From Supply Chain Formation to Multi-agent Coordination (Doctoral Consortium)

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ABSTRACT

Supply Chain Formation is the process of determining the participants in a supply chain, who will exchange what with whom, and the terms of the exchanges. Decentralized supply chain formation appears as a highly intricate task because agents only possess local information and have limited knowledge about the capabilities of other agents. The decentralized supply chain formation problem has been recently cast as an optimization problem that can be efficiently approximated using max-sum loopy belief propagation. This mapping can be improved by encoding the problem into a *binary* factor graph (containing only binary variables) and deriving model-specific equations for max-sum. First, this paper introduces the state-of-the art methods for decentralized supply chain formation. Second, it presents future short-term lines of research in this problem. Finally, it argues that the binary model can be extended to other problems than that of the supply chain formation.

Categories and Subject Descriptors

I.2.11 [**Distributed Artificial Intelligence**]: Multiagent Systems

Keywords

Supply chain; belief propagation; scalability

1. DECENTRALIZED SUPPLY CHAIN FORMATION

Supply Chain Formation (SCF) is the process of determining the participants in a supply chain, who will exchange what with whom, and the terms of the exchanges [12]. Unlike traditional firms regulated by long-term contracts, today's companies are required to dynamically form and dissolve trading relationships at a speed and scale that is getting unmanageable by humans, giving rise to the need for automated SCF.

Automating SCF poses an intricate coordination problem to firms that must simultaneously negotiate production relationships at multiple levels of the supply chain, with interdependencies between inputs and outputs holding at each level. The SCF problem has been already tackled by the AI literature, mostly through auction-based approaches. In particular, several contributions [13, 2, 1] have addressed the problem by means of combinatorial auctions that compute the optimal supply chain allocation in a centralized manner. Unfortunately, since even finding any feasible supply chain allocation is NP-Complete [12], sufficiently large SCF problems will be intractable, hence hindering the scalability of the global optimization performed by auction-based approaches. Furthermore, as argued in [12], even when the computation is tractable, no one entity may have global allocative authority to compute allocations over the entire supply chain.

Walsh et al. [12] propose to solve the SCF problem in a fully decentralized manner. Each good in the supply chain is auctioned separately and all auctions run simultaneously without direct coordination. Therefore, each auction allocates a single resource considering the offers to buy or sell submitted by agents. However, the approach proposed by Walsh et al. suffers from high communication requirements [11]. Later on, Winsper et al. [14] cast the decentralized SCF problem as an optimization problem that can be approximated using (max-sum) loopy belief propagation [3]. Nonetheless, the problem representation employed by Winsper et al. leads to exponential memory, computation, and communication requirements that largely hinder its scalability.

In [4] we described a novel approach to the decentralized SCF problem, the so-called Reduced Binary Loopy Belief Propagation (RB-LBP), which significantly outperforms the approach in [14] in terms of scalability. Specifically, RB-LBP's communication, memory and computational requirements scale linearly, whereas Winsper's scale exponentially in markets with high degrees of competition. Moreover, RB-LBP displays large savings in terms of communication, memory and computation time required to obtain a solution. RB-LBP allows agents to form supply chains requiring only local communication and limited knowledge of other participants. The main contributions of RB-LBP are: (i) a novel encoding of the SCF problem into a binary factor graph (containing only binary variables); and (ii) a derivation of simplified messages that dramatically lowers the communication requirements of message passing. Unfortunately, as the number of agents at trade increases, the value of the SC assessed by both LBP and RB-LBP gets further from the optimal one [5].

Recently, in [5], we introduce CHAINME, a decentralized method for SCF that builds on the idea of using mediators on behalf of the goods. In CHAINME there is a mediator for each

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of the goods in the SC. Mediators facilitate the negotiations between agents over the good they mediate. CHAINME is able to assess SC of higher value than the other state-of-the-art methods. Moreover, CHAINME finds the optimal SC more often than the other methods. Furthermore, CHAINME computation and communication requirements are from one up to four orders of magnitude less than the competitors while having similar memory requirements.

Previous work on decentralized SCF only applies to markets whose agents can produce at most a single good. Although we have not tested CHAINME and RB-LBP in scenarios were agents can produce more than one good, CHAINME and RB-LBP can readily be applied to these scenarios. Currently, we are working on evaluating our model in such scenarios and over a variety of actual-world network structures. We also plan to extend our current model to markets in which goods are exchanged in multiple units and where producers are able to supply several units of each of their outputs. Another open line of research is to study the behaviour of CHAINME and RB-LBP in dynamic scenarios. That is, scenarios where agents can join or leave the process at any given time or change their valuation over their task they perform.

2. TOWARDS MULTI-AGENT COORDINATION

Max-sum has been successfully applied to decentralized coordination of multi-agent systems. In [10], Stranders et al., propose a model that operates over max-sum to coordinate a team of mobile sensor monitoring and predicting the state of spatial phenomena. Moreover, in [3], Farinelli et al., use max-sum to solve the problem of efficiently coordinating teams of low-power embedded devices in environments with lossy communication. Therefore, studying whether the model we described in [4] can be applied to other areas of research in the multi-agent coordination field appears to be an interesting line of research.

Particularly, collaborative environments in which agents share a common goal pose as ideal subjects for further study. Problems not so distant from SCF such as *task allocation* appear as ideal candidates to test the suitability of CHAINME and RB-LBP to be applied to other areas of multi-agent coordination. For instance, Scerri et al. [9] describe the problem of allocating tasks to teams that operate in dynamic environments such as large-scale service organizations and disaster rescue scenarios. In a step forward to the generalization of our method for agent coordination we find also *coalition formation* problems. Coalition formation is a fundamental form of interaction that allows the creation of coherent groupings of distinct, autonomous agents in order to efficiently achieve their individual or collective goals [6]. Efficiently assessing coalitions for problems with large numbers of agents and tasks remains an open problem [7, 8]. Therefore, we think that the high scalability of CHAINME and RB-LBP a good candidate to tackle such problems.

To sum up, future work will go towards turning the methods described in [4, 5] into a general distributed optimization technique to solve large-scale multi-agent coordination problems.

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4. REFERENCES

[1] J. Cerquides, U. Endriss, A. Giovannucci, and J. A. Rodríguez-Aguilar. Bidding languages and winner determination for mixed multi-unit combinatorial auctions. In *IJCAI*, pages 1221–1226, 2007.

[2] J. Collins, W. Ketter, and M. Gini. A multi-agent negotiation testbed for contracting tasks with temporal and precedence constraints. *Int. J. Electron. Commerce*, 7:35–57, October 2002.

[3] A. Farinelli, A. Rogers, A. Petcu, and N. R. Jennings. Decentralised coordination of low-power embedded devices using the max-sum algorithm. In *AAMAS*, pages 639–646, 2008.

[4] T. Penya-Alba, M. Vinyals, J. Cerquides, and J. A. Rodriguez-Aguilar. A scalable Message-Passing Algorithm for Supply Chain Formation. In *26th Conference on Artificial Intelligence (AAAI 2012)*, 2012.

[5] T. Penya-Alba, M. Vinyals, J. Cerquides, and J. A. Rodriguez-Aguilar. CHAINME: Fast Decentralized Finding of Better Supply Chains (Extended Abstract). In *12th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2013)*, In Press.

[6] T. Rahwan, S. Ramchurn, V. Dang, A. Giovannucci, and N. Jennings. Anytime optimal coalition structure generation. In *Proceedings of the national conference on artificial intelligence*, volume 22, page 1184, 2007.

[7] T. Rahwan, S. Ramchurn, V. Dang, and N. Jennings. Near-optimal anytime coalition structure generation. In *Proceedings of the Twentieth International Joint Conference on Artificial Intelligence (IJCAIâĂŹ07)*, pages 2365–2371, 2007.

[8] S. Ramchurn, M. Polukarov, A. Farinelli, C. Truong, and N. Jennings. Coalition formation with spatial and temporal constraints. In *Proceedings of the 9th International Conference on Autonomous Agents and Multiagent Systems.*, pages 1181–1188, 2010.

[9] P. Scerri, A. Farinelli, S. Okamoto, and M. Tambe. Allocating tasks in extreme teams. In *Proceedings of the fourth international joint conference on Autonomous agents and multiagent systems*, pages 727–734, 2005.

[10] R. Stranders. Coordinating teams of mobile sensors for monitoring environmental phenomena. May 2009.

[11] W. E. Walsh. *Market protocols for decentralized supply chain formation.* PhD thesis, University of Michigan, 2001.

[12] W. E. Walsh and M. P. Wellman. Decentralized Supply Chain Formation : A Market Protocol and Competitive Equilibrium Analysis. *Artificial Intelligence*, 19:513–567, 2003.

[13] W. E. Walsh, M. P. Wellman, and F. Ygge. Combinatorial auctions for supply chain formation. In *2nd ACM Conference on Electronic Commerce*, pages 260–269, 2000.

[14] M. Winsper and M. Chli. Dcentralized Supply Chain Formation using Max-Sum Loopy Belief Propagation. *Computational Intelligence*, 2012.