

# 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://jhudatascience.org/chromebookdatascience/>)) 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?](https://url.sciviews.org/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.]

### 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 it 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 te 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 that 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 favour 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

Liste des idées développées dans cette section :

- exam versus project 2018 et 2019 => elimination de l'examen
- profiles analyse SOM => sous-groupes + analyse des groupes y compris comparaison avec les grades
- temporel présentiel -> distanciel
- learnrs (+ perception) -> apprentissage sur le très long terme (> 1 ou deux quadris)

[Next paragraph to be translated and reworked]

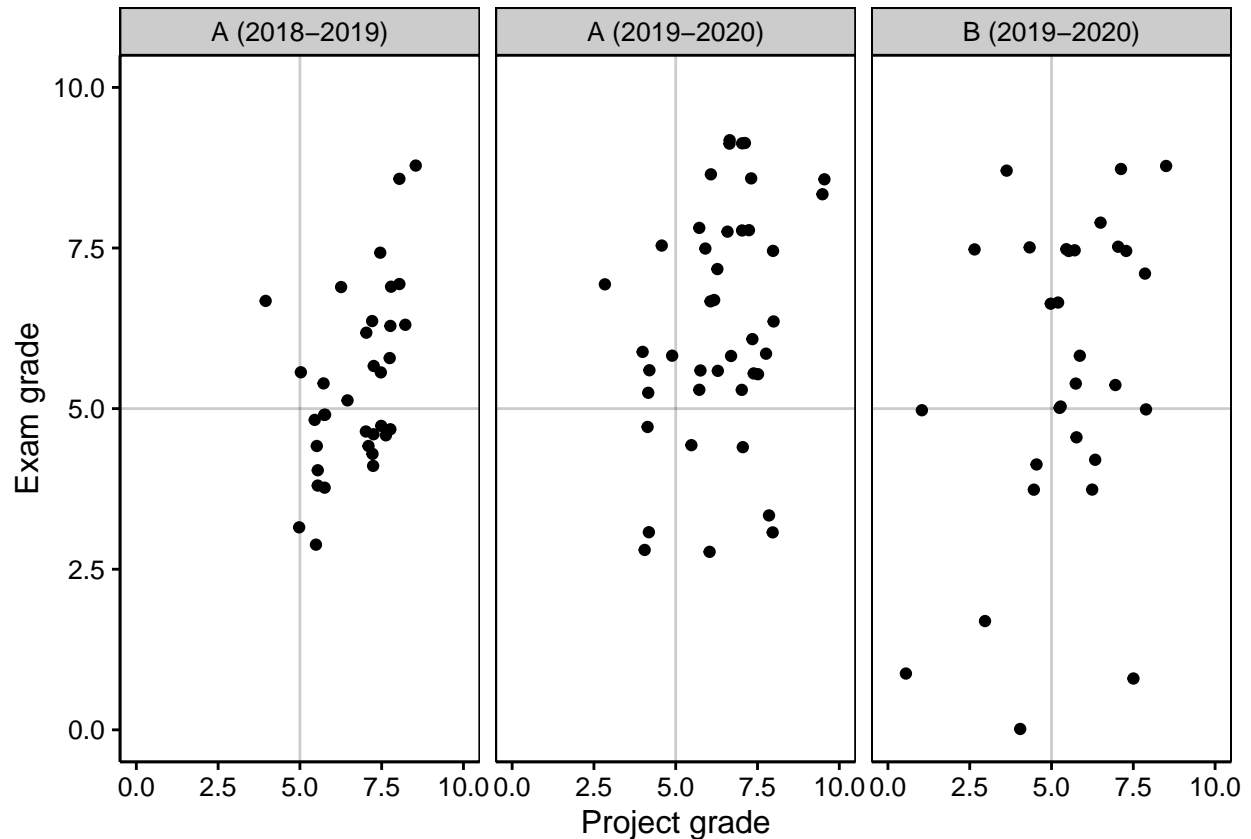
Our in-service training includes 26 complementary modules over 3 years and 3 consecutive courses from bab2 to MA1. The number of exercises per type is shown in Table XXX. The goal and the difficulty levels of the exercises are presented in table xxx. The completion of each exercise is recorded in a database which allows an objective grade to be constructed for each student.

Table 2: Number of users, modules, exercises with h5p, learnr tutorial, individual project and group project by course. The number of question by learnr tutorial are in the parentheses.

course	user	module	h5p	learnr	ind. github	group github
A	42	12	59	24 (211)	10	4
B	40	8	29	11 (108)	12	2
C	25	6	19	7 (37)	7	1

### 4.1 Exams versus project

Until the first four months of the 2019-2020 academic year, students' grades were based on the completion of a project and a more conventional examination during the examination period. The projects are assessed using a grading grid since the 2019-2020 academic year.



The comparison of the marks obtained between the project and the exam mark shows a strong disparity between these two types of evaluation.

The 2018-2019 year is the first year of transition to data science courses. Only one student failed the project, while almost one third of the students failed their exams. The level of requirements is being raised for the 2019-2020 academic year. The new expectations and the introduction of evaluation grids to assess projects show a greater disparity in students' grades.

Despite an examination that includes theoretical and practical questions, this type of assessment does not assess a student's ability to correctly process and analyse biological data.

Following these results and the monitoring of more precise exercises, the examination is definitively abandoned for the 2020-2021 academic year to be replaced by a continuous assessment.

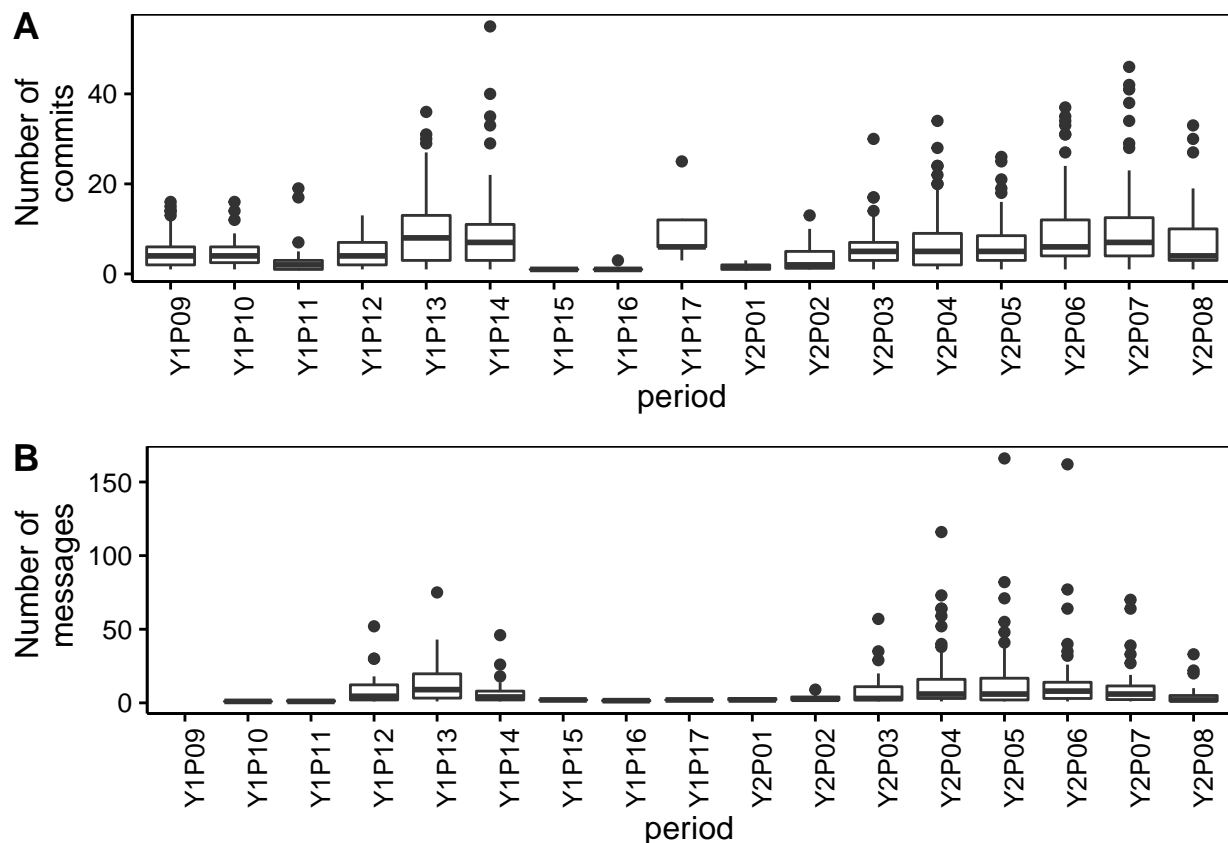
## 4.2 Students' profiles

[TODO : Add SOM analyses, This analysis is stand by as we validate the metrics]

Les groupes réalisés créent des profils d'apprenants ayant des stratégies très différentes. Puisque certains profils sont plutôt associés aux notes plus faible, ces groupes devront faire l'objet d'une attention particulière et peut-être aussi d'une adaptation du matériel ou de l'approche pédagogique vers un apprentissage plus inclusif.

## 4.3 Transition between face-to-face and distance learning

Due to Covid-19 lockdown periods, distance learning had to be adopted abruptly. We analyze 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.

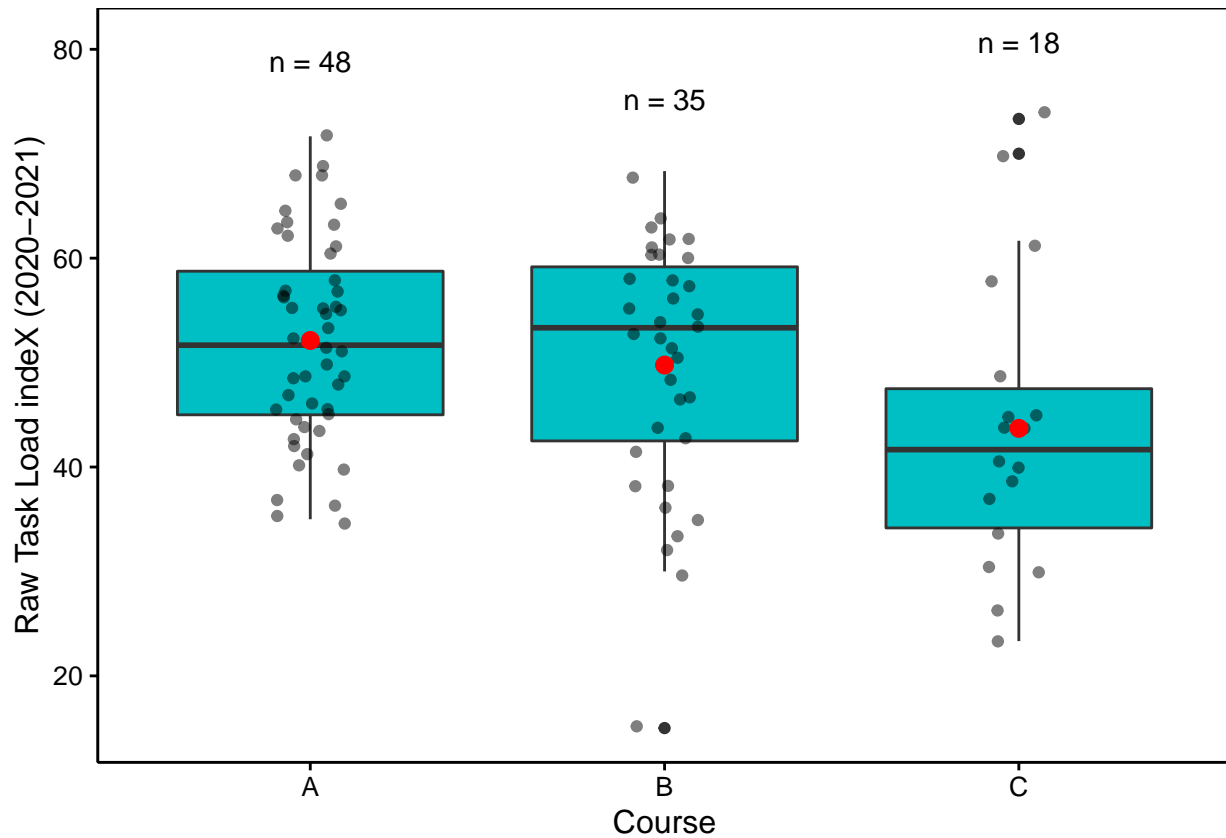
In 2019-2020, a drop in the number of commits is observed in Y1P11 which corresponds to the beginning of the first lockdown. After one period of transition, students start again to work and interact with teachers. The last hours of lessons are given in period Y1P13. The higher number of commits in Y1P16 and Y1P17 corresponds to the third term.

In 2020-2021, the number of commits gradually increases from Y2P01 to Y2P03 and stabilises until Y2P08. The number of messages increases from the beginning of the second containment (Y2P03). There is no lag period. The number of commits remains constant. The students no longer needed an adaptation period.

#### 4.4 Learnr tutorials perceived cognitive workload

The 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 analyze 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 analyzed 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 [indicate here the level of participation of the students for each course].



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). The cognitive load perceived by the students diminishes. This may be a consequence of a more fluent R coding and the better mastering of all the software tools the students have to use.

```
## 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
##
##
## 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)
```

## 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 le 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 3ième 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 pourrons 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 une challenge vu le nombre important de notions a 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 pratiqués 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.

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