

**Developing a software for
analysing data from online
learning quizzes.**

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Abstract

Acknowledgements

Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

(Salvador Garcia Gonzalez)

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Chapter 1

Introduction

Here goes the introduction

Chapter 2

Background

2.1 Item response theory (IRT)

2.1.1 Latent and observable variables

2.1.2 Latent Variable Models

2.1.3 Latent Trait Theory

2.2 The Rasch model (RM)

2.2.1 The sigmoid function

2.2.2 Rasch model

2.2.3 The model assumptions

2.2.4 Parameter estimation

Item parameters

Joint Maximum likelihood Estimation (JML)

Marginal Maximum likelihood Estimation (MML)

Conditional Maximum likelihood Estimation (CML)

Advantages of CML and MML

Person parameters

2.2.5 The Item Characteristic Curve (ICC)

2.2.6 The Person-Item Map (PIM)

2.2.7 The Person-parameter plot (PIM)

2.3 Other learning analytics interfaces

Chapter 3

The lanalytics package

The *lanalytics package*¹ is an R package designed to analyze the answers to online quizzes. The package is able to perform different analysis according to the desired aggrupation level: per quiz, per group and per person. To accomplish this, the data can be plotted in seven different ways, varying on the distinct aggregation levels and the different objectives of the analysis. At the group level, the package contains the *guessing* and the *Time-easiness* plots; at the quiz level, it contains two descriptive statistical graphs, a *boxplot* and a *histogram* of the obtained scores of the online quizzes takers and the *Easiness-Time* and the *Easiness-Time-Level* plots. Finally, at the individual level, the user can plot the grade history of a student. The explanations and objectives of each one of these will be explained throughout this chapter.

3.1 Quiz and course objects

The basic structure in the lanalytics package is the quiz object which is implemented with a *tibble* [8]². This object contains a tibble in long format with one entry per student-question. For each row, another two variables are required: the score (a binary variable indicating if the answer was correct) and the date-time when the question was answered (in *POSIXct* format). All this information should be provided in a **.csv* file.

To allow more interesting analysis, the quiz object can be augmented with other two columns computed by R. The first is the spent time per question and the second is the answering order (a number is assigned to each row according to the order in which it was answered). An example of the quiz object is in the [fig. 3.1].

¹The package is open source and it is hosted in Github.

²A tibble is data structure build on top of the *data.frame* class and give it more functionalities.

	email.address	question	responded.at	score
1	ADRXM8548M@gmail.com	1	2017-02-11 22:11:46	1
2	ADRXM8548M@gmail.com	2	2017-02-11 22:12:00	1
3	ADRXM8548M@gmail.com	3	2017-02-11 22:12:16	0
4	ADRXM8548M@gmail.com	4	2017-02-11 22:12:41	1
5	ADRXM8548M@gmail.com	5	2017-02-11 22:13:01	1
6	ADRXM8548M@gmail.com	6	2017-02-11 22:13:49	1
	quiz	order	answer	time.per.question
1	datasets/sample_dataset/Q01.csv	1		NA secs
2	datasets/sample_dataset/Q01.csv	2		14 secs
3	datasets/sample_dataset/Q01.csv	3		16 secs
4	datasets/sample_dataset/Q01.csv	4		25 secs
5	datasets/sample_dataset/Q01.csv	5		20 secs
6	datasets/sample_dataset/Q01.csv	6		48 secs

Figure 3.1: Quiz object

Finally, all the quizzes can be grouped in a course object, which joins them in the same tibble. This is very useful if you want to save the all the records of your course in just one file.

3.1.1 Documentation

In R, the documentation is stored as *.Rd* files in the *man* directory, but it is not a good idea to create this files by hand. The main reason is that you have to write twice, one to comment the code (the *.R* files), and the other to write the *.Rd* files. The *roxygen2* [7] package solves this problem; it creates a standard in which you only need to document the *.R* files and all the *.Rd* files will be created automatically. Also this package creates the *Namespace* [6] file for your package. On the other hand, the *pkgdown* package helps you to create a website for your package (with the advantage that the examples in the documentation are executed and displayed). This package works side by side with the *roxygen2* package: it takes the generated documentation in the *man* directory and creates a webpage in the *docs* directory, then the *README* file is used as the home page of the website.

3.2 Group level analysis

3.2.1 Guessing plot

The idea of the *guessing plot* [4] [fig. 3.2] is to detect if a student is answering the questions in a very fast pace. Some students can answer the quizzes really fast, but even the fastest of them answers the questions above some time threshold. This threshold

is relative to the item difficulty and to the student's ability, so one way to find a lower bound is to insert a really easy question in some section of the quiz and record the time that each student spends on it. If some other question is answered below this time threshold then it should be analyzed. As the fast question answering does not give more information about the student behavior (he could be answering randomly or he could know the answer from another student), the score that the student obtains should be analyzed. In the guessing plot if some student spend less time than the threshold, then a point will appear. If he got correct the answer, the color of the point will be red. Otherwise, it will be blue.

The idea behind this plot is that if the student gets many red points in the same quiz, it is possible that somehow he previously knew the quiz answers. If he get red and blue points, it is possible that he just randomly answers the quiz. The ideal situation is that any or just a few points appear per student in the graph.

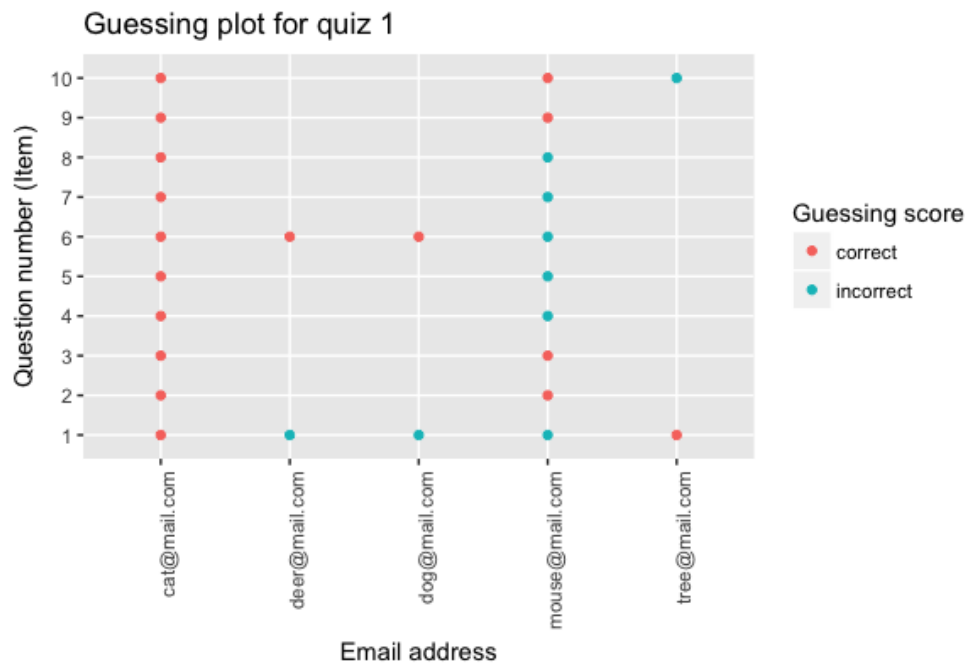


Figure 3.2: Guessing plot. A point indicates that the user answers the item faster than some threshold. If it is red, the answer is correct, otherwise is incorrect.

For example, in the fig. 3.2 we have 5 users. The users *cat@mail.com* and the user *mouse@mail.com* answered really fast all the questions, but the difference is that the user *cat@mail.com* got every question correct while the other user does not. Because of the defined threshold, it is possible that the first student previously knew the answers, while the second one just answers randomly.

3.2.2 Easiness time per quiz and tercils

In the Easiness-Time plot fig. 3.3 the students are grouped by tertiles according to the time that they spent in the corresponding question. This way the first tercile contains the fastest students and the third tercile the slowest ones.

For example, if both the fast and slow answering students score correctly in the question, then it is an easy one. On the other hand, if there is a score gap between the fast and slow students, then it may be interpreted differently. If the fast-answering students get a better result, then it may be interpreted as they know the solution, so they answer it faster. On the other hand, if the slow-answering students have a better result, this item might be a little bit confusing, so the students spend more time trying to figure out the solution to get it correctly.

In the fig. 3.3 we can see these patterns. For example, in the questions 5 and 6 all the students got an average of 90. Conversely, in the questions 2,3,4 the faster students got better results.

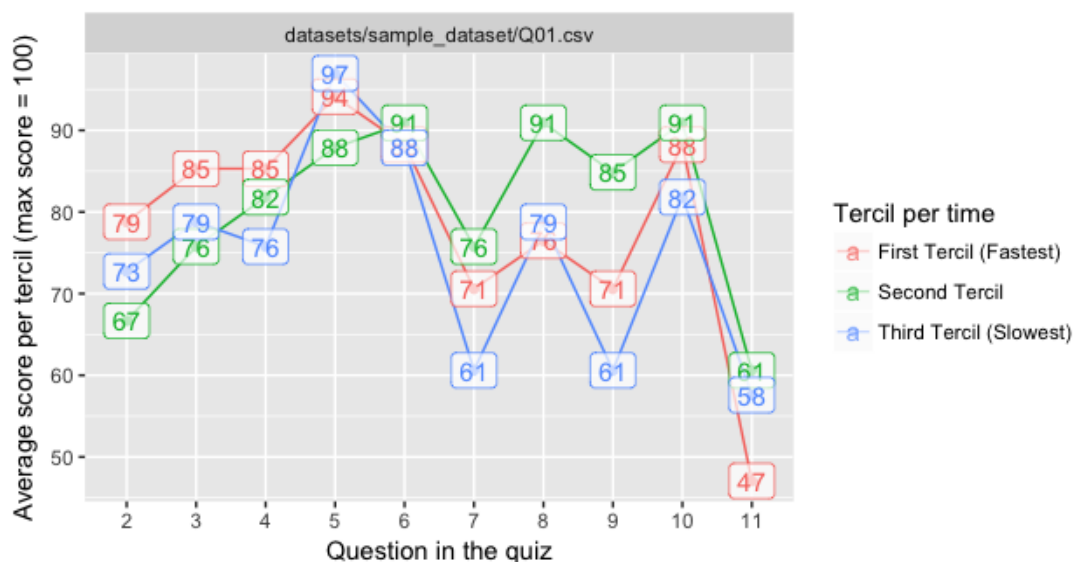


Figure 3.3: Easiness-Time per group and tercil. In the x-axis is the question of the quiz and in the y-axis the average score per time-tercil.

It is impossible to calculate the time that student spends on the first question. The reason is that the unique time that is recorded is when the user submits the question, so it is impossible to establish the start time for the first question (unless you explicitly start recording the time at the begin of the quiz).

3.3 Quiz level analysis

In the quiz level four different plots are proposed: Histogram of grades, Boxplot of grades, the Easiness-Time plot (ET plot) and the Easiness-Time-Cognitive Level plot (ETL plot) [4]. The objective of the first two is to identify the dispersion, the skewness and the outliers points. For the last two plots, it's important to define the three levels of cognitive levels in the questions. The first level is the easiest questions, that only implies a *factual knowledge*. These are questions that only require knowing the definition of a concept. The second level is the *understanding of the concept* [4], where the student should not only know the definition, but also understand its implications. In the last level, *application of concept*, the student should know how to apply the concept in real problems or situations.

3.3.1 Histogram of quizzes

To identify the dispersion and skewness of the data we can analyze the histograms per quiz. With the histograms is easy to detect if there are subpopulations in the data (for example if the distribution is similar to a bimodal normal distribution). For example in the [fig. 3.5] the quiz 01 looks normally distributed, the quiz 02 looks like a bimodal distribution, and the quiz 04 looks uniform in the range from 60 to 90.

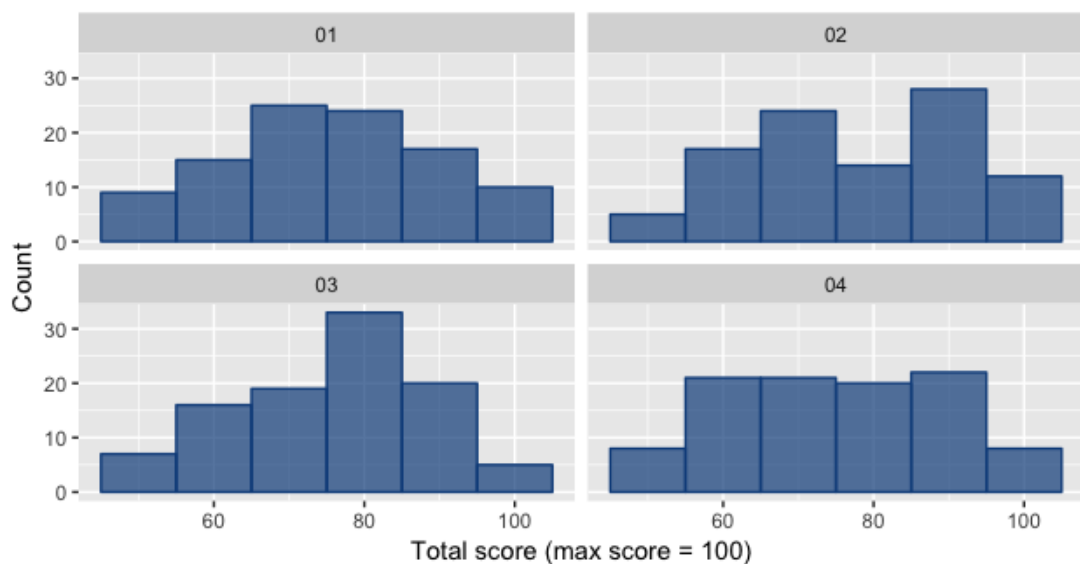


Figure 3.4: Quiz scores histogram. In this plot four quizzes are displayed. In the x-axis the score is showed and in the y-axis the frequency. The total population for this example is 100 students.

3.3.2 Boxplot of quizzes

Another way to verify the distribution and the skewness of the data is to analyze the boxplots of the scores. A useful aspect of these plots is that they allow you to detect outliers. This is important because the instructor can detect how many students are performing really bad or really good (depending on what kind of outlier is presented). Then he can analyze these points individually and see what topics are confusing for them.

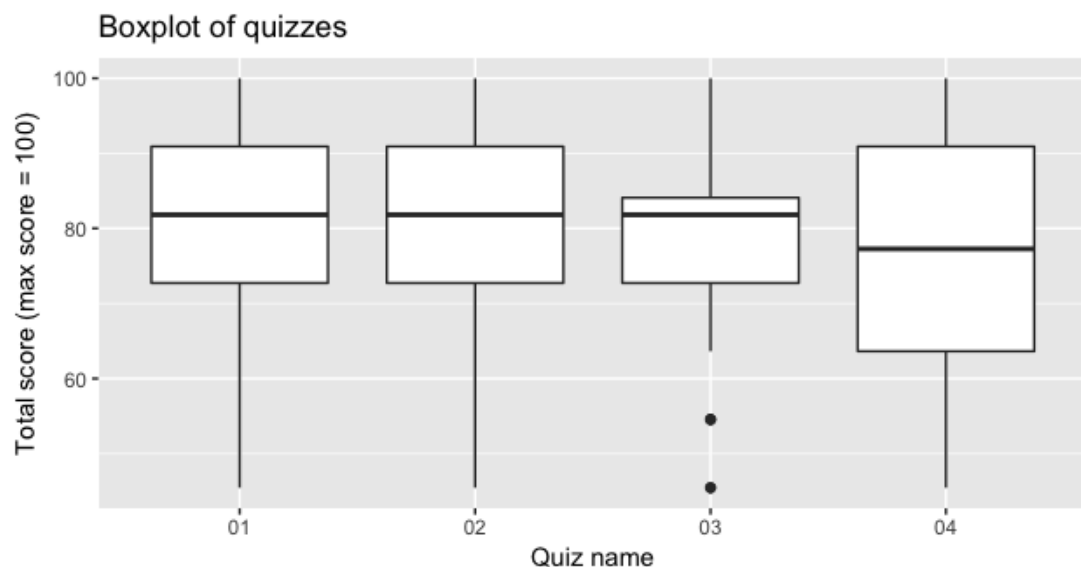


Figure 3.5: Quiz scores boxplot (Also called box and whiskers diagram). This plot display five different summary statistics: median, two whiskers and two hinges. In addition the plot display the outlier points.

The implemented boxplot in the ggplot2 package [5] is the Tukey boxplots³, which use the first and third quartile as the hinges and limit the length of the whiskers to 1.5 of the interquartile IQR length. For the upper whisker, if the value is greater than the maximum value of the data, then the whisker is reduced to this value (An equivalent rule apply for the lower whisker). If a point in the data is outside these ranges, then it is classified as an outlier.

For example, in the boxplot of the fig. 3.5 we can see that the lower whisker of the quiz 03 is much smaller than the other quizzes and, as seen in the histogram of the quiz 03, we can identify that this distribution has a much bigger mode than the other 3. As a consequence, the 50% of the data is contained in a smaller interval, which is reflected in its boxplot.

³Basically the other types of boxplots differ in the way that the whiskers are constructed.

3.3.3 Easiness-Time plot

The objective of the Easiness-Time plot (ET plot) is to analyze the relationship between the required time for each item versus the average score obtained in the corresponding item. In the quiz design it is important to consider the required time that each student should spend on each item, this way the instructor can design quizzes according to some pre-established time and discrimination criteria. With this plot, the instructor can analyze both points. If an item is requiring more time than the necessary and all the students get it correctly, then the spent time was effectively used by the students, but the although the discrimination level of the item is low, so the instructor should analyze the trade-off of this question. In addition a tendency line is displayed in the plot.⁴.

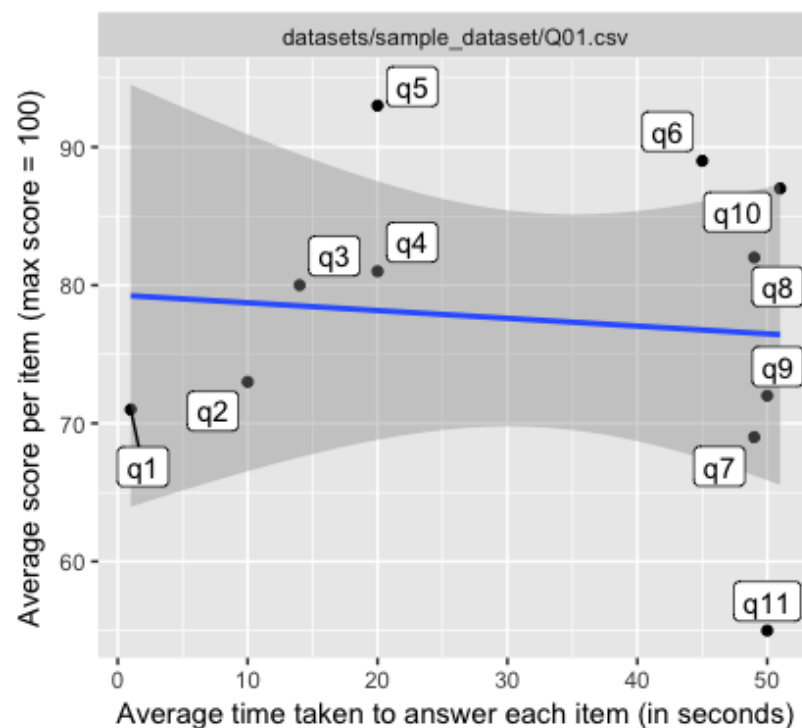


Figure 3.6: Easiness-Time plot

For example, in the fig. 3.6 we can see that question 5 is taking 20 seconds to answer (an intermediate time in this example), but the students achieve a high average score. On the other hand, the question 11 is taking too long for the students and many of them get it wrong. Then, the instructor can examine why the students are getting wrong the question (because it seems that it is not a matter of time).

⁴To avoid overlay in the labels of the points, the ggrepel package was used.

3.3.4 Easiness-Time-Level plot

The ETL plot adds the extra layer of the cognitive level to the ET plot. As stated in the beginning of the section, in this package we consider three different cognitive levels. The hypothesis is that difficult questions (in the sense of cognitive level) should take more time to answer than the easy ones. If we color the points by the cognitive level, we might see that the high cognitive levels take in average more time to answer them (because you need to know the concept, then apply it). Moreover, in questions that require a high cognitive level, the students may get a lower score. The reasoning behind this idea is that, if the students don't know the factual knowledge (Low cognitive level), they will not know the application of this concept (High cognitive level), so the score is lower.

The importance of this plot is to detect questions that have a strange behavior. For example, if a low cognitive level question is taking too long to be answered, it could mean that this question is being difficult to understand or that the topic in general is difficult for the students (For example, in fig. 3.7, the question 6 and 10). The option of open quiz book can change the perspective. If it is an open book quiz, then the student can spend more time and have correct the question (he did not know the answer, but he spent time learning it). But if a student spends some time, and gets the question incorrect, then it is a valuable information for the instructor or quiz designer.

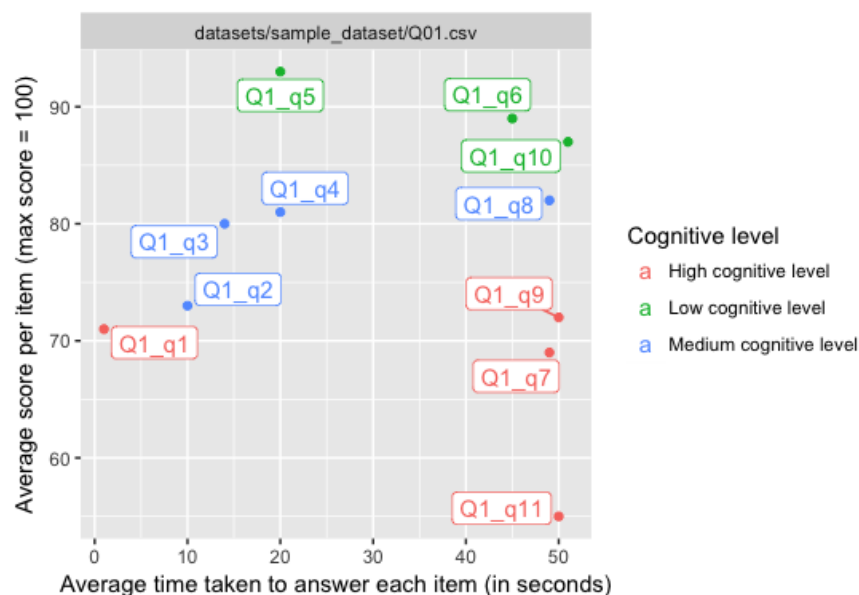


Figure 3.7: Easiness-Time-Level plot.

3.4 Individual plot

Finally, if the instructor detects some outlier in the group analysis, he can search for this particular student to see its performance in all the tests. This way, he can look for a specific way to support this student or group of students in order to avoid a possible failure. To explore and understand the history of these particular students, an individual history plot is implemented. For this plot the instructor needs to filter the required students from a list and then observe its history and scores in different quizzes.

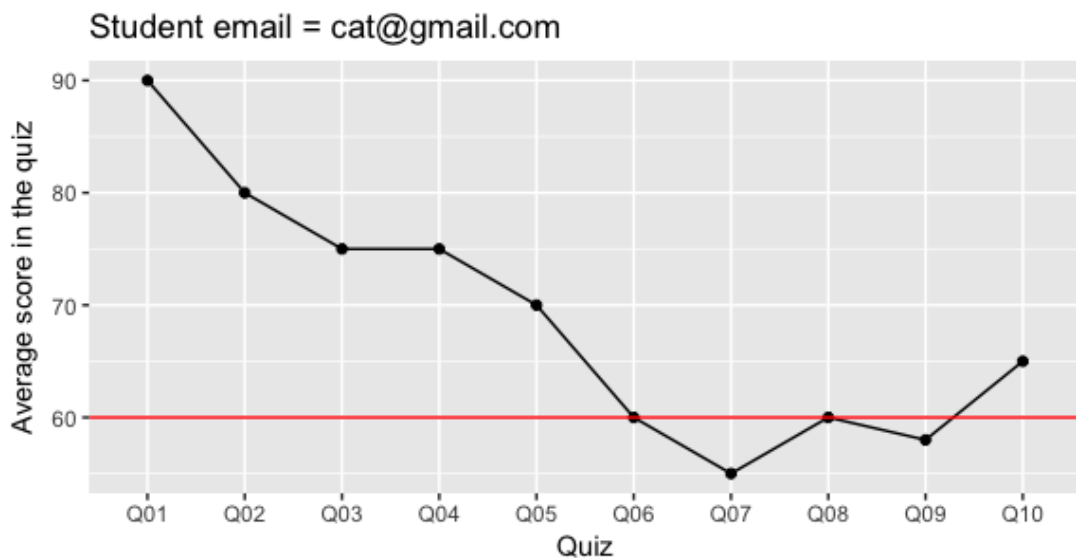


Figure 3.8: Individual performance

In addition, when the course finishes, the instructor can upload a file with the final grade of the students and observe distinct patterns that can lead to failure of the test. An example of this graph is in the fig. 3.8. We can see that this student is getting worse in his evaluations, so an opportune intervention can lead that this student approves the course of the final exam.

Chapter 4

Shiny interface

Right now the *lanalytics* package is freely available for all the R users. But for people that are not R users, an interface should be implemented. The option to do this was a Shiny dashboard [3] [1] containing the plots of the *lanalytics* package. Shiny was selected because it is native to R (although it is a wrapper for HTML and CSS code). Also it is designed to have the R console as backend (allowing to use any R package). The suggested dashboard contains five different tabs related to different aspects of the *lanalytics* package. The first tab only contains general instructions, the next two tabs are focused on importing and displaying the databases, while the last two tabs are focused on analyzing the data in three different aggregation levels. Furthermore, the last tab is used as an interface to the Rasch models of the eRm (extended Rasch model) package [2]. The usability of this Shiny Dashboard was evaluated with a focus group consisting of 3 people, but future evaluations with more people is imperative to make it usable for users in general.

4.1 Technologies for the dashboard

The interface of the *lanalytics* package was created with the *shiny* and *shinydashboard* packages, two web application frameworks that are native in R. There are three ways to connect to this dashboard: the first is to connect to the free service provided by RStudio in the website <http://www.shinyapps.io/>, although this is limited by a monthly quota. The second way is to host it in Github and run it locally with the command `runGitHub()` and the third way is to clone the repository and run it locally. Due to the quota restrictions, it is suggested to run locally the project. To do it correctly, some packages need to be pre-installed:

Table 4.1: My caption

Package	Usage
shiny	Provides the functions to create interactive applications.
shinydashboard	Build on top of shiny, provides a template for Dashboards.
DT	Provides useful functions to display tables and interact with them.
tidyverse	A collection of useful packages to analyze data.
stringr	A package to manipulate strings.
eRm	A package that implements extended Rasch models.
ggrepel	Functions to separate overlapping text labels.
devtools	Package with different tools for developers.

4.2 Design of the dashboard

Tab 1 and Tab 2: Instructions and import data tab

As mentioned, the lanalytics dashboard ¹ contains five tabs that group all the plots presented in section 3. In the *instructions* tab (the left image of the fig. 4.1) a brief introduction of the lanalytics package and general instructions for the dashboard are given. In the *import data* tab (The right side of the fig. 4.1) the all the data from quizzes files, cognitive levels file and final grade file can be uploaded.

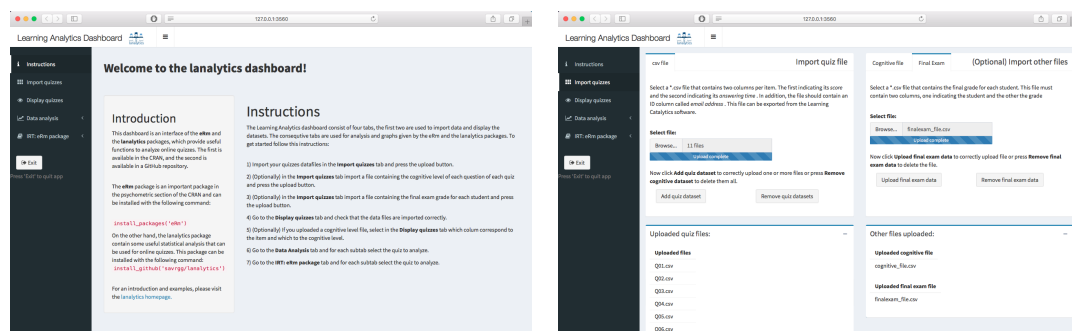


Figure 4.1: In image in the left shows the design of the *Instructions* tab. In the right the *import quizzes* tab is displayed.

¹In this section only small screenshots of the dashboard are displayed. Is it not intended to explore at detail each tab and instruction, just to give a general introduction to the dashboard

Tab 3: Display data tab

The next tab (*display data*) shows the uploaded datasets. It uses the DT package that is an interface to the DataTables library from JavaScript. In this tab the user can observe if the files were uploaded correctly and can filter different students or quizzes. The fig. 4.2 shows a small screenshot of the design of this tab.

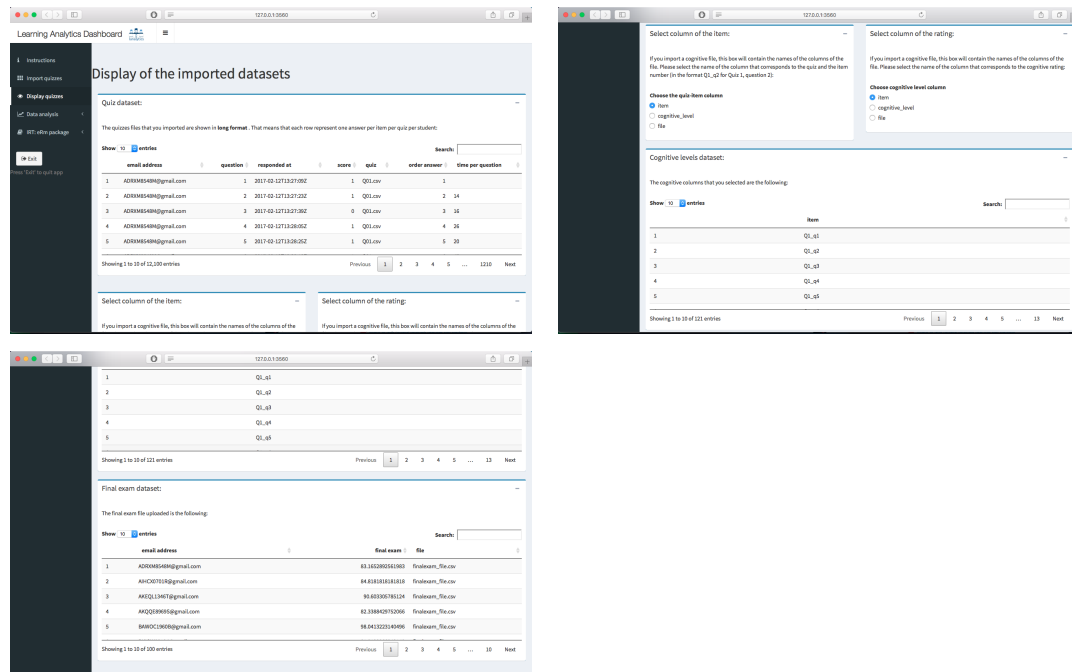


Figure 4.2: Design of the *Display quizz* tab.

Tab 4: Data analysis tab - Group analysis

When this tab is clicked it displays another three sub panels. Each one of these uses a different level of aggregation. In the group level analysis fig. 4.3, the user can filter the quiz he wants to analyze. Only one plot at a time can be displayed.

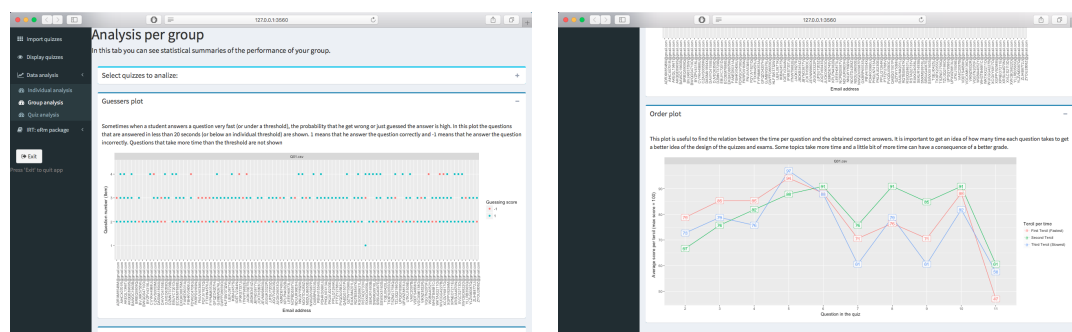


Figure 4.3: Design of the *Group analysis* tab. In the left the guessing plot is shown and in the right the easiness-time per quiz and tercils

Tab 4: Data analysis tab - Quiz analysis

In the same fourth tab, but in another sub panel the quiz analysis is displayed. In this, the boxplot, the histogram, the ET-plot and the ETL-plot are shown [fig. 4.4]. Additionally, multiple quizzes can be selected, but the user must be careful because if too many quizzes are selected, then it will take some time.

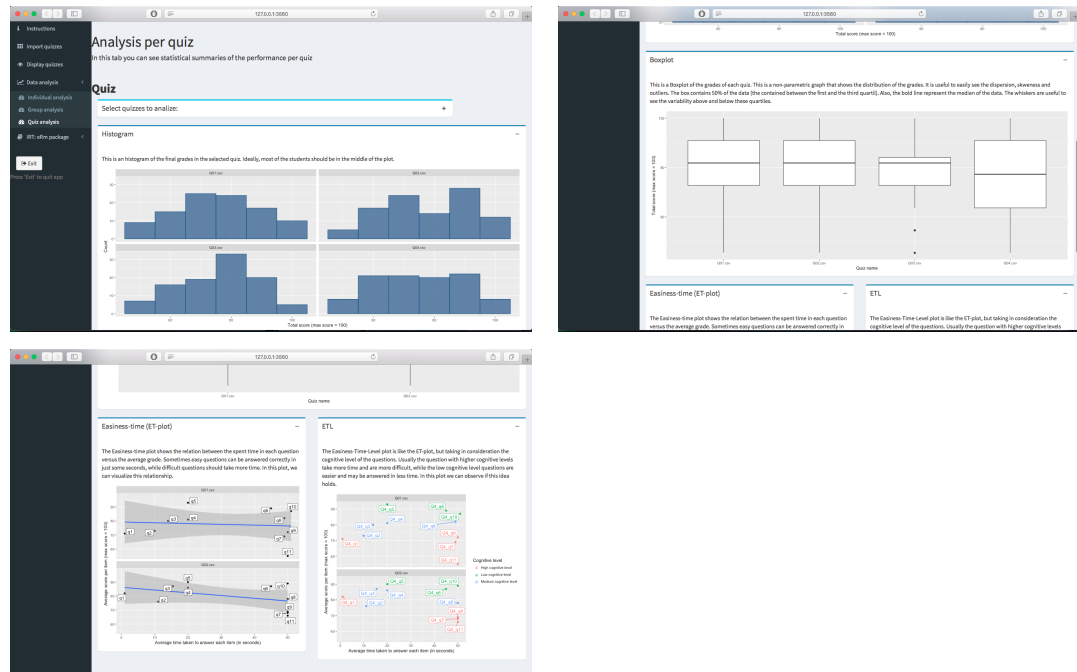


Figure 4.4: Design of the *Quiz analysis* tab. In the top left image the histograms are shown. In the top right the boxplot of four quizzes are shown and in the bottom left image the ET-plot and ETL-plot are displayed.

Tab 4: Data analysis tab - Individual analysis

In another sub panel of the fourth tab the individual analysis is displayed [fig. 4.5]. Here the user can filter a specific student and see its records.

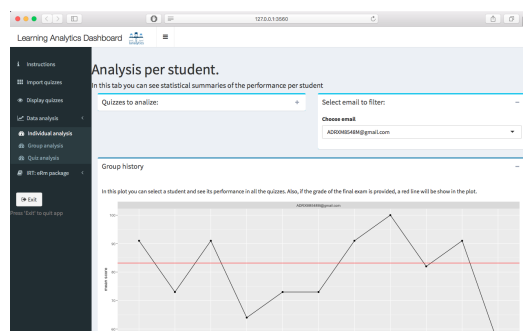


Figure 4.5: Design of the *Individual analysis* tab.

Tab 5: Rasch model

This is the last tab in the dashboard [fig. 4.6]. Different plots derived from the Rasch model can be visualized (Item Characteristic Curve, Person-Parameter plot and Item-Person map). In addition, the user can easily see the estimations of both person and item parameters. This way, he can compare them and get a conclusion.

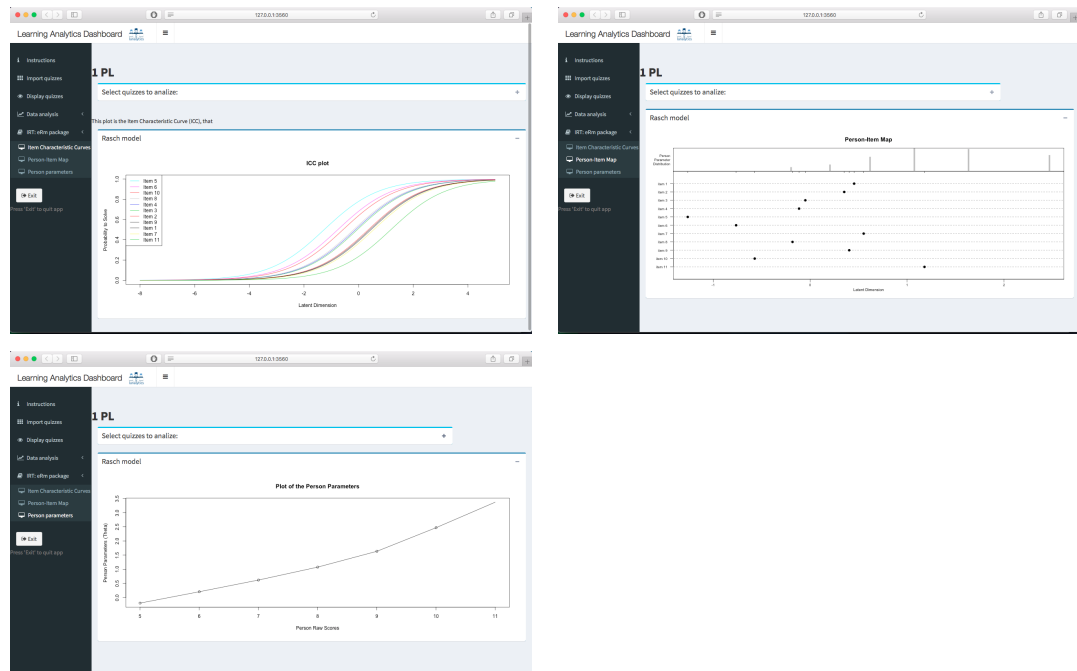


Figure 4.6: Design of the *Rasch model* tab. The top left image shows the ICC, the top right the person-item map and the bottom left the person parameter.

4.3 Syntethic dataset

To test the usability of the first version of the lanalytics package and dashboard, a synthetic dataset was created. This dataset consists of 12 quiz data files, 1 file for the cognitive levels and 1 file containing the final grades of the students. These were specially designed to show some specific patterns in the plots, so in this section the dataset will be described.

To generate the 100 email users a 10-character string was randomly generated, then each of these students was assigned to one of three groups (thinking of subpopulations inside the same group; for example, students that usually get high scores, students that get medium scores and students that get low scores). Then, for each email, 12 quizzes with 11 question each were generated.

Now, the probability of obtaining the right answer for each question was distributed as a Bernoulli distribution with distinct probability according to the group that the user belongs (of the three groups randomly generated). The table 4.2 states the exact probabilities for each subpopulation and item.

Table 4.2: Probability to get correct the answer

Item	High skilled students	Medium skilled students	Low skilled students
1	0.83	0.73	0.63
2	0.85	0.75	0.65
3	0.90	0.80	0.70
4	0.95	0.85	0.75
5	0.95	0.90	0.80
6	0.70	0.65	0.60
7	0.70	0.65	0.60
8	0.95	0.85	0.75
9	0.85	0.80	0.70
10	0.85	0.85	0.85
11	0.70	0.60	0.50

Now, for the answering time per question, two assumptions were taken. The first is that the date for any answer of quiz 1 might be answered before of the date of any question of quiz 2 and so on. To ensure this, each quiz was in different months. Now, for the answering time of the questions in the same quiz, it was assumed that the students answered the quiz in order and in a continuous consecutive interval of time. Then, if we calculate the time difference between the two questions, it would represent the spent time in the question. To create this synthetic variable, a normal distribution with different mean and standard deviation was used.

The final exam file was generated with the same users as the quizzes files and the final grade was normally distributed with center in the student mean score of the quizzes. Finally, the cognitive file was generated based on the probabilities of getting correct a question table 4.2. This way, the items that were easier would have a cognitive level of 1 (the easiest one) and consecutively until the cognitive level 3.

4.4 Evaluation: Focus group

As stated in previous chapters, the Learning Analytics Software was created with two principal objectives. The first is to monitor the performance of the students in different levels: individual, per quiz and per group. The second is to ease the understanding of the items in online quizzes in order to improve the design of future quiz items². These two objectives were evaluated with a focus group that consisted of 3 persons working with online quizzes and interested in learning analytics topics.

The general structure of the focus group consists of two big sections of 30 minutes each. The first was a general introduction to the Learning Analytics objectives, the implemented models and its capabilities. During this section a sheet of paper with a series of questions related to objective accomplishment was provided. The second 30 minutes of the focus group consisted of a user interface evaluation. 10 tasks were given and the participants had to evaluate some affirmations.

4.4.1 Introduction of the software (30 minutes)

This section of the focus group was divided into two parts, one of 10 minutes and the other of 20 minutes. The first part was used to introduce the capabilities of R and Shiny in order to motivate future uses and further implementations. The second part consisted of an introduction of the Learning Analytics Package objectives and its Shiny interface. In this phase the motivation of the models and the generated plots were explained.

As part of the evaluation five questions were asked in a sheet of paper for each of the participants. The objective was to discuss if the presented models were consistent with the objectives. The list of the five questions presented are the following:

- Do the shown figures in the **Individual analysis** help you to monitor how an individual student is performing? What else would you like to understand about the student?
- Do the shown figures in the **Group analysis** help you to monitor how the group is performing? What else would you like to understand about the group?
- Do the shown figures in the **Quiz analysis** help you to understand the difficulty of the items as well as the required time per quiz? What are the main points that you consider when designing an item of a quiz?

²The second objective is focused on the understanding of the Item Response Theory.

- The **Rasch model** helps you to understand the easiness-difficulty of your items?
- The Rasch model plots (**ICC, Person-Item, Person-parameter**) gave you actionable information to improve the design of your quizzes?

4.4.2 User experience evaluation (30 minutes)

Once the presentation of the software was concluded, the synthetic dataset was provided and a 20 minutes user experience evaluation started. In this part, the users had 10 tasks to accomplish [table 4.3], with the central objective to evaluate the usability of the dashboard. In particular, they had to evaluate the easiness of the instructions as well as the easiness of the elements in the dashboard.

Table 4.3: Tasks to accomplish

Tab	Task
Import quizzes tab	Upload the quizzes files
Import quizzes tab	Upload the cognitive file and the final exam file
Import quizzes tab	Remove the cognitive file and upload it again
Display quizzes tab	View if the uploaded files are correct
Display quizzes tab	Select the Item and the Cognitive level column for the cognitive file.
Individual Analysis tab	Search one student and view its grades.
Group Analysis tab	Select one quiz and view the guessers and order plot
Quiz Analysis tab	Observe the histogram and boxplot.
Quiz Analysis tab	Observe the ET and ETL plot. Do you see some pattern with the cognitive level?
eRm package tab	Select one file and view the ICC, the person item map and the person, parameters plot.

To measure the usability of the dashboard, some affirmations were given and the users have to agree with them according to a Likert scale (1 = Strongly disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly agree) [table 4.4].

Table 4.4: Likert evaluations

Tab	Question	SD	D	N	A	SA
Import Quizzes	It is easy to upload files.	1	2	3	4	5
Import Quizzes	It is easy to remove files.	1	2	3	4	5
Import Quizzes	It is clear when a file is uploaded.	1	2	3	4	5
Import Quizzes	It is clear when a file is removed.	1	2	3	4	5
Display quizzes	It is clear the format of the quizzes.	1	2	3	4	5
Display quizzes	It is clear how to select the columns of the cognitive file.	1	2	3	4	5
Individual	It is easy to search for an student email.	1	2	3	4	5
Individual	It is easy to visualize which quiz is displayed in the plot.	1	2	3	4	5
Individual	The plot is easy to read.	1	2	3	4	5
Group	It is easy to visualize which quiz is displayed in the plot.	1	2	3	4	5
Group	It is easy to identify possible guessing or cheating misconducts.	1	2	3	4	5
Group	It is easy to understand the relation of time per question versus the grade.	1	2	3	4	5
Quiz	It is easy to visualize which quiz is displayed in the plot.	1	2	3	4	5
Quiz	It is easy to interpret the histogram and boxplot.	1	2	3	4	5
Quiz	The ET and ETL plots are easy to interpret.	1	2	3	4	5
eRm	The Item Characteristic Curve is easily understandable.	1	2	3	4	5
eRm	The person-item plot is easily understandable.	1	2	3	4	5
eRm	The person parameters are easily understandable	1	2	3	4	5

After this, some general perceptions of the dashboard were asked (in the same likert scale) table 4.5.

Table 4.5: Likert evaluations

Tab	Question	SD	D	N	A	SA
General	In general the models agree with the general objectives	1	2	3	4	5
General	In general it is easy to use the buttons.	1	2	3	4	5
General	In general it is easy to navigate between tabs.	1	2	3	4	5
General	In general the colors of the dashboard are adequate.	1	2	3	4	5
General	In general the instructions are clear.	1	2	3	4	5

Finally, in the last section of the focus group, a final round of 10 minutes of open commentaries and suggestions was made. The objective of this final round was to provide a guideline for future work based on the different necessities of the users.

4.5 Results

In general, the qualitative result from this focus group was favorable for the package, just minor issues and further capabilities were suggested. Concerning the user interface, it needs to be improved in order to make it user-friendly and suitable for all kinds of audiences. More detailed areas of improvement are:

Table 4.6: My caption

Analysis	Ideas to improve
Individual analysis	- Allow the user to display multiple students in the same plot
Group analysis	- Include a plot indicating the group average score in all quizzes (not only by tercils)
Rasch model	- Needs better explanation to make interpretable and actionable the results.

Now, we can see the Likert evaluation of the tasks in the fig. 4.7. It is important to say that only 3 people were in the focus group, so the confidence interval that is displayed is only to show the variability for these persons.



Figure 4.7: Evaluations in likert scale with a confidence interval of 1.5 standard deviation. Only 3 persons were in the focus group, then the lines are only for reference.

From these evaluations and the commentaries from the focus group we can conclude four main points:

- In terms of the content in the plots, these display good and useful information
- There are some minor issues with the dashboard usability that can be improved
- The rasch model should be explained in a more detailed way
- The instructions should be more clear and detailed

By analyzing the qualitative and the Likert evaluations, we can give more detailed areas of improvement. Concerning the *lanalytics* package, the majority of the plots were useful, but some suggestions were given to improve them. Some of them were as put some filters or additional characteristics, like being able to display more students in the same graph.

For the user interface evaluations, useful insights were given. There are tabs where it is not intuitive what to do (in special the box related to the cognitive file import and the buttons to upload files) and some instructions are not clear.

For the third point, the Rasch model is a complex topic that should be explained in a much more detailed way. Currently, the instructions given in this section are not enough. Also, there should be more examples and interpretation of the parameters.

The fourth is the one that can improve a lot. It was suggested that the instructions should be more clear and explicit. Also they suggested that there should be one button that displays more detailed instructions and information. In addition it was suggested that a native English speaker proofread the dashboard in order to make the instructions clearer.

Chapter 5

Conclusions

Before the a public realease of the dashboard, more usability test should be done

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