CHAPTER 1

Catalyzing the Generation of Knowledge

1.1. THE LEARNING PROCESS

Knowledge is power. It is the key to innovation and profit. But the getting of new knowledge can be complex, time consuming, and costly. To be successful in such an enterprise, you must learn about learning. Such a concept is not esoteric. It is the key to idea generation, to process improvement, to the development of new and robust products and processes. By using this book you can greatly simplify and accelerate the generation, testing, and development of new ideas. You will find that statistical methods and particularly experimental design catalyze scientific method and greatly increase its efficiency.

Learning is advanced by the iteration illustrated in Figure 1.1. An initial idea (or model or hypothesis or theory or conjecture) leads by a process of *deduction* to certain necessary consequences that may be compared with data. When consequences and data fail to agree, the discrepancy can lead, by a process called *induction,* to modification of the model. A second cycle in the iteration may thus be initiated. The consequences of the modified model are worked out and again compared with data (old or newly acquired), which in turn can lead to further modification and gain of knowledge. The data acquiring process may be scientific experimentation, but it could be a walk to the library or a browse on the Internet.

Inductive–Deductive Learning: An Everyday Experience

The iterative inductive–deductive process, which is geared to the structure of the human brain and has been known since the time of Aristotle, is part of one's everyday experience. For example, a chemical engineer Peter Minerex* parks

*Can you guess why he's called Peter Minerex?

Statistics for Experimenters, Second Edition. By G. E. P. Box, J. S. Hunter, and W. G. Hunter

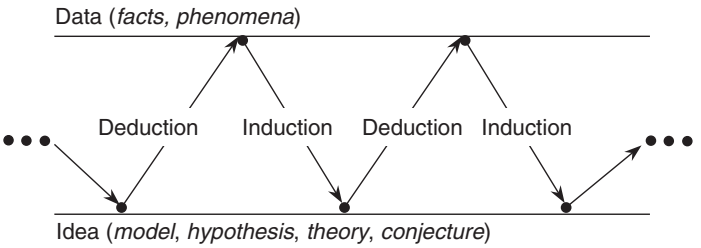

Figure 1.1. Iterative learning process.

his car every morning in an allocated parking space. One afternoon after leaving work he is led to follow the following deductive–inductive learning sequence:

Model: Today is like every day.
Deduction: My car will be in its parking place.
Data: It isn't.
Induction: Someone must have taken it.

Model: My car has been stolen.
Deduction: My car will not be in the parking lot
Data: No. It's over there!
Induction: Someone took it and brought it back.

Model: A thief took it and brought it back.
Deduction: My car will have been broken into.
Data: It's unharmed and unlocked.
Induction: Someone who had a key took it.

Model: My wife used my car.
Deduction: She probably left a note.
Data: Yes. Here it is.

Suppose you want to solve a particular problem and initial speculation produces some relevant idea. You will then seek data to further support or refute this theory. This could consist of some of the following: a search of your files and of the Web, a walk to the library, a brainstorming meeting with co-workers and executives, passive observation of a process, or active experimentation. In any case, the facts and data gathered sometimes confirm your conjecture, in which case you may have solved your problem. Often, however, it appears that your initial idea is only partly right or perhaps totally wrong. In the latter two cases, the difference between deduction and actuality causes you to keep digging. This can point to a modified or totally different idea and to the reanalysis of your present data or to the generation of new data.

Humans have a two-sided brain specifically designed to carry out such continuing deductive–inductive conversations. While this iterative process can lead to a solution of a problem, you should not expect the nature of the solution, or the route by which it is reached, to be unique.

Chemical Example

Rita Stoveing,* a chemist, had the following idea:

Model Because of certain properties of a newly discovered catalyst, its presence in a particular reaction mixture would probably cause chemical *A* to combine with chemical *B* to form, in high yield, a valuable product *C*.

Deduction Rita has a tentative hypothesis and deduces its consequences but has no data to verify or deny its truth. So far as she can tell from conversations with colleagues, careful examination of the literature, and further searches on the computer, no one has ever performed the operation in question. She therefore decides she should run some appropriate experiments. Using her knowledge of chemistry, she makes an experimental run at carefully selected reaction conditions. In particular, she guesses that a temperature of 600°C would be worth trying.

Data The result of the first experiment is disappointing. The desired product *C* is a colorless, odorless liquid, but what is obtained is a black tarry product containing less than 1% of the desired substance *C*.

Induction At this point the initial model and data do not agree. The problem worries Rita and that evening she is somewhat short with her husband, Peter Minerex, but the next morning in the shower she begins to think along the following lines. Product *C* might first have been formed in high yield, but it could then have been decomposed.

Model Theory suggests the reaction conditions were too severe.

Deduction A lower temperature might produce a satisfactory yield of *C*. Two further runs are made with the reaction temperature first reduced to 550°C and then to 500°C.

Data The product obtained from both runs is less tarry and not so black. The run at 550°C yields 4% of the desired product *C*, and the run at 500°C yields 17%

Induction Given these data and her knowledge of the theory of such reactions, she decides she should experiment further not only with temperature but also with a number of other factors (e.g., concentration, reaction time, catalyst charge) and to study other characteristics of the product (e.g., the levels of various impurities, viscosity).

*Can you guess why she's called Rita Stoveing?

To evaluate such complex systems economically, she will need to employ designed experiments and statistical analysis. Later in this book you will see how subsequent investigation might proceed using statistical tools.

Exercise 1.1. Describe a real or imagined example of iterative learning from your own field—engineering, agriculture, biology, genomics, education, medicine, psychology, and so on.

A Feedback Loop

In Figure 1.2 the deductive–inductive iteration is shown as a process of feedback. An initial idea (hypothesis, model) is represented by M_1 on the left of the diagram. By *deduction* you consider the expected consequences of M_1—what might happen if M_1 is true and what might happen if M_1 is false. You also *deduce* what data you will need to explore M_1. The experimental plan (design) you decide on is represented here by a frame through which some aspects of the true state of nature are seen. Remember that when you run an experiment the frame is at your choice* (that's *your* hand holding the frame). The data produced represent some aspect (though not always a relevant one) of the true state of nature obscured to a greater or lesser extent by "noise," that is, by experimental error. The analyzed data may be compared with the expected (deduced) consequences of M_1. If they agree, your problem may be solved. If they disagree, the way they disagree can allow you to see how your initial idea M_1 may need to be

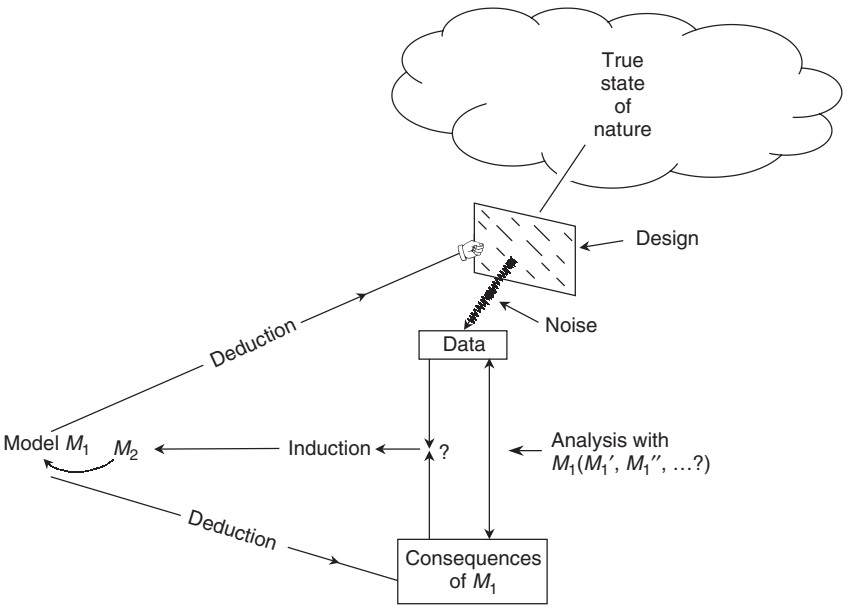

Figure 1.2. Iterative problem solving seen as a feedback loop.

* This is not true, of course, for happenstance data over which you have no control.

modified. Using the same data, you may consider alternative analyses and also possible modifications of the original model M_1', M_1'', ... It may become clear that your original idea is wrong or at least needs to be considerably modified. A new model M_2 may now be postulated. This may require you to choose a new or augmented experimental design to illuminate additional and possibly different aspects of the state of nature. This could lead to a satisfactory solution of the problem or, alternatively, provide clues indicating how best to proceed.

1.2. IMPORTANT CONSIDERATIONS

Subject Matter Knowledge

Notice the importance of subject matter knowledge to perceive and explore tentative models and to know where to look for help.

The Route to Problem Solving Is Not Unique

When he first noticed that his car was missing, Peter Minerex might easily have behaved differently. For example, he might immediately have phoned the police and thus initiated different (but perhaps not equally effective) routes to discovery. Similarly, in the chemical investigation a different experimenter, after studying the disappointing results, might have decided to explore an entirely different chemical route to obtain the desired product. The object is to *converge* to a satisfactory solution—the starting point and the route (and sometimes the nature of the solution) will be different for different investigators.

The game of 20 Questions illustrates these points. In the game the object is to identify an unknown object using no more than 20 questions, each of which has only one of two distinct answers. Suppose that the object to be guessed is *Abraham Lincoln's stove pipe hat.* The initial clue is *vegetable with animal associations*. For a competent team of players presented with this initial clue the game might go as follows:

TEAM A

Question	Answer
Are the animal associations human?	Yes
Male or female?	Male
Famous or not?	Famous
Connected with the arts	No
Politician?	Yes
USA or other?	USA
This century or not?	Not
Nineteenth or eighteenth century?	Nineteenth
Connected with the Civil War?	Yes
Lincoln?	Yes
Is the object Lincoln's hat?	Yes

But for a different team of competent players the game would almost certainly follow a different route. For example:

TEAM B

Question	Answer
Is the object useful?	Yes
Is it an item of dress?	Yes
Male of female?	Male
Worn above or below the belt?	Above
Worn on the head or not?	Head
Is it a famous hat?	Yes
Winston Churchill's hat?	No
Abraham Lincoln's hat?	Yes

The game follows the iterative pattern of Figures 1.1 and 1.2, where the "design" is the choice of question. At each stage conjecture, progressively refined, leads to an appropriate choice of a question that elicits the new data, which leads in turn to appropriate modification of the conjecture. Teams *A* and *B* followed different routes, but each was led to the correct answer because the data were generated by the truth.

The qualities needed to play this game are (a) subject matter knowledge and (b) knowledge of strategy. Concerning strategy, it is well known that at each stage a question should be asked that divides the objects not previously eliminated into approximately equiprobable halves. In these examples the players usually try to do this with questions such as "male or female?" or "worn above or below the belt?"*

Knowledge of strategy parallels knowledge of statistical methods in scientific investigation. Notice that without knowledge of strategy you can always play the game, although perhaps not very well, whereas without subject matter knowledge it cannot be played at all. However, it is by far best to use *both* subject matter knowledge and strategy. It is possible to conduct an investigation without statistics but impossible to do so without subject matter knowledge. However, by using statistical methods convergence to a solution is speeded and a good investigator becomes an even better one.

1.3. THE EXPERIMENTER'S PROBLEM AND STATISTICAL METHODS

Three problems that confront the investigator are *complexity, experimental error*, and the difference between *correlation and causation*.

* From a dictionary containing a million words a single word can be found playing 20 Questions. The questions begin, "Is it in the front half or the back half of the dictionary?" If the answer is, say, "The front half," then the next question is, "Is it in the front half or the back half of that half?" And so on. Note that $2^{20} \gg 10^6$.

Complexity

In experimentation for process improvement* and discovery it is usually necessary to consider simultaneously the influence of a number of "input variables" such as temperature, feed rate, concentration, and catalyst on a collection of output variables such as yield, impurity, and cost. We call controllable input variables *factors* and output variables *responses*. In studying the question as to how to improve a process the prime question is,

"What does what to what?"

With k factors and p responses there are $k \times p$ entities to consider. Further, while a certain subset of factors (e.g., temperature and pressure) might be available to change one response (e.g., yield), a quite different or likely overlapping subset (e.g., temperature and concentration) might influence a different response (e.g., purity). Compromises may be necessary to reach a satisfactory high yield and adequate purity. Also, some factors will interact in their influence on a particular response. For example, the change in yield induced by a particular change in temperature might itself change at different concentrations. To take account of all these matters simultaneously faces the experimenter with a daunting challenge. Pick and try guesses and the use of the "change one factor at a time" philosophy of experimentation is unlikely to produce a good result quickly and economically.

The use of statistical experimental design makes it possible while minimizing the influence of experimental error, to experiment with numbers of factors simultaneously. In this way you can get a clear picture of how they behave separately and together. Such understanding can lead to empirical solutions to problems, but it can do much more. A subject matter specialist provided with the results from a well-run experiment may reason along the following lines: "When I see what x_3 does to y_1 and y_2 and how x_1 and x_2 interact in their effect on y_3, this suggests to me that what is going on is thus and so and I think what we ought to do now is this." Theoretical understanding can spring from empirical representation.

Experimental Error

Variability not explained by known influences is called *experimental error*. Since some experimental error is inevitable, knowing how to cope with it is essential. Frequently, only a small part of experimental error is attributable to errors in measurement. Variations in raw materials, in sampling, and in the settings of the experimental factors often provide larger components. Good experimental design helps to protect real effects from being obscured by experimental error and conversely having the investigator mistakenly believe in effects that do not exist.

*The word *process* is used here in its general sense. Thus a process might be an analytical method, the manufacture of a product, or some medical procedure.

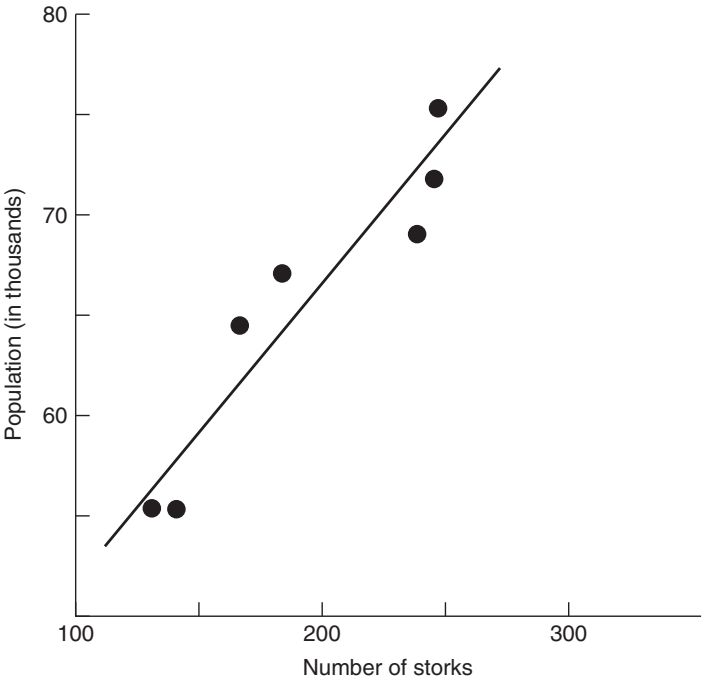

Figure 1.3. Number of storks versus population of Oldenburg.

The confusing influence of experimental error is greatly reduced by the wise use of statistical experimental design.* In addition, statistical analysis provides *measures of precision* of estimated quantities under study (such as differences in means or rates of change). This makes it possible to judge whether there is solid evidence for the existence of real effects and greatly increases the probability that the investigator will be led along a true rather than a false path.

Confusion of Correlation with Causation

Figure 1.3 shows the civilian population of Oldenburg plotted against the number of storks observed at the end of each of 7 years.† Although in this example few would be led to hypothesize that the increase in the number of storks *caused* the observed increase in population, investigators are sometimes guilty of this kind of mistake in other contexts. Correlation between two variables Y

* Another way to state this is to say that designed experiments can greatly increase the signal-to-noise ratio.

† These data cover the years 1930–1936. See *Ornithologische Monatsberichte*, **44**, No. 2, Jahrgang, 1936, Berlin, and **48**, No. 1, Jahrgang, 1940, Berlin, and *Statistiches, Jahrbuch Deutscher Gemeinden*, 27–22, Jahrgang, 1932–1938, Gustas Fischer, Jena. We are grateful to Lars Pallesen for these references.

and X often occurs because they are *both* associated with a third factor W. In the stork example, since the human population Y and the number of storks X both increased over this 7-year period, the common factor W was in this case *time*.

Exercise 1.2. Give other examples where correlation exists but causation does not.

1.4. A TYPICAL INVESTIGATION

To illustrate the process of iterative learning and to provide simultaneously a preview of what is discussed in this book, we employ a description of an imaginary investigation aimed at improving the quality of drinking water. Our investigators are the chemist Rita Stoveing and the chemical engineer Peter Minerex. As you read what follows, consider how identical *statistical* problems could confront investigators in any other experimental science.

The Problem

There is of course only a limited amount of usable water on this planet and what we have must be used and reused. The following investigation was necessary because a particular water supply contained an unacceptably high level of nitrate. Minerex and Stoveing had developed a new ion exchange resin that absorbed the offending nitrate. The attractive feature of this new resin was that it was specific for nitrate and potentially much cheaper to use and to regenerate than currently available resins. Unfortunately, it could only be made under laboratory conditions in experimental quantities. It was realized that a good deal of further experimentation might be necessary before a commercially viable product could be produced. The following outline shows how, as their investigation proceeded, they would be led to consider different questions and employ different statistical techniques* of varying degrees of sophistication.

Iterative Cycles of Investigation

Rita and Peter knew that observations recorded under apparently similar conditions could vary considerably. Thus, before beginning their investigation every effort was made to stabilize procedures and to reduce process variation. Furthermore, they expected to have to experiment with a number of different factors and to look at several different responses. To make such a study efficient and economical, they would need to make extensive use of statistical methods.

*This imaginary investigation has the property that in successive iterations it uses most of the techniques discussed in this book approximately in the order in which they appear. This is, of course, merely a pedagogical device. However, many investigations do go through various phases of statistical sophistication in somewhat the manner described here.

Commentary	The two investigators had each taken a statistics course but were currently a bit rusty.
	ITERATION I
Question	Where can we find a quick summary of elementary statistical principles?
Design and Analysis	Chapter 2: Basics
Findings	Studying this chapter provided the needed review and prepared them for what followed.
	ITERATION II
Commentary	Minerex believed, and Stoveing did not, that using a very pure (and more expensive) version of their resin would improve its performance.
Question	How does their "ordinary" resin compare with the more expensive high-purity version?
Design and Analysis	Chapter 3: Comparing Two Entities
Findings	Their expensive high-purity resin was about equal in performance to the ordinary resin. (She was right!)
	ITERATION III
Commentary	Minerex was wrong about the high-purity version, but their ordinary resin still looked promising. They now decided to compare laboratory samples of their new resin with five standard commercially available resins.
Question	How does their new ordinary resin compare with the five commercially available resins?
Design and Analysis	Chapter 4: Comparing a Number of Entities
Findings	The laboratory samples of the new resin were as good as any of the commercially available alternatives and perhaps somewhat superior.
	ITERATION IV
Commentary	The new resin had been shown to be capable of doing as well as its competitors. However, under the conditions contemplated for economic manufacture the removal of nitrate was insufficient to achieve the standard required for drinking water.
Question	What are the most important factors influencing nitrate removal? Can modifications in the present manufacturing equipment affecting such factors as flow rate, bed depth and regeneration time lead to improved nitrate removal?
Design and Analysis	Chapters 5, 6, 7, and 8: Studies using factorial and fractional factorial designs

Findings	With suitable modifications of the equipment, sufficiently low nitrate levels could be achieved.
	ITERATION V
Commentary	The company now concluded that manufacture of this new resin was possible and could be profitable. To learn more, a pilot plant was built.
Question	How do the settings of the process factors affect the quality and cost of the new resin? What are the best settings?
Design and Analysis	Chapters 10, 11, and 12: The method of least squares, multidimensional modeling, and response surfaces
Findings	The pilot plant investigation indicated that with appropriate settings of the process factors a product could be produced with satisfactory quality at a reasonable cost.
	ITERATION VI
Commentary	Before the process could be recommended for production the problems of sampling and testing had to be solved.
Question	How can sampling and testing methods be refined to give reliable determinations of the characteristics of the new resin?
Design and Analysis	Chapter 9: Multiple Sources of Variation
Findings	Components of variability in the sampling and chemical analysis of the product were identified and measured. Using this information, a sampling and testing protocol was devised to minimize the variance of the determinations at least cost.
	ITERATION VII
Commentary	Before the new resin could be recommended commercially its behavior had to be considered under a variety of environmental conditions that might be encountered at different locations and at different times. It was necessary to design the resin process system so that it was insensitive to variations due to different environments in which the resin would be required to operate.
Question	How can the nitrate adsorption product be designed so as to be insensitive to factors likely to be different at different locations, such as pH and hardness of the water supply and the presence of trace amounts of likely impurities?

Design and Analysis	Chapter 13: Designing Robust Products and Processes
Findings	A process design was possible that ensured that the manufactured new resin was insensitive to changes in pH, water hardness, and moderate amounts of likely impurities.

ITERATION VIII

Commentary	The regeneration process for the resin was done automatically by a system containing a number of electronic and mechanical components. It was known that manufacturing variations transmitted by these components could affect system performance.
Question	How can the regeneration system be designed so that small manufacturing changes in the characteristics of its components do not greatly affect its performance?
Design and Analysis	Chapter 13: Designing Robust Products and Processes
Findings	It was found that in some instances it would be necessary to use expensive components with tightened specifications and that in other instances less expensive components with wider specifications could be substituted. A system that gave high performance at low cost was developed.

ITERATION IX

Commentary	It was found that the full-scale plant was not easy to control.
Question	How can better process control be achieved?
Design and Analysis	Chapter 14: Process Control, Forecasting, and Time Series
Findings	By the process of debugging using monitoring techniques and simple feedback adjustment, adequate control was obtained.

ITERATION X

Commentary	The initial process conditions for the full-scale process were arrived at from pilot plant experiments.
Question	How can improved conditions from the full-scale process be achieved?
Design and Analysis	Chapter 15: Evolutionary Process Operation
Findings	Operation in the evolutionary mode provided a steadily improving process.

The above by no means exhausts the application of statistical methods that might have been necessary to produce a marketable and profitable product. For example, it would be necessary to determine the extent of the possible market and to judge the performance of the new resin relative to competitive products. Also, production scheduling and inventory controls would need to be organized and monitored.

1.5. HOW TO USE STATISTICAL TECHNIQUES

All real problems have their idiosyncrasies that must be appreciated before effective methods of tackling them can be adopted. Consequently each new problem should be treated on its own merits and with respect. Being too hasty causes mistakes. It is easy to obtain the right answer to the wrong problem.

Find Out as Much as You Can About the Problem

Ask questions until you are satisfied that you fully understand the problem and are aware of the resources available to study it. Here are some of the questions you should ask and get answers too. What is the object of this investigation? Who is responsible? I am going to describe your problem; am I correct? Do you have any past data? How were these data collected? In what order? On what days? By whom? How? May I see them? How were the responses measured? Have the necessary devices been recently checked? Do you have other data like these? How does the equipment work? What does it look like? May I see it? May I see it work? How much physical theory is known about the phenomenon? If the process concerns a manufacturing process, what are the sampling, measurement, and adjustment protocols?

Don't Forget Nonstatistical Knowledge

When you are doing "statistics" do not neglect what you and your colleagues know about the subject matter field. Statistical techniques are useless unless combined with appropriate subject matter knowledge and experience. They are an adjunct to, not a replacement for, subject matter expertise.

Define Objectives

It is of utmost importance to (1) *define clearly the objectives* of the study; (2) be sure that all interested parties concur in these objectives; (3) make sure that the necessary equipment, facilities, scientific personnel, time, money, and adequate management support are available to perform the proposed investigation; (4) agree on the criteria that will determine when the objectives have been met; and (5) arrange that if the objectives have to be changed all interested parties are made aware of the new objectives and criteria. Not giving these matters sufficient attention can produce serious difficulties and sometimes disaster.

Learn from Each Other: The Interplay Between Theory and Practice

While experimenters can greatly gain from the use of statistical methods, the converse is even more true. A specialist in statistics can learn and benefit enormously from his or her discussions with engineers, chemists, biologists, and other subject matter specialists. The generation of really new ideas in statistics and good statistical tools seem to result from a genuine interest in practical problems. Sir Ronald Fisher, who was the originator of most of the ideas in this book, was a scientist and experimenter who liked to work closely with other experimenters. For him there was no greater pleasure than discussing their problems over a glass of beer. The same was true of his friend William S. Gosset (better known as "Student"), of whom a colleague* commented, "To many in the statistical world 'Student' was regarded as a statistical advisor to Guinness's brewery; to others he appeared to be a brewer who devoted his spare time to statistics .... Though there is some truth in both these ideas they miss the central point, which was the intimate connection between his statistical research and the practical problems on which he was engaged." The work of Gosset and Fisher reflects the hallmark of good science, the interplay between theory and practice. Their success as scientists and their ability to develop useful statistical techniques were highly dependent on their deep involvement in experimental work.

REFERENCES AND FURTHER READING

Box, G. E. P. (1987) In memoriam: William G. Hunter, 1937–1986, *Technometrics*, **29** 251–252.

Two very important books about the use of statistical methods in scientific investigations are:

Fisher, R. A. (1925) *Statistical Methods for Research Workers*, Edinburg and London, Oliver and Boyd.

Fisher, R. A. (1935) *The Design of Experiments*, Edinburg and London, Oliver and Boyd.

For some further information on statistical communication and consulting see the following articles and the references listed therein:

Derr, J. (2000) *Statistical Consulting: A Guide to Effective Communication*, Australia, Duxbury.

Chatfield, C. (1995) *Problem Solving: A Statistician's Guide*, London, Chapman and Hall.

Bajaria, H. J., and Copp, R. P. (1991) *Statistical Problem Solving*, Garden City, MI, Multiface Publishing.

Hoadley, A., and Kettenring J. (1990) Communications between statisticians and engineers/physical scientists, *Technometrics*, **32**, 243–274.

*L. McMullen in the foreword to "*Student's" Collected Papers,* edited by E. S. Pearson and J. Wishart, University Press Cambridge, London, 1942, issued by the Biometrika Office, University College, London.

Kimball, A. W. (1957) Errors of the third kind in statistical consulting, *J. Am. Statist. Assoc.*, **57**, 133.

Daniel C. (1969) Some general remarks on consultancy in statistics, *Technometrics*, **11**, 241.

Examples of "nonsense correlation" similar to the one in this chapter about storks and the birth rate are contained in:

Hooke, R. (1983) *How to Tell the Liars from the Statisticians*, Dekker, New York.

Huff, D. (1954) *How to Lie with Statistics*, Norton, New York.

Tufte, R. (1983) *The Visual Display of Quantitative Information*, Graphics Press, New York.

For discussion and illustration of iterative experimentation see, for example:

Box, G. E. P. (1976) Science and statistics, *J. Am. Statist. Assoc.*, **71**, 791.

Crouch, T. (2003) *The Bishop's Boys*, W. W. Norton, New York. (The Wright brothers' sequential experiments in developing and designing the first airplane.)

Deming, W. E. (1953) On the distinction between enumerative and analytic surveys, *J. Am. Stat. Assoc.*, **48**, 244–255.

Medawar, P. B. (1990) *Advice to a Young Scientist*, Sloan Science Series, Basic Books, New York.

Watson, J. D. (1968) *The Double Helix: A Personal Account of the Discovery of the Structure of DNA*, Touchstone: Simon & Schuster, New York.

Some useful references on statistical computing are:

Ross, I., and Gentleman, R. (1996). R, A language for data analysis and graphics, *J. Computat. Graphical Stat.*, **5**(3), 299–314.

R Development Core Team (2005). *R: A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing, Vienna, Austria. http://www.R-project.org

NIST/SEMATECH e-Handbook of Statistical Methods, URL: http://www.itl.nist.gov/div898/handbook, 2005.

Some suppliers of statistical software useful for readers of this book are:

NIST/Dataplot URL: http://www.itl.nist.gov/div898/software.htm, 2005.

SCA: Scientific Computing Associates URL: http://www.scausa.com

JMP: The Statistical Discovery Software URL: http://www.jmp.com

MINITAB: Statistical Software URL: http://www.minitab.com

R: A Language and Environment for Statistical Computing URL: http://www.R-project.org

S-PLUS: Insightful S-PLUS URL: http://www.insightful.com/products/splus

QUESTIONS FOR CHAPTER 1

1. What is meant by the iterative nature of learning?

2. In what ways can statistics be useful to experimenters?

3. What is achieved by good statistical analysis? By good statistical design? Which do you believe is more important?

4. What are three common difficulties encountered in experimental investigations?

5. Can you give examples (if possible from your own field) of real confusion (perhaps controversy) that has arisen because of one or more of these difficulties?

6. Which techniques in this book do you expect to be most useful to you?

7. How should you use the techniques in this book?

8. Can you think of an experimental investigation that (a) was and (b) was not iterative?

9. Read accounts of the development of a particular field of science over a period of time (e.g., read the books *The Double Helix* by J. D. Watson and *The Bishops Boys* (the Wright brothers) by T. D. Crouch, 1989). How do these developments relate to the discussion in this chapter of a scientific investigation as an iterative process? Can you trace how the confrontation of hypotheses and data led to new hypotheses?