

Interactive User Feedback in Ontology Matching Using Signature Vectors

Isabel F. Cruz, Cosmin Stroe
ADVIS Lab, Department of Computer Science
University of Illinois at Chicago
USA
{ifc,cstroel}@cs.uic.edu

Matteo Palmonari
DISCo
University of Milano-Bicocca
Italy
palmonari@disco.unimib.it

Abstract— When compared to a *gold standard*, the set of mappings that are generated by an automatic ontology matching process is neither complete nor are the individual mappings always correct. However, given the explosion in the number, size, and complexity of available ontologies, domain experts no longer have the capability to create ontology mappings without considerable effort. We present a solution to this problem that consists of making the ontology matching process interactive so as to incorporate user feedback in the loop. Our approach clusters mappings to identify where user feedback will be most beneficial in reducing the number of user interactions and system iterations. This feedback process has been implemented in the AgreementMaker system and is supported by visual analytic techniques that help users to better understand the matching process. Experimental results using the OAEI benchmarks show the effectiveness of our approach. We will demonstrate how users can interact with the ontology matching process through the AgreementMaker user interface to match real-world ontologies.

I. INTRODUCTION

The ontology matching problem, which is related to schema matching in databases [1], consists of mapping concepts in a *source* ontology to semantically related concepts in a *target* ontology. The resulting set of mappings is called an *alignment* [2]. As ontologies increase in number and size, automatic matching algorithms, which we call *matchers*, become not only important but absolutely necessary. However, in real-world scenarios, and even in the systematic ontology matching benchmarks of the Ontology Alignment Evaluation Initiative (OAEI), alignments are neither correct nor exhaustive when compared against a *gold standard*, also called *reference alignment*, created by domain experts.

By virtue of our collaboration with expert users in the geospatial domain [3], we came to realize the importance that they give to interacting with the matching process and to understanding why some mappings are present. In particular, users want to understand the provenance of the mappings, that is, they want to identify the reason why a mapping is part of an alignment. This is especially important when combining several matchers that evaluate different ontology features, a common technique in ontology matching.

We have therefore incorporated in the AgreementMaker system [4] a semi-automatic matching strategy in which domain experts are directly involved in an iterative feedback loop to validate mapping suggestions. At each iteration, the user is asked to validate one or more mappings. Our main objective

is to improve the matching result as much as possible, while minimizing the user’s effort. In order to do this, we answer the following two questions:

Q1 : “Which specific candidate mappings should be presented to the user for validation?”, and

Q2 : “How can the user feedback be exploited to improve the existing alignment?”

We have developed visual analytic methods with the dual purpose of showing provenance of the mappings and of managing the overall matching process. To validate our approach, we conducted experiments using the OAEI benchmarks. The iterative feedback loop and the visual analytic methods described in this paper upgrade AgreementMaker by introducing new features that have not been presented elsewhere.

The importance of user feedback has been recently emphasized [5]. The “pay-as-you-go” approach [6] is based on the principle that integration at a large scale needs to be an ongoing process; it supports user feedback to improve upon initially found mappings over time. Two other approaches consider user feedback in ontology matching [7], [8]. However, in one of them [8] mappings that were either validated or refuted by the user are not remembered by the system. In fact, an infinite loop could potentially occur. In the other approach [7], there is no selection of candidate mappings with the aim of maximizing the information gain (e.g., by extrapolating to other mappings) in each iteration. As for our visualization component, it differs from that of a recent approach [9] as follows: (1) it displays the results of several matchers, not of a single matcher; (2) it is meant to be an integral part of the iterative matching process, not an *a posteriori* analytical tool.

II. FEEDBACK LOOP CORE PRINCIPLES

Given a source ontology S with m concepts, a target ontology T with n concepts, and l matchers, for each matcher $M_k, 1 \leq k \leq l$, we define an $m \times n$ similarity matrix Σ_k where the value $\sigma_k(i, j)$ of each element is in the interval $[0, 1]$. We can then define a *signature vector* $\vec{v}_{i,j}$, where $\vec{v}_{i,j}(k) = \sigma_k(i, j), 1 \leq k \leq l$.

When determining the final alignment, a mapping cardinality and a similarity value threshold must be set, below which two concepts are not considered similar. Then an optimization algorithm is run to select the final alignment so as to maximize the overall similarity [10]. Similarly to several of the OAEI

tracks, we adopt a 1-1 cardinality, meaning that each concept in the source (resp. target) ontology must be mapped to at most one single element in the target (resp. source) ontology. The final alignment is an $m \times n$ matrix A such that each row and each column of the matrix have a single non-zero element representing a *mapping* $(s_i, t_j, \sigma(s_i, t_j))$ between concept s_i in the source ontology and concept t_j in the target ontology, with similarity $\sigma(s_i, t_j)$ (a combination of $\sigma_k(i, j), 1 \leq k \leq l$ [10]) greater than the threshold.

Our feedback mechanism is based on the idea that the signature vector is key to the selection of which candidate mappings are presented next to the user as well as how that feedback is propagated to validate other mappings without presenting them to the user (so as to avoid presenting all possible mappings). We also do not present mappings that cannot be part of the final alignment due to cardinality constraints.

Taking into consideration question Q1 of Section I and the definition of the signature vector $\vec{v}_{i,j}$, we define a *disagreement* metric among the k similarity values. That is, if the matchers mostly agree on that mapping, then disagreement is low, but is otherwise high when the matchers produce different outcomes for that mapping. We select candidate mappings to be presented to the user at each step by ranking the mappings using the *Disagreement-based Top-k Mapping Selection* method.

As for question Q2, we use a *vector similarity* metric to *cluster* mappings based on their respective signature vectors. Once the user validates a mapping by confirming or refuting it, we *propagate* that information to those mappings whose signature vectors are most similar to the one associated with that mapping. This process uses the *Signature-based Mapping Clustering* and *Similarity Update and Propagation* methods.

Disagreement-based Top-k Mapping Selection. Different matchers consider different, possibly orthogonal, features of the ontologies to be aligned. Mappings over which matchers disagree upon are those mappings whose concepts are evaluated with high similarity according to some features and with low similarity according to other features. For this reason, these mappings represent potentially critical matching patterns. For example, concepts can be similar when evaluated by a syntactic matcher but dissimilar when evaluated by a structural matcher. User feedback can decide which criteria to favor when validating a mapping.

Given a signature vector $\vec{v}_{i,j}$, we define our *disagreement* metric as the variance of the similarity values in that vector. All mappings are then ranked according to this metric and the top- k mappings are selected for user feedback.

Signature-based Mapping Clustering. Given a user validated mapping and its corresponding signature vector, our approach identifies similar mappings by adopting a double threshold $th = (th^\uparrow, th^\downarrow)$, with th^\uparrow and th^\downarrow being two positive rationals in the interval $[0, 1]$. For each dimension of the signature vector, we create a set of mappings whose similarities are within the threshold th of the similarity of the validated mapping. Having done this for all l -dimensions, we then take the intersection of the sets in order to select those mappings that belong to the cluster associated with the validated mapping.

Similarity Update and Propagation. Once a mapping is confirmed by the user it is added to the set of correct mappings; conversely, if it is refuted by the user, it is added to the set of incorrect mappings. To propagate the user’s feedback on a mapping, we reward or penalize the similarity value associated with every mapping in the same cluster by a linear function that increases (resp. decreases) the similarity values; the similarity of mappings that have been validated (resp. refuted) is set to 1 (resp. 0) and not updated anymore.

III. SYSTEM ARCHITECTURE

As shown in Figure 1, our system consists of seven components, described in detail below.

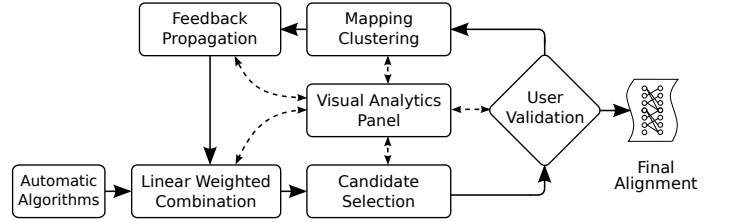


Fig. 1. System architecture.

Automatic Matching Algorithms. The automatic matchers include four syntactic-based matchers, among which are the *Advanced Similarity Matcher (ASM)*, the *Parametric String-based Matcher (PSM)*, and the *Vector-based Multi-word Matcher (VMM)* [4]. We also include a structural and a syntactic matcher, namely the *Iterative Instance and Structural Matcher* and the *Lexical Synonym Matcher* [11]. We run these automatic matchers in parallel and the result of each matcher k is stored in a similarity matrix Σ_k as defined in Section II.

Linear Weighted Combination (LWC). In this component, the similarity matrices of the automatic matchers are linearly combined [10] using weights determined by the *local confidence quality measure* [4]. The combined similarity value for each mapping is stored in the corresponding element of the similarity matrix Σ_{LWC} . An alignment is selected from this matrix that includes the best mappings. Similarity updates are performed on this matrix.

Candidate Selection. This component is responsible for the selection of the mappings that are presented to the user. The mappings that a user has validated in previous iterations are filtered out from the candidate mapping selection, so that the same mapping will not be validated twice. The *Disagreement-based Top-k Mapping Selection* mechanism is used to identify the k candidate mappings that are presented to the user. In addition, the user can add other mappings by inspection of the *Visual Analytics Panel* (Figure 2).

User Validation. This component allows the user to provide feedback on one or more candidate mappings. Candidate mappings are displayed in the *Visual Analytics Panel*, so as to facilitate the user’s understanding of the corresponding signature vector. The system flags the mappings that have been confirmed or refuted and updates the alignment produced by the LWC component.

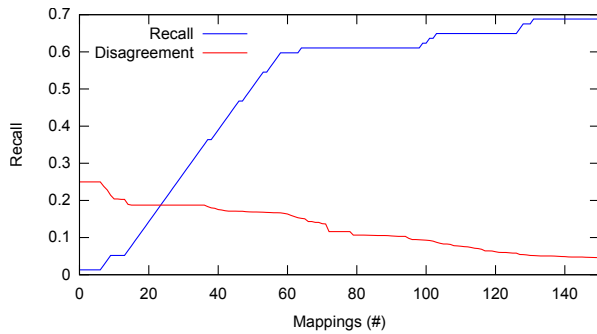


Fig. 4. Candidate selection evaluation.

already high average F-Measure of 80.6%, which was obtained using the automatic matchers, and that it was realized with 50 iterations, which represent only 1.26% of the mapping search space.

The *Visual Analytics Panel* of Figure 2 brings a whole new light to the matching process allowing users to discover matching patterns that were previously hidden in the complexity of the process. In particular, this panel greatly helped us in pinpointing correct and missed mappings in the course of our own experiments.

V. DEMONSTRATION SCENARIO

We demonstrate our ontology matching system by having users match OAEI and Linked Open Data ontologies (e.g., DBpedia) [12]. The users can follow step by step the flow of the interactive feedback-based matching method (see Figure 1), while visualizing and controlling each step from the user interface of AgreementMaker.

A first set of mappings is automatically computed by the automatic matchers. As the first step to completing or correcting this set of mappings, a list of top- k most disagreed-upon mappings is presented. Users can visualize a candidate mapping's concepts in the ontology view, and also visualize the mapping signature of each candidate mapping in the analytics panel in order to make a decision whether to confirm or refute the candidate mapping. In addition, users can also visualize the mapping cluster to which their feedback is propagated and compare it with the reference alignment they are building. They can decide whether to propagate their feedback, to adjust the cluster size via the threshold, or to validate another mapping. Once a choice is made, the effects of the user-provided feedback are highlighted in the analytics panel. To informally demonstrate the importance of the visual analytics panel, during the demonstration users will be invited to use the system with and without that panel and draw their own conclusions. Another demo mode will simulate the next step based on the reference alignment. At each step the chosen mapping will be highlighted and full interaction with the user interface will also be allowed.

ACKNOWLEDGMENTS

The work on this paper was partially supported by NSF Awards IIS-1143926 and IIS-0812258 and by the Intelligence

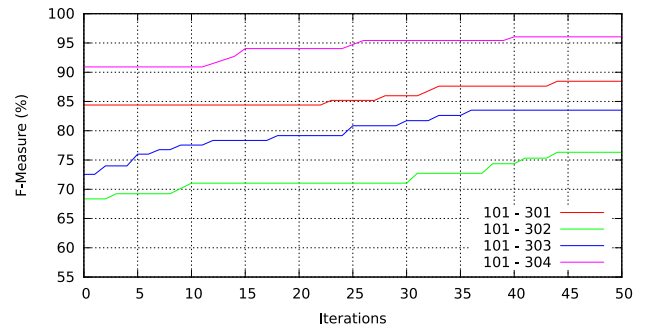


Fig. 5. Similarity propagation evaluation on the OAEI test cases.

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REFERENCES

- [1] E. Rahm and P. A. Bernstein, "A Survey of Approaches to Automatic Schema Matching," *VLDB Journal*, vol. 10, no. 4, pp. 334–350, 2001.
- [2] J. Euzenat and P. Shvaiko, *Ontology Matching*. Heidelberg (DE): Springer-Verlag, 2007.
- [3] I. F. Cruz and W. Sunna, "Structural Alignment Methods with Applications to Geospatial Ontologies," *Transactions in GIS, Special Issue on Semantic Similarity Measurement and Geospatial Applications*, vol. 12, no. 6, pp. 683–711, December 2008.
- [4] I. F. Cruz, F. Palandri Antonelli, and C. Stroe, "AgreementMaker: Efficient Matching for Large Real-World Schemas and Ontologies," *PVLDB*, vol. 2, no. 2, pp. 1586–1589, 2009.
- [5] K. Belhajjame, N. W. Paton, A. A. A. Fernandes, C. Hedeler, and S. M. Embury, "User Feedback as a First Class Citizen in Information Integration Systems," in *CIDR Conference on Innovative Data Systems Research*, 2011, pp. 175–183.
- [6] S. R. Jeffery, M. J. Franklin, and A. Y. Halevy, "Pay-as-you-go User Feedback for Dataspace Systems," in *ACM SIGMOD International Conference on Management of Data*, 2008, pp. 847–860.
- [7] S. Duan, A. Fokoue, and K. Srinivas, "One Size Does Not Fit All: Customizing Ontology Alignment Using User Feedback," in *International Semantic Web Conference (ISWC)*, ser. Lecture Notes in Computer Science, vol. 6496. Springer, 2010, pp. 177–192.
- [8] F. Shi, J. Li, J. Tang, G. Xie, and H. Li, "Actively Learning Ontology Matching via User Interaction," in *International Semantic Web Conference (ISWC)*, ser. Lecture Notes in Computer Science, vol. 5823. Springer, 2009, pp. 585–600.
- [9] E. Peukert, J. Eberius, and E. Rahm, "AMC—A Framework for Modelling and Comparing Matching Systems as Matching Processes," in *IEEE International Conference on Data Engineering (ICDE)*, 2011, pp. 1304–1307.
- [10] I. F. Cruz, F. Palandri Antonelli, and C. Stroe, "Efficient Selection of Mappings and Automatic Quality-driven Combination of Matching Methods," in *ISWC International Workshop on Ontology Matching (OM)*, ser. CEUR Workshop Proceedings, vol. 551, 2009, pp. 49–60.
- [11] I. F. Cruz, C. Stroe, M. Caci, F. Caimi, M. Palmonari, F. Palandri Antonelli, and U. C. Keles, "Using AgreementMaker to Align Ontologies for OAEI 2010," in *ISWC International Workshop on Ontology Matching (OM)*, ser. CEUR Workshop Proceedings, vol. 689, 2010, pp. 118–125.
- [12] I. F. Cruz, M. Palmonari, F. Caimi, and C. Stroe, "Towards 'On the Go' Matching of Linked Open Data Ontologies," in *IJCAI Workshop Discovering Meaning On the Go in Large & Heterogeneous Data (LHD)*, 2011, pp. 37–42.