YAM: a Schema Matcher Factory

Fabien Duchateau, Remi Coletta, Zohra Bellahsene, Renée J. Miller

YAM: a Schema Matcher Factory

Fabien Duchateau, Remi Coletta, Zohra Bellahsene
LIRMM
Univ. Montpellier 2
34392 Montpellier - France
firstname.name@lirmm.fr

Renée J. Miller
Univ. of Toronto
40 St. George Street
Toronto ON M5S 2E4, Canada
miller@cs.toronto.edu

ABSTRACT

In this paper, we present YAM, a schema matcher factory. YAM (Yet Another Matcher) is not (yet) another schema matching system as it enables the generation of *a la carte* schema matchers according to user requirements. These requirements include a preference for recall or precision, a training data set (schemas already matched) and provided expert correspondences. YAM uses a knowledge base that includes a (possibly large) set of similarity measures and classifiers. Based on the user requirements, YAM learns how to best apply these tools (similarity measures and classifiers) in concert to achieve the best matching quality. In our demonstration, we will let users apply YAM to build the best schema matcher for different user requirements.

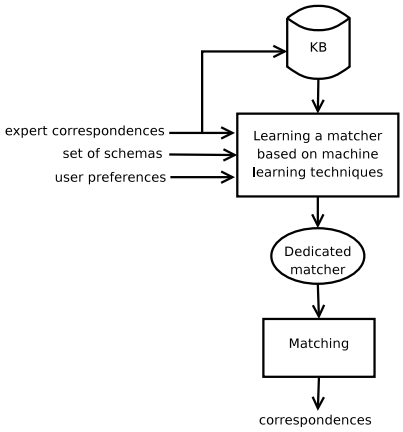
1. OVERVIEW OF YAM

YAM (Yet Another Matcher) is a **meta-matching tool**, which generates a **dedicated schema matcher**, i.e., a schema matcher which is best suited, in terms of quality, for a given schema matching scenario and according to user inputs. The motivations leading to our work are:

• There is no schema matching tool which performs best for all matching scenarios. Although matching tools enable the user to tune some parameters (strategies, weights, thresholds, etc.), the algorithm used by the matching tool stays the same, for instance, COMA++'s aggregation function [1] or Similarity Flooding's graph propagation algorithm [4]. eTuner [2] automatically tunes schema matching tools by tuning the input parameters used by the matcher. Specifically, eTuner finds the best parameter settings for a given matching algorithm. On the contrary, YAM is able to produce the best schema matcher for a given scenario. Each generated schema matcher may use a different algorithm (an aggregation function, Bayes network, decision tree, etc.) and different similarity measures.

• YAM uses some user input(s), but of a different form. Specifically, YAM can use an (optional) preference between precision and recall, and some expert correspondences (that is, a small number of correct matches). This small amount of input enables the use of supervised learning to create a dedicated schema matcher. YAM is able to convert user time spent to give preferences into better quality results. Indeed, most schema matching tools focus on a better precision, but this is not the best choice in terms of post-matching effort, i.e., the quantity of work required by an expert to correct discovered correspondences. Technically speaking, it is easier for the expert to validate (or not) a discovered correspondence than to manually browse two large schemas for new correspondences that the tool may have missed.

Figure 1: YAM Architecture



1.1 Architecture

Figure 1 depicts the YAM architecture. YAM has two phases: a learning phase that produces a dedicated schema matcher and a matching phase in which the dedicated matcher is used over new input schemas. The learning process can use a *preference* for precision and recall tradeoff and some expert correspondences (from a domain of interest, or for the schemas to be matched). The Knowledge Base (KB) stores a set of classifiers, a set of similarity measures, and pairs of schemas which have already been matched (with correspondences). Thanks to these inputs and the KB, the learning process is able to generate a dedicated schema matcher. This step is described with more details in Section 1.2. Note that using the whole content of the KB enables learning of a robust schema matcher, i.e., a default matcher that provides the best average results. This robust schema matcher is useful when YAM must directly work as a generic schema matcher, i.e., when the user has not provided any inputs. The second phase performs the matching. It requires as input the schemas to be matched, and the dedicated schema matcher that has been previously generated. It outputs a list of discovered correspondences between the schemas. The current version of YAM includes 20 classifiers from the Weka library[1] and 30 similarity measures, including all the measures from the Second String project[2]. YAM is able to parse edge-labeled trees (a simple abstraction that can be used for XML schemas, web interfaces, etc.) and the knowledge base contains a large set of real schemas from various domains

[1]http://www.cs.waikato.ac.nz/∼ml/weka
[2]http://secondstring.sourceforge.net

(betting, hotel booking, dating, etc.) gathered from the web [3]. The current KB contains more than 250 schemas, among which 200 pairs have already been matched.

1.2 Learning Process

Similarly to machine learning classifiers, a matching tool classifies each pair of schema elements (or correspondence), by labelling them either as *relevant* or *irrelevant*. In YAM, we train a large set of classifiers on schemas which have already been matched, i.e. training schemas. Two errors can occur while training: discovering an irrelevant correspondence (a.k.a. false positive) and missing a relevant correspondence (a.k.a. false negative). The first error decreases precision while the second one decreases recall. Classifiers usually assign the same weight for both errors. But it is possible to promote one of them. Thus, YAM also takes as input a user preference for either recall or precision. It is able to generate a schema matcher that favors this preference.

Among the 20 classifiers that have been learned, the final step consists of selecting the best one. To fulfill this goal, a cross-validation is applied against the training schemas. The classifier which manages to discover, between the training schemas, most of these expert correspondences and the fewest irrelevant correspondences is selected as the dedicated schema matcher.

2. DEMONSTRATION SCENARIOS

In this demo, we show the capability of our tool for generating a dedicated schema matcher, according to user inputs. We have used 10 scenarios from various domains (*hotel booking*, *currency*, *courses*, etc.). They are available with the demo. We run our experiments 30 times to limit impact of randomness during learning.

Without input. Let us imagine that we would like to match two hotel booking webforms. A user selects the schemas to be matched by clicking on the *add schemas* button. In this first case, (s)he does not want to give more input and (s)he clicks the *learn and match* button both to generate a schema matcher and to use it to match the schemas. As the user did not give any expert correspondences, YAM uses the whole KB to learn the most **robust** schema matcher, which is based on *C4.5*, a decision tree. First, this robust schema matcher is displayed in the bottom left part of YAM's interface. Then, the discovered correspondences are shown in the right part of YAM using lines between schema elements. The robust schema matcher achieves an average 58% f-measure on the 10 scenarios.

Promoting recall. Suppose the user thinks the **recall** is too low. That is, (s)he feels the matcher has missed some correspondences. (S)he adjusts the *precision / recall* slide to promote recall and restarts the learning and matching process. After that the matcher promoting recall, based on *NNge*, a nearest-neighbor-like classifier, has been generated, it discovers more relevant correspondences (13% increase for recall). Promoting recall slightly decreases precision, but average f-measure reaches 62%.

Training with similar schemas. Now, let us imagine that the user has some **similar** schemas than the ones to be matched, for instance other schemas dealing with *hotel booking*, *currency*, *courses*, etc. domains. (S)he decides to train on those similar scenarios instead of the whole KB by clicking the *choose training scenarios* button. (S)he then selects the similar scenarios and runs the *learning and matching*. Another schema matcher has been generated, based on *JRip*, a propositional rule learner. This matcher achieves an average 66% f-measure. Thus, training the matchers on similar schemas can improve the results.

Providing expert feedback. As the user is not satisfied with these results, (s)he finally provides **expert feedback** as input. Thus, (s)he selects some discovered correspondences (5% in our experiments, which represents at most 5 correspondences to provide), and validates them by clicking the *validate* button. These validated correspondences (along with the schemas) are then added to the KB, and are also automatically added to the *input expert correspondences* panel. The user then clicks the *learn and match* button. With this new input[3], YAM generates the dedicated schema matcher, *Bayes Network* in this case, in 630 seconds. Since it does not need to focus on the input expert correspondences, this matcher enables an f-measure improvement up to 89%.

Table 1 sums up the results and provides a comparison with other reputed matching tools, COMA++ and Similarity Flooding (SF). We notice that YAM robust (without user input) achieves similar results than those of COMA++ and SF. However, when user spends some time to provide some inputs, YAM is able to strongly improve the matching quality.

Table 1: Average results of the different matchers on the 10 scenarios

	precision	**recall**	**f-measure**
YAM-**robust**	52%	65%	58%
YAM-**recall**	51%	**78%**	62%
YAM-**similar**	55%	81%	**66%**
YAM-**feedback**	88%	90%	**89%**
COMA++	74%	45%	56%
SF	64%	54%	58%

3. CONCLUSION

In this paper, we have presented YAM, a factory of schema matchers. The main contributions of our work are: (i) implementation of the first tool capable of producing a dedicated schema matcher, and (ii) impact of various user inputs on the quality. By means of demonstration, we will show how YAM generates different schema matchers according to user requirements. More information (scenarios and demo) can be found at *http://www.lirmm.fr/∼duchatea/yam*.

4. REFERENCES

[1] D. Aumueller, H. H. Do, S. Massmann, and E. Rahm. Schema and ontology matching with coma++. In *SIGMOD, Demo paper*, pages 906–908, 2005.

[2] E. Y. Lee, M. Sayyadian, A. Doan, and A. Rosenthal. etuner: Tuning schema matching software using synthetic scenarios. volume 16, pages 97–122, 2007.

[3] A. Marie and A. Gal. Boosting schema matchers. In *CooPIS*, 2008.

[4] S. Melnik, H. G. Molina, and E. Rahm. Similarity flooding: A versatile graph matching algorithm and its application to schema matching. In *ICDE*, 2002.

[3]If there is not enough input expert correspondences to train correctly, YAM adds some randomly training schemas from the KB.