

Teaching Data Science to Students in Biology using R, RStudio and Learnr: Analysis of Three years Data

1 Abstract

This is the original abstract that should be reworked according to final content of the manuscript.

The courses in biostatistics in biology at the University of Mons, Belgium, were completely refactored in 2018 into data science courses (see <http://bds.sciviews.org>). The content is expanded beyond statistics to include computing tools, version management, reproducible analyses, critical thinking and open data. Flipped classroom approach is used. Students learn with the online material and they apply the concepts on individual and group projects using a preconfigured virtual machine with R and RStudio. Activities (H5P, learnr or Shiny applications) are recorded in a MongoDB database (300,000+ events for 180+ students and 2,000+ GitHub repositories at <https://github.com/BioDataScience-Course>). The analysis of these data reveals several trends. (1) There is a relatively long lag period required for the students to get used to the computing environment, the teaching method and the data science in general. (2) Implication is very high, with more than 85% of the students that complete all the activities and got good to excellent assessment. (3) There is a gap between students' own perception of their skills achievements and their assessment results: they tend to underestimate their progress. (4) During COVID-19 pandemic lockdown, the intensity of the activities largely decreased during two weeks before returning to previous level, but for 3/4 of the students only. The remaining fraction never caught up. We hypothesize that the technical requirements or the lack of motivation during the lockdown were detrimental to roughly one student over ten, despite all the efforts the University deployed to reduce the social fracture.

2 Introduction

In a context where there is an exponentially growing mass of data (Marx 2013), a reproducibility crisis in Science (Baker 2016), and a progressive adoption of Open Science practices (Banks et al. 2019), statistics were broaden to a larger discipline called Data Science. For the Data Science association, “the Data Science means the scientific study of the creation, validation and transformation of data to create meaning” (<http://www.datascienceassn.org/code-of-conduct.html>). These changes also led to the emergence of data science programs in universities and higher schools (Donoho 2017; Çetinkaya-Rundel and Ellison 2021). One example is the Harvard Data Science initiative (<https://datascience.harvard.edu/about>) initiated in 2017. With a broader approach, comes also a broaden public. The data science courses are not just limited to computer scientists, mathematicians or statisticians, but also welcome students in humanities, social sciences, and natural sciences (for instance, the data science training at Duke University (Çetinkaya-Rundel and Ellison 2021)). Main focus of such courses is for students to develop the ability to deal with “real” datasets in all their complexities and to realize reproducible analyses to interpret these data in the light of knowledge in their field of expertise.

The data transformation part of the job is a challenge for students with a poor or no background at all in computing. Students that are not used to deal with computer languages enter in a foreign world and have to deal with many exotic concepts, techniques and tools. This is the same for the analysis of these data when students have no background in mathematics or statistics. It generates anxiety (see for instance (Onwuegbuzie and Wilson 2003), for students in biology). The course must be organized in a way that such students progress by little steps in order to avoid exposition to much intimidating concepts and tools at once. Hence, a student in computing science already masters one or more computing languages, is acquainted with

version control systems, with databases and with the way data are represented in a computer. A student in mathematics or statistics is familiar with various concept that underpin the techniques to analyse the data. On the other hand, students in biology, medicine, psychology, social sciences, economics, ... have very different *a priori* knowledges. Version control systems like git, and their internet hosting counterparts like GitHub, Gitlab or Bitbucket also make part of the tools that data science course teach and use (Fiksel et al. 2019; Hsing and Gennarelli 2019). Presentation of the results and the use of documents formats that dissociate content from presentation, namely LaTeX, Jupyter Notebook, or R Markdown also contribute to the large number of potentially new tools students have to learn (Baumer et al. 2014).

Suitable computer hardware and software environments are required in the practical sessions of the courses. Different approaches range from inline software (RStudio Cloud (<https://rstudio.cloud/>), Chromebook data science (<http://jhudatasience.org/chromebookdatasience/>)) to local installation on the Student's computers. The former requires an infrastructure to run the software on a server, nad that software is only accessible to the students during the course. The later raises problems of license for proprietary software, but also installation and configuration issues. An intermediary solution uses preconfigured virtual machines, or containers (e.g., Docker) (Çetinkaya-Rundel and Rundel 2018 ; Boettiger 2015). Such a solution is the most flexible because it can be deployed almost anywhere (in the computer lab, at home, using a laptop, ...). To fix theoretical concepts through applied exercises is a key aspect of learning data science (Larwin and Larwin 2011). Correct choice of software is critical and exposing students early with the tools they are most susceptible to use later in their work is desirable. This was highlighted by (Auken and Barthelmess 2020) for instance, for the analysis of ecological data.

These data science courses pose several challenges to pedagogy because various, numerous and unfamiliar concepts must be acquired by a population of potentially very diverse students. Learning objectives span a large range of cognitive abilities (Krathwohl 2002). [We need to develop here things like flipped classroom, continuous evaluation, pedagogy by projects, and inclusive pedagogy]. The flipped classroom approach allows students to be active in their learning, which has the benefit of improving student outcomes (Freeman et al. 2014).

[Partie pédagogie à détailler un peu, probablement sur 2 ou 3 paragraphes]

Recently, data science is also used to analyze the effect of different pedagogical practices on the outcome of these courses [Estrellado et al. (2020); second ref to add]. A vast amount of data can be collected on students activities, and the analysis of these data allows to compare the impact of different pedagogical approaches, or to quantify and document the impact of changes in the courses.

At the University of Mons in Belgium, we have started to rework our biostatistics courses in the biology curriculum in 2018. A series of Data Science courses were introduced, both for our undergraduate and graduate students. These courses are inspired from precursor initiatives cited here above. The goal of these courses is to form biological data scientists capable to extract meaningful information from raw biological data, and to do so in a reproducible way, with correct application of statistical tools and an adequate critical mindset. A preconfigured VirtualBox virtual machine with R, RStudio, Rmarkdown, git, and a series of R packages preinstalled is used (url sciviews box?) as a very flexible way to deploy the same software environment both on the university computers and on student's own laptops.

As our course were completely reworked, we also decided to use flipped classroom and progressive adoption of suitable pedagogical practices with a cyclical approach that consists in stating goals, building pedagogical material with a large emphasis on numerical tools and collection of student's activities, and finally, analysis of the data collected. Conclusions of these analyses initiate another cycle the following academic year with refined goals and pedagogical materials and techniques. Here, we present the main results spanning on three successive academic years from 2018 to 2021, including two particular periods where distance learning was forced due to COVID pandemic lockdown.

[TODO: present here the 3-4 research questions that will be elaborated in the manuscript.]

- examen final versus évaluation de projet
- profils d'étudiants.

- timing et support présentiel - distanciel.
- charge cognitive learnr

3 Methods

The course materials are available online (<https://wp.sciviews.org>) and are centralized in a Wordpress site. Students have to login with their GitHub account and their academic data are collected from the UMONS Moodle server. The courses are break down into modules that amount roughly to 15h of work each in total. There are two sessions of 2h and 4h in the classroom (outside of lockdown periods, of course). Main activities in the class are actual data analysis (projects), answering student questions, and very sort lectures of 1/4h on selected topics. Students propose and vote for the topics to be covered during these short lectures. Finally, we encourage students to help each other and to explain what they understand to their colleagues. Indeed, students' questions may be redirected to other students that have already mastered the topic by the educators. On the other hand, teachers rarely answer questions directly. When it is possible, they rather propose new tracks or ideas to investigate in order to find the solution by oneself. Students that have finished the work before the others are encouraged to help their colleagues too.

Regarding the timing, one module is taught every second week so that students have enough time to prepare the material at home and then, to finalize their projects before the next module. Since a term is 14 weeks, we do not teach more than six modules in a course unit to avoid compacting them in time at a faster pace than one module every second week.

All student activities in H5P exercises for their auto-evaluation, and in learnr tutorials to transition smoothly from the theory to the practice are recorded in the MongoDB database. The `learnitdown` R package (<https://www.sciviews.org/learnitdown/>) provides the functions required to manage user login, user identification and activity tracking in the interactive material.

Projects with the data, the analyses and the reports are hosted in GitHub repositories. These repositories are cloned and edited locally with RStudio, either on a PC in the computer lab, or directly on the student's laptop. We encourage our students to install the virtual machine on their own computer so that they can use it for other courses too. Assignment and creation of the GitHub repositories for each student, or group of students is orchestrated with GitHub Classroom. All repositories are ultimately cloned in a centralized area on our servers and data about commits (git logs) are collected using git version [XXX] and R version 4.0.5. To give an idea of the amount of data recorded, in 2020-2021 we have a little bit more than 2,500 events per student.

In distance learning, support to the students was done via email and Discord. At the end, all messages that were exchanged are collected together into text files. These files are scraped using R code to create a table with key information (basically, who, when, and what) for each message. Surveys are periodically conducted during lessons by means of Wooclap questionnaires (see, for instance, the Nasa-LTX questionnaire analysis in the results section). Wooclap allows to export data into Excel files. These data are then converted into a table in our database.

Information about users, courses, lessons and projects, as well as grading items (on average, more than 130 grading items were established for each student in 2020-2021) are anonymized: name, email and all the personal information are replaced by random identifiers. The different tables are ultimately exported into CSV files and made public. These data are available at [... Zenodo?]. Data collection, treatment, and use respect European GDPR (General Data Protection Regulation) since each student had to agree explicitly with the way data are collected and used (including for research purpose) before the course begins. They can visualize their own data through personalized reports at anytime.

The course material is organized in a way that favours autonomy and auto-evaluation (direct feedback in the exercises, hints and retry button in case of wrong answer). Activities span into a sequence of exercises of increasing difficulty, ranging from Level 1 to level 4. Table 1 summarizes main characteristics of the exercises according to the level.

Table 1: for levels of increasing difficulties in the exercises.

Level	Description	Type
L1	Short exercise directly integrated in the course and with direct feedback for auto-evaluation	h5p
L2	Guided exercise with contextual feedback within a short tutorial	learnr
L3	Individual and guided data analysis	individual project
L4	More complex and free data analysis and reporting (group of 2 or 4 students)	group project

[one or two paragraphs to describe statistical methods used here...]

The NASA-LTX questionnaire is composed of six questions on a Likert scale to quantify the perceived workload to complete a task (Hart and Staveland 1988). The questions concern mental load, physical load, time pressure, expected success, effort required, and frustration experienced during the accomplishment of the task. The average value for the six questions constitutes a Raw Task Load index (RTLX) (Byers, Bittner, and Hill 1989) that we use to quantify how students perceive the workload of a given task.

4 Results

In all our three courses in biological data science, practice is the most important activity. Our goal is to ensure that our students are able to analyse all kind of real datasets, using the right techniques and with a critical mind. They also learn how to write these analyses by using R and R Markdown to create reproducible reports managed under version control (git). There are several critical stages:

- Once they have learnt the principles in the book and auto-evaluated their comprehension of the concepts using H5P exercises (level 1 difficulty), they have to get used to the software environment. Learnr tutorials (level 2) are used to gently introduce them to the R code required for the analyses by guiding them through their first data analysis. These tutorials are thus the entry point for the practice. We assess here the perceived workload of these tutorials to make sure they engage the students without exhausting them.
- Projects, but individual (level 3) and in group of 2 to 4 students (level 4) represent the core activity. Evaluation of these projects constitute, thus, the core information to assess the competences of our students. However, an exam at the end of the course is a common practice. So, we compare grading our students obtain from such an exam with score they obtain directly in their projects. The final exam is written in learnr, and it mixes questions about the theory with partly solved data analyses they have to explain, criticize and continue during the exam session.
- Despite we have relatively homogeneous classes of students with similarly (low) level of knowledge for statistics and computing at the beginning, the flipped class approach and the proactive attitude they have to develop (they must formulate their questions whenever they face a problem), we observe they develop very different strategies. Not all students ask questions. Some of them try to find solutions on their own. Some other prefer to ask their questions in private, while others have no problems to expose their difficulties on a public forum (a Discord channel for the course). The way and the timing they progress in the exercises also largely varies. The schedule is not tight and only suggest the rhythm of progression. No student is penalized if the exercises are done later, as soon as they are completed before the final deadline. Some strategies are more efficient than others. We analyse traces from the student activities to separate the different profile and we correlated them with the grade they obtain at the end of the course.
- Finally, lockdown was imposed relatively abruptly and may interfere with the learning strategies they have developed. We analyse whether the switch to face-to-face activities to distance teaching and back has an impact on their productivity.

This study is performed all along the three courses that comprise 26 modules in total in 2020-2021. Table XXX summarizes the number of H5P, learnr, individual and group GitHub projects that students have to complete. It should be noted that for course C, we also introduced a challenge in machine learning that replaced one group GitHub project.

Table 2: Number of students, modules, and exercises for each course. For the learnr tutorials, the first number is the amount of tutorial documents and the second number in parentheses is the total number of questions in these tutorials.

Course	Students	Modules	H5P	Learnr	Indiv. projects	Group projects
A	59	12	59	24 (211)	10	4
B	45	8	29	11 (108)	12	2
C	26	6	19	7 (37)	7	1

4.1 Perceived cognitive workload in learnr tutorials

In our courses, learnr tutorials play an essential role in the progressive acquisition of competences because they are at the transition between the theory (online book chapters) and the practice (projects where student analyse real biological data by themselves). Our goal is to prepare our students optimally for the practice of data science. In the other hand, we don't want to exhaust their mental energy in these tutorials before they start their projects. The efficiency of these tutorials is qualitatively determined by observing the behaviour of the students when they start their practical work.

A few tutorials were elaborated during the academic year 2018-2019, and positive feedback on their utility (both by direct observation of the pupils, and by their remarks) led us to systematize them into what we now call level 2 activities (see Table XX) in the form of learnr documents in 2019-2020. The tutorials were further refined in 2020-2021: we added contextual hints thanks to the gradethis R package. When students submit their answer to the exercises, the R code is analysed and the results are compared with the solution. In case of differences, heuristics are used to provide contextual hints. Students can then refine their solution and resubmit it. This appears very efficient in self-teaching and self-evaluation of their competences before switching to the practice. However, the cognitive load required to perform these exercises has, as far as we know, not been studied yet. We used a NASA LTX questionnaire to assess it across all three courses. Participation was 48/59 (81%), 35/45 (78%) and 18/26 (69%) for courses A, B, and C respectively.

The difficulty of the course, and thus, of the exercises in the tutorials increase from one course to the other. However, we do not observe an increase in the RTLX index. On the contrary, it is significantly lower for course C than for course A (Tukey HSD, p-value = 0.023) TODO: INCOMPLETE REFERENCE FOR THE TEST (MUST INDICATE ANOVA RESULTS FIRST!). The cognitive load perceived by the students diminishes. This may be a consequence of a more fluent R coding and the better mastering of the software environment.

```
## Analysis of Variance Table
##
## Response: rtlx
##           Df Sum Sq Mean Sq F value Pr(>F)
## course      2   926.9   463.47   3.5883 0.03134 *
## Residuals 98 12658.0   129.16
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Simultaneous Tests for General Linear Hypotheses
##
## Multiple Comparisons of Means: Tukey Contrasts
```

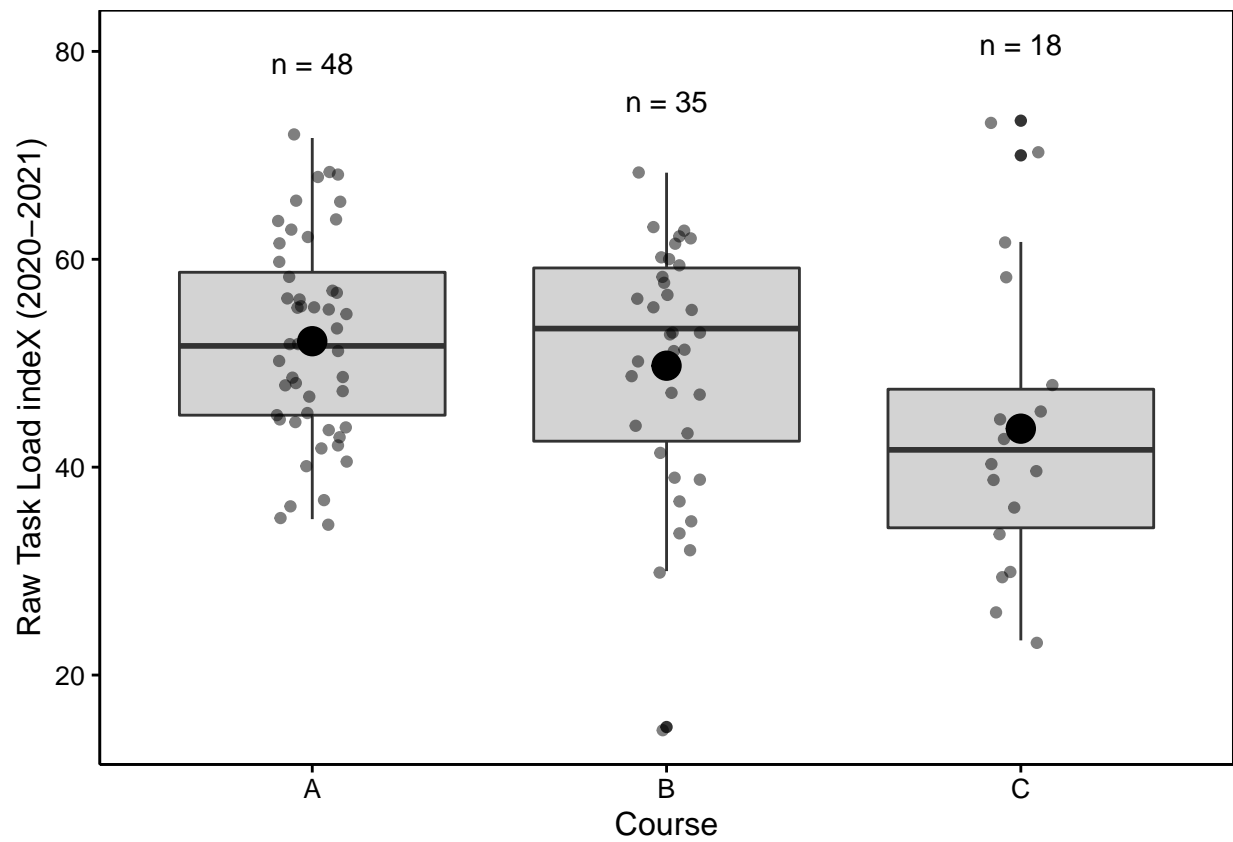


Figure 1: Perceived workload for the learnr tutorials in the three courses. The black circle is the mean RTLX value. The number above each box is the number of respondents.

```
##
##
## Fit: lm(formula = rtlx ~ course, data = workload_rtlx)
##
## Linear Hypotheses:
##           Estimate Std. Error t value Pr(>|t|)
## A - B == 0      2.356      2.526   0.933  0.6183
## C - B == 0     -6.058      3.296  -1.838  0.1607
## C - A == 0     -8.414      3.141  -2.679  0.0229 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## (Adjusted p values reported -- single-step method)
```

4.2 Final exam *versus* project

In 2018-2019 and 2019-2020, the evaluation was based on the completion of a project and on a more conventional examination at the end of the term. [describe a little bit the questions in the exams as being focused on the practice].

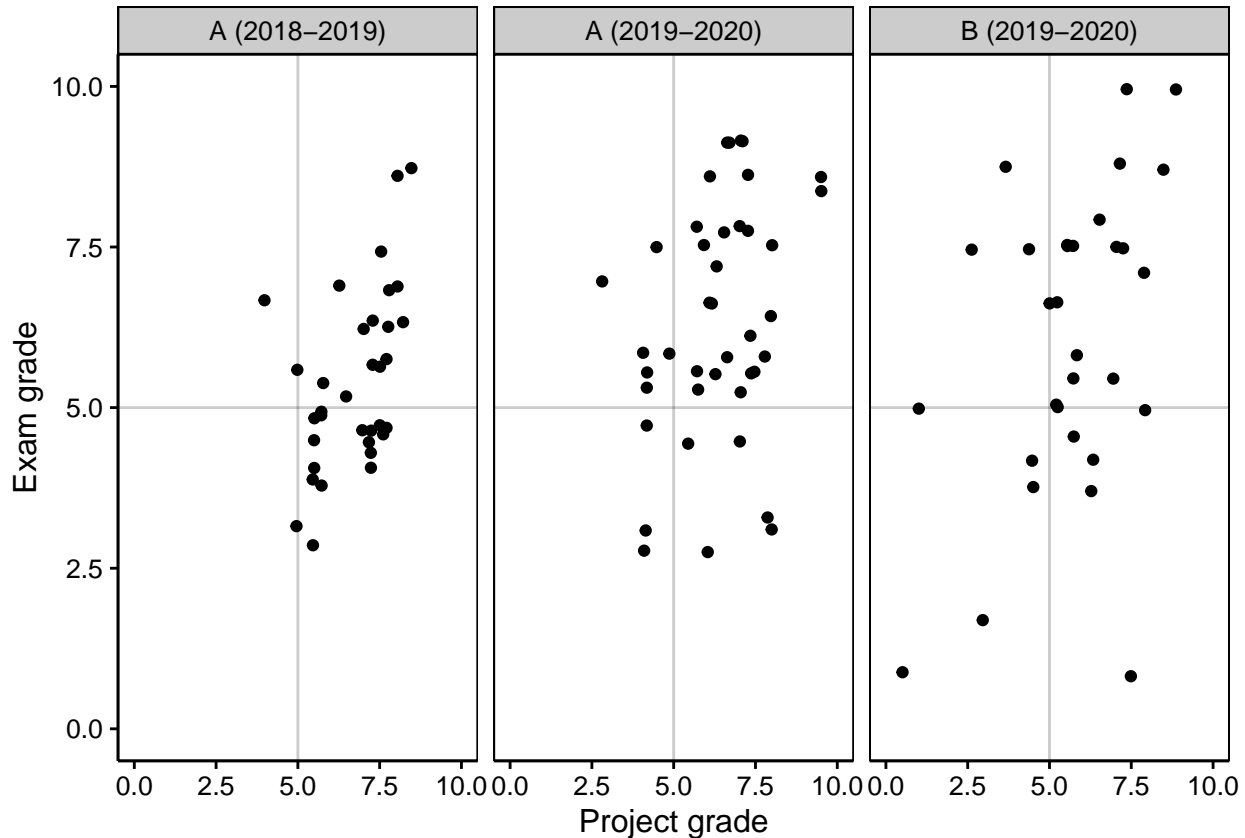


Figure 2: Grade (/10) obtained at the final exam in function of grade obtained for the projects for courses A and B (two successive years for A).

The comparison of the marks obtained by each student for a project and a final exam shows only a weak correlation between these two types of evaluations. Year 2018-2019 marks the transition to our flipped classroom approach in teaching data science. Only one student failed in the project, while almost one third of the students failed their final exams. In 2019-2020, we raised a little bit the difficulty for the project, resulting in a more widespread distribution of the results, but with a similar pattern showing very little

correlation between the two evaluation methods. The same conclusion can be drawn for course B.

Despite a final examination that includes a series of practical questions (writing R code to analyse data, as in the projects), this type of assessment does not reflect the ability of the students to correctly process and analyse biological data. Following these results, the final examination is abandoned for the year 2020-2021, and it is replaced by a continuous evaluation of the students' activity across all four level exercises (H5P, learnr, individual and group projects). These activities are analysed in the following section.

4.3 Students profiles

In 2020-2021, the course material is enriched with exercises organized into four increasing difficulty levels, as presented in Table XXX. The activity of the students in the level 1 (H5P) and 2 (learnr) exercises is directly recorded in a database. For the GitHub projects (levels 3 and 4 exercises), it is the git log data that are analyzed. During lockdown periods, exchange with the students and answers to their questions were exclusively done by email, text or voice messages on Discord, either on private or public channels. Students were allowed to freely choose their favourite way to interact with the teachers, and with each other. All these exchanges were recorded too. Finally, traces in all activities were used to establish the final grade for the course. Final grade is the weighted average of the scores obtained at all four levels. The weight was adjusted from course to course according to the importance of the different projects, mainly. To give an idea, for course A second term, level 1 H5P exercises accounted for 5%, 10% for level 2 learnr tutorials, 35% for level 3 individual projects and 40% for level 4 group works. On average, each student received more than 130 assessments that accounted for the final grade. Two thirds of these assessments were determined manually, using evaluation grids, on their projects. The other third are scores automatically calculated from the various online exercises.

For the three courses, we recorded a total of more than 450,000 events, which makes on average, almost 3,500 events for each student. These data are summarized into sixteen metrics.

For H5P exercises: - trials/H5P ex.: the average number of trials for each H5P exercise (students can retry as much as they wish), - correct H5P ex.: the fraction of H5P exercises that were correctly answered,

For learnr tutorial exercises:

- trials/learnr ex.: the average number of trials for each learnr exercise (here also, students can retry as much as they want),
- hints/learnr ex.: in learnr exercises, students can display hints to help them to solve the problems (but they lose 10% of the score of the exercise for each hint). This is the average number of hints per exercise that were displayed,
- correct learnr ex.: the fraction of learnr exercises that were completed with a correct answer,
- time/learnr ex.: the average time required to finish one learnr exercise involving R code writing.

For individual and group projects:

- commits / ind. projects: the average number of commits done by a student in one individual project,
- contributions/ind. projects: the number of lines changed (added or subtracted) in a .Rmd file, an R Markdown report by one student in one individual project, on average,
- commits / group projects: same as above, but for group projects,
- contributions/group projects: same as above, but for group projects,
- percentage of contribution to group projects: the fraction of work the student did, relative to all the work done in group projects (still only counted for .Rmd files).

For support:

- questions/module: the number of questions student asked in total, divided by the number of modules in the course,
- percent of public question: the fraction of questions that the student posted in a public channel (a channel dedicated to the course that all the student can read),

- contributions/question: a metric that catches the relative “productivity” of the student related to the number of questions they ask. A high value could mean lot of production and less questions. At the extreme, we catch students that rarely ask questions, evn if their production is low.

Finally, global measurements:

- work done: the fraction of all exercises that the student finished,
- work done in time: the fraction the the exercises done in the right time, that is, during preparation or classes related to the same module for H5P and learnr, or during classes or the completion period left before the next module starts.

[TODO: supplementary data: distribution of the metrics and correlation between them]

A Kohonen’s self-organizing map is used to create student profiles according to their activity, see Fig. XXX. A 3x3 hexagonal cells pattern was chosen, and students are thus classified into nine different groups.

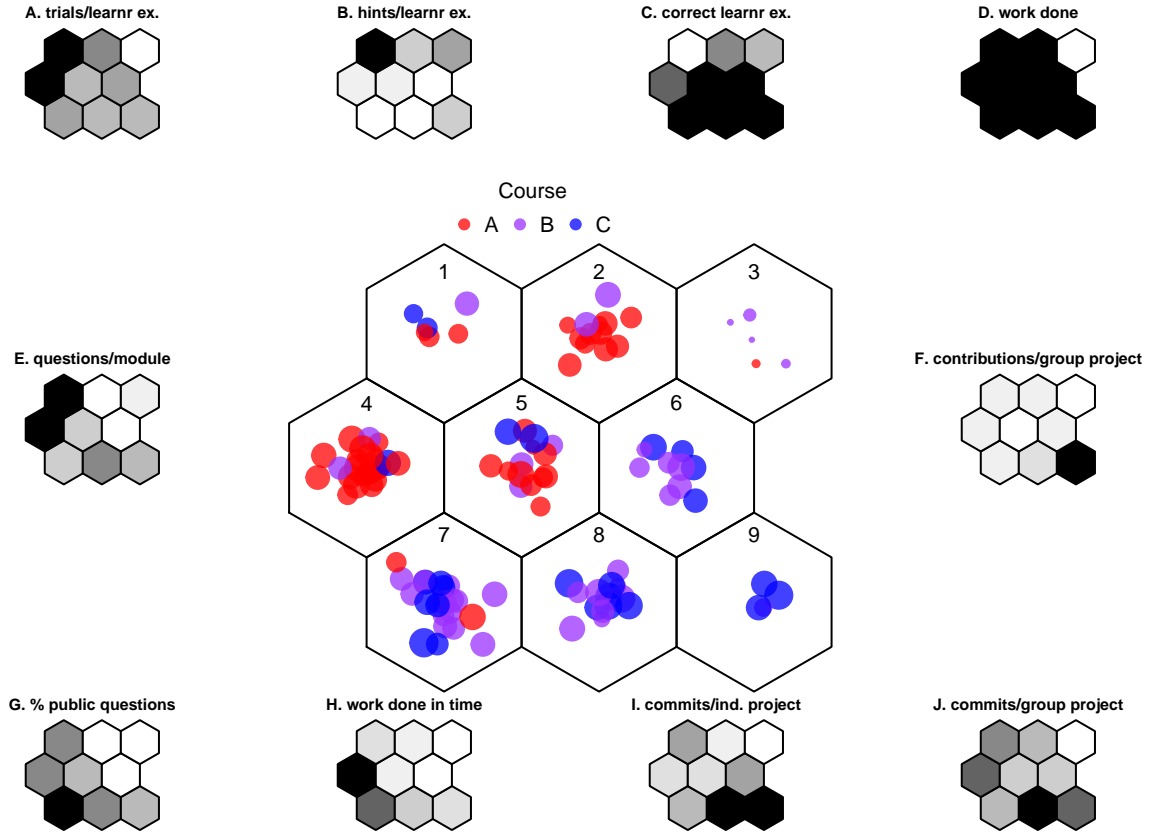


Figure 3: Self-organizing map of the student activities across the three courses in 2020-2021.

In Fig xxx, the small plots in gray scales show how selected metrics distribute in the nine cells, from lowest value in white to highest value in black. They allow to understand the way students behave according to their profile. Metrics that are not represented behave similarly than others (for instance H5P metrics exhibit a similar pattern as learnr traces and therefore, they are not represented). Dots in the central plot are the various students, with colour representing the course and the diameter of the dots representing the grade the students obtained at the end of the course. The following paragraphs details information in that figure. The numbers between brackets mean the cell number in the central plot, and the uppercase letters in brackets refer to the peripheral subplots.

Although most students performed all, or almost all exercises (D), cell (3) collects the few student that did only a very small part of the exercises. These students obtained very low grades, of course. They belong

to courses A and B. On the other hand, heavy workers are at the bottom (I & J), and good performers in learners (C) are in cells (5-9).

- Besides the totally absent students of cell (3), cells (2 and 6) collect students that also seldom ask questions (E), and that rarely appear on the public channel (E). Minor differences separate them. For instance, cell (2) sometimes use learnr hints (B), while cell (6) never does, also because they find the correct answer to the exercises more often by themselves (C). Asking questions is at the core of our pedagogical approach. So, these students do not play the game. However, they can possibly succeed. Some of them exchange with other students probably through different channels that we do not monitor. It is interesting to note that the cell (2) -more difficulties with learnr tutorials- are mainly students of course A, while cell (6) collects students of courses B and C. There is a clear evolution in their behaviour from one course to the other.
- Speaking about the students that have hard time to figure out the answer of auto-evaluation exercises, cell (1) reassemble students that most heavily rely on learnr hints (B), and also are among those who need to retry those exercises more often before figuring out the correct answer (A), a characteristic they share with cell (4). These students also ask a lot of questions (E), both on the public and private channels that are available. Main difference between those two groups, is that students in cell (4) try harder to find the answer without looking at the hints, while in cell (1), they give up faster. Also they respect the proposed schedule much more closely (H). We have students in all courses there, but a majority from course A.
- All these cells (1-4 plus 6) are students that exhibits sub-optimal behaviours. The remaining cells (5 & 7-9) correspond to students that perform very well. Cell (5) has a majority from course A, but otherwise, also from course B and C. These are average actors in all categories, except they are fluent with level 1 (H5P, not shown) and level 2 (learnr, C) exercises.
- Moving from cell (5) to (7), (8) and (9), we encounter top performers. The number of students from course A becomes progressively lower, while course B, and especially C dominate. Cell (7) use largely the public channel (G) and respect the schedule quite well (H). Students in cells (8) and (9) less so, but this is because they are heavier workers in the projects, both individuals (I) and in groups (J). In cell (9) we have also the students that contributes the most to he reports in term of lines added or deleted (F).

In overall, at the top, cells (1-4, plus 6) contain students with not optimal behaviour, cell (5) are average students, and cells (7-9) at the bottom exhibit profiles corresponding to best performers. The pattern is also visible between courses A (more at the top or center) to B and C (more represented at the bottom). This suggests that students need time to get used to the course and its pedagogical approach. They also take time to get used to the software environment used and to write commands in the R language.

4.4 Transition between face-to-face and distance learning

Due to Covid-19 lockdown periods, distance learning had to be adopted abruptly. We analyse the activity and support data collected during academic years 2019-2020 and 2020-2021 to assess the impact of this transition on the progression of the students. The academic year is divided into work periods of approximately 2 weeks. The courses of the second term of the year 2019-2020 start in period Y1P09 and the courses of the first term of the year 2020-2020 start in period Y2P01. The first lockdown started in period Y1P11 and the second in Y2P03. During the first lockdown, support rapidly switched to the proposed channels, by email and via Discord.

The activity in the reports remains relatively proportional to the number of questions the students sent by email or Discord messages, no matter the period and the intensity of the work as indicated by the number of modules to be completed during the period, all three courses pooled together. Only the number of students that ask questions by there channels change between face-to-face and distance teaching (much less in face-to-face because most of the students ask their questions directly in the classroom). Transition from direct interaction to electronic exchange was quasi immediate during lockdown. Consequently, support provided by the teachers in distance learning ... to be continued.

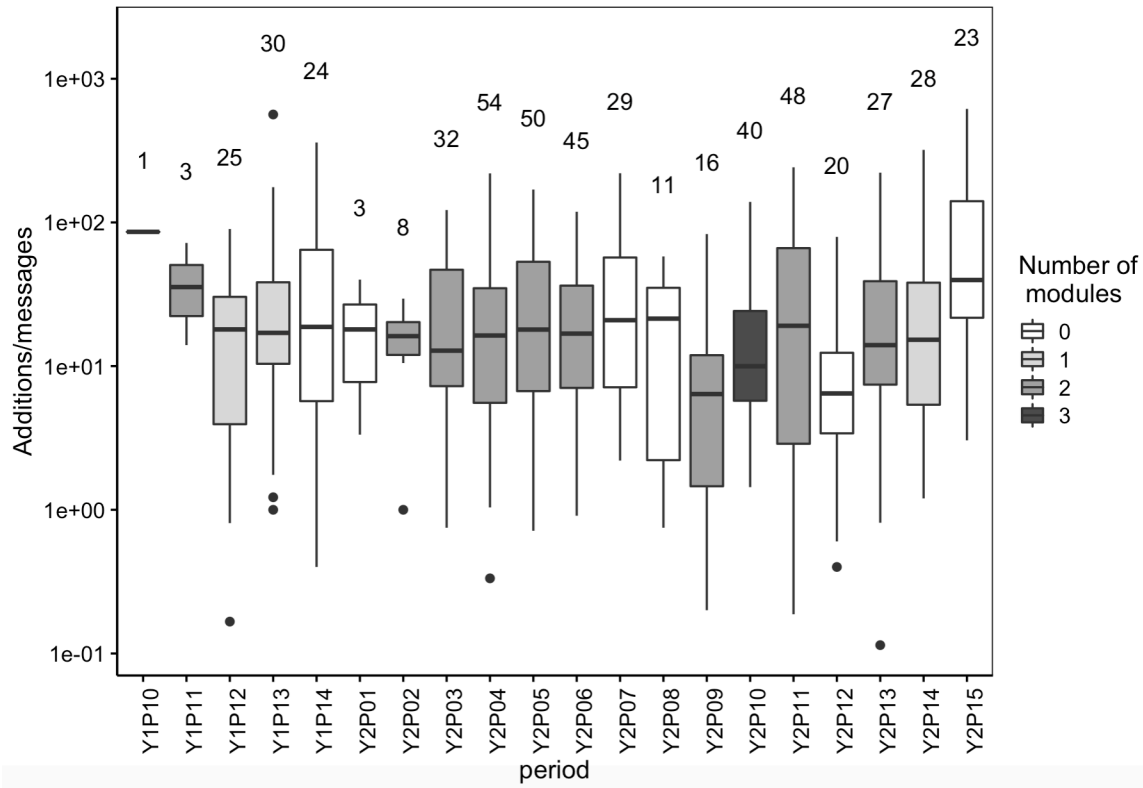


Figure 4: Support productivity as the number of lines added in the project reports divided by the number of message sent via Discord or by email (log scale). The total number of students that sent one or more messages during each period is indicated on top of the boxplots.

5 Discussion

[juste quelques idées... à développer et à traduire en anglais bien sûr.]

- L'examen en fin de période, même s'il reprend des questions liées à de la pratique et de l'utilisation d'outils, ne mène pas à une évaluation fortement corrélée avec l'activité qui nous intéresse le plus, à savoir, la capacité de l'étudiant à analyser des données biologiques réelles. Cette capacité est parfaitement évaluée dans les projets de niveau 1, et surtout de niveau 2 qui correspondent très précisément à une telle activité. Par conséquent, l'évaluation ne se fait plus via un examen final, mais uniquement via les prestations des étudiants dans les projets, ainsi que (pour une part relativement faible de 15% de la note finale), leur progression dans l'apprentissage de la matière via la réalisation des exercices de niveau 1 et des tutoriels de niveau 2, ceci afin de les encourager à réaliser complètement tous les exercices et à les faire dans l'ordre croissant de difficulté.
- Même au sein d'une cohorte d'étudiants ayant un parcours académique similaire, nous notons de très grosses différences de stratégie dans les activités d'apprentissage. Si plusieurs stratégies différentes sont associées à une acquisition bonne à excellente des compétences telle qu'attestée par les notes obtenues, plusieurs profils sont systématiquement associés à des performances faibles. Les profils ainsi établis via cartes auto-adaptatives permettront à l'avenir de détecter plus tôt les étudiants à suivre plus particulièrement et à réfléchir à des approches alternatives pour eux afin de les aider (pédagogie inclusive).
- Les études portant sur les changements d'attitudes au sein de semestre ne montre pas différence significative. La comparaison entre les 3 cours met en avant qu'il faut plusieurs cours en continu afin d'observer un changement de la charge cognitive des étudiants.
- Apprentissage en continu sur 3 années successives (cohérence entre le programme et l'approche pédagogique), les résultats sont meilleurs vers la 3^{ème} années.
- Pendant les périodes de confinements, le passage brutal à des cours en présentiel vers des cours en distanciel nécessite une période d'adaptation que nous avons quantifié dans notre cas à environ 2 semaine. Il s'agit ici du temps d'adaptation des étudiants, sachant que du côté des enseignants, nous avons réagit immédiatement (et même anticipé) en mettant en place très rapidement les canaux de communication alternatifs via le mail et Discord.
- Les tutoriels learners jouent un rôle charnière entre la théorie et la pratique. Ils offrent la possibilité de préparer les étudiants de manière optimale à l'analyse de données en pratique. Nous avons quantifié la charge cognitive perçue. Si la valeur absolue de l'index RTX n'est pas informative, la comparaison d'index obtenus dans des situations différentes permet de déterminer laquelle de ces situations est la mieux perçue. La comparaison des trois cours successifs montre une diminution de cette charge cognitive perçue dans le dernier cours qui est pourtant le plus avancé et le plus difficile. A l'avenir, nous pourrions utiliser ces points de référence pour encore améliorer ces tutoriels de ce point de vue.

6 Conclusions

- Exam classique évalue mal la capacité d'évaluer des données biologiques par eux même
- Les biologistes non expert de l'informatique est un challenge vu le nombre important de notions à apprendre utilisation d'un ordi, gestion de projet, statistique. Il faut décomposer ces notions en petites étapes successives si nous ne voulons pas les perdre rapidement. Notre approche en 3 cours étalés sur 5 quadrimestres successifs et étalés sur 3 années semblent correspondre à un bon timing pour ce type d'étudiant qui, au départ, n'a aucune notion de statistique, et très peu de connaissance des outils des logiciels couramment utilisés par le scientifique des données.
- Néanmoins, malgré leur habitude progressive, ces logiciels restent vus comme pointu et difficile d'utilisation (SUS) [à voir si on met cela dans l'article: on a déjà beaucoup ! => réserver cela pour un autre article l'année prochaine peut-être ?].

- l'évaluation continue et l'analyse de projet via des grilles critérié semble une approche intéressante pour juger de la capacité des étudiant à bosser [on a pas développé cela au final, il me semble].
- la catégorisation des étudiants en différents profils d'apprenants ayant adopté des stratégies très contrastées démontre une grande diversité des apprenants, même à l'intérieur d'un groupe a priori homogène (nous ne nous trouvons pas ici dans une grande classe qui regrouperait des étudiants d'horizons très différents comme les cours d'introduction à la science des données tels que pratiques dans certaines grandes universités américaines). Ceci est un premier pas vers une pédagogie différencié et plus inclusive qui s'avèrent être des éléments importants ici.

References

- Auker, Linda A., and Erika L. Barthelme. 2020. "Teaching R in the undergraduate ecology classroom: approaches, lessons learned, and recommendations." *Ecosphere* 11 (4): e03060. <https://doi.org/https://doi.org/10.1002/ecs2.3060>.
- Baker, Monya. 2016. "1,500 Scientists Lift the Lid on Reproducibility." *Nature* 533 (7604): 452–54. <https://doi.org/10.1038/533452a>.
- Banks, George C., James G. Field, Frederick L. Oswald, Ernest H. O'Boyle, Ronald S. Landis, Deborah E. Rupp, and Steven G. Rogelberg. 2019. "Answers to 18 Questions About Open Science Practices." *Journal of Business and Psychology* 34 (3): 257–70. <https://doi.org/10.1007/s10869-018-9547-8>.
- Baumer, Ben, Mine Cetinkaya-Rundel, Andrew Bray, Linda Loi, and Nicholas J. Horton. 2014. "R Markdown: Integrating A Reproducible Analysis Tool into Introductory Statistics." *Technology Innovations in Statistics Education* 8 (1). <https://doi.org/10.5070/t581020118>.
- Boettiger, Carl. 2015. "An Introduction to Docker for Reproducible Research." *SIGOPS Oper. Syst. Rev.* 49 (1): 71–79. <https://doi.org/10.1145/2723872.2723882>.
- Byers, J C, A Bittner, and S Hill. 1989. "Traditional and raw task load index (TLX) correlations: Are paired comparisons necessary? In A." In.
- Çetinkaya-Rundel, Mine, and Victoria Ellison. 2021. "A Fresh Look at Introductory Data Science." *Journal of Statistics Education* 0 (0): 1–27. <https://doi.org/10.1080/10691898.2020.1804497>.
- Çetinkaya-Rundel, Mine, and Colin Rundel. 2018. "Infrastructure and Tools for Teaching Computing Throughout the Statistical Curriculum." *American Statistician* 72 (1): 58–65. <https://doi.org/10.1080/00031305.2017.1397549>.
- Donoho, David. 2017. "50 Years of Data Science." *Journal of Computational and Graphical Statistics* 26 (4): 745–66. <https://doi.org/10.1080/10618600.2017.1384734>.
- Estrellado, Ryan A., Emily A. Bovee, Jesse Mostipak, Joshua M. Rosenberg, and Isabella C. Velásquez. 2020. *Data science in education using R*. London, England: Routledge. <https://datascienceineducation.com/>.
- Fiksel, Jacob, Leah R. Jager, Johanna S. Johanna S Hardin, and Margaret A. Taub. 2019. "Using GitHub Classroom To Teach Statistics." *Journal of Statistics Education* 27 (2): 110–19. <https://doi.org/10.1080/10691898.2019.1617089>.
- Freeman, Scott, Sarah L. Eddy, Miles McDonough, Michelle K. Smith, Nnadozie Okoroafor, Hannah Jordt, and Mary Pat Wenderoth. 2014. "Active learning increases student performance in science, engineering, and mathematics." *Proceedings of the National Academy of Sciences* 111 (23): 8410–15. <https://doi.org/10.1073/PNAS.1319030111>.
- Hart, Sandra G., and Lowell E. Staveland. 1988. "Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research." *Advances in Psychology* 52 (C): 139–83. [https://doi.org/10.1016/S0166-4115\(08\)62386-9](https://doi.org/10.1016/S0166-4115(08)62386-9).

- Hsing, Courtney, and Vanessa Gennarelli. 2019. “Using GitHub in the Classroom Predicts Student Learning Outcomes and Classroom Experiences: Findings from a Survey of Students and Teachers.” In *Proceedings of the 50th ACM Technical Symposium on Computer Science Education*, 672–78. SIGCSE ’19. New York, NY, USA: Association for Computing Machinery. <https://doi.org/10.1145/3287324.3287460>.
- Krathwohl, David R. 2002. “A Revision of Bloom’s Taxonomy: An overview.” *Theory Into Practice* 41 (4): 212–18. <https://doi.org/10.1207/s15430421tip4104>.
- Larwin, Karen, and David Larwin. 2011. “A meta-analysis examining the impact of computer-assisted instruction on postsecondary statistics education: 40 years of research.” *Journal of Research on Technology in Education* 43 (3): 253–78. <https://doi.org/10.1080/15391523.2011.10782572>.
- Marx, Vivien. 2013. “The big challenges of big data.” *Nature* 498 (7453): 255–60. <https://doi.org/10.1038/498255a>.
- Onwuegbuzie, Anthony J., and Vicki A. Wilson. 2003. “Statistics Anxiety: Nature, etiology, antecedents, effects, and treatments—a comprehensive review of the literature.” *Teaching in Higher Education* 8 (2): 195–209. <https://doi.org/10.1080/1356251032000052447>.