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Tourist services management through clients scoring using a bio-inspired agent architecture ⋆

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Abstract. Tourism has become an economic engine for several countries during the last decades. Each time more and more individuals consider visiting other places during their vacation period. These places cover very different options, from the typical beach and mountain tourism to the less common urban and cultural trips. These travels hoard multiple transport means and facilities in the destination place that have to be correctly managed. Therefore, the rise of automatic systems to address the related operations and processes is a crucial issue nowadays. These systems are usually focused on the final users (the tourists) and make recommendations about their available possibilities. However, it is not easy to find a multi-purpose recommendation system covering all the needs from the perspective of the travel agency. In this paper, a complete framework called *Pharaoh* able to make recommendations to customers covering the final user perspective, and to provide support to the travel agents, is presented. This assistance filters the best travel, accommodation, and activity options according to the desires of the customers. This novel functionality allows selecting the customer with the best propensity to book a tourist service. This workload is distributed using a bio-inspired Multi-Agent System (MAS). Moreover, *Pharaoh* considers the feedback from clients after the completion of the tourist opportunity to improve future recommendations. Several experiments in real environments have been addressed to show the viability of the proposal. It can be concluded that the system enhances the quality of the service provided by the travel agency and its profits.

Keywords: Tourism, Recommendation system, Propensity assessment, Intelligent agents, Smart assistant framework

1. Introduction

Today, tourism is one of the world's most profitable industries [10]. Each year several tourists travel to visit famous cities and mythic architectures or to meet new cultures

⋆ It is an advanced release of a previously published conference paper: Moreno, R., Viajes, M., Fernández-Isabel, A., de Diego, I. M., Moguerza, J. M., Lancho, C., & Cuesta, M. (2022, September). Automatic detection of potential customers by opinion mining and intelligent agents. In 2022 17th Conference on Computer Science and Intelligence Systems (FedCSIS) (pp. 93-101). IEEE and ways of living. Moreover, other tourists only look for revelry or calm and relaxation during vacation time, where wonderful landscapes and beaches light up the stage [42].

All these travel events produce the use of several means of transport like airplanes, trains, buses, and cars [12]. These events generate millions of bookings in hotels, apartments, and other similar buildings specifically dedicated to hosting tourists.

All these issues must be managed by travel agencies, retrieving the information from destination places, and the preferences of the different tourists [34]. Therefore, the appearance of systems focused on providing support to the final user (the tourist and the travel agent) that simplifies the booking process is necessary.

Furthermore, travel agents also need support to provide customers with the most interesting options to capture their interest. Therefore, systems able to manage this task automatically, making recommendations of the most suitable places and trips, or selecting the best transport schedules according to the client´s needs are also basic [46].

Nevertheless, these systems have their limitations. The main bottleneck consists of the difficulty of elaborating budgets by the travel agency employee. It is a very time-consuming task since the configuration of a trip increases its complexity when multiple destinations are selected. Another relevant problem is the typical inability to provide feedback about the tourist services offered to clients. This point is essential for travel agencies because they need to know if the work achieved was adequate and if customers were satisfied after finishing the contracted tourist event. In this sense, the recommendations that filter the initial preferences of the clients are the key point. These usually mark the proper evolution of the tourist services, as they must capture the interest of the client in the first instance.

The COVID-19 outbreak is another point to consider in the tourism area. The pandemic situation all over the world has caused governments to implement several restrictions to control the spreading of the coronavirus. This has had a drastic impact on the mobility of the population, reducing the number of travels, and, as a consequence, tourism has suffered significant economic losses [6]. However, with the advances in vaccination programs and the relaxation of the measures against the contagion of the virus, the rise of tourism is going to become a reality very soon.

For these reasons, it is mandatory the development of a complete framework that can cushion this new growing demand. This system must be able to address the weak points detected, managing and encompassing all the possible issues produced since a client shows interest in a tourist event, providing support to the travel agent in the selection of the possibilities, and finally obtaining the feedback of the client when the tourist service concludes.

Notice that the strength of a framework of this type lies in the management of tourist packages where multiple destinations and services are contracted. Typical examples of these trips are, among others, honeymoons and cruises.

In this regard, this paper presents the *Pharaoh* framework. It is an automatic analytical Enterprise Resource Planning (ERP) and Costumer Relationship Management (CRM) system for Travel Agencies that includes several graphical assistants to provide complete support to travel agents and tourists. Its novelty resides in the next points:

– It covers all the processes related to tourist services sales, focusing mainly on the interest of the client and the specific bargains that fit better for the travel agency.

Thus, travel agents and clients are guided synchronously by the opinion produced by the system at each step of the sale.
- It generates budgets in a fast way and with quotations in real time. This fact facilitates the decision-making tasks of the travel agencies and the client can be informed at the moment about the best individual available options or combinations in specific tourist packages.
- It can learn from the experience and can prioritize those clients who are prone to commit the book of tourist services. Notice that this ability is one of the most differential strengths of the proposal regarding other existing approaches. An Machine Learning (ML) model to estimate the probability of the sale has been included in the system to achieve that point.
- Intelligent agents following a Multi-Agent System (MAS) have been included to establish communication and knowledge interchange. This MAS has been built according to the rules of a bio-inspired anthill, efficiently promoting the distribution of the workload [35]. This is relevant because companies usually need real-time interactions to satisfy the requests made by customers and maximize the benefits through saving computer resources (e.g., possible expenses in specific cloud computing architectures).

A set of experiments has been achieved to show the viability of the proposal. The module in charge of selecting the best clients has been tested independently to evaluate its potential. Then, the complete system and its functionalities have been put into the spotlight. Promising results have been obtained from these tests.

The remainder of the paper is organized as follows. Section 2 introduces the foundations and relevant literature. Section 3 details the architecture and the different features of *Pharaoh*. Section 4 presents a set of experiments to illustrate the performance of the system. Finally, Section 5 concludes and provides further guidelines.

2. Background

This section introduces the foundations of the *Pharaoh* framework, covering the different perspectives included in it together with the existing state of the art in the tourism domain. First, an overview related to the knowledge management systems is achieved. There, it is detailed how this kind of system works, and similar approaches that provide interesting features are addressed. Second, recommendation systems are introduced explaining how they are used in real environments. The different perspectives of these systems are also detailed in this point. Finally, previous approaches oriented to managing tourism-related processes by travel agencies and customers are presented.

2.1. Recommendation systems

Recommendation systems are mainly focused on filtering the information they store. This filter is flexible and adaptable to the requirements and interests of the users [1].

Delving into the filtering process, these systems produce a profile for each one of the users. This profile contains the different parameters that are used to measure (and consequently compare) the interests of the user.

The parameters that produce the user´s profile can be provided to the system during the registration process of the user, or they can be included and modified during the interaction of the user with the system. This latter is the more relevant, as it allows the system adaptation to possible fluctuating opinions and interests of the users. Moreover, it also eases the improvement of the system, making it more accurate in the recommendations each time, as it can know if the previous recommendations were satisfied for the user. A well-known instance of this approach is the recommendation systems based on reinforcement learning [24].

Recommendation systems usually use three main perspectives to achieve the recommendation process: the selected topics, the relevance of the content, and the associated reputation. Notice that these perspectives are not excluded and they could be found mixed in some recommendation systems.

Systems that consider the topic recommendation perspective focus on the most common elements the users usually select. Thus, the software learns from the user according to the preferences [30]. For instance, if a user shows interest in beach destinations on a travel website, the recommendations should be related to other beach spots they might find appealing. This method aims to offer visitors new yet potentially attractive destinations, based on the preferences of users with similar profiles.

Systems for the relevance of content perspective are focused on the importance or popularity of the element to make recommendations. This importance is measured according to the number of users interacting with the product. Thus, these systems usually generate popularity rankings to promote the easy consultation of the products [25]. In tourism recommendation systems, if a point of interest attracts many visitors and stands out for its popularity at a given time, the system highlights it, presenting it among the top suggestions to the user.

A system based on reputation provides recommendations according to the obtained feedback [32]. In hotel competitiveness, where good service is crucial, positive feedback boosts the hotel's importance, improving its reputation. In contrast, negative feedback lowers its value, affecting its place in the market. They are specifically designed to reduce the uncertainty for the users and facilitate trust between entities [7]. A well-known instance is shared online where several users sell different products. Those systems usually support products and users with a better reputation.

In the case of the *Pharaoh* framework, it is a recommendation system that includes the three perspectives. Thus, it can organize different travels according to the topic (e.g., business, relaxation, or party among others), according to the relevance (e.g., well-known travel companies can be filtered), and also according to the reputation thanks to the feedback the users can provide when the travel finishes. Moreover, the system can also make recommendations to the travel agent regarding the possible customers. Therefore, this fact could be classified into the relevance-based recommendation perspective.

2.2. Intelligent agents to distribute the workload

Intelligent agents are software abstractions able to establish communication channels (direct or indirect), sharing a common environment. There, they interact with other agents and with the environment extracting and providing different pieces of information. These particularities allow the agents to simulate complex behaviors from the real world [18].

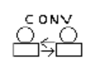
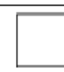
Concept	Meaning	Icon
Agent	An active element with explicit goals that is able to initiate some actions involving other elements of the simulation.	
Role	A specific collection of tasks performed by agents when pursuing a goal or offering some service to the other members of the society. It has as a result a specific behavior.	
Environment Application	An element of the environment. Agents can act on the environment using its actions and perceive information through its events.	
Goal	An objective of a role/agent. Roles/agents try to satisfy their goals executing tasks. A goal is achieved or fails if some elements (i.e. frame facts and events) are present or absent in the agent groups or the environment.	
Task	A capability of a role/agent. To execute a task, certain elements (i.e. frame facts and events) must be available. The execution produces/consumes some elements as result.	
Frame Fact	An element produced by a task, and therefore by the roles/agents.	
Mental State	Part of the internal state of a role/agent. It groups goals, frame facts and events, and specify conditions on them.	
Belief	Part of the mental state. It contains the knowledge (specific, role-based or general) that an agent possesses. This knowledge can be used to interact with its surrounded environment.	
Conversation	Communication between two or more agents to exchange information. One of these agents plays the role of initiator of the conversation, while the others are the receptors.	
Plan	Representation of the means by which a goal can be satisfied. It is usually structured to provide a deterministic meaning to the operations.	
Mental State Manager	Part of the internal state of a role/agent. It provides for operations to create, destroy and modify mental entities.	
Mental State Processor	Part of the internal state of a role/agent. It determines how a mental state evolves, described in terms of rules or planning.	

Fig. 1. Main concepts of INGENIAS for developing MASs

Regarding the features of the agents, they are proactive, autonomous, and independent. Agents base their knowledge on predefined rules to tackle the raised problems. Their ability to interact can be exploited to solve complex issues or to distribute the workload with certain coordination.

The life cycle of intelligent agents consists of satisfying a collection of goals following the knowledge available (from a predefined set of rules or dynamically acquired from the environment or other agents), and through several associated concepts (see Fig. 1). These goals can be independent, or they can be organized hierarchically. This latter promotes the idea of having sets of sub-goals that accomplish other goals at higher levels when they are satisfied. Goals are associated with a task (or a set of them) that is executed by the agents. Both goals and tasks are elements of the mental state of agents. This mental state plays the role of a mind, being the place where the set of rules and knowledge are stored. Therefore, it supports the execution of the tasks and the satisfaction of the goals.

On the other hand, agents can take advantage of their ability to interact with the environment to solve complex problems having partial or reduced knowledge about a problem. The organization in MASs opens the collaboration, the competition, and also the negotiation. Agent-Based Modeling (ABM) [43] and Agent-Oriented Software Engineering (AOSE) [17] are standards in the domain that provide the elements and entities to address this issue. Well-known approaches that use MASs to solve complex problems or simulate real environments are road traffic simulations [13], distributed decision support systems [20], bio-inspired ML-based systems [9], and computer games [44].

MASs are usually designed using specific artifacts and entities to address the development phases of complex systems. It allows the production relationships and interactions between agents that are graphically represented and later transformed to source code automatically. INGENIAS, GAIA, Prometheus, and Tropos are well-known agent modelling methodologies in the domain [40].

Agent platforms are usually the standard solution to implement a previously modelled MAS. These platforms are commonly organized into source code libraries of a specific programming language. There, they include features to ease the distribution of the agents and manage their communication channels. Highlighted approaches in this area are JADE (Java) [8] and MESA (Python)[26].

For the development of *Pharaoh*, the selected agent methodology has been INGENIAS, adapting the agent model to the MESA framework for implementation purposes. The agent model is a bio-inspired distribution model based on the organization of ant colonies to generate a MAS distributed in several cumuli of agents (anthills) working together or independently according to the workload of the system.

2.3. Automatic managing of tourism

Automatic tourism management is one of the basic tasks in the area due to the large number of different processes to consider related to available offers, journey configurations, marketing opportunities, and customer indications and preferences [27]. In addition, travel agencies are evolving to manage tourist packages and customer preferences through the Internet. This means that personal relationships and face-to-face meetings have been changed for interactions with web pages that provide support and guidance.

The tourism management process is based on two main perspectives: the client and the seller (i.e., the final destination or the travel agency). The first one is the most widely addressed by the different studies and the developed systems. This issue is related to the implementation of new technologies and e-tourism (i.e., marketing and offers of tourism services on the Internet), which means that the tourist provider has direct contact with the customer [21].

Regarding the approaches that automatize the different tourism-related processes, most of the systems are recommendation systems for both perspectives.

In the case of the perspective of the travel agencies, they usually face clients who do not know where to travel and what their preferences are. Therefore, systems able to extract and process information from clients could provide support to the decision-making or to select the optimal vendor from the company for that customer [23]. The information can be textual content [28] or generated through the creation of profiles [2].

In the case of the perspective of customers, there are several possibilities to address. For instance, systems able to elaborate specific trip configurations for clients with special needs are very useful [36]. However, other approaches are more general. Examples of these general approaches are those that are focused on the selection of the best route according to the current weather or traffic conditions [41], or the recommendation of the best tourist trips for individuals or groups [22]. These latter are like virtual trip planner designers [3] that are usually based on the tastes of the clients and their former trips already completed [16]. For destination selection, similar systems have also been considered. They process the opinions of the tourists to find the most popular places for them [48] and also produce rankings of interest [4]. Finally, the issue of finding a suitable residence to live in during the journey according to the specific features of the client has also been considered. These features are mainly the needs of the clients [14], and their economic capacity [38].

The *Pharaoh* framework is mainly focused on the travel agency perspective providing specific elements to interact with the clients. In the first case, the vendor obtains real-time recommendations according to the indications made by the clients and their interests. Moreover, the system presents a novel component able to inform the vendor about the clients who are more prone to buy a tourist activity. This eases the work and increases the profit of the agency. In the second case, clients can introduce their particularities and interests. The system uses these to provide filtered information to the vendor.

3. The Pharaoh framework

The main objective of the *Pharaoh* framework is to support customers and travel agents (i.e., the final users in the tourism domain). Therefore, the system is a ERP and CRM that covers both perspectives related to tourist service management.

From the tourist perspective, *Pharaoh* provides different tourist services according to specific preferences and features (i.e., customer searches and filters the available options). From the travel agent's perspective, the system makes available the most relevant tourist services according to the preferences provided by the customer, the previously configured ratings, and the feedback provided by former customers about previous experiences with the tourist service of interest. Moreover, *Pharaoh* includes a novel functionality for easing the selection of the optimal customers (i.e., those prone to complete the booking process of a tourist service). This functionality allows travel agents to establish priorities and different actions according to each customer.

The system uses several information sources to obtain the desired knowledge like available hotels, flights, cars, etc. It also includes a visualization tool where users (customers and travel agents) can interact. This tool is composed of different graphical assistants to support the different tasks implemented by *Pharaoh*.

The following sections detail the architecture of the *Pharaoh* framework considering the different modules and emphasizing the processes that cover its functionalities.

3.1. General architecture and modules

The architecture of the *Pharaoh* framework consists of five different modules: the *Information gatherer*, the *Tourist service manager*, the *Customer manager*, the *Travel agent*

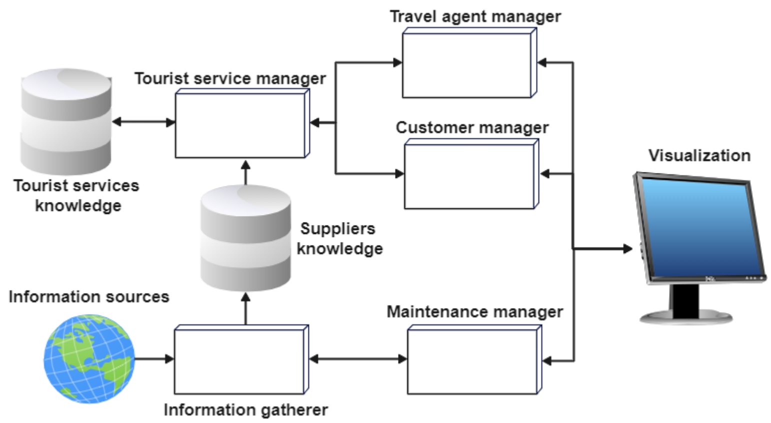


Fig. 2. Overview of the architecture of the *Pharaoh* framework

manager and the *Maintenance manager*. These modules are completed with two knowledge bases to persist the information: the *Suppliers knowledge* and the *Tourist services knowledge* repositories (see Fig. 2). These modules are capable of carrying out the three main processes: sale of a tourist service, customer feedback, and information update.

The *Maintenance manager* module serves as a central point for the maintenance of information and common parameters used by the rest of the modules of *Pharaoh*. Typical examples of maintenance of the information are related to the modifications of the tourist resource (e.g., name changes of hotels, new appearance of companies in the market, or permanent close events). It is also necessary to have the mapping of the same tourist resource from different providers to facilitate the system to generate services with different rates. It uses the *Information gatherer* module to achieve these actions (see Fig. 3).

The *Information gatherer* module collects the information from the virtual tourism market. This market is based on the exchange of information coming from web sources between suppliers and consumers through XML and JSON technologies. The module retrieves two types of information: static and dynamic. The first is not frequently modified, like the name, description, features, and relevant pictures. The second one fluctuates several times daily. Typical instances of this type of information are the occupancy level of a hotel or the rates. This information is gathered through web scraping techniques to automate the process and stored in the *Suppliers knowledge* repository. It is important to indicate that some sensible information is not stored due to contracts with suppliers, being only passively consumed by this module.

The *Suppliers knowledge* repository has as the main objective to manage the acquired knowledge corresponding to suppliers. The visual interface of *Pharaoh* provides specific graphical assistants to guide the user in managing this task. The system uses this stored information to produce automatic recommendations.

The *Tourist service manager* module is in charge of managing tourist opportunities and creating personalized offers to make recommendations (see Fig. 4). These recommendations are based on the calculations focused on providing the best tourism-related resources for an operation ordered by interest. Thus, it is defined the type of each tourism resource grouped by category. In the transport category, flights, collective public transport

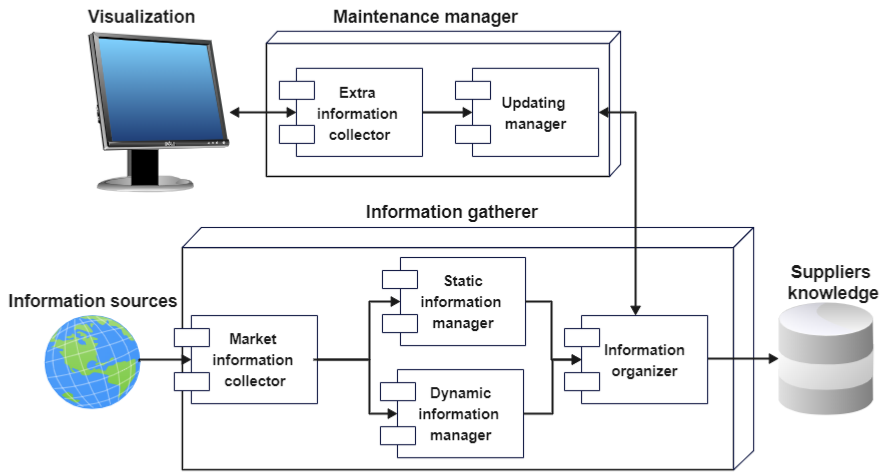


Fig. 3. Except of the *Maintenance manager* and *Information gatherer* modules

(e.g., trains or buses), and renting of private vehicles are included. In the accommodation category, hotels, apartments, and similar places are considered, Finally, in the extras category, tourist activities (e.g., tourist visits or reserved circuits in the destination) and insurance are classified here.

The expression that provides the best tourist resources to configure a complete tourist service (TS) is described as follows:

$$TS = \max_{k \in \{1,\ldots,|T|\cdot|A|\cdot|E|\}} TS_k = \sum_{C \in \{T,A,E\}} \theta_C \cdot Score^C \tag{1}$$

where T is for transport, A is for accommodation, and E is for extras. In addition, the θ values are weights from 0 to 1 to indicate relevance. Note that the sum of these weights must be 1. Moreover, $Score^C$ is the average value of the values $Score_j^C$ corresponding to the selected tourist resources of the tourist service. Thus, $Score_j^C$ is defined as follows:

$$Score_j^C = w_{u,j}^C \cdot f_{u,j}^C + w_{e,j}^C \cdot f_{e,j}^C \tag{2}$$

where $j \in \{1, \ldots, |C|\}$, where $|C|$ is the number of elements in category C. The values denoted with w are the weights of the partial contributions to the global score subsequently defined.

The element $f_{u,j}^C$ is about the preferred variables, and it is expressed as follows:

$$f_{u,j}^C = \frac{1}{n} \sum_i^n preferred_{j,i}^C \tag{3}$$

where $preferred_{j,i}^C$ is a value $\in [0, 1]$ indicating the feedback value provided by customers based on their previous experience. Thus, $f_{u,j}^C$ is the average value of the opinions of the customers.

In the case of the element $f_{e,j}^T$, it depends on the considered category (T, A, E):

$$f^T_{e,j} = w^T_{quality} \cdot quality^T_j + w^T_{stopovers} \cdot stopovers^T_j + w^T_{time} \cdot time^T_j + w^T_{price} \cdot price^T_j \quad (4)$$

$$f^A_{e,j} = w^A_{quality} \cdot quality^A_j + w^A_{location} \cdot location^A_j + w^A_{services} \cdot services^A_j + w^A_{price} \cdot price^A_j \quad (5)$$

$$f^E_{e,j} = w^E_{quality} \cdot quality^E_j + w^E_{flexibility} \cdot flexibility^E_j + w^E_{services} \cdot services^E_j + w^E_{price} \cdot price^E_j \quad (6)$$

At each category, it is considered a set of measures with values $\in [0, 1]$. With the Transport Category: *quality* means the quality of the transport, *stopovers* means the number of possible stopovers, *time* means the estimated time spent to reach the destination, and *price* means the expensiveness. With the Accommodation Category: *quality* means the quality of the accommodation, *location* means the location concerning the distance to the tourist areas and the safety of the area, *services* means the level of the provided services, and *price* means the expensiveness. Finally, with the Extras Category: *quality* means the quality of the extra, *flexibility* means the flexibility in hours and hiring, *services* means the level of the provided services, and *price* means the expensiveness. Note that these measures are pondered by weights w whose sum is 1 for each category.

With the measures from each one of the categories, the system intends to answer the following key questions for a trip:

– *HOW*: by defining the quality or level of the resource.
– *WHEN*: by classifying the time needed for reaching the destination.
– *WHERE*: by classifying the place and its surroundings.
– *WHAT*: by classifying the acceptability of the extra resource in terms of what is offered.
– *WHY*: that defines the set of extras and safety offered by the resource.

The module is responsible for filtering customers according to their propensity to complete the purchase. A propensity purchase estimation algorithm is in charge of establishing this classification. This algorithm uses classic scoring processing techniques and two different ML methods in a two-layer architecture to categorize the clients into five groups according to their booking probability. More details about this issue are presented later.

The module comprises three components: the *tourist services organizer*, the *tourist service filter* and the *customer feedback gatherer*. The first contains a MAS to distribute the workload and achieve the decision-making task parcelled out. The second is in charge of filtering activities according to the requests made by the customers, and the third manages the feedback provided by these latter.

Regarding the MAS, it achieves tasks related to the ML methods using a bio-inspired structure based on an anthill with a queen (one per anthill), soldiers and several workers agents. The queen agent distributes the different tasks between the soldiers and builds the final result. The soldiers organize the requests and make use of the workers to tackle the problem. This agent architecture is relevant for applying possible load-balancing politics.

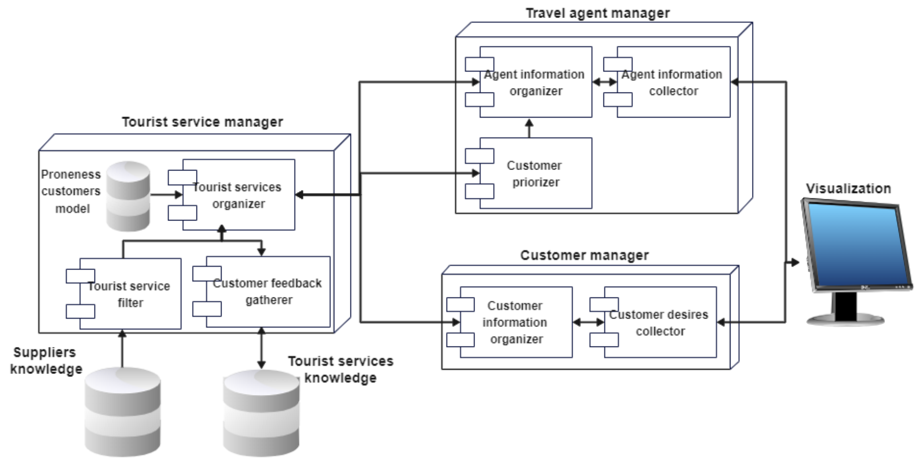


Fig. 4. Except of the *Tourist service manager*, *Travel agent manager*, and *Customer manager* modules

These politics consist of creating new soldiers and workers, or even new complete anthills to increment the capability of the system. More details about the MAS are provided in the next sections.

The *Tourist services knowledge* repository stores the information related to contracted tourist services for subsequent modifications or consultations made by the travel agents. This information refers to the management decisions and configurations made by the *Tourist service manager* module. Thus, it serves as a guide in the processes of composition or self-generation of tourist services. The feedback returned from the customers after the tourist service concluded is also considered.

The *Customer manager* module has as the main functionality to provide support to the customer to perform the necessary operations to create a tourist activity in real-time. This module communicates with the *Tourist services knowledge* and *Suppliers knowledge* repositories through the *Tourist service manager* module to make compositions of different elements to include in the complete tourist service. The created service is stored for later verification and approval by the travel agent.

The *Travel agent manager* module has as a purpose to serve as the internal central management point for the operations related to the tourist service creation. It is also in charge of the review of these activities created by customers through the *Customer manager* module. It is directly connected to the graphical interface, being able to take information about the requests made by the users. These requests are used to consult the *Tourist services knowledge* and the *Suppliers Knowledge* repositories through the *Tourist service manager* module and to obtain interesting tourist services for the user. This module can produce a tourist activity from scratch by selecting different possibilities. Note that the main difference for this module with respect to the previous one resides in the configuration of privileges of the end-user (i.e., a travel agent has more privileges than a customer).

Regarding the visual interface, it provides different configurations according to the two perspectives: the customer and the travel agent. For the first case, the visualization supports the creation of travel services (i.e., a complete set of tourist activities). Graphical assistants try to alleviate the complexity of the travel service design by reducing customer decision-making through a finite set of guided options. When the customer approves the travel service, it is sent to the travel agency for its management: approval or modification. A series of exchanges take place between the customer and the travel agency until the customer confirms the tourist service firmly and in turn is approved. Once the services have been confirmed and the full payment has been verified, a process of sending the necessary documentation is executed for the client to enjoy the service. In addition, a user area is made available to the customer to facilitate the consultation of the travel information and its associated legal documentation. For the second case, similar functionalities are provided. However, travel agents have the initiative here, generating multiple travel services for the customers. Note that more details about the sale processes are addressed in the next sections.

3.2. Algorithm for the detection of potential customers

The *Tourist service manager* module contains a propensity purchase estimation algorithm. It classifies the potential customers according to their propensity to commit the book of a tourist service. This algorithm provides valuable information to the travel agency and enables the travel agent to differentiate between good and bad clients (customers who book a tourist service or not). The algorithm consists of three key elements: variable transformation, clustering, and classification. The first element prepares the inputs for the probability estimation, conducted by clustering and classification methods. The second element provides an initial purchase probability, and the last element refines the probability in some of the clusters. The algorithm's output categorizes the probability into five groups according to the conversion rate (i.e., the proportion of clients who finally book a tourist service).

The variable transformation element is carried out by Weight of Evidence (WoE) encoding [45]. This type of transformation and its benefits have been studied within the scope of credit scoring deeply [5, 47]. It helps deal with categorical and numerical data simultaneously; besides, it can lead to missing data with any additional technique. Traditionally, WoE encoding is used to separate bad clients from good clients, which fits perfectly with an algorithm of propensity purchase estimation. The equation of the WoE transformation is:

$$WoE = ln\frac{\%non\_events}{\%events} \tag{7}$$

where *events* value refers to good clients, and *non-events* value represents bad clients.

One of the most powerful advantages of WoE for the current scope is that variables with too many discrete values lead to numeric variables, and they will be ordered according to a monotonic relationship to the dependent variable. WoE provides a numeric variable that regroups huge discrete values into densely populated categories that express information for the new category. The other great advantage that benefits the proposed solution is that WoE is a standardized value. The former allows using Decision Tree (DT) algorithms. Note that a tree-based algorithm can reduce its predictive potential with categorical variables with too many categories [15]. The latter allows using distance-based algorithms like *k-means* clustering algorithm, which needs variables with comparable values because it employs Euclidean distance [33].

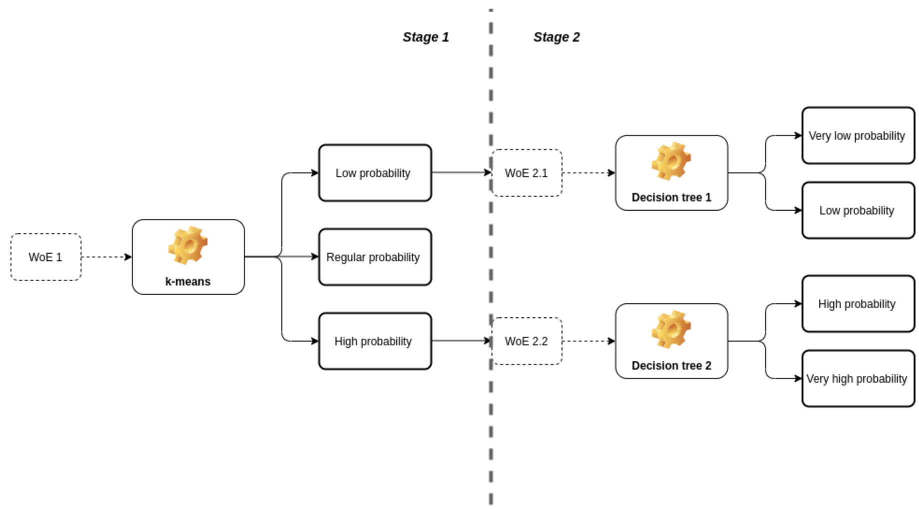


Fig. 5. Bi-stage model for the probability estimation of propensity to commit the book of a tourist service

The algorithm is a bi-stage model as depicted in Figure 5, that first applies *k-means* clustering to achieve three clusters with different conversion rates (low, regular, high). Secondly, for more accurate results, a DT classifier acts over the low and high clusters by subdividing them into low and very low, and high and very high respectively. Hence, the proposed algorithm eventually provides five output categories: very low, low, regular, high, and very high. This type of output is calculated on the base of the prior probability of propensity to purchase [37], and it offers an interpretable result for a travel agent.

The key to the model is how to group the variables in the two stages. In the first stage, WoE transformation is applied to the set of variables that contains information about how the customer is and where they come from. Examples of these kinds of variables are: means of contact (e.g., web, email, physical presence in the agency or phone), getting information for short term, or large term, the travel is related to a particular event (e.g., wedding or anniversary). With these variables, clustering is developed to first obtain three groups (low, regular, and high), which later will be split into the final desired five groups. Then, in the second stage, WoE transformation is applied to variables inherent in travel information like the number of places to be visited, trip duration, flexibility, final price, etc. Note that WoE encoding must be applied separately to low and high-probability clusters, even concerning the same variable, because the goal is to capture the patterns related to each independent cluster. Finally, two DT applied into low and high probability clusters subdivide those clusters into two groups each, resulting in five categories with different propensity purchases.

3.3. Bio-inspired MAS organization

Intelligent agents are independent entities that are used by *Pharaoh* to tackle the ML methods. They establish cooperative activities organized through the hierarchical architecture of a MAS.

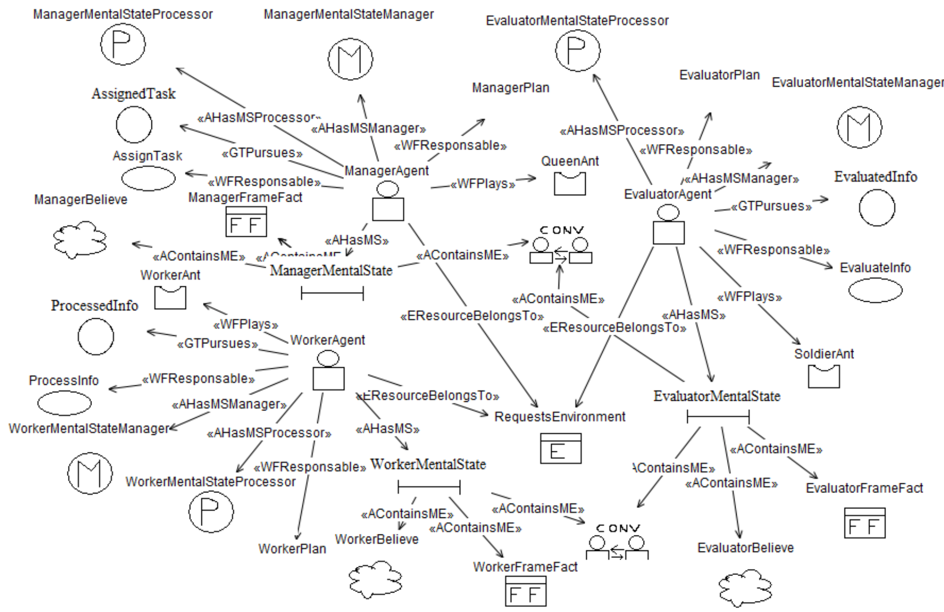


Fig. 6. Excerpt of the main entities involved in the anthill MAS

The proposed MAS consists of an anthill that comprehends agents playing three types of ant-roles: queen, soldiers, and workers (see Fig. 6). Therefore, it is organized following a bio-inspired ant social structure. The queen (i.e., the manager agent) is responsible for the anthill, receiving the requests to analyze. Notice that several requests can be sent to this agent. These requests come from the customers' preferences for a specific tourist service. Then, the queen agent assigns the activity of evaluating the elements of the request to one soldier agent (i.e., the evaluator agent). This agent is in charge of assigning the relevant information to the worker agents. Thus, this information is decomposed into more simple requests organized by the different features indicated by the customer. Worker agents process the information and apply the ML methods provided by the system. Notice that a copy of the ML model is available for each worker and they have access to the relevant information provided by the suppliers to configure the possible tourist packages that are offered to the customer. Once the worker agents have concluded their task, the soldiers join the result if necessary (protecting and supervising the result obtained by a worker or a set of them) and they return the result to the queen agent.

This process is based on the Belief-Desire-Intention (BDI) model [11] where each agent presents a goal or a set of them that must be satisfied to complete its life cycle. In this sense, the queen has the *assignedtask* goal, the soldiers have the *evaluatedinfo* goal and the workers have the *processedinfo* goal. All the goals usually include associated tasks that are actions to achieve. Agents have at least one task that solves their corresponding goals. These tasks are applied in the shared environment. In this case, the environment is formed by the requests of the possible customers. Each agent incorporates a mental state, its processor and manager, and a set of beliefs (motivations). The queen has rules and a plan to manage the requests, while soldiers present similar rules to distribute the information about the requests between the workers. However, workers include the ML model in their mental states to achieve the evaluation of the information, a plan, and some simple rules to organize the process in the beliefs. Finally, interactions between the individuals follow the hierarchical structure which mainly consists of direct conversations. Notice that in this case, workers do not need to establish conversations with other workers since they tackle their commitment individually according to the orders of the soldier.

Regarding the design of the anthill model, it has been addressed through the INGENIAS agent methodology. Then, the resulting composition has been transformed to be compliant with the MESA framework. The conversations and interactions of the agents have been implemented following the Foundation for Intelligent Physical Agents (FIPA) standards [31].

3.4. Internal system processes

The *Pharaoh* framework presents three main processes according to its architecture. The first process encompasses the different actions achieved by the travel agent and the customer until the sale of a tourist service is completed. The second process refers to the feedback task. Finally, the third process comprehends the steps to update the information about rates, services, and other relevant information.

The sale of a tourist service process consists of a set of steps most of them common to both types of end-users (i.e., travel agent and customer). It occurs due to both roles interacting several times during the process (see Fig. 7). Initially, the end-users are logged into the system. If the users are customers, they can request a tourist service and ask the travel agents about it. However, if the users are travel agents, they can take the initiative (the customers are physical with them) or they answer the possible requests made by customers previously. Then, the system analyzes the customers to decide if they are prone to sale or not. In case they are prone, the travel agents prioritize their demands. If the customers respond to the answer provided by the travel agents and one of the tourist services is interesting to them, the system finishes the process of sending the documents with the transaction and the tourist service-related information. However, the customers could not respond to the tourist services stipulated by the travel agents. In this case, the process concluded. Moreover, the customers could not find interesting the offers made by the travel agents. In this case, the travel agents should produce new tourist services more adjusted to the desires of the customers.

The feedback process follows a set of steps where the customers introduce feedback about a tourist service previously bought and concluded (see Fig. 8). It is a simple and optional process carried out only by the customers where their opinion is stored in the system. The information provided is used to update the formulas for the recommendations that are considered by *Pharaoh* to select the best options.

The updating information process is the typical maintenance work in the system. It mainly modifies the stored knowledge in the two repositories: the *Suppliers knowledge* and the *Tourist services knowledge*. This task must be daily performed to maintain the *Pharaoh* framework up to date. This process is achieved by a complete Extract, transform and load (ETL) architecture that automatizes the steps to manage the actions and simplifies the task for the administrator. Note that the administrator is not considered an end-user by the system (see Fig. 7).

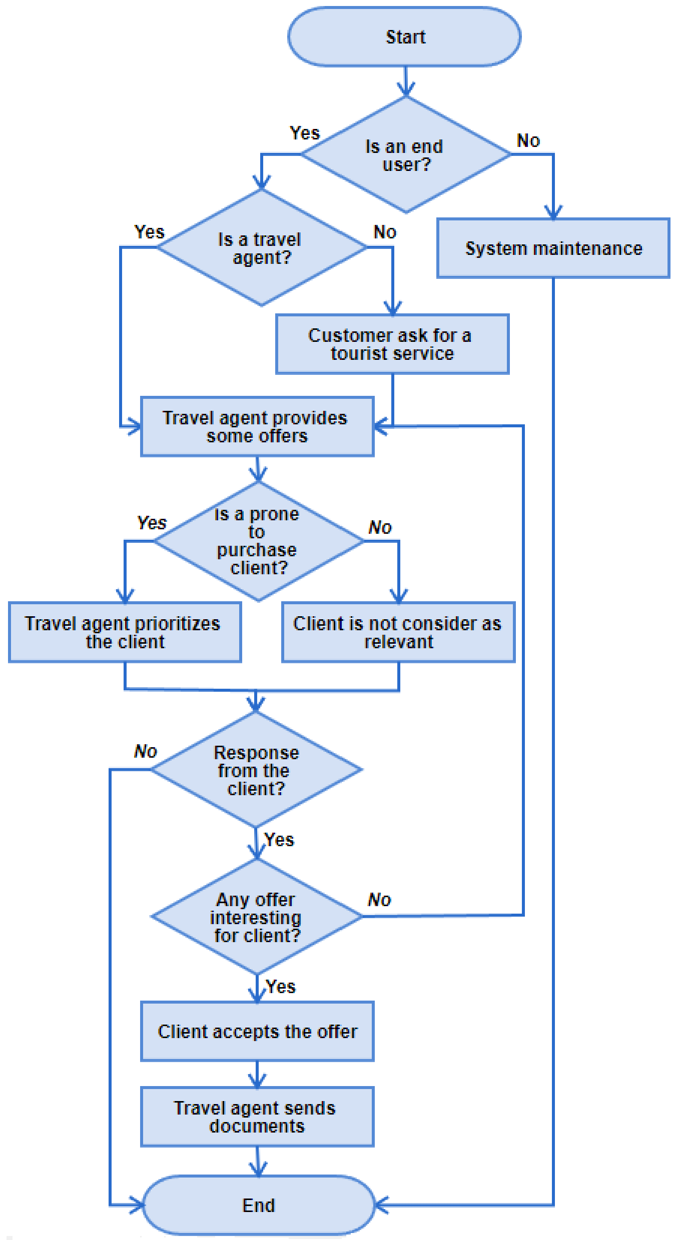


Fig. 7. Offer and sale processes of a tourist service provisioning

4. Experiments

This section details the experiments carried out to validate the performance of the *Pharaoh* framework. Three experiments have been considered and developed in a real environment.

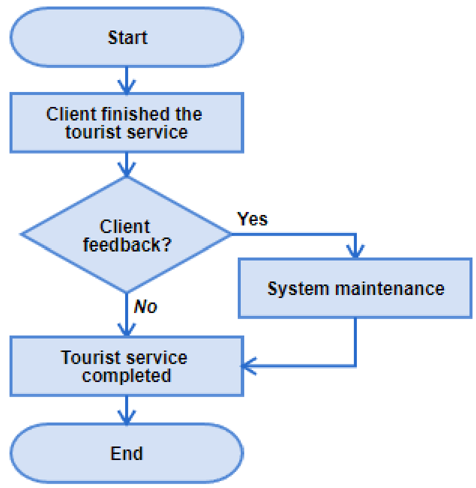


Fig. 8. Information updating process based on the feedback of the customer

JOF ASSOCIATES SLU also called Madox Viajes S.L. [1] was the selected travel agency used to develop the experiments. Notice that this is the first company where the system has been implanted in production once the development stage has been completed.

Regarding the MAS included in the system, it presents a basic configuration adapted to the needs of the company. These needs have been previously tested by adjusting the parameters before the presented experiments. Thus, the MAS comprises two anthills, with five soldiers and ten workers.

The first experiment covers the parameters configuration and the setup of the system. Moreover, a basic test is presented to evaluate the satisfaction level produced by the system between travel agents and customers according to the recommendations made. The second experiment details the performance of the detection of potential customers algorithm. A comparison with other methods of the state-of-the-art is included. The third experiment evaluates the performance of the system once it is implanted in the travel agency. Comparisons between the profits of the travel agency using and not using the *Pharaoh* framework are addressed. This fact illustrates the relevance of the system during the management of a travel agency.

4.1. Parameters configuration and initial validation of the system

The first experiment consists of a set of steps to show how the proposed system works. Initially, the parameters of the *Pharaoh* framework were configured to produce recommendations about tourist services to customers and travel agents. These values were provided by 3 experts in the domain from the selected travel agency (i.e., the people responsible for the company). Then, 10 customers (preserving their anonymity) and 3 travel agents of the company (i.e., some of the workers of the company) evaluated the obtained recommendations for their specific tourism desires. Finally, these actors provided feedback

[1] https://www.madoxviajes.com/

Table 1. Satisfaction values provided by the travel agents

Role	Satis VAS
Agent A	0.85
Agent B	0.93
Agent C	0.73
Mean* $\pm$ *S.D.	***0.84*** $\pm$ ***0.10***

Table 2. Satisfaction values provided by the customers

Role	Satis VAS
Customer 1	0.71
Customer 2	0.62
Customer 3	0.89
Customer 4	0.76
Customer 5	0.95
Customer 6	0.58
Customer 7	0.78
Customer 8	0.69
Customer 9	0.92
Customer 10	0.76
Mean* $\pm$ *S.D.	***0.77*** $\pm$ ***0.12***

about the performance of the system and their satisfaction with the obtained results. This satisfaction has been measured according to a Satisfaction Visual Analogue Scale (Satis VAS) [29]. This VAS was included in an anonymous document. The result of the VAS was converted to a range of values from 0 to 1 to obtain the resulting opinion.

Regarding the parameters configuration (see Section 3.1), the travel agency experts decided the next values for them. For θ_T. θ_A, and θ_E, the values were fixed to 0.3, 0.45 and 0.25 respectively. This decision was motivated by the assumption that customers give more importance to the hosting and the location than the rest of the features of the tourist service. Then, $w^C_{u,j}$ and $w^C_{e,j}$ were fixed to 0.4 and 0.6, giving a moderate relevance to the feedback provided by previous customers. Lastly, the weights of the elements of each category (transport, accommodation, and extras) are established. For the transport category, $w^T_{quality}$, $w^T_{stopovers}$, w^T_{time}, and w^T_{price} are configured to 0.3, 0.1, 0.2, and 0.4 respectively. This decision of the experts was motivated by the assumption that users usually consider very relevant the price of the transport over the other features. For the accommodation category, $w^A_{quality}$, $w^A_{location}$, $w^A_{services}$, and w^A_{price} are configured to 0.35, 0.25, 0.15, and 0.25 respectively. These values correspond to the assumption that users usually consider as relevant the price and the quality of the hostage unless the location and the provided services are also very important. For the extras category, $w^E_{quality}$, $w^E_{flexibility}$, $w^E_{services}$, and w^E_{price} are configured to 0.45, 0.15, 0.15, and 0.25 respectively. This decision follows the assumption that the users give more importance to the price and the quality of the extras.

Once the parameters of the system are completely fixed, the three travel agents make petitions to *Pharaoh* to obtain recommendations according to their preferences. These preferences were selected as heterogeneous as possible to validate the system through a wide spectrum of possibilities.

Next, the customers provided indications of the system being assisted by the travel agents to solve possible problems related to the operation of the system. Travel agents also provided users with the best configurations obtained by the system. If a customer agrees with one of the offered tourist services, the system completes the corresponding booking process.

Finally, the anonymous document with the VAS was given to the participants. The results are shown in Table 1 and Table 2. The average satisfaction of the travel agents was 0.84, while the average of customers was 0.77. Similar Standard Deviations were obtained in both cases. Thus, the global average satisfaction of the system was 0.80 ± 0.11.

In conclusion, it can be said that the result is very acceptable from both perspectives (customers and travel agents). Furthermore, customers are more pressing and demanding than the travel agents in the evaluation of the satisfaction produced by the recommendations made by the *Pharaoh* framework.

4.2. Propensity purchase estimation algorithm validation.

This experiment addresses the performance of the proposed propensity purchase estimation model (*bi-stage* model). The proposal is compared with the most typical state-of-the-art ML classifiers [39, 19]: Random Forest (RF), Gradient Boosting (GB), k-Nearest Neighborhood (kNN) and Logistic Regression (LR).

JOF ASSOCIATES SLU has provided the dataset for the development of this experiment. It contains about 10^4 instances presenting an initial conversion rate of 14%, that is, the percentage of customers who finally purchased the tourist service (i.e., the data are unbalanced). Each instance includes a variety of attributes: contact details, contact channel, service, travel destination, type of trip, etc. In this particular case, more precise information of the data is not available because of confidentiality. All the selected algorithms are trained with 80% of the whole data and tested using the remaining 20%. This division is carried out with stratified sampling. The hyper-parameters of the ML alternatives are selected by 10-fold-cross-validation. The output of each algorithm is presented into five categories attending to the output probability distribution on the train set. The performance is measured in terms of conversion rate and relative frequency on each classification group, expressed in percentage of the overall total. The predictive power is evaluated by checking the conversion rate in the different groups, and the frequency provides the significance of the group. Finally, to assess the possible overfitting train and test agreement are evaluated.

The results are shown in Table 3. The RF has a poor agreement between train and test, in both frequencies and conversion rates. Indeed, one of the groups has no representation in the test dataset. The kNN has similar behavior in train and test agreement, with differences up to 21%. This situation makes no sense to evaluate any other performance measure. The GB has a generally good agreement between train and test instances, except in conversion rates for *high* and *very high* categories with differences higher than 20%. These differences make, like in RF and kNN, no sense to evaluate the rest of the evaluation items. The LR has the best agreement between train and test, in both frequency and conversion rates. The data distribution is highly unbalanced throughout the categories,

Table 3. Performance of the ML classification algorithms in terms of relative frequency (freq.), expressed in percentage about the overall total, and conversion rate (c.rate), for each category

		RF		GB		kNN		LR		Bi-stage model	
		freq.	c.rate	freq.	c.rate	freq.	c.rate	freq.	c.rate	freq.	c.rate
Train	very low	75.0	0.0	74.2	5.8	0.0	100.0	72.5	11.5	16.6	1.7
	low	9.9	0.0	10.3	25.2	54.2	0.0	9.0	17.8	17.1	5.1
	regular	9.9	89.1	10.3	34.5	29.8	20.6	13.2	19.6	44.7	10.9
	high	3.9	100.0	4.1	63.4	11.9	42.2	4.2	26.7	15.8	32.8
	very high	1.2	100.0	1.0	87.3	4.1	100.0	1.1	28.2	5.9	48.0
Test	very low	57.5	4.9	73.6	7.0	0.0	-	72.3	6.7	17.0	2.5
	low	17.1	16.5	10.0	25.0	75.2	7.5	2.0	25.0	17.0	6.7
	regular	25.2	30.9	9.8	28.8	17.4	26.7	5.8	22.9	46.1	10.2
	high	0.0	-	4.8	41.4	5.3	40.6	7.3	34.1	14.6	34.2
	very high	0.2	100.0	1.8	63.6	2.0	58.3	12.6	35.5	5.4	51.5

where *low probability* group comprises more than 70% of the data. Besides, the five categories do not have enough distance between them in the conversion rate term, 2% in some cases, making it difficult to differentiate between close groups. Eventually, the proposed *bi-stage* model has an excellent agreement between train and test instances, with a maximum deviation of 3%. The data distribution is the most balanced of the models tested, where the *regular* category is the densest with 45% of the data and the *very high* the lower dense with 6% of the data for train, and 46% and 5% for test respectively. The probability categories obtained are different with five representative probability values, and it is validated in the test dataset with minimum deviations.

In conclusion, the experiment carried out shows that this particular problem needs an ad-hoc approach, such as the *bi-stage* model presented. This solution is adequate to solve the propensity to purchase problem provided by *JOF ASSOCIATES SLU*. The *bi-stage* model is the one that best classifies in the different probability categories with balanced frequencies. In addition, it is the one that provides the best concordance between training and testing, thus guaranteeing the non-existence of overfitting. Hence, according to the performance requirements, the proposed method serves better than the state-of-the-art classifier for the current aim.

4.3. Efficiency evaluation of the complete system

The last experiment checks the efficiency of *Pharaoh* in a real situation. The setup of the system with the parameters configuration has been maintained, being the same ones as the first experiment.

The experiment starts by organizing randomly and proportionally 184 potential customers into two groups: *Traditional* and *Innovators*, for making comparisons between them. All of them are looking for the same type of tourist services: *National Coasts*, *National Islands*, *Dubai-Maldives*, and *Safaris*. In addition, web canal and other canals such as phone calls, family recommendations, in-person visits to the office, etc., are considered. Note that these services comprehend a set of specific tourist services.

Table 4. Summary of the obtained results for *Traditional* and *Innovators* groups for each tourist service. n is the number of potential customers in each service and group. Time is the average time (in hours) each travel agent spends processing the tourist service until it is accepted or dismissed. The conversion rate (c.rate) and the number of recommendations (Rec.) are presented

		Traditional				**Innovators**			
	Services	n	Time	c.rate	Rec.	n	Time	c.rate	Rec.
Web	N. Coasts	20	3.2	15.0	2	20	2.9	25.0	3
	N. Islands	20	5.2	10.0	2	20	4.8	15.0	3
	Dubai-Maldives	16	10.1	6.3	1	16	9.6	12.5	2
	Safaries	12	11.2	16.7	1	12	10.7	16.7	2
Other	N. Coasts	8	4.2	37.5	1	8	2.7	50.0	2
	N. Islands	8	5.7	25.0	0	8	3.0	37.5	1
	Dubai-Maldives	4	12.0	25.0	1	4	8.0	50.0	1
	Safaries	4	12.5	25.0	0	4	9.0	25.0	1

Traditional group consists of 92 customers who were attended maintaining the traditional way that the company has been used (i.e., without the support of the *Pharaoh* framework). On the other hand, *Innovators* group consists of 92 customers who attended using the *Pharaoh* framework to carry out the requests made by the users and the configurations provided by the travel agents. Both groups worked with the same travel agents to minimize possible variations in the results.

The experiment considers three main variables: the average time (in hours) each agent spends processing the tourist service offered to customers, the conversion rate, and the number of recommendations. These results are presented in Table 4 for both groups.

For *Traditional* group, the results show that the average time to manage the services is less in national destinations. That is, the customers are more demanding when the travel destination is in the same country. The conversion rate fluctuates in the web canal, having a low value for the service *Dubai-Maldives* (i.e., only a few customers complete the purchase), while *Safaris* and *National Coasts* have a high percentage. A total of 8 recommendations have been obtained for this group.

For *Innovators* group, the service *Dubai-Maldives* has the lowest conversion rate and *National Coasts* has the highest one in the web canal. Relevance differences in the number of inverted hours, the number of recommendations, and the conversion rate between *Traditional* and *Innovators* have been detected. The system incremented acceptably the conversion rate, the number of hours was reduced significantly, and the number of recommendations was also higher. A total of 15 recommendations have been obtained for the *Innovators* group. The changes in the conversion rate and the number of hours spent are motivated by the propensity purchase estimation algorithm. It allowed the selection of the best customers for the travel agents, discarding the customers with less interest in the sale. Moreover, the visual information provided by the system, and the precise recommendations could have also done that customers more easily accepted the tourist service.

In conclusion, *Pharaoh* has demonstrated that it works perfectly with the daily issues of a travel company. Moreover, it could increase the conversion rate that is translated into profits for the company, and reduce the number of hours until the customer accepts or dismiss the different possibilities offered for a specific tourist service. This fact is translated into less stressful situations for employees and more agility in the booking process.

5. Conclusions

The *Pharaoh* framework, a system devoted to completely covering the management of the sales of tourist services from the side of the travel agent and the customer, has been presented. It includes as a novelty a bio-inspired MAS based on the structure of anthills and a proneness customer model based on ML techniques. This latter can classify customers according to their proneness of completing a booking (i.e., it detects the most interesting customers). The model consists of three elements: variable transformation, clustering, and classification. The output categorizes the probability into five groups based on the conversion rate.

The system has been tested empirically through several experiments. They have illustrated that *Pharaoh* enhances the performance of a travel agency, increments the quality of the service, and generates interesting profits. Thus, it can be said that the framework provides very desirable functionalities and new insights in the tourism domain thanks to the proposed bio-inspired MAS and the ML techniques.

Future research will focus on the communication between the customer and the travel agent, trying to improve it by simplifying the steps during the conversation. The introduction of improvements at the graphical level both during the sale and feedback processes will also be considered. Moreover, in the domain of intelligent agents, it could be very interesting to include a complete MAS. It could cover all the functionalities of the system to distribute and emulate the competencies of travel agents. This will lead to developing a completely independent intelligent framework that could interact with customers becoming a virtual travel agent.

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References

1. Adomavicius, G., Tuzhilin, A.: Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. IEEE transactions on knowledge and data engineering 17(6), 734–749 (2005)
2. Adriana, S.M.: The customer orientation principle - a prerequisite for increased efficiency in tourism. Ovidius University Annals, Economic Sciences Series 18(1), 405–408 (2018)
3. Al Fararni, K., Nafis, F., Aghoutane, B., Yahyaouy, A., Riffi, J., Sabri, A.: Hybrid recommender system for tourism based on big data and ai: A conceptual framework. Big Data Mining and Analytics 4(1), 47–55 (2021)
4. Alrasheed, H., Alzeer, A., Alhowimel, A., Althyabi, A., et al.: A multi-level tourism destination recommender system. Procedia Computer Science 170, 333–340 (2020)
5. Anderson, R.: The credit scoring toolkit: theory and practice for retail credit risk management and decision automation. Oxford University Press (2007)

6. Bakar, N.A., Rosbi, S.: Effect of coronavirus disease (covid-19) to tourism industry. International Journal of Advanced Engineering Research and Science 7(4), 189–193 (2020)
7. Bedi, P., Agarwal, S.K., Jindal, V., Richa: Marst: Multi-agent recommender system for e-tourism using reputation based collaborative filtering. In: Databases in Networked Information Systems: 9th International Workshop, DNIS 2014, Aizu-Wakamatsu, Japan, March 24-26, 2014. Proceedings 9. pp. 189–201. Springer (2014)
8. Bergenti, F., Caire, G., Monica, S., Poggi, A.: The first twenty years of agent-based software development with jade. Autonomous Agents and Multi-Agent Systems 34(2), 1–19 (2020)
9. Cabezas, J., Fernandez-Isabel, A., Fernández, R.R., González-Fernández, C., Alonso, A., de Diego, I.M.: Bio-inspired agent-based architecture for fraud detection. In: Proceedings of the 2020 3rd International Conference on Information Management and Management Science. pp. 67–71 (2020)
10. Camilleri, M.A.: The tourism industry: An overview. Travel marketing, tourism economics and the airline product pp. 3–27 (2018)
11. De Silva, L., Meneguzzi, F.R., Logan, B.: Bdi agent architectures: a survey. In: Proceedings of the 29th International Joint Conference on Artificial Intelligence (IJCAI), 2020, Japão. pp. 4914–4921 (2020)
12. Dinu, A.M., et al.: The importance of transportation to tourism development. Academic Journal of Economic Studies 4(4), 183–187 (2018)
13. Fernández-Isabel, A., Fuentes-Fernández, R., de Diego, I.M.: Modeling multi-agent systems to simulate sensor-based smart roads. Simulation Modelling Practice and Theory 99, 101994 (2020)
14. Forouzandeh, S., Berahmand, K., Nasiri, E., Rostami, M.: A hotel recommender system for tourists using the artificial bee colony algorithm and fuzzy topsis model: A case study of tripadvisor. International Journal of Information Technology & Decision Making 20(01), 399–429 (2021)
15. Friedman, J.H.: The elements of statistical learning: Data mining, inference, and prediction. springer open (2017)
16. Garcia, I., Sebastia, L., Onaindia, E., Guzman, C.: A group recommender system for tourist activities. In: International conference on electronic commerce and web technologies. pp. 26–37. Springer (2009)
17. Garro, A., Mühlhäuser, M., Tundis, A., Baldoni, M., Baroglio, C., Bergenti, F., Torroni, P., et al.: Intelligent agents: Multi-agent systems. Encyclopedia of Bioinformatics and Computational Biology: ABC of Bioinformatics 315 (2018)
18. Garro, A., Mühlhäuser, M., Tundis, A., Mariani, S., Omicini, A., Vizzari, G.: Intelligent agents and environment. Encyclopedia of Bioinformatics and Computational Biology: ABC of Bioinformatics p. 309 (2018)
19. González, S., García, S., Del Ser, J., Rokach, L., Herrera, F.: A practical tutorial on bagging and boosting based ensembles for machine learning: Algorithms, software tools, performance study, practical perspectives and opportunities. Information Fusion 64, 205–237 (2020)
20. González-Fernández, C., Cabezas, J., Fernández-Isabel, A., Martín de Diego, I.: Combining multi-agent systems and subjective logic to develop decision support systems. In: International Conference on Information Processing and Management of Uncertainty in Knowledge-Based Systems. pp. 143–157. Springer (2020)
21. Hamid, R.A., Albahri, A.S., Alwan, J.K., Al-qaysi, Z., Albahri, O.S., Zaidan, A., Alnoor, A., Alamoodi, A., Zaidan, B.: How smart is e-tourism? a systematic review of smart tourism recommendation system applying data management. Computer Science Review 39, 100337 (2021)
22. Herzog, D., Laß, C., Wörndl, W.: Tourrec: a tourist trip recommender system for individuals and groups. In: Proceedings of the 12th ACM Conference on Recommender Systems. pp. 496–497 (2018)

23. Hsu, P.F., Lan, K.Y., Tsai, C.W.: Selecting the optimal vendor of customer relationship management system for medical tourism industry using delphi and ahp. International Journal of Enterprise Information Systems (IJEIS) 9(1), 62–75 (2013)
24. Intayoad, W., Kamyod, C., Temdee, P.: Reinforcement learning for online learning recommendation system. In: 2018 Global Wireless Summit (GWS). pp. 167–170. IEEE (2018)
25. Kang, E.y., Kim, H., Cho, J.: Personalization method for tourist point of interest (poi) recommendation. In: Knowledge-Based Intelligent Information and Engineering Systems: 10th International Conference, KES 2006, Bournemouth, UK, October 9-11, 2006. Proceedings, Part I 10. pp. 392–400. Springer (2006)
26. Kazil, J., Masad, D., Crooks, A.: Utilizing python for agent-based modeling: the mesa framework. In: International Conference on Social Computing, Behavioral-Cultural Modeling and Prediction and Behavior Representation in Modeling and Simulation. pp. 308–317. Springer (2020)
27. Kler, B.K.: Tourism and restoration. In: Philosophical issues in tourism, pp. 117–134. Channel View Publications (2009)
28. Loh, S., Lorenzi, F., Saldaña, R., Licthnow, D.: A tourism recommender system based on collaboration and text analysis. Information Technology & Tourism 6(3), 157–165 (2003)
29. Lynskey, S.J., Ling, F., Greenberg, A.M., Penny-Dimri, J.C., Sutherland, A.G.: The influence of patient resilience and health status on satisfaction after total hip and knee arthroplasty. The Surgeon 19(1), 8–14 (2021)
30. Meehan, K., Lunney, T., Curran, K., McCaughey, A.: Context-aware intelligent recommendation system for tourism. In: 2013 IEEE international conference on pervasive computing and communications workshops (PERCOM workshops). pp. 328–331. IEEE (2013)
31. Melo, L.S., Sampaio, R.F., Leão, R.P.S., Barroso, G.C., Bezerra, J.R.: Python-based multi-agent platform for application on power grids. International transactions on electrical energy systems 29(6), e12012 (2019)
32. Moguerza, J.M., Martín-Duque, C., Fernández-Muñoz, J.J.: The importance of service quality as an instrument for client customization: a methodological and practical approach within the hotel sector. Quality & Quantity pp. 1–12 (2021)
33. Mohamad, I.B., Usman, D.: Standardization and its effects on k-means clustering algorithm. Research Journal of Applied Sciences, Engineering and Technology 6(17), 3299–3303 (2013)
34. Moliner, M.A., Sánchez, J., Rodríguez, R.M., Callarisa, L.: Relationship quality with a travel agency: The influence of the postpurchase perceived value of a tourism package. Tourism and Hospitality Research 7(3-4), 194–211 (2007)
35. Moreno, R., Viajes, M., Fernández-Isabel, A., de Diego, I.M., Moguerza, J.M., Lancho, C., Cuesta, M.: Automatic detection of potential customers by opinion mining and intelligent agents. In: 2022 17th Conference on Computer Science and Intelligence Systems (FedCSIS). pp. 93–101. IEEE (2022)
36. Novikova, N.G., Kortunov, V.V., Krasnova, O.N., Zorina, N.M., Kireenkova, Z.A., et al.: A client with special needs in tourist services. Journal of Environmental Management and Tourism 6(2), 338 (2015)
37. Pons, J., Granados, A., Espinas, J., Borras, J., Martin, I., Moreno, V.: Assessing open heart surgery mortality in catalonia (spain) through a predictive risk model. European journal of cardio-thoracic surgery: official journal of the European Association for Cardio-thoracic Surgery 11(3), 415–423 (1997)
38. Ray, B., Garain, A., Sarkar, R.: An ensemble-based hotel recommender system using sentiment analysis and aspect categorization of hotel reviews. Applied Soft Computing 98, 106935 (2021)
39. Sen, P.C., Hajra, M., Ghosh, M.: Supervised classification algorithms in machine learning: A survey and review. In: Emerging technology in modelling and graphics, pp. 99–111. Springer (2020)
40. Siswahyudi, P., Kurniawan, T.A., Sugiarto, V.: Agent-oriented methodologies comparison: A literature review. Advanced Science Letters 24(11), 8710–8716 (2018)

41. Subramaniyaswamy, V., Logesh, R., Vijayakumar, V., Keerthana, K., Rakini, K., Swarnamalya, B.: Dynamo: dynamic multimodal route and travel recommendation system. In: 2018 International Conference on Recent Trends in Advance Computing (ICRTAC). pp. 47–52. IEEE (2018)
42. Tureac, C.E., Turtureanu, A.: Types and forms of tourism. Acta Universitatis Danubius. Œconomica 4(1) (2010)
43. Uddin, M., Wang, Q., Wei, H.H., Chi, H.L., Ni, M.: Building information modeling (bim), system dynamics (sd), and agent-based modeling (abm): Towards an integrated approach. Ain Shams Engineering Journal 12(4), 4261–4274 (2021)
44. Wang, J., Hong, Y., Wang, J., Xu, J., Tang, Y., Han, Q.L., Kurths, J.: Cooperative and competitive multi-agent systems: From optimization to games. IEEE/CAA Journal of Automatica Sinica 9(5), 763–783 (2022)
45. Weed, D.L.: Weight of evidence: a review of concept and methods. Risk Analysis: An International Journal 25(6), 1545–1557 (2005)
46. Zapata, G., Murga, J., Raymundo, C., Dominguez, F., Moguerza, J.M., Alvarez, J.M.: Business information architecture for successful project implementation based on sentiment analysis in the tourist sector. Journal of Intelligent Information Systems 53(3), 563–585 (2019)
47. Zdravevski, E., Lameski, P., Kulakov, A.: Weight of evidence as a tool for attribute transformation in the preprocessing stage of supervised learning algorithms. In: The 2011 international joint conference on neural networks. pp. 181–188. IEEE (2011)
48. Zheng, X., Luo, Y., Sun, L., Zhang, J., Chen, F.: A tourism destination recommender system using users' sentiment and temporal dynamics. Journal of Intelligent Information Systems 51(3), 557–578 (2018)

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