The Political Methodologist

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Notes From the Editor

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How should we train political methodologists? In a discipline primarily absorbed by substantive questions, where does the methods subfield fit in our curricula? These questions lend themselves to endless (and often useless) speculation and pontification, yet they are vital to the future development of our discipline. At its core, methods is about epistemology: how we know what we know. It is the language in which we express our hypotheses and it provides the criteria for judging the evidence supporting our theories. In this sense, without methods there can be no political science. How, then, do we and how should we train our students?

The usual complaint among teachers of graduate methods courses is that students arrive with virtually no preparation in statistics. Many have not had a math course since high school and very few have done serious statistical work as undergraduates. Thus we must devote the first year of graduate training in statistics to remedial work, bringing students to the point of competency with basic multiple regression. For most programs, that is the end of the required training.

Why are students so ill prepared? Largely, I think, because so few of our undergraduate majors are actually interested in political science. Large segments are bound for law school (or at least they think they are) or they are seeking a general liberal arts degree and politics is at least moderately interesting (or at least easy). As a result, departments make a very rational decision to go light on any undergraduate methods requirements. While economics departments may require calculus and a semester of statistics for their undergrad majors, very few political science departments do so. Even if students did acquire these skills, few of our undergraduate programs would have much use for them.

The persistent problem we face in our graduate courses, then, has its roots in our undergraduate programs. By going light on methods preparation in the undergraduate years, we create later problems for our best students, those who go to graduate school.

How are we to resolve this dilemma? One solution would be to simply require a year of calculus and a serious course in statistics of all undergraduate majors. Such a proposal would not only irritate students, but probably wouldn't pass a vote of the department faculty. Which reveals another source of our problem: many of our colleagues don't see the value of methods training any more than does the typical sophomore major.

A more limited approach would be to establish a submajor in "political analysis", a program designed to prepare students for graduate school, including appropriate training in mathematics and statistics. Such a program could be tied to department honors, thus providing the incentive for students to undertake the more rigorous training.

Or, we can continue to ignore the problem. Our graduate students will continue to fall behind the state of the art in methodology (and consequently lag in ability to read much of the substantive literature as well), and will fall further behind as the field advances. At that point, we can begin to require in graduate school what students should take as freshmen and sophomores. We can refuse to admit students to our methods courses until they have completed a prerequisite in calculus and statistics. Will we be better or worse then, for our failure to require adequate training of undergraduates?

WE ARE MOVING!! As of June 1, the editorial office (and the editor) will be moved to the University of Wisconsin, Madison. After that date all correspondence related to *TPM* should be sent to the editor at Department of Political Science, 110 North Hall, University of Wisconsin–Madison, Madison, WI 53706. E-mail should be sent to FRANKLIN@WISCGPS.Bitnet. After July 1, the e-mail address will be FRANKLIN@POLISCI.WISC.EDU.

I would like to take this opportunity to thank Washington University, and especially Dean Martin Israel, for supporting *TPM* during my editorship. Dean Israel has provided generous funding for the newsletter and I am grateful for his support. —*CHF*

Methods Training: Student Perspectives

In putting together this issue on teaching methodology courses, I thought it would do us some good to hear from the consumers. I've asked four graduate students, who are at different stages of their education, to comment on their experiences as students of methodology. What have their courses been like? What do they wish they had done differently? What were the major influences on them as they encountered methodology? Their comments are revealing and interesting.

By way of introduction, Michael Alvarez is finishing his dissertation on uncertainty and political behavior at Duke University and will be joining the faculty of the California Institute of Technology in the fall. Janet Box-Steffensmeier is at the University of Texas at Austin and is just getting started on a dissertation on the dynamics of campaign contributions. Jeffrey Bernstein is a first year student at the University of Michigan and is interested in elections and political behavior. Charles Smith is nearing completion of a dissertation on party identification at The Ohio State University.

Methods Madness: Graduate Training and the Political Methodology Conferences

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My purpose in this essay is to give my perspective on two subjects: what graduate students gain from participation in the summer Political Methodology Conferences, and what this implies about the current status of graduate methods training. What have I taken from participation in the past three summer methods conferences?

First, I have learned a lot more about methods than I ever would have believed possible (or desirable). As most who read *TPM* know, there are a number of quite intense debates among those who admit to be methods practitioners– debates about vector-autoregression models, discussions about multidimensional scaling, endless arguments about measurement strategies, elaborations on discrete variable models, controversies about the utility of maximum-likelihood, and much more. Instead of unanimity, I have been impressed with the amount of debate in the methods conferences.

But what is exciting about these debates for a graduate student is that with rare exceptions, these are topics which are not covered in the usual methods sequences. In other words, many of the interesting contemporary developments in political science methodology don't seep into graduate courses. Attending the methods conferences has exposed me– and a good number of other graduate students– to these contemporary developments and debates.

Second, other than just raising my level of methodological awareness, participation in the methods conferences has increased my own ability to assimilate sophisticated material. In small part this is the result of osmosis, since I've tended to pick up the jargon after sitting for days in a small room talking about matrices and likelihood functions. But mainly this is the result of quickly seeing my own mathematical inadequacies, and being stimulated to try to learn more math.

This, I feel, underscores another problem in methods training. My own math background before graduate school was inadequate, and I have been playing catch-up ever since. There does seem to be an increasing level of math competence among graduate students in political science, and I've witnessed a trend toward a more mathematically-oriented training of graduate students. But, in general, mathematical training seems to be overlooked as a prerequisite to methodological training.

Third, participation in the methods conferences has dramatically opened new doors to interesting research problems and types of data which I would never have been exposed to. For example, there has been discussion of event count data, which initially mystified me. Also, there have been presentations about interesting and important topics like the endogeneity of campaign expenditures and voting outcomes in congressional elections and applying vector-autoregression models of "long cycles" in international relations. All of these discussions have utilized a combination of new data and new methods to approach classic problems.

This taps into an even more troubling problem with graduate training in methods. I've served for a few semesters as a teaching assistant in our linear regression course, and the biggest complaint is the "Relevance Question." Many, if not most, people who make it through even the introductory methods classes have an extremely difficult time seeing how any of the subjects they cover are relevant to their work. Why should the person who wants to study ethnic violence in African nations understand two-stage least squares? What relevance does the maximum-likelihood approach have for research on the development of state-level political parties in the late 1800's?

The answers to these questions really are quite apparent. Yet they tend to get submerged in methods courses. But one of the greatest deficiencies in graduate methods training has to be that we are not getting across that methods training is essential for doing quality research in virtually every subfield of our discipline. To do this it is essential that current research controversies, and current and timely data, be introduced into graduate methods classes.

Having the chance to hang out with the "witch doctors" in the summer methods conferences has been an important part of my graduate training. It has been very stimulating and exciting. It has underscored some very troubling gaps in my own mathematical and methodological abilities, and it has done the same for other graduate student participants. Generally, my participation in the methods conferences has underscored three deficiencies in how methods training in political science currently stands:

1. Mathematics needs a much greater emphasis in graduate training. Much of political science research is formally developed and is statistically analyzed. To be able to understand this research, to teach it, and to produce it requires at least a rudimentary understanding of algebra and calculus.

2. While continuing to teach the basics in methods courses, some of the focus needs to shift toward contemporary issues in methodology. It is important for graduate students to know the linear model. But since political phenomena are not always linear, since our data are often inadequate and poorly-measured, and since just about everything is endogenous, it is imperative that students "get up to speed" quicker.

3. We need to impress graduate students that knowing methodology is useful, important, and even sometimes, interesting. Teaching, researching, and getting jobs are all dramatically enhanced by knowing methods – we need to get that across more effectively.

While these are more general points rather than specific proposals, I believe that by crossing these hurdles in graduate methods training some important changes could be produced. Certainly, at a minimum, students would be better trained and more interested in methods. However, even such minimal changes will result in a considerable increase in the quality of political research.

The Evolution of A Political Methodologist

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The evolution from an undergraduate to a political methodologist is a challenging and rewarding process. Ways of easing the transition are suggested by examining the common experiences of those undergoing this metamorphosis. One of the most significant events affecting my own transition has been participating in the Political Methodology Conferences.

Beginning graduate students have a wide variety of undergraduate training in regard to methodology. Some come with bachelor's degrees and higher in mathematics, statistics, engineering, or economics, while others have sworn off numbers since high school algebra. This variety has an immediate impact on what constitutes the entry-level methodology courses, which are often required of all students. I remember my own cohort quite well, which ranged from the hopelessly lost to the hopelessly bored. That semester convinced me that blanket requirements ought to be extinct. A few of us should have been spending our time in the more challenging methodology courses offered by the department and others should have been sent outside the department to pick up the simplest basics. I am sure the professor shared our frustration.

The wide variety of backgrounds also led to many students tuning out methodology completely due to their lack of preparation for such a course. One way to keep their attention, as well as the attention of more methodologically advanced students, is to begin the first methods course by presenting possible strategies and tactics for research. Such a course would cover choosing a problem, pursuing a topic, collecting evidence, presenting an argument and then showing students how methodology can be used to test the validity of their theories. Thus, students are exposed to the importance of methodology and are then more receptive to the statistical areas. Another reason to include such a course is to minimize the floundering that many students encounter after completing their course work and comprehensive exams. By requiring such a course early, students would have experience utilizing these critical strategies and tactics for research in courses in their substantive areas of interest. Thus, class papers can essentially become "mini-dissertation" trial runs.

Students also seem to have difficulty when attempting to go from the text to real data analysis. This problem is easily solved by incorporating the use of data and computer software into the assignments and lectures.

The opportunities readily expand for those with adequate undergraduate preparation in methods or those who obtain it. The wide variety of classes available in the Government department at the University of Texas is a valuable asset. For example, very few departments are fortunate enough to be able to offer a course in Spectral Analysis. While some may argue against such "specialized" courses and wish to have more general courses, one needs to realize that methods courses, in contrast to courses in most other fields, build upon and complement each other to a much greater degree. For example, Spectral Analysis necessarily teaches one about Time Series Analysis.

Methodological training also provides the opportunity to distinguish oneself from many graduate students and professors in social science. It is a valuable asset for colleagues and allows one to offer critiques that are broader than if one just had expertise in a particular substantive area in political science. Such skills also allow one to bring concrete evidence to bear on a theoretically divided substantive political science question. There can be eloquent, logical arguments for both sides, but methodology provides tools to rigorously test these arguments.

Stage I: From Undergraduate to Graduate Student

While I think that my undergraduate preparation, a bachelor's degree in mathematics and political science, did adequately prepare me for methodology courses in graduate school, I realize that most undergraduate students do not take nine courses in mathematics. The material I learned in courses such as Probability and Statistics and Complex Variables was directly applicable to my graduate classes, but the type of reasoning taught in all my mathematics classes also facilitated the transition to graduate level courses in methodology. It is unrealistic to expect all incoming graduate students to take four years of mathematics, but it is not unreasonable to expect them to have some exposure to mathematical reasoning or to go outside the political science department to receive such exposure. In addition to learning the content of these courses and mathematical reasoning skills, such courses help one to learn to teach one's self. This is valuable for the problem solving inherent in choosing a research design and for professionalization when the student is responsible first and foremost to himself or herself, not to a professor.

One problem I had as an undergraduate was the lack of integration between political science and mathematics. It was my own passion for both fields that led me to a double major. Neither department showed any appreciation for my interest in the other, which may have been a result of being at a small college. I became aware of how important statistical training in political science can be through my undergraduate internship at the Program Evaluation and Methodology Division of the General Accounting Office.

Professors can illustrate how methodological and traditional political science courses can be integrated by providing examples of how methodology is involved in answering numerous questions of interest to political scientists in all undergraduate classes. Picking up any major political science journal and choosing an article in any substantive area of political science will readily provide such examples. Even the introductory undergraduate classes can be exposed to the important role of methodology. For example, a discussion of how popularity polls are conducted and what they mean would be applicable. Basic American Government courses could also cover the issue of social welfare programs. A discussion of how to determine whether or not a program is effective in reducing the poverty rate could illustrate the importance of methodology and incorporate a discussion about the adequacy of how poverty is measured.

This encouragement may go a long way towards reducing the numbers of incoming graduate students who lack any interest and training in methodology.

An even more intriguing idea for an upper division undergraduate class has been successfully implemented at the University of Texas. The procedure is to choose an issue of the *American Political Science Review* and evaluate and critique the articles in it throughout the term.

Changes in undergraduate education should also be considered in order to ease the transition to the graduate level. One way would be to introduce the use of computer analyses in undergraduate political science courses. While not feasible in the large lower division courses, it would be a reasonable expectation for political science majors. This could lead to more students actively acquiring methods training as an undergraduate since the relevance would be clear.

Based on my own experience of teaching undergraduates, they usually do not see any connection between my undergraduate majors of mathematics and political science. However, a few examples or articles such as those discussed above readily make the connection clear. I believe it is important to provide integration of methods into all political science undergraduate courses through examples, simple statistics, articles, etc.

Undergraduates also have a clear need to know *why* such methodological training would be beneficial. A discussion of how to best answer a question they have posed is very convincing. Students are motivated in different ways and thus trying a variety of techniques is the best way to ensure success. Lastly, cross-listing undergraduate political science methodology courses in departments such as mathematics, statistics and economics may help attract students to graduate school in political science who already have a strong methodological background.

Stage II: From Graduate Student to Professional Methodologist

An equally important stage in the evolution from an undergraduate to a political methodologist is the transition from a graduate student to a professional. Thus, rather than focusing further on the adequacy of preparation for graduate study I turn to the adequacy of graduate study for life thereafter.

While course work is irreplaceable for teaching statistical material, most classes provide little instruction to graduate students about what is required at the professional level. One suggestion for changing this would rely on an advantage of methodology that was discussed earlier. That is, the ability to offer critiques that are broader than if one just had expertise in a particular substantive area in political science. A course could be designed such that the focus was on the methodology employed to answer a question in any substantive area. This would emphasize the versatility of methodological skills and perhaps entice others into the field as well as serve as a vehicle for professionalization. Graduate students' papers, professors' papers and published papers could all be critiqued. Such a course may well attract students in other disciplines like statistics, economics, or mathematics to political science as well. This course may also give students who are otherwise not interested in methods a taste of what methods research is like (in contrast to what most methods courses are like) and entice them into the field by covering a wide range of substantive interests. Lastly, such a course would help professionalize students by teaching skills needed for presenting and discussing papers at conferences and critiquing articles for refereed journals.

A second avenue for graduate students to acquire information about professionalization is through a mentor. Such valuable and necessary information may be passed on through the mentor's instructive and personal guidance. However, the potential problems with acquiring professionalization in this manner is the lack of a mentor and the reality that such a process is necessarily slow, imperfect and sometimes inconsistent.

The contrast between graduate training and what is required at the professional level was highlighted most clearly by the Political Methodology Conferences which I attended in 1990 and 1991. One of the most apparent contrasts is the disparity between current methods research and applications, and the knowledge learned in the classroom. The knowledge gleaned from the meetings is the cutting edge of research in the field and is usually not available in textbooks. One way the gap between what one learns in the classroom and what is needed at the professional level can be and has been partially bridged is through the study of published articles utilizing the techniques being studied in the class. However, oral presentation skills, in contrast to teaching skills, are more difficult to acquire in the classroom.

The methods conferences are also very valuable because they expose students to the work-in-progress of the best in the field. One gets the opportunity to see the exchange that occurs during the discussion and compare the final published product. The unique format of the meetings– a small group, more time spent on each paper, and lots of access to presenters and discussants– help make it the most valuable conference I have attended. The format facilitates in-depth discussions with the experts in the field about their work and one's own in an informal atmosphere. The expertise shared with graduate students and the attention given to them at the meetings undoubtedly raises the quality of the graduate students' work and personally has had a decisive influence on the topic I have chosen for my dissertation.

The conferences also lead to an exchange of papers with expert methodologists and other graduate students who are interested in similar questions. This valuable resource could not be achieved through the university itself. Such contacts are especially important because colleagues interested in methodology are often not available within every university and networks allow one to stay abreast of the most current research, rather than waiting to read about it in a journal.

An awakening, of sorts, occurs to most graduate students at the conferences when one realizes the breadth of knowledge that the professional methodologist must master. This inspiration tends to lead to the acquisition of methodological skills in additional areas once returning to the university. This long, challenging evolution from an undergraduate to a political methodologist is truly a metamorphosis.

Perspectives on Methods Training from a First-Year Graduate Student

Jeffrey L. Bernstein
The University of Michigan

As a college senior choosing among graduate schools in political science, the quality of methods training I could receive at each school was an important element of my decision process. While working on my senior honors thesis, I noticed that in the subfield of electoral behavior, my intended area of concentration, statistical analysis played a large role in the journal articles and books. I realized then that if I intended to do work on elections and on Congress, I would need not only to understand these statistical techniques, but to be able to do my own work with them. Making this conceptual leap would require strong training in methods, and was one of the reasons I chose The University of Michigan for graduate school.

In retrospect, I now realize that I began graduate school far readier to embark on methods training than had most others in my entering cohort. As an undergraduate, I had taken numerous upper-level mathematics courses, including statistics. While doing my thesis, I strove to understand as much of the statistical base of the literature as I could, which helped prepare me for what lay ahead. This, coupled with my inclination to use mathematical techniques to solve problems, made me well prepared for the methodology training I would receive when I started graduate school.

After almost a year at Michigan, during which time I have taken the first two statistics courses as well as an empirical modeling class in the methods subfield, my desire to become a competent methodologist is even stronger than it had been. As I read items on my professors' syllabi, or leaf through the APSR or AJPS, it becomes apparent to me that my methodology training will likely be the most important part of my graduate education. Further, when classes have used concrete, substantive examples to illustrate uses and misuses of the methodological techniques we have learned, my classmates and I realize that the training we receive in statistics relates closely to the more substantive work we intend to do in political science.

The biggest problem with the methods training I have received results from the differing backgrounds of students in the program. Few have been trained in mathematics or engineering, which came as no surprise. What did surprise me is how many people have not taken any statistics courses, and have taken no mathematics beyond 11th or 12th grade of high school. Obviously, mathematics classes at the university level are usually attempted only by those who need the classes for some degree program; it's difficult to imagine anyone studying differential equations "just for the fun of it." Unfortunately, political science programs rarely require mathematics or statistics, the result of this being that many political science graduate students are almost math illiterate when they enter graduate school.

Therefore, the introductory methodology courses in graduate school must meet the goals of two different sets of students. They must serve as both a simplified, broad overview for those without prior training who wish not to go further in the statistics field, and as a gateway class for those intending to major or, in my case, do a first minor, in methods. It is difficult for professors to satisfy both types of students in one class. Thus, the students desiring stronger training in methods must move along with the class at a pace that does not challenge them enough, while those who enter without a math background end up struggling and becoming frustrated with the material. I can only presume that this problem occurs in methods classes in political science programs throughout the country.

The most obvious solution to this problem is to standardize the methods backgrounds that students bring with them when they enter graduate school. For instance, at my undergraduate institution, all psychology majors are required to take a statistics course, giving them at least a basic introduction to the blissful world of quantitative data analysis. Thus, when these students enter graduate school, they are at least able to hold their own in the basic statistics sequence; further, those who wish to do quantitative research have a head start. Statistics is not required for political science majors at that university; thus, unless motivated to do so on their own, political science majors who graduate from there and enter graduate school do not have a sufficient background in quantitative techniques.

Additionally, many graduate schools do not make it clear enough to their incoming graduate classes that a certain level of mathematical competence is highly recommended, if not required. Of the schools to which I applied, none appeared to require either calculus or statistics classes, nor did they indicate in their literature that it would be helpful to have taken such classes before entering their programs. Unless clear efforts are made to encourage students who expect to do some work in the methods field to enter graduate school semi-competent in these areas, methods classes almost inevitably will be two-tracked, working to the benefit of no one.

Overall, I have been pleased by the training in methods I have received here at Michigan. As I have already mentioned, the proclivity of professors to give homework assignments and readings which involved real-world problems has helped us to understand how the statistics we are learning can work for us as social scientists. Furthermore, by taking classes in subfields such as electoral behavior and legislative behavior, I have seen statistical and formal modeling techniques used in such a way that I am now aware of when I may want to use them in my own work. My assessment is that this approach to learning methodological techniques allows the greatest understanding and synthesis of the material.

The nature of political science in the 1990s seems to be that almost every graduate student needs to have at least a rudimentary knowledge of statistics, and that some must know a good deal more than that. At schools which excel in training a strong group of methodologically rigorous political scientists, students who succeed in the methods sequence will be well trained to do the kind of quantitative work done in political science today. However, when an introductory statistics sequence must address students of widely disparate abilities, those on both ends of the spectrum fail to be fully satisfied with what they take out of the class.

Graduate Training Outside the Department: Taking Full Advantage of the Methodological "Trade Deficit"

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If there existed a balance of trade in methodology, political science's deficit would surely outdistance those of many other social sciences, particularly economics, psychology, and sociology. And unfortunately, over-indulgence in research norms developed in and for other areas of science can be very costly. Substantive research progress may come to rely heavily on the mindless recycling of old and highly inappropriate quantitative techniques. In addition (and perhaps as a result), substantive revisions may come to depend in detail on the importing of new and exotic strategies developed specifically for other purposes.

However, increased emphasis on formal organization in the subfield has gone some distance toward insuring a reduction of the "deficit." The emergence of forums (the Political Methodology Conferences; *TPM*) and the maintenance of channels for publication (*Political Analysis*; *AJPS* workshop) have encouraged sustained originality in the subfield. In the process, I believe these developments have to some degree insulated political methodology from any untoward effects that might result from encouraging graduate training outside the fold of political science.

In this note, I briefly sketch some arguments recommending out-of-department graduate training for students interested in political methodology. My view is that the current emphasis on a more political, political methodology provides the measure of freedom we need in fully availing ourselves of resources outside the department. I suggest that opting for methods courses in other departments can help graduate students get past shortages in their own departments. I also argue that outside training can be beneficial in its own right by providing an invaluable (perhaps necessary) background in the diverse methodological traditions of a discipline with substantive roots spread throughout the social sciences.

Limited Resources

The most practical argument for encouraging training in other departments stems from the simple fact that demand often exceeds supply. Typically, formal graduate training in political methodology is limited to a few courses in the department and perhaps a few weeks in Michigan at the ICPSR Summer Program. But the truth is that demand for courses and personnel within departments will often outstrip departmental resources. The Michigan option goes some distance in making up the difference, but demand from students serious about methodology will be (or should be) year-round. Moreover, for financial or other reasons, the Michigan option is not always feasible.

At most research universities, methodology courses in other departments will constitute the best resource available for addressing imbalances between supply and demand. This is not to insist that we look to other departments as a matter of general policy. Indeed, an ideal solution would have every university hiring more political methodologists to teach more courses inside our own departments. However, in lieu of this unlikely event, aspiring methodologists should be encouraged to venture into statistics, economics, psychology, sociology, or any other department with serious methods offerings.

In particular, statistics departments offer a natural match. Upper-level undergraduate or introductory graduate-level courses may be reasonable options. My own experience is somewhere in between: a course in statistics aimed at both. Courses at this level will typically assume few if any formal prerequisites, but still may offer a more mathematically demanding cut at a topic than an analogous course in political science. One great advantage of shopping in the statistics department is that there will ordinarily be multiple options. Courses in everything from probability theory to nonparametric statistics are available for the more ambitious.

Interdisciplinary Heritage

Presently, most advanced methods courses in political science (in individual departments and in the ICPSR summer program) are very much of the import variety.[1] Were it not so, methodological training in social sciences other than political science might be routinely required by graduate programs. This is true of course because political science owes so much of its substantive heritage to disciplines like economics, psychology, and sociology. Methodological paradigms grew up along with the conceptual/theoretical frameworks that characterize these disciplines, and for the simple reason that applications of the concepts abound (perhaps even dominate) in political science, some basic familiarity with the corresponding methodological traditions is a must.

It is also important to keep in mind that methodologists in these disciplines are making progress of their own; developing and testing new strategies; ushering new trends in and out. Political methodologists should stay abreast of these developments. Many come about as a result of emerging theory that will quickly and inevitably make its way to political science. In order to remain prepared, we will always need political methodologists with special skills in econometrics, psychometrics, and sociometrics. And the very best training in these fields will of course be found in the respective departments.

"Sampling" rather than specializing will be the norm, and political science's substantive linkages with other disciplines works to make sampling especially productive. For example, methodologists are constantly called upon for consultation. Often (almost always), consultation will involve working with someone from another substantive specialty. In my limited experience, I have found that I can rely heavily on my exposure to economics and psychology in trying to cut to the quick of the substantive issues animating methodological problems in areas of political science about which I know little. The interdisciplinary nature of political science works well for us in this respect. And even limited methodological training in psychology or economics (or sociology) can provide the necessary background for managing a wide variety of political science problems in areas as distinctly different as international political economy and U.S. political behavior.

The hypothetical ideal might have each political scientist tailoring a home-spun methodology to each substantive problem and each data set encountered. But in the process, we would surely waste a good deal of time and effort as we went about re-inventing wheels. The truth is that many political science problems are expressly economic – many others expressly psychological or sociological. If a solution already exists, we should be aware of it and be able to explain it, recommend it, and use it. Having some general exposure to other disciplines can facilitate the beginner methodologist's ability to recognize problems that have already been solved and recommend the appropriate solutions. Formal methods training in other departments is a sure strategy for gaining the necessary exposure.

Conclusions

Political scientists are only partly to "blame" for the discipline's methodological trade deficit. Indeed, the lion's share of the "blame" may belong to economists, psychologists, and sociologists for out-doing political scientists in the development and maintenance of discipline-wide methodological standards and unique research traditions. As we work to make up ground, we can learn quite a bit about what we need to do– and perhaps something about how to go about doing it– from those who have already done it.

Hearing or reading about the need to tailor quantitative techniques to substantive research needs is one thing; first-hand experience with disciplines that have managed this to some extent is quite another, and quite superior. Moreover, in the ideal situation, the attentive "consumer" of outside methods courses comes away with a well-developed first-hand knowledge of the origins and underpinnings of a number of techniques and strategies used (and abused) by political scientists. A deeper and more critical understanding of applications (and mis-applications) emerges as a result.

There are pitfalls of course. My experiences have included instructor reactions ranging from near-amazement to near-hostility. Initially, instructors may have questions about the ability of a political science student to manage (our discipline is not well known for methodology!). There may also be some resistance to the general idea of training a graduate student from another department. For these reasons, and because substantial backgrounds in calculus are sometimes assumed, students determined to maintain straight "A"s may want to choose their courses and instructors carefully.[2]

Wiser students will of course focus less heavily on getting a grade and more directly on getting some useful training. Skeptical instructors will generally come around in the end, and some self-imposed remediation in mathematics can have long-term advantages. The message then is that there

[1] Standard "linear models" courses are examples; most follow the familiar line of introductory econometrics, usually complete with econometrics texts.

[2] One piece of advice: I have found comfort (if not safety!) in numbers. Students who can find a cohort with similar interests will find that it is altogether less intimidating to venture to other departments in pairs.

is much to recommend about out-of-department methods training. And importantly, the existence of a well-developed methods subfield in our own discipline will help insure that availing ourselves of these resources will not end up taking us too far astray.

Methods Instruction: A Labor-Intensive Product in a Labor-Short Market

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James A. Dyer
Texas A&M University

It is our observation, both from what is happening at our universities and the quality of the articles that we review, that methods teaching is facing a crisis even more serious than that suggested by the observation that we are trying to teach "increasingly advanced techniques to graduate students who are as unprepared as ever" (Franklin, 1991). It is optimistic to think that entering students simply "are as unprepared" as those who entered previously; and serious problems in teaching methods would exist even if we did not attempt to teach "increasingly advanced" techniques. Attempting to get more poorly trained entrants to more advanced levels–while still giving solid training in the fundamentals–creates a real crisis in instruction.

At the heart of the crisis are enormously increasing student/teacher ratios in political science. Increasing ratios have already caused serious cutbacks in our undergraduate training and threaten the current levels of graduate instruction. Far from expanding training, we are fighting losing battles to keep training at its earlier levels.

It is our experience that good instruction in methods requires very low student/teacher ratios. When we teach methods, we teach application and evaluation, not memorization and recall. Every step in the research process must be done and evaluated by students, critiqued by instructors, and redone and reevaluated by students. And there are many discrete steps in the process: many different skills that have to be acquired. Some of the critiquing can be done by computer, but much of it requires one- on-one interaction between teacher and student to determine where and why each student is misapplying or misevaluating, so that those mistakes will not be made in the future.

There was a time when our universities had low enough student/teacher ratios to allow substantial one-on-one instruction, even at the undergraduate level. As late as 1983, Texas A&M had 40 professors teaching just over 300 majors and 35 Master's students. We had one-on-one meetings with each student on each stage of that student's research project: hypotheses, research review, sample, measures, research design, analysis, and so on. Co-authored research papers from introductory graduate and undergraduate classes ended up in major political science journals.

However, the teaching load grew far faster than the faculty. A&M now has 40-45 faculty to serve more than 1,100 majors, and about 75 Ph.D. and Masters students.

Demands on those willing to teach methods increased at both the graduate and undergraduate level. At the graduate level, the desire to teach more advanced techniques increased the number of required methods courses for most students. Combining that with the increased numbers of students, meant that class size could only be held constant by offering at least four times as many methods sections as previously. At the undergraduate level, the nearly four-fold increase in majors meant that class size could be held at previous levels only if there were a nearly a four-fold increase in the number of sections.

Furthermore, teaching demands on the whole department increased markedly. Although total undergraduate enrollment grew more slowly than did the number of majors, more students per year did have to be processed through the required service courses. During the 1980's, the number of students in survey courses increased by over 50% to more than 7,000 per year. Some of that demand could be accommodated by increasing class size; but there were limits.

As methods classes became larger, student/teacher contact was reduced, and we couldn't supervise as many different kinds of research. In self-defense, we began limiting the types of data students could work with. With 30 students in a class, it was too time-consuming to help each one with original data collection, or even to get each one access to a different archived dataset. For many students, measurement, sampling, and data-entry problems became abstractions: problems one read about rather than problems one wrestled with.

Student/teacher ratios got even worse. At the undergraduate level, we went to classes of 48, with students divided into 4 labs with graduate students once a week. At the graduate level classes went to 15 or 20. Now research design had to be sharply constrained. There simply was not time, especially at the undergraduate level, to help develop the varied causal models and research designs that would have been appropriate for all those students. For many students, problems in causal modeling and research design also became abstractions.

Finally, the demands in the service courses became so great that we lost the use of graduate students for labs. The lab requirement died, and with it the chance that undergraduates would have the experience of applying what they learned to an actual research project. The particular irony is that at A&M, a newly remodeled building provides teaching facilities ideally designed for methods laboratories.

Two rooms with thirteen personal computers each (twelve for students, one for the professor), all networked and linked to the university mainframes are now available. Unfortunately, the classes for which they were designed no longer exist.

Nor were things much better at the graduate level. With required courses focusing on advanced techniques, students became well-versed in statistical application; but increasing student/teacher ratios in the basic course gave students relatively little experience handling the fundamental problems involved in measurement, sampling, data collection, and causal modeling.

Auburn University now faces the increasing student/teaching ratios that Texas A&M faced somewhat earlier. In the past five years, we have gone from less than 15 to more than 40 Masters students, and we have added 20 Ph.D. students. Undergraduate majors have increased by over 30%. The introduction of a new core curriculum promises to increase the number of students in service courses by 3,000 per year. But faculty size has remained constant.

Consequences of the increasing student load are just now being felt in the methods courses. In order to teach more advanced techniques, we should be adding at least one methods course at both the graduate and undergraduate levels, but the faculty is already spread as thinly as possible to cover current offerings. If more sections are not added at the graduate level, we will be unable to develop even traditional skills at that level. Next year, at the undergraduate level, we go to the A&M procedure of enlarging the undergraduate methods courses and splitting them into labs directed by graduate students once a week. Students' ability to apply and evaluate will suffer–yet the problem of increasing demand will only be postponed. Inevitably, the increased service load is going to have to be turned over to graduate students; fewer graduate students will be available for methods labs, and the lab solution will have to be abandoned here as it was at A&M.

The problems at Texas A&M and Auburn are similar to those faced at universities throughout the U.S. Faculty freezes and cutbacks are omnipresent. So, too, is growing student demand in liberal arts. Larger and larger methods classes are the inevitable consequence.

However, application and evaluation are cognitive skills that cannot be taught effectively in large sections. Consequently, more poorly trained undergraduates are entering our graduate programs. They need more training than we gave to previous generations of students. Yet we lack the staff even to match our previous levels of service.

At some universities, these problems are avoided by eliminating all methods requirements. A recent survey of departments (Dyer, 1991) indicates that only about 40% have methods requirements for all majors (yet all but about a quarter of the departments recommend or require them for at least some students). Unfortunately, students often make the decision to pursue graduate work independent of such "tracking." Thus, we end up with more students who have been allowed to avoid methods courses in our graduate classes.

One of the results of all this is students who learn in graduate school advanced statistical techniques without being grounded in the fundamentals of methodology. We have no doubt that more graduates than previously can compute LISREL models, survival equations, and two-stage least squares. But knowing how to compute two-stage least squares is not nearly as important as knowing how to derive causal models, knowing how to develop measures, and knowing when (if ever) it is appropriate to apply two-stage least squares. We greatly fear that if graduate and undergraduate training continues to be understaffed, those more fundamental skills will be the ones that will be most poorly learned.

Is There a Solution?

Frankly, we're pessimistic about the prospects for getting the staffing to resolve these problems. In part, the problem is that those of us who teach methods have been unable to convince our colleagues that transferring methodological skills, like transferring writing, music, art, or foreign-language skills, must be done in relatively small classes. At Auburn, e.g., English composition has been able to hold the line at classes of 25; methodology will be lucky to hold the line at 60. People would think it bizarre if we said that one could learn to write without actually writing. Unfortunately, they do not think it bizarre that students can learn how to research without actually researching.

A partial solution may be available to both the undergraduate and graduate problems if, in recognition of the kind of cognitive learning that has to be emphasized in methods classes, departments are willing to shift substantial graduate student resources from teaching and grading service courses to teaching undergraduate methodology. Most departments use professors to teach majors, and graduate students to help teach service courses. In an era of scarce resources, that seems to reflect a misunderstanding of the kinds of learning involved in each course. It also overlooks the learning of fundamentals that one gets when teaching.

Application and evaluation of methodology cannot be taught effectively in classes of 100, even if a professor does the teaching. Application and evaluation can be taught in classes of 20, even if graduate students are doing the teaching. Furthermore, having to teach undergraduate methodology will greatly improve graduate students' understanding of methods. Nothing clarifies the fundamentals of methodology as much as trying to make it clear enough so that undergraduates can understand it.

Admittedly, using five graduate students to teach methods in place of one professor leaves many sections of service courses uncovered or much grading undone. However, the instruction in most of our service courses emphasizes transmission of knowledge rather than transmission of skills. Transmission of knowledge can be done in very large sections. Furthermore, virtually all of the grading and record keeping that is done in very large sections can now be done by computer. Combining the five uncovered sections of the service course under the instruction of the one professor is unlikely to greatly reduce the quality of learning in those courses.

In the long run, if states continue to try to squeeze more student contact hours out of every F.T.E., methods instruction will have to suffer. You can effectively teach introduction to art in sections of 1,000; but you can effectively teach people to paint only in small sections. Similarly, you can effectively teach introduction to American institutions in sections of 1,000; but you can effectively teach research methods only in small sections.

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"Creating" Good Problem Sets

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The Problem of the Problem Set

Arranging good problem sets is the most vexing part of teaching any methodology course. Texts and articles demonstrating both good and less than adequate applications of different techniques are selected without too much difficulty. Problem sets are another matter.

The first step is to scour the existing well documented datasets in the ICPSR catalogue, many of which are probably already available locally. This excursion reveals several discouraging facts. The substantive content of many existing data sets is too complicated to be neatly excerpted for a methodology problem set. Imagine a simple four variable model of political attitudes or growth in the public sector. In other instances, because of the "real world" nature of the data, the particular problem to be identified and treated is intertwined with other statistical problems that greatly complicate the analysis, and may even dominate the problem being illustrated. Getting students to diagnose and treat autocorrelation in circumstances that also present problems with limited dependent variables, with errors in variables, or with simultaneity is a daunting task, much like trying to replace one fixture in an old house. (A circumstance that led to a $10,000 disposal in one former house.) At this point, one usually makes do by simplifying what is in the data and telling the students to ignore other estimation problems. None of this seems very satisfactory.

There is another way: "fake it." I decided several years ago in an advanced methods course to create my own problems and datasets using Monte Carlo simulation. This approach has a number of nice features, some of which were not evident until after students began their analysis. This article describes some of these advantages, the procedures used, and offers one example taken from the advanced methods course.

Creating a Problem Set

The concept of the Monte Carlo simulation is very simple. (See E. A. Hanushek and J. E. Jackson, *Statistical Methods for Social Scientists*, New York: Academic Press, 1977, for repeated pedagogical uses of these simulations.) The problem set is defined by the substantive scenario used to frame the exercise and by the particular parameters chosen by the instructor, such as the number of variables and observations. Random numbers are then drawn to represent the stochastic elements in the model and included in this structure. The specification of the random numbers and the way they are included in the structure are determined by the problem being assigned. For example, if one is simulating autocorrelation, the stochastic term at time t is a function of the stochastic element at time $t-1$ and a random term, $u_t = \rho u_{t-1} + e_t$. This term is included in the structure in an additive manner. If an errors in explanatory variables problem is assigned, the random number drawn is added to the relevant exogenous variables, $X_{tk} = X_{tk} + e_t$. Separate datasets can be created using the same values for the exogenous variables and different draws from the distribution of random numbers. In this way, each student gets a separate "problem" set to analyze.

The key to the problem set is the scenario that describes the substantive arguments, the hypothesized model, the data, and the conditions that lead to an estimation problem. Often, these scenarios build on articles read as part of the assignments. For example, the early assignments in the methods course include several papers modeling growth in government expenditures in democratic countries. The first problem set describes two data sets measuring public sector expenditures and a set of exogenous variables reflecting the core hypotheses. The variables are the same in each set. One dataset represents cross sectional data collected from a set of forty countries while the second set represents data taken from a single country over a forty year period. Students are asked to estimate and compare the relationship between various factors and the size of government with these two data sets. It is suggested that the cross section data may present heteroskedastic problems, with the variance of the deviation of actual expenditures from expected expenditures being positively related to national income. They are also told to expect serial correlation problems with the time series data. Students are asked to select and justify an estimation procedure appropriate for each data set and to compare methods if several methods are used.

There are several advantages to these simulated datasets. The most obvious one is that the instructor can make sure that the condition to be diagnosed and overcome exists within the data. For example, in the above examples, the simulations are designed so that heteroskedasticity and autocorrelation are very evident in the data. Conversely, the data are developed so that other possible problems are minimal or non-existent. These conditions, though idealized and not characteristic of real data, are very useful in helping students to recognize the problems at issue and to see the effects of different estimation methods. My experience is that students learn better when their first encounter with situations are clear and dramatic. It is important for them to go, "Oh! So that's what autocorrelation looks like," and, "Wow! GLS makes a difference in the standard errors but not much in the estimated coefficients." I have found that it is harder to get these revelations of truth with real datasets.

Some of the less obvious advantages turn out to be even more important. We usually work with, and teach, the assumption that any dataset is just one possible draw from a distribution of many possible outcomes.[1] Consequently, the results obtained from analyzing any particular dataset are unique to those data and will not equal the true structure presumed to generate the data. Our statistical analysis is designed to allow us to say something about the distribution of possible results, given the distribution of possible datasets, and how that distribution relates to the presumed structure that generated the data.

I have found this concept of a dataset and the associated results being simply one draw from a distribution to be a very difficult concept to grasp, and not just for students. People often see one dataset and the results obtained from analyzing those data and presume they have the answer to the question of how certain variables relate to each other. The Monte Carlo simulations offer as many different datasets as there are students, more if the instructor wants to pursue the matter. Consequently, when students compare results, as they surely do, and when it comes time to discuss the problem in class, people discover a wide range of "answers." (This lesson is aided by tabulating estimates for each coefficient on a blackboard.) Even more revealing is the explanation that each of these answers is correct. Correct in the sense that the proper procedures were followed and correct given the particular dataset.

The distribution of student results produces a second important lesson. Revealing the "true" values used in the simulation is necessary at this point. (If this is the first problem set, Monte Carlo simulation needs to be explained.) Some– many– of the estimated values will differ substantially from the true values. The pedagogically useful ones are those with a different sign from the true value, with extra points given for the ones of these that are statistically "significant." Students emerge from this demonstration, particularly after several exercises, with a healthy skepticism for what truth about social processes is contained in one set of results. At this point, it is again useful to underscore the fact that, we hope, everyone did their statistical analysis correctly. The deviations of the results from the true structure is not attributable to incorrect method or technique, but to the vagaries of data.

Invariably, at this point someone asks, "Then, what can be learned from a dataset!?" My answer is that empirical research is a game played against nature. The objective of empirical work, the game, is to make the best possible guess about the natural structure that generated the data measuring the behavior of interest. Nature, of course, keeps the information about this structure secret. The hypothesized model, or models, are the initial guesses about this structure and the statistical analysis indicates how "good" these guesses are, as assessed by their consistency with the data.

This game against nature must be played according to very specific rules by people who are patient and clever. (Remember the advertisement that, "It is not nice to fool Mother Nature.") I have found that most students develop a better appreciation for the purpose of empirical work and for the complexity of the task after seeing the distribution of results and how they differ from the systematic part of the data generation process. It is also evident at this point that statistical technique and data alone are not sufficient to play the game successfully. One must always be making guesses and checking them against the data. After all, students have direct evidence that some "correct" analysis just led to results that are completely contradictory to the structure nature used.

The answer just outlined also establishes the instructor as a very important figure for the rest of the class. The person controlling the simulations is, in effect, nature and the students are trying to "guess" what structure nature has used. This is a social scientist's one (only?) chance to

[1] Even if we have all years in some time period or all cross section units, such as states or legislators, we are still sampling behavior. The observed outcomes are not the only possible outcomes for that year, that state, or that legislator.

play God in some aspect of the world. (We may be doctors, but we are not physicians.)

The example exercise based on simulated datasets that I offer illustrates this notion of the students playing a game against nature. The section on limited dependent variables presents alternative ways of conceptualizing the responses to simple trichotomous choice questions, such as the agree, disagree, no opinion/don't know found in survey research. One option is that the responses constitute an ordinal assessment of preferences with no opinion/don't know constituting indifference. In this case, the responses are best modeled by an ordered probit model. Secondly, the no opinion/DKs may be a completely separate category of response that is quite distinct from preferences. In this case, the responses constitute a categorical variable which may be modeled by a multinomial logit expression. Lastly, we discuss a decision tree type model. In this model, people first decide if they have an opinion when asked the question. If they decide they have an opinion, then they indicate whether it is an agree or disagree. In this model, we first model the probability a person has an opinion. Next, we model the probabilities people agree, conditional on their having an opinion. Each of these models implies a different statistical estimator and test for consistency with the data.

The problem set presented below presents students with data about preferences commonly found in survey research. They are asked to guess the process underlying this choice behavior and to estimate the effect of individual differences on the likelihood of opposing, favoring, or having no opinion. The estimate of these individual differences varies considerably with the model hypothesized and selected by the student. Each student is given a dataset with 300 simulated responses and corresponding values for the explanatory variables. The simulated responses were generated with the conditional choice model described above, with an expected no opinion/DK response from 20% of the sample.

An Example

In estimating a simple model of attitudes towards increased local school expenditures, the following variables were constructed from a survey of residents:

Y = Attitude (1 = Oppose, 2 = Favor, 3 = No Opinion),

X_1 = Education in years of schooling,

X_2 = Black,

X_3 = Age in years,

X_4 = School age children in family,

X_5 = Income in thousands of dollars,

X_6 = School age children in non-public school,

X_7 = Employed as teacher.

Compare the probability of having no opinion or of favoring increased expenditures of a 28 year old black, with 18 years of education, earning \$50,000, who has a child in public schools and who is not a teacher with that of a childless, 65 year old white, with 12 years of education, earning \$20,000 and who also is not a teacher. What is the marginal effect on these probabilities if schooling were to decrease by a year?

There is considerable discussion in the methodological literature about how to treat the no opinion response in survey research. Does this response indicate indifference, i.e. an intermediate point on the oppose-favor continuum? Or is it indicating the absence of an attitude, which constitutes a separate category, that is not on the continuum? How would you treat each of these alternatives in answering the above questions?

Student Reaction

Student's adapted very quickly to the idea that they were not dealing with "real" data. I had been concerned that they might be unable to suspend belief in a way that would permit them to take the problem sets seriously. This turned out to be no problem. Maybe graduate students are better than faculty at suspending belief, at least about certain things. They take the model and data in the problem so seriously that I regularly get discussions of omitted variables, possible simultaneity among variables, and other "real world" comments.

Students seem to get very caught up in the game against nature aspect of the problem sets. In a friendly and constructive way, they compete with each other to see who comes the closest to getting the correct specification. They also see it as a game against the instructor to guess the right model. These games within games add interest and get their attention. I also observe a lot of exploration of different hypotheses, models, and even other techniques as students try to figure out what nature gave them.

My feedback has been that they find the problem sets one of the most valuable parts of the course. I am concerned about what that says for the readings and lectures, but it does indicate success in the applied parts of the methods course.

A Primer on Simulation of Statistical Models

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One of the best ways to learn about statistical models is to simulate the process and then analyze the data you generate. This way you know what the true model is and can observe the effects of model misspecification directly.

In order to construct such simulations, it is important to know a few facts about generating the data to simulate a model. This primer provides a quick overview of these points. For more detail, in a difficult but useful treatment, see Mitrani, 1982.

Pseudo-Random Number Generators

Virtually all statistical software packages provide some mechanism for generating pseudo-random numbers. These are called pseudo-random because computers are not capable of generating truly random numbers. Instead, they generate numbers using a function which is known to produce a long series of numbers which possess some of the characteristics of a random process. Such sequences eventually repeat themselves. Choosing an appropriate function to produce a long cycle is a complex art. The details of this process are discussed by Knuth, 1969, but need not concern us here. I will assume that the software you use has a well constructed generator (though such an assumption should not be automatically made if you have a critical application.) While all such sequences are pseudo-random, I will use the less accurate but more convenient term random.

Random number generators begin with an initial value, called the *seed*, and generate the rest of the sequence based on this. This is convenient because it means that you can generate the same sequence of numbers by using the same seed. Most of the time, we don't care about this, but it is important to be able to replicate a sequence exactly if we need to. The seed is usually generated automatically by the software using the time of day clock to get the number of milliseconds since midnight, or some such, though some software may require you to provide the seed. Once the random number generator has a seed, it can generate a sequence of numbers.

Random number generators produce values from some specific distribution. The most common distributions supported are the uniform and the normal. While the terminology differs across packages, they usually have obvious names like "rndu" or "urand" or "random" or some such. You *must* know what distribution your random number generator produces or your work will be worthless.[1] Uniform generators produce real numbers on the open interval $(0,1)$, that is, numbers between 0 and 1 but not including 0 or 1. Normal generators produce a standard normal distribution with mean zero and variance 1.[2]

Generating Variables

In a typical simulation, you need to construct some independent variables, a disturbance term, and a dependent variable. The first step is deciding what model you wish to simulate. For example, simple regression models might be $y = \alpha + \beta x + u$ or $y = \beta_1 + \beta_2 X_2 + \beta_3 X_3 + u$. How do you simulate these?

The first step is to generate the right hand side variables. Then use these and the model to generate values for y. In the first case above, we generate values for x and u. Picking a model includes assigning numerical values to the parameters, such as $\alpha = 5$ and $\beta = 1.5$. Then multiply x by β, add α and add u to get y. This is precisely the process we assume is at work in the world when we model some phenomenon by fitting a simple linear regression. In constructing your simulations, you duplicate that process.

Before you generate data, however, you must decide what distribution to use for each of the variables. The only assumption the standard regression model makes is that u is normally distributed. But it says nothing about the distribution of X or the variance of u. These are model parameters which you must choose. (Or they may be given by the problem.) For example, if you were given that $x \sim N(0,1)$ and $u \sim N(0,1)$ then you could just use the random number generator to create the variables directly. However, if the variances or means are different, then you must construct them in some fashion.

Manufacturing Variables to Specifications

Suppose you are given that $u \sim N(0,4)$. How can you construct this, given that your random normal generator produces values $z \sim N(0,1)$? Recall what you know about linear transformations of variables and the relation of the new distribution to the old. First, for the mean:

$$\begin{aligned} y &= a + bx \\ \bar{y} &= \frac{1}{n}\sum(a+bx) \\ &= \frac{1}{n}\sum(a) + \frac{1}{n}\sum(bx) \\ &= a + b\bar{x} \end{aligned}$$

[1] For example, some programs have a "RANDOM" function which produces random integers. Mistaking this for a continuous distribution would not be good.

[2] This is almost always true, but check your manual to be sure.

For the variance:

$$\begin{aligned} y &= a + bx \\ V_y &= \frac{1}{n}\sum(y-\bar{y})^2 \\ &= \frac{1}{n}\sum(a+bx-a-b\bar{x})^2 \\ &= \frac{1}{n}\sum(bx-b\bar{x})^2 \\ &= \frac{1}{n}\sum b^2(x-\bar{x})^2 \\ &= b^2 V_x \end{aligned}$$

In the example, we have $z \sim N(0,1)$ and we want $u \sim N(0,4)$. To create u then we simply let $a = 0$ and $b = 2$ and construct $u = 2z$, since $2^2 = 4$, giving us the desired mean and variance. By choosing a and b appropriately, you can generate u with any mean and variance you like.

For uniform numbers, the process works the same way. A uniform distribution on the $(0,1)$ interval has mean 0.5 and variance $1/12$ or $.08333\ldots$. If you want to construct X with mean zero and variance 1, but with a uniform distribution then first generate $z \sim U[0,1]$ where $U[0,1]$ means uniform on the interval $(0,1)$. Then let $x = (u - .5)\sqrt{12}$. You can verify that this has the desired mean and variance. (What is the range of x?)

Using these methods, you can construct individual variables with any mean and variance you like, from either a normal or a uniform distribution.

Generating Correlated Variables

The sequences you create from the random number generator are uncorrelated with each other. This is often desirable. However, there are times when you need to construct two variables which are correlated by some amount. How can you create, say X_2 and X_3 where $r_{23} = .5$?

The strategy here is to create two independently distributed variables, say t and u. Then construct x and y from these in such a way that the variances and covariance (and hence correlation) are what we need. Assume that you have generated t and u with mean 0 and variance 1. We want to construct x and y as linear combinations of t and u Here are the facts we need.

Define x and y in terms of t and u:

$$\begin{aligned} x &= at \\ y &= bt + cu \end{aligned}$$

Find the variances of x and y:

$$V_x = a^2 V_t \text{ (see above)}$$

and

$$\begin{aligned} V_y &= \frac{1}{n}\sum(bt+cu-b\bar{t}-c\bar{u})^2 \\ &= \frac{1}{n}\sum(b(t-\bar{t})+c(u-\bar{u}))^2 \\ &= \frac{1}{n}\sum(b^2(t-\bar{t})^2+c^2(u-\bar{u})^2+2bc(t-\bar{t})(u-\bar{u})) \\ &= b^2V_t + c^2V_u + 2bcC_{tu} \end{aligned}$$

The covariance of x and y is:

$$\begin{aligned} C_{xy} &= \frac{1}{n}\sum(x-\bar{x})(y-\bar{y}) \\ &= \frac{1}{n}\sum(a(t-\bar{t})(b(t-\bar{t})+c(u-\bar{u}))) \\ &= abV_t + acC_{tu} \end{aligned}$$

The correlation of x and y is:

$$r_{xy} = \frac{C_{xy}}{\sqrt{V_x V_y}}$$

These are the general formulas. However, we can simplify them by recalling that we start out with t and u having variances of 1.0 and the covariance between them is zero. Simplifying and collecting results gives:

$$\begin{aligned} V_x &= a^2 \\ V_y &= b^2 + c^2 \\ C_{xy} &= ab \\ r_{xy} &= \frac{b}{\sqrt{b^2+c^2}} \end{aligned}$$

Solving for a, b and c gives

$$\begin{aligned} a &= S_x \\ b &= r_{xy}S_y \\ c &= S_y\sqrt{1-r_{xy}^2} \end{aligned}$$

and recall

$$C_{xy} = S_x S_y r_{xy}$$

where S_x is the standard deviation of x and similarly for y.

From this, given the desired variances of x and y, and their correlation, you can easily find a, b and c and construct x and y from t and u. Once constructed, the variables will have mean zero. If some other mean is desired, simply add the mean as the final step.

Example: Create x and y where $V_x = 3$, $V_y = 7$ and $r_{xy} = .50$. Solving for a, b, and c gives

$$\begin{aligned} a &= \sqrt{3} \\ b &= .5\sqrt{7} \\ c &= \sqrt{7}\sqrt{1-.5^2} \end{aligned}$$

Create t and u using the random number generator. Then let

$$\begin{aligned} x &= \sqrt{3}t \\ y &= .5\sqrt{7}t + \sqrt{7}\sqrt{.75}u \end{aligned}$$

The resulting x and y will have variances of 3 and 7, respectively, and correlation of .50.

Advanced Note: The coefficients a, b and c can also be found from the Cholesky decomposition of the variance-covariance matrix for x and y. Let

$$vc = \begin{pmatrix} V_x & C_{xy} \\ C_{xy} & V_y \end{pmatrix}$$

The Cholesky decomposition of vc is the matrix y such that $y'y = vc$. It turns out that

$$y = \begin{pmatrix} a & b \\ 0 & c \end{pmatrix}$$

Since $C_{xy} = S_x S_y r_{xy}$ is easily computed, use of the Cholesky decomposition may prove simpler if you have a matrix oriented program, such as Gauss.

Generating y

In most statistical simulations, the dependent variable is composed of two components: a systematic function of independent variables and a stochastic disturbance term. In linear models, these are simply added to create y. For example, if the true model is $y = 5 + 1.5X + u$, with $X \sim N(4, 2)$, $u \sim N(0, 3)$ and $C_{Xu} = 0$, you construct X and u with proper mean and variance, as shown above, from independent series. Then multiply X by 1.5, add the constant 5, and add u.

Replications

Many statistical simulations are run repeatedly in order to build up a plot of the behavior of parameter estimates under particular conditions. Thus it is not enough to generate the data and run the statistical program once. Rather, the program may be run dozens or hundreds of times. For each replication, the appropriate statistic (say the slope estimate) is recorded. The collection of these coefficients are then used later to describe the distribution of the statistic.

In replicating the model it is critical that you control variation according to the model. The most important point here is the assumption that X is fixed. This means that once X is created, the same values are used in each replication. Only the values of the stochastic disturbance are allowed to vary from replication to replication.

For example, to replicate a model of $y = \alpha + \beta X + u$, you would generate X. Next create u. Finally, make $y = \alpha + \beta X + u$. This constitutes a single replication. For the next replication, generate a new u, and create y as before, using the same X as last time. If you generate X again each time, your model will have an extraneous source of variation, and your parameter estimates will vary more than they should. (Of course, you might *want* to model the case in which X varies across replications, but for most of our purposes we assume that X is fixed.)

Analysis of Simulation Results

Once the simulation has been run, our interest turns to the behavior of the parameters we are investigating. The point of the simulation is to see how these parameter estimates behave across replications of the simulation. This means that the estimate from each replication must be saved for later analysis. It is easiest if your software allows you to do this directly. If not, you must save the output from each replication and enter this as data for further analysis.

The typical concern in this analysis is the distribution of the parameter estimates. Usually this involves simple descriptive statistics, such as the mean and variance, and plots of the estimates, using histograms, box plots, stem and leaf plots and so on. In some cases, we care about the relationship between two parameters, and so we may want scatter plots of one parameter against another.

Such analysis is easily done once the parameter estimates are saved in a machine readable form. If you can have your software save these automatically, it will save having to reenter them by hand after the replications are done.

Cases versus Replications

People are often confused by the distinction between the number of cases used in a simulation and the number of replications run. For example, if you build a simulation of 100 observations, then replicate this simulation 50 times, you have 100 cases and 50 replications. When you analyze the results of the simulation, you use the 50 parameter estimates (one from each replication) as your database.

The precision of your simulation results depends both on the number of cases used in each simulation and the number of replications. Few replications will produce a ragged distribution of estimates because there are so few replications. Few cases, on the other hand, will generally produce a large variance in the distribution of the estimator across replications. In choosing the number of cases and replications, the first consideration should be the purpose of the simulation. If the aim is to study the small sample behavior of an estimator, then it makes no sense to have a large number of cases, though many replications may well be used. For a given number of cases, more replications are better in the sense that the distribution of the estimator will become smoother with more replications. The cost here is time, both computational and human. A reasonable decision rule is to run as many replications as are required for the pattern of estimator behavior to become clear.

References

Knuth, Donald E. 1969. *The Art of Computer Programming, Vol. 2*, Addison-Wesley: Menlo Park, CA.

Mitrani, I. 1982. *Simulation Techniques for Discrete Event Systems*, Cambridge: Cambridge University Press.

A Survey of Political Science Research Methods Courses

James A. Dyer
Texas A&M University

Methods training varies considerably across departments of political science. This article describes a survey of methods programs in graduate degree granting departments of political science. The results cast light on the state of methods training in the discipline.

Survey Description

The survey was conducted during the last two weeks in July and the first week in August, 1991. A sample of 177 departments of political science out of approximately 250 listed in the Guide to Graduate Studies were selected randomly. Calls were made to the department. The interviewer asked to speak to someone who taught methods in the department, or someone who could discuss the methods courses the political science students might be taking.

We completed a total of 100 interviews. There were eight bad numbers, 14 no answers after multiple attempts. The remaining 55 were not available during the period in which we were collecting data. Two of these called in and completed the survey, but the data was not included in the sample reported here.

Methods Requirements

There is a fairly even split between departments which require methods courses of at least some students and those which do not. Table 1 shows that 40% of departments require at least one methods course of all students while about a quarter have no methods requirement at all.

Departments differ somewhat between those offering the Ph.D. and those which do not. Masters only programs are somewhat more likely to require methods training of all students.

It is sometimes argued that larger departments may avoid requiring methods classes because of the relative difficulty in teaching methods to large numbers of students. The data do not support that argument. There is no relationship between the number of majors in the department and the methodology requirement.

Virtually all (92 percent) of the departments requiring or recommending methods courses teach one or more of the methods courses in the department.

Table 1: Distribution of Departments on Methodology Requirements

	Departments
All required	40%
Some required	14%
Recommended	22%
None	24%
N	(100)

Table 2: Methods Requirement By Department Type

Requirement	Department Type	
	MA only/None	PhD
Required all	47.8%	33.3%
Required some	17.4%	9.8%
Recommended	13.0%	31.4%
None	21.7%	25.5%
	(46)	(51)

Course characteristics

We asked about how much emphasis was given in the methods class to research design, data collection, statistical analysis, computer analysis, and learning to use a statistical package. The response "a great deal" was coded 1, "some" coded 2, "not very much" coded 3, and "none" coded 4. The means from these responses for each of the five areas are presented in Table 3.

Table 3: Emphasis In Methodology Course

	Mean	(SE)
Design	1.71	(.08)
Data Collect	2.01	(.08)
Stat Analysis	1.67	(.09)
Computer Analysis	1.90	(.10)
Statistical Package	2.07	(.12)

Table 4: Gamma Correlations Among Emphasis Rankings In Methodology Course

	Data Collect	Stat Analysis	Computer Analysis	Statistical Package
Design	.520*	-.103	.067	-.055
Data Collect		.251	.220	.303*
Stat Analysis			.809*	.655*
Computer Analysis				.987*

*gamma significant at .05 level.

Design and statistical analysis are given more emphasis than data collection or the computer related activities, although the mean differences are small. The apparent similarities in mean rankings are masking significant differences in priorities. This can be seen in the correlations among the rankings of the different emphases. The gamma correlations among the rankings are presented in Table 4.

There is a slightly negative correlation between emphasis on design and statistical analysis. Of those with methods course requirements or recommendations, 25 percent say there is greater emphasis on design than on statistical analysis, 28 percent say there is greater emphasis on statistical analysis than design, and the remaining indicate equal emphasis. We use this typology of greater emphasis on design, equal emphasis, and greater emphasis on statistical analysis in the subsequent analysis.

Data collection is weakly associated with both design and statistical analysis emphases. As indicated by the low correlations between computer analysis emphasis and design and the relatively high correlation between computer analysis emphasis and statistical analysis, emphasis on computer analysis tends to occur in courses with greater emphasis on statistical analysis. Among those with a statistical analysis emphasis, over half (55 percent), also indicate a high emphasis on teaching computer analysis; among those with equal emphasis, one-third indicate high emphasis on computer analysis; among those with a design emphasis, only 6 percent indicate high emphasis on computer analysis. The gamma between computer emphasis and the topology of design versus analysis approaches is .581.

The correlation of .987 between the items indicates that virtually all who emphasize computer analysis also place a high emphasis on learning a particular computer analysis package.

Table 5: Percent of Course Teaching Computing by Laboratory in Course

Teaching Time	Lab	No Lab
None	7%	33%
LT 10%	16%	23%
10-15%	40%	27%
GT 15%	37%	17%
	(43)	(30)

We asked whether the students used the computer at all in the course, and if so, what proportion of the instruction time was spent using the computer. The time spent ranged from 0 to 50 percent. The average percentage of time spent in instruction using the computer is 16 percent among those reporting using the computer at all. Of those departments with required or recommended methods classes, 18 percent spent no time on computers, 19 percent spent less than 10 percent, 34 percent spent 10-15 percent, and 29 percent spent over 15 percent.

A majority (60 percent) of the methodology classes are taught with a laboratory. As would be expected, those with a statistical analysis orientation are more likely to have a laboratory. However, the relationship is quite weak. Half of those with a design orientation have a laboratory and 35 percent of those who have a statistical analysis emphasis do not. The percentage of time spent instructing on the use of the computer is higher for the those classes with a laboratory (Table 5).

Computing environment

Three-quarters of the departments report that computing in the methods class involves personal computers in some way. Only 25 percent indicate that computing is done only on a mainframe. An additional 32 percent indicate that some combination of mainframes and personal computers are used. A total of 43 percent use stand alone personal computers or personal computers hooked into a network. The distribution is presented in Table 6. We asked about minicomputers and found only one where a minicomputer was used exclusively and three other cases where one was used with PCs or PCs and mainframes. We collapsed these cases into the mainframe categories. The relative absence of minicomputers should be noted, however.

Of particular interest in terms of the statistical packages is the nearly complete dominance of SPSS and its variants and the near absence of computer packages designed to run primarily in the PC environment.

Table 6: Distribution of Types of Hardware

Mainframe	25%
Personal	18%
PC-Networked	25%
PC/Mainframe	27%
PC Network/Mainframe	5%

Table 7: Distribution of Statistical Packages

SPSS-X	19.7%
SPSS-PC	23.0%
SPSS-MIXED	18.0%
SAS	6.6%
SAS-PC	1.6%
MINITAB	3.3%
SPSS-SAS	8.2%
SPSS-MINITAB	1.6%
MIDAS	1.6%
OTHER PC	8.2%
SPSS-OTHER PC	8.2%
	(61)

Statistics Texts in Political Science

A variety of texts are used for teaching political methodology. This spring *TPM* asked several well known methodologists what they used in their courses. Here are their comments.

Bert Kritzer, University of Wisconsin–Madison:

Wonnacott & Wonnacott, *Introductory Statistics* (5th edition) (first semester), supplemented by the Minitab handbook and a packet of algebra review materials.

Neter, Wasserman and Kutner, *Applied Linear Regression Models* (2nd edition), second semester, supplemented by a couple of Sage monographs and some xeroxes (including a section reviewing logarithms).

Walter Mebane, Cornell University:

In response to your message, here's a list of the books I'll be using in a course (Government 602, "Field Seminar in Methodology") this spring term.

Warwick, Donald P., and Charles A. Lininger. 1975. *The Sample Survey: Theory and Practice.* New York: McGraw-Hill.

Levy, Paul S., and Stanley Lemeshow. 1991. *Sampling of Populations: Methods and Applications.* New York: John Wiley & Sons.

Agresti, Alan. 1990. *Categorical Data Analysis.* New York: Wiley.

Greene, William H. 1990. *Econometric Analysis* New York: Macmillan.

Gujarati, Damodar N. 1988. *Basic Econometrics.* 2d ed. New York: McGraw-Hill.

Achen, Christopher H. 1986. *The Statistical Analysis of Quasi-experiments.* Berkeley: University of California Press.

Gary King, Harvard University:

I'm going to use Kmenta this year, although I like Goldberger's text best. It's just too terse for political science grad students.

Chris Achen, University of Michigan:

I use DeGroot's book, *Probability and Statistics.* It uses calculus, so I supplement with references to Kleppner and Ramsey's *Quick Calculus.* I also like Dudewicz, Edward, *Introduction to Statistics and Probability*, for a more advanced reference. I find that students swear at it but use it later at dissertation time.

People around here also use Hays, or Hays and Winkler. I think they're quite good, too. I occasionally assign Freedman, Pisani, Purves and Adhikari, *Statistics*, for the people who've never had stats before—that's a quirky but intellectually very serious introductory text.

Neal Beck, University of California, San Diego:

In the past, I've used Kmenta and Johnston. This year I plan to use

Raymond H. Myers, *Classical and Modern Regression with Applications*, 2nd ed. PWS-Kent, 1990

Another nice book worth mentioning is William H. Greene, *Econometric Analysis*, Macmillan, 1990. Very up to date, good references, two nice big chapters on limited dependent variables.

Jim Stimson, University of Iowa:

I haven't done the regular stats course for several years. When I last did I used Wonnacott and Wonnacott, *Econometrics.* For more intro stuff, I like Mendenhall for its non-theological approach to inference.

What I do teach with some regularity is time series, where I have used Box and Jenkins. I am currently using Mills, *Time Series Techniques for Economists.*

Bill Jacoby, University of South Carolina:

Here are the three texts that I've used in the intro stat course.

Bohrnstedt, George W. and David Knoke, *Statistics for Social Data Analysis*, (Second Edition), F.E. Peacock.

Sprinthall, Richard C., *Basic Statistical Analysis* (Third Edition), Prentice-Hall.

Wonnacott, Thomas H. and Ronald J. Wonnacott, *Introductory Statistics* (Fifth Edition), Wiley.

Michael Lewis-Beck, University of Iowa:

I use Pindyck and Rubinfeld, *Econometric Methods and Models*, 3rd ed. McGraw-Hill; John Fox's *Regression Diagnostics*, Sage; and (what else?) Lewis-Beck, *Applied Regression: An Introduction*, Sage.

Don Green, Yale University:

Judge, George G., R. Carter Hill, William E. Griffiths, Helmut Lutkepohl, Tsong-Chao Lee. 1988. *Introduction to the Theory and Practice of Econometrics.* 2nd Ed. New York: John Wiley and Sons.

R. Carter Hill. *Learning Econometrics Using Gauss: A Computer Handbook to Accompany Judge et. al.* 2nd Ed. New York: John Wiley and Sons.

Kennedy, Peter. *A Guide to Econometrics.* 2nd Ed. Cambridge: MIT Press.

Hayduk, Leslie. *Structural Equation Modeling with LISREL.* New York: Johns Hopkins Press.

John Brehm, Duke University:

Here's what I use in the second semester statistics class.

Hanushek and Jackson, *Statistical Methods for Social Scientists.*

Namboodiri, *Matrix Algebra.*

Achen, *Interpreting and Using Regression Analysis.*

1992 ICPSR Summer Program

Henry Heitowit
Inter-university Consortium for Political and Social Research

Members of the Political Methodology Section of the American Political Science Association may be interested in some of the recent innovations and additions to the courses offered by the Inter-university Consortium for Political and Social Research (ICPSR) Summer Program in Quantitative Methods of Social Research.

A new course initiated recently is Maximum Likelihood Estimation and is based around Gary King's new book, *Unifying Political Methodology.* The course will be team taught by Charles Franklin (University of Wisconsin–Madison), Gary King (Harvard University), Nancy Burns (University of Michigan), Nathaniel Beck (UCSD) and others.

Another new course is a lecture series Dynamic and Longitudinal Analysis. This course will devote one week each to the following topics: Panel Analysis (Greg Markus, Political Science, University of Michigan), Pooled-Time Series (Markus), Event History Analysis (Charles Denk, Sociology, University of Virginia) and Time Series Tests (Walter Labys, Economics, West Virginia University).

For the last several years we have offered three courses in the general area of "mathematical modeling:" Game Theory (Jim Morrow, Hoover Institution), Rational Choice (Jack Knight, Washington University), and Formal/Dynamic Models of Social Systems (Courtney Brown, Emory University).

Other recent additions to the Program include one-week (5-day), intensive courses on Network Analysis (Stanley Wasserman, Psychology, University of Illinois), Logit and Log-Linear Models (Mike Berbaum, Psychology, University of Alabama), General Structural Equation Models – Introduction and Advanced Topics (Ken Bollen, Sociology, University of North Carolina), and Item Response Theory and Measurement (Jeff Tanaka, Psychology, University of Illinois).

In addition to the above, there are the traditional 4-week Program offerings in such areas as Causal Analysis, "LISREL" Models, Time Series, Categorical Analysis, and Advanced ANOVA models.

The advanced topics (guest) lecture series this year will include presentations on "Chaos" and Non-linear Dynamics, Resampling Techniques: Jackknife and Bootstrap (Bob Stine, Statistics, Wharton School), Smoothing Functions (Werner Stuetzle, Statistics, University of Washington), and Graphical Presentation and Analysis of Data (John Fox, Sociology, York University).

The ICPSR Summer Program dates are June 29-July 24 for the first session, and July 27-August 21 for the second session

The Summer Program curriculum is guided by an Advisory Committee composed of Chris Achen, Greg Markus, Jim Stimson, Ken Bollen, John Fox and Cliff Clogg.

Individuals interested in receiving the Program brochure and an application should contact: ICPSR Summer Program, P.O. Box 1248, Ann Arbor, MI 48106.

Event History Summer Course

Paul D. Allison
University of Pennsylvania

A five-day course on event history analysis will be offered July 13-17 in Philadelphia. The instructor is Paul D. Allison, Professor of Sociology at the University of Pennsylvania. He is the author of the Sage monograph *Event History Analysis*, and has conducted this course for the past six summers.

The course will emphasize models for longitudinal event data in which the rate of event occurrence is a log-linear function of a set of explanatory variables. Topics include censoring, accelerated failure time models, proportional hazards models, partial likelihood, time-dependent covariates, competing risks, repeated events and discrete time methods. Participants will get hands-on experience with IBM-AT's.

The fee of $700 covers all course materials, but does not include lodging or meals. For further information contact Paul D. Allison, 3718 Locust Walk, Philadelphia, PA 19104-6299, 215-898-6717, ALLISON@PENNDRLS.UPENN.EDU

Redistricting Software Available

Gary King
Harvard University

I write to indicate the availability of an easy-to-use computer program that implements statistical procedures designed to solve a class of problems in evaluating electoral systems and redistricting plans. The program, written by Andrew Gelman and me, is called *JudgeIt*, and it is available at no charge.

This program can evaluate electoral systems in three general situations: (1) When an election has already taken place; (2) when an election has not yet been held but a new redistricting plan (or plans) have been proposed or implemented, and (3) when an election has taken place but you wish to evaluate what the electoral system would have been like if certain specified counterfactual conditions had occurred (such as if no minority districts had been drawn or if term-limitations prevented incumbents from running for reelection).

The evaluation of electoral systems and redistricting plans are based on concepts developed in our scholarly work. For example, JudgeIt will calculate several measures of *electoral responsiveness* and *partisan bias*. These have been used in the academic literature for some years now, and are at least part of the operational version of the concepts outlined in the recent Supreme Court case of *Davis v. Bandemer* (106 U.S. 2797 (1986)), where the Justices first declared political gerrymandering justiciable but gave only the outlines of what an acceptable measure of it would be. In addition to calculating measures of partisan bias and electoral responsiveness, JudgeIt will also calculate and graph seats-votes curves, and make specific predictions for district-level analyses (including the general partisan makeup of, or the likely winner in, individual districts, or the number of minorities likely to be elected). The program also provides many other useful procedures, descriptive statistics, and graphics. JudgeIt provides means of evaluating the model, its fit to the data, and the adequacy of any predictions made. It is useful for any legislature with two main parties and predominantly single member districts.

This is also the only program that provides estimates of uncertainty (i.e., standard errors) for bias, responsiveness, seats-votes curves, and virtually every statistic calculated. Uncertainty estimates have long been recognized as essential by social scientists and even the Supreme Court in some areas of the law.

The only additional software required to run JudgeIt is the DOS operating system. This program will run on any IBM personal computer or true compatible with a 386 processor (and 387 math coprocessor) or a 486 processor. A hard disk is desirable but not required. If you wish to use the graphics procedures, you must have a graphics card and monitor. JudgeIt supports 27 different graphics cards and monitors and 30 different printers and plotters. The program will use as much RAM as you have installed on your system.

You may obtain this program by anonymous FTP (computer: Haavelmo.Harvard.Edu, username: anonymous, password: your Internet account name). The documentation is in LaTeX format. Alternatively, contact me at the following address: Gary King, Department of Government, Harvard University, Cambridge, MA 02138 Internet: gmk@isr.harvard.edu, Phone: 617-495-2027, FAX: 617-496-5149

Event Data Coding Software Available

Philip A. Schrodt
University of Kansas

KEDS: the Kansas Event Data System, is a program for the machine coding of international event data using pattern recognition and simple grammatical parsing. It is primarily designed to work with short news articles such as those found in wire service reports or chronologies. To date, KEDS has been used primarily to code WEIS events from Reuters wire service lead sentences but in principle it can be used for other news sources and other event coding schemes such as COPDAB.

KEDS is a stand-alone program with a standard Macintosh interface; it is reasonably user-friendly and runs on any Macintosh computer with 1 Mb of memory. The system currently has English-language verb and actor patterns for 3-digit WEIS events based on the leads from Reuters reports (downloaded from the NEXIS data service) for the Middle East for 1988- 1990. We also have German language patterns developed from coding Eastern European events from foreign policy chronologies in Informationen, a fortnightly publication of the German Ministry for Inter-German Relations in Bonn, for the same period. Since Eastern Europe shows less variety of behavior, the German patterns are less complete than those in English. The coding accuracy for the Reuters data is around 80%-85%; for Informationen it is around 90%. The patterns will probably need to be modified when used with other news sources, and these accuracy levels may not be typical.

KEDS uses a simple input format: a flat-ASCII (i.e. TEXT) file containing news items prefixed with a date and separated by blank lines. The output is event data in the usual <date><source><event><target> format. The actor and verb patterns can be modified from within the program or with a text editor. In English, the system handles some simple grammatical tasks such as the recognition of compound subjects and phrases, pronoun references and passive construction. The system can be used for either machine-assisted coding, with the coder making corrections to the machine's suggested codes, or fully automated coding. In fully-automated mode, the system codes about 200 Reuters leads per minute, a rate substantially faster than most work-study students.

For a copy of the program, documentation (Microsoft Word format) and some sample data, send me a blank 800K disk at the address below. An MS-DOS version of the program should be available in late 1992. This work has been funded by the NSF Data Development in International Relations (DDIR) project.

Phil Schrodt, Dept of Political Science, Blake Hall, University of Kansas, Lawrence, KS 66045, tel. 913-864-3523, fax 913-864-5208, schrodt@ukanvm.cc.ukans.edu.

Preliminary Program for the Ninth Political Methodology Conference

The Ninth Annual Political Methodology Conference will be held at Harvard University, July 16–19, 1992. Below is the preliminary program for the conference. Please note that this is subject to change.

The conference is open to any who wish to attend, though only invited participants can be reimbursed for their travel, meals and lodging. The Tenth meeting of the conference is scheduled for Florida State University in July, 1993. A call for papers will appear in the fall issue of *TPM*.

Thursday, July 16

Stephen Ansolabehere *University of California, Los Angeles* and R. Douglas Rivers *Stanford University*: "Using Aggregate Data to Correct for Response Bias in Surveys".

Michael B. MacKuen *University of Missouri, St. Louis*, Robert S. Erikson *University of Houston* and James A. Stimson *University of Iowa*: "Aggregation, Moving Attractors and the Character of Partisan Change".

Donald Rubin *Harvard University*: "TBA".

Robert S. Erikson *University of Houston* and Thomas R. Palfrey *California Institute of Technology*: "The Puzzle of Incumbent Spending in Congressional Elections".

Tse-min Lin and Janet M. Box-Steffensmeier *University of Texas*: "A Dynamic Model of Campaign Spending in Congressional Elections".

Friday, July 17

Charles H. Franklin *University of Wisconsin–Madison* and R. Michael Alvarez *California Institute of Technology*: "Measuring Uncertainty in Political Perceptions".

Elisabeth R. Gerber and Jeffrey A. Dubin *California Institute of Technology*: "Finite Mixture Models for Qualitative Choice: A Study of Voter Heterogeneity".

Nathaniel Beck and Jonathan Katz *University of California, San Diego*: "Model Assessment by Cross-Validation".

Kathleen Knight *University of Houston*: "Computer Aided Content Coding"

Philip Schrodt *University of Kansas*: "Machine Coding of Events Data"

Saturday, July 18

Melvin Hinich *University of Texas*: "Estimating the Parameters of Spatial Models"

Joshua S. Goldstein *University of Southern California*, "Reciprocity in Superpower Relations: An Empirical Analysis".

Jonathan Nagler *Texas A&M University*: "Testing the Symmetry Assumption of our Non-Linear Models: Alternative Specifications to Logit and Probit for Dichotomous Dependent Variables".

Kenneth F. McCue *California Institute of Technology*: "A Test of the Transition model and the Homogeneity Model".

Sunday, July 19

Walter Mebane *Cornell University*: "A Dynamical System Model of Federal Expenditures and Congressional Campaign Finance"

John Londregan *Princeton University* and Keith Poole *Carnegie–Mellon University*: "Political Economy of Growth, Nonconstitutional Rule, and Leadership Succession".

1992 APSA Preliminary Methods Program

Stanley Feldman
SUNY-Stony Brook

The following methodology panels are scheduled for the 1992 meeting of the American Political Science Association. The meetings will be held August 27–30, 1992 in Chicago, IL.

Panel 5-1

Title: "Roundtable: Party Identification: A New Look at the New Look?"

Chair: R. Michael Alvarez, California Institute of Technology

Participants:

Paul Abramson, Michigan State University

Robert Erikson, University of Houston

Charles Franklin, University of Wisconsin, Madison

Donald Green, Yale University

Warren Miller, Arizona State University

Panel 5-2

Title: The Case Study Method in Comparative Politics

Chair: Helmut Norpoth, State University of New York at Stony Brook

Papers:

"The Comparative Case Study Method"
Barbara Geddes, University of California, Los Angeles

"How Decision Time and Degree of Anticipation Affect Decisionmaking: An Application of Structured, Focused Comparison"
Kent Bolton, Arizona State University

Disc:
Helmut Norpoth, State University of New York at Stony Brook
Robert Jackman, University of California, Davis

Panel 5-3

Title: "New Directions in Time Series Analysis"

Chair: John Williams, Indiana University

Papers:

"Short-run Reciprocity, Credibility, and the 'Long Peace': An Empirical Test of Some Game Theoretic Propositions"
Scott Gates and Charles W. Ostrom, Jr., Michigan State University

"Partisanship and Presidential Approval: An Error Correction Analysis"
Brink Kerr, Texas A&M University

"Long and Short Term Causal Linkages: An Application of Cointegration and State Space Modeling to the Dynamics of Partisanship and Presidential Approval"
Michael MacKuen, University of Missouri, St. Louis

"Estimation and Inference in Cointegrated Systems: A Comparison of Estimators"
Renee M. Smith, University of Rochester

Disc: John Williams, Indiana University

Panel 5-4

Title: "Problems of Estimation"

Chair: John Jackson, University of Michigan

Papers:

"Censoring in U.S. House Elections"
Walter R. Mebane, Jr., Cornell University

"Testing the Symmetry Assumption of Non-Linear Models: Alternative Specifications to Logit and Probit for Dichotomous Dependent Variables"
Jonathan Nagler, University of California, Riverside

"Race, Aggregation, and OLS"
Carol W. Kohfeld, University of Missouri-St. Louis and John Sprague, Washington University

Disc: John Jackson, University of Michigan

Panel 5-5

Title: "Identification and Estimation in Generational and Cohort Models"

Chair: Herbert M. Kritzer, University of Wisconsin, Madison

Papers:

"Intergenerational Class Mobility and Political Preferences in Germany, The Netherlands, United Kingdom, and the United States"
Paul Nieuw Beerta, University of Nijmegen, Anthony Heath, Oxford University, and Nan Dirk de Graaf, University of Nijmegen

"Theoretical and Empirical Identification: The Case of Cohort Models"
Herbert M. Kritzer and Brent Andersen, University of Wisconsin, Madison

Disc: Marco Steenbergen, State University of New York at Stony Brook

Panel 5-6

Title: "The Nature of Candidate Evaluations"
Co-sponsored by Section 41: Political Psychology

Chair: Stephen Ansolabehere, University of California, Los Angeles

Papers:

"The Dimensionality of Candidate Schemata"
Hans Anker, University of Amsterdam

"Modeling Voter Uncertainty"
R. Michael Alvarez, California Institute of Technology and Charles H. Franklin, University of Wisconsin, Madison

Disc: Simon Jackman, Princeton University and The University of Rochester
Stephen Ansolabehere, University of California, Los Angeles

Panel 5-7

Title: "Issues in Survey Research"

Chair: Robert Shapiro, Columbia University

Papers:

"Party Identification: An Experimental Comparison of the Gallup and Michigan SRC/NES Measures"
George Bishop, Alfred Tuchfarber and Andrew Smith, University of Cincinnati

"Gender of Interviewer Effects on Gender Related Attitudes"
Leonie Huddy and John Bracciodieta, State University of New York at Stony Brook

"Testing the Characteristics of the Seven-Point Issue Scales: An Empirical Assessment Based upon New Survey Questions"
William G. Jacoby, University of South Carolina

Disc: Robert Shapiro, Columbia University

Panel 5-8

Title: "Applications of Computer Methods in Political Science"

Chair: Charles Taber, State University of New York at Stony Brook

Papers:

"Information Conductivity Across Issue Spaces for Dynamic Simulation Models of Political Decision Making"
Eric Browne, University of Wisconsin, Milwaukee, Peggy A. James, University of Wisconsin, Parkside, and Martin A. Miller, Engineering Plastics

"Machine Coding Techniques for Generating International Event Data"
Philip A. Schrodt, University of Kansas

Disc: Charles Taber, State University of New York at Stony Brook
G. R. Boynton, University of Iowa

Panel 5-9

Title: "In Search of Robust Methods"

Chair: Nathaniel Beck, University of California, San Diego

Papers:

"Truth in Error: Using Cross-Validation to Choose Models'
Nathaniel Beck and Jonathan Katz, University of California, San Diego

"A Monte Carlo Evaluation of Bootstrap Statistical Inference"
Christopher Mooney and Robert Duval, West Virginia University

Disc: Gary King, Harvard University
Walter Mebane, Cornell University

Panel 5-10

Title: "Evaluating Inequity in Politics"

Chair: Richard Niemi, University of Rochester

Papers:

"Evaluating Electoral Systems and Redistricting Plans"
Andrew Gelman, University of California, Berkeley and Gary King, Harvard University

"Inequity, Inequality and Disproportionality: Measuring Deviations from a Distributional Standard"
Burt L. Monroe, University of Oxford

Disc: Richard Niemi, University of Rochester
Douglas Rivers, Stanford University

The Gauss Corner: Model Fit and Parameter Estimation

Regardless of how one stands on the usefulness of R-square in statistical analysis (King, 1986, 1990a, 1990b; Lewis-Beck and Skalaban, 1990a, 1990b, 1991; Luskin, 1991a, 1991b), it is important for students to understand that high R-squares do not necessarily mean that the "true model" has been found. Fitting the data and knowing the truth are two different things. The difference, however, is often difficult for students to understand. After all, if we fit the data perfectly, wouldn't that mean that we must have found the true model? No, but let's see why not.

This exercise sets up a simple bivariate regression model with known parameters. Let $y = 5.0 + .5x + u$ where the variance of x is 9.0 and the variance of u is 4.0. Both u and x are normally distributed with mean zero. (For x, this is simply a matter of convenience. It might be instructive to repeat the simulation with different distributions of x to see that the same results hold.)

In this case, the true value of β is $.5$. As in any Monte Carlo simulation, we could generate repeated samples of u, and build up the empirical distribution of $\hat{\beta}$. In this case, however, I want to focus on R-square.

While R-square is properly considered a descriptive statistic, and so is dependent on the data at hand, we can also consider a population analogue. R-square in a sample is the ratio of "explained" (or systematic) to "total" variance. In the real world, we never know what these variances actually are. In a simulation however, we can go a bit further. Here we know that y is composed of x and u, and we know the true relationship of y and x. From this, we can calculate the "true" total variance of y:

$$\mathrm{V}(y) = \beta^2 \mathrm{V}(x) + \mathrm{V}(u)$$

(noting that x and u are independent). In this case, we have a total variance of y of $.25 \times 9 + 4 = 6.25$. The systematic variance due to x is $.25 \times 9 = 2.25$. Thus the population analogue of R-square, the ratio of systematic (or explained) variance to total variance is $2.25/6.25 = .36$.

The observed R-square will vary from sample to sample. This is a function of the particular set of us which nature draws for us. Across samples, two important quantities will vary: the variance of u and the covariance between u and x. These will affect both the estimates of $\hat{\beta}$ and of R-square.

As with any regression, the estimated slope depends on the parameter value and the sample covariance of x and u:

$$\hat{\beta} = \beta + \frac{\mathrm{C}(xu)}{\mathrm{V}(x)}.$$

Likewise, the R-square can be written as

$$R^2 = \hat{\beta}^2 \frac{\mathrm{V}(x)}{\mathrm{V}(y)}.$$

In a particular sample, the variance of y is

$$\mathrm{V}(y) = \beta^2 \mathrm{V}(x) + \mathrm{V}(u) + 2\mathrm{C}(xu)$$

Across samples, both $\mathrm{V}(u)$ and $\mathrm{C}(xu)$ will vary, since u is a random variable. The estimated slope, $\hat{\beta}$ will therefore vary as $\mathrm{C}(xu)$ varies, and the R-square will vary with both $\mathrm{C}(xu)$ and $\mathrm{V}(u)$. Thus there will be a positive relationship between the estimated slope and the R-square. However, this relationship has nothing whatsoever to do with the true slope of the model. High values of R-square will be associated with high values of $\hat{\beta}$ which overestimate the true slope. Low R-squares will be associated with underestimates of the true slope.

This shows that high R-squares tell us nothing about whether we have good estimates of the parameters. In this example, the further the R-square gets from .36, the greater the likely difference between the estimated slope and its true value.

The Gauss code below generates data for this example. Figure 1 shows the relationship between R-square and the estimated slope while Figure 2 shows the relationship between the R-square and the deviation of $\hat{\beta}$ from the true β.

```
/*
**
**    Homework 4, Spring 1992
**    Relationship between R-Square and
**    true value of beta
**
**    This exercise shows that large R-square
**    values need not imply that the estimated
**    value of b is close to the true value of
**    beta.
**
**    Comments in @ ... @ describe the code.
**
*/
@ access graphics lib  @
@ initialize graphics  @
library pgraph;
graphset;
@ Set True Coefficients,    @
@ generate 500 obs of x     @
@ and create Yhat           @
     let beta=5 .5 ;
     x=ones(500,1)~rndn(500,1)*3;
     yhat = x*beta;
@ Suppress output from          @
@ each regression               @
@ and use constant term in data @
     __output=0;
     __con=0;
@ Do 1000 replications @
     i = 1;
     do until i > 1000;
@ Create U and Y       @
        y=yhat+rndn(500,1)*2;
@ Do OLS               @
        {vnam,m,b,stdb,vc,stderr,sigma,cx,
         rsq,resid,dwstat} = ols(0,y,x);
@ Collect estimates    @
@ in vector "est"      @
        if i eq 1;
           est=b'~rsq;
        else;
           est=est|b'~rsq;
        endif;
@ Increment counter    @
     i = i + 1;
@ End replication loop @
     endo;
@Turn output back on   @
@Send output to file   @
@Set output format     @
@compute and print     @
@descriptive stats     @
@for estimated b & r^2 @
     __output=1;
     output file=rsqr.out reset;
     format /m1 /rd 10,5;
     call dstat(0,est);
@Close output file     @
     output off;
@ Make figures of estimates data @
@ Send plot to file     @
@ Set title for graph   @
@ Set x-label           @
@ Set y-label           @
@ Turn date off         @
@ plot symbols only     @
@ set size of symbols   @
@ set symbol type       @
@ plot the data         @
     _ptek="rsqrfig1.tkf";
     title("Estimated bhat by r-sqr");
     xlabel("R-Square");
     ylabel("bhat");
     _pdate="";
     _plctrl=-1;
     _psymsiz=0.80;
     _pstype=8;
     call xy(est[.,3],est[.,2]);
@ Now do it again for figure 2 @
     _ptek="rsqrfig2.tkf";
     title("Estimated Abs(bhat-beta) by r-sqr");
     xlabel("R-Square");
     ylabel("Abs(bhat-beta)");
     _pdate="";
     _plctrl=-1;
     _psymsiz=0.80;
     _pstype=8;
     call xy(est[.,3],abs(est[.,2]-.5));
@ End of Program  @
```

```
---------------------Output-----------------------
--------------------------------------------------
Variable       Mean   Std Dev    Minimum   Maximum
--------------------------------------------------
Intercept    4.9960    0.0868     4.7340    5.2484
Slope        0.4997    0.0303     0.4062    0.5986
R-Square     0.3571    0.0317     0.2631    0.4457
```

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Software News and Views

Aptech Systems has released version 3.0 of Gauss. This major revision provides a number of improvements, including a very welcome source level debugger. Among the recent developments are a dataloop recode facility which allows direct use of variable names in recodes. Upgrades are a rather steep $195. Gauss-386 3.0 lists for $895 but is available at an academic discount of $626.50. Student versions of the earlier Gauss 2.2 are available for $50 ($115 with graphics option.)

The Computing Resource Center has released a new version of Stata. Version 3.0 comes with new manuals and a variety of nice statistical additions, including logistic regression, tobit, survival models and some nice new confidence interval options. The new version also offers quantile regression which allows minimization of the absolute values of the residuals. The limit on number of variables has also been expanded for the 386/486 versions, from 254 to 2047. In addition to a large selection of statistical models, Stata also provides excellent graphics capabilities. Academic upgrades from version 2.1 are $95 (if purchased before 12/91, less for newer copies) and $125 for upgrading from version 2.05 or earlier. Stata lists for $695 ($795 for 386/486 version). Academic prices for new users are $165 for basic Stata and $265 for the 386/486 version. Student lab versions are also available at very reasonable rates.

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Subscriptions to *TPM* are free to members of the APSA's Methodology Section. Please contact APSA to join the section. Dues are $8.00 per year.

Submissions to *TPM* are welcome. The editorial office will move from Washington University to the University of Wisconsin–Madison on June 1, 1992. After that date articles should be sent to the editor, Charles H. Franklin, Department of Political Science, 110 North Hall, University of Wisconsin–Madison, Madison, WI 53706. If at all possible, please send articles via Bitnet or Internet to the editor at FRANKLIN@WISCGPS.Bitnet. After July 1, the e-mail address will be through internet as FRANKLIN@POLISCI.WISC.EDU. Submissions may also be made on diskette as plain ascii files. LaTeX format files are especially encouraged, though we can read most word processor files. The deadline for submissions for the next issue is October 1, 1992.