Aggregation of Similarity Measures in Ontology Matching

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Abstract. This paper presents an aggregation approach of similarity measures for ontology matching called n-Harmony. The n-Harmony measure identifies top-n highest values in each similarity matrix to assign a weight to the corresponding similarity measure for aggregation. We can also exclude noisy similarity measures that have a low weight and the n-Harmony outperforms previous methods in our experimental tests.

1 Introduction

Ontology matching is a promising research field that discovers similarities between two ontologies and is widely used in applications such as semantic web, biomedical informatics and software engineering. Most of current ontology matching systems combine different similarity measures. For instance, the authors in [4] applied the Ordered Weighted Average(OWA) to combine similarity measures and Ichise[3] proposed a machine learning approach to aggregate 40 similarity measures.

Harmony[5] measure is a state-of-the-art adaptive aggregation method that assigns a higher weight to reliable and important similarity measure and a lower weight to those fail to map similar ontologies. The harmony weight for a similarity measure is calculated according to the number of the highest values in the corresponding similarity matrix. However, the harmony measure has drawbacks when there exist other similarity measures that are as important as the ones with the highest similarity value. Hence, we extended the harmony measure by considering top-n values in each row and column of similarity matrices and we call this method as n-Harmony measure. The top-n is calculated according to the number of concepts in two ontologies. Our extended n-Harmony considers more values in similarity matrices and only aggregates similarity measures that have a high harmony weight.

2 n-Harmony Measure

We applied 13 different similarity measures for aggregation which include 4 string-based, 1 structure-based and 8 WordNet-based similarity measures[2]. The final aggregated similarity matrix is $\frac{\sum_k (nH_k \times SMatrix_k(O_s,O_t))}{|SMatrix|}$, where nH_k is n-Harmony weight and SMatrix is the similarity matrix of each similarity measure between ontology O_s and O_t. Before combining the similarity matrices, we remove min(L-1, nH $\times$ L) lowest values in each row and column of similarity matrix, where L is the minimum number of concepts in two ontologies and nH represents harmony weight of corresponding similarity matrix. Furthermore, only those similarity matrices with a high harmony weight are aggregated for the final similarity matrix. The final decision of whether a ontology pair is matching or not depends on the final similarity matrix and manually tuned threshold.

Directory data sets[3] and Benchmark data sets[4] from OAEI[5] are tested with our system. The n-Harmony measure returns best result on Directory data sets when the threshold is 0.45 with 0.86 recall and 0.70 F-measure while the original harmony measure returns 0.81 recall and 0.68 F-measure. This result is also better than the results of best systems in OM2009[1], such as ASMOV which reaches 0.65 recall and 0.63 F-measure on the Directory data sets. On the Benchmark data sets, n-Harmony performs the same as the original harmony measure or returns slightly better recalls and F-measures than harmony. Comparing with the ASMOV, n-Harmony performs almost the same on data sets #101-104 and #221-247 and returns higher precisions on #302-304, but slightly lower recalls.

3 Conclusions and Future Work

Experimental results show that our n-Harmony outperforms original harmony measure on most of the Directory and Benchmark data sets and also comparable with the best systems attended in OM2009. However there are still rooms to improve our n-Harmony measure by exploring advanced structure-based similarity measures and by investigating automatic threshold selection method rather than manually tuning the threshold to find out the best performance.

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