Investigating Student Mistakes in Introductory Data Science Programming

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ABSTRACT

Data Science (DS) has emerged as a new academic discipline where students are introduced to data-centric thinking and generating data-driven insights through programming. Unlike traditional introductory programming education, which focuses on program syntax and core Computer Science (CS) topics (e.g., algorithms and data structures), introductory DS education emphasizes skills such as studying the data at hand to gain insights and making effective use of programming libraries (e.g., `re`, `NumPy`, `pandas`, `scikit-learn`). To better understand learners' needs and pain points when they are introduced to DS programming, we investigated a large online course on data manipulation designed for graduate students who do not have a CS or Statistics undergraduate degree. We qualitatively analyzed incorrect student code submissions for computational notebook-based programming assignments in Python. We identified common mistakes and grouped them into the following themes: (1) programming language and environment misconceptions, (2) logical mistakes due to data or problem-statement misunderstanding or incorrectly dealing with missing values, (3) semantic mistakes from incorrect usage of DS libraries, and (4) suboptimal coding. Our work provides instructors valuable insights to understand student needs in introductory DS courses and improve course pedagogy, along with recommendations for developing assessment and feedback tools to better support students in large courses.

KEYWORDS

Introductory Data Science Programming, Types of Mistakes, Qualitative Analysis, Data Manipulation in Python

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1 INTRODUCTION

The growing importance of Data Science (DS) education demands more research on the curriculum and assessment practices in DS courses [29]. From degree programs to Massive Open Online Courses, DS courses attract many students from diverse backgrounds [42]. The rapid growth of enrollment in DS courses requires pedagogy and assessment approaches that work at scale, which requires a deeper understanding of students' difficulties in these new courses. This is particularly important for introductory DS (hereafter referred to as DS1[1]) courses, such as data manipulation, which form the foundation of students' future DS undertakings.

Data manipulation courses typically cover topics such as data cleaning, preparation, and exploration [9, 12], e.g., selecting, filtering, aggregating, and transforming values in a `DataFrame` (the core DS1 data structure). In a `DataFrame` each row represents a single observation, and each column represents an attribute (or variable in the statistics sense) of the observations. Practitioners spend significant time on data manipulation activities, yet there have been few efforts to formalize data exploration and cleaning. Such topics are relatively neglected in teaching, especially when compared to data modeling topics—covered in Statistics and Machine Learning courses—using datasets that are already cleaned and ready for ingestion [17, 47]. While significant efforts have been employed to understand CS education, including the formation of the ACM SIGCSE conference, CS1 pedagogy research may not generalize to DS1 [36]. Beyond learning how to solve DS problems computationally, two other important aspects of DS education are precise knowledge of the problem domain and data literacy [17] (a term used to broadly describe the set of abilities around the use of data for solving real-world problems [50]). While both CS1 and DS1 require the students to learn the fundamentals of a programming language, the DS1 approach tends to embed this in data manipulation activities that vary with the data being analyzed in contrast with the CS1 approach of solving general-purpose computing tasks [19]. This

[1]We use *DS1* as a moniker for introductory DS, noting that there is currently no such standard term.

can cause fundamental differences in how a student considers computation: for instance, while it is typical to teach iteration very early in a CS1 approach, many DS libraries contain *vectorized* functions, promoting functional programming approaches. Consequently, DS1 programming heavily relies on the effective use of libraries to manipulate data, as opposed to implementing algorithms and data structures through student-defined functions or classes [29, 36].

Our work advances knowledge of the nascent field of DS Education through an evidence-based approach. We focus on DS1 student programming challenges (an approach used in several educational contexts including CS1 [41]) by investigating a large, online data-manipulation course. Described in more detail in Section 3, this Masters' degree course is designed for novice DS learners who have only introductory computing and statistics knowledge. The course curriculum introduces data manipulation and cleaning techniques using the popular `Pandas` DS library in Python. By understanding some of the challenges these novice DS learners face, we aim to understand the skills and competencies on which DS1 learners require additional guidance and feedback. Therefore, we explore the following research question:

RQ: *What are learners' mistakes and inappropriate strategies when they are introduced to programming in data manipulation courses?*

We explore this question by qualitatively analyzing 50 students' 140 incorrect code submissions. Our key contribution is a categorization of DS1 mistakes that instructors can use to understand student needs and pain points, revise curricula, and provide directed feedback. To understand the competencies on which to support learners, we consider both students' mistakes and inappropriate programming strategies given the course's learning objectives. We show that students' code needs to be evaluated along five axes that should accordingly inform the nature of instructional support they receive: (1) programming in computational notebooks, (2) data literacy, (3) programming with DS libraries, (4) programming strategies, and (5) writing optimal code using vectorized operations and functions. However, current assessment tools [6, 23, 33, 37, 51] focus primarily on the correctness of the code output and do not support students' skills acquisition along all of these competencies. Based on the identified mistake types, we provide pedagogical recommendations for supporting learners in data manipulation courses and insights for developing assessment and feedback tools to help students acquire skills even in large courses. We also contribute a dataset of 140 incorrect student code submissions labeled with mistake categories[2].

2 RELATED WORK

Data Science Education. There are several publications on course design and experience reports of conceptualizing and teaching specific DS courses [3, 5, 9, 10, 12, 15, 19, 43, 44]. The 2019 report by the ACM Task Force on DS Education [16] provides suggestions for core competencies a graduating DS student should leave with and suggests topics that a full DS curriculum should integrate. Some instructors have documented their teaching experiences in informal contexts such as teaching computational data analysis to academic researchers [11, 49]. Kross and Guo shared their findings from interviewing DS practitioners who taught novices in both industry and academic settings [29]. They highlighted that practitioners often lack formal pedagogical training, which raises the importance of conducting more research on DS pedagogy for novices. Recently, Lau et al. [30] reported their experience of balancing the Statistics and CS concepts while launching a DS1 course. They demonstrated how CS and Statistics instructors typically approach DS differently. This body of work reveals that despite the growing importance of DS, due to its recent formalization as an academic discipline, more consensus is needed on DS1 teaching practices. Our work contributes to this research gap by identifying student mistakes in DS1 courses to improve DS1 pedagogy.

Diagnosis of Programming Difficulties. Capturing and understanding students' common errors and misconceptions are important to enhance instructors' pedagogical content knowledge [41]. As a result, several computing-education researchers have analyzed students' difficulties in CS1, using a diverse set of definitions and approaches [1, 2, 8, 26, 28]. Yizhou et al. [41] surveyed relevant literature on students' difficulties in CS1 and categorized them into a lack of syntactic, conceptual, and strategic knowledge. We draw upon this work by proposing a similar categorization of students' mistakes in DS1, but name the categories to be more relevant to DS1. Luca et al. [13] developed a curated inventory of programming language misconceptions, focusing primarily on syntax and semantic errors. They described a way to organize a collection of such misconceptions to present a synthesis of past research to educators in an accessible form, thus, bridging the gap between research and educational practice. Similarly, we provide actionable insights to improve DS1 curriculum and assessment practices.

Limited research has explored student difficulties in learning DS. Nguyen et al. [36] took a first step towards analyzing DS students' code at scale by leveraging metrics from traditional software engineering (e.g., Halstead Volume [24] and Cyclomatic Complexity [34]) in combination with DS-specific metrics such as number of library calls. They identified metrics indicative of task complexity, submission runtime, and submission score. However, these metrics operate over the entire code as a single entity and, thus, cannot be used to isolate incorrect parts of the code.

While scalable code analysis methods for DS1 are limited, there is significant research on identifying students' mistakes in CS1 courses using unsupervised techniques, such as code clustering [22, 25, 46], which typically rely on static code analysis by representing code as Abstract Sytnax Trees (ASTs) or neural embeddings [38]. While these approaches work well in CS1, a challenge in DS1 is that two qualitatively different solutions to a problem may have similar ASTs, which is not commonly observed for CS1 problems. This is due to the nature of DS1 programming, which relies extensively on using existing API and library functions, where changing the function parameter values does not lead to a change in the AST. Since CS1 code clustering techniques do not generalize to DS1, we qualitatively analyzed students' incorrect code submissions to reveal student mistakes. To instigate future research in this area, we identified features of DS1 code that can be useful for automatically detecting mistakes using semi-supervised approaches [18].

[2]Dataset will be released upon paper acceptance.

3 METHOD

Course Context and Study Population. The DS1 course we analyzed is the first technical course offered as part of a one-year online graduate program in applied DS offered by <Anonymous University>. This program attracts students from diverse backgrounds, many of whom are mid-career professionals looking to acquire DS skills. Students in this program are required to have introductory programming and statistics knowledge. All the courses in the program are fast-paced 4-week courses. All of the technical instruction is provided in the JupyterLab computational notebook environment [27] and Python is used as the programming language. The environment is cloud-hosted and set up with all the necessary libraries to complete the course. Graduates of this program are expected to have practical skills in a breadth of DS topics (e.g., applied machine learning, experiment design, information visualization, etc.) using Python-based toolkits.

The DS1 course's learning objectives include learning basic data manipulation and cleaning techniques by effectively using the `re` [45] and `pandas` [39] libraries. This includes ingesting, cleaning, manipulating, and transforming data and performing basic inferential statistical analyses. Weekly programming assignments (4 in total) are automatically graded using nbgrader [35], a tool that facilitates creating and grading Jupyter-based assignments. Each assignment consists of 3–4 individually graded questions. A series of unit tests are used to provide feedback to learners regarding the correctness of their solutions. Each question is graded as pass or fail, and the overall assignment grade is equally weighted among all questions. Importantly, students are allowed unlimited submissions for each assignment until the deadline (one week after the assignment is released), resulting in most students eventually achieving full points for the assignment.

Data. We sampled submissions from a collection of 542 notebook solutions submitted for the second assignment by 151 students enrolled in the Fall'21 offering of the course. The assignment had 3 questions on selecting parts of the provided dataset, performing simple manipulations, aggregating dataset values, dealing with missing values, and performing a basic statistical correlation test. All questions are based on the 2017 data on immunizations provided by the U.S. Center for Disease Control (CDC) and its accompanying 252-page data guide. The assignment was designed as an authentic DS inquiry with the goal of emulating typical *data cleaning* and *wrangling* tasks performed by data scientists as the first step in a DS workflow following data acquisition. We did not analyze the first assignment as it was based on the `re` library and was significantly easier than the other assignments. All the other assignments were based on the `pandas` library. The second assignment was chosen for analysis since it was the first one assessing `pandas` knowledge, and we were interested in understanding learners' mistakes when they are *introduced* to DS1 programming. Figure 1 shows the instructions for the second question in this second assignment.

Sampling Procedure. We sampled notebooks for one assignment question at a time. First, all notebook submissions were autograded using nbgrader. Then, from the subset of students who had at least one incorrect submission for a given question, we iteratively picked a student at random and qualitatively analyzed a sequence of their incorrect submissions until a correct submission was found. Therefore, the sample consisted of multiple notebooks per student including both intermediate and final submissions. The sampling procedure was repeated until we achieved data saturation [20] for each question (i.e., new mistakes were no longer discovered in subsequent submissions that were analyzed). In this way, we sampled 140 notebooks submitted by 50 students in total. Table 1 shows aggregates of the analyzed data.

Statistic	Sampled Data	Question 1	Question 2	Question 3
# students	50	26	24	10
# analyzed submissions	140	48	50	42
Max # submissions analyzed for a student	15	7	7	15
Mean (± std err) # submissions per student	2.8 (± 0.46)	1.85 (± 0.31)	2.08 (± 0.33)	4.2 (± 1.48)

Table 1: Summary of the data sample used in our analysis. The second column presents statistics for the full sample, and other columns represent each question in the data sample.

Qualitative Analysis. We qualitatively analyzed the sampled submissions to understand learners' mistakes and inappropriate strategies, one question at a time. The unit of analysis was a student's code, which they were asked to write in a single notebook cell. After reading the code line-by-line, we referred to the other notebook cells if we were unable to understand the student's approach. For instance, some students defined variables outside the cell in which they coded. In our analysis, we also looked at: (i) the code output and compared it with the correct output and (ii) Python interpreter errors (if any). While analyzing a sequence of incorrect submissions by a student, we noted all the mistakes in each submission.

Using thematic analysis [7] to explore the emergent themes, the first author, who had previously been a teaching assistant for another data manipulation course, consolidated a coding scheme for mistake categories. They developed and refined the mistake categories as they became more familiar with the data sample after repeated readings. Following this, the first author and another author (who had taught the DS1 course previously) independently coded a random sample of 30 (20%) submissions using the coding scheme, and labeled each submission with one or more mistake categories. An 82.76% agreement was achieved by averaging the Jaccard similarity (the intersection of all applied codes over the union of all applied codes) for all 30 pairs of coded submissions. All discrepancies were discussed and resolved to finalize the mistake categories in this round of coding. Then the first author updated the coding scheme and coded all the data.

4 RESULTS: TYPES OF DS1 MISTAKES

We now describe the types of DS1 mistakes we identified following the method described in Section 3. To demonstrate how mistakes in each category are manifested in students' code, we primarily use examples of incorrect code submissions for the second question of the assignment. In this question, students are asked to calculate, for the genders male and female, the ratio of the number of children who contracted chicken pox but were vaccinated against it (i.e., received at least one varicella dose) versus the number of children who were vaccinated but did not contract chicken pox. Students were instructed to return the output as a dictionary with the keys "male" and "female". In the dataset, the column `'P_NUMVRC'` indicates the number of varicella doses received by a child, column `'HAD_CPOX'` indicates whether a child contracted chicken pox (`'HAD_CPOX' =`

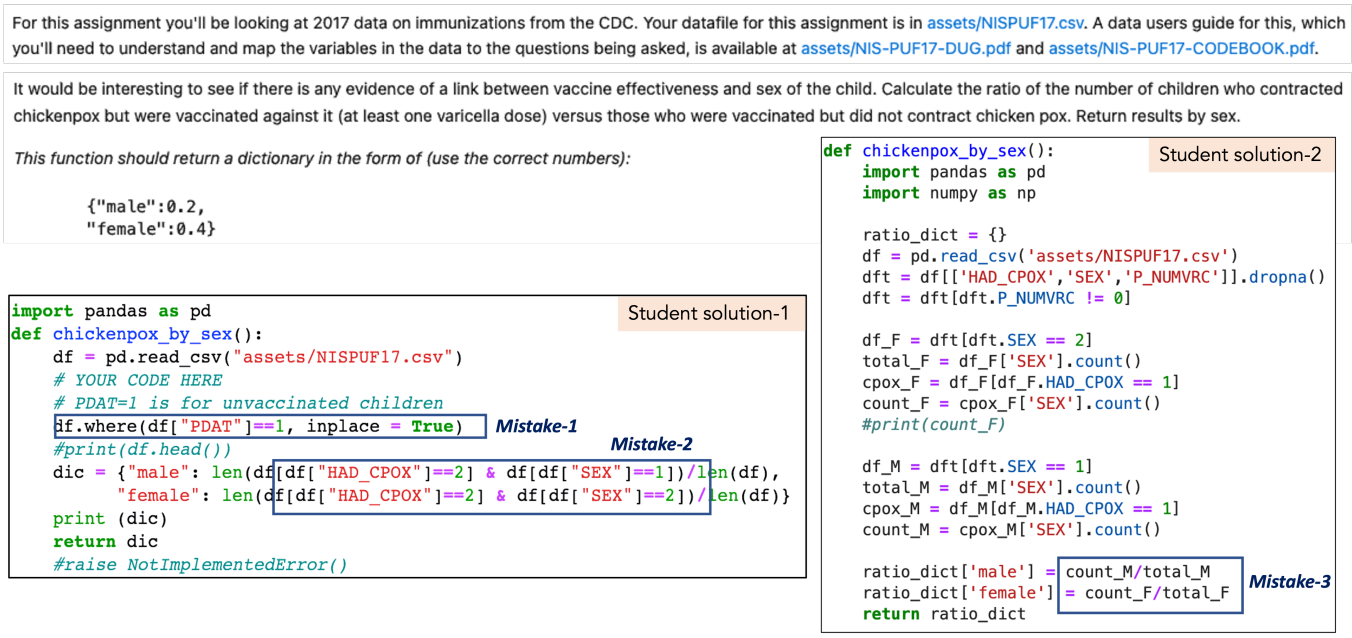

Figure 1: A snapshot of the analyzed assignment and two student submissions. Mistake-1 is a semantic mistake (function `where()` used incorrectly), and a logical mistake due to dataset misunderstanding (attribute `'PDAT'` incorrectly used instead of `'P_NUMVRC'`). Mistake-2 is another semantic mistake due to incorrect use of the bitwise AND (&) operator on two `DataFrame` objects, which is an invalid operation. Mistake-3 is a logical mistake due to problem-statement misunderstanding (ratio denominators incorrectly computed as the number of *all* vaccinated children instead of vaccinated children who did not contract chicken pox).

1) or not (`'HAD_CPOX' = 2`), and column `'SEX'` indicates gender (1 for male and 2 for female).

A common categorization for programming errors is to divide them into syntactic, semantic, and logical errors [26]. We extend this categorization further to DS1 programming as follows:

4.1 Logical Mistakes

A program with logical mistakes does not behave as expected (in our case, does not produce the expected output) according to the problem statement. This typically does not throw a runtime error. We further divide logical mistakes into the following subcategories (some mistake types may belong to multiple subcategories):

4.1.1 Dataset misunderstanding. This category includes mistakes from misunderstanding the dataset, its schema, or associated data guide. Such mistakes can be caused due to the following reasons:

- *Selecting incorrect dataset attributes (columns in a* `DataFrame`*).* Mistake-1 in Figure 1 is an example of this category. Instead of using the column 'P_NUMVRC' from the `DataFrame`, the student has used the 'PDAT' column which denotes whether a child has adequate provider data. Based on the comment written by the student before the line of code with Mistake-1, they misinterpreted the meaning of the 'PDAT' column.
- *Using incorrect dataset values or selecting the wrong rows from a* `DataFrame`. For instance, a student incorrectly used the values `'male'` and `'female'` instead of 1 and 2 when filtering rows using the `'SEX'` column.

4.1.2 Problem-statement misunderstanding. This category includes mistakes due to incorrectly translating the problem-statement instructions into code due to misinterpretation. Sometimes it may be difficult to conclude whether a student made a mistake because of misunderstanding the problem statement or the dataset. For this reason, we only categorize mistakes as belonging to the 'problem-statement misunderstanding' subcategory if they do not involve any misinterpretation related to the dataset.

Mistake-3 in Figure 1 is a mistake of this type as instead of returning the ratio of vaccinated children who contracted chicken pox versus vaccinated children who did not, the student returned the ratio of vaccinated children who contracted chicken pox versus *all* vaccinated children. Other examples include rounding up the ratios instead of returning the actual ratios as instructed, using an incorrect order of dictionary keys, and returning percentages instead of ratios.

4.1.3 Incorrectly dealing with missing values. Mistakes where students incorrectly deal with a `DataFrame`'s missing values typically belong to one of the two aforementioned sub-categories in addition to this sub-category. For instance, instead of using the condition `df['P_NUMVRC'] > 0`, a student used the condition `df['P_NUMVRC'] != 0` to select rows indicating children who received at least one varicella dose. This is incorrect as the column `'P_NUMVRC'` consists of missing values, which are counted in addition to the number of rows where 'P_NUMVRC' is greater than 0. Another example is from a solution to the third question, which required computing the correlation between the `'P_NUMVRC'` and `'HAD_CPOX'` columns. A student replaced all missing values in both columns with `0`, which leads to incorrect computation of the correlation as missing values from the `'P_NUMVRC'` column are incorrectly counted towards children receiving 0 doses.

4.2 Semantic Mistakes

Semantic mistakes arise from incorrectly selecting or using a DS library, function, or operator, which may or may not throw a runtime error. In addition to a logical mistake (mentioned in Section 4.1.1) Mistake-1 in Figure 1 contains a semantic mistake as the student has incorrectly attempted to use the `where()` function from `pandas` to select the rows that satisfy a given condition. However, this does not filter out the remaining rows (where the condition isn't satisfied), as `where()` is used for replacing values where the condition is `False` to some specific value (specified in the call through a parameter named `other`, with the default set to `NaN`). Consequently, in the subsequent lines of code, `len(df)` returns the length of the full `DataFrame` rather than only those rows where the condition is satisfied. Another example of a semantic mistake is Mistake-2, where the student attempted to use the bitwise AND (`&`) operator directly on two `DataFrame` objects, which isn't a valid operation. The correct way of computing the numerator for the key "`male`" is: `df[(df["HAD_CPOX"] == 2) & (df["SEX"] == 1)]`, i.e., combining two boolean masks[3] using a bitwise operator, with parentheses around each mask to override the default operator precedence rules.

Some other examples of semantic mistakes that we observed were: (i) dividing a `DataFrame` slice[4] by another slice rather than dividing their lengths to compute a given ratio, and (ii) using the `groupby()` function incorrectly, where the student misunderstood the output format of the object returned by `groupby` and consequently performed incorrect operations in subsequent lines of code.

4.3 Suboptimal Coding

A data-processing code is suboptimal if it lacks proper optimizations like vectorized operations, and, therefore, fails to scale to large datasets. Suboptimal code may or may not throw an error. In our data sample, we found instances of for-loops being used to iterate over `DataFrame` rows such as to count the number of rows that satisfy a given condition, instead of the more optimal method of applying a Boolean mask to do the same. While it is not necessarily incorrect to do so, this is an inappropriate DS programming strategy as it can slow down the performance of the code, especially when working with large datasets. Iterating through a `DataFrame` row by row is a relatively slow operation in Python compared to using vectorized operations (e.g., `map()`, `groupby()`, `join()`, `merge()`, and filtering using Boolean masks), which have the ability to run an operation across a whole `DataFrame` at once.

4.4 Language & Environment Misconceptions

This category consists of mistakes because of misunderstanding the syntax or the programming environment (in our case, JupyterLab), leading to Python interpreter errors, e.g., (i) incorrectly specifying the path to the dataset file, (ii) using incorrect python syntax, (iii) not defining a variable or failing to import a library, and (iv) defining a variable or importing a library in a cell different from the one in which the solution is being written, such that it is out of scope. For instance, some students defined variables used within a function in another function used for answering a different question, thus making those variables out of scope. Another mistake in this category was not defining `df` (a common variable name used for a `DataFrame`) or `pd` (a commonly used alias for `pandas`) or defining them in a cell below the one where they were referred.

[3] A `pandas` feature that enables filtering a `DataFrame` based on a set of conditions.
[4] A subset of a `DataFrame` that includes selected rows and/or columns.

5 DISCUSSION AND IMPLICATIONS

We now discuss the results by structuring our discussion around the DS1 competencies that emerged from our analysis.

Data Literacy and Programming Strategies. Beyond strategic knowledge, problem-solving in DS requires accurate domain knowledge. The mistakes related to misunderstanding the dataset and problem statement or incorrectly dealing with missing values highlight students' struggle with understanding the *dataset domain*. The skills needed include going over the dataset and its data guide (which can be very long and tedious to read) and finding associations between the ask in the problem statement and the information gathered from the data. This is even more challenging for novices who lack prior exposure to real-world datasets and, therefore, cannot quickly identify candidate data elements from the data guide and reduce those to the correct ones for a given question. Furthermore, data guides may describe several different dataset attributes that have similar yet slightly different meanings, which can be confusing for novices. This applies to the 2017 CDC immunizations data guide used in the analyzed assignment, which had several attributes with similar meanings as the `'P_NUMVRC'` attribute (which denotes the number of varicella doses). For instance, the following is mentioned on page 18 of the data guide: *"Use PDAT = 1 to identify children with adequate provider data (includes unvaccinated children)"*. It is likely that the student who made Mistake-1 in Figure 1 quickly read this line and misunderstood that `PDAT = 1` is for unvaccinated children.

For novices, learning a new programming language is a high-cognitive-load task [21]. In our case, even though students were expected to have taken a CS1 course previously, they still had to learn new libraries and functions. This raises the importance of supporting DS1 students in developing correct assumptions about the data and dataset domain, especially when they are going through the early stages of learning about new programming libraries and functions. This can be achieved by providing facilitative hints with specific details regarding the dataset domain.

Programming in Computational Notebooks. Our analysis revealed mistakes that were caused due to misconceptions about computational notebooks and defining libraries and variables inappropriately, which made them out of scope. Supporting students in understanding how the programming model of a computational notebook environment works, along with the tools to identify, understand, and address errors in code authored in notebooks can be helpful. Introducing students to debugging tools, such as JupyterLab's built-in debugger, can be helpful in this regard. Further, validating students' knowledge of computational notebooks through formative assessments before they are taught the main course concepts can equip them with the necessary skillset for programming in notebooks.

Code Optimality. Several students did not use vectorizated operations to write code in a functional paradigm, as was taught. The autograder used in the course was not equipped to detect suboptimal code. Therefore, students received full points and were not

Competency	*What it Means*	*Pedagogical Recommendations*
Programming in computational notebooks	• Can effectively program and debug in the computational notebook environment	• Demonstrate how the programming model of a given computational notebook environment works, along with debugging strategies using DS debugging tools • Validate this competency early on before students move on to the main concepts
Data literacy	• Can adequately study the data and its schema • Can relate the data to the data guide while programming • Can appropriately handle missing values in datasets from different domains	• Emphasize the conceptual principles of data cleaning and how alternative approaches are realized in code and effect analyses • Discuss a diversity of authentic datasets with missing or anomalous values and familiarize learners with the implications of various data cleaning and missing value imputation techniques • Support students in understanding the dataset domain through facilitative hints containing knowledge of the dataset domain
Programming with DS libraries	• Can choose appropriate libraries and their functions, methods, attributes, and operators • Can appropriately set function parameters	• Provide worked examples to help students understand the usage of libraries or functions; as `pandas` documentation is enriched with worked examples, specific examples could be extracted from there
Programming strategies	• Building upon 'data literacy' and 'programming with DS libraries', can devise effective strategies for problem-solving	• Remind students of the task constraints that their incorrect code does not satisfy, e.g., by highlighting the specific part of the problem-statement that the student misinterpreted and elaborating on it
Code optimality	• Can write code that scales for large datasets, using vectorized operations and functions	• Explain why certain strategies are suboptimal; demonstrate using examples of optimal code by comparing runtimes with suboptimal code over large datasets

Table 2: Implications for supporting novice data science learners corresponding to each of the five identified competencies.

discouraged from writing suboptimal code. In CS1, one of the widely reported causes of student difficulties is the misapplication of their prior knowledge [41, 48]. In the course we analyzed, students may have leveraged their prerequisite knowledge of iteration to DS1 programming. Therefore, DS1 instructors should help students *unlearn* some CS1 concepts that do not transfer well to DS1. This can be done through both directed pedagogy and autograder tools that detect suboptimal code and provide feedback to make the code more optimized. Setting limits on runtime and memory may be useful, as done by the UNCode autograder [23]. However, the use of such limits may be problematic, as underlying computational architectures rapidly undergo iteration, necessitating the need to regularly verify that the set limits are appropriate. We recommend computing the number of times a loop executes or using static code analysis [31] to detect whether a loop is used to iterate over a `DataFrame`.

Programming with DS Libraries. Semantic mistakes were primarily caused due to incorrect knowledge of `pandas` functions. In CS1, the focus is on teaching language constructs and then building up an understanding of algorithms and data structures using those constructs. In DS1, particular libraries (as opposed to language constructs) are taught immediately, and learners then apply their understanding of the library functions to accomplish tasks. The libraries are generally sophisticated software products, and understanding their implementation details is beyond students' skillset. For instance, `pandas` uses many levels of inheritance and is layered on top of `NumPy`, making exploration of its inner workings difficult for novices. Further, `pandas` has an order of 100 methods, and each method has an order of 10 arguments [14], which makes navigating the library and its built-in functions even more challenging for novices. Providing students with worked examples of DS functions and operations can be helpful, and tools such as Pandas Tutor [40] can be used to visualize how different functions and operations transform `DataFrames` in a step-by-step manner.

Based on the aforementioned DS1 competencies, we provide pedagogical recommendations for supporting learners in Table 2.

Towards Automatic Feedback Tools for DS1. Scaling feedback generation is necessary to provide individual support to each learner in large classes. One way to do so is using automatic methods to detect DS1 mistakes from student code. However, as discussed in Section 2, scalable program analysis methods for DS1 are limited. Moreover, the lack of portability of unsupervised approaches from CS1 to DS1 suggests that semi-supervised or supervised approaches may be more useful for DS1. One such approach has been described by Effenberger et al. [18], which utilizes domain knowledge to define context-specific features (e.g., variable value sequences in CS1) to generate interpretable clusters of student code. Based on our findings, some useful features of DS1 code (other than ASTs) that can be used to generate interpretable clusters are: (i) *code output*, (ii) *library and function calls*, (iii) *function parameter values*, (iv) *dataset attributes and values*, and (v) *code optimality metrics*, e.g., number of loop executions. Features (ii)–(iv) can be extracted by parsing the code's AST. Features (i) and (v) require code execution. These features can further be used to analyze students' DS1 code at scale, rather than manually, as we did. These features can also be used to prompt Large Language Models [4, 32] (which can generate high-quality text-based responses to natural language prompts) along with relevant information such as the problem statement, a correct solution, the incorrect solution, and students' prior knowledge in the prompt text, to generate hints for incorrect DS1 code.

6 LIMITATIONS AND FUTURE WORK

Based on an analysis of various types of mistakes and inappropriate programming strategies of learners in a data-manipulation course, we provided guidelines for improving DS1 pedagogy and assessment tools. As we focused specifically on a single course at a single institution, our findings may not generalize to all DS1 courses. Additionally, our analysis may not provide enough context about the factors contributing to the students' mistakes, such as their prior knowledge and motivation. Thus, there is a need to broaden such inquiry both within and across the different courses in DS programs.

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