

EDUCATION PROGRAMMES AND TRAINING
IN STATISTICS

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THE ROLE OF CONSULTANCY IN UNIVERSITY EDUCATION AND PROFESSIONAL TRAINING IN STATISTICS

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1. Introduction

Statistical education and training at tertiary level encompasses a very wide range of activities. There are the short "service" courses for students studying, say, engineering or medicine or politics (often of just 10 or 20 hours providing familiarisation with basic concepts or instruction in particular techniques e.g. testing or regression) often nowadays linked to some computational software system. At the next level we encounter in some disciplines such as agriculture, economics or social sciences, a number of "designer" courses spanning a fair proportion of the study time, perhaps up to one third of the overall programme. Finally, there are full statistics programmes for students of statistics *per se* (or mathematics programmes oriented to non-deterministic mathematics) where most of the study time is spent on the concepts, methods and practice of probability and statistics, with the inevitable supporting coverage of relevant mathematical material.

We shall be concerned in this paper specifically with the education and training of *professional statisticians*: those who will make their career in developing statistical science and/or solving statistical problems on a day to day basis. These are not likely to be found in our first category above. The second category will yield some, but in highly specific form perhaps as *biometricians*, *econometricians* or *psychometricians*. The majority of the professional statistical fraternity particularly those who will ply their trade and do methodological (or even conceptual) research across the disciplines will come from the third category. Here is the dilemma! There is a fundamental conflict of aim (or at least of interpretation) in the statistical education and training of this group, which usually takes place through the avenue of the universities.

What is this conflict? All would agree that it is important to encompass the variety of aspects of the subject:

- (i) *concepts and principles*
- (ii) *methodology*
- (iii) *applications and practice*

and that each requires appropriate in-depth coverage. The conflict arises in the different interpretations of what is meant by "in-depth" and "coverage". Consider what happens in practice. Different departments are not all large enough, nor necessarily have the capability (or even the desire or time) to meet all the needs. Some may express through their teaching programmes quite different interpretations. Let us note some examples of this.

- (a) In presenting *concepts* and *principles* (and indeed methodology) there are differences of view on what are the appropriate background skills, e.g. in mathematics or computation. For some these involve detailed calculus, algebra, systems analysis, etc. at a high honours level. ("How can we start to deal with stochastic processes without extensive complex variable theory, or software engineering?"). For others a modest understanding of linear algebra and use of a few software systems may be felt to be adequate.
- (b) Wide-ranging exposure to *statistical methods* is crucial for the professional statistician. Does this mean statistical tests, confidence intervals and a few linear model methods; or does it extend to time series, multivariate analysis, nonparametric methods, survey sampling, spatial modelling, design of experiments, robust methods, Bayesian analysis, design theory, programming, specific statistical software systems, etc?
- (c) Coverage of "*applications*" is essential, and widespread *practice* of the techniques and methods is vital (otherwise it is akin to training an airline pilot on a flight simulator without ever letting the trainee in the cockpit of a plane). It is here that the greatest differences are to be found in what is regarded as appropriate "practical" experience. On some courses only occasional sterilised "practicals" are given. For example a one-way analysis of variance is explained and some numbers given on which to work out the sums of squares and to do an *F*-test. And "applications" might consist of remarking that some particular methods tend to be used in industry and medicine. Of course this is a parody! But how many programmes of study really stress the applications in real depth, have a comprehensive programme of practical case-study work from the beginning to the end, and have a structured professional approach to training the student to become a skilled

statistician for various workplaces (whether these are the pharmaceutical industry, the finance sector, the research bench or the university)?

Do I ask too much? Perhaps so! There is space for different aims and emphases and all-too-little time to achieve any of them. Such is the widely expressed response. This is not really good enough, however, and the big-wide-world is ever critical and demanding. One consideration is paramount and cannot be sidelined. Whatever the subsequent destination of the statistician, an ability to *use his knowledge* is vital for judicious choice of methods as are *research skills* for the inevitable demands of constantly needing to develop the subject for the practical environment. We should never forget that what we teach is essentially illustrative, not all-embracing. "Who has ever carried out a *t*-test on normal data, knowing that the data were in fact normal, and that such a basic procedure was fully adequate for the problem in hand?"

Of these three areas of conflict it is the question of what is the appropriate in-depth coverage of *practical statistical and applications* that is the most important, and where the greatest failure arises in many education and training programmes for statisticians.

We shall consider what the real needs are in this respect how they are sometimes not met and how the situation can be improved, particularly through close contact with consulting work. The general principles will be illustrated with examples from consulting experience.

2. The practical emphasis

About 20 years ago, from a university stance, I remarked: "a conflict ... can sometimes arise between the commercial pressures which demand a quick and easy answer and the academic aim of a full study and formal solution. We can detect some reluctance in the profession to 'soil hands' with messy real-life problems" (Barnett, 1976).

Nonetheless there is no doubt in my mind that the function of statistics is to solve real problems (across all subjects from agriculture, through medicine to zoology). The stimulus to research (however mathematical it may become) should be a practical one: the end product of statistical analysis is to clarify understanding of, or the taking of decisions in, down-to-earth problems involving indeterminism.

Let us consider an example where the premium was on a simple and quick answer.

Barnett and Hilditch (1993) describe such a problem in the context of *the*

use of artificial pitch (AP) surfaces in English football. The Football League was preparing a report (Football League, 1989) giving its future policy on whether APs should continue to be used in the four Divisions of the English Football League. The concern was that APs might confer an unfair advantage on the home team. To determine this they sought statistical evidence, requiring a *rapid response* from *limited data* on an *issue which was poorly reflected* in the database (very few teams had APs).

These were typical consulting difficulties but make good “case-law” for teaching practical statistics. Thus in the education and training of statisticians a central component must be instruction on how to answer real-life practical problems – to a deadline – across different disciplines – and with clearly understood answers.

The only data available in the football problem were the end of season results (points, outcomes, goals) for the four divisions over an eight-year period during which only 4 out of more than 80 teams used an AP (and then not for all the time). In fact only 362 out of 32468 games were played on an AP. Could we hope to detect an effect in such sparse data?

Results can be expressed in terms of *points* (3 for a win; 1 for a draw), *outcomes* (win, draw, lose) or *goals* (scored for each team in a match). These provide alternative (but not independent) measures of relative performance. Consider just *points*. The points scored at home and away for teams with home APs or NPs (natural grass pitches) were as follows (percentages of points scored at home and away are in parentheses):

	<i>Home</i>	<i>Away</i>
AP	718 (66.1)	368 (33.9)
NP	10860 (62.6)	6476 (37.4)

So we see that AP teams score a higher proportion of their points at home compared with NP teams (0.661 and 0.626, significantly different at 5%). Does this mean that using an AP confers an advantage? This is not immediately clear. Suppose *better* teams tended to score a lower proportion of their points at home, and AP teams tended to be *poorer* teams. We would expect to see the sort of effect observed without it necessarily reflecting in any way on use of AP. In fact the proportion of points scored at home $p_H / (p_H + p_A)$ did depend on team quality: see Fig. 1 (reproduced with permission from Barnett and Hilditch, 1993). It was also noted that the AP teams did not seem to cluster at the top or bottom of the division, so that such dependence might therefore not be too critical. However the dependence (between end-of-season league position and

proportion of points scored at home) sounded a cautionary note and it was felt necessary to seek measures of relative performance (*H versus A*), which were *not related to the intrinsic quality of the teams*.

This was studied for all three ways of expressing performance: points, outcomes, goals. Such positionally independent relative measures were found in each case. For points, the measure took a particularly simple

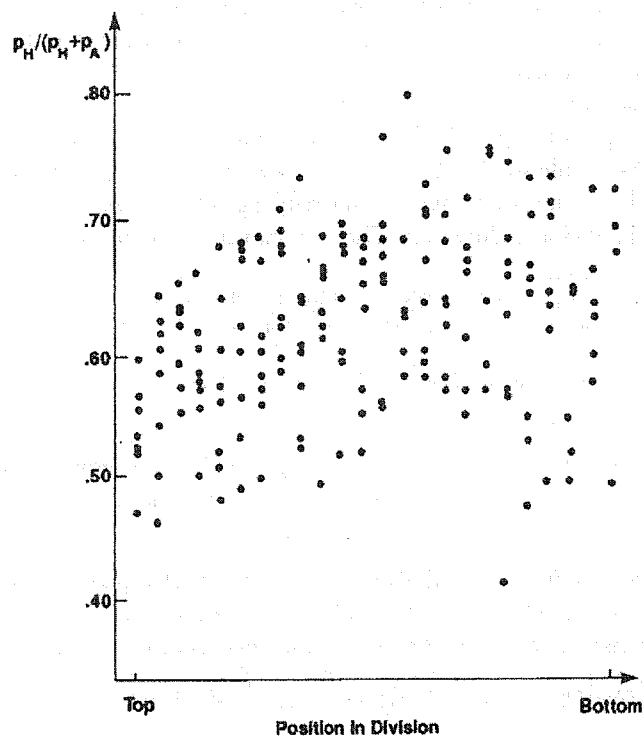


Figure 1. Points ratio and end-of-season positions (1987/88 and 1988/89)

form, $p_H - p_A$. The overall results in terms of average values of this measure yielded 1.50 for the AP group and 1.36 for the NP group, a highly significant difference.

We could be much more confident that we were seeing differential perfor-

mance more related to pitch effect (in that it is no longer confounded with team quality). It was not a trivial difference: the AP seemed to be worth about an extra 5-6 points (or 2 wins) per season.

3. Teaching practical statistics

The teaching of *practical statistics* is not straightforward; it is accordingly often played-down. Sometimes this is from genuine belief that fundamental philosophical, conceptual and mathematical components are paramount. More often it arises (I believe) from the lack of experience or confidence of the lecturer, who has probably never worked as a practical statistician or even faced a client across the consulting table.

Many have written on how to teach practical statistics in particular contexts (see for example: Bishop, 1964; Deane, 1964; Finney, 1968; Greenfield, 1979; Spicer, 1964). Anderson and Loynes (1987) present a detailed general study of this topic, basing it on a unique and powerful type of practical course that we pioneered in Sheffield University. They too start from the premise:

"Statistics as a subject is inseparable from its application and practice ..., any statistical education should take account of this connection".

Anderson and Loynes (1987) identify several components of practical training. These include:

- *drill exercises* (rather obvious methodology applied to simplified datasets with only limited reference to the practical environment: these must have a limited role to play);
- *statistical experiments* (practical problems set up in the teaching environment leading to data collection, analysis and report: important but time-consuming and necessarily rather remote from real-life in order to be manageable);
- *critical reading* (of well selected practical publications: a useful secondhand experience);
- *projects* (varying in size from 2 weeks to several months: vital study of extensive datasets with much background practical detail and requirements for written, and possibly oral, reports);
- *outside contacts* (meetings with applied statisticians to hear from the workbench how it should be done! This could usefully include sitting-in on consulting sessions, and hearing detailed presentations of case-studies);

- *placements* (in different applied fields and for long enough to gain valuable experience, but who manages to find the time for this?).

In all these contexts action and interaction are essential, with copious opportunity to work in a group, be involved in discussions, and make presentations of practical work. There is one underlying aim: to teach the student how to *communicate* with the research worker, often on matters of social concern. "The statistician gains in experience and ability to employ his art by contact with diverse disciplines. This also stimulates new developments within the armoury of statistical methods. The research worker gains in the realisation of what Statistics has to offer for the understanding of his own subject area. Thus this role of the statistician as a consultant and collaborator has vital educative overtones" (Barnett, 1983). Many others have written on this, e.g. Bartholomew (1973), Benjamin (1971), Sprent (1970), Chanter (1978), Freeman (1978), Greenfield (1979), Marquardt (1979), Hooke (1980).

An example of social-impact consulting with much potential for developing cogent teaching material recently arose in the field of *false alarms from security systems*. It is well-known that the false-alarm rate is high (whether in intruder alarms in industry, shops or the home). But how high? The false-alarm rate can be as high as 85%-90% overall, with the contingent vast waste of natural resource due to security companies or the police making unnecessary responses.

The conventional way of trying to deal with this problem is to seek to make alarm systems more and more reliable and sophisticated (and inevitably more expensive). One large security company posed the question in *statistical*, rather than *technical*, terms: was it possible to obtain a more accurate assessment of whether an alarm call was genuine by taking account of a variety of concomitant information such as day, time of day, type of property, weather conditions, nature of alarm system, and so on? The argument was that if an alarm call from a corner shop at 3 am on a clear Sunday morning was ten times as likely to be genuine as an alarm call from a supermarket at 5 pm on a wet Monday, we would want to give the former higher priority for attention than the latter.

To examine such prospects of differing false alarm rates, a major police database of over 100,000 calls over a three-year period was statistically analysed. A *multiparameter log-linear model* was fitted including as many main effects and interactions as were necessary to obtain the maximal significant fit. Sure enough, major influences were found. For example, the estimated genuine alarm rates varied from less than 2% to more than 25% (a twelve-fold difference) at different times of the day (peaking between midnight and 3 am). Different days also produced quite different levels of estimated genuine alarm

rates (with Saturday, Sunday, Monday and the remaining days all differing from each other), as did the different types of property (from as low as 2% for private houses to approaching 20% for certain classes of retail and public property), and so on for other factors.

Whilst some of these differences were qualitatively not surprising, the wide discrepancies of value were not previously known. Most importantly, however, major interactions were found even up to the 4-factor level. Consider as an example of first order interaction the estimated genuine alarm rates (in percentages) for retail properties at different times of different days:

Hours:	02-06	06-10	10-14	14-18	18-22	22-02
Saturday	25	1	1	3	6	14
Sunday	36	2	2	7	10	19
Monday	47	2	3	3	8	28
Other days	39	2	2	3	7	22

These differences (from 1% to nearly 50%) are enormous in their relative import and surely provide a vital basis for differential response to alarm calls depending on time, day (and other factors). They show high potential for a *source-sensitive approach to response* which could save much of the unnecessary expense of an undifferentiated response system.

Of course there are problems: social attitudes to police and security-firm policy, geographic effects, and so on. But the real potential is demonstrated, for a diagnostic computerised software system to aid responsible attention to calls for help! And what a rich field for practical illustration of statistics in the teaching process.

Thus, returning to our main theme, we conclude that consultancy is central to the role of the statistician. It is obvious that we should seek *to teach consultancy* (see Cox, 1968; Rustagi and Wolfe, 1982; Zahn, 1982) as an integral part of statistical education (even if not all are agreed on how to, or are personally equipped to be able to, do it).

What is less obvious but even more important is the converse: the *role of consultancy in teaching practical statistics*. Our two examples already illustrate the possibilities.

Let us consider in more detail what this means!

4. Consultancy as a basis for statistical education

Consider again the main problem. How do we instill an ability to *actually*

do statistics rather than just *knowing in principle how we might do statistics*. This includes being able to provide confident, rapid response; knowing that sometimes sophisticated methodology may be needed, whilst on other occasions it may not be and ingenious data-dexterity will yield the answer; recognising that basic research is required in some problems but that a “quick and easy” answer should be offered as a stop-gap; developing the manner and skills to impress others with the fact that we understand their problem and know how to provide an answer. Another recent consulting experience completes the spectrum: from *simple data-analysis* (e.g. the football problem), through *formal methods* (the alarm systems example) to *fundamental research* (in the example we now consider).

The problem arose in the public domain in seeking methods of estimating road-accident rates at junctions from data on traffic flows and the physical geometry of the road junctions. The work is described in Barnett and Wright (1992), and is shown to have applications in many other fields (e.g. medicine and biology). It looked initially to be the fairly standard regression type of investigation so often encountered in consultancy situations, but it turned out on detailed consideration to be much more complicated: in fact to be a previously unresolved fundamental research issue.

Essentially we had observations of a discrete random variable Y (long-term accident rates) of Poisson form with mean value function $\mu(x)$ depending on a variety of predictor variables x , some of which were also discrete counts. The specific form of $\mu(x)$ was

$$\mu(x) = \exp(\alpha'x)$$

where α is a set of parameters. Thus it had the characteristics of a generalised linear model (GLM) with logarithmic link function and Poisson error structure. However, there was a “sting in the tail”. The predictor variables were in two distinct groups x_1 and x_2 , with x_1 referring to traffic flow rates and x_2 to physical characteristics of the road junction. The x_2 values were able to be measured very accurately but the flow rates could only be estimated from short-term traffic counts, and were correspondingly inaccurate (“measured with error”).

Thus

$$\mu(x) = \exp(\alpha_1'x_1 + \alpha_2'x_2) \quad (1)$$

where x_1 and x_2 are of dimensions r and s (in fact $r=2$), with x_2 observed without error and x_1 only measurable with error.

This latter property moved us away from the GLM to a model of functional

form, so that we had what might be termed a *generalised linear functional (Poisson) model*. Essentially we had an independent random sample y_1, y_2, \dots, y_n of observations of a Poisson random variable Y with mean (1) subject to the different status of x_1 and x_2 . The client required a maximum likelihood solution implementable as a macro in one of the principal statistical software systems.

Here was pressure indeed ("miracles take a little longer!"), but in fact a solution was obtained and a macro produced, all to the required deadline.

Thus we have reached a stage where it is clear that all aspects of statistical education depend vitally on close contact with the consulting world.

The key to how this can be achieved is that the teaching environment itself (the university department, say) *should be fully committed to consultancy even to the extent of running a commercial and comprehensive consultancy service*. Should university statisticians do (industrial, medical, commercial, etc.) consulting? Depending on background qualifications, experience and (particularly) nationality, the immediate answer lies on a wide spectrum, from

Of course not - we do the important (difficult) fundamental work

→ to ←

Of course, how else can we teach, do research, extend the subject?

I am biased (I come from a totally *empirical* tradition in the UK). I automatically regard statistics as designed *to answer real life questions*. From the outset (over 30 years ago) I have always as a university statistician done "consulting" in this sense.

So my answer is "of course"! I earlier observed (Barnett, 1983):

"The service, and statistical advisory, role, of a university Statistics Department is vital for creating the proper educational environment. I believe that any Statistics Department must be seen as providing a university-wide practical facility, both in the teaching of students from other disciplines but, more important, in *offering a full statistical advisory service* to all university staff, and postgraduate students (and to outside organisations, if logistically feasible). See Tukey, Box, Hartley and Kempthorne (1968), Gibbons and Freund (1980). This requires more than just a casual attitude of being prepared to help if anyone happens to ask. The advisory service should be widely advertised. Staff (not necessarily all) must be committed to providing the service, and have the confidence to do so.

The university needs to recognise and welcome the facility, to the extent of providing adequate resources, including computing equipment and a staff member to conduct computational work. There is nothing worse than offering a service and saying that someone's problem is soluble in principle, *but* that lack of time, computing power, etc. prevents it from actually being solved".

In advancing the importance of a consulting base in a department of statistics we need to ask:

Why?

How?

What are the benefits?

What are the difficulties?

In recognising that the practical skills have to be passed on to students and trainees, we must also remind ourselves that the "teachers" often do not possess the experience on which to do this, either in terms of what or how. It is in this dilemma that the consultancy base of a department can be so vital. It provides the very experience that may be lacking, day by day, in an exemplary manner.

Specifically in response to the question, *why?*, we might respond:

- for practical case material for teaching
- for consulting experience for teacher and student
- for research stimulus
- for social responsibility (we should solve problems)
- for income generation (*why not?*)

But can we do this: *how?*

- by encouraging every individual to develop and promote external links (with no financial redress)
- by setting up (in due course of time) a formalised advisory or consulting service (even a limited company) with its own staff augmenting the tasks done by those of the general teaching and research staff of the department who wish to be involved.

What are the difficulties? These are readily summarised:

- staff inertia (*personal lack of confidence*)
- official obstacles (*institutional lack of confidence*)
- lack of time (*claimed*)

- legal constraints (*usually resolvable*)
- fear of responding to immediate pressures (*customer wants the answer yesterday!*)
- difficulties (*or lack of know-how*) in drawing up and costing contracts.

Such problems are real, but I do believe that they are more than outweighed by the great benefits that accrue to a statistical education and training programme from operating its own consulting service. These should be obvious and clearly include:

- stimulus to professional development (*individual and departmental*)
- enhancement of reputation and of contact base
- improved research and teaching climate
- financial flexibility.

What is most important is that the modern world will no longer be prepared to accept (as it did in the past) statistical education and training which is not demonstrably being provided to satisfy practical needs. And this must be done by statisticians, themselves well-equipped and well-experienced in carrying out the practical professional performance they claim to be presenting to their students. *Can any one of the statistical educators avoid being a consultant?*

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