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Teaching Tip
Teaching About Ambiguity in Analytics: A Student-Centered Semester-Long Project to Raise Awareness of Ambiguity by Predicting Student Exam Performance

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ABSTRACT

The growing use of analytics has increased the demand for more highly data literate graduates. Awareness of ambiguity in data has been suggested as a new data literacy skill. Here, we describe a student-centered semester-long project that can be used to teach this skill in an introductory analytics or database course. The project requires students to anticipate and collect survey data about themselves and their fellow students that can be used to predict student exam performance later in the course. We summarize relevant prior research on ambiguity, describe the project in which ambiguity is explained and applied, present a preliminary analysis of the lesson's impact on student awareness of ambiguity, and discuss implications and future research.

Keywords: Data literacy, Data cleansing, Analytics, Teaching tip, Learner-centered education

1. INTRODUCTION

Data literacy is becoming an essential educational objective (Hamilton et al., 2009; Miller, 2009), which needs more research (Courtney & Wilhoite-Mathews, 2015; Julien et al., 2018; Mandinach & Gummer, 2013; Pothier & Condon, 2020). Studies on data literacy have begun to organize taxonomies for data literacy (Ridsdale et al., 2015; Wolff et al., 2016). In many of these taxonomies, critical thinking about data is an essential skill. However, the resources necessary for training in data literacy critical thinking are inconsistent and underdeveloped (Pothier & Condon, 2020; Ridsdale et al., 2015).

One underdeveloped data literacy critical thinking skill is the awareness of ambiguity in data (McKinney & Bhatia, 2023; McKinney & Shafer, 2023). In this innovative teaching tip, we describe how a student-centered project for an undergraduate or graduate analytics or database course can improve ambiguity awareness, and how this skill can be measured. This teaching tip covers content over a semester-long duration (Lending & Vician, 2012).

We proceed as follows: First, we summarize relevant prior research on ambiguity; next, we describe an analytics course project in which ambiguity is explained and applied; then we present preliminary analysis of the project's impact on student awareness of ambiguity; and we conclude with discussions of implications and future research. The project requires students to create surveys to collect data from their fellow students and use the responses to predict future exam scores. The key aspect of the project is context experience; students have many years of experience and familiarity with the context of student performance.

We define ambiguity as multiple reasonable interpretations of data. Ambiguity is present in all types of data—raw, processed, and results data. Underdeveloped or naïve views of ambiguity lead individuals to believe they have the "right" answer rather than "an" answer. Without ambiguity awareness, students often believe that data is dispositive, that it proves results, that alternative explanations are unnecessary, and that the data speaks for itself. Scholars have long recognized ambiguity in interpretation (Bresciani & Eppler, 2015); we suggest that the project we describe can raise student awareness of this ambiguity.

As stated, raw data, processed data, and results data all display ambiguity, and we seek to provide students with opportunities to observe each. Moreover, results data ambiguity comes in various forms. The three we teach are ambiguity about the presence of a statistical pattern, the various potential causes of a pattern, and the variety of consequences of the pattern.

Elsewhere, a method to assess awareness of ambiguity is described (McKinney & Bhatia, 2023), along with how the topic can be briefly introduced to general business or computer science students in a one-hour lecture (McKinney & Shafer, 2023). While the single hour lecture had positive effects, it was intended for use in an IS class; this paper is designed for use in a semester-long analytics course. Both seek the same outcome—raising awareness of ambiguity. The current paper's contributions include a description of a project for analytics students and our results from using the project in a US business school and in an Austrian Fachhochschule. Both address the educational need to raise awareness of ambiguity in data.

2. BACKGROUND

2.1 Ambiguity and Awareness and Context

As mentioned, the topics of ambiguity and awareness of ambiguity are more completely developed elsewhere (McKinney & Shafer, 2023) and are only briefly explained here. Ambiguity is defined as polysemy or equivocality, which is the way a symbol, sign, or performance can have multiple possible meanings (Baldassarri, 2018). Ambiguity permeates everyday life (Abbott, 1997; Belshaw & Higgins, 2011; Robinson, 1941) and has become an essential phenomenon in many research domains, such as language (MacDonald et al., 1994), anxiety (Caplan & Jones, 1975; Dibner, 1958), economics (Shackle, 2010), decision-making (Ellsberg, 1961), and machine learning (Campagner et al., 2019; Chen et al., 2018; Peysakhovich & Naecker, 2017). Most studies distinguish ambiguity from uncertainty, which is often associated with unknown probabilities (Gilboa, 2011) or insufficient information (Adjerid et al., 2023). Numerous IS studies address ambiguity (Daft & MacIntosh, 1981; Webb & Weick, 1979). Most of them address decision-making and information's role in reducing ambiguity (Daft & Lengel, 1986). Ambiguity can exist in the data, the organizational task, or the individual (Adjerid, et al., 2023; House, 1971). In this course, we focus only on ambiguity in interpreting data.

In recent studies, equivocality has been linked to few task precedents, poorly structured problems, or diverse and pluralistic contexts (Cooper & Wolfe, 2005; Daft & MacIntosh, 1981; Goodhue et al., 1992; Te'eni, 2001). Most recently, Adjerid et al. (2023) found that equivocality moderates the effect of hospital analytic capability on patient outcomes; as equivocality increases, clinical healthcare analytics become less effective in improving patients' experiential quality.

Awareness is an individual's ability to perceive, distinguish, and classify states often represented by data (Merikle, 1984). Awareness of data ambiguity is an individual's ability to perceive and understand that there are multiple reasonable interpretations of a set of data. Individuals who cannot recognize more than one interpretation have no awareness of ambiguity, while those who can perceive multiple reasonable interpretations have awareness of data ambiguity. This is the skill of awareness of data ambiguity: *an individual perceives and understands that data has multiple reasonable interpretations*. As a result, no individual can be certain their interpretation is the "right one," the most valid, or the most useful. The standard of "reasonable" implies the ability to provide explanations, and the term "interpretation" is synonymous with meaning.

Awareness of data ambiguity enables an individual to look at raw data and realize it could mean many things, or an individual could examine processed data, such as totals or statistics, and know that many interpretations are possible, and an individual could see the results of analysis, such as a regression value or model goodness of fit and have various explanations of what the results mean.

Awareness depends on context. We deliberately use a particular context—student performance on an exam—that is common among students and with which they have considerable experience. The idea of context has roots in philosophy, linguistics, law, and expertise. Frequently undefined and taken for granted, definitions of context often include where you are, whom you are with, and nearby resources (Schilit & Theimer, 1994); the physical and conceptual states of interest to a particular participant (Pascoe, 1998); or how to characterize the situation for an individual (Dey, 2001). In analytics, the design of analytics tools features a deep appreciation and understanding of the context and the details of the problem space (Ahn et al., 2019; Beyer & Holtzblatt, 1999).

2.2 Data Literacy

For our purposes, data are facts and statistics collected for reference or analysis, the quantities, characters, or symbols on which a computer performs operations or manipulations such as storage, transmission, and calculations (Data, 2022; McKinney & Yoos, 2010, 2019). In analytics courses and practice, data are often classified as raw, processed, or results data, also called data products (Wang et al., 1995).

Data literacy is the ability to collect, manage, evaluate, and apply data in a critical manner (Ridsdale et al., 2015)—an essential skill often lacking in professionals and students (Hamilton et al., 2009; Miller, 2009). The collection skill includes the ability to discover relevant data, assess its quality, and organize and manipulate it. Data management includes the ability to convert, curate, secure, and preserve the data and create metadata. Data evaluation involves interpreting the data, identifying problems with it, making decisions from it, and creating visualizations. Finally, data application involves critical thinking, culture, ethics, citation sharing, and evaluating decisions from data.

The need for better data literacy is not new, but awareness of ambiguity has only recently been introduced (McKinney & Bhatia, 2023). Interpreting any data always contains an element of ambiguity. Awareness of this data ambiguity should be a component of critical thinking within data literacy.

Like other literacy skills, awareness of ambiguity can change for an individual over time. Another study found GPA, academic major, work experience, and nationality affect awareness of ambiguity in undergraduate students and that students can improve their awareness over the course of a semester in an analytics course (McKinney & Bhatia, 2023). While students can change their awareness, there is little evidence to suggest that students change their tolerance of ambiguity.

2.3 Project and Context

We have found that a project method based on a context students know well is effective for teaching ambiguity awareness. In our student-centered project, students are already highly experienced in the context of performance—academic assignments, student behaviors, and grades. A project using data with which they are familiar allows students to see more ambiguity. By revisiting the subject during the semester-long project, they peel back the layers and notice details rather than just trying to understand the arcane vocabulary used in short-term cases with unfamiliar settings. They have advanced understanding of the student performance context, a vocabulary to describe it, and an understanding of some of its limits and challenges. This experience-based deep understanding of the context allows them to appreciate the ambiguity of the data and propose a greater number and wider variety of interpretations for that data. Experience with a context allows an individual to generate new knowledge in response to questions (Goldman, 2001), new options, and new solutions (Ahn et al., 2019; Beyer & Holtzblatt, 1999). In contrast, students bring little experience to most business case projects—strategic decision-making of companies, financial choices of professionals, or resolution of technology challenges—and in those cases, students learn new content and topics, not ambiguity. In these unfamiliar contexts, students do not understand enough to see the ambiguity or to propose reasonable alternative interpretations.

The student-centered project described here unfolds over several lessons. Project-based learning enables students to understand some material more deeply, as it allows them to construct their own understanding, which can differ among individuals (Krajcik & Blumenfeld, 2006). Effective projects include driving questions, authentic inquiry by students, collaboration, and a work product (Kokotsaki et al., 2016). Projects should include data relevant to the students' interests and in an engaging context, not just data for the sake of data. Increased engagement in working with data can foster innovation, improve learning, and increase the likelihood of lifelong learning. Projects should offer students the opportunity to go further than expected (Ridsdale et al., 2015).

Our semester-long project allowed students to develop deeper understandings of the ambiguity in data. They collaborated with other students on the meaning of the data collected and observed the variety of interpretations among their peers.

3. METHOD

The primary educational objective of this project is to raise awareness of ambiguity in data. Along the way, students also gain experience with the life cycle of data from conception to analysis and practice model building and analysis with authentically messy data.

Our project requires students to pose questions for fellow students and then analyze responses to predict student exam performance. The method of assessing awareness of ambiguity among students conducting this project has been presented in McKinney and Bhatia (2023).

We used the project in two very different courses. The first was a US introduction to analytics course for business students who were neither analytics nor statistics majors. In this course, two sections, an undergraduate and a graduate, each had about 40 students who predicted their own grades. The following semester, the second course was an Austrian Fachhochschule graduate practicum/hands-on class of four students who were technical majors in game design or web programming and who predicted the grades of students in another course.

A key difference in the Austrian class was the inclusion of weekly student surveys in addition to the initial survey, which was the only data collection for the US course. Also, in the Austrian class, due to its small size, students did not predict their own final exam grades but instead predicted those on the final exam of another course, which they were taking in parallel together with other students; the US students predicted their own scores on the mid-term exam. The Austrian class met for 90-minute classes 13 times during the semester, while the US class met for 30 class meetings of 75 minutes each. This project was the dominant feature of the Austrian course, while it was only a part of the US course. The six phases or steps of the project are explained next.

3.1 Step 1. Initial Questions for the Survey (20-30 minutes)

3.1.1 US University. To generate questions for the initial survey, students were given the assignment illustrated in Figure 1. The students were not given lessons on how best to ask questions, as the course focuses on analytics and the goal of the project is to notice ambiguity, not to ask effective questions.

- This semester your team will create an analytical model that predicts student scores on the final exam. Points are awarded to your Final at the end of the course for teams with the most accurate model.
- Your model will use data from your peers. Today, as a team, write down the data fields you need to build your model. For example, one data field might be the GPA of the students. The data fields must be numeric (GPA=3.3) or multiple choice, but not fill in blank.
- After each team submits their list of data fields, I will create an on-line survey of the questions from the teams that all students will complete. I will ensure student anonymity by removing any identifying data from the survey.
- A few rules. You can request up to five data fields. At least one field must be a category, not a number. For example, eye color, hometown, favorite NFL team are categories of data, different from a number, a measure, that has a quantity associated with it such as weight, number of siblings, miles on your car.
- Today turn in:

Question (data field)	Type of data (category/number)
Example: GPA	Number
1.	
2.	
3.	

Figure 1. Assignment for Initial Class Survey in US Course

Examples of questions the teams generated are shown in Figure 2. Possible responses are shown in parentheses after the questions.

1. What is the average time in hours you spend studying during the week? (0 to 20)
2. What is your previous test score? (Enter a value between 0 and 100)
3. How many hours a week do you spend working or doing extracurricular activities? (0 to 60)
4. Did you read the textbook? (Yes, No, Skim)
5. How competent are you with the material in the textbook? (1 to 5)
6. What is your current grade in the class? (A to D)
7. What is your interest level in the class? (Enter a value between 0 and 10)
8. What is the average hours of sleep you get per night? (Enter a value between 1 and 12)
9. What did you predict your midterm exam score would be? (A to D)
10. How often do you work out per week? (5 more than 2; 4 twice; 3 once; 2 less than once; 1 never)
11. How many hours of work per week (0-50)
12. How many hobbies/responsibilities outside of work/school? (0-10)
13. What is your stress level (5 high; 0 low)
14. How many total classes, not just this one, do you miss per week on average? (0 to 10)
15. Anticipated grade on final? (0-100)

Figure 2. Initial Questions From Students for the Survey in US Course

3.1.2 Austrian Fachhochschule. The goal of this semester was explained to the students in the first class: predict the grades of students in another class based on questionnaire data from the students, not including their current grades. Students were told that this project would unfold in three phases during the semester as shown in Figure 3.

1. Generate questionnaires to collect the data for the factors possibly influencing the grade
2. Motivate students in the other class to participate and ask initial and weekly survey questions to acquire the data
3. Build machine learning models to predict grades and give feedback on the most influential factors to the participating students

Figure 3. Project Educational Goals in Austrian Course

To achieve the first goal, brainstorming and discussion in class were used to generate ideas about the factors that influence grades and potential questions that might predict grades. After the first session, we required students to nominate the five most relevant questions with possible answers. The results were discussed in the second class, and the instructor extracted the factors associated with the top-rated questions. As a subsequent task, students had to rate which questions should be asked one time at the beginning of the semester and which should be asked repeatedly during the semester. Students were also asked to formulate the three most subjectively important questions for the initial questionnaire and for the weekly questionnaire.

3.2 Step 2. Editing and Establishing the Survey (20-30 minutes)

3.2.1 US University. After the first step, the instructor drafted a survey using Microsoft Teams and recorded which teams contributed which questions. Several topics (work, age, classes taken, etc.) generated multiple similar questions from different teams. During the discussion, the instructor encouraged teams to consolidate similar questions into a single question. The goal was to winnow the list to distinct, non-overlapping questions.

A second goal, not stated to the students at this time, was for the professor to demonstrate awareness of ambiguity. When discussing survey questions, the professor suggested ways that different students might interpret them. While this appeared to be a display of carefulness or experience, the professor later used it as an example of how awareness of ambiguity—awareness that survey-takers will interpret questions differently—can improve survey questions. In class, the professor demonstrated how to anticipate interpretations and edit questions. To save time and enhance commitment, the instructor assigned each student team several questions each to edit, and each team presented its corrected questions to the class.

3.2.2 Austrian Fachhochschule. Based on the results from the initial questions, the instructor proposed two surveys that the class edited extensively during class time. One questionnaire (Figure 4) was administered only at the beginning of the semester, and the other (Figure 5) was administered weekly during the semester to collect data on attitudes toward current content and homework assignments. The instructor posed each question to the class, and students were asked how others might interpret it. Students were often surprised as the teachers and some students suggested ways in which survey respondents might interpret questions. Editing the questions was tedious, but students recognized it later as essential during the semester.

The unstated goal of this step was for students to begin to appreciate the ambiguity in their questions. The term ambiguity was not highlighted, but the seed was planted.

Starting Questionnaire:
- Question: Average grade in the last semester? – Answer: the numeric average grade
- Question: Grade in "Data Analysis" in the last semester? – Answer: the numeric grade
- Question: Expected grade in current lecture? – Answer: the numeric expected grade
- Question: Subjective importance of lecture for the personal future? – Possible answers: Not important / less important / important / very important
- Question: How many paid working hours do you perform per week? – Answer: the number of hours
- Question: Bachelor in STEM topics? – Possible answers: Yes / No
- Question: Bachelor studies at the Fachhochschule Salzburg? – Possible answers: Yes / No
- Question: Major in Master Studies. – Possible answers: Game / Web

Figure 4. Initial Survey

The course grade in Data Analysis in the previous semester was used because this course has content-based similarities to the class in which the final exam scores were predicted.

Weekly Survey Questions:

- Question: Content of the last lecture – Answer: Rating from zero to five stars.
- Question: Last homework – Answer: Rating from zero to five stars.
- Question: Time for the last homework in hours: – Answer: hours needed
- Question: Effort needed for last homework – Answer: multiple choice with choices: less than expected, as expected, more than expected
- Question: Solution of last homework alone or in group – Answer: 11 Point Likert Scale from "solved alone" to "solved in group"
- Question: Active listening time in the last lecture – Answer: multiple choice with choices: 15 min, 30 min, 45 min, 60 min, 75 min, 90 min
- Question: Understandability of the last lecture – Answer: Rating from zero to five stars.

Figure 5. Survey Questions Administered Weekly During Semester

If no last homework was given, the questions concerning homework were omitted from the weekly questionnaire.

3.3 Step 3. Take Initial Survey (10-15 minutes)

3.3.1 US University. The professor published the survey of approved questions and distributed it as a Microsoft Form (see Figure 6 for an example). During class, students completed the survey individually and made notes of their reactions to the questions for later discussion.

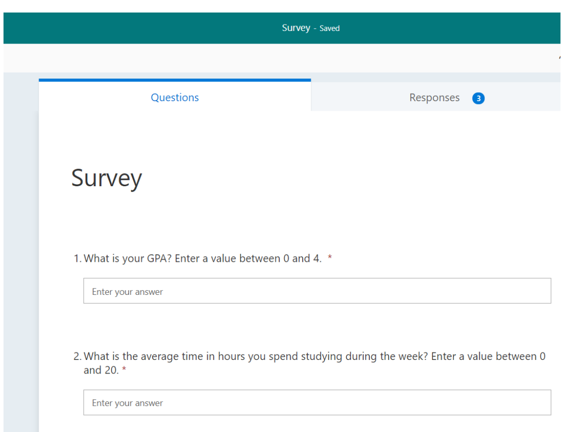

Figure 6. Online Survey in US Course

3.3.2 Austrian Fachhochschule. The 22 participating students were informed about the project using a short presentation stating the main goal and the voluntary nature of participation. Students who volunteered were promised the results of the study detailing which factors most affected their grades in the course. Nineteen of 22 students chose to participate, suggesting strong interest in this topic.

3.4 Step 4. Teach about Ambiguity (30-45 minutes)

At both institutions, we taught the same lesson on ambiguity. We teach students about ambiguity and ambiguity in data using material described in McKinney and Shafer (2023). In that lesson, we show students a variety of data from everyday life and identify the ambiguity in it. Topics include language, humor, pattern identification, and social dating.

After teaching about ambiguity in general, we examine ambiguity in data used in analytics settings. We begin addressing data ambiguity using an example of a sales visualization, then shift the conversation to the survey data used in our class and ask students to identify ambiguity in it. We address processed data ambiguity in the sales visualization by asking students to notice that the yearly revenue values contain ambiguity—does the sales total include a discount, does it include returns, and does it correct for inflation. To teach the various types of results ambiguity, we ask students to consider how many year-over-year patterns exist in the trend line, the possible causes, and the different consequences those causes would generate.

We then shift the conversation to the student survey and ask students to suggest examples of raw data ambiguity. The discussion refers to the earlier class activity when the original questions were edited. Students recognize that, although the questions were made more specific and detailed, ambiguity persists in the raw words and in each student's raw responses. Most students conclude that, while questions can be improved and ambiguity perhaps reduced, ambiguity in questions remains.

Finally, we shift the conversation back to the sales data and ask students to imagine they are professionals in their favorite hobbies or pastimes—settings for which they have considerable knowledge. We ask them how many different interpretations professionals might use when analyzing data and results in contexts for which they are experts. For example, the visualization we use shows sales data, and we ask students to imagine how the professionals meeting to discuss the sales data might interpret it—some will interpret the data with a supply chain explanation, others with marketing, others with personnel changes, and still others with decision-making explanations. Further, we suggest it is reasonable to assume that most of us underestimate the number of different experiences other people will bring. During the discussion, we remind students of underdeterminism and induction lessons taught earlier in the semester.

3.5 Step 5. Clean the Data and Create Predictive Models (30-45 minutes)

3.5.1 US University. After the midcourse exam, we provide the class with exam scores individually matched to the survey response data for each student (each record is anonymous). Student teams inspect the data and notice several examples of dirty data. Microsoft Forms saves students' number inputs in Excel columns in text format. Having learned about ambiguity earlier in the term, students encounter it here when they inspect other students' survey responses.

For example, some survey questions asked respondents to input hours (e.g., hours of study), but some responses were clearly in minutes. Some survey responses were left blank, and one student completed the survey twice. Students asked the instructor, "What does this response mean? What should we do about it?"

We remind the students that some ambiguity will always be present in data, but the additional ambiguity of dirty data should be addressed. We tell the student teams to make choices in this cleaning process (e.g., convert minutes to hours, delete duplicates, fix dates) and to note each step and decision they make as they clean the data. As a result of different decisions, model accuracy and statistics vary from team to team.

Once the data is clean, teams use Python to perform regression, ANOVA, or decision tree analysis to assess the predictive value of each of the questions that they nominated at the beginning of the term. Then student teams identify five questions from the original survey that best predicted midcourse exam scores.

3.5.2 Austrian Fachhochschule. These students had much greater statistical training than the US students, so the task to create a predictive model was more sophisticated. Generation of the predictive models was distributed over four tasks during the last four class meetings:

Class 1:

- First, we inspected students' original replies to the survey. We discussed options for cleaning the dirty data and, as a class, produced a single common dataset of clean data to be used for the rest of the semester.
- Using this data, we tried building linear models. We soon realized that there were far too many features (a data column for each question on each survey) for too few rows (students) of data, which results in seemingly perfect but not generalizable models (vast overfitting). Instead, we obtained data on the score of each student in the class up to that day, and we used Power BI to identify three features (data columns) that correlated most strongly with this current grade measure. We also combined questions (columns) into new dimensions by arithmetic operations and assessed them against current grades. The class discussed the reasonableness of each new dimension/feature. Using visualizations in Power BI, the students identified three features (data columns) that correlated most strongly with the percentage of points achieved up to that time. It was also possible to combine multiple data columns by arithmetic operations into one new feature. Students provided a short argument for the relevance of each chosen feature.

Class 2:

The following task was given to the students in advance:

- Transform the data columns using sklearn PCA and extract the first four principal components (PC).
- Transform the original data using the transform function on the original data and add the four new coordinate columns to the original data.
- Do six pairwise scatterplots in Power BI: PC1-PC2; PC1-PC3; PC1-PC4; PC2-PC3; PC2-PC4; PC3-PC4.
- Give your personal interpretation.

Class 3:

- Build the first two predictive models using sklearn in Python. During class, discuss the statistical results of the models.
- Build a regression model which uses the first four principal components from Task 2 for the prediction. Be careful that when calculating the principal components, the current points in the class are never used.
- Build a regression model which uses all available features initially and subsequently performs feature reduction by using lasso-regression (https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.Lasso.html). You can build additional features by combining features (averaging …). There are a variety of solutions.
- Evaluate both models by leave-one-out cross validation.

Class 4:

- Train a decision tree to predict the percentage of combined points. Try to find solutions around the disadvantages (overfitting, sensitivity to unbalanced data, ... see https://scikit-learn.org/stable/modules/tree.html for more ideas).
- Evaluate the decision tree using a 5-fold-cross validation (not LOOCV as the decision tree is sensitive to changes in the data).
- Find at least 2 strategies against overfitting (indirect feature selection using the tree parameters or pruning, direct feature selection using ideas from https://scikit-learn.org/stable/modules/feature_selection.html#feature-selection).
- Generate a prediction using your preferred method (might also be one of the linear regression methods) for each participant and generate a human readable automated message which explains the factors that have the strongest contributions to the prediction. Enter your prediction and the explanation of the most important factors in a spreadsheet

3.6 Step 6. Interpreting Student Results (30-45 minutes)

3.6.1 US University. Near the end of the semester, the professor led a discussion of the questions and their relationship to the mid-term exam scores. The goals were for students to practice interpreting analytics results and to learn how to discuss ambiguity. The professor discussed processed and results data ambiguity. For example, *what* would the processed data on average time on homework mean when some students include time on their cell phones during homework and others subtract it, some students chronically overestimate their study efforts, and some students guess their times while others record them.

To address results ambiguity, the professor asked how much evidence is enough to establish a pattern, for example between homework time and exam score and, if the models prove significant, what are the causes, and what might the professor do next semester. For example, if the class uses the survey again and some students are predicted to struggle on the test due to their low homework times, should the professor notify those students, ask for more involvement, or intervene in other ways? Can we classify the students into groups and engage them more effectively? The discussion also asked students to interpret the results' generalizability to other classes.

The actual predictive value of the questions during the first use of this project was low. The only significant predictor of final exam scores was GPA. Other questions that were most correlated but not significantly were hours spent studying and hours spent working/extracurriculars.

3.6.2 Austrian Fachhochschule. The final exam for the class with predicted grades occurred prior to the final class. The class discussed the results of their models and provided feedback about the project which is listed in Figure 7.

- Cleaning data is an important exercise
- Less class time should be spent on developing the questionnaires
- Part of the development of the questionnaires should be performed outside of the class to be more time efficient
- It was important to learn how hard it is to ask reliable questions
- Always use the same language for the questionnaires during development
- The work helped to learn about ambiguity

Figure 7. Discussion Feedback in Austrian Course

4. RESULTS

To assess the project's effectiveness, we administered a survey instrument developed to assess the awareness of ambiguity (McKinney & Bhatia, 2023). The scale ranges from 0 to 31 based on six questions. The survey is included in the Appendix.

We administered this ambiguity awareness survey and a tolerance of ambiguity survey at the beginning and at the end of the semester. Table 1 includes that data. The first use of the ambiguity awareness survey occurred very early in the course, before any discussion of ambiguity. This is the Pre-Project Ambiguity Awareness column in Table 1, which shows the average score for the class. Then, our students took the survey again near the end of the course after the project was finished; the Post-Project Ambiguity Awareness column in Table 1 shows this average. Students were not compensated or rewarded for participation in the survey; we had nearly a 90% participation rate for each semester in the US school and 4 of the 5 students in the Fachhochschule (FHS). For the US school, Table 1 also shows data from this course a semester prior to introducing the project, the semester using the project, and the general business school student population.

The initial results in Table 1 demonstrate a statistically significant effect for the project in the US school with a .01 level of significance. For the FHS, the small number of participants showed a similar increase in awareness, but the small sample precluded a statistical analysis of significance.

Table 1 also shows the results of the survey used to assess tolerance of ambiguity. This widely used instrument is the AT-20 survey (MacDonald, 1970); it requires yes/no answers to 20 questions, with higher scores indicate more tolerance for ambiguous situations. We only used 14 of the 20 questions. Tolerance changed little during both semesters. The final two columns in Table 1 show class averages for Pre-Project Tolerance of Ambiguity and Post-Project Tolerance of Ambiguity.

The project impacted awareness of ambiguity and significantly improved the course. Table 2 shows data from the end-of-course student evaluation forms in the US school. Three prompts on the form indicate the project's impact. These are 1) overall, how would you rate this instructor; 2) the instructor encourages student participation; and 3) do you think the instructor's grading of homework, quizzes, tests, and the course is fair?

In the last two columns, data from the university was included for comparison and to help rule out university or COVID attendance effects. The first column shows an average of five prompts about the course, and the second column is the same as the student participation prompt for the project.

As Table 2 shows, assessments of the course improved substantially after the project was introduced. With the same teacher, exams, textbook, and many other aspects of the course being the same as the previous semester, all three prompts showed significant improvement, while the university had only a modest change.

	Number of Students	Pre-Project Ambiguity Awareness	Post-Project Ambiguity Awareness	Change	Pre-Project Tolerance of Ambiguity	Post-Project Tolerance of Ambiguity
US University						
Spring 2021 Before Project	102	19.9	22.5	2.6	7.0	7.2
Fall 2021 With Project	98	19.3	24.2	4.9*	7.4	7.3
Students outside of class	305	19.2			7.6	
Austrian Fachhochshule	4	20.7	26.2	5.5	5.7	6.2
* < .01 significance						

Table 1. Ambiguity Awareness Survey Results

	Project Class			University	
	Overall	Grading	Student Participation	Overall	Student Participation
Spring 2021 No Project	4.31	.92	4.24	4.33	4.37
Fall 2021 With Project	4.96	.98	4.80	4.31	4.36

Table 2. Spring and Fall Course Evaluations for the Class and for the University in US

The FHS provides few course evaluation statistics. Based on qualitative data, the teacher sensed that students perceived development of the questionnaires as tedious. However, the overall process increased awareness of the complexity of what students viewed initially as a simple task. Cleansing the data also seemed to contain important learning. Data ambiguity is a new topic; students reported that they first learned about it in the prediction project.

In both locations, students also provided course feedback at the end of the term. We asked whether the case should be used again and whether it was effective in helping them learn ambiguity. The qualitative results and spoken feedback strongly encourage continued use. One student wrote, "I saw that I was very low on tolerance but scored high on the second assessment of awareness. This fits me to a 'T'; I thought I could see ambiguity and hate it and avoid it in most courses. I'm glad I now have confirmation."

5. DISCUSSION

This study presents a student-centered semester-long project to help improve student awareness of data ambiguity, an underdeveloped data literacy skill. The project provided students a rare opportunity to create their own data and, despite its messiness, attempt to analyze it and build models. Initial results were encouraging, as a significant number of students increased their awareness of ambiguity. Making the students the center of the data collection and interpretation activities and providing them a context in which they are highly experienced seemed to provide an appropriate setting to help raise their awareness of data ambiguity. Raising awareness of ambiguity also seemed to improve student evaluations of the instructor and student assessments of their participation and course grading.

Clearly, this study is a preliminary step in better understanding how to raise awareness of data ambiguity. This study reports the first two semesters of experience with a limited number of students. These limits are partially mitigated by students' variety of courses and programs and the project's successful use in two very different universities. Additionally, we have continued to use this project each semester since.

It should be noted that our ambiguity instrument is designed and tested to assess the ambiguity in visualizations. We assert that it is reasonable to use this visualization metric and generalize from ambiguity in a visualization to ambiguity in data in general. Our results showed significant improvement in awareness of visualization ambiguity even though the course did not specifically teach about ambiguity of visualizations, only more general data ambiguity. We understand visualization ambiguity to be a subset of data ambiguity.

Raising student awareness of ambiguity should become an essential skill in data literacy taxonomies, specifically within data evaluation and interpreting. Without awareness of ambiguity, students might not realize the variety of interpretations available in a dataset. Without greater awareness of ambiguity, students might believe data has absolute answers or unique and conclusive interpretations and be overconfident that their interpretation is the one true answer, that their results are proven, that alternative explanations are unnecessary, and that the data speaks for itself.

Collaboration in business is essential and is improved when individuals recognize the reasonableness of other viewpoints. Absent the construct of awareness of ambiguity, it is difficult to persuade individuals that they lack awareness and that others will generate diverse alternative interpretations of data and results, disadvantaging them in workplaces where collaboration, iteration, and flexibility are valuable (Bentley, 2012; Handy, 2011). Awareness of ambiguity can help students and analysts be more inclusive of diverse, reasonable interpretations.

While this study only involves students, it has some limited implications for practice. Most definitions and theories of analytics suggest that analytics produces results for decision-making (Ghasemaghaei et al., 2018; Sharma et al., 2014). The present study suggests that an extra step, an interpretation of analytical results, occurs before decision-making.

In this study, awareness of ambiguity is distinct from tolerance of ambiguity. Awareness of ambiguity is a cognitive skill, whereas tolerance of ambiguity is an affective reaction to a situation an individual finds themselves in or anticipates. In prior research and at the US school, tolerance of ambiguity seems to change little over time (Furnham & Ribchester, 1995; McKinney & Bhatia, 2023). However, while only four FHS students participated, their tolerance of ambiguity scores improved remarkably. We believe this is due to this project's centrality to the class. With the American students, the project was one of several assignments. At FHS, students every week were confronted with the ambiguity of the data and the unknown, unstructured implications. Perhaps their tolerance grew more than at the US school where the students did not have to deal with this uncomfortable ambiguous data as frequently or as intensely.

We believe this student-centered project includes the fundamental elements of projects mentioned earlier. While our data is too general to explain why the project is effective, we believe the key element is the context—student performance. In most academic projects, students are not highly experienced in the contexts. Using this context, students can generate countless reasonable interpretations of the data—data from the surveys, processed survey data, or results data.

We learned several lessons in our first two offerings. We expected the Austrian offering to have a larger class and for students again to predict their own grades; however, the project was flexible, and we used it effectively to generate in-class discussions and presentations with the smaller class predicting grades in another course. In both classes, we learned that collecting initial student survey questions can be time consuming and used common collaboration documents on shared drives for students to upload questions. We also learned that students write vague, careless, and unsophisticated survey questions that required more significant editing and discussion than we, or they, expected.

In another paper, McKinney and Shafer (2023) describe a one-hour interactive lesson designed to help students learn about ambiguity and the ambiguity in data. The current work is offered as a semester-long method that incorporates that one-hour lesson but allows students to experience how ambiguity impacts all stages of an analysis project.

Finally, it should be noted that this project supports and applies other course topics; the project's goal was not just to raise awareness of ambiguity. Students learn about survey data collection tools, data cleaning, merging and joining datasets, analyzing data with Python and other tools, and reporting results. In short, they do an analysis project from beginning to end with actual data they understand.

This study has limitations that suggest opportunities for future research. Research could identify which parts or elements of the project are important for raising ambiguity awareness. Other projects could be designed that remove elements of action, decision-making, emotion, currency, relevance, authentic inquiry by students, collaboration, and work product. Perhaps this project on predicting exam scores differs from other projects in which students are highly experienced, such as dorm life, food items at school, traveling, or socializing.

The sample chosen was a convenient student sample. Future studies could broaden the variety of students beyond business and beyond just two schools to include non-business students or students from other universities. Future studies could evaluate professional analysts' awareness of ambiguity and assess awareness of ambiguity in raw data, tables, or other summaries of data. Studies could examine whether awareness varies by type of data (financial, production, accounting, social media) or by domain (human performance, organizational, financial, political, educational). Finally, the effects of language could be examined more closely. Differences in the context dependency of languages might affect US and Austria students (Klein, 2013).

In conclusion, we have presented an innovative, semester-long assignment designed to fill the current paucity of methods to raise student awareness of the ambiguity in data. Of course, our own results are ambiguous; perhaps we generalize inappropriately, measure a part of another unknown construct, or miss intervening constructs that would also explain why our student measurements improved. That said, educators have long understood relentless ambiguity as a fundamental tenet of the human experience. Our goal was to introduce a student-centered project study to help raise awareness of ambiguity in analytics courses. The primary element in the project is the context familiarity of student performance. Involving students in a project using this context raised their awareness of ambiguity in all types of data.

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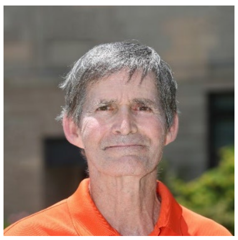

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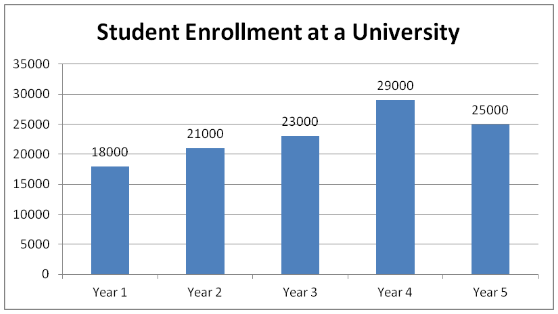
APPENDIX

Awareness of Visualization Ambiguity Survey Instrument

1. In visualization 1, how many reasonable interpretations can you identify?
   1 or 2
   About 5
   About 10
   About 15
   About 20
   More than 25



Visualization 1

2. When I create a data visualization at work, I expect others to interpret my visualization differently than me.
   Strongly disagree
   Disagree
   Neutral
   Agree
   Strongly agree

3. Data visualizations only have one interpretation. (Reverse coded)
   Strongly disagree
   Disagree
   Neutral
   Agree
   Strongly agree

4. Data visualizations have an obvious meaning. (Reverse coded)
   Strongly disagree
   Disagree
   Neutral
   Agree
   Strongly agree

5. When I look at a data visualization, I try to see if there are several good ideas.
   Strongly disagree
   Disagree
   Neutral
   Agree
   Strongly agree

6. If done right, a data visualization will have just one meaning. (Reverse coded)
   Strongly disagree
   Disagree
   Neutral
   Agree
   Strongly agree

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