A New Data-Focused Introductory Programming Course

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Research Project

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Many universities are creating undergraduate data science curriculum in order to fulfill increasing demand in industry for quantitative skills across disciplines. The first such course is often an "Introduction to Data Science" course that provides an introduction to computation and statistics in a single semester. At some schools – UC Berkeley in particular – this course can be quite large and consist of a student population with varying levels of prior experience in the field. Some students, particularly those without prior computing experience, can feel intimidated and hesitate to take such courses, even though they often are designed without any prerequisites.

We identified an opportunity for a small-scale pre-introductory data science course focusing on computational thinking rather than data science as a whole, with the goal of encouraging students to pursue data science further while equipping them with the confidence and skills to do so. We designed and taught such a course in Spring 2021 at Berkeley to a class of 18 students. All 18 students reported being happy or very happy to have taken the course, and many plan on pursuing data science further in some capacity.

1 Introduction

Undergraduate data science programs and courses have exploded in popularity over the past several years, complementing a longer-term trend of increased demand for computer science coursework [6]. While there have been some efforts to standardize how undergraduate data science majors are structured [41], such programs vary significantly between institutions based on a variety of factors – sponsoring department, target audience, and program size, to name a few. However, in most of these programs, the first course that students are required to take is some sort of "Introduction to Data Science" course.

As such courses courses exist to introduce students to the field of data science as a whole, they generally serve as an introduction to both computing and statistics. At many universities, including UC Berkeley, such courses do not prevent students with prior experience in either field from taking the course. Evidence shows that students with prior programming experience tend to be more confident and perform better in such courses compared to students without prior programming experience [32, 43, 5], who can feel intimated by their peers' expertise on Day 1. To address this issue at Berkeley, we designed and taught a new pre-introductory course that largely focused on programming in the context of data science, rather than on core "data science" content.

This report is organized into four main sections.

- **Section 2** discusses Data 8, *Foundations of Data Science*, the introductory data science course at Berkeley.
- **Section 3** details the design of Data 94, *Introduction to Computational Thinking with Data*, a new course which serves as the basis for this report.
- **Section 4** highlights the key differences between Data 94 and Data 8.
- **Section 5** shows the results of some preliminary analyses of student survey data from the pilot offering of Data 94.

2 *Foundations of Data Science*

Data 8 [12], *Foundations of Data Science*, is the introductory undergraduate data science course at Berkeley. It was piloted in Fall 2015 [38] by a team of Statistics and Electrical Engineering and Computer Sciences faculty, led by Ani Adhikari and John DeNero. It is designed to introduce students to computational and inferential thinking in the context of real-world examples. It has no prerequisites and is aimed at a lower-division audience, though junior and senior students regularly take the course as well (see Figure 1). All students pursuing a major or minor in Data Science must take Data 8.

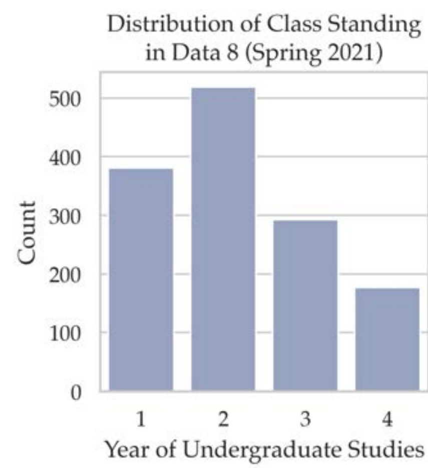


Figure 1: Distribution of class standing in the Spring 2021 offering of Data 8.

2.1 *Course Content*

Data 8 is organized into three modules. This split is discussed at the start of the semester in a regular offering of the course and is also how the EdX offering of the course [19] is divided.

In Table 1, we present an overview of the key topics covered each week, as of the Spring 2021 offering of the course. Non-summer Berkeley semesters are 15 weeks long; Week 10 is omitted due to Spring Break. A more detailed syllabus can be found on the Data 8 website [12].

Module	Topics
Computation	• Week 1: Introduction • Week 2: Tables and Data Types • Week 3: Scatter Plots, Line Plots, and Bar Plots • Week 4: Histograms, Functions, Applying and Grouping • Week 5: Pivoting and Joining
Inference	• Week 6: Iteration, Conditional Statements, Probability, and Sampling • Week 7: Hypothesis Testing • Week 8: Causality and Review (**Midterm Week**) • Week 9: Confidence Intervals • Week 11: Variance and Sampling Distributions
Prediction	• Week 12: Correlation and Simple Linear Regression • Week 13: Residuals and Regression Inference • Week 14: Classification, k-Nearest Neighbors, Bayes' Rule • Week 14: Conclusion

Table 1: Topics covered in Data 8.

Here, we focus on the first module as it is most relevant to the current discussion. All of the programming in Data 8 is done in Python in the Jupyter Notebook environment. The course teaches using `datascience` [4], a library created by course staff specifically for teaching tabular manipulation, instead of `pandas`, which is often used in more advanced courses and in industry.

Students are introduced to tables, the central data structure in data science, as early as the third class session. While this is now common in introductory data science courses [18, 44] (in large part because of Data 8 itself), this is a markedly different approach than more traditional introductory programming courses, where students are introduced to more sophisticated data structures later on in the course. This choice is well-justified – Data 8 is a data science course first and foremost, and it's quite difficult to talk about data science without knowing how to look at data.

In Data 8, core programming concepts are only brought up as they are made relevant, rather than all at the start. For example, the concept of defining a function does not appear until after students have learned how to create visualizations; it is introduced in the context of applying a procedure to every element of a column in a table. Similarly, students are introduced to for loops at the same time they are taught about statistical simulations, at the start of the second module.

A consequence of this approach is that only the programming concepts that are absolutely necessary for basic tabular data analysis and inference are taught. While a traditional introductory programming course would teach while loops, other data structures such as dictionaries, and recursion, Data 8 covers only what is necessary and saves the remaining time for an in-depth treatment of inference.

Most of the computational foundations in the course are established in the first module, with the exception of iteration, which is introduced in the second module and used quite frequently throughout the rest of the course.

2.2 *Course Demographics*

Despite being designed for students without programming and statistics experience, a considerable fraction of students in Data 8 each semester have experience in either or both. Specifically:

- 813/1395 (58%) of students in the Spring 2021 offering reported having taken a programming course before Data 8 (including high school courses, such as AP Computer Science)

- 553/1395 (40%) of students in the Spring 2021 offering reported having taken both a programming course and a statistics course before Data 8 (including high school courses)

Studies have shown [32, 43, 5] that students with prior programming experience outperform students without prior programming experience in introductory programming courses. This phenomenon is relevant here even though Data 8 is not an introductory programming course, rather, a course that introduces programming as part of a broader goal.

We have evidence, provided in Section 5, that some subset of the student population at Berkeley is interested in the course but hasn't considered enrolling due to its large size; recent semesters have seen enrollments of over 1300 students. Given the existing landscape, we hypothesized that a new, smaller-scale pre-introductory course would benefit students without prior programming experience, who otherwise would have struggled in or not have considered taking Data 8. In more traditional introductory programming courses, this approach has shown to be helpful in strengthening the confidence and abilities of such students [37].

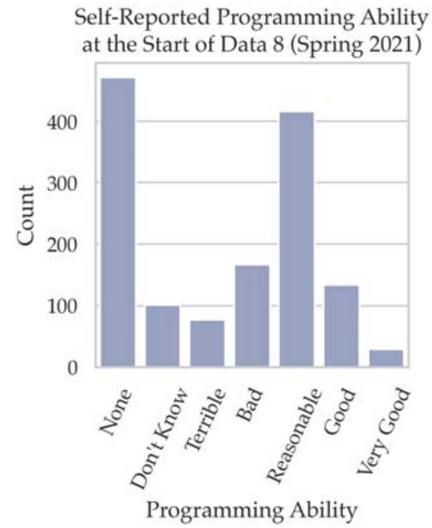


Figure 2: Distribution of self-reported programming ability at the start of the semester in the Spring 2021 offering of Data 8.

3 *Course Design*

In order to help prepare students for Data 8, we developed and taught a new course, *Introduction to Computational Thinking with Data*, listed as Data 94 [25] in Spring 2021. This section of the report details the goals and design of this course.

3.1 Course Goals

We designed Data 94 around two main goals:

1. Entice students to study data science further.
2. Prepare and build confidence in students for when they pursue further data science coursework.

While developing course materials, a tangential goal arose – give students the tools they need to work on projects of their own without having to take any future coursework. Such a course could serve as an alternative for non-STEM students to CS 10 [9], Berkeley's instantiation of *The Beauty and Joy of Computing* [20], and CS 61A [8], *Structure and Interpretation of Computer Programs*, Berkeley's first required course for CS majors. The former is often recommended as preparation for the latter for students without prior programming experience.

It should be noted that *Introduction to Computational Thinking with Data* was taught at Berkeley twice prior to our offering. In Summer 2017, the course was taught as Data 8R [13] by Henry Milner, as part of the Summer Bridge program for incoming freshmen [39]; materials from this offering can be found at `http://data8r.org`. In Summer 2020, the course was revived by a team led by Ian Castro, and was taught with the label Data 6 specifically for students in the SEED Scholars program, which supports STEM students from historically underrepresented backgrounds [23].

These prior offerings served largely the same purpose as our course, though they differed in their approach. While we developed content from the ground up, we referenced material from Data 6, Data 8, CS 61A, and CS 10 at Berkeley, as well as CS 106A: *Programming Methodologies* at Stanford [10] and CSE 160: *Data Programming* at the University of Washington [11].

3.2 Syllabus

As shown in Table 2, the course was divided into three main modules, with a fourth "Special Topics" module at the end. This delineation was made explicit at the start of the semester and was revisited each time the course transitioned from one module to the next.

Module	Topics
Python Fundamentals	• Week 1: Introduction and Arithmetic • Week 2: Variables, Boolean Expressions, and Functions • Week 3: Conditional Statements, While Loops, Lists, and Strings • Week 4: Review, Quiz 1 • Week 5: For Loops
Table Manipulation	• Week 6: Dictionaries, File Formats, and NumPy • Week 7: Table Fundamentals • Week 8: Applying, Grouping, Pivoting, and Joining • Week 9: Review, Quiz 2
Visualization	• Week 11: Encodings, Bar Plots, and Histograms • Week 12: Scatter Plots, Line Plots, and Maps • Week 13: Review, Quiz 3
Special Topics	• Week 14: Randomness, Simulations, and Creating Websites • Week 15: Human Context & Ethics, Conclusion

Table 2: Topics covered in Data 94.

3.3 *Course Format*

Most computing and data science courses at Berkeley, including Data 8, serve hundreds of students per semester. The pilot offering of Data 94 was much smaller; we set the enrollment cap to 30 students, and had 18 students by the end of the semester. This allowed us to focus our efforts on content and pedagogy without having to consider issues of scale, while also providing students with a small, personable learning environment that they wouldn't have been able to experience in larger courses.

Over the next few subsections, we'll briefly discuss key components of the course. A guiding design principle was the University of California's official guidance [2] that a course worth n units should not take students more than $3n$ hours per week on average, including class time. (This principle is not adhered to by many computing and data science courses at Berkeley.) As our course was listed for 3 units, we wanted students to spend no more than 9 hours per week on it on average, and devised the following breakdown:

- 3 hours of lecture
- 1 hour of lab
- 5 hours of work on assignments, including time spent in office hours

A more detailed description of each course component can be found at the student-facing syllabus, `http://data94.org/syllabus/`.

- **Lectures, active learning, and readings**

  The course was developed during the COVID-19 pandemic, which gave us flexibility with how to structure the course. While we considered offering lectures asynchronously as a series of pre-recorded lecture videos with conceptual questions in between [22], we ultimately decided to deliver lectures synchronously. This gave us the flexibility to make changes to pace and content ad-hoc while building a stronger personal relationship with students than we may have otherwise, especially given the small class size.

Figure 3: Example Quick Check on EdStem (taken from Lecture 14).

  We delivered three 50 minute lectures each week. Most of the lecturing itself contained a mix of slides and live coding as is common in other similar courses. In order to promote active learning [30, 31], each lecture contained a few breaks for students to answer short questions, called Quick Checks. These questions were either short answer or multiple choice, and were graded on completeness, not correctness. After giving students a few minutes to answer a question, we'd take up the solution by asking students for their approaches. We encouraged students to fill them out during the allocated time in class so that they could benefit more from the discussion, though there was no penalty for completing them afterwards; on average, 60%-70% of students filled them out in class. Quick Checks were hosted on the EdStem [17] platform (see Figure 3), and like lecture attendance, were as a whole worth 5% of students' grades in the course.

  As the course contained a mix of traditionally covered in multiple courses, there was no single textbook that followed the course. Instead, we linked relevant readings whenever possible. The most common sources were `https://inferentialthinking.com`, the textbook for Data 8, and `https://cs.stanford.edu/people/nick/py/`, the course notes for Stanford's CS 106A (*Programming Methodologies*); the former was referenced for table methods and visualization, and the latter was often referenced for core Python fundamentals, as we felt that it provided an accessible treatment of the relevant material.

- **Lab sections**

  To supplement lecture, we hosted a 50 minute lab section each week, held immediately after lectures on Friday. Unlike other similar courses at Berkeley, Data 94 had no "lab assignment" – rather, the goal of the lab section was to give students a head start on the week's homework assignment, which was generally released the day before lab.

The first 20 minutes of lab consisted of the course TA walking through a practical demo using that week's material; this was done to give students a second look at relevant concepts before they'd need to apply them on their own. In the final 30 minutes, students were put in breakout rooms with roughly 4 other students and a member of course staff. Here, students were encouraged to start working on the homework assignment and to ask any questions that arose to their peers and assigned helper. Breakout rooms were randomized each week.

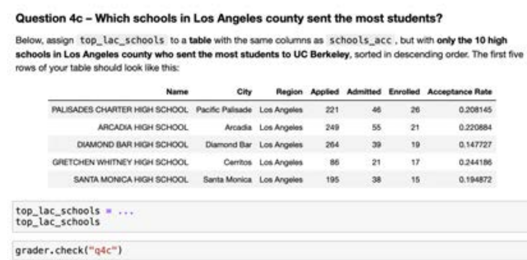
3.4 *Assignments*

Students spent the majority of their time in the course in most weeks completing homework assignments. Students accessed assignments by clicking links on the course website that would bring them to DataHub [42], a service that provides cloud-hosted Jupyter Notebook servers for all members of the Berkeley community. Used by most data science courses at Berkeley, DataHub allowed students to dive right into writing code without needing to worry about environment setup.

Assignments consisted of a mix of programming problems (see Figure 4) and written interpretation questions, as in Data 8 and other similar courses. After completing an assignment, students would download their notebook as an `.ipynb` file and upload it to Gradescope [15], where their code would be autograded (using public test cases) and their answers to written questions would be extracted into a separate PDF for human grading. We used Otter-Grader [33] to facilitate the autograding of these Jupyter Notebooks.

9 homework assignments were released throughout the semester. We released homeworks roughly once a week, but gave students additional time to work on them during quiz weeks. A typical week would see a homework released on Thursday and due the following Thursday; such a homework would only include content from the week in which it was released.

In Table 3, we show a summary of the topics covered in each homework, and the datasets used if applicable.



Question 4c – Which schools in Los Angeles county sent the most students?

Below, assign `top_lac_schools` to a **table** with the same columns as `schools_acc`, but with **only the 10 high schools in Los Angeles county who sent the most students to UC Berkeley**, sorted in descending order. The first five rows of your table should look like this:

Name	City	Region	Applied	Admitted	Enrolled	Acceptance Rate
PALISADES CHARTER HIGH SCHOOL	Pacific Palisade	Los Angeles	221	46	26	0.208145
ARCADIA HIGH SCHOOL	Arcadia	Los Angeles	249	55	21	0.220884
DIAMOND BAR HIGH SCHOOL	Diamond Bar	Los Angeles	264	39	19	0.147727
GRETCHEN WHITNEY HIGH SCHOOL	Cerritos	Los Angeles	86	21	17	0.244186
SANTA MONICA HIGH SCHOOL	Santa Monica	Los Angeles	195	38	15	0.194872

```
top_lac_schools = ...
top_lac_schools
```

```
grader.check("q4c")
```

Figure 4: Example programming problem (taken from Homework 5).

HW #	Topics	Datasets
1	Boolean Expressions and Functions	COVID cases
2	If-Statements, While Loops, Lists, and Strings	N/A
3	Review and For Loops	Billboard music charts
4	Dictionaries and NumPy Arrays	Google Maps API queries, State of the Union addresses, and Images
5	Table Fundamentals (Sorting and Filtering)	2020 Berkeley Freshman Admissions
6	Grouping, Pivoting, and Joining	2020 Restaurant Ratings
7	Bar Plots and Histograms	Antarctic Penguins [26]
8	Scatter Plots, Line Plots, and Maps	SFO Flights
9	Create a Website	Bring-your-own-dataset

Table 3: Homework assignments in Data 94.

It should be noted that in Homeworks 1 through 4, students did not yet know how to use tables. As such, the datasets served to expose students to core programming concepts in a way that was motivated by real data; see Section 4.1 for a detailed discussion of this approach.

Homework 9 was an outlier. Instead of answering questions about preselected datasets, students followed a tutorial [24] to find a dataset on their own, create a visualization from it, and host it on a website (using GitHub Pages [21]) along with explanatory text.

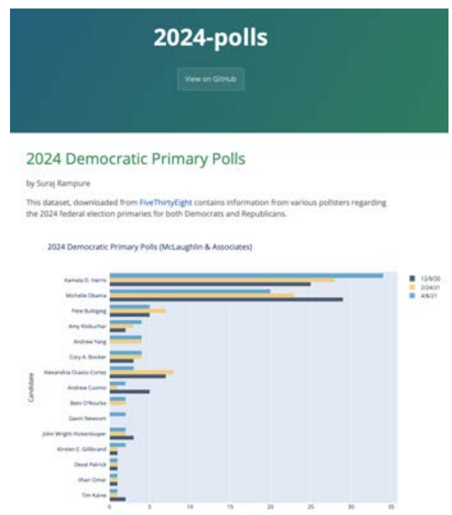


Figure 5: Website created in the tutorial for Homework 9; students created similar sites.

3.5 *Assessments*

In lieu of a traditional midterm, we held a quiz at the end of each of the first three modules, each worth 5% of students' grades. As such, Quiz 1 was designed to assess students' understanding of the first module. However, after covering while loops and lists, we realized that we hadn't allocated enough time in lecture for these concepts to really sink in with students, and decided to spend a few lectures reviewing rather than covering more material before the quiz. As a result, Quiz 1 only covered material through lists, and did not include for loops, a topic in the first module.

Quiz 1 was administered in the form of a Jupyter Notebook; this was done to have students program in the environment they were comfortable with [7, 28] from homeworks. Unlike homeworks, Quiz 1 had hidden tests that students were not shown while working. After students submitted Quiz 1, we discovered a major flaw with the format. Since students were still getting accustomed to Python syntax, most submissions contained multiple syntax errors which rendered the autograder practically useless. As a result, we had to manually grade all submissions in order to assign partial credit, and decided to use a different format for assessments moving forward.

For Quiz 2, Quiz 3, and the Final Exam, we used Gradescope's online assignments functionality (see Figure 6). This enabled us to mix multiple choice, short answer, and free response problems, allowing us to ask both conceptual and programming questions. Though the platform did not support code autograding, the limited scale of the course made it possible for us to grade all submissions and provide feedback relatively quickly. Since the format was brand-new, we provided students with "practice quizzes" before Quizzes 2 and 3 in order to familiarize them with the format.

Quizzes were always held on Fridays during lecture, giving students 50 minutes to complete them. On the Monday and Wednesday before each quiz, we spent lecture reviewing relevant topics and, when applicable, taking up the practice quiz. Since lab sections were also on Fridays, we gave students a chance to debrief and discuss the quiz in their breakout rooms afterwards.

Figure 6: Example problem from Quiz 2, using Gradescope's online assessments functionality.

4 Key Differences from Data 8

While the topics in Data 94 overlapped with those in Data 8, there was a noticeable difference in the order in which these topics were introduced, and in many cases, the depth to which they were discussed. In addition, a sizeable amount of content in Data 94 is not covered at all in Data 8, and vice versa – very little from the umbrellas of inference and prediction was covered in Data 94, save for two special-topics lectures towards the end on randomness and simulation.

In this section, we present some of the key differences between the content of Data 94 and Data 8, with an emphasis on the ideas that were covered in Data 94. In 4.4, we discuss why we believe the content in Data 94 will complement – not replace or clash with – the content in Data 8 for students who decide to take it afterwards.

There are several references to assignments and lectures; all content can be found on the aforementioned course website, and public code links can be found at `https://github.com/surajrampure/data-94-sp21`.

4.1 Placement of Tables

Perhaps the largest difference between Data 94 and Data 8 was the placement of tables. In Data 8, tables are introduced in Week 2 [29], at the same time that the anatomy of a function call is discussed.

In Data 94, tables were not touched at all until Week 7 [40], well after students were introduced to other ideas in programming. We spent the first module establishing more traditional fundamental computing skills before transitioning to tabular manipulation, hoping that students would grasp tabular manipulation more easily in this manner. As evidenced in Section 5, by the end of the semester in the pilot offering, students felt much more comfortable with tables than they did with content from the first module.

However, this approach prohibited us from focusing on tabular data early on, which made it challenging to motivate some of the earlier ideas in the course given that students signed up to take a "data science" course. There were a few solutions to this; here, we discuss some of them in the context of homework assignments.

- **Using visualizations**

  Occasionally, we would ask students to write a function that performed some task that was not directly linked to any table or visualization. After they implemented the necessary behavior, they would run a pre-populated cell that loaded in a dataset and created a visualization that was in some way related to the function they just wrote.

  There were a few of these examples in the very first homework of the semester, Homework 1, where we thought it would be extremely important to capture students' interests. One such example had them compute an individual's Body Mass Index (BMI) given their height in inches and weight in pounds.

```
def bmi_from_in_lb(height_in, weight_lb):
    # SOLUTION denotes a line that students had
    # to write on their own
    height_m = height_in * in_to_cm * cm_to_m  # SOLUTION
    mass_kg = weight_lb * lb_to_kg # SOLUTION
    bmi = mass_kg / (height_m ** 2) # SOLUTION
    return bmi
```

  The interactive visualization created afterwards, shown in Figure 7, depicts the relationship between the weight, height, and BMI of several individuals whose measurements we read in from a CSV file. Students were not responsible for the mechanics of loading in the data or creating the visualization at that point in the course, though they became familiar with these steps later on. They were, however, asked an interpretation question to the effect of "as height increases, does BMI tend to increase or decrease?" Such questions are commonplace in data science coursework.

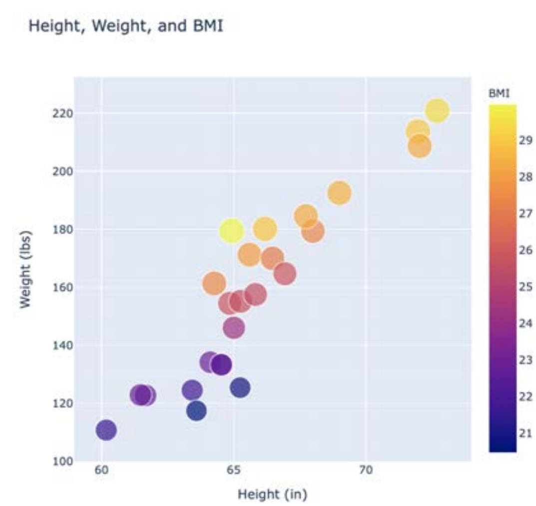


Figure 7: Scatter plot shown to students in Homework 1 after they implemented `bmi_from_in_lb`.

Another example in Homework 1 had students work towards drawing a line graph of the number of COVID-19 cases in Sweden in November 2020.

- **Using interactivity**

  While the aforementioned visualizations supported some interactivity (e.g. hovering and dynamic resizing) by virtue of being created using `plotly` [34], we also used `ipywidgets` [27] to create engaging interfaces that used students' functions.

  For instance, in Homework 4, we asked students to create a dictionary that mapped five specified keywords to emojis of their choice. They then had to create a function that would take a string and replace all instances of the specified keywords with their corresponding emojis.

```
def emojify(message):
    # This line ensures your code replaces correctly if any of
    # the keys in fav_emojis appears in uppercase in the message
    message = message.lower()
    # BEGIN SOLUTION
    for emoji in fav_emojis:
        if emoji in message:
            message = message.replace(emoji, fav_emojis[emoji])
    # END SOLUTION
    # Don't change this
    return message
```

  Afterwards, students ran a cell to generate an interactive text box that dynamically applied their implementation of `emojify` to their input text. The code that enabled this behavior was remarkably short.

```
def emojify_live(type_here):
    display(HTML('<h2>' + emojify(type_here) + '</h2>'))
interact(emojify_live, type_here="I LOVE food");
```

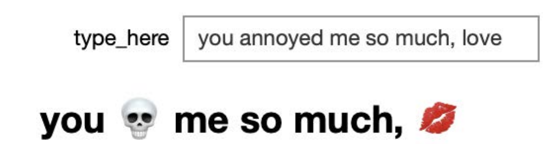


Figure 8: Interactive text box in Homework 4 shown to students after they implemented `emojify`.

  Figure 8 shows a snapshot of the final product. Another such example, also in Homework 4, had students use `np.dot` and `np.mean` to replicate popular image filters such as greyscale and sepia. Through functionality enabled by `ipywidgets`, students were able to upload their own images to see the results of their filters.

4.2 Additional Programming Constructs and Data Structures

In line with our course's title, *Introduction to Computational Thinking with Data*, we incorporated more traditional programming constructs than are covered in Data 8, in order to build students' computational thinking skills.

Before covering tables, we introduced three key ideas that aren't covered or emphasized in Data 8.

- **While loops**

  We covered while loops after covering basic control flow (i.e. if-statements), as is done in a few other introductory computing courses, including CS 61A [8] and Stanford's CS 106A [10].

  We used while loops as an opportunity to introduce the idea of tracing code. Figure 9 shows the hand-written notes in class for the following example.

```
def sum_first_n(n):
    j = 1
    total = 0
    while j <= n:
        total += j
        j += 1
    return total
```

  It is worth noting that a for loop is a more common choice for implementing functions like `sum_first_n`. We intentionally introduced this example before covering for loops in order to contrast it with its for loop implementation later on; this allowed us to drive home the point that for loops are generally more convenient when dealing with ranges of numbers.

  As is discussed in Section 5, students found while loops to be quite challenging. In future semesters, we'd consider delaying the introduction of while loops until after for loops are covered; we did not do this in our initial offering as we felt that while loops were a natural continuation of if-statements.

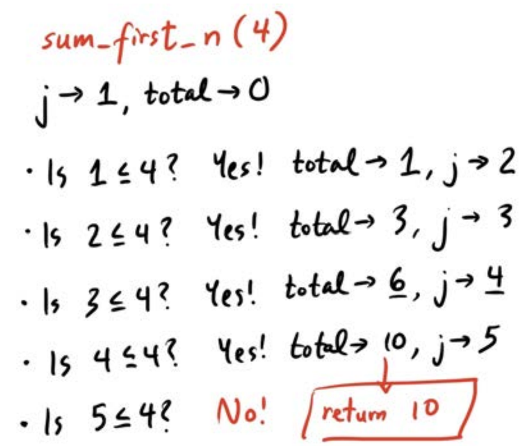


Figure 9: Screenshot of class notes in which we traced the execution of `sum_first_n`.

- **Lists**

  In Data 8, NumPy arrays are introduced quite early, as each column of a `datascience.tables.Table` is stored as a NumPy array. Lists are introduced shortly after, and are motivated by the fact that table rows can't be stored as NumPy arrays since NumPy arrays can't contain values of different types. However, lists are not mentioned frequently in Data 8, and notably, there is no mention of list indexing. As per the creators of Data 8, list indexing was once covered but was removed after students struggled with understanding the difference between square brackets and parentheses. We hoped that by being able to dedicate more time to these ideas, we would be able to bring students to understand them.

In Data 94, lists were introduced well before NumPy arrays. Indexing and slicing were introduced as core list behavior. This approach had a few benefits:

- When we introduced tables, the idea of selecting rows and columns by their numerical index (e.g. extracting the first column of a table with `tbl.column(0)`) was not new, and rather a natural extension of material that had been presented before. This is opposed to Data 8, where zero-based indexing is only introduced in the context of selecting a subset of rows.
- It enabled us to discuss string indexing, which was introduced in the same lecture as lists. String indexing, and string methods more generally, appeared quite frequently throughout the semester, especially in the context of data cleaning. Indexed-based string methods, such as the example from Homework 2 below, do not appear in Data 8.

```
def extract(s, char):
    # Check for the number of occurrences of char here
    # BEGIN SOLUTION
    if s.count(char) != 2:
        return ''
    # END SOLUTION
    pos1 = s.index(char) # SOLUTION
    pos2 = s.rfind(char) # SOLUTION
    return s[pos1 + 1 : pos2] # SOLUTION

>>> extract('510-642-1000','-')
'642'
```

- It allowed us to discuss the differences between lists and NumPy arrays in-depth. When discussing lists and loops, we covered several examples involving applying some arithmetic procedure to every element of a list. When introducing NumPy arrays, then, we were able to highlight the power of NumPy arrays for such tasks. The example below is taken from the lecture in which NumPy arrays were introduced.

```
c_temps = [17, 18, 22, -4.5, 15, 9, 0, 3, 8]
# Using vanilla lists:
f_temps = []
for c in c_temps:
    f = (9 / 5) * c + 32
    f_temps.append(f)
# Using arrays: no for loop!
f_temps_arr = (9 / 5) * np.array(c_temps) + 32
```

Furthermore, in Data 8, students create new NumPy arrays using the function `make_array` built into `datascience`. Its implementation [14] is shown below.

```
def make_array(*elements):
    return np.array(elements)
```

This function largely exists to circumvent the fact that instantiating NumPy arrays normally requires code of the form `np.array([...])`, which may appear foreign to students due to the double brackets. In Data 94, we explicitly addressed this issue; see Figure 10.

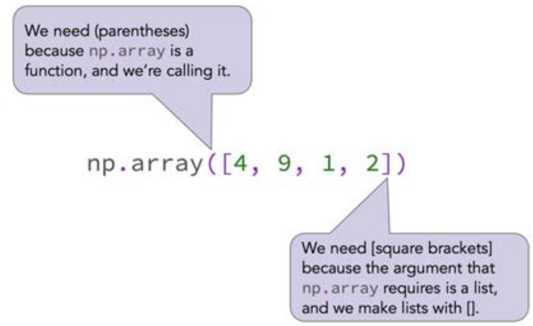


Figure 10: Slide from lecture in which NumPy arrays were introduced, explaining how new NumPy arrays are created from lists.

Students found array operations to be more straightforward than list operations, likely because the latter required iteration. By the end of the semester, students did not have issues with the syntax for creating and interfacing with both lists and arrays (and, by extension, strings).

- **Dictionaries**

  Like while loops, dictionaries are not touched at all in Data 8. In Data 94, they appeared during a transitory week where we were moving from core Python constructs to explicitly data-centric programming. The inclusion of dictionaries also had several benefits:

  – Dictionaries allowed us to have meaningful discussions comparing index-based and key-based data structures, which we found to be valuable in progressing towards our goal of building computational thinking skills. We hoped that this would make the transition to tables smooth, as tables are also key-based data structures (though we did not introduce tables with that exact terminology).

  – Dictionaries also served as a host for a variety of engaging examples; in addition to the `emojify` example from Figure 8, we used real data in multiple dictionary examples. The example shown in Figure 11, taken from the lecture introducing dictionaries, involved converting a dictionary containing mappings from area codes to states to a dictionary with mappings from states to lists of area codes.

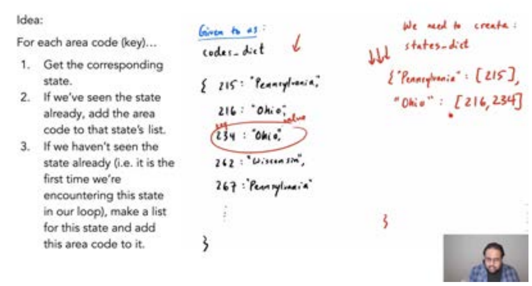


Figure 11: Screenshot from lecture video covering "Area Codes", a rich application of dictionaries using real data. The video can be found at `https://www.youtube.com/watch?v=9Buj7RslMno`.

  – Lastly, the coverage of dictionaries enabled us to discuss different forms of stored data. In a lecture dedicated to file formats, we introduced both the CSV and JSON formats, and stated that while the vast majority of data we will deal with is tabular in nature and stored as a CSV, JSON is also a common file format and is intimately tied to the dictionary data structure that we covered earlier. We used the example of a family tree to illustrate hierarchical data.

The corresponding homework assignment had students load in a JSON file generated by a call to the Google Maps API, and index into its dictionary representation to extract the latitude of a business.

4.3 Placement of Visualization

In Data 8, visualization techniques are introduced alongside core table manipulation techniques. Students are taught how to sort and filter tables, then taught to create select visualizations, and finally are taught about applying, grouping, pivoting, and joining (see Figure 12, which shows a few chapters of Data 8's textbook, which Data 8 follows directly). Some of the latter ideas are introduced in the visualization unit and are reinforced until later. The motivation for this is clear – in practice, visualization complements table manipulation when performing exploratory data analysis. Furthermore, visualization is engaging, as students can see the results of their work in satisfying ways.

Data 94 followed a different approach. Our second module consisted solely of table manipulation, with the goal being to build students' familiarity with table methods before moving to visualization. As such, we used the visualization module as a way to reinforce several table methods, rather than introduce them for the first time. As is discussed in Section 5, students found the visualization module to be the easiest of the three core modules in the course, by far. Notable differences between Data 94 and Data 8 with regards to visualization are enumerated below.

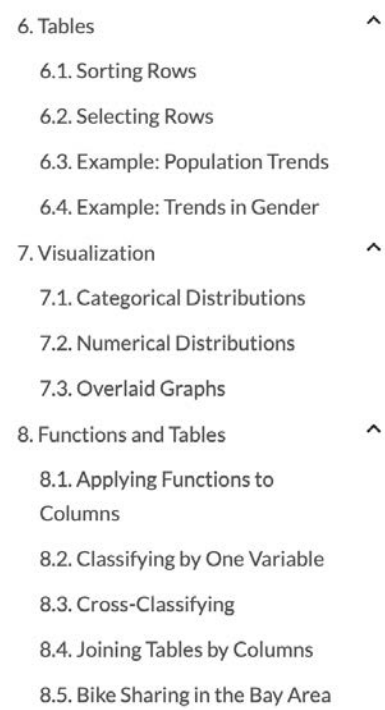

6. Tables
6.1. Sorting Rows
6.2. Selecting Rows
6.3. Example: Population Trends
6.4. Example: Trends in Gender
7. Visualization
7.1. Categorical Distributions
7.2. Numerical Distributions
7.3. Overlaid Graphs
8. Functions and Tables
8.1. Applying Functions to Columns
8.2. Classifying by One Variable
8.3. Cross-Classifying
8.4. Joining Tables by Columns
8.5. Bike Sharing in the Bay Area

Figure 12: Index of Chapters 6 through 8 of `inferentialthinking.com`, the textbook for Data 8.

- **Different order**

  While we largely covered the same specific visualization techniques that are taught in Data 8 – bar plots, histograms, scatter plots, and line plots – we introduced them in a slightly different order.

  In Data 8, scatter plots and line plots are introduced before bar plots and histograms. In this approach, students are introduced to multiple plots they are likely more familiar with from earlier schooling before they are introduced to histograms, which have far more nuance. We tried a different approach – we covered bar plots, then histograms, and then scatter and line plots, with the intention of discussing single variable distributions before discussing relationships between two variables. This approach was influenced by Data 100 [35], the followup course to Data 8.

- **Lighter treatment of histograms**

We did not cover histograms in as much detail as Data 8 does. Specifically, we only covered frequency-based histograms, while Data 8 teaches density-based histograms. We did this to avoid calculations that students often find challenging in Data 8, specifically, thinking about proportions as areas and, by extension, areas under curves. We told students that they would study histograms in more detail in Data 8; we felt that this trade-off was worthwhile, as most histograms in the real-world are frequency-based.

- **`plotly` instead of `matplotlib`**

  The `datascience` module recently built in support for `plotly`, which we used instead of the historical default `matplotlib`. This allowed us to create rich, interactive visualizations that we believed would excite students more than the static plots created by the `matplotlib`. However, to call the standard visualization methods built into `datascience` – `.barh`, `.hist`, `.scatter`, and `.plot` – students did not need to know any specifics about how their visualizations were created, since these methods worked directly on their tables.

  We spent time talking about the differences between `plotly` and `matplotlib` to make them aware of the technology underpinning their work. We also dedicated a lecture to using `plotly` directly, allowing us to expose students to visualization techniques that aren't built into `datascience` (such as pie charts and animated scatter plots).

  In previous semesters, we were part of the team that taught Data 100. Then, we hesitated to move to `plotly`, as `plotly` visualizations don't appear in the automatically-generated PDFs of students' written work that are created by existing infrastructure, meaning that they could not be manually graded. However, we were able to create a lightweight solution that doesn't involve changing any infrastructure, and we recommend others use it moving forward.

- **Maps**

  The `datascience` package now supports mapping functionality through a `folium` backend. In Data 8, mapping is covered in the textbook and used for an example in lecture, though it does not currently appear in any assignments. In Data 94, we dedicated an entire lecture to creating maps with various markers (see Figure 13 for an example), and students created multiple maps in Homework 8, the second homework dedicated to visualization.

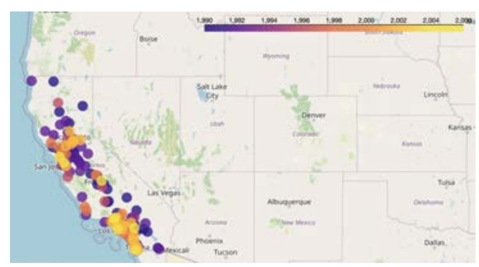


Figure 13: Example map created in lecture, describing the year in which each Walmart in California was opened.

4.4 Relationship to Data 8

In Data 94, we presented many ideas that are also presented in Data 8 but with a different approach, and covered topics that don't appear in Data 8 at all. This is not because we disapproved of Data 8 and wanted to replace it, but rather because our course was designed to serve different goals than Data 8, one of which was essentially to prepare students for Data 8 itself. As such, we believe that our choice and presentation of content will benefit students if and when they take Data 8.

Most of the Python fundamentals, table manipulation, and visualization introduced in the first module of Data 8 will be review for Data 94 students; even though we covered this material in a different order than Data 8 does, the actual coverage of the overlapping content from lecture to lecture was similar. This would allow students who go on from Data 94 to Data 8 to focus on details in the first module of Data 8 that we omitted in Data 94, such as interpreting data in the context of the real-world and a detailed coverage of histograms, without getting lost in syntax. By starting off strong in Data 8, these students will ideally gain confidence in their ability to succeed in Data 8 and beyond.

Starting Week 6 in Data 8, almost all of the material will be new to Data 94 students. From that point forward, they will be more experienced programmers than they otherwise would have been, and will be able to spend their time developing a deep understanding of the inference and prediction that is presented rather than still discovering the nuances of Python. This is especially important as the material from the latter two modules of Data 8 is heavily relied on by more advanced courses that require Data 8 as a prerequisite.

Students will still be introduced to new programming paradigms from Week 6 of Data 8 onwards, and their experiences from Data 94 will only help them. For example, a common use of for loops in Data 8 is to create a NumPy array storing the results of many simulations of some process – for example, bootstrap resampling and computing a statistic for each bootstrapped sample. While we did not cover this specific process in Data 94, we covered several other instances of the accumulator pattern [3], which students will be able to draw parallels to. More broadly, the additional computational thinking experience will allow students to decompose problems and identify logical errors in their code more easily.

It's worth noting that none of the content in Data 94 "clashed" with content in Data 8. There are two examples where we covered specific ideas in a markedly different way than Data 8:

- Histograms – students were told that they will see a different, more sophisticated version of histograms in Data 8. Many of the high-level ideas from Data 94's treatment of histograms remain the same, such as the concept of binning and the fact that the distribution within a bin is unknown when looking at a histogram. We believe that the Data 8 treatment of histograms will not feel foreign, but rather like a natural extension of what students are already familiar with.

- Creating arrays – as was discussed in Section 4.2, students were shown to create NumPy arrays using `np.array([...])` instead of `make_array(...)`, which is used heavily in Data 8. We believe that students will not struggle with moving from the former to the latter as they studied how the former works in depth, and will see that the latter is simply a shortcut. Furthermore, they can simply use the former in place of the latter.

In both examples, we covered an idea from Data 8, just with more or less detail. This means that students moving from Data 94 to Data 8 will still be able to leverage their prior experience when seeing these ideas again in Data 8.

The additional computing content in Data 94 that doesn't appear in Data 8 – while loops, lists (in detail), dictionaries, file formats, creating websites – will not hinder students' ability to understand concepts in Data 8, but will broaden their perspectives on what the field of data science entails as a whole.

It should be noted that neither of our two primary goals introduced in Section 3.1 mentioned programming or computing. While we could've created a pre-introductory data science course that focused on inference and prediction rather than computation, our impression was that students feel like the most intimidating and challenging aspect of Data 8 is the programming, not the inference and prediction.

5 Survey Analysis

Alongside each homework assignment, we released a survey that asked students to indicate their level of familiarity with the latest lecture content and to give feedback on the current homework; regular surveys have been shown to provide insightful information in previous studies [36]. In surveys following a quiz, we also asked for their feedback on the length and difficulty of the quiz they had just completed. The final survey of the semester was due right before the final exam and asked students for their comfort level with each of the key topics in the course.

In this section, we will use the data from the above surveys along with the enrollment application for the course to assess the progress we made towards achieving our design goals and identify areas for improvement in future offerings. There are a few notable limitations of our analysis – namely, we don't have information on what students did and how they performed in subsequent courses after Data 94, nor do we have their final exam scores and hence their letter grades in Data 94. This is due to the timeline of this project; this report was largely written before the final exam for the course.

5.1 Enrollment

In order to receive a spot in the pilot offering of the course, students had to fill out an application. The application asked students to answer the following questions, as well as to provide their transcripts:

- Have you ever programmed before? If yes, please elaborate.
- What is your expected graduation semester?
- Why do you want to take this class? (Answer in two sentences or less.)

Only the first two questions factored into whether or not students were accepted. The first question was asked to ensure that only students without prior programming experience were in the course, as this was our target audience. As one of the overarching goals of the course was to encourage students to pursue more data science coursework, Data 8 in particular, we reserved 22 of the 30 seats in the course for non-seniors, who we filtered via the second question. (This constraint ended up being irrelevant as fewer than 30 students ended up in the course.) Students who met the criteria were admitted on a first-come-first-serve basis.

Overall, 62 students applied to enroll in the course. Of those, 21 had prior experience of some sort (through a course or self-study) and were denied. All 41 other students were offered a seat; roughly 25 were in the class by the first week, and 18 were in the class for the final exam.

Below, we present a few of the responses to the question "Why do you want to take this class? (Answer in two sentences or less.)" by students who finished the course.

- "Studying primarily humanities, I wanted to gain experience in another fairly unrelated sector (like coding) to help with potential careers, but was apprehensive about taking a large course like Data 8. Since I have no experience I was worried I would fail Data 8, thus this course seems much more doable and supportive."

- "I have always wanted to learn Python and other programming languages, but I did not want to struggle in a class full of expert programmers where I lacked the basic knowledge to even pass. This class allows me to actually learn CS in a setting where the teachers understand that I am starting from ground zero."
- "I really need the small learning environment that Data 94 provides in order to learn the basics of coding to succeed at higher level classes required for the Data Science Major while also being able to ask questions and be more involved in class."

Of the 18 students who finished the course, 10 explicitly mentioned the small class size of the course as a draw in their application. Though these numbers are relatively small on Berkeley's scale, we believe that there is a need for a course like Data 94 in the Berkeley data science ecosystem, and perhaps at other institutions with similar programs as well.

Figure 14 shows the distribution of "major categories" of enrolled students. To compute this distribution, we categorized all declared students' majors as being either STEM or non-STEM; we cannot show specific majors for privacy reasons. Only 3 out of 18 students had declared a STEM major prior to taking the course.

As is depicted in Figure 15, 12 of the 18 enrolled students were juniors or seniors. This is likely a consequence of how the course was marketed; we advertised the course to the major advisors of many non-STEM disciplines, and students who received communications from major advisors are likely to be declared (explaining Figure 14) and hence older.

While older students still benefited from taking the course, they were less likely to pursue further coursework in data science, as was indicated by many older students in the final survey of the semester. In the future, we'd market more to undeclared first-year and sophomore students.

It is worth noting that the course was quite gender-balanced, with roughly 50% of students identifying as female and male, respectively.

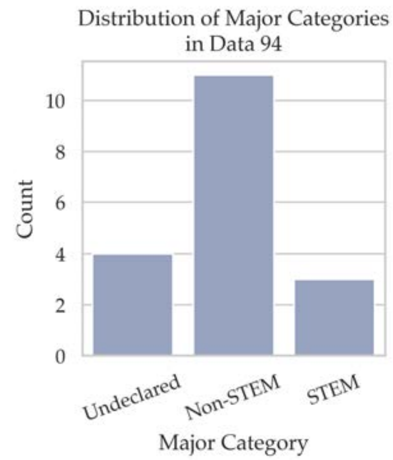


Figure 14: Distribution of "major categories" amongst students enrolled in Data 94 in Spring 2021.

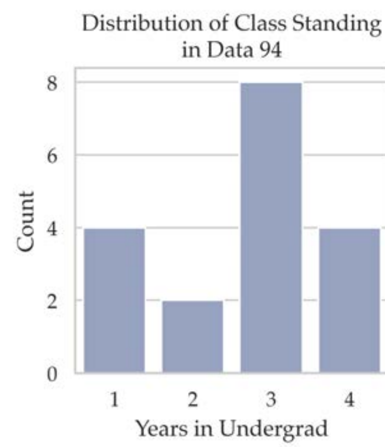


Figure 15: Distribution of class standing amongst students enrolled in Data 94 in Spring 2021.

5.2 Understanding of Content

In the final survey of the semester, students were asked to answer the question "How well do you feel like you understand each of the topics presented in class, as of right now?" in a grid consisting of 17 core topics. Possible answers were "Don't understand at all" (1), "Barely understand" (2), "Understand somewhat" (3), "Understand well" (4), and "Understand very well" (5). For the purposes of creating Figure 16, we computed the mean response per question.

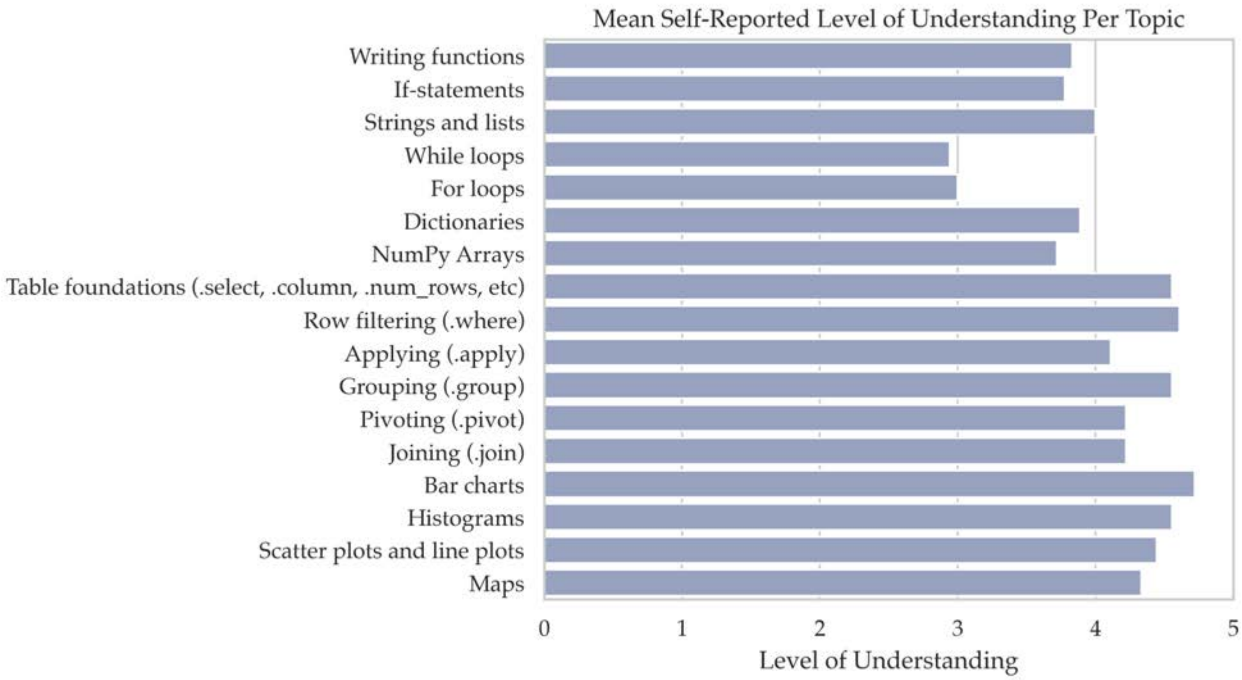


Figure 16: Mean self-reported level of understanding per core topic. Only topics in the first three modules were included.

While students were generally comfortable with most topics by the end of the semester, there were a few clear trends. For one, students seemed to be much more confident in their table manipulation and visualization skills than they were in their core Python skills.

This is likely due to a confluence of factors.

- Over the last two months of the course, table methods were emphasized far more than core Python concepts were. Of note, iteration did not appear very frequently; for loops appeared more often than while loops.
- The pace of the course at the start was much quicker than the pace after the first few weeks; it took us a while to get calibrated to the students' level of comfort.
- Students expressed that table methods and visualization felt "easier" since they were able to see a graphical representation of their work at each stage.
- Students were simply more experienced programmers by the time they reached the later topics.

However, students did not feel that the material at the start of the semester was unimportant. In the final survey, several students remarked that they recognized the importance of iteration in the course and wished more time was dedicated to it.

5.3 *Difficulty and Enjoyment of Assignments*

As mentioned earlier, students were polled on the difficulty (on a scale of 1 to 5) and amount of time spent on each homework assignment right when they submitted it. As such, the results in Figure 17 do not reflect end-of-semester self-reflection, unlike Figure 16. Homework 9 is not included in these figures as it was in a different format than the first 8 homework assignments and was significantly shorter.

It appears that students found homework assignments to be easier as the semester progressed, which corroborates the findings in the previous subsection. However, there is a notable outlier, Homework 6, which students spent by far the most time on and found to be the most difficult homework, on average.

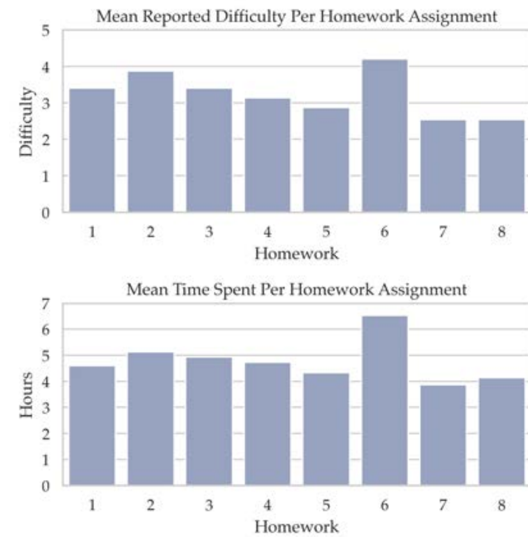


Figure 17: Mean reported difficulty and time spent per homework assignment, as per regular surveys.

Interestingly, Homework 6 covered applying, grouping, pivoting, and joining, ideas which students reported being quite comfortable with by the end of the semester. Homework 6, more so than any other assignment, pushed students outside of the boundaries of what was covered in the corresponding lectures. One question asked students to join two tables on multiple columns, when only single-column joining was covered in lecture; though we provided several hints, including telling students to provide a list as the first argument to `.join`, many students struggled with this problem. Another paradigm that appeared multiple times in Homework 6 that did not appear in lecture was the idea of grouping to determine categories that satisfy certain criteria, then filtering only those categories from the table. This is the behavior of `df.filter` in `pandas` though there is no direct analogue in `datascience`. Code for one of these problems is given below.

```
common_segments = chains_growth.group('Segment_Category') \
                                .where('count', are.above_or_equal_to(10)) \
                                .column('Segment_Category') # SOLUTION
common_chains = chains_growth.where('Segment_Category',
                                    are.contained_in(common_segments)) # SOLUTION
```

We believe that Homework 6 positively contributed to students' understanding of these topics, despite being perceived as more difficult on average than the other homeworks.

The bottom graph in Figure 17 shows that on average, students spent around 4-5 hours per week on homework assignments. This means that we largely adhered to our target of having students spend roughly 9 hours per week on the course (see Section 3.3). In the end-of-semester survey, the majority of students reported spending 7-9 hours per week on the course on average.

The end-of-semester survey also asked students for their favorite and least favorite homework assignments of the semester. For favorite, 12 of the 15 students who answered the question answered either Homework 4 or Homework 9, neither of which focused on table manipulation (see Table 3). For least favorite, 6 of 15 students answered either Homework 2 or Homework 6; Homework 6 was discussed in detail above, and Homework 2 (a local maximum with regards to self-reported difficulty and time spent) introduced while loops, a known challenging topic. 7 of 15 students didn't specify a least favorite homework; some of these students stated that they enjoyed all homeworks, and some stated that they didn't enjoy many of the earlier assignments.

5.4 Future Plans

The final survey also asked students whether they planned on pursuing data science further, and if so, in what capacity. As shown in Figure 18, not many students planned on pursuing a major or minor in Data Science at Berkeley, however the majority of students in the course were in the second half of their undergraduate studies coming into the course; in an open-ended question, most students noted that they felt that they didn't have enough time to complete either the major or minor before graduating. However, all students reported some interest in learning more about data science in some capacity, and many indicated that they'd be taking domain-specific data science courses as part of their existing field of study.

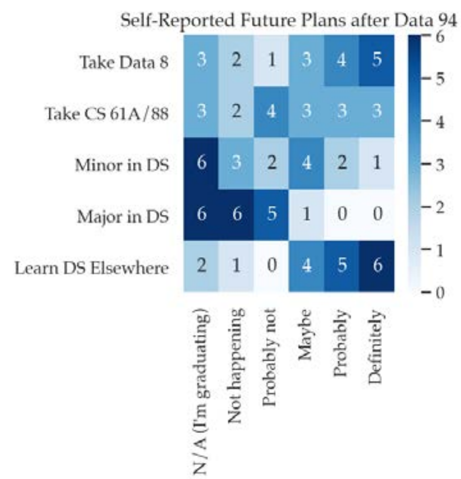


Figure 18: Distribution of the responses to the question "Which of the following are you likely to take or pursue in the future?" for several potential pathways.

6 Conclusion

6.1 Future Work

Throughout this report, we identified a few areas of improvement for future offerings. Most notably, we would spend more time on initial topics, particularly iteration, and reintroduce these ideas more frequently throughout the semester. To attract younger students who are more likely to pursue majors or minors in data science, we would advertise the course more broadly. We also believe a more thorough integration of ethics and social sciences content would make the course more engaging and responsible.

While other similarly-purposed courses are offered at much larger scales (for instance, CS 10 had 138 students in Spring 2021 [1]), and it is logistically feasible to offer Data 94 at a much larger scale, we believe that the small size is what enticed students to enroll in the course in the first place. One possible model for scaling if the demand exists is to offer many smaller lecture sections of approximately 30 students. This model is not common in Data Science at Berkeley, but is in practice at other institutions, including Johns Hopkins University [16].

We hope that this report will help future instructors of the course at Berkeley understand our design decisions and the student-perceived effectiveness of our pilot offering. We also hope that instructors at other institutions with courses similar to Data 8 will use this report to identify if there is a need for a course similar to Data 94 in their school's data science curriculum, and if so, what components from Data 94 could be adopted. All materials are available for public use; contact the author for more details.

6.2 Parting Thoughts

We created Data 94, *Introduction to Computational Thinking with Data*, to serve as an introductory-level course that would encourage students to study data science further while preparing them to do so and instilling a level of confidence in them if they chose to.

Due to the timeline of this project, we are unable to conclude how effectively we prepared students for future work in data science. However, students seem to be content with the course. On a scale of 1-5, all 18 students responded either 4 or 5 to both "How much do you feel you learned in Data 94, in terms of new ideas and skills?" and "How happy are you about your decision to take Data 94?", with a mean response of 4.95 for both.

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