Aspects of statistical consulting not taught by academia

R. Kenett*

KPA Ltd, Raanana, Israel and University of Torino, Torino, Italy

P. Thyregod

Technical University of Denmark, Lyngby, Denmark

Education in statistics is preparing for statistical analysis but not necessarily for statistical consulting. The objective of this paper is to explore the phases that precede and follow statistical analysis. Specifically these include: problem elicitation, data collection and, following statistical data analysis, formulation of findings, and presentation of findings, and recommendations. Some insights derived from a literature review and real-life case studies are provided. Areas for joint research by statisticians and cognitive scientists are outlined.

Keywords and Phrases: statistical consulting, graphs, problem solving, interpersonal skills.

1 Introduction

Statistical consulting involves many aspects typically not covered by statistical educational programs. The objective of this paper is to explore these issues by combining a review of the literature with real-life examples. The paper is organized around a five-step statistical consulting process model derived from the experience of the authors.

In the Encyclopedia of Statistical Sciences (Kotz *et al.*, 2005) Brian Joiner states that a statistical consultant, to be fully effective, should have many diverse skills. Ideally, he or she should:

- Have a genuine desire to solve real problems and help others to solve problems.
- Be able to help investigators formulate their problem in quantifiable terms.
- Be able to listen carefully and to ask probing questions.
- Have a broad knowledge and true understanding of statistical and scientific methods.
- Be able to adapt existing statistical procedures to novel environments.

---

*ron@kpa.co.il

- Be able to locate or develop good statistical procedures in a timely fashion.
- Be able to keep abreast of developments in statistics.
- Be willing to meet deadlines, even if it requires substantial extra effort.
- Be able to understand something about the clients' subject matter and speak a bit of the clients' language.
- Be a good teacher—much success in consulting depends on being able to help others understand statistical tools, and their strengths and weaknesses.
- Be willing to settle for a reasonably correct approximate solution, then go on to the next problem.
- Be able to identify important problems (and thus avoid spending too much time on projects of little significance).
- Have the confidence to use as simple a procedure as will get the job done, be it design or analysis.
- Be able to convince others of the validity of a solid solution and see to it that proper action is taken.
- Be able to use computers effectively and direct others in their use.
- Be a good problem solver.
- Be willing to meet clients regularly on their home ground, and take the responsibility to meet and communicate with all members of the working team.
- Be diplomatic and know when to bend, when to stand firm, and how to help smooth conflicts over among other team members.
- Be willing to get some experience in the actual collection of the data.
- Be willing to take the time to check and double-check procedures and results.
- Be able to communicate effectively in writing as well as orally (this often includes helping clients write their reports as well).
- Be able to make a good estimate of how much effort will be required to solve the problem without actually having to solve the problem itself.

Over the years, the statistics community has addressed the skills needed for successful consultancy operations, and the teaching of these skills, see, e.g. SNEE *et al.* (1980), MARQUARDT (1981, 1987), HUNTER (1977) and BASKERVILLE (1981). For a bibliography of literature prior to 1977 see WOODWARD and SCHUCANY (1977). To some extent, these efforts have influenced courses in statistical consulting, see KENETT and STEINBERG (1987) and TAPLIN (2003) for references to courses for students who are at an early stage in their studies.

Despite the fact that statistical science has been developed in a fruitful interaction with subject matter application fields, the so-called "examples" in textbooks and methodological papers serve to illustrate the computations associated with a specific technique rather than the solution of a problem from real life. A quote attributed to A. Ehrenberg articulates this observation: "*I feel that the kind of examples of statistical analysis that tend to be considered in professional discussions are so grossly over-simplified as to make a pretentious mockery of real-life situations and statistical consultancy*".
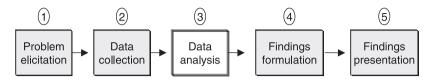
Fig. 1. The statistical consulting cycle (steps covered in this paper are emphasized).

In general, the statistical consulting cycle involves five main steps including:

1. problem elicitation;
2. data collection and/or aggregation;
3. data analysis using statistical methods;
4. formulation of findings their consequences and derived conclusions;
5. presentation of findings and conclusions/recommendations.

This article is focused on Steps 1–2 and 4–5 (see Figure 1). Typical courses on statistics taught by academia focus only on Step 3. Our long-term objective is to encourage academic courses to cover the full 1–5 cycle. We begin by a brief literature review to set the stage for our discussion in later sections. The review is neither meant to be exhaustive nor comprehensive; its purpose is to provide a suitable backing to our analysis and suggestions.

2   Literature review

KIMBALL (1957) introduced the concept of errors of the third kind in statistical consulting to denote *the error committed by giving the right answer to the wrong problem.* Such an error does not only occur when the consultant knowingly sells "snake oil", but also in other situations where the consultant fails to identify the core problem.

MARQUARDT (1981) suggested criteria for evaluating the performance of internal statistical consultants in industry. It should not come as a surprise that one of these criteria was an *impact on the success of the company*, frequently quantified in terms of money. A similar point of view is used in the selection of six-sigma projects.

TRIBUS (1989) points out that enterprises that intend to compete in world markets will find it essential to be managed in the new style where statistical reasoning plays an essential role. The applications that will be posed are often quite different from those for which statisticians have been trained. In the transition process, statisticians will need to learn to be mentors as well as advisors.

DRANSFIELD, FISHER and VOGAL (1999) expands in more detail this view on the role of statistical thinking, and the challenge for statisticians taking part in this process of management change.

Table 1. Types of consulting engagements (from McLachlin, 2000).

	Types of consulting engagements	
	Core needs addressed	Core needs not addressed
Expectations met	*Meaningful engagement* Example: consultant diagnoses and implements changes in core operation capabilities	*Clean contract* Example: consultant organizes and delivers a seminar, as promised
Expectations not met	*Unstable relationship* Example: consultant reports a correct diagnosis that the boss/client is the real problem	*Outright failure* Example: consultant sells whatever is in the toolkit (snake oil) without regard for client

Kenett and Zacks (1998) present as a preamble to their book on *Modern Industrial Statistics* different approaches to the management of industrial organizations using a four-steps Quality Ladder, namely: (1) fire fighting; (2) inspection; (3) process control; and (4) quality by design and strategic management. To each management approach corresponds a particular set of statistical methods and the quality ladder maps management approach onto corresponding statistical methods.

Managers involved in reactive fire fighting need to be exposed to basic statistical thinking. Managers attempting to contain quality and inefficiency problems through inspection and 100% control can have their tasks alleviated by implementing sampling techniques. More proactive managers investing in process control and process improvement are well aware of the advantages of control chart and process control procedures. At the top of the quality ladder is the quality by design approach where up front investments are secured to run experiments designed to impact product and process specifications. At that level, reliability engineering is performed routinely and reliability estimates are compared with field returns data to monitor the actual performance of products and improve the organizations' predictive capability. Efficient implementation of statistical methods requires a proper match between management approach and statistical tools management system.

McLachlin (2000) discussed service quality in general consulting engagements, and considered the distinction between meeting client expectation and addressing client needs. Often these concepts overlap, but they may be differentiated as sketched in Table 1. Outright failure occurs when the consultant sells whatever is in the toolkit (snake oil) without regard for client. In such a situation, core needs are not addressed, and it is most unlikely that snake oil will meet customers' implicit expectations. One of the conclusions of that paper was that it is risky to ask a consultant to both determine one's need and to implement solutions. However, as this is the common situation in statistical consulting, this puts even more emphasis on the skills and integrity of the consultant.

Kenett and Albert (2001) provide a general framework for planning and deploying corporate initiatives, such as Six Sigma, in global companies. They focus on the task of translating quality concepts into different cultures that requires knowing **what** to do, **why** it should be done and **how** to do it.

HAHN (2003), in his Youden address at the 47th Fall Technical Conference, presents a list of what an "embedded statistician" brings to global corporations:

- Expertise in:
  - quantitative problem definition;
  - proactive data acquisition;
  - tools for data analysis;
  - communicating the results in an understandable manner.
- A systems-oriented approach:
  - understanding of the big picture;
  - appreciation of variability;
  - catalysts and potential advocates for change.
- Some promising technical arenas:
  - up-front reliability improvement (Meeker's "other dimension of quality");
  - "just-in-time" maintenance;
  - business processes and commercial transactions.

KENETT, COLEMAN and STEWARDSON (2003) discussed the concept of practical statistical efficiency (PSE) and suggest a quantitative formulation of PSE for assessing the impact of solutions provided, for example, by improvement projects. PSE considers the overall impact of the proposed statistical solution, both short term and long term.

2.1 Step 1: problem elicitation

Like doctors, statisticians also are exposed to being consulted at dinner tables. The consultation often starts with "You are a statistician, so this will only take you a minute", and then you are presented with some fragment of a statistical procedure and asked your expert opinion about whether it is correct or incorrect. Like "*I am in the nuts and bolts business. What kind of statistics do I need for that, t-tests or regression analysis?*" GREENFIELD (1987) presents some humoristic examples of similar encounters illustrating the widespread opinion of many clients that a consultation with a statistician is not very different from a consultation with a dentist: you give him a hint about your symptoms, you are placed in the chair, he looks into your mouth, diagnoses and solves the problem, all in less than an hour.

BISGAARD and BISGAARD (2005) outline three different consulting roles:

- a pair of hands;
- the expert;
- the catalyst/collaborator/coach.

In either of these roles, it is important that the consultant is aware of the client's expectations as well as his needs. They are not necessarily clearly formulated by the client. Often a collaborative effort is needed to have them unearthed, but the consultant has a major part of the responsibility for this. When a project terminates

with the consultant saying "*They never said they needed that! How was I supposed to know?*, he himself is the one to blame.

It is a challenge to be an active listener. One should listen carefully and ask probing questions to check your own understanding, and to check the consistency in a client presentation. A consultant should keep the customer focused, and yet not forget relevant details. Process maps often serve as a useful tool for structuring the presentation. Moreover, process maps should be supplemented by walking around in the process area. Going to the location where data is collected typically provides more insights on possible sources of variation.

The legendary American consultant in industrial statistics, Cuthbert Daniel, when interviewed about his consulting experience (TUFTE, 1988) used the quote "*You can observe a lot by watching*".

One should read the clients body language. Maybe he has a hidden agenda and hides some information from you. Might be that he wants you to cover up for some internal blunders, or that he wants you to settle an internal dispute in the company.

Sometimes, as a statistical consultant, your client makes an effort to formulate his problem in – what he considers to be – statistical terms. In such cases, diplomacy is needed to get him to reformulate the problem in his own technical language and leave it up to you to make the translation.

DANIEL (1969) noted that sometimes the problem is not clearly formulated until the intervention of consultant, and that the consultant's help on this matter may later be judged to be his major contribution.

HUNTER (1979) in a personal communication to the first author, described that two chemists entering his office, when asked to describe the problem they came to get advice on, entered a lengthy discussion that eventually lead to a common reformulation of the problem. Once they had the problem clearly formulated they knew how to solve it and did not need the help of a statistical consultant any more.

2.2 Step 2: data collection

COBB and MOORE (1997) argued that "Statistics requires a different kind of thinking, because *data are not just numbers, they are numbers with a context*". Sometimes the term *metadata* is used to denote the context domain. However, very few textbooks address the mapping between the context domain of a real problem and abstract statistical models.

KENETT (2006) addressed the issue of context in designing survey questionnaires. Research in cognitive science has shown that self-administered questionnaires are sensitive to the context generated by the sequence and type of questions of the questionnaire. One implication is that in customer satisfaction surveys, overall satisfaction questions positioned after questions on specific issues provide for better control and interpretability. Such an ordering provides a context that focuses respondents on what the overall satisfaction question is meant to measure.
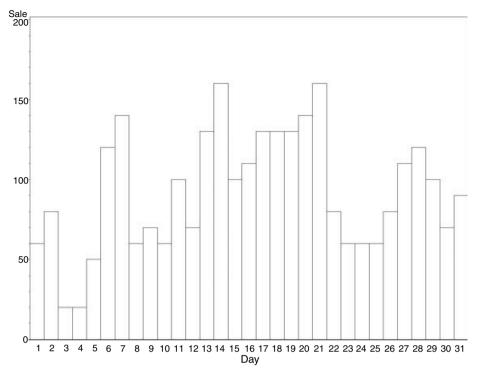
Fig. 2.   Ice cream vendor's daily recordings of the number of ice creams sold in July.

The importance of context is illustrated in Figure 2. The graph is reproduced from an exercise in a textbook for fourth grade pupils in a Danish school.

The pupils were asked the following questions:

- For each day in July an ice cream vendor recorded the number of ice creams sold. The recordings are shown in Figure 2.
- Determine which days are Sundays
- In July it was very hot for a period of nine consecutive days.
- Determine which days.

The graph in itself is just a representation of 31 numbers. However, given the context, and the associated implicit information (weekly calendar cycle with fathers more inclined to offer ice cream treats in week ends, and on sunny days), it is possible even for these young children to separate signal from noise in this set of 31 numbers. The pupils are able to solve this elementary statistical exercise because even these young children have an understanding of variation, and the effect of various sources of variation, and moreover, they have the ability to distinguish between the effects of different patterns of variation.

Using the terminology of Walter Shewhart, one would say: They are able to identify systems of causes, and separate the effect of a constant system of chance causes (noise), from the variable systems of causes, the cyclic pattern of the weekdays, and

the 9-day spell of hot weather. Unfortunately, these abilities are sometimes lost when the children continue through the educational system.

In university courses, students seldom take part in the collection of data. Usually in textbooks and course material, a set of numbers is presented to the students, and a rudimentary context description is provided that mainly serves to indicate the type of standard statistical analysis intended. This practice has led some graduates to be of the opinion that taking part in the collection of data is a waste of the statistician's precious time, and it even implies the risk of getting dirt on your hands. Also, the practice has given rise to the caricature statistician sitting isolated in his cell, receiving data in his mailbox, and sending a smoke signal when he has finished his "analysis" without any other communication with the client.

The context domain of data is revealed where data are generated, on the shop floor, in the laboratory, etc. Therefore, to be able to respond properly to the needs of the client, it is important to take part in the collection of data, or at least have the opportunity to watch data being collected or generated. Do not rely on your client telling the whole story. Not that he deliberately hides information, but to him some features are just as obvious as the repetitive pattern of the week in the example above, and, therefore, he forgets to bring them forward.

The client is the subject matter expert with knowledge and experience, the statistical consultant is an expert in treating variation and the transfer of variation. Therefore, when visiting the customer premises, the consultant should be on guard for all sources of variation, and either literally or just mentally sketch an Ishikawa diagram listing these sources, and indicating their nature and their dynamics such that they can be adequately represented in the data. Like a detective looking for clues, the statistical consultant should be alert in looking for sources of variation. This does not necessarily mean that all sources of variation should be effective within the whole range represented in the data, but one should carefully consider whether this source can be controlled, or not, and whether one wants to include the potential effect of this variation, or not. Also, one should make sure that traceability is secured. Individual parts should be traceable, measurements should be traceable to the measuring device, and the calibration history of measuring devices should be recorded and be available.

The statistical consultant should not confuse high-frequency and low-frequency variation. In control chart applications, for example, it is sometimes seen that a subgroup of four items is used to represent an hour's production but that all four are taken consecutively at the same time instant. In such cases the within subgroup variation only represents the (small) instantaneous high-frequency variation. The "natural" variation of the process might better be represented by the low-frequency variation, with samples taken at equal intervals within, say, an hour.

Often the client has data relating to the issue that will give you valuable insight in the order of magnitude of variation because of various sources. It might even have the potential to solve the problem as shown in the following examples reported by ABRAHAM and BRAJAC (1995).

2.2.1 The automobile part example

An automobile part is produced by injection moulding followed by baking and other finishing process steps. The moulding is performed in three parallel streams. Suddenly the reject rate of the part due to cracks increased dramatically, and as a result of this increase, it was decided to investigate the process. The engineers from the plant had just completed a course in Design of Experiments, and were eager to practice their newly acquired skills. Therefore, they designed a rather comprehensive 32-run experiment with 11 factors focusing on injection moulding machine factors like speed, clamp time, etc. Very little was learned from the experiment that could reduce the scrap rate, and, therefore, a second experiment was planned to focus on differences in moulds. This experiment clearly demonstrated that most of the scrap came from one mould, and in the search for the root cause it was discovered that during routine maintenance some minor changes had been made to one of the moulds, and that these changes were the source of the problem.

In hindsight, the team realized that as each part carried a mark indicating which mould produced the part, the problem could solved without experimentation. As the plant was having high rates of scrap, it would have been rather easy to use the existing data and utilize the traceability of the parts to the mould. A histogram of scrap by mould would have revealed that scrap was not evenly distributed over the moulds, and clearly identify the culprit.

Although the production in parallel streams strongly suggested that stratification would be a meaningful analytical tool, the power of this simple analysis on existing data was overlooked in the eagerness of the team and the consultants working with them to perform an experiment.

2.2.2 The rubber compounding example

In another case, reported by the same authors, a manufacturer was conducting an experiment in a rubber compounding process. The purpose of the experiment was to identify the factors which were important in controlling the process so that the plant could implement more effective process control plans. The company had assembled a multi-disciplinary team that included chemists, engineers, quality assurance, and the operators of the process. One group (the chemists) were not convinced of the idea of performing designed experiments, and insisted on what appeared to be a very narrow range for the factors levels. One of them even suggested that the corresponding factor should be left out of the experiment. The remainder of the team insisted that the factor was important and should be included in the experiment. The team became deadlocked and turned to the consultants working with them for help. The consultants also felt that the range was too narrow, but lacked supporting data. Fortunately, although the company was poor in information, it was rich in data. The consultants reviewed process history data and found that there was a great deal of variation in the level of the factor, and presented a chart showing the operational variation of the factor over time. After examination of the chart, the

chemists relented and more reasonable levels were chosen. Thus, because data was available, the choice of factor levels could be based on facts rather than just feelings.

One should listen very carefully to the persons with the process knowledge. The statistical consultant should be open-minded and humble towards their experience, and realize that it is a collaborative effort to obtain relevant data, and therefore, as the following example shows, it is also important that he challenges their knowledge.

2.2.3 The rolling bearings example

In the early 1980s, SKF, the world's largest manufacturer of rolling bearings with manufactures in 14 countries experienced problems with a standard bearing design that was not performing satisfactorily in a certain application. It was decided to use a full two-level factorial design to investigate the effect of varying design parameters. The three factors selected were heat treatment, outer ring osculation and cage design.

HELLSTRAND (1989) had reported the experimental design and the experimental result. According to statistical folklore, the engineers were very reluctant to include the cage design as an experimental factor because they felt convinced that the rather expensive cage design presently in use was superior to a cheaper alternative. One would think that this company that had been world leader for decades knew their product and processes so it would be a waste of time not to trust their belief, but investigate this cheaper alternative. However, the experimental data revealed that the choice of cage design did not make a lot of difference, and as a consequence the design was changed which resulted in great savings.

The context domain of data associated with an experiment contains the whole idea of experimenting including experiences from conducting designed experiments. It is important that all this information is shared among the whole team. It is an almost classical mistake to forget to involve the operators of a process in the planning of experiments to be performed on real processes. When operators have not been part of the planning team, it is most likely that they will react to process output and make adjustments to the settings when they observe unsatisfactory process output. The conflict in this situation is that if the operator changes settings in the middle of an experimental treatment, the result for that treatment would be confounded. However, the operators' reaction should come as no surprise because operators have been trained to avoid producing scrap. Therefore, communication within the whole team, including operators is important. When operators are told that "*In order to understand how to make good product, we must learn how bad product is made*", it is more likely that they will follow the experimental procedure.

It is a collaborative effort and responsibility to collect data that reflects the variation that is relevant to the problem in hand. One should listen carefully to the people with the process experience, and use engineering knowledge and understanding combined with statistical skills to assure that all relevant data are collected and properly organized in the database.

Finally, we should mention again the role of interpersonal relationship. It is important to recognize possible interpersonal anxiety. When the client's and the consultant's intentions or personal and professional goals conflict, it is likely to result in ineffective consulting sessions.

As mentioned in Section 1, this paper does not cover aspects related to Step 3, i.e. data analysis using statistical methods, and we, therefore, move immediately to Step 4.

2.3 Step 4: formulation of findings

Statistical analysis produces outputs with various features such as *P*-values, standard errors, regression models, principal components, discriminant score functions, ANOVA tables, control charts, descriptive statistics. To translate statistical results into relevant findings, careful formulation of findings is required. To carry out this translation process, cognitive science can be invoked again. We initially referred to cognitive science when discussing survey questionnaire design (KENETT, 2006). In the formulation of findings we need to translate features into benefits and eventually core values. REYNOLDS and GUTMAN (1988) provides an introduction to "laddering", originally a marketing methodology used to design and position products and services. The methodology relies on cognitive science where means-end chains have been studied for achieving such a mapping. The approach can also be used to formulate findings from statistical data analysis. For example, if a control chart indicates a point out of control, the process engineer should launch an investigation to characterize the possible out-of-control condition that this signals. The immediate benefit for the process engineer is that, by sending early warning signals, he performs his role professionally and gets the recognition he deserves. If that engineer has, as a core value, satisfaction from his professional responsibility, we have completed the means-end chain, linking feature to benefit and value.

The formulation of findings is a conscious effort to translate statistical reports into the language of the customer. It involves identifying consequences of the findings of importance to the customer and requires an understanding of the context of the problem investigated and effective communications and intensive interaction with the customer. In that context, statistical consultants are many times drawn into organizational internal issues where their findings are instrumental in setting internal disputes over responsibility for problems and budget allocation.

2.4 Step 5: presentation of findings

At this final step, the consultant should demonstrate that he is worth his money by effectively communicating his findings to the client. For the communication to be effective, it is important to use the language of the customer, and not to distract attention from the problem. Concepts and models from mathematical statistics will usually restrain communication, and should, therefore, be avoided.

For most people, graphical displays are more effective communication tools than mathematical formulae. Findings that cannot be demonstrated in a graph are probably not worth communicating. One should, however, keep graphs and slides simple and avoid the temptation to overload them with unnecessary "information" like logos, fancy symbols, etc.

2.4.1 Use of graphs: the Challenger disaster

One virtue of a good graphical display is to allow us to see patterns, trends or other structures which would otherwise be concealed. It may be heartbreaking to find out that some important information was there, but the graph designer missed it. The story behind the Challenger disaster is perhaps the most poignant missed opportunity in the history of statistical graphics. Such failures often provide useful lessons.

The US space shuttle Challenger exploded 73 seconds after take-off on 28 January 1986, and all seven crew members were lost. Subsequent investigation determined that the cause was failure of the O-ring seals that were used to isolate the fuel supply from burning gases.

For some time, engineers from Morton Thiokol, manufacturers of the rocket motors, had been worried about problems with the O-ring seals. They feared that low temperatures greatly and adversely affected the ability of O-rings to create a seal on solid rocket booster joints. On the night before the flight, the temperature predicted at launch time was $-3°C$, and the engineers expressed their concerns over the effect of the unseasonable cold weather on the O-rings and suggested to abort the flight. A telephone conference among NASA engineers and managers and Thiokol engineers and managers was quickly summoned. With short notice the Thiokol engineers presented their case via 13 telefaxed charts and their commentary and argument, but they failed to convince the managers that temperature was a factor in O-ring performance or damage, and it was decided to go ahead with the launching.

Lighthall (1991) has analyzed the organizational effectiveness of this process leading to the decision not to delay the launching. To have averted the disaster would have required both a perceptive analysis and an effective presentation. Lighthall argues that they did neither. Neither the 13 charts circulated to the teleconferences nor the participants' commentary focused on a relationship between the 22 available launch temperatures and the 22 recordings of O-ring conditions for previous launches. Nor did anyone at the teleconference ask for or make reference to either (1) temperature data on non-damaged flights, or (2) the full set of pairs of temperature-damage data points from all flights to date.

Tufte (1997) in his book about envisioning information makes his central argument in a chapter discussing the misrepresentation of data related to the Challenger disaster. He criticizes several of the data displays and suggests a rather simple display with temperature as the *x*-variable and O-ring condition on the *y*-axis. Such a chart would clearly have demonstrated that some type of O-ring failure had occurred on all launches below $18°C$. Such clear demonstration of the relationship between low

Challenger Space Shuttle, O-ring failures
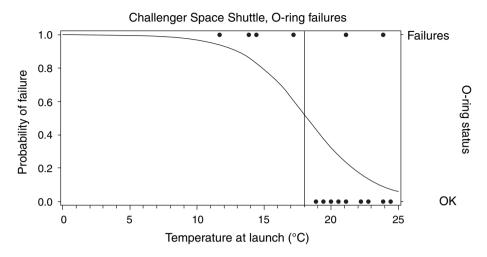

Fig. 3.   O-ring status versus temperature at launch for the 22 launches prior to the launch on 28
           January 1986. Failures had occurred on all launches below 18°C (vertical line). The curve
           indicates the predicted probability of failure fitted by a logistic regression.

temperature and O-ring failure might have convinced NASA officials not to launch the shuttle. Figure 3 is an example of such a chart.

When properly analyzed and displayed the information in the data from the previous launches is so strong that the Challenger case is used as an example in many statistics courses. Although the data speak by themselves even without further analysis, the example is often used to introduce logistic regression models, see, e.g. DEVORE (2004). A logistic regression model would be an appropriate parametric model for the probability of failure as a function of temperature. In Figure 3, the estimated logistic regression curve has been added to the simple graph of failures and no-failures.

2.4.2 Use of presentation software: the PowerPoint effect

Usually the consultant presents his findings at a meeting with a group of representatives from the client. With the widespread availability of presentation software and projectors, it is often seen that the engineering presentation in PowerPoint is also used to substitute a proper technical report. This is not to be recommended. The cognitive style that is appropriate for a presentation is different than the style of a technical report.

Unfortunately, presentation software like PowerPoint, with its excess of styles, templates, fonts and animations, is encouraging presenters to spend too much time on the prettifying of their work and distracting them from the meaningful development of contents and of clarity to enhance perception.

GODIN (2001) provides illustrative examples of bad PowerPoint presentations and suggests various dos and don'ts. He warns against using the slides as a teleprompter,

and suggests instead writing cue cards to make sure that you are saying what you came to say, and to make slides that reinforce your words rather than repeat them. Communication is about getting others to adopt your point of view, to help them understand why you are excited. The audience uses both sides of the brain, the analytical left side as well as the emotional right side. Your presentation should address both sides. You can use the screen to talk emotionally, and your words to talk to the left brain. Consequently, there is no need to hand out printouts of your slides. Instead, Godin suggests that you create a written document with as many footnotes and details as you like, and at the start of the presentation tell the audience that you will give them all the details after it is over, and they do not need to write down everything you say, but they can – and shall – concentrate on the presentation.

TUFTE (2005) reports his observations as a NASA consultant on technical presentations for shuttle risk assessments, etc. and notes the lack of formal engineering information and documentation resulting from the widespread use of presentation slides in place of technical reports. The report of the investigation (COLUMBIA ACCIDENT INVESTIGATION BOARD, 2003) into the loss of the Space Shuttle Columbia concludes that the NASA management practices constitute a major cause of the accident. One of these practices was "Engineering by Viewgraphs" where technical documentation consisted of slide presentations where every single text slide used bullet-outlines with four to six levels of hierarchy, and then another list of bullets starts afresh for a new slide. On p. 191 of the report the Board makes the following observation "*In this context it is easy to understand how a senior manager might read this PowerPoint slide and not realize that it addresses a life-threatening situation*", and further "*The Board views the endemic use of PowerPoint briefing slides instead of technical papers as an illustration of the problematic methods of technical communication at NASA*".

Godin's emphasis on using a cognitive style for presentation that differs from the documentary style in technical reports makes perfect sense in the light of these observations. Also, it is understandable that GODIN (2001) rather provocatively warns against putting more than six words on a slide.

3 Conclusions

This paper is an attempt to demonstrate, through examples, different aspects of the full statistical consulting cycle.

The paper has focused on:

- problem elicitation;
- data collection;
- formulation of findings;
- presentation of findings.

The examples indicate that effective statistical consulting is much more than properly applying statistical methods. In particular, we have tried to emphasize that

statistical consulting is a collaborative venture whose success depends essentially on the effectiveness of the communication between the consultant and the client. The consultant needs to exercise social and communicative skills outlined in the introduction for his consultancy work to be successful.

Further joint research of statisticians with experts in cognitive science on topics such as data collection, especially in survey data, and formulation of findings, can lead to breakthrough developments. Moreover collaborative work of statisticians with computer scientists on modern data display technology is already generating new approaches for data analysis, especially when accounting for multi-dimensional data.

Perhaps the overall insight from this work is that statistical consulting in particular and statistical science in general are necessarily collaborative exercises. Hopefully, we will have helped stimulate such initiatives.

References

ABRAHAM, B. and M. BRAJAC (1995), *Real experiments, real mistakes, real learning!*, Research Report 95-05, The Institute for Improvement in Quality and Productivity, Waterloo, ON, Canada.

BASKERVILLE, J. C. (1981), A systematic study of the consulting literature as an integral part of applied training in statistics, *The American Statistician* **35**, 121–123.

BISGAARD, S. and S.-E. BISGAARD (2005), ENBIS workshop on statistical consulting and change management, Newcastle, UK, Available at: http://www.enbis.org/Workinggroups/consultancy/ws_consultancy_05.html (12 December 2005).

CAMERON, J. M. (1969), Statistical consultant in scientific laboratory, *Technometrics* **11**, 247–254.

COBB, G. W. and D. S. MOORE (1997), Mathematics, statistics, and teaching, *American Mathematical Monthly* **104**, 801–823.

COLUMBIA ACCIDENT INVESTIGATION BOARD (2003), Report volume 1, Superintendent of Document, US Government Printing Office, Washington, D. C. Available at: http://caib.nasa.gov/news/report/volume1/chapters.html (12 December 2005).

DANIEL, C. (1969), Some general remarks on consulting in statistics, *Technometrics* **11**, 241–245.

DEMING, W. E. (1965), Principles of professional statistical practice, *Annals of Mathematical Statistics* **36**, 1883–1900.

DEVORE, J. L. (2004), *Probability and statistics for engineering and the sciences*, 6th edn, Brooks/Cole Publishing Company, San Francisco.

DRANSFIELD, S. B., N. I. FISHER and N. I. VOGEL (1999), Using statistics and statistical thinking to improve organisational performance, *International Statistical Review* **67**, 99–122, Discussion on pp. 122–150.

GODIN, S. (2001), Really bad PowerPoint (and how to avoid it), Available at: http://www.sethgodin.com/freeprize/reallybad.html (12 December 2005).

GREENFIELD, T. (1987), Consultant's cameos: a chapter of encounters, in: D. J. HAND and B. S. EVERITT (eds.), *The statistical consultant in action*, Cambridge University Press, Cambridge, 11–25.

HAHN, G. (2003), *The embedded statistician*, W. J. Youden Address, 47th Annual Fall Technical Conference, El Paso, Tx.

HELLSTRAND, C. (1989), The necessity of modern quality improvement and some experience with its implementation of rolling bearings, *Proceedings of the Royal Society Industrial Quality and Reliability* **33**, 51–56.

HUNTER, W. G. (1977), Some ideas about teaching design of experiments, with 2sup5 examples of experiments conducted by students, *The American Statistician* **31**, 12–17.

HUNTER, W. G. (1979), *Private communication to RSK*, Madison, WI, USA.

KENETT, R. S. (2006), On the planning and design of sample surveys, *Journal of Applied Statistics* **33**, 405–415.

KENETT, R. S. and D. ALBERT (2001), The international quality manager, *Quality Progress* **July**, 45–51.

KENETT, R. S. and D. M. STEINBERG (1987), Some experiences teaching factorial designs in introductory statistics courses, *Journal of Applied Statistics* **14**, 219–228.

KENETT, R. S. and S. ZACKS (1998), *Modern industrial statistics: design and control of quality and reliability*, Duxbury Press, San Francisco, CA.

KENETT, R. S., S. COLEMAN and D. STEWARDSON (2003). Statistical efficiency: the practical perspective, *Quality and Reliability Engineering International* **19**, 265–272.

KIMBALL, A. W. (1957), Errors of the third kind in statistical consulting, *Journal of the American Statistical Association* **57**, 133–142.

KOTZ, S., B. CAMPBELL, N. READ and B. V. BALAKRISHNAN (2005), *Encyclopedia of statistical sciences*, 2nd edn, John Wiley and Sons, New York.

LIGHTHALL, F. F. (1991), Launching the space shuttle Challenger: disciplinary deficiencies in the analysis of engineering data, *IEEE Transactions on Engineering Management* **38**, 63–74.

MARQUARDT, D. W. (1981), Criteria for evaluating the performance of statistical consultants in industry, *The American Statistician* **35**, 216–219.

MARQUARDT, D. W. (1987), The importance of statisticians, *Journal of the American Statistical Association* **87**, 1–7.

MCLACHLIN, R. D. (2000), Service quality in consulting: what is engagement success?, *Managing Service Quality* **10**, 239–247.

REYNOLDS, T. J. and J. GUTMAN (1988), Laddering theory, method, analysis and interpretation, *Journal of Advertising Research* **28**, 11–31.

SNEE, R. D., T. J. BOARDMAN, G. HAHN, W. J. HILL, R. R. HOCKING, W. G. HUNTER, W. H. LAWTON, L. R. OTT and W. STRAWDERMAN (1980), Preparing statisticians for careers in industry: report of the ASA Section on Statistical Education Committee on training of statisticians for industry. *The American Statistician* **34**, 65–75, Discussion on pp. 76–80.

TAPLIN, R. H (2003), Teaching statistical consulting before statistical methodology, *Australian & New Zealand Journal of Statistics* **45**, 141–152.

TRIBUS, M. (1989), The statistician's stake in the managerial revolution, *Philosophical Transactions of the Royal Society of London*, Series A **327**, 487–497.

TUFTE, E. R. (1988) A conversation with Cuthbert Daniel, *Statistical Science* **3**, 413–424.

TUFTE, E. R. (1997), *Visual explanations: images and quantities, evidence and narrative*, Graphics Press, Cheshire CT.

TUFTE, E. R. (2005), Power Point does rocket science, *The Work of Edward Tufte and Graphics Press*, September 6, 2005. Available at: http://www.edwardtufte.com/bboard/q-and-a-fetch-msg?msg_id=0001yB&topic_id=1&topic=Ask+E%2eT%2e (12 December 2005).

WOODWARD, W. A. and W. R. SCHUCANY (1977), Bibliography for statistical consulting, *Biometrics* **33**, 564–565.