

# THE FUTURE IS DATA LITERATE: A GUIDE TO DEVELOPING A STATISTICS COURSE FOR STUDENTS IN NON-QUANTITATIVE FIELDS<sup>1</sup>

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## Abstract

Statistics courses are typically in mathematics or statistics departments or in social and natural sciences such as economics, political science, psychology, and biology. Here we discuss how to construct a statistics course for students in non-quantitative fields, with a goal of integrating statistical material with students' substantive interests, using modern teaching methods and technology to increase student involvement. Data literacy for students in non-quantitative fields is important as statistics become the grammar of research and how the world's decisions are made. We demonstrate this kind of hybrid course with the example of an introductory applied statistics class at the University of Toronto's Anne Tanenbaum Centre for Jewish Studies.

## Keywords

Quantitative Methods, Data Literacy, Pedagogy, Undergraduate, Scaffolded Assignment, Course Design, Data Science, Jewish Studies

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# Introduction

Non-mathematically-minded undergraduates express hesitancy about enrolling in statistics courses (Slootmaeckers et. al., 2013; Bradstreet, 1993; Rumsey, 2017). Some students have inadequate quantitative training, others lack numerate confidence, and still others fail to see the relevance of statistics to them. And yet, one does not need to be a statistician to depend on numbers in everyday life (Oceans of Data Institute, 2015). News outlets habitually use graphs and charts to illustrate information for their readers. And journalists, non-profit leaders, and policy analysts use quantitative tools and statistical methods to measure trends, identify patterns, and interpret results. Indeed, data literacy is vital across industries, lifestyles, and the curriculum (GAISE 2016; Bhargava et al, 2015; Prado and Marzal, 2013; Bargagliotti et al., 2020). So how can educators best help students to build a numerate life?

In this article, we present our “Build A Custom Statistics Course” template as suggested by Gelman (2019) which can be modified to appeal not only to students in the social sciences and humanities, but also to students affiliated with theological institutions, centers for ethnic or diaspora studies, and journalism schools. This course not only meets all six of the American Statistical Association’s Guidelines for Assessment and Instruction in Statistics Education (GAISE) recommendations,<sup>4</sup> but it also builds upon these guidelines by specifically targeting students from non-quantitative fields, perhaps attracting students from traditional quantitative disciplines to programs in the arts and humanities, philosophy, or business. What we propose is a holistic and multidisciplinary introductory course in statistical reasoning, statistical methods, *and* in the substantive case knowledge that facilitates applied understanding of how data on all aspects of the human experience can be analyzed quantitatively.

This course can be provided by any department or center, whether a non-quantitative department that wishes to provide statistical training to its students in a way that connects to their preexisting interests, or a traditionally quantitative department that wants to provide more opportunities for applying statistical knowledge to substantive areas through cross-listed courses or other similar partnerships. What makes this type of hybrid course unique are the substantive topics used to teach statistical methods; this is accomplished through the use of topic-based readings, instructor and guest lectures, and datasets relevant to the discipline or subject-matter. The course we present also highlights tools critical for teaching a hybrid course, such as pre/post-tests,

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<sup>4</sup> These recommendations are listed as: 1. Teach statistical thinking; 2. Focus on conceptual understanding; 3. Integrate real data with a context and purpose; 4. Foster active learning; 5. Use technology to explore concepts and analyze data; and 6. Use assessments to improve and evaluate learning. For more detail, see the 2016 Revised GAISE College Report.

just-in-time teaching tools, and collaborative research projects. Using our modified template, educators can accomplish two separate and complementary goals:

1. Teach introductory statistics to non-statistics students
2. Teach substantive content through the perspective of statistics.

## Template

All new courses need consideration about what material will be covered, how student learning will be assessed, and which texts will be used. What makes this course unique is its multidisciplinary and multimethod approach, as it bridges together both methods and topics that have not historically been connected. Further, it is directed toward students in non-quantitative fields that may have limited statistical offerings, thereby heightening data acumen across disciplines. Data literacy matters not only in statistics departments, but rather across the curriculum and this course facilitates that vital learning. In the following section, we outline the major components of this course. In order to facilitate integrated statistical and subject matter learning, we suggest that the objective of such a course is some combination of a critical ability to interpret data within the context of a substantive case, as well as secondary analysis skills (e.g., descriptive analytics, causality and basic regression, data illustration). Follow this template to construct a course.

### What materials are needed?

Students should have access to computers, loaded with basic computing and visualization software, such as Tableau and R. Particular exercises may require further materials; for example, when we teach students how to compute and understand error terms, we use 10-15 photographs of individuals for the age-guessing demonstration of Gelman and Nolan (2017). Instructors may also find it useful to have access to a document camera and computer projector in order to provide visuals to students. For collaborative assignments, we recommend a cloud-based platform that students can edit in real time (e.g., Google Drive, Dropbox, GitHub, Microsoft One Drive).

### Evaluation: How should students be assessed?

If the goal is getting students to learn, instructors need tools for evaluation. We suggest that course instructors employ a variety of summative (how much someone has learned) and formative (how someone is learning) assessment tools. They are described as follows:

## Pre-test and Post-test

Pre-test/post-test followup is a useful pedagogical tool for student learning because it is both a summative and formative evaluation model. First, the pre-test can provide early feedback to the instructor, as it shows where the students have substantial pre-existing knowledge and where they are limited. A pre-test can help an instructor craft their semester, determining whether more or less introductory material is necessary. Further, a post-test can operate both as a final exam, when it helps to leverage final judgment on student learning and retention, as well as a formative tool for showing and illustrating student growth, and therefore for reinforcing future student learning in the realm of statistics.

For students, the pre-test/post-test model is useful because it can be low-stakes. For example, one can grade the pre-test on a pass-fail basis, with the grade accounting for approximately five percent of their overall grade. This means that, on day one, each student has an A+ in the course, which alleviates some of their anxieties about taking a statistics class. While they may not correlate with a perfect final grade in the course, pre-tests help to build early confidence for students that may come in with a fear of all-things numerical, in turn leading this group to be more willing to take chances, make mistakes, and engage with course material (Reid and Barrington, 1997; Meer and Chapman, 2014).<sup>5</sup>

Toward the end of the course (e.g., on the second-or-third-to-last day of class), the post-test should be administered. We suggest that this be graded and account for a larger percentage of students' overall grade. Every question on the post-test must be addressed over the course of the semester through course materials, lectures, and assignments. We suggest that the post-test include similar topical questions to those on the pre-test with slight deviations in the numbers or content so that post-test scores are not confounded with the pre-test. This post-test serves as the final exam in the course, but other educators may want to provide an additional exam depending on their pedagogical preferences and institutional expectations. In the class following the administering of the post-test, an instructor may redact student names and go over the results of the post-test collectively. In our experience, students appreciate this process because they are able to see where they did well and, if they got a question wrong, that others got it wrong, too.

We suggest that students be required to include for each question a self-reported confidence level (on a range of 0-10, where 0 is low and 10 is high) for their answer. This confidence level allows students to signal to their instructor when—and to what degree—they were guessing, in order to

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<sup>5</sup> We do not provide explicitly the solutions to pre-test questions. However, everything on the pre-test is by design covered in the course. Therefore students gain the answers indirectly over the term.

account for lucky guesses and to assess overconfidence. This model of assessment also helps to measure student growth and skill acquisition without relying on post-course student evaluations, which have been proven to be biased against female and minority educators and therefore may focus on arbitrary features of the instructor (such as their age, clothing, or appearance) rather than on the quality of the course and its delivery (Mitchell and Martin, 2018; Chávez and Mitchell, 2019).

### Just-in-time-teaching (jitt) tasks

In *just-in-time-teaching* (jitt), the course is supplemented by a short online assignment (informally, “jitts”) to be done before each class period (Novak et. al., 1999; Simkins and Maier, 2010; Watkins and Mazur, 2010). These short online tasks, graded according to a binary pass-fail system, are great pedagogical tools for getting students to think critically about course materials prior to class and to provide feedback to the instructor. For our jitts, we typically include three short questions in a simple online form: one to check on the readings, one that is a short problem, and one feedback on the class. As an example, a student may be asked to perform tasks introduced in class (e.g., “Calculate the appropriate sample size for the given variables. Show your work.”), to explain a concept (e.g., “In your own words, explain the debate surrounding Unz’s claims about Ivy League admissions.”), or to provide feedback (e.g., “What is one question you still have about the material in Unit 3?”).

The link to the jitt is sent out through the university’s learning management system, or by email, approximately 48 hours prior to class. Therefore, a class that meets, for example, on Tuesdays at 10am will receive the jitt on Sundays at 10am. The jitt is intended to take about 15 minutes to complete, and students are graded not on their correctness but just for seriously attempting it.<sup>6</sup> Therefore, the jitt operates as a low-stakes formative assessment, similar to a reading quiz given at the beginning of class. In our experience, the vast majority of students complete these assignments each week, as long as we remind them on the occasions that they don’t.

Low-stakes formative assessments are understood to improve student preparation, material recall, and grades on later assessments (Hodges et al 2015; Pape-Lindstrom 2018; McDaniel et al 2012). A jitt can be completed at home and students can use it to identify a gap in their class preparation that they can address prior to class, with the effect of being more adequately prepared. For those students that complete their jitts immediately before class, we expect that this gets them in the mood for the class period. Gelman (2013) provides guidance on how to set up jitts, some discussion about jitts, and examples of how we implement jitts in our class.

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<sup>6</sup> A serious attempt is one that seems to demonstrate that the student has read the material, completed the practice problem, or thought critically about the question.

Both authors of this paper integrate jitts in all of our classes by opening student answers on the computer projector so that we may go through the answers together as a class. The answers appear to the students as anonymous, which allows students to see what a correct answer looks like without being publicly shamed for an incorrect answer. This benefits students by boosting their confidence, not only because they are able to see how they did in relation to their peers, but also because they are able to fail at individual assignments without severe penalty. Jitt answers are discussed anonymously in class, but names are attached to answers for the instructor. This allows the instructor to grade jitts for effort on a pass-fail basis. It is also possible to fully redact names and identifying information (and instructor feedback) from the jitts, and to share the answers with students as a study tool.

Populating the syllabus with frequent, small assignments—such as these jitts—can help motivated students to earn higher grades; in a statistics class like this one, these frequent, small assignments help students feel like their hard work is, to some degree, paying off.

## Papers and Projects

A combination of solo, partnered, and collaborative projects is a good way to promote student learning. After all, if a student can solve a homework assignment correctly on their own, they demonstrate proficiency. However, a student that can *explain their thought-process to a peer*, navigate complicated ideas and processes in order to produce a deliverable, and influence the learning of classmates in a positive manner demonstrates mastery while improving their communication skills.<sup>7</sup> This is the principle behind peer instruction and group work (Mazur, 1997; Crouch and Mazur, 2001; Davidson, 1990). Collaborative assignments are particularly interesting because of their enmeshed free rider problem, where some group members tend to do more work than others, but the group earns a uniform grade, thereby allowing weak group members to free ride on the coattails of stronger students (LaBoeuf et. al., 2016).

In a statistics course, free riding in collaborative projects can operate differently. Consider the topic of linear regression. It is helpful to involve students in every step of the process. Therefore, instead of using a pre-made dataset, have students create a codebook together and decide on how different observable traits will be operationalized (Boger 2001). Students can collect this data easily using participant observation or survey questions (Taylor and Doehler, 2014). In this case, by working collaboratively, students are able to work with a larger dataset without having to collect it all on their own, which provides for greater analytical leverage. For example, if each student in a class of 15 surveys five strangers on campus, a dataset will have a total of 75

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<sup>7</sup> We are able to assess whether a student is successful in explaining a thought process to a peer by walking around the class to listen to conversations, joining in on small group discussions, and inviting groups to share their exchange with the class.

observations.<sup>8</sup> The instructor can use the jitt to request that students get approval to use their data in subsequent iterations of the course, which would further increase the number of observations in the dataset (e.g., 75 the first year, 150 the second year, and so on).

This kind of collaborative assignment can solve the free rider problem, because a free rider would produce missing data, which negatively impacts the results for every single person in the class, including the free rider. Using a cloud-based database, such as Google Sheets, further mitigates the free rider problem, as students are able to observe their own progress as compared to the progress of their peers in real-time.

After building their collaborative dataset, students can practice uploading it into whichever computing program is being used, cleaning it, and using it to run models or to illustrate exploratory findings. This process can even be used to teach library science fundamentals regarding the organization and preservation of data for optimal readability across researchers. This collaborative assignment can be concluded with an individual short paper on findings, takeaways, and illustrations. We outline the details of such papers in the section of this article, titled “The Collaborative Dataset Applied.”

## Choice of textbooks and readings

We suggest organizing the syllabus by weekly statistical objectives. These should begin with basic theoretical concepts that answer the general questions, "what is data?" and "who is involved in constructing a dataset?" Answers to these questions should include not only texts that explain the concept from a statistical perspective, whether something written for the non-STEM reader such as Wheelan (2012) or something more traditional like Gelman, Hill, and Vehtari (2020), as well as texts that consider data from a post-positivist perspective (e.g., including Fujii (2010) on the topic of meta-data). Supplementary readings can cover specific topics on research design (e.g., case selection, avoiding bias) and statistical concepts (such as comparisons of means or how to perform regression or classification analyses).

Most importantly, a conversation about what makes data *data* must include, well, data. Therefore, we recommend that including a weekly or biweekly dataset in the syllabus that complements concept-based readings; in the case above, examining an archive works well

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<sup>8</sup> While there is much attention in this course to inadequate and misleading survey questions, as well as to the misuse of survey data, an instructor that wishes to have students *collect* this kind of survey data on campus would need to provide further training to their students. Institutional ethics requirements for course-related survey collection varies and it is advisable for an instructor to consult their institution's IRB or REB representative.

because of its specificity. In more advanced discussions about, for example, multilevel models or sample sizes, it is possible to introduce the responses from most any survey-based dataset.

Each new dataset introduced on the syllabus, should come with some primary materials from its researchers (e.g., an Executive Summary or other reports, details regarding the scope and methodology of the study, or a list of questions asked in the case of a survey). We also recommend including on the syllabus some secondary materials (e.g., public lectures, opinion pieces in the press, blog posts from credible sources) about how the results of the study were received. Assuming that students learn in a number of different ways, we suggest that they are more likely to be engaged if the text included in the syllabus are diversified. By joining traditional materials with niche datasets, students can actively apply the statistical material that they learn to real-world examples, which strengthens and deepens their understanding of both.

Finally, we recommend that students are incentivized to review relevant, assigned substantive materials each term, such as background texts on a particular topic, research articles based on datasets covered in class, or multimedia resources, such as short films or podcasts, that can help to deepen a student's understanding of a topic. Instructors can incentivize students to come to class having prepared these materials by offering additional credit for introducing the text to the class and posing a few questions for further discussion—this form of incentive can work effectively both in-person and online, using a classroom management platform like Blackboard, Canvas, or Packback.

## What happens in class?

One primary objective of this approach is for non-STEM students to learn introductory statistics. In order for these students to take the intellectual risks necessary to succeed in a statistics course, they need to increase their confidence and buy-in. One way to increase both of these is to provide lots of low-cost opportunities for participation through discussion, collaboration, and in-class activities. Drawing from the 1992 Cobb Report and the 2016 GAISE College Report, we recommend that statistical lessons are couched in experiential education whenever possible.

The book *Teaching Statistics: A Bag of Tricks* (Gelman and Nolan, 2017) and the 2016 update of the GAISE College Report offer comprehensive lists of in-class demonstrations, activities, and projects for teaching introductory statistics. A themed course takes this learning one step further as statistics exercises are reinforced by substantive reading and lectures, which allow students to integrate their statistical understanding within a greater curriculum. For instance, in an exercise that teaches about error terms, discussed at the beginning of this paper, one might estimate the

ages of individuals known within a discipline (e.g., guessing the age of Barbara Streisand for students in Jewish Studies or the age of Steve Jobs for business school students).<sup>9</sup>

A secondary goal of a data literacy course for non-STEM students is building substantive expertise within a particular discipline, whether Italian Studies or History. As such, some of each class period will inevitably need to be lecture-based. This is necessary, for example, when an instructor provides background information about a particular dataset or its context. Some instructors will come to this course fluent in teaching both data science *and* a subject, while others will find themselves learning alongside students and partnering with other faculty and departments in order to broaden their interdisciplinary teaching.

From a practical perspective, each class meeting begins with a review of anonymous jitt answers. This process can take up to about 15 minutes, and both correct and incorrect jitt answers can be used as teaching opportunities. Students are then invited to go over the exercise problems that they received as homework. Students are incentivized to work together on problems and to submit work collaboratively, as it increases not only the likelihood that they will *complete* the homework, but also that they are successful in doing so (Little, Akin-Little, and Newman-Eig, 2010). In both of our classrooms, we often invite guest lecturers. In a course on Communication in Statistics, we invited Amanda Cox, a statistician and expert data illustrator from the *New York Times*, to talk about illustrating uncertainty and writing about statistics for a non-STEM audience. Alexis brought in Dr. Betsy Anthony, a researcher and administrator at the US Holocaust Memorial Museum, to speak with her Applied Statistics and Data Science course (discussed in detail in the following section) at the University of Toronto about her data-related work with the International Tracing Service Archive (now, the Arolsen Archives) and the International Committee of the Red Cross. Visitors need not be face-to-face, especially given the prevalence of video-meeting technology. Former students and colleagues are also welcome to share relevant papers and works-in-progress with students. By introducing a diversity of voices into the classroom, students were encouraged to explore career paths related to statistics and data science, discuss niche questions with area experts, and apply their knowledge in a topical manner.

## Application: a course in Jewish Studies

In the spring of 2019, and in both the spring and fall semesters of 2020, Alexis used this model in an introductory applied statistics and data science course at the University of Toronto (Lerner, 2022; Pitic, 2020; Jankovic, 2019; Csillag, 2019). The course was titled, “Introduction to

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<sup>9</sup> For more information on how to adapt and perform this activity in class, see section 2.1 of Gelman and Nolan (2017).

Applied Statistics and Data Science for Students of Jewish Studies,” and had no prerequisites. An abbreviated syllabus is available in Appendix B of this paper and a full syllabus is available to view on the American Political Science Association’s APSA Educate platform (Lerner, 2020).

Alexis came up with the idea for this course when reading a *New York Times* article reporting that two-thirds of millennials did not know about the Auschwitz concentration camp. As a scholar of authoritarianism and the Holocaust, the news piece left her with many unanswered questions, such as how the questionnaire measured millennials and how it determines whether a respondent does or does not know about Auschwitz. This reporting motivated her to build a course to teach data literacy in this niche topic area so that students could properly assess and dissect charts, graphs, and claims both inside and outside of the classroom.

Each iteration of the 13-week seminar-style course hosted approximately 15 undergraduate students, who came from disciplines across the university, including Jewish Studies, English Literature, Russian Literature, Peace and Conflict Studies, Political Science, Economics, Geography, and Business. Students were mostly second, third, and fourth-year undergraduates and were able to use the course to satisfy a faculty-wide mathematical breadth requirement. In its capacity to satisfy this breadth requirement, the course also posed a benefit to the department—in this case, the Anne Tanenbaum Centre for Jewish Studies; not only did the course allow the centre to increase its offerings in the social and statistical sciences, but it also presented a way for existing Jewish Studies majors and minors to complete their breadth requirement in-unit.

As this was a course geared toward students of Jewish studies, the datasets used to teach general concepts were chosen with the goal of engaging Jewish studies as a discipline. This is one of the fundamental features that makes this course substantively unique, compared to other introductory statistics courses assigned in mathematics or statistics departments. For example, students used the Arolsen Archives to learn about "where data come from" and the Anti-Defamation League’s “Global 100: Index of Anti-Semitism” to discuss problems related to operationalization as well as the process of turning a nuanced concept (in this case, anti-Semitism) into a measurable factor. They also used datasets such as the 2018 “Survey of Jews in Canada” to practice simple and multiple linear regression (Brym, Neuman, and Lenton, 2019). By the end of the course, students gained not only new information about demographics, politics, and culture within the scope of Jewish studies, but they also gained applicable tools for making and evaluating empirical claims within its purview.

The first iteration of this course’s offering included several students of geography, and so included a special week on how spatial mapping can be used in Holocaust and Genocide Studies (e.g., Knowles, Cole, and Giordano, 2014; Jaskot, 2000). The third iteration of the course was

cross-listed with the Department of Sociology and included a special week on nationwide demographic surveys, such as the 2018 Survey of Jews in Canada and the PEW Research Center's 2013 "Portrait of Jewish Americans" Survey.<sup>10</sup>

To supplement in-class learning, students read much of Charles Wheelan's *Naked Statistics: Stripping the Dread from the Data* (2013),<sup>11</sup> in addition to a variety of academic writing on data science and statistics, such as Fujii (2010) on atypical sources of data, Cleveland (1994) on the best practices of graphing data, Gelman (2016) on *p*-values, and Lerner (2022; 2021) on data ethics. Students complemented scholarly works with news articles (e.g., Zauzmer (2018) reporting for the *New York Times* on millennial knowledge about the Auschwitz concentration camp and Unz (2012)'s allegations that Jews are overrepresented at Ivy League universities in *The American Conservative*, first-hand accounts by researchers (e.g., Brym et al (2020) in conjunction with his guest lecture about conducting regression analysis on his own dataset) and archivists (e.g., Shapiro (2011) on the opening of the International Tracing Service archive of primary Holocaust materials), and multimedia resources (e.g., the *NPR Code Switch* podcast about the definition of Judaism (2018) or *A Night at the Garden* (2017), a 7-minute documentary about a 1939 pro-Nazi rally in New York City).

In addition to low-stakes assignments such as the jitts and pre-tests discussed in this article, students were evaluated through a five-part scaffolded assignment—here, referred to as the scaffolded “Collaborative Dataset” assignment—that stretched across the semester. We strongly recommend a collaborative dataset template, not only due to the applied and communal nature of this approach, but also because it creates a sense of unified substantive expertise and exploration, as opposed to a course that only relies on test or siloed datasets which change from week to week. A combination of these is preferable, with students beginning the course with individual datasets and later transitioning to a larger project that can tie together and challenge the skills acquired in earlier weeks. However, for an instructor that does not wish to do a large project like this, it is possible to teach an applied statistics course with only the reading list and datasets.

The scaffolded Collaborative Dataset assignment incorporates individual, collaborative, and peer review elements, with the objective of teaching students how to turn archival and observational materials into a usable data-set, how to illustrate the correlations, patterns, and stories in that dataset, and how to discuss candidly the limitations of a dataset or method of analysis. In particular, each student uses the content analysis skills learned throughout the semester to code one English-language, Holocaust survivor testimony from a pre-selected subset of the USC Shoah Foundation's Visual History Archive (VHA), a collection of 55,000 videotaped

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<sup>10</sup> For more on efforts to build statistics acumen into the sociological discipline, see Wilder (2010).

<sup>11</sup> Another good alternative is the introductory textbook by Utts and Heckard (2007).

testimonies given by survivors of the Holocaust and eight other genocides (e.g., interviews with survivors of the Rwandan Genocide or the Nanjing Massacre). In order to provide adequate context for the USC Shoah Foundation VHA dataset, Alexis includes a full lecture on Holocaust history that concludes with a guided virtual tour of both the Arolsen Archives, a collection of 50 million primary documents appropriated from the Nazis by the Allied Forces at the end of World War Two, and the VHA.

Using VHA testimonies, students build and analyze a collaborative dataset in a scaffolded assignment with five deliverables:

*Deliverable One:* Meta-Data Analysis

*Deliverable Two:* Design Collaborative Codebook

*Deliverable Three:* Perform Collaborative Code

*Deliverable Four:* Conduct Analysis and Workshop Visualization

*Deliverable Five:* Communicate Results

Each deliverable builds on the last, so it is of utmost importance that students complete each assignment fully and on time. Educators can encourage the on-time delivery of assignments with a combination of grade incentives and cloud-based collaborative tools that make each student's progress visible to their instructor and their peers (e.g., when completing a coding assignment). In Appendix A, we describe each deliverable in greater detail for those interested in learning more or in replication.

## Discussion

This successful course model could be applied in many other settings, which could be used to attract potential students. Here we list a few that fall outside the usual domains of mathematics, natural and social sciences, and engineering.

## Disciplinary Applications

This course can be modified to be used in a non-STEM department (e.g., literature, anthropology, or religious studies), as well as in a non-numerical institute (e.g., a theological seminary, a school of education, or a business school). The first step is to consider what level of substantive knowledge students are expected to have, and then to select datasets accordingly. For example, an introductory course might include more basic demographics or feeling thermometer-type datasets, whereas a more advanced group of students might be able to focus on

a nuanced theme (e.g., data on a particular ethno-national conflict or on a specific sub-group).<sup>12</sup> For example, a theological institute could include datasets that trace the membership and attendance of practitioners from different religious movements and a school of education could include datasets on the effectiveness of particular pedagogies or state-wide testing policies.

## Language Study

This course can also be modified to teach introductory statistics within the context of an advanced language course. For example, in the four-stage deliverable outlined earlier in this article, students learning Russian at an advanced-level could focus on a Russian-language survivor testimony. This would allow them to practice close listening in a foreign language. Instructors could also require the illustration or papers to be submitted in the language of instruction. This could help students expand their language learning beyond literature and current events-based study.

## Level of Quantitative Expertise

The third avenue of modification is in the level of quantitative or computational expertise prior to this course. For example, in the four-stage deliverable model, instructors could substitute more advanced analytics in stage three (e.g., requiring that students clean the dataset in R or build a multilevel model). This would likely require a larger dataset in order to go beyond a classroom exercise and to reach compelling conclusions. This approach could also be adapted for introductory computer science exercises—e.g., web scraping or the design of natural language processing algorithms. Lab sections in Stata, R, or Stan can also be added to supplement the course. Further, instructors working with more advanced students can use programs like GitHub instead of Google Drive for collaborative assignments and version management.

Discussions of statistics teaching often consider the challenges of reaching students with varying quantitative backgrounds. In this case, when considering the design of a statistics course outside of traditional statistics departments (or related quantitative subfields such as psychometrics, econometrics, or political methodology), we also need to consider the preparation of the instructor. To put it bluntly, how can you build your own statistics course if you barely know statistics? How can you teach R or Stata to students with little to no programming background if your own knowledge of computing is sketchy? We believe it can be helpful here to be open about

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<sup>12</sup> A feeling thermometer is a survey question that offers respondents to rank their feelings or views about a subject (e.g., a political movement, a place, or their quality of life), ranging from 0 (strongest disapproval or "coldest" feeling) to 100 (strongest approval or "warmest" feeling). For more on such questions, see Lavrakas (2008).

your own struggles here and to set clear goals for computing skills that you would like students to be able to achieve during the course.

## Remote Instruction

During the spring and fall of 2020, this course was adapted for online instruction when the University of Toronto moved online during the COVID-19 global pandemic. Remote instruction can be complicated because it assumes that all students have computer and internet access, as well as a physical environment conducive to learning. However, if students do have these conditions, the course's cloud-based collaborative tools, focus on digitally-available databases, and library access make this course easily adaptable for remote instruction.<sup>13</sup>

## Conclusion

In this paper, we presented a template for teaching statistics and data science to non-mathematically-minded undergraduates. We strongly believe that data literacy is a vital component of any higher education program across the hard sciences, the social sciences, and the humanities. Graduates of history and engineering should be equally capable of reading and assessing basic numerical information, such as in the charts and graphs used to supplement news articles. We suggest that the best way to establish data literacy is to build confidence and skills in quantitative methods, and provide a template—from what materials are needed, to evaluation methods, and assignment details—for achieving this with a non-numerate audience. We include a case application of how this template has been used in Jewish studies, before concluding with a number of possible applications for student variation in discipline, language skill, and quantitative expertise. We also outline how this course can be modified for remote instruction.

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<sup>13</sup> There is a large body of pedagogical scholarship on the best practices of remote and hybrid learning (e.g., Everson and Garfield, 2008; Mills and Raju, 2011; Mocko, 2013; Tudor, 2006; Ward, 2004).

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# Appendix A

## The Collaborative Dataset Applied

### ***Deliverable One: Meta-Data Analysis***

Students begin by choosing a testimony from a list of pre-selected options that the instructor compiles. In each iteration of the course, Alexis chose to focus on a different subset of survivors: in the first iteration, students focused on the testimonies of survivors that lived in Budapest, in the second iteration, students studied on the testimonies of those that survived the Minsk Ghetto, and in the third iteration of the course, students were assigned to survivors that immigrated to Canada after World War II.

Students then complete an individual short paper about the archive and the meta-data of the individual testimony that they chose to focus upon. They answer questions, such as: who built the archive, who conducted the interview and in which language, what are the contents of the archive, and whether there are any potential ethical concerns related to the archive, the interview method, or the indexing of these testimonies. To prepare students to navigate ethical concerns with this particular archive, Alexis assigns readings such as Lerner (2021)'s "Quantifying the Archives," Presner (2016)'s *Ethics of the Algorithm*, Luft (2020)'s "How Do You Repair a Broken World," and Smith (2016)'s "On the Ethics of Technology and Testimony." Students also identify possible testable hypotheses (e.g., Does a particular postwar migration pattern correlate with certain language used to describe those that helped or hurt them during the Holocaust?), consider the operationalization or statistical measurement of their selected variables, and explain why the VHA would be an appropriate "dataset" for the proposed question. This assignment allows students to *apply* in-class activities and lectures that supplement assigned readings to promote learning about variable types, statistical modeling, and common biases. The Meta-Data Analysis assignment can be graded on a scale of the instructor's choosing; a rubric is recommended.

### ***Deliverable Two: Design Collaborative Codebook***

After, in Deliverable One, students determine a research puzzle that is of interest to them, in Deliverable Two they plan how to measure and record the variables that they will use in their model. In Deliverable Two, students design a collaborative codebook on a cloud-based platform (such as GoogleDocs). At this point in the course, students have read and discussed several other codebooks closely, which gives them an understanding of what makes a codebook thorough or lacking. This deliverable facilitates experiential learning about the codebook; through this

exercise, students understand that a good codebook will discuss, step-by-step, every variable collected, how it will be measured, and how a study can be replicated, as well as how to deal with predictable problems and outliers, or observations that fall outside of the expected range for a variable (Lerner 2021, 450).

Practically, students compile a draft of the cloud-based codebook together in class. Instructors may choose to have students work in pairs, in small groups, or collectively. This is useful when teaching statistical principles, because students sometimes disagree about how a particular phenomenon ought to be measured; debating these specifics of data measurement results in the application of statistical principles learned in class. This exercise is well-suited for accompanying lectures on data types, replication and falsification, operationalization, and data management. Following the drafting of the codebook, Alexis requests that students submit two “comments” directly into the cloud-based document as homework. These comments are useful as they improve the codebook while presenting to quiet students an opportunity to voice their opinions about the crafting of the codebook. Alexis grades the two codebook comments in a low-stakes manner (e.g., check, check minus, check plus).

### ***Deliverable Three: Perform Collaborative Code***

In Deliverable Three, students put the codebook into practice by transforming archival materials—such as speech, body language, tone, and objects—into numerate data stored in a cloud-based spreadsheet (Lerner 2021, 451). Students complete this deliverable individually, though their individually-collected data is inputted into a collaborative, cloud-based dataset that all can access. Alexis provides three weeks for completing this assignment; in the first week, she hosts a coding session where students meet in-person in a computer lab or online in a synchronous session for approximately 2 hours. During this initial coding session, students work individually at their computers and are able to ask questions as they arise to the instructor or to their peers. Holding this session as a class operates as a sort of “group office hours,” where one student’s question may also be relevant for their peers. Above all, this is an opportunity for students to become comfortable navigating an online archive or dataset and with the process of coding. Students are usually able to complete about a quarter to a third of the code in this allotted time period; the remainder has to be completed outside of class.<sup>14</sup>

Alexis grades this deliverable on a scale that includes whether the student provided complete information, adheres to the codebook with precision, and writes adequate notes in an appropriate

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<sup>14</sup> At institutions where outside time is particularly limited, such as at the United States Naval Academy, where Alexis teaches this course to midshipmen with leadership, physical, and technical training obligations in addition to their schoolwork, it may be necessary to reserve 2-3 additional in-class periods for performing this code.

column. She cross-checks the spreadsheet at random with the original testimony to ensure that the student's reported code accurately reflects the material it claims to represent. Further, in order to receive a grade for this assignment, students need not only to complete their portion of the code, but to download the file as both an excel file and a CSV file. They were also required to download a CSV file of the composite results of their classmates and course alumni. This exercise of downloading different formats of a document prepares them for Deliverable Four, in which they conduct their analysis of the data. If time permits at this stage, an instructor can include a hands-on lesson on how to check an excel or CSV file for errors.

#### ***Deliverable Four: Conduct Analysis and Workshop Visualization***

Deliverable Four may look different, depending on the instructor and the level of pre-existing computational knowledge among the students. Students could use any computing or illustration platform for this assignment, such as ggplot2 in R, Microsoft Excel, or D3. With first-time statistics students from non-quantitative disciplines, Alexis opts to use Tableau, a data visualization platform that is free of cost to students and available as both a downloadable or a web-based program. Instructors can leverage open-source online guides or their university libraries to assist them in delivering this information. Alexis uses one full class period to teach students about data visualization best practices and to train them to use the Tableau software for data analysis.<sup>15</sup>

After learning about data visualization best practices and software tools in class, students design an original illustration, including a title, a key (if relevant), and a caption that explains the main features of the graph and highlights what the reader should take away from the illustration. Students share their illustrations in class informally through a workshop-style presentation. The workshop, a common tool for stimulating intellectual discourse on a work-in-progress in the fine arts, humanities, and social sciences, provides students with the opportunity to give and receive feedback on a work-in-progress. The workshop doubles as a professionalization initiative, as students learn to give informed feedback on the effectiveness of an illustration in an empathetic manner.<sup>16</sup> Alexis divided the grade for Deliverable Four into two equal parts: a scaled grade

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<sup>15</sup> Instructors unfamiliar with Tableau can avail themselves of the many tutorials available on the Tableau website and even assign tutorials to students to complete alongside weekly readings. Alternatively, some institutions may have a data science librarian with expertise in Tableau, who can advise students as they navigate the project.

<sup>16</sup> Sample questions on the peer review worksheet ask students to describe the illustration prior to the presenter speaking or answering any questions about it, with the idea that a good illustration should be able to communicate using its basic features (labeled axes, caption, title, and key) without further explanation. Students then invited the presenter to speak about their illustration and answer any questions, after which time students journaled about what was effective and what

based on the quality of a students' own submission and a second scaled grade for the quality of the feedback that they gave to their peers in the workshop.

As an example of this assignment, we share with permission the illustration of one student, Hui Wen Zheng, a 4th year undergraduate double-majoring in Contemporary Asian Studies and Peace and Conflict Studies, who took this course in the Fall of 2020. While Zheng had previously studied genocide and the Holocaust as units in her other courses, this was her first quantitative course and first formal Jewish Studies course. Zheng participated actively in class, including in the construction of the collaborative dataset. She used it to produce the visualization shown in Figure One, which illustrates the confluence of physical displays of emotion in the videotaped testimony and a remembered encounter with someone perceived to be in the Red Army, a Russian national, or a Soviet.<sup>17</sup> In particular, she asked about variation in how Holocaust survivors, in their videotaped testimonies, spoke about their encounters with members of the Red Army, Russians, and Soviets. She illustrated disaggregated responses by sex, finding that females responded most positively to memories of encounters with the Red Army and most negatively for encounters with individuals they recalled as being Soviets. This pattern reversed for male survivors. Following the illustration workshop and necessary revisions of their figure, students integrate and analyze their illustration in final papers and projects, discussed in *Deliverable Five*.

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could improve the illustration. The activity concluded with the reviewer talking through their comments directly to the presenter.

<sup>17</sup> This differentiation of Red Army/ Russian/ Soviet is not determined by the student that is coding a testimony, but rather by the survivor sharing the memory. For more on the ethics of memory, consent, and conducting a quantitative analysis of conflict archives and Holocaust testimony, see Lerner (2021), Lerner (2022), and Presner (2016).

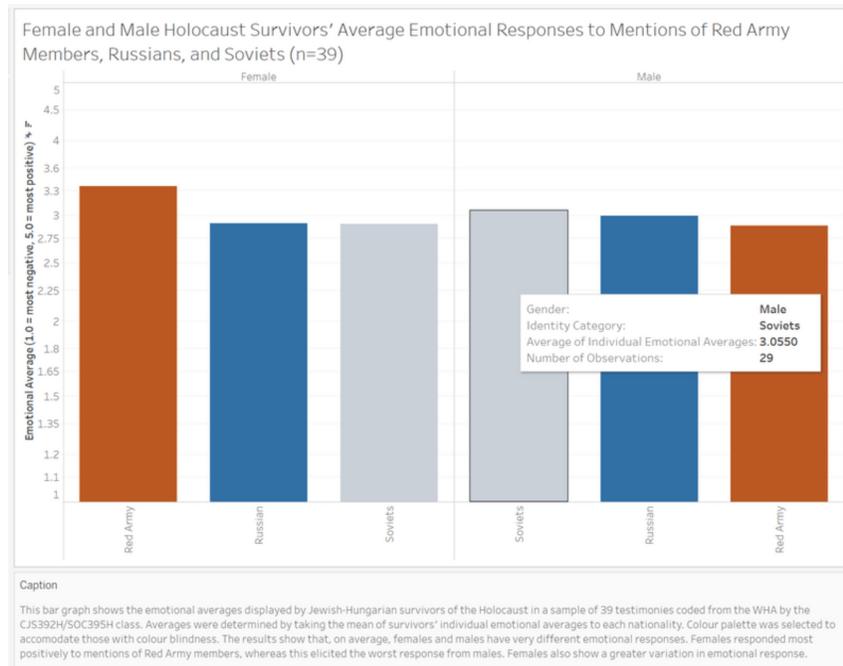


Figure One: Example of Student Illustration. From *Introduction to Applied Statistics and Data Science for Students of Jewish Studies, Winter 2020*.

After workshopping her analysis, Zheng produced a final video presentation for Deliverable Five of the scaffolded assignment. Further detail on this assignment is as follows.

### ***Deliverable Five: Communicate Results***

Individually, students produce a short (800-word) essay or a 6-7 minute videotaped presentation that incorporates their tested hypothesis, their revised illustration, and an answer to the following question:

*How do quantitative methods, organizational systems, and data visualization tools help scholars to learn new things about archival or observational materials?*

This deliverable operates as a “final paper” and can be graded on the scale of an instructor’s choosing; once again, a rubric is recommended. In her presentation, Zheng spoke about what she learned in the course and through the scaffolded assignment. She began by describing her relationship with data prior to the course:

“I considered myself more of a qualitative researcher and I only engaged with data insofar as it was useful evidence to support my findings, but I would never create that sort of data for myself and I did not really understand the process which went behind [working with] quantitative data.”

Zheng then spoke about her research puzzle, the operationalization of her variables, and the limitations of this dataset, before discussing the overall merits of quantification, of which she highlighted four. First, she praised the ability of statistics to empower students to build systematically on their own intuition and “to make quick and easy comparisons.” Second, she held up the way statistical methods can facilitate “practical and evaluative insights” while ensuring the researcher minimizes the typical pitfalls, such as “cherry-picking, sampling biases, [and] conflating correlation with causation.” Third, she highlighted how quantification and visualizations enhance numerate communication, making clear its persuasive power. Finally, and most importantly, acknowledging as she put it that “statistics are everywhere,” she underlined how quantitative learning enhances ethical and critical thinking both inside and outside of the classroom.

Zheng advanced from a data-averse to data-literate student, capable of integrating statistical reasoning and methods with case-based expertise. She began the course viewing herself as a “qualitative researcher,” but by the end stated a revised perspective that quantitative and qualitative approaches are, as she put it, “co-dependent.” Zheng’s assessment reflected the general student view of the course; for example, an anonymous student in Winter 2020 reported,

“I am not one to usually write course evaluations. But in terms of this course, I felt compelled to describe how much this course has shifted the path of my academic endeavours. At first, I was not even signed up for this course, but after some research I signed up for it on a whim. It was the best decision I ever made. Before enrolling in this course, I thought I had a strong knowledge on the Holocaust but this completely proved me wrong in the best way possible. I was able to learn about different perspectives from groups I was not even aware were impacted by this genocide. I also gained hard skills and learned about opportunities where I could utilize quantitative methods in the realm of humanities.”

Overall, students across all three iterations reported that this course helped them to build confidence in statistical reasoning and methods, as well as substantive knowledge in Jewish studies.<sup>18</sup>

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<sup>18</sup> This qualitative assessment is representative of a larger sample, based on class evaluation responses at a 54% response rate. For example, across all three iterations of the course and on a numerical scale of 1 to 5 (where one is not at all and five is definitely/always) students responded with an average score of 5/5 in regard to the statement “The course provided instruction on how to evaluate the credibility of various sources of information.” Students also responded with an average score of 4.9/5 on both the statement “Course projects, assignments, tests, and exams provided opportunity for me to demonstrate an understanding of the course

## **Applied Statistics and Data Science for Jewish Studies Syllabus**

### **DESCRIPTION OF THE COURSE:**

*What are data? Where does data come from? How can scholars use data to tell stories (and lies!)? This course offers an introduction to data science and applied statistics, with an emphasis on demystifying data through quantitative methods, research design and ethics, and digital humanities tools. The course teaches students how to read, evaluate, and plot data in tables, charts, and graphs, and includes a training in Tableau software. We will draw from datasets of interest within the interdisciplinary field of Jewish Studies, such as the PEW Research Center's "Portrait of Jewish Americans" (2013), the Anti-Defamation League's Global 100 Index (2015) on anti-Semitism, the Armed Conflict Location and Event Data Project (2018), and the International Tracing Service's Digital Collection Archive (2015). No prior training in research methods is necessary for this course. Students will complete the course with the skills necessary to recognize bias in data, identify appropriate methods for different research puzzles, and communicate the stories in numbers.*

### **COURSE OBJECTIVES**

- Students will learn to identify the data best suited to their research puzzle and theory.
- Students will gain technical skills in downloading datasets, reading .csv / .xls files, and building datasets from archival or observational material.
- Students will learn to build arguments around data and discuss candidly the limitations of any given data source (and what it means for a particular study).
- Students will learn to illustrate the stories in their data using data visualization tools that will aid them in future research projects.

### **Week 1: Basics of Empirical Research**

Course Introduction and Pre-test

*Readings:*

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material” and “Course projects, assignments, tests, and exams improved my understanding of the course material.” These can be compared to much lower divisional averages (for the Faculty of Arts and Sciences) of 3.9/5 for these two questions.

1. Wheelan. Ch 1 (pp 1-14)
2. Astor, Maggie. 2018. "Holocaust Is Fading From Memory, Survey Finds." *The New York Times*, April 12.

### **Week 2: What is/ are Data?**

Types of Variables and What You Can Do With Them; Descriptive Statistics

Readings:

1. Wheelan. Pp 110-118 (of Chapter 7) and Chapter 2 (pp.15-35).
2. Fujii, Lee Ann. "Shades of Truth and Lies: Interpreting Testimonies of War and Violence," *Journal of Peace Research* 47, 2 (March 2010): 231-241.

### **Week 3: Why Data? How Data?**

Where does data come from and what can we do with it?

Readings:

1. Wheelan. Chapter 9.
2. [Video] Shapiro, Paul. 2011. "Bad Arolsen."
3. Stout, David. 2006. "Germany Agrees to Open Holocaust Archives." *NYTimes*.
4. Black, Edwin. 2007. "Survivors Outraged at Holocaust Museum Over Bad Arolsen." *History News Network*.

### **Week 4: Puzzles and Research Questions**

Operationalization, Mechanisms, and the Problems of Causality

Readings:

1. Wheelan. Chapters 5, 5 ½, and 6 + Pp 118-126.
2. Unz, Ron. 2012. "The Myth of American Meritocracy." *The American Conservative*.
3. Gelman, Andrew. 2013. "Ivy Jew Update." *Statistical Modeling, Causal Inference, and Social Science*. October 22.

### **Week 5: Qualitative Methods**

Fieldwork and Interviewing; Archival Material

Readings:

1. Babbie, Earl, and Lucia Benaquisto. *Fundamentals of Social Research*. 2014. Toronto: Nelson Education Limited. Chapters 10 and 11.
2. Weinraub, Bernard. 1994. "Spielberg Recording Holocaust Testimony." *NYTimes*.
3. Greenspan, Henry. 2011. "Collaborative Interpretation of Survivors' Accounts: A Radical Challenge to Conventional Practice." *Holocaust Studies: A Journal of Culture and History* 17, 1 (Spring 2011): 85-100.

### **Week 6: Introduction to Data Visualization and Human Geography**

## Introduction to Quantitative Data Analysis and Data Visualization

### Readings:

1. Knowles, Anne. “Historical Uses of GIS.” *PACSCSCL Symposium on Future Foundations: Mapping the Past*. 2005.
2. Jaskot, Paul. “A Plan, a Testimony, and a Digital Map: Analyzing the Architecture of the Holocaust.” *YouTube*. 2018.

## **Week 7: Communicating Statistics and Hands-on Tableau Workshop**

### Readings:

1. Wickham, Hadley. 2014. “Tidy Data.” *Journal of Statistical Software* 59 (10).
2. Babbie, Earl, and Lucia Benaquisto. *Fundamentals of Social Research*. 2014. Toronto: Nelson Education Limited. Chapter 14.
3. Cleveland, William. 1994. *The Elements of Graphing Data*. Hobart Press. Chapter 2.

## **Week 8: Regression**

### Regression-Based Inference and its Pitfalls

### Readings:

1. Wheelan. Chapters 11 and 12.
2. 2013. “A Portrait of Jewish Americans: Overview.” *PEW Research Center*. Pp 1-20.
3. Saxe, Leonard. “The Sky is Falling! The Sky is Falling! A Reanalysis of Last Year’s Important PEW Study Contradicts Persistent Alarmism About ‘Vanishing’ American Jewry.” *The Jewish Journal of Sociology* 57, 1-2 (2015).
4. Hirschfield, Brad. “What PEW’s Jewish Poll Reveals About the Faithful--and Faithless.” *Washington Post*. Oct 1, 2013.
5. Eisen, Arnold. “Understanding American Jews.” *PEW Research Center*. 2018.

## **Week 9: Statistical Ethics**

### How to Lie with Data (But Don’t Do It!)

### Readings:

1. Black, Edwin. 2001. *IBM and the Holocaust: The Strategic Alliance Between Nazi Germany and America’s Most Powerful Corporation*. New York: Crown. Introduction.
2. Wernicke, Sebastian. 2010. *Lies, Damned Lies, and Statistics*. TED Talks.

## **Week 10: Surveys and Experiments**

### Readings:

1. Wheeler. Chapters 10 & 13.
2. Lerner, Alexis. 2015. “Crime and Punishment: Hate Crime Legislation, Public Opinion Polling, and the Jewish Minority in Post-Soviet Russia.” *Jewish Thought*, no. 5: 57–72.

3. Cohen, Jeffrey. 2018. "From Antisemitism to Philosemitism? Trends in American Attitudes toward Jews from 1964 to 2016." *Religions* 9 (4): 107.
4. [Skim] ADL Global-100 Executive Summary (2014)

**Week 11: Student Presentations and Post-test**

**Week 12: Course Conclusion and Analysis of Post-test**