Incorporating Research Skills in the Classroom

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1 Introduction

As educators, we spend a lot of time working to engage students while also ensuring that they retain skills acquired, and content learned, in the classroom. At the same time, there is often an immense disconnect between the way we teach core concepts and techniques and the way they are discussed and implemented in professional circles. Without compromising the ideal of education as more than just job training, there are ways that we can introduce students to research and critical thinking that both improve learning outcomes and prepare them with creativity, curiosity, and intellectual resilience.

While this guide is written primarily from a STEM perspective (and often a computational one at that), many of these same principles apply anywhere data or research activities can be used to augment or enhance course material. When research practices are incorporated into the classroom organically, they enrich the learning environment. All students will benefit from the increased engagement with the academic enterprise; gifted students will appreciate the (potential) challenge of doing more practical, intellectually rigorous work in the classroom; and this sort of coursework creates pipelines into department research, including by potentially informing students of opportunities they did not previously know existed.

2 Why Expose Students to Research

Motivation drives learning (see especially Ch. 6 of National Academies of Sciences, Engineering, and Medicine, 2018, and references therein, for a longer discussion), with students experiencing greater motivation when given purpose and some amount of control. This effect is even stronger in topics for which they have an affinity, allowing students to enjoy content mastery as its own reward. In that vein, incorporating "research" in the classroom is critical professional development, giving interested students the tangible benefit and goal of skill-building and potentially inspiring other students to care by being clear about the *real world* application (or basis) of the often simplified or sanitized classroom material.

Giving students the opportunity to engage with research – whether through the literature or through experience in collecting or analyzing data – also establishes a framework for understanding science as a process rather than just a result. Real science is messy and, frankly, imperfect, often limited by the quality or availability of data or the intrinsic complication of physical systems, but non-practitioners are often aware only of the press releases and high-impact results that, in their final, polished form, are shared by news outlets and excited individuals. Most adults in the United States recognize that scientific outputs (like the internet, weather forecasts, and nutrition facts) are important in their daily lives, but are completely disconnected from how science happens and is sustained (Klein & Palma Kimmerling, 2025).

Producing graduates who are informed not just about their immediate discipline, but who are equipped to take in and assess information broadly has always been a goal of university education. Engaging students in research has been shown to promote the development of critical thinking skills (e.g., Kelp et al., 2023; García-Carmona, 2025). Simultaneously, understanding scholarship and how researchers relate to society has profound social benefits (Howell & Brossard, 2021; Tuttle et al., 2023).

From a purely pedagogical perspective, research-focused coursework aids learning. Active learning strategies, which include a myriad of different practices that engage students beyond a typical "sage on a stage" lecture, have been shown to improve student outcomes (e.g., Freeman et al., 2014). Developing a curriculum focused on, or even just minimally incorporating, academic research provides a number of different avenues by which to naturally add more "active" moments to your coursework.

3 Encouraging Engagement with the Literature

Being able to read and comprehend academic literature is a core research skill. Students are often intimidated by the nature and volume of content shared in journal articles and primary sources. Instruction in reading published academic work is generally focused first on demonstrating how to approach the information, with subsequent assignments focused on the deep-reading of an individual paper or passage (e.g., Hartman et al., 2017; Goudsouzian et al., 2023). In many cases, these efforts take a more limited view of students' classroom engagement with the literature, framing it primarily in terms of exposure to content, rather than skill acquisition. While there are certainly short-term benefits to encouraging students to just *look* at scholarship, helping students develop independence in critically engaging with published results builds intellectual confidence and curiosity and helps inoculate them against misinformation.

In introducing the literature to students, I liken acclimation to the organization, style, and prose of scholarly articles to reading Shakespeare: when you start one of his plays, the differences between Early Modern English and our day-to-day language are obvious and, at turns, distracting, but by the end of the play, you're generally invested in the characters and story and no longer notice linguistic conventions that once distracted. In truth, this means that real literacy comes from repeated, long-term exposure to published articles, but there are also strategies that can hasten understanding.

Instructor-provided marginal comments that tie ideas together offer insight into interpretation, and otherwise add context or information have been shown to improve student comprehension (e.g., Kararo & McCartney, 2019). As an example of this in a science communication context, I quite like Claire Lamman's annotated paper summaries[1], which have inspired others to follow suit (she collects others' summaries here[2]).

In a similar vein, though one that aims more at critical engagement with a text, you may consider sharing popular write-ups of a particular result (as from Scientific American[3], Quanta Magazine[4], or another trusted source) alongside an article that students are reading. They can then assess what others found important against their own takeaways from an article. In my own discipline, I often direct students to astrobites[5], which are paper summaries written specifically for undergraduates by a volunteer group of graduate students. (The ScienceBites Network[6] has expanded beyond astrobites and there are now a number of disciplines covered, with a huge swath of the scientific literature turned into accessible summaries.) Depending upon the order in which students read the original article and the summary, they will either (a) be able to confirm their understanding of the paper or (b) be primed to focus on the most critical parts of the paper and how it adds to the larger disciplinary context.

"Social" reading offers an additional avenue by which students can engage with the literature and with their peers, annotating a text, while also asking and answering questions. Crowd-sourcing clarification can spur discussions, give students more ownership over aspects of the content that they understand, and offer a low-stakes way to ask specific questions that

[1] https://cmlamman.github.io/paper_summaries.html
[2] https://cmlamman.github.io/paper_doodles.html
[3] https://www.scientificamerican.com
[4] https://www.quantamagazine.org
[5] https://astrobites.org
[6] https://sciencebites.org/sciencebites-sites-galaxy/

may otherwise be daunting to vocalize in front of a classroom. In addition to classic low tech implementations of this practice, including in-class opportunities to read in small groups, there are ed-tech solutions that facilitate group annotation, like Persuall[7] or Hypothesis[8], which are built for exactly this purpose. Such practices tap into the benefits of peer-to-peer education (e.g., Topping, 1996) *and* engagement with the literature.

Even simpler than (though not mutually exclusive with) any specific intervention to encourage students in reading primary sources is to simply add relevant articles to your syllabus as optional supplements to the main course text. I personally frame this in my own syllabi as "suggested" reading, which is at a level appropriate for the course, and "further" reading, which expands significantly in either breadth or detail from class content. This approach allows students who wish to engage more with the literature to do so, giving them a vetted starting point, but does not force disinterested or overwhelmed students to pick up that particular skill.

4 Demonstrating Technique During Lecture

Lab demos are common, but rarely focus on fundamental research skills, instead either illustrating a concept attendant to lecture or providing a practical example of what's expected of students during a condensed lab period. In more computational fields, students are more often exposed to research outputs, but rarely see any experimental or analysis techniques demonstrated directly.

Practical demonstrations have the potential to go wrong. If you want to show analysis of a sensitive sample that requires careful treatment, consider showing a video of the sample processing taken in a research lab. Alternatively, organizing lab visits, where small groups or the class as a whole (most tractable with lower enrollment courses) visit working laboratories or research group meetings within the university. If it's too hard to negotiate schedules based on class size or lab availability, it may be more feasible to create an "interest" form to prioritize visits for students who are most interested in seeing research work in action.

While there are certainly famous cases of students being used as research participants for course credit, most people likely don't condone the perhaps coercive nature of consent informed by needing a grade or good will (it may be that this is actually pervasive in some

[7] `https://www.perusall.com`

[8] `https://web.hypothes.is`

disciplines and so an expectation of students enrolling in a course). Instead, students can still engage with social research in a class-only version of a study (as opposed to one that will eventually be published for the benefit of the instructor), with data retained by the students to process in example analyses.

In more computational coursework, having code pre-written and ready to run reduces the risks that come with live coding tutorials. If you are publishing course notes, you may consider using something like Jupyter Book[9], which is explicitly designed to run code on recompile, so your examples and tutorials are included immediately alongside the relevant material. Similarly, tools like RISE[10] can be used to convert Jupyter notebooks into slideshows so that working code is integrated directly into your lecture materials.

5 Preparing Data for the Classroom

Working with real data promotes "data literacy" (Kjelvik et al., 2019), giving students a more realistic sense of the process of science, and builds research capabilities by exposing students to practical data collection and analysis techniques (e.g., Gade & Wallace, 2023). Students who better understand the strengths and limitations of data and analysis display more capable critical thinking and intellectual discernment. Having students work with data also impacts their feelings of agency and self-efficacy in the classroom, both of which are important for developing and maintaining learning motivation.

5.1 Sanitizing Archival Data

Research can be *tedious*, and as academics we tend to embrace that reality, but students, who are often exposed primarily to the more menial parts of day-to-day science, experience little respite as from, for instance, the excitement of discovering something new or sharing novel results. Much of current science education centers on having students do the same rote undergraduate-level tasks and repeating them to gain proficiency. Even though it's good practice, having students repeat the same task ad nauseam without variation may discourage them in the long run. Just adding in more scaffolding to the curriculum, giving students a widening set of data analysis tools with which they're familiar and increasing

[9]`https://jupyterbook.org`

[10]`https://github.com/damianavila/RISE`

autonomy in their treatment of data can help push through those feelings of tedium. That means, though, that some work may be necessary to prepare existing datasets for students' "free" exploration.

There are many wonderful datasets that are publicly available and are, largely, ready for analysis: e.g., NASA EARTHDATA[11], the UCSC Genome Browser[12], or the NASA Exoplanet Archive[13]. (As a caveat: Unified datasets developed without domain expertise are notably becoming increasingly common in the age of generative AI, as people vie to share compilations of foundational training data. These datasets are often put together with little or no regard for the sourcing, provenance, or accuracy of the included information. Of course, most of us would urge caution in using or sharing such unvetted repositories when asked, but it may be worth an explicit warning to students that convenient data of uncertain quality and origin is now proliferating the internet.) Still, there are steps that you can take as an instructor to facilitate student engagement with the data, which apply to any dataset you present.

Rather than using specialized discipline-specific data formats, convert files, where possible, to common formats. If files cannot be converted – or if the converted file type retains a complex data structure – share simple instructions for how to access the most salient parts of the data to give students a place to start. Similarly, if it's appropriate for the course content, offering students a quick tutorial on discipline-specific formats can make it easier to present diverse data in the classroom. For particularly large datasets, truncating them to only share the most relevant entries can help students focus on the intended engagement with the data. On the flip side, if the goal is for students to freely explore a particular dataset, sharing one or two (non-comprehensive) ideas of what might be interesting to examine in more detail can give students critical momentum in looking through the data while also contextualizing the assignment.

5.2 Collecting New Data

It has been found that, as beneficial as general engagement with data is, individuals who participate in data collection show better learning outcomes across the board (Mady et al., 2023). Depending on your discipline, it may be possible to use either university or external

[11] https://www.earthdata.nasa.gov
[12] https://genome.ucsc.edu
[13] https://exoplanetarchive.ipac.caltech.edu

resources to involve students in data collection.

Allowing students to collect their own data increases feelings of agency in the classroom. Setting aside class time, even outside of “lab” sessions, to allow students to conduct their experiments or observations ensures that they view the act of procuring data as a priority while also having equal access to troubleshooting, supplemental instruction, and clarification. If the data collection procedure is in any way variable, having a standard backup dataset available for students who are unable to successfully gather their own data creates a critical safety net and allows them to continue to analysis without compromise. If instead of engaging students in data collection, you are giving them a dataset that has been developed at your university or in your department (particularly relevant in courses where collecting new data might come with IRB considerations or require expensive or highly specialized equipment), taking a “field trip” to see where (and ideally how) the research takes place can nicely complement any work students are doing to explore the data itself.

There's also a whole market around providing key facilities for student projects. To illustrate the level of adoption of these contracted facilities, in my own discipline, which is perhaps uniquely suited to remote data collection, examples include iTelescope[14] and Slooh[15]. Despite the extremely hands-on nature of some fields, there are still options available to facilitate data collection and analysis at a distance (e.g., Baudin et al., 2022), though some practical aspects of the lab exercise may be lost for students. It should also be noted that while these services are designed to fit into coursework, they generally charge in blocks based on allocated resources, so there may be logistical limits to the scope of project students or groups of students can undertake.

There are other ways to stretch available data. Students can take a hybrid approach in which they collect some data, which is then augmented by existing datasets (e.g., Lichti et al., 2021). Similarly, collating data from different sources – such as individual papers, public catalogs, and even participatory science datasets – and repurposing it to answer a different question can flex many of the same muscles as more traditional data collection, even if it doesn't practice all of the same skills.

[14] `https://www.itelescope.net`

[15] `https://www.slooh.com`

6 Facilitating Data Analysis and Exploration

Once data are in hand, it can still be a long road for students to derive meaning from the material they are exploring. Not all results will be equally easy to discern, and if students have collected their own data, this will be doubly true with differences in the quality and nature of the data they're analyzing. Facilitating, or even just minimally guiding, students' interactions with the data can help make sure that everyone stays on track, with their analysis and exploration enhancing the classroom experience rather than distracting from the intended content and skill acquisition.

6.1 Using Interactives and Visualizations

Presenting information visually[16] leads to greater retention of material (e.g., Maisto & Queen, 1992; Mayer, 2002; Schoenherr et al., 2024; Ciccione et al., 2025).

In creating your own visualizations, both design and accessibility best practices should apply. Graphics should be designed to easily convey the intended information without clutter; Edward Tufte's *The Visual Display of Quantitative Information* is often considered the gold standard for creating aesthetically pleasing, but still information-dense figures. It is also critical to use high contrast colors, perceptually uniform colormaps, and sufficiently large font sizes to ensure that students with visual impairments can access the information. You can check your images with tools like COBLIS[17] or DaltonLens[18]. There's also a nice guide to accessible image/interactive design here[19] (see also, e.g., Ramsey & Schröder, 2025), which goes into greater detail about how to ensure a varied audience has equal opportunity to engage with your visuals. As an added legibility measure, you can include annotations directly in your graphics to add information or help draw attention to critical trends.

It can be a useful exercise for students to create their own visualizations. Learning outcomes improve when students participate in the creation of visualizations including by imaging a system or drawing a diagram (Bobek & Tversky, 2016). Students may similarly benefit from being asked to explain errors or inconsistencies in diagrams and illustrations, particularly when those errors are already highlighted for students (Jaeger, 2025).

[16] Admittedly, something I am not modeling in this guide.

[17] `https://www.color-blindness.com/coblis-color-blindness-simulator/`

[18] `https://daltonlens.org`

[19] `https://www.a11y-collective.com/blog/accessible-charts/`

With only a slightly higher degree of complication, it is possible to create interactives (using static HTML) or dashboards (requiring you to run things either server-side or client-side). The advantage of these sorts of visualizations is that they allow students the flexibility to define what data are shown and/or how data are shown, serving as a bit of an intermediate step between asking students to interpret specific results and giving students complete freedom in examining a dataset. Many (free) tools now exist to aid in the creation of interactive plots and dashboards: e.g., Plotly[20], Vega-Altair[21], and Marimo[22]. Certainly, some instructors (or students) may be able to create yet-more-flexible implementations of interactives using libraries like Flask[23], but even simple interactives can shape how students engage with data, better aligning their exploration with course objectives.

Beyond exploring the data, the same principles apply. Giving students easy-to-use (or at least easy-to-interpret) graphical user interfaces (GUIs) to facilitate analyses and measurements can also smooth the student experience and give you control over where students spend the most time and energy. Depending on your coding language of choice, there are many options to aid in GUI creation, including, perhaps most ubiquitously at the moment, React.js[24].

Students can also be charged with developing analysis tools then sharing them with, and testing them for, their peers. Building specific calculators (which may or may not be published as a web application) is a very common assignment in this genre as the accuracy and reproducibility are easy to check, and there are many ways for students to make the assignment their own in style or level of detail/complication. While these were not student projects, the diversity of calculators – even of the same values – can be seen between Ned Wright's Cosmology Calculator[25] (Wright, 2006), which many in my discipline use as the de factor way to recover cosmological values quickly, and the more recent Colossus Cosmology Calculator[26] (Diemer, 2018), which adds illustrating figures and other features.

[20] `https://plotly.com`

[21] `https://altair-viz.github.io`

[22] `https://marimo.io`

[23] `https://flask.palletsprojects.com/en/stable/`

[24] `https://react.dev`

[25] `https://www.astro.ucla.edu/~wright/CosmoCalc.html`

[26] `https://colossus.astro.umd.edu`

6.2 Having Students Follow an Established Protocol

Though it's not endemic to every discipline, the idea of a laboratory protocol can be very useful in guiding students through data analysis, whether prescriptive or open-ended and curiosity-driven.

A protocol can easily turn into an assignment or project. If you want students to develop their own analysis method or tool, you can give students the outline of steps and/or features they should include, but not the details of their implementation. I tend to think of this sort of exercise as looking a bit like the Technical Challenge in the Great British Bake Off; the assignment relies heavily on both student understanding and ingenuity, while offering enough direction and constraint to keep people on track. There are many ways to balance structuring an assignment and providing instruction vs. building student reliance on their own intuition, while retaining the helpful mental load of the exercise.

Some ideas for consistent, but less structured work may include allowing students to define their own endpoint – i.e., encouraging everyone to work to a minimum point, but giving students free rein beyond it – or having students answer their own question and define their own analysis (ideally one that's been introduced before in the course, taking a scaffolding approach) on a uniform dataset. Students who thrive when given more autonomy can then elect to pursue more complicated or out-of-the-box projects, while students who prefer a safer, more deterministic academic experience can more closely follow the established "protocol". Allowing students to choose their own adventure gives them agency and meets students in a potentially varied classroom where they are most comfortable without compromising the integrity of the assignment.

Such efforts can also offer a low-stakes opportunity for students to get acquainted with basic research best practices, such as using isolated software environments and disentangling strict version requirements (sometimes especially necessary with conflicting dependencies) in computational fields or writing reproducible protocols that demonstrate knowledge of both experimental design and professional communication. Especially in more collaborative contexts, it can also be a chance for students to explore task delegation, data management, software versioning with `git` or similar, and effective team communication. These *practical* aspects of the assignment are critical for students' pre-professional development and set them up for success outside of the classroom, too. Enforcing, or at minimum explaining, such practices also helps level the playing field for students who have had different extracurricular experiences. Many of these skills are taught in formal research programs (like NSF REUs), but those opportunities are generally extremely selective and not available to all students.

6.3 Creating Bespoke Tools

If the focus of an exercise is on the *results* of a particular analysis rather than collecting, manipulating, or analyzing the data itself, it may be helpful to write a software package – or distribute similarly easy-to-use code – that glosses over the arithmetic or computational complexities, allowing students to focus on the salient parts of the activity or assignment. Software that you share does not need to be complicated; in fact, it may be beneficial to limit the scope and features of such packages, as too many bells and whistles may make interaction with the software more difficult and otherwise distract from the intended pedagogical purpose. Remember that tools that will take you 30 minutes and $\lesssim 150$ lines of code to produce would take students much longer and, while it's immensely beneficial to be able to develop one's own analysis software, students' time may be better spent on the activity itself. (A good example of this is a single-script package I wrote – `gaiacmds`[27] (Polzin, 2025) – which I am then able to use in a more focused lab assignment[28].)

Writing – or simply providing – working software to engage with data places the priority back on the lesson's intended learning objectives, rather than having the creation of necessary infrastructure serve as a distraction. To mix approaches, it may be beneficial to provide students a working example adjacent to a later assignment that involves the creation or implementation of other methods, giving them inspiration and direction, while also asking them to develop their own approaches to data analysis.

7 Building Toy Models and Using Simulations

In physics, we often use Gedankenexperiments (or simplified thought experiments) to build physical intuition when we introduce new concepts of phenomena. They are immensely effective because they probe student understanding *before* having contact with the scientific consensus. This practice is called "pretesting," and has been shown to improve long-term retention and learning outcomes (Richland et al., 2009; Pan & Carpenter, 2023; Mera et al.,

[27] https://github.com/avapolzin/goodenough_gaia_cmds

[28] https://github.com/avapolzin/ASTR11901_Summer2025/blob/main/labs/ASTR11901_Lab3_StellarPopulations.ipynb

2025). In many disciplines, research "pretesting" comes in the form of hypothesis creation (and then designing experiments to test that hypothesis). In the classroom, where time constraints preclude more complete experimentation, idealized test cases can still help build intuition. Instead of designing an experiment, students can interrogate their assumptions about the nature or behavior of a system through those controlled tests.

Building or running analytic models may help illustrate the behavior of *simple* systems. For instance, in physics coursework, it's common to use (and often *write*) N-body integrators to better understand gravitational interactions. Different initial conditions will result in different outcomes, and students can assess, and actively reassess, their understanding of the system as the simulation evolves. Similarly, beginning from the equation for a simple harmonic oscillator, one can test the impact of additional forces, perturbations, and non-linearity, complicating the system until it becomes chaotic.

More complex behavior can be simulated with pared down tools (see also Sections 6.1 and 6.3). A terrific example of this is the hydrodynamics code `Ulula`[29] (Diemer, 2025). `Ulula` is explicitly designed as a research tool that encourages student experimentation by lowering the barrier to entry for working with a hydrodynamics solver, allowing students to run existing example simulations while also offering the infrastructure for students to develop their own two-dimensional hydrodynamics simulations.

8 Effective Assessment of Skill-building

As is always recommended in discussing pedagogical best practices, your course assessments should match your learning objectives. In fact, structuring your learning objectives around active, measurable goals can create direct translation between your assignments/tests and your intended outcomes for student content and skill acquisition. One way to achieve this is to frame your learning objectives using the phrase "Students will be able to...,", which turns the objectives into actionable goals for students and helps shape your assessment. At the same time, it is critical to choose specific phrases that align best with what you expect students will be able to *do*. (Bloom's taxonomy can be very helpful in developing scaffolded learning objectives for research-focused courses that will, by necessity, emphasize higher level skills.) For instance, instead of saying the more generic "students will be able

[29] `https://bdiemer.bitbucket.io/ulula`

to discuss X and Y", you might list your course objective as "students will be able to differentiate between X and Y, enumerating the ways they are treated differently in the literature". Your assignment will then ask students to use primary sources to demonstrate how scholars distinguish X and Y.

Critically, when giving students open-ended research-like assignments, the emphasis in assessment and grading should align with the learning objectives instead of the project or assignment output. Generally, this means that the rubric will be based on the procedure followed rather than the recovery of specific results, which may be inhomogeneous across student projects. If the goal of an assignment is demonstrating specific skills and successfully (defined in terms of curiosity, depth, or breadth) exploring a particular dataset or research question, then it is only fair to decouple the project result from the grade students receive. Course timelines rarely allow time for students to fully revamp a project if the direction is not fruitful; as long as it aligns with your learning objectives, students in research-focused courses, or completing research-focused assignments, may best be evaluated on their approach to the work rather than on getting some concrete outcome or answer. One of the primary challenges in early research is persisting through challenges. Students grow the most, and best learn the contours of a problem, while troubleshooting (e.g., Sinha & Kapur, 2021). Intellectual resilience is critical in academic research, as is having the creativity to reassess and re-approach a problem, and aligning your rubric with the practice of science rather than returning any one result helps give students the space to develop those skills.

One reason students report feeling they "need to" resort to cheating is in response to (perceived) pressure to succeed (e.g., Miles et al., 2022). Using mastery-focused rubrics can allay student concerns and discourage patently unethical behavior (Anderman & Won, 2019), like using generative AI to fabricate a dataset or analysis, as well as less extreme academic integrity violations that students may resort to if their experiment or data collection do not go to plan under a results-based assignment structure.

9 Some Hard-Learned Considerations

One challenge with including "research" in the classroom is that data and analysis can be unpredictable. I list here some considerations I've taken away from common pitfalls I've experienced – or seen happen – when giving students data- or analysis-driven activities and assignments.

When giving students leeway in engaging with primary sources: Students have little context for what constitutes quality work in any academic discipline. If they approach the literature as though all published results are equal, they can easily go in the wrong direction. You can mitigate this tendency by providing a list of "safe" or "preferred" journals from which to read papers. Going a step farther, you can also provide an approved list of articles or primary sources with which you would like them to engage.

When having students work with existing tools: You should make sure that any required software will install broadly (across OSes, language versions, ...), especially if that software was updated recently. Be prepared to serve as IT support for students while they are installing the software (and plan to publish a detailed installation guide alongside the assignment/activity). In the (ideally unlikely) event that the package cannot be installed for some students, prepare and offer an alternative activity/assignment.

When having students download data on the fly: Sometimes one class trying to access a resource simultaneously can be enough to strain a server to the point of significant delay, if not failure. If you have students using an API or otherwise trying to access a server – particularly via repeated calls – it will be helpful to (1) stagger attempts to access the site, having students rotate through activities so that only some students are trying to access it at one time, lightening load; (2) keep a backup of the most critical files on the LMS or course site, giving them a second means of downloading it; and/or (3) have an alternative assignment or dataset available in the event that the server remains inaccessible. The latter is a good redundancy plan regardless given how frequently sites undergo maintenance or experience DDOS – or similar – attacks that result in significant downtime.

When encouraging students to pursue open-ended projects or assignments: It is critical to establish realistic expectations for students who are charged with selecting the topic, method, and scope of an assignment or project. If their previous experiences center on sanitized data or provided software, they will have little understanding of the real complexity of some datasets or tools they might hope to use. You neither want students to be frustrated by attempting something too far above their level, nor is it a good use of your time to devote resources to facilitating that level of project. To both allay student concern and ensure that everyone is on the same page, you may consider forcing students to check in with you (and/or the teaching assistants) in advance to share their project idea/plan. You can also provide topic ideas that are well-defined (and assured to work) for students who crave more structure. Providing rubrics that are clear about learning objectives and expected, tangible deliverables will similarly go a long way toward keeping everyone on track with the planned assessment.

When students are using newly collected data: If students have collected their own data, it should be deposited in a safe, version-controlled repository on collection. Especially in group projects, having a centralized backup will prevent students from accidentally deleting or overwriting the data. It also ensures that the raw data are readily available for comparison against the ultimate result (figures or findings) of the project.

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