SOI Based Video Recommender Systems: Interaction Design Issues and Collective Intelligence

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ABSTRACT

Recommender systems help users to cope with information overload and have become one of the most powerful and popular tools in electronic commerce. In order to provide better recommendations and to be able to use recommender systems in arguably more complex types of applications, most of the typical used approaches need significant extensions. On the video recommendation domain, one of these extensions is based in Segments of Interest (SOI), i.e., video segments that the user liked more or is interested. For this work, our intention is to stress and discuss interaction design issues about SOI based video recommender systems and discuss the relation between SOI and collective intelligence. We present two approaches to marking SOI on a Web social environment and discuss their advantages and disadvantages, and we show why SOI can be seen as a source of collective intelligence and that information and knowledge emerged from a community that had marked SOIs can be used on consensus decision-making and to bring improvements to society.

Author Keywords

Recommender systems; video; segment of interest; collective intelligence.

ACM Classification Keywords

H.3.3 Information Search and Retrieval.

RESUMO

Sistemas de Recomendação auxiliam usuários a lidar com o problema da sobrecarga de informação e se tornaram uma das ferramentas mais populares e poderosas do comércio eletrônico. De modo a prover melhores recomendações e para que possam ser utilizados em tipos cada vez mais complexos de aplicação, grande parte das abordagens tipicamente utilizadas precisam de extensões significativas. No domínio de vídeos, uma dessas extensões é baseada em Segmentos de Interesse, i.e., trechos de vídeo que o usuário mais gostou ou está interessado. Neste trabalho, nossa intenção consiste em analisar e discutir questões de design de interação em sistemas de recomendação de vídeo apoiados por segmentos de interesse, além de discutir a sua relação com inteligência coletiva. Para tanto, apresentamos duas abordagens para realizar a marcação de segmentos em um ambiente social Web e discutimos suas vantagens e desvantagens. Além disso, mostramos porque os segmentos podem ser vistos como uma fonte de inteligência coletiva e que a informação e o conhecimento que emerge de uma comunidade que marcou seguimentos pode ser usada na tomada de decisões consensuais e trazer melhorias para a sociedade.

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Palavras-chave

Sistemas de Recomendação; vídeo; segmento de interesse; inteligência coletiva.

INTRODUCTION

Recommender Systems provide recommendations for items to be of use to a user. They help users to cope with information overload and have become one of the most powerful and popular tools in electronic commerce.

In these systems, recommendations are generally made by two types of filtering: collaborative and content-based. Many systems use these types combined in a hybrid approach. Furthermore, in order to provide better recommendations and to be able to use recommender systems in arguably more complex types of applications, most of the typical approaches need significant extensions. On video recommendation domain, one of these extensions is based on Segments of Interest (SOI), i.e., video segments that the user liked more or is interested.

In a previews work [7] we developed a website with a video recommender engine based on collaborative filtering, and it presented an approach that uses SOI to enhance the accuracy of rating predictions of video recommender systems.

For this work, our intention is to stress and discuss interaction design issues and the relation between SOI and collective intelligence. We present two approaches to marking SOI and discuss their advantages and disadvantages, and we show why SOI can be seen as a source of collective intelligence and discuss that information and knowledge emerged from a community that had marked SOIs can be used on consensus decision-making and to bring improvements to society.

RECOMMENDER SYSTEMS AND SEGMENTS OF INTEREST

The recommendations provided by recommender systems are aimed at supporting users in various decision-making processes, such as what items to buy, what music to listen, or what news to read. Recommender systems have proven to be valuable means for online users to cope with the information overload problem [17].

As already stated, recommender systems are generally made by two types: collaborative filtering (CF) and content-based filtering (CBF). For them, various algorithms and techniques have been proposed and successfully evaluated. CBF takes the descriptions of the previously evaluated or currently accessed items by the user to calculate the similarity between items, and, then, recommend items of interest to the user. This type of filtering enables personalized recommendations for users. CF calculates the similarity between users and recommends items that are liked by similar users. This uses ratings given by users in the past to find the best item to a similar user. Another approach is to calculate the similarity between items to produce recommendations [10].

These two approaches present some issues, if used alone. For CBF, for instance, the two main disadvantages are: (i) it depends on one objective description of the items; and (ii) it tends to overspecialize recommendations [14]. For CF, the two main disadvantages are: (i) the early-rater problem that occurs when a user is the first from his/her neighborhood to rate an item; and (ii) the sparsity problem that is caused when there are few ratings for the items [17]. On the other hand, these types recommendation can be combined in a hybrid recommender system that takes the advantages of both in order to overcome their disadvantages alone.

Furthermore, according to [1], in order to provide better recommendations and to be able to use recommender systems in arguably more complex types of applications, most of the typical approaches need significant extensions. On the video recommendation domain, one of these extensions is based on Segments of Interest.

Segments of Interest (SOI)

A SOI is a segment on video that the user liked more or is interested. Users tend to like particular segments of the video more than the rest [3] and, therefore, they can mark their segments of interest on video. Figure 1 illustrates SOIs marked by a user in a video. The first one was marked from t_1 to t_2 seconds related to video timeline, the second one from t_3 to t_4 seconds, and the third one from t_5 to t_6 seconds.

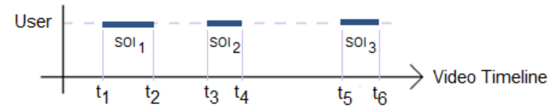


Figure 1. SOIs marked by a user in a video.

In our previous work, we show that SOIs from a community of users can be used to find similar people, i.e. people who have similar interests about videos. When a pair of users has a quantity of intersections of SOIs above a threshold (and with a minimum acceptable size) in one video and this pattern occurs in a certain quantity above a threshold in a set of videos, they have similar interests about video. Figure 2, for instance, illustrates that users u_2 and u_4 will have similar interests about video if it is considered that similar users have at least 2 intersections of SOIs on a set of 3 or more videos.

We also show, in our previous work, that this similarity between pairs of users based on SOI can be used to enhance the accuracy of ratings predictions of video recommender systems with user based nearest neighbor collaborative recommendation.

Marking SOI

One important aspect is how users can mark SOIs in video. The way users mark SOIs is directly related to the user interface of the system. This interface must provide specific components for marking SOIs. We have proposed two approaches for this purpose:

- Buttons with predefined time slices: in this case, different buttons, with different time slices, are presented to the user. Each time the users want to indicate a SOI, they click on the button that corresponds better to the size of SOI they want (whose the end coincides with the current instant of time in the video). An example of this approach is presented in Figure 4.
- Sliders that allow users to mark the beginning and the end of each SOI. In this case, users can mark videos while they are watching the video (like the previous approach) or after watching it. An example of this approach is presented in Figure 3.

The approach for marking SOI must be chosen accordingly to the context and to the user tasks, because both have advantages and disadvantages. Marking SOI with the use of buttons on the user interface (or buttons in a remote control) is indicated for video websites, video/movie on demand services and personal video recorders, where the user's goal is to enjoy entertainment or get information. The advantage is that users do not lose so much attention when they want to mark SOIs on the video, and this marking occurs quite effortlessly, quickly and easily. The drawback is that the beginning and the end of a segment may not be as precise as intended (since the intervals are predefined). If SOI are used to enhance the accuracy of the ratings predictions of recommenders systems, this precision is relevant for the accuracy [7].

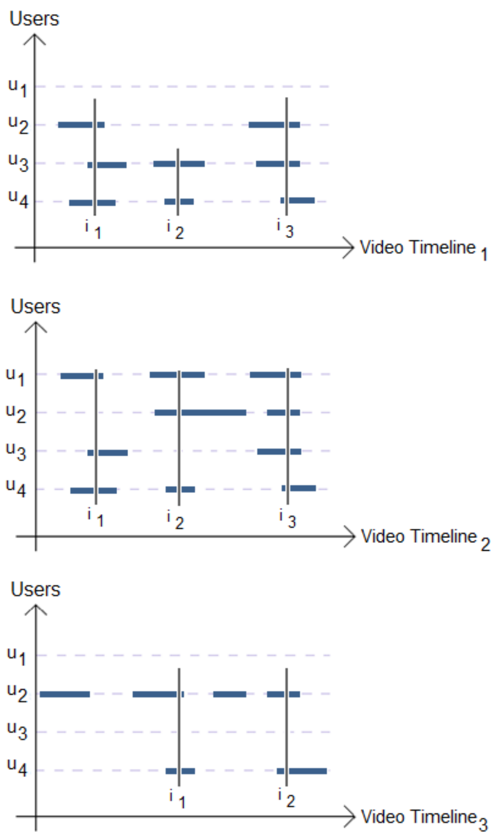


Figure 2. Intersections of SOIs in a set of videos.

The approach for marking SOIs delimiting the beginning and the end of the segment can be provided, for example, through widgets as a pair of sliders bellow the progress bar (video timeline) of the video player. It is suitable for environments where users have more freedom (since they can fast forward and rewind the video, or watch it as many times as they want), such as websites and video on demand services with more specific goals, such as websites with educational videos. The advantage is that users can define the exact beginning and end of each SOI. If SOIs are used to enhance the accuracy of recommender systems ratings predictions, this approach is better suited. The disadvantage is that the marking of SOIs requires a greater effort from the user, as it needs to locate and define exactly each segment of interest on the video timeline. There may be users who prefer to watch the whole video and then rewind it to mark a specific SOI, but others may want to mark the segment while they are watching the video. In the first case, users may forget to mark some SOI, and, in the second case, users can lose attention while watching the video and marking SOI at the same time.

The approach to mark SOI, that is part of the interaction design, is extremely important. The designer of SOI based recommender systems must be aware that users are reluctant to give explicit feedback (in this case, marking SOIs), that not everyone likes to participate more actively and more interactively, and that, in our approach, there is a significant level of user involvement [7]. As we discussed before, the context and user tasks impose the choice of the approach to be implemented and it is related to the success of the system and their recommendations.

THE DEVELOPED SYSTEM

In our previews work we developed a video website with a recommender engine as a web application. The server hosts the application, and its interface is similar to many current video websites, i.e., it has a screen containing a video gallery where the user can browse videos, and a screen to watch videos. The client can be any device that contains a web browser, such as a desktop computer, a notebook, a smartphone, a tablet or a smart TV. This system only stores metadata to catalog videos and data generated during the use of the system. Videos are loaded directly from clients on demand from a video content provider (YouTube, in the specific case).

For performing an experimental evaluation of our recommender system approach, we have used educational videos of a given subject, but the system can deal with several domains, such as news, sports and movies. For this purpose, we have created a catalog containing 50 educational videos up 20 minutes of duration from YouTube.

Figure 3 shows part of the screen of the system where users watch videos. Through it, users can rate videos (rating options are, "Very bad", "Bad", "Ok", "Good" and "Very good"), and the users can also mark their SOIs. This is performed through a double slider below the progress bar of the video player. Users drag and drop the sliders to mark the beginning and the ending of each SOI. This approach to marking segments was used previously in video remix tasks [18]. Additionally, the screen presents a sorted list of SOIs already marked and the user can delete incorrect or unnecessary SOIs, if necessary. SOIs from this list could be used after by the users to directly access their segments of interest into the video as a shot index [13]. This approach for marking SOIs is suitable for educational environments where users usually are near the screen, and move forward and rewind the video several times during their learning activities.

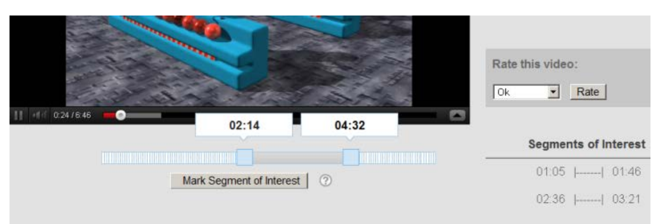


Figure 3. Partial view of the system's screen containing sliders.

If the context was other, like watching movies in a smart TV, the segments of interest could be marked in another way, using specific buttons on remote control or on a smartphone application, for example, while the user watches the video. Figure 4 illustrates the approach based on buttons on the user interface of the video website. There, three buttons can be seen: ‘10 seconds’, ‘20 seconds’, and ‘30 seconds’. If the user is watching a video and click on the "20 seconds" button, a SOI is marked from the current position on the video timeline until 20 seconds back. It is easy and fast, and could be even done remotely, if the buttons are in a remote device (remote control or smartphone).

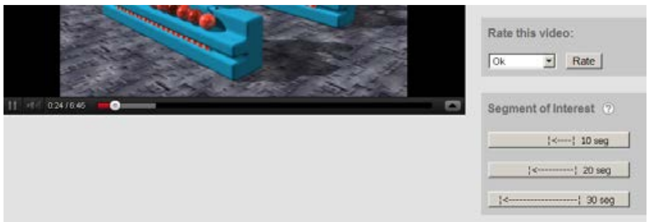


Figure 4. Partial view of the system's screen containing buttons with predefined time slices.

EXPERIMENTAL EVALUATION

As already stated, the system was described in a previous work [7]. There, we also described an experiment in which the system was used by three different groups of students. We will not detail the experiments and its results here, but it is important to state that the subjects were free to choose videos among the catalog created, and also were free to evaluate them and to mark SOIs. Based on the interaction of the users with the system, a historical dataset was built. This dataset contains 88 user profiles (students of computer science, at the age of 20 years), 764 video ratings and 269 SOIs.

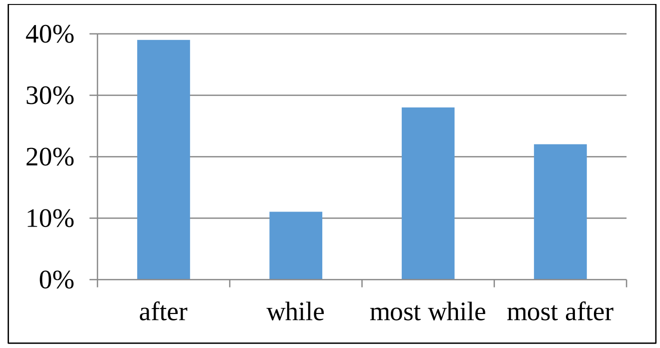
The focus of our previous work was to compare different recommender system strategies. In this sense, we have conducted an offline experimental evaluation based on the leave-one-out strategy [17]. Based on it, we compared a traditional collaborative strategy against the same approach, but boosted by SOI. The results showed that it is possible to find similar people based on SOI and that the system´s accuracy improvement is directly related to the level of participation of people marking SOI, so, as more people collaborate and interact, better is the result of the system.

In this work, our intention is to stress and discuss interaction design issues related to our SOI video recommender system. Therefore, we have used a questionnaire that is described below.

Questionnaire

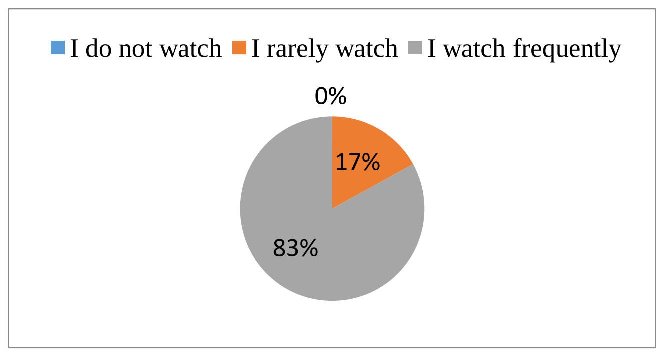
We have built a questionnaire to understand the user´s experience related to marking SOI on our system, to know about their collaboration habits on the Web, and about their habits related to watching video on the Web. In this sense, we have asked the subjects of the previous experiment to answer a questionnaire (anonymously) available on the Web. Results are described below. It is important to state that only 18 of 88 users have answered the questionnaire.

Question #1: Did you mark segments of interest in what moments?

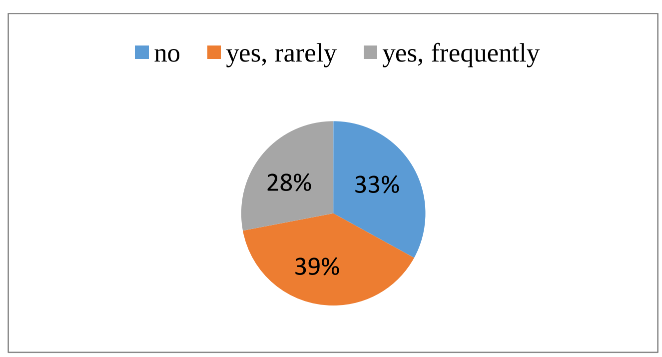


In this question, "after" means "I marked *after* I watched the video", "while" means "I marked *while* I was watching the video", "most while" means "I marked after and while I was watching the video, but in the *most of times after*", and, finally, "most after" means "I marked "after" and "while" I was watching the video, but in the *most of times while*".

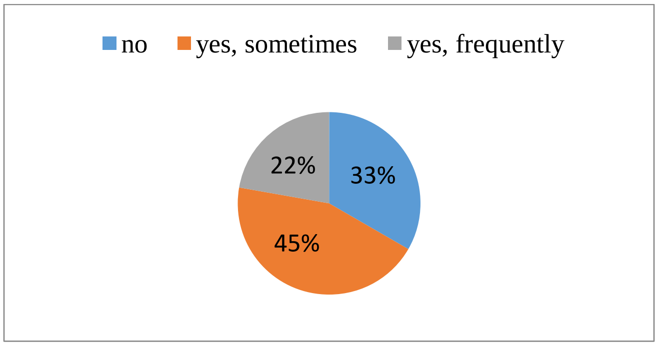
Question #2: How often do you watch videos on Web?



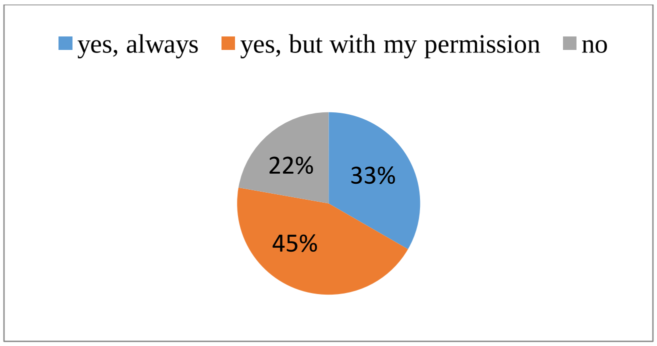
Question #3: Do you often collaborate with some information on the Web (such as 'add a comment', 'submit a link to a friend' or give a "like"')?



Question #4: Do you usually use somehow the information collaboratively added by others on websites?



Question #5: Would you like to share your segments of interest with other people?



Analysis of the questionnaire´s results

The results showed that in the context of educational videos, considering the approach used to mark SOIs, most of users prefer to mark SOIs after watching videos. In another question, not viewed by graphs, 100% of the subjects answered that they enjoyed using the system to watch the educational videos offered.

About the habits of the subjects, they frequently watch videos on the Web and use collaboration mechanisms to obtain information. However, very few subjects effectively collaborated with others (to provide information). Finally, most of them stated that they would like to share their SOIs. It could be done, for instance, in a social network among their friends.

Segments of Interest on Video and Collective Intelligence

In this work, another relevant aspect to discuss is the relation between SOI and collective intelligence.

Collaboration among people has been gaining attention due to the popularity of social media tools such as forums, blogs, wikis and social networks. These tools are collaborative systems that enable users to share their knowledge, skills and other information. As a result, they are becoming important sources of collective intelligence [4]. The science of collective intelligence, proposed from the discussions of Pierre Lévy [12], tries to harness the potential of social networks as a mean to exercise the citizenship. It assumes that individual intelligences are summed and shared across society.

Collective intelligence led to the rise of a new business model known as crowdsourcing. This term describes a model that takes advantage of several creative solutions that people can propose [9]. The initial idea of crowdsourcing was to send a task to the crowd instead of running it using its own resources. This approach is known as explicit crowdsourcing. For instance, on Internet users can evaluate particular items like books or movies, or share by posting products or digital content. Users can also build artifacts by providing information and editing other people's work. Linux operating system and Wikipedia are examples of explicit crowdsourcing results.

The other approach is known as implicit crowdsourcing, which can take two forms: standalone and piggyback [8]. The standalone allows people to solve problems as a side effect of the task they are actually doing, whereas piggyback takes users' information from a third-party website to gather information. Implicit crowdsourcing is less obvious because users do not necessarily know with whom they are contributing, yet it can still be very effective in completing certain tasks [2]. For instance, piggyback crowdsourcing can be seen most frequently in websites such as Google, which mine users' search history and websites in order to discover keywords for ads, spelling corrections, and finding synonyms [11]. Google's PageRank algorithm harness collective intelligence. Every time users write a link, or even click on one, they are feeding their intelligence into Google’s system [15]. On video domain, [5] proposes to leverage implicit user activity on video player (e.g., pause/play, seek/scrub) in order to dynamically identify segments of interest on video, and presents an implicit user-based key-frame detection system.

In this sense, SOI, which is collected in an explicit way and is used to enhance the accuracy of rating predictions of video recommender systems, can be used implicitly as source of information and knowledge about a user community. For instance, depending of the context, a cluster of SOIs can sign something relevant in one video. For instance, in the entertainment video domain, a cluster of SOIs can represent the most popular segments of a particular movie for the community; similarly, in the educational environment, a cluster of SOIs can be the starting point for a teacher to discover the more relevant segments for a community of students and, based on this information, figure out why that point is important for learning. In this sense, SOI can be seen as a source of collective intelligence.

SOI Data Visualization

To discover clusters of SOIs we have implemented a data visualization display in the developed system. This display presents the set of SOIs marked by each user in a video. As we had only two dimensions (SOI vs. users), we have used a simple data visualization technique that uses rectangles on orthogonal axes to represent intervals [6].

The display illustrated in the Figure 5 corresponds to the aforementioned visualization technique. There, users are represented on the vertical axis and the horizontal axis is the length of the video. For instance, in this figure, most users marked just one SOI, one marked two and another marked three.

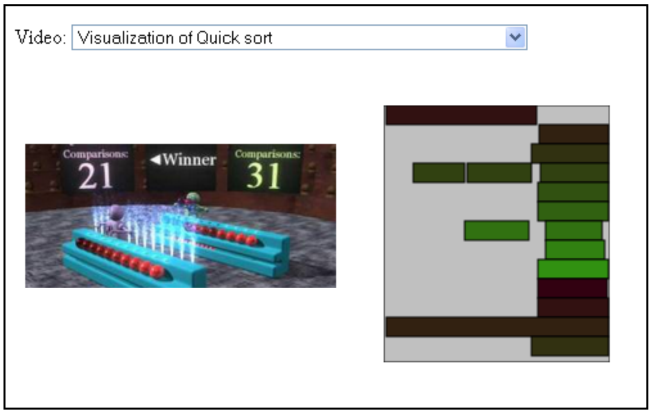


Figure 5. Data visualization of SOI by users on a video.

In the display, each rectangle represent a SOI. The size of each rectangle indicates the size of the interval in relation to the video timeline. The position of the rectangle (and it size) corresponds to where it was marked in the video timeline.

To aid the analysis, we included a combo box to allow browsing videos. Once a video is selected, one key frame is shown to illustrate the video selected. With this tool, we were able to discover the parts that were most marked by the community of users. For instance, Figure 5 shows the data visualization display for video "Visualization of Quicksort", with the 13 users who had marked SOIs in it. The video is an animation about sorting algorithms. As we can see, many users had marked SOI in a special part of the video (on the right). Such part is the moment where the animation starts to compare the Quicksort and the Bubblesort algorithms, running side-by-side in a dispute. When we pass the mouse pointer over a rectangle representing a SOI, a tooltip presents its exact beginning and end, in seconds.

It was another example that shows why SOI can be seen as a source of collective intelligence. Information and knowledge that emerged from a community that had marked SOI can be used on consensus decision-making and to bring improvements to society. For instance, using information and knowledge originated from SOI clusters a video on demand provider can improve its recommender engine, or a TV channel can discover groups, segment viewers and send personalized ads.

CONCLUSION AND FUTURE WORK

Segments of interest, which can be used to enhance the accuracy of rating predictions of video recommender system, can be marked by different ways. Each way is directly related to the user interface of the system that contains the recommender system. In this work, we showed that each way have advantages and disadvantages. Therefore, the designer of SOI based recommender systems must be aware that the approach chosen to allow users to mark SOIs may be directly related of the success or failure of the system and its recommendations.

Furthermore, we have evaluated the use of SOI concerning collaboration and user's habits about consuming video on the Web. The results showed that, in the context of educational videos and considering the approach used to mark SOIs, most of the subjects prefer to mark SOI after watching videos, and all subjects enjoyed to use the developed system to watch videos. About their habits, they stated that the frequently watch videos on the Web and use advices obtained through collaboration. However, very few of them admitted to collaborate with others on the Web. In relation to sharing their SOIs, most of them stated that they would like to share them with friends, for instance, in a social network.

We also discussed why SOI could be seen as a source of collective intelligence. Information and knowledge emerged from a community that had marked SOIs can be used on consensus decision-making and to bring improvements to society. We implement data visualization over the developed system to illustrate how SOI can be such a source of collective intelligence.

In future works, we will make more experiments to compare even further the presented approaches. The goal is to verify which one is better suited for different contexts and scenarios.

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