Chapter 2
A Survey on Pre-Processing Educational Data

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Abstract Data pre-processing is the first step in any data mining process, being one of the most important but less studied tasks in educational data mining research. Pre-processing allows transforming the available raw educational data into a suitable format ready to be used by a data mining algorithm for solving a specific educational problem. However, most of the authors rarely describe this important step or only provide a few works focused on the pre-processing of data. In order to solve the lack of specific references about this topic, this paper specifically surveys the task of preparing educational data. Firstly, it describes different types of educational environments and the data they provide. Then, it shows the main tasks and issues in the pre-processing of educational data, Moodle data being mainly used in the examples. Next, it describes some general and specific pre-processing tools and finally, some conclusions and future research lines are outlined.

Keywords Educational data mining process · Data pre-processing · Data preparation · Data transformation

Abbreviations

AIHS	Adaptive and intelligent hypermedia system
ARFF	Attribute-relation File Format
CBE	Computer-based education
CSV	Comma-separated values

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DM	Data mining
EDM	Educational data mining
HTML	Hypertext Markup language
ID	Identifier
IP	Internet Protocol
ITS	Intelligent tutoring system
KDD	Knowledge discovery in databases
LMS	Learning management system
MCQ	Multiple choice question
MIS	Management information system
MOOC	Massive Open Online Course
OLAP	Online Analytical Processing
SQL	Structured Query Language
WUM	Web Usage Mining
WWW	World Wide Web
XML	Extensible Markup Language

2.1 Introduction

Educational Data Mining (EDM) is a field that exploits Data Mining (DM) algorithms in different types of educational data in order to resolve educational research issues [1]. Data mining or Knowledge Discovery in Data-bases (KDD) is the automatic extraction of implicit and interesting patterns from large data collections [2]. The first step in the KDD process is the transformation of data into an appropriate form for the mining process, which is usually called data pre-processing in data mining systems [3]. It allows raw data to be transformed into a shape suitable for resolving a problem using a specific mining method, technique or algorithm [4]. In fact, the better raw data are pre-processed, the more useful information is possible to discover. However, the data pre-processing phase typically requires a significant amount of manual work, this phase coming to consume 60–90 % of the time, efforts and resources employed in the whole knowledge discovery process [5]. In particular, educational environments store a huge amount of potential mining data (raw, original or primary data) but often the data available to solve a problem are not in the most appropriate form (or abstraction), that is, the discovered models are not useful.

For example, obtaining a model with too many rules only containing very low level attributes would not be of interest to the instructor since it would not indicate how to improve the course. To resolve this difficulty it is necessary to pre-process data. It is often considered that once you have the correct transformation of the data (modified data), the problem is almost solved [6] and it is well known that the

success of every data mining algorithm/technique and the resulting or discovered model/pattern are strongly dependent on the quality of the data used.

Data pre-processing in educational context is considered the most crucial phase in the whole educational data mining process [7], and it can take more than half of the total time spent in solving the data mining problem [3]. EDM users (such as an instructor, teacher, course administrator, academic staff, etc.) have to apply the most appropriate data pre-processing techniques for a particular data set and purpose. Thus, it is necessary that EDM users actively participate in the whole pre-processing process in order to select the pre-processing steps/tasks to be done and to decide how they should be ordered. Classical Web Usage Mining (WUM) pre-processing techniques, originally targeted at e-commerce, can be used in most cases, but new approaches more related to learning environments are required to reach interesting results [8].

There are some other special issues concerning educational data, e.g. data integration from multiple sources, integration of data with different granularities, etc. Thus, in the specific case of educational data, for example, the large number of attributes collected with information about each student can be reduced and summarized in a table for a better analysis with multi-relational analysis methods; attributes can be re-represented in binary representation whenever it is appropriate to allow association rule analysis; continuous attributes can be discretized to categorical attributes to improve the comprehensibility of data, etc. However, to our knowledge there are very few previous works exclusively focused on the pre-processing of educational data [7, 9, 10]. Therefore, in order to fill the gap of specific references about this important topic, this paper surveys the pre-processing task of educational data.

Our main goal is to survey different issues on data pre-processing to provide a guide or tutorial for educators and EDM practitioners.

Throughout this paper, Moodle is used as a coherent framework of pre-processing, and data extracted from Moodle learning management system [11] have served as case under study in most examples. The paper is organized as follows: Sect. 2.2 shows the different types of educational environments, whilst Sect. 2.3 discusses the different type of data they provide. Section 2.4 describes the main tasks and issues involved in the pre-processing of educational data. Section 2.5 lists most of the currently existing general and specific data pre-processing tools. Finally, some conclusions and further research are outlined in Sect. 2.6.

2.2 Types of Educational Environments

Traditional education or back-to-basics refers to long-established customs found in schools that society has traditionally deemed to be appropriate.

These environments are the most widely-used educational system, based mainly on face-to-face contact between educators and students that is organized through lectures, class discussion, small groups, individual seat work, etc. These systems

gather information on student attendance, marks, curriculum goals, and individualized plan data. Also, educational institutions store many diverse and varied sources of information [12] such as administrative data in traditional databases (student's information, educator's information, class and schedule information, etc.). In conventional face-to-face classrooms, educators may attempt to enhance instruction by monitoring students' learning processes and analyzing their performance on paper and through observation. But with the increasing use of computers as educational tools, it is much easier for instructors to monitor and analyze students' behavior starting from their usage information.

Computer-Based Education (CBE) means using computers in education to provide guidance, to instruct or to manage instructions to the student. CBE systems were originally stand-alone educational applications that ran on a local computer without using artificial intelligence techniques. However, both the global use of Internet has led to today's plethora of new Web-based educational systems, together with artificial intelligence techniques has induced the emergence of new educational systems such as: learning management systems, intelligent tutoring systems, massive open online courses, etc. Each one of them provides very different data sources that have to be pre-processed in different ways depending on both the nature of available data and the specific problems and tasks to be resolved by DM techniques.

2.2.1 Learning Management Systems

Learning Management Systems (LMS) are a special type of Web-based educational platform for the administration, documentation, tracking, and reporting of training programs, classroom and online events, e-learning programs, and training content. They also offer a great variety of channels and workspaces to facilitate information-sharing and communication among all the participants in a course. Some examples of commercial LMSs are Blackboard and Virtual-U, while some examples of free LMS are Moodle, Ilias, Sakai and Claroline.

These systems accumulate massive log data with respect to students' activities and usually have built-in student tracking tools that enable the instructor to view statistical data [13]. They can record any student activities involved, such as reading, writing, taking tests, performing various tasks in real or virtual environments, and commenting on events with peers. LMSs normally also provide a relational database that stores all student information in different tables such as: personal user information (profile), academic results (grades), and the user's interaction data (reports).

2.2.2 Massive Open Online Courses

Massive Open Online Courses (MOOC) are growing substantially in numbers, and also in interest from the educational community [14]. MOOC is an online course

aimed at large-scale interactive participation and open access via the Web that made it possible for anyone with an internet connection to enroll in free, university level courses. Some examples of MOOCs are Udacity, MITx, EdX, Coursera and Udemy. MOOCs store very similar student's usage information than LMSs but from thousands or hundreds of students. Thus, they also generate large amounts of data that makes necessary the use of data mining techniques to process and analyze it.

2.2.3 Intelligent Tutoring Systems

Intelligent Tutoring Systems (ITS) are systems that provide direct customized instruction or feedback to students. An ITS models student behavior and changes its mode of interaction with each student based on its individual model [15]. The ability of ITS to log and pool detailed, longitudinal interactions with large numbers of students can create huge educational data sets [16]. Although ITSs record all student-tutor interaction in log files or databases, there are some other data stores available within an ITS, for example, a domain model that incorporates a set of constraints relevant to the tutor's domain, a pedagogical data set that contains a set of problems and their answers, and a student model that stores information about each student with respect to all the constraints, satisfactions, and violations recorded.

2.2.4 Adaptive and Intelligent Hypermedia Systems

Adaptive and Intelligent Hypermedia Systems (AIHS) are one of the first and most popular kinds of adaptive hypermedia and provide an alternative to the traditional just-put-it-on-the-Web approach in the development of educational courseware [17]. They attempt to be more adaptive by building a model of the goals, preferences, and knowledge of each individual student and using this model throughout the interaction with the student in order to adapt to the needs of that student. The data coming from these systems is semantically richer and can lead to a more diagnostic analysis than data from traditional Web-based education systems [18]. In fact, the data available from AIHs are similar to ITS data; that is, AIHs store data about the domain model, student model and interaction log files (traditional Web log files or specific log files).

2.2.5 Test and Quiz Systems

Test and quiz systems are among the most widely used and well-developed tools in education. A test is an instrument consisting of a series of questions/items and other prompts for the purpose of gathering information from respondents.

The main goal of these systems is to measure the students' level of knowledge with respect to one or more concepts or subjects. There are different types of questions/items [19] such as: yes/no questions, multiple choice questions (MCQ), fill-in questions, open-ended answered questions, etc. Test systems store a great deal of information, such as questions, students' answers, calculated scores, and statistics.

2.2.6 Other Types of Educational Systems

There are also other types of educational environments, such as: educational game environments, virtual reality environments, ubiquitous computing environments, learning object repositories, wikis, forums, blogs, etc.

2.3 Types of Data

Most of the data provided by each of the above-mentioned educational environments are different, thus enabling different educational problems to be resolved using data mining techniques. In fact, they have conceptually different types of data that can be grouped in the next main types showed in Table 2.1.

2.3.1 Relational Data

Relational databases/data sets are one of the most commonly available and richest information repositories. A relational database is a collection of tables, and each is assigned a unique name. Each table consists of a set of attributes (columns or fields) and usually stores a large set of tuples (records or rows). Each tuple in a relational table represents an object identified by a unique key and described by a set of attribute values [2]. Relational data can be accessed by database queries

Table 2.1 Different types of data and DM techniques

Type of data	DM technique
Relational data	Relational data mining
Transactional data	Classification, clustering, association rule mining, etc.
Temporal, sequence and time series data	Sequential data mining
Text data	Text mining
Multimedia data	Multimedia data mining
World Wide Web data	Web content/structure/usage mining

Table 2.2 Some important Moodle database tables about student interaction

Name	Description
mdl_user	Information about all the users
mdl_user_students	Information about all students
mdl_log	Logs every user's action
mdl_assignement	Information about each assignment
mdl_assignment_submissions	Information about assignments submitted
mdl_forum	Information about all forums
mdl_forum_posts	Stores all posts to the forums
mdl_forum_discussions	Stores all forum discussions
mdl_message	Stores all the current messages
mdl_ message_reads	Stores all the read messages
mdl_quiz	Information about all quizzes
mdl_quiz_attempts	Stores various attempts at a quiz
mdl_quiz_grades	Stores the final quiz grade

written in a relational query language, such as Structured Query Language (SQL), or with the assistance of graphical user interfaces.

Moodle uses a relational database with a great number of tables (all their names start with mdl_ followed by a descriptive word) and the relationships between them. However, it is not necessary to take them all into account at a glance. For example, there are some tables called mdl_quiz_something. If the quiz module is the object of interest, then it is obviously necessary to understand these tables. But if the quiz module does not interest us, it can be ignored. The same is true for each activity module. Table 2.2 shows some examples of the most important Moodle tables from the point of student's usage information.

Relational data mining is the data mining technique used in relational databases. Unlike traditional data mining algorithms, which look for patterns in a single table (propositional patterns), relational data mining algorithms look for patterns among multiple tables (relational patterns). In fact, for most types of propositional patterns, there are corresponding relational patterns such as relational classification rules, relational regression trees, relational association rules, and so on.

In the area of EDM, relational data mining has been used, for example, to find association rules about student behavior in e-learning [20]. However, relational data are normally transformed into transaction data before the data mining is done [21].

2.3.2 Transactional Data

A transactional database/data set consists of a file/table where each record/row represents a transaction. A transaction typically includes a unique transaction identity number and a list of the items making up the transaction [2].

In our case, Moodle does not provide directly any transactional database or data set in itself. However, transactional data can be derived in Moodle, though it is not explicitly stored in its database. In fact, this chapter explains how to create a transactional summary table (Table 2.5 and Fig. 2.10) starting from some relational database tables (see Table 2.2) which contain student usage information on Moodle activities.

A great number of data mining methods can be applied over this type of data. In fact, most of the well-known and traditional data mining techniques, such as classification, clustering and association rule mining, work with this type of data. In fact, in the area of EDM, all these data mining techniques have been applied to Moodle student usage data to provide feedback to the instructor about how to improve both courses and student learning [21].

2.3.3 Temporal, Sequence and Time Series Data

Temporal, sequence and time series data consists of sequences of values or events changing with time [2]. A temporal database typically stores relational data that include time-related attributes. These attributes may involve several time-stamps, each one involving different semantics. A sequence database stores sequences of ordered events, with or without a concrete notion of time. A time-series database stores sequences of values or events obtained over repeated measurements of time (e.g., hourly, daily, weekly).

An example of a sequential database used by Moodle is a student's log. A log can be thought of as a list of a student's events, in which each line or record contains a time-stamp plus one or more fields that holds information about an activity at that instant. In particular, a Moodle log (see Fig. 2.1) [1] consists of the time and date it was accessed, the Internet Protocol (IP) address accessed from, the

Time	IP Address	Full name	Action	Information
Fri 15 January 2010, 12:49 PM	150.214.110.166	[redacted]	forum view forum	Foro de discusión sobre los Ejercicios de Reglas
Fri 15 January 2010, 12:05 PM	150.214.110.166	[redacted]	resource view	Ejercicios resueltos de Reglas
Fri 15 January 2010, 12:05 PM	150.214.110.166	[redacted]	resource view	Relación de Ejercicios Reglas
Fri 15 January 2010, 12:05 PM	150.214.110.166	[redacted]	course view	Prácticas IA
Thu 14 January 2010, 07:43 PM	150.214.110.166	[redacted]	resource view	Ejercicios resueltos de Reglas
Thu 14 January 2010, 07:38 PM	150.214.110.166	[redacted]	resource view	Relación de Ejercicios Reglas
Thu 14 January 2010, 07:38 PM	150.214.110.166	[redacted]	resource view	Relacción de Ejercicios Hechos
Thu 14 January 2010, 07:38 PM	150.214.110.166	[redacted]	assignment view	Entrega de la Relacción de Ejercicios de Hechos.
Thu 14 January 2010, 07:38 PM	150.214.110.166	[redacted]	upload upload	Relacion_Hechos.rar
Thu 14 January 2010, 07:38 PM	150.214.110.166	[redacted]	assignment upload	Entrega de la Relacción de Ejercicios de Hechos.
Thu 14 January 2010, 07:02 PM	150.214.110.166	[redacted]	assignment view	Entrega de la Relacción de Ejercicios de Reglas.
Thu 14 January 2010, 07:01 PM	150.214.110.166	[redacted]	assignment view	Entrega de la Relacción de Ejercicios de Hechos.
Thu 14 January 2010, 07:01 PM	150.214.110.166	[redacted]	assignment view all	
Thu 14 January 2010, 07:01 PM	150.214.110.166	[redacted]	assignment view	Entrega de la Relacción de Ejercicios de Hechos.
Thu 14 January 2010, 06:10 PM	150.214.110.166	[redacted]	resource view	Introducción a CLIPS
Thu 14 January 2010, 06:09 PM	150.214.110.166	[redacted]	resource view	Hechos
Thu 14 January 2010, 06:09 PM	150.214.110.166	[redacted]	course view	Prácticas IA
Thu 14 January 2010, 05:56 PM	150.214.110.166	[redacted]	forum view discussion	duda ejercicio 8
Thu 14 January 2010, 05:56 PM	150.214.110.166	[redacted]	forum view discussion	duda en ejercicio 8

Fig. 2.1 Example of Moodle log file

[1] The full name column covers the identification of subjects.

name of the student, each action (view, add, update and delete) performed in the different modules (forum, resource, assignment, etc.) and additional information about the action.

Sequential data mining, also known as sequential pattern mining, addresses the problem of discovering all frequent sequences in a given sequential database or data set [22]. In the area of EDM, sequential data mining algorithms can be used, for example, to recommend to a student which links are more appropriate to visit within an adaptive educational hypermedia system based on previous trails of students with similar characteristics [23].

2.3.4 Text Data

Text databases or document databases consist of large collections of documents from various sources, such as news articles, research papers, books, digital libraries, e-mail messages, chat and forum messages, and Web pages. Text databases may be highly unstructured, such as some Hypertext Markup Language (HTML) Web pages, or may be somewhat structured, that is, semi-structured, such as e-mail messages and eXtensible Markup Language (XML) Web pages.

Moodle provides a great amount of information in text format, such as: students' messages to forums, messages to chats and e-mails, and anything that students can read or write within the system.

Text mining or text data mining is roughly equivalent to text analytics [24], and can be defined as the application of data mining techniques to unstructured textual data. Typical text mining tasks include text categorization, text clustering, concept/entity extraction, production of granular taxonomies, sentiment analysis, document summarization, and entity relation modeling (i.e., learning relations between named entities). In the area of EDM, text data mining has been used, for example, to assess asynchronous discussion forums in order to evaluate the progress of a thread discussion [25].

2.3.5 Multimedia Data

Multimedia databases store image, audio and video data. Multimedia databases must support large objects, because data objects such as video can require gigabytes of storage. Specialized storage and search techniques are also required. Because video and audio data require real-time retrieval at a steady and predetermined rate in order to avoid picture or sound gaps and system buffer overflows, such data are referred to as continuous-media data. Multimedia information is ubiquitous and essential in many applications, and repositories of multimedia are numerous and extremely large.

Moodle also stores a great amount of multimedia data, for example, all the files uploaded by the instructors and the students. These files can be, for example, an

Fig. 2.2 Example of Moodle files

instructor's presentations (in Microsoft PowerPoint or PDF format, etc.), an instructor's images (in JGP or GIF format, etc.), a student's work and exercises (in Microsoft Word or PDF format, etc.), instructor's videos (in AVI, MOV or FLASH format), etc. All these files are stored in a Moodle data directory. Instructors can browse directly through all these files using Moodle files interface (see Fig. 2.2) or they can also download them to their own local disk in a backup ZIP file.

As seen in Fig. 2.2, Moodle data directory has a root directory (where all the files uploaded by the instructor are placed) and several default directories, such as the *Moddata* directory, which contains all the data submitted by the students, and the *Backupdata* directory, containing backup files of the entire course.

Multimedia data mining is a subfield of data mining that deals with an extraction of implicit knowledge, multimedia data relationships, or other patterns not explicitly stored in multimedia databases [26]. In EDM, for example, mining educational multimedia presentations has been used to establish explicit relationships among the data related to interactivity (links and actions) and to help predict interactive properties in multimedia presentations [27].

2.3.6 World Wide Web Data

World Wide Web (WWW) provides three main types of source data [28]:

- Content of Web pages. This usually consists of texts, graphics, videos and sound files, that is, text and multimedia data.
- Intra-page structure. Data that describe the organization of the content. Intra-page structure information includes the arrangement of various HTML or XML tags within a given page. The principal kind of inter-page structure information consists of hyper-links connecting one page to another.
- User usage data. Data that describe the patterns of Web page usage. Web-based systems record all the users' actions on Web logs, also known as click-streams records, which provide a raw tracking of the users' navigation on the site.

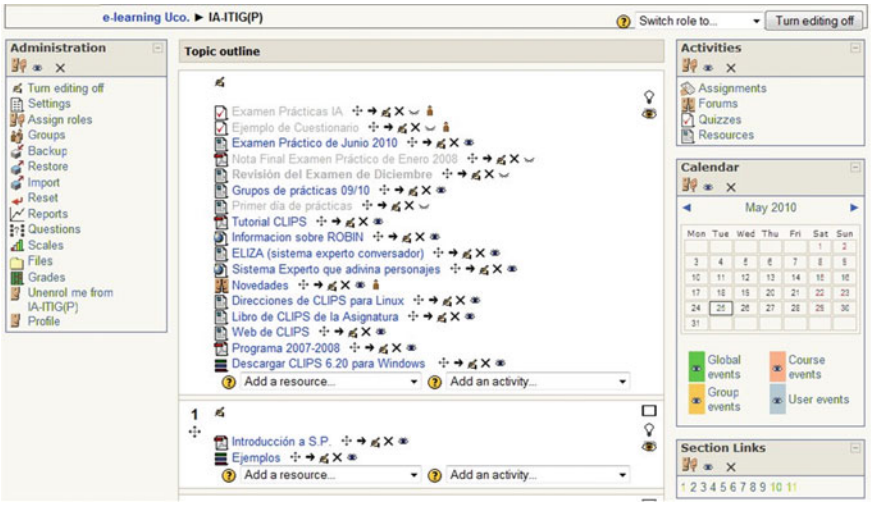


Fig. 2.3 Example of the main window of a Moodle course

In our case, Moodle has the same types of data sources as any other Web-based system. For example, user's usage data are stored in Moodle log files (see Fig. 2.1), some contents of Web pages are stored in the Moodle data directory (see Fig. 2.2), and some others, such as the Web page's text and the intra-page structure, can only be browsed and edited but not saved in files (see Fig. 2.3). This Fig. 2.3 shows the main windows of a Moodle course in editing mode. In the middle of this screen are the course activities and resources grouped into sections or blocks.

The instructor can manage this type of WWW data (contents and intra-page) by adding new resources and activities (using the "Add a resource" and "Add an activity" list boxes, respectively), modifying them, deleting them, hiding them and moving them (using the icons that appear below the text of the specific resource or activity).

Web mining [28] is the application of data mining techniques to extract knowledge from Web data. There are three main Web mining categories: Web content mining, which is the process of extracting useful information from the contents of Web documents; Web structure mining, which is the process of discovering structure information from the Web; and WUM, which is the discovery of meaningful patterns from data generated by client–server transactions on one or more Web localities. In EDM, there are many studies about applying Web mining techniques in educational environments. For example, different techniques such as clustering, classification, outlier detection, association rule mining, sequential data mining, text mining, etc. have been applied to Web educational data for different purposes [29].

2.4 Pre-Processing Tasks

Pre-processing of data [4] is the first step in any data mining process [2]. In educational domain, it is especially relevant to acquire adequate data sets and to make an extra effort for gathering and preparing data in order to include all potentially useful information [30]. The tasks or operations performed in a pre-processing process can be reduced to two main families of techniques [31]: Detection techniques to find imperfections in data sets and transforming techniques oriented to obtain more manageable data sets. Summarizing the overall process of pre-processing educational data, Fig. 2.4 shows the main steps/tasks.

As we can see, pre-processing educational data is in general very similar to the pre-processing task in other domains. However, it is important to point out that the pre-processing of educational data has certain characteristics that differentiate it from data pre-processing in other specific domains, such as the fact that:

- Educational systems provide a huge amount of student information generated daily from different sources of information (see Sects. 2.4.1 and 2.4.2).
- Normally, all the students do not complete all the activities, exercises, etc. In consequence, there is often missing and incomplete data (see Sect. 2.4.3).
- The user identification task is not normally necessary (see Sect. 2.4.4).
- There are usually a great number of attributes available about students and a lot of instances at different levels of granularity. So, it is necessary to use attribute selection and filtering tasks in order to select the most representative attributes and instances that can help to address a specific educational problem (see Sects. 2.4.5 and 2.4.6).
- Finally, some data transformation tasks, e.g. attribute discretization, can be normally applied for improving the comprehensibility of the data and the obtained models (see Sect. 2.4.7).

2.4.1 Data Gathering

Data gathering brings together all the available data, i.e. those that are critical to solve the data mining problem, into a set of instances. An instance can be defined as an individual, independent example of the concept to be learned by a machine learning scheme [32]. Numerous terms are used to describe data gathering and storing aspects such as data warehousing, data mart, central repository, meta-data, and others.

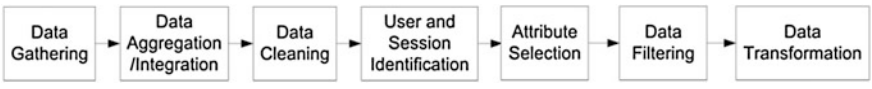


Fig. 2.4 Main pre-processing steps/tasks with educational data

Table 2.3 Examples of different data sources

Name	Description
Log file	Records all students-system interactions
Quiz/test	Stores information about quiz/test usage
Portfolio	Contains information about the students

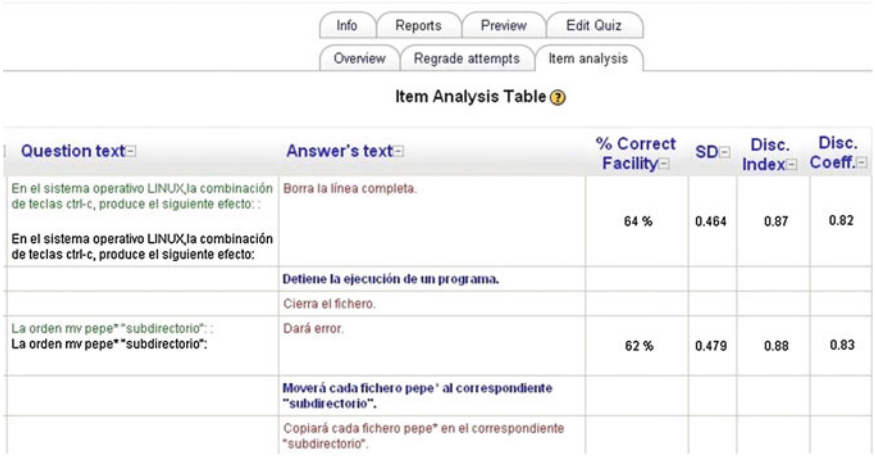
Educational data are normally gathered from various sources (see Table 2.3) since they have been generated in different places at different times [33]: profile data that contains information about the students and instructors, content data and learning material, communication data that stores the information communicated between students, and activity data that records the students' learning process and the instructors' instruction activities.

Most of the learning tools and systems usually capture all students' fingertip actions (mouse and keyboard) in log files [34]. A typical log file usually takes the form of an ordered list of events occurring on the user interface of a software tool. It contains a record of the activity of one or more students, from the rather restrictive point of view of their fingertip actions. Intelligent tutoring systems commonly also record their interactions in the form of log files. Log files are easy to record, flexible in the information they capture and useful in debugging. Normally, Web server log files contain the access date and time, the IP address of the request, the method of the request and the name of the file requested [35]. However, log files generated by Moodle are a little different because they not only contain the access date and time and IP address, but also other more specific information such as the user name (full name of the student), action (module and specific action performed by the user), and additional information about the action (see Fig. 2.1).

On the other hand, quizzes and test data are stored and organized in a matrix in different ways. An example is the score matrix that is a collection of student scores for a set of questions [36]. This is a data matrix of student ratings (see Table 2.4) in which the first column is the student's name or ID (Identifier), and the first row shows the testing items. For example, in Table 2.4, R*ij* represents the score of item-*j* rating received by the student-*i*, in which the value 1 represent a correct answer, −0.5 if it is wrong, and 0 when not answered [37].

Table 2.4 Score matrix or data matrix of students' rates

Student	Item-1	Item-2	…	Item-j	…	Item-n
Student-1	0	1	…	1	…	−0.5
Student-2	1	1	…	1	…	1
…	…	…	…	…	…	…
Student-i	−0.5	0	…	Rij	…	0



Question text	Answer's text	% Correct Facility	SD	Disc. Index	Disc. Coeff.
En el sistema operativo LINUX,la combinación de teclas ctrl-c, produce el siguiente efecto: : En el sistema operativo LINUX,la combinación de teclas ctrl-c, produce el siguiente efecto:	Borra la línea completa.	64 %	0.464	0.87	0.82
	Detiene la ejecución de un programa.				
	Cierra el fichero.				
La orden mv pepe* "subdirectorio": : La orden mv pepe* "subdirectorio":	Dará error.	62 %	0.479	0.88	0.83
	Moverá cada fichero pepe* al correspondiente "subdirectorio".				
	Copiará cada fichero pepe* en el correspondiente "subdirectorio".				

Fig. 2.5 Example of Moodle item analysis

In our case, Moodle provides the score matrix when mark details are selected in the quiz results panel. Moodle also shows the full names of the students, and information about when they started and when they completed the quiz, the total time taken, as well as the final grade obtained together with the score for each question (score matrix). Quizzes can provide much more information, for example, the students' knowledge state can be determined from test question responses using a q-matrix. A q-matrix is the one that shows relationships between a set of observed variables (e.g. questions), and latent variables (concepts) that relate these observations [38]. In the context of education, for a given q-matrix Q, the value of Q (concept, question) represents the probability a student has of incorrectly answering the question due to the fact that he/she does not understand the concept involved. Learning management systems also provide some statistical information about quizzes. For example, Moodle has statistical quiz reports which provide item analysis (see Fig. 2.5). This table presents processed quiz data in a way suitable for analyzing and judging the performance of each question by way of assessment.

The statistical parameters used are calculated as explained by classical test theory (Facility Index or % Correct, Standard Deviation, Discrimination Index, Discrimination Coefficient). The teacher can see the most difficult and easiest questions for the students (% Correct Facility) as well as the most discriminating ones (Disc. Index and Disc. Coeff.). This information can also be downloaded in text-only or Excel formats in order to use a spreadsheet to chart and analyze it.

Another important educational data source is the portfolio. An e-portfolio can be seen as a type of learning record that provides actual evidence of achievement. An e-portfolio is a complete profile of a student that includes raw logged data and/or filled (predefined) templates; like traditional portfolios, it can facilitate the analysis of student learning behavior.

Portfolios can include all the records of students' activities during the learning process, such as their interaction with others, notes, assignments, test papers, personal work collections, their discussion content, online learning records and reports, etc. [39]. Learning portfolios can also include the students' learning path (routes used by students throughout the courses), preferred learning styles (approaches or ways of learning preferred by such groups as visual learners, auditory learners, kinesthetic learners, etc.), students' learning time (time used by students in each activity and/or the full course), course grade and difficulty, etc. [40].

Finally, it is important to highlight that software agents have been used to automatically capture students' interaction data. Although in general there are no differences between using an agent-based architecture or another type of architecture for logging, gathering and data analysis, agents can provide modularity, autonomy, persistence and social ability. A software agent or intelligent agent is a complex software entity capable of acting with a certain degree of autonomy in order to accomplish tasks on behalf of its user.

They have been used for extracting and evaluating log data from e-learning software and organizing that data in intelligent ways [41] to capture ITS data based on an agent communication standard [42], and for automatically recording useful information and organizing it into its corresponding tables in the database [43].

2.4.2 Data Aggregation/Integration

The goal of data aggregation/integration is to group together all the data from different sources [44]. The data can come from various sources, and so can be stored in different formats [30]. After the previous step of gathering all the required/desired data, the process of aggregation/integration can begin for combining data from multiple sources into a coherent recompilation, normally into a database. Aggregation and integration are different terms used to distinguish between the aggregations of the same type of data over multiple problems/sessions/students/classes/schools from the integration of different types of data about the same problem/session/student/class/school.

Educational systems normally provide several data sources that can be aggregated and/or integrated into one single database. Some of these data can be available for read in form of files, even when a certain part has to be transcribed manually from paper documents, because not all the useful information has been stored digitally [30]; this is the case of the attendance paper, in which all students sign at in-person classes. For example, Web log information can be used in conjunction with data from surveys, usability studies and other sources [45]; log files can be mixed with other inputs, such as student demographics and performance data and survey results [46].

Online learning environments normally store all the students' interactions not only in log files but also directly in databases [46]. And if this is not the case, during the pre-processing process, data for each individual student (profiles, logs,

etc.) can be aggregated into a database [47, 48]. In a similar way, although ITSs use log files, it has been found that storing logging tutorial interactions directly into a properly designed and indexed database instead of using log files eliminates the need to parse them [49]. So, relational databases are more powerful than usual log text files and provide easier, more flexible and less bug-prone analyses [49].

In fact, most universities today have large and complex structure and activities (Multiversity) that are collected into one or several databases [50]. An example of a relational database is the Moodle database, which stores all the Moodle course information [11]. Moodle also provides different types of reports accessible from the Moodle interface. These reports are available to the course's instructor/s as an option in the Administration block and in some activities. All these reports can also be saved into files with .TXT, .ODS or.XLS format. Excel Pivot Tables have been also proposed to conduct a flexible analytical processing of Moodle usage data and gain valuable information [51]. A Pivot Table is a highly flexible contingency table that can be created from a large data set and offers the possibility to look at one section at a time.

Data warehouses have also been proposed for data gathering and integration [13]. A data warehouse schema can represent information about the structure and usage of the courses and can include several data sources, for example, the university Management Information System (MIS), Web server log files and LMS databases [52]. Data warehouses and data marts require concise, subject-oriented schemas that facilitate the analysis of data. For example, a star model (a modeling paradigm of educational data) of a data mart for a course of a LMS can contain a central access fact table that contains keys for each of the other tables, such as a time-dimension table, a user-dimension table and a learning-resource dimension table [53].

Finally, a multi-dimensional data cube structure has been used for carrying out an Online Analytical Processing (OLAP) operation on a database [54]. A data cube provides remarkable flexibility for manipulating data and viewing it from different perspectives. Building a Web log data cube allows the researcher to view and analyze Web log data from different angles, derive ratios and measure many different dimensions [55]. For example, in a study on Web-based education systems [56], student data were observed from three dimensional views (see Fig. 2.6): learning-behavior pattern dimension, student-personality characteristic dimension,

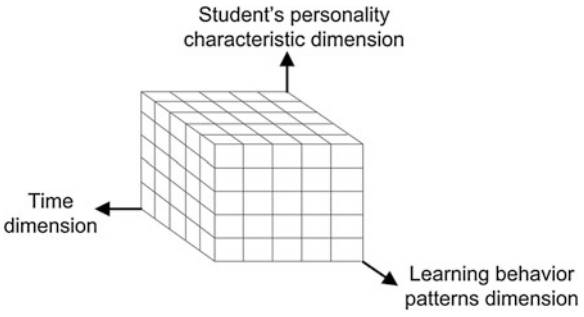


Fig. 2.6 Example of data *cube*

and time dimension. Each dimension was related to the so-called dimension table. One dimension may also describe a different level, for example, a time dimension may describe a level from a year, quarter, month, date and so on [56]. So, OLAP provides us with the possibility of analyzing different levels of aggregation, e.g. per day, per month, per duration of the course, or per student, per group, or the whole population, etc.

2.4.3 Data Cleaning

The data cleaning task consists of detecting erroneous or irrelevant data and discarding it [2]. The most common type of inaccuracies, such as missing data, outliers and inconsistent data [57], are described below.

Missing data are a common issue in the application of data analysis methods. In statistics, missing values occur when no value is stored for the variable in the current observation [58].

Some possible solutions are to use a global constant to fill in the missing value or to use a substitute value, like the attribute mean or the mode. For example, missing values have been replaced using linear interpolation of the previous and posterior 4 values for emotion detection in an educational scenario [59], or by determining what is the most probable value to fill in the missing value using regression [60]? A different and simple approach is to codify missing/unspecified values by mapping incomplete values [9], using for example the labels "?" (Missing) and "null" (unspecified).

In educational data, missing values usually appear when students have not completed or done all the activities in the course, or when we combine data from different sources and students have skipped some tasks [61]. For example, students who enroll in a course but do not actually participate, or those whose information or data are incomplete (missing data) [62]. In some extreme cases, in order to clean data and ensure their completeness, students who have all or almost all their values missed can be removed from data. For example, in e-learning courses some users only enter to a specific course one time (by error or in order to see one specific resource or to do an activity) but later they never come back to the course [21]. But normally, in the case that students show some missing values, whenever possible, these specific students may be contacted and asked (by the instructor) to complete the course, so that their information can be used and/or evaluated. When this is not possible, the missing information regarding students could be replaced by a predetermined value or label [9].

The elimination of noisy instances is one of the most difficult problems in data pre-processing. Frequently, there are samples in large data sets that do not comply with the general behavior of the data [63]. Such samples, which are significantly different from or inconsistent with the remaining set of data, are called outliers. Outliers can be caused by measurement error or they may be the result of inherent data variability, in which case the term "outlier" just refers to unlikely or

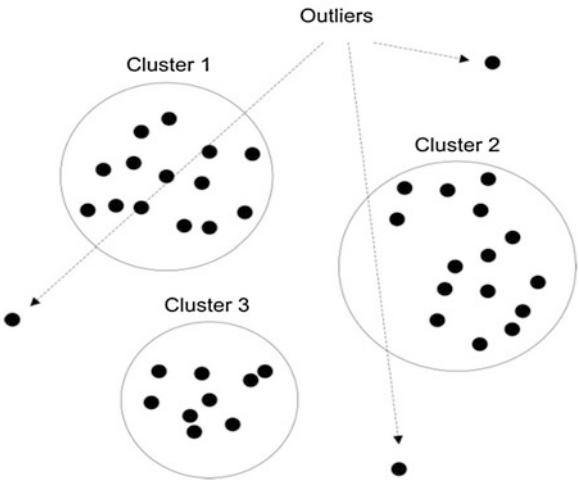


Fig. 2.7 Plot of *three* data clusters and some *outliers*

unexpected distribution, rather than outside a limit. For example, the value could be a typographical error, or it could be correct and represent real variability for the given attribute.

Many data mining algorithms try to minimize the influence of outliers in the final model, or eliminate them in the pre-processing phases. For example, in a 1-dimensional value a simple way to keep outliers from distorting results is to use medians instead of means [64]. This method has the added advantage of solving the prickly problem of distinguishing outliers from real values. It is also important to highlight that although outliers normally can be due to noise, in educational data they can be often true observations. For example, there are always exceptional students, who succeed with little effort or fail against all expectations. However, making the distinction between the outliers that should be accepted and those that should be rejected is not always easy. This requires knowledge of the domain in which the data was collected and depends on the aims of the analysis [65]. In this case, a relatively simple technique that can help to detect outliers is by visualizing data clusters, where values that fall outside the set of clusters may be considered outliers (see Fig. 2.7).

An example of data cleaning in a Web-based educational system [48] is to detect and eliminate both long periods of time between two actions carried out by the same student (longer than 10 min) and incomplete data (incompletely visited chapters, and unfinished tests and activities). Another similar example [61] shows that very high values were often recorded for attribute time because the student had left the computer without first exiting the exercise, concept or section. In order to address this problem, any times that exceeded a maximum established value (between 20 and 30 min is a common criterion) are considered noisy data, and this maximum value is assigned to any apparently erroneous data. A different approach is to use association rule mining for filtering data that match a predefined type of rule [66]. In this case, if results have the rule containing the conclusion *NO*, which

indicates that students are not interested in the course, then the courses with the lowest students count are removed, as well as those students having the lowest course count.

Finally, inconsistent data appear when a data set or group of data is dramatically different from a similar data set (conflicting data set) for no apparent reason. In fact, some incorrect data may also result from inconsistencies in naming the conventions or data codes in use, or inconsistent formats for input fields, such as a date. For example, duplicate tuples can require data cleaning, e.g. Age = "42" and Birthday = "03/07/1997", shows discrepancy between duplicate records or oxymoron (self-contradiction).

2.4.4 User and Session Identification

One of the key issues in the pre-processing phase is to identify users. This step distinguishes the users as individuals, and as a result, different users are identified. This can generally be done in various ways, like through the use of IP addresses, cookies, and/or direct authentication (login/password).

Identifying users based on Web log files is not a straightforward problem, and so various methods have been developed [67]. On the other hand, user sessions also have to be identified. A session is a semi-permanent interactive information interchange between two or more communicating devices, for example, a login session is the period of activity between a user logging in and logging out.

Although user and session identification is not specific to education, it is especially relevant due to the longitudinal nature of student usage data. However, computer-based educational systems provide user authentication (identification by login and password). These logs include entries that identify the students/users who have logged on, thus identifying sessions a priori since users may also have to log out [68].

So it is not necessary to do the typical user identification task to identify sessions from logs, and session determination ceases to be a problem. In fact, all records can be sorted in an ascending order with the user ID as the primary key, and the event time as a secondary key [69]. After this sorting step, it is easy to identify user sessions by grouping contiguous records from one login record to the next one. Specifically, browsing records picked out between two successive login records are grouped into a browsing session, and an upper limit of the time interval between two successive clicks has to be set (from 15 to 45 min) in order to break the sequence of one student's click stream into sessions [35]. This value may result in increasing or decreasing the total number of identified sessions.

However, to our knowledge, there is no research on the relation between timeout of user session and its impact on quality of discovered knowledge [70]. It is also important to construct not only learning sessions but also learning episodes from logs [71] and tasks and activities [72]. A learning episode is a high level model of the student's learning task with information about the system situation at

the beginning of the episode, the actions performed by the student, and the system situation at the end of the episode. A task is defined as a sequence of user interactions within one resource that ranging from passive reproductions of paper-based documents to sophisticated interactive resources [72]. An activity is defined as an interaction within the site and categorized to indicate whether the activity involved browsing or reading, or more interactive use.

Another noteworthy aspect to consider is that accessing to some information about users/students can be restricted due to privacy issues and special measures and permission may be required. It is also necessary to preserve student data anonymity/privacy but enabling that different pieces of information are linked to the same person without explicitly identifying but making sure that users can be de-coupled from their sessions if local, state or federal laws require it. Petersen [73] points to the importance of the de-identification of data before the data is made available for institutional use, including the option to retain unique identifiers for individuals in the data set, without identifying the actual identity of the individuals. A common solution for it consists in using a number randomly or incrementally generated, like a user ID or other kind of personal information, such as e-mail or an identification card instead of using someone's real name (see *id_student* attribute in Fig. 2.10). But, a better mechanism for assigning unique, disassociated IDs (from a specific name), may be required in some systems.

A different approach to protecting student identity consists in not revealing any private information in reports, tables, figures, etc. For example, notice that in some figures shown in this chapter (see Figs. 2.1 and 2.9), student names were blurred to protect their identity. Finally, whereas educational institutions have always had requirements to protect student and teacher privacy, new amendments to the existing regulations increase access to data for research and evaluation (including sharing across levels, such as from high school to college) while maintaining student privacy and parents' rights [74].

2.4.5 Attribute/Variable Selection

Feature selection and extraction chooses a subset of relevant attributes from all the available attributes [75]. This is also known as variable selection, feature reduction, attribute selection or variable subset selection. Choosing the right variables is one of the main tasks before applying data mining techniques [76], because the variables can be correlated or redundant. Consequently, the data must be pre-processed to select an appropriate subset of attributes and ignore irrelevant and redundant ones. An attribute may be redundant if it can be derived from another attribute or set of attributes. There may be redundancy, where certain features are correlated so that it is not necessary to include all of them in modeling; and interdependence, where two (or more) features together convey important information that is obscure if either of them is included on its own [77].

Attribute selection is very important in education because there could be a large number of attributes for learning schemes to handle in many practical situations [78] and this number of attributes can result in reducing the accuracy of a learning model due to overfitting problems. One solution to this issue is to select only the most important attributes/variables. For example, a ranking of several feature selection algorithms has been used for identifying which features or attributes have the greatest effect for predicting school failure [79]. A decision tree technique has been also used to choose the right variables (relevance analysis or feature selection) in educational data [76]. This method is used to obtain the most consistent variables by presenting them at various tree levels. Another solution is not to use irrelevant data that do not really provide any useful information to solve the problem. Some examples of well-known attributes that can be irrelevant are user password, student's e-mail, student's phone number, student's address, student's picture, etc.

Learning management systems, such as Moodle, store a huge amount of attributes/variables about courses, students and activities. So it is really relevant to select only a representative group of attributes in order to reduce the dimensionality of data. There are some proposals of indexes and metrics [80] in order to properly facilitate the evaluation of the course usage. However, even when there are many of these metrics in Web usage analysis for e-commerce, it is not the same situation in the case of e-learning. Then, these selected attributes can be stored all together in a new table comprising all the relevant information related to the students enrolled in the course [21].

For example, in the problem/case of predicting what it is the students' final performance in a course, starting from the usage information with Moodle, there is a lot of variables about the interaction between the students and Moodle system. Thus, it is necessary to select only the most related attributes with the student performance. Table 2.5 shows a list of the selected features/attributes for each student in a Moodle course, i.e. the fields of each summary record.

Table 2.5 Example of list of attributes selected per student in Moodle courses

Name	Description
id_student	Identification number of the student
id_course	Identification number of the course
num_sessions	Number of sessions
num_assigment	Number of assignments done
num_quiz	Number of quizzes taken
a_scr_quiz	Average score on quizzes
num_posts	Number of messages sent to the forum
num_read	Number of messages read on the forum
t_time	Total time used on Moodle
t_assignment	Total time used on assignments
t_quiz	Total time used on quizzes
t_forum	Total time used on forum
f_scr_course	Final score of the student obtained in the course

Finally, notice that some student-related variables or attributes might introduce a great degree of variance and this instability could represent a non-trait measure (i.e. a non- specific trait that a student has), denoting that this variable does not and should not describe the student [81]; for example, the consistency of students' behavior regarding the pace (also referred as speed or rate) of their actions (i.e. the number of logged actions divided by the session length in minutes) along the sessions of an online course. Nevertheless, some other variables (e.g. session length, response time, intensity of activity, preferred tasks) might have a great variance when they are repeatedly measured for the same student: this instability may also represent a non-trait measure.

2.4.6 Data Filtering

Data filtering selects a subset of representative data in order to convert large data sets into manageable (smaller) data sets [2]. Data filtering allows the huge amount of information available to be reduced. Data sets for analysis may contain hundreds of attributes, many of which may be irrelevant to the mining task or redundant. Some of the most common types of filtering techniques for educational data are the selection of data subsets relevant to the expected purpose, and the selection of the most convenient grain size to the research at hand.

Educational systems provide a huge quantity of information about all the events and activities performed by the students enrolled in courses. However, the instructor or educational research can be only interested on a certain subset of events, students or courses depending on the specific problem or task to be solved. For this reason filtering can be used to select only a specific subset of desired data [82]. These data can be filtered by defining the conditions of one or more attributes and removing the instances that violate them [83]. For example, Moodle allows log files to be filtered by course, participant, day, and activity.

A novel data preparation approach uses activity theory, which considers three levels of human activity, has been also used to pre-process data in order to get more interesting results to study what happens in a collaborative learning platform [10]. They propose to map the original data to a higher level, analysis-oriented representation by using activity theory.

A specific characteristic of data collection from the educational system is that there are different levels of granularity such as: keystroke level, answer level, session level, student level, classroom level, and school level [84]. Therefore, it is necessary to choose an appropriate level of granularity in order to only identify the variables that can be recorded at that specific level of granularity [83]. Logging data with multiple grain size facilitates viewing and analyzing data at different levels of detail [16]. Figure 2.8 shows various levels of granularity and amounts of data related to each level. It can be observed that a higher grain is related to a smaller amount of data and, on the other hand, a lower grain is related to a larger amount of data.

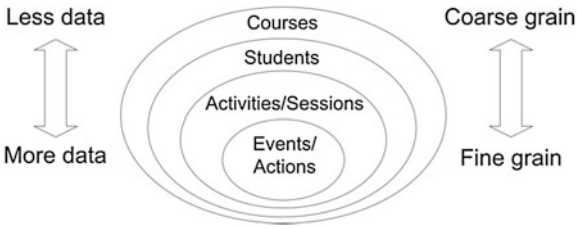


Fig. 2.8 Different levels of granularity and their relationship to the amount of data

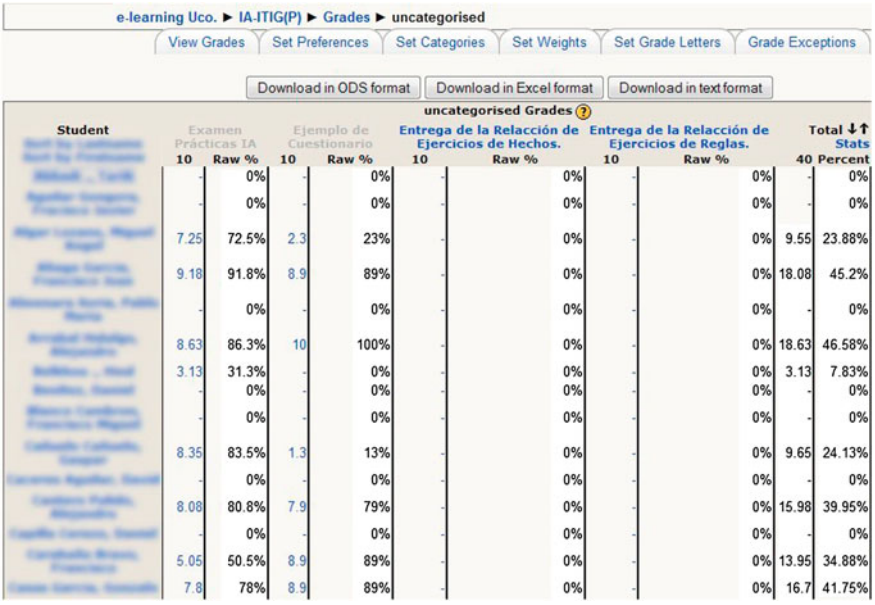
The level at which events are logged constrains their analysis. For example, logging a mouse click by its x and y coordinates may help to analyze the student's motor skills. In contrast, logging the menu item selected may allow a student's reply to a multiple choice question to be scored. So, the level of granularity affects analysis, that is, the granularity of data should fit its intended analysis because the resulting temporary table would only contain attributes and transactions from students with respect to the level selected [61].

Sometimes, the raw learning logs collected by computer systems may be excessively detailed. To analyze these logs at the behavioral unit or grain size required by the educational research, we need to reformat the raw learning logs by systematically aggregating them and pass from low level events to high level learning actions [85]. Thus, it is necessary to define different abstractions of the log file data, such as:

- Event. It is a single action or interaction recorded on the log file.
- Session. It is a sequence of interactions of a user from a login to the last interaction.
- Task. A sequence of interactions of a user within one resource.
- Activity. A series of one or more interactions to achieve a particular outcome.

Moodle also provides several levels of data granularity. For example, as previously described, Moodle log reports provide fine grain information about all students' actions (see Fig. 2.1). In this case, there can be hundreds of instances or records or rows in the log file belonging to each student. However, Moodle also provides coarse grain information about students, for example by grades. Moodle grades show the grades of quizzes and other activities that students have done. In this case, there is only one instance or row for each student with columns for each activity. For example, Fig. 2.9[2] shows the grades of a course that has two quizzes (*Examen Practicas IA* and *Ejemplo de Cuestionario*) and two assignments (*Entrega de Relacción de Ejercicios de Hechos* and de *Ejercicios de Reglas*) evaluated using a scale from 0 to 10. The instructor can download the entire grade book as an .ODS, .XLS or .TXT file.

[2] The *student* column covers the identification of subjects.



e-learning Uco. ► IA-ITIG(P) ► Grades ► uncategorised

View Grades | Set Preferences | Set Categories | Set Weights | Set Grade Letters | Grade Exceptions

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uncategorised Grades

Student	Examen Prácticas IA		Ejemplo de Cuestionario		Entrega de la Relación de Ejercicios de Hechos.		Entrega de la Relación de Ejercicios de Reglas.		Total ↓↑ Stats	
	10	Raw %	10	Raw %	10	Raw %	10	Raw %	40	Percent
[redacted]	-	0%	-	0%	-	0%	-	0%	-	0%
[redacted]	-	0%	-	0%	-	0%	-	0%	-	0%
[redacted]	7.25	72.5%	2.3	23%	-	0%	-	0%	9.55	23.88%
[redacted]	9.18	91.8%	8.9	89%	-	0%	-	0%	18.08	45.2%
[redacted]	-	0%	-	0%	-	0%	-	0%	-	0%
[redacted]	8.63	86.3%	10	100%	-	0%	-	0%	18.63	46.58%
[redacted]	3.13	31.3%	-	0%	-	0%	-	0%	3.13	7.83%
[redacted]	-	0%	-	0%	-	0%	-	0%	-	0%
[redacted]	-	0%	-	0%	-	0%	-	0%	-	0%
[redacted]	8.35	83.5%	1.3	13%	-	0%	-	0%	9.65	24.13%
[redacted]	-	0%	-	0%	-	0%	-	0%	-	0%
[redacted]	8.08	80.8%	7.9	79%	-	0%	-	0%	15.98	39.95%
[redacted]	-	0%	-	0%	-	0%	-	0%	-	0%
[redacted]	5.05	50.5%	8.9	89%	-	0%	-	0%	13.95	34.88%
[redacted]	7.8	78%	8.9	89%	-	0%	-	0%	16.7	41.75%

Fig. 2.9 Example of Moodle grades

2.4.7 Data Transformation

Data transformation derives in new attributes from already available attributes [2]. Data transformation can facilitate a better interpretation of information. Some examples of transformation such as normalization, discretization, derivation, and format conversion, are described next.

Normalization is a data transformation technique where the attribute values are scaled within a specified range, usually from −1.0 to 1.0, or between 0.0 and 1.0. Within one feature there is often a great difference between maximum and minimum values, e.g. 0.01 and 1,000. Hence, normalization can be performed to scale the value magnitudes to low values. In this way, normalization may improve the accuracy and efficiency of the mining algorithms involving distance measurements [2].

Normalization also helps to prevent attributes with initially large ranges from outweighing attributes with initially smaller ranges. For example, one of the most important steps in data pre-processing for clustering is to standardize or normalize data in order to avoid obtaining clusters that are dominated by attributes with the largest amounts of variation [86].

There are many other methods for data normalization. However, in education, the most commonly used method is the *Min–max* normalization, which performs a linear transformation of the original data [87]. Suppose that *minA* and *maxA* are the minimum and maximum values of an attribute *A*, respectively. Then, the *Min–max*

normalization maps a value, v, of A to v' in the range ($new\ minA$, $new\ maxA$) using the Eq. (2.1):

$$v' = \frac{v - \min_A}{\max_A - \min_A}(new\_\max_A - new\_\min_A) + new\_\min_A \tag{2.1}$$

Discretization divides the numerical data into categorical classes that are more user-friendly than precise magnitudes and ranges. It reduces the number of possible values of the continuous feature and it provides a much more comprehensible view of the data. Generally, discretization smooths out the effect of noise and enables simpler models, which are less prone to overfitting. It can be included as a reduction method that uses some data mining algorithms that do not work well with continuous attributes. For example, association rule mining algorithms usually work only with categorical data. A special type of discretization is the transformation of ordinal to binary representation, that is, from numbers denoting a position in a sequence to 0 or 1 value. This type of codification is used for example in frequent pattern mining research. Some discretization methods [2] are the following:

- Equal-width binning divides the range of possible values into N sub-ranges of the same size in which (2.2) For example, if our values are all between 0 and 100, 5 bins could be created as follows: [0–20], [20–40], [40–60], [60–80] and [80–100].

$$bin\_width = (\max value - \min value)/N \tag{2.2}$$

- Equal-frequency or equal-height binning divides the range of possible values into N bins, each of which holding the same number of instances.
- For example, there are the following 10 values: 5, 7, 12, 35, 65, 82, 84, 88, 90 and 95. Now, in order to create 5 bins, the range of values would be divided up so that each bin holds 2 values in the following way: [5, 7], [12, 35], [65, 82], [84, 88] and [90, 95].
- Manual discretization lets the user directly specify the cut-off points. A typical educational example of a manual discretization method is normally done with marks/scores. For example, if a range of values between 0.0 and 10.0 is applied, they could be transformed into the next four intervals and labels [21]:

$$\text{mark} = \begin{cases} FAIL: \ if\ value\ is < 5 \\ PASS: \ if\ value\ is \geq 5\ and < 7 \\ GOOD: \ if\ value\ is \geq 7\ and < 9 \\ EXCELLENT: \ if\ value\ is \geq 9 \end{cases} \tag{2.3}$$

Another example is the grade point average (normally a value between 0.0 and 4.0), which can also be translated into a letter grade, e.g. A, B+, B, C+ and C [88]. A different approach is to use fuzzy intervals, in which fuzzy sets for grading are

used instead of crisp intervals [89]. Finally, the most extreme but simplest discretization case is when attributes are binarized (0 or 1). Here, even if some information is lost, the resulting model can produce, for example, a more accurate classification [90].

Another technique of data transformation is the derivation, which enables to create new attributes starting from the previous ones. So, new attributes can be offshoots of other current attributes in a specific attribute derivation. In many cases, a new attribute needs to be derived from one (or more) of the attributes in a data set. The new attribute may result from a mathematical transformation of another attribute [83], such as the time difference attribute that could be converted to minutes instead of seconds. The most commonly used type of derivation performs some kinds of aggregation on another attribute. For example, when the constraints related to each attempt are grouped into an attribute of the attempt data set, then a "violated count" attribute is included as an attribute of the analysis data set. This attribute identifies the total number of violated constraints in each attempt [83].

A hash code has been also used as the encoding scheme for combining student information into a single hash number [9]. This hash number was simply created by multiplying each field with a distinct power of ten, in descendant order. Some other examples of attributes [91] derived from the information provided by an e-learning system is shown in Table 2.6.

A different approach is to enrich data (normally log files) by using expressions, annotations, labels, text replays, etc. However, it is important to note that data annotations and labeling are very labor-intensive tasks. Some other authors [92] propose making log files more expressive by overcoming a historical tendency to make log files cryptic in order to save file space. This change involves altering the representation of events in the log file and enriching the logged expressions so that more inferences can be drawn more easily. Other approach is to completely represent each event using English words, using English grammar and using standard log file forms [92].

Other authors [84] have also proposed using text replays as a method for generating labels or tags. Text replays produce data that can be more easily used by data mining algorithms. It is an example of distillation for human judgment that

Table 2.6 Example of derived attributes

Attribute	Description
UserId	A unique identifier per user
Performance	Percentage of correctly answered tests calculated as the number of correct tests divided by the total number of tests performed)
TimeReading	Time spent on pages (calculated as the total time spent on each page accessed) in a session
NoPages	The number of accessed pages
TimeTests	The time spent performing tests (calculated as the total time spent on each test)
Motivation	Engaged/disengaged

tries to make complex data understandable by humans to leverage their judgment. Text replays represent a segment of the student's behavior from the log files in a textual "prettily-printed" form. For example, the coder can see the time when each action has taken place, as well as the problem context, the input entered, the relevant skill and how the system assessed the action. Then the coder can choose one among a set of behavior categories and tags or can indicate that something has gone wrong. Other authors propose the use of hand-labeled data and the mapping of events to variables through intelligent tutors' data [16]. In this case, annotations about the level of students' engagement were made by an expert with tutoring experience to annotate sequences of students' actions with the label engaged or disengaged. A current approach proposes to create a grammar (i.e., a set of rules) to unambiguously combine some low-level entries into high level actions that correspond to functions provided at the user interface level of the Alice programming environment [93].

Finally, pre-processed data have to be transformed into the format required by the data mining algorithm or framework that will be used later. Therefore, data have to be exported to a specific format, such as the Weka's ARFF format (Attribute-Relation File Format) [32], Keel DAT format [94], Comma-separated values (CSV), XML, etc. Fig. 2.10 shows an example of a summary file in the ARFF format. Either the WekaTransform tool (http://sourceforge.net/projects/wekatransform/) or the Open DB Preprocess task in Weka Explorer (http://www.cs.waikato.ac.nz/ml/weka/) can be used in order to transform data directly from a database into ARFF format. Datapro4j (http://www.uco.es/grupos/kdis/datapro4j) can also be used to programmatically transform multiple data formats

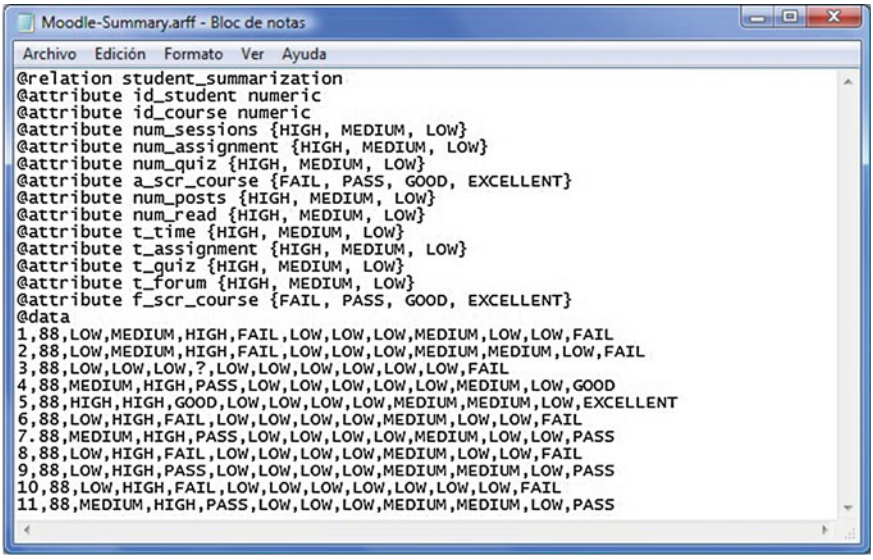

Fig. 2.10 Example of Moodle summary ARFF file

using the Java language. Figure 2.10 is a snapshot of a Moodle summary file in ARFF format. Rows of the file represent a summary of all the online activities completed by the students and their final marks obtained in the Moodle course. Notice that the attributes defined in the file were already described in Table 2.5, although most of them are discretized.

The declaration section indicates that numeric attributes are specified by the keyword numeric, whereas nominal attributes are specified by the list of possible attribute values in curly brackets. Finally, the list containing all the instances is detailed right after the @data tag. Instances are listed in the comma-separated format, and a question mark represents a missing value.

2.5 Pre-Processing Tools

Data pre-processing phase requires strong efforts in the KDD process, which needs to be mitigated somehow with the use of software tools. These applications allow the EDM user to perform semi-automatic tasks for preparing data before accomplishing knowledge extraction. In general, these tools can be grouped in two categories: general purpose tools and specialized tools for pre-processing data.

2.5.1 General Purpose Data Pre-Processing Tools

Nowadays, the most mature software applications available for data preparation are general purpose tools, both in their scope of application and in the number of techniques and algorithms. They can be grouped in the next three groups:

- Data analysis tools. These tools are primarily oriented to data statistical treatment, but they are also used for pre-processing data because they provide operations related with missing values, data transformation, feature manipulation or meta-data handling. The most common data analysis tools in EDM are: Matlab (Preprocess GUI), R (incl. Rattle and RDatamining), IBM SPSS Modeler (formerly, Clementine), SAS (Enterprise Miner), Statistica and Microsoft Excel.
- Data mining tools. These general purpose data mining software applications are the most used tools for data preparation because they provide both basic and advanced operations for data transformation, feature selection and meta-data handling. There is a large variety of software solutions in this field, being Weka (http://www.cs.waikato.ac.nz/ml/weka/), RapidMiner (http://rapid-i.com/) and Knime (http://www.knime.org/), the top cited packages; all of them are freely available.
- Business intelligence software applications. These tools are focused on business data analysis and visualization for supporting decision making, and oriented to the treatment of large amounts of data. They provide advanced functionalities

for data exploration and transformation. Some examples are: Orange (http://orange.biolab.si), Angoss (http://www.angoss.com) and Amadea (http://alice-soft.com/html/prod_amadea_en.htm).

2.5.2 Specific Purpose Data Pre-Processing Tools

The number of tools exclusively devoted to data pre-processing is marginal. Although some specific tools have been developed for preparing data in any domain, as well as others especially well-suited for educational data, most of the currently existing tools are just prototypes providing restricted features or they are oriented to work only with a very specific type of data.

A sample of specific tool for data pre-processing is DataPreparator (http://www.datapreparator.com), a freely available proprietary and multi-platform software tool, that provides functionalities for data load (text files, relational databases, excel), data reduction (including attribute selection), data transformation (discretization, missing values, scaling, sorting) and outlier handling. In contrast to prior approaches, DMPML-TS [95] is a visual tool founded on the use of Data Mining Preparation Markup Language (DMPML), an XML notation designed to represent the data preparation phase of the KDD process in general domains. Its authors stand for the use of this type of representation, and claim that it facilitates data codification, cleaning and data transformation using XSLT transformations.

As for data pre-processing solutions in the field of EDM, we can also find some prototypical proposals in the literature. These tools are mainly oriented to the preparation of data extracted from log files in Web learning environments. A first proposal in the field of WUM was presented by Zaïne and Luo [96]. They highlighted the variety of Web log analysis tools available but specially tailored for e-business and, consequently, difficult to use by educators. Therefore, they proposed a novel tool based on a three-tier architecture for data gathering and pre-processing.

Its constraint-based approach allowed the educators to express restrictions and filters during the preparation phase, the patterns discovery phase, or the patterns evaluation phase. Having domain-specific filters during the first stages considerably reduces the search space and controls the performance and accuracy of the pattern extraction.

Similarly, Marquardt et al. [8] proposed an early tool prototype for the automation of the most typical tasks performed by the instructor in the pre-processing phase for the mining of data extracted from Web courses. Their tool, called WUM Prep, offered a set of scripts implementing classical WUM pre-processing techniques, i.e. data cleaning and filtering, user and session identification, path completion, data enrichment, and transaction identification.

Ceddia et al. [97] proposed Web Analysis Tool (WAT) to allow the educator to describe activities from sequences of Web site interactions that could be meaningful in the course context. The aim of this approach is to provide the teacher with an indication of how successful the educational Web course has been in assisting the students meet their objectives, based on the navigation path recorded. Even when it is

also a prototype application, WAT provides a usable GUI and defines a process in two phases: activity definition, where the log files are preprocessed extracting those fields that are valuable for the activity and imposing some meaning to the selected interaction attributes; and activity extraction, where the file is processed according to the previous configuration, and the information about activities is extracted and shown to the educator.

More recently, Sael et al. [7] have proposed a specific pre-processing tool for e-learning platform using Moodle logs. It uses not only access log information but also SCORM activities in order to identify different levels of access to a course and thus to define episodes according to these levels.

Finally, EDM Workbench [98] is a specific tool that helps educational researchers with processing data from various sources (PLC shop, SQL tutor, Collaborative Learning System Database and Streamed Log Files). Though still in beta version, this application provides a GUI with some basic operations and algorithms specialized for EDM. It provides operations for collaborative labeling of log files, extraction of information for its subsequent use in machine learning and data transformation (e.g. random sampling, clipping, and a few others).

2.6 Conclusions

Nowadays, there are very few specific data pre-processing tools and so, EDM users normally use general software and DM tools for pre-processing. For example, database GUI administrator tools are used to data aggregation/integration, text editors or spreadsheets are used to manually eliminate some incomplete students' data, and DM tool are used for automatic attribute selection and filtering. However, most of the current data mining tools and general pre-processing tools are normally designed more for power and flexibility than for simplicity and thus, they do not suitably support pre-processing activities in the educational domain.

Most of the currently existing tools can be too complex for educators, EDM researchers and users who are not expert in data mining, since their features go well beyond the scope of what an educator may want to do. So, a very important future development will be the appearance of free EDM pre-processing tools and wizards in order to automate and facilitate all the pre-processing functions in an easy-to-use framework. In this way, the typical workload of the pre-processing phase could be significantly reduced by the automation of the most usual tasks.

On the other hand, there is currently only one public educational data repository, the PSLC DataShop [99] that provides a great number of educational data sets about ongoing courses. However, all this log data comes from ITSs, so it will be also useful to have in the future more public data sets available from other different types of educational environments such as AIHS, LMSs, MOOCs, etc. In this way, a wide range of educational benchmark data sets could be used directly without need to be pre-processed. Finally, the following main lessons have been learned with respect to the pre-processing of educational data:

- Pre-processing is always the necessary first step in any data mining process/application. This task is very important because the interestingness, usefulness and applicability of the obtained DM models highly depend on the quality of the used data.
- There are different types of educational environments that provide different type of data, and several pre-processing tasks can be applied. Although, this paper recommends the use of a specific flow or sequence in applying different pre-processing tasks/steps, some variations in the order of some tasks can also be possible. For example, data cleaning can be done later; attribute selection, data filtering and data transformation can be mixed or put in different order.
- Not all these pre-processing tasks/steps have to be applied in all the cases. That is, depending on the data and the specific issue to address, it might or might not be necessary to apply some of them. Examples are aggregation/integration (only if there are multiple sources), cleaning (only if there are erroneous, missing or incomplete data), user identification (only if the educational system does not provide user identification), data filtration and attribute selection (only if there is a huge amount of data and/or attributes respectively).
- Different types of techniques have also been used in each task/step, although there is no recipe or rule about which specific technique should be used in each pre-processing task. Therefore, the user will be the one in charge of selecting which one to apply each time depending on several issues, such as the specific characteristics of the data, the tools and algorithms available, and the final objective or data mining problem to be solved.

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