Quantitative Analysis of Multimedia Audit Trails

Graeme Salter Teaching Development Centre University of Western Sydney, Macarthur g.salter@uws.edu.au

Abstract

Audit trails provide a rich source of data that can be used in the evaluation and research of interactive multimedia (IMM). Indeed, one of the major problems with their use is that they provide so much data that meaningful methods of quantitative analysis prove difficult. Most of the studies incorporating analyses of such data are restricted to qualitative analysis. This is obviously quite legitimate where the nature of the problem dictates a qualitative approach, but I suspect that some studies are conducted in this manner due to a lack of alternative quantitative models. This paper looks at models of quantitative analysis of audit trail data for use in research and evaluation.

Keywords

evaluation, quantitative analysis, audit trails.

1. Introduction

It is a relatively simple matter to collect the responses of users in an interactive multimedia (IMM) package. The problem with such data collection is that it can quickly grow to a volume where meaningful analysis becomes difficult or even impossible. As a result, many of the studies involving audit trail data use qualitative methods such as case studies. Of course, these methods are perfectly valid where the research problem dictates their use, but it is possible that quantitative methods are being under utilised due to the lack of robust tools and methods of analysis.

While there has correctly been some reaction against the predominance of quantitative studies in this area (Reeves, 1993), we should not lose sight of a potentially useful source of data. Indeed, the use of audit trails has some advantages over more traditional empirical studies in that the data is collected unobtrusively in a natural setting. It should also be noted that the data need not be wholly analysed using one technique. The use of both quantitative and qualitative methods could prove to be a quite powerful combination in the examination of patterns of use in IMM.

2. Capturing data

The first problem to overcome is to determine which data to collect. Williams and Dodge (1993) summarised the items of learner action typically collected as '*What*, *Where and When*' i.e., the type of interaction, the screen it occurs on (and perhaps the location within that screen) and the time of each interaction. Other sundry items such as the learner identification, time of the start and stop of the lesson will also need to be considered.

There are numerous variables that may affect the navigation patterns of users. Ability in English, gender (Beasley and Vila, 1992) motivation and information-seeking strategies (Small and

Grabowski, 1992) are some that have already been shown to have a significant effect. Where possible, the questions that will be asked and the variables required should be determined prior to establishing data collection techniques in order to avoid having to reconstruct or recollect data files. For example, if it was decided after collecting the data that a comparison between groups based on gender was of importance, but this was not part of the original data collection this would necessitate either editing the raw data files or, if this was not possible, recollecting data including the category of interest. Another reason for avoiding post hoc analysis is that the volume of data can be overwhelming and it is possible that 'data snooping can be raised to absurd heights' (Misanchuk and Schwier, 1992).

Audit trail data is usually collected and analysed with custom-built tools. The development of generic analytical software tools is difficult as the type, location and format of data collected varies considerably. Nevertheless, there could well be a demand for such software. A number of authors (e.g. Laurillard, 1993; Hedberg and Alexander, 1994) have noted that while many IMM developers pay particular attention to evaluation in funding proposals, they often pay scant attention to it in the actual development. Any tools that could assist in this process would probably be welcome.

3. Representing Quantitative Data

Aggregated data is usually represented by tables or, to highlight patterns, in pictorial form. It is of obvious benefit if the computer automatically generates such diagrams.

3.1 Raw nodal frequencies

A representation of the raw frequencies of paths chosen (Misanchuk and Schwier, 1992). Data can be represented as frequencies or proportions. For example :-

Node 1	Resp		1			2	
	Freq		2			13	
Node 2	Resp	1	2	3	1	2	3
	Freq	0	0	2	3	6	4
Node 3	Resp	123	123	123	123	123	123
	Freq	000	000	011	021	150	013

This approach may suit more didactic packages with set choices, but would quickly become unmanageable within a hypermedia environment. Nevertheless, this method may be of use when analysing a smaller unit such as an individual screen.

Data can also be represented in pictorial form as an audit trail tree.



The number of learners taking any given path is represented by the thickness of the line drawn. A dashed line indicates that no students have taken a possible path. The resolution of the lines is an obvious limitation although actual figures can be printed next to lines.

3.2 Transition matrix

A matrix that shows the frequency of moves from one node or state (rows) to another (columns) (Evans, 1994). For example :-

	а	b	с	d	Total
a-Node 1		30	60	25	115
b-Node 2	22		10	50	82
c-Node 3	45	35		24	104
d-Node 4	102	45	15		162

This table allows a quick examination of paths from one node to another for large groups of users. Again this can be represented in the form of a diagram -



With this method, 'clusters' of behaviours stand out. There are variations on the construction of the diagram. For example, similar to the audit trail tree, the width of a line can be adjusted to indicate the frequency of movement. Shading can also be used to give an indication of the relative amount of activity within a section. Transition diagrams tend to become very complex, resembling spider webs, where a large number of nodes or sections are examined at one time.

Spatial mapping techniques lose the potentially important dimension of time. Temporal mapping techniques such as that used by Fritze (1994) can illustrate an individual's path over time.



However, it is difficult to represent visually aggregated data in this fashion apart from printing a number of such charts together. When comparing individuals over time, the question of whether to view time in an absolute or relative sense needs to be determined.

3.3 Pictorial

A representation of the history of mouse clicks or 'hits' on actual screens by placing a round button or other symbol on the location of every click stored (Williams and Dodge, 1993). This provides a ready visual comparison of button use.



3.4 Descriptive statistics

Simple frequencies and averages of numerous variables can be displayed. For example :-

Usage (Hours)	Number of students
0-2	3
3-5	12
6-8	7

Node	Visited
1	24
2	55

Data aggregated in these ways lend themselves to standard statistical tests.

Graphical representations are common (e.g. Frequency of Visits) :-



3.5 Sequence analysis

The antecedent events of a location of interest can be displayed for a selected range (Evans, 1994). For example -

Sequence of 3 Prior States	Frequency	Percent
Node 6 <- 4 <- 2 <- 3	2	8
Node 6 <- 3 <- 12 <- 2	10	40
Node 6 <- 3 <- 12 <- 1	8	32
Node 6 <- 3 <- 12 <- 3	5	20

The choice of the location of interest and length of the range to view would be important. Using the computer to calculate the sequences and frequencies would allow a greater range of locations to be examined with ease. Results can be readily graphed.

4. Analysing Data

4.1 Observation

The reason for going to the effort of representing data visually is to look for patterns. This may be sufficient. Where patterns are detected (or at least suspected) more intensive qualitative techniques such as video tracking and user interviews may be used to gain greater insight into the possible causes.

While patterns are more likely to be detected using aggregated data, Fritze (1994) suggests that patterns may also be detected by rapidly scanning between the traces of different individuals.

4.2 Statistical

Collapsed or averaged data is well suited to statistical analysis. Raw data not only presents problems due to its sheer volume, but it may also need to be transformed or manipulated in some way before being amenable to standard statistical tests. While this is only a small barrier, it may deter some from considering such analyses. As stated previously, the development of standard collection and analysis tools for audit trail data to simplify the process is an area worthy of consideration.

4.3 Analysing user-defined categories

Rather than trying to discover any inherent patterns that may exist, it is possible to search for 'userdefined' categories. This may be a single index (e.g. achievement / time) or a pattern that fits certain criteria. A common pattern that is searched for is 'linearity'. For example, Horney (1993) calculated linearity functions based on path probabilities which in turn were based on the ratio of 'parent-child' traversals to the total number of node visits.

One of the problems associated with such categories is that different researchers often use the same term based on different criteria. This is to be expected given the relative immaturity of the field. However, in some cases, new terms (eg. browsing) are used without specifying the accompanying criteria making replication of studies impossible and understanding difficult.

4.4 Mathematical models

Apart from traditional statistical analyses, there are other mathematical models that have promise in the analysis of audit trails. For example, the Analysis of Patterns in Time (APT) method given by Frick (1990) attempts to measure temporal relations directly by counting their occurrence rather than the more traditional approach of measuring variables separately and then trying to relate them mathematically. While such a method does not necessarily indicate causal relationships it can be used for prediction and to suggest areas of possibly fruitful further research.

5. Interpretation of Results

Due to the nature of hypermedia, there are some inherent dangers in the interpretation of quantitative analyses. Students usually do not experience the same events. (This can also lead to problems in analysis as there may be large sections of missing data). Similar paths may be chosen for quite diverse reasons. Identical movements through a lesson do not necessarily reflect a cognitive correlation. Particular paths taken by individuals or even groups may be chosen relatively randomly rather than having any external meaning.

This highlights the importance of triangulating findings using a number of techniques where possible to avoid imposing the wrong meaning or a meaning where none exists. For example, it may be misconstrued that because students have spent a small amount of time on a task that it represents low cognitive demand whereas interviewing reveals that students had the quite separate aim of finishing an irrelevant research-imposed lesson in the shortest possible time. There are potential dangers in qualitative approaches too. For example, students may have trouble accounting for their actions and it must be remembered that they have no knowledge of paths not taken.

6. Conclusion

The analysis of audit trail data can shed light on the strategies and problems that learners have in using increasingly complex webs of information. There is room to develop tools and strategies that can assist in this process. Such tools may incorporate one or more of the techniques shown here or may be modelled on more innovative strategies currently under development such as 3-D representations and movies (Evans, 1994). Perhaps a more difficult task than selecting appropriate qualitative analytical techniques will be knowing what questions to ask in the first place.

7. References

Beasley, R. and Vila, J. (1992). The identification of navigation patterns in a multimedia environment: A Case Study, *Journal of Educational Multimedia and Hypermedia*, Vol. 1, pp. 209-222.

Evans, P. (1994). Investigating the use of interactive hypermedia systems, *Interactive Multimedia in University Education: Designing for Change in Teaching and Learning (A-59), IFIP*, Elsevier Science B.V (North Holland), pp. 259-271.

Frick, T. (1990). Analysis of patterns in time: A method of recording and quantifying temporal relations in education, *American Educational Research Journal*, Vol. 27, No. 1, pp. 180-204.

Fritz, P. (1994). Investigating the use of interactive hypermedia systems, *Interactive Multimedia in University Education: Designing for Change in Teaching and Learning (A-59), IFIP*, Elsevier Science B.V (North Holland), pp. 273-285.

Hedberg, J. and Alexander, S. (1994). Evaluating technology-based learning: Which model?, *Interactive Multimedia in University Education: Designing for Change in Teaching and Learning (A-59), IFIP*, Elsevier Science B.V (North Holland), pp. 233-244.

Horney, M. (1993). A measure of hypertext linearity. *Journal of Educational Multimedia and Hypermedia*, Vol. 2, No. 1, pp. 67-82.

Laurillard, D. (1993). *Rethinking university teaching: A framework for the effective use of educational technology*. London: Routledge.

Misanchuk, E. and Schwier, R. (1992). *Representing interactive multimedia and hypermedia audit trails*.

Reeves, T. (1993). Conducting science and pseudoscience in computer-based learning. *ASCILITE* 93 Conference Proceedings, Lismore.

Small, R and Grabowski, B. (1992). An exploratory study of information-seeking behaviours and learning with hypermedia information systems. *Journal of Educational Multimedia and Hypermedia* Vol. 1, No. 4, pp. 445-464.

Williams, M. and Dodge, B. (1993). Tracking and analysing learner-computer interaction. In M. R. Simonson and K. Abu-Omar (Eds.), *Annual proceedings of selected research and development presentations at the 1993 national convention of the association for educational communications and technology*. New Orleans. pp. 1115-1129.