Applying Data Mining in Moodle

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KDISLab
KNOWLEDGE DISCOVERY AND INTELLIGENT SYSTEMS

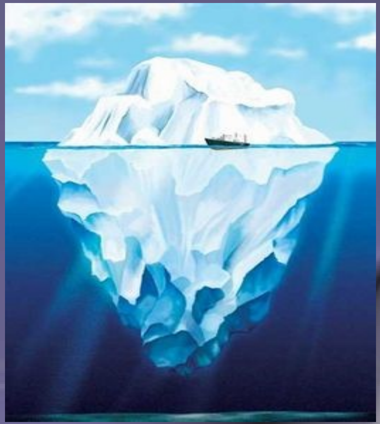
Outline

- Introduction to EDM
- Exporting Moodle data
- Preprocessing Moodle data
- Association Rule Mining in Moodle
- Classification and Clustering in Moodle

Introduction to EDM

Introduction

- The development of web-based educational systems has been rising exponentially in the recent years.
  – These systems produce information of high educational value, but usually so abundant that it is impossible to analyze it manually.
  – Tools to automatically analyze this kind of data are needed.
- Educational institutions have information systems that store plenty of interesting information.
  – This available information can be used to improve Strategic Planning of these institutions. In this case, tools to analyze that data automatically are also needed.



What do we call it?

- Statistics
- Machine Learning
- Data mining
- Knowledge Discovery in Data
- Business Analytics/Intelligent
- Data Analytics
- Big Data
- Data Science
- …?

Same Core Idea:
Finding Useful Patterns in Data

Different Emphasis

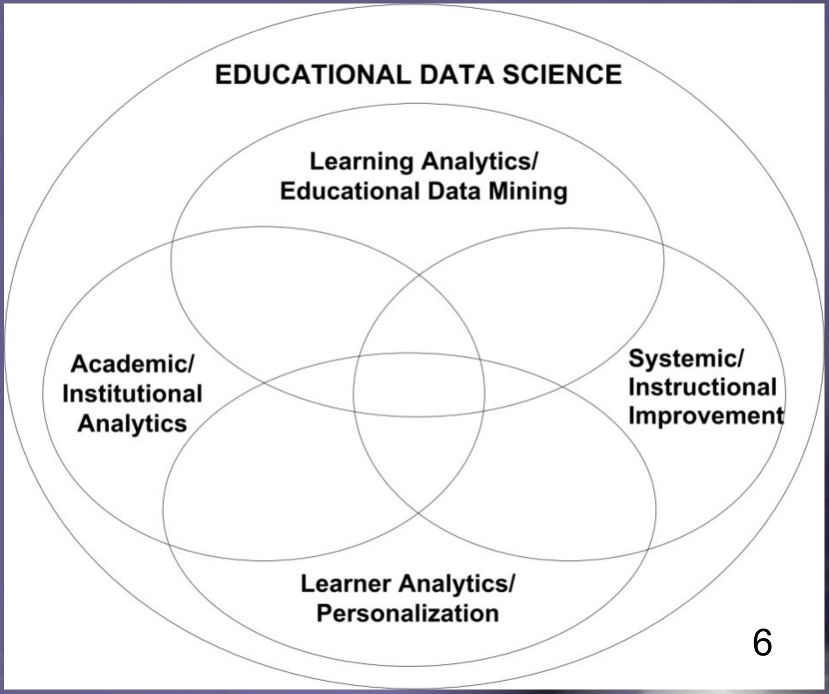
"In god we trust, all others must bring Data"
William Edwards Deming (1900-1993)

Introduction

What is EDS?

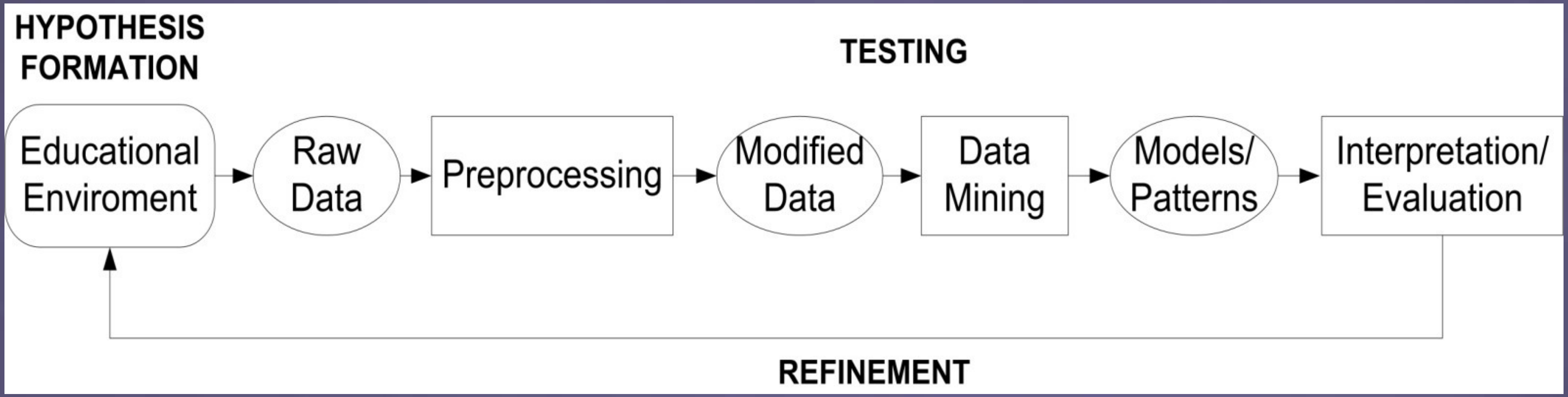
- **Educational Data Science (EDS)** that only works with data gathered from educational environments/setting for solving educational problems.

- **Educational Data Science (EDS)** is a multidisciplinary domain (computer science, education, statistics) with several related communities:



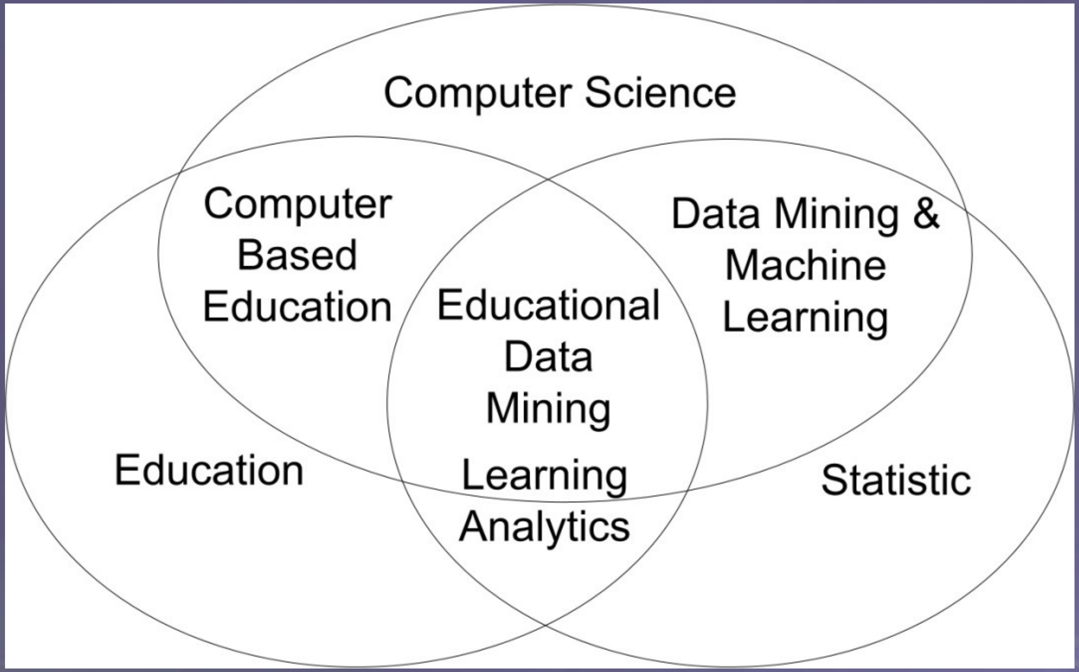
Introduction
What is EDM?

- ***Educational data mining (EDM)*** is the application of data mining techniques to educational environments.



Introduction
Multidisciplinary domain

- ***Educational data mining (EDM)*** is a multidisciplinary domain that is an intersection of 3 domains: computer science, education, statistics.



Introduction

Other areas closely related to EDM

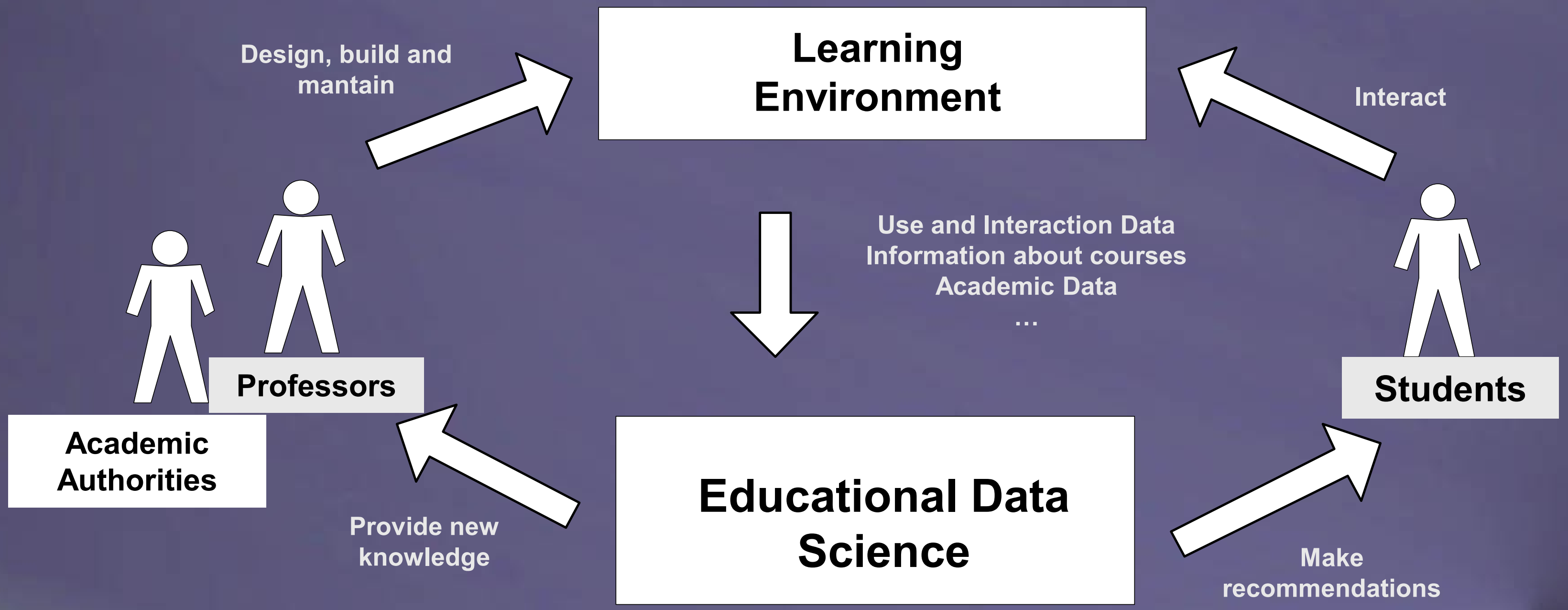
- **Learning analytics**
  - The measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs.
- **Academic analytics**
  - Bussiness intelligence applied to institutional academic data.

Introduction
Background on EDS

- 1991-3 ---------------------- First Papers about prediction
- 2000 ---------------------- Specific Workshops
- 2005 ---------------------- Data Mining in e-learning Book
- 2008 ---------------------- First EDM conference
- 2010 ---------------------- Handbook on EDM
- 2011 ---------------------- First LAK conference
- 2014 ---------------------- First L@S conference

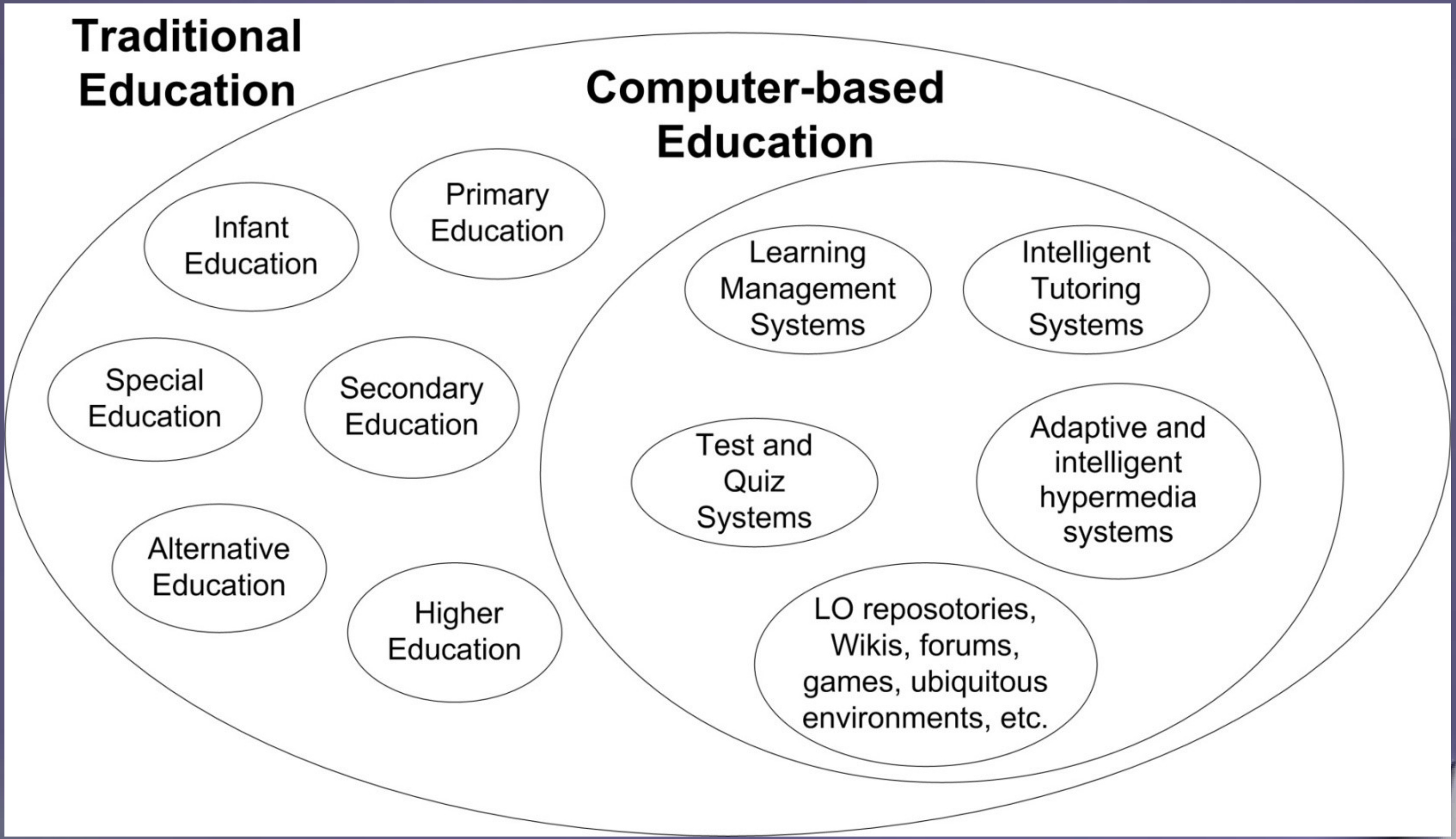
Process and actors

The Lifecycle of Educational Data Science:



Educational Data

Types of Educational Environments



Educational Data

Characteristics

- The information come from different sources of data.
- There are a lot of incomplete and loss data because not all students carry out all the activities.
- User/Students are clearly identified.
- There is a great number of available instances and attributes that may required tasks of filtering for selecting the most important.
- Educational data have different level of granularity.
- Some transformation such as discretization of number are normally used for improving the comprehensibility of data and the obtained models.

Educational Data

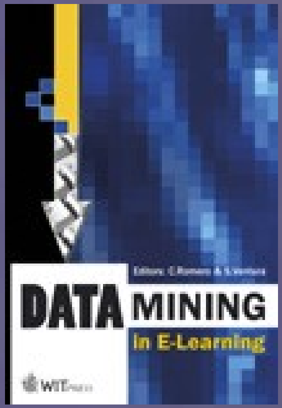
DM Tecnique used for each type of data

- Different types of data and DM techniques used:

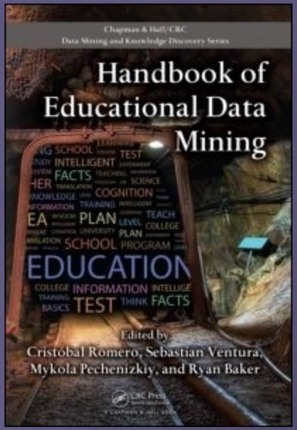
Type of data	DM Technique
Relational data	Relational data mining
Transactional data	Classification, clustering, association rule mining, etc.
Temporal, sequence and time series data	Sequential data mining
Text data	Text mining
Multimedia data	Multimedia data mining
World Wide Web data	Web content/structure/usage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

EDS Publications

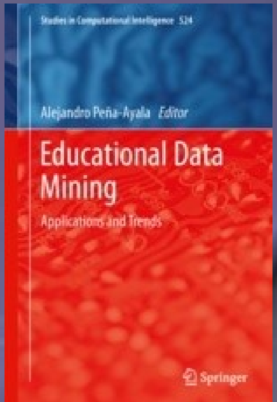
Books



- *[Data Mining in E-Learning]*.
  C. Romero & S. Ventura (Eds).
  Editorial WIT Press, 2006.



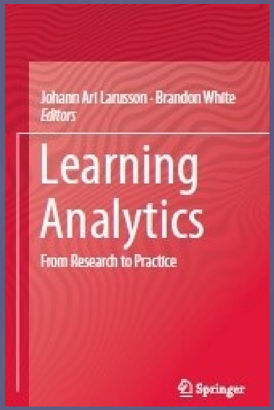
- [Handbook of Educational Data Mining].
  C.Romero, S. Ventura,
  M. Pechenizky, R. Baker. (Eds).
  Editorial CRC Press, Taylor & Francis Group. 2010.



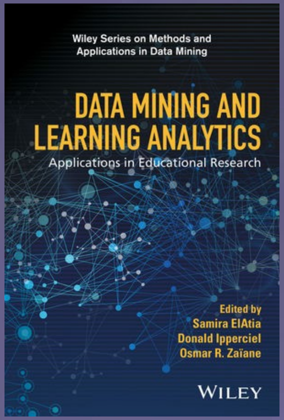
- *[Education Data Mining: Applications and Trends]*.
  A. Peña-Ayala (Eds).
  Springer, SCI Vol. 524, 2014

EDS Publications
Books

- Learning Analytics: From research to practice.
  J.A. Larusson, B. White (Eds).
  Springer, SCI Vol. 524, 2014



- Data Mining and Learning Analytics: Applications in Educational Research.
  S. ElAtia, D. Ipperciel, O.R. Zaïane.
  Wiley, 2016



EDS Publications
Surveys/Reviews

- C. Romero & S. Ventura. Educational Data Mining: A survey from 1995 to 2005. Expert Systems with Applications 33:1, pp. 135-146, 2007.
- C. Romero, S. Ventura. Educational Data Mining: A Review of the State-of-the-Art. IEEE Transactions on Systems, Man, and Cybernetics--Part C: Applications and Reviews. 40:6, pp. 601 – 618. 2010.
- Karen Cator. Enhancing Teaching and Learning Through Educational Data Mining and Learning Analytics. Report of the U.S. Office of Educational Technology. 2012.
- C. Romero, S. Ventura. Data Mining in Education. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery. Volume 3, Issue 1, pages 12–27, 2013.
- C. Romero, S. Ventura. Educational Data Science In MOOC. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery. Volume 7, Issue 1, pages 1–12, 2017.

DM Software

Weka is one of the most popular software packages for Data Mining

http://www.cs.waikato.ac.nz/~ml/weka/

This is a very popular DM tool, developed in Java

http://rapidminer.com

R is a programming language that was initially created to perform statistics, but it has also used in DM

https://www.r-project.org/

Specific EDS Software

Tool	Objective	Reference
WUM tool	To extract patterns useful for evaluating on-line courses.	(Zaïane and Luo, 2001)
EPRules	To discover prediction rules to provide feedback for courseware authors.	(Romero et al., 2004)
GISMO/CourseVis	To visualize what is happening in distance learning classes.	(Mazza and Milani, 2004)
TADA-ED	To help teachers to discover relevant patterns in students' online exercises.	(Merceron and Yacef, 2005)
O3R	To retrieve and interpret sequential navigation patterns.	(Becker et al., 2005)
Synergo/ColAT	To analyze and produce interpretative views of learning activities.	(Avouris et al., 2005)
LISTEN Mining tool	To explore huge student-tutor interaction logs.	(Mostow et al., 2005)
MINEL	To analyze the navigational behavior and the performance of the learner.	(Bellaachia and Vommina, 2006)
LOCO-Analyst	To provide teachers with feedback on the learning process.	(Jovanovic et al., 2007)
Measuring tool	To measure the motivation of online learners.	(Hershkovitz and Nachmias, 2008)
DataShop	To store and analyze click-stream data, fine-grained longitudinal data generated by educational systems.	(Koedinger et al., 2008)
Decisional tool	To discover factors contributing to students' success and failure rates.	(Selmoune and Alimazighi, 2008)
CIECoF	To make recommendations to courseware authors about how to improve courses.	(Garcia et al., 2009)
SAMOS	Student activity monitoring using overview spreadsheets.	(Juan et al., 2009)
PDinamet	To support teachers in collaborative student modeling.	(Gaudioso et al., 2009)
AHA! Mining Tool	To recommend the best links for a student to visit next.	(Romero et al., 2009)
EDM Visualization Tool	To visualize the process in which student solve procedural problem in logic.	(Johnson and Barnes, 2010)
Meerkat-ED	To analyze participation of students in discussion forums using social network analysis techniques.	(Rabbany et al. 2011)
E-learning Web Miner	To discover student's behavior profiles and models about how they work in virtual courses.	(García-Saiz and Zorrilla, 2011)
MMT tool	To facilitate the execution of all the steps in the data mining process of Moodle data for newcomers.	(Pedraza-Perez et al., 2011)

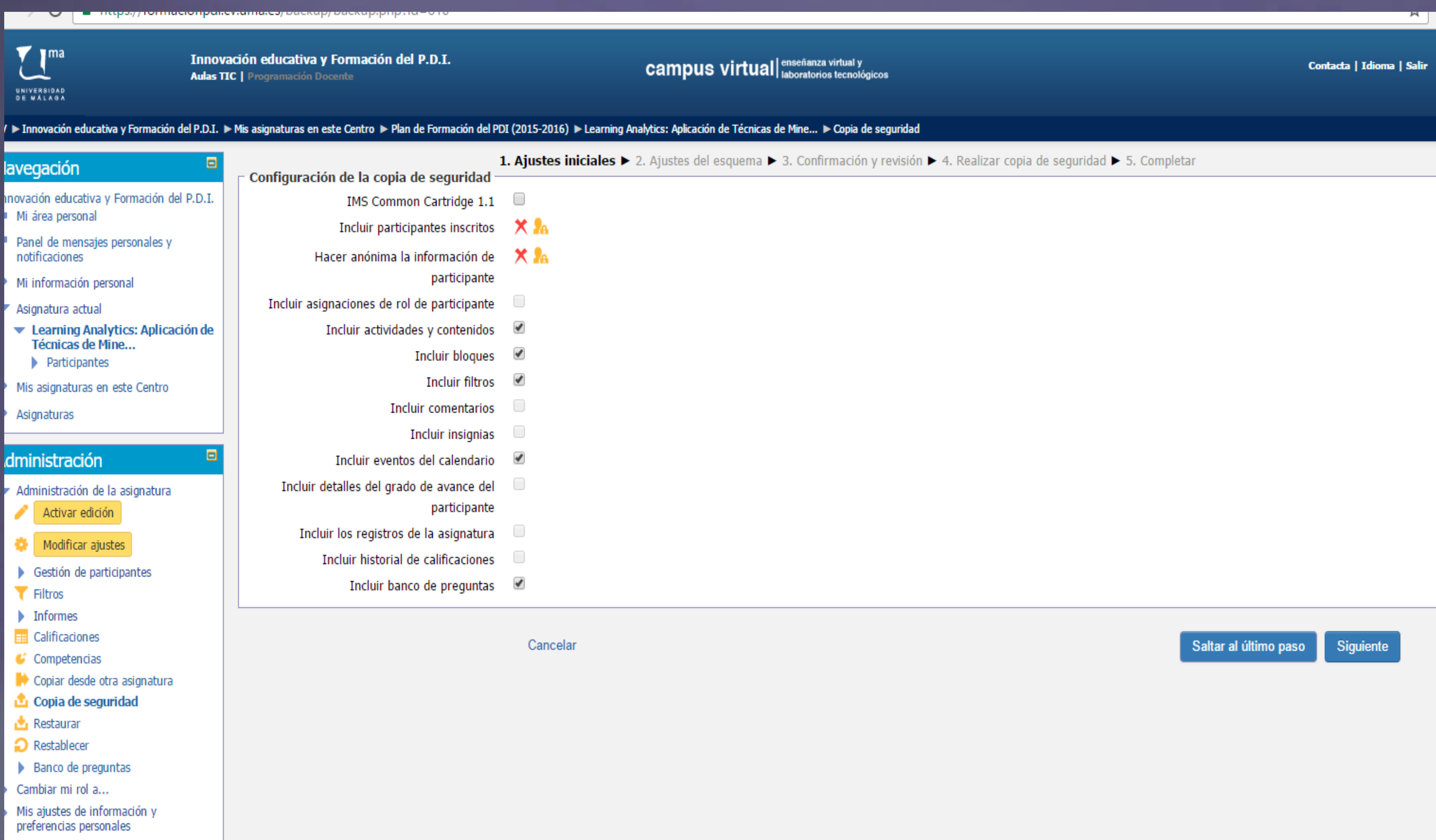
Specific Moodle EDS Software

Tool	Free	Integr.	Language	Vis.	Preproc.	Supervi.	Unsupervi.
CoSyLMSAnalytics	No	No	VisualBasic	No	No	No	Yes
ViMoodle	No	No	Java	Yes	No	No	No
CIECoF	No	No	Java	No	No	No	Yes
Meerkat-ED	No	No	Java	Yes	No	No	Yes
MMT	No	No	Java	No	Yes	Yes	Yes
DRAL	No	No	Java	No	No	Yes	No
GISMO http://gismo.sourceforge.net/	Yes	Yes	PHP	Yes	No	No	No
SNAPP	Yes	Yes	JavaScript	Yes	No	No	No
AAT	No	No	PHP	No	No	No	No
MOClog http://moclog.ch/	Yes	Yes	PHP	Yes	No	No	No
E-learningWebMiner	No	No	Java	Yes	No	No	Yes
CVLA	No	Yes	Phyton	Yes	No	Yes	No
IntelliBoard.net http://intelliboard.net/	No	Yes	PHP	Yes	No	No	No
SmartKlass http://klassdata.com/	Yes	Yes	PHP	Yes	No	No	No
Engagement Analytics https://moodle.org/plugins/browse.php?list=set&id=20	Yes	Yes	PHP	Yes	No	No	No
Analytics Graphs https://moodle.org/plugins/block_analytics_graphs	Yes	Yes	PHP	Yes	No	No	No

Exporting Moodle data

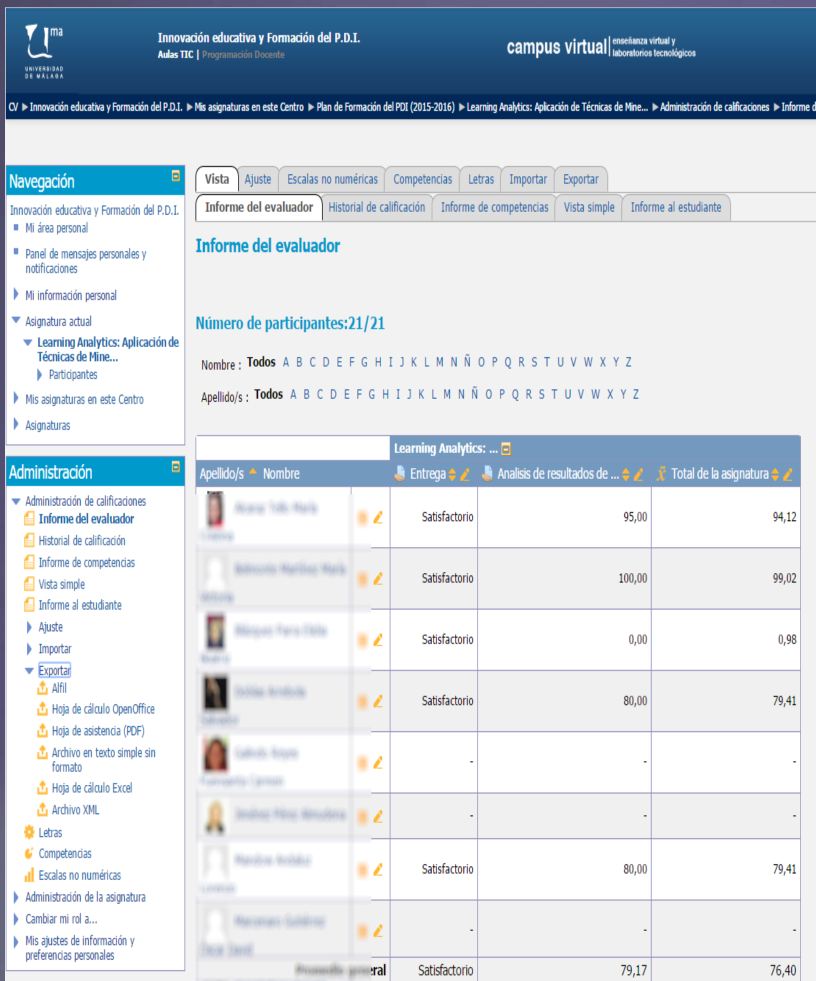
Back up course content

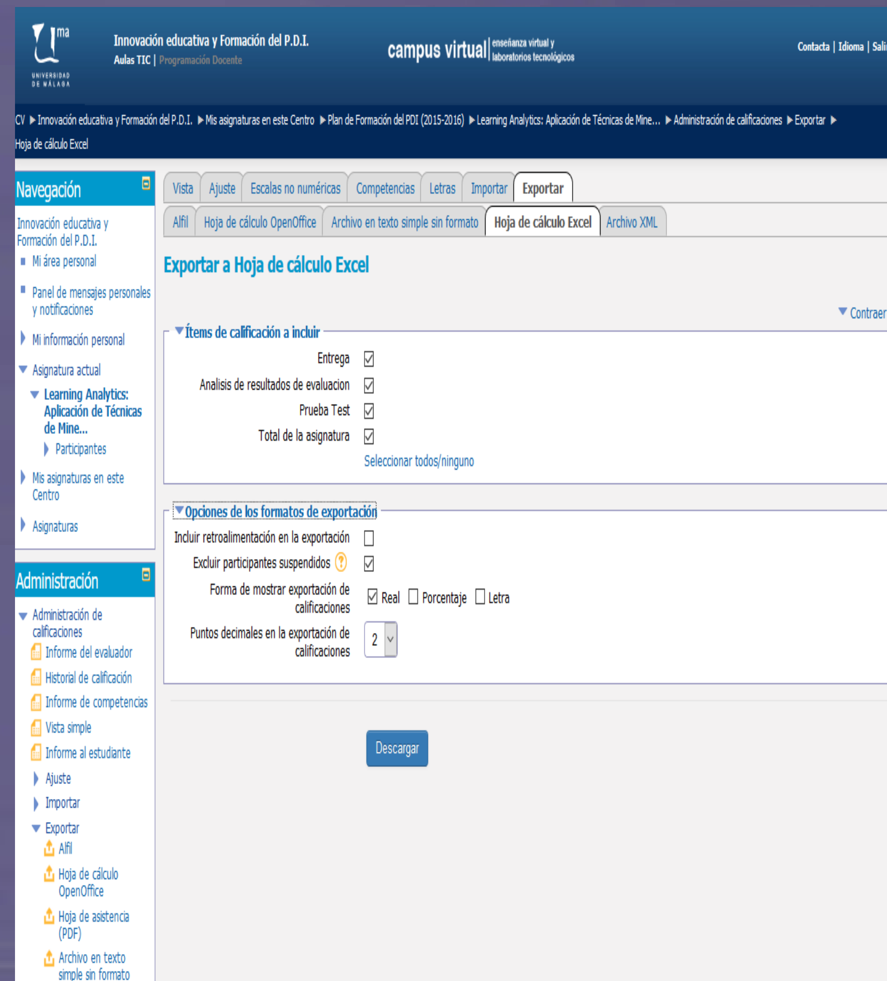
- Administracion -> Copia de seguridad



Export gradebook

- Administración -> Calificaciones
- Administracion de calificaciones -> Exportar





Export reports

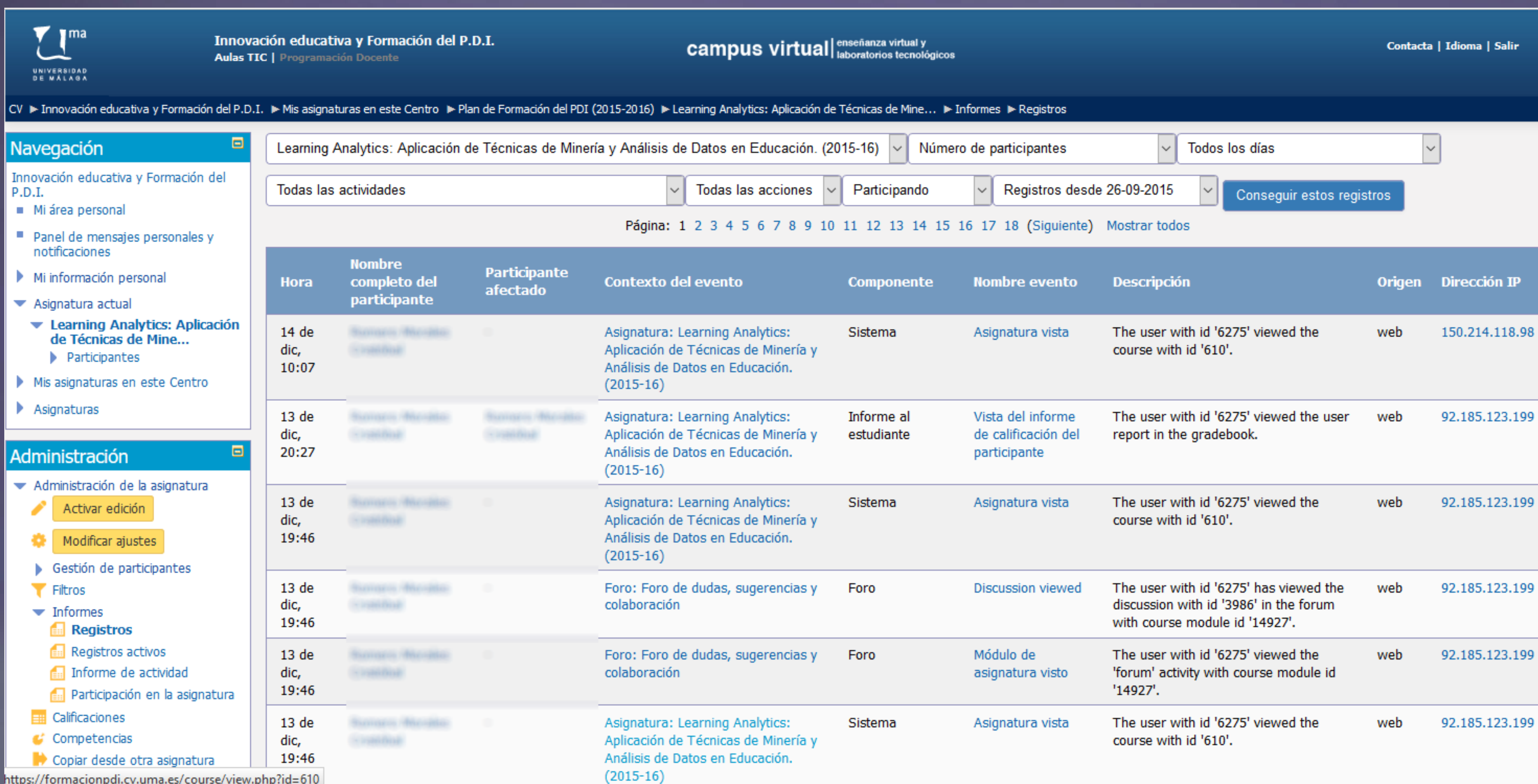
Administracion de asignatura -> Informes

Moodle allows instructors to request reports telling which resources and activities of a course have been accessed, when, and by whom. Moodle produces several kinds of reports:

- **Logs** generates a filtered report showing information about a particular activity or student.
- **Activity report** generates a simple unfiltered report showing all activity in the course that you can sort by column header.
- **Course participation** provides a sortable list showing all class members, with details about a particular resource or activity. You can see who has viewed a resource or submitted an activity. From this screen, instructors can also send a message to all students, or only to those students who have not completed an activity.

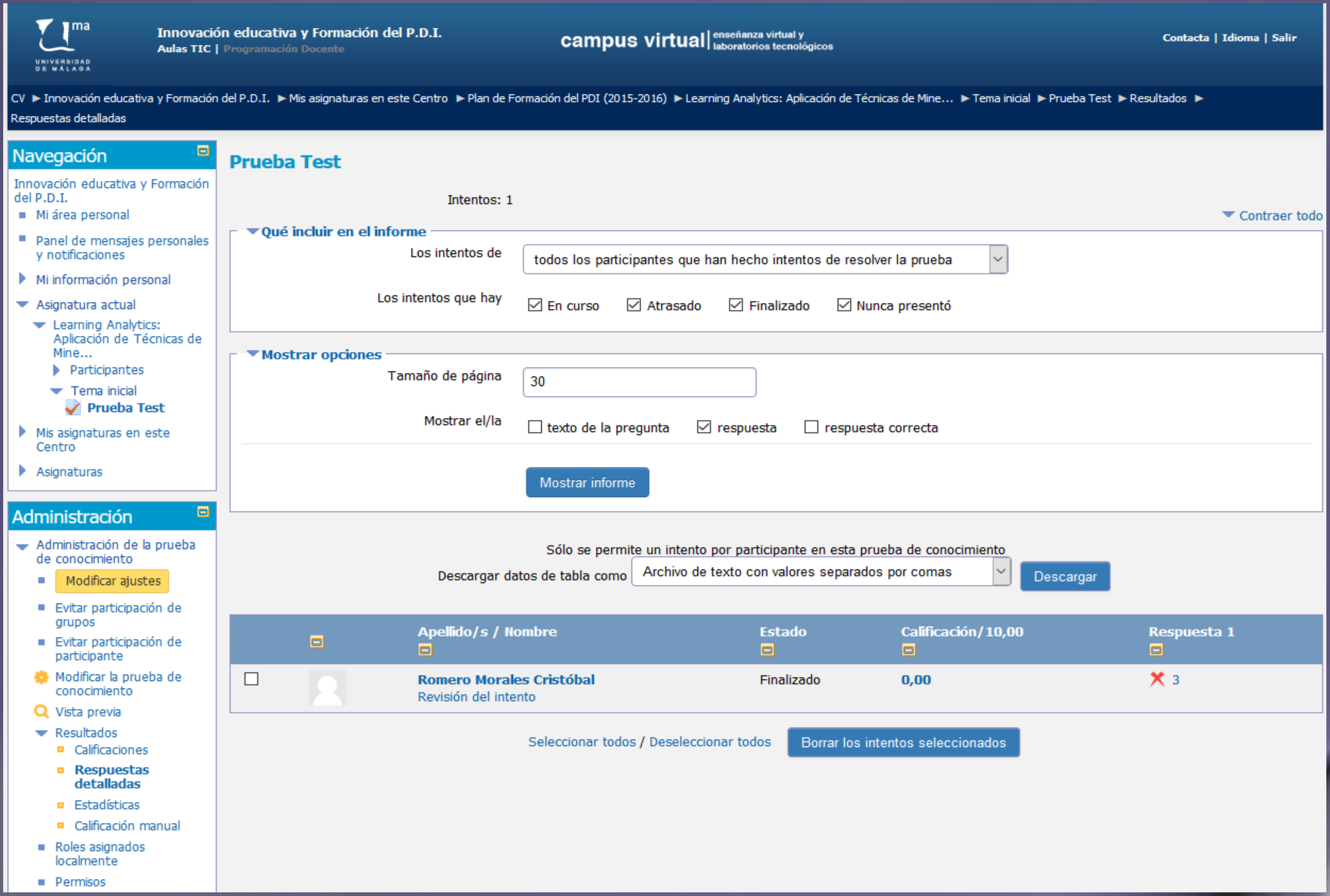
Export reports (logs)

- Administracion de asignatura -> Informes -> Registros



Download Quiz Data

- Pulsar sobre el enlace del Test.
- Administracion de la prueba de conocimiento -> Resultados -> Respuestas detalladas

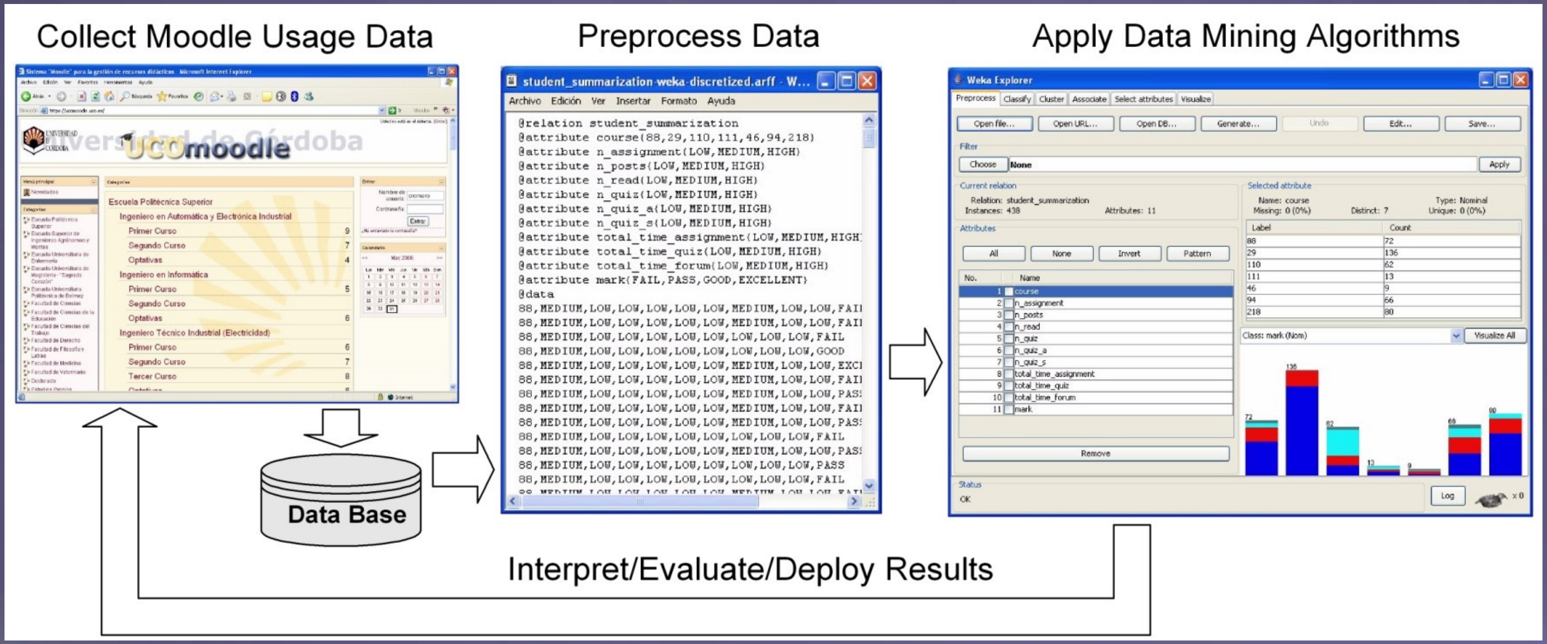


Preprocessing Moodle Data

Preprocesing Data

Introduction

- Data Mining Process with Moodle data:



Preprocesing Data

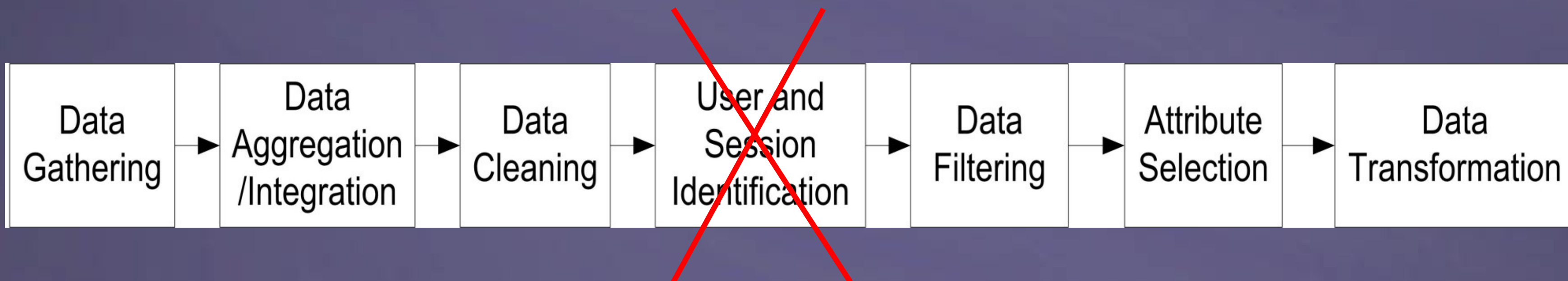
Introduction

- The first step in any KDD process is the transformation of data into an appropriate form for the mining process.
- Data pre-processing in educational context is considered the most crucial phase in the whole educational data mining process, and it cantake more than half of the total time spent in solving the data mining problem.
- The data pre-processing phase typically consumes 60-80% of the time of the KDD process.

Preprocesing Data

Introduction

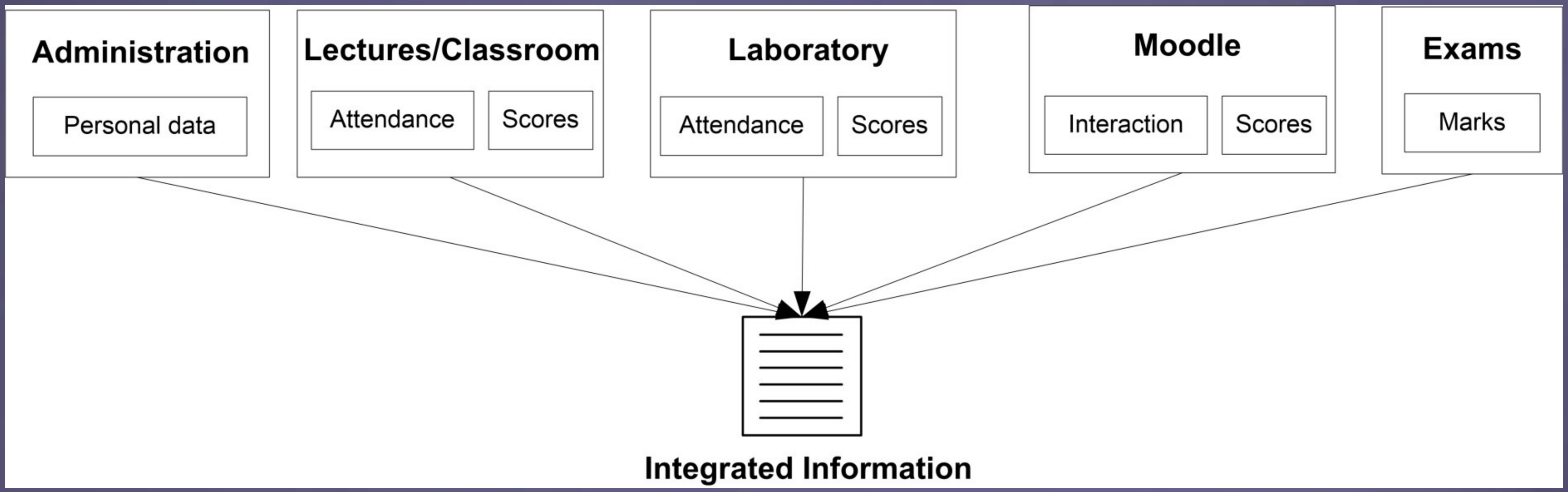
- The main steps/tasks of the overall process of pre-processing educational data are:



Preprocesing Data

Data Ghatering/Aggregation/Integration

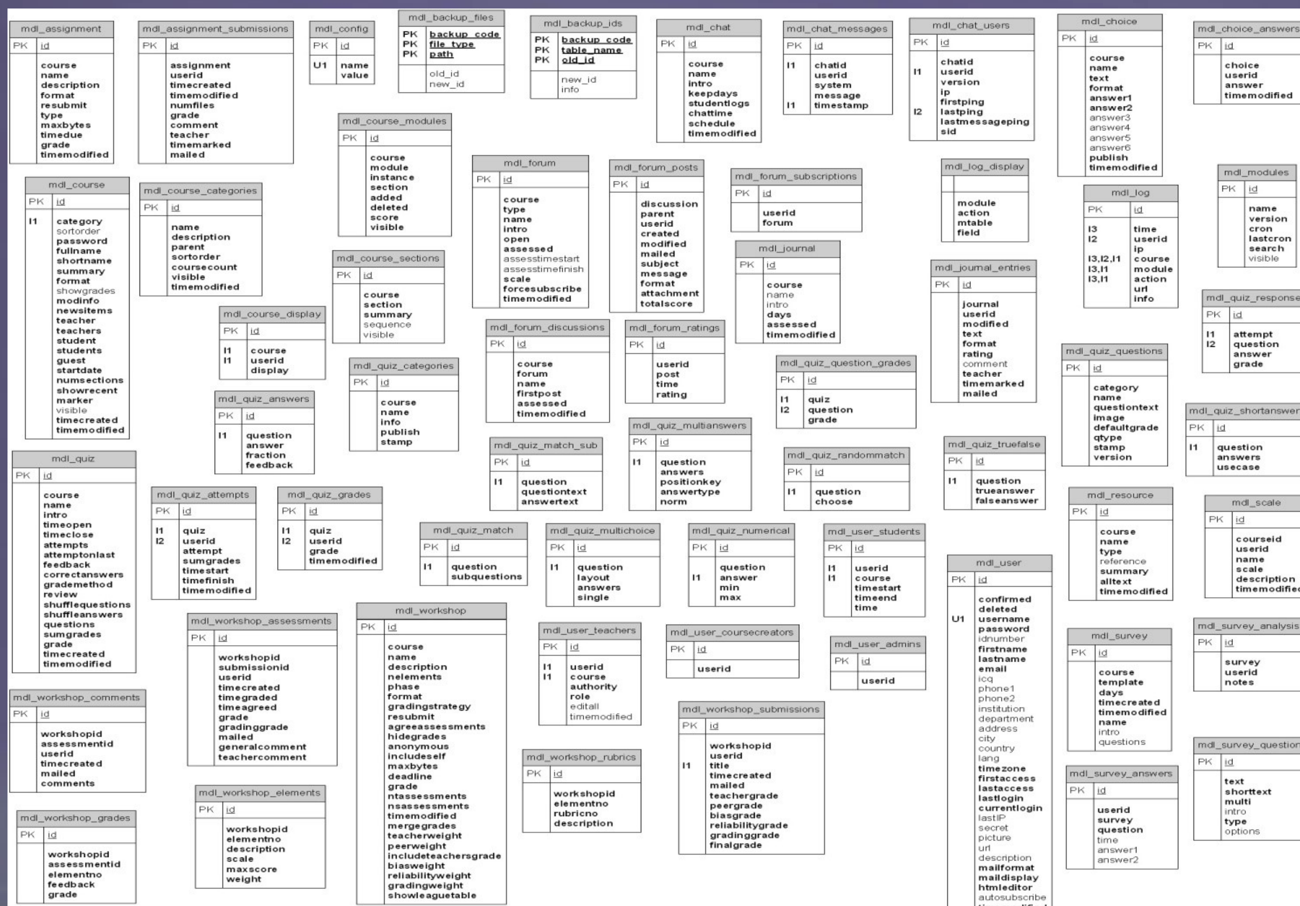
- Example of **gathering, data aggregation and integration**:



Preprocesing Data

Data Ghatering/Aggregation/Integration

- Moodle's Data Base has more than 200 Tables:

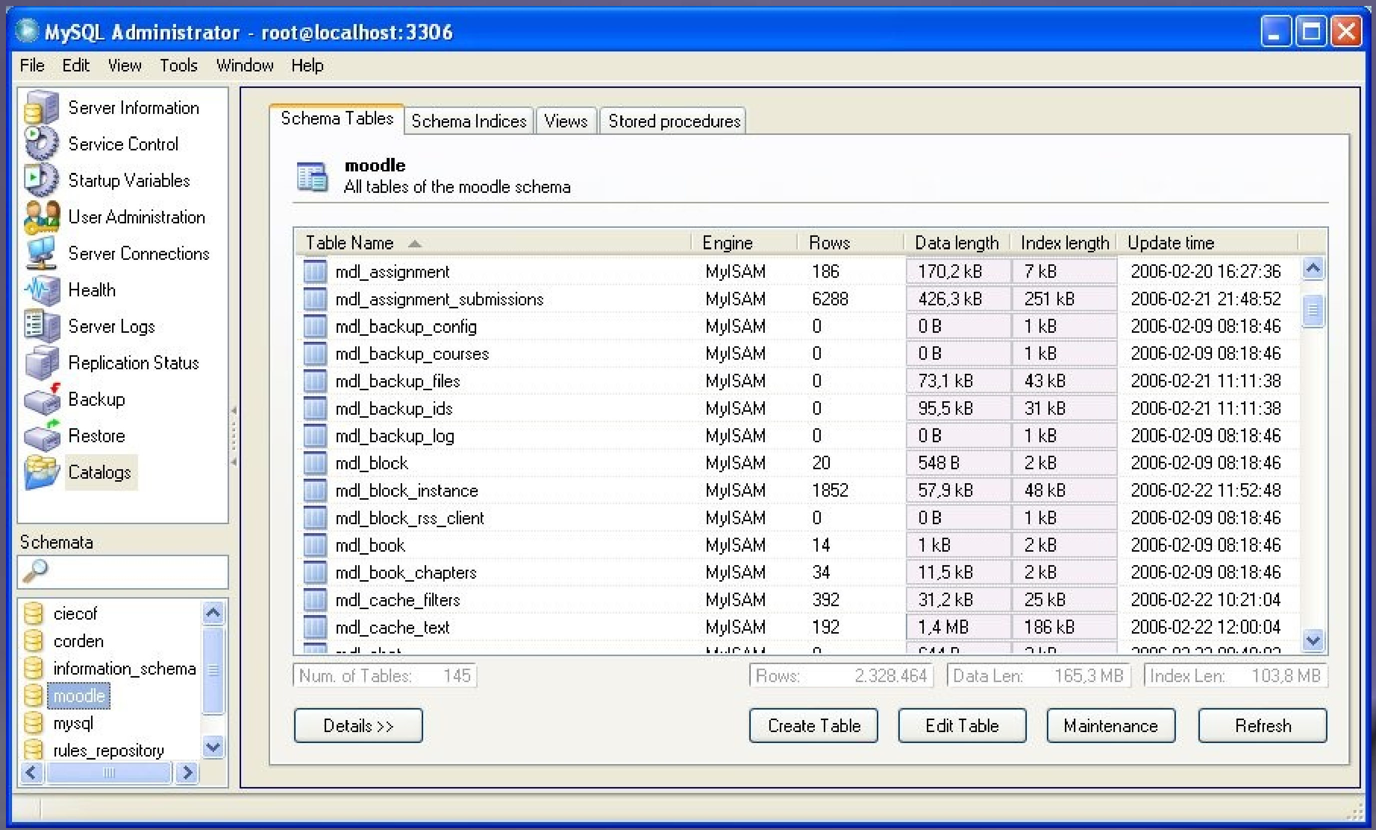


Preprocesing Data

Data Ghatering/Aggregation/Integration

- Using SQL to access Moodle's Tables:

```
SELECT COUNT(*) FROM mdl_quiz,mdl_quiz_grades  WHERE mdl_quiz_grades.userid= "
+userid+ " and mdl_quiz.course= " + id + " and mdl_quiz.id = mdl_quiz_grades.quiz
```



Preprocesing Data

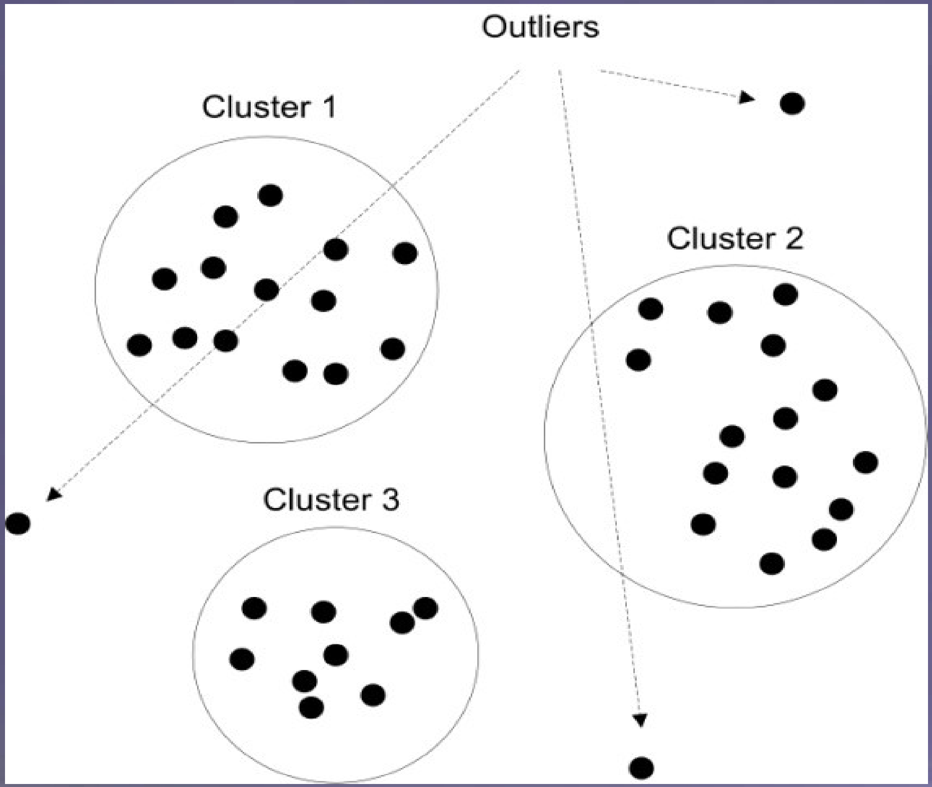
Data Ghatering/Aggregation/Integration

- List of important **tables** in Moodle database 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.

EDM Data
Data Cleaning

- Example of **data cleaning** by plotting data clusters and discovering outliers or rare/anormal students:



EDM Data

Data Cleaning

Missing data is a common issue in education (usually appear when students have not completed or done all the activities in the course) and some possible solutions are:

- Students who have missing values can be removed.
- Whenever possible, these specific students may be contacted and asked (by the instructor) to complete the course.
- To codify missing/unspecified values by mapping incomplete values using for example the labels “?” (missing) and “null” (unspecified).
- To use a global constant to fill in the missing value or to use a substitute value, like the attribute mean or the mode.

EDM Data

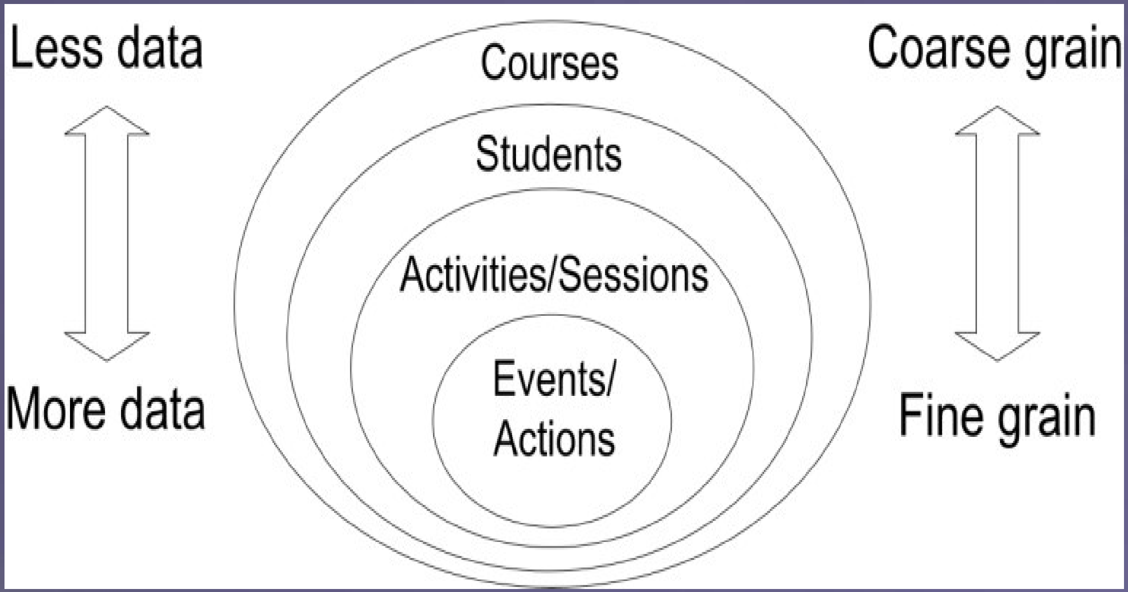
User and Session Identification

- Although **user and session identification** is not specific to education, it is especially relevant due to the longitudinal nature of student usage data.
- Computer-based educational systems provide user authentication (identification by login and password). So it is not necessary to do the typical user and session identification.
- It is also necessary to preserve student data anonymity/privacy but enabling that different pieces of information are linked to the same person. A common solution for it consists in using a number randomly or incrementally generated, like a user ID.

EDM Data

Data Filtering

- Example of **filtering** at different levels of granularity and their relationship to the amount of data:



EDM Data

Attribute Selection

- Example of **Summary Table** with a set 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.

EDM Data

Data Transformation

- Example of **transformation** is Discretization:
  - **Manual discretization** has the user himself directly specifying the cut-off points. Example (Marks/Scores depend on the country):

    FAIL: if value is < 5

    PASS: if value is ≥ 5 and < 7

    GOOD: if value is ≥ 7 and < 9

    EXCELLENT: if value is ≥ 9

EDM Data

Data transformation

- Example of derived attributes, which enables to create new attributes starting from the current ones:

Name	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.

EDM Data
Data transformation

- Example of Moodle **Summary ARFF file**:

Moodle-Summary.arff - Bloc de notas

Archivo Edición Formato Ver Ayuda

```
@relation student_summarization
@attribute id_student numeric
@attribute id_course numeric
@attribute num_sessions {HIGH, MEDIUM, LOW}
@attribute num_assignment {HIGH, MEDIUM, LOW}
@attribute num_quiz {HIGH, MEDIUM, LOW}
@attribute a_scr_course {FAIL, PASS, GOOD, EXCELLENT}
@attribute num_posts {HIGH, MEDIUM, LOW}
@attribute num_read {HIGH, MEDIUM, LOW}
@attribute t_time {HIGH, MEDIUM, LOW}
@attribute t_assignment {HIGH, MEDIUM, LOW}
@attribute t_quiz {HIGH, MEDIUM, LOW}
@attribute t_forum {HIGH, MEDIUM, LOW}
@attribute f_scr_course {FAIL, PASS, GOOD, EXCELLENT}
@data
1,88,LOW,MEDIUM,HIGH,FAIL,LOW,LOW,LOW,MEDIUM,LOW,LOW,FAIL
2,88,LOW,MEDIUM,HIGH,FAIL,LOW,LOW,LOW,MEDIUM,MEDIUM,LOW,FAIL
3,88,LOW,LOW,LOW,?,LOW,LOW,LOW,LOW,LOW,LOW,FAIL
4,88,MEDIUM,HIGH,PASS,LOW,LOW,LOW,LOW,LOW,MEDIUM,LOW,GOOD
5,88,HIGH,HIGH,GOOD,LOW,LOW,LOW,LOW,MEDIUM,MEDIUM,LOW,EXCELLENT
6,88,LOW,HIGH,FAIL,LOW,LOW,LOW,LOW,MEDIUM,LOW,LOW,FAIL
7.88,MEDIUM,HIGH,PASS,LOW,LOW,LOW,LOW,MEDIUM,LOW,LOW,PASS
8,88,LOW,HIGH,FAIL,LOW,LOW,LOW,LOW,MEDIUM,LOW,LOW,FAIL
9,88,LOW,HIGH,PASS,LOW,LOW,LOW,LOW,MEDIUM,MEDIUM,LOW,PASS
10,88,LOW,HIGH,FAIL,LOW,LOW,LOW,LOW,LOW,LOW,LOW,FAIL
11,88,MEDIUM,HIGH,PASS,LOW,LOW,LOW,MEDIUM,MEDIUM,LOW,PASS
```

Association Rule Mining in Moodle

Introduction
Association Rule Mining task

- **Association Rule Mining (ARM)** is one of the most popular and well-known data mining methods for discovering interesting relationships between variables in data
- The extracted knowledge has the form of rules, that can be applied on a fraction of the examples stored in the database.
- Types: frequent AR, rare AR, general AR, interesting AR…

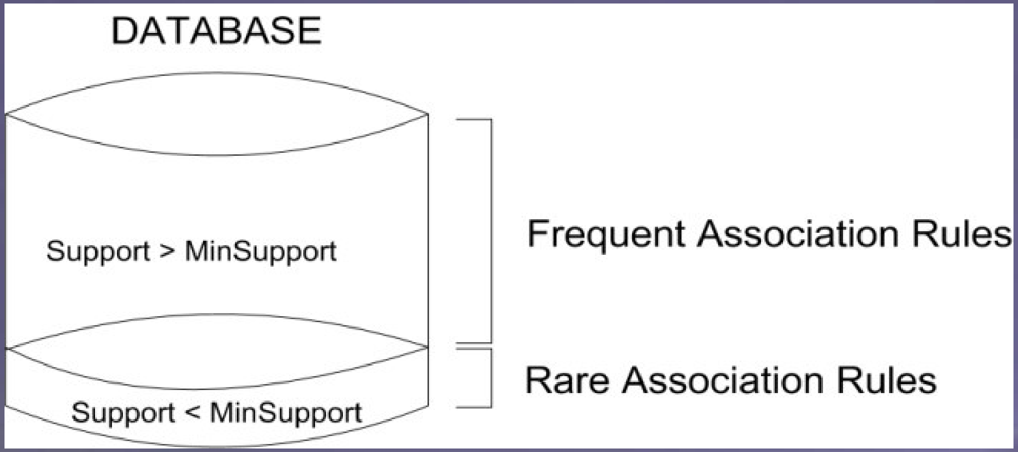
IF (asignments > 10) **THEN** (grade > 6)   support 80% confidence:90%

antecedent   consequent   Rule quality measure

- Related task: Sequential pattern mining, subgroup discovery, etc.

Introduction
Rare Association Rules

- **Rare Association Rules** also known as non-frequent, unusual, exceptional or sporadic rules are those that only appear infrequently even though they are highly associated with very specific data
- Rare itemsets are those that only appear together in very few transactions or some very small percentage of transactions in the database.
- They have low support and high confidence in contrast to general association rules which are determined by high support and a high confidence level.



Introduction

- **ARM** has been applied extensively in e-learning to discover frequent student-behavior patterns.
- However, **RARM** has been hardly applied to educational data, despite the fact that infrequent associations can be of great interest since they are related to rare but crucial cases. These rules could help the instructor to discover a minority of students who may need specific support with their learning process.
- The greatest reason for applying RARM in the field of EDM is the imbalanced nature of data in education in which some classes have many more instances than others.
- Furthermore, in applications like education, the minor parts of an attribute can be more interesting than the major parts; for example, students who fail or drop out are usually less frequent than those students who fare well.

Experimentation and Results

Data

- In order to test the performance and usefulness of applying ARM and RARM to e-learning data, we have used student data gathered from the Moodle system.
- These data are from 230 students in 5 Moodle courses on computer science at the University of Córdoba about all activities that students perform on-line (e.g., assignments, forums and quizzes).
- This student usage data has been preprocessed in order to be transformed into a suitable format to be used by our data mining algorithms.

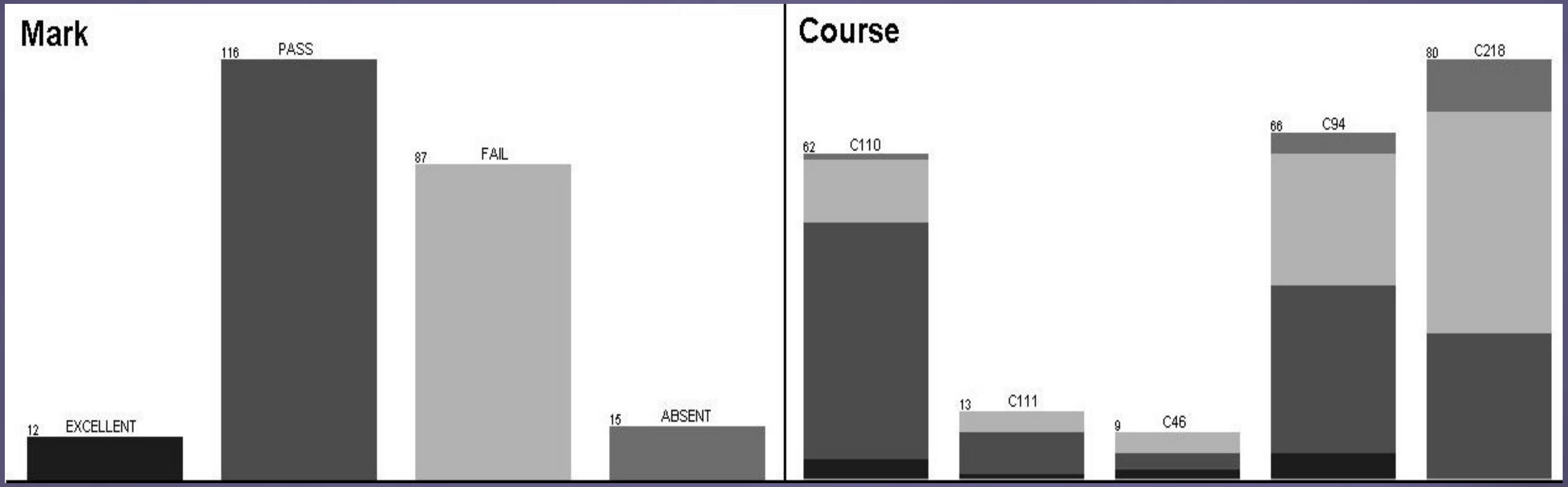
Experimentation and Results
Summary Table

- We have created a summary table which integrates the most important information about the on-line activities and the final marks obtained by students in the courses.

Name	Description	Values
course	Identification number of the course.	C218, C94, C110, C111, C46
n_assigment	Number of assignments done.	ZERO, LOW, MEDIUM, HIGH
n_quiz	Number of quizzes taken.	ZERO, LOW, MEDIUM, HIGH
n_quiz_a	Number of quizzes passed.	ZERO, LOW, MEDIUM, HIGH
n_quiz_s	Number of quizzes failed.	ZERO, LOW, MEDIUM, HIGH
n_posts	Number of messages sent to the forum.	ZERO, LOW, MEDIUM, HIGH
n_read	Number or messages read on the forum.	ZERO, LOW, MEDIUM, HIGH
total_time_assignment	Total time spent on assignments.	ZERO, LOW, MEDIUM, HIGH
total_time_quiz	Total time spent on quizzes.	ZERO, LOW, MEDIUM, HIGH
total_time_forum	Total time spent on forum.	ZERO, LOW, MEDIUM, HIGH
mark	Final mark obtained by the student in the course.	ABSENT, FAIL, PASS, EXCELLENT

Experimentation and Results
Imbalanced Attributes

- Due to the way their values are distributed, the course and mark attributes are clearly imbalanced, i.e., they have one or more values with a very low percentage of appearance.



Experimentation and Results

Class Association Rules

- We performed a comparison between ARM and different RARM algorithms to discover **Rare Class Association Rules**.
- A **Class Association Rule** is a special subset of association rules with the consequent of the rule limited to a target class label (only one predefined item in our case Mark attribute).

$$\boldsymbol{Item1 \cap item2 \cap \ldots \cap Itemn \rightarrow Class}$$

- In our specific context, these rules are very useful for educational purposes, since they show any existing relationships between the activities that students perform using Moodle and their final exam marks.
- To obtain Class Association Rules we have modified ARM and RARM algorithms in order to obtain only those rules that have a single attribute (in our case, the mark attribute) in their consequent.

Experimentation and Results

Parameters

- We evaluated the four different Apriori proposals with the following configuration parameters:

  - **Apriori-Frequent**, setting the minimum support threshold at a very low value (0.05).
  - **Apriori-Infrequent**, **Apriori-Inverse** and **Apriori-Rare** setting the maximum support at 0.1.

We also assigned the value 0.7 as the confidence threshold for all the algorithms.

Experimentation and Results

Summary of Results

- Comparison Table of ARM and RARM proposals:

Algorithm	# Freq. Itemsets	# UnFreq. Itemsets	# Rules	Avg Support/ ± Std Deviation	Avg Confidence/ ± Std Deviation
Apriori-Frequent	11562	--	788	0.162±0.090	0.717±0.211
Apriori-Infrequent	--	1067	388	0.058±0.060	0.863±0.226
Apriori-Inverse	--	3491	46	0.056±0.070	0.883±0.120
Apriori-Rare	--	5750	44	0.050±0.080	0.885±0.108

Experimentation and Results

Examples of discovered rules

- Next, we show some examples of rules that were obtained using A) the ARM (Apriori) and B) RARM (Apriori-Rare) algorithms.
- For each rule, we show the antecedent and the consequent constructed, as well as some evaluation rule measures such as the support, the confidence and two different versions of the conditional support.

Experimentation and Results

Rule Evaluation Measures

- Due to the imbalanced nature of our data, we use different versions of the conditional support [Zhang et al. 2009]:
  - Traditional support: $Sup(A \rightarrow C) = \frac{n(A \cap C)}{N}$
  - Conditional support with respect to the mark attribute:

$$SupM(A \rightarrow Mark) = \frac{n(A \cap Mark)}{n(Mark)}$$

  - Conditional support with respect to the course attribute:

$$SupC(A \cap Course \rightarrow Mark) = \frac{n(A \cap Course \cap Mark)}{n(Course)}$$

Experimentation and Results
Examples of discovered rules

- Rules extracted using the Apriori-Frequent algorithm.

Rule	Antecedent	Consequent	Sup	SupC/SupM	Conf
1	total_time_forum=HIGH	mark=PASS	0.24	--/0.47	0.82
2	n_posts=MEDIUM AND n_read=MEDIUM AND n_quiz_a=MEDIUM	mark=PASS	0.13	--/0.25	0.71
3	course=C110 AND n_assignment=HIGH	mark=PASS	0.14	0.52/0.27	0.89
4	total_time_quiz=LOW	mark=FAIL	0.21	--/0.55	0.78
5	n_assignment=LOW	mark=FAIL	0.23	--/0.60	0.70
6	n_quiz_a=LOW AND course=C218	mark=FAIL	0.18	0.51/0.47	0.83

Experimentation and Results

Examples of discovered rules

- Rules extracted using the Apriori-Rare algorithm.

Rule	Antecedent	Consequent	Sup	SupC/SupM	Conf
1	n_quiz=HIGH AND n_quiz_a=HIGH	mark=EXCELLENT	0.045	--/0.69	0.86
2	total_time_assignment=HIGH	mark=EXCELLENT	0.045	--/0.69	0.86
3	n_posts=HIGH AND course=C46	mark=EXCELLENT	0.045	1.00/0.69	1.00
4	total_time_assignment=ZERO AND total_time_forum=ZERO AND total_time_quiz=ZERO]	mark=ABSENT	0.050	--/0.76	0.78
5	n_posts=ZERO AND n_read=ZERO	mark=ABSENT	0.050	--/0.76	0.78
6	n_quiz=ZERO AND course=C111	mark=ABSENT	0.050	0.88/0.76	1.00

Classification and Clustering in Moodle

Tasks
Classification

- Identifying to which set of categories a new observation belongs on the basis of a training set containing observations (instances) whose category membership is known (supervised learning method).
- Example: *Build a model to predict if a given student will pass or not from certain information*.
  - To do that…
    - I have information about students previously graded as “pass” or “fail”. Those examples can contain different kind of information.
    - I build a model using a classification algorithm.
    - The model allow us to predict if a new student, whose information is provided to the model, will pass or fail.

Tasks
Clustering

- Grouping a set of objects in such a way that objects in the same group (called a **cluster**) are more similar (in some sense or another) to each other than to those in other groups or **clusters**.
- Example: Defining group of similar students from the usage informacion taken of a virtual learning system
  - To do that…
    - We have a set of **unlabelled** data.
    - The cluster algorithm search similarities between data and defines group of students with similar features.
    - The final model includes the description of the resulting groups.

Introduction

- Mining data generated by students communicating using forum-like tools can help reveal aspects of their communication.
- The more students participate in the forum for a certain course, the more involved they will be in the subject matter of that course.
- Following this line, in this study we try to test whether or not there is a correlation between the participation of students in Moodle forums and their final course marks.

Background

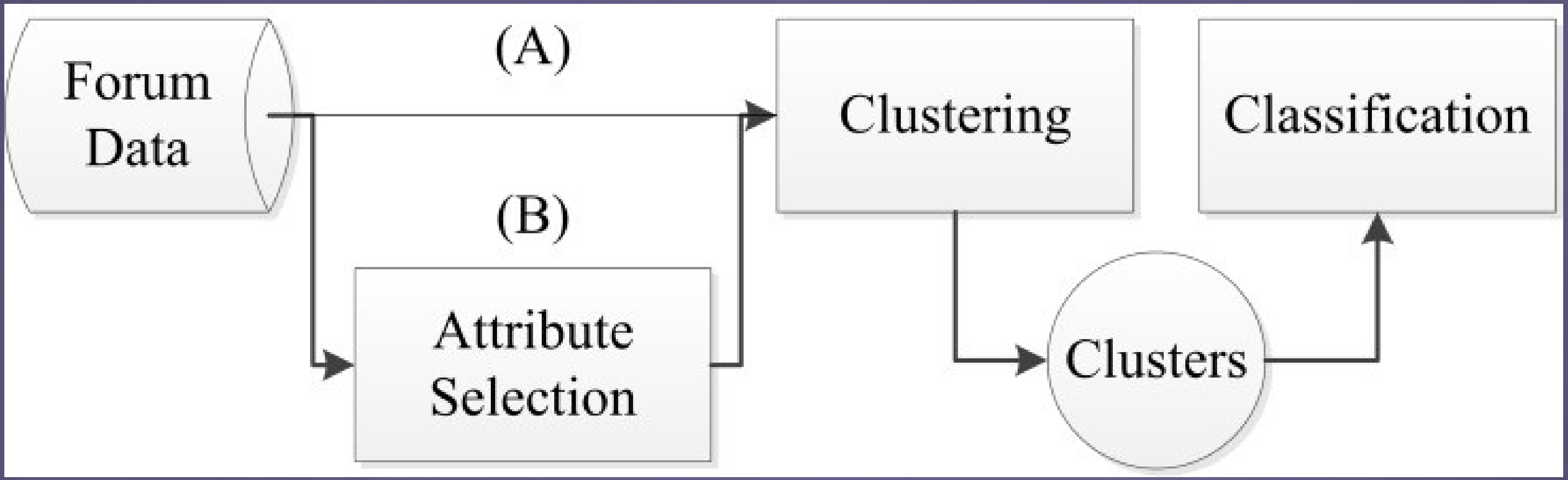
- The use of data mining is a potential strategy for discovering and building alternative representations for the data underlying discussion forums.
- There is less published work on the use of data mining to predict student performance based on forum usage data.
- Furthermore, the use of clustering for classification has not yet been applied in an educational context.

Proposed Approach

- We propose to use a meta-classifier that uses a cluster for classification approach based on the assumption that each cluster corresponds to a class.
- For all cluster algorithms, the number of clusters generated is the same as the number of class labels in the dataset. We use this approach to test if student participation in forums is related to whether they pass or fail the course.

Proposed Approach

- Proposed classification via clustering approach



Description of the data used

- The dataset used in this work was gathered from a Moodle forum used by university students during a first-year course in computer engineering in 2011.
- We developed a new module for Moodle specifically to obtain a summary dataset file.

Student	nMessages	nThreads	nReplies	nWords	nSentences	nR
[illegible]	3	0	3	67	3	
[illegible]	6	1	5	513	1	
[illegible]	1	1	0	17	2	
[illegible]	2	0	2	43	2	

Description of the data used

- Some forum statistics are:

Number of students	Number of messages	Number of threads	Number of replies
114	1014	81	933

- The variables relating to forum usage are:

Attribute	Description
nMessages	Number of messages sent per student
nThreads	Number of threads created per student
nReplies	Number of replies sent per student
nWords	Number of words written by student
nSentences	Number of sentences written by student
nReads	Number of messages read on the forum
tTime	Total time, in hours, spent on forum
aEvaluation	Average score of the messages
dCentrality	Degree centrality of the student
dPrestige	Degree prestige of the student
fMark	Final mark obtained by the student

Experimental Results

- In the first experiment, we executed the following clustering algorithms provided by Weka for classification via clustering using all attributes: EM, FarthestFirst, Xmeans, sIB HierarchicalClusterer and SimpleKMeans.
- In the second experiment, we repeated all the previous executions using fewer attributes, based on the assumption that not all the available attributes are discriminative factors in the final marks.

Experimental Results

- We apply a range of feature-selection algorithms. To rank the attributes, we counted the number of times each attribute was selected by each attribute-selection algorithm.
- We selected as the best attributes the first six attributes in the ranking, because these were selected by at least half of the algorithms.

Experimental Results

Attribute	Frequency
dCentrality	9
nMessages	8
nReplies, nWords	7
dPrestige	6
aEvaluation	5
nSentences, nReads, nThreads	3
tTime	1

Experimental Results

- The table shows the overall accuracy (rate of correctly classified students) using all the available attributes (A) and using only the six selected attributes (B).

Clustering algorithm	**(A)**	**(B)**
EM	**0.842**	**0.894**
FarthestFirst	0.526	0.535
HierarchicalClusterer	0.578	0.570
sIB	0.710	0.578
SimpleKMeans	0.666	0.640
Xmeans	0.666	0.640

Experimental Results

- In the third experiment, we compared the accuracy of the previous classification via clustering approach with that of traditional classification algorithms by executing a representative number of classifications of different types: Rules-based algorithms, Trees-based algorithms, Functions-based algorithms and Bayes-based algorithms.

Experimental Results

Algorithms	**(A)**	**(B)**
DTNB	0.859	0.833
JRip	0.833	0.815
NNge	0.842	0.807
Ridor	0.833	0.842
ADTree	0.859	0.842
J48	0.824	0.807
LADTree	0.868	0.850
RandomForest	0.850	0.833
Logistic	0.859	0.850
MultilayerPerceptron	0.842	0.868
RBFNetwork	0.868	0.886
SMO	0.868	0.886
BayesNet	**0.877**	0.842
NaiveBayesSimple	0.859	**0.894**

Experimental Results

- Finally, we show the cluster centroids for the EM algorithm when using the six selected attributes that have yielded the best accuracy.

Attributes	Cluster 0	Cluster 1
nMessages	1.2199	14.8905
nReplies	1.1599	13.6718
nWords	18.4599	668.8039
aEvaluation	0	0.7751
dCentrality	0.0011	0.1565
dPrestige	0	0.1021