Bringing Underused Learning Objects to the Light: A Multi-Agent based Approach

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Abstract. The digital learning transformation brings the extension of the traditional libraries to online repositories. Learning object repositories are employed to deliver several functionalities related to the learning object's lifecycle. However, these educational resources usually are not described effectively, lacking, for example, educational metadata and learning goals. Then, metadata incompleteness limits the quality of the services, such as search and recommendation, resulting in educational objects that do not have a proper role in teaching/learning environments. This work proposes to bring an active role to all educational resources, acting on the analysis generated from the usage statistics. To achieve this goal, we created a multi-agent architecture that complements the common repository's functionalities to improve learning and teaching experiences. We intend to use this architecture on a repository focused on ocean literacy learning objects. This paper presents some steps toward this goal by enhancing, when needed, the repository to adapt itself.

Keywords: Agent · Multi-Agent Systems · Repositories · Metadata · Learning Objects · Analytics

1 Introduction

Due to the advance in e-learning, stakeholders have been employing platforms, tools, and storage widely. At the center of e-learning interactions, the Learning Objects (LOs) have to be concerned with technological and pedagogical aspects for an effective teaching-learning process [21]. LOs also support the Active Learning concept, where instructional methods engage students in the process of learning.

The development of LOs must consider monitoring different aspects that compose the LO's lifecycle, such as authoring, maintenance, and evaluation [9] [21]. Along with these, Learning Object Repositories (LORs) arose to cope with the cited issues. They provide management, discovery, use, and reuse of LOs. Underlying metadata supports LOs' location, dissemination, and harvesting from other applications to handle these subjects [17]. In order to provide some interoperability for repositories, metadata standards also address information for retrieval and exchange. We can cite widespread initiatives to describe LOs at repositories such as Dublin Core [5] as a generic metadata standard, and IEEE-LOM [15] that provides pedagogical aspects.

The advance of open repositories enables the aggregation of several kinds of learning objects that once were at individual websites. With that, it is possible to guarantee the availability of materials, improving the learning experience for students and teachers.

However, Santos-Hermosa *et al.* [17] indicate that most open education-related repositories lack educational metadata and learning goals for LOs. Another issue is that data and metadata fragments have been replicating over repositories, such as authors or intended end-user groups [6]. Furthermore, there is a lack of high-quality services, such as search and recommendation services. Although attempts to automatize quality assessment, they do not rely on models that can predict the quality based on metadata or an intelligent model [19].

In order to improve the user experience, repositories have been incorporating general recommender techniques, such as Content-Based Filtering, Collaborative Filtering, and Hybrid, that focus on the user's behavior (and historical activity) and similarity among users and items [1]. However, they also have to deal with the insufficient existence of data in literature called the Cold Start problem. Besides, some search mechanisms employ ranking metrics to sort results that benefit items with more activity, such as the number of views, downloads, and rates [14]. These approaches can isolate and render obsolete some learning objects in the repository, and users will have difficulty reaching them.

As learning objects are available in a repository, metadata tends to be duplicated or poorly filled. Though, it could bring unsatisfactory services, such as search and recommendations, leading users to use their preferred generalist search engines instead of searching suitable educational material in the repository. These can lead to an underused repository, especially with few accessed learning objects.

Another issue is related to how the users perceive the repository. Most users can consider it just a library of resources and not a place for collaborative learning. So, the possibility of social interaction at repositories does not necessarily entail user participation. Users tend to consume rather than contribute in this kind of environment.

Multi-agent Systems (MAS) are an interesting alternative to deal with these issues, because it is able to model and simulate entities like human behavior. Beyond that, agent-based software systems can be developed in various contexts and interact with several systems [10].

This work combines a repository of learning objects and agents to manage the LO lifecycle in a repository contributing to its proper use. Agent technology is also employed to look at the other side of usage to bring up-to-date underused learning objects in cooperation with their owners. Also, it tries to repackage its metadata to improve its visibility. To evaluate and act on that, we designed the Active-Learning Object Repository (A-LOR) system for learning object repositories improvement, contributing to a more active sharing of LOs, using collaborative agents advising or assisting users in making decisions and reconfiguring metadata.

In the next section, we contextualize this work with our learning object repository Re-Mar. We revise and describe related current works about multi-agent systems and learning objects. The following section presents some technical aspects of the A-LOR based on a multi-agent interaction to provide dynamics in learning object repositories. The paper ends with a discussion and a conclusion to guide future works.

2 Re-Mar: Repository of Marine Learning Objects

Re-Mar[10] [3] is a learning object repository in the context of the multidisciplinary project SeaThings[11]. The project focuses on ocean literacy improvement, providing LOs related to ocean subjects for students and teachers. The repository intends to provide Artificial Intelligence (AI) aspects of LO authoring, recommendations, usage, and searching supported by agent-based tools and ontologies. It is important to note that the marine literacy theme is of primordial relevance in archipelagic regions such as the Azores. Thus, active repository maintenance is a way to introduce this theme in the classroom. Re-Mar follows the MILOS' infrastructure architecture [8] and has a three-layered architecture composed of Ontologies, Agents, and Interface Facilities, as depicted in Fig. 1.

The Ontology level is responsible for the specification of knowledge that the agents will share among them, such as ontologies for the Agent-based Learning Objects (OBAA) metadata, learning domain, and curricular structure. OBAA is a Brazilian metadata standard effort to describe learning objects, compliant with IEEE-LOM metadata that also extends it in several ways to deliver a complete description [20]. Complementary to it, Re-Mar reuses the GEMET[12] thesaurus to provide related marine domain concepts (with Azores terms extension) at searching. A Linked Data repository also stores the LOs' metadata to build a knowledge graph that is machine compliant. Agents could benefit from these machine-understandable artifacts accessed by the Jena[13] framework and Web Ontology Language (OWL) Application Programming Interface (API).

[10] http://re-mar.uac.pt
[11] https://fgf.uac.pt/en/content/sea-things-objetos-de-aprendizagem-para-promover-literacia-oceanica
[12] https://www.eionet.europa.eu/gemet/en/exports/rdf/latest
[13] https://jena.apache.org/

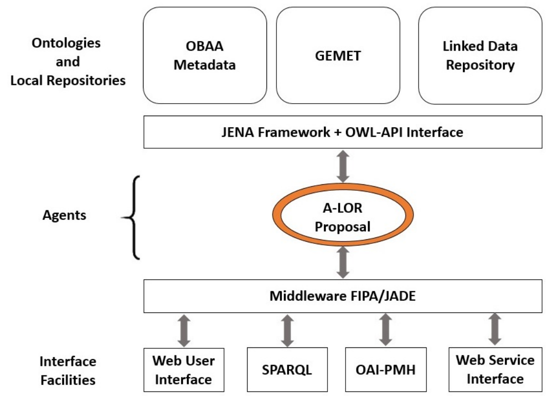

Fig. 1. Overview of Re-Mar infrastructure architecture [4].

The Interface and Facilities level ensures communication with the Agents level by Java Agent DEvelopment Framework (JADE) under the standard Foundation of Intelligent Physical Agents (FIPA) for message exchange. JADE is one of the most widely used tools to create agent-based software systems [10] and supports messages with common understanding through ontology. At this level, e.g., Virtual Learning Environments (VLE), LORs, web servers, and different services can communicate with agents.

At Re-Mar, there is a workflow submission to publish a learning object. After logging, the user uploads the learning object file(s) and thumbnail. Then fill out a form with metadata fields, such as title, description, keywords, learning objectives, and pedagogical strategies. After that, there are the scientific and pedagogical review steps before the learning object is available at the repository.

To monitor the user interaction with LOs, Re-Mar has been storing some useful statistics. Thus, it tracks when a user visualizes, downloads, likes, or rates a LO. As time goes by, the repository naturally separates frequently used LOs from others that are not.

This work will explore the communication among Agents and Re-Mar LOR to get along with this non-generative behavior of users through its use statistics. Agents are employed to cope with the burden of the LO lifecycle, bringing collaborative intelligence between human and computer agents.

3 A review on Multi-Agents Systems and Learning Objects

Diverse techniques can be applied with the agent technology to improve LO reuse, especially in search and recommendation. This section will depict some works related to multi-agents and learning objects.

SIMROAA [13] is a multi-agent system for recommending accessible learning objects. The agents promote the recovery and the recommendation of LOs.

One human agent and another three agents: recommender, analyzer, and data, composed the architecture. The Data Agent leads with the repository metadata. There are no further details on how the Analyzer Agent uses history and knowledge to perceive the environment. The recommender, a content-based model, calculates a similarity measure between the new object and liked objects.

Agents can be used to find suitable partners through conversations and produce a chain-like sequence of LOs. Then, a Multi-Agent Systems (MAS) could automatically create a course content package by remixing LOs based on the input syllabus from different repositories. In the [12] approach, the system has two types of agents: a set of LORs Agents and a single Coordinator Agent. LOs are assigned to the syllabus by a fuzzy coefficient interpreted as a coverage probability.

In the context of learning management systems, the concept of an Intelligent Learning Object (ILO) is presented in [2]. An ILO is an "agent capable of playing the role of a LO, which can acquire new knowledge" of its interaction with students and other ILOs. The system uses the Jadex framework[14] that supports a Belief-Desire-Intention (BDI) agents' architecture. Within this system, additional LOs could be displayed to the student during a learning session, depending on the student's performance. There are no further details about this recommendation.

In [7], a combination of multi-agent systems provides independent services for a LOR. In this work, an ontology-based search engine system has been integrated to catalogue and edit learning object metadata, and assist users without technical knowledge of LO metadata standards.

Learning objects repository and a multi-agent system can also be combined to generate recommendations using clustering learning [11]. LO recommendation results are related to learning style, evaluation by other users, and students' prior knowledge. The clustering agent retrieves numeric metadata from the federation agent to apply the k-means algorithm.

Both tasks of monitoring and incorporating learning object changes can employ Agents. The proposed framework by [18] was composed of Content Change Receptor Agent, Learning Object Change Analyser Agent, Manage Learning Repository Agent, and Learning Content Change Revision Agent. Besides, agents can interoperate through different baseline ontologies for modeling the learning contents, such as lessons, topics, subtopics, and their annotations and instances.

In [16], multi-agents also adapt multimedia documents to users and their devices' interfaces. Agents' cooperation may optimize service plan selection, composition, and execution. Several agents, such as client-server, reasoning, decision, facilitator, and adaptation service, can compose the MAS. The reasoning agent uses ontologies to deduce the adaptation guideline corresponding to one or more context constraints.

All previous works intervene, at some point, in the learning object lifecycle with multi-agents. However, none of them monitor LOs' use and reconfigure

[14] https://www.activecomponents.org/

metadata of unused learning objects. Also, we work with a multi-criteria methodology to analyze not only likes or numeric metadata.

4 Active-Learning Object Repository (A-LOR)

In this section, we present an overview of the multi-agent architecture that supports the A-LOR. It is expected to provide engagement to LOs in their repository lifecycle and to improve their usage by users over time. The main idea is to carry LO's information by agents to furnish a set of features that can turn LOs more proactive in a repository. In this way, the agents will always be concerned about the shared educational resources repository, providing an active ("dynamic") environment.

4.1 A-LOR's agents overview

A-LOR has seven agents, as depicted in Fig. 2. They communicate using FIPA Agent Communication Language (ACL) messages and may share an ontology with typed communicative acts. We start by explaining the role different agents have in this architecture. Then we present what we have done regarding achieving the objectives.

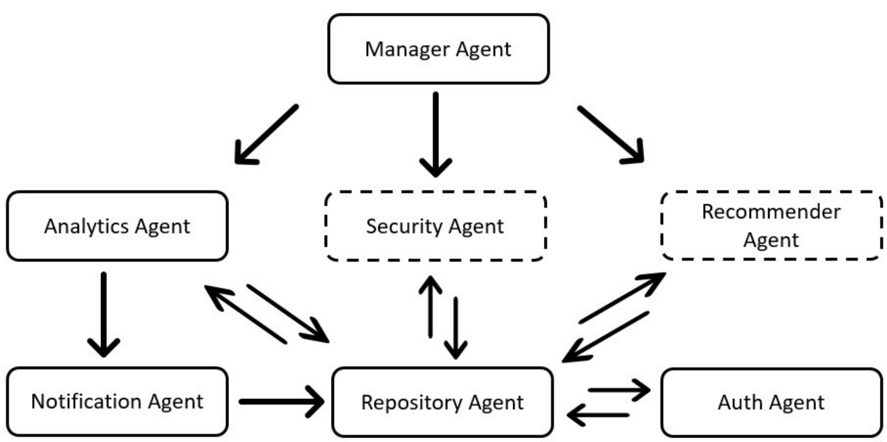

Fig. 2. A-LOR overview of agents' in a communication diagram.

The Manager Agent is the central agent of the social organization. This agent knows the majority of agents and their functions. Its purpose is to act as a "daemon" and enable the other agents' tasks according to a certain period.

One of the seven agents, the main scope of this work, is the Analytics Agent. It is responsible for the evaluation and management of the learning object repository. It reaches all available LOs communicating with the Repository Agent.

After evaluation, it reports to the Notification Agent that calls the Repository Agent to store a notification. Then the LO's owner (who submitted) could show the LO on the Re-Mar's main page, update its metadata, share the LO on social networks, or even do nothing about it at the moment.

Furthermore, this agent can perceive the LO usage and usability statistics. For instance, it can identify the most prolific authors, often LOs used to generate new LOs, main knowledge areas with more examples of LOs, or keywords used by users with scarce LOs examples. In addition, it can understand which LOs are underused and propose to the owners to edit the metadata or make a new classification to improve its use.

The Repository Agent is responsible for the tasks related to the local repository that stores LO's metadata and statistics. Some repository-related tasks are search, store, update, and delete. Before performing these database operations, this agent has to call the Auth Agent to obtain a valid JSON Web Token (JWT) for authorization privileges.

After well-established analytics, a Recommender Agent will interact in the organization. It can assist users while they are filling in metadata for authoring. For example, with title and description, it can suggest suitable keywords. The offered suggestions can concern reusing already described previous metadata fragments. This agent is also responsible to provide LOs suggestions by analyzing users' profiles and ontologies. It can help in LO searching by providing related concepts to terms searched by users through a semantic search in local/external ontologies.

Another concern is related to the security aspects of the learning object repository. Thus a Security Agent could monitor the repository, searching for malicious files or users.

The Recommendation Agent and the Security Agent have not been implemented yet. For this reason they are with dotted ellipses in Fig. 2.

4.2 Analytics from statistics of use

The Analytics Agent can process a large volume of data. As depicted in the sequence diagram of Fig. 3, this agent is dynamic, and the Manager Agent can active it with a call after a time window, e.g., each month. In its task, the Analytics Agent evaluates all active LOs by requesting them to the Repository Agent. After the evaluation, it sends a message to the Notification Agent to organize the information stored by the Repository Agent. This stored notification will advise the user in the repository after a new login.

This agent evaluates LO's usage statistics (s_i) in the repository, such as the number of visualizations, downloads, rates, and likes. Re-Mar also monitors the owner's actions in the notification loop, how to show OA on the main page, and edit metadata doing a review. Note that reviews here are the number of times LO stepped back to the workflow submission for the edition. It is natural for recent learning objects to have lower scores, so LOs more recent than the time window is not considered in the assessment.

Due to the previous history of interactions, it is clear that usually are more views than downloads, likes, and rates. To balance these attributes (n), we employ a weighted average score function stated as:

$$Score = \sum_{i=1}^{n} \frac{w_i * s_i}{w_i} \tag{1}$$

Our score function provides a higher weight (w_i) to reviews than other measures such as being on the first page, notifications, rates, likes, downloads, and views. In the current round of tests, we attached 20, 15, 10, 8, 7, 4, and 2 as weight values, respectively. The weights reflect the importance degree of the measures in the final score used for the decision. These can drive underused LOs to gain preference and visibility. This approach uses multi-criteria decision analysis concepts, namely a weighted decision method.

Table 1 exemplifies the learning objects' data (by id) organized by groups and ordered by score. We can note, for example, that the LO with id 53 (LO_{53}) has more downloads and views than the LO_{16}. However, the LO_{53} score is lower than the LO_{16} because of the number of rates and likes. As is common in weighted decision methods, compensations and trade-offs are possible. Another concern is to preferably LOs that have not been notified yet For example, the LO_{37}, even with more balanced usage statistics than the LO_{50}, has a lower score because it has no notifications.

Table 1. Tracking user interactions to score learning objects

w_i	s_i	LO_{54}	LO_{53}	LO_{16}	LO_{47}	LO_{37}	LO_{50}	LO_{38}	LO_{40}	⋯
20	#review	0	0	0	0	0	0	0	1	
15	#atMainPage	0	0	0	0	0	1	1	1	
10	#notification	0	0	0	0	0	1	1	1	
8	#rate	0	1	2	3	5	2	10	21	
7	#like	1	1	5	1	5	3	7	13	
4	#download	1	4	3	5	7	3	16	28	
2	#view	1	7	5	13	15	38	44	51	
	Score	0.1970	0.6818	1.1061	1.1667	2.0152	2.2727	4.6364	7.8485	⋯

In this way, we consider an ascending score ranking to underused LOs (with lower scores) in the repository. With that information, the agents can suggest actions to concede more visibility to specific LOs.

4.3 User Notification

When the Analytics Agent completes the evaluation, it generates a list of interactions for each LO in the repository based on the pre-defined weights, as depicted in Table 1. Then it gets the first five items of the list ordered by an ascendant score to deliver to the Notification Agent. Then this agent prepares the data to be stored by the Repository Agent.

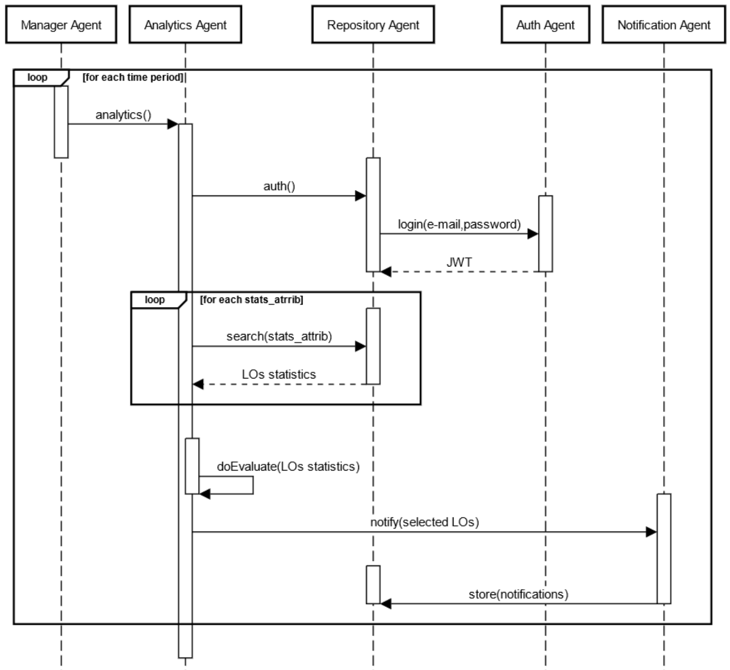

Fig. 3. Sequence diagram for analytics.

In this way, after login, each owner of these five learning objects is notified, as depicted in Fig. 4. The owner can accomplish four static actions related to the LO. (i) Present it on the main page for a while (the same time window that Analytics Agent waits to act). (ii) Edit its metadata to add/modify some information. (iii) Share it on social media. (iv) Do nothing about it this time. When the owner chooses no action, the Notification Agent expires the previous list before storing the new notifications. There is also a limit of three times in sequence with option iv selection.

5 Discussion

The concrete utilization of a learning object is difficult to notice. In the ReMar repository, interactions such as rating and likes are measures to understand when a user interacted with the learning object since download and visualization measures may not reflect such attention.

Instead of giving the spotlight to trending learning objects in a repository, A-LOR's focus is on trying to balance proper use. It hopes to reach some key points to promote the dynamism of LOs. (i) Flexibility: with an adjunct agent architecture, it is possible to add or modify agents without affecting the main functionality of the repository. Agents can also communicate with users inside and outside

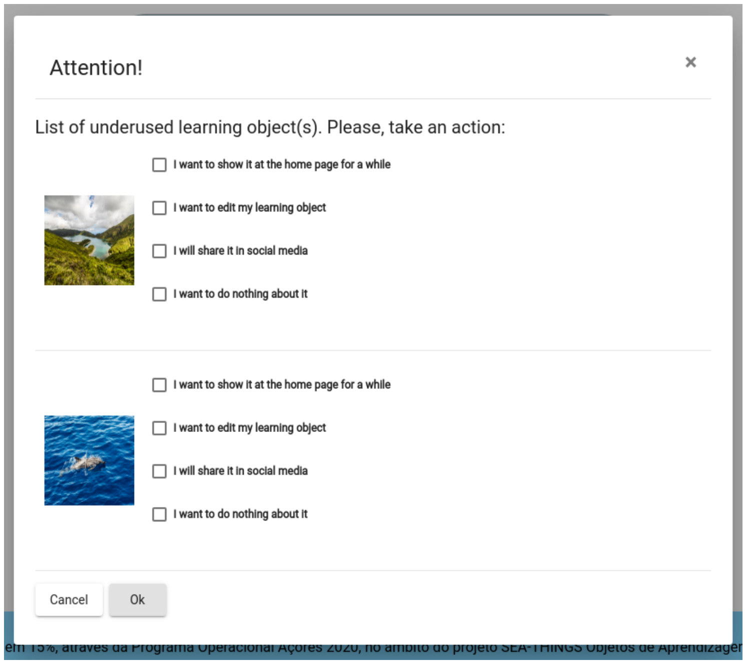

Fig. 4. Notification window for user decision-making in Re-Mar.

(*e.g.* social networks) the repository, promoting LOs or requesting some LO improvement. (ii) Advanced search: use the agents' interface to search across multiple linked data endpoints, helping users fill in metadata and search the repository through a knowledge graph. (iii) Feedback: request comments/assessment of users to improve LO recommendations. (iv) Analytics-oriented: wrapper similar group of learning objects to provide helpful new metadata and classification. Also, employ a usage rank for users and LOs based on related search terms, views, downloads, and reuse relations. (v) External repositories: to have more than one repository for searching related material and use agents as a communication interface. (vi) Metadata verification: utilize OBAA metadata ontologies to group close-matching LOs and verify metadata consistency.

The analytics granularity also can be taken into account. Aspects considering a specific LO, LOs groups, or even an entire repository. Some statistics assess the richness of the repository. The need to estimate how the repository's assessment uses some metric is relevant to provide managers feedback continuously. Statistics from the number of users vs. active users, LOs submitted vs. LOs reused, accesses vs. downloads, and knowledge area vs. LO type are possibly related the way LOs disseminate in the user community.

Temporal aspects are also relevant in defining a time window for analysis. How to define when a LO was widely used? How long should be the time window? Do students tend to consume the LOs just in-class semesters? The Analytics

Agent could act to answer these questions with gathered statistics. In addition, it still has to consider a learning process that improves weights and attributes (usage statistics) over time.

With a considerable amount of data and the use of unsupervised learning techniques, such as clustering and other methodologies (*e.g.* analog search), we can predict the usage of new LOs. Using examples of a similar group of LOs that have been in the repository for some time, it is also possible to predict what type of user can utilize a new LO for learning. This information could be sent to LOs producers to improve the construction of new LOs or enhance the ones already in use.

Furthermore, exploring AI techniques can support agents learning through their lifecycle and interaction. Suggest a LO classification within a group could be achieved with Machine Learning techniques. Also, Deep Learning technology with active learning algorithms can explore LOs interactions among them. LO usage and how metadata values are defined could use Reinforcement Learning.

6 Conclusion

General repositories have not achieved their full potential yet. They usually operate as the old libraries where the LO stays, waiting for someone to get interested in it. This behavior, allied to common recommender systems, usually favors just the trending learning objects. In this way, LOs tend to be like immutable artifacts.

This work aims to enhance learning objects in repositories to be more active in their lifecycle through an agent-based auxiliary system. The goal is that agent groups could interact among them to provide new functionalities to the repository to embrace the LO owners' side despite the related works that usually involve the LO users.

The proposed A-LOR system has seven main agents that cooperate in providing LOs with improved performance on LORs. Our approach shows that agents afford a flexible solution and that a multi-criteria decision analysis can be used with agents to deliver a decision method.

The next objective, continuing this work, is that agents could interact and learn among themselves to enhance LORs to be more active. Therefore, agents can help users concerned about the impacts of LO metadata in the environment (repository).

In future work, with the amount of LOs growing in the Re-Mar repository, it is expected to re-evaluate the A-LOR to have a continuously active repository. With a critical mass of data, Artificial Intelligence techniques can play a major role in helping agents to reach their goals.

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