

# Collaborative Decision Making in Organic Business Environments

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**Abstract:** This paper presents a multiagent architecture and algorithms for collaborative, self-organizing learning in distributed, heterogeneous and dynamic business systems, where the participating agents have local, incomplete knowledge about the whole business transaction. The agents are self-organized for integrating their individual learning based on the business context. This is illustrated by a supply chain scenario with proactive monitoring of logistics processes. Experiments run on a large real-world order data set indicate that our approach effectively improves the performance of decision making in distributed business systems.

## 1 Introduction

Globalisation and mass customisation are business trends that have created a development where business processes are distributed and need to be planned and enacted across multiple partners. This leads to highly distributed architectures of business systems with amplified complexity and increased need for collaboration among the participating organizations. Organic computing based on decentral multiagent collaboration and coordination is a promising technology to tackle this complexity and to enable flexible business systems. Organic computing provides self-organizing structures and context aware-problem solving for distributed business applications [MBB02], which can autonomously monitor business environments, learn from experiences, predict unforeseen events, and engage in automated action on behalf of humans and organizations. In this paper, we propose an organic computing architecture and algorithm for collaborative decision making in distributed and heterogeneous business environment. Some examples of distributed business systems which can be enhanced in this context are:

- **Supply chain management:** Supply networks reveal highly distributed architectures with heterogeneous information distribution, i.e. the partners have incomplete knowledge based on their local views of process definitions, status, and outcomes. Collaborative learning can improve adaptive process planning, monitoring, and coordination of the overall process.
- **Customer relation management:** Customer services are usually implemented by different business units, such as product sales, delivery, and technical support. Each unit keeps specific service information, which can be seen as partial views of the

overall customer information. Collaborative learning of these business units can help towards better understanding of the customers' context and preferences, and provide assistance to product recommendation or fraud detection applications.

There're several properties and challenges to enable collaborative learning in these distributed business systems:

- **Distributed:** Centralization of data is often neither feasible nor desirable in many cases, because of high transaction volumes, quickly changing local situations and information policies of different organizations. So the collaborative learning will be in distributed architecture and minimizes information centralization.
- **Heterogeneity:** The participating organizations usually have incomplete knowledge based on their partial local views on the whole business transaction. So collaborative learning method needs integrating different learning models of the agents.
- **Dynamic:** The collaborative learning strategy should be adaptive to the changing business context, instead of fixed strategy.

In this paper, we present a multiagent collaborative learning approach for distributed, heterogeneous and dynamic business systems. The agents are self-organized for integrating agents' individual learning with awareness of the business context. It's illustrated with the supply chain scenario, and in particular, proactive monitoring of logistics processes. Experiments run on a large real-world order data set indicate that the collaborative multiagent learning approach effectively improves the learning performance of local learning.

The following sections is structured as follows: Section 2 presents the agent collaborative learning algorithm. Section 3 describes the result of an empirical evaluation on a large real-world data set. Section 4 gives an overview of related research. Finally, conclusions and perspectives of future research are discussed in Section 5.

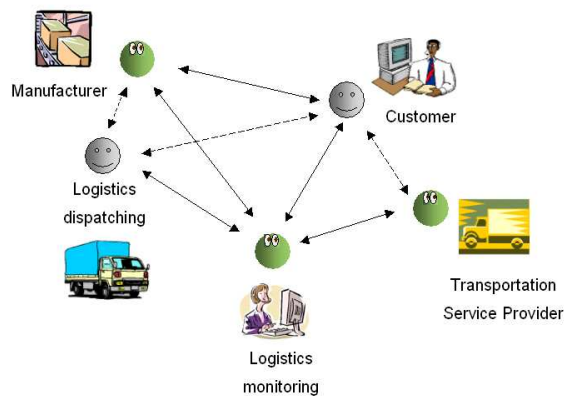


Figure 1: Multiagent collaborative learning in the distributed logistics process.

## 2 Multiagent collaborative learning algorithm

The supply chain application is predicting transaction parameters (e.g., whether a transaction will be delayed or not) in a logistics process. It's based on a real-world use case and real application data obtained from a major logistics service provider (see [GMB04]), as shown in Figure 1. A logistics order can be defined as an  $n$ -tuple  $\mathbf{x} = (x_1, x_2, \dots, x_n)$ , where  $x_i$  is the value of the  $i$ -th attribute. These attributes characterize the order by origins and destinations around the world, various product types from automation systems to medical equipment, different packaging, and different local and international transportation service providers. Whereas these information are distributed over a group of agents, i.e., agents only know sub-sets of the transaction attributes. So each agent has a local, partial view of the overall transaction-related information and uses this view to construct models.

To enable collaborative decision making in such a distributed, heterogenous and dynamic business environment, we propose a multiagent learning method by extending the *stacking* meta learning strategy [PC00]. First, the agents build individual learning models with their local information. Second, a collaborative learning scheme is formed by analyzing their properties on current context. Then the agents are self-organized with this collaborative learning scheme to make predictions for new logistics orders. Bayesian classifier is used for agent local learning models and Support Vector Machine (SVM) is adopted to learn the multiagent collaborative learning model based on the analysis of agents' individual learning models on current business context. The proposed collaborative learning algorithm consists of the following steps:

1. Each agent  $i$  learns its model  $C_i$  using the Bayesian classifier on its own training data set.
2. Each agent  $i$  makes predictions on its *context set*  $V_i$  based on  $C_i$ .
3. Agents exchange their predictions on the *context set*.
4. Agent  $i$  build a *meta set*  $T$  with the agent predictions on the *context set*.
5. Learn a *meta model*  $M$  on  $T$  with Support Vector Machine (SVM).
6. Use  $M$  to make predictions on the test set.

Here, the *context set* is a small data set from recent business transactions. It is used for analyzing the properties of the agents' models with respect to current business context. The *context set* has the same attribute partition as the training set. The *context set* and the learned agents' individual models are used to build a *meta set*. In this paper, the attributes of a meta set instance are composed of the predictions with agents' local models and the attributes of the logistics orders. The model prediction attributes are based on predicted probabilities of delay instead of predicted labels, and only the high relevant order attributes are selected to be the order attributes in the meta set based on mutual information analysis. The meta learner based on Support Vector Machine (SVM) will learn a *meta model* with the *meta set*. The SVM learner has good generalization ability and reveals good performance even when the size of the training set is small, which enables using small context set. For a new input of unlabelled logistics transaction instance, the *meta model* can provide prediction of future status based on its attribute values and the individual agent local predictions.

Table 1: Learning performance of local and collaborative learning

Experiment	Learning model	DR	DP
EXP_1-EXP_5	Agent local learning (average)	0.41	0.37
EXP_6	Collaborative learning	0.59	0.40

### 3 Empirical analysis

The empirical analysis is based on a large data set from the data warehouse of a major logistics service provider collected over 2003. There're 390505 transaction instances in the training set, which are vertically partitioned into five separate groups and maintained by five agents. These agents would represent different parties in the supply chain. The context set has 6088 instances from the first week of August 2003 and the test set contains 87994 transaction instances from the rest of August 2003. The following experiments are performed on the test set: EXP\_1 to EXP\_5 are results of local learning of the five agents and collaborative learning is applied in EXP\_6. All experiments were repeated ten times with differing data sets, all reported figures are average figures.

To evaluate the learning performance, we adopted two standard measures from information retrieval: *delay recall* (DR) and *delay precision* (DP), which are defined as

$DR = \frac{n_{D \rightarrow D}}{n_{D \rightarrow D} + n_{D \rightarrow S}}$  and  $DP = \frac{n_{D \rightarrow D}}{n_{D \rightarrow D} + n_{S \rightarrow D}}$ , where  $n_{D \rightarrow D}$  is the number of correctly predicted *Delay* orders,  $n_{D \rightarrow S}$  and  $n_{S \rightarrow D}$  are the number of *Delay*  $\rightarrow$  *Success* and *Success*  $\rightarrow$  *Delay* errors. It is known from information retrieval that there is a trade-off between recall and precision. The experimental results of individual and collaborative learning are shown in Table 1. It shows that the collaborative learning methods can effectively improve the learning performance of agent local learning.

### 4 Related work

Multiagent collaboration based technology is becoming increasingly often used to model and implement distributed business systems. A multiagent approach for cooperative transportation scheduling is investigated in [FMP96]. A variety of approaches from multiagent systems, maybe most notably represented by the ADEPT project [JFN<sup>+</sup>96], have explored the use of multiagent collaboration and coordination techniques in the context of business applications. However, these approaches were generally not focused on aspects of adaptation and learning.

Our work particularly draws on research results in learning from heterogeneous distributed data. The collective Bayesian network learning algorithm proposed in [CSK04] performs two stage learning for local and central Bayesian networks, but it requires centralization of part of the data set at the training stage and that it relies on the exchange of row data in the prediction stage. To prevent centralization, [MS01] propose a distributed decision tree

(DDT) based method enabling a multiagent learning of classification tasks. The algorithm does not provide a training stage, nor is an explicit model learnt. At the prediction stage, the results of the iterative learning at the individual agents is correlated, also leading to a considerable computation and communication effort.

## 5 Conclusions

This paper presents a multiagent architecture and algorithms for collaborative learning in distributed, heterogeneous and dynamic business systems. The agents are self-organized for integrating agents' individual learning based on the business context. It's illustrated with the supply chain scenario for proactive monitoring of logistics processes. Experiments run on a large real-world order data set indicate that our approach effectively improves the performance of agent individual learning. Further research will investigate hybrid learning strategies geared towards distributed business systems with more complex heterogeneous information distribution and organization models.

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