

# Remote teaching data-driven physical modeling through a COVID-19 open-ended data challenge.

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Physics can be seen as a conceptual approach to scientific problems, a method for discovery, but teaching this aspect of our discipline can be a challenge. We report on a first-time remote teaching experience for a computational physics third-year physics laboratory class taught in the first part of the 2020 COVID-19 pandemic (March-May 2020). To convey a “physics of data” approach to data analysis and data-driven physical modeling we used interdisciplinary data sources, with an openended “COVID-19 data challenge” project as the core of the course. COVID-19 epidemiological data provided an ideal setting for motivating the students to deal with complex problems, where there is no unique or preconceived solution. Our results indicate that such problems yield qualitatively different improvements compared to close-ended projects, as well as point to critical aspects in using these problems as a teaching strategy. By breaking the students’ expectations of unidirectionality, remote teaching provided unexpected opportunities to promote active work and active learning.

## INTRODUCTION

Physics is on one hand a corpus of knowledge and a set of technical and quantitative tools, but on the other hand it is also a conceptual approach to scientific problems, a way of “discovering” that has had a profound impact on other fields of science [1–3]. When we teach a physics class, the corpus may be technical and difficult to convey, but it is straightforward and usually well defined. For a particular “subject matter”, the set of facts and techniques is also what the students instinctively expect to learn. Conversely, the flavor for what is a “physics approach” is comparatively elusive and complex to communicate. It is rooted in how we “do” physics, how physicists perform their work in research. Once data is collected (the act of ‘measuring’ and acquiring data is the other specialty of physicists) physics digs into this information through “physical models”, simple mathematical representations of empirical observations that have the ambition to capture the essence of a process. These physics models thus aim to be predictive, i.e. able to forecast the outcome of independent experiments [1], ideally also beyond the range used to inspire and test the model [4]. This approach is extremely successful within various branches of physics, and today thanks to detailed datasets from various other fields it also has a great potential in interdisciplinary and traditionally non-physical science fields. Teaching how to use the physics approach productively is difficult, because it is an unstructured and

complex set of skills, composed of different layers. For many students the acquisition of these skills is delayed to the first time they are required to produce original research, such as in their graduation or PhD work, and for some others these skills are just not acquired.

Certainly what a physicist would call ‘doing physics’ includes many skills that apply well to all sciences, such as the ability to formulate hypotheses [5], and a set of problem-solving and guess-estimating skills [6], which include being able to question and “filter” information, data, common beliefs, as well as our own results [7]. Some of these skills intersect with what is sometimes called the “nature of science” [8], a label that characterizes the research process as well as the scientific knowledge including socio-cultural aspects. They also represent what is at the heart of theoretical science, and one of the most creative and arguably most significant parts of our work as scientists in general.

During the COVID-19 crisis in Italy, Two of us (MCL and MG) were teaching for the first time a computational physics laboratory class for third-year physics students (the other authors of this studies contributed as students or external supervisors, see below). Our aim was to convey a “physics of data” approach to data analysis and data-driven physical modeling. We were also committed to using interdisciplinary data sources rather than conventional physics data sets, in order to show the students the interdisciplinary potential of a physics approach to data [9]. The course started in March 2020, when a national lockdown took effect, so that we had to rapidly convert the material of the course previously conceived for traditional frontal live teaching to remote teaching, and we decided to use “hot” data from the ongoing pan-

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dem. What follows is an account of this teaching experience with two objectives: (1) describe how the “hands on” philosophy described above was formalized and put in practice and (2) the role of the remote-teaching settings in this experience. We found that remote teaching, while being a big challenge, also offered significant and unexpected opportunities for this course, leading to effective bi-directional communication with the students.

The recent literature on computational physics education research is fairly extensive, due to an original weak integration of computation into the physics curriculum, as detailed in ref. [10]. The importance of computation to contemporary physics research is large, as well its impact on the future employment of physics students beyond physics and science [11, 12]. As teachers and researchers (non-experts of education research), we were interested in a possible instructive role of open-ended projects (similar to those encountered professionally) in this context. The inclusion of such an open-ended part of the course is the main point of originality of our approach. The account that follows does not have the ambition of being systematic, but rather we intend this study to be first and foremost a testimony of our experience, which can be used to replicate our approach effectively, with an awareness of its potential and its limitations. Previous, more systematic, efforts to build courses around expert practice [12] proved to be successful, but were limited to close-ended projects and exercises. On the other hand, there is evidence that productive results can stem from learning environments that problematize topics, put students in charge of addressing problems, as well as holding them accountable [13].

#### **BOX 1: course essential content.**

- The *scientific toolbox* of the course (covered in approximately 16h of lectures) aims to provide a bare-bone scientific set of tools for model-driven data analysis, including basic tools from modeling, critical scientific thinking, essential probability and statistics and data visualization.
- The *computational toolbox* of the course (estimated in 16h of lectures) includes essential Python tools to treat, analyze and plot data (based on the Scipy package, and using NumPy, Pandas, and Matplotlib libraries), and typesetting of LaTeX documents, useful for the reports. We also provided command-line tools to treat, analyze and plot data (based essentially on Bash scripting, the awk language, and the gnuplot plotting program) and an introduction to C++ tools for efficient data analysis and simulations (including Standard Template Library data structures).

## **STRUCTURE AND CONTENT OF THE COURSE**

### **Course layout**

The course fits in the 3rd year physics curriculum at the University of Milan as a computational physics laboratory class. It is scheduled over 66 hours during one semester, which are normally spent “in the lab” with the teaching shared across two instructors. The expected hours of coursework are approximately 30-40. The purpose of the course is to provide (i) basic notions of computational tools (C++, shell and scripting languages, python, latex) and (ii) skills in “physics of data”, i.e. model-guided data analysis and data visualization, in the form of three short projects.

The course was structured in a two parts. The first part of the course (described in BOX 1) is an essential technical and scientific toolbox for taking off with the projects. The second part of the course addresses three one-week long “data challenge” individual projects (DC1, DC2, DC3). In these data challenges, students start from a dataset and work on it to extract and present conclusions. At the end of each data challenge, students submit a three-page report written in LaTeX, to describe the results achieved and to include their own graphics and figures. We decided that DC1 would be fully supervised and guided, with the students working in close contact with the tutors. DC2 and DC3 would be more autonomous. To be able to manage the supervision of the students, we restricted the attendance to a maximum of 25 students (originally the restriction was also due to the number of available workstations in the classroom).

The data challenges followed the pipeline: “Get data → Clean up data → Explore data → Model data → Interpret data”. And the students were given the prescriptions to take into account the limits (and possible biases) of the data, to prefer models with fewer parameters, and to be strict and question every interpretation. They were also warned about the relevant cultural problems that emerge in interdisciplinary applications of physics there, where it is necessary to acquire some specific knowledge of the domain, to be humble and trust the experts of the field.

### **Conversion to remote teaching.**

Soon before the course started in early March 2020, it became clear that it would have to be delivered remotely. We decided to use a Slack workspace and Zoom meetings. Lectures were mostly asynchronous, delivered as posts on the Slack space, which students had to go through on their own. Lectures were posted on Slack using text and externally linked material (example code, lecture notes, external resources). For example, the YouTube channel “Calling Bullshit in the Age of Big Data” [7] was used as a complement for several aspects of statistics, data visualization, Fermi estimates, etc. but we also gave the students our own lecture notes and handouts on all

these topics, including exercises and example codes to plot data, perform fits (see BOX 1 and the Supplementary Appendix, providing a compendium of the course).

After each set of lectures, we organized a “Questions and Answers” session (Q&A) on Zoom, where we discussed the material with the students. Next to the material, we also posted guided exercises on the computational and scientific parts of the course. In each Q&A session, besides leaving the meeting open to any questions, each student was interviewed and requested to update the instructors on the study work and exercises that he/she had already done, whether she/he encountered any difficulty, and was asked to state her/his plans for the coming days. These sessions lasted 2-3 hours and took place once or twice a week depending on the course development. The interviews took place over a consecutive three-hour slot and each student had 5-15 minutes where he/she could present the work done on the asynchronous material and the coding exercises performed in the past few days. Starting from these reports, the instructor would address the questions and common problems encountered in the study, and any barriers encountered in the coding or in the conceptual implementation of the exercises.

The Slack space was an efficient way to interact bidirectionally with the students throughout the week (Fig. 1). We structured it in several channels for posting teaching material, planning of the course, receiving material from the students (e.g. the reports from the data challenges), and we included a forum where instructors, supervisors and students could post material, tips, pointers to external materials and data sets, problems and general questions. The forum turned out to be a very active platform during the course. One-to-one chats were used and proved efficient for replying to specific questions. Slack includes an App for cell phones, which we found useful for real-time communication (and depending on the teacher’s availability, it can be silenced for prescribed time periods, whilst avoiding email clutter).

Most students had the right resources to take the course from home. Five students dropped out when we announced the switch to remote or during the course. We contacted them through the Slack and email, but it was difficult to reconstruct the precise reasons (e.g. pressure from other courses or lack of equipment). We provided instructions to install all necessary code at home, but each student could also connect remotely to Linux-based university machines where all the softwares were available. All codes, software, compilers supported by the course (essentially, Python, C++, gnuplot, shell scripting and LaTeX for typesetting) were free, although the students were left free to adopt any tool and judged solely by the end results of their work.

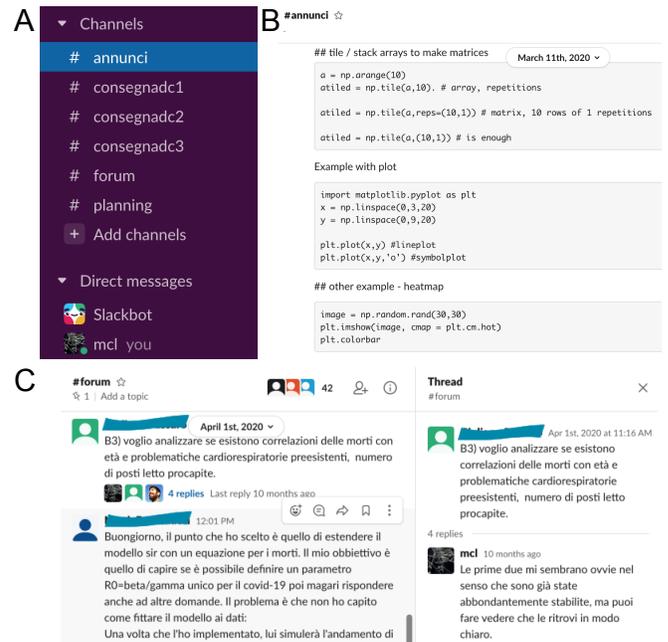


Figure 1: The Slack space facilitates organization of the course, posting of lecture material and bi-directional communication. A. Subdivision of information into channels for planning of the lectures and Q&A sessions, posting of lecture material, turning in data challenge reports. Channels are accessible from a side pane of the PC app and as a menu for the mobile app. B. Example of a portion of a posted lecture on Python, with highlighted code. Through the interface, a lecturer can include attachments in several formats (code, pdf, images, etc.) and links to external websites, which the app automatically shows in pretty-print preview. C. Example of the interactive “forum” channels where teachers could post external material, and the students could post questions publicly. Questions can be addressed in a connected “thread” conversation (right-hand panel).

### The COVID-19 data challenge.

With the pandemic expanding globally, we decided that the first data challenge would be a COVID-19 data challenge. Instead, we kept the second data challenge as a more standard close-ended (interdisciplinary) physics project on multiplicative diffusion processes, which used data on software packages [14, 15]. As the course got under way, we saw that DC1 had (perhaps in hindsight not surprisingly) taken a lot of time and commitment on both student and teaching staff. Extensive feedback was being provided to the students on their projects DC1, so to provide an outcome for this we switched our original plan and made the third data challenge, DC3, optional, and we decided that it would consist of a revision and integration the work carried out in DC1, based on the feedback received from the instructors. This enabled students to build on the detailed feedback provided by the instructors on the student reports for DC1. 14 out of 21

students chose to address DC3. The feedback to students included a number of positive propositions to expand and revise aspects of each project.

We planned the first data challenge, DC1, to be a supervised project, so the students were free to ask questions and seek advice on any level. Since the course started during the COVID-19 crisis (and during the complete lockdown) in Lombardy and Italy, we thought that putting their hands on the surge of data that were discussed every day all over the news and the internet could be both motivating and challenging. As mentioned above, in order to supervise the projects more efficiently during that week, we obtained the help of four (volunteers) external “supervisors” for DC1 (FB, FC, PC, JG, co-authors of this study). These scientists provided some ideas for the projects and interacted directly with the students, individually and through the Slack forum. The supervisors were based in other cities in Italy and in the UK, but the Slack interface made it easy for them to interact with the students through the forum and individually, and to help them carry out their individual projects.

The external supervisors had different areas of expertise, statistical and interdisciplinary physics (FC,JG,PC), probability and statistics (FB), experimental physics (PC) and data analysis (FB,FC,PC,JG). Each supervisor provided his individual perspective to the different problems and contributed defining possible directions of the Data Challenge assignment, which was produced as a document with contribution from instructors and external supervisors. Students were left free to find their way to the specific potential supervisors whose background and vision best suited their goals and perspective. The resulting partitioning of student between supervisors was even. Each external supervisor was in touch with 2-4 students, and the main instructors were in contact with 5-8 students.

Part of the instructions provided for the DC1 were tips on where to get the data, but the students were encouraged to explore autonomously different data sources. Part of the technical skills that they acquired from the first part of the course were on how to “scrape” data using command line and Python, and how to manipulate data and assemble an organized data set (for example, using the Pandas and Numpy packages in Python). As a basis, the students were encouraged to get the daily data from:

- the Italian Civil Protection agency. [16]
- The COVID-19 Repository at Johns Hopkins University [17][18]
- Our World in Data [19]
- the EU ECDC web site [20]
- national data from the Italian, French and German ministries of health.
- the Italian National Institute of Statistics (ISTAT)[21]

The challenge was divided into a first point (A) that was common to all students and a second one (B) that the students could choose. The common point was the empirical prediction of the “infection peak”. The students were asked to find a suitable and efficient empirical definition of the peak of the infection. The challenge was to provide an empirical estimate of the peak using data from different countries and regions, and propose/validate an empirical method to predict the peak as accurately as possible. The assignment also provided some tips on the limitations of the data, some caveats on the requested analysis, and different possibilities to tackle the question.

Point (B) of the challenge was to identify and address a well-defined question within a theme chosen from a set of the following proposed options, all of which concern open scientific problems.

- (B1) Fit / analysis using a standard epidemiological (SIR or SEIR) model, asking whether unified parameters could be defined for the spreading of the SARS-CoV-2 virus before the lockdown[22].
- (B2) Use fits from a SIR/SEIR model to quantify the effect (measured as change in parameters) of social distancing, lockdown and other non-pharmaceutical interventions [23].
- (B3) Empirical correlative analysis. In the wake of point (A), define some purely empirical observables from the data such as delay outbreak-intervention time, delay infections / death etc. evaluate these quantities in various regions (see above, staying as local as possible) and correlate them with other possibly interesting covariates such as population density, public transport / commuting properties, fine dust pollution, temperature, capacity of hospitals, etc[24, 25].
- (B4) “Bullshit calling” exercise. Find on the web or in the news a scientific claim made by a scientist in a pseudoscientific context (e.g. a plot posted on facebook or twitter, there are various Italian and international threads) and then challenge, refute or debunk it using data (and models if necessary).
- (B5) Explore possible explanations for the very large variations of case/fatality ratios across countries and regions (e.g. 14% case fatality ratio in Italy vs 0.6% in Germany. The case fatality ratio is known to be a very bad estimate of the death rate because of delays and other factors [26, 27]. A circulating hypothesis was that a confounding factor is the age distribution: the Italians are older and therefore die more likely of the disease. Another common hypothesis (which quickly turned out to be the most reasonable) was that the number of cases was underestimated. Another possibility (now ruled out) was that a strain of the virus has different death rates.

- (B6) Spatial spreading. Identify simple observables to quantify spatial spreading from available data. Check whether containment measures have an effect on this observable. Test if the opposite has happened: when the measures are announced, everyone jumps on the train and spreads the virus around the country [28].

## I. ANALYSIS OF THE COURSE OUTCOME

DC1/3 project classification	
Empirical analysis of epidemiological data	20/21
Epidemic model fitting	9/21
Correlation of epidemiological data with covariates	10/21
Case-fatality ratio	3/21
Spatial Spreading	4/21
DC1/3 productive findings	
New dataset / Data integration	8/21
Creative use of mathematical models	9/21
Display of technical rigor	14/21
Careful controls / statistical analysis	9/21
DC1/3 problems encountered	
Evident technical flaws	4/21
Misplaced/misleading conclusions	5/21

Table I: Classification of DC1/3 projects performed by the students. Since the projects were open ended, the students could choose to engage different aspects and follow routes. The right column reports our classification of the projects by keywords, productive findings, and class of problems encountered by the students. The right column reports the fraction of projects that fall into each (non-exclusive) category.

### Results of the COVID-19 data challenges

From the educational viewpoint, the problem setting was conceived to encourage the students to put critical thinking into practice and search for original solutions. Encouragingly, multiple students came up with approaches to the data that were original and effective. Perhaps even more importantly, some students able to reflect critically on their own work, revising and correcting their own analyses. For example, one student developed a technique to predict the infection peak from a logistic fit of the cumulative curve. In the second report for DC2, she decided to perform a critical analysis of her own proposition, showing that it did not work well with data. Other students showed creative behavior on the level of data assembly and data curation. For example, one student collected NASA data sets on pollution and correlated these data with the local COVID-19 case fatality rate. Table I collects our classification and counts of the kinds of project strategies chosen by the students,

the different kind of productive findings they were able to achieve, and the main kinds of problems they encountered.

What follows is a list of some scientifically remarkable findings by the students, some of which are presented in more detail in Appendix (Figures A1 and A2).

- The time delay between the first case in a given Italian province and the first case reported in Italy correlated negatively with provincial mobility estimated from 2011 census data.
- There was a factor of 1.5-2.5 (varying from city to city) between total deaths in March in cities in the Bergamo area and the sum of COVID-19 registered deaths plus the average deaths in the three previous years in the same month. Assuming the measured 1.2% mortality, one student could estimate that total cases could be up to 50 fold larger than the number of registered cases.
- Compared to a suitable null model, Italian provinces with a first-reported new infected are closer to provinces with already ongoing COVID-19 outbreaks compared to a null model where new infections travel without spatial constraints.
- There is a phenomenological (mildly sublinear) power law relating the number of reported infected at the peak, and its value on the day a lockdown was put into effect, valid across regional data from China, Italy and Spain.
- The date of the infection peak is roughly independent from the date of the lockdown measures, using as reference system for time an origin when the new cases are 25.
- Bad or biased sampling can be spotted by the time constancy of the ratio of positive/tested individuals.

DC1/3 improvements	
Addressing questions with modesty	6/14
Choosing circumscribed questions	4/14
Supported conclusions / appropriate controls	10/14

Table II: Evidence of achievement of different goals in the revision work from DC1 to DC3. The right column reports the three main lessons that we aimed to convey to the students. The right column reports the fraction of projects where we found evidence that the revisions showed improvements towards achieving these goals.

Beyond the scientific results above, which were only a part of the goals (see below), we believe that the COVID-19 data challenge conveyed important specific lessons to the students. First, to address questions with modesty. Physics provides modeling and data analysis skills, but

no knowledge of epidemiology or other disciplines. First of all, one must be aware that one is not an expert in trying to figure out simple things from the data. Second, choosing circumscribed questions, makes it feasible to reach a goal. Third, an important result can be positive or negative, but in both cases the conclusions must be argued carefully, and supported with the appropriate controls. To support the hypothesis that these lessons were (at least sparsely) appreciated by the students, we went back to the comparison of the outcomes of DC3 (the revision) compared to DC1 (the original project report), and we counted the examples where the revisions appeared to incorporate these lessons. The results, summarized in Table II suggest that (as perhaps one might expect), the third lesson is the easiest to learn, and the second is the hardest (it is a problem that most professional scientists struggle with).

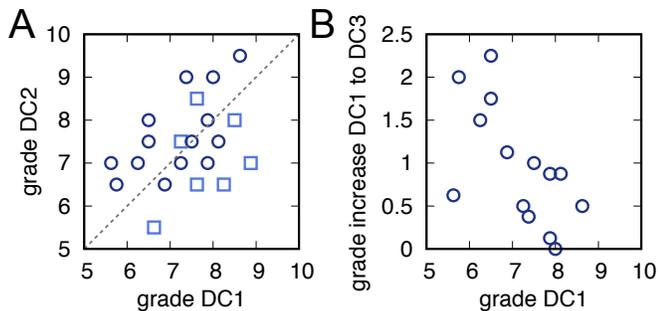


Figure 2: The three-challenge layout allowed comprehensive evaluations and offered the students the possibility to increase their marks significantly. A. DC1 grades ( $x$  axis) and DC2 grades ( $y$  axis) obtained by all students (circles correspond to those who also completed DC3, squares are the others). B. The net increase in grade between DC1 and DC3 ( $y$  axis) versus the grade obtained in DC1. Dashed lines are the bisectors  $y = x$ , as a guide to the eye.

### Grading and evaluation of student improvement

Ours was a laboratory course, focused on the practical aspects, and whose cornerstone are the data challenges. It was not trivial to develop suitable criteria for the evaluation. We wanted the final grade to reflect the quality of the “practical” work done rather than the acquisition of notions (which can easily be evaluated by an oral exam). Hence, we decided that the grade should be based on assessing the reports of the three data challenges. The reports were graded based on four criteria: (i) Logical structure and communication; (ii) Data visualization; (iii) Technical aspects of the analysis; (iv) Scientific aspects of the analysis and support of the claims. The benchmarks for a passing grade under these criteria were, respectively, (i) a clear logical structure divided in sections, paragraphs, clear result statements and correct reference to figures, (ii) readability of plots and effective choice of visual aids, (iii) sound technical choices and

controls and absence of clear technical mistakes (iv) scientifically sound analyses and adequate support of the conclusions.

t-tests	DC1 $\rightarrow$ DC3	DC1 $\rightarrow$ DC2
COM	p=0.001	p=0.8
VIZ	p=0.0003	p=0.03
TECH	p=0.002	p=1
SCI	p=0.2	p=0.8
Overall	p=0.0004	p=0.14

Table III: Paired-sample t-tests for the changes in the mean grade of students across different data challenges (significant results for increased average grades are in green). The significant changes from DC1 to DC3 suggest that students improved their communication (COM), data visualization (VIZ) and technical (TECH) performance in the revision of the COVID-19 open-ended challenge. The increase in the scientific quality (SCI) category was not significant. Conversely, the changes between open-ended DC1 and close-ended DC2 are largely not significant, likely because of the different nature (and attitude in the evaluation) of the project.

Additionally to the grade, we provided extensive feedback for DC1, from two instructor, in a form similar to a manuscript “referee report” for each student, which included discussion of the weak and strong points of his/her work and suggestions to correct and/or improve specific technical, scientific and presentation aspects. The final grade was proposed based on the results of all the data challenges carried out by each student. For those students who did three data challenges, the final grade was the sum of the three grades. For those who did two data challenges, we based it on the sum multiplied by 1.5. We decided that enrolling in the voluntary DC3 could not lower the grade obtained with the first two data challenges, at worst it would leave it unchanged. For those who were not satisfied by the final grade, we made it possible to request an oral exam. The oral exam could cause both reduction and increase of the grade based on the students’ reports. No student opted for the oral exam.

Fig. 2 summarizes the grading across the three data challenges. Grades received in DC1 and DC2 were correlated only very mildly (Pearson  $r=0.39$ , Fig. 2A). This suggests that the two dissimilar challenges allowed us to evaluate complementary skills and therefore reach a more comprehensive evaluation of each student. On the other hand, all of the 14 students who addressed DC3 received a grade at least equal to that of DC1, with 5 students increasing by more than 1 grade (Fig. 2B). Moreover, the increase in grade was negatively correlated with the grade obtained in DC1 (Pearson  $r=-0.63$ ). This suggests that lower performing students may have managed to capitalize on the feedback they received. While lower initial grades leave more room for improvement, which may explain the correlation, the relative increase in grade

(normalized by the gap to the top grade, which is the maximum possible increment) still showed weak negative correlation with the grade obtained in DC1 (Pearson  $r=-0.27$ ), supporting the hypothesis (although a larger sample would be needed to establish this point with confidence).

It is interesting to use the outcomes of the grading to evaluate the overall impact of the course on the students. The average grades systematically improved from one data challenge to the next, suggesting that the students gradually acquired skills to reach the course goals. Specifically, the average grades (in tenths) for individual were  $7.27 \pm 0.9$  for DC1,  $7.68 \pm 1.07$  for DC2, and  $8.12 \pm 0.72$  for DC3. To gain more insight on these changes, we performed t-tests for the increase of the mean grades (Table III). We treated the grades as paired samples, regarding the performance of a student in different data challenges as different tests of the same criteria in the same subject. Interestingly, under this test the overall increase of the mean scores as very significant for the changes between DC1 and DC3 (revisions of an open-ended challenge), but are largely not significant. Even more interestingly, students appear to improve their performance from DC1 to DC3 specifically

In support of these results, we also note that the Pearson correlation between the grades of DC1 and DC2 is 0.1-0.2 (depending on the evaluator), while the one from DC1 to DC3 is around 0.5 (regardless of the evaluator).

### A. Student evaluation

At the University of Milan, student feedback is provided through anonymous questionnaires based on a set of closed-answers questions, plus space for open comments. Generally the questionnaires are filled by a small fraction of students, but this was not the case for our course. We carefully read the answers to the open questions. From these comments it is clear that the course has aroused “high variance” reactions, both positive and negative. Multiple students felt they were thrown into deep waters in a “sink or swim” approach, which disappointed them. Others were enthusiastic about some aspects of the course, such as being given an opportunity to develop their independence, or praising the detailed and constructive feedback that we provided for their reports, or some specific lectures, such as the lecture on data visualization (defined by one student as a “gem”). 5/20 students later on decided to carry out their Undergraduate thesis projects under the supervision of one of the teachers. The large amount of feedback provided by the students is positive in itself, in the sense that it testifies that the course has aroused interest and commitment on the part of the students, albeit with a great variability of starting points in terms of independence and scientific maturity, which definitely needs to be addressed in the next editions of this course.

In order to provide more insight into why some stu-

dents end up engaging productively and enjoying the realistic scientific setting science in the course, while others tend to “sink”, we performed two analyses.

First, we looked at the closed-answers questionnaires for evidence of motivation or frustration that could lead to an antagonistic attitude. We found that 7/21 students thought that the preliminary knowledge was insufficient, and 12/21 students were not happy about the material and the mode of the exam (i.e., having to produce a report for each data challenge). Additionally, 9 students commented that the charge on the students should be slightly reduced. Conversely, 19/21 students declared that they were interested in the topics (13/21 very interested), 14/21 students felt that the main instructor motivates their interest toward the topic, but only 3/21 declared that they felt strongly about this.

As a second attempt to gather more evidence, we looked at the anecdotal evidence from the open questions filled by the students. TO organize this material, we tried to extract what we found to be key comments, and relate these comments to a “sink phenotype”, or a “swim phenotype”.

**SINK PHENOTYPE:** *“I believe that synchronous remote teaching, for example without frontal lectures where code was explained in detail, slowed me down a lot in learning the tools necessary for the DCs”; “I believe that the frontal lessons are necessary, even if via webcam or multimedia board”; “For DC1, the provided material was insufficient to address the question: to carry out the analysis, it is necessary to know the SIR model, which was not explained to us except by posting links, and it is also necessary to know how to integrate a differential equation, but this has not been explained.”; “The required computer skills were taken for granted, so much so that in DC the low familiarity I had with computational tools slowed me down a lot. I would have preferred to spend more time on the preparation part to become familiar with the various tools rather than having to do it while writing the reports”; “A negative aspect, which I would recommend to review, is that often the answers were not exhaustive or clear, in fact they were often questions themselves.”; “The course needs more focus on statistics, models, null models, and hypothesis testing”; “We students ended up doing a self-taught course; for this, I would not have enrolled in university”; “We developed the subjects in an extraordinarily autonomous way. We had to do all by ourselves”; “The course has been radically changed from last year, and I only became aware of it when it started”; “The partial assessments of DCs were USELESS for the purpose of having an indication of the final grade”.*

**SWIM PHENOTYPE:** *“The teaching material was excellent, the grading was clear and above all I appreciated the mixture of positive and negative remarks in the reports of the DCs”; “The discovery of the Command Line has opened up a new world for me and, even if it is as powerful as it is illegible at times, I will certainly delve into this and other tools that have received only an introduction in this course”; “The lesson on DataViz is a*

*gem. I have used very little of the C++, material, some examples of implementation on simulations would help a lot to make it feel an integral part of the course”; “I have learned to write a scientific paper decently, I can work (very roughly) with a dataset and I have learned many techniques of data visualization”; “The course is valid for the acquisition of scientific and computer skills for the production of a scientific paper”; “The many computer methods of data analysis covered at the beginning of the course are interesting, my plotting skills have improved a lot, even if Matplotlib becomes a nightmare as soon as you try to make a custom graph”; “Really useful course: -Teaches to use programming as a tool to face and solve concrete problems -Teaches to reflect on the data and on the results obtained -Teaches the basic principles of scientific communication”; “Very useful step for the university journey of a student who follows this curriculum. Quick exam, useful for the possibility of studying other exams quickly”; “The topics covered were interesting and made me discover and deepen topics that, not being strictly related to physics, I would not have dealt with in my studies, but I still found them to be important and useful in a scientific context, for example “bullshit calling” and methods for effective data visualization”; “However, I realize that it is the main challenge of the course to provide answers supported by logic and statistics without ever having used these tools in this way, since the laboratory 1 and 2 courses are bland and the projects are fully guided”.*

In our opinion, these comments fully report on the frustration (of some students) stemming from feeling abandoned, and also on the recognition (from some students) of some of the key aspects of the course. A parallel consideration is that open-ended challenges open the opportunity for students and teacher to join sides against common problems, but this process does not happen automatically for all students. We think that an important factor underlying the almost bimodal reactions is linked to the independence that we asked students to achieve: one of the training objectives is precisely to make the student autonomous in learning new tools for analyzing and exploring data. Before the conversion to remote teaching, the philosophy behind the course was already to promote active learning through data-analysis projects. However, some students, due to lack of information, or simply due to the fact that the course has radically changed compared to previous years, expected a more standard course (as witnessed by some of the comments). This impact should automatically soften over time.

“Inquiry-based learning” [29–31] is an approach to teaching that starts from the assumption that a primary route for a student to learn something is to ask him/herself questions and then actively look for answers on his/her own (by contrast classic teaching may give answers to questions that many would never ask). For this approach, there are various schools. Typically one tries to engage the students on a problem by arousing curiosity and stimulating questions. A “gradual release of responsibility” strategy [32] fits our project, as it aims at

the gradual empowerment of students for their activities, by showing examples, and gradually “ramping up” the scale of difficulty and independence (which is the most delicate step).

## DISCUSSION

Unfortunately with the COVID-19 crisis there is likely to be a big turn away from the experiments in teaching physics in the coming years, although some initiatives are trying to address practical teaching suitable for social distancing and remote learning [33]. It seems urgent and useful to set up and systematically improve teaching materials and experiences such as the one we experimented on here. Such a setting would lead students to work on real data, analyze curves and distributions, perform fits, ask questions and look for answers in the data. It would be a recovery of an important part of what a student normally learns in laboratory work.

Beyond the contingency of a completely remote learning, the course offered us an occasion to reflect on general problems related to the formalization and the implementation of a hands-on approach in a course aimed at teaching through the supervision of active student projects. A full evaluation of the course outcome would require a larger sample, as well as further efforts towards defining different cohorts of students and appropriate “controls” (for example a quantitative comparison to an equivalent course with close-ended projects only). Despite these limitations, our analyses are in support the idea that including open-ended challenges may open the possibility to address and promote student skills that are otherwise hard to access.

Our experience can be replicated in other contexts, not only to physics students, but also in other quantitative curricula such as mathematics, engineering or computer science. A crucial aspect is how many students such a course structure can support. With two instructors we found that 25 students is a realistic sustainable upper bound. However, during DC1, the presence of the external supervisors was essential. These are 10-15 days of the course where at least 2-3 extra teachers are involved to support the students’ questions and provide feedback. This need should not be underestimated when planning a similar course, but we believe it would not be too hard to implement it e.g. through PhD students or postdocs (also providing a valid supervision experience for early-career scientists). Not to underestimate, the supervision activity is probably easier to implement remotely than in a classroom setting. In such a setting, the extra supervisors can provide feedback through a chat interface in the time slots and time-frame they want, and the forum structure leaves a question open to be addressed for any supervisor (or even other students). It also leaves answered questions available to any students, who may spot a relevant issue even in cases when they are not able to crystallize it in a well-defined question.

## CONCLUSIONS

In brief, we judge that the practical implementation of the philosophy behind the course was successful, but a crucial aspect is to soften as much as possible the initial barrier for a student to become active on the “data challenge” projects. Our results support the idea that teaching through open-ended scientific challenges leads to qualitatively different results than close-ended projects, and can improve communication and technical skills, as well as stimulating creativity at different levels. However, at the same time the same results also point to some critical aspects of this way of teaching. Keeping the focus on our main objectives, we intervened in several ways in the 2021 edition of the course: a) clarifying from the beginning which skills (soft and hard) we expect the students to develop, and how they are evaluated in the exam; b) expanding the description of specific tools, so that students can be immediately operational; c) providing lectures including “frontal” explanations, combined to the posted study material and the individual Q&A tutoring sessions on Zoom, in order to reduce the amount of material to be processed individually; d) reducing the overall load, passing from three to two data challenges, and extending the time dedicated to each, so that students can work under a lower time pressure. To some extent, the ongoing health crisis helped driving student interest in the course activities. This fact was still valid in 2021. In the future, to achieve the same level of engagement from students, the choice of future topics for open-ended data challenges could be crucial.

From the point of view of Faculty in the physics curriculum, the constraints enforced by the pandemic led us to innovate on both the teaching methodology and the

subject matter, in ways that we had not previously explored. While admittedly far from perfect, we believe that our experience is something to build on. While the course corpus and toolbox can be improved, they are nothing special *per se*. It is the “hands on” part of the course that provided a valuable access for the students to elements of knowledge, practice and “nature of science” that are typically not accessible in standard courses, and are often developed through laboratory practical experiences. For many, learning “the physics way” of addressing problem was a real hitpoint of the course. Two aspects were specifically very interesting. First, COVID-19 data was an ideal setting to learn how to deal with poorly defined “messy” problems, where there is no unique or preconceived solution [9]. The students had to come to terms with the exercise of isolating well-defined sub-problems, and to find compromises of different kinds in order to analyze the data and draw conclusions, which is what invariably happens outside of a classroom, in a research or a workplace setting. To this end, the interactive Q&A sessions on Zoom where each student could report their findings and questions were particularly effective. Second, remote teaching provided unexpected opportunities to stimulate an active role of students, via oral and written communication. The possibility to keep a constant communication feedback collectively and individually via the Slack space was certainly an unexpected benefit for us. Additionally, and perhaps more importantly, remote teaching breaks the student expectations of unidirectionality. Looking at a frontal lecture on line may become extremely boring, and exploring alternatives is a necessity, but also an opportunity to promote active work and active learning from the students.

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- [1] Laurie M. Brown and Richard Tilghman Weidner, “Physics,” in *Encyclopaedia Britannica* (2020).
  - [2] Philip Nelson, *Physical models of living systems* (W.H. Freeman & Company, New York, NY, 2015).
  - [3] Lena Hansson and Lotta Leden, “Working with the nature of science in physics class: turning ‘ordinary’ classroom situations into nature of science learning situations,” *Physics Education* **51**, 055001 (2016).
  - [4] Note that “model” is a concept used with quite distinct meaning in various fields of science: physics, chemistry, biology, engineering. We will use “model” as shorthand for “physical model”.
  - [5] Itai Yanai and Martin Lercher, “Night science,” *Genome Biology* **20** (2019), 10.1186/s13059-019-1800-6.
  - [6] Clifford Swartz, *Cliff’s nodes : editorials from the physics teacher* (Johns Hopkins University Press, Baltimore, 2006).
  - [7] Carl Bergstrom and Jevin West, *Calling bullshit : the art of skepticism in a data-driven world* (Random House, New York, 2020).
  - [8] Randy L Bell, “Teaching the nature of science: Three critical questions,” *Best Practices in Science Education* **22**, 1–6 (2010).
  - [9] Erin L. Dolan and James P. Collins, “We must teach more effectively: here are four ways to get started,” *Molecular Biology of the Cell* **26**, 2151–2155 (2015).
  - [10] R.G. Fuller, “Numerical computations in US undergraduate physics courses,” *Computing in Science & Engineering* **8**, 16–21 (2006).
  - [11] Norman Chonacky and David Winch, “Integrating computation into the undergraduate curriculum: A vision and guidelines for future developments,” *American Journal of Physics* **76**, 327–333 (2008).
  - [12] Christopher J. Burke and Timothy J. Atherton, “Developing a project-based computational physics course grounded in expert practice,” *American Journal of Physics* **85**, 301–310 (2017).
  - [13] Randi A. Engle and Faith R. Conant, “Guiding principles for fostering productive disciplinary engagement: Explaining an emergent argument in a community of learners classroom,” *Cognition and Instruction* **20**, 399–483 (2002).
  - [14] Marco Gherardi, Salvatore Mandrà, Bruno Bassetti, and Marco Cosentino Lagomarsino, “Evi-

- dence for soft bounds in ubuntu package sizes and mammalian body masses,” *Proceedings of the National Academy of Sciences* **110**, 21054–21058 (2013), <https://www.pnas.org/content/110/52/21054.full.pdf>.
- [15] Salvatore Mandrà, Marco Cosentino Lagomarsino, and Marco Gherardi, “Soft bounds on diffusion produce skewed distributions and gompertz growth,” *Phys. Rev. E* **90**, 032805 (2014).
- [16] <https://github.com/pcm-dpc/COVID-19>.
- [17] (JHU CSSE COVID-19 Data <https://github.com/CSSEGISandData/COVID-19>).
- [18] Ensheng Dong, Hongru Du, and Lauren Gardner, “An interactive web-based dashboard to track COVID-19 in real time,” *The Lancet Infectious Diseases* **20**, 533–534 (2020).
- [19] <https://ourworldindata.org/coronavirus>.
- [20] <https://data.europa.eu/euodp/en/data/dataset/covid-19-coronavirus-data>.
- [21] <http://dati.istat.it/>.
- [22] Anca Rădulescu, Cassandra Williams, and Kieran Cavanagh, “Management strategies in a SEIR-type model of COVID 19 community spread,” *Scientific Reports* **10** (2020), 10.1038/s41598-020-77628-4.
- [23] Giulia Giordano, Franco Blanchini, Raffaele Bruno, Patrizio Colaneri, Alessandro Di Filippo, Angela Di Matteo, and Marta Colaneri, “Modelling the COVID-19 epidemic and implementation of population-wide interventions in italy,” *Nature Medicine* **26**, 855–860 (2020).
- [24] Andrew J. Stier, Marc G. Berman, and Luis M. A. Bettencourt, “COVID-19 attack rate increases with city size,” (2020), 10.1101/2020.03.22.20041004.
- [25] Haroldo V. Ribeiro, Andre S. Sunahara, Jack Sutton, Matjaž Perc, and Quentin S. Hanley, “City size and the spreading of COVID-19 in brazil,” *PLOS ONE* **15**, e0239699 (2020).
- [26] Nick Wilson, Amanda Kvalsvig, Lucy Telfar Barnard, and Michael G. Baker, “Case-fatality risk estimates for COVID-19 calculated by using a lag time for fatality,” *Emerging Infectious Diseases* **26** (2020), 10.3201/eid2606.200320.
- [27] Tetsuro Kobayashi, Sung mok Jung, Natalie M. Linton, Ryo Kinoshita, Katsuma Hayashi, Takeshi Miyama, Asami Anzai, Yichi Yang, Baoyin Yuan, Andrei R. Akhmetzhanov, Ayako Suzuki, and Hiroshi Nishiura, “Communicating the risk of death from novel coronavirus disease (COVID-19),” *Journal of Clinical Medicine* **9**, 580 (2020).
- [28] Marino Gatto, Enrico Bertuzzo, Lorenzo Mari, Stefano Miccoli, Luca Carraro, Renato Casagrandi, and Andrea Rinaldo, “Spread and dynamics of the covid-19 epidemic in italy: Effects of emergency containment measures,” *Proceedings of the National Academy of Sciences* **117**, 10484–10491 (2020), <https://www.pnas.org/content/117/19/10484.full.pdf>.
- [29] Angela Brew, “Teaching and research: New relationships and their implications for inquiry-based teaching and learning in higher education,” *Higher Education Research & Development* **22**, 3–18 (2003).
- [30] Rachel Spronken-Smith and Rebecca Walker, “Can inquiry-based learning strengthen the links between teaching and disciplinary research?” *Studies in Higher Education* **35**, 723–740 (2010).
- [31] Margus Pedaste, Mario Mäeots, Leo A. Siiman, Ton de Jong, Siswa A.N. van Riesen, Ellen T. Kamp, Constantinos C. Manoli, Zacharias C. Zacharia, and Eleftheria Tsourlidaki, “Phases of inquiry-based learning: Definitions and the inquiry cycle,” *Educational Research Review* **14**, 47–61 (2015).
- [32] P. David Pearson and Margaret C. Gallagher, “The instruction of reading comprehension,” *Contemporary Educational Psychology* **8**, 317–344 (1983).
- [33] <https://www.smartphysicslab.org/>.
- [34] Robert Verity, Lucy C Okell, Ilaria Dorigatti, Peter Winskill, Charles Whittaker, Natsuko Imai, Gina Cuomo-Dannenburg, Hayley Thompson, Patrick G T Walker, Han Fu, Amy Dighe, Jamie T Griffin, Marc Baguelin, Sangeeta Bhatia, Adhiratha Boonyasiri, Anne Cori, Zulma Cucunubá, Rich FitzJohn, Katy Gaythorpe, Will Green, Arran Hamlet, Wes Hinsley, Daniel Laydon, Gemma Nedjati-Gilani, Steven Riley, Sabine van Elsland, Erik Volz, Haowei Wang, Yuanrong Wang, Xiaoyue Xi, Christl A Donnelly, Azra C Ghani, and Neil M Ferguson, “Estimates of the severity of coronavirus disease 2019: a model-based analysis,” *The Lancet Infectious Diseases* **20**, 669–677 (2020).
- [35] Eco di Bergamo, “Coronavirus, the real death toll: 4.500 victims in one month in the province of bergamo,” (2020).

**Appendix: Examples of students results.**

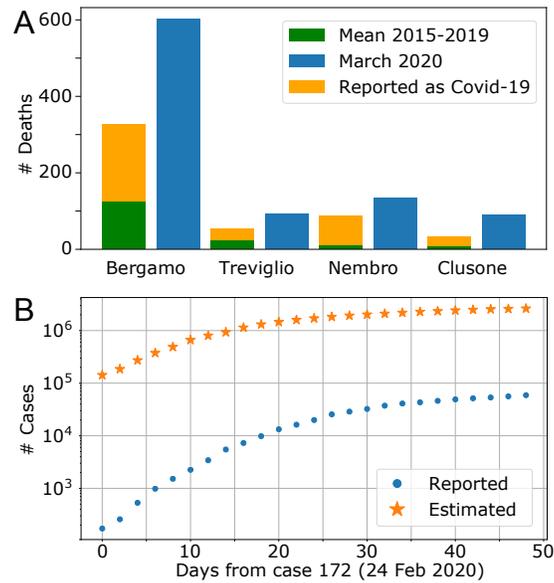


Figure A1: Examples of students' results on COVID-19 epidemiological data combined with mortality data. Panel A compares the total deaths reported in four cities in the Bergamo area in March 2020 (blue bars) with the sum of the COVID-19 deaths reported in the same month (orange bars) and the average of the total reported deaths in the same month of the previous five years (green bars). In all cases the sum of average mortality and reported COVID deaths (green plus orange) was well below the total mortality, pointing to widespread unreported cases. Panel B reports an estimate of the actual total number of cases in Lombardy (orange stars) from the number of reported cases (blue circles) based on the excess mortality. The estimate assumed a common overall fatality rate for the virus of 1.2 % and an average delay of 18 days between infection and death [34]. Based on these estimates, the actual number of cases in that area could have been between one and two orders of magnitude higher than estimated from swabs. 2015-2019 mortality data was downloaded from the Italian National Institute of Statistics (ISTAT). Mortality data from the cities in the Bergamo area were obtained from the newspaper l'Eco di Bergamo (each city had shared these data directly with this newspaper [35]). Data were obtained from the Italian Civil Protection Repository.

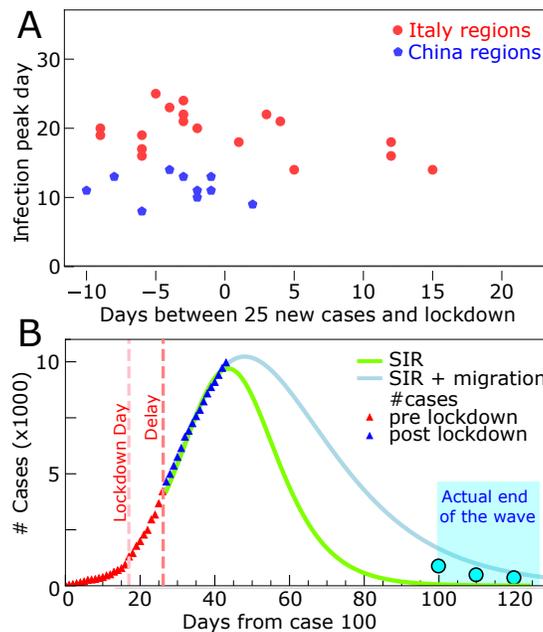


Figure A2: Examples of students' results on COVID-19 epidemiological data. A. The infection peak, defined empirically as the maximum in the observed new cases after a lockdown, depends on the level of the infection at lockdown. The scatter plot reports the day of the infection peak ( $y$  axis, defined as the maximum in the number of current cases vs the time from lockdown, measured in days from lockdown) reached by a region compared to the delay between the implementation of lockdown and the day the number of new cases reached 25 ( $x$  axis). Italian regions (red circles) are compared to Chinese regions (blue pentagons). The plot shows that different regions took a similar time to reach the infection peak after lockdown, but the delay was longer in Italy than in China, possibly because of underreporting or less strict confinement measures. B. Different infection models lead to different predictions. The plot shows two fits of SIR disease spreading models performed by two students, using two different model variants on data from the Veneto region (triangles). One model (green solid line) was the standard SIR, while another model (light blue solid line) also included immigration/emigration. This variant of the SIR model adds parameters that describe immigration ( $\Lambda$ ) and emigration ( $\mu$ ) and both variants were used to estimate the effective transmission rate ( $\beta$ ), the hospitalization rate ( $\gamma$ ) and the basic reproduction number ( $R_0 = \beta/\gamma$ ). The model divides the total population ( $N$ ) into three categories: susceptible ( $S$ ), infected ( $I$ ), and removed ( $R$ ), with  $N = S + I + R$ , and following the ODEs  $dS/dt = \Lambda - \mu S - \beta SI/N$ ;  $dI/dt = \beta SI/N - (\gamma + \mu)I$ ;  $dR/dt = \gamma I + \mu R$ . The standard SIR model has  $\Lambda = \mu = 0$ . Introducing the model variant lead to a different prediction of the end of the epidemic wave. The actual data, which came after the Data Challenge, displayed a behavior in between the two model predictions. The end of the wave took place about 110 days after lockdown (cyan circles), so that the model with migration parameters resulted to be more accurate. The model fits kept into account the fact that the the average number of contacts per unit time changed after lockdown (blue triangles), compared to before (red triangles) considering a delay of 9 days for developing the disease. Data from the the Italian Civil Protection and the JHU CSSE COVID-19 Data Repositories.