Category-based Inductive Learning in Shared NeMuS

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1 Introduction

One of the main objectives of cognitive science is to use abstraction to create models that represent accurately the cognitive processes that constitute learning, such as categorisation. Relational knowledge is important in this task, since it is through the reasoning processes of induction and analogy that the mind creates categories (it later estabilishes causal relations between them by using induction and abduction), and analogies exemplify crucial properties of relational processing, like structure-consistent mapping[2].

Given the complexity of the task, no model today has accomplished it completely. The associacionist/connectionist approach represents those processes through associations between different informations. That is done by using artificial neural networks. However, it faces a great obstacle: the idea (called propositional fixation) that neural networks could not represent relational knowledge. A recent attempt to tackle the symbolic extraction from artificial neural networks was proposed in [1]

The cognitive agent Amao uses a shared Neural Multi-Space (Shared NeMuS) of coded first-order expressions to model the various aspects of logical formulae as separate spaces, with importance vectors of different sizes. Amao [4] uses inverse unification as the generalization mechanism for learning from a set of logically connected expressions of the Herbrand Base (HB). Here We present an experiment to use such learning mechanism to model a simple version of train set from Michalski's train problem[3].

2 Shared NeMuS Approach to Train Problem

In Michalski's train problem, there are 10 trains: 5 eastbound and 5 westbound. Whether a train is going east or west is determined by its properties. Using these trains, a simple base has been created, taking into account the size of the train wagons (short or not) and whether these wagons are closed or not. The number of wheels, wagon format and other attributes have been ignored in order to make the base simpler.

All the eastbound trains have at least one wagon which is both short and closed. That is what determines whether a train is eastbound or westbound. The idea is to use the shared NeMuS structure to induce the rule eastbound knowing that `t1` (the first train) is going east. Having that information, we can select all predicates in the base that have `t1` as an attribute, which are the following:

```
train(t1).
car(t1, c1_t1).
car(t1, c2_t1).
car(t1, c3_t1).
car(t1, c4_t1).
short(c1_t1).
closed(c1_t1).
```

The predicate car links `t1` to all its wagons (or carriages, which is why the name of the predicate is car), so `car(t1, c1_t1)` means that `c1_t1` is a wagon that belongs to `t1`. Taking the first instance of the predicate `car`, we now know that `t1` has a wagon named `c1_t1`. Amao, through its shared NeMuS, accesses `c1_t1`'s bindings and using a polynomial search, finds both occurrences of `c1_t1` in `short` and `closed`, as seen above. This mechanism is called linkage pattern in Amao's learning mechanism.

At this point `t1` is a train that has `c1_t1` as a wagon, and this wagon is not closed. Amao also has the linkage predicate connecting both `c1_t1` and `t1`. Thus, a candidate hypothesis generated would look like `eastbound(X)` ← `car(X, Y)` ∧ ∼ `short(Y)` ∧ ∼ `closed(Y)`. However, this may not be the only possible hypothesis, so the other wagons being carried by `t1` need to be considered.

```
short(c2_t1).      ~short(c3_t1).      short(c4_t1).
closed(c2_t1.      ~closed(c3_t1).     ~closed(c4_t1).
```

Among the possible hypotheses that may define a train as being eastbound, we have:

```
eastbound(X) ← car(X, Y) ∧ ~short(Y) ∧ ~closed(Y).
eastbound(X) ← car(X, Y) ∧ short(Y) ∧ closed(Y).
eastbound(X) ← car(X, Y) ∧ short(Y) ∧ ~closed(Y).
```

Adding negative examples, we can reduce the number of possible hypotheses. In this case, the simplest way to do that is to use the 10th train `t10` as a negative example. Using the same method as explained above, the structure can select all predicates that have `t10` as an attribute:

```
car(t10, c1_t10).
car(t10, c2_t10).
```

Then, all the predicates that have `t10s` wagons as attributes:

```
short(c1_t10).           ~short(c2_t10).
~closed(c1_t10).         ~closed(c2_t10).
```

Thus, the hypotheses that definitely do not define a train as being eastbound are:

$$\texttt{eastbound(X)} \leftarrow \texttt{car(X, Y)} \wedge \texttt{short(Y)} \wedge \sim\texttt{closed(Y)}.$$
$$\texttt{eastbound(X)} \leftarrow \texttt{car(X, Y)} \wedge \sim\texttt{short(Y)} \wedge \sim\texttt{closed(Y)}.$$

Both hypotheses are among the possible options defined above. Excluding them, the correct option remains. The target `eastbound(X)` can be defined by:

$$\texttt{eastbound(X)} \leftarrow \texttt{car(X, Y)} \wedge \texttt{short(Y)} \wedge \texttt{closed(Y)}.$$

3 Concluding Remarks

The knowledge base created is only a simplification of the original train problem. As explained before, many attributes such as number of wheels, wagon format, load shape and roof shape have been ignored. Had they been included, more hypotheses could have been generated through Amao's inductive learning mechanism over the shared NeMuS. One current limitation is not being able to deal with predicate invention, that would allow to automatically create categories by means of abstraction/new predicates.

Another goal we aim to pursue is to make use of weights to implement neural mechanisms. We expect to envisage more efficient heuristics to guide hypotheses generation, improving Amao's learning mechanism.

References

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