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Distributed Control for Robust Autonomous Logistic Processes[1]

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Abstract

Logistic processes are inherently complex and dynamic. This motivates the application of robust distributed methods, such as multiagent systems, for logistic planning and control. In the present paper we outline a knowledge management oriented approach for multi-agent-based autonomous logistic processes. Recent results from simulations give rise to the assumption that efficient usage of knowledge and distributed control can improve the robustness and service quality in logistic processes to a significant degree. We discuss the role of ontologies as a formal knowledge representation component, present a framework based on agent knowledge management roles, and demonstrate how knowledge management in a distributed system can contribute to risk reduction by situation awareness at different levels of logistic processes.

1 Introduction

Due to the increasing demands on efficiency and flexibility of logistic strategies new paradigms for planning and control are required. An emerging approach to this is the analysis and design of *autonomous logistic processes* (cf. Scholz-Reiter et al. 2004). Software agents represent a modern approach for implementing autonomous systems. The challenge for the design of agent systems is to integrate the complex and dynamic knowledge required for reliable decision-making.

Distributed decision making systems, e.g., multiagent systems (MAS), have been attributed to be more robust and more flexible than systems which depend on exactly one centralized (global) decision-making unit. This property is important for large-scale deci-

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sion making systems for complex and dynamic environments, e.g., in the area of transportation and supply networks.

In the current paper we will outline different aspects of an approach to distributed decision-making in logistics which addresses knowledge management and risk management for software agents in autonomous logistic systems. We will sketch the architecture of the system, as a whole, and the structure of the agents, therein. Results from simulation experiments with the above-mentioned system emphasise the importance of knowledge in logistic processes with decentralised decision systems.

The remainder of this paper is organized as follows: In section 2 (Distributed Control in Logistics) we discuss the application of distributed AI methods and particularly multi-agent systems in the logistics domain. Section 3 gives an overview on the usage of ontologies in our framework and introduces a role-based approach to knowledge management. In section 4 we investigate how distributed control, knowledge sharing, and situation awareness contribute to the logistic performance and reduction of risk in different transportation scenarios. Section 5 presents conclusions and outlines future work.

2 Distributed Control in Logistics

Increasing demand for customization of products and their delivery has brought about a sea change in today's economy. Markets that were predominantly controlled by sellers evolve to markets that are now rather driven by buyers and their demands. These trends lead to complex and partially conflicting requirements on logistic planning and control systems. An upcoming approach to meet these requirements is to allow for more autonomy of local sub-systems in order to provide flexibility and rapid response when reacting to customer requests as well as more robustness in case of system disturbances. The emergence of new hardware technologies including GPS-based telematics, more reliable and longer ranging wireless communication and item identification facilities as well as low-power sensor devices enable new approaches in controlling and monitoring logistic processes. In addition, software with artificial intelligence is being developed to support autonomous decision-making on the local level of logistic objects (e.g., transport containers) and to provide the right information when it is needed (Langer et al. 2006). This section introduces the basic software approaches and techniques toward distributed control in logistics.

2.1 Distributed Artificial Intelligence

Distributed Artificial Intelligence (DAI) is a subarea of general Artificial Intelligence (AI) which has a special focus on distributed problem solving. DAI has been influenced by the upcoming of parallel hardware and by several theoretical and practical results on distributed knowledge representation and parallel algorithms. There is a wide range of methods in DAI, including, e.g., distributed theorem proving, artificial neural networks, swarm intelligence, and multiagent systems. Swarm intelligence approaches have been successfully applied to particular logistic tasks such as the travelling salesman problem and the vehicle routing problem (Svenson et al. 2004).

An important motivation for DAI is the study and simulation of processes and systems with different "actors". Typical domains are games (e.g., robot soccer) and the simulation of collaboration and competition in complex social and technical systems. Another motivation for using DAI methods is that they turned out to be appropriate methods for solving or, at least, approximating difficult optimisation problems. A third motivation for DAI is its robustness: Changing just a few bits in a standard software system can have completely unpredictable effects and will usually result in fatal errors or a system breakdown. In DAI systems the modification or deletion of one or few actors typically has only slight effects and preserves the overall behaviour of the system. On the other hand, the delegation of decision-making authorities to autonomously acting software agents can also imply loss of control and, hence, new risks, especially when strategic decisions are subject of a delegation. Therefore, autonomous agents have to have an integrated risk management, either as an internal component of the agent itself or as an external control mechanism. A generic architecture of risk-aware agents that emphasises the importance of knowledge about the state of the world is discussed by Lorenz et al. (2005).

2.2 Intelligent Agents and Multiagent Systems

For the purposes of modelling more complex logistic processes which presuppose that the actors are able to use background knowledge, strategic planning, and reasoning, the multiagent system (MAS) paradigm is more appropriate than other DAI methods (e.g., Swarm Intelligence). Autonomous agents and MAS have been applied in many domains such as manufacturing (Kirn et al. 2006; Pechoucek et al. 2005b), logistics and supply chain management (Kirn et al. 2006; Dorer & Callisti 2005), as well as cargo online quality monitoring on embedded systems (Jedermann & Lang 2008).

Multiagent systems consist of software agents who are situated in a (virtual) environment. They interact with each other based on high-level interaction protocols. These protocols are inspired by work on linguistic pragmatics by Austin and Searle in "Speech Act Theory" (cf. Austin 1962; Searle 1969). An intelligent agent is considered as an entity that perceives through sensors, reasons about its next actions, and acts upon the environment it inhabits (Wooldridge 2000). Wooldridge and Jennings (1995) define the following minimal criteria an agent should comply with: *autonomy*, *proactiveness*, *reactivity*, and *social ability*. That is, an intelligent agent should be able of independent and goaldirected decision making, reaction on changes in its environment, and communication with other agents.

The basic kind of agent is the *simple reflex agent*. This agent is governed by condition-action rules and always selects the same action given the same perception, i.e., it acts deterministically. The *rational agent* "chooses to perform actions that are in its own best interests, given the beliefs it has about the world" (Wooldridge 2000, p. 9). Rationality is a fundamental requirement of safety-critical autonomous systems. The *belief-desire-intention* (BDI) model (Bratman 1987; Bratman et al. 1988) became a prevalent approach for deliberative software agent architectures (cf. Wooldridge 2000; Timm 2004; Kirn et al. 2006). BDI is based on a theory of Bratman (1987) which describes human practical reasoning as deliberation, i.e., deciding what state should be achieved, and means-ends reasoning, i.e., deciding how to achieve it. In the BDI model, an agent is represented by its subjective knowledge about the world (*beliefs*) and persistent goals that should be achieved (*desires*). Desires and current beliefs result in achievable goals and possible actions towards them. Finally, in a process of deliberation, the agent commits to a goal and a corresponding plan with sub-goals (*intentions*). Since this more sophisticated design of an agent explicitly models the decision-making in a "human-like" way, it has been chosen a starting point for implementing autonomously acting logistic units, discussed below.

2.3 Autonomous Logistics

The control paradigm of *autonomous cooperating logistic processes* applies the concept of decentralized decision-making and self-organisation to logistics (Scholz-Reiter et al. 2004; Windt & Hülsmann 2007). That is, autonomous agents accompany logistic entities (e.g., vehicles, transport containers, or even single parcels) during a logistic process, monitor their state, and decide about their intentions and actions. This may include communication and cooperation with other agents if necessary to achieve their goals. Radio frequency identification (RFID) helps identify and keep track of load modules (e.g., pallets).

The decentralized approach provides easier access to local information needed for making the best decision and, due to reduced complexity for frequent (re-)planning, it is less vulnerable to environmental changes such as new transport orders or breakdown of vehicles. Decentralized local decision-making cannot guarantee optimal solutions in global or company-wide scale. But in practice, the goal of having a steadily optimized plan for a large-scale set of resources that face unpredictable events in a dynamic environment becomes unachievable. A seemingly optimal solution may prove bad in the end when situation changes. In a recent diploma thesis (Kordes 2008) simulation results were presented which support the hypothesis that decentralization can contribute to a more robust behavior of a planning system. Kordes compared a centralized transportation planning system with a hybrid (i.e., partially decentralized) alternative and found that the decentralized planner had advantages w.r.t. the number of time-of-delivery deviations, although the average route length computed by the centralized system was significantly better.

Engineering autonomous processes in logistics includes three perspectives: material, information, and management. Autonomous agents cover the information as well as the management perspective because they process and exchange information and have some autonomous decision behaviour. High-level decision behaviour of agents is challenging and may not be realised by simple reflex agent architectures. Therefore, we assume that intelligent agents with deliberative decision behaviour and explicit knowledge representation and reasoning capabilities are required to meet these requirements (e.g., BDI agents).

The challenge in logistics arises from complexity and dynamics of a spacious environment and the different interests within the system. On the interaction level, agents should maximize their own utility. But each agent is also a representative of an enterprise and, therefore, its behaviour should improve the performance of the corresponding enterprise. This may call for actions that are conflicting with the agent’s local utility. Furthermore, agents may need to communicate or even cooperate with agents of potentially competing companies. Thus, strategic considerations and preferences in cooperation with other companies as well as information hiding issues have to be addressed. Cross-company communication of agents also requires standards for encoding and interpretation of data for information interchange. Formal ontologies, which are currently the predominant method to represent the semantics of information interchange between agents, are subject of section 3, below.

3 Ontologies and Knowledge Management in Logistics

Knowledge representation using ontologies is an important research topic in Artificial Intelligence and in many related application-oriented research areas. For example, most Semantic Web applications presuppose ontologies as a basic component. Although ontologies are typically well-defined formal objects, the term *ontology* itself is actually an informal concept. Hence, it is often difficult to separate *ontology* from related terms such as *taxonomy*, *semantic network*, *thesaurus*, etc. A frequently cited definition, derived from Gruber (1993), states that an ontology is a “specification of a conceptualization”.

In contrast to taxonomies, ontologies typically not only define a hierarchy of concepts (concepts and their sub-concepts and super-concepts), but also offer many other relations, which are often domain-specific. In our application ontologies play an important role. First, ontologies are used to represent knowledge about the logistic tasks and objects the agents have to deal with and, secondly, the ontologies define the semantics of the expressions which the agents use to communicate with each other.

The conceptual knowledge is represented as an OWL (Web Ontology Language, cf. Bechhofer et al. 2004) ontology. For the purpose of our logistic application domain, this ontology includes a representation of the transportation or production network, the properties of infrastructure (such as highways, depots, etc), and the types of logistic objects and their properties. For a vehicle this includes, e.g. its maximum speed, the types of routes in the network it can use, the type of storage space and its capacity.

In our framework, knowledge representation and reasoning of each individual agent is accompanied by a role-based distributed knowledge management infrastructure (Langer et al. 2006). In contrast to previous approaches to agent-based knowledge management, we do not presuppose a one-to-one correspondence between agents and knowledge management functions, such as providing knowledge or brokering knowledge. In our approach these functions are implemented as *roles*. A knowledge management role includes certain reasoning capabilities, a visibility function on an agent's beliefs, a pattern of action (i.e., a plan how to accomplish the knowledge management task), and a communication behaviour with interacting agents. The latter is defined by specific interaction protocols for each pair of interacting roles.

The aim of knowledge management roles is to provide a formal description of knowledge management tasks that simplifies the development of agents and agent interactions. One agent can assume different roles and may change them over time. The minimum role model consists of one or more knowledge providers and a knowledge consumer that may negotiate for knowledge transfer using the *Contract Net* (Smith 1980) agent interaction protocol standardised by the Foundation for Intelligent Physical Agents (FIPA). We introduced an extended role model that incorporates, e.g., brokers that help discover information sources provided by other agents or mediation services able to integrate multiple data sources (Langer et al. 2006). In figure 1 some of the knowledge management roles and their interaction characteristics are depicted.

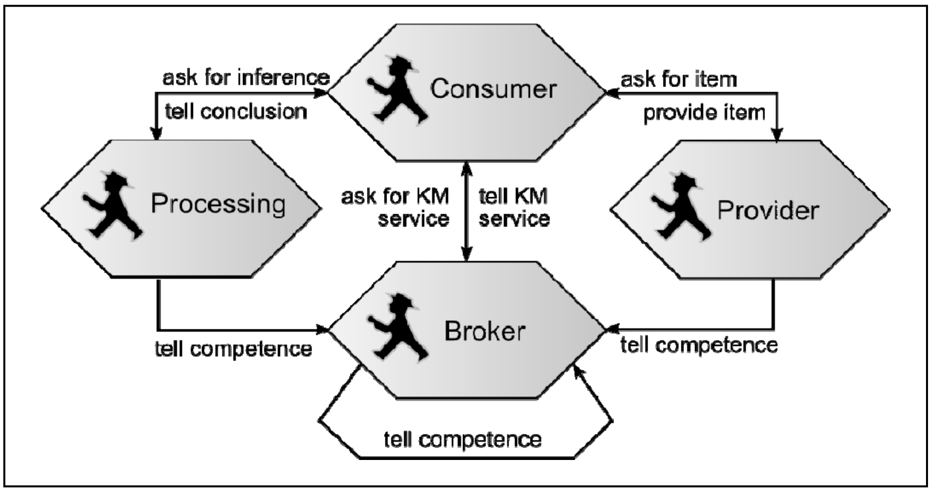

Figure 1: Agent Knowledge Management Roles

4 Coping with Risks by Situation Awareness

On the one hand, autonomous systems reduce certain risks but, on the other hand, they also raise new risks in system operation. The decision process of autonomous agents in logistics depends to a large extent on accurate, comprehensive, and up-to-date knowledge and information about themselves, their environment, and other logistic processes they may need to synchronise with. Whereas humans, to some degree, may be aware of what information is currently relevant for their decisions and whether they have that information or not (*known unknowns*), autonomous agents are not aware of missing information in general. Thus, these systems also need some kind of situation awareness (Endsley 2000) and a measure for its quantification. A potential measure for situation awareness can be derived from information value theory (Howard 1966), i.e., by the difference in expected utility given more information, or sensitivity analysis (Saltelli et al. 2000), i.e., dependency of system output on potentially uncertain inputs.

In this section we will focus on two different examples for risk related to a lack of situation awareness. Both examples are taken from the transportation domain, and both illustrate how the level of risk relates to the level of uncertainty about the environment conditions in logistic processes. The first risk concerns potential transport orders a vehicle agent passes up because it is not aware of them. The other risk concerns the loss of service quality in transportation processes, when the vehicle agent's knowledge about the environment is insufficient with respect to the weather and traffic situation.

4.1 Scenario 1: Knowledge Exchange

In autonomous logistics there will be an increasing amount of orders that are not assigned to contractors based on a long-term general cooperation agreement. In contrary, cooperation is also established on an ad hoc basis. The official parties in such an ad hoc agreement remain companies. But the focus is on particular logistic objects and resources such as freight and its means of transport. The acting representatives in the corresponding negotiation are either humans or, more importantly, software agents that handle one specific logistic object.

The technical foundations of such an agent-based agreement are already available with (mobile) Internet communication and agent negotiation protocols standardized by the IEEE FIPA Standards Committee. But considering an open infrastructure that supports participation of arbitrary companies, there are practical issues that have to be addressed. These issues concern the administration and distribution of information that enable a large number of potential cooperation partners to find each other. A simple broadcast of a principal’s call for proposals would flood the IT infrastructure and overburden other agents with many useless messages. Also a central service brokerage instance is not appropriate because it creates an IT bottleneck as well as a major risk to overall system stability when breaking down. Furthermore, brokers would call for fees and there may be also orders that should be distributed only to a selected group of possible contractor agents.

Cooperation networks could be a solution for these problems. Whenever an order is discovered, e.g., by *local* wireless broadcast communication of such an order by some cargo to surrounding means of transport, and the corresponding call for proposals does not fit a receiver’s requirements, the receiver agent may forward this proposal to cooperating agents. Thereby the cargo’s call for transport proposals is spread over the network (Fig. 2). In order to avoid useless communication agents may have filters to select interesting orders based on general requirements (price, size etc.) or specific interests told by cooperation partners (“Need follow-up cargo in Hamburg area from 4pm”). This is where our distributed agent knowledge management infrastructure comes into play (Sect. 3).

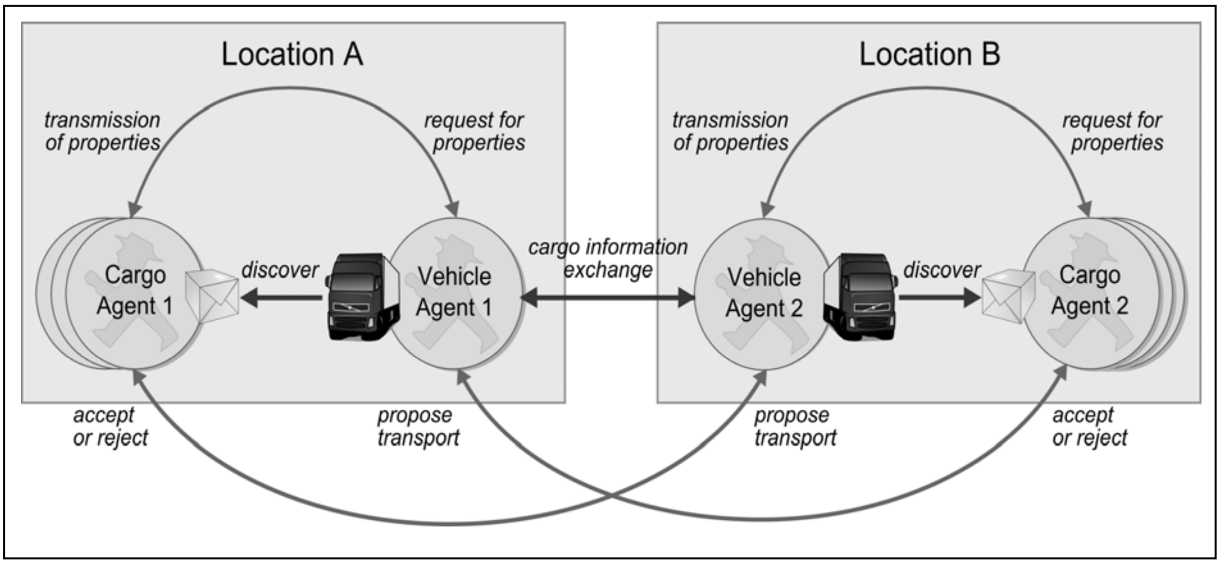

Figure 2: Knowledge exchange on available cargo between cooperating transport vehicles in autonomous logistics.

We conducted multiagent-based simulations (MABS), using the *PlaSMA* simulation platform (Gehrke & Ober-Blöbaum 2007), that model such a collaboration network and distributed service infrastructure. In this setting, a group of four to twelve collaborating transport agents represent single trucks. Another group of truck agents does not collaborate and thus depends on information on potential orders gathered solely on their own. The physical infrastructure they act in was simulated as a torus-shaped 250,000 km^2 area that is structured by a graph of road links. Each node in the graph represents a potential source or sink of transport orders.

The experiments showed that cooperating agents actually profit from knowledge exchange significantly. 20 to 36 per cent of their orders resulted from information previously obtained from cooperation partners. The cooperating agents transported 2 to 10 per cent more cargo than their non-cooperating opponents. Also their downtime could be reduced by 13 per cent in average. Most importantly, they acquired more attractive orders: Their profit increased by 16 to 52 per cent. The difference depends on the size of the cooperation group. Bigger groups were more successful in comparison to non-cooperating agents but less in comparison to the smaller cooperating groups in other experiments. This is because the overall number of available orders (system load) remained the same. That is, cooperation by knowledge exchange is even more rewarding when competition increases. This stresses the importance of situation awareness for agents in autonomous logistics.

4.2 Scenario 2: Knowledge about the Environment

Uncertainty in vehicle route planning is an everyday problem in transportation over longer distances. The shortest route is not always the fastest. Even when considering maximum allowed or average expected speed on single roads the planned routes may prove to be suboptimal. While suboptimal solutions are a natural property in dynamic, open environments with partial observability, usual classical route planning does not make use of much up-to-date or background information that would be obtainable and correlates with travel time. As an exception, many retail car navigation systems include traffic reports in their calculations by excluding congested roads which are within a certain, usually fixed spatial distance from the vehicle.

Thus, we conducted simulation studies (Gehrke & Wojtusiak 2007) that help find the utility or importance of environmental information for evaluating travel time and its application in route planning cost functions. We included location-specific weather information (in pre-processed or even plain textual format) and background knowledge on road traffic. The single-destination vehicle route planning in our simulations applies an A* search algorithm (Hart et al. 1968) with cost function

$$f(r,d,t_{dep}) = g(r,t_{dep}) + h(end_r, d)$$

for reaching destination d when using (partial) route r at departure time t_{dep} with g as the estimated driving time for r and with h as the estimated remaining driving time to d after passing r. Heuristics h is calculated as driving time at straight line distance from end_r to d at maximum vehicle speed. The route r consists of n consecutive road links $l_i \in r$ with $0 \le i < n$. The route segment of first k road links is denoted by $r_{k\text{-}1}$. The estimated driving time g on route r is calculated by:

$$g(r,t_{dep}) = \sum_{i=0}^{n-1} \frac{length(l_i)}{v_{est}(l_i, t_{dep,l_i})}$$

with v_{est} as the estimated vehicle speed on a road. The estimation depends on the vehicle agent implementation. Road link departure time for $i > 0$ is defined by

$$t_{dep,l_i} = g(l_i, t_{dep}) .$$

Because this setting ensures the criteria for the A* algorithm (non-negative costs and optimistic heuristics) it guarantees the optimal solution. However, the route found is optimal only provided that knowledge about the environment used in the cost function for the determination of v_{est} is complete and correct. But assumptions on future road and weather conditions are possibly wrong because the environment continuously changes in a way that cannot be predicted precisely.

We conducted simulation experiments with a traffic model based on real-world traffic census data within the simulation platform *PlaSMA* (Gehrke & Ober-Blöbaum 2007). In a first experiment setting, the vehicle agent determined v_{est} only based on weather information for the locations the vehicle might pass and background knowledge on how weather might influence maximum safe vehicle speed. The experiments (16,000 itera-

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tions for each setting) revealed that the inclusion of uncertain *textual* weather information reduces travel time by 3.5 to 5.1 per cent on average. The simulation model presupposed a moderate weather-to-speed influence model with a difference in expected speed of only 6 meters per second between best and worst weather conditions.

As an adaptation of that study, we included learned travel time predictions in the vehicle agent's route planning (Gehrke & Wojtusiak 2007). This predicting agent is an extension of the above weather-aware agent and uses previous experiences as input to learn situation- and road-specific rules for expected speed with weather conditions, time of day, and day of week as parameters. The applied *Natural Induction* learning approach (Michalski 2004) and machine learning program AQ21 (Wojtusiak et al. 2006) yielded human-readable predictions rules such as

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[Speed=60]
    <= [Day=Mo] & [Time=morning] & [Weather=moderate..good]
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i.e., on a specific road link expected average speed is 60 km/h on Monday mornings when weather is from good to moderate. Rule base queries use the road, available road-specific weather information, and estimated arrival time t_{dep,l_i} as input, with t_{dep,l_i} depending on other predictions. On average, this agent was 6.3 per cent faster than naïve ignorant agents and standard deviation of travel time was reduced by 31 per cent. The predictions were also robust in settings with greater uncertainties (Gehrke & Wojtusiak 2007). Applying such a situation-aware route planning could enhance quality of logistic service and thus bring about a considerable competitive advantage and economic impact.

5 Conclusions

In this paper we discussed two key factors for the robustness of logistic processes, the decentralization of control and the role of information and knowledge. We pointed out that distributed control helps improve robustness, but can also imply new risks because decisions are delegated to autonomous software agents with limited situation awareness. We, therefore, suggest the integration of an explicit knowledge management component into a rational agent that enables reasoning about lack of information about the environment. We sketched a multiagent-based framework for knowledge management and reported the results of simulation experiments which gave strong evidence that, at least in the restricted scenarios which were used in the simulations, the outlined knowledge management approach in fact improves the performance of logistic agents significantly. The experiments also suggested that the relevance and value of additional information in highly dynamic domains is hard to determine without prior experiences in practice or simulation. In future work, we will focus on formal models to measure situation awareness of autonomous systems in order to conduct agent knowledge acquisition as a rational and well-founded reasoning process.

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