

THE **BASICS**
OF **DATA**
LITERACY

HELPING YOUR STUDENTS *(AND YOU!)*
MAKE SENSE OF DATA

MICHAEL BOWEN
ANTHONY BARTLEY

NSTApress
National Science Teachers Association

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CONTENTS

| | |
|---|------------|
| Acknowledgments..... | VII |
| Foreword..... | IX |
| SECTION I: FUNDAMENTALS OF SHOWING, ANALYZING, AND DISCUSSING DATA..... | 1 |
| CHAPTER 1: Introduction: Data and Science..... | 3 |
| CHAPTER 2: An Introduction to Understanding Types of Variables and Data..... | 13 |
| CHAPTER 3: Data in Categories: Nominal-Level Data..... | 19 |
| CHAPTER 4: Data in Ordered Categories: Ordinal-Level Data..... | 25 |
| CHAPTER 5: Measured Data: Interval-Ratio-Level Data..... | 31 |
| CHAPTER 6: Structuring and Interpreting Data Tables..... | 41 |
| CHAPTER 7: How Scientists Discuss Their Data..... | 45 |
| SECTION II: MORE ADVANCED WAYS OF COLLECTING, SHOWING, AND ANALYZING DATA..... | 49 |
| CHAPTER 8: Simple Statistics for Science Teachers: The <i>t</i>-Test, ANOVA Test, and Regression and Correlation Coefficients..... | 51 |
| CHAPTER 9: Doing Surveys With Kids: Asking Good Questions, Making Sense of Answers..... | 63 |
| CHAPTER 10: Somewhat More Advanced Analysis of Survey Data..... | 77 |
| AFTERWORD..... | 89 |
| APPENDIX I: Class Worksheets for Marble-Rolling Activities..... | 91 |
| APPENDIX II: Other Scaffolded Investigation Activities..... | 99 |
| APPENDIX III: Structure and Design of an “Ideal” Graph and Table..... | 117 |
| APPENDIX IV: Ideas for Evaluating Laboratory Reports..... | 119 |
| APPENDIX V: Concept Maps and Vee Maps..... | 123 |
| APPENDIX VI: Web Resources..... | 131 |
| APPENDIX VII: An Introduction to Data Management From a Mathematics Perspective by Eva Knoll..... | 135 |
| APPENDIX VIII: <i>t</i>-Test of Example Data..... | 139 |
| APPENDIX IX: Worksheets for Statistical Analysis..... | 143 |
| Resources..... | 165 |
| Index..... | 167 |

ACKNOWLEDGMENTS

The idea for this book started developing 16 years ago when I was interviewing preservice teachers and other science program graduates about their interpretations of graphs as part of my PhD research. As I explored those issues further as a science methods instructor, I began creating resources and activities on this topic with my friend and colleague Tony Bartley. We subsequently produced a workshop that we have presented many, many times at NSTA conferences over the last decade. At those workshops, we gained more insights into the data literacy issues confronting teachers, in part from the many comments we collected from participants about resources they could use when doing investigations with their own students. The content and approach used in this book arose from those observations. At those meetings and others, Tony and I sat and hashed out the various activities, use of language, and explanations offered here.

My own interests in data and representations of it began during my undergraduate studies in 1982 when I took a research methods course with Hank Davis in the psychology department at the University of Guelph. The seed that Hank planted at that time in his long and productive career may be one that took the longest to flower, but I am glad that his efforts with me in that most interesting (and somewhat bizarre) class 30 years ago have borne such fruit. Thanks Hank. Then, my MS supervisor, John Sprague, pushed me into doing multidimensional modeling as part of my research in behavioral toxicology, and I was fortunate that software tools for the newly developed personal computers allowed me to play with graphical representations of data in his laboratory in ways that hadn't been possible even a few years earlier. That work was influential during my PhD research in science education because it gave me insights into how individuals gain competency in working with data. John Haysom, my science methods instructor (and now author of numerous NSTA Press books), further pushed me to figure out ways to develop children's interest in science investigations and, additionally, how to make abstract relationships more "real" to them by developing hands-on activities to help students experientially understand those relationships. Finally, my main academic influence has been Wolff-Michael Roth at the University of Victoria. My PhD work with him helped cast light (for me and others) on the role of graphical and tabular representations in science and how individuals at various educational levels gain understandings of (abstract) science concepts from those. He continues to push boundaries in these areas, and I admire his tenacity at teasing out the details of how understanding of science evolves. His academic achievements and his friendship have tremendously impacted my work on this project.

Finally, I would like to thank the many teachers and students who—through support, comments, advice, suggestions, and participation in hands-on activities with us—have helped generate this book.

It is my, and our, profound hope that you find this book useful for developing your students', and your own, understandings of how to work with data.



Mike Bowen
Halifax, Nova Scotia

ACKNOWLEDGMENTS

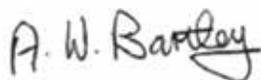
My journey in science education started in Liverpool (England!) many years ago when I completed a postgraduate certificate in Education at Saint Katherine's College of Education (now Liverpool Hope University). It was there I realized that most students I would meet in schools had very different views about their own education and where science fit in. I became a physics and chemistry teacher, first in Staffordshire, then West London, and finally in Kent; by extension, I also became a teacher of mathematics because we worked with data and problem sets.

Many of the people I worked with in England have now retired, but I remember both their mentorship and collegiality: Geoff Morris of the Ounsdale School (Wombourne), Hamish Miller of Christ's School (Richmond-upon-Thames), and Rick Armstrong of the Eden Valley School (Edenbridge) all deserve a mention, and thanks.

I moved to Canada in 1985 and taught in Victoria, British Columbia, from 1986 to 1989. In 1989 the University of British Columbia beckoned me for a PhD; it was here that I was lucky enough to work with Gaelen Erickson, Bob Carlisle, Jim Gaskell, and Dave Bateson as the home faculty members; Peter Fensham, Rosalind Driver, Cam McRobbie, and Ruth Stavy were notable visitors; and Tony Clarke and René Fountain were magnificent in their support as they too completed the doctoral journey.

I'm now approaching my 20th year at Lakehead University in Thunder Bay, Ontario. Mike was here for 5 of these years, and we have an enduring friendship through a broad range of collaborations in science education and other overlapping interests. My colleague now and for the last 8 years at Lakehead has been Wayne Melville, whose support for open inquiry has been consistent and strong; it helps us both that we have one of the strongest schools on the continent, Sir Winston Churchill Collegiate and Vocational Institute, just a few miles away. My appreciation as a university-based educator for the school-based support from the Churchill science department in learning science through inquiry, and its chair Doug Jones, cannot be overstated.

I have enjoyed this writing project and have learned a lot as Mike and I worked through our approaches over the last few years. I hope that this book and its ideas work for you and your students.



A. W. Bartley
Thunder Bay, Ontario

FOREWORD

If you are a scientist or a science student, data literacy matters because it helps you make sense of information you've collected in lab investigations. But most students aren't going to be scientists, so why should developing data literacy be important? Isn't it enough to get them to know science concepts, remember facts and patterns, and draw graphs on tests? Where else would they encounter scientific data other than in a laboratory?

Although it may not seem like it, we are surrounded by data. When you open the newspaper and see a graph or a table as part of an article, what you're looking at is data. When you listen to news on the television or radio, what you're hearing are conclusions drawn from data someone else has collected. And they've collected that data to understand something, argue a position, make a point, or persuade the listeners to adopt a particular view. Some of these arguments are better than others because the data has been collected, analyzed, or summarized more effectively. This book is about understanding what good data and data analysis is so that you can make stronger arguments and better evaluate the arguments of others. It's important to realize that everyone has an agenda of some sort, and being more data literate helps you understand if others are making a fair argument.

Part of being able to take a more informed (some might say skeptical) view of data is being literate in how data are manipulated and subsequently presented: how they are collected, made into tables, and shown in pictures or graphs. Once you know how to do this the right way, such as you might learn in a science classroom, you can start asking if someone else is doing it in a way that is fair, or if they are distorting the data for their own purposes.

Data literacy is important for your students even if they aren't going to be scientists because data are used to argue and persuade people to, among other things, vote for political agendas, support specific types of spending within organizations, sell life insurance, or lease a car. An improved understanding of data practices means that better questions can be asked in all of these situations.

Even in everyday life, data collection can be important. Bakers often keep diaries when they're learning how to bake a new type of biscuit. Gardeners keep a log about the growth of their gardens, and birdwatchers keep track of where and when they see what types of birds and what the weather conditions were. Drivers keep track of vehicle mileage, and homeowners keep track of their electrical bill month to month. This is all real-life data. We could go on with examples like this forever, but now you can probably think of some data that you keep track of.

The point is, data literacy is an important skill to develop in students, and science classrooms are a good place to do that because data collection and interpretation are part of the science curriculum in most jurisdictions. Almost every teacher has faced the challenge of helping students make sense of some data set; many times, that teacher has sat there, scratched his or her head, and wondered how to help

the students make sense of the data they collected. In science, there are some fundamental concepts that help scientists make sense of data, particularly the messy data found in the real world, and yet these fundamentals are infrequently taught in undergraduate science courses. Teachers who have their students do inquiry lab investigations can face data analysis challenges, even in a middle school science class, that exceed what they learned in their college science courses.

Learning about how to analyze and make better sense of data also helps you learn the best way to collect data. And learning how to collect, summarize, and analyze data is a very important science skill, central to the newly released *Next Generation Science Standards (NGSS)*.

Lab investigations used to be pretty simple and straightforward (i.e., “cookbook labs”): The teacher provided a clear set of instructions; the students all engaged in the same activity, followed the same procedure, and were marked on getting the same “correct” answer. Then inquiry investigations came along, and classroom investigations got a lot more difficult. Many of us teachers didn’t have a background sufficient for helping our students do those types of inquiry investigation activities.

The contrast between the two different types of lab activities could not be starker (Table F.1).

TABLE F.1

Comparing traditional laboratory activities with inquiry-based science investigations

| | Traditional, structured, laboratory activities | Inquiry-based science investigations |
|-------------------------------------|--|--------------------------------------|
| Basis of learning | behaviorist | constructivist |
| Curricular goals | product-oriented (i.e., everyone gets the same answer) | process-oriented (with some product) |
| Role of student | following directions | problem solver/arguer |
| Student participation | passive/receptive | active |
| Student ownership of project | lower | higher |
| Student involvement | lower responsibility | higher responsibility |
| Role of teacher | director/transmitter | guide/facilitator |

As every teacher understands, supporting students who are doing laboratory investigations of the student-directed and open-ended type (such as those in the Inquiry-Based Science column would usually be) is a considerable challenge and can require a lot more background knowledge than undergraduate teaching programs often provide. Some teacher preparation programs have specific courses that deal with doing inquiry, thus allowing student teachers to learn the basics of data literacy, but many do not.

What we (the authors) realized some years ago is that the challenge in encouraging teachers to do inquiry investigations exists in part because of aspects of data collection, analysis, synthesis, and presentation that teachers of science often just do not know. Nor, as far as we could tell, are there good resources geared toward helping them learn the material in a way that would be useful for their students. To address this, we developed and have presented a workshop on data literacy at the national NSTA conferences for the last several years. The workshop has been quite popular, but what we have since realized is that a more comprehensive resource, building on the workshop, would be useful for science teachers. This book grew out of that realization. We've tried to write it so that it is pretty approachable by using a minimum of technical language. And we've tried to use examples that relate to classrooms and the types of data collection activities that teachers have students do. We hope you find it useful in helping your classes become more data literate.

WHO IS THIS BOOK FOR?

- Teachers who need to read government and school board documents that present data in tables or graphs will find most chapters useful to read over to help their understanding of those documents.
- Teachers of lower elementary grades (whenever they start students interpreting bar charts or histograms) will find the early chapters useful.
- Middle school teachers will find the first eight chapters helpful.
- High school teachers will benefit from reading the entire book, and in particular the later chapters if they have advanced students who need to be challenged with more complex work.
- Individuals working on a graduate degree that involves data collection will find this a good introduction to any research methods course they might need to take.

The appendixes provide laboratory investigation activities (Appendixes I and II) to help you teach these data representation and analysis concepts to your students at various grade levels. In addition, there are appendixes to help you evaluate the laboratory activities your students have handed in (Appendixes III and IV) as well

as a collection of data analysis worksheets with examples of quantitative data analysis (Appendixes VIII and IX) that can be used by upper-level students to help them conduct more detailed analyses of data they've collected in lab investigations.

CONNECTIONS TO THE *FRAMEWORK* AND THE STANDARDS

Our work in writing this book took place at the same time as the development of the NGSS in the United States. The guiding document for the NGSS—*A Framework for K–12 Science Education: Practices, Crosscutting Concepts, and Core Ideas* (Framework; NRC 2012)—sets out eight scientific and engineering practices, of which Analyzing and Interpreting Data is the fourth on the list. The *Framework* identifies the grade 12 goals for analyzing and interpreting data as follows:

- Analyze data systematically, either to look for salient patterns or to test whether data are consistent with an initial hypothesis.
- Recognize when data are in conflict with expectations and consider what revisions in the initial model are needed.
- Use spreadsheets, databases, tables, charts, graphs, statistics, mathematics, and information and computer technology to collate, summarize, and display data and to explore relationships between variables, especially those representing input and output.
- Evaluate the strength of a conclusion that can be inferred from any data set, using appropriate grade-level mathematical and statistical techniques.
- Recognize patterns in data that suggest relationships worth investigating further. Distinguish between causal and correlational relationships.
- Collect data from physical models and analyze the performance of a design under a range of conditions. (NRC 2012, pp. 62–63)

PROGRESSIONS IN THE *FRAMEWORK*

This is a quick look at the Analyzing and Interpreting Data progressions found in the *Framework* document.

In elementary classes, we would see students

- make a start at recording and sharing observations; and
- engage in scientific inquiry and begin collecting categorical or numerical data for presentation in forms that facilitate interpretation, such as tables and graphs.

In middle school, students would learn the use and justification of some of the standard techniques for displaying, analyzing, and interpreting data, including

- different types of graphs;
- the identification of outliers in the data set; and
- averaging to reduce the effects of measurement error.

In high school, as the complexity of investigations increases, we see a broadening of the techniques for the display and analysis of the data. Examination of the relationships between two variables sees students produce x - y scatterplots or crosstabulations.

THE NGSS

The table below is taken from the NGSS (p. 9, Appendix F; NGSS Lead States 2013); it clearly shows the significance of data literacy and the related progressions that have been developed at the state standard level (Figure F.1).

FIGURE F.1

Progression of the practice of analyzing data in the NGSS

| Grades K-2 | Grades 3-5 | Grades 6-8 | Grades 9-12 |
|--|--|---|---|
| <p>Analyzing data in K–2 builds on prior experiences and progresses to collecting, recording, and sharing observations.</p> <ul style="list-style-type: none"> • Record information (observations, thoughts, and ideas). • Use and share pictures, drawings, and/or writings of observations. • Use observations (firsthand or from media) to describe patterns and/or relationships in the natural and designed world(s) in order to answer scientific questions and solve problems. • Compare predictions (based on prior experiences) to what occurred (observable events). • Analyze data from tests of an object or tool to determine if it works as intended. | <p>Analyzing data in 3–5 builds on K–2 experiences and progresses to introducing quantitative approaches to collecting data and conducting multiple trials of qualitative observations. When possible and feasible, digital tools should be used.</p> <ul style="list-style-type: none"> • Represent data in tables and/or various graphical displays (bar graphs, pictographs and/or pie charts) to reveal patterns that indicate relationships. • Analyze and interpret data to make sense of phenomena, using logical reasoning, mathematics, and/or computation. • Compare and contrast data collected by different groups in order to discuss similarities and differences in their findings. • Analyze data to refine a problem statement or the design of a proposed object, tool, or process. • Use data to evaluate and refine design solutions. | <p>Analyzing data in 6–8 builds on K–5 experiences and progresses to extending quantitative analysis to investigations, distinguishing between correlation and causation, and basic statistical techniques of data and error analysis.</p> <ul style="list-style-type: none"> • Construct, analyze, and/or interpret graphical displays of data and/or large data sets to identify linear and nonlinear relationships. • Use graphical displays (e.g., maps, charts, graphs, and/or tables) of large data sets to identify temporal and spatial relationships. • Distinguish between causal and correlational relationships in data. • Analyze and interpret data to provide evidence for phenomena. • Apply concepts of statistics and probability (including mean, median, mode, and variability) to analyze and characterize data, using digital tools when feasible. • Consider limitations of data analysis (e.g., measurement error), and/or seek to improve precision and accuracy of data with better technological tools and methods (e.g., multiple trials). • Analyze and interpret data to determine similarities and differences in findings. • Analyze data to define an optimal operational range for a proposed object, tool, process or system that best meets criteria for success. | <p>Analyzing data in 9–12 builds on K–8 experiences and progresses to introducing more detailed statistical analysis, the comparison of data sets for consistency, and the use of models to generate and analyze data.</p> <ul style="list-style-type: none"> • Analyze data using tools, technologies, and/or models (e.g., computational, mathematical) in order to make valid and reliable scientific claims or determine an optimal design solution. • Apply concepts of statistics and probability (including determining function fits to data, slope, intercept, and correlation coefficient for linear fits) to scientific and engineering questions and problems, using digital tools when feasible. • Consider limitations of data analysis (e.g., measurement error, sample selection) when analyzing and interpreting data. • Compare and contrast various types of data sets (e.g., self-generated, archival) to examine consistency of measurements and observations. • Evaluate the impact of new data on a working explanation and/or model of a proposed process or system. • Analyze data to identify design features or characteristics of the components of a proposed process or system to optimize it relative to criteria for success. |

WHAT ABOUT MATH? WHERE DOES DATA LITERACY FIT IN THERE?

Two guiding documents connect math to data literacy. The *Principles and Standards for School Mathematics* (NCTM 2000) has a strand entitled Data Analysis and Probability and the *Common Core State Standards, Mathematics* (NGAC and CCSSO 2010) has Measurement and Data as well as Statistics and Probability.

USE OF DATA IN THE NCTM PRINCIPLES AND STANDARDS

The big ideas guiding the NCTM Principles and Standards are that all students should be able to

- formulate questions that can be addressed with data and to collect, organize, and display relevant data to answer them;
- select and use appropriate statistical methods to analyze data;
- develop and evaluate inferences and predictions that are based on data; and
- understand and apply basic concepts of probability.

Looking at graphing, we see the following progression:

- K–2: Represent data using concrete objects, pictures, and graphs
- 3–5: Represent data using tables and graphs such as line plots, bar graphs, and line graphs
- 6–8: Select, create, and use appropriate graphical representations of data, including histograms, box plots, and scatterplots
- 9–12: Understand histograms, parallel box plots, and scatterplots and use them to display data

REFERENCES TO USE OF DATA IN THE COMMON CORE STATE STANDARDS, MATHEMATICS

The strand Measurement and Data runs from first to fifth grade, with Statistics and Probability running from sixth grade to high school. Let's look at the progression.

MEASUREMENT AND DATA

- Grade 1: Organize, represent, and interpret data with up to three categories
- Grade 2: Draw a picture graph and, in high school, a bar graph (with single-unit scale) to represent a data set with up to four categories
- Grade 3: Draw a scaled picture graph and a scaled bar graph to represent a data set with several categories
- Grade 4: Make a line plot to display a data set of measurements in fractions of a unit ($\frac{1}{2}$, $\frac{1}{4}$, $\frac{1}{8}$)

- Grade 5: Use operations on fractions for this grade to solve problems involving information presented in line plots

STATISTICS AND PROBABILITY

- Grade 6: Recognize a statistical question as one that anticipates variability in the data related to the question and accounts for it in the answers
- Grade 7: Use measures of center and measures of variability for numerical data from random samples to draw informal comparative inferences about two populations
- Grade 8: (1) Construct and interpret scatter plots for bivariate measurement data to investigate patterns of association between two quantities
- Grade 8: (2) Know that straight lines are widely used to model relationships between two quantitative variables. For scatter plots that suggest a linear association, informally fit a straight line, and informally assess the model fit by judging the closeness of the data points to the line

INTERPRETING CATEGORICAL AND QUANTITATIVE DATA

Grades 9–12: High School

- Summarize, represent, and interpret data on a single count or measurement variable
- Summarize, represent, and interpret data on two categorical and quantitative variables
- Interpret linear models

The above information on science and math standards was obtained directly from the documents listed in the Reference section (and as such much of the text is a direct copy from those documents).

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CHAPTER 8

SIMPLE STATISTICS FOR SCIENCE TEACHERS: THE *t*-TEST, ANOVA TEST, AND REGRESSION AND CORRELATION COEFFICIENTS

In earlier chapters (Chapters 3 and 4), we looked at patterns in nominal data using bar graphs and ordinal data using line graphs. We “eyeballed” differences from those graphs, looking at the size of the circles drawn around the tics, and drew conclusions that we discussed using hedging language. But is that what scientists do?

Actually yes, in the early stages of their research or as the research is progressing—but it’s not how they write their final reports. Those final reports often contain statistical analyses that allow the scientist to state with more certainty what differences and patterns they have found in their data. Remember what we mentioned earlier? That science was a probabilistic endeavor? Well, part of it being probabilistic is that scientists want to state with as much certainty as possible what the patterns and relationships are that they are looking at. Using statistics helps scientists improve the certainty of their statements so they can be as precise as possible.

In this chapter, we’re going to look at three basic statistical tests. The first is the *t*-test, which is used when you have nominal or ordinal data and *only* two test variables you are comparing (e.g., the speed of cats and dogs). The second is the analysis of variance (ANOVA) test for when you have nominal or ordinal data and *more* than two test variables (e.g., the speed of cats and dogs and pigs). The third statistical analysis is correlation and regression analysis, which is for interval-ratio data when you are comparing two things you have measured (e.g., the amount of salt in the pot and how long it takes potatoes to cook). These three basic tests cover most of the types of inquiry studies we’ve seen grade 7–12 students conduct. There

are tests for more complicated designs, but this is a basic introduction, and understanding these will help you understand more complicated designs if you need to.

In a book like this, we should probably mention *why* this chapter is here. Statistical tests don’t *seem* very basic do they? We agree that they’re not; however, we’ve seen projects by grade 7 students (at science fairs) in which they used *t*-tests and could describe how the tests worked and why they used them. Correctly, we should add. We’ve seen ANOVA tests used by grade 10 students in the same settings, and by grade 12 students as part of inquiry investigations in their regular classes. As a teacher you never know when you’re going to have that hyper-keen student in grade 8, so we thought you might appreciate having some resources to help you work with them. If nothing else, the worksheets we provide will give you something to give them to enhance their learning when they’ve raced ahead of the rest of the class. Besides that, this chapter might help you understand some of those mail-outs from boards of education with statistics in them that most of us have trouble making heads or tails of.

In Appendix IX we provide three resources: Worksheets that do a step-by-step calculation of each of these types of statistical analysis, critical value tables that let you determine if there are statistically significant differences, and a worked-through example for each test from data used in previous chapters in this book. We’ll also mention that in the Resource section (Appendix VI) there are links to websites that also conduct these tests if you insert the data into them.¹ This chapter is an

1. We also intend to provide a resource page with analysis tools at the NSTA Press website for the book.

introductory description of what these tests are doing and the conditions that should be met for doing them.

THE *t*-TEST

The *t*-test is used when you compare *two* means to see if they are statistically different from each other. You should *not* use a *t*-test over and over to compare many pairs of means (see the ANOVA test description for how to deal with that situation). What the *t*-test is doing is determining what the likelihood is that the difference between the two means happens because of chance or because of the variable you tested. In simple terms, it's comparing how much data scatter there is for each variable and then comparing how different the means are in relation to that data scatter so that the likelihood of the differences between the means being due to random chance can be determined.

It might be a bit simpler if we looked at a graph of data (Figure 8.1 here, which you might recognize from Figure 1.7, p. 10).

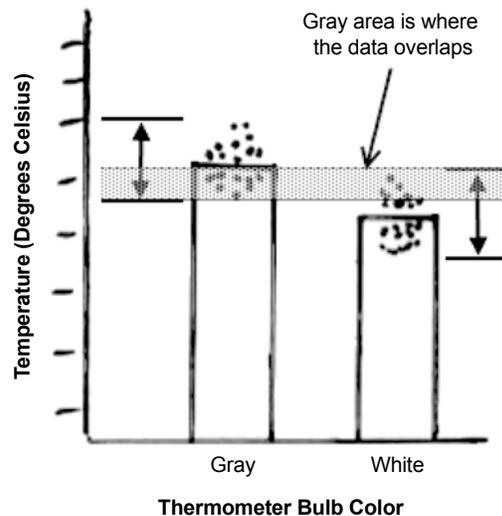
A *t*-test would help you determine whether the amount of overlap in the data would be statistically significant so that you could argue that the two means are different from each other.²

Every test has conditions (also known as assumptions) that must be met for the results to be valid. If you meet those conditions, statistical tests are pretty good at letting you know whether there's a statistically significant difference between means, but if you violate those assumptions then the tests might not be accurate. Here are the assumptions that should be met to do the *t*-test:

2. We've actually done this in Appendix IX. Go and take a look at whether the means are significantly different or not for this data set.

FIGURE 8.1

Graph of temperature data with arrows depicting range of response and the gray area depicting where the data overlaps

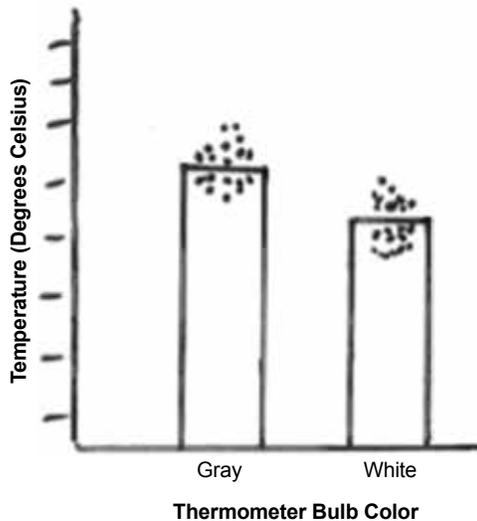


1. The data scatter is reasonably the same for the two categories (in statistical terms, the *variation* is close to the same).
2. There is more data toward the middle of the circles than at the nearest and farthest points away from the middle (in statistical terms, the data has a reasonably *normal distribution*).
3. The data are *randomly* chosen (in statistical terms, this means you didn't choose data to include so that you showed what you wanted to show).
4. The replicates in the two treatments need to be *independent* of each other. For instance, the data *cannot* be before and after measures on the same individuals (there's a separate test for that called the paired *t*-test).

It might be easier to show you what this means on a graph. Let's look at Figure 1.7 (the gray and white thermometer data, p. 10) again in Figure 8.2.

FIGURE 8.2

Depiction of gray and white temperature data portraying even data scatter

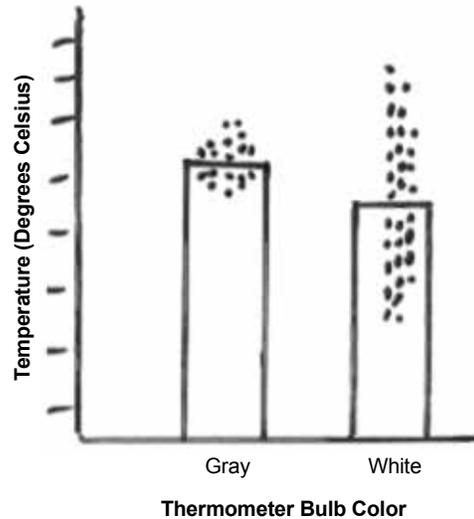


You'll notice that the data in this graph meets the assumptions listed above: The raw data depicted around the two bars is about the same distance from top to bottom, and there are more data points close to the horizontal line than far away from it.

Let's look at a couple of extreme versions of data for the same variables that do not meet those assumptions for a *t*-test (Figure 8.3).

FIGURE 8.3

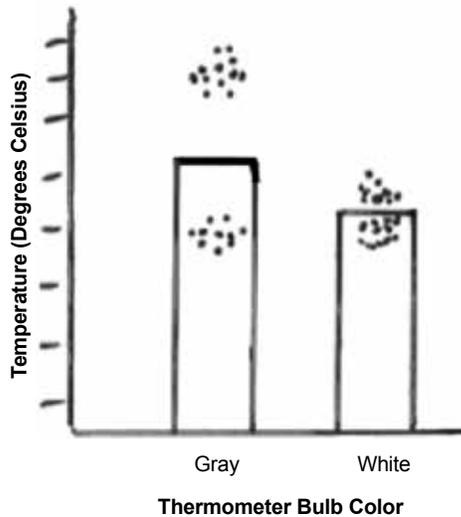
Depiction of gray and white temperature data portraying uneven data scatter



Notice that in Figure 8.3, the data on the right bar is much more scattered (has a greater variation) than the data on the left. This violates assumption 1. Now we'll look at a graph that violates assumption 2 (Figure 8.4, p. 54).

FIGURE 8.4

Depiction of gray and white temperature data portraying discontinuous data scatter



Here, you'll notice that on the left bar data are not close to the horizontal line at all; the horizontal line is at the average of two separate clusters. This condition violates assumption 2 because the data are not normally distributed (i.e., more toward the horizontal line than away from it).

The more your data looks like the last two graphs (and data could look like a combination of both of them), the less likely it is that the results of the *t*-test are reliable. In that situation you might *hedge* how you phrased your interpretation of the data analysis. For instance, if you found a significant difference (as we will describe below), you could write, "Despite finding a significant difference between the mean temperatures for the gray and white thermometer, there is still some room for doubt because of the amount of variation in the data for the white thermometer, which was much greater than that for the gray thermometer."

However, having described the problem, realize that the *t*-test is a reasonably robust test and is fairly accurate even if its assumptions are violated.

So, how do you calculate a *t*-test? The step-by-step worksheet and example in Appendix IX will show you. When you calculate your *t*-test statistic using the worksheet, compare your calculated value to the table value in Table 8.1.

TABLE 8.1

Critical values for the *t*-test statistic

| 5% Significance Table | | | |
|-----------------------|----------------|--------------------|----------------|
| Degrees of freedom | Critical value | Degrees of freedom | Critical value |
| 4 | 2.78 | 15 | 2.13 |
| 5 | 2.57 | 16 | 2.12 |
| 6 | 2.48 | 18 | 2.10 |
| 7 | 2.37 | 20 | 2.09 |
| 8 | 2.31 | 22 | 2.07 |
| 9 | 2.26 | 24 | 2.06 |
| 10 | 2.23 | 26 | 2.06 |
| 11 | 2.20 | 28 | 2.05 |
| 12 | 2.18 | 30 | 2.04 |
| 13 | 2.16 | 40 | 2.02 |
| 14 | 2.15 | 60 | 2.00 |
| | | 120 | 1.98 |

If the *t*-statistic you calculated is *less than* the critical value in the table above (for the correct degrees of freedom, which you calculate on the worksheet) then the difference between the two means is not statistically significant.

If the calculated *t*-statistic is *greater than* the critical value in the table above (for the correct degrees of freedom) then the difference between the two means is statistically significant at 5%. This means we're 95% confident that the difference between the means is a real one (i.e., not due to chance).

THE ANOVA TEST

The ANOVA test is used when you have several different treatments you are testing (in other words, more than two treatments). Sometimes people do multiple *t*-tests instead of an ANOVA—this is *bad, bad, bad*. Very bad. Ghostbusters bad. Why? Because you considerably increase the likelihood that you'll report a statistically significant difference when there is *not* one. All of those "only 1 in 20 chances of being wrong" possibilities add up so it becomes *very* likely that you're wrong. An ANOVA test stops that from happening.

Note that the treatments have to be either nominal- or ordinal-category-type data categories, treatments, or groups, and you have to have collected measured data about them.

If, for instance, you measured how fast three different breeds of dogs (with increasing sizes) could run 30 m, then that would be the type of data you would do an ANOVA test on. You have ordinal categories, and you have the times it took to cover the distance.

But why would you?

You can *see* the differences in the graph can't you?

Well, an ANOVA test allows you to figure out if the differences between the mean times to run 30 m are different enough, given the way the data are scattered about the mean, to say *with certainty* that the breeds of dogs can run at different speeds. It might seem a bit odd to "test" this, because you can *see* that the means look

different on a graph, but scientists care about how much data scatter there is too, which is why these statistical tests were created! And doing an ANOVA test allows you to be more convincing when making arguments about your findings to others (that's why scientists do statistical analyses: They remove some of the personal bias that might influence their interpretations, so they become more convincing with their claims).

First, it's important to note that the ANOVA test has some conditions that must be met (just as the *t*-test did; in fact, they're basically the same conditions, so you can look at the graphical examples from the *t*-test if you need to). Here are the conditions that must be met to perform an ANOVA test:

1. The data scatter is reasonably the same for the two categories (in statistical terms, the *variation* is close to the same).
2. There is more data scatter toward the middle of the circles than at the nearest and farthest points away from the middle (in statistical terms, the data has a reasonably *normal distribution*).
3. The data are *randomly* chosen (in statistical terms this means you didn't choose only data to include so that you showed only what you wanted to show).
4. The replicates in the treatments need to be *independent* of each other (one treatment cannot be influencing another).

We've been using the phrase *data scatter* to discuss how the raw data spreads out around the mean, but the more correct term is *variance*. So, an ANOVA test really is—ready for it?—an ANalysis Of VAriance. An ANOVA test analyzes the variance around each of the means

CHAPTER 8

and the overall variance to figure out how certain you can be about whether the means are different from each other.

Okay, so let's say that we've collected data looking at how fast the three different dog breeds can run a 30 m distance, and we've tested five different dogs of each breed (Table 8.2).

That data would give us a graph that looks like Figure 8.5.

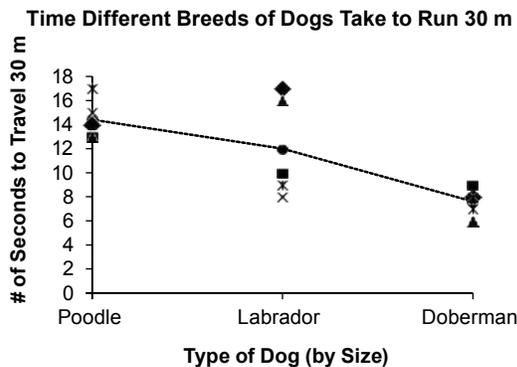
TABLE 8.2

Time in seconds that different dog breeds can run 30 m

| Dog | Poodle | Labrador | Doberman |
|------|--------|----------|----------|
| 1 | 14 | 17 | 8 |
| 2 | 13 | 10 | 9 |
| 3 | 13 | 16 | 6 |
| 4 | 15 | 8 | 8 |
| 5 | 17 | 9 | 7 |
| Avg. | 14.4 s | 12 s | 7.6 s |

FIGURE 8.5

The time it takes different dog breeds to run 30 m, ordered by dog size

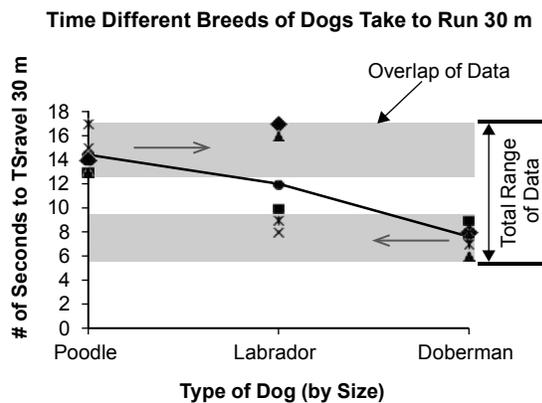


Notice that this graph looks a little bit different from those you might get from a

spreadsheet. That's because all of the data are on it, not just the average of the times each breed ran 30 m. Because you can see the data scatter around each average (at the dot where the line is), you can get a bit of an idea about what an ANOVA test does. Basically, it compares the data scatter around each mean *and* the overall data scatter *and* where each mean is and figures out if the means are different from each other. Essentially, the ANOVA test is analyzing how much the data you see on the graph overlap *in relation to the total amount of data scatter*. If the data do not overlap enough, then the means are probably different from each other. If they overlap a lot, in relation to the total amount of data scatter, then the means probably are *not* different from each other. The graph in Figure 8.6 might help you picture this.

FIGURE 8.6

The time it takes different breeds of dogs to run 30, ordered by dog size with an arrow depicting the overall range of response and the gray area depicting where the data overlaps for the pairs of variables



As with the *t*-test, the ANOVA test is a pretty robust test, and this means that the variation in the data scatter around the mean can be a

bit off (as it is with the Labrador) and the test will still be valid.

However, it gets a bit more complicated drawing conclusions from the ANOVA test compared to the *t*-test. In the *t*-test, there was only one pair of data, and we knew that the significant difference was just between that pair. But in the ANOVA, if the means are found to be statistically significant from each other overall, we still don't know *which* means were statistically significant from each other; we *cannot* assume that they all were. In this dog study, for instance, we know that there is a statistical difference between means (see Appendix IX for a worked-out example) but not whether Dobermans are faster than poodles, Labradors are faster than poodles, or Dobermans are faster than Labradors (the three possible pair comparisons).

There are tests, called *post hoc* (meaning after) tests, which can be done for this, but they're complicated enough that we're not going to include them here.³

That does not, however, mean that you cannot draw conclusions—we can look at the graph. The *first* important point is this: if you do an ANOVA test and do not find a statistically significant result for the whole data set, then it does *not* matter what the graph looks like—how far apart the means are—because there is *no statistically significant difference*, and that result means a whole lot more than any eyeballing differences. We're emphasizing this point because even undergraduates in science have difficulty understanding this. No statistical significance means, wait for it, waaiiiittt for it ... no statistical significance ... no difference between means. Just what it says. Okay? None.

But what if you *do* find statistical significance for the whole data set after doing an ANOVA test? Well, then looking at the graph to help figure out the paired means is completely valid.

Let's look at our data in Figure 8.5 again. How would we analyze it? Let's assume that our ANOVA was significant. Now we have to figure out the differences between pairs of data. We should probably look at the amount of overlap.

When you do this, you note that the lack of overlap of the two gray areas (one drawn across covering the poodle data, the other drawn across covering the Doberman data) *probably* means that the average times of poodles and Dobermans are significantly different from each other. (Note the use of hedging language in that statement? Also note that we haven't used the word *statistically* because we don't know about that specific pair statistically since we haven't run a statistical test.) However, there was so much variation in the Labrador data that it's difficult to draw any strong conclusions about the differences in the mean times of the different breeds. The average times for the Labradors and the Dobermans were pretty far from each other, and the time data of each breed only overlapped a little, so the mean times are quite possibly different from each other (so, significantly different from each other). However, the time data for the poodles and the Labradors overlapped enough that it's possible that the means for those breeds are *not* different from each other—or in other words, that there is no difference between the means for the poodle and the Labrador dogs. So, from an inspection of the data scatter on the graph it would be safe to conclude that

- poodles are *very probably* slower than Dobermans;

3. A common post-hoc test for dog data such as in the example is called Tukey's test.

- Dobermans are *possibly* faster than Labradors; and
- poodles *might be* the same speed as Labradors.

Without statistical testing this is a qualitative determination and therefore hedging language is used for all of the pair comparisons.⁴

Again, with an ANOVA analysis these differences would have a percentage certainty, or likelihood of error, associated with them just like the *t*-test, and in the tables provided with the worksheets (see Appendix IX) there is a 95% certainty in your answer (of statistical significance of differences in the entire data set), or a 5% possibility of error rate.

CORRELATION AND REGRESSION ANALYSIS

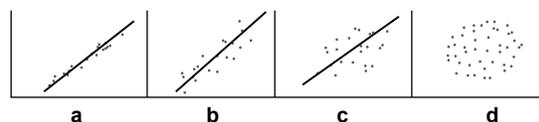
This type of data analysis is done on interval-ratio measures for which you want to find out if one factor (or variable) changes when another one does. Basically, when you have a graph of data, the regression analysis (or line of best fit analysis) is determining what the best average line is through the data set, and the correlation coefficient analysis is a measure of just how good that average is (i.e., how much the data are scattered about that line). This calculation is *not* a significance test (as the *t*-test and ANOVA test were), so you're not determining whether the slope of the line of best fit is significantly different from something else.

A correlation coefficient is a calculated statistic representing how close the data points are to the line of best fit. If you multiply the correlation coefficient by itself (see the

worksheet in Appendix IX), then you obtain a value that tells you the percentage of variation in variable *y* as explained by variable *x* (in a *causal* relationship). The closer this value is to 1 (or 100%, since you often multiply the product by 100), then the closer the values are to the line. In Figure 8.7 (a–c), you see three lines of best fit with different amounts of data scatter around them.

FIGURE 8.7

Examples of different types of scatterplot relationships



In this example, (a) would have an *r*-squared value close to 100%. At the other extreme, (d), any plotted line of best fit would have an *r*-squared value close to 0% (in other words, there is no relationship between the two variables). There are no hard and fast rules in science as to how much of an *r*-squared value is needed to talk about relationships between the variables. It can vary quite considerably depending on the circumstances. However, the *r*-squared value *does* give you guidance as to how you should be using hedging language to talk about the relationship between the variables.

Remember, in Appendix IX we provide worksheets for doing *t*-tests and ANOVA tests as well as worked-through examples. Appendix VIII also demonstrates a *t*-test analysis.

As a conclusion to this chapter we are going to provide an example of a correlation analysis in the form of a case study. In this case study, you'll find a student report on an investigation and then a teacher's feedback on that report.

4. A Tukey's test at 5% indicates that there is a significant difference between the poodle and Doberman means, but *no difference* between the poodle-Labrador or Labrador-Doberman mean times. This reflects the broad scatter in the Labrador times.

CASE STUDY: STUDENT REGRESSION AND CORRELATION ANALYSIS WITH TEACHER COMMENTARY

STUDENT RESEARCH QUESTION: DOES MY GUINEA PIG SLEEP MORE WHEN IT EATS MORE?

METHOD

1. Put 100 g of pellet food in my guinea pig's bowl each day.
2. Each morning replace the food bowl with a new one with 100 g of pellet food, pick up any pellets lying around and put them in the old food bowl, and weigh the old food bowl. Subtract the total remaining food from 100 g to get how much my guinea pig has eaten. Record the data in the data table.
3. Use a video camera with a time counter attached to my computer to record the amount of time my guinea pig sleeps in its box (I used a special camera with an infrared light that could see my guinea pig in the dark). Each day, fast-forward through the recording and keep track of how many minutes the guinea pig lies down with its eye facing the camera (mostly) closed (What looks like sleep ... most sleep with their eyes open, mine usually doesn't). Record the number of minutes in the data table (Table 8.3).
4. Keep hay and water in the cage so that there is always some. The only food being tracked is the pellets.
5. Do steps 2–4 for 30 days.

TABLE 8.3

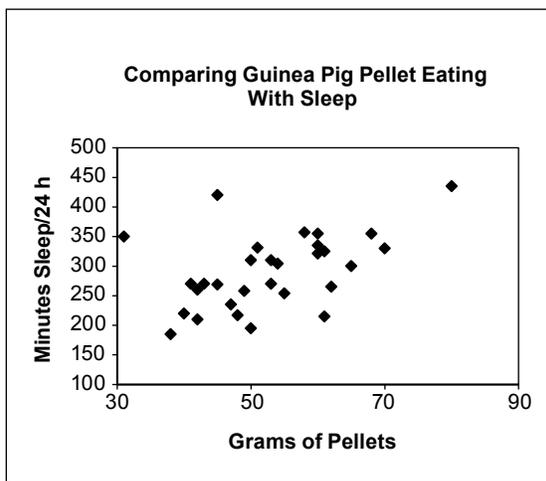
A student's data on how much guinea pigs sleep in relation to how much they eat

| Day | Pellets eaten (g) | Sleep in 24 h (min) |
|-----|-------------------|---------------------|
| 1 | 38 | 185 |
| 2 | 40 | 220 |
| 3 | 48 | 217 |
| 4 | 42 | 260 |
| 5 | 41 | 270 |
| 6 | 47 | 235 |
| 7 | 50 | 195 |
| 8 | 43 | 270 |
| 9 | 45 | 269 |
| 10 | 49 | 258 |
| 11 | 53 | 310 |
| 12 | 45 | 420 |
| 13 | 31 | 350 |
| 14 | 50 | 310 |
| 15 | 42 | 210 |
| 16 | 53 | 270 |
| 17 | 54 | 304 |
| 18 | 51 | 331 |
| 19 | 60 | 321 |
| 20 | 61 | 215 |
| 21 | 62 | 265 |
| 22 | 55 | 254 |
| 23 | 65 | 300 |
| 24 | 61 | 325 |
| 25 | 60 | 335 |
| 26 | 60 | 355 |
| 27 | 68 | 355 |
| 28 | 80 | 435 |
| 29 | 58 | 357 |
| 30 | 70 | 330 |

Because I had x - y data, I graphed it in a scatterplot so that I could see any pattern better (Figure 8.8).

FIGURE 8.8

A scatterplot of the data shown in Table 8.3, p. 59



I also calculated the regression formula and correlation coefficient using the worksheets you gave us, so I knew how good my calculated line of best fit represented the data.

Regression formula: $y = 2.7x + 145$

Correlation coefficient: 0.23 or 23%

CONCLUSION

I only have one guinea pig, so I can't say anything about all guinea pigs, but I can say that when mine eats more it seems to sleep longer, at least reasonably often. The correlation coefficient is only 23%, which means that the line doesn't fit the data really well, but those two high amounts of sleep on the top left of the graph might have made it weaker. Maybe I should calculate the regression line and the

correlation coefficient without them because when I draw the line on the graph from the regression formula the line seems kind of high. I would do the study with more guinea pigs if I had them because maybe my pig isn't normal and doesn't sleep in the same way as others.

INSTRUCTOR FEEDBACK TO STUDENT

You did a good job studying your guinea pig and figuring out the relationship between the amount of food and the amount of sleep. You wrote about it really well. You described how strong the relationship is (shown by your correlation coefficient) quite effectively by using the hedging language we've talked about in class. You're right, the relationship between the pellet consumption and the amount of sleep each day isn't a strong one (as indicated by the 23% value), but it is there. We haven't talked about this in class, but in physics that number might be really low, but when you're describing animal behaviour and many other things, a 23% correlation is actually really good. It means you're predicting 23% of what an animal is doing. I also think you're right by the way, if you excluded those two values on the top left of your page (who knows why your pig slept longer on those days—maybe it ate more hay than normal, or maybe it ran on its wheel more than it normally does) then your correlation would be *much* higher. When I exclude them and calculate your correlation coefficient it jumps up to 53%, and for animal behaviour that is really high.

I have a question for you: Why are you sure that it is the pellet consumption that is causing the amount of sleep? We did talk about the difference between *correlation* and *causation* in class. On the one hand, it does seem reasonable. I'm always sleepy after a big dinner. On

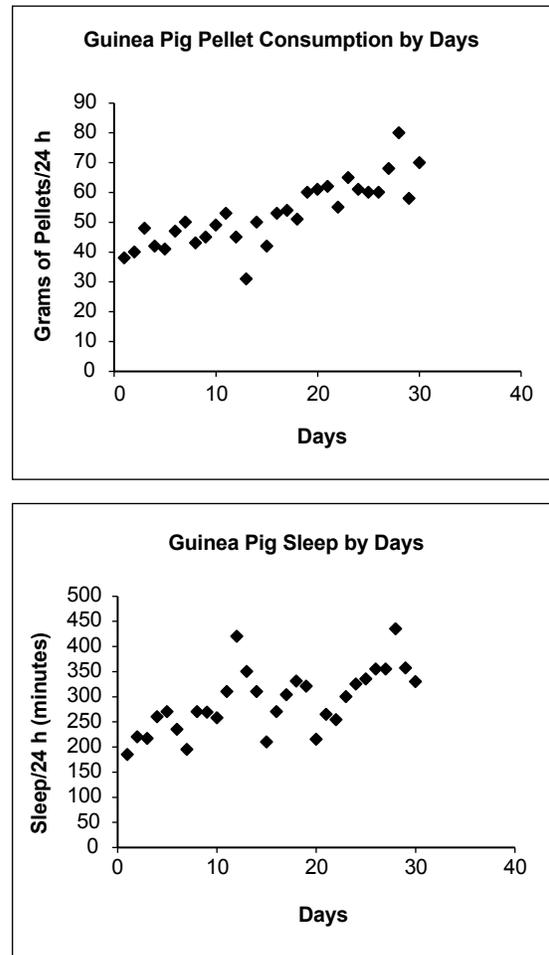
the other hand, something else is also going on that might affect how the guinea pig behaves. Winter is coming, right? What else happens then? I bet if you think about it you'll remember that when winter comes it's darker for a longer time—the daytime is shorter. What effect might less daylight have on the amount of sleep a guinea pig would want to get? Do they have alarm clocks? What do you think wakes them up? So how would we look at this? If it were the length of the day, you'd think your pig would eat more later in your study than earlier *and* would sleep more later in your study than at the beginning. Let's graph this (Figure 8.9).

So, do you see that? The food consumption goes up over the 30 days of your study and the sleep *also* goes up over those 30 days. So maybe the amount of daylight is affecting both how much your pig sleeps and how much it eats. This probably means that the amount of pellets consumed is *correlated* with the amount of sleep, but *not* the *cause* of the amount of sleep. Other than missing that (which even I admit was pretty tricky), your study and your report were both well done.

If you want to test whether it was daylight that had an effect, you could do your study again in the spring when the length of daylight is getting longer and see if there was a decrease in the amount of time your guinea pig slept. Let me know what you find out.

FIGURE 8.9

The teacher's graphs compare sleep and food consumption over a number of days



INDEX

- Abstract, laboratory report, 120
- Adjective checklist, 71
- Alpha calculation, 86
- Ambiguities, experiencing, 6
- ANOVA, 51–61, 65, 67, 134, 150–151, 153–154
 - worksheet, 150–155
- Assumptions, 47, 52–54, 121
 - in laboratory report, 121
 - t*-test, 52
- Axes
 - x*-*y* graph, 3
 - x*-*y*-*z* graph, 4
- Bar charts, 23, 85, 134
- Bar graphs, 1, 9, 11, 13–15, 19–21, 23, 25–26, 28, 49, 51, 65, 67, 69, 77, 121–122
- Biology4all* website, 131
- Brief questions, 68
- Calculators, 133–134
 - statistical, 134
 - t*-test, 133
- Captions, use of, 47–48, 117–118, 122
- Causality vs. correlation, 38–39
- Central tendency measure, 78
- Chi-squared test, 77
- Clear phrasing, 64
- Communication, scientific, 45–48, 133
- Comparative scale, 71
- Concept maps, 123–129
- Conclusions in science, 8–11
- Confirmatory factor analysis, 86
- Control, giving students, 128
- Controlled variables, 21–22, 37, 93–94, 124
- Controversial statements, 74
- Correlation analysis, 49, 58–60, 87, 133–134, 143
 - worksheet, 156–159
- Correlation coefficient, 51–61, 133, 158
- Correlation vs. causality, 38–39
- Correlational relationship, 37, 39
 - cause, effect covariance, 39
 - lack of alternatives, 39
 - temporal precedence, 39
- Count questions, 66–67
- Covarying relationships, 79–84
- Cronbach's alpha calculation, 86
- Crosstabulation table, 8, 79–82, 84
- Current student knowledge, 6
- Curvilinear relationship, 37
- Data scatter, 5, 9–11, 15, 21, 28, 38, 52–58, 140
- Data table, 19–20, 31–32, 41–44, 59, 77, 79–81, 83, 87
- Deterministic language states, 45
- Directionality of questions, 87–88
- Discrete categories questions, 42, 64–67
- Discursive practices, 6
- Discussing data in reports, 47–48, 121
- Disorder, finding structure in, 8
- Distribution, 52, 55, 135
- Double-barreled questions, 71
- Double-negative statements, 73–74
- Dual answers, 72
- Excel, 15, 131–134
- Expertise of others, drawing on, 6
- F*-table critical values, 160–163
- Face validity, 86
- Feedback, 58, 60–61
- Fixed sum scale, 71
- Focused questions, 68, 72
- Forced ranking scale, 71
- Format, interval-ratio data table, 44
- Frequency data analysis, 65, 79–84
- Graphs, 1, 3–5, 8–11, 13–21, 23–29, 32–39, 41–44, 46–49, 51–58, 60–61, 65, 67, 69, 77–79, 83, 86, 91, 93–95, 99, 108, 110, 112,

INDEX

- 117–122, 124–125, 131–134, 137, 139, 141
 - appropriateness of, 122
 - interpretation, 16–17
 - predicting from, 15
 - raw data importance, 14–15
 - structure, 117–118
 - student misconceptions, 132
- Harvard Forest Schoolyard Science Program, 131
- Hedging language, 6, 14, 24, 30, 45–47, 51, 57–58, 60, 79, 82
- Higher-order thinking, 7–8, 14, 16, 66, 84, 86
 - skills, 7–8
 - uncertainty with, 8
- Higher-order variables, scaffolding toward, 16
- Histograms, 1, 19, 134
- Imposition of meaning, 8
- Independent variable types, 13, 36, 42, 117
- Inquiry levels, 7
- Interpretation, 7, 15–16, 19, 36–37, 47, 64, 117, 121, 136
 - bar graphs, 23–24
 - data analysis, 54
 - graphs, 16–17, 47
 - laboratory report, 121
 - line graphs, 29–30
 - nuanced, 7
- Interval-ratio data, 13–14, 16, 19, 27, 30–39, 42–44, 46, 49, 51, 66–67, 69, 77, 79, 86–87, 99, 101, 107, 113, 134
 - causality vs. correlation, 38–39
 - correlational relationship, 39
 - cause, effect covariance, 39
 - lack of alternatives, 39
 - temporal precedence, 39
 - curvilinear relationship, 37
 - interpretation, 35–38
 - non-discrete, 37–38
 - relationships between variables, 38
 - traditional scatterplot, 37
 - trend bar, 34
 - x- and y- axis, 35
 - x-y data, 32
 - x-y graphs, interpreting, 33–34
- Interval-ratio variable tables, 42–44
- Introduction, in laboratory report, 120
- Investigation reports, discussing data in, 47–48
- Kruskal-Wallis test, 77
- Laboratory reports, 47–48, 119–129
 - abstract, 120
 - assumptions, 121
 - discussion, 121
 - interpretations, 121
 - introduction, 120
 - methods, 120
 - results, 120
 - title, 120
- Learner communities, sharing with, 6
- Levels of science inquiry, 7
- Likert question, 68–71, 73, 77, 82, 84–85, 122
- Limitations to data, 24, 30
- Line graphs, 1, 14–15, 25–29, 33, 51, 67, 108, 121–122, 133
- Loaded statements, 74
- Mann-Whitney *U* test, 77
- Marble-rolling lab activity, 91–97
 - data sheet layout, 91–92
 - equipment setup, 91
 - focus questions, 93–96
- Mathematics, data management, 23, 29, 132, 135–137
- Meaning, imposition of, 8
- Measure of central tendency, 78
- Median, 22, 27, 36, 69, 78, 118, 135
- Memory, data tables as, 41–44
- Methods, in laboratory report, 120
- Missing categories, 74
- Multichotomous questions, 66
- Multiple criteria, application of, 7
- Multiple solutions, higher-order thinking, 7
- National Center for Education Statistics, 132
- Nominal-level data, 13, 16, 19–24, 122
 - controlled variables, 21
 - interpreting bar graph, 23–24

- limitations to data, 24
 - outliers, 19–20, 22, 46–47
 - representing data, 22–23
- Nominal variable tables, 41–42
- Non-discrete interval-ratio data, 37–38
- Nonalgorithmic thinking, 7
- Nonparametric data, 77, 86–87
- Nonparametric equivalents, 77
- Normal distribution, 52, 55
- Nuanced judgement, 7

- The Open Door Web Site*, 131–132
- Open-ended written responses, 70
- Open inquiry, 6–7
 - higher-order thinking, 7–8
 - laboratory activities, 6–7
 - student work, 6
- Ordinal-level data, 13, 25–30, 35, 46, 66, 69, 85, 122
 - bar graphs, 28
 - interpreting line graph, 29–30
 - limitations to data, 30
 - line graphs, 28
- Ordinal scale, 71
- Ordinal variable tables, 41–42
- Outliers, 19–20, 22, 46–47

- Paired-comparison scale, 71
- Parametric data, 77, 84, 86–87
- Post-hoc test, 57
- Probabilities, science and, 4–5, 9

- Question types, 63, 67–69, 71
- Questionnaires, 49, 63–68, 70, 72–73, 75, 77
- Questions, in surveys, 71–75

- R*-squared calculators, 134
- Randomly chosen data, 52
- Raw data graphing, importance of, 14–15
- Real-world data, 5–6
- Regression analysis, 49, 51, 58–60, 84, 133–134, 156, 158
 - worksheet, 156–159
- Regression coefficients, 51–61

- Regulation of thinking process, 8
- Relationships, certainty regarding, 46
- Relationships between variables, 4–6, 38
- Relative ordered relationship, 13
- Representation of data, 22–23
- Research investigation reports, 47–48
- Results, in laboratory reports, 120
- Reviewing laboratory reports, 119–122

- Scaffolded investigation, 7, 16, 99–115
 - ball-bounce activity, 102–103
 - effect of solutes, 100–101
 - elastic-stretch activity, 104–105
- Scale construction, 84–87
- Scatter, data, 5, 9–11, 15, 21, 28, 38, 52–58, 140
- Scatterplots, 1, 14, 32, 35, 37–39, 58, 60, 69, 79, 82–83, 87, 108, 122
- Science-class.net*, 132
- Science inquiry, levels of, 7
- Self-regulation of thinking process, 8
- Semantic differential scale, 69, 71
- Sharing with learner communities, 6
- Signed-rank test, 77
- Significant, vs. substantive difference, 48
- Social desirability issues, 72
- Specific questions, 65
- Stapel scale, 71
- Statistical analysis, 10, 49, 51, 85, 143, 145, 147, 149, 151, 153, 155, 157, 159, 161, 163
- Statistical analysis worksheets, 145–163
- Statistical calculators, 134
- Statistics, 14–15, 51, 53, 55, 57, 59, 61, 118, 120–121, 131–134
 - ANOVA test, 51–61
 - case study, 59–60
 - correlation analysis, 58–60
 - correlation coefficient, 51–61
 - data scatter, 5, 9–11, 15, 21, 28, 38, 52–58, 140
 - distribution, 52
 - feedback, 60–61
 - interpretation of data analysis, 54
 - normal distribution, 52
 - post-hoc test, 57
 - randomly chosen data, 52
 - regression analysis, 58–60

- regression coefficient, 51–61
 - student research question, 59–60
 - t*-test, assumptions, 52
 - t*-test statistic, critical values, 54
 - t*-tests, 51–61
 - temperature data graph, 52
 - Turkey's test, 57–58
- Statistics Canada, 133
- Structure in disorder, 8
- Student research question, 59–60
- Substantive vs. significant difference, 48
- Substantive vs. statistical difference, 48
- Summed scale, 87–88
- Survey, 49, 63–69, 71–75, 77–81, 83–88, 122
- Survey questions, 49, 64, 71–75, 86, 122
- Survey tables, 68
- Surveys, 49, 63–75, 77–88
 - adjective checklist, 71
 - brief questions, 68
 - chi-squared test, 77
 - clear phrasing, 64
 - comparative scale, 71
 - confirmatory factor analysis, 86
 - controversial statements, 74
 - count questions, 66–67
 - covarying relationships, 79–84
 - Cronbach's alpha calculation, 86
 - crosstabulation table, 8, 79–80, 84
 - data table, 77
 - directionality of questions, 87–88
 - double-barreled question, 71
 - double-negative statements, 73–74
 - dual answers, 72
 - face validity, 86
 - fixed sum scale, 71
 - focus in question, 72
 - forced ranking scale, 71
 - frequency data, 65, 79–84
 - Kruskal-Wallis test, 77
 - Likert/attitude items, 68–70
 - Likert question, 77
 - loaded statements, 74
 - Mann-Whitney *U* test, 77
 - measure of central tendency, 78
 - median, 78
 - missing categories, 74
 - multichotomous questions, 66
 - nonparametric data, 87
 - nonparametric equivalents, 77
 - open-ended written responses, 70
 - ordinal scale, 71
 - paired-comparison scale, 71
 - parametric data, 87
 - question types, 71
 - questionnaire, 73
 - questions, 64–75
 - scale construction, 84–87
 - semantic differential scale, 69, 71
 - social desirability issues, 72
 - specific questions, 65
 - Stapel scale, 71
 - summed scale, 87–88
 - survey table, 68
 - table questions, 67–68
 - unclear instructions, 73
 - verbal frequency scale, 71
 - Wilcoxon signed-rank test, 77
 - yes/no questions, 64–65
- T*-tests, 49, 51–61, 65, 67, 69, 77, 84, 86–87, 133–134, 139–141, 143–144, 146–147
 - assumptions, 52
 - calculators, 133
 - statistic, critical values, 54
 - worksheet, 144–149
- Tables, 1, 3–4, 7, 13, 18–20, 25, 31–32, 39, 41–44, 48–49, 51, 54–56, 58–60, 67–70, 77, 79–87, 91, 99, 105–106, 108–110, 112, 117–122, 124–125, 131–134, 139–140, 144–145, 147–148, 150–151, 153–154, 156, 158, 160
 - format, interval-ratio data table, 44
 - interval-ratio variable tables, 42–44
 - memory, data tables as, 41–44
 - nominal variable tables, 41–42
 - ordinal variable tables, 41–42
 - questions, 67–68
 - structure, 117–118, 121–122
 - survey, 68
- Temperature data graph, 52
- Thinking process, regulation of, 8
- Three-axis *x-y-z* graph with labeled axes, 4
- Title of laboratory report, 120
- Trend, 14–15, 33–34, 36–38, 47, 95–96, 122, 133

- Trend bar, 34
- Turkey's test, 57–58
- Types of independent variables, 13
- Types of questions, 63–71
- Types of variables, 13–24
 - Excel, 15
 - graphing, 16–21
 - higher-order variables, scaffolding toward, 16
 - independent variables, 13
 - interpreting graphs, 16–17
 - interval-ratio data, 13–14
 - nominal data, 13
 - nominal variables, 13
 - ordinal data, 13
 - predicting from graphs, 15
 - raw data graphing, 14–15
 - relative ordered relationship, 13
- Typography, data variables, 13–14

- Uncertainty with higher-order thinking, 8, 132
- Unclear instructions, 73

- Variables, 1, 3–6, 13–32, 35–39, 41–44, 46–47, 49, 51–53, 56, 58, 67, 78–80, 82, 84, 86, 93–94, 97, 99, 108, 110, 117–118, 122, 124, 133, 135–137, 157, 159
 - Excel, 15
 - graphing, 16–21
 - higher-order variables, scaffolding toward, 16
 - interpreting graphs, 16–17
 - interval-ratio data, 13–14
 - nominal data, 13
 - nominal variables, 13
 - ordinal data, 13
 - predicting from graphs, 15
 - raw data graphing, 14–15
 - relationships between, 38
 - relative ordered relationship, 13
 - types of independent variables, 13
 - typography of data variables, 13–14
- Vee maps, 97, 119, 123–129
- Verbal frequency scale, 71
- Visual data, 132–133

- Web resources, 89, 131–133, 143
- Wilcoxon signed-rank test, 77
- Worksheets, 14, 51, 54, 58, 60, 89, 91, 93, 95, 97, 131, 143–145, 147, 149–151, 153, 155–159, 161, 163
 - ANOVA, 150–155
 - correlation analysis coefficients, 156–159
 - regression analysis coefficients, 156–159
 - statistical analysis, 145–163
 - t*-tests, 144–149

- X- and y- axis, 35
- X-y data, 32, 60
- X-y graphs
 - interpreting, 32–34
 - with labeled axes, 3
- X-y-z graph, labeled axes, 4

- Yes/no questions, 64–65

THE BASICS OF DATA LITERACY

HELPING YOUR STUDENTS (AND YOU!) MAKE SENSE OF DATA

“Part of being able to take a more informed (some might say skeptical) view of data is being literate in how data are manipulated and subsequently presented: how they are collected, made into tables, and shown in pictures or graphs. Once you know how to do this the right way, such as you might learn in a science classroom, you can start asking if someone else is doing it in a way that is fair, or if they are distorting the data for their own purposes.”

—From the foreword to *The Basics of Data Literacy*

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- reflects the ways scientists use and make sense of data, and
- extends the ways of understanding to simple statistical analysis.

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