

Ontology Mapping Neural Network: An Approach to Learning and Inferring Correspondences among Ontologies

Yefei Peng^{1*}, Paul Munro¹, and Ming Mao²

¹ University of Pittsburgh, Pittsburgh PA 15206, USA,
yep3@pitt.edu, pmunro@pitt.edu,

² SAP Labs, Palo Alto CA 94304, USA,
ming.mao@sap.com,

The Ontology Mapping Neural Network (OMNN) extends the ability of Identical Elements Neural Network (IENN) and its variants' [4, 1-3] to represent and map complex relationships. The network can learn high-level features common to different tasks, and use them to infer correspondence between the tasks. The learning dynamics of simultaneous (interlaced) training of similar tasks interact at the shared connections of the networks. The output of one network in response to a stimulus to another network can be interpreted as an analogical mapping. In a similar fashion, the networks can be explicitly trained to map specific items in one domain to specific items in another domain. A more detailed version is published on the main conference [5].

The network architecture is shown in Figure 1. A_{in} and B_{in} are input sub-vectors for nodes from ontology A and ontology B respectively. They share one representation layer AB_r . RA_{in} represents relationships from graph A; RB_{in} represents relationships from graph B. They share one representation layer R_r .

In this network, each to-be-mapped node in graph is represented by a single active unit in input layers (A_{in} , B_{in}) and output layers (A_{out} , B_{out}). For relationships representation in input layer (RA_{in} , RB_{in}), each relationship is represented by a single active unit. The network shown in Figure 1 has multiple sub networks shown in the following list.

1. $Net_{AAA} : \{A_{in}-AB_r-X_{AB}; RA_{in}-R_{RA}-X_R\}-H_1-W-H_2-V_A-A_{out};$
2. $Net_{BBB} : \{B_{in}-AB_r-X_{AB}; RB_{in}-R_{RB}-X_R\}-H_1-W-H_2-V_B-B_{out};$
3. $Net_{AAB} : \{A_{in}-AB_r-X_{AB}; RA_{in}-R_{RA}-X_R\}-H_1-W-H_2-V_B-B_{out};$
4. $Net_{BBA} : \{B_{in}-AB_r-X_{AB}; RB_{in}-R_{RB}-X_R\}-H_1-W-H_2-V_A-A_{out};$

Selected OAEI ³ benchmark tests are used to evaluate OMNN approach. Wilcoxon test is performed to compare OMNN with the other 12 systems participated in OAEI 2009 on precision, recall and f-measure. The result is shown in Figure 1. Green means OMNN is significantly better than the system; Red means the system is significantly better than OMNN. Yellow means no significant difference. Significance is defined as $p-value < 0.05$. It shows that OMNN

* The author is working at Google now. Email: yefeip@google.com

³ <http://oaei.ontologymatching.org/>

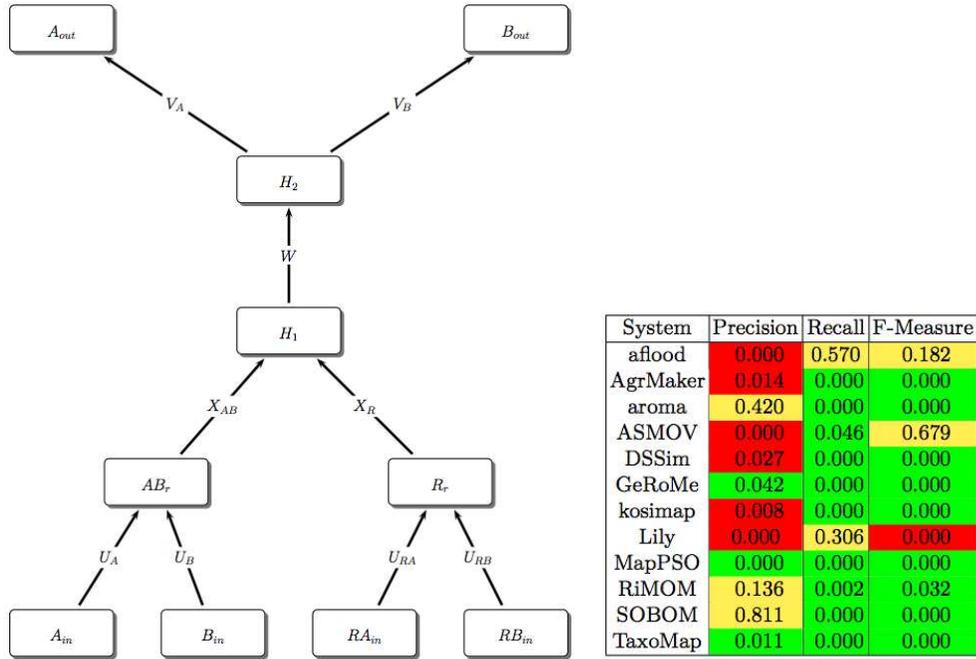


Fig. 1. Proposed network architecture and Results

has better F-measure than 9 of the 12 systems, OMNN's recall is significantly better than 10 of the systems. It should be noted that $p\text{-value} < 0.05$ means there is significant difference between two systems compared, then detailed data is visited to reveal which is one is better than the other.

References

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