



**Master in Artificial Intelligence (UPC-URV-UB)**

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## **Master of Science Thesis**

# **Development of a Tourism recommender system**

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### 3 Abstract

Nowadays, many people rely on online services to plan a trip. However, they are usually faced with the problem of being supplied with lots of information. In consequence, they have to invest a great deal of time to decide what to visit, when, etc. This huge amount of possibilities available on the net makes it difficult for users to discern the more interesting offers from the rest. As a result, the more appealing offers can go unnoticed.

In order to improve the tourist experience, recommender systems offer personalised information to users. In other words, the system selects the more suitable and adequate offers for users and offers activities appropriate to their profile.

In this thesis, we present the EnoSigTur system, a smart recommender system for tourists interested in experiences related to the wine sector. It has been developed in the Parc Científic i Tecnològic de Turisme i Oci of Vila-seca with the collaboration of researchers in the Universitat Rovira i Virgili.

Trough a web application, the system allows users to know wine production activities available in the region of Tarragona. Users just have to indicate their interests in general terms and the system will select the more convenient activities for them. EnoSigTur is capable of modifying the initial information of the users preferences by studying the interaction between the user and the system, and offering them more adjusted recommendations. This system also allows users to plan a trip by providing advanced planning services; for example, date, length of the trip, etc. A mobile phone application will permit users to monitor the planned trip while it is taking place.

EnoSigTur is designed to supply a user-friendly and flexible service either to visitors with a superficial knowledge of the wine production area, or to experienced visitors who have already been in contact with these types of activities. Moreover, as we suggested before, it provides personalised recommendations according to users interests, gives clients the necessary tools to plan the trip and makes it possible for them to discover other activities in the region.

In the following chapters we will deal with the main problems that tourism presents in terms of information search and decision-making processes. We will also present the recommender systems and the ontology, so that the reader will be able to grasp the gist of the project. Finally, we will give details of our recommender system.



## 4 Introduction

### 4.1 Motivation

Sometimes we take decisions unaware of the existence of other alternatives. This may be the reason why many people nowadays trust in third parties rather than in themselves to take decisions. This lack of awareness, and also the increasing amount of information that new technologies, such as the Internet, supply are having a positive effect on the importance of having filtering and selection methods that facilitate the decision-making process.

Users are given such a large quantity of information that they eventually get overwhelmed. The recent appearance of new and practical tools is lending a hand to tackle this matter in a more effective way. These tools provide users some directions that can help them understand the information needed to make a more advantageous use of it.

The combination of the large amount of information accessible, the great range of alternatives available and the users inexperience in some sectors make it clear the need of automatic or semiautomatic systems, capable of helping users in the decision-making process through directions and suggestions.

### 4.2 Background

Tourism has to do with the activities that people carry out during their trips in places that are different from their regular environment. It is a consecutive period that can last for more than a day and less than a year, and has to do with leisure or business reasons, among others.

Although in the ancient Babylonia there were evidences of trips, it was not until the Roman Empire period that we could identify activities similar to the ones that today we associate with tourism.

Between the XVI and XIX century, the basis of the modern tourism began to take shape. During this period, the first holiday centres were established and many of them still exist, like in Bath, England. "Tourism" has not always been the term to refer to these types of activities. In fact, it was the term "*Grand Tour*" that was used at that time, but eventually was substituted by "tourism".

From the 1970s, a new stage in this field was initiated. It was in that moment when many countries, stimulated by the economic benefits, started to promote tourism through the creation of holiday centres with the support of development international organizations.

Progressively, the tourism sector has become one of the main activities that collect more money around the world; not only for the direct contribution it supplies, but also for the expansive effect that has exerted on a large range of related activities.

Present tourism is characterized by the appearance of new markets, greater opportunities to select receptive centres, higher participation and interest in being in contact with the nature, possibility to distribute holidays through the year, and application of new technologies in the tourism industry. International studies point out that in the following years the tourism market share will be reduced in favour of other options.

In Spain, the sun and sand tourism is and will be in the future the most popular and appealing type of tourism in our country. Spain occupies one of the leadership positions in a worldwide scale, thanks to an enviable climate and the resources and variety present in the Spanish coast.

In 2011, Spain received 56,7 millions of international tourists, which meant a growth of 7,6 % from 2010. In 2011, the total tourist income in Spain amounted to 52,795.7 million euros, which meant an increase in 7,9 % from 2010. Catalonia (21,4 %), Canary Islands (19,2 %), and Balearic Islands (17,9 %) were the most popular destinations. Canary Islands, on the other hand, were the region that accumulated the maximum percentage, +13,1 % (10,119 millions).

The tourism market, which is under constant changes, is in need of a great diversity of products and activities that are appealing enough to meet customers' expectations. As a consequence of this and during the past years, Spain has tripled the variety of offers and has become a suitable alternative to enjoy short-term holidays for a reasonable amount of money.

People these days are getting more used to turn to new technologies when planning a trip. This reality can be explained by the fact that Internet is part of our daily life. For this purpose, several institutions and companies that offer varied touristic information about the destination have been set up.

The touristic information that these kinds of services offer has the following characteristics:

- General and identical information is presented. That is to say that all users are systematically given the same information, regardless their profile.
- A great amount of information is presented to the users, who have to process it in order to select those offers that can be interesting or suitable for them.

Generally, the user or the traveller starts from an elementary knowledge of the place to visit and of the places that can be of interest for them, either for the artistic, social or leisure value they may have. Besides this, each person can adopt different profiles depending on the trip they want to do or the circumstances that surround them; therefore, several profiles can be distinguished, such as cultural, gastronomic, or family profile, among others.

Users can have access to a huge deal of data and information related to a specific place, but surely they will prefer to filter that information and get those elements or activities that match their profile or particular interests. Each of these profiles determines the different places to visit or the different ways to plan a trip. For instance, gastronomic travellers will put their culinary preferences in the first place; that is, the restaurant they want to eat, and will leave in the second place, the places and monuments to visit around it. For example, users who travel with children will avoid visiting many museums, and will consider practicing outdoor activities, such as gardens or amusement parks.

For the purpose of improving tourist experiences, computer recommender systems supply personalised information to users. In other words, the system selects the most suitable options from a large list of offers, by taking the users profile and interests into account.

In the past years, the Artificial Intelligence Community has developed a strenuous work related to recommender systems. These systems, which help people find what they need on the net, have had a great success. As we stated before, the objective of these agents is to explore and filter the best options considering the user profile (interests, circumstances, characteristics, etc.).

### 4.3 Objectives

The purpose of this thesis starts from the assumption that the development of a recommender system can contribute to the field of Tourism, especially in the wine sector. The recommender system we have designed combines both recommender techniques based on content, and recommender techniques based on collaboration. Its domain is represented through an ontology. In order to meet the purpose of this work, it is necessary to take several aspects into account:

- Represent the knowledge of the field in a structural way with the use of an ontology, as there are many items that can be recommended. Moreover, the inferences can improve the recommendations.
- Categorize users with the help of cluster analysis and differentiate them according to several aspects, such as demographical data, motivations, etc.
- Introduction of a basic knowledge in the system for the initial stages, which allows the system to learn and improve the decision-making process.
- Collect the information that the users provide when interacting with the system, in order to obtain more information of users profiles and, therefore, improve the recommendations.

Apart from the aspects commented above, the closeness of the users to the activities offered, their economic status, ways of transport and length of the trip will also be regarded. The recommender system will count on a web and phone interface, so that users will be able to access it either from a computer or from a state-of-the-art mobile phone.

### 4.4 Memory organization

This work is organized as follows:

- **Chapter 5.** Recommender Systems and Their Application to Tourism. This chapter summarizes the state of art of recommender systems and what are the basic techniques used. Also sweeps recommendation systems in the domain centered tourism.
- **Chapter 6.** Ontology: This chapter introduces the ontology and the benefits in the systems of a recommendation system.
- **Chapter 7.** EnoSigTur. This chapter sets out our recommender system, architecture, development, functionality, etc.
- **Chapter 8.** Conclusions. This chapter summarizes the most important contributions of this work and gives some open lines along which this work can be continued.



## 5 Recommender systems and their application to Tourism

### 5.1 Background

Nowadays users can find a lot of information on the Internet. That is why sometimes it becomes a hard and complex task to select the information a user is interested in. The user is often unable to look through all the available information. Therefore, highly interesting information can get lost in the middle of a sea of data.

In the following paragraphs, we are going to mention the first three kinds of systems for searching information: search engines, helping systems and information filtering and retrieval systems:

- **Search engines** (such as Google [1] or Yahoo [2]): They are computer systems that index files stored in web servers. Searches are made with key words or hierarchical trees based on different topics. The result of the searches is a list of URLs in which the topics related to the introduced key words appear. Usually, the vast majority of information that search engines offer does not suit the user interests.
- **Helping systems**: They teach the user how to use a particular program by describing it and explaining how it works. For instance, Microsoft includes a helping system that gathers information about the user characteristics and its actions, the state of the program, and the words that the user has searched, in order to calculate the probability of help that the user will need in related issues. These systems usually link web pages that provide additional information.
- **Information filtering [3] and retrieval systems [4]**: The goal of these systems is to obtain the most relevant information for the user, minimizing the number of irrelevant items. Thus, filtering systems remove a huge amount of unwanted information. However, they could be more useful if they took user preferences into account with automatic learning techniques. If these systems were provided with artificial intelligence, they would supply users the content they are interested in, instead of just offering them a huge amount of information.

Before defining the concept of a recommender system itself, we should specify the difference between adaptable and adaptive systems [5, 6]. On the one hand, in the adaptable systems, the user decides the degree of adaptation, since he chooses the values of certain parameters. In the adaptive systems, on the other hand, the system adapts the suggestions without the intervention of the user. Both of these features can coexist in a single system without affecting its capacity. In fact, the combination of both aspects can increase the system effectiveness and efficiency.

## 5.2 Definition

A recommender system (RS) [7, 8] is a specific kind of adaptive information filter. It is a technique, which tries to provide the user the information he is interested in.

The central axis of a RS is the term “personalization” [9]. The goal of the personalization is to provide users what they need without explicitly asking for it. The system can infer what the user demands not only according to the information that he initially provides, but also by comparing his profile with others users with a similar one and by considering his demographic data (demographical profile).

In short, a RS offers the possibility of customizing the information available on the Internet thanks to a filter. Thus, the RS will provide an amount of information easy to manage, adapted to the user needs, preferences and, above all, interests.

The results of the recommendation process are a set of elements that are provided to the user in the way described in the interface. The personalizing process is divided into three stages:

- **Compiling user information:** compile information about users in order to know them better. This information is stored in the user profile.
- **Recommending items:** offer the user items based on the knowledge that the system has acquired.
- **Satisfaction degree:** measures the impact of personalization with users opinion on the recommended items. This step is used as a feedback of the first one, since it takes user opinion into account and so, the system knows him better.

The recommender systems appeared in the 90s. The interest in this field was considerable, both in academic and industrial contexts [10]. The first RS was Tapestry [11], which used the term “collaborative filtering” for the first time. Now there are lots of web services that use RS to customize information, such as Amazon [12], Audioscrobbler of Last.fm [13], Like-i-Like [13], MovieLens (RS of cinema) [14], MyStrands [15], Photoree [16], among others.

Although RS are gaining more and more popularity these days, there is still a long way to go. For example, there should be improvements on the techniques to represent better user behaviour and the information of the recommended items; on the modelling algorithms of the recommendation; on punctuating items in a multiplicity of criteria; or on the application of evolutionary computation techniques, among others.

The RS field is related to many fields, such as cognitive science [17], approximation theory [18], information retrieval [19, 20], forecast theory [21], business management and marketing [22, 23]. It was in the 90s when researchers began to focus on the ratio structures common in the RS. That is, the simplest formulation of a RS is reduced to the problem of estimating ratios for those items the user has not seen yet, since once the estimation is made, items with higher estimated ratio can be recommended to the user.



### 5.3 Advantages and disadvantages of Recommender Systems

The incorporation of RS in web pages makes it possible to customize the use of the service, offering the user only the information he needs or is interested in. The main benefit of the RS is the removal of unnecessary information thanks to its general preferences.

Currently, however, the RS introduces certain social problems, such as guiding the recommendation to economic interests either because the recommender mainly offers recommended items of a particular kind, guided by certain interests, or either because users logged in the system mark favourably recommendations of a company in detrimental of another one. The solution to this problem depends on the level of confidence that the user gives to the web page.

Another important problem is the lack of privacy that implies the fact that different systems obtain information about the users preferences. There are some studies trying to solve or, at least, soften this problem [24].

### 5.4 Classification of Recommender Systems

In this section, we are going to describe recommender systems, which are classified depending on how they work:

- **Recommender Systems based on content.** The recommender system based on content is the one that provides recommendations taking into account the profile created from the content analysis of the items that the user has bought, used or visited in the past.

In other words, they compare the characteristics of the items that have not been presented to the user yet, and compare them with the user profile, in order to predict his preferences on those items. In this way, this system tries to recommend items similar to those that it knows for sure the user likes, as they appear in the user profile.

The filtering based on the content was the most popular recommender system until the appearance of the collaborative filtering. However, the main problem that this system faced was the overspecialization. The overspecialization takes place when the contents of recommendations are very similar and do not care about the interests of the users. Another problem of the recommender systems based on the content is that it only offers partial information (usually textual information), whereas the contextual, visual or semantic information is more difficult to know and, therefore, connections between similar objects get lost in a less obvious way.

- **Collaborative Recommender Systems [25, 26].** Recommender systems based on collaborative filtering are those in which recommendations only consider the similarity of terms between users. That is, collaborative systems recommend items that other users with similar interests like.

In order to make a proper collaborative recommender system (that is, a system that offers quality recommendations) is necessary to use an adequate algorithm of collaborative filtering. These algorithms can be classified in two categories: algorithms based on the memory or on the user, and algorithms based on models or items.

The popularity of these recommender systems, several problems have been pointed out such as the shortage, the scalability and the problem of the new item. Great deals of studies and experiments have been carried out in order to try to minimize these problems.

- **Recommender Systems Based on Knowledge [27].** Recommender systems based on knowledge consider the needs and preferences of each user to suggest recommendations.

Unlike other recommender systems, these recommender systems do not depend on the quantity of information about rated items (based on content) and particular users (based on collaboration). In fact, the only thing they need is a general knowledge about the group of items and an informal knowledge of the user needs.

The main problem of these recommender systems is that although they do not require that much information, they require a lot of human effort to do the recommendations using all kinds of heuristics inference.

- **Demographic Recommender Systems.** Demographic recommender systems have the objective of classifying the user according to his demographic information; therefore, recommendations are based on demographic categories. A first example of this kind of recommendation was Grundy, a system that recommended books based on the personal information stored in the system using an interactive dialogue. Thus, it considered the correspondence between the user answers in the dialogue, and a library of user stereotypes, which had been manually compiled. More recent recommender systems also use this kind of techniques; for instance, there are systems that use demographic categories to carry out a marketing research, in order to suggest a range of products and services. Another example could be to classify a user in a specific demographic category with the help of a short survey. In other systems, learning methods in machines are used to classify the users by their demographic data.

The representation of the demographic information in a user model can vary considerably. Features of the users were used and they were manually introduced with certain confidence intervals. Nowadays, however, there are demographic techniques that make “person to person correlations”, which are similar to collaborative filter but with different data. Contrary to collaborative systems and based-on-content techniques, the benefit of the demographic approach lies on the fact that it may not need a user data record.

Regarding the problems and requirements of this kind of recommender systems it is worth to say that it is difficult to collect the necessary demographic data, since normally people is reluctant to provide personal information. Moreover, this is not an anonymous system, so that there are privacy problems. Statistical and social research is needed to know how to translate the people cultural groups into information needs.

- **Hybrids.** All of the recommender systems we have talked about have their weak and strong points, so it is logical to try to maximize its profits and reduce its weaknesses by hybridizing two or more recommender techniques.

Hybrid systems between the ones based on the content and the ones based on collaboration save the user preferences and combine them with the most relevant items to make the recommendations.

There are also hybrid systems between the ones based on knowledge and the ones based on collaboration; the ones based on content and the ones based on knowledge; and even between the collaborative ones and social networks.

## 5.5 Problem of recommender techniques

Depending on the type [28], recommender systems can present the following problems:

- **Ramp-up.** This problem entails two other problems:
  - Problem of the new user or start-up problem. When a user logs in a system, he must rank enough ratios to be recommended with certain guarantees. Usually, the amount of ratios needed is large. Recommender techniques are based on the rankings that the user gives to items, so if the user is new, it is possible that he has few ranked elements and, therefore, there will be few elements to compare. This problem appears in RS based on content and RS based on collaboration.
  - Problem of the new element. An element is not recommended until enough users have ranked it. In this way, there will be a little probability that the system recommends a new item that very few users have ranked. When a user punctuates an item for the first time, he will not get a lot of profit from it, since it does not allow the system to infer new information. This problem is present in collaborative recommender systems.
- **Sparsity or ratio diffusion.** Current user ratios may not match up with other users ratios and, therefore, there way be few users to compare with or few similar elements to look for. This problem is present in RS based on content and collaborative RS. It exists a higher possibility to provide right recommendations to a user with common preferences.
- **Compilation of demographic information.** Demographic RS require user personal information in order to provide recommendations based on his demographic profile. The user may find it tedious to provide all this information. However, the larger the amount of information is, the higher the quality of the given information will be. Moreover, the user may be reluctant to give valuable information to the system, maybe because he is concerned about the lack of privacy or maybe because he does not totally trust the service. A way to solve this problem is to determine an optimum number of ratios that the system must request to the user (it can be conceived as a problem of optimization), or use non-intrusive techniques.

- **Portfolio effect.** several RS should not provide an item that is very similar to another that a user has already. For example, the system should not suggest buying a book that the user already has in a new edition or with a different binding. In other systems, however, similarity will be a criterion to suggest an item to the user (e.g. an article that is similar to another one that the user has read before).
- **Poor or excessive results.** RS take for granted that requirements and restrictions of the user will be met by using the suitable recommender techniques; so that, a recommendation will be always given to the user. However, the recommender process may fail and not provide any recommendation that satisfy the user requirements. It can also be the case that the recommender process produces too many results.
- **Serendipity.** Some RS offer the user only items similar to the ones he has visited before, taking for granted that those are the ones that the user wants to see. It would be desirable to offer new items that he may like. The lack of novelties is a problem, basically in RS based on content and in the demographic ones. Collaborative RS do not present this problem.

## 5.6 Real Examples of Recommender Systems

- **Amazon.** The powerful American e-commerce company that began as an online bookshop is a paradigmatic example of the hybrid recommender system that combines both the based-on-content and the based-on-collaboration systems. The system saves the user preferences and matches them with relevant objects to create recommendations. They usually use a sentence such as “People who bought this item also bought these ones...”
- **IMDB Recommendation Centre.** It is the largest database of movies and TV of the entire world and one of the most popular websites on the Internet. Moreover, it has a recommender system called Recommendation Centre, which is based on content. The user searches the movie or the TV show he wants and the system will offer him a list with ten recommendations. As feedback, the user can specify his agreement or disagreement with the suggested recommendations. Thanks to the interaction between the system and the user, the algorithm can be refined and provide other recommendations. In any case, this is not the most successful service that IMDB offers as the recommender system it has is not as good as it could be.
- **Entrée Chicago.** It is a recommender system based on knowledge developed by the Intelligent Information Laboratory (Infolab) of the University of Chicago that helps users to decide among 700 restaurants of Chicago, according to their favourite restaurants in other American cities. Apart from offering recommendations, it also has reviews and maps of all the restaurants.
- **One Llama!** A researcher of the National Centre for Supercomputing Applications, called Tcheng, worked for the development of this software that analyses music and categorizes it. It uses the “artificial ear” technology. This system helps users to arrange their music collection and it also recommends them songs that they may like.

The strong point of this system is that it processes each song, creates a group of data to each one by data mining process, and suggests songs with similar features and from the same music style.

- **Silver Egg.** It offers trading web services that work with artificial intelligence. The most important service is Aigent, an ASP service used in the leader electronic trade web pages to give customized recommendations of products. It uses collaborative filtering based on Bayes networks to choose the products that are going to be recommended. It constantly adapts the recommendation to the changes of the user.

## 5.7 Recommender Systems of Tourism and Leisure

Tourism is an activity closely linked with personal interests and preferences. That is why many leisure and tourism web applications incorporate RS. With this, they try to simulate the interaction with a human travel agent. However, it is not easy to apply recommender techniques to leisure and tourism services. These are some of the problems they present:

- The basic recommender technique, the collaborative recommendation, may be difficult to apply to most of these systems. In order to apply it, users must rank a lot of elements. However, as these activities are not very usual, users cannot rank many items. Some systems use conversational techniques to solve this problem.
- Recommendations for groups. Usually we travel with other people, so preferences of several users should be bore in mind. Thus, recommendations should be adequate for the majority of the group.
- The recommendation given to the user does not only depend on his own preferences or others preferences, but also on the surrounding information: the distance between two places, transport facilities, time of the year, or timetables, among others.

Despite the problems presented by the use of recommender systems in tourism and leisure services, there is a high interest in this area, In fact, nowadays there are numerous teams, which are carrying out researches in this field, such as the search team ITAKA (Computer Engineering and Maths Department of the URV), the research team GRATET (Geography Department of the URV) and the Scientific and Technologic Park of Tourism and Leisure of Vila-seca in the projects SigTur and EnoSigTur.

## 5.8 The Main Recommender Systems of Tourism and Leisure

In Figure 1 we can see the comparison between the main recommender systems of tourism and leisure. The comparison between systems is focused on several aspects:

- At the interface level, there are few RS that supports all interfaces. Among these few, we can find the recommender system we present in this thesis.
- The great majority of systems only give individual recommendations.
- Again, there are few that use more than a recommender method. The most popular method is the one based on content. EnoSigTur uses the three main recommender methods.
- According to its functions, all systems make recommendations of isolated activities, but others also offer an itinerary.
- Few RS use artificial intelligence techniques. EnoSigTur takes advantage of ontologies and clustering techniques to improve recommendations.
- Most of the recommender systems take information from the user both in an explicit and implicit way.

Name of the system	Brief description	Interface		Type of recommendations		Recommendation method				Functionality				Use of Artificial Intelligence techniques					Preferences management	
		Web	Mobile	Graphical	Individual	Group	Content	Collaborative	Demographic	Recommendation destination	Recommend activities	Arrange plan library	Tourism pack	Ontologies	Agents, SMA	Neural networks	Genetic algorithms	Clustering		Bayesian networks
Tourist	Personalised recommendation based on agents of tourism activities	No	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	No	Yes	No	No	No	Yes	No	Yes
San-Fit	Expert hotel recommender system	Yes	No	No	Yes	No	Yes	No	No	No	No	No	Yes	No	No	No	No	No	No	No
e-Tourism	Recommendation of lists of individual or group activities	Yes	No	No	Yes	Yes	No	Yes	No	Yes	Yes	No	Yes	No	No	No	No	No	No	Yes
Intelligence	Organization of group tours	Yes	Yes	No	Yes	Yes	No	Yes	No	Yes	Yes	No	Takonomy	No	No	No	No	No	No	No
Ohnam	Planner of routes	Yes	No	No	Yes	No	No	No	No	Yes	Yes	No	No	No	No	No	No	No	No	Yes
SPEETA	Recommendation of tourism activities	No	Yes	Yes	Yes	No	Yes	No	No	Yes	Yes	No	Yes	No	No	No	No	Yes	No	Yes
City Trip Planner	Planner of activities in cities by days and hours	Yes	Yes	Yes	Yes	No	No	No	No	Yes	Yes	No	No	No	No	Yes	No	No	No	Yes
SALMAP	Generates plans from the preferences of users with similar profiles	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	No	Yes
CT Planner2	Tour plans	No	No	Yes	Yes	No	Yes	No	No	Yes	Yes	No	No	No	No	No	No	No	No	Yes
Pat'ac	Urban and ubiquitous tourist services based on software agents and oriented to semantic web	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	No	No	No	No	Yes
GoOasis	System that says (orally) the places of interest where the user goes	Yes	No	Yes	Yes	No	Yes	No	No	Yes	No	No	Yes	No	No	No	No	No	No	No
InteCities	Push notification service to send personalized tourist information	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No	No	No	No	No	No	No	No	No	Yes
ePlanner	Pre-dating post trip to offer personalised push information	Yes	Yes	No	Yes	No	Yes	No	No	Yes	No	No	No	No	No	No	No	No	No	Yes
iTravel	Activities recommender system for mobile phones	No	Yes	Yes	Yes	No	No	No	No	Yes	No	No	No	No	No	No	No	No	No	No
Map4Mobile	Integrates a conversational preference acquisition technology based on critiquing	No	Yes	Yes	Yes	No	No	No	No	Yes	No	No	No	No	No	No	No	No	No	Yes
MTRS	Mobile activities recommender. Mainly based on collaborative filtering	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes	No	No	No	No	No	No	Yes, k-means	No	No	Yes
more4tourism	Mobile recommender system. Brief description, but very interesting aspects	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	No	Yes	No	No	No	No	No	No	Yes
Signar	Smart recommender system of tourism activities and resources	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes	No	No	Yes	No	No	No	Yes	No	No	Yes
EngSigTur	Smart recommender system of activities and resources of the wine sector	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	No	No	No	Yes	No	No	Yes

Figure 1. Comparison of the main RS for Tourism and leisure.

The main innovation of our system, compared to others, is the incorporation of semantic knowledge of the domain, represented with ontologies, to improve the capacity of the classical methods of collaborative or based-on-content recommenders. This knowledge makes it possible the use of learning mechanisms, which analyses the interaction between the user and the system and gradually adapts the information about the user cultural and leisure preferences.

In the next chapter, we will deal with the concept “ontology” and we will specify the main benefits it contributes to improve the selection of activities to be recommended.



## 6 Ontology

### 6.1 Backgrounds

Tourism is a sector that has enjoyed a boom during the past two decades, and for many regions and countries it has come to be one of the main income sources. The appearance and development of the Internet has had a significant impact on the way people access information, specially on how they get information about the destination they want, on how they contract their trips, or on how they book hotels or transport. Given the huge deal of information related to this sector and its decentralization and lack of normalization, it is becoming more and more difficult for agencies and tourism services portals to provide complete and up-to-date offers.

In the tourism sector, new technologies based on the Internet currently play a very important role, as they can supply more complex and complete products that meet users demands. But before presenting any suggestion to the user (hotels to stay, places to visit, cultural or leisure activities to perform, etc.), the system will have to explore several sources of information.

In order to manage and organize the available information of the growing and decentralized database that the Internet has become, it is essential to face up to the challenge of locating, processing and integrating all the relevant and available information. The vast majority of information on the net has been uploaded under neither control nor organization. As a result, it is necessary to create a system that allow computers to process such content from a semantic point of view in order to classify it and use it as wanted. Hence, the concept of “Semantic Web” emerges; a booming sector in the field of information that let computers have a good degree of comprehension of the web in order to make the access to information easier and more natural. This system is capable of integrating data from different sources, of obtaining more precise results, and of automating more complex tasks.

In order to represent the related information (of this or other fields) the concept of “ontology” or “conceptual model” is applied. It pursues the aim of facilitating the communication and the exchange of information between different systems and organizations. The number of studies conducted after several years of research, either in the academic and the business dimension, have generated various ontologies related to the sector of tourism, which constitute the basis for the development of the most specific ontologies, and others as the final solution to the most concrete problems.

### 6.2 Definition

The word *Ontology* derives from the Greek *ontos* (study of beings) and *logos* (word). In philosophical terms, *Ontology* is the science of *what* it is; that is, a systematic explanation of life and existence, of types of structures, categories of objects, characteristics, events, processes and connections within areas of reality [29].

Ontology is the explicit explanation of a concept [30]. In other words, it provides straightforward and precise structure and contents, which codify the implicit rules present in a part of the reality, regardless the purpose and the field of application in which its definitions will be used or reused.

An Ontology defines the vocabulary of an area through a bunch of basic terms and connections between those terms. Moreover, it specifies the rules that combine terms and connections and that improve the definitions of terms. The concept “ontology” refers to the attempt to formulate an exhaustive and rigorous conceptual framework of a specific field, which contributes to communicate and share information between different systems. The use of ontologies leaves room for a thorough treatment of knowledge, a useful tool to receive information in an automated way.

### 6.3 Characteristics and types of ontologies

Ontologies can be considered as repositories of information linked to particular facts, through which a specific data interpretation is made. The knowledge of an ontology can be true (codified in an ontology), or deduced (derived from a reasoning).

#### 6.3.1 Features that ontologies must have

These are characteristics that ontologies must have:

- **Clarity.** Communicate the intended meaning of the defined terms.
- **Coherence.** Avoid interferences that are consistent with the definitions.
- **Extensibility.** Anticipate the use of shared vocabulary.
- **Minimal encoding bias.** Specify at the knowledge level without depending on a particular symbol-level coding.
- **Minimal ontological commitment.** Make as few claims as possible about the world being modelled.

#### 6.3.2 Classification according to the area of knowledge

There are four types of ontologies depending on its reach and chance of being applied:

- **Application ontology.** Used by the application. For example, ontology of production processes, ontology of security holes, ontology of ship intermediate design, etc.
- **Domain ontologies.** Specific for a particular device. These ontologies are designed to represent knowledge present in a specific domain type. For example, ontology of the production process.
- **Basic techniques ontologies.** Describe the general characteristics of devices. For example: components, processes and functions.
- **Generic ontologies.** Describe the higher-level category, giving details of general concepts (such as time, space, object, etc.). There are other possible classifications of ontologies according to its perspective, for example: appearance, behaviour, structure, topology, etc. Depending on the level of abstraction and logical reasoning they allow, for example: descriptive ontologies, which include concept taxonomies or concept connections, and do not permit logical inferences and logical ontologies. The ones that permit logical inferences use a number of components, such as the inclusion of axioms.

Our recommender system contains a domain ontology, specialized in the wine tourism.

## 6.4 Ontologies design

Ontologies can be used as a computational science tool. It is very common in fields such as Artificial Science or Robotics and Knowledge Engineering. Programming techniques oriented to objects are being more and more common these days thanks to its representation in terms of types, attributes, objects and class inheritance hierarchy, which have influenced a number of languages and diagrams used for the representation of the digital knowledge. Ontology is the theory of objects in terms of criteria, which allow us to distinguish different types of objects and its connections, dependencies and features.

### 6.4.1 Basic elements of an ontology

The ontology defines base models, which will contain the semantic definition that represents a type of objects in the ontology. The bunch of representative terms described in an ontology are called “concepts”. Domain-dependent ontologies provide concepts in a specific field; thus, the focus is on a limited area of knowledge [31]. Generic ontologies, on the other hand, supply concepts in a variety of domain types.

Concepts are the fundamental units for specification in an ontology. They provide the basis to describe the information. Each concept is made of three basic components: terms, attributes and connections. Firstly, the terms are the names used to refer to a specific concept and can be a set of synonyms. Secondly, the attributes are the features or characteristics of a concept and so, provide a more detailed description of it. And finally, the connections are used to represent correspondences between different concepts and to supply a general structure of the ontology.

Each concept defines a type, which constitutes the representation of similar terms in a conceptual group. For instance, a computer could be represented as a type, which has many subclasses, such as personal computers, mainframes or workstations, among others.

Ontologies contain the following components, which will be useful to represent the knowledge of any specific field [32]:

- **Concepts.** Are the basic ideas. Concepts can be types of objects, methods, plans, strategies, reasoning processes, etc.
- **Connections.** Represent the interaction and the link between the concepts in a field. They usually form the taxonomy of a field. For example: subclass, subset, etc.
- **Functions.** Are concrete types of connection, where an element is identified by the calculation of a function that considers several elements of the ontology. For example: categorize-class, etc.
- **Instances.** Are used to represent specific objects of a concept.
- **Axioms.** Are theorems that specify the connections that the elements of an ontology must have. For instance: “If X and Y are Z-type, then X is not subclass of Y”.

The ontologies can be conceived as a set of concepts and definitions, and these concepts can be split into hierarchies of taxonomies and have associated features.

As for the management of knowledge, ontologies, which are a tool to represent the semantics of information and the automation of the retrieval process, are the vehicle for the representation and the exchange of knowledge in different levels of granularity in different fields.

## 6.5 Recommender systems based on ontologies

A feature common in the vast majority of recommender systems —and so is ours— is the use of profiles that represent the needs of information and interests of the users. In this way, users profiles turn into a key piece of recommender systems in order to obtain an efficient filtering. An inadequate profile modelling can lead to poor quality and little relevant recommendations for the users.

In a recommender system, the ontological domain permits the classification of objects to be suggested. In our recommender system, we consider that each object is an instance of one (or several) of the lowest level classes of the ontology and we use the ontological domain to represent the users preferences. In this sense, concepts are represented as subsets of the domain in which users can be interested with. Considering that the degree of interest can be different in each concept, preferences are represented by fuzzy sets.

### 6.5.1 A fuzzy approach to store the user profile in an ontology

In our recommender system based on ontologies we suggest that:

**Proposal 1.** We are going to consider a fuzzy set for each concept  $c$  of the ontology, so that, for each user  $u$ ,  $\mu_c(u)$  gives the membership degree of  $u$  to the concept  $c$ .

The membership degree is personal for each user and represents the degree of interest in a specific concept. If a user  $u$  is interested in a concept  $c$ , then,  $\mu_c(u)=1$ . On the contrary, if  $\mu_c(u)=0$ , we assume that the user  $u$  is not interested in the concept  $c$ .

When a user  $u$  needs a recommendation, we intend to find the value of  $\mu_c(u)$  for each concept of the ontology. Once all values have been found, the recommender system will be able to find the most suitable object for the user by considering that each object is an instance of one of the concepts. The value  $\mu_c(u)$  is calculated using implicit and explicit information obtained by the interaction between the user and the system.

On account of the uncertainty that this estimation process creates regarding the values of preference, we suggest the following degree of confidence.

**Proposal 2.** We consider the degree of confidence  $CL_c(u)$ , a value between 0 and 1 that quantifies the confidence associated to the estimation of the membership degree of  $u$  and a concept  $c$ , labelled as  $\mu_c(u)$ .

High values in  $CL_c(u)$  indicate that we can trust in the value of  $\mu_c(u)$  and low values in  $CL_c(u)$  show that the estimation is not reliable. The recommender system ignores low values, because it means that the user is not sufficiently interested, and contemplates the higher ones to make a better recommendation.

All in all, each user profile consists of a copy of the ontology that keeps the degree of interest of a user in each concept, as well as the degree of confidence on those interests.

### 6.5.2 Profile initial point

Each ontological concept has a degree of interest  $\mu c(u)$ , which is estimated by the system. The degree of interest is calculated with the information collected during the user session in the system, either in an explicit or implicit way. To initiate the degree of the user interests, the user has to fill in a form in which he can express his interests in general aspects of the domain, which are the ontological concepts in the first level. The value goes from 0.0 (not interesting) to 1.0 (very interesting). The degree of confidence associated to the value 1.0 is completely reliable, as the user has introduced it.

### 6.5.3 Propagation of the initial preference and certainty values

The structure of the ontology can be used to transfer the information through nodes using a downward propagation of the initial preferences and degree of confidence obtained for the ontological concepts of the first level. For example, if a user explicitly expresses a high interest in routes, a node that is in a high level in the ontological hierarchy, ( $\mu Routes(u)=0.8, CLRoutes(u)=1.0$ ) it will mean that the is interested in the different types of routes (descendants of the node). Thus, the system has to transfer the interest in the most general concept to its subclasses will the lowest level concepts, which are used to create instances of the recommender elements. However, it is not certain that the degree of interest will be the same for all of their sons, so the uncertainty increases as the deepest levels of the ontology are propagated.

In our recommender system, we suggest to copy the degree of membership of the user from the highest level to all of its descendants. In this way, the degree of confidence in each level will decrease in a  $\alpha$  factor, which can be personalised with the needs of the application and represents the decrease of the confidence when we go down the hierarchy of the ontology, far from the general concepts that have been explicitly valued by the user.

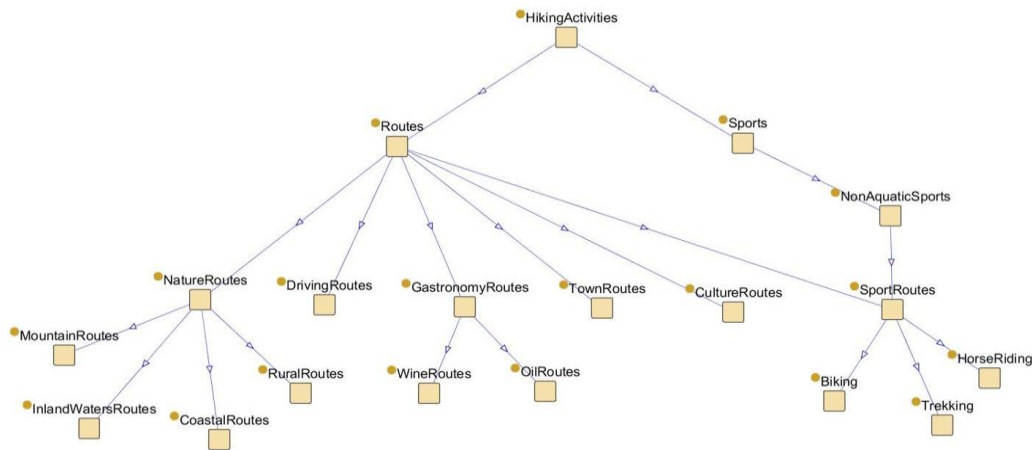


Figure 2. Portion of the ontological domain

### 6.5.4 Dynamic improvement of the user profile

During the user session, the system can obtain additional information of the user thanks to his actions. These actions allow the system to modify the user membership degree of a concept and its degree of confidence.

Two types of information obtained from the interaction between the user and the system can be distinguished:

- As each concept is labelled with a low-level concept of the ontology, user interests regarding specific concepts can be deduced by studying his actions and movements. These actions can be positive (keep a recommended object) or negative (remove a stored object). The impact on the degree of confidence will be low, as the system will deal with indirect actions of the user.
- The recommender system can ask the user to assess some of the elements available. These values can be used to estimate the user membership degree in low-level concepts of the ontology. The impact on the degree of confidence can be high, because the system has obtained explicit information from the user.

Figure 3 summarizes the scores  $s$  (between -1 and 1) and the weights  $w$  (between 0 and 1) associated to each user action. This feedback is useful to refine the estimation of the membership degree of the user by inferring his interests based on the behaviour of the user in front of the previously recommended objects.

User actions	Explicit	Implicit	s	w
Save recommended item		•	0.5	0.5
Remove recommended item		•	-0.5	0.5
Request detailed information about an item		•	0.1	0.2
Request item similar to the current one		•	0.15	0.3
Rate an item	•		[-1.0, 1.0]	1.0

**Figure 3.** User actions collected by the system

Assume that we have observed a set of actions  $A_c$  on a group of objects that are instances of the concept  $c$ . The scores and weights associated to these actions are aggregated together as follows:

$$\Delta_c = \frac{\sum_{a \in A_c} s_a w_a}{\sum_{a \in A_c} w_a} \quad CA_c = \frac{MIN(\lambda, \sum_{a \in A_c} w_a)}{\lambda}$$

As can be seen in equation, the aggregated confidence of the actions is normalized using a parameter  $\lambda$ , which indicates the level above which a higher amount of evidence is not required to have a full aggregated confidence of 1. For instance, it could have a value of 2.4 if 3 good reviews ( $0.8*3$ ) are considered enough to have a full confidence. If the aggregated confidence in the actions is higher than the current confidence level of the concept ( $CA_c \geq CL_c$ ), then its preference and confidence values are updated as follows:

$$\mu_c = \begin{cases} \text{if } (\Delta_c > 0) & \text{MIN}(1, \mu_c + \beta \times \Delta_c) \\ \text{else} & \text{MAX}(0, \mu_c + \beta \times \Delta_c) \end{cases} \quad CL_c = \beta \times CA_c + (1 - \beta) \times CL_c$$

$\beta$  is a parameter between 0 and 1 that graduates the level of change between the current values and the scores and weights given by the user actions. The higher its value, the bigger is the impact of the user actions on the concept information. For instance, if it is 0.75, the new confidence will be computed taking into account the confidence in the last action 3 times more (0.25) than the previous confidence.

#### 6.5.5 Upward propagation

The user opinion can modify the information stored in the lowest values of the ontological level. Once the system has collected enough information from the user actions, values can be propagated through the ontology to upgrade values of related concepts. In the first place, an upward propagation is made to the father of the modified son, and so on and so forth until reaching the initial root of the ontology. The further the propagation is, the higher the uncertainty will be.

Note that several children of the same concept may have been modified (e.g., the user may have interacted with instances of WineRoutes and OilRoutes, both children of GastronomyRoutes). Let us assume that  $\varphi^c$  is the set of concepts that are children of  $c$  and have confidence values higher than a certain threshold (concepts that don't have enough confidence should not influence on their parents). The aggregated preference and confidence values of the children of  $c$  may be computed as follows:

$$\Delta_c = \frac{\sum_{i \in \varphi^c} \mu_i CL_i}{\sum_{i \in \varphi^c} CL_i} \quad CA_c = \frac{\sum_{i \in \varphi^c} CL_i}{|\varphi^c|}$$

If the aggregated confidence of the children of  $c$ ,  $CA_c$  is higher than a threshold, then its preference and confidence values are updated as shown in next equation.

$$\mu_c = \frac{(1-\beta) \times \mu_c CL_c + \beta \times \Delta_c CA_c}{(1-\beta) \times CL_c + \beta \times CA_c} \quad CL_c = \beta \times CA_c + (1-\beta) \times CL_c$$

### 6.5.6 Downward propagation

Once the upward propagation has been completed, the downward propagation takes place and the son nodes of the concept  $c$  are upgraded. A concept  $c$  will be modified according to the membership degree and confidence of its father,  $\chi^c$ , as long as the degrees of confidence go beyond an established limit. The aggregation of the information of the parents is done equivalently to the upwards case, as follows:

$$\Delta_c = \frac{\sum_{i \in \chi^c} \mu_i CL_i}{\sum_{i \in \chi^c} CL_i} \quad CA_c = \frac{\sum_{i \in \chi^c} CL_i}{|\chi^c|}$$

Now that we have presented the ontology-based management of the user profile in EnoSigtur, in the following chapter we will go into our recommender system in depth.



## 7 EnoSigTur

### 7.1 Introduction

EnoSigTur is a smart recommender system for tourists interested in experiences related to the wine sector, and has been developed in the Parc Científic i Tecnològic del Turisme i Oci (Tourism and Leisure Scientific and Technological Centre), in collaboration with researchers at the Universitat Rovira i Virgili. Through a web application, the system allows users to know the wine activities in the region of Tarragona. Each user points out his interests in general terms and the system selects the most suitable and appealing activities for him. The system is capable to improve the data of the user preferences from the interaction between the user and the system itself; so that, it progressively provides more adjusted and adapted recommendations. EnoSigTur also allows users to plan a trip by offering advanced planning services that check timetables, dates, length, etc. Moreover, with the mobile application, users can track their trip while it is taking place.

The place where this system has been of is not fortuitous. In fact, it responds to the challenge of the wine sector in the region Tarragona, in terms of competitiveness and sustainability. In this region of Catalonia we can find Costa Daurada, one of the most important areas in the Spanish coast to carry out sun and sand activities. Regarding the growing instability of this sector, this region has assumed the challenge to be different and innovative. The supply has been diversified in order to offer alternatives to sun and sand activities towards less appreciated landscapes out of the most tourist areas. And this is the case of the wine tourism, which has top-level resources.

The counties or regions of Tarragona have a great specialization in the wine sector. The number of wine denominations of origin is very high, taking into account that is a relatively small place. It has five wine denominations of origin and other three shared with the bordering regions. In total, eight out of ten regions of Tarragona are included in some denominations of origin. Although each region has its peculiarities, there are common features that add value to the whole area, such as the Cathedrals of Wine (monumental modernist wine cellars) or the popular events of the symbolic wine patrimony, which try to promote through the brand of “Wine Country”.

Even though the great potential that this sector has, international tourism is still not very familiar with this brand. Instead, international tourists only associate the region of Tarragona to a summer resort. For this reason, new revitalizing tourist strategies are being considered, both in the interior of Tarragona and in the wine-producing places across Catalonia in order to attract potential visitors.

EnoSigTur is designed to provide a user-friendly and flexible service addressed to specialized and non-specialized public. It supplies personalised recommendations, offers practical support for planning a trip and facilitates and gives users the opportunity to know more activities to do in the area.

## 7.2 Wine information systems

Although there are recommender systems designed to plan trips to important cities, this technology has still not reached all tourist sectors with the same intensity, which is the case of the wine sector.

These are web and mobile applications dedicated to wine tourism that have been developed between the end of 2010 until the present day:

- Vins et Tourisme en Bourgogne (<http://www.vins-tourisme-bourgogne.com>)
- Pesquisa de vinhos y Rotas do Vinho (<http://www.infovini.com>)
- Wine Regions of Victoria - VicWineries (<http://www.visitvictoria.com>)
- Finger Lake Wine Country (<http://www.fingerlakeswinecountry.com>)
- Vin Vaudois (<http://www.vins-vaudois.com>)

In the Figure 4, we can find a table that compares the different systems.

	Web	Mobile	Geographic Information System	Itinerary	Wine Cellars	Events	Hotels	Information
Vins et Tourisme en Bourgogne	x	x	x		x	x	x	
Pesquisa de Vinhos y Rotas do Vinho	x		x	x	x	x		
Wine Regions of VicWineries	x	x	x	x	x	x	x	x
Finger Lake Wine Country	x		x		x	x	x	x
Vin Vaudois	x	x	x		x	x	x	x

**Figure 4.** Wine applications analysis

All applications have a GPS device to use interactive maps that identifies both the user and the wine cellar positions.

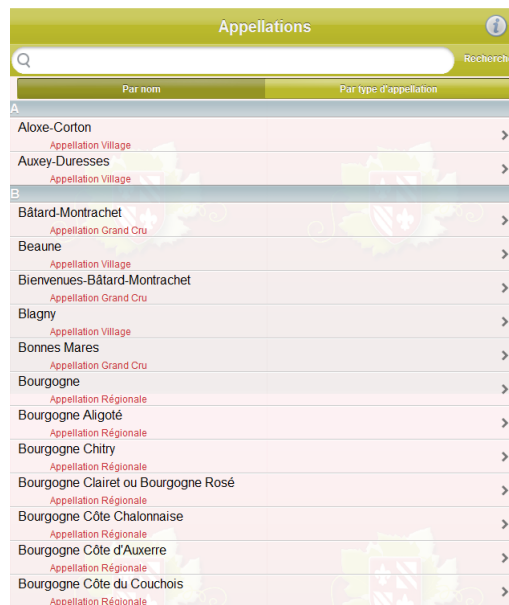
Apart from selecting punctual activities, tourists are normally interested in planning a travel route of one or more days. Most of the analysed applications do not allow users to plan an itinerary in an automatic way. However, some of them have the option to plan an itinerary manually and select and arrange the activities. In this sense, users have to check previously the timetables and the availability to arrange the itinerary. Other applications only offer fixed tours of wine cellars in specific places. For example, the Portuguese website *Rotas Do Vinho* offers prearranged tours that cannot be personalised nor modified. Another example could be *VicWineries*, which provides users the opportunity to arrange an itinerary in all tourist towns in the Australian region of Victoria.

The disadvantage of this application is that it does not suggest any means of transport nor temporal information, and online booking is not allowed.

Finally, as we can conclude from the results of the table, some of the applications give users the chance to know events related to wine, such as activities with a cultural and creative nature: exhibitions, fairs, etc. This additional information is very interesting for the visitors, as they can experience a richer tourist experience in the region. In the following pages, we are going to describe the abovementioned systems.

- **Vins et Tourisme en Bourgogne.** Vins et Tourisme en Bourgogne is a multilingual mobile application on wine tourism and cultural tourism in the Burgundy region. This application is the result of a public-private partnership that brings together the le Comité Régional du Tourisme de Bourgogne, le Bureau Interprofessionnel des Vins de Bourgogne, le Conseil Régional de Bourgogne, la Chambre Régionale de Commerce et d'Industrie de Bourgogne, l'Agence NTIC Bourgogne and Réseau CONCEPT.

The application allows you to search by location and view information about the wines, producers (producer's name, hours, types of wine ...), hotels and restaurants as well as wine-related festivals.



**Figure 5.** Search for origin denominations by name and type



Figure 6. Search for producers, hotels and restaurants by name, region and closeness



Figure 7. Information sheet with static map

- **Pesquisa de vinhos y Rotas do Vinho (infovini)** is a project that aims to be the paradigm of the use of the Internet to market and promote Portuguese wine and the sector's culture, not only nationally, but also internationally.

The portal's mission is to create a large community made up of motivated consumers and users connected with the sector. Infovini will enable them to share knowledge and experiences related to wine and its culture.

Careful promotion of Portuguese wine via the Internet is essential to convey an image of innovation and quality combined with the tradition and singularity of Portuguese wines. In this way, the Infovini portal is an important marketing tool for the sector, approaching the different types of users in a segmented manner, whether they are experienced connoisseurs or novice consumers.

The information available at Infovini allows different levels of interaction, always oriented towards action and knowledge. Thus, one can clarify doubts such as how Port wine is made, get information on a certain wine route and learn how to get there, or search for information on a specific brand. There is also a limited-access area where one can manage a virtual cellar and add personal notes to each wine on one's personal list, as well as create a list of events or favourite pages. Producers and bottlers are able to interact with the information on their products uploading tasting notes, information on awards and technical information sheets.



**Figure 8.** Prearranged tours across several regions in Portugal

Wines Regions Learning Shopping News Events Multimedia Search

A wine for each occasion  
Wine search  
Types of wine  
Find your wine  
Drink in Moderation

### Find your wine

Home > Wines > Find your wine

- 1. People tend to see you as:**
  - a relaxed person
  - a delicate person
  - an adventurous person
  - an ironic person
  - a persistent person
  - an understanding person
- 2. Its a party day! What will you wear?**
  - something comfortable and casual
  - designer clothes
  - something trendy
  - something formal
  - something simple, though with a classy touch
  - something extravagant, impossible not to be noticed
- 3. What is best in wine is:**
  - to feel its aromas
  - to gently taste it, imagining the steps involved in its production
  - the chance its taste might surprise us
  - the variety it offers
  - that it is versatile and ideal for any occasion
  - that it is a good way of using grapes
- 4. Your favourite food is:**
  - shellfish
  - vegetables
  - meat
  - fish
  - fruit
  - chocolates and biscuits
- 5. The ideal occasion to have wine is:**
  - with friends
  - at parties

**Figure 9.** Form used to discover the wines appropriate for the user

Wines Regions Learning Shopping News Events Multimedia Search

### Events

Home > Events

All events Tasting Fair Other

Location: United Kingdom

July '12

Previous month Next month

**3** Imbibe Fair London  
03 to 04 July '12

> <http://imbibe.com/live>

> More information

Previous month Next month

Most viewed news

- "Fabelhaft 2007": the best red wine of the year 2009 in the German market
- Angola is the biggest importer of Portuguese wine
- Portuguese Wines Offer Tremendous Quality and Value
- Portugal port's image changed to attract younger fans
- 100 points for Taylor's Scion by Robert Parker

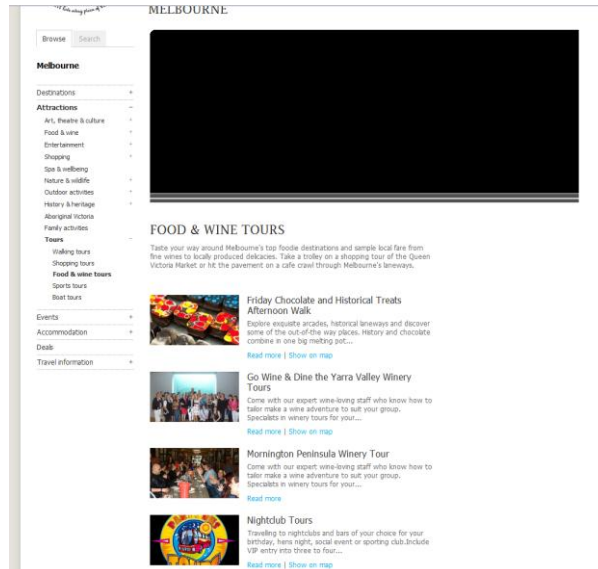
STONVIRTUOL

"Coloquei e vendi no próprio dia!"

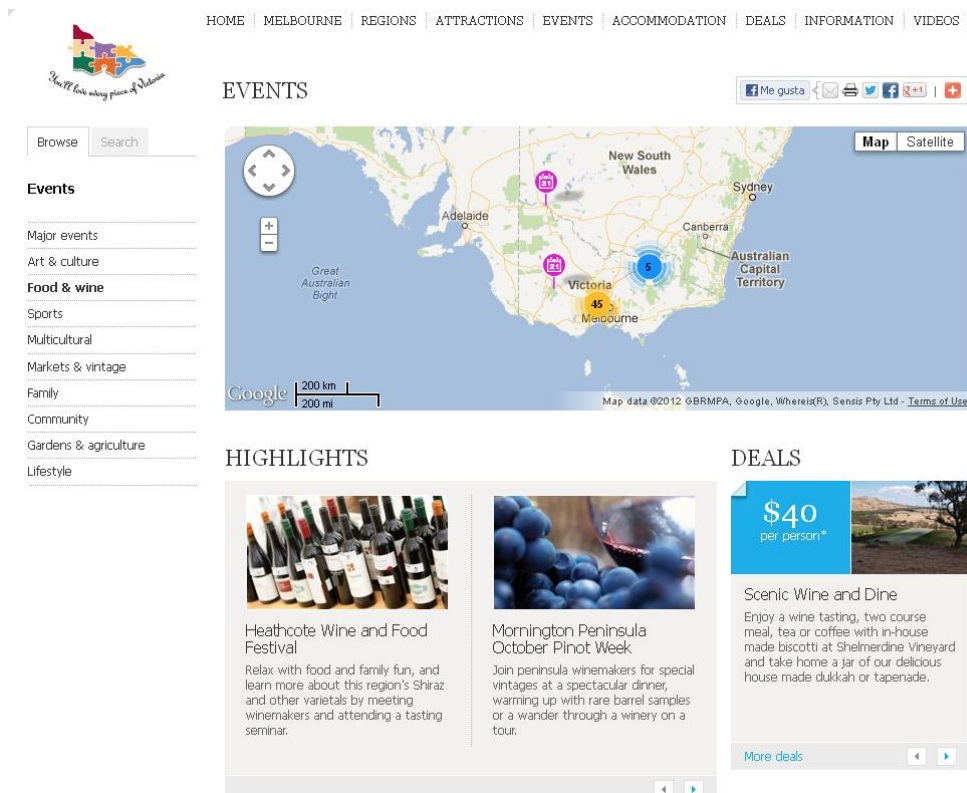
**Figure 10.** Events related to wine tourism in different countries

- Wine Regions of Victoria (VicWineries)** is the official website of the state of Victoria (Australia). Victoria boasts over 850 wineries, of which 650 have cellar doors, in 21 distinct wine regions.

The website shows all sorts of information about wines (events, foods, etc...).



**Figure 11.** It only provides instructions to go from one place to another



**Figure 12.** Allows geolocation events

HOME | MELBOURNE | REGIONS | ATTRACTIONS | EVENTS | ACCOMMODATION | DEALS | INFORMATION | VIDEOS

See the best of Victoria

FOOD & WINE

Browse Search

Attractions

Top attractions

Art, theatre & culture

Food & wine

Wineries

- Around Melbourne
- North-east Victoria
- Central Victoria
- Western Victoria
- South-east Victoria

Dining

- Local produce
- Craft breweries

Entertainment

Shopping

Spa & wellbeing

Nature & wildlife

Outdoor activities

History & heritage

Aboriginal Victoria

Family activities

Touring routes

Tours

Victoria boasts over 850 wineries, of which 650 have cellar doors, in 21 distinct wine regions. Enjoy cellar door tastings and dine on local produce at winery restaurants. From the cool-climate varieties of the Yarra Valley to the big reds of Rutherglen, create your own Victorian wine experience.

Wine regions around Melbourne

From pinot on the Mornington Peninsula to sparkling in the Macedon Ranges, discover five distinct wine regions within an hour and a half of the city.

Wine regions in north-east Victoria

The vineyards of north-east Victoria fall into five distinct regions – Rutherglen, Beechworth, Glenrowan, King Valley and Alpine Valleys.

DEALS

\$40 per person\*

Scenic Wine and Dine

Enjoy a wine tasting, two course meal, tea or coffee with in-house made biscotti at Shelmerdine Vineyard and take home a jar of our delicious house made dukkah or tapenade.

More deals

Figure 13. Shows information about all kinds of wines

- **Finger Lake Wine Country** is a website and mobile app, interactive, location-aware travel guide, with hundreds of listings for accommodations, restaurants, wineries, and things to do options.

ATWATER ESTATE VINEYARDS

5055 State Route 414, Burdett, NY 14818  
607.546.8463

Price: Tasting Fee  
Rating: not yet rated  
[view/write review](#)  
[visit website](#)

SENECA LAKE WINE TRAIL MEMBER

Atwater Estate Vineyards and Winery is located on the southeastern shore of Seneca Lake in the heart of Fing... [more](#)

+ ADD TO TRIP BUILDER BUY WINE VIEW MAP

Amenities:

Restaurant  Accommodations  Tours Available  Group Packages  Banquet/Conference Options  Handicap Accessible  Picnic Area

Figure 14. Wine cellar data sheet



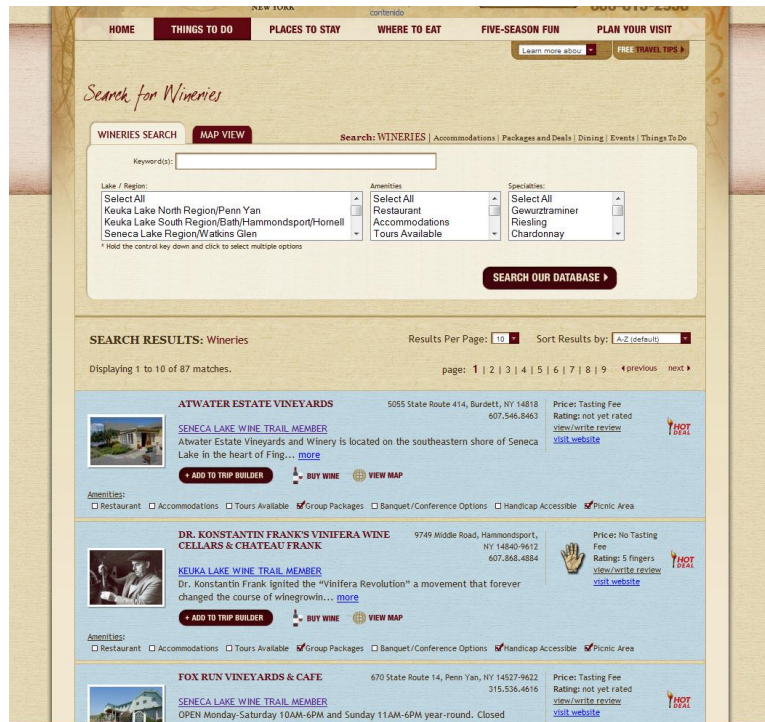


Figure 15. Wine cellar searcher

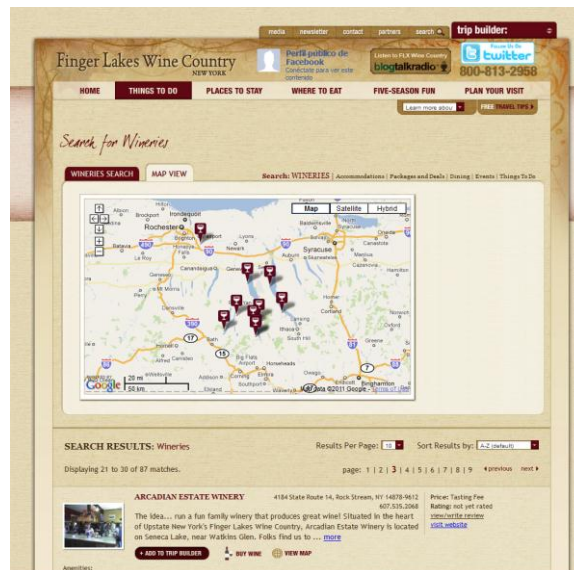
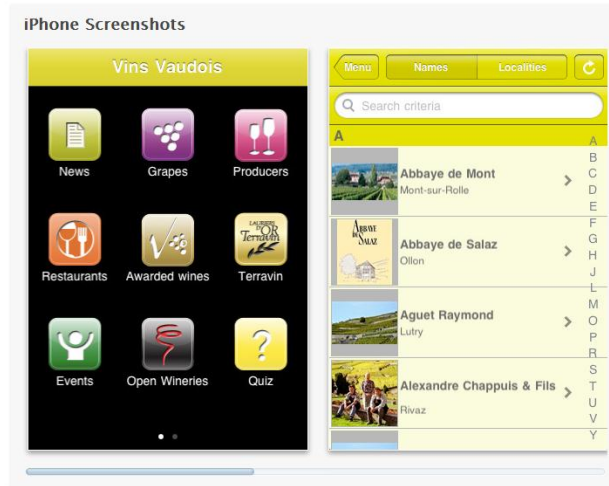


Figure 16. You can only add items to the planner

- **Vin Vaudois application** is a complete eno-touristic information tool on the canton of Vaud. the user has a powerful tool for visiting whatever cellars he wishes, to plan his route according to the location, to dine in pleasant places and to discover an area rich in wines, good food and an infinite variety of breathtaking landscapes and panoramas.



**Figure 16.** Interface and facilities provided by iPhone



**Figure 17.** Contest to win a bottle of wine of Vaud, are held monthly



**Figure 18.** Allows share all your information with your friends on Facebook or by e-mail

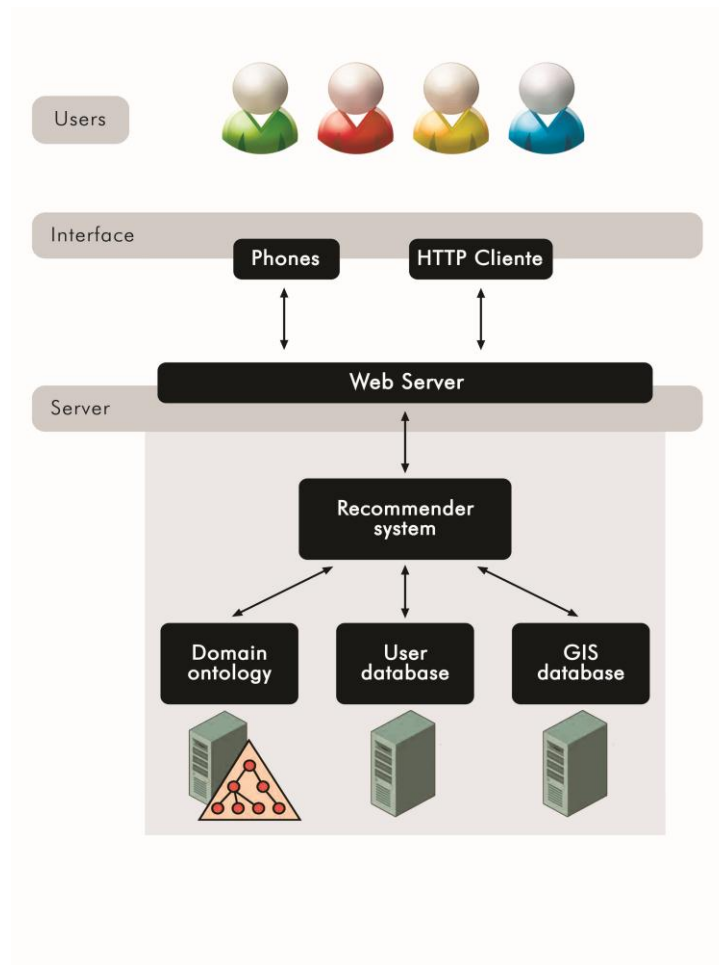
### **7.3 Recommender system design and development**

In this section, the architecture of EnoSigTur and its main components will be described.

#### **7.3.1 System architecture**

The Figure 19 shows the general architecture of EnoSigTur. All modules have been developed using open-source software and are organized in a client-server structure. The most relevant aspect of the system is the meticulous combination of different technologies, what has made it possible for the system to use advanced artificial intelligence techniques in an efficient way and with a shorter execution time.

Users can access the system through any of the interfaces. The web server has been built up with Java Server Faces together with the extension ICEfaces, which is an Ajax framework that puts powerful web applications into operation.



**Figure 19.** Architecture of EnoSigTur

The representation of the geographical resources in the maps of the web interface has been designed with Google Maps API. API has allowed us to create integrated maps in the application, and also to use other services such as Street View, the geocoding and the calculation of itineraries to from one place to another. Mobile phones use Google Maps libraries, which are integrated in the device itself, to represent geographical resources.

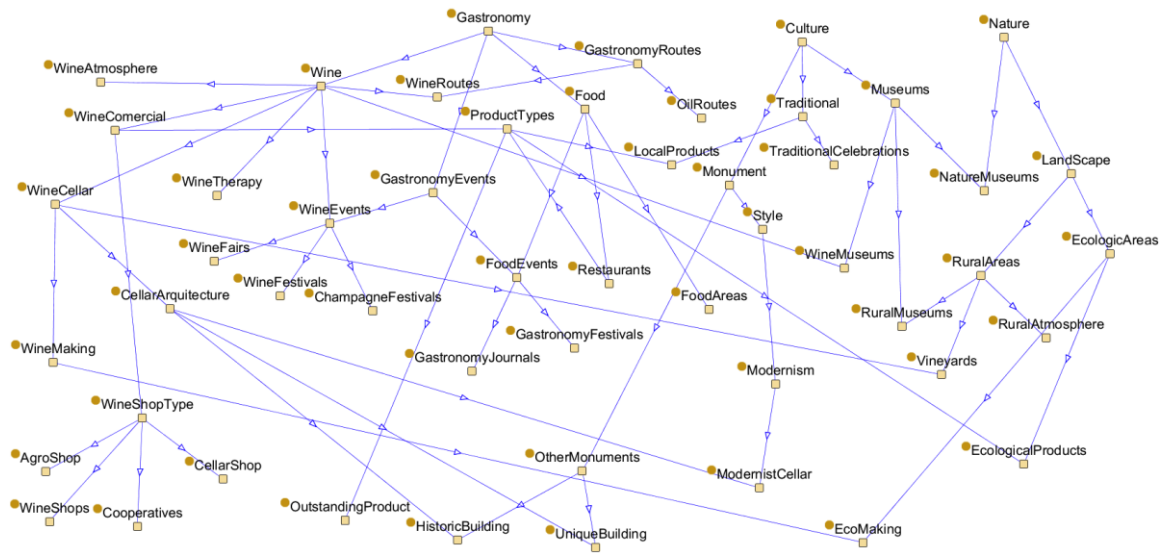
The heart of the architecture is the recommender system developed by Java, which is the responsible for the interaction between all modules. In addition, it manages the user profile in a dynamic way, as it upgrades his state after each action or movement he does.

Data is stored in two databases. One of them contains touristic resources, which include all the geographical information that will appear on the maps, and the other one stores all users profiles. Touristic information is managed by PostGIS and users information by PostgreSQL. Connections in databases are handled by Hibernate with a spatial extension that deals with the geographical data. We have used JTS Topology Suite to process touristic resources spatial functions, like distance calculation between two places. Databases are not only used to manage data, but also to optimize search functions.

Furthermore, Scripts SQL that execute data mining techniques have been programmed and POstGIS spatial functions have been used to filter geo-referenced resources in order to optimize consultations in databases.

### 7.3.2 Ontology

To represent the domain, an ontology has been applied. Thus, touristic activities have been described in a hierarchical way. The ontology represents up to 203 concepts interrelated in five levels of the hierarchy. As we can see in Figure 20, the ontology is structured in four main concepts that constitute the first level of the hierarchy: “Wine”, “Gastronomy”, “Culture”, and “Nature”. The ontology is not a pure taxonomy, as it contains multiple inheritances between concepts. For example, “Wine Routes” is a subclass of both “Wine” and “Gastronomy Routes”.



**Figure 20.** Part of the domain of the ontology

The ontology has been developed using the Thesaurus of the World Tourism Organization as a reference guide that represents the tourist and leisure activities in Costa Daurada and Terres de l’Ebre. A Committee of Experts in the field of tourism in the Tourism and Leisure Scientific and Technological Centre has determined which concepts and connections have to be represented. The degree of precision in each part of the ontology depends largely on the number of activities available in the region. For instance, there is detailed information of the concepts related with “Wine”, because the importance that wine sector has in this area. In any case, the ontology can be easily expanded with more concepts.

The ontology is used to classify explicitly the activities to suggest from a predefined set of main concepts that are used by the recommender systems during its reasoning processes.

Each activity is labelled with one or more concepts of the ontology, which are usually low-level nodes in the hierarchy. The ontology only contains classes that describe the different types of activities. Thus, the activities are stored in a database maintained through a web content management system.

Ontological classes are stored in memory for each user; thus, the recommender system can associate a degree of preference to each of the classes, according to the explicit and implicit information that the user provides. These preferences are the key information to decide which activities have to be recommended to the user.

As we have explained in the previous chapters EnoSigTur uses automatic learning techniques to dynamically upgrade the user interests from the analysis of his actions: see detailed information of an activity, add or delete an activity from the trip or grade an activity. These actions allow the system to deduce the type of activities that the user is interested in and also to increase the degree of interest of related concepts. These values are transferred through the hierarchical structure of the ontology in order to upgrade the preferences of all concepts.

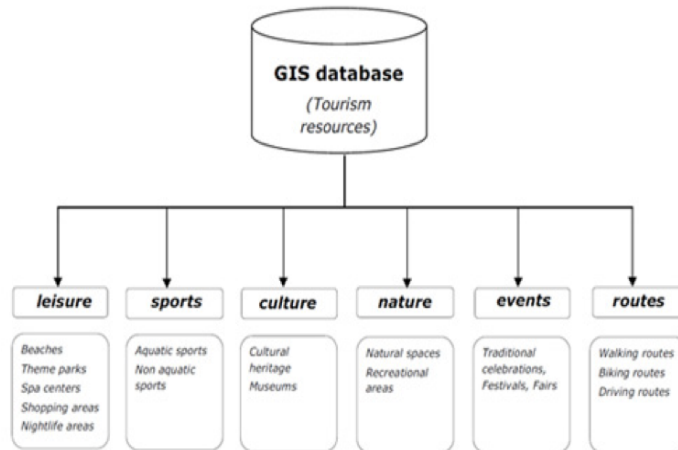
The ontology has been developed with the Protégé Editor and is represented with the Web Ontology Language (OWL). EnoSigTur manages the ontology with Jena Framework Web, which supplies the necessary tools to carry out the process.

### 7.3.3 GIS database

The first step to develop EnoSigTur was to gather the tourist resources data (leisure activities, cultural heritage, nature areas, sports activities, routes and events) in Costa Daurada and Terres de l'Ebre, with the goal of building a GIS database. This data was available in different city councils, so that, the first task was to ask them for the information. Tarragona Regional Council provided us most of the information, although the Government of Catalonia contributed too. Data was received in a multiplicity of formats: GPS, spreadsheets, etc. Thus, we had a lot of work shifting the formats before we could upload all the information to the GIS database.

We considered several databases, but we finally decided to use PostGIS, a module that allows PostgreSQL to turn into a spatial database, which organizes, visualizes and analyses the information efficiently. Moreover, it is easily accessible through other GIS open source software.

Activities in the database are grouped into six categories: leisure, sports, culture, nature, events and routes. The last two play an important role, as they can be associated with any other category. As for the "Leisure activities" group, it contains five labels: *beaches*, *theme parks*, *spa centres*, *shopping areas*, and *nightlife areas*. The data of these subclasses has been added carefully to the database, since they are the main tourist attractions in Costa Daurada and Terres de l'Ebre. Regarding the group "Sports", it has been classified into two subcategories: *aquatic sports* and *non-aquatic sports*. The label "Culture" includes two subclasses: *cultural heritage* and *museums*. In this case, the data has been stored in differentiated tables, as they came from different sources and it was not easy to combine the information. The group "Nature" contains two subgroups: *natural spaces* (which covers all natural areas protected by law), and *recreational areas* that we can find within these natural areas. The group "Events" incorporates *temporal activities*, such as fairs, festivals, traditional *celebrations*, etc. that can be programmed throughout the year. Finally, the label "Routes" contains three subclasses that can be related to other categories: *walking routes*, *biking routes* and *driving routes*. In Figure 21 we can see the structure of the database:



**Figure 21.** GIS database

Geographical entities in a GIS database have geometric properties, which can be modelled by the measures, properties and connections of dots, lines, angles, and areas. Spatial databases mainly use two types of geometrical data: bitmap data and vector data. Bitmap data is characterized by a dot matrix, where each dot represents the value of an attribute for an area of the real world. Vector data, on the other hand, has to do with the dots, lines and polygons that represent areas of real-world entities. EnoSigTur GIS database uses vector data.

Now, the GIS database contains more than 700 tourist resources. However, there is still a great job to do as for the addition of new resources and the upgrade of the existing ones. Therefore, the GIS database has been designed for the purpose of facilitating these future additions and upgrades. In addition, the structure of tables makes it easy to manage the database and massive operations.

### **7.3.4 Ontology and GIS database integration**

The GIS database and the domain of the ontology have been designed following the same structure and categories, in order to improve the consistency of the system. Furthermore, each activity in the database is represented by an entity of the ontological domain. For instance, there are three types of museums in the GIS database (archaeological museums, historical museums and anthropological museums); so, there are three entities that are part of a museum class in the ontological domain.

Each resource stored in the GIS database has a label that connects the entity with the domain. These labels make it easy to classify each element and, moreover, they allow the system to generate correct recommendations. In this moment, the number of ontological entities is higher than the types of activities in the GIS database. This fact makes the system more efficient, since it facilitates the addition of new types of activities in the GIS database and also the migration of the data model to other scenarios.

Morover, the GIS database includes a table that defines the connections between all kinds of tourist activities. This table has been built using two procedures. The first one is based on the position of resources, and the second one is based on qualitative criteria. In this way, the system is able to provide more detailed and adjusted to the tourist profile recommendations.

For example, if a user wants to travel with his family and he is interested in nature, the system will be capable to suggest him the natural areas that contain leisure areas (based on the position), or if the user likes both hiking and culture, the system will offer him cultural itineraries (based on qualitative criteria).

### ***7.3.5 Users profiles database***

In a user database, the information of each user is stored. This database consists of two parts:

- A static part with information of the user trips.
- A dynamic part with a particular version of the ontology, in which the degree of interests is stored in each of the classes and is upgraded thanks to the user actions. Therefore, the application deduces the user preferences with the explicit and implicit information that it receives from the user.

### ***7.3.6 Explicit information***

The first thing the user has to do is to complete a form in order to create an initial profile. The objective is to obtain as much information as possible with few questions. The partners of the project EnoSigTur elaborated a questionnaire to discover the most common motivations of the tourist who visit Costa Daurada and Terres de l'Ebre. A survey of thousands of people revealed that the main motivations in order of importance are the following ones: going to the beach, going shopping, relaxing, amusement parks, culture, nature, gastronomy, sports, shows and events. The user interested in the wine sector, however, will choose between wines, culture, nature and gastronomy. All of these preferences constitute a concept of the ontology.

Demographic data and information about the user trip are also obtained through forms. This data includes the country of origin, destination, length of the trip, etc. Some of these variables are used to filter the results before they are show to the user.

Apart from the explicit information obtained at the beginning of the user first session, the system is able to get explicit information from the user ratings about the activities that he has performed during the trip. Users rate the activities in a scale from 1 to 5. The system reminds them the possibility of ranking their trips, which is only possible through the web interface.

### ***7.3.7 Implicit information***

The system takes also into account the actions made by the users during their interaction with the system with the aim of improving its recommendations. Once the user has been given a list of recommendations, he can carry out several actions with the suggested activities. Meanwhile, the system will be able to deduce the user interests thanks to the analysis of these actions. This is very useful not only to adapt in a dynamic and automatic way the user profile, but also to improve the degree of the his interests in each activity. This process has been detailed in the previous chapter.



The user can select the activities he is interested in and add them to a trip plan. The user can also see detailed information of an activity, look for similar activities or ask for related activities. All of these actions prove the user interest in a particular activity. It could be the case that the user asks for a new list of recommendations, which will mean that the user is not really interested in the activities initially provided. All in all, these actions will supply implicit information, which is essential for the success of the recommendation process.

#### **7.4 Personalized recommendation of wine activities**

The EnoSigTur recommender system allows the user to obtain personalized information about the wine sector in the Catalan region of Tarragona. This information is mainly focused on activities related to wine (visits to wine cellars, vineyard landscapes, wine-tasting bars, etc.). However, it also includes other cultural and leisure activities that supplement a wine trip, such as visits to museums and monuments or nature routes. Moreover, the user can also get information of accommodation and places to eat. Thus, the user can obtain detailed information of each and every activity, and plan a trip selecting the most appealing activities for him.

The designed recommender system gives the user the opportunity to filter and rank the information according to his preferences, characteristics or the rankings of other users with a similar profile. The system analyses the user actions in order to improve the adequacy of the recommendations, both for current and future users.

In order to provide personalized information to the user, several techniques common in the recommender systems have been used: collaborative filter, content recommendation, and use of socio-demographic data. Furthermore, these methods have been improved with the use of ontologies, which categorize the activities of the domain in a hierarchy. The system also takes into account the user context to filter the activities that he cannot perform.

During the creation of a recommender system, it is common to use hybrid methods that combine the techniques based on content and collaboration, since they offer individualized techniques, which can improve the user satisfaction. EnoSigTur is a hybrid system that uses techniques based on content and techniques based on collaboration.

In the following sections, we will explain how the system predicts the degree of the user interest in each activity. In other words, how an ontology-based profile operates. The purpose then is to elaborate a list ranked according to the user interests, combining recommender systems methods based on contents and collaboration.

##### ***7.4.1 Recommender system based on contents***

Recommendation methods based on contents generate recommendations of objects in the domain thanks to the user preferences. All EnoSigTur users indicate at the beginning of the session, their interest in a number of general motivations. Then the system analyses the user actions and shapes the initial preferences with the help of machine learning algorithms.

Recommendations are based on a direct correspondence between the characteristics of the suggested activities and the user interest in each of these characteristics. EnoSigTur contains a database with all the tourist activities available in the region.

The main objective that pursues the recommender system is to specify a degree of preference to each concept of the ontology, which will make it possible to calculate the interest that the user has in each activity.

The system also stores the degree of confidence (between 0 and 1) in each concept. This degree of confidence will depend on the evidences received from the user.

#### 7.4.1.1 Motivations

We obtained the main tourist motivations from a survey to 30,000 people conducted between 2001 and 2009 in Costa Daurada and Terres de l'Ebre. The most common motivations are "Health", "Culture", "Leisure", "Gastronomy", "Sports", "Fairs" and "Events".

The initial information that the user provides has to do with his motivations. The user ranks his degree of interest in each motivation with a scale from 0 to 100. Low value indicates little interest, and high value indicates great interest. If users do not modify the value by default of a motivation, it will mean that they are not worried about that motivation. Therefore, the system can suggest related activities having other parameters into consideration. If the user is not interested in activities of a certain motivation, he will have to introduce a zero in that motivation.

All this information, therefore, has been obtained in an explicit way, sine each concept has been associated with the user motivations, and the system origins a degree of confidence 1.0 to the preferences given by the tourists. For example, if a user specifies a value of 0.7 in the motivation "Nature", this concept will have a 1.0 degree of confidence and a 0.7 degree of preference.

#### 7.4.1.2 User interaction with the system

The analysis of the interaction between the user and the system also gives implicit information about his interests, which can be used to calculate the degree of preference in each concept of the ontology. When the user is given a list of recommendations, he can carry out several actions. According to the actions, the system will determine if the user is interested in the activities or not.

Figure 22 shows the value of interest and confidence associated with each user action.

<b>Action ID.</b>	<b>Action type</b>	<b>Interest score</b>	<b>Confidence level</b>
action1	Add activity to travel planner	1.0	0.5
action2	Remove activity from travel planner	-1.0	0.5
action3	Request detailed information about an activity	1.0	0.2
action4	Request activities similar to the current one	1.0	0.3
action5	Request activities near the current one	1.0	0.3
action6	Rating of an activity	[-1.0, 1.0]	1.0
action7	No actions on a recommended item	0.0	0.15

## Figure 22. User actions and his values

The system can also extract information from the absence of actions in a specific activity. For instance, if the user asks for a new list of recommendations, we can infer that there have not been any actions; that is, that the user has not considered the suggested activities. Thus, the associated percentage of interest decreases.

### 7.4.1.3 Ontological propagation of the value of preference and confidence

The ontology offers a hierarchical representation of the main types of activities in the domain. The information obtained from the user actions will determine the preference of concepts associated to specific activities, which are the nodes of the lowest level in the ontology. It is important to propagate the information across the hierarchy, since the interest in a particular activity can also mean some interest in the corresponding superclasses.

Therefore, an algorithm of propagation has been used to spread the value of preference in the nodes inferior to their predecessors. Each node sends a degree of interest to its superclasses. All nodes that receive information from their children nodes calculate the average of the received values.

In each hierarchical level, a factor that reduces the values is applied. Thus, the influence decreases as we climb up the hierarchy. After that, as we have explained in the previous chapter, a downwards propagation is performed to modify the preferences and uncertainties of related concepts.

### 7.4.2 *Recommender system based on collaborations*

The suggestions of this type of recommender system are based on the users opinions and are focused on either the elements or on the users.

- **Collaborative recommender systems based on elements:** predict the user interest in a particular activity, thanks to the user assessment of similar activities.
- **Collaborative recommender systems based on users:** predict the interest in an activity according to the assessments of other users with a similar profile.

Our recommender system is focused on the similarities between users. Thus, the system will recommend activities that other users with similar profiles considered interesting. The idea is to offer suggestions of the kind: who chose this activity, also chose this other one. The system can also offer suggestions that although they do not exactly match the user preferences, they could be interesting for him.

The similarities between users can be calculated in two different ways. On the one hand, the system can consider the closeness of users demographic data (if two users live near) and, on the other hand, it can consider the explicit information it receives from users. EnoSigTur combines both strategies. At the beginning, when the user has not provided enough information yet, the system considers demographic data. However, when the user has carried out several actions, it considers the explicit information it receives.

#### 7.4.2.1 Estimated interests according to motivations

We used the K-means clustering algorithm to differentiate the respondents referred to in paragraph 7.4.1.1. In the ends, there were 100 types of tourists. Each of these groups has a representative element, which has been obtained from the average between its members.

When a new user enters EnoSigTur, the system looks for the group that best fits his characteristics, comparing his motivations with the representative elements of all groups. The degree of similarity between the user and the group is understood as the degree of confidence that will be attached to the concepts of the ontology.

#### 7.4.2.2 Users estimated interests according to demographic data

Estimated interests based on motivations only allow the system to suggest general recommendations. However, it is necessary to provide a more specific recommendation. It is in this moment when users demographic data is used.

A user has to specify his demographic data and his trip motivations in the first time he visits the system. In this way, the system will be able to look for other users, who have similar demographic data. Thanks to this association, the system is able to calculate the degree of preference and the degree of confidence in concepts of the ontology.

#### 7.4.2.3 Estimated interests of users with similar assessments

After an initial recommendation, the user can be unsatisfied with the suggested activities, since they do not match his demographic data and motivations. However, once the user has interacted with the system and has manipulated the suggested activities, EnoSigTur is capable of offering more precise recommendations taking into account the actions of other users with a similar profile. In this case, users are classified according to their assessments of activities with the algorithm K-means.

Once the user has been classified, the system calculates the degree of preference and the degree of confidence associated to concepts of the ontology, according to both the actions carried out by the closest group to the user and the distance between the user and this group.

### 7.4.3 *Integration of all recommendations techniques*

Throughout the previous sections we have presented several methodologies. Thanks to them, the system can calculate the final degree of preference and confidence of a user  $u$  associated to each concept  $c$  of the ontology. Both values of preference and confidence are the average of all preference and confidence values, respectively, which have been obtained through the different ways.

Once the calculations have been carried out, the system gathers all the activities related to concepts and establishes an assessment of preference ( $S^u(a)$ ) and a value of confidence ( $CL^u(a)$ ) for each activity.

The final recommendation is the result of two lists: one based on the content and the other one based on collaboration methods. The list based on content is initially made of activities that consider user motivations and later on, it improves with the user actions. The list based on collaboration methods is made of activities in which other users with a similar profile have been interested with.

After adjusting the values of preference and confidence for each activity, the system ranks the list of recommendations with the aim of supplying activities more appealing to the user.

The following heuristic rules have been defined in order to know if an activity should be above or below another one.

1. If  $CL^u(a_1)$  is high and  $CL^u(a_2)$  is low, then  $a_1$  will be above  $a_2$ .
2. If  $S^u(a_1)$  differs from more than 0.01 above  $S^u(a_2)$ , then  $a_1$  will be above  $a_2$ .
3. If the difference between the distance of  $a_2$  and the location of the user with the distance of  $a_1$  is more than 3 km, then  $a_1$  will be above  $a_2$ .
4. If none of the prior rules can be applied, the activities ordered randomly.

The suggested activities are also ranked by several filters:

- **Filter based on the price:** the activities that exceed the specified budget will be removed.
- **Filter based on the diversification of activities:** the list of the main activities to suggest can be too similar. This problem is known as over-specialization. We use an algorithm of diversification that diversifies the recommended activities according to the similarities of its characteristics. Thus, in the initial list, the similarities between all elements are analysed. Moreover, the difference of the activity and the rest is added up to each activity. The list is ranked again with the upgrades of the activities assessments; so that, the system offers diversified activities instead of similar activities.
- **Geospatial filters:** the user can specify the region to visit through a list that contains all possible destinations. When the user asks for a recommendation, the system calculates the distance of the destination chosen by the user and each suggested activity. This distance is used in the recommendation process in such a way that, for example, if there are two activities with the same punctuation, the activity closest to the destination will be situated at the top of the recommendation list. Therefore, the closest the activity is from the destination, the more positions it will climb up the list. In some cases, this filter can produced non-desirable recommendations. For example, if two activities are very close to the destination. Let's imagine, for instance, that a user chooses Tarragona as destination and he is interested in museums, which all have similar punctuations. In this case, the system will first suggest the ones that are closer to the city centre and will dismiss the ones that are far from it.

In this sense, in order to decide if an activity has to be recommended before another one taking the distance as a filter, the distance between the first and the second activity and the destination has to be considerably high to avoid the problem, between 1 and 5 km to be precise.

Filters, rules and the order of these rules are established in such a way that they solve problems associated with the recommendations. For example, they can avoid that the most popular activities always appear before others. If this happened, the diversity would be poor and new activities would be situated at the end of the list.

## **7.5 Functions of Enosigtur**

The system design is generic and modular, and can be easily adapted to other wine-producing regions. Usability criteria have been taken into consideration in order to conceive a comprehensible and easily accessible application. The application can be used in three different periods: before, during, and after the trip. Before the trip, the user can plan it in the web application. Furthermore, if the user signs in, he will have the opportunity to download the planning of the trip to his mobile phone.

Mobile application gives also the chance to modify the trip depending on the position of the GPS. Thus, the user will receive recommendations of activities close to his location. Finally, after the trip, the user will be able to add comments and punctuate the activities he has carried out during the trip. All in all, this information is very useful, since it gives clues about the user profile and so, the system can improve and adapt the suggested activities. In the following lines, we will deal with the functions of the system, both of the web and the mobile format.

## **7.6 EnoSigtur in web format**

The website is the first entry point for two types of customers. On the one hand, there are people who want to have general information of Costa Daurada or book their trip. On the other hand, there is a more specific and select group of people, who looks for detailed information about the wine-producing regions and also wants to make a booking.

Now we are going to explain briefly how the EnoSigTur web application works.

### **7.6.1 Front page**

In the front page, the user can find several images that represent some of the most beautiful places in the wine-producing area of Tarragona. It also includes a brief explanation of what the user will find in the application.

This page allows the user to perform one of the following options:

- Create a new trip.
- Get detailed information of a resource by clicking in the photo gallery.
- Access to mobile applications.
- Share the application on Facebook and Twitter.

The upper bar, present in the other pages, allows users to access the front page, choose the language, and log in or sign in a session.



**Figure 23.** Front page

### **7.6.2 Main page with trips created by the user**

If the user creates his own trips, he will be able to see the detailed list of these trips in the main page (Figure 24). He will also get information about the date, activities, and length of the trip. The actions that the user can carry out are the following ones:

- Explore a trip.
- Edit preferences.
- Download the trip.
- Delete the trip.

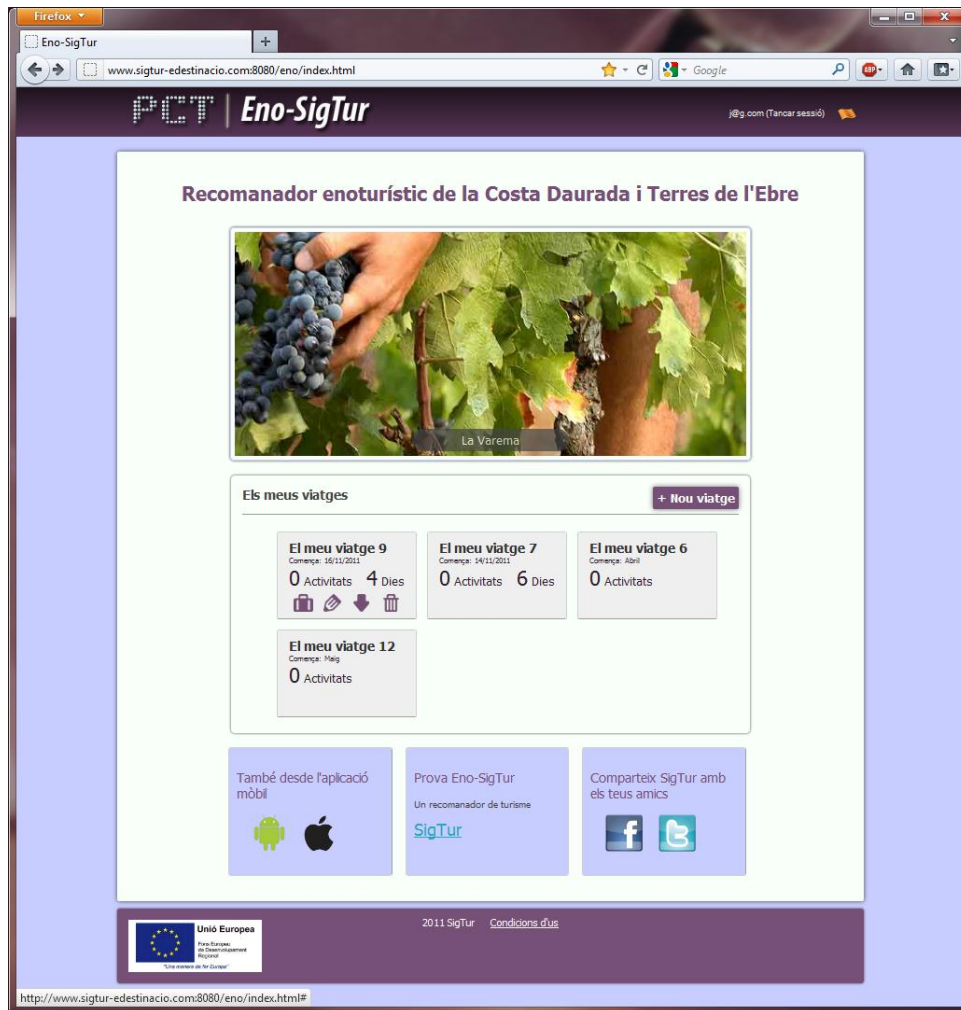


Figure 24. Main page with trips created by the user

### 7.6.3 Trip preferences

In order to create a new trip, the user has to fill in the following form (Figure 25):

- **Name of the trip:** the name “My trip n<sup>o</sup>” will appear by default, being  $n$  the number of the user trip. The user can edit the text by clicking on the box. It is useful for the user to easily identify his trips.
- **Place of origin:** list of countries available. In the case of Spain, the user can specify the region or county he comes from. Thanks to this information, the recommender system can put users with similar profiles into groups.
- **Travel group:** determines how the travel group is made. With this information, the recommender system will be able to:
  1. Gather users with similar profiles.
  2. Associate activities depending on the user profile.



The options that appear are:

- Alone.
  - Family or friends.
  - Couple.
  - Senior group.
  - Companies and other groups
- **Do you travel with children?** Yes or no.
  - **Number of people.**
  - **Destination:** if the user specifies a destination, the recommender system will suggest him activities close to it.
  - **Date of the trip:** the user can either specify the dates or give an approximate period of a month.
  - **Other interesting activities:** the user can select other motivations, which are not related with the wine sector: The options are:
    - Culture.
    - Natural areas.
    - Sports.
    - Health and welfare.
    - Leisure.

The screenshot shows a web browser window with the URL 'http://www.eno-sigtur.com'. The page title is 'Preferencias del viaje'. The form is titled 'Mi primer viaje' and contains the following fields and options:

- Pais de origen:** España
- ¿De qué provincia?:** Málaga
- ¿Con quién?:** Con pareja
- Total de adultos:** 2
- Con niños
- ¿Has decidido tu población de destino?:**  No  Sí
- ¿Cuándo?:** Desde 16/06/2012 hasta 17/06/2012 2 Dias
- Aún no lo sé
- ¿Cuáles son tus motivaciones del viaje?:** Sliders for Cultura, Naturaleza, Deportes, Salud y bienestar, and Ocio y entretenimiento.

At the bottom of the form is a button labeled '!Recomiéndame!'. The footer includes the European Union logo, '2011 SigTur', 'Condiciones de uso', 'Ayuda', and 'Un recomendador de turismo SigTur'.

Figure 25. Trip preferences

Once the user has filled in the form, he will press “Give me suggestions” and the map with the suggested activities will appear (Figure 26)

### 7.6.4 Map of recommended activities

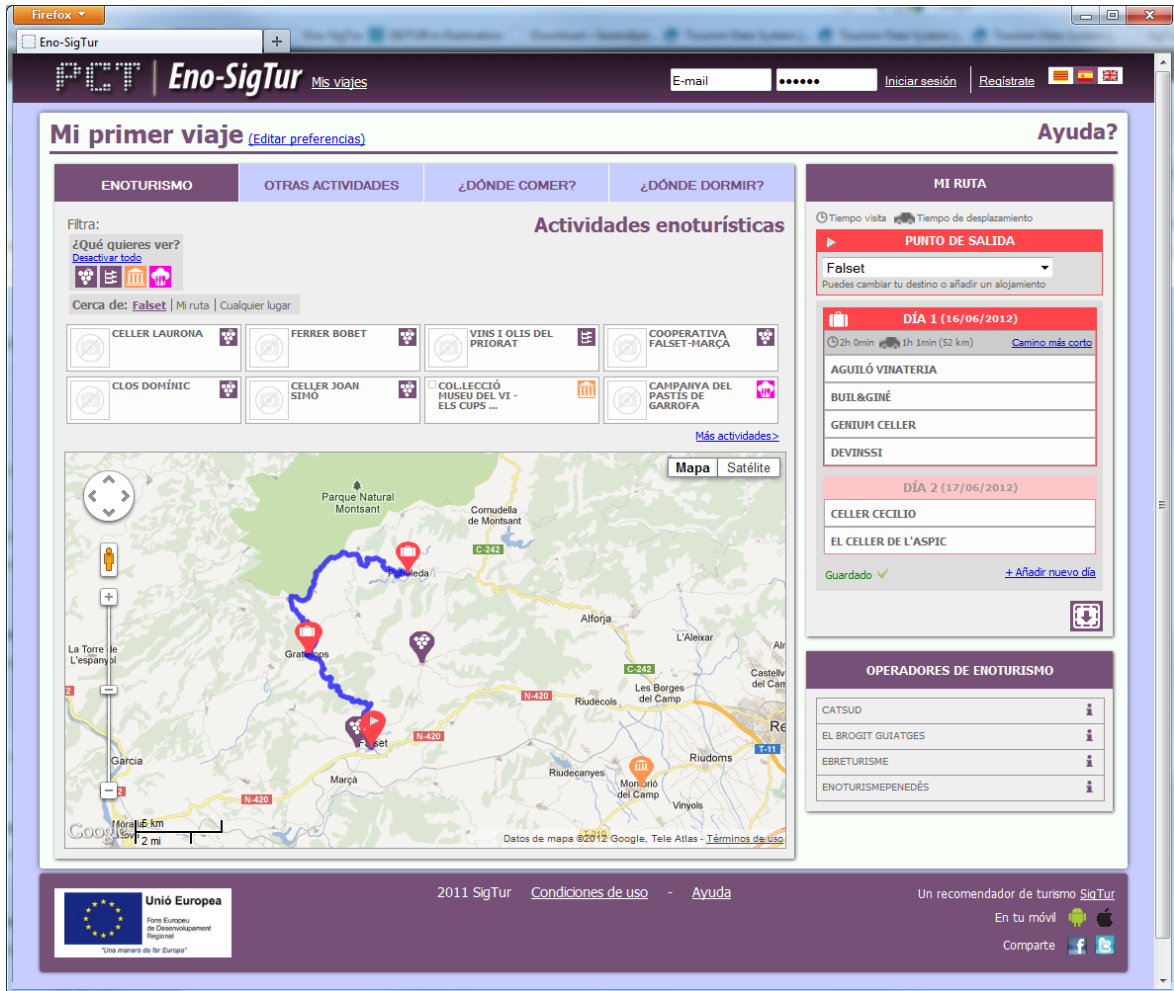


Figure 26. Detailed map of activities

#### 7.6.4.1 Schedule of activities

Above all it shows the list of recommended activities to be added to the planner. The user can:

- Choose to be show the activities near the destination point, activities near the created route created or activities in any place.
- Choose to show him only the activities of a certain category.
- Ask to be shown other activities, places to eat or places to stay.

## Mi primer viaje [\(Editar preferencias\)](#)

**ENOTURISMO** | OTRAS ACTIVIDADES | ¿DÓNDE COMER? | ¿DÓNDE DORMIR?

Filtra: **Actividades enoturísticas**

¿Qué quieres ver?  
[Desactivar todo](#)

Cerca de: **Falset** | Mi ruta | Cualquier lugar

<input type="checkbox"/> CELLER LAURONA	<input type="checkbox"/> FERRER BOBET	<input type="checkbox"/> VINS I OLIS DEL PRIORAT	<input type="checkbox"/> COOPERATIVA FALSET-MARÇA
<input type="checkbox"/> CLOS DOMÍNIC	<input type="checkbox"/> CELLER JOAN SIMÓ	<input type="checkbox"/> COL·LECCIÓ MUSEU DEL VI - ELS CUPS ...	<input type="checkbox"/> CAMPANYA DEL PASTIS DE GARROFA

[Más actividades >](#)

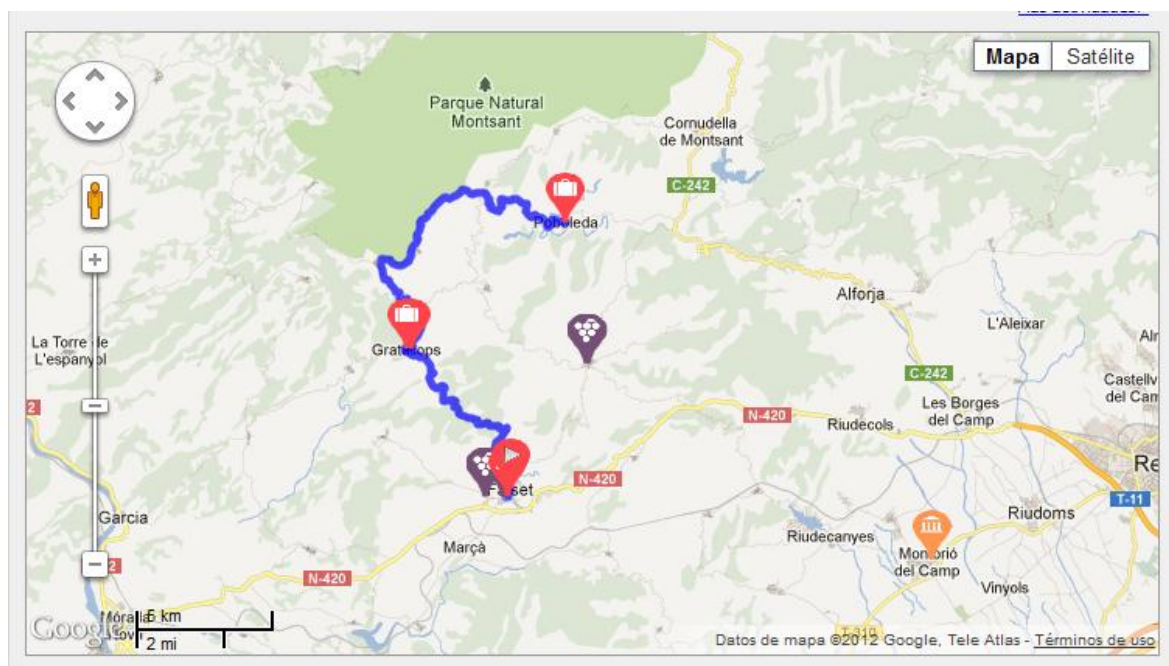
**Figure 25.** List of recommended activities

### 7.6.4.2 Map

In the map, the activities will be displayed in big icons (first-level recommendations). Moreover, other activities will be displayed in small icons in the map, since they can also be interesting for the user (second-level recommendations). The number of activities to be displayed in this second level is ten.

If the user zoom the map, the list of activities will be upgraded. Thus, the objective is to display those activities that the user can carry out within the area he has specified.

The map also shows the chosen activities and the route formed by them.



**Figure 27.** Map

### 7.6.4.3 Planner

The activities are added to the right panel. The planner is divided into several days. Normally, the days will correspond to the ones that the user has specified in the initial preferences. In case the user has not specified any, the system will provide two days by default. The user can add more days with the option “new day”. When the user edits the day, the suggested activities will be upgraded, according to its schedules.

Added activities will form a route. The user can choose if the route is formed according to the order in which the activities have been added or as the shortest path.



Figure 28. Planner

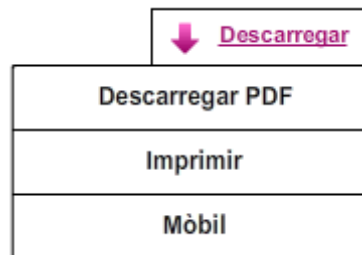
To add an activity in the planner, the user just has to select it from the list or drag it to the planner. He will be able to place the activity in any of the time slots. If an activity cannot be done in the specified time slot, an explanatory message will appear.

When the user accesses an activity of the main page, he is not planning any trip in particular. Therefore, if he wants to add it to a trip, he will have to click on one of the trips displayed in the pop-up list.

However, the user can edit the itinerary by dragging any activity to the desired position. Each time the itinerary is upgraded, suggested activities in the second level will also be upgraded in order to offer activities that are close to the route.

In addition, the system will provide an approximate time of the route. This information does not specify the hours to carry out each activity. It is only useful to give users a rough idea of the time they will need.

After planning the trip, the user will be able to print the itinerary with a pdf format or download it with the mobile application (see Figure 29). The pdf document will contain the list of activities to carry out, and a map with the routes of each day. The mobile phone application will allow the user to consult offline the document, which will contain detailed information and a static map of each activity. If the user has access to the Internet, he will have the opportunity to see the activities in a dynamic map, and also obtain detailed information of each activity.




**Figure 29.** Options menu to download the trip plan

### 7.6.5 Activity file


The detailed information of each activity (images, description and comments, see Figure 30) will be displayed in a new tab. If the user has performed an activity, he will be able to provide a score and add comments. Moreover, he will be able to add it to the trip and he will be able to share an activity on Facebook or Twitter.

It is important to emphasize that non-registered users will not be able to do the following actions:

- Download the trip planning.
- Add comments and punctuate activities.

CAT 

## Celler...

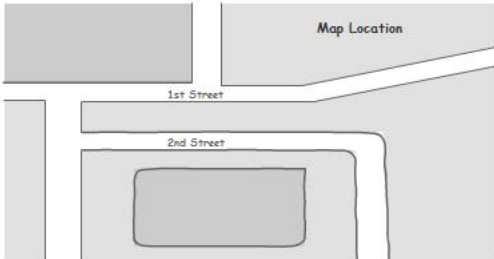



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Tel 977878787  
www.web.com  
info@web.com



Carinyena  
Garnatxa  
Garró  
Monastrell  
Chardonnay

Descripció del celler .....

Map Location




Afegir al viatge 


**Si has estat aquí, dóna la teva opinió!**

☆☆☆☆☆

Intriduir comentari...

Dia de la visita:  

Per lliure
  Amb guia
 Idioma de la guia:



2011 Eno-sigtur

[Condicions d'ús](#)

**Figure 30.** Activity

### 7.6.6 Charts

Figure 31 and 32 shows the flows described above.

We do not include the user registration and login pages, since they can be accessed from any page. To access the page “Route/Trip” it is necessary to be registered.

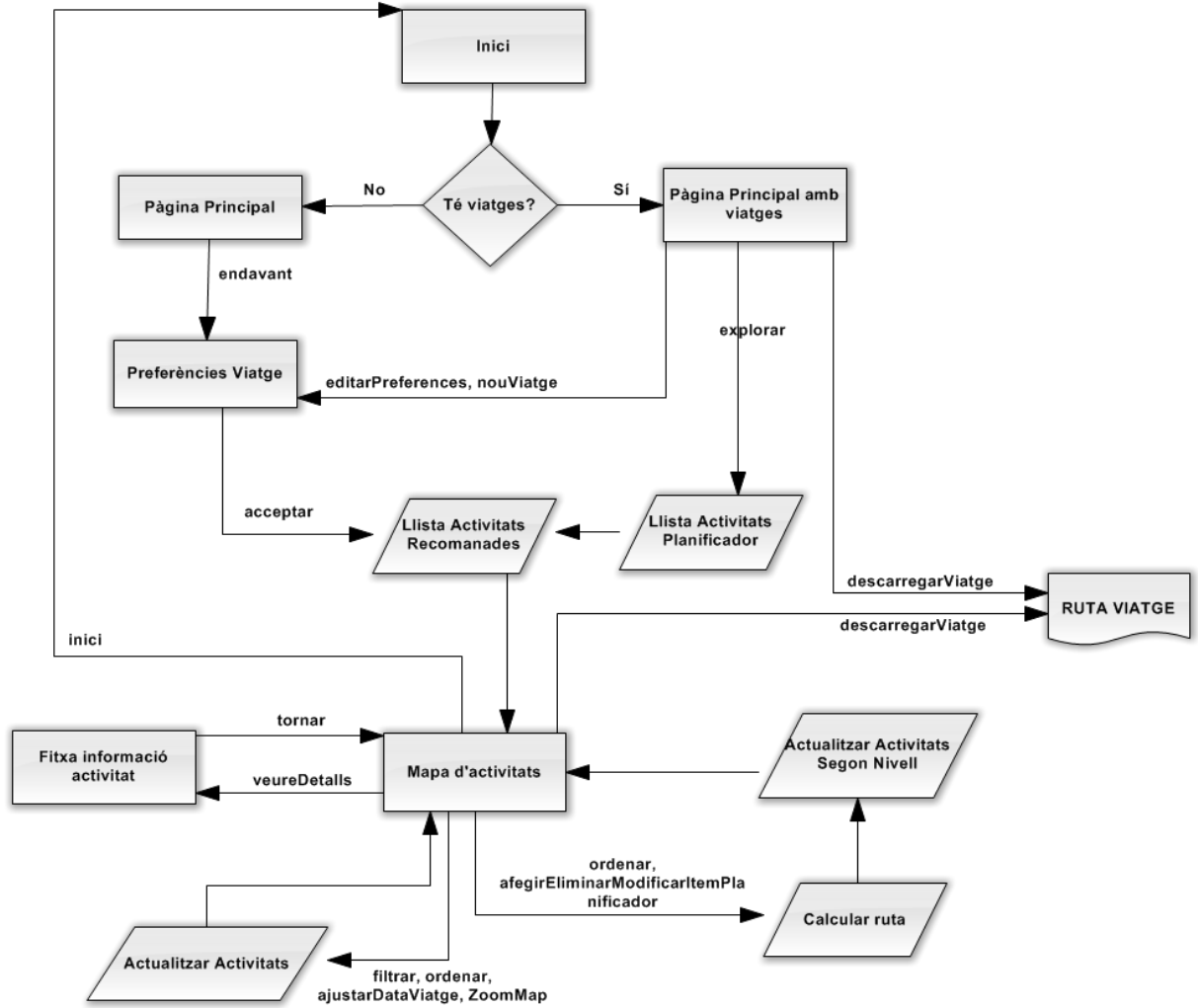


Figure 31. Flow Chart

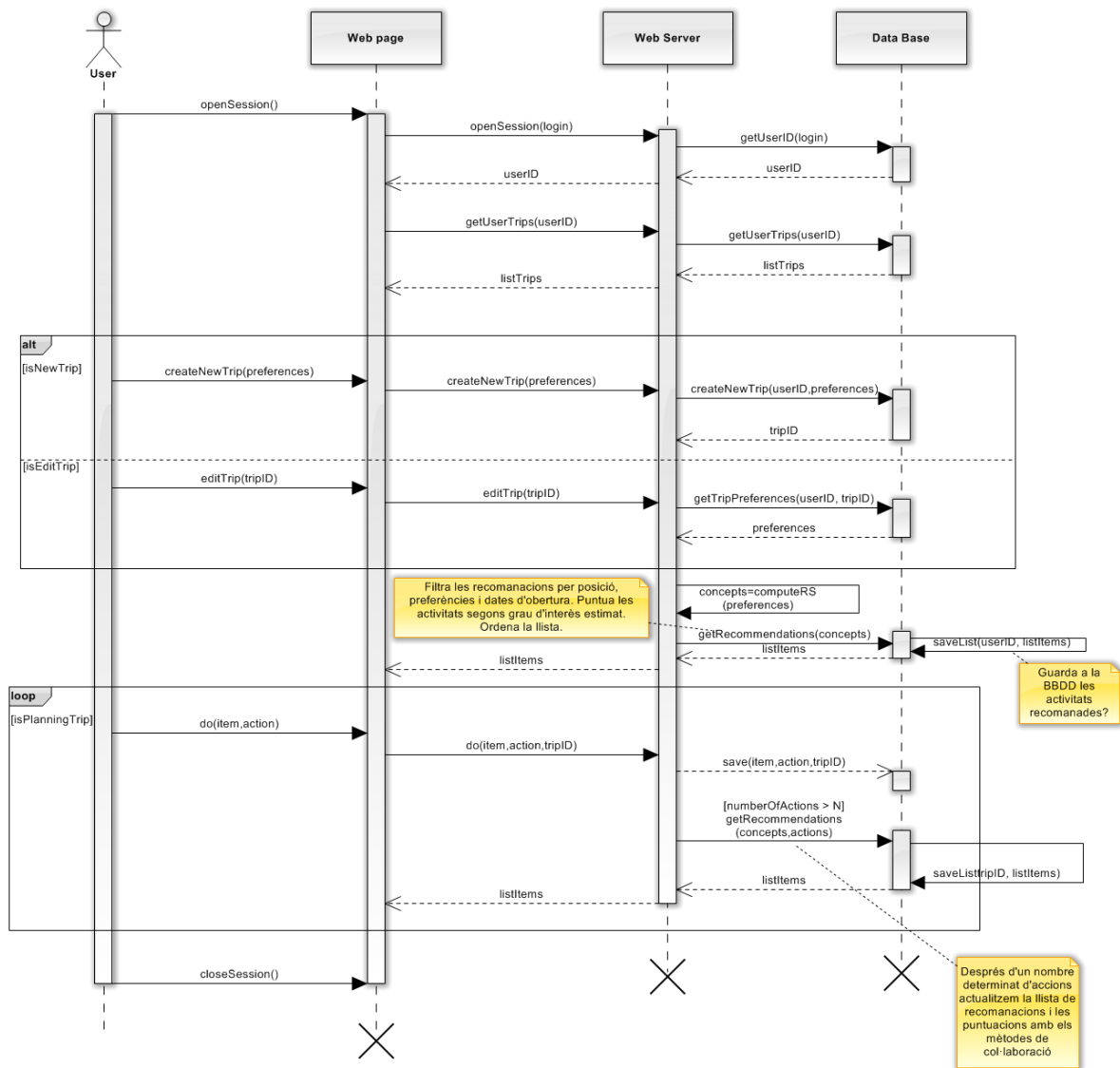


Figure 32. Sequence diagram



## 7.7 Enosigtur in mobile phone format

The mobile phone application can be used by two types of users. On the one hand, a user who has first accessed the system through the web, has saved the itinerary and wants to consult it throughout the trip. On the other hand a user that has not accessed the system before and, thanks to the advertising spots, for example, discovers the application and accesses it directly from his mobile phone.

In the following lines, we will briefly explain how EnoSigTur mobile phone application works.

### 7.7.1 Splash

When the user initiates the application, a main page like the one in Figure 33 will appear. This screen loads all the data necessary for the application to work properly.



Figure 33. Splash

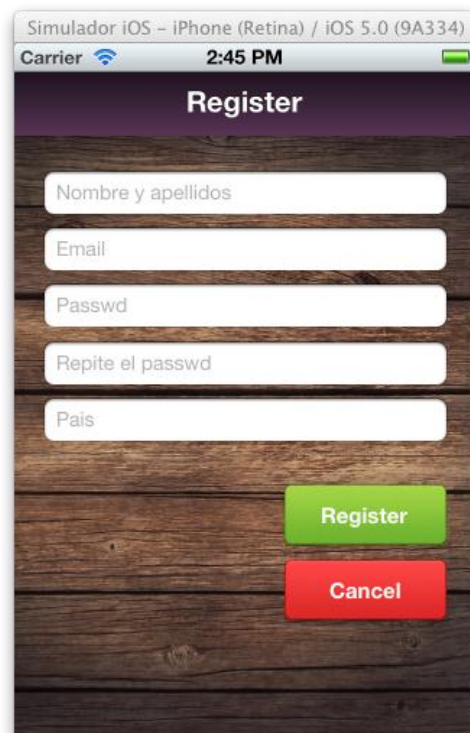
### 7.7.2 User data screen

Figure 34 shows the next screen that appears only if the user does not have an active session.

In this screen the user can start a session or register.



**Figure 34.** Login



**Figure 35.** Register

### 7.7.3 Main page

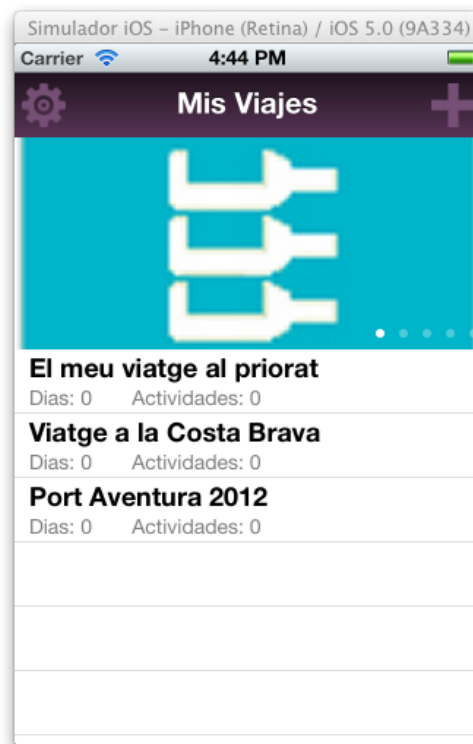
In the main page (Figure 36), the user can either click on the option to create a new trip or select a previous trip. At the top of the main page, several images that represent the beauty of the region will appear. If the user clicks on one of these images, he will access the detailed information of the activities he can carry out.

Tool button located at the top left allows:

- Change the language.
- Close the session.
- Display information about EnoSigtur.

If the user has already created one or more trips, the list will be displayed below the images. The user can create a new trip with the button at the top right. If he clicks on a trip, a pop-up with the following options will appear (see Figure 37):

- Explore a trip.
- Edit preferences.
- Delete.



**Figure 36.** Main page with created trips



**Figure 37.** Options pop-up

#### **7.7.4 Explore a trip**

When exploring a trip, two items will be displayed:

- Recommendations: It will show the list of recommended activities.
- Travel Plan: This section allows the user to manage their trips.



**Figure 35.** Explore a trip

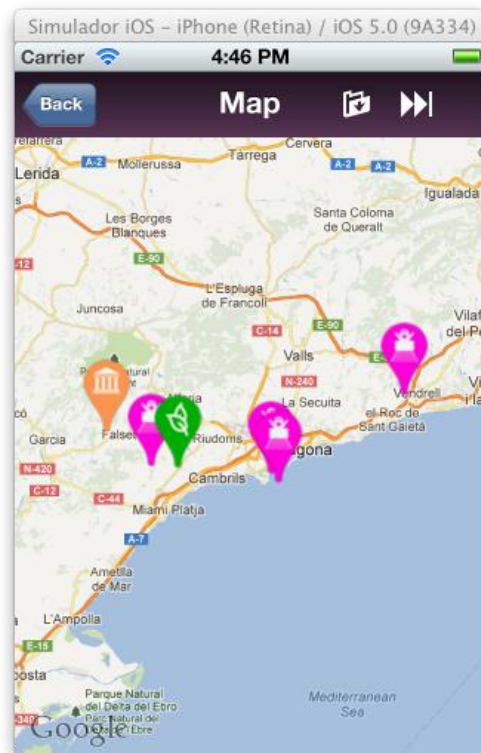
#### 7.7.4.1 Recommendations

Each time the user enters the recommendations section, the server will send to the mobile application a list of activities to be recommended.

In this view, the user can press in the pins map to interact with the activities. When you click on a pin, it will display a pop-up that allows the user to:

- See activity.
- Add to travel plan.

The list of activities can be presented on a map or in a list (upper icons)



**Figure 38.** Map with activities

#### 7.7.4.2 Travel Plan

The travel plan lists all the activities introduced in the recommendations section.

The recommendations are arranged in order of inclusion. The user can change the order and move activities to other days. The user can click on an activity to view its information or delete it. Initially the user is presented with a list of activities in list mode, but pressing the button "Map" the activities will be presented on the map.

All changes are sent to the server so that it can improve on its recommendations.



**Figure 39.** Travel plan

#### 7.7.5 Trip preferences

When the user creates a new trip, he will have to fill out the fields in Figure 40 and 41. As for the web, the motivations advanced section has been reduced.

When the user presses "Accept", the data is stored and the system redirects him to the previous page (Main page).

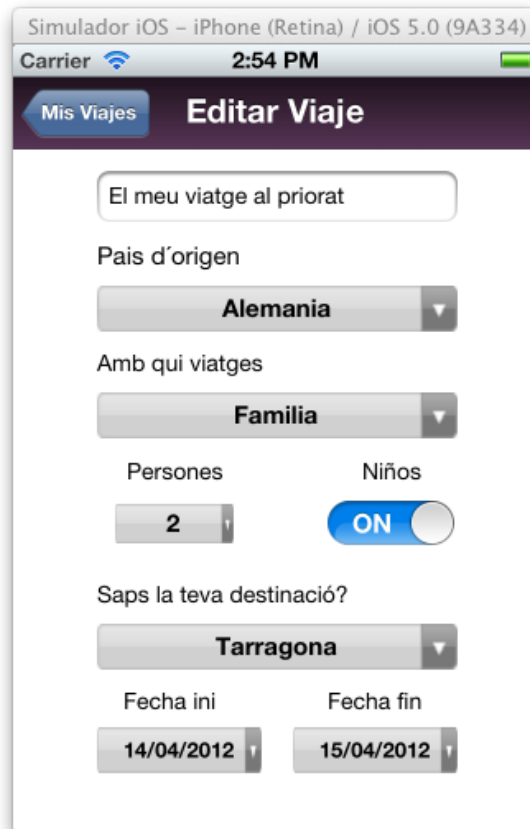


Figure 40. Trip preferences 1



Figure 41. Trip preferences 2

### 7.7.6 Activities files screen

In this screen, we can obtain detailed information of the activities. The user can add activities to the planner, as we were explaining before and see the activity on the map.

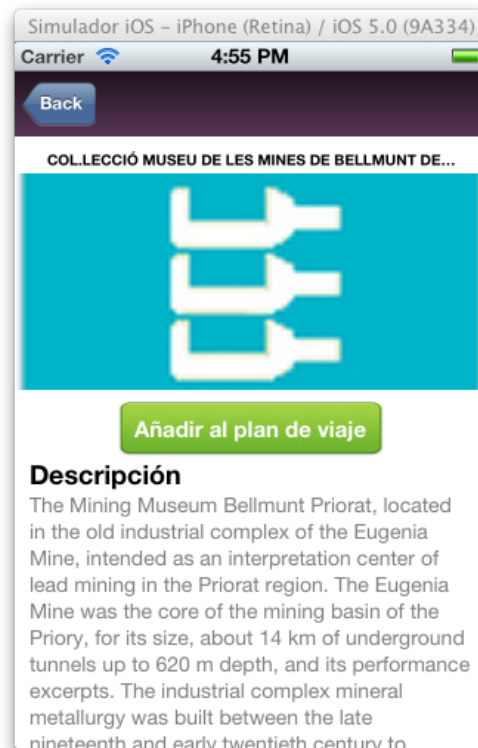


Figure 42. Activity information 1

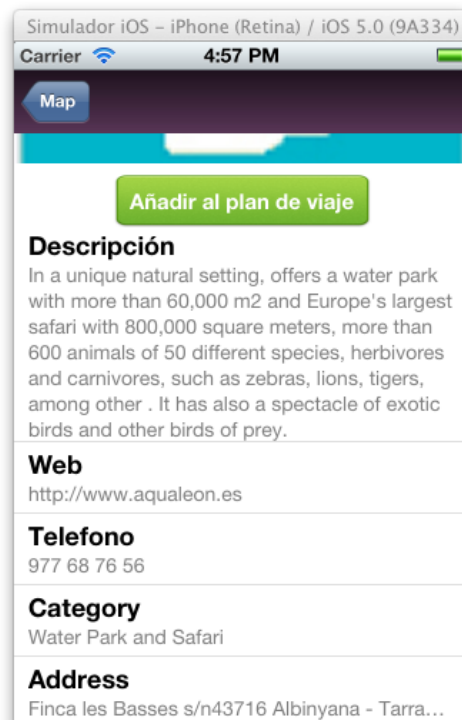


Figure 43. Activity information 2



### 7.7.7 Charts

Figure 44 and 45 shows the flows described above.

We do not include the user registration and login pages, since they can be accessed from any page.

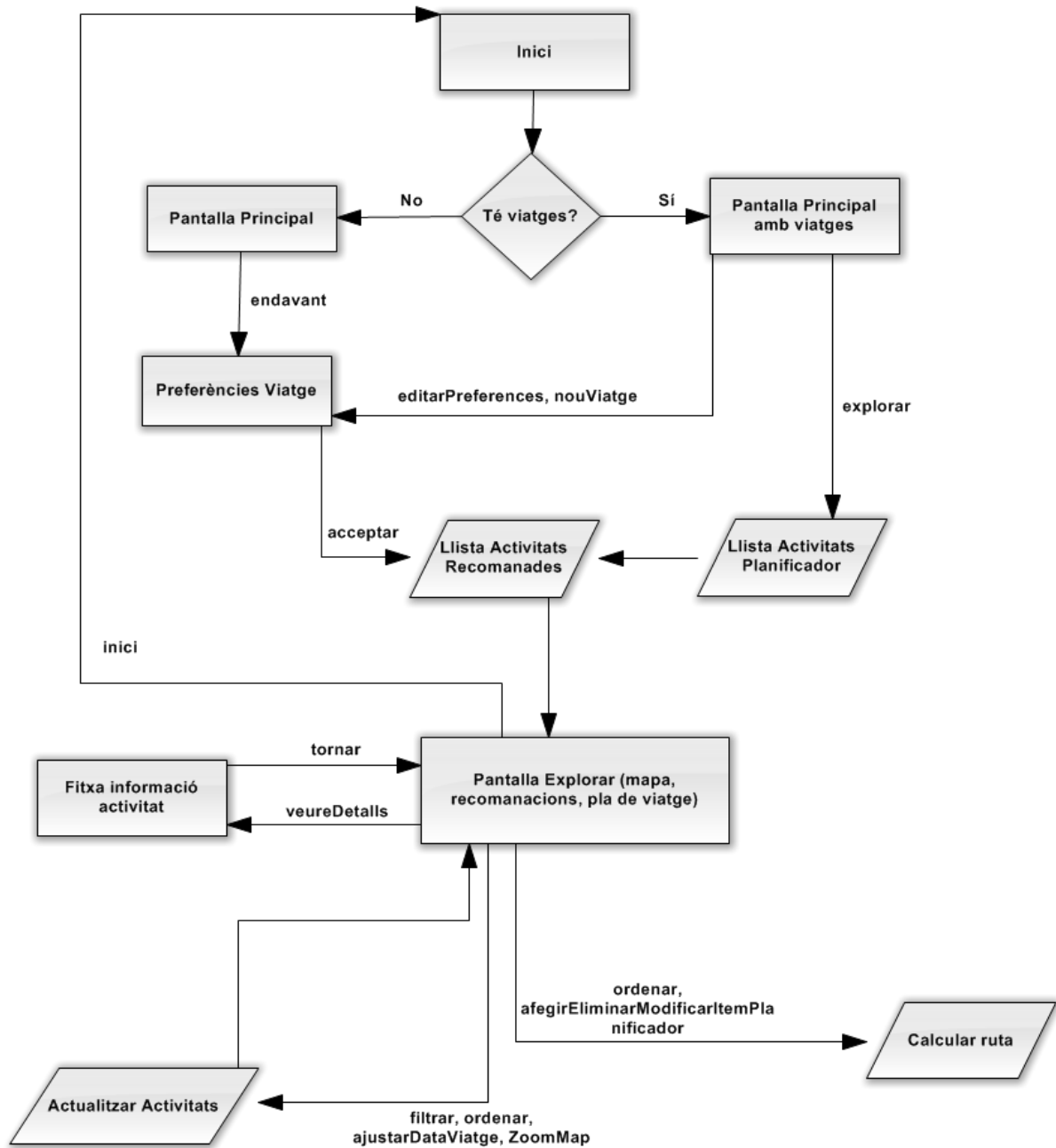


Figure 44. Flow Chart

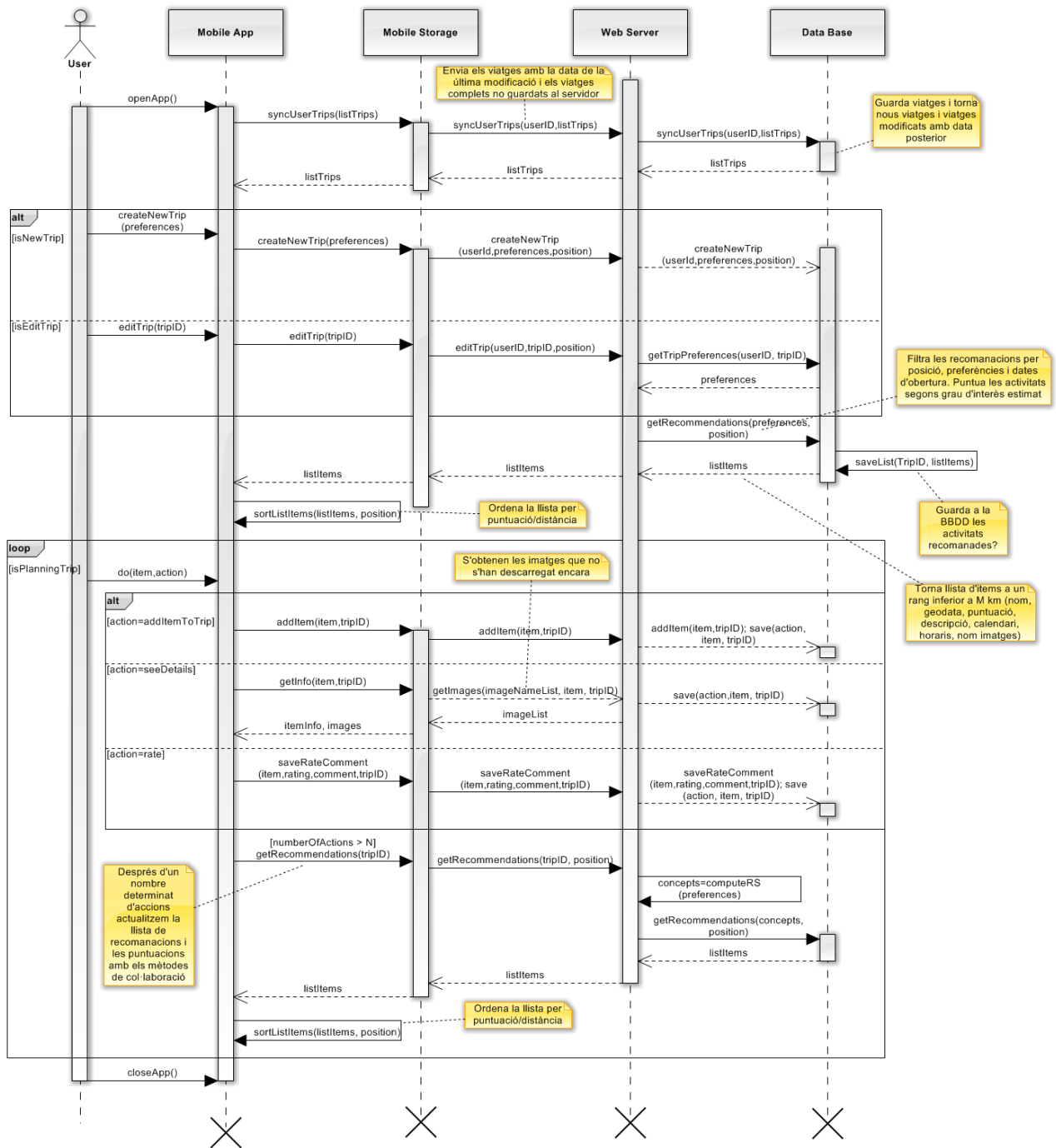


Figure 45. Sequence diagram

## 8 Conclusions and further works

Throughout the elaboration of this thesis, which is the largest I have ever written, this project has been developed within a workgroup (URV-Itaka/Gratet + PCTTO) in which different languages are used, new technologies and operating systems are the main protagonists. This piece of work has not only helped me to know in depth the recommender systems, the ontology, or data mining techniques, but also to become familiar with the geographical surroundings of Tarragona and, specially, everything related to the wine-producing sector. Furthermore, the creation of a mobile interface has been a great opportunity for me to access in the world of the state-of-the-art mobile phones, which is nowadays a growing market.

All I have used in this thesis was new for me. However, I must say that the Master in Artificial Intelligence has helped me a lot to learn to operate the new software easily, and also to make use of methodologies and techniques of the field. In particular, the most useful subjects have been: Artificial Intelligence and Software Engineering 1 and 2, Electronic Commerce and Graphic Interfaces Design.

As we mentioned at the beginning, our aim was to use innovative technological tools, as a way to boost wine tourism sector. Thus, in this piece of work we suggest the use of innovative Intelligence Artificial mechanisms; principally, personalised recommendations based on semantic content, through an application that allows the system to plan and combine wine itineraries with other cultural and leisure activities according to each user preferences.

Further work involves the implementation of this system through the different regional tourism companies in Tarragona, and the testing of its efficiency with tourists interested in carrying out activities related to the wine sector in this region. Therefore, the criteria to success would be the degree of general satisfaction of visitors during their trip, and the capability of this system to redistribute efficiently tourism to sectors that are not so popular and do not have “semiotic accessibility”.



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