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AN INTERACTIVE APPROACH TO INFORMATION VISUALIZATION IN THE CONTEXT OF LEARNING ANALYTICS

In recent years, information visualization techniques were adopted in a wide field of disciplines which had to deal with the processing and / or the presentation of huge datasets. These efforts were aiming at assisting the discovery and analysis of data through visual exploration. To support the easy and mostly inituative perception of visualy encoded information, diffenrent techniques can be used to support pre-attentative perception as well as a good overall usability experience. This article exemplifies different visual concepts we implemented within our learning analytics application called LeMo (Learning Monitoring).

Keywords: *Learning analytics, information visualization, big data, usability*

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ИНТЕРАКТИВНЫЙ ПОДХОД К ВИЗУАЛИЗАЦИИ ИНФОРМАЦИИ В КОНТЕКСТЕ АНАЛИТИКИ ПРОЦЕССА ОБУЧЕНИЯ

В последние годы методы визуализации информации были задействованы в широком поле дисциплин, которые занимались обработкой и / или представлением огромных наборов данных. Эти усилия были направлены на содействие открытию и анализу данных с помощью визуальных исследований. Для поддержания легкого и в основном интуитивного восприятия визуально закодированной информации, могут быть использованы различные методы предварительного восприятия. Эта статья иллюстрирует различные визуальные концепции, которые мы реализовали в приложении для аналитики процесса обучения под названием LEMO (Learning Monitoring).

Ключевые слова: *аналитика процесса обучения, визуализация информации, большие объемы данных, удобство использования*

Андреас Пурсіан

ІНТЕРАКТИВНИЙ ПІДХІД ДО ВІЗУАЛІЗАЦІЇ ІНФОРМАЦІЇ В КОНТЕКСТІ АНАЛІТИКИ ПРОЦЕСУ НАВЧАННЯ

В останні роки методи візуалізації інформації були задіяні в широкому полі дисциплін, які займалися обробкою та / або поданням величезних наборів даних. Ці зусилля були спрямовані на сприяння відкриттю та аналізу даних за допомогою візуальних досліджень. Для підтримки легкого і в основному інтуїтивного сприйняття візуально закодованої інформації, можуть бути використані різні методи попереднього сприйняття. Ця стаття ілюструє різні візуальні концепції, які ми реалізували в додатку для аналітики процесу навчання під назвою LEMO (Learning Monitoring).

Ключові слова: *аналітика процесу навчання, візуалізація інформації, великі обсяги даних, зручність використання*

Introduction

Learning analytics is an emerging research field with the goal of an better understanding of learner and learning processes particularly in the context of e-learning environments and the utilization of this knowledge for the improvement of learning opportunities [1]. Here, in addition to the collection and processing of large data sets, the descriptive and intuitive presentation of the analysis data play an important role. In this respect, especially the visual exploration of data may support an better understanding and a faster perception of large data sets [2, 3].

Within the research project learning process monitoring (LeMo), we developed a prototypical learning analytics software with a strong focus on an explorative and interactive approach to data visualization. Users are allowed to explore a visualization through features like translation, rotation, filtering, zooming. Furthermore we utilized different visual concepts supporting pre-attentative perception like information encoding through shape, size, color and position or object constancy during transitions [4, 5, 6]. Within this paper, I present our approach to visualization of learning analytics data from three analysis categories: quantitative accesses to learning objects – “Usage analysis” - navigation through learning objects – “User path analysis” and the exploration of typical navigationl pattern “Frequent path analysis“.

While this paper is only focusing on the visual aspects of presenting analytical educational data, it strongly depends on a long chain of prerequisites like data extraction, data processing, data encoding which were implemented by the LeMo team. This work builds the foundation for everything which is discussed here.

Visual perception

The user interface follows an explorative metaphor “Overview first, filter and details on demand”. Herewith we try to assist the analysis of learning data in an explorative way. Especially when displaying large amounts of data, this shall support a widely intuitive reception of analysis data.

The analyses supported so far can be classified within two categories: quantitative accesses to learning objects and navigation through learning objects. An important objective in the context of our prototype development was an easy and mainly intuitive access to the results of our analysis. To meet this goal we followed three basic design guidelines while creating our visualizations:

- *supporting pre-attentative perception*: through the use of visual attributes such as shape, size, color and position [7,8];
- *details on demand*: detailed information on a specific learning object are context sensitive available, but do not overload the initial visualization;
- *exploration*: the interface provides the possibility to customize the visualization to best fit the personal expectations through features like translation, rotation, filtering, zooming.

A large part of the functionality demanded by our project partners deals with the analysis of the navigation of users within the learning systems. A teacher might want to know if the learning objects (A user path is a list of learning objects, ordered in the way they have been accessed by the user) he has prepared for his e-learning course are processed in the intended order, or if some objects were missed by a significant number of users. To answer these and other questions we have to determine the paths and navigational pattern of the users. Hence, this paper focus on our work dealing with different aspects of navigational analysis.

Usage analysis

The usage of e-learning resources within an e-learning course can be visualized in terms of clicks per time interval using a line chart (fig. 1). Concepts like details on demand and exploration are implemented through the possibility to interact with the graph. Via drag and slide gestures in the lower thumbnail, it is possible to get an enlarged view at the top. The filter located top right – trigger to show and hide certain data items - are introduced via transitions. This means, the range of values of the y-axis which is visible to the user, smoothly increases or decreases depending on the dataset which is currently displayed.

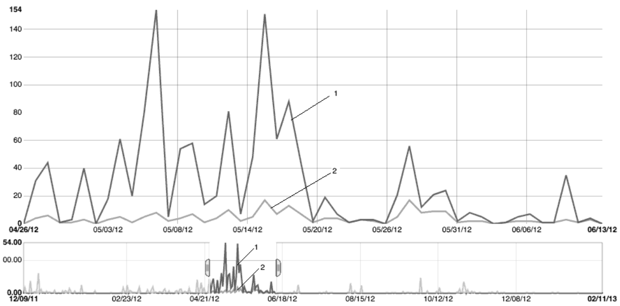

Fig. 1. Usage analysis by time and requests:
1 – Formale Grundlagen der informatik,
2 – Formale Grundlagen der informatik user

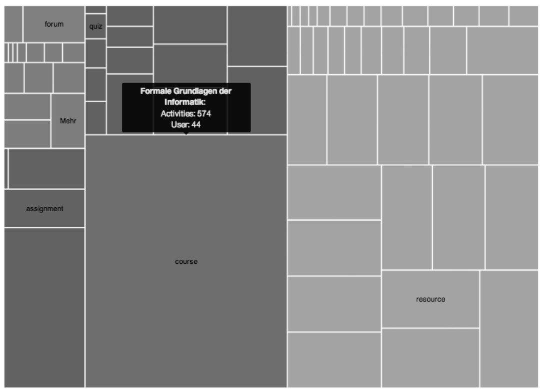

Fig. 2. Usage analysis with treemap view

Within the treemap visualization (fig. 2), the requests (clicks) on the various learning object types (e.g. wiki, forum, quiz, files, etc.) within an e-learning course are presented by means of spatial distribution. The spatial distribution shows the percentage breakdown of user activity within a e-learning course. Clicking one color coded area reveals the previously hidden subhierarchy of this area. Via mouse-over, additional information can be displayed context-sensitive to all areas.

Activity graph analysis

The "Activity graph" allows the analysis of user activities based on their interactions with the learning system. The analysis’s results are represented by a visualization of a navigation network, which users have characterized by the sum of their individual navigation steps. This analysis can be used to obtain information about the degree of crosslinking of a learning object. An important challenge during the implementation of this visualization was the reduction of typical network visualizations problems like the "hairball" effect [5, 9].

For the implementation of this visualization, we utilize concepts of the graph theory. Theoretically, the graph representation of a path is represented by a sequence of edges and nodes with G = (V, E) and a set of nodes vi where {vi-1, vi} represents an edge in E. There is a node vi for each specific learning object of a path. An edge ei = {vi-1, vi} symbolizes a navigation step of learning object vi-1 to vi. Furthermore the following premises were crucial for the visualization:

- learning objects (nodes) are color-coded to support the visual perception of content type transitions, e.g. when a user moves from the forum to a learning resource. Therefore each category of learning objects like forum, assessment, resource, etc. is encoded with an individual color. Furthermore, learning objects are adjusted in size to encode the absolute number of user requests;

- navigational steps between learning objects are illustrated using transitions (edges). These edges are weighted and color-coded to encode the amount of navigational steps;

- edges have direction markers (arrows) indicating the direction of navigation between two learning objects;

- detailed information on specific elements of the graph can be made visible by interacting with the visualization. Hovering over a node will bring up a tool tip that includes information concerning the learning objects name, the learning object type and the total number of requests;

- to further explore a specific node a single click on that node will rearrange the graph in a way that the node of interest is focused, neighboring nodes are displayed in the immediate proximity, and other nodes are located further away.

The "Activity graph" (fig. 3) visualization provides an overview of navigation processes by means of a network visualization. The arrangement of the graph is done by a algorithm simulating gravity forces (Our implementation is based on technics used within the d3.js visualization framework by Mike Bostock [10]. The approach is similar to technics described by Fruchterman and Reingold [11]). Each node is pushed away from each other and is tightened simultaneously to an invisible gravity situated in the center of visualization. Through the interplay of forces a stable network configuration could be achieved in a reasonably short cool-down time (on average approx. 3 seconds for graphs up to 100 nodes).

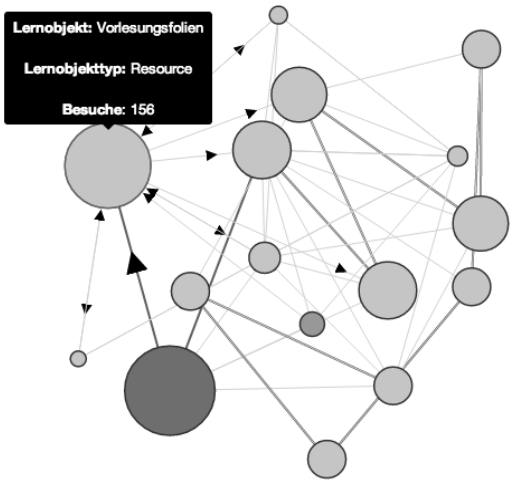

Fig. 3. Activity graph

We reduced typical problems of this type of representation, such as the strong overlap of nodes and edges in large networks by functions like focus of learning objects and dynamically calculated and adjustable edge lengths.

Sequential pattern analysis

Sequential pattern analysis is aiming at supporting the discovery and analysis of frequent navigation pattern. For the computation of these user paths (A user path is a list of learning objects, ordered in the way they have been accessed by the user) data mining techniques were utilized. Frequent paths are basically those (click) routes through the resources of an e-learning course which several (many) users consume in identical (or similar) order. The visualization (fig. 4) shows a quantity of frequent paths ordered by length. The visualization depends on results calculated by the BIDE algorithm [12]. The following premises are crucial for the visualization:

- a path is visualized by a sequence of nodes (learning objects) and edges (navigation steps). The path is read from top to bottom, starting with the learning object accessed first on top.
- individual learning objects are color-coded to allow an easy visual correlation of navigational pattern even across different paths.
- the visualization follows the Details on demand directive. The initial presentation hides further information like the learning objects description.
- paths are sorted by length (number of unique navigation steps from one learning object to another)

All resources of a path are color-coded while the same resources keep the same color within the whole visualization. Paths are thus comparable. Further information on specific elements of the path is available through interaction with the visualization. A click on the desired path triggers the display of learning object names of all path nodes (fig. 5). While hovering over, a tool-tip provides context sensitive information for each node.

Summing up, our current visualization for frequent paths supports the quick reception of recurring navigational patterns. Paths are visualized arranged by length and minimal support, starting with the longest paths. In result sets with more than 24 paths, a scrolling function is provided. As part of our future work we will further investigate, if other attributes of a path are well suited for a direct graphical visualization.

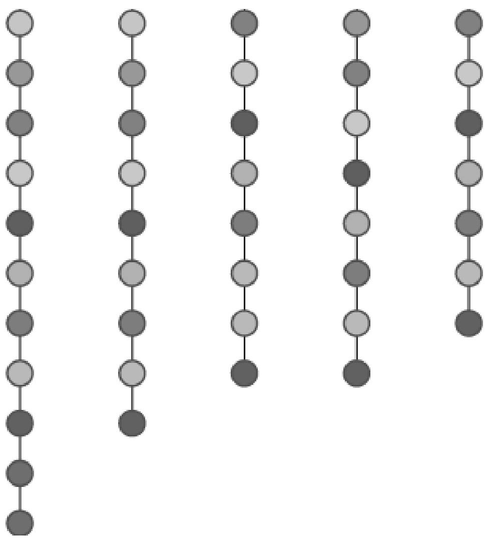

Fig. 4. Frequent paths without description

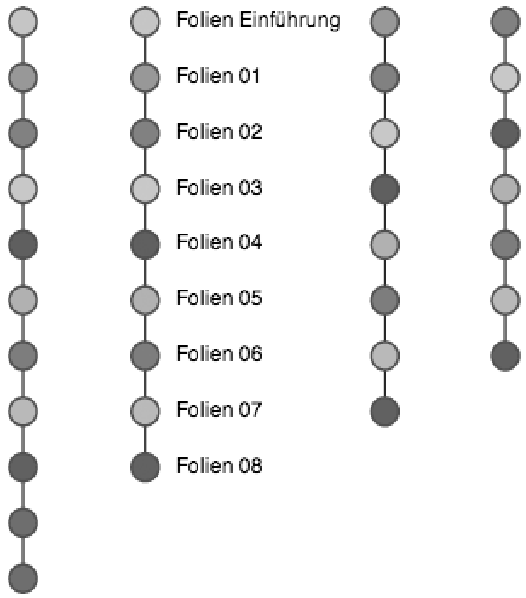

Fig. 5. Frequent paths with description

Conclusion

In this paper I presented our interactive approach to information visualization in the context of learning analytics. I gave insight in the basic concepts we used as as foundation we building our information visualizations. So far visualizations for different domains of learning analytical questions were implemented. This includes questions regarding the quantitative access to learning objects over time as well as questions regarding the user navigation.

This paper focuses on visualizations regarding «user path analysis» as they cover the most requested needs from our target group and are not common in similar tools. For this purpose the LeMo application incorporates two visual analysis: the «Activity graph» which provides a spatially mapped overview about navigational pattern within an e-learning course and the «Frequent path» analysis which provides insides about an ordered group of learning resources which were frequently accessed by a multitude of users.

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