# **Enabling Knowledge Refinement upon New Concepts in Abductive Learning: Appendix**

## **A** Experimental Details

**Perception Models** All compared methods share the same structure of perception model. We use PyTorch<sup>1</sup> to implement the CNN model. We use the Adam optimizer with a learning rate of 1e-3 and choose a batch size of 256, while other hyperparameters remain default. For the new class detector, we use the Local Outlier Factor (LOF) implementation from scikit-learn package<sup>2</sup>.

**Reasoning Models** We use the ASP solver clingo implementation from its website <sup>3</sup> as the reasoning model and use the ILASP implementation from its website<sup>4</sup> as the rule learning model.

**Abductive Learning** We implement the abductive learning framework that leverages a similarity-based consistency measure (Huang et al. 2021) with the default hyperparameters in its source code.

**Datasets** The datasets in the experiments have been described in the main text. There are 90% examples in the training set and 10% examples in the test set.

### A.1 Less-Than with New Digits

**ILASP** In Table 1, we show part of the domain knowledge in ILASP program used in this experiment.

**Training Time** It takes about 10 minutes for the training of  $ABL_{nc}$  in the experiment.

New Concept Matching in KG The converted triplets are in the form like  $(new, IsA, higher\_number\_than\_1)$  and  $(new, IsA, higher\_number\_than\_7)$ . For the knowledge graph, starting from entity number, we extract a subgraph from the ConceptNet (Speer, Chin, and Havasi 2017) with depth d=2, and the sub-graph consists of 2345 triplets. It takes about two minutes to train a knowledge graph embedding model.

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succ(X,Y) := zero(X), one(Y). \\ succ(X,Y) := one(X), two(Y). \\ less(X,Y) := succ(X,Y). \\ less(X,Z) := less(X,Y), less(Y,Z). \\ \#modeb(1,less(var(box),var(box)), (anti\_reflexive, positive)). \\ \#modeb(1,zero(var(digit))). \\ \#modeb(1,new(var(digit))). \\ \#modeb(1,new(var(digit),var(digit)), (anti\_reflexive)). \\ \\
```

Table 1: Sample domain knowledge used in *Less-Than with New Digit* task.

#### A.2 Chess with New Pieces

**ILASP** In Table 2, we show part of the domain knowledge in ILASP program used in this experiment.

```
\begin{split} & \text{diag\_forward}((X1,Y1),(X2,Y2)) :- \text{left\_forward}((X1,Y1),(X2,Y2)). \\ & \text{diag\_forward}((X1,Y1),(X2,Y2)) :- \text{right\_forward}((X1,Y1),(X2,Y2)). \\ & \text{attack}((X1,Y1),P,(X2,Y2)) :- \text{king}(P), \text{ one\_step}((X1,Y1),(X2,Y2)). \\ & \text{attack}((X1,Y1),P,(X2,Y2)) :- \text{bishop}(P), \text{diag}((X1,Y1),(X2,Y2)). \\ & \text{attack}((X1,Y1),P,(X2,Y2)) :- \text{pawn}(P), \text{diag\_forward}((X1,Y1),(X2,Y2)). \\ & \text{attack}((X1,Y1),P,(X2,Y2)) :- \text{new}(P), \text{new\_cond}((X1,Y1),(X2,Y2)). \\ & \text{#modeb}(1,\text{left}(\text{var}(\text{pos}),\text{var}(\text{pos})), (\text{anti\_reflexive}, \text{positive})). \\ & \text{#modeb}(1,\text{left\_forward}(\text{var}(\text{pos}),\text{var}(\text{pos})), (\text{anti\_reflexive}, \text{positive})). \\ & \text{#modeb}(1,\text{right\_forward}(\text{var}(\text{pos}),\text{var}(\text{pos})), (\text{anti\_reflexive}, \text{positive})). \\ & \text{#modeh}(1,\text{new\_cond}(\text{var}(\text{pos}),\text{var}(\text{pos})), (\text{anti\_reflexive}, \text{positive})). \\ & \text{#modeh}(1,\text{new\_cond}(\text{var}(\text{pos}),\text{var}(\text{pos})), (\text{anti\_reflexive}). \\ \end{aligned}
```

Table 2: Sample domain knowledge used in *Chess with New Pieces* task.

**Training Time** It takes about 50 minutes for the training of  $ABL_{nc}$  in the experiment.

New Concept Matching in KG The converted triplets are in the form like  $(new, \mathtt{UsedFor}, move\_one\_space)$  and  $(new, \mathtt{UsedFor}, move\_diagonally)$ . Starting from entity chess, we extract a sub-graph from the ConceptNet (Speer, Chin, and Havasi 2017) with depth d=2, and the sub-graph consists of 889 triplets. It takes about one minute to train a knowledge graph embedding model.

<sup>1</sup>https://pytorch.org/

<sup>&</sup>lt;sup>2</sup>https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.LocalOutlierFactor.html

<sup>&</sup>lt;sup>3</sup>https://potassco.org/clingo/

<sup>4</sup>https://www.ilasp.com/

## A.3 Multiples of Three

**ILASP** In Table 3, we show part of the domain knowledge in ILASP program used in this experiment, where divisible(X, 2) is equivalent to  $div_2(X)$ .

```
even(X,Y):-div_2(X), div_2(Y).
odd(X,Y):-not_div_2(X), not_div_2(Y).
div_2(X):-two(X).
div_3(X):-six(X).
#modeb(2,div_2(var(digit))).
#modeb(2,div_3(var(digit))).
#modeb(2,div_4(var(digit))).
#modeb(2,div_5(var(digit))).
#modeb(1,new(var(digit),var(digit)), (anti_reflexive)).
```

Table 3: Sample domain knowledge used in *Multiples of Three* task.

**Training Time** It takes about 20 minutes for the training of  $ABL_{nc}$  in the experiment.

New Concept Matching in KG The converted triplets are in the form like (6, HasProperty, new) and (9, HasProperty, new). For the knowledge graph, we first augment ConceptNet (Speer, Chin, and Havasi 2017) with 25 triplets that describes the properties of each number, such as  $(8, \text{HasProperty}, multiple\_of\_2)$ ,  $(6, \text{HasProperty}, multiple\_of\_3)$ ,  $(8, \text{HasProperty}, multiple\_of\_4)$ . Then, starting from the entity number, we extract a sub-graph from the augmented ConceptNet with depth d=2, and the sub-graph consists of 2370 triplets. It takes about two minutes to train a knowledge graph embedding model.

#### References

Huang, Y.-X.; Dai, W.-Z.; Cai, L.-W.; Muggleton, S. H.; and Jiang, Y. 2021. Fast Abductive Learning by Similarity-based Consistency Optimization. In *NeurIPS*, 26574–26584.

Speer, R.; Chin, J.; and Havasi, C. 2017. Conceptnet 5.5: An open multilingual graph of general knowledge. In *AAAI*, 4444–4451.