) → sub-symbolic knowledge

Transfer Learning V



source: [Yang et al., 2019]

Next in Line. . .

Limitations of Sub-symbolic TL

- Opaqueness [Brachman and Levesque, 2004]
  - ! sub-symbolic knowledge/model is not interpretable by humans

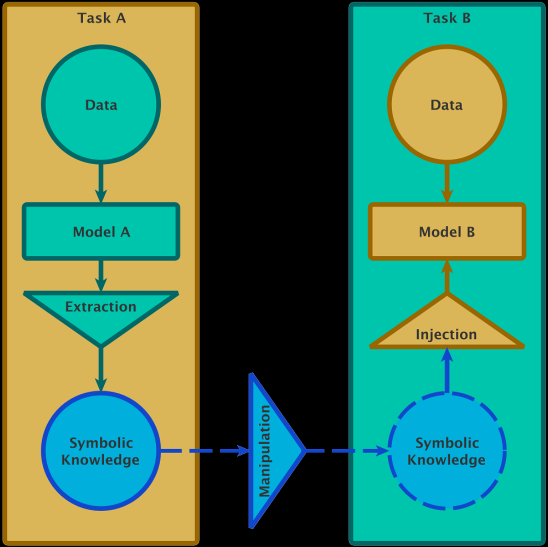
- Why it (does not) works?
  - we have no guarantees on what happens under the hood
  - fails when tasks are different
  - fails when there are biases in the data

Symbolic TL I

A not exhaustive list of benefits of symbolic knowledge: [Besold et al., 2017]

- Interpretability
  - ! symbolic knowledge is understandable by both humans and machines
- Concision
  - intensional representation
  - natural support to recursion
- Lingua Franca
  - no bound to a specific class of models

Symbolic TL II



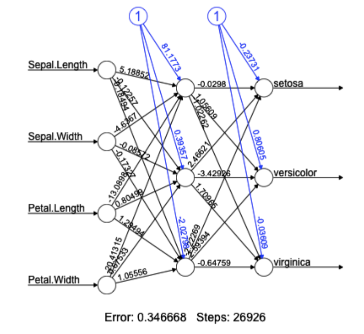
Next in Line...

Symbolic Knowledge Extraction I

Extract symbolic knowledge from a sub-symbolic model: [Guidotti et al., 2019]

- Families
  - pedagogical → model agnostic
  - decompositional → model inspection
- Logical Rules
  - propositional logic
  - first-order logic
  - other logics
- Scope
  - global explanations
  - local explanations

Symbolic Knowledge Extraction II



$\rightarrow$

$$\mathit{Class} = \texttt{setosa} \leftarrow \mathit{PetalWidth} \leq 1.0.$$

$$\mathit{Class} = \texttt{versicolor} \leftarrow \mathit{PetalLength} > 4.9 \wedge \mathit{SepalWidth} \in [2.9,\ 3.2].$$

$$\mathit{Class} = \texttt{versicolor} \leftarrow \mathit{PetalWidth} > 1.6.$$

$$\mathit{Class} = \texttt{virginica} \leftarrow \mathit{SepalWidth} \leq 2.9.$$

$$\mathit{Class} = \texttt{virginica} \leftarrow \mathit{SepalLength} \in [5.4,\ 6.3].$$

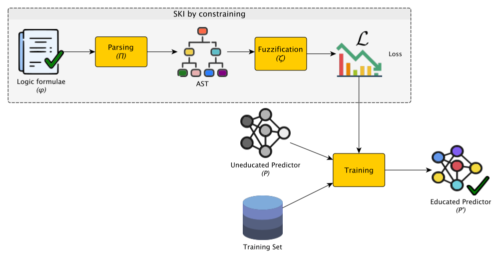
$$\mathit{Class} = \texttt{virginica} \leftarrow \mathit{PetalWidth} \in [1.0,\ 1.6].$$

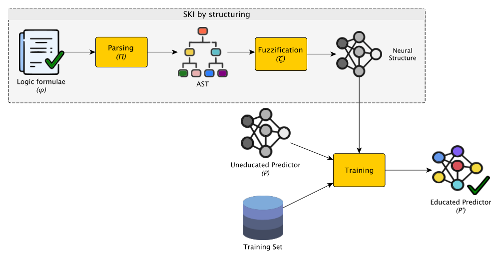
Symbolic Knowledge Injection I

Inject symbolic knowledge into a sub-symbolic model: [von Rueden et al., 2021]

- Families
  - constraining → loss function
  - structuring → model architecture
  - alternatively keep model(s) and knowledge separate
- Logical Rules
  - propositional logic
  - first-order logic
  - other logics

Symbolic Knowledge Injection II





Next in Line...

Open Problems

1. What is in between?
   - it is rare to be able to use the extracted knowledge as is
   - different tasks may require different representations
2. Full recursive concept support?
   - formal logic can represent recursive predicates
   - sub-symbolic models like NN (based on backpropagation) are direct acyclic graphs
3. Evaluation
   - accuracy is not the only dimension
   - need for other metrics (e.g., interpretability, robustness) [Agiollo et al., 2023]
4. Technological support
   - public and maintained tools for symbolic knowledge extraction and injection [Sabbatini et al., 2021, Magnini et al., 2022]

Working Plan

1. Design knowledge manipulation methods:
   - similar tasks
     → partially affects variables and constants
   - dissimilar tasks
     → affects all the knowledge
     → inductive logic programming [Muggleton, 1991]
2. Design injection methods to fully support recursion:
   - new symbolic knowledge injection methods
     → the knowledge is actually injected into the model
   - but also neuro-symbolic approaches
     → model(s) and knowledge are two distinct entities of the system

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