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Semantic Spiral Timelines Used as Support for e-Learning

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Abstract: This article presents Semantic Spiral Timelines (SST) as an interactive visual tool aimed at the exploration and analysis of additional academic information stored in current e-learning platforms. Despite the development of contents specifically for these platforms, and in spite of the various features they provide, knowledge of the actual use made by individual participants is emerging as an unavoidable necessity, so as to ensure proper operation and effective use of e-learning platforms. SST supports the discovery of temporal patterns by incorporating an innovative highly interactive visual representation, which can be explored at various levels. This tool makes it possible to assess, at first glance, the use of the e-learning platform during the development of courses; one can also perceive how it is used by class participants. Then, through different interaction mechanisms, it is possible for students and professors to uncover specific details about courses, which would otherwise remain hidden.

Keywords: Visualization, e-learning, timeline, spiral, Moodle
Categories: L.2, L.3, L.6, M.0.

1 Introduction

Currently, the increasing use of new technologies to support learning has fostered the creation of tools that help extract information that is not available at first sight. This is essential for the improvement of the learning process from the point of view of institutional decision makers, educational content providers, teachers, and students, all of whom will benefit from the use of effective analytical tools for current e-learning platforms. This can be done through the analysis of a user's recorded activities, stored in their e-learning platforms, which can provide a means to understand the students' behavior throughout their learning period.

E-learning is commonly supported by Learning Content Management Systems (LCMS) or Courses Management Systems (CMS). Such Web-based training environments are characterized by the usage of very high amounts of information, with strong interactivity and no restrictions on space and time.

LCMS and CMS store a log of the students' course activities in a database. They usually have a built-in student monitoring feature that enables the instructor to view some statistical data, such as the number of accesses made by the student to each resource, a registry of visited pages, the number of logins for each day and so forth. Instructors may use this information to monitor students' activities and to identify potential problems. However, this information is usually provided in a way that poses several problems. For instance, it is highly focused on detail, and it is detached from the courses' context and/or from the whole e-learning platform of the institution. The information is shown as a text file, or by means of very basic charts. In addition, information of this type has a very simple logical organization that consists of an enormous list of numbers and identifiers. Therefore "one cannot see the wood for the trees", and these platforms tend to offer limited interactivity, if any. As a result, the user becomes frustrated due to very straightforward statistics. Monitoring raw activity data is difficult; one can hardly perceive what is happening, and in many cases the data turn out to be almost incomprehensible. Besides, the system does not offer knowledge acquisition, nor does it convey any use patterns or highlight specific cases that would require special attention.

According to [Thomas, 06], Visual Analytics is an emerging area of research and practice that aims to support analytical reasoning through interactive visual interfaces. Following a Visual Analytical approach, we seek to propose and develop innovative interactive visual solutions so as to help different users of e-learning platforms extract specific knowledge related to the complex process of education and learning. In this study we were particularly interested in the evolution of the learning process and also in how and when people are involved in it. In addition, the different roles that they may be playing, their use of technological tools and finally how their own particular behavior affects their learning. Thus, we have designed and implemented a very interactive visual tool that simplifies an exploratory analysis of activities. The information our research has revealed is the result of several years of work. In order to validate our proposal, we have chosen one of the most popular CMS current systems, Moodle, and also its recorded dataset.

The article is then organized as follows: the next section is a review of related works that deal with the visualization of CMS systems; the third section is concerned with the presentation of our proposed interactive analysis tool, Semantic Spiral Timeline (SST); the fourth section presents a case study in which the user wants to find patterns in the daily use of a Moodle platform; and the last section discusses the main conclusions reached and proposes future lines of work.

2 Related Works

Because e-learning and information visualization have both experienced growth and obtained excellent results as separate fields of research, few efforts have been made to bring the two disciplines into a cooperative setting in order to realize their enormous potential. However, the literature in educational research has established that monitoring student learning is a crucial component of high quality education. Once instructors and students are not in a face-to-face traditional environment, new forms of student monitoring must be explored. The effective use of CMS requires that instructors be provided with appropriate means of diagnosing problems so that they can take immediate actions to prevent or overcome those difficulties.

Due to limited space, some experiences in the literature that deal with the analysis of information generated by the CMS through visual representations are listed and briefly explained below.

The reviewed works focus on different aspects of online learning and some basic concepts will be explained.

Each message has a sender, date, and topic. A set of posts on the discussion topic, comprised of an initial post and all its responses is called a thread. The person who sent the initial message in a thread is called the originator. Mazza and Milani [Mazza, 04] showed the instant in which users enter the platform and a representation of the frequency of reading and writing in the fora, as well as the thread originator. In [Hardless, 99] the visits and posts over time for each person in a CMS were shown, while in [Gibbs, 06] the authors presented the mapping of temporal relations of discussions on software, aimed at helping analyse temporal aspects of online educational course discussions. Finally, Mazza and Dimitrova [Mazza, 05] suggested a scatter-plot-based representation of the online discussions and a matrix to visualize the students' performance on quizzes related to domain concepts.

Another group of works dealt with the use of visualization, rather than information analysis, as part of the learning process or as a supportive resource for coursework [Robling, 06] [Lauer, 06]. Dichev et al. [Dicheva, 05] make use of ontologies and propose the display of thematic maps with the support of semantic information, in addition to their interactive administration.

In our previous work [Gómez, 08], we have proposed interactive visualizations of the social networks that are formed among the participants around an activity on the educational online platform. For a review of the search patterns in the interaction of the learning networks refer to [Laat, 07].

Finally, a work closely related to the present article is [Williams, 07], who addressed the display of narrative structures and the learning style of students in the systems of e-learning and also the use of a simple time line for selecting the narrative structures.

On the other hand, outside the field of educational computer science, the visual representation of evolution over time has propitiated numerous works that, to some extent, show similar features to our work. The visualization techniques employed in our proposal are spiral timelines, semantic zoom and visual temporal data filtering.

Examples of customary ways of representing a timeline abound in the literature. One is to use a linear arrangement (using Cartesian coordinates) with time represented on the x-axis. Following this approach, and trying to solve the problem that representing extensive timelines poses, [Dachselt, 06] proposed a bifocal deformation; while [André, 07] suggested a visual filter in the timeline for the data that will be represented in detail.

Much less commonly, time may be represented on a spiral. [Carlis, 98] explores this in both 2D and 3D. A similar work can be found in [Weber, 01], but in this case the spiral itself serves as a filter for 3D data. In [Bergstrom, 07] this concept is applied to a much more restricted dataset, as is the case of a single conversation.

Apart from examining the representation of timelines, the ways of interaction with the user have also been the object of study. [Koike, 97] proposed an efficient slider and a temporal window that serves as a filter. In addition, [Daassi, 06] reviewed the different techniques of temporal visualization available and classified them. Finally, another work by [Aigner, 07] reviewed different ways of displaying temporary data according to the features each one offered.

3 Interactive Analysis through SST

As we have previously mentioned, our proposal, Semantic Spiral Timeline (SST), is an interactive visual tool that can be used to analyse the usage of a CMS over time. We have adopted the Moodle platform and make use of several years of logs stored in the CMS database. However, the design principles were general enough so that SST could be adapted, without too much effort, to work with any other CMS or dataset.

The main goal of SST is to provide a compact representation of the overall use of the CMS, thus providing an overview of the e-learning platform. The global aspect of the tool can be observed in Figure 1. Later, this view can be adapted to the user's requirements, so he/she can explore all the available temporal data, going from the overview to the detail of a given person or activity within a period of time.

The represented data can be filtered per course, person, time or activity. SST consists of 6 zones, three of which provide different views of the data, and three panels that are used for customization of the tool.

SST also features a visual technique to balance the detail and context in data visualization, known as semantic zooming or multi-scale interfaces. A physical zoom, on the one hand, changes the size and visible detail of objects. A semantic zoom, on the other hand, changes the type and meaning of information displayed by the object [Modjeska, 97]. SST allows both types of zooming, but the emphasis is on the different shapes that are formed depending on the chosen degree of detail, i.e., semantic zoom in the spiral timeline, and thus the name of the tool.

The main representation is the spiral timeline, which, in its simplest form, is merely a sequence of color-coded events. These are ordered clockwise with the oldest data at the center of the spiral and the outermost data depicting the most recent event.

The distribution of the graphical interface, beyond the central area where the spiral is located, is laid out in the following way. At the bottom-right there is a panel for activity/course filtering, zooming and customization of other graphic information; at the bottom-left, a panel for drawing, filling and homogenization of color can be found; then, to the left of the spiral, one can find the size and orientation panel, which controls those parameters both for the event shapes and for the spiral itself.

The remaining two panels provide additional views of the data shown in the spiral. In the top view the temporal data is drawn in a linear fashion showing the current data on focus. Finally, on the right hand side, you find the data overview (i.e., the context), which also includes a slider for selecting the period in focus.

These three views are inter-linked. This means that, since all the views are different ways of conveying the same information, when the user interacts with one of them and changes the representation, the other views are also changed depending on the action originally performed by the user and on how that action affects the shared dataset.

These three interactive linked views provide better opportunities of comprehension of the educational facts that are stored in the database as a number of recorded activities, but they would remain hidden if a single and fixed view were used. Thus, it is possible to find cyclic patterns in a selected period of time using the spiral. However, the same data could better exhibit some features by using a classical linear timeline (top view).

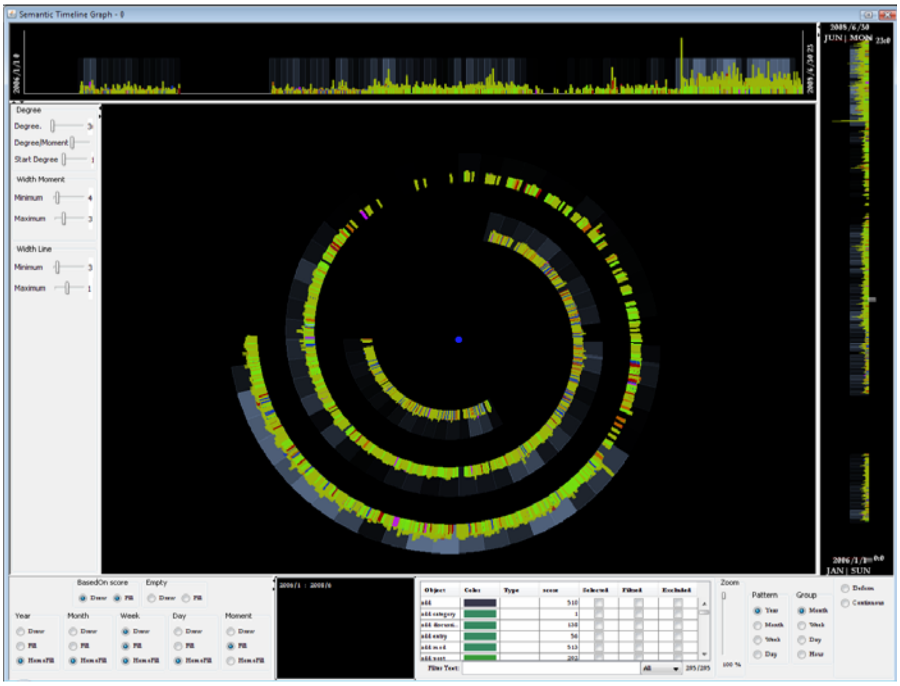

Figure 1: Global aspect of SST

Finally, even when inspecting the details which are the focus of our exploration (for example, an instructor could be interested in showing all the activities that a student has done during the last month), it is crucial not to lose sight of the context (in the previous example, it would also be interesting to have a visual summary of the student's performance during the whole semester in all the courses). This contextual visualization is provided in the right view, which also serves as an interactive visual filter by means of its sliders, enabling the selection of a time period that will show up in the other two views.

This exploratory approach will offer representations of the dataset that highlight temporal use patterns. This way, answers as to whether the CMS capabilities are being explored to the fullest and other questions related to the learning process could become evident.

One of the key aspects of our proposal is that the total length of the spiral can be adjusted through the controls of the different panels, thus allowing one full rotation (360 degrees, starting at a zero degree angle with time events ordered clockwise) in the spiral to conform to a specific duration (years, months, weeks and days). This way, the lower level units (months, weeks, days, and hours, respectively) occupy the same sector of the spiral, and so monthly, weekly, daily and hourly patterns are highlighted. This feature brings tremendous versatility to the tool and is illustrated with examples in the next section.

Another way of maintaining the context within the spiral while focusing on a single filtered-out activity is by drawing the whole dataset with very light colors in the background. That would be interesting if we wanted to assess the performance of students regarding participation in fora discussions (a post event would be drawn in a bright color in the spiral), but we still wanted to relate this activity with other actions performed by the students (which would be drawn in light colors in the background) within the same period of time.

The user can assign colors to different activities, filter out activities, look for events related only to one course or person, and so on. This capability supports the exploration of the whole content stored in the CMS, so as to find patterns related to educational situations of interest.It is also important to take into account the enormous amount of data that must be represented (bearing in mind that for years, the CMS logs events to the minute in which the activity occurred). This makes the ability to perform a semantic zoom become critical, so that the representation can convey different levels of information.

In Figure 1 the total length of the spiral is covering the time period from January 2006 to June 2008 (the exact dates are shown in the linear timeline). The rectangles wrap months. This way, even without any interaction with the SST, the user can easily conclude that the last four months were the most active period.

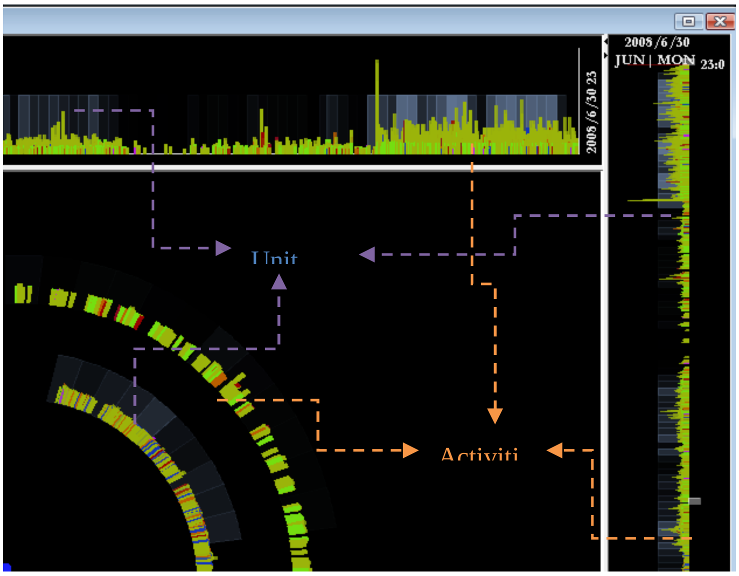

Figure 2: Information elements represented

3.1 Information Elements Represented

Two information elements are considered in the body of the timelines (Figure 2). The main one is a coloured bar that represents activities (Figure 2, indicated with orange lines), which in this case is the type of the activities but it can be personalized in such a way that it could also represent the course or student. Also these elements can be drawn in the same colour, for example when the objective of the exploration is to create a general temporal pattern, rather than the patter of a particular course, person or activity. In both methods for calculating a drawing, the colour of the figures can be customized at any moment of the analysis.The position and orientation of each bar is given in a clockwise order and for that purpose the time log (in minutes) for every activity is used. The height of the bar depends on the amount of activities of the same type that occurred at exactly the same minute.

The second element is used to depict higher level time units (Figure 2, highlighted with blue lines) which can be customized, depending on the aim , in days, weeks, months or years. It is possible to paint one or more of them at a time, so, for instance, the activities (bars) that occurred within a day are wrapped within a rectangle, and the colour of the rectangle (time unit) can be designated according to the time (day, week, month, year) or the frequency. In the case of Figure 2 the colour depends on the total number of activities performed during one day: the more activities performed, the brighter the filled rectangle is (designated by frequency). This approach provides two benefits: first, the brightest rectangles provide a pre-attentive distinction of the most active period of time, and secondly, different coloured rectangles naturally separate higher-level periods of time.

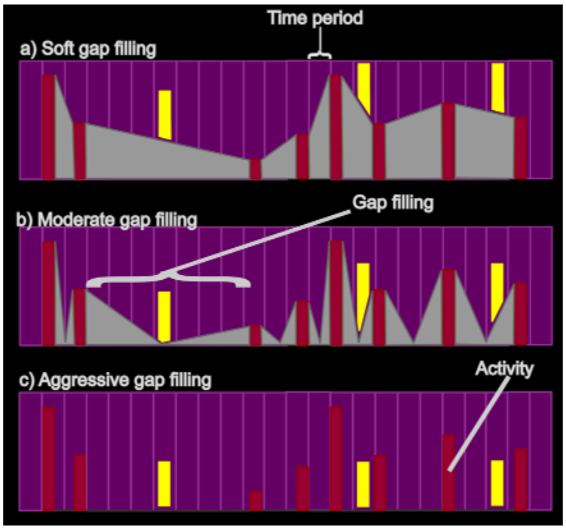

Figure 3: Spiral distortion

3.2 Distorted Spiral

The above-explained representations of temporal events in the CMS included in SST provide an excellent tool for analysts. However, some temporal patterns remain hidden due to the regular shape of the spiral. In this section we describe some distortion techniques applied to the spiral that are very useful to unravel evolution patterns. The general idea behind spiral distortion is the following: instead of having a regular spiral shape, with a constant increase in radius, the distance from the centre to the next bar to be drawn depends on the height of the previous bars on the same angle. Put into a simple metaphor: the evolution of the spiral is quite similar to that of tree-rings. We have previously explored the use of a tree-ring metaphor as a representation of the evolution of hierarchies [Therón, 06]. In the present work, the different widths of the concentric lines produce a shape similar to a distorted spiral, where the width variation is produced by the accumulation of various activities per unit of time.

However, there are several ways to represent these accumulations that yield diverse aesthetic results and also differ in how well they help us unravel temporal patterns. SST provides three types of accumulation or gap filling that are graphically explained in Figure 3. The difference between the three gap-filling methods is the compactness of the distorted spiral. This can be seen in Figure 3, where the red bars are the activities, the gray polygons represent periods of no activity, which will form an envelope for every 360º spin of the spiral, and finally, the yellow bars are the activities of the next turn. We have distinguished three degrees of gap-filling softness (as opposed to the compactness of the spiral).

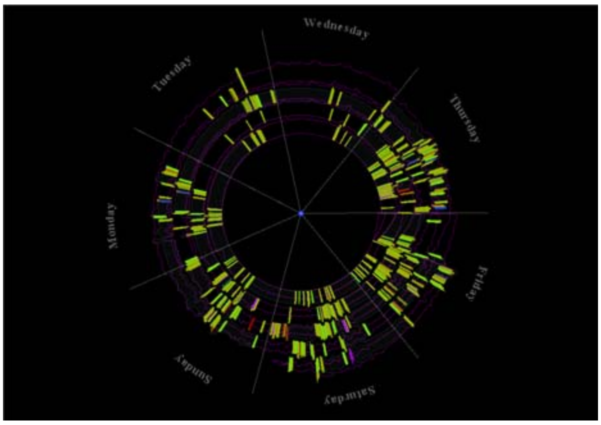

Figure 4: Soft gap filling

Soft gap filling (Figure 3.a): in the same spin, a line connecting the ends of one bar to the following one is drawn. The polygon built after connecting all of the bars in a complete spin is the envelope. Then, in the next spin, the bars are seated over the envelope of the previous spin. In Figure 4 it is shown how this gap-filling method permits the understanding of time patterns without losing a clear view of the activities, whose representation preserves the continuity of the timeline. For that reason this method is also called continuous deformation.

Moderate gap filling (Figure 3.b): in this case, instead of using a line for the connection between two consecutive bars, the gaps (periods of no activity) between bars are considered, taking the zero line in the middle of the gap, so that the envelope grows on both sides up to the height of the connected bars.

This method is more realistic regarding how activities are accumulated and it provides a greater area within which the spiral is allowed to deform, thereby, compressing empty space more. Although the structure of the timeline is maintained, it is not as evident as in the previous method. On the other hand, this deformation shows time patterns more vividly. Figure 5 shows the same example as in Figure 4 but with moderate gap filling.

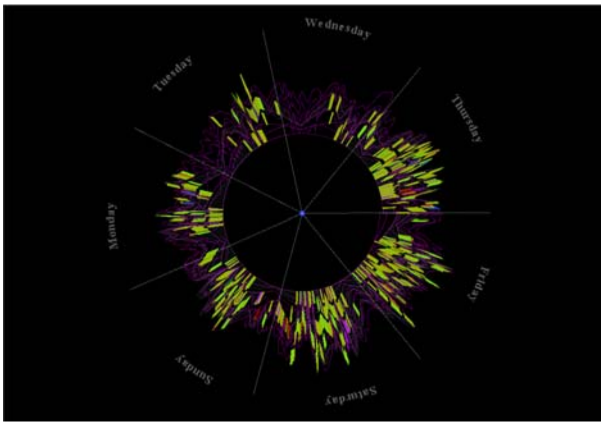

Figure 5: Moderate gap filling

Aggressive gap filling (Figure 3.c): the activities are plotted as histogram bars following the spiral and the gaps between bars are covered with activities of the next spin of the spiral, should they exist. This deformation loses the structure of the timeline almost completely; at first sight this makes it difficult to recognise which period of time each activity belongs to, yet it enhances the recognition of time patterns. That is the reason why this method is also called non-continuous deformation. The result of applying this method to the same data used to illustrate soft and moderate gap filling is shown in Figure 6.

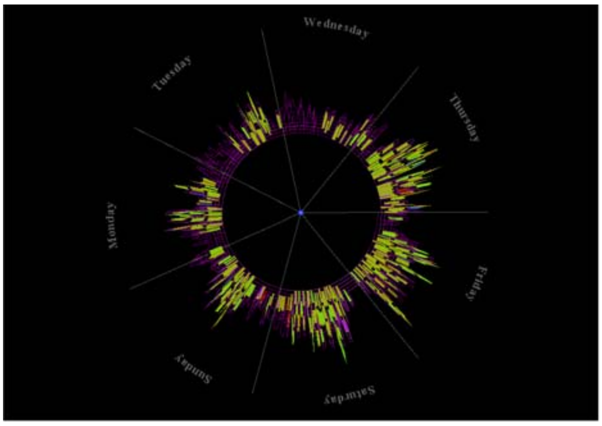

Figure 6: Aggressive gap filling

It is important to mention that these deformations depend directly on the width of the space between activities, and therefore the wider the gaps (periods of no activity), the greater the differences between the deformations, and therefore, the greater the chance of visualising patterns.

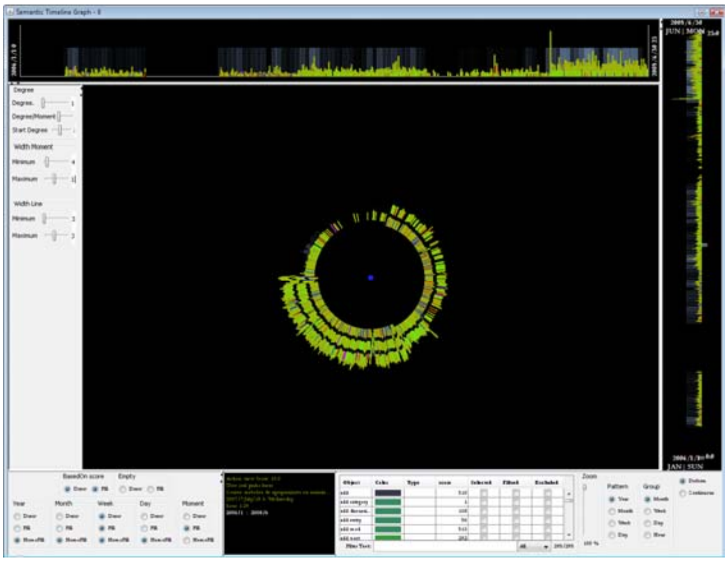

Figure 7: Global aspect of distorted SST

For example, Figure 7, contains a distorted depiction of the spiral shown in Figure 1. In an almost pre-attentive way, the figure below uses green to highlight when the greatest concentration of activity in the platform took place. The highest density in the whole dataset stored in the platform, encoded in green, is highlighted even further by its location in the bottom left quadrant (which covers a period of time running from May to August). In addition to this overview, the user has access to details (in the information panel against a black background at the bottom) and he or she can observe the bulk of activities in the platform indicated in the green area of the spiral which corresponds to the “view” activity.

It should be noted that all this knowledge is more clearly conveyed in the visualization of Figure 7 with respect to Figure 1.

4 Case Study

The analysis was applied to a LSMC Moodle that contained a total of twenty-two (22) courses, forty-five (45) different types of activities, two hundred forty-three (243) students and fifty-six thousand nine hundred thirty-two (56,932) activities in various courses, covering a period of two and a half years. Any attempt to draw conclusions regarding such a large number of data using with the information access tools provided by Moodle itself is unworkable.

Hence, our starting point was the new knowledge provided by our previous work [Gómez, 08] that faced the dataset mentioned above. We are currently interested in finding temporal patterns in the data that suggest ways to better explore virtual education tools in years to come.

In [Gómez, 08] we found that even with the help of social network visualization tools, the data corresponding to a single course was enough to form an extremely connected, and therefore so overly cluttered, social network that one could not draw interesting conclusions. The appropriate way to advance in the analysis was by filtering the data into activity types, which led to the identification of the most connected person(s).

Figure 8: Focusing on a course

The actual goal was to study temporal patterns in the data and to complete the previously acquired knowledge about the identified course(s) and person(s), as well as to discover further knowledge related to specific users' activities on the platform. In addition, it is our purpose to bring to the surface potential problems that cause misuses of the CMS and to be able to start envisioning some solutions, thus improving usage and maximizing our exploration of the resources offered by this technology as applied to education.

As a result, the first step was to focus on a single course and proceed by highlighting all the activities of the desired course, which was done by performing a name search in the proper panel. The result can be seen in Figure 8. Note that a full spin in the spiral corresponds to one year, taking into account that January the first is located at a zero degree angle and time moves clockwise. One can also see that the course (highlighted in white) occupies merely one quadrant of the spiral, which means that it was active from March to June 2006, (additional details such as the exact dates of events are provided as text labels); the data on this course corresponds to 34% of the total dataset stored in the platform.

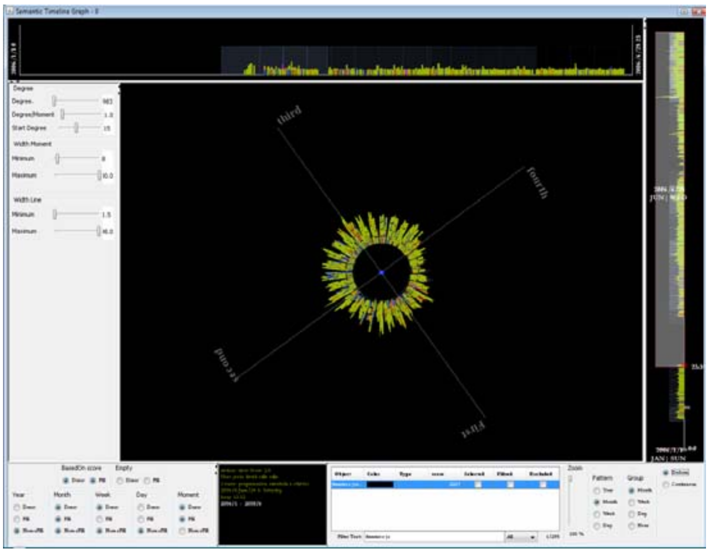

Figure 9: SST showing only the data of a time period

Next, we filtered out any data related to other periods of time. This was achieved by dragging the sliders in the timeline overview. As can be seen in Figure 9 (right panel) the context of the problem is maintained in the background (blurred areas of the overview for the periods of time not selected). The focus is now on the selected period, and as a result both the spiral and the linear timeline will only show four months of activities. The next step was to activate the deformation of the spiral, specifically by using the technique called non-continuous deformation, which helped us to better visualize the patterns. With the help of the patterns panel, the spiral representation was adjusted so that a full spin corresponded to a month, thus enabling us to make better use of screen space available and making the patterns stand out. The result can be seen in Figure 9, which represents a single course, with 57 students and 11,893 different types of activities (coded by colour) within a period of 4 months.

Now, with a full spìn of the spiral representing a month, the first day of each month begins at an angle of 0 degrees. Moreover, the spiral is divided into 4 quadrants corresponding to the 4 weeks of the month. Thus, in Figure 9 it can be seen that, for every month of the course, the weeks in which less work has been done (the spiral is narrower at a specific angle), are usually the first and the last one. On the other hand, during the second and third weeks more activities in the learning platform have been carried out.

As we previously mentioned that colour-coding was used in the visualization, now we will explain how it works: each different colour in the spiral represents a different type of activity (the SST platform examines each activity at intervals of one-minute minimum), but it can also be observed that colour is used in the linear timeline (top panel, Figure 9) and in the rectangles (which, in this case, represent weeks). The rectangles are coloured homogeneously grey, with the most brightly shaded ones representing the largest amount of accumulated activities; hence the second and third week of the course are the ones in which the e-learning platform has been most used.

This means that even though the first four weeks of the period had the largest accumulation of activities per week, this was not enough to make a notable difference on the period in a global sense. An example of this is the first week of every month, which over the entire period of the course tended to be the most prolific but overall did not accumulate the most activities. Another advantage of distorted spiral visualization is that by further reducing the spin from 360 degrees to a week (using the pattern panel, located in the lower right in Figure 9), a different spiral with seven sectors representing each of the days of the week can now be generated. This change highlights the fact that three days (Thursday, Friday and Saturday) contain the largest accumulation of activities, with Thursday being the day with the highest concentration.

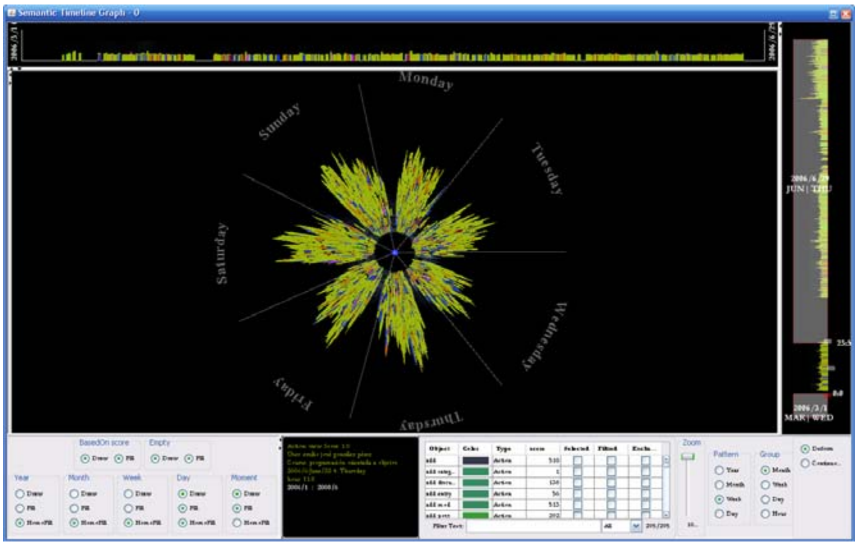

Figure 10: Weekly pattern for the chosen course

It is also quite obvious in the Figure 10 that the most popular activity is the one which is colour-coded green ("view", i.e., looking at pictures of other participants in the platform). A further step in the analysis would be to explore the activities of a given person. This way we could assess the use this individual is making of the educational platform.

Thus, what we did next was filter out some data by searching for the name of the person that we wanted to analyze (possibly one of the persons identified in the analysis of social interaction in our previous work). Then we adjusted the representation in such a way that a full spin in the spiral corresponded to a week. The graphical zoom function can be used to personalize the image for end-user analysis.

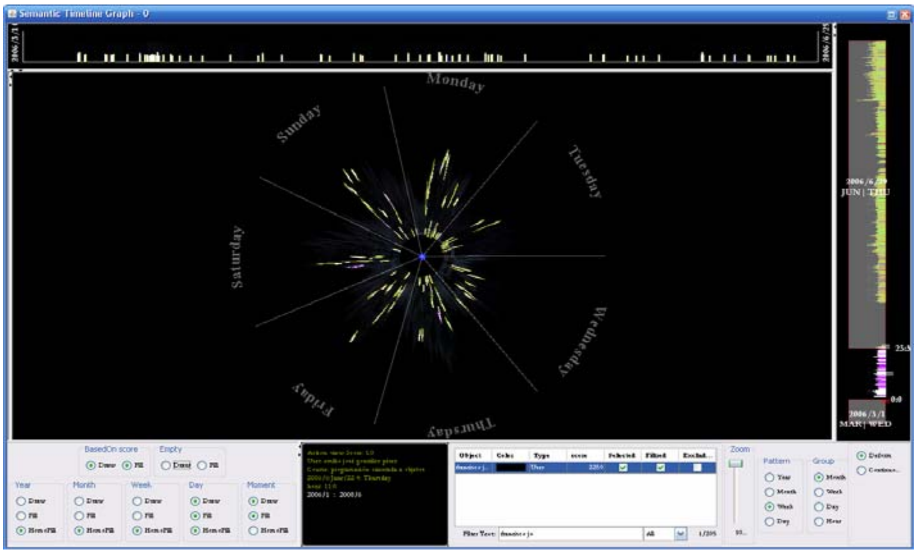

Figure 11: Weekly activity pattern for a person

The result of these operations is that the activities performed by the selected user are highlighted in white (see Figure 11). At this point, it is important to notice that SST implements a focus plus context technique which blurs the context into the background (note the grey halo) without making the complete pattern disappear. This facilitates comparison with the pattern of our focus.

So the details of the focused individual tell us that he or she has made a total of 2308 activities during the four months of the course. The reader should remember that a spiral spin corresponds to a week's time, which is divided in seven sectors, one for each day of the week. It is curious to note that, despite the fact that online platforms allow free scheduling of the learning activities, the analysed person makes a very methodical use of it. Note that this person used the platform seven days a week (including Saturdays and Sundays) and when he did it, most of the activities were performed within the second 6 hours of each day (i.e., in the early hours of the morning). In addition, Sundays and Mondays were busier regarding platform use, then usage decreased on Wednesdays and Thursdays and rose again to the same level of usage as on Sundays. It can be added that this is the person with the highest ratio of activity, as he or she contributed up to 4% of the total activities on the platform.

Finally, we were also interested in the analysis of activities. So, proceeding in a similar manner to the previous step and using the same course as the basis for our analysis, we searched for the name of the activity we wanted to explore. In our example, we selected the activity "add post" and the result is shown in Figure 12. The SST represents a total of 181 activities of the "add post" type, which are highlighted by the tool, while the remaining activities are shaded but in context for ease of analysis. This is clearly a very small amount of activities with respect to the total course activities.

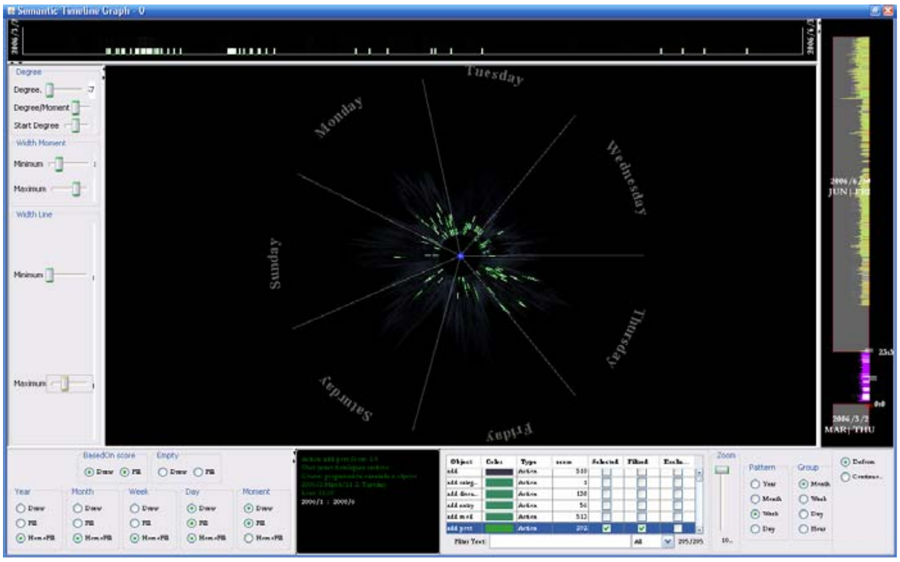

Figure 12: Weekly pattern for the "add post" activity

Again, a complete spin of the spiral corresponds to a week, so the pattern indicates that this type of activity has been carried out much more frequently at the beginning of the course (activities mostly appear at the inner spins). However, on Mondays and Thursdays in the last part of the course there was an increase in this type of activity. Also on Thursdays and Mondays the platform was used for adding posts, and a notable decrease was experienced on Fridays, Saturdays and Sundays.

One of the startling facts that SST easily reveals is that Mondays break with the general "ad post" pattern and are not among the days with the most accumulation of activities, as there is no blurred shape for Mondays. Another interesting fact that SST helps to visualise (Figure 13) is that the general and the individual accumulation of activities per month do not coincide in the same month. If we consider the sum of all activities per month over the whole period, June 2008 is the most active (the brightest rectangle in the linear timeline and the spike on the outermost shape in June).

On the other hand, the accumulation of activities for the whole period shows that March is the month with the most activity (the white shape in the central spiral visualization), i.e., March averaged more activities over the years than June, which in only one year had an increase of activity.

Also, with the help of this tool we have noticed that there are patterns that reveal limited use of the learning platform. Among these uses we can highlight: viewing the profiles of users, reading the discussions without providing any comments, exploring the course contents without actually accessing the content, and so on.

Thus, we can analyse the actual use of the platform. Figure 14 refers to the same example course we have been analysing so far. If we select the "view" activity, we will learn that 57 pupils performed 8266 "view" activities, which are highlighted. It is very striking to compare Figure 12 (activity with strong educational content, "add post") and Figure 14 (activity with minimal educational content, "view").

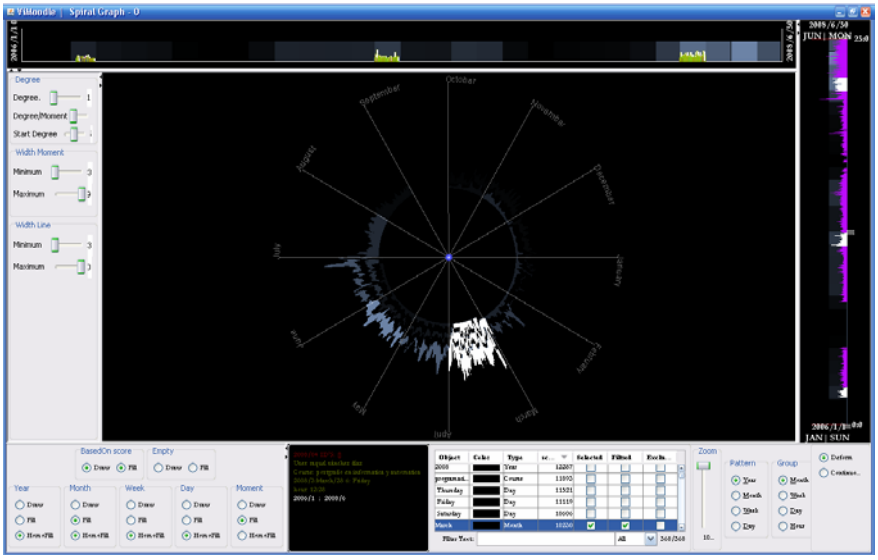

Figure 13: An example of the need of both the linear and the spiral timeline

It is important to mention that the tool offers the possibility to filter out this kind of activities, if we wanted to analyse only the educational content and not the "noise" that non-educational activities like "viewing" would add.

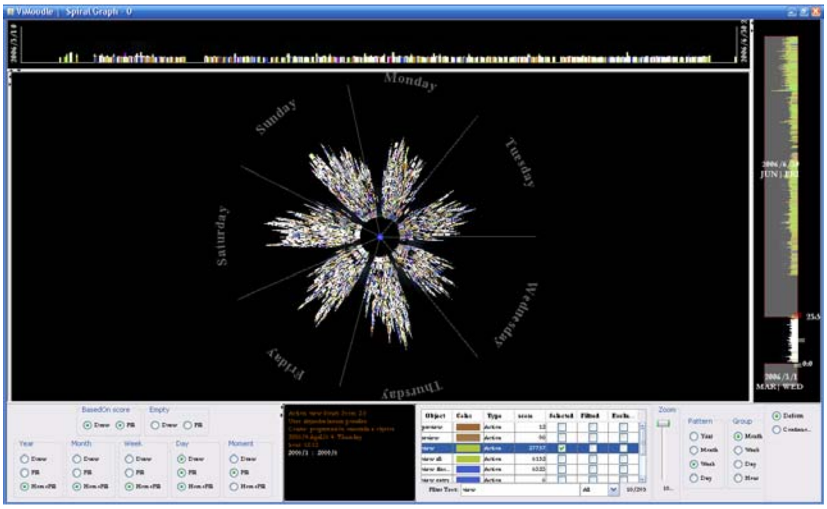

Figure 14: Weekly pattern for the "view" activity

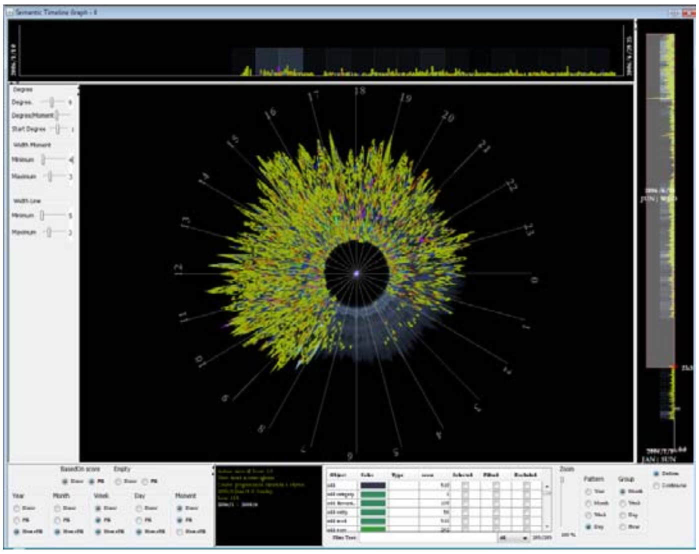

Figure 15: Daily pattern for the chosen course

Given that the representation by weeks of the spiral showed a slight difference in the hourly use of the tool in the morning in comparison with the rest of the day, to continue the analysis, we changed spin of the visualization to a day, dividing the spiral in 24 hours. In this way we had the powerful opportunity to see the hourly distribution of the activities of the e-learning platform (Figure 15).

As can easily be seen, the time when there is the greatest amount of activity on the platform are just before and just after lunch (note that in Spain lunch time is around 14:00), so 11:00 a.m, 12:00 a.,m. and 3:00 p.m. were the busiest times. Also we noticed some empty sectors, which corresponded to nighttime, which of course, is normally when the users of the platform are asleep. However, there is an exceptional case of one person that used the platform several times between 2:00 to 7:00 a.m.

To complete our analysis, the same person as in the case of Figure 12 was selected, but this time we ensured that the visualization presented the data using a distorted spiral and a daily pattern. The result of filtering out the activities performed by other users is shown in Figure 16. The selected user had a greater amount of activity in the second six hours of the day. It is curious to see that there exists a concentration of activity around 6:00 p.m., in addition to a concentration of activity at around 8:00-9:00 a.m.

Finally, it is also interesting to discover that, on the contrary as it might be expected in a non-scheduled educational platform, all of these activities were performed either just before going to work or just after work, as the most common working day is from 9:00 a.m. to 2:00 p.m. and 3:00 p.m. to 6:00 p.m. We can conclude that this person is also working besides using the educational platform or is involved in other activities, which is why he or she normally uses the platform after and before a specific time.

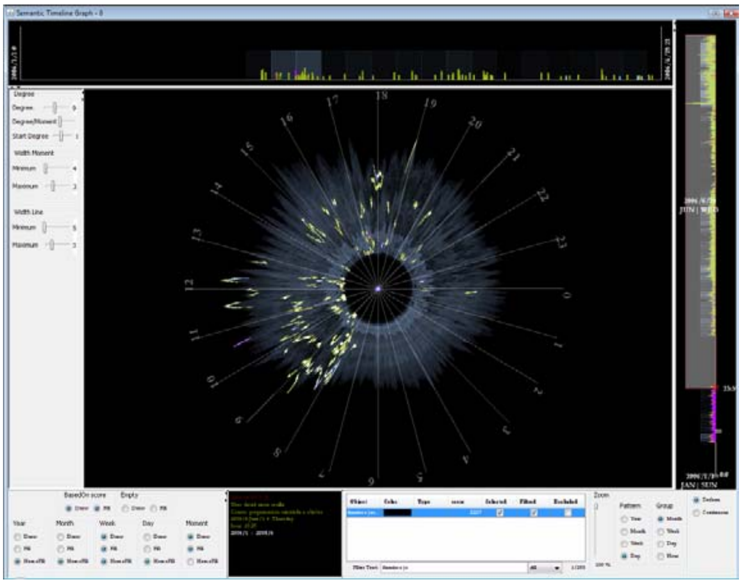

Figure 16: Daily pattern for one person

5 Conclusions and Future Work

Through this work we have shown the enormous potential that using the tools of visual analysis offers, as they can bring e-learning platforms' patterns of usage to light. Current technology allows for the storing of enough information for a study of this nature to be feasible. However, the size of these datasets requires specially designed tools.

It is necessary that the users of these platforms mature so that they make the most of the available resources. It is surprising, for instance, the difference between the number of visitors who use the platform to interact in fora and discussions in comparison with the number who simply look at the others' profiles. This may suggest that we should not allow such activities and therefore encourage more interaction in fora, questionnaires and other major educational and constructive activities.

The next step of our work will be to integrate SST with the tools developed in our previous work [Gómez, 08] and in this way we aim to provide a powerful tool with multiple-linked visualizations that can perform analyses of both social interaction and evolution of use. The implementation of other deformations that increase the power of the semantic zoom in visual analysis is also intended.

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