# Learning to Map Ontologies with Neural Network

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**Abstract.** In this paper the authors applied the idea of training multiple tasks simultaneously on a partially shared feed forward network to domain of ontology mapping. A "cross training" mechanism was used to specify corresponding nodes between the two ontologies. By examining output of one network in response to stimulus from the other network, we can test if the network can learn the correspondence that was not cross-trained. Two kinds of studies on ontology mapping were conducted. The result shows the network can fill in the missing mappings between ontologies with sufficient training data.

**Keywords:** neural network, shared weights, transfer, analogy, ontology mapping

An early implementation of IENN appeared at Munro's work [2], which used feedforward network with two hidden layers and trained on three simple analogous tasks: three squares with different orientation. In this study, we use partially shared network architecture [3] [4]. It should be noted that the partially shared network architecture used here is virtually identical to the network used in Hinton's [1] classic "family trees" example. The network in that paper also had independent inputs and shared hidden units, but only briefly addresses the notion of generalization.

The ontologies used in our experiment were Ontology A and B shown in Figure 1. There are four types of relationship: identity, parent, child, and sibling. So there are 4 nodes in $S_{in}$. Training in $Net_A$ include all possible training data in Ontology A, i.e. possible combinations of 6 nodes and 4 relationships. The same for $Net_B$.

The network is cross trained on the following pairs: (r, R), (a, A), (b, B), (c, C) and (d, D).

Totally 100 trials were performed. In each trial, networks were initialized by setting the weights to small random values from a uniform distribution. The network was trained with two vertical training tasks ($Net_A$ and $Net_B$), and two cross training tasks($Net_{AB}$ and $Net_{BA}$).

One training cycle of the networks is

1) randomly train a record for $Net_A$
2) randomly train a record for $Net_B$
3) with a probability train a record for $Net_{AB}$ and the same record for $Net_{BA}$.

The probability of cross training is 0.6.

After each trial, cross-testing was performed for A:1, B:2, B:3, and B:4. "self" relationship was used during cross-testing.

In 100 trials, 93 of them yield correct mapping for A:1maps to B:2. The accuracy is 93%. There is no doubt that B:2's correct mapping should be A:1, which is (Car, Car). But B:3 (Luxury Car) and B:4 (Family Car) do not have exact correspondences in ontology A, since B:3 and B:4 are on the additional layer of ontology B compared to ontology A. They can either go up one layer and map to A:1, or go down one layer and map to A:C and A:D. So here the correct mapping will be (A:1, B:3), (A:C, B:3); (A:1, B:4), (A:D, B:4). Totally the four correct cases contain 75 trials in 100 trials. The accuracy is 75%.

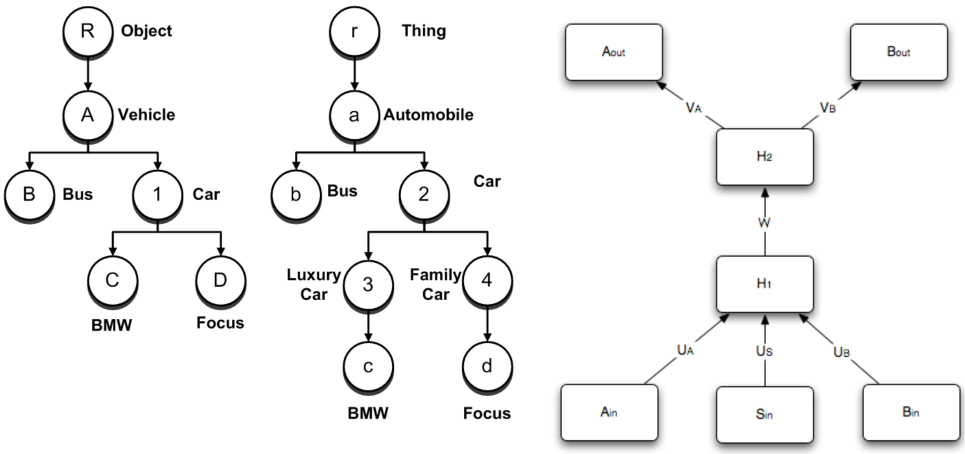


**Figure 1. Left:Two sample ontologies about vehicle. Right: Network architecture**

The ability to establish correspondences between similar situations is fundamental to intelligent behavior. Here, a network has been introduced that can identify corresponding items in analogous spaces. A key feature of this approach is that there is no need for the tasks to use a common representation. Essentially the first hidden layer provides a common representational scheme for all the input spaces.

In our approach, only structure information is used for ontology mapping. Normally in ontology mapping methods, textual information plays an important role. Future work will be to include textual information in our neural network. For example, training pairs could be from high confident mappings from textual information.


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