# Decentralized Semantic Coordination Through Belief Propagation.

# (Extended Abstract)

George A. Vouros
Dept. of Digital Systems, University of Piraeus, Greece
georgev@unipi.gr

## ABSTRACT

This paper proposes a generic decentralized method for interconnected entities to compute globally coherent sets of mappings with respect to the semantics of ontological specifications and their subjective mapping preferences. This problem is formed as an optimization problem between interdependent agents. Globally coherent sets of mappings are computed by means of a distributed extension of the max-plus algorithm, taking also into account the feedback entities receive on their subjective mappings from distant others. Experimental results from a large number of networks of varying complexity show the strengths of the proposed approach and point to further work.

## Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

## General Terms

Algorithms, Measurement

## Keywords

Semantic Coordination, Ontology Alignment, Semantic Agreement

## 1. INTRODUCTION

Although interconnected entities can be of any type (peers, software or human agents, things on the web, orchestrated services), subsequently, and for the clarity of the presentation we distinguish between entities that are referred as peers, and agents that implement decision-making processes on behalf of these peers. To interact effectively, peers in inherently open and distributed settings need to establish semantic correspondences (mappings) between own ontology elements and ontology elements of their acquaintances. These computations depend on the alignment method each entity uses and on the information made available to that method: Therefore, entities may not agree on their mappings. In this case, information propagated along paths in the network may not preserve its original intended meaning.

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This article proposes a generic decentralized method for peers to reach agreements regarding subjective semantic correspondences between terms lexicalizing ontology elements, via belief propagation. It does this to a great extent than previous contributions that either use centralized methods for locating mapping decisions that introduce inconsistencies (e,g, [5],[6],[8]), or propose distributed probabilistic message passing techniques for detecting erroneous mappings [1]; and differently than approaches that aim to the establishment or development of common vocabularies (e.g. [2],[7]). The proposed method is independent of the specific mapping methods used by the peers, and also applicable to any possible setting of information sharing entities. As far as we know, this is the first approach towards semantic coordination in networks of arbitrarily inter-connected peers.

## 2. THE OVERALL METHOD

Let us consider a network of peers represented by a directed graph $G = (V, E)$. Each node in $V$ is a peer $P_1$ with a specific ontology $O_1$. Each directed edge $(P_1, P_2)$ in $E$ specifies the fact that $P_1$ has a specific (complete, partial, vague or abstract ) view of $P_2$'s ontology. $P_1$ can compute subjective correspondences between the elements of $O_1$ and $O_2$ using *any* mapping method.

Given the ontologies $O_1 = (S_1, A_1)$, $O_2 = (S_2, A_2)$ (where $S_i$ denotes the signature, and $A_i$ the axioms that specify the intended meaning of terms in $S_i$) of two peers $P_1$ and $P_2$ in $G$, and an element $E_i^1$ in the signature $S_1$ of $O_1$, the mapping method of $P_1$ computes an *ordered set* of subjective correspondences for $E_i^1$. Each correspondence is of the form $(E_i^1, E_j^2, r, \gamma)$, where $E_j^2$ is an element in $S_2$, $r$ can be any relation between elements, and $\gamma$ is a number that represents the preference to relating $E_i^1$ with $E_j^2$ via $r$, i.e. $P_1$'s confidence on this correspondence. Correspondences in the set are ordered according to $\gamma$. In this paper we deal only with *equivalences* between *classes*, although other mapping relations whose transitive closure can be exploited, can be considered as well.

A *locally coherent set of correspondences* for a peer in $G$ is a set of correspondences to a specific target ontology that preserves the semantics of specifications for this peer. A *globally coherent set of correspondences* for peers in $G$ is a set of correspondences that is agreed among peers and preserves the semantics of specifications for each of the peers.

The problem of computing a globally coherent set of correspondences between peers in any network $G$ is rather complicated if we consider that each peer is connected to numerous other peers, each with distinct ontologies and mapping methods, with the latter being arbitrarily connected with others and/or among themselves. This problem includes two highly intertwined, computation phases: (a) The computation of locally coherent correspondences to the ontologies of neighbor peers, and (b) exploiting these correspondences to reach agreements between (even distant) peers in $G$.

Correspondences and their confidences are given as input to the proposed method.To preserve the local coherency of mappings with respect to the semantics of specifications, peers build *internal dependency graphs* (aka coordination graphs [3]) whose nodes are inter - constrained decision-making agents. Each of these agents makes a mapping decision for a specific ontology element, regarding a specific target ontology. The mapping decisions of two neighbor agents $i$ and $j$ are inter-dependent and must satisfy a *validity constraint*. Such a constraint restricts agents' decisions to those mappings that preserve the semantics of ontological specifications. Further details on the construction of dependency graphs are given in [10]. Decisions are made with respect to the preferences to correspondences: Towards this objective, the agents propagate their payoffs via messages, according to the max-plus [4][9] algorithm. A message from $i$ to $j$ maximizes the utility of $i$ given a mapping choice of $j$, and all incoming messages to $i$, except from $j$.

Peers, after their internal computations, can further revise their locally coherent mapping decisions towards reaching agreements by propagating their mapping decisions to their acquaintances. Doing so, they aim to exploit the transitive closure of their mappings in existing cycles in their network. Given a cycle ($P_1 \to P_2 \to \cdots \to P_k \to P_1$), then for each correspondence ($E_i^1$,$E_j^2$, $\equiv, m$) forwarded from $P_1$ to $P_2$ the originator $P_1$ must get a correspondence ($E_x^k$,$E_i^1$, $\equiv, m$') from the last peer in the cycle, $P_k$. I.e. it must get a correspondence to the element $E_i^1$, rather than to any other element of $O_1$. In such a case, for each such correspondence, $P_{node}$ counts a positive feedback. In case this does not happen, then there are one or more mappings through this path that according to the subjective view of $P_1$ result to a disagreement. Then, $P_1$ counts a negative feedback. It must be noticed that disagreements may still exist when $P_1$ gets the expected correspondence but several correspondences along the path compensate their errors: These are detected by the corresponding peers as the mapping history propagates in the network. To detect cycles and get feedback, peers construct and exploit mapping histories, i.e. ordered list of correspondences between elements along any cycle in $G$. The propagation of beliefs in peers' internal graphs as well as between peers, together with the construction/exploitation of mapping histories, as well as the incorporation of feedback to agents' decision making are presented in detail in [10].

In few words, the problem is addressed as an optimization problem between inter - constrained agents in dependency graphs: Agents target the establishment of agreements, aiming to increasing their social welfare, i.e. the sum of their utilities w.r.t. to their mapping preferences and the semantics of specifications, taking also into account the feedback received from other peers.

# 3. EXPERIMENTAL EVALUATION

Given that the complexity of the method increases as the length and number of cycles in the network of peers increase, and as the number of classes in the ontologies increases, the performance of the method has been measured using a variety of networks with an increasing complexity. Specifically, experiments concern four types of networks in which peers' average degree is 2,3,4 or 5. Each type of network comprises at most 10 different networks. Each peer is been assigned a specific distinct ontology with 13 classes and has the ability to compute correspondences with a constant precision in {1,0.9,0.8,0.7,0.6,0.5}. The precision specifies the proportion of the true positive correspondences w.r.t. reference correspondences between ontologies.

Experiments show the following: (a) The method manages to increase the f-score of each peer w.r.t. the reference correspondences. In other words, the peers with the "best" mapping methods manage to drive the others towards an *agreed* and *correct* set of correspondences. (b) The method must consider both, the validity constraints and the feedback received, although semantic constraints play a vital role in the process. (c) The method is scalable w.r.t the average degree of peers in the network and the number of elements in ontologies. (d) The method converges (as expected) in early rounds, given that the dependency graphs are acyclic.

# 4. FUTURE WORK

Future work concerns including other mapping relations whose transitive closure can be exploited by peers in cycles, also concerning properties and instances, in conjunction to classes. We also aim to address subtle issues concerning communication. Preliminary experiments showed that various heuristics for reducing the communication messages result to sacrificing considerably methods' effectiveness. Finally, the study of sub-optimality, as well as the integration of the proposed method in an open and heterogeneous information sharing setting, are issues to be investigated.

# 5. REFERENCES


[1] Cudre-Mauroux P., Aberer K., and A. Feher. Probabilistic Message Passing in Peer Data Management Systems, ICDE 2006.

[2] Diggelen J., et al. Optimal Communication Vocabularies and Heterogeneous Ontologies. Agent Communication, LNCS 3396, 2005.

[3] Guestrin, C., Koller D., R. Parr. Multiagent planning with factored MDPs. NIPS 14, MIT Press 2002.

[4] Kok J.R. and N.Vlassis. Collaborative Reinforcement Learning by Payoff Propagation, JMLR, 7:1789-1828, 2006.

[5] Meilicke C. and H. Stuckenschmidt. An efficient method for computing alignment diagnoses. RR 2009.

[6] Qi G., Q. Ji, and P. Haase. A conflict-based operator for mapping revision, ISWC 2009.

[7] Reitter D. and C.Lebiere. How groups develop a specialized domain vocabulary: A cognitive multi-agent model. Cognitive Sys. Res. 12, pp 175-185, 2011.

[8] Ruiz E.J., Grau B.C., Horrocks I. and R.Berlanga. Ontology integration using mappings: Towards getting the right logical consequences. ESWC 2009.

[9] Wainwright M. J., Jaakola T.S. and A.S. Willsky. Tree consistency and bounds on the performance of the max-product algorithm and its generalizations. Statistics and Computing, 14, pp 143-166, April 2004.

[10] Vouros G. Decentralized Semantic Coordination Through Belief Propagation. AT 2012, http://ceur-ws.org/Vol-918/.