2006 AIR/NPEC Research Grant Proposal

An Investigation of University Expectations of Work

Database of Interest: Course Syllabi, Faculty Workloads, and Personnel Policies

Amount Requested: $30,000

Principal Investigator
Patricia B. Cerrito, Professor of Mathematics
Patricia B. Cerrito
Department of Mathematics
University of Louisville
Louisville, KY 40292
502-852-6826
852-852-7132 (fax)
pcerrito@louisville.edu

Authorized Institutional Representative
Judy L. Bristow
Acting Director of Grants and Contracts
Office of Grants Management
205A Jouett Hall
University of Louisville
Louisville, KY 40292
502-852-8367
502-852-8375 (fax)
jlbris01@louisville.edu

Principal Investigator

Authorized Institutional Representative

Project Summary

The purpose of this project is to measure university expectations of work. Most work expectations are measured qualitatively rather than quantitatively. In many cases, quantitative analysis is considered difficult, if not impossible, so that evaluations of work rely primarily on peer review and expertise for faculty and upon faculty expertise for students. Whenever the method of evaluation is not transparent, variability occurs. However, with the introduction of text analysis and text mining, qualitative material can be quantified and analyzed to determine the level of variability, and to increase the objectivity of the accountability. We will work with the following documents that are generally publicly available from various universities:

1. Course syllabi
2. Catalog information of degree requirements
3. Course descriptions
4. Number of courses taught by faculty and at what course level
5. Number of publications by faculty members, and in what journals
6. Federal grants with faculty as PI and co-PI
7. Administrative positions held by faculty

As these documents are generally in text format, they cannot be analyzed without first quantifying the information contained within. One way to do this is to extract the quantitative information through manual coding. The number of tests, percentage of grade, and similar information can be extracted manually. Unfortunately, manual extraction is very time intensive, and will be compared to a more automated process of extraction using text mining. The specific aims of the project are

Aim 1. To collect university-wide course syllabi and to manually extract information concerning expectations of student work-exams, papers, homework, quizzes, and final. To examine the results within departments for consistency and across departments for differences.

Aim 2. To do a similar extraction and analysis for documents concerning faculty workloads to examine them for consistency within and across departments.

Aim 3. To determine whether there is a relationship between faculty and student work expectations; that is, where there are higher expectations of faculty work, are there also higher expectations of student work and conversely.

Aim 4. To compare work expectations across different universities to determine whether there is any standardization or consistency within disciplines.

This project is innovative in that work expectations have not really been quantified in the literature. While there is anecdotal information that the sciences are very demanding of student time, information concerning student time expectations has not been studied in a significant way. One of the reasons that it has not been studied is that the information is locked in text documents, and text has been very difficult to analyze statistically. With the development of new text mining software, such analyses are now possible. This project will demonstrate how universities generally can make similar comparisons.

This study differs from the National Survey of Student Engagement (NSSE) in that it will drill down into specific details of work required of students rather than to use student perceptions of work. It will also look at details concerning faculty expectations of student work.

Table of Contents

Cover Sheet	1
Project Summary	2
Contents	4
Project Description	
Statement of Problem and Variables	5
Proposed Plan of Work	7
Innovative Aspects of Project	15
Policy Relevance	16
Dissemination Plan	19
Audience for Project	19
References	20
Biographical Sketches	24
Budget and Budget Justification	29
Current and Pending Support	30
Facilities, Equipment, and Other Resources	31
Supplementary Documentation	32

Project Description

Statement of Problem and Variables

The overall objective of this project is to use data and text mining techniques to investigate the expectations of work for both faculty and students, and to determine how these expectations interact. The material will be collected primarily from online sources through university and professional internet sites. Web mining will be used to extract the relevant information when needed. Course syllabi are routinely published on the web by faculty members. University catalogs containing degree requirements are also readily available. The study will be restricted to major research public universities; approximately 20 schools will be included in the initial study. The schools will be selected from schools in the south; if time permits, the geographic region under study will be expanded. The study will also be restricted to physical science (biology, chemistry, computer science, and physics) and mathematics departments. In addition, the awards databases from the National Institutes of Health and the National Science Foundation will be used to relate the instructional work expectations of faculty to federal grants. Electronic databases containing information on publications will also be mined for information on publication histories of faculty in relationship to instructional efforts. These databases include MathSciNet, Science Citation Index, and so on.

Once the information is gathered, it will be coded and analyzed using data mining techniques. The methods will consist primarily of unsupervised learning to determine just how work expectations are recorded in course syllabi. Similarly, faculty work expectations will be examined using supervised learning to determine the relationship between publications, grants, and administrative positions to the number of courses taught and at what course level. Faculty work expectations will be related to expectations of student work efforts.

The following specific variables will be examined in the analysis

Syllabi Extraction	Faculty Workload Extraction	Additional Information Extracted
Number of tests, and weighting for each	Number of courses taught per semester	Undergraduate and graduate catalog information on degree requirements
Quizzes, and weighting	Supervision of students	Number and level of courses required for degrees
Homework, and weighting	Publications, and journals published	Examination or internship requirements for degrees conferred
Number of homework problems assigned per class	Administrative positions held	Number of electives versus required courses
Papers and number of pages required	Federal grants awarded	General education requirements
Opportunities to revise and resubmit papers	Type of course (by student enrollment) and whether taught online	Course descriptions
Attendance and participation requirements	Faculty Rank	

While the information gathered is publicly available, it is not readily contained within any collected database. Therefore, there are some limitations to this study. While most of the material is accessible on the internet, it is not certain that it will be representative of course syllabi generally. Care will be taken to ensure that the syllabi collected are representative of courses taught, and that the extracted syllabi are representative of the department and school under study. It is also not certain that the databases examined will contain all possible locations of faculty publications. However, it will include the most prominent journals and will be fairly representative. Nevertheless, the feasibility of using this public information for detailed analysis will be clearly demonstrated.

Proposed Plan of Work

Aim 1. To collect course syllabi and to manually extract information concerning expectations of student work-exams, papers, homework, quizzes, and final. To examine the results within departments for consistency and across departments for differences.

Aim 2. To do a similar extraction and analysis for documents concerning faculty workloads and to examine them for consistency within and across departments.

It is anticipated that data collection will be the most time consuming aspect of the problem. Twenty public universities with approximate enrollment of 20-30,000 students will be selected systematically from the southern region of the United States, in addition to the University of Louisville so that we can use a fairly homogeneous sample. Once selected, syllabi published through department web sites will be collected. The departments will be restricted to biology, chemistry, mathematics, physics, and computer science. Once collected, the syllabi will be examined to ensure that they are fairly representative, meaning that courses from general education through doctoral level are included, and that syllabi from different instructors in these courses are available. If not, additional schools will be selected until the sample is representative. It is anticipated that information from course catalogs and class schedules will be readily available and representative. Degree requirements and course descriptions will be extracted from current undergraduate and graduate catalogs from each site. Since universities now provide course schedules for online registration, these will be examined to find faculty course assignments and workloads. In addition, the web sites will be examined for faculty administrative assignments.

Additional information will be gathered from the following sources:

1. Digital Dissertations faculty for supervision of students, and student success with thesis and dissertation degree requirements.
2. Electronic databases for publication information
    a. ERIC

b. MathSciNet
c. Science Citation Index
d. IEEE Electronic Library
e. Current index to Statistics
f. Biological Abstracts
g. Internet publications

3. CRISP awards database from the National Institutes of Health
4. National Science Foundation Awards Database

While these databases are not complete, they will be fairly representative of the science disciplines. Names from department websites will be searched in the different databases.

Once the information has been gathered, it needs to be coded into databases manually. The following list of variables will be collected from the course syllabi:

1. Number of tests, and proportion of final grade
2. Final examination (yes or no) and proportion of final grade (0% if not given)
3. Attendance or participation as a proportion of the grade
4. Graded homework, and proportion of grade
5. Quizzes, and proportion of grade
6. Papers assigned, and number of pages, if any
7. Additional requirements, if any

For example, consider the web site for the Department of Mathematics at the University of Kentucky (http://www.ms.uky.edu/%7Emath/). It lists all graduate degrees awarded since 1973 along with faculty research publications and a department directory including graduate students at http://www.ms.uky.edu/~math/Info/directory.html. Choosing a faculty member from the Department's directory links to a website containing numerous syllabi that can be downloaded electronically. Once in a directory, a macro program can pull the syllabi into a data file available for text analysis. Other syllabi are more directly linked to the Department's web page at http://www.ms.uky.edu/~ma109/. The degree requirements are posted at http://www.uky.edu/Registrar/bull0102/colleges/a&s/math.html and the course descriptions are available at http://www.uky.edu/Registrar/bull0203/courses/ma.html. Therefore, with little time spent searching the publicly available web sites, the information needed is posted and can be retrieved. The online schedule is available at http://www.uky.edu/Registrar/schedtmp.htm and lists all courses by instructor name so that the course assignments per semester are readily accessible.

Because manual coding is time-intensive, the syllabi will also be scanned and text mining will be used to compare the manual results to those of text mining, to determine if text mining can be used to achieve similar results. The dataset defined by manual coding will also be compared by school and department to see if the results are the same. If so, text mining will be used to complete the study.

In text mining, a term by document matrix is created. Then the matrix is compressed using singular value decomposition and similar documents are clustered together. A preliminary analysis was performed using syllabi from English, Mathematics, and Physics to demonstrate the feasibility of performing text analysis after scanning the syllabi using pdf format and then clustering using the text. In the preliminary study, the text mining analysis found a natural division between English courses that require papers and science courses the rely primarily on tests. This study will extend the work by examining finer distinctions in science classes rather than the broader division between science and humanities.

Once clustered, the documents can be compared by school and by department. These comparisons will be made by chi-square analysis and logistic regression, and examined using other predictive models such as artificial neural networks and decision trees.

In addition, the following information will be collected from the degree catalogs (both undergraduate and graduate):

1. Number of courses in the major

2. Course descriptions
3. Number of general education requirements divided into science and math, social science, and humanities
4. Number of required courses in the major
5. Number of electives in the major, or generally
6. Thesis and dissertation credits (required or optional)
7. Language and computer requirements
8. Capstone requirements (project, seminar, examination)

These, too, will be compared by school and department. In particular, course descriptions will be analyzed using text mining.

From the general university web sites, we will collect:

1. Faculty names
2. Assigned courses for 2005-2007
3. Administrative positions
4. Minimum admission requirements for students
5. Number of graduate students in each department

The faculty names will be used to search the electronic databases posted above, and all publications and grants will be related to the faculty name, along with authorship position and grant information.

Once the data have been collected and coded, unsupervised learning will be used to cluster the results. After clustering, predictive modeling will be used to determine whether there are differences across departments, universities, and also within departments. Similarly, the variables concerning faculty workloads will be clustered to examine differences. The tests we will consider are the following logistic regression models using a complimentary log log link function because the outcome variable is non-binary (Littell, Milliken, Stroup, Wolfinger, & Schabenberger, 2006):

a. Department (or school)=a+$ß_1$*syllabi clusters

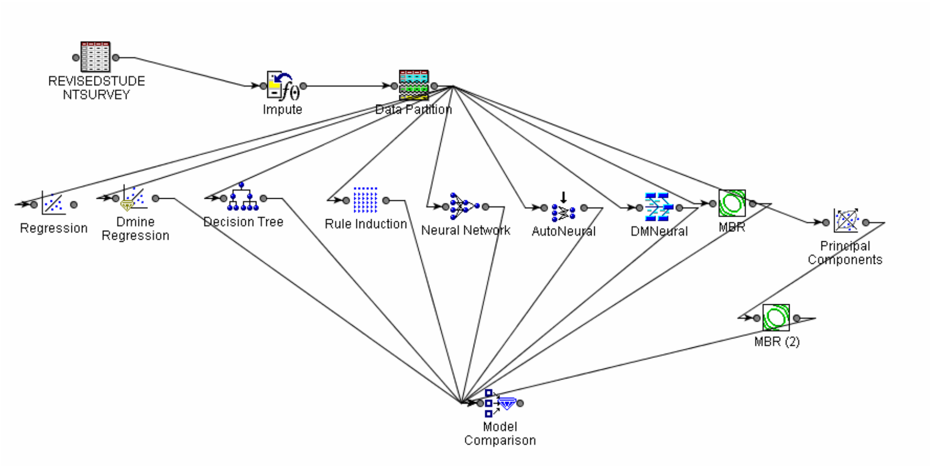
b. Department (or school)= a+$ß_1$*proportion for tests+ $ß_2$*proportion for exam+ $ß_3$*proportion for papers+ $ß_4$*proportion for homework+ $ß_5$*proportion for participation and attendance

c. Text mining syllabi cluster= a+$ß_1$*proportion for tests+ $ß_2$*proportion for exam+ $ß_3$*proportion for papers+ $ß_4$*proportion for homework+ $ß_5$*proportion for participation and attendance

In addition, other predictive models will be compared and contrasted with the logistic regression function to determine whether they are better predictors of Department or school given the work expectations as outlined on course syllabi. The SAS data mining component of Enterprise Miner will be used for this analysis (SAS Institute; Cary, NC). Figure 1 gives the outline of the predictive modeling process as used in SAS Enterprise Miner. Neural networks have often provided results that are superior to those of logistic regression.(Patricia Cerrito, 2006) Decision trees are useful in examining choices that lead to the final results. SAS Enterprise Miner has several types of predictive modeling algorithms available. One additional model is the Memory Based Reasoning, or k-nearest neighbors, a nonparametric method of discriminant analysis.

In predictive modeling, the datasets are sufficiently large so that they can be partitioned into training, testing, and validation sets. Then the models can be compared based upon the misclassification rate. The optimal model is the one with the misclassification rate on the validation and testing sets. The accumulated error that results from comparing so many different models is not significant because of the large data size.

Figure 1. Diagram of Predictive Modeling Process



Aim 3. To determine whether there is a relationship between faculty and student work expectations; that is, where there are higher expectations of faculty work, there are also higher expectations of student work and conversely.

Student engagement requires time, and time spent on homework assignments is important. Graded homework is more closely related to student engagement compared to other forms of assessment. However, consistent homework grading takes time. Faculty engagement in teaching, and in the improvement of teaching is important to improvement in the engagement of students.(Akerlind, 2004; G. D. Kuh, Kinzie, Schuh, & Whitt, 2005) We will define a rank measure of faculty time involved in grading the activities in the course syllabi and use a predictive model to determine the relationship of faculty work assignments (courses, grants, administration, etc.) to the ranked time measure using predictive modeling. The most time consuming practice is the regular grading of student homework assignments. Giving direct feedback to students collecting homework for credit without grading requires less faculty time but does not provide feedback to students; quizzes require still less faculty time in grading but more time in preparing. We will also examine faculty web sites to determine whether they contain information on how the faculty member is engaged in teaching, and in the improvement of teaching. The linear model we consider here is

a. Rank of faculty effort in course= a+$ß_1$*number of publications+ $ß_2$*rank of administrative responsibility+ $ß_3$*federal ranks+ $ß_4$*number of courses taught

Aim 4. To compare work expectations across different universities to determine whether there is any standardization or consistency within disciplines.

One model that will be considered is the amount of material covered in comparable courses across universities in relationship to minimum ACT or SAT requirements. Universities that have higher admission standards can have higher expectations of student learning in courses. Therefore, the expectations of work will be considered in terms of the basic entrance requirements for each school. Another important measure of work is in the content of the courses themselves. The course descriptions for electives and for requirements will be clustered by discipline across schools. Course titles will also be examined for consistency, and for differences.

Course descriptions will be entered into a database, and text mining will be used to cluster the descriptions. Then predictive modeling will be used to determine whether course requirements are comparable. Differences will be noted and examined in relationship to entrance requirements.

To continue the analysis of work expectations, the relationship between qualifying type and completion of the dissertation will be compared to determine whether departments are project and research oriented, or whether they are examination oriented. It is anticipated that project oriented departments will have higher success rates. Since most departments post graduate student names on their web sites, the number of graduate students can be compared to the number of students graduating in any one year. In addition, the dissertation abstracts will be used in a database and clustered using text mining to determine relationships in the dissertation topics by school and department. The predictive model we use is

a. Number of degrees awarded= a+$ß_1$*number enrolled in program+ $ß_2$*number of qualifying examinations+ $ß_3$*Defense of research+ $ß_4$*number of required courses

In this model, both primary and secondary effects will be considered to see if the number of qualifying examinations is confounded with the number of students enrolled.

Preliminary Results

The PI has worked with course descriptions and course syllabi using text mining to investigate expectations in terms of student assignments and dissertation content. The resulting papers are contained in the supplementary documentation for this proposal. These two studies clearly demonstrate the feasibility of using text mining to investigate faculty expectations of student work. In addition, the PI has investigated student perceptions of study time and work on a local basis; the results correspond to the national results of the NSSE study; again, the results are included with the supplementary documentation. A fourth study included reports the results when testing was standardized for the course, Intermediate Algebra. One of the interesting results of that analysis is that some adjuncts and graduate students still raised grades in spite of the standardization; indicating that grade inflation is intrinsic to the university environment. Because of the autonomy that each instructor enjoys to assign grades, little could be done to prevent the grade inflation. The final study included in the supplementary documentation was an analysis of faculty work requirements. While this study was for one department at one university, it was discovered during the analysis that most of the information was readily available publicly on faculty and department web pages, so that it is possible to duplicate the analysis across departments and schools. The preliminary studies reported here and provided in the appendix indicate the feasibility of the analysis proposed here. The innovation lies in the comprehensive nature of the study, and in the analysis of the widely scattered data fields.

The statistical software, SAS (SAS Institute; Cary, NC), will be used, especially its data mining component, Enterprise Miner. The PI has considerable experience in using data mining to investigate complex data and she has recently completed a textbook on the use of data mining (Introduction to Data Mining with Enterprise Miner, SAS Press, 2006). The methods used for this project are clearly outlined in the published text. In particular, this book has considerable information on the use of text analysis to examine qualitative information. It also contains instructions on how to web crawl to extract necessary information for analysis purposes.

Project Timeline

Objective	Time
To collect information from department websites on course syllabi, degree catalogs, faculty, courses taught.	June-August
To code information on work expectations located in course syllabi and to analyze work expectations. Submit initial results to AIR	July-September
To collect information on faculty publications and grants	October-December
To code information on degree requirements and to analyze it; to correlate degree requirements with work expectations in course syllabi	October-December
To code information on faculty work, and to relate publications and grant activity to courses taught	January-March
To correlate expectations of faculty work to expectations of student work. Present at AIR.	April-May

Innovative Aspects of Project

This project is innovative in that it takes advantage of information that is generally provided by universities and collects it into a meaningful database that can be analyzed for detailed information about work expectations; information that is not generally analyzed because it is so scattered and time consuming to collect. While surveys have been used (specifically the NSSE) to examine student perceptions of faculty expectations, course syllabi themselves have not been examined quantitatively. In addition, the project is innovative in its comparison of faculty to student work. The project is also innovative in that data and text mining techniques will be used to analyze the qualitative data collected through the different sources. Therefore, this project is innovative in both the use of publicly available data and in the use of data mining techniques.

Policy Relevance

Public universities are becoming more accountable for their successes while that accountability has had little impact on university performance.(Burke, 2001; Fogg, 2007) There is a serious lack of standardized instruments that can provide that accountability. With the exception of professional board certification that exists for some professions, there are no standardized examinations that allow comparisons between schools, or even within departments of one school. Graduation rates can be considered; however, graduation can be confounded by the preparedness of students upon admission. Schools that have more restrictive admissions policy can easily show higher graduation rates. For example, the University of Louisville will admit students with a composite ACT score of 23; Murray State requires an ACT of 18. While the University of Kentucky does not specify a minimum ACT score for admission, most majors within the university have defined selective criteria for admission, and students who transfer from one major to another must satisfy those criteria.

Another issue confounding graduation rates is the issue of grade inflation (Brumfield, 2005), to the point that some researchers are calling for adjustments to grades to account for this inflation factor.(Felton & Koper, 2005) Students who receive high grades in their courses are much more likely to graduate compared to students who fail or withdraw. Therefore, one way to increase graduation rates is to curve grades so that the majority of students receive high course grades. With no accountability as to the amount of learning that takes place in courses, the pressure to rank graduation rates creates considerable pressure to increase grades. In fact, faculty are more likely to be penalized for grading harshly than they are for grading leniently.(*Martin Eisen Versus Temple University*, 2002; Sung, 2003) Felton and Koper (2005) go so far as to say, “It is clear that wide variations in the grades given by different instructors in the different sections of the same course, different instructors in the same departments, differences in the difficulty of subject matter in different areas and differences in the ability of students in different areas seriously undermine the GPA as a reliable measure of education….they therefore have no useful connection to educational achievement at all, measuring rather how well students have accommodated the biases of a dominant group or individual." Grade inflation is related to faculty status and rank.(Cheng & Chen, 1998; Kezim, Pariseau, & Quinn, 2005) It can also be a factor in limiting diversity in enrollment in the physical sciences.(Dowd, 2000) Unfortunately, when instructor status is related to grade outcomes, the use of grades and of the GPA as an objective standard of comparison cannot be used to compare departments or schools. Expectations of work will form a better means of comparison.

To provide some accountability, we now have the National Survey of Student Engagement (NSSE), with an equivalent for the community colleges (CCSSE).(G. Kuh, 2006; McClenney, 2004) Other studies use similar methods to examine the perception of learning.(Bird & Rosaen, 2005) Unfortunately, this survey, while examining the issue of how involved students are in their learning by asking some general questions about assignments and study time, does not demonstrate what actual learning takes place nor does it drill down into specific courses (Pike, 2006a, 2006b). The NSSE does provide summary statistics based upon a student's major, but only by using a student's information as to major. Also, learning and engagement do not always correlate well.(Stoering & Lu, 2002) Therefore, its use can provide some general guidelines for improvements in teaching and learning, but cannot provide any specific details.(Belcheir, 2003; El-Khawas, 2003)

There is considerable variability in the type of testing and accountability of students that can take place in the classroom; therefore, there can be considerable variability in measurement that can lead to disparities in grading.(Griffiths & McLone, 1984) It is well known that there are "hard" and "easy" professors in the level of assessment. The anecdotal conclusion clearly demonstrates not only that there are disparities in grading but that these disparities have long been accepted in higher education. It is also known that grading practices can influence learning.(Tobias & Raphael, 1997)

There is a question of whether instructors have sufficient training to construct relevant examinations, or to grade them consistently.(Boothroyd, 1992; Mead, 1992) Grading habits can differ across disciplines as well as within the same discipline.(Bridges et al., 1999) In addition, the level of student engagement in the course is critical, and teaching methods that increase this engagement can increase the amount of learning; however, engagement level is not used in accountability measures for specific courses.(Wiebe, 1982) There is also the question of whether the students and faculty have similar expectations of engagement and work; measuring actual work expectations will help to measure the separation of students and faculty on the issue by looking at specific work requirements rather than generalities.(G. D. Kuh, 2003) While there are a number of methods used to assess teaching effectiveness, student learning is usually not one of them as such an assessment requires pre- and post-testing, and standardized examinations.(Burbach, Matkin, & Fritz, 2004; Ediger, 2000) There are some attempts to use capstone assignments to assess learning as well as longitudinal assessment in a specific area of knowledge and skill. (Jones, Simonds, & Hunt, 2005; McCune, 2004)

Another item to consider is how instructors plan assignments and activities to foster learning, as well as the choice of testing instruments.(Maclellan, 2004) Homework, essays, and research projects are available options (Cherry, 2005). While there is learning that takes place with these different options, there is little quantitative information to examine their success.(Shah & Treby, 2006) Some instructors attempt innovative practices to improve student learning, and we will gather information through course syllabi as well.(Bilica, 2004; Cecire, 2005) The extent to which innovations are noted in the syllabi will indicate whether there is a successful campus initiative for improvement in teaching.(Tagg, 2005) Our study will document the extent to which instructors rely on different assignment types to increase the level of student learning, and to analyze the collected information by school and discipline. While this study will not specifically document student work in any one course, studies have shown that students generally expect to be engaged approximately 5 hours outside of class.(PB Cerrito & Levi, 1999; Zuriff, 2003) It is also known that there is a relationship between the amount of study time and the amount of learning.(Peters, Kethley, & Bullington, 2002) Therefore, we focus on expectations listed in the course syllabi that increase the amount of student engagement.

Data mining, although it is used some in institutional research (Burley, 1996), it has not reached great prominence. Data mining is very successful when examining multiple variables, and when searching for patterns of relationships in the data.(Thomas & Galambos, 2002) However, given the complexity of the data, and the need to "drill down" into details to find patterns and relationships, data mining techniques provide a superior means of analysis.(Patricia Cerrito, 2006) Data-mining tools come in three general categories: query-and-reporting tools, multidimensional analysis tools, and intelligent agents. Query-and-reporting tools include all traditional statistical methods, including kernel density estimation. They require close interaction with the investigator and data in a specialized database or spreadsheet format. Multidimensional analysis tools include the more recently developed artificial neural networks and Bayesian decision trees and still require relatively structured data. The intelligent agents can investigate unstructured data and are the tools used to examine text. The three categories of data mining tools can all be used in sequence to solve problems. This project will demonstrate how textual data from a wide variety of sources can be analyzed using data mining tools to find meaningful results about university expectations of work.

Dissemination Plan

Locally, the results will be presented to administration officials with the intent of implementing results. They will be presented at the Annual Meeting of the Association for Institutional Research, and at the Educause Annual Meeting.

Audience for Project

This project is intended for use to improve student advising, and for use by administrators to devise interventions to improve graduation and retention rates. Therefore, it has a wide audience of university administrators, advisors, institutional researchers, and interested faculty and staff.

References

Akerlind, G. S. (2004). A new dimension to understanding university teaching. *Teaching in Higher Education, 9*(3), 363-375.

Belcheir, M. J. (2003). *The campus environment as viewed through the lens of the National Survey of Student Engagement*. Boise, Idaho: Boise State University.

Bilica, K. (2004). Lessons from experts: improving college science instruction through case teaching. *School Science & Mathematics, 104*(6), 273-278.

Bird, T., & Rosaen, C. L. (2005). Providing authentic contexts for learning information technology in teacher preparation. *Journal of Technology and Teacher Education, 13*(2), 211-231.

Boothroyd, R. A. (1992). What do teachers know about measurement and how did they find out?, *Annual Meeting of the National Council on Measurement in Education*. San Francisco: ERIC ED 351 209.

Bridges, P., Bourdillon, B., Collymore, D., Cooper, A., Fox, W., Haines, C., et al. (1999). Discipline-related marking behaviour using percentages: a potential cause of inequity in assessment. *Assessment & Evaluation in Higher Education, 24*(3), 285-300.

Brumfield, C. (2005). *Current trends in grades and grading practices in higher education: results of the 2004 AACRAO Survey*. Washington, DC American Association of Collegiate Registrars and Admissions Officers.

Burbach, M. E., Matkin, G. S., & Fritz, S. M. (2004). Teaching critical thinking in an introductory leadership course utilizing active learning strategies: a confirmatory study. *College Student Journal, 38*(3).

Burke, J. C. (2001). *Accountability, reporting, and performance: why haven't they made more difference*. New York: Ford Foundation.

Burley, H. (1996). A CHAID analysis of a diagnostic writing sample as a placement tool for freshman composition, *Annual Meeting of the Southwest Education Research Association*. New Orleans: ERIC.

Cecire, S. (2005, June, 2005). *Uncommon uses for common tools in an on-line environment.* Paper presented at the ASCUE Conference, Myrtle Beach, SC.

Cerrito, P. (2006). *Introduction to Data Mining Using SAS Enterprise Miner*. Cary, NC: SAS Press.

Cerrito, P., & Levi, I. (1999). An investigation of student habits in mathematics courses. *College Student Journal, 33*(4), 584-588.

Cheng, D. X., & Chen, S. (1998). Factors affecting grading practices, *Annual Meeting of the Northeast Association for Institutional Research*. Philadelphia, PA: ERIC.

Cherry, N. L. (2005). Preparing for practice in the age of complexity. *Higher Education Research & Development*, *24*(4), 309-320.

Dowd, A. C. (2000). Collegiate grading practices and the gender gap. *Education Policy Analysis Archives, 8*(10).

Ediger, M. (2000). *Assessing teaching quality in higher education*

El-Khawas, E. (2003). *Using NSSE data for assessment and institutional improvement*. Washington, DC: American Association for Higher Education.

Felton, J., & Koper, P. T. (2005). Nominal gpa and real gpa: a simple adjustment that compensates for grade inflation. *Assessment & Evaluation in Higher Education, 30*(6), 561-569.

Griffiths, H., & McLone, R. (1984). A critical analysis of university examinations in mathematics. Part I: a problem of design. *Educational Studies in Mathematics, 15*(3), 291-311.

Jones, A. C., Simonds, C. J., & Hunt, S. K. (2005). The use of application essays as an effective tool for assessing instruction in the basic communication course. *Communication Education, 54*(2), 161-169.

Kezim, B., Pariseau, S. E., & Quinn, F. (2005). Is grade inflation related to faculty status? *Journal of Education for Business, 2005*(July/August), 358-363.

Kuh, G. (2006). *National Survey of Student Engagement*. Retrieved December, 2006, from http://nsse.iub.edu/index.cfm

Kuh, G. D. (2003). What we're learning about student engagement from NSSE. *Change, 2003*(March/April), 24-32.

Kuh, G. D., Kinzie, J., Schuh, J. H., & Whitt, E. J. (2005). Never let it rest: lessons about student success from high-performing colleges and universities. *Change, 2005*(July/August), 44-51.

Littell, R., Milliken, G., Stroup, W., Wolfinger, R., & Schabenberger, O. (2006). *SAS for Mixed Models* (2nd ed.): SAS Press.

Maclellan, E. (2004). How convincing is alternative assessment for use in higher education? *Assessment & Evaluation in Higher Education, 29*(3), 311-321.

Martin Eisen Versus Temple University, (2002).

McClenney, K. M. (2004). Redefining quality in community colleges *Change, 2004*(November/December), 16-21.

McCune, V. (2004). Development of first-year students' conceptions of essay writing. *Higher Education 47*, 257-282.

Mead, J. V. (1992). *Teachers' evaluation of student work*. Washington, DC: National Center for Research and Improvement.

Peters, M., Kethley, B., & Bullington, K. (2002). The relationship between homework and performance in an introductory operations management course. *Journal of Education for Business, 2002*(July/August), 340-344.

Pike, G. R. (2006a). The convergent and discriminant validity of NSSE scalelet scores. *Journal of College Student Development, 47*(5), 550-563.

Pike, G. R. (2006b). The dependability of NSSE scalelets for college- and department-level assessment. *Research in Higher Education, 47*(2), 177-195.

Shah, A., & Treby, E. (2006). Using a community based project to link teaching and research: the Bourne Stream partnership. *Journal of Geography in Higher Education, 30*(1), 33-48.

Stoering, J. M., & Lu, L. (2002). Student portfolio assessment, *Association for Institutional Research Annual Meeting*. Ontario, Canada: ERIC.

Sung, E. (2003). *Mending the federal circuit split on the first amendment right of public university professors to assign grades.* Unpublished manuscript, New York.

Tagg, J. (2005). Venture colleges: creating charters for change in higher education. *Change, 2005*(January/February), 35-43.

Thomas, E. H., & Galambos, N. (2002). What satisfies students? Mining student-opinion data with regression and decision-tree analysis, *AIR 2002*. Ontario, Canada: ERIC.

Tobias, S., & Raphael, J. (1997). The hidden curriculum-faculty-made tests in science. Part 2: upper-division courses. Innovations in Science and Technology, *Science, Mathematics and Environmental Education*. New York: Plenum Press.

Wiebe, J. H. (1982). Using graded quizzes, homework, and attendance for motivating study in a college math class. *Mathematics and Computer Education, 16*(1), 24-28.

Zuriff, G. (2003). A method for measuring student study time and preliminary results, *College Student Journal*.

Biosketch

Patricia B. Cerrito

Education

University of Cincinnati	1979-1982	Ph.D.
Indiana University	1976-1979	M.A.
Butler University	1973-1976	B.S.

Employment History

University of South Florida	1982-1989	Assistant Professor
University of Louisville	1989-1993	Assistant Professor
University of Louisville	1993-1998	Associate Professor
University of Louisville	1998-Present	Professor

Papers completed and submitted

1. **Cerrito PB,** Hook, A. Analyzing the Student Diversity by School. College Student Journal. 40(3). 664-669. 2006.
2. **Cerrito PB,** Cerrito JC. Use of Pharmacy Database to Investigate Patterns of Physician Practice as Related to Patient Outcomes. Journal of Pharmacy Technology. 22(3)143-147. 2006.
3. **Cerrito PB.** Data Mining Methods to Link Multiple Drug Purchases. PharmaSug 2006 Proceedings. May, 2006.
4. **Cerrito PB.** From GLM to GLIMMIX. PharmaSug 2006 Proceedings.
5. **Cerrito PB.** Data and Text Mining the Electronic Medical Record to Improve Care and to Lower Costs. SUGI31 Proceedings. March, 2006.
6. **Cerrito PB.** Invited book chapter, Mining the Electronic Medical Record to Examine Physician Decision-Making, Computational Intelligence In Healthcare, Lakhmi Jain editor. Berlin:Springer. In Press. 2006.
7. **Cerrito PB.** Mathematics as Gatekeeper: Data Mining the Registrar's Database. ERIC Database. April, 2006.
8. **Cerrito PB.** Using SAS Enterprise Miner to Examine General Education Issues. SESUG Proceedings. October, 2006.
9. **Cerrito PB.** Invited Book Chapter. Text Mining Coded Information. Emerging Technologies of Text Mining: Techniques and Applications. Big Idea Group: New York. In Press. 2006.
10. **Cerrito PB.** Book submission, Data Mining Healthcare and Clinical Databases, submitted, SAS Press, June, 2006. Expected publication date: November, 2006.
11. **Cerrito PB.** Invited Paper. Journal of Intelligent Decisions, Antibiotic decisions in bypass surgery. September, 2006.
12. **Cerrito PB.** Invited Paper. Global Forum Proceedings. Text Mining and PROC KDE to rank nominal data. September, 2006.
13. **Cerrito, PB.** Comparing the SAS Forecasting System with PROC HPF and Enterprise Miner, 5/05. Proceedings, SUGI 30.
14. **Cerrito, PB.** Combining Text Miner with the Association Node in Enterprise Miner to Investigate Inventory Data. , 5/05. Proceedings, SUGI 30.
15. **Cerrito PB**, Badia A, Cerrito JC. Data Mining Medication Prescriptions for a Representative National Sample. 6/05. PharmaSug Proceedings.
16. **Cerrito PB,** Pecoraro, D. Visits to the Emergency Department as Transactional Data. Submitted 3/05. Health Policy Management.

17. **Cerrito PB.** Data Mining Methods to Examine Thousands of Possibilities in Categorical Data. Invited Paper, SESUG Proceedings 2005.
18. **Cerrito PB. .** Comparison of Enterprise Miner and SAS/Stat for Data Mining. MWSUG Proceedings 2005.
19. **Cerrito PB.** Cerrito JC. Data Mining Methods to Link Multiple Observations in a Dataset for market Basket Analysis. SUGI 31 Proceedings. 9/05.
20. **Cerrito PB.** Data Mining the Hospital Emergency Room. SUGI 31 Proceedings. 9/05.
21. **Cerrito PB.** A Certificate Program in Data Mining with Developing Online Courses, MWSUG Proceedings. 6/05.

Presentations Made

Date	Presentation
1. March, 2006	**Cerrito PB**. Invited Address. Data and Text Mining the Electronic Medical Record to Improve Care and to Lower Costs. SUGI31. San Francisco
2. March, 2006	**Cerrito PB.** Which Model to Choose? School of Nursing.
3. May, 2006.	**Cerrito PB**. Data Mining Methods to Link Multiple Drug Purchases. PharmaSug. Bonita Springs.
4. May, 2006.	**Cerrito PB.** Experimental Design: Choosing the Right Model. PharmaSug. Bonita Springs.
4. May, 2006.	**Cerrito PB.** ½-day pre-forum workshop. Data Mining the Institutional Databases to Examine the Issue of Student Success. AIR 2006 Forum. Chicago.
5. May, 2006	**Cerrito PB.** Mathematics as the Gatekeeper to Success, AIR 2006 Forum, Chicago.
6. June, 2006	**Cerrito PB**. **Invited address.** Predicting Transactional Time Series. SAS Institute Forecasting Conference. Cary, NC.
7. June, 2006	**Cerrito PB.** A Pereira, J. McKnight**.** Methods to Analyze the Electronic Medical Record to Improve Care and Decrease Costs. 2006 AHRQ Patient Safety & Health IT Conference - Strengthening the Connections. Washington, DC.
8. June, 2006	**Cerrito PB. Invited Address.** Data Mining the Clinical Database. Annual Forum on Business Intelligence. Mt. Pleasant, MI.
9. August, 2006	**Cerrito PB. Invited Address. Interactive Web Cast.** Compressing Categorical Data.
10. October, 2006	**Cerrito, PB**. ½ Day Workshop, Enterprise Miner to Investigate Healthcare Data. SESUG.
11. October, 2006	**Cerrito, PB. Invited Address.** Using SAS Enterprise Miner to Examine General Education Issues. SESUG.

Research showcased in locally and nationally distributed articles.

1. Dstar, SAS Text Mining Software Turns Prose into Profit, http://www.taborcommunications.com/dsstar/02/0611/104352.html, 2/11/2006.
2. Awarded Silver Circle Award, SAS Institute, August, 2006.

Continuing Grant Activity for 2007.

1. $150,000, NIH, Academic Research Enhancement Award. Data mining to enhance medical research of clinical data. 2004-2006. Annual report submitted April, 2005.
2. NIH, $1.5 million. Project Implementation Grant. ED Information Systems-Kentucky and Indiana Hospitals. 2005-2007. co-PI (40% time).
3. $30,000, AIR, Methods to Examine the Gatekeepers to Graduation.

Consulting Projects Completed

1. Analysis of risk survey, SL Ridner, School of Nursing, 1/06.
2. Analysis of Caregivers Survey, Karen Robinson, School of Nursing, 1/06.
3. Development of Grant Proposal, Justin Moore, School of Education, 1/06.
4. Analysis of post-partum depression, MC Logsdon, School of Nursing, 3/06.
5. Analysis of previous loss, Deborah Armstrong, School of Nursing, 3/06.
6. Analysis of pain in surgery, Carla Herman, School of Nursing, 4/06.
7. Grant preparation, Bob Topp, SL Ridner, Barbara Speck, Celeste Schawler, 5/06.

Training Activities

1. SAS Institute, Forecasting, June, 2006
2. SAS Institute, Predictive Modeling, June, 2006.

Instructional Activities

1. Completion of Text in Data Mining, SAS Press, May, 2006.
2. New course, CECS 694, Data Mining with Linear Models
3. New course, CECS 694, Methods of Classification.
4. New course, Math 591. Time Series Analysis.

Mentored student research in refereed publications:

1. Battioui, Chakib. Data Mining Techniques to Analyze a Library Database. Proceedings SUGI31, March, 2006.
2. Ferrell, Jennifer. A Comparison of PROC MIXED and PROC GLIMMIX. Proceedings SUGI31, March, 2006.
3. Nfodjo, David. Socio-economic factors to utilization of the emergency department. PharmaSug Proceedings. May, 2006.
4. Twagilimana, Joseph. Length Of Stay Analysis With Combined Statistical and Data Mining Methods. SESUG Proceedings, 2006.
5. Hook, Arnold. Using Nominal Variables in Proc Fastclus as a Method for Classifying College Benchmarks. SESUG Proceedings, 2006.
6. Petrou, Christiana. Data Mining of Dental Information. SESUG Proceedings, 2006.
7. Karem, Andrew. Logistic Regression in Predicting Lung Cancer Origin. SESUG Proceedings, 2006.
8. Battioui, Chakib. Predictive Modeling To Analyze Hospital Charges Versus Reimbursements. SESUG Proceedings, 2006.
9. Tesfamicael, Mussie. Gene Expression Profiling of DNA Microarray Data using Association rules. SESUG Proceedings, 2006.

10. Nowrouzi, Fariba. Water Usage Distribution and Its Relation with Income Using SAS and ArcGIS. SESUG Proceedings, 2006.
11. Dennison, Rebecca. Time to Failure in UPS Data Collector and UPS Thermal Printer. MWSUG Proceedings. 2006.
12. Risov, Marie. Dependent scores within KAI and MBTI instruments. MWSUG Proceedings. 2006.
13. Battioui, Chakib. Calculation of Health Disparity Indices. Submitted 1/05. ArcUser.
14. Schwarz, John. Statistical Tools Used to Identify Geographic Trends. Submitted 1/05. ArcUser.
15. Twagilimana, Joseph. Time Dependent Data Preprocessing: Doing It All by SAS. MWSUG Proceedings. 10/05
16. Ferrell, Jennifer. A Comparison of General Linear Mixed Models to Generalized Linear Mixed Models: A Look at the Benefits of Physical Rehabilitation in Cardiopulmonary Patients. MWSUG Proceedings. 10/05.
17. Petrou, Christiana. Using SAS for Spatial Analysis MWSUG Proceedings. 10/05.
18. Tesfamicael, Mussie. Calculation of health disparity Indices Using Data Mining and the SAS Bridge to ESRI. MWSUG Proceedings. 10/05.
19. Battioui, Chakib. Relationship between the total charges and the reimbursements in the outpatient visits. MWSUG Proceedings. 10/05.
20. Hook, Arnold. Using SAS Proc Fastclus to determine Benchmark Institutions for a College or University. MWSUG Proceedings. 10/05.
21. Schwarz, John. Clustering Analysis of Micro Array Data. SESUG Proceedings. 10/05.
22. Kashan, Fariba. Medicare Cost Estimation for Heart Disease. MWSUG Proceedings. 10/05.

Theses Completed as Primary Advisor

1. France, Tyson. Investigating the cultural diversity of the University of Louisville, Undergraduate Honors Thesis, May, 2006.

PhD Dissertations Completed as Primary Advisor.

1. Twagilimana, Joseph. Combining Data Mining and Statistical Techniques for Analysis of Outcomes in a Hospital Emergency Department. May, 2006.
2. Nfodjo, David, Social-economic factors to utilization of the emergency department at a Jefferson County Hospital. September, 2006.

Mentored Student Presentations at Professional Conferences:

1. France, Tyson. The Impact of International Culture on Learning at the University of Louisville. Posters at the Capital, Frankfort. 2006.
2. Battioui, Chakib. Data Mining Techniques to Analyze a Library Database. SUGI31, March, 2006. National Award. Award for Best Student Paper, 1 of 5 nationally. 2006.
3. Ferrell, Jennifer. A Comparison of PROC MIXED and PROC GLIMMIX. SUGI31, March, 2006. Award for Best Student Paper, 1 of 5 nationally. 2006.
4. Tang, Guoxin. Data mining to investigate university expectations of work. M2006. Las Vegas. Given travel award to present, 1 of 5 nationally. 2006.
5. Zahedi, Hamed. Developing a decision model concerning the treatment of osteomyelitis with MRSA. M2006. Las Vegas. Given travel award to present 1 of 5 nationally. 2006.
6. Battioui, Chakib. Text mining solutions to analyze hospital charges versus reimbursements. M2006. Las Vegas. 2006.
7. Tesfamicael, Mussie. Data mining to investigate the prescribing of medications longitudinally. M2006. Las Vegas. 2006.

Mentored student grant submissions:

1. Battioui, Chakib. NSF, Internship Grant.
2. Ferrell, Jennifer, NSF. Dissertation Grant.

Supervisor of Student Internships in Summer, 2006.

1. Tesfamicael, Mussie, Data mining information from the VA.
2. Battioui, Chakib, Data mining information from Norton Healthcare
3. Tang, Guoxin. Examination of Institutional Data.
4. Zahedi, Hamid, Develop cost model of treatment of osteomyelitis and MRSA
5. Petrou, Christiana, Data mining information from the UofL Dental Clinic.

Other Instructional Activities

1. Member of the PhD committee of Bin Cao in the Department of Computer Engineering and Computer Science.
2. Member of the MSPH committee of Jennifer Ferrell in the Department of Bioinformatics and Biostatistics.

Service Activities

1. Section co-chair, Pharmasug 2005-2006. Statistics and Pharmacokinetics Section.
2. Section co-chair, SESUG 2005-2006. Statistics and Data Mining Section.
3. Developing web site and marketing of certificate in collaboration with CECS and the SAS Institute.
4. Reader, Kentucky Junior Science & Humanities Symposium.
5. Member, Distinguished Teaching Award Committee.
6. CTSA Planning Grant, NIH, 3/26. Craig McClain, PI.
7. Invited to advise SAS on Data Mining Certificate, May, 2006. Member of development committee.
8. Editor, Journal of Intelligent Decision Making. 2006.

Budget

Personnel		
Principal Investigator	2-FTE academic year months @ $9500/month	$19,000
Graduate Student	1-FTE summer months @ 2000/month	$2000
Total Salaries and Wages		$21,000
Fringe Benefits @ 25%		$4750
Travel (AIR Forum and Educause)		$3000
Total Benefits and Travel		$7750
Other Direct Costs		
Software purchases		$1250
Total Other Direct Costs		$1250
Total Amount of Award		$30,000

Budget Justification

The budget includes time for the PI to perform the required analyses with the support of a graduate student intern well trained in data mining techniques.

Travel support is requested for trips to AIR, and to Educause to disseminate the research.

The statistical software to be used is SAS and SAS Enterprise Miner (SAS Institute; Cary, NC). There is a yearly renewal cost for use of this software.

Current and Pending Support

Patricia B. Cerrito

1. NIH, Academic Research Enhancement Award. Data mining to enhance medical research of clinical data. 2004-2007. 20% Time.
2. NIH, Project Implementation Grant, ED Information Systems-Kentucky and Indiana Hospitals. 2005-2007. 40% Time
3. $30,000, AIR, Methods to Examine the Gatekeepers to Graduation.

4. **Facilities, Equipment, and Other Resources**

The PI currently has a Xeon dual-processor available for the project. The processor has 4 gb RAM that is of sufficient size to complete the project.

The institutional Research Office is providing access to the data. The project has received IRB approval.

The PI, Patricia Cerrito, has been very active in the examination of student data related to the success of students in mathematics courses. She also has considerable experience in investigating large, complex databases. She has a number of publications in the field.

Preliminary Research

Work Expectations in Remedial Mathematics Courses

By

Patricia B. Cerrito
Department of Mathematics
University of Louisville
Louisville, Kentucky 40202
502-852-6826
502-852-6010
pcerrito@louisville.edu

1. Introduction

Students advancing into a mathematics course from a preceding course need to be prepared for that course. Instructors need to assume that students are prepared to learn the material in that course. Anything less is simply grade inflation. However, if a course is taught in multiple sections with multiple instructors, such preparation cannot always be guaranteed. This is particularly true if the course is largely taught by part-time instructors and graduate teaching assistants with a large turnover rate. In this case, there is a lack of continuity from semester to semester.

At Duke University, the average grade has become an A- and is increasing. Duke has now defined an AI index to replace the gpa. This index accounts for grade inflation factors by weighting the result in terms of the average grade in the course (Newsweek, 1997). According to Jennings (1995), this inflation trend has developed throughout the American education system. It is stated in this paper that the solution is to "match form with substance." The grade given should indicate something about the ability of the student to succeed in subsequent material. Inflating grades, in the long run, does not do a student any favor.

Instructors of mathematics consistently complain about the lack of skills possessed by students in entry level mathematics courses. Yet they continue to contribute to the problem by giving students passing grades when they have not mastered the course material and will have little chance of passing subsequent courses due to their lack of mastery. As stated in the Chronicle of Higher Education (1994):

> Teachers' awarding of higher grades for students' performance is a cause of concern for college officials. 'Grade inflation' results in weaker students' lackadaisical attitude toward improving their performance. Humanities students generally get better grades than science students, but humanities professors argue that this is because essays are comparatively more subjective than formulae and problem sets.

Dressel (1983) puts it very clearly, "[Grades are] an inadequate report of an inaccurate judgment by a biased and variable judge of the extent to which a student has attained an undefined level of mastery of an unknown proportion of an indefinite material."

This lack of student interest and effort is certainly well observed at the University of Louisville. Student attendance in entry-level mathematics courses borders upon the dismal (Cerrito and Levi, 1997). Assigned homework is frequently unfinished, whether graded or ungraded. However, it has been observed that graded homework does result in an increase in study time. Although there are many arguments as to why students lack involvement in their courses, including an increase in outside responsibilities, it has been shown that students in the 18-22 age range with no outside responsibilities also devote little time to their academics.

However, there is a greater outcry for accountability in higher education with the intent to connect funding formulas to accountability outcomes. In addition, accrediting agencies such as SACS (Southeastern Accreditation of Colleges and Schools, 1998) mandate the implementation of evaluation procedures. It is much better to develop and implement such procedures than to have such procedures imposed. Such an evaluation system has already been imposed on K-12 education in Kentucky (Koretz and Barron, 1998).

Remedial mathematics courses serve a purpose and have a very definite goal. Students who pass the course with a C or better should be prepared to advance into a general education mathematics course also with a passing grade. Therefore, accountability can be more concrete than in more advance courses, or in non-mathematics courses. The learning goals of remedial courses can be very clearly stated.

Ordinarily, there is some coordination of effort with all instructors using the same textbook and the same syllabus with the same material listed on the syllabus. However, there is little verification that the instructors all cover the same material or emphasize the same concepts. Instructors are free to write and administer their own tests and grades. Some quality control is attempted at times through the use of a uniform final examination. Yet little is done if the students of one instructor score low on the uniform final. When this happens, students are passed into the next course only to fail there.
At the same time, there is very little sequential tracking of students to determine longitudinal performance in classes.

It is possible to devise an objective method of grading in mathematics courses which will provide a true indication of student performance. However, this must be done uniformly across a department; otherwise professors who try to assign grades lower than the norm will “anger students, parents, college officials and their own colleagues” (Chronicle of Higher Education, 1997). This is also well documented in the book, *Generation X Goes to College* (Sacks, 1996).

One school developed a systematic policy toward coordination. At Johnson County Community College in Kansas (Duckwall and Wilson, 1996), the mathematics faculty developed “core components” for ten of their mathematics courses. The core components were designed by the faculty teaching the course and were designated as essential elements in the course. The faculty teaching the course agreed to grade the core components identically and to assess them in the course final examination. Scores on the core components were correlated with results on the final examination. There still remained a lack of uniformity in the examinations themselves.

Another attempt was made to use homework and straight grading to increase student study time and student involvement in an elementary statistics class (Sokol, 1993). In this case, there was a strong correlation between exam grades and homework scores. However, fully 40% of the students did not like this system, demonstrating a detrimental effect on student evaluations.

2. Uniformity of Assessment

That grade inflation exists is clearly demonstrated by an investigation of four sections of a data analysis course. The average grade in the section was compared to the average overall gpa of the students (Figure 1).

Similar problems were seen in entry level mathematics courses where multiple instructors with differing standards resulted in extreme variability in outcome.

2.1. Investigation Of Quality

The implementation of quality control was motivated by problems which occurred during the spring, 1996 semester (and semesters previously). None of the students taught by one instructor scored above a D on the uniform final examination. Yet the majority of students in these sections received a passing grade. Some students complained about instructor performance and there was no way to investigate the legitimacy of complaints other than by classroom observations. Upon investigation, it was discovered that many students who passed the course failed their subsequent courses in mathematics. However, there was little to determine just how much the students learned in the course. Therefore, it was decided that a pre-test and post-test should be used to investigate student learning.

The first 12 questions of the pre-test pertained to prerequisite material which students should know prior to taking Intermediate Algebra. The next 18 questions of the pre-test covered the most basic material of Intermediate Algebra. Students should master this material by the time they complete Intermediate Algebra. It was determined that students who missed 2 or more of the first 12 problems did not take the final examination. Therefore, the material forms an excellent diagnostic tool to advise students who score poorly to take the Elementary Algebra course before attempting Intermediate Algebra.

There were approximately 700 student enrolled in this course in the spring semester, 1996. Approximately 2/3 of them took the final examination. The grade distribution of the students who took the final is as follows (Figure 1)

Of the students who took the final examination, 57% received a C or better in the course. It should be expected that these students would score well on the 18 post-test questions. However, as show in figure 2, there are many who did not.

There was a small percentage of students with a final grade of A who correctly answered 8 out of the 18 problems; the same percentage answering correctly only 12 out of the 18. Fewer than half of the A students demonstrated mastery of the most basic material. Students who received a B or a C demonstrated an even lesser understanding of this material (Figure 3). In fact, if the students who received a C, which should indicate that the student can advance, is compared to the students receiving a D or an F, which indicates that the student should not advance, the scores are interchangeable (Figure 4).

It is clear from this result that students were not fully prepared to succeed in the next level of mathematics. The introduction of uniform testing and uniform grading in Intermediate Algebra provides an absolute standard of achievement by which to measure student progress.

2.2. Implementation of Quality

During the Fall, 1997 semester, in the Department of Mathematics at the University of Louisville, a quality control program was initiated for the Intermediate Algebra course. This course carries university credit toward graduation but does not carry credit towards fulfilling the general education requirement. Therefore students enrolled in Intermediate Algebra must take at least one additional mathematics course. It acts as a prerequisite for all general education mathematics courses. The course is taught exclusively by part-time instructors and graduate teaching assistants; approximately 15-20 instructors teach one to three sections of the course each semester.

One laboratory hour was added to each section of Intermediate Algebra. This hour was reserved for a weekly test. Students were tested in multiple sections using uniform tests. These tests were generated via computer using a test generator package. The textbook for the course was chosen so that a good test generator was available. To oversee the testing process, a testing coordinator was appointed.

There were 14 weeks of testing. This allows for 9 short tests that cover partial chapters and 4 major tests that cover 1 or more chapters in the course. The grade for the course is assigned as follows:

Pretest	0%
9 Short Tests (lowest one dropped)	30%
4 Major Tests	40%
Final Examination	20%
Homework	10%

Thus students can miss one of the short tests. Makeup examinations are possible for the four major tests but only with a legitimate, documented excuse. The Pretest is used for diagnostic purposes only. It tests prerequisite material.

3. Mechanics Of Testing

3.1.Test Coordination

The test coordinator prepared multiple forms of each test on a weekly basis and was responsible for having them copied and distributed. All tests were multiple choice. Students used scantron sheets for their answers. The completed tests were sent to the testing center where they were scored within 24 hours. The raw data and scores were sent as attached files to the system administrator of the Department of Mathematics where they were printed and distributed to individual instructors.

3.2. Proctoring

Since multiple sections were tested simultaneously, it was necessary to coordinate the proctoring. Each section instructor was required to provide 10 hours of proctoring time (to replace time ordinarily spent in constructing and grading examinations). There were a minimum of three proctors per examination session: one to walk around and observe, one to collect examinations and verify identification, and one to check off students as they submitted their answer sheets. This was to ensure that students were taking their own examinations and also to ensure that all tests are accounted for. If extreme care was not taken, it would be easy to lose a scantron sheet, or to have a student falsely claim to have turned in an answer sheet unaccounted for.

3.3. Student Responsibilities

Students had to be prepared with number 2 pencils with erasers and a picture ID with identifying photograph (driver's license or university ID). Students who did not have the proper identification were not allowed to take the examination. Students also had to attend all testing sessions unless they had an excused absence.

3.4. Excused Absences

Absences were an ongoing problem. Students had to appeal to the test coordinator and have a letter of admission in order to take an examination at a time other than regularly scheduled. However, for illness or emergencies, a makeup for the major tests was scheduled immediately after the final examination. For short tests, 9 were taken but 8 were counted. Therefore, students had the option of missing one in case of emergency. Again, students needed a letter of admission to take the makeup.

The letter of admission was only issued to students who had documentation of an emergency. Out of 700 enrolled students, only 25 makeup examinations were administered.

One problem encountered with this option of dropping the short test was that students used their option early in the semester for a non-emergency. Then they believed they were entitled to a makeup on the second short test when it was an emergency. Fortunately, this did not happen often. It happens often enough to be a constant source of irritation. As an anecdotal example, one student came in to ask for a makeup on a short test because his daughter had become ill and he had to take her to the doctor. This was a legitimate excuse. Unfortunately, he had also missed the first two weeks of the course because he was out of town. This was not a legitimate excuse. Having missed one short test for an unexcused absence, he felt strongly entitled to take a makeup for his excused absence.

To avoid such problems again, students were required to present an appeal in writing with justification and documentation. The appeal was considered by the course coordinators. However, unless there were two emergencies which prevented the student from taking two of the short tests, it was denied. Two emergencies wouldl be a very rare occurrence. The requirement of documentation reduced the number of appeals to a minimum. When reminded of the requirement, few students actually made a formal appeal.

4. Problems Encountered

4.1. Lack Of Enforcement Of Prerequisites

Currently, the University of Louisville has no means of enforcing prerequisites. Therefore, many students who do not pass Intermediate Algebra go on to take general education courses with little success. The advising staff in the College of Arts and Sciences encourages students to skip Intermediate Algebra and take the general education course, Contemporary Mathematics. While students do need a certain level of mathematical skill for this course, the material in the course is not algebra-based.

4.2. Instructor Autonomy

Even though the course in Intermediate Algebra was intended to have uniform testing and uniform grading, several instructors inflated the grades by “curving” the final scores. This is grade inflation at its absolute worst. Regardless of the outcomes on the uniform testing, student grades were increased simply to pass more students.

It was not made abundantly clear at the beginning of the semester that the grading should be uniform. Approximately 5% of the part-time instructors and 5% of the graduate teaching assistants curved grades upward. Fortunately, this changing of grades actually translated into a total of 1% of students with grades higher than they should be. Because of instructor autonomy, this curving could not be prevented; however, it is strongly discouraged. Part-time instructors are hired and retained by the needs of the Department. The class outcomes of instructors has little to do with their retention for future hiring. Increased accountability by the Department might make them more accountable.

5. Outcomes Observed

5.1. Consistency in Grading and in Student Performance

The first goal of the uniform grading policy was to achieve more uniform grading outcomes across sections of the course. The outcomes on the pretest for each section of Intermediate Algebra are given in the Figure 5.

Note that there is considerable variability in outcomes. The section average ranges from 12% to 60%. The overall average score was 27%. This strongly indicates that course sections are not homogeneous and that outcomes assessment must consider this lack of homogeneity. When the results were compared with post-test scores (the post-test consisted of the same 20 questions with randomized numbers and responses), it should be noted that the results across sections became very consistent (Figure 6).

This demonstrates the effectiveness of uniform testing and grading procedures. The overall average increased to 72% and all sections were within 10-12% of that average value.

5.2. Outcomes in Subsequent Courses

Students who received grades of A-C in their Intermediate Algebra course should be ready to move on to their general education mathematics course. Students should be able to get a grade of A-C in their subsequent course. If the majority of students do this successfully then the uniform grading policy in Intermediate Algebra satisfies its primary purpose which is to prepare students for these subsequent courses.

To determine the effectiveness of the standards, student performance in the subsequent general education courses was tracked. The results were compared to those prior to the adoption of uniform standards. As expected, the results for non-algebra based courses were similar in both years:

Table 1. Performance of Students in Non Algebra-Based General Education Courses After

Passing Intermediate Algebra With a Grade of C or better.

Grades	Contemporary Mathematics		Finite Mathematics		Elementary Statistics	
	96-97	97-98	96-97	97-98	96-97	97-98
Pass (C or better)	84%	82%	56%	57%	86%	100%
No Pass (D, F, W)	16%	18%	44%	43%	14%	0%

For the most rigorous algebra courses, there was a statistically significant improvement when the uniform grading was first adopted:

Table 2. Performance of Students in Algebra-Based General Education Courses After Passing Intermediate Algebra With a Grade of C or better.

Grades	Elementary	Calculus	Precalculus	& Calculus
	96-97	97-98	96-97	97-98
Pass (C or better)	67%	71%	35%	58%
No Pass (D, F, W)	33%	28%	65%	42%

The results for College Algebra were mixed. Consider the proportion of students who passed College Algebra given a passing grade in Intermediate Algebra:

Table 3. Proportion of Students Passing College Algebra (C or better) Given a Passing Grade in Intermediate Algebra

Grade in Intermediate Algebra	College Algebra 96-97	College Algebra 97-98
A	97%	88%
B	67%	85%
C	43%	46%
D	20%	22%
F	0	0

Note that the greatest improvement occurred in the group of students receiving a B in Intermediate Algebra. Now, there is a high probability that students who receive an A or a B in Intermediate Algebra will pass their general education course; prior to the uniform grading policy this high probability was reserved for students who received an A.

5.3. Study Habits

For each test, students were asked about their study habits. The results were batched for each test to determine if there were shifts in attitudes. The questions asked were

- Q1: I have missed ___ Intermediate Algebra class(es) last week.
- Q2: I have spent ___ outside of class studying for this test or doing homework problems.
- Q3: To get an “A” on this test, I would have to study ___ hour(s).

Test 1 represents the pretest, test 2-9 are the short, 30 minute tests given and 11-14 are the four major tests given in the semester. One of the short tests had to be combined with another one because of a snow closure. Consider a summary of the responses for the questions (Figures 7)

Note the drop in the number of responses thath occurred after the final withdrawal date. Note also that there were a large number of students who did not attend class prior to the first major test (#11). Although there was a drop in the total number of students, and a corresponding drop in the number of students who said they missed no classes, the number of students who skipped 2 or 3 classes remained relatively the same. Therefore, there is a core of students who do not believe that they need to attend class.

The course syllabus emphasizes that students should spend 2-3 hours studying for every hour spent in class. Only a very small percentage (3-8% range) spent more than four hours per week on course material. Although there are no guarantees, for the most part, students who do not put in sufficient time on course material will not perform well on tests (Figure 8).

Not only are students not putting in the time needed to succeed in Intermediate Algebra, a significant proportion believed that such a short time is sufficient to get an A in the course (20-30%). The proportion who believed that six or more hours were necessary was small (5-10%). Therefore, it is clear that students have unreasonable expectations about what is required to prepare for Intermediate Algebra (Figure 9).

It seems clear that this is where effort needs to be made to improve student performance. There are a variety of well-known methods for increasing study time; however an emphasis on homework continues to be the most productive.

6. Conclusion

Standards in remedial mathematics courses need to remain high. Otherwise students will continue to perform poorly through poor attendance and little study. One of the best ways to retain standards is to use uniform testing and grading. As demonstrated here, uniformity leads to more consistent performance across multiple sections and improves student performance in subsequent courses. The major hindrance remains the lack of involvement by the students and their unreasonable expectations of effort and attendance.

Another method to improve subsequent results is to require mastery learning and requirements for a minimum study time monitored through a computer-based algebra management system. Students would be required to complete each required course module with 80% mastery. However, students should then be able to take more than one semester to complete all course modules.

References

Cerrito, Patricia, Levi, Inessa (1999). An investigation of student habits in mathematics courses, College Student Journal. 33(4). 584-589.

Dressel, P. (1983). Grades: One more tilt at the windmill, in A.W. Chickering ed., Bulletin, Memphis State University Center for the Study of Higher Education.

Duckwall, J.M. And Wilson, S. J. (1996). Can core components in mathematics courses replace comprehensive common course finals? Presented at the AIR 1996 Annual Forum.

Gose, B. (1997). Efforts to curb grade inflation get an F from many critics. The Chronicle of Higher Education v.43 #46. PA41(2).

Koretz, Daniel M., Barron, Sheila I., Rand Education. (1998). The validity of gains in scores on the Kentucky Instructional Results Information System. (KIRIS-MR-1014). Santa Monica, CA.: Rand Corporation.

Jennings, J.F. (1995). Matching form and substance in American education. Daedalus. V124. #4. P131(3).

Pederson. D. (1997). When an A is average: Duke takes on grade inflation. Newsweek. V129. #9. P64.

Peters, Roger. (1994). Some snarks are boojums: Accountability and the end(s) of higher education. Change. 26:16-23.

Sacks, P. (1996) Generation X Goes to College, Open Court Publishing: Chicago.

SACS (1998). www.sacscoc.org/coc/secIII.htm. May, 2000.

Shea, C. (1994). Grade inflation's consequences. The Chronicle of Higher Education. V40. #18. PA45(2).

Sokol, P.E. (1993). Improvement in introductory physics courses. New Directions for Institutional Research. #78. P41-44.

Figure 1. Comparison of Grades in Statistics Courses to Overall Student GPA.

Figure 2. Final Grades for Students Taking Final Exam

Figure 3. Grades of Students in Intermediate Algebra (C or Better) Compared to Score on Posttest

Figure 4. Grades of Students in Intermediate Algebra (C or Worse) Compared to Score on Posttest

Figure 5. Student Grades on Pretest by Course Section

Figure 6. Student Grades on Posttest by Course Section

Figure 7. Student Response Concerning Number of Classes Skipped Per Week

Figure 8. Student Response Concerning Study Time

Figure 9. Student Response Concerning Expected Study Time

Figure 1.

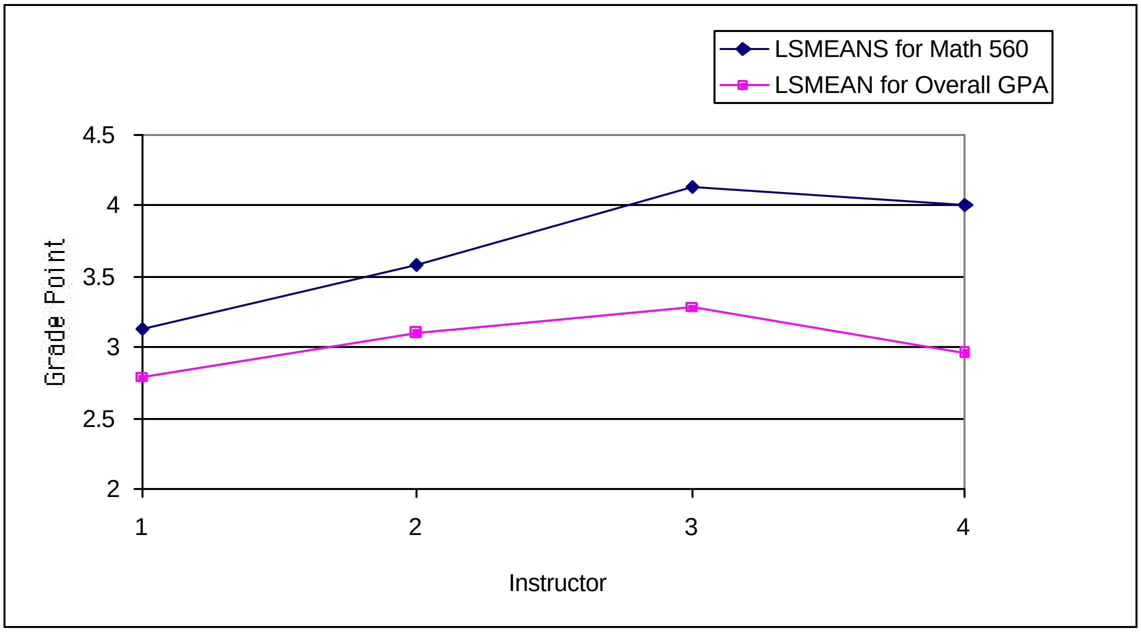

LSMEANS for Math 560
LSMEAN for Overall GPA
Grade Point
4.5
4
3.5
3
2.5
2
1
2
3
4
Instructor

Figure 2.

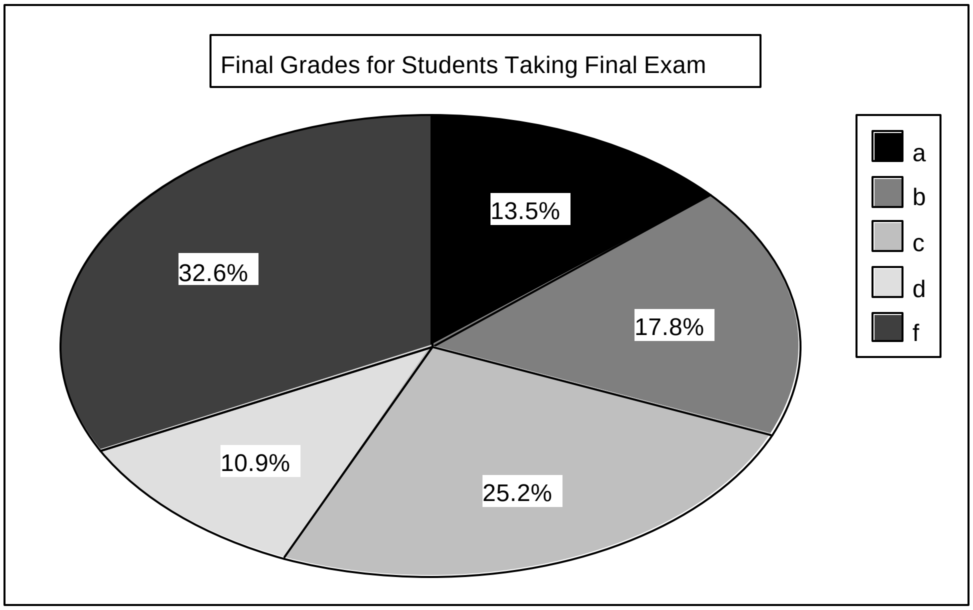
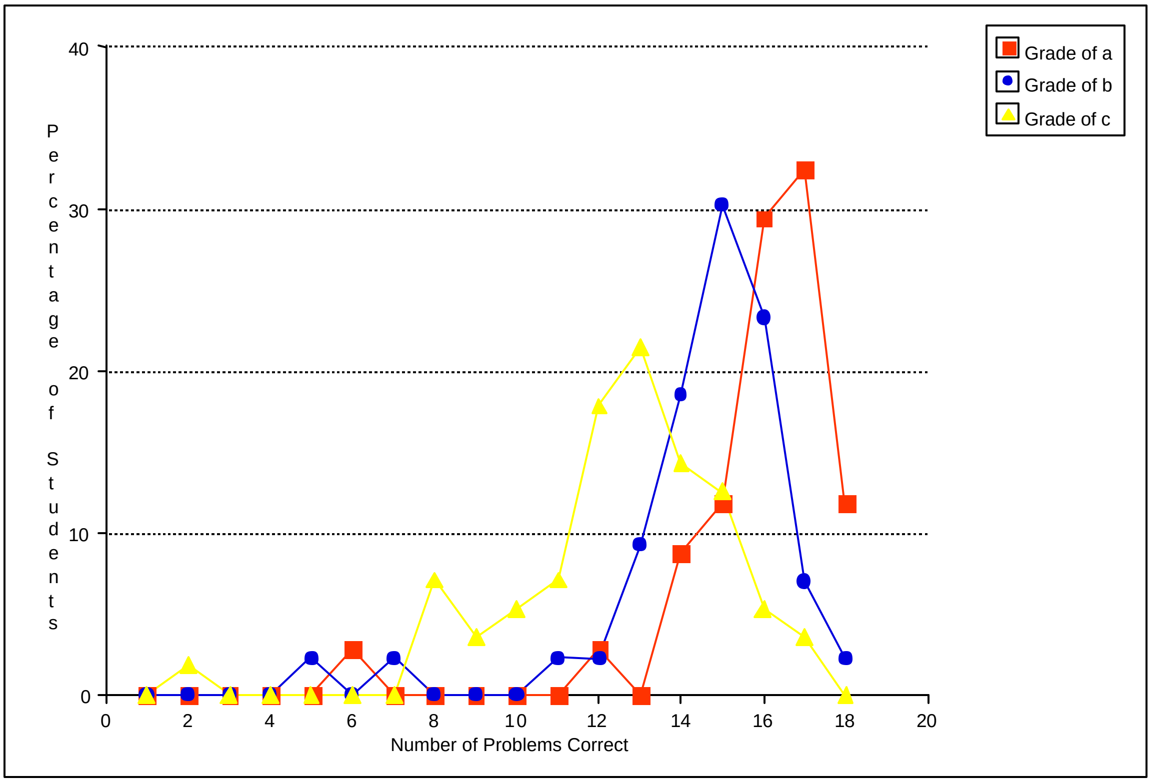
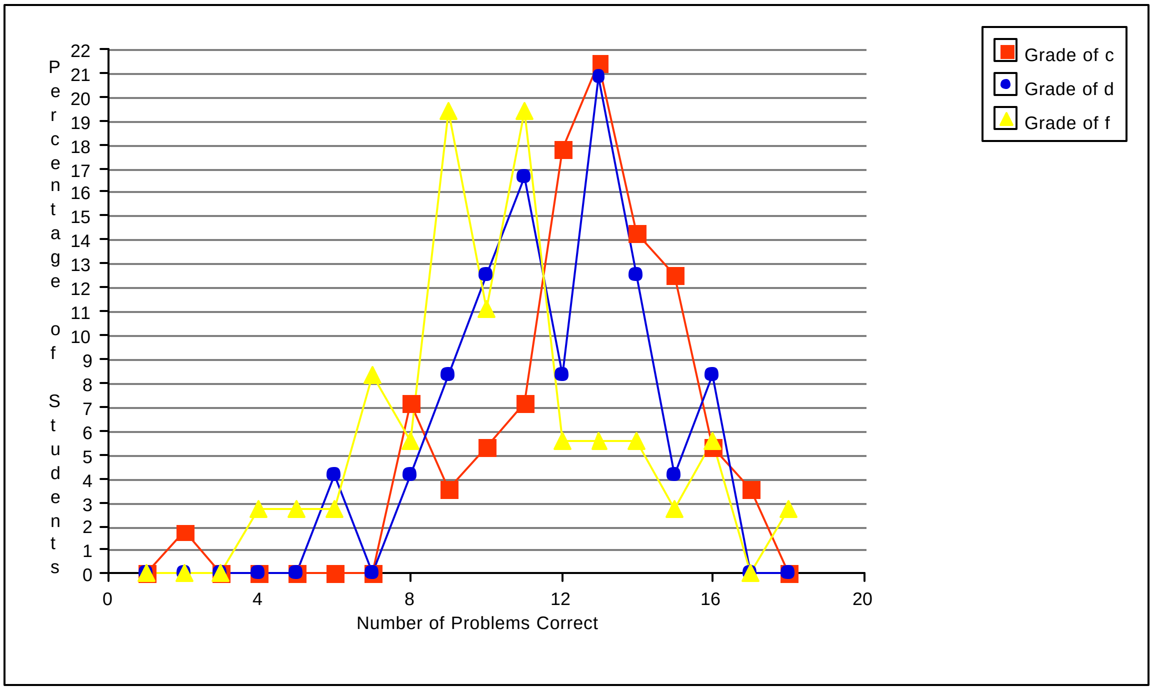

Final Grades for Students Taking Final Exam
13.5%
32.6%
17.8%
10.9%
25.2%
a
b
c
d
f

Figure 3.



40
30
20
10
0
Percentage of Students
0
2
4
6
8
10
12
14
16
18
20
Number of Problems Correct
Grade of a
Grade of b
Grade of c

Figure 4.



Percentage of Students
22
21
20
19
18
17
16
15
14
13
12
11
10
9
8
7
6
5
4
3
2
1
0
0
4
8
12
16
20
Number of Problems Correct
Grade of c
Grade of d
Grade of f

Figure 5

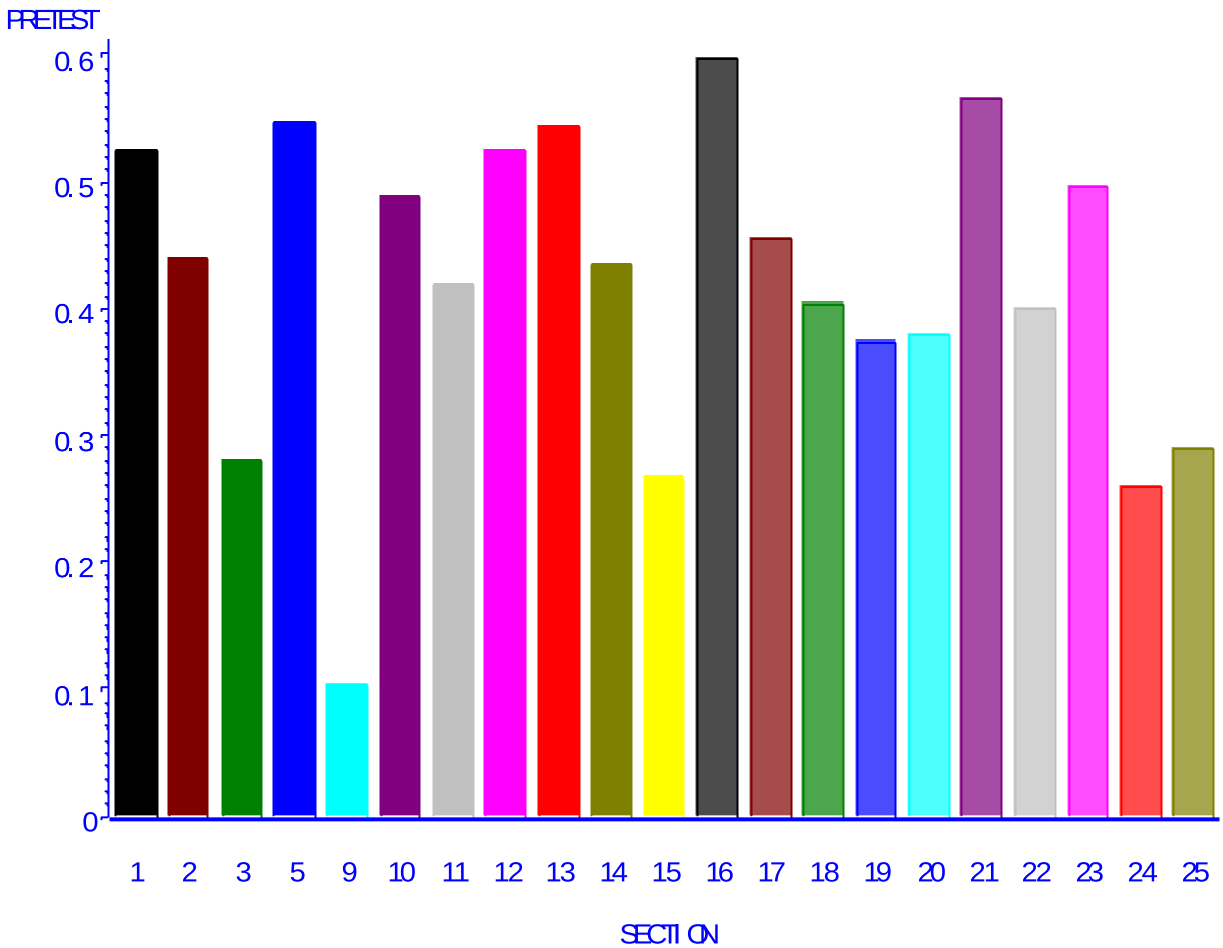

PRETEST
0.6
0.5
0.4
0.3
0.2
0.1
0
1
2
3
5
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
SECTION

Figure 6.

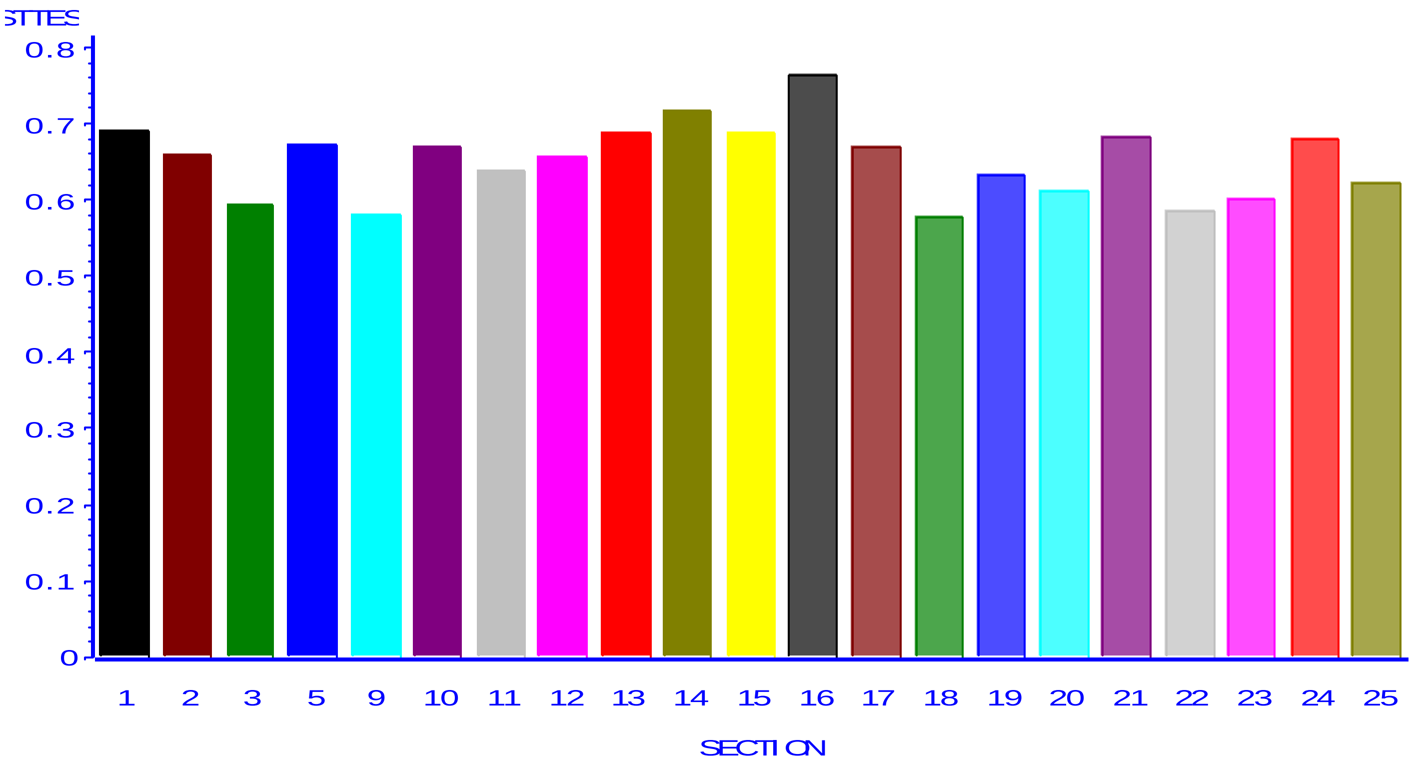
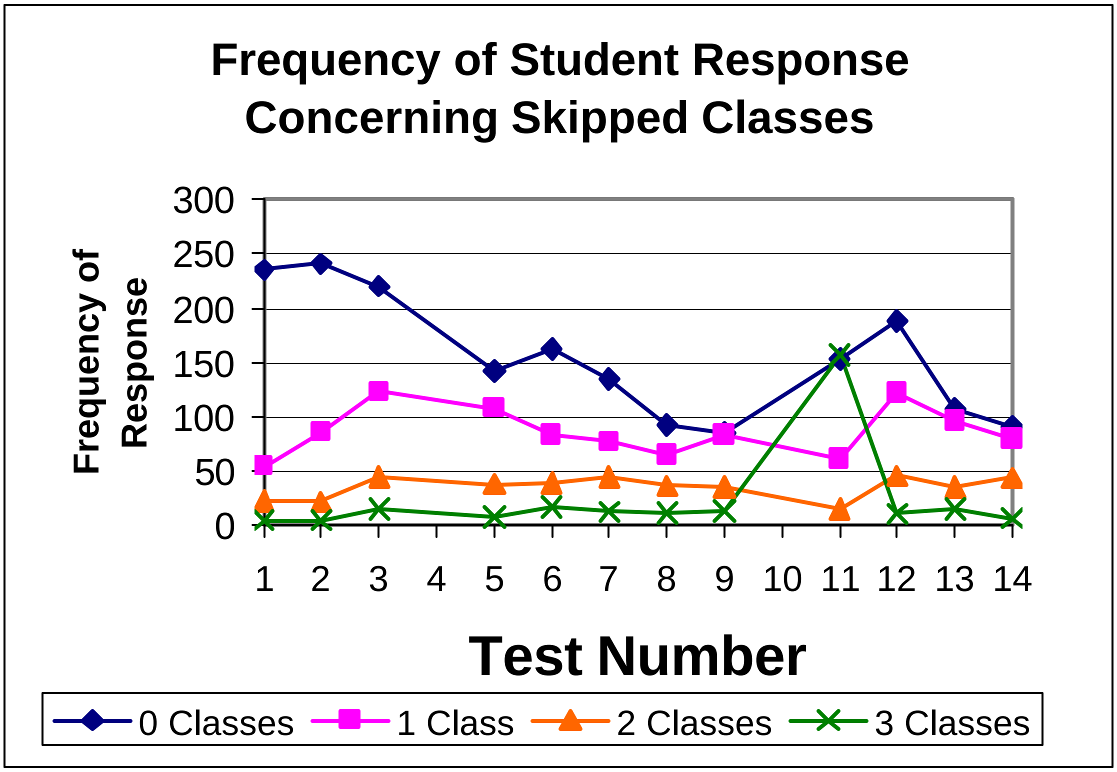
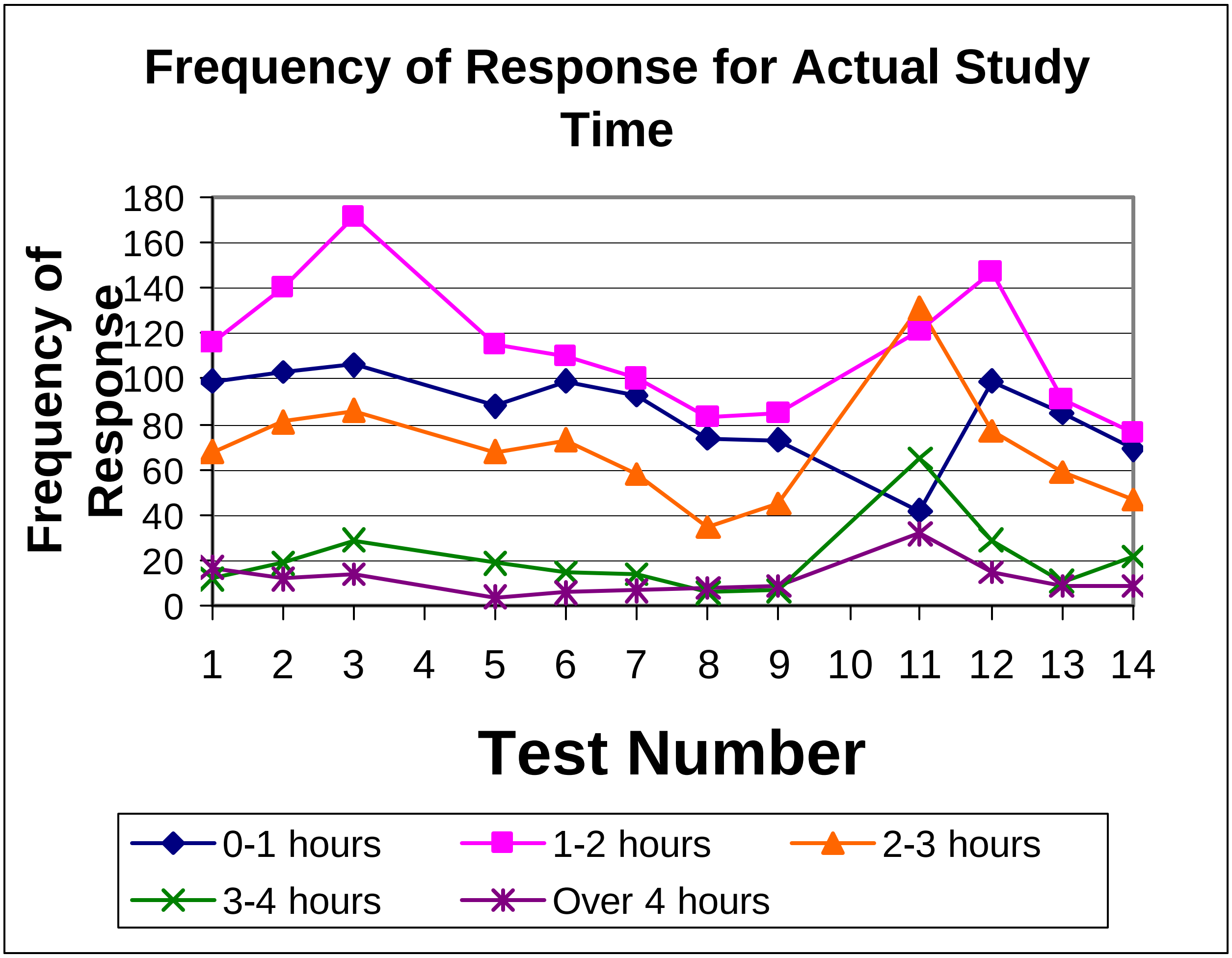

0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1 2 3 5 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
SECTION

Figure 7.



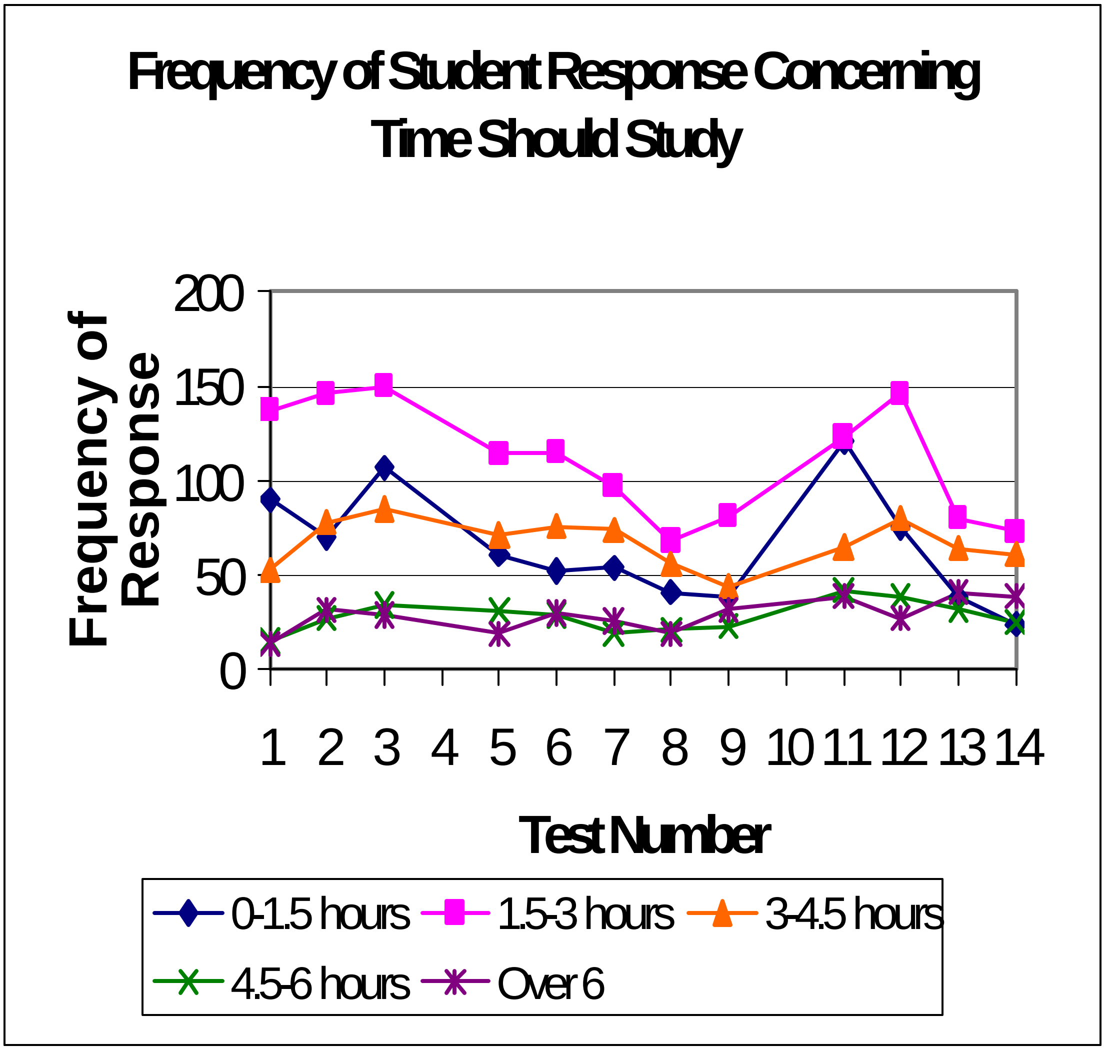
Frequency of Student Response Concerning Skipped Classes
Frequency of Response
300
250
200
150
100
50
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
Test Number
0 Classes
1 Class
2 Classes
3 Classes

Figure 8.



Frequency of Response for Actual Study Time
Frequency of Response
180
160
140
120
100
80
60
40
20
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14
Test Number
0-1 hours
1-2 hours
2-3 hours
3-4 hours
Over 4 hours

Figure 9.


Frequency of Student Response Concerning Time Should Study
Frequency of Response
200
150
100
50
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14
Test Number
0-1.5 hours
1.5-3 hours
3-4.5 hours
4.5-6 hours
Over 6

An Assessment of General Education Mathematics Courses via Examination of Student Expectations and Performance

Patricia B. Cerrito

Department of Mathematics
University of Louisville
Louisville, KY 40292

502-852-6826
502-852-7132 (fax)
pcerrito@louisville.edu

Abstract

It is the purpose of this paper to discuss the method and results of an evaluation of general education mathematics courses. Students were surveyed in the first week of the fall, 2000 semester to determine their expectations for their mathematics course. Student grades were examined to determine how student expectations related to student outcomes. The workload expected by students is substantially different from that expected by faculty, and this difference is reflected in final course grades.

Introduction

Continuous review of general education courses is important to maintain the vitality of the courses. The Mathematical Association of America (2000) has recently developed a new set of guidelines for higher education. The guidelines include a statement regarding the necessity of the development of

> "Procedures for measuring the extent to which the educational goals are being met. These measures will, of necessity, be multi-dimensional since no single statistic can adequately represent departmental performance with respect to most departmental goals. Measures of student learning and other student outcomes should be included in the procedures."

The Department of Mathematics offers several general education courses. To satisfy the general education requirements, a student needs to take at least one three-hour mathematics course; the specifics of the course may be determined by the student's program. The Department offers several courses below the level of Calculus I, a course for science and mathematics majors. These courses are listed in Table 1. The courses are fairly standard with the exception of Contemporary Mathematics and Mathematics for Elementary Education; the university catalog descriptions of these two courses are as follows:

> **Contemporary Mathematics.** Use of mathematical modeling to solve practical problems. Applications include management science, social choice, population growth, and personal finance.
> **Mathematics for Elementary Education.** Recommended only for majors in elementary or middle school education. Does not count toward mathematics major or minor. Basic concepts of real numbers, measurement, geometry, probability and statistics. Emphasis on problem solving.

In addition, at the time the survey was conducted, the Mathematics Department taught a remedial course in Intermediate Algebra. This course provided university but not general education credit. Another unit of the University taught Pre-algebra and Elementary Algebra as no university credit courses. A subsequent change in university programs emphasis resulted in a shift of the remedial instruction to a local community college.

It is important to measure student learning (Bers, 2000). It is also important to ascertain student perceptions of the subject matter, and how they believe the subject ought to be taught, as well as students' self assessment of their own knowledge, as these issues are also closely related to the process of learning. The necessity of assessing student perceptions is recognized in various disciplines (Redish at al., 1998):

> "Students understanding of what science is about and how it is done and their expectations as to what goes on in a science course, play a powerful role in what they can get out of introductory college physics. This is particularly true when there is a large gap between what the students expect to do and what the instructor expects them to do."

Students do not always recognize their weaknesses (Osterland, Robinson, and Nickens, 1997). As part of a measure to monitor and evaluate the general education program, the Department of Mathematics administered a survey to all students in general education mathematics courses as well as in

Intermediate Algebra. For the algebra based courses (College Algebra, Precalculus and the first semester Calculus), student grades over a period of time were examined to determine how students were succeeding or failing in subsequent courses. The purpose of this paper is to suggest methods for some quality assessment of general education mathematics courses. The paper reports the results obtained by using these methods.

This study supports previous findings (e.g. Grob and Kuehl, 1997) that students are unwilling to invest the necessary time and effort into their study of mathematics. In addition, students generally have an inflated sense of their own mathematics knowledge. This over confidence translates into a willingness to enroll in courses for which the students do not have the necessary prerequisites, as well as a belief that a very small investment in study time to learn the course material should bring on satisfactory results.

Student Survey

To examine students' perceptions about mathematics classes, teaching, learning, and their own achievements and accomplishments, students in all the general education mathematics courses were surveyed in August 2000. There were a total of 1613 responses from students in the general education courses (100-level). The distribution by class and major or proposed major is given in Table 2 (twenty seven students did not provide valid responses regarding either major or class).

There are a number of survey instruments developed to examine student perceptions (Ramsden, 1981; Voeller, et.al., 1983; Schonwetter, et.al., 1993; Redish, 1998). A decision was made to develop an instrument within the Department that addresses issues perceived as most crucial to the local situation. The process allowed the faculty to maintain ownership of the process. Prior to administration of the survey, two faculty members developed the questions with input from the Department Chair. The survey was distributed to additional faculty members in the Department to provide a chance for comments. The final survey form was submitted to the University's Human Studies Review Committee for approval. The survey process was set up so that students would put their anonymous responses on scantron sheets. The surveys were administered during the first week of classes in the fall, 2000 semester. The purpose was to examine student expectations in the courses at the start of the courses. A copy of the survey questions is given in the Appendix.

The reliability and validity of the survey instrument were examined by analyzing a subset of question (Questions 10-20 in the survey in the Appendix)) dealing with students' perceptions of how difficult is the course and how reasonable is the instructor, students' prior mathematical knowledge, and study habits. A factor analysis was performed on the whole data set using the varimax rotation to identify this particular factor. There were a total of four factors. The first factor included all questions 10-20 indicating that the responses concerning student perception of difficulty of the course, workload, and instructor were highly related, and these were related to self-reported mathematics ACT scores and self-assessed level of mathematical knowledge. The second factor included questions 1-4 concerning the numbers of attempts of both remedial and general education courses. Factor 3 included questions 7-9 concerning the use of a computer in the class and factor 4 included responses to questions 5,6 concerning the student's major and whether the course was required. The course in which the students were enrolled was also related to the students' major. Cronbach's alpha was used on questions 10-20 and was equal to 0.94 indicating a high degree of reliability (Table 3).

The distribution of numbers of student responses by courses is presented in Figure 1. Many of the students enrolled in general education classes needed to take at least one remedial course in mathematics (Figure 2). Indeed, 47% of students in general education 100-level courses self-reported taking at least one remedial mathematics class previously, 21% took just one remedial mathematics class, 22% took two remedial mathematics classes, and 4% took three remedial mathematics classes. A number of students had several attempts at taking a remedial mathematics class.

Although the University of Louisville accepts both the SAT and ACT test scores, most students prefer to take the ACT. The ACT has 4 parts, with one of the parts for mathematics. A perfect score is 36. The self reported mathematics ACT scores may provide an explanation for such a large number of students enrolled in remedial mathematics (Figure 3). Note that even at the level of Precalculus, at least 10% of the students have an ACT mathematics score below 20. The median ACT mathematics score is 19 (2001 ACT National and State Scores). Since students with an ACT mathematics score below 23 are required to take one of the remedial mathematics courses, average score is not sufficient for success. Students with an ACT score of 23-27 are assumed to be ready for general education mathematics courses, but only students with an ACT above 27 are assumed to be ready for Calculus for mathematics and science majors without further preparation (such as Precalculus). Nevertheless, there are many students with much lower ACT scores who perceive their mathematics preparation as "strong" or "very strong" (Figure 4, the vertical axes represents percentages). Specifically 18% of students with mathematics ACT scores of 19 or less view their mathematics skills as "strong" or "very strong". While this opinion may be influenced by the fact that an ACT score of 20 is above average, this is precisely the case when the average is simply not sufficient for success (without remedial work). It is imperative that we, as educators, deliver this message to grade schools.

Of the students with an ACT less than 20, only 25% enroll in the pre-algebra course; 52% enroll in elementary algebra while the remainder attempt intermediate algebra initially. Thus there is a considerable percentage of students who enroll in courses for which they are not fully prepared. The consequences are obvious with high fail and withdrawal rates in these courses.

There is also a disconnect between students' knowledge and faculty expectations. Knowledge of background material is extremely important in mathematics, as very often the new material is built from the material learned in prior mathematics classes. Students are aware of this, but not all the students accept the responsibility for knowing the background material (Figure 5). The proportion of students who believe that instructors frequently, usually or always expect them to know things that were never previously covered in class varies with the class. It is higher in algebra based courses that require firm knowledge of the previously covered material (44% in Intermediate or College Algebra, 40% in Precalculus), and lower in more applied courses that do not depend as heavily on the previous material (28% in contemporary mathematics, 37% in finite mathematics. It seems that there is a problem with a long term retention of the learned material. A previous, longitudinal survey demonstrates that students' beliefs in their own abilities do not change during the semester (Ache, 1996).

Almost 10% of the students do not expect to spend time outside of class studying. Almost another 25% expect to spend only one hour per week studying mathematics (Figure 6). Only 4% expect to spend 6 or more hours per week outside of class. Yet virtually every syllabus for a 3-hour mathematics course states that 6-9 hours studying outside of classroom should be the norm for every student. Although the majority of students expect the workload to be just right, almost 40% of the students believe that too much is demanded of them in their mathematics course (Figure 7).

Two thirds of the students believe that the assigned workload is just about right. This proportion is similar for students with all levels of ACT scores. Two thirds of the students believe that their work and study habits are adequate for their mathematics course. Yet, as we discuss in the next section, the proportion of students with grades of C or better is undesirably low.

Course Grades

In addition to student perceptions, student grades and outcomes (such as performance in subsequent courses) were also examined. Accountability with respect to grades focused on the algebra based courses (College Algebra, Precalculus and the first semester calculus, Calculus I) as these courses were prerequisites for subsequent courses for mathematics and science majors. Data from Fall, 1996 through Summer, 2000 were examined. A total of 5399 students took College Algebra, 1564 students took Precalculus, and 1325 took Calculus I during this time period. The numbers of students enrolled in Precalculus and Calculus who were previously enrolled in College Algebra during the stated time period are presented in Figure 8. More than a half (59%) of Precalculus students took College Algebra previously, although the University Catalog states explicitly that credit for both of these classes is not allowed. About half of the students in Calculus I (52%) took College Algebra prior to taking Calculus I. Of the 690 students in Calculus I who previously took College Algebra, 309 or 44% also took Precalculus prior to taking Calculus I, so that more than half of the students in Calculus I who took College Algebra did not have a full benefit of completing prerequisites for Calculus I. A total of 381 out of 5399 students (7%) in College Algebra went on to take Calculus I without the intermediate step of Precalculus.

For students who take College Algebra, the success rate in subsequent mathematics courses remained low (Figure 9). Only 35% of the students receiving an A in College Algebra, who subsequently took Precalculus, received an A or B in that course. Many of the B students (over 50%) in College Algebra withdrew or failed Precalculus. Students who attempt to complete Calculus I with only the background in College Algebra do very poorly as well. Students taking both, College Algebra and Precalculus, prior to taking Calculus I, still tend to do poorly in calculus (Figures 10,11).

Discussion

The TIMSS study has shown that students in the United States are behind their peers in other industrial nations (Jakwerth, 1999). There is a mandate now in California to move algebra into eighth grade instruction. However, there is some resistance (Ralston, 2000):

> "One reason is sixth and seventh grades have become mathematical wastelands in which little new material is introduced and almost all the time is spent reviewing what was supposed to have been learned earlier. The excuse for this - when one is given – is often that these are bad years to push kids too hard because they are years when kids spend most of their time thinking from the neck down, not the neck up. The remarkable thing about this argument is that it seems to assume that children go through puberty only in the United States."

As the above quote indicates, there are low expectations of student performance in elementary and secondary education. Therefore, many students are unaware of the expectations in higher education. Higher education, too, appears to be lowering expectations by awarding inflated grades (Wilson, 1999). In a recent poll of 1,004 college students, Zogby International found that students were aware of the grade inflation (Zogby International, 2000). Successful programs to recruit minorities into advanced mathematics courses have high expectations for student involvement, demanding up to 20 hours per week in study (Garland, Treisman, 1993).

There are no easy solutions of improving the overall performance of our students in mathematics. It is imperative that the students get a better preparation in grade schools, so that the majority of incoming university freshman are able to take university general education courses. A requirement of four years of mathematics in high school should be helpful. The students need to be made aware that an average ACT score does not secure an “average” performance in college. In fact, an average ACT score may not be sufficient to be admitted into general education university classes.

Being a successful university student requires a serious commitment in terms of time and work. We need to continue sending this message to grade school and university students alike.

References

1. Ache, PS III. http://www.maa.org/data/sigmaa/arume/arumeldb.txt. 1996.

2. Bers, Trudy. Assessing the achievement of general education objectives: a college-wide approach. Journal of General Education. 49(3):182-210. 2000.

3. Garland, May; Treisman, Uri. The Mathematics Workshop Model: An Interview with Uri Treisman. Journal of Developmental Education. 16(3):14-16. 1993.

4. Grob, Leonard, Kuehl, James R. Coherence and assessment in a general education program. Liberal Education. 83:34-9. 1997.

5. Jakwerth, Pamela. TIMSS performance assessment results-United States. Studies in Educational Evaluation. 25(3):277-81. 1999.

6. MAA's Guidelines for Programs and Departments in Undergraduate Mathematical Sciences. http://www.maa.org/guidelines/guidelines_intro.html. 2000.

7. Osterlind, Steven J, Robinson, Richard D, Nickens, Nicole M. Relationship between collegians’ perceived knowledge and congeneric tested achievement in general education. Journal of College Student Development. 38:255-65. 1997.

8. Ralston, Anthony. Teaching: Why Johnny Can’t Do the Math. Sacramento Bee, January 28, 2001.

9. Ramsden, Paul. Student learning: a neglected policy issue. Education Policy Bulletin. 9(1):67-81. 1981.

10. Redish, Edward F. Jeffery M. Saul, and Richard N. Steinberg,Student expectations in introductory physics, Am. J. Phys. 66, 212-224 (1998)

11. Redish, Edward F. Physics Education Research Group,University of Maryland, College ParkMeasuring Student Expectations in University Physics: The MPEX Survey, Phoenix meeting of the AAPT, January 1997.

12. Schonwetter, Dieter J. Key factors for college student achievement, cognition, affects, and motivation: student locus of control and quality of instruction. ERIC#ED360891. 1993.

13. Voeller, Diane. The relationship between students' and instructors' perceptions of feedback and the students' perceptions of the instructors' teaching effectiveness. Grand Forks: ND. Bureau of Educational Research and Services. 1982.

14. Wilson, Bradford P. The phenomenon of grade inflation in higher education. Phi Kappa Phi Journal. 79(4):38-42. 1997.

15. Zogby International, Report on academic life survey. www.gofast.org/academiclifesurvey.htm. April, 2000.

16. 2001 ACT National and State Scores, http://www.act.org/news/data/01/t4.html. October, 2001.

Appendix

1. I took Math 075 *A=never B=once C=Twice D=more than twice.*

2. I took Math 099 *A=never B=once C=Twice D=more than twice.*

3. I took Math 102 *A=never B=once C=Twice D=more than twice.*

4. This is the *A=first B=second C=third D=more than third* time I am attempting a general education mathematics course.

5. This course is *A=required for my major B=required for general education C=both.*

6. I am majoring or plan to major in *A=education B=business C=humanities D=social science E=science.*

7. I *A=expect B=do not expect* a computer to be used in this course.

8. I think a computer *A=should B=should not* be used in this course.

9. I think using a computer would make this course *A=harder B=easier C=about the same.*

10. I expect this course to be *A=too hard B=hard but manageable C=about right D=easy E=too easy*.

11. In comparison with other students in mathematics, I think my skills and knowledge are *A=very weak B=weak C=average D=strong E=very strong.*

12. I think this math course will be *A=very useful B=somewhat useful C=somewhat useless D=totally useless* to my future success.

13. I usually spend *A=0 B=1 C=2-4 D=5-6 E=more than 6 hours* per week studying mathematics.

14. I want the instructor to require *A=a lot of homework B=some homework C=no homework* to prepare for this class.

15. Course instructors *A=rarely B=occasionally C=frequently D=usually E=always* expect me to know things that were never previously covered in class.

16. Course instructors *A=rarely B=occasionally C=frequently D=usually E=always* expect me to know things that I remember seeing in a previous class but have forgotten.

17. There is *A=way too much B=too much C=about right D=too little E=way too little* material taught in mathematics courses.

18. The work load required is *A=way too much B=too much C=about right D=too little E=way too little.*

19. My work habits and study methods *A=are inadequate B=are adequate C=are more than adequate* to really succeed in this course.

20. My math ACT score was *A=less than 20 B=21-23 C=24-27 D=28-30 E=31 or more.*

Table 1. General Education Mathematics Courses and the Minimal Mathematics ACT Scores for the Initial Student Placement

Course Number	Title	Math ACT Scores for Initial Student Placement
105	Contemporary Mathematics	21
107	Finite Mathematics	23
109	Elementary Statistics	23
111	College Algebra	24
112	Trigonometry	24
150	Mathematics for Elementary Education	23
180	Elements of Calculus	24
190	Precalculus	24

Table 2. Number of Surveys by Course and Major Discipline

Course	Education	Business	Humanities	Social Science	Science	Total
102	75	230	51	99	162	617
105	32	27	26	26	13	124
107	32	117	8	5	0	162
109	11	6	9	15	27	68
111	35	181	24	41	92	373
112	2	1	1	4	16	24
150	22	0	0	0	0	22
180	5	1	0	22	22	50
190	10	13	3	60	60	146
Total	224	576	122	272	392	1586

Table 3. Cronbach's alpha for responses 10-20.

Response	Cronbach's Alpha
Difficulty of course	0.933
Skill level	0.931
Usefulness	0.940
Study Time	0.936
Amount of Homework	0.935
Expectation of Previous Material Covered	0.939
Expectation of Earlier Knowledge	0.938
Amount of Material	0.932
Course Workload	0.931
Work Habits	0.934
ACT Scores	0.937

Figure 1. Distribution of Numbers of Student Responses Across Courses.

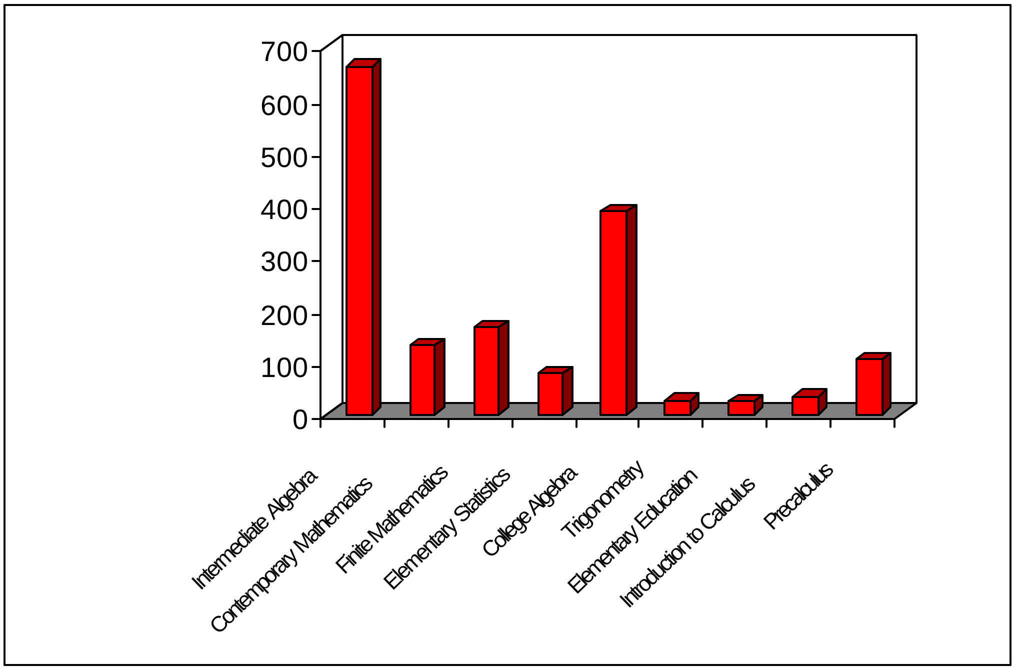


Figure 2. Number of Students Reporting One or More Remedial Mathematics Courses

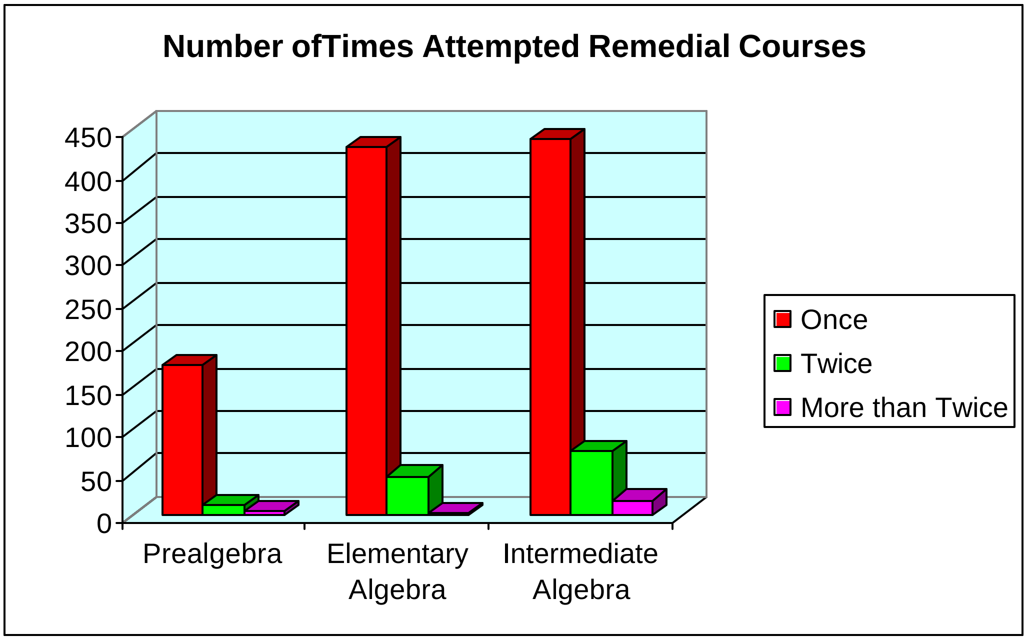


Figure 3. Self-reported Mathematics ACT Score by Course

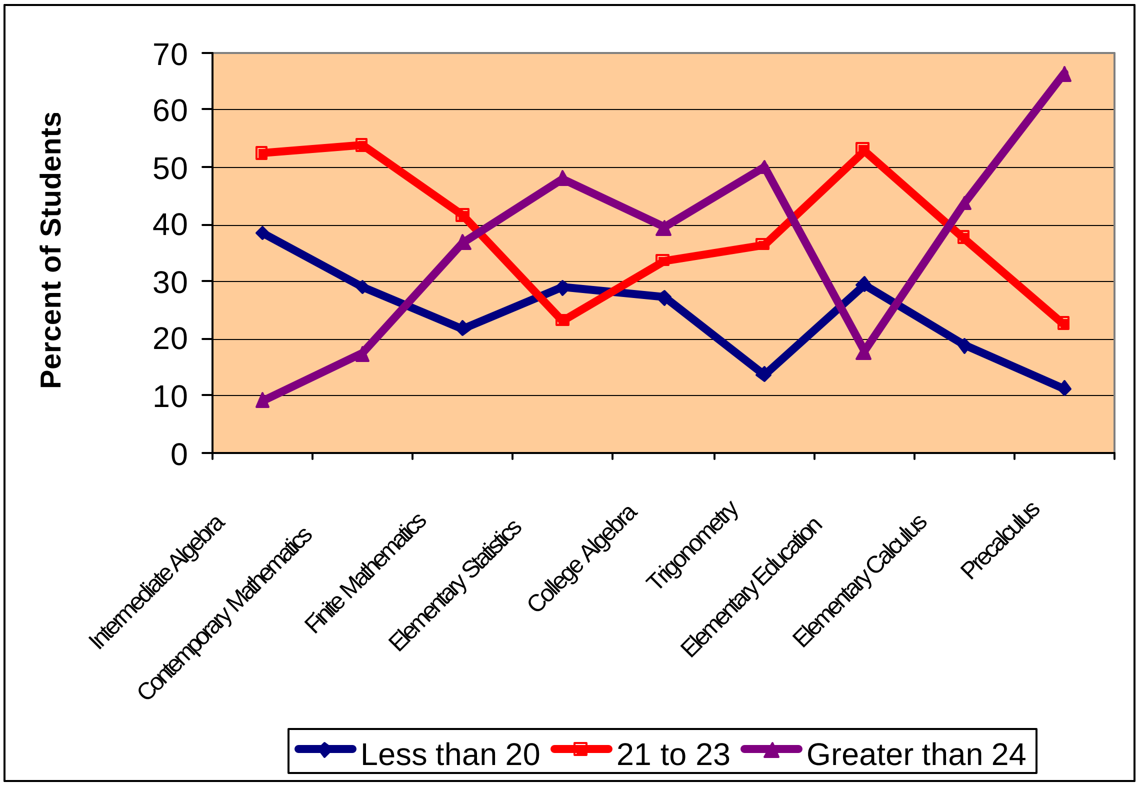


Figure 4. Student Perception of Their Own Skills Versus Self-reported Math ACT Scores

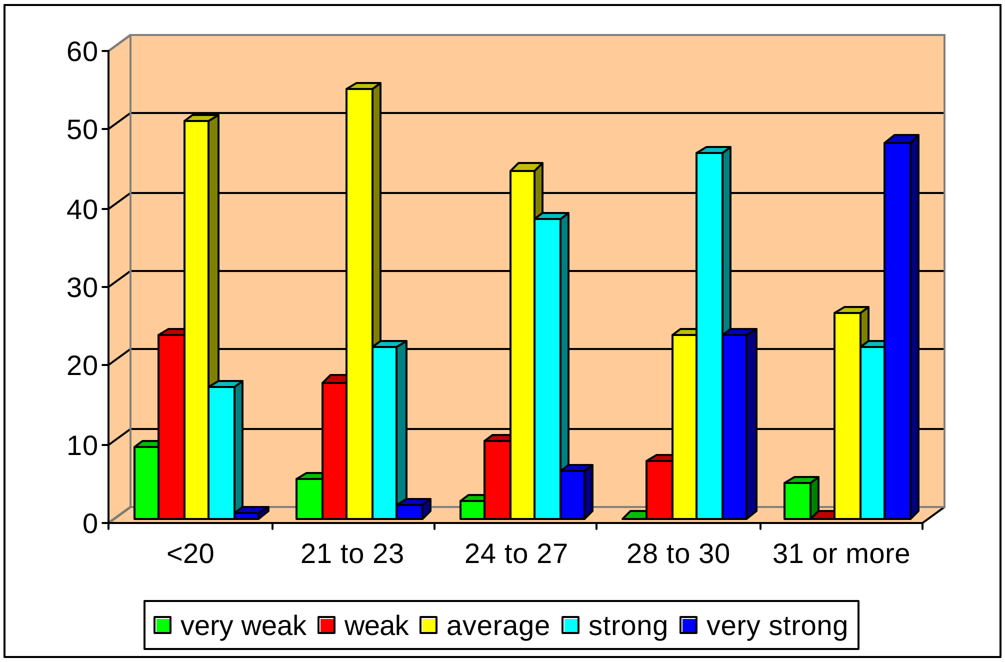
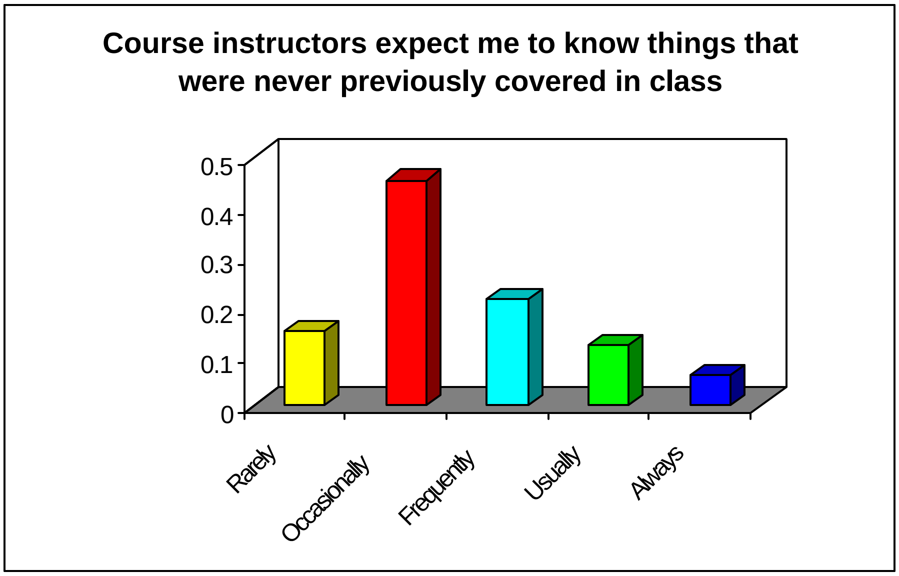


Figure 5. Students Beliefs Concerning Faculty Expectations of Background Knowledge



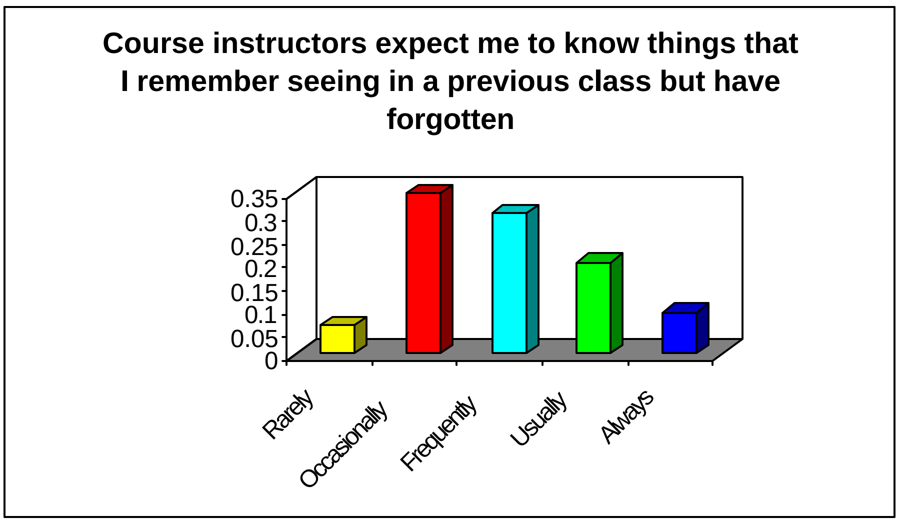


Figure 6. Hours per Week Studying Mathematics

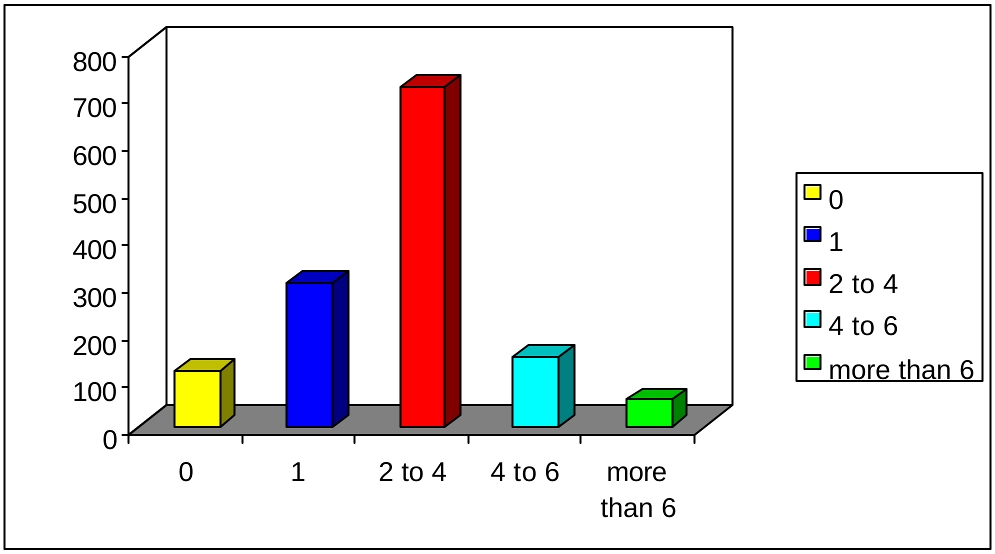


Figure 7. Student Perception of Course Work Demands

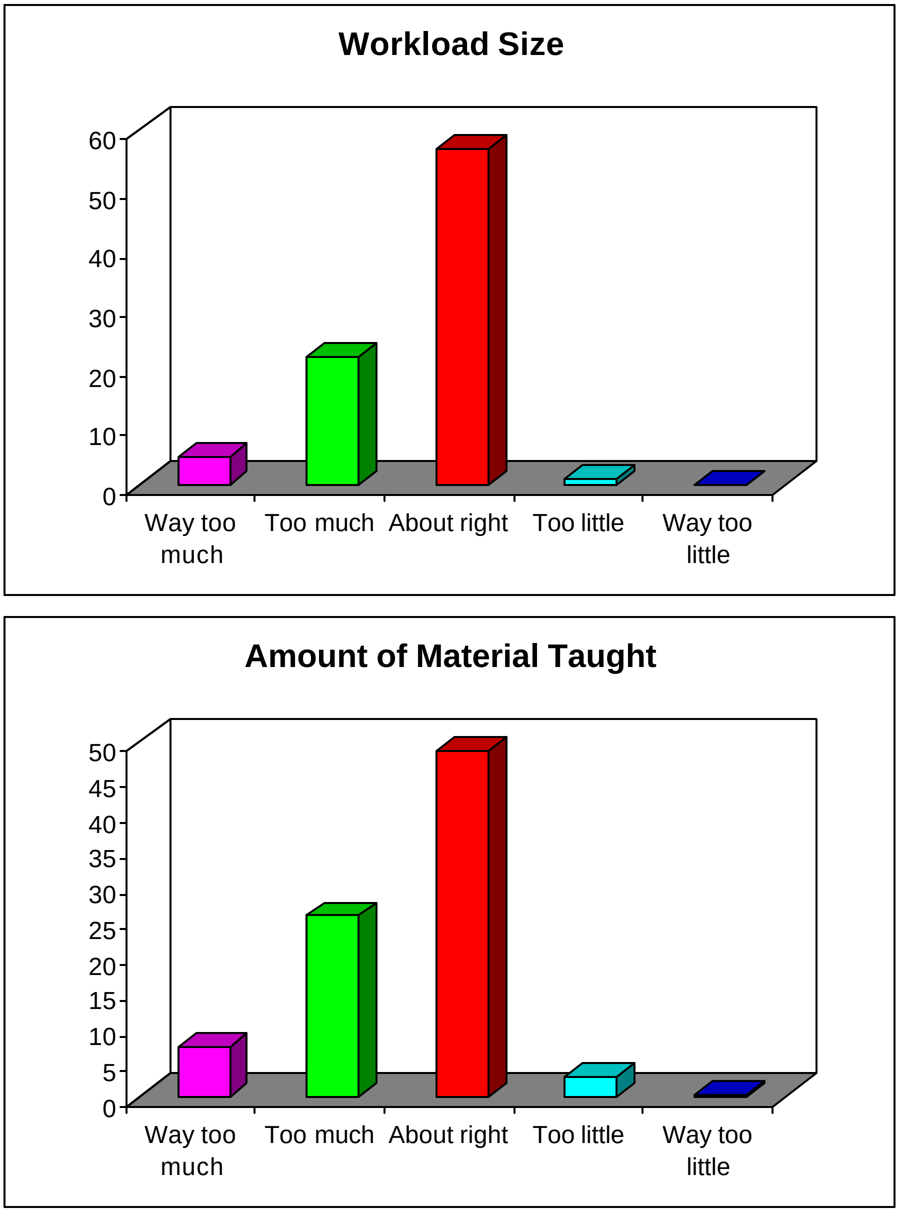


Figure 8. Enrollment of College Algebra students in Precalculus and Calculus I

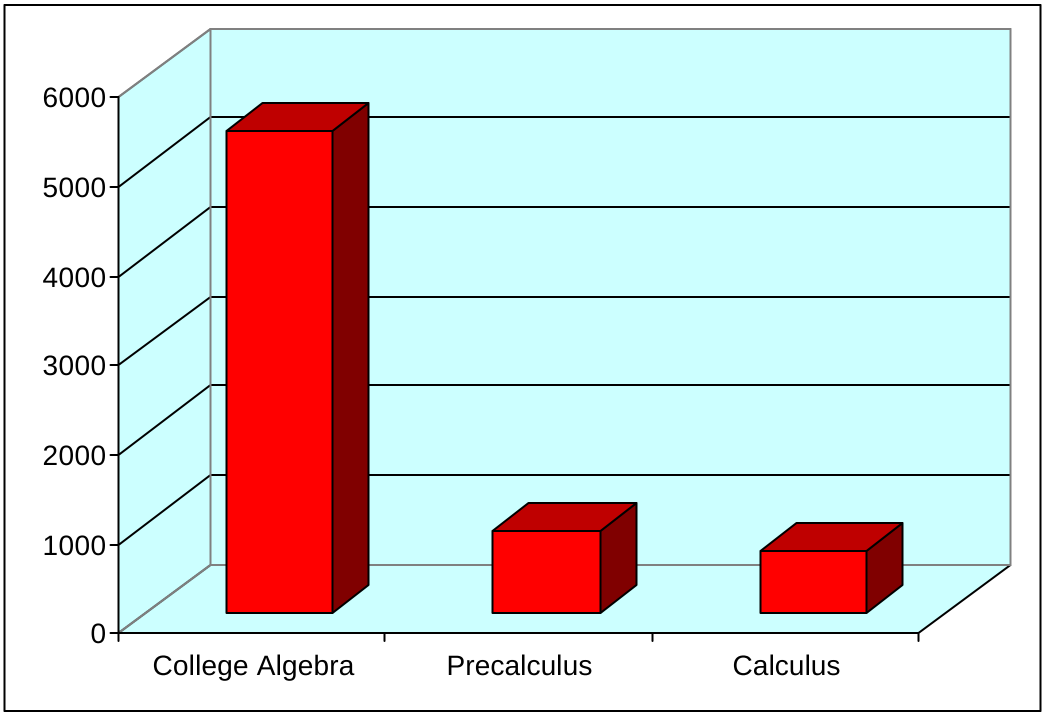


Figure 9. Comparison of Grades From College Algebra to Precalculus. X-axis represents the grade in Precalculus; Y-axis represents the proportion of students; Line graphs represent grade in College Algebra.

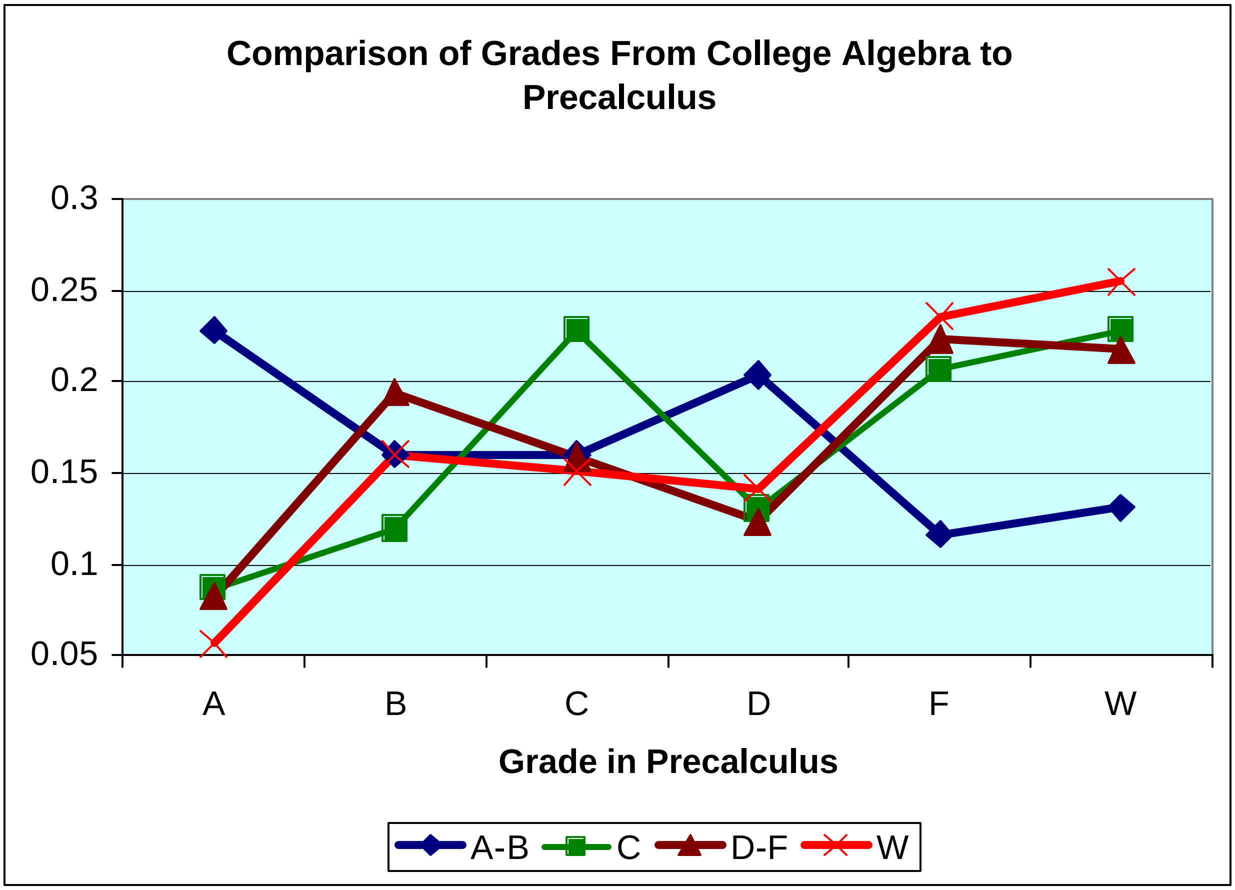


Figure 10. Comparison of Grades From College Algebra to Calculus I with Precalculus as an Intermediate Step. X-axis represents the grade in Calculuss; Y-axis represents the proportion of students; Line graphs represent grade in College Algebra.

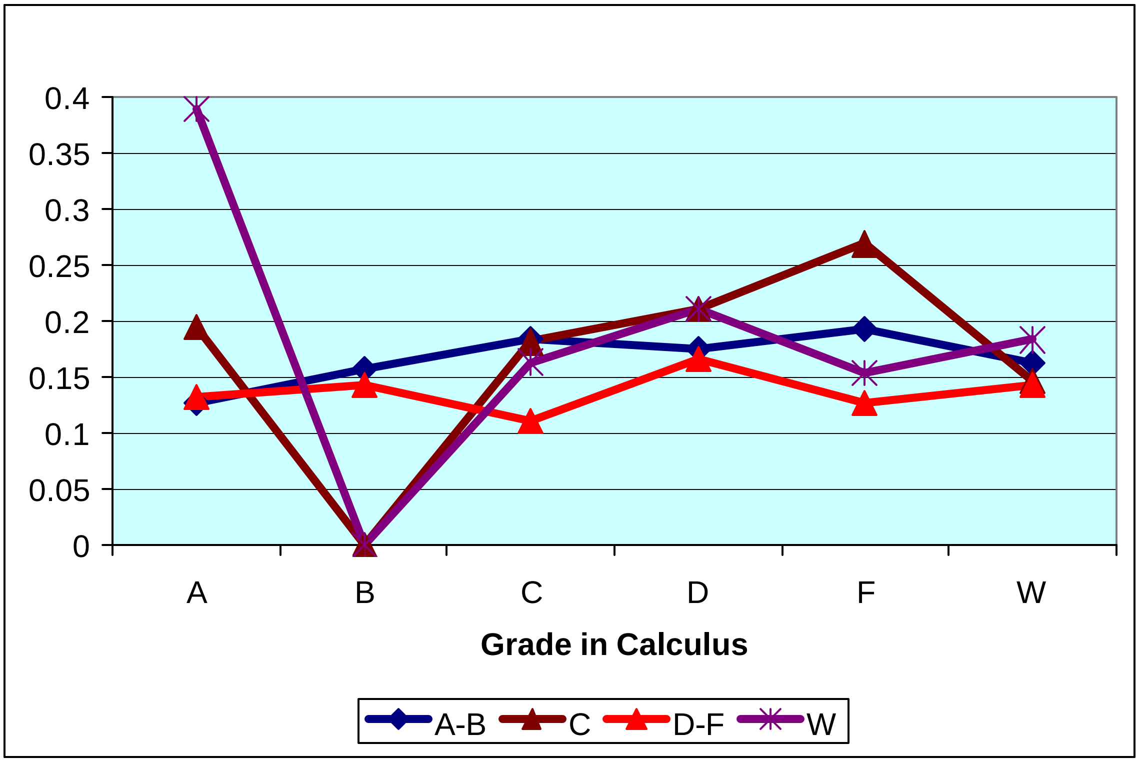
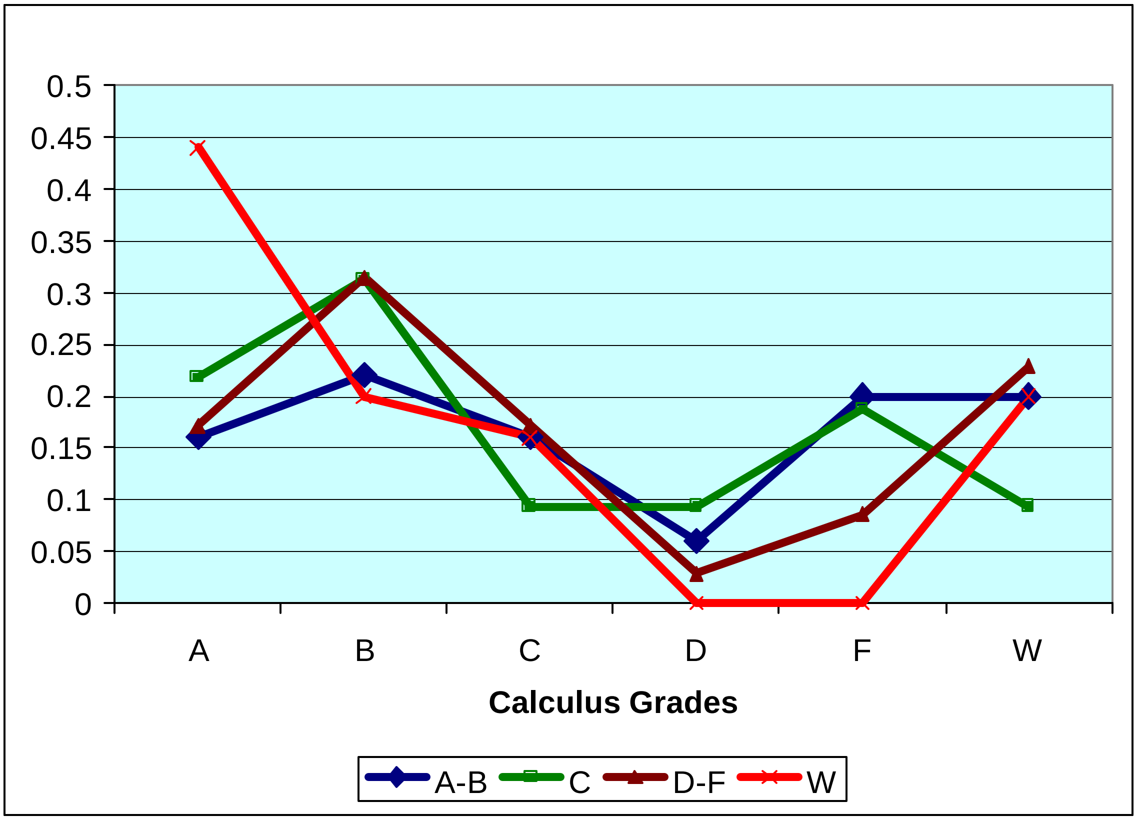


Figure 11. Comparison of Grades From College Algebra to Calculus Without Enrolling in Precalculus. X-axis represents the grade in Calculus; Y-axis represents the proportion of students; Line graphs represent grade in College Algebra.



Data Mining to Investigate University Expectations of Work

Guoxin Tang, University of Louisville, Louisville, KY
Advisor: Patricia B. Cerrito, Department of Mathematics, University of Louisville

ABSTRACT:

Objective: To investigate the expectations the faculty has of students, and how varied those expectations are.

Method: Course syllabi from representative departments were collected to investigate variability in course requirements between faculty within a department, and across departments (107 total). In addition, information will be collected to examine department expectations of faculty work. For this study, we used SAS Text Miner to investigate the syllabi. In addition, the syllabi were coded for the number of tests, quizzes, and homework assignments, the presence of participation requirements or attendance requirements, and weighting of the final to compare manual coding to SAS Text Miner results. The syllabi were coded as to whether they included a statement indicating the expected number of hours each student should spend studying course material.

Results: Text Miner divided the 107 syllabi into 10 clusters. The examination reveals that most syllabi, including those from the mathematics, physics and English departments, focused on requirements and grading. Approximately 58% of syllabi were concerned about requirements; the interest in course requirements was maximal for the mathematics department.

INTRODUCTION:

Course syllabi contain information concerning expectations of student work. The primary purpose of a syllabus is to communicate to one's students what the course is about, why the course is taught, and what will be required of the students for them to complete the course with a passing grade. It is the purpose of this paper to demonstrate the variability in expectations of different departments.

There are many different expectations of the faculty work in different departments, even in the same department. Consider Figure 1, for example, which shows the proportion of syllabi that include paper assignments. Such assignments are clearly very important for the English department, compared to Mathematics and Physics Departments. There are no requirements for papers in those two departments. However, there is considerable variability within the English Department.

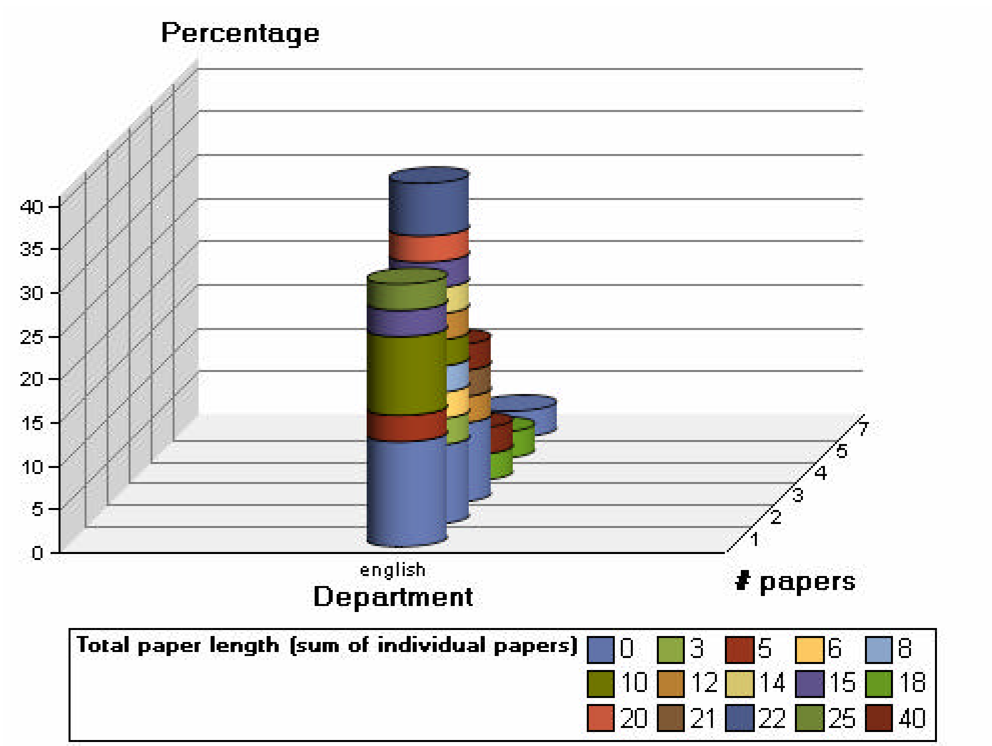


Figure 1. Total paper length required by the English Department. There is considerable variability in the required total length required of the semester.

In this study, data analysis and text mining are used to examine the relationship between expectations of faculty and student work for the purpose of teaching skill improvement. It is also of interest to compare the results based on two different analysis methods: text mining versus manual coding.

METHOD

A total of 107 copies of syllabi from English, Mathematics and Physics departments were collected to examine department expectations of faculty work. The syllabi were scanned individually into a computer directory, and then the macro, %tmfilter, was used to create a SAS dataset. Information in the syllabi was also manually coded into a SAS dataset. The variables include the number of papers, total paper length (sum of individual papers), number of tests, final exam, quiz, midterm exam, percent for discussion (or participation), percent for attendance, percent for regular homework, percent for final exam, percent for quiz, and percent for the midterm exam. We used SAS Enterprise Guide to examine the data. It made the information of syllabi more visible. The other method used was SAS text mining to examine all materials in text version. Here Text Miner provides an alternative method to analyze data and collect useful information.

RESULTS

Results from Manual Coding

Firstly, manual coding was used to examine expectations of work. Figure 2 to Figure 6 show the information derived from syllabi according to the final exam, quiz and midterm exam. Note that the English department requires papers as a big part of the final grade. Tests are used for reference.

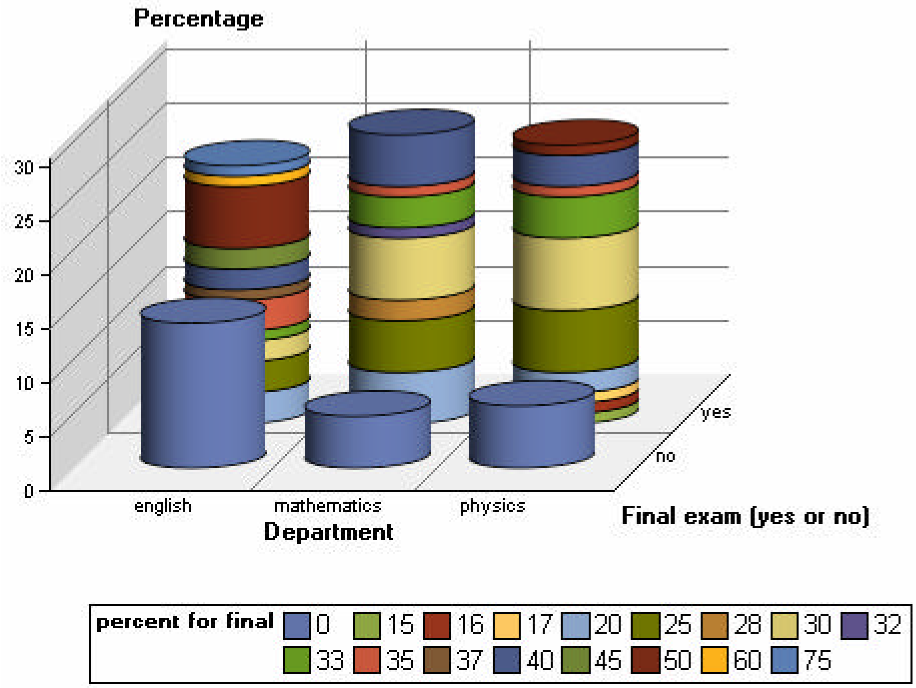


Figure 2. The importance of final exam in the three departments.

Note that the final exam is required for most courses in the departments of mathematics and physics. The percentage of the final grade for the final exam, however, varies from 20% to 40%.

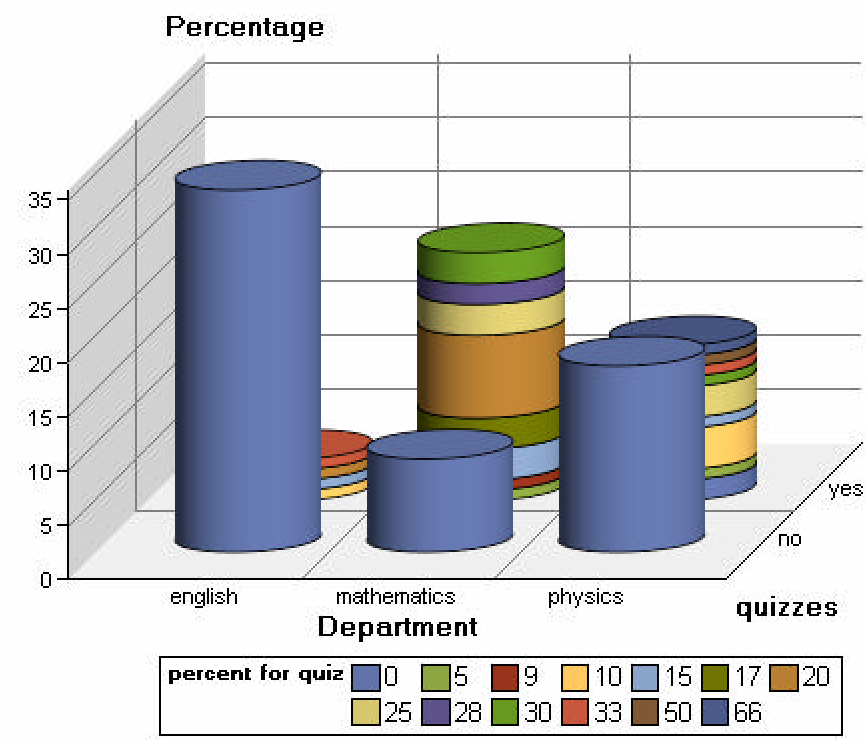


Figure 3. The importance of quizzes for the three departments.

It shows that quizzes play an important role in the final grade of Mathematics and Physics compared with the English department. More than 75% of the courses in the Mathematics Department and about 50% courses in the Physics Department require quizzes, compared with 15% of the courses in the English department.

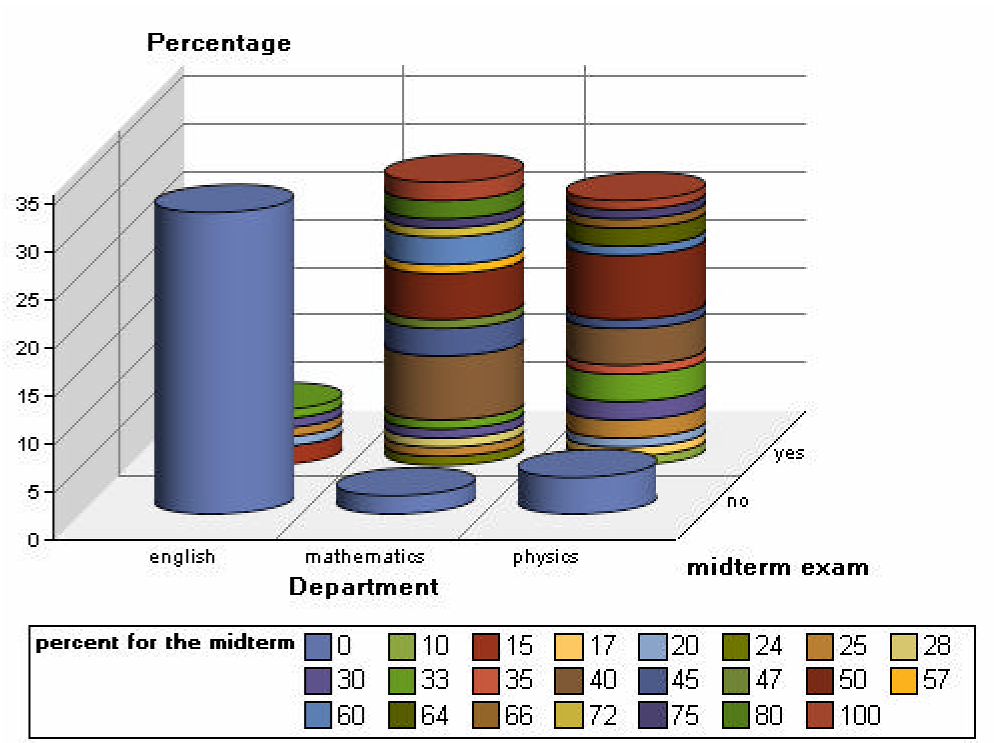


Figure 4. The importance of the midterm exam for the different departments.

Note that about 95% and 90% courses in the Mathematics and Physics Departments respectively require a midterm exam, and so do about 15% of the courses in English.

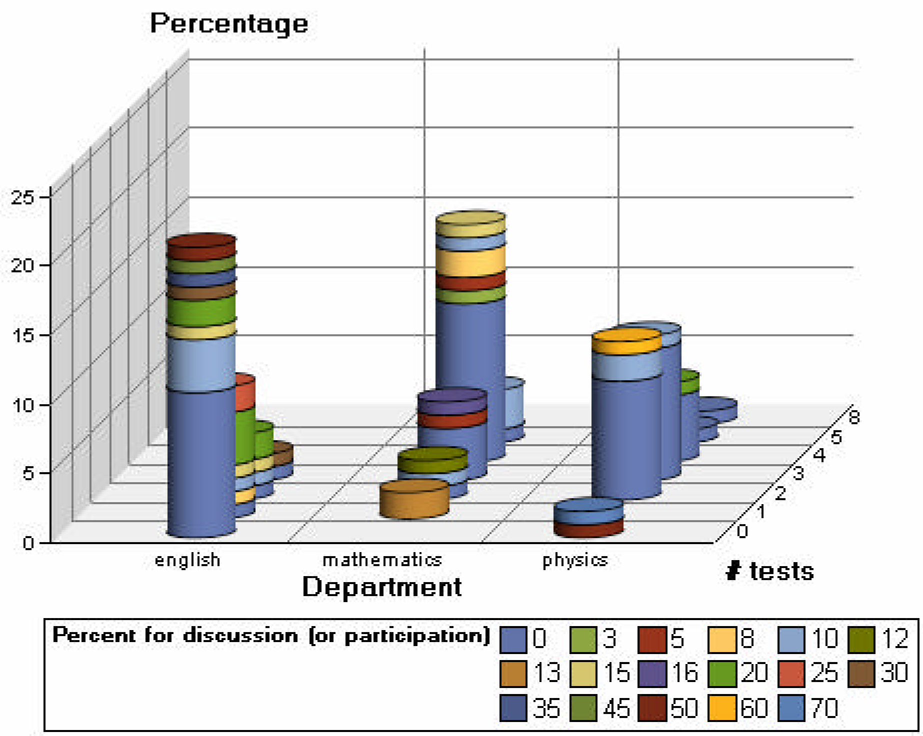


Figure 5. The percentage of discussion according to the number of tests for the different departments.

It is clear that for most courses of the Mathematics and Physics departments, the percentage of the grade from discussion decreases as the number of tests increases.

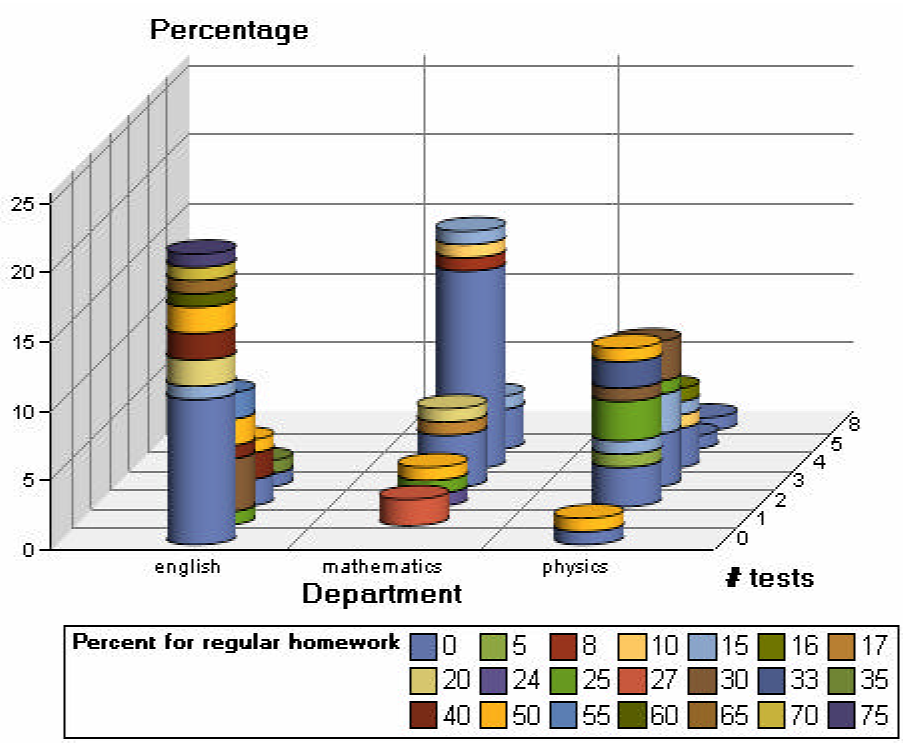


Figure 6. The percentage of homework according to the number of tests and different departments

Note that the percentage of homework decreases with increasing of number of tests. For mathematics, when the number of tests is more than 2, the weight of homework in the final grade becomes very small.

Text Miner Results

Another step was to investigate all the syllabi by using text mining. All syllabi were scanned into a Windows directory as text. Text mining can cluster syllabi into similar groups to identify the weights of expectation. The %tmfilter macro can read documents of different formats that are stored on the file system, and create a SAS data set that can be used as input for the text miner node. The following code shows how to generate a SAS data set:

```
%tmfilter(dataset=work.txtinput, dir=c:\testdir, numchars=32000);
```

In this analysis, Text Miner divided the 107 syllabi into 10 clusters. Table 1 gives the clusters. From the description, cluster 1 with a frequency of 15 shows the discussion and writing assignments in the English Department. Cluster 5, with frequency 24, shows exams and requirements in Mathematics.

Table 1. Table of Clusters of Syllabi

#	Descriptive Terms	Freq	Percentage	RMS Std.
1	+ teach, + practice, + presentation, + discussion, + late, + project, + include, + write, + discuss, + day	15	0.135135135...	0.1462852...
2	+ binder, + perform, + analysis, + article, + attach, + evaluation, + complete, + report, + technique, + check	3	0.027027027...	0.0121200...
3	+ essay, + reading, + paper, + discussion, + text, + work, 's, + write, + do, + discuss	9	0.081081081...	0.1325407...
4	+ discussion, + late, + reading, + do, + have, + meet, + discuss, + material, + text, + complete	9	0.081081081...	0.1532258...
5	+ calculator, math, + exam, + disability, + section, + requirement, + test, + cover, + require, + problem	24	0.216216216...	0.0837102...
6	+ homework, + lecture, + date, + work, + email, + test, + cover, + grade, + exam, + make	10	0.090090090...	0.1043340...
7	+ test, + material, + make, can, + expect, + cover, + grade, as, + do, + week	14	0.126126126...	0.1311981...
8	+ story, + submit, + offer, + write, + page, + reading, + paper, + do, + give, + discussion	6	0.054054054...	0.1401303...
9	+ grade, physics, + score, + exam, + physic, + homework, + encourage, office, + follow, no	9	0.081081081...	0.0963927...
10	+ physic, physics, according to, + test, + assign, + grade, + score, + reserve, + problem, right	12	0.108108108...	0.0955300...

Cluster labels for Table 1 are suggested below:

1. Discussion & writing
2. Evaluation of writing
3. Essay reading & discussion
4. Discussion & reading

5. Math exam
6. homework
7. tests
8. story writing
9. physics exams
10. physics tests

Text Miner can also give concept links, showing how different terms are related in the documents. Figures 7 to 9 show the results of analysis by using text mining.

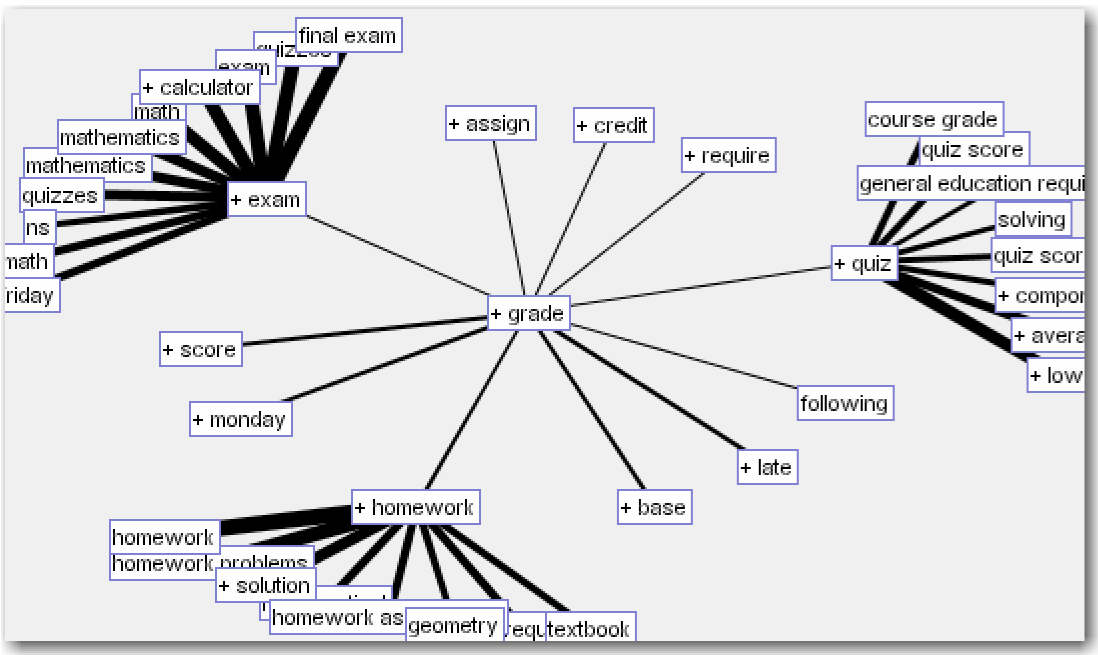


Figure 7. Concept links for the term "grade".

Here, 'grade' is related to 'exam', 'quiz', and homework, and so on. It is clear that the exams, quizzes and homework are the most important parts for the final grade. Note that the emphasis here is on mathematics.

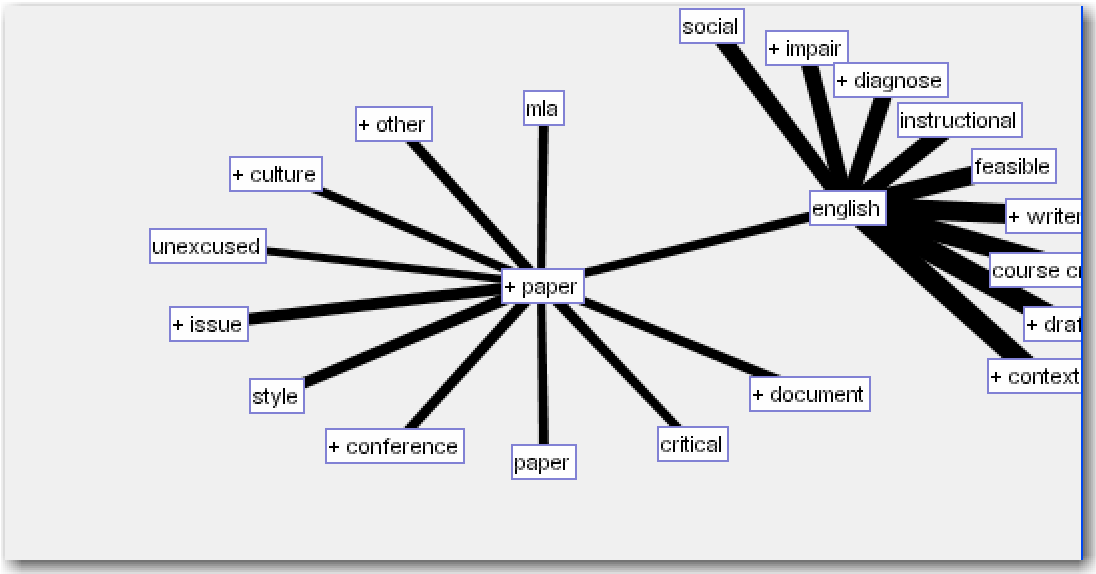


Figure 8. Concept links for the term "paper".

The most meaningful term related to "paper' is 'english'. This shows clearly that the English Department requires papers as the way to grade.

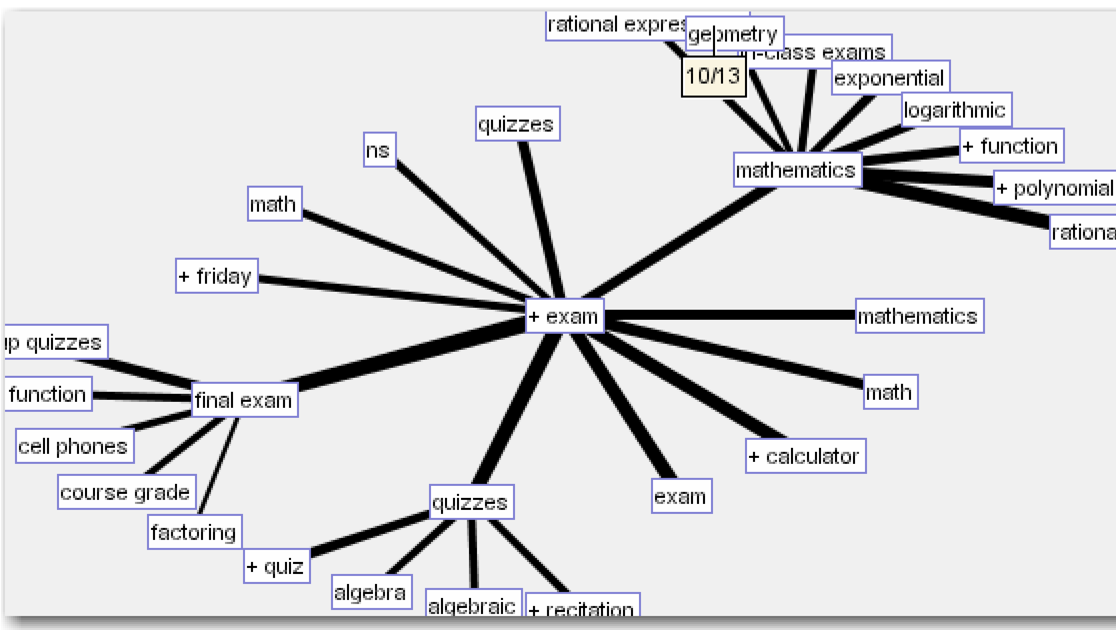


Figure 9. Concept links for the term "exam".

Note that the linked terms are 'final exam', 'quizzes' and 'mathematics', etc. Exam is the primary way to evaluate a student in mathematics department.

CONCLUSION

The analysis tells that most syllabi, including those from the mathematics, physics and English departments, focused on grading and requirements about papers and exams. The writing plays an important role in English and exam does in mathematics and physics departments.

Manual coding and text mining present the similar results. Therefore, the use of SAS Text Miner and text analysis can be substituted for the time-consuming process of manual coding and analysis.

The results of this research reveal the relationship between the expectations of faculties and student work. Then the faculty can develop the teaching skill to improve the teaching purpose.

An Investigation of the Content of Mathematics Dissertations

Patricia B. Cerrito

Department of Mathematics

University of Louisville

Louisville, KY 40292

502-852-6826

502-852-7132 (fax)

pcerrito@louisville.edu

Introduction

Several professional mathematical societies have called for mathematics to be more integrated with other disciplines, and to create more interdisciplinary degrees. Still others have speculated on the nature of a dissertation in a program oriented toward industrial rather than academic employment. For example, in a report provided by the National Academies it states(Anonymous, 1995),

> "Students interested in nontraditional careers could design dissertations that meet high standards for originality but require less time than would be customary for a career in academic research.

In a paper published in the Notices of the American Mathematical Society, it states(Chan, 2003),

> "I would even go as far as advocating that we require some formal interaction with at least one other science during doctoral training. This is probably common practice for 'applied' mathematics students, but it should not be limited to them."

The author, Tony Chan, goes on to list several changes that should be made. Among them is this:

> "Shorten the time to degree. For example, departments could streamline qualifying examinations without lowering academic standards. We could offer summer courses to better prepare the students for their examinations. We could also bring students into research groups as early as possible rather than after several years spent preparing for these examinations."

There exists very little information in the mathematics literature discussing the nature of a mathematics dissertation. Guidelines for the dissertation are virtually non-existent. Successful completion, then, is determined by the decisions of the student's advisor and committee. A keyword search on Google using "mathematics dissertation content" yields sites for various PhD programs. A similar search in Education Abstracts yielded one paper on the actual content of dissertations-but that was in the field of management.(P.-l. Chang & Hsieh, 1997) The ERIC database yielded no articles at all. Specific searches in the American Mathematical Monthly and the Journal of Statistical Education also were not profitable. While there is a constant demand for proof and documentation concerning mathematical ideas, there is almost no call to discuss methods for examining dissertation content and mathematics quality.

It is the purpose of this paper to examine the content of applied and interdisciplinary dissertations to determine how they should change in content so that the time to degree can be shortened, and so that students can get involved in research early in their careers. Suggestions concerning qualifying examinations will also be given.

Dissertation Content

The problem with analyzing dissertation content is that the content is primarily text. It is possible to count the number of equations, theorems, and proofs in the body of the text in order to quantify what is essentially qualitative information. However, text analysis has been developed in order to examine the information more directly. The database, Dissertation Abstracts, was used to find the dissertations. The first keyword searches were for “applied mathematics” and “applied statistics”. This search yielded 146 dissertations dating from 1986, of which 27 were identified as statistics. Text analysis found a total of 5 different clusters (Table 1).

Cluster Number	Descriptive Terms	Frequency	Label
1	High school, achievement, education, curriculum, score, teacher, vocational, instruction, secondary, edd, significant, grade, attitude, enroll, teach, prog	39	Education content, primarily for Edd and PhD in education
2	Equation, solve, numbericcal, solution, differential, stability, domain, aprtial, nonlinear, system, condition, boundary, approximation	27	Modeling content primarily with numerical analysis and differential equations
3	Wavelet, nonparametric, signal, applied statistics, distribution, test, function, discuss, perform, technique, theory	30	Statistics content, including application of statistical technique and development of statistical models
4	Tool, model, simulation, structure, science, property, statistics, approach, technique, develop, obtain, base, theory	35	Simulation models, some of which are statistics
5	Matrix, graph, network, architecture, parallel, algorithm, efficiency, computation, computer, implement	15	Computer science models

Concept maps (Figures 1,2) reinforce this grouping of dissertations. Concept maps are a method of investigating the content of text information. (K.-E. Chang, Sung, & Ine-Daichen, 2002) Text mining software uses the technique of association rules to create the concept maps.(Anonymous, 2002) The term “mathematics” linked primarily to terms involving education. It seems clear that most of the dissertations that have the keywords “applied mathematics” in fact are in the area of mathematics education. In contrast, dissertations linked to “statistics” tend to focus on the type of model.

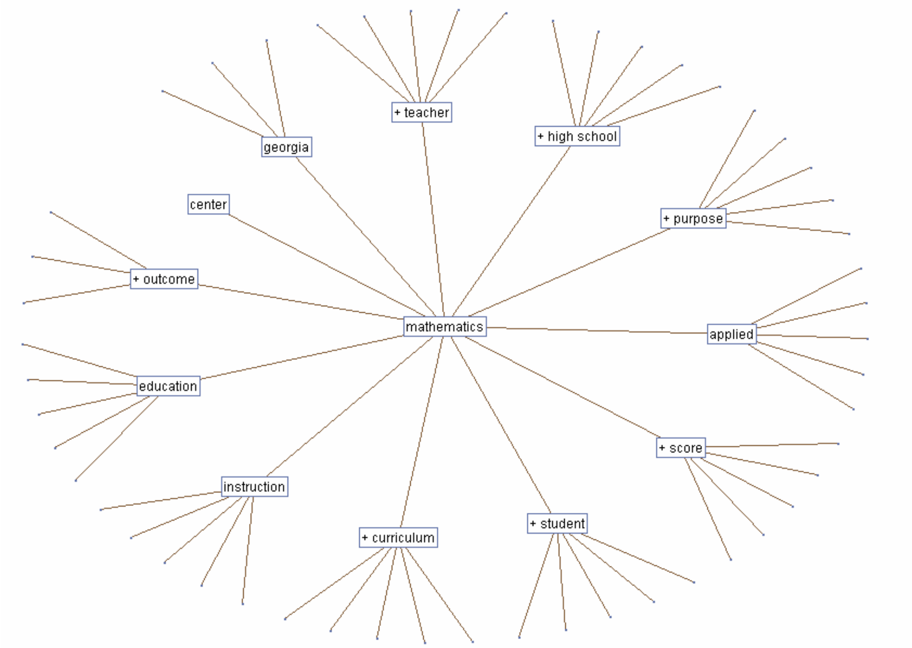


Figure 1. Concept links to the term "mathematics"

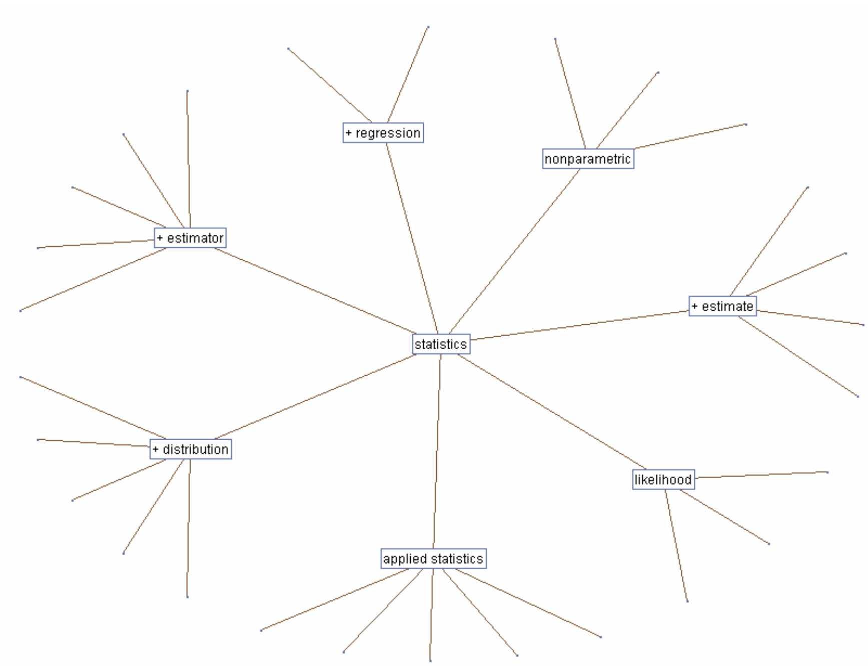


Figure 2. Concept links to the term "statistics"

Contrast this table with Table 2, clustered using the terms "logistics", "actuarial science", "data mining", and "biostatistics" where the dissertations are based upon particular topics.

Cluster Number	Descriptive Terms	Frequency	Label
1	Biostatistics, statistics, gene, biology, distribution, parameter, regression, method, simulation, model,	51	Biostatistics, including examination of genes

Cluster Number	Descriptive Terms	Frequency	Label
	variable, study, function		
2	Business, product, chain, firm, manufacturer, administration, market, supply, customer, relationship, logistics, management, performance	37	Logistics and supply-chain management
3	Structure, database, application, computer	3	Data mining; investigations of the database
4	Transportation, solution, facility, operations research, optimal demand, logistics operation, optimization, cost, decision, supply	25	Logistics and transportation issues
5	Computer, rule, discover, data mining, database, pattern, knowledge mining, algorithm, technique, data, application	86	Data mining techniques
6	Health, education, clinical, health sciences, group, response, practice, field, science, environment	66	Biostatistics and clinical trials
7	Political science, political history, century, policy, engage, United States of America, theory, implication, power	20	Applications to history and political science

To examine the clusters in Table 2, a table analysis was performed (Table 3)

Cluster	Actuarial Science	Biostatistics	Data Mining	Logistics
1	11 (48%)	18 (35%)	21 (18%)	1 (1%)
2	2 (9%)	1 (2%)	3 (2%)	31 (33%)
3	0	1 (2%)	2 (2%)	0
4	0	0	3 (2%)	0
5	0	3 (6%)	82 (68%)	1 (1%)
6	7 (30%)	28 (54%)	9 (8%)	22 (24%)
7	3 (13%)	1 (2%)	0	16 (17%)

It is of interest to note that most of the dissertations defined by topic appear to be more concerned with outcome than with method. Again, the concept maps reinforce the relationship of the concept to the outcome (Figures 3,4).

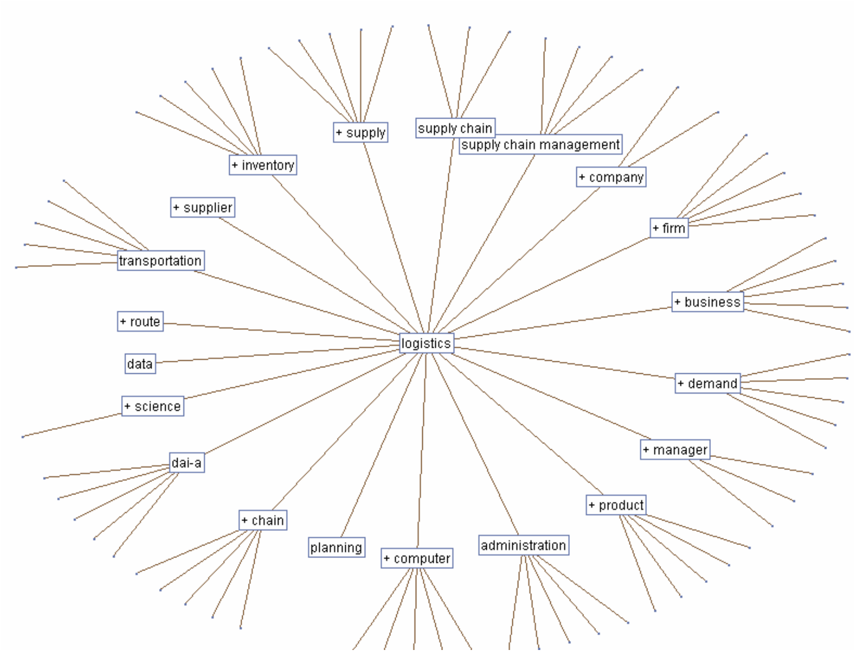


Figure 3. Concept map of the term "logistics".

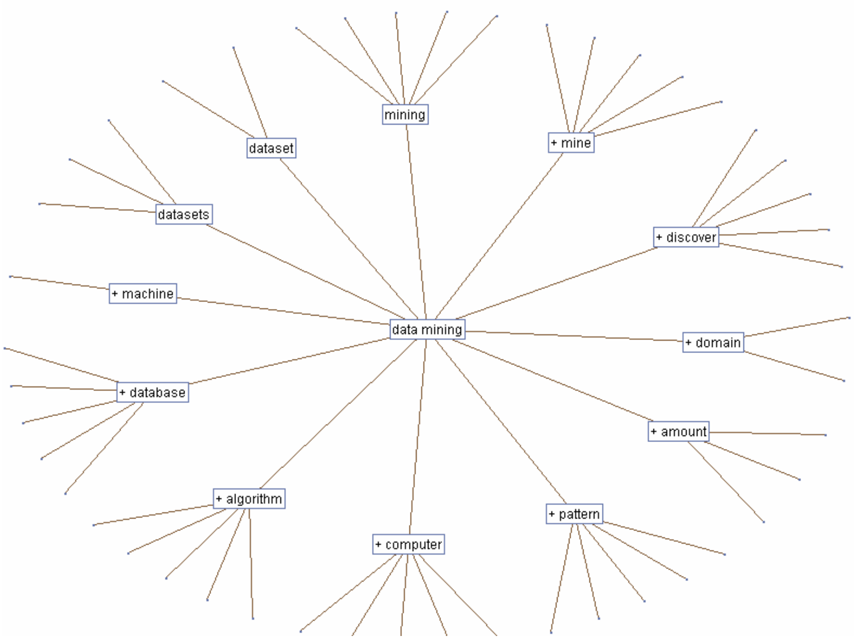


Figure 4. Concept map of the term "data mining"

Biostatistics and actuarial science are more directly related to mathematics. However, they, too, are concentrated on outcomes rather than method.

Dissertation Abstracts does not identify the authors by individual department or discipline. Therefore, it is not possible to determine the proportion of the papers listed in Table 3 that were completed by mathematics students. However, the papers on logistics that focus on "supply chain management" indicate a business major while the data mining papers indicate computer science. It is clear that there is much mathematics being examined outside of mathematics departments.

Discussion

Additional examinations of dissertations with mathematics content clearly show that there is significant mathematical content. Students who seek employment in industry can clearly demonstrate expertise without completing a mathematics doctorate. It becomes imperative that mathematicians carefully examine the content of dissertations that are expected by industrial employers, and to fashion an industrial degree that is in line with those expectations.

References

Akerlind, G. S. (2004). A new dimension to understanding university teaching. *Teaching in Higher Education, 9*(3), 363-375.

Anonymous. (1995). *Reshaping the graduate education of scientists and engineers,* 2003, from http://stills.nap.edu/html/grad/

Anonymous. (2002). *Knowledge Compilation from the Web*, 2003, from semanticweb2002.aifb.uni-karlsruhe.de/ slides/sem5-compilation.ppt

Belcheir, M. J. (2003). *The campus environment as viewed through the lens of the National Survey of Student Engagement*. Boise, Idaho: Boise State University.

Bilica, K. (2004). Lessons from experts: improving college science instruction through case teaching. *School Science & Mathematics, 104*(6), 273-278.

Bird, T., & Rosaen, C. L. (2005). Providing authentic contexts for learning information technology in teacher preparation. *Journal of Technology and Teacher Education, 13*(2), 211-231.

Boothroyd, R. A. (1992). What do teachers know about measurement and how did they find out?, *Annual Meeting of the National Council on Measurement in Education*. San Francisco: ERIC ED 351 209.

Bridges, P., Bourdillon, B., Collymore, D., Cooper, A., Fox, W., Haines, C., et al. (1999). Discipline-related marking behaviour using percentages: a potential cause of inequity in assessment. *Assessment & Evaluation in Higher Education, 24*(3), 285-300.

Brumfield, C. (2005). *Current trends in grades and grading practices in higher education: results of the 2004 AACRAO Survey*. Washington, DC American Association of Collegiate Registrars and Admissions Officers.

Burbach, M. E., Matkin, G. S., & Fritz, S. M. (2004). Teaching critical thinking in an introductory leadership course utilizing active learning strategies: a confirmatory study. *College Student Journal, 38*(3).

Burke, J. C. (2001). *Accountability, reporting, and performance: why haven't they made more difference*. New York: Ford Foundation.

Burley, H. (1996). A CHAID analysis of a diagnostic writing sample as a placement tool for freshman composition, *Annual Meeting of the Southwest Education Research Association*. New Orleans: ERIC.

Cecire, S. (2005, June, 2005). *Uncommon uses for common tools in an on-line environment*. Paper presented at the ASCUE Conference, Myrtle Beach, SC.

Cerrito, P. (2006). *Introduction to Data Mining Using SAS Enterprise Miner*. Cary, NC: SAS Press.

Cerrito, P., & Levi, I. (1999). An investigation of student habits in mathematics courses. *College Student Journal, 33*(4), 584-588.
Chan, T. F. (2003). The Mathematics Doctorate: A Time for Change? *Notices of the American Mathematical Society, 50*(896-903).
Chang, K.-E., Sung, Y.-T., & Ine-Daichen. (2002). The effect of concept mapping to enhance text comprehension and summarization. *The Journal of Experimental Education, 71*(1), 5-23.
Chang, P.-l., & Hsieh, P.-n. (1997). A qualitative review of doctoral dissertations on management in Taiwan. *Higher Education, 33*, 115-136.
Cheng, D. X., & Chen, S. (1998). Factors affecting grading practices, *Annual Meeting of the Northeast Association for Institutional Research*. Philadelphia, PA: ERIC.
Cherry, N. L. (2005). Preparing for practice in the age of complexity. *Higher Education Research & Development, 24*(4), 309-320.
Dowd, A. C. (2000). Collegiate grading practices and the gender gap. *Education Policy Analysis Archives, 8*(10).
Ediger, M. (2000). *Assessing teaching quality in higher education*
El-Khawas, E. (2003). *Using NSSE data for assessment and institutional improvement*. Washington, DC: American Association for Higher Education.
Felton, J., & Koper, P. T. (2005). Nominal gpa and real gpa: a simple adjustment that compensates for grade inflation. *Assessment & Evaluation in Higher Education, 30*(6), 561-569.
Fogg, P. (2007). A new standard for measuring doctoral programs. *Chronicle of Higher Education, 53*(19), A8.
Griffiths, H., & McLone, R. (1984). A critical analysis of university examinations in mathematics. Part I: a problem of design. *Educational Studies in Mathematics, 15*(3), 291-311.
Jones, A. C., Simonds, C. J., & Hunt, S. K. (2005). The use of application essays as an effective tool for assessing instruction in the basic communication course. *Communication Education, 54*(2), 161-169.
Kezim, B., Pariseau, S. E., & Quinn, F. (2005). Is grade inflation related to faculty status? *Journal of Education for Business, 2005*(July/August), 358-363.
Kuh, G. (2006). *National Survey of Student Engagement*. Retrieved December, 2006, from http://nsse.iub.edu/index.cfm
Kuh, G. D. (2003). What we're learning about student engagement from NSSE. *Change, 2003*(March/April), 24-32.
Kuh, G. D., Kinzie, J., Schuh, J. H., & Whitt, E. J. (2005). Never let it rest: lessons about student success from high-performing colleges and universities. *Change, 2005*(July/August), 44-51.
Littell, R., Milliken, G., Stroup, W., Wolfinger, R., & Schabenberger, O. (2006). *SAS for Mixed Models* (2nd ed.): SAS Press.
Maclellan, E. (2004). How convincing is alternative assessment for use in higher education? *Assessment & Evaluation in Higher Education, 29*(3), 311-321.
Martin Eisen Versus Temple University, (2002).
McClenney, K. M. (2004). Redefining quality in community colleges *Change, 2004*(November/December), 16-21.
McCune, V. (2004). Development of first-year students' conceptions of essay writing. *Higher Education 47*, 257-282.
Mead, J. V. (1992). *Teachers' evaluation of student work*. Washington, DC: National Center for Research and Improvement.
Peters, M., Kethley, B., & Bullington, K. (2002). The relationship between homework and performance in an introductory operations management course. *Journal of Education for Business, 2002*(July/August), 340-344.

Pike, G. R. (2006a). The convergent and discriminant validity of NSSE scalelet scores. *Journal of College Student Development*, *47*(5), 550-563.
Pike, G. R. (2006b). The dependability of NSSE scalelets for college- and department-level assessment. *Research in Higher Education*, *47*(2), 177-195.
Shah, A., & Treby, E. (2006). Using a community based project to link teaching and research: the Bourne Stream partnership. *Journal of Geography in Higher Education*, *30*(1), 33-48.
Stoering, J. M., & Lu, L. (2002). Student portfolio assessment, *Association for Institutional Research Annual Meeting*. Ontario, Canada: ERIC.
Sung, E. (2003). *Mending the federal circuit split on the first amendment right of public university professors to assign grades.* Unpublished manuscript, New York.
Tagg, J. (2005). Venture colleges: creating charters for change in higher education. *Change*, *2005*(January/February), 35-43.
Thomas, E. H., & Galambos, N. (2002). What satisfies students? Mining student-opinion data with regression and decision-tree analysis, *AIR 2002*. Ontario, Canada: ERIC.
Tobias, S., & Raphael, J. (1997). The hidden curriculum-faculty-made tests in science. Part 2: upper-division courses. Innovations in Science and Technology, *Science, Mathematics and Environmental Education*. New York: Plenum Press.
Wiebe, J. H. (1982). Using graded quizzes, homework, and attendance for motivating study in a college math class. *Mathematics and Computer Education*, *16*(1), 24-28.
Zuriff, G. (2003). A method for measuring student study time and preliminary results, *College Student Journal*.

Faculty Productivity and the Cost of Instruction

Patricia B. Cerrito
Department of Mathematics
University of Louisville
Louisville, KY 40292
502-852-6826
502-852-7132 (fax)
pcerrito@louisville.edu

Abstract

It is the purpose of this study to use data mining techniques to investigate faculty issues. Each year, faculty are required to self-report on their activities. Also, faculty are required to negotiate a work plan on their activities for the next year. Annual merit reviews reconcile the self-report of activities with the work plan. In addition, faculty have the option of requesting a sabbatical, they can also request unpaid leave. This study examines the impact of sabbaticals and administrative assignments on the cost of instruction.

Data mining tools can be used to investigate the complex and subjective data available for analysis. Data mining is a process that can be used to examine patterns and relationships in the data. While tools such as artificial neural networks and decision trees can be used for data mining, sometimes filtering and data visualization suffices to investigate the data. In this study, patterns indicate a shift in teaching workloads, with considerable variability in research productivity.

Introduction

It is difficult to make a quantitative evaluation of university faculty performance; it is even more difficult to make a meaningful qualitative evaluation. Faculty are usually evaluated on the teaching, professional activity and service. Merit, tenure and promotion decisions are made on the basis of these evaluations. In the absence of clear qualitative-guidelines, simple, easily available scores, such as student teaching evaluations may be used for assessment of teaching (Centra, 1993; Huberty, 2000). However, teaching is a complex activity, including direct instruction, curricular development, scholarship of teaching, student recruitment and support. Faculty devote different percentages of their time to these activities. What is rewarded tends to be performed; what is not rewarded tends to be ignored. If teaching evaluations are, in fact, the sole measure of teaching performance, then other aspects of teaching such as development will not be performed. Therefore, an assessment of productivity must begin with an assessment of workload (Hinrichsen, et.al., 2002; Meyer, 1998; McCall, 2000).

It is a frequently accepted practice for faculty to provide annual self-evaluations for performance and merit assessments. The information provided in these self-evaluations can be used to examine multiple outcomes of faculty activity, and to examine the relative performance of individual faculty members. In some institutions, faculty may negotiate yearly workload agreements to identify the percentage of their work time allocated to teaching, professional activity, and service. Consequently, statistical measures can be defined in the context of individual performance agreements. The personnel committee and/or Department Chair may use these statistical measures to make recommendations concerning merits of performance of each faculty member (Antony & Raveling, 1998. Baldwin, 1997; MacFarland, 2000).

Instruction can become more cost effective if part-time instructors are used as often as possible, if full-time faculty can buy-out as many courses as possible, and fewer courses are offered by maximizing enrollment in each course. For example, if a full-time faculty member earning $80,000 per year as a grant buy-out of 20% ($16,000) for one course, then a part-time instructor paid $5000 to teach that one course allows the difference of $11,000 to be returned to the university as a cost-saving measure. That does not include the overhead that is also returned to the university for the grant buyout. Post-docs also are cost-effective for faculty members who are on leave, often drawing half the salary of a full-time faculty member. Graduate students have greater cost than part-time faculty and post-docs once tuition levels, particularly out-of-state rates, are computed. However, graduate students still cost less compared to full-time faculty. Strict cost guidelines cannot be followed because there are trade-offs in quality, including high turnover of instructors and instructors with fewer credentials who are teaching in the place of faculty members with greater credentials.

Usually, workload numbers are summarized in tables. However, tables can give sums, averages, and medians; they cannot represent the whole distribution. The purpose of this paper is use statistical methods and data mining measures to examine yearly reviews based upon faculty self-evaluations and general information. The methods can be used to examine teaching, professional activity, and service outcomes.

The following variables were analyzed in the dataset:

- Faculty workloads
- Faculty course assignments
- Faculty leaves given

- Courses scheduled
- Course enrollment
- Cost factors

It is not enough to investigate average values for the cost of instruction. Enrollments vary from fall to spring, and from year to year. Therefore, it is important to examine the problem of variability, and to account for it in any analysis of cost, enrollment, and scheduling. Otherwise, the Department will have insufficient funds in high demand years to offer a sufficient supply of courses, and in low demand years will have extra funds. It would be ideal to use the funds available during low demand to cover courses in high demand. However, that will mean allowing carry-over of continuing funds.

Annual Workload Assignments

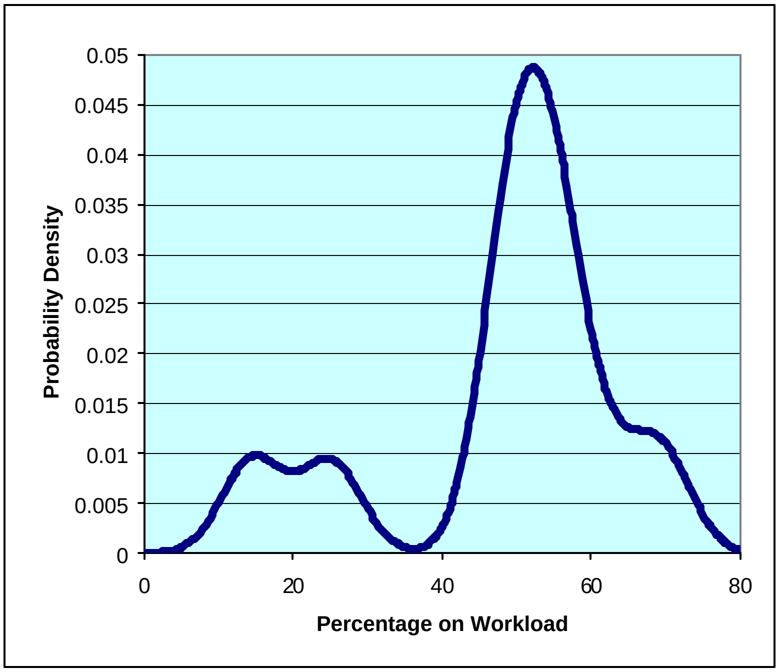
Teaching

The average values associated with time allocated to teaching activities are given in Table 1. The total percentage assigned to teaching ranged from 14% to 70% (Figure 1), with a 3-hour course assignment counted as 10% of an FTE. Note that the distribution provides more information than averages alone. The method used in Figure 1 is that of kernel density estimation (Silverman, 1986). There is some variability in the teaching allocations with faculty assigned less than 40% having course buyout from external grants, or from administrative assignments.

Table 1. Faculty Time Allocated to Teaching Activities

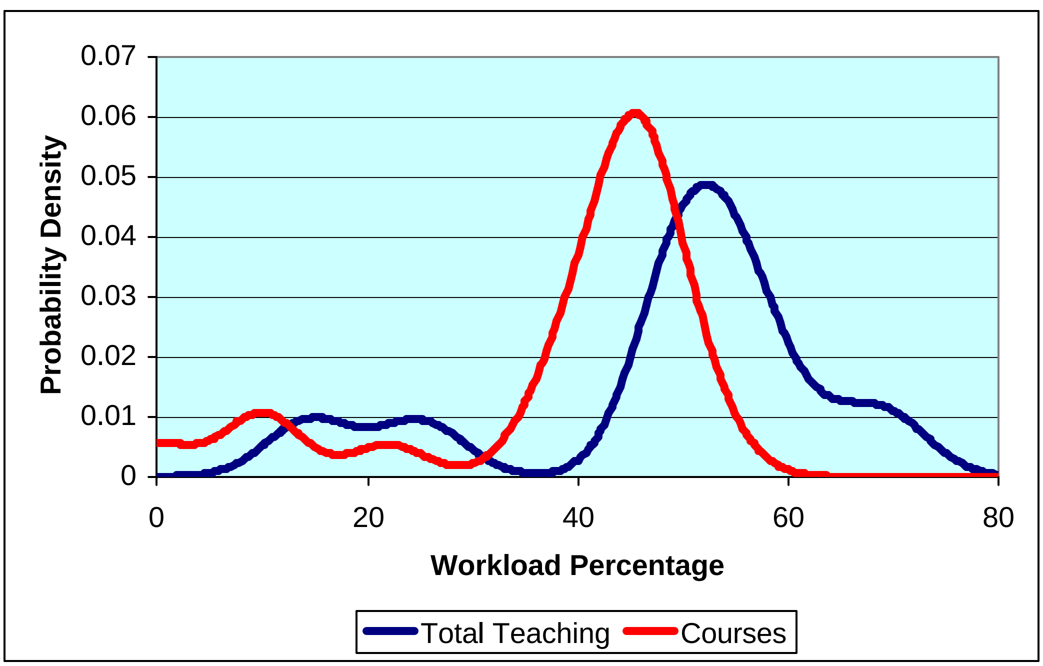
Variable	Mean	Median
Courses Assigned	38.33	46.00
Supervision of Students	3.70	1.00
Independent Study	3.09	2.00
Other	3.43	3.00
Total	48.38	53.00

Figure 1. Probability Distribution of Teaching Percentages on Faculty Workload



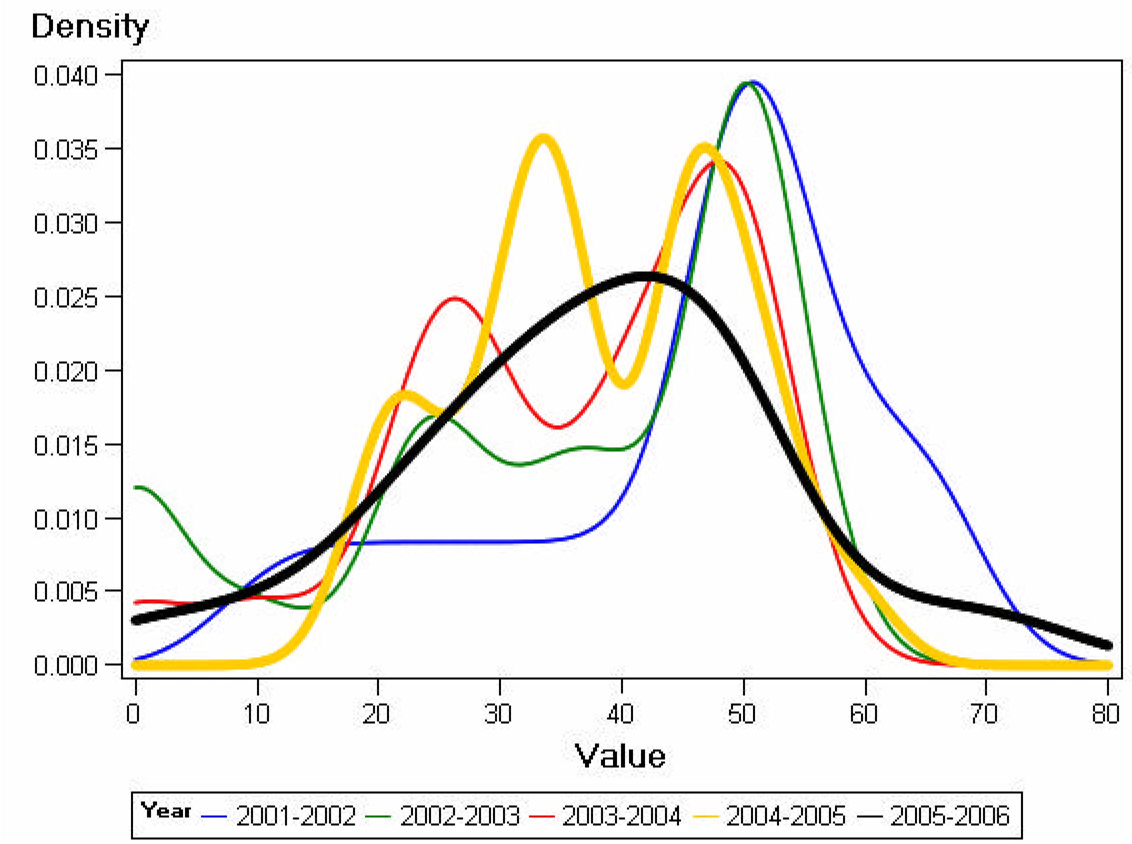
Teaching responsibilities other than classroom instruction increase the teaching allocations for the department by an additional 10% (Figure 2). The additional assignments include thesis supervision and supervision of GTAs (graduate teaching assistants) in recitation classes, new course preparation, computer laboratories associated with regular classes, as well as teaching-related administrative duties (e.g. course coordination).

Figure 2. Comparison of Total Teaching to Course Load



An examination of the teaching assignments from the academic year 2001-2002 through 2005-2006 indicates that there is a shift towards lower allocations. In 2001-2002, the peak load was 55% with very few having less than 40%. By 2003-2004 and 2004-2005, there is a real bimodal distribution of teaching assignments with one peak at 50% and a second peak at 25% for 2003-2004 and at 32% for 2004-2005. By 2005-2006, the two peaks merge to a peak of 40% as the standard teaching load.

Figure 3. Teaching Proportions by Year



Additional information associated with curricular and course material development should be taken into consideration in evaluation of teaching (Table 2). However, if development is identified on the annual workload plan, information in the faculty self-evaluation should be provided as to what development was performed.

Table 2. Percentage of Courses with Curriculum Development

Course Level	Curriculum Development	No Curriculum Development
100	17 (55%)	14 (45%)
200-300	15 (100%)	0 (0%)
400-600	15 (54%)	13 (46%)

Curriculum development was reported in about half of the general education and advanced under-graduate and graduate courses; this number increased to 100% in the beginning courses for mathematics and science majors. Within the last 3 years, the Department instituted a required computer laboratory associated with its calculus sequence, which was discontinued in 2003. Many faculty members developed their own materials to be used in the lab. Faculty members were also asked to report on computer usage in their classrooms (Table 3). The requirement of the computer in the calculus sequence is clear from the percentages. Note that only 1/3 of the general education courses use the computer for instruction. Again, the faculty self-evaluation should indicate what materials were developed.

Table 3. Use of the Computer in the Classroom

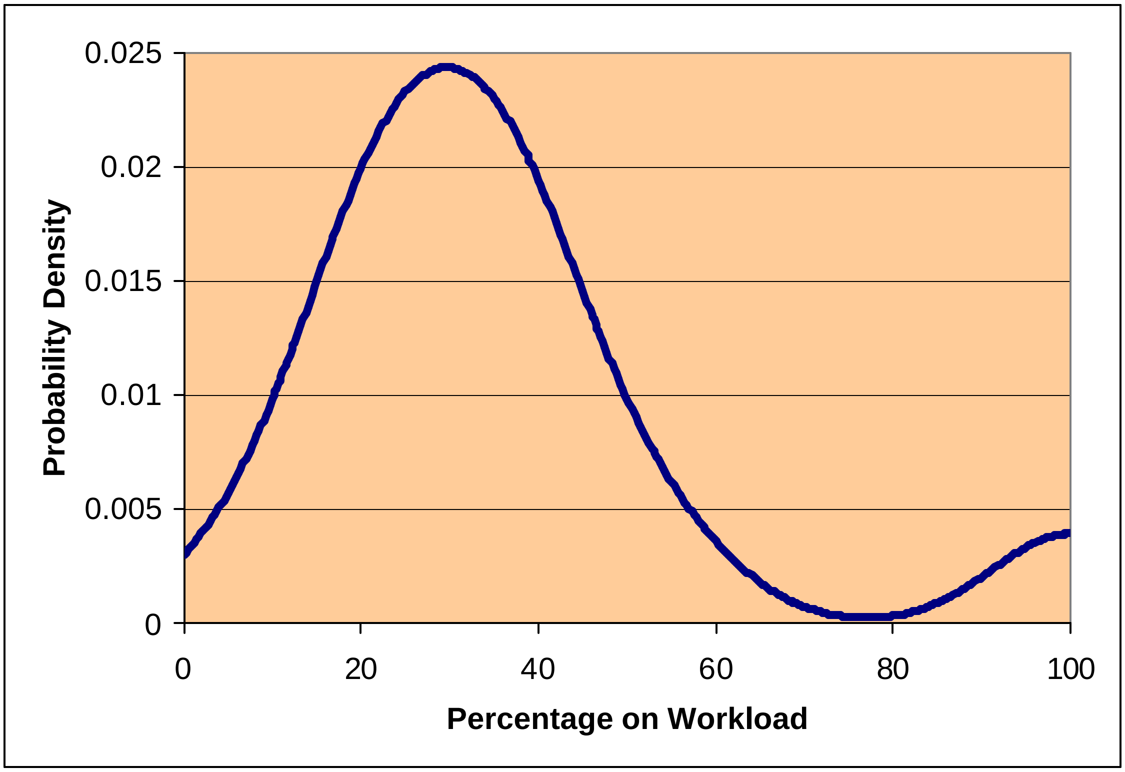
Course Level	Computer Usage	No Computer Usage
100	10 (32%)	21 (68%)
200-300	14 (97%)	1 (3%)
400-600	17 (61%)	11 (39%)

Research

With increased level of specialization amongst faculty, significance of results is difficult to judge across disciplines even within a given department. It is even more difficult to judge the significance of results in interdisciplinary work. Effective communication of results depends upon the definition of the target audience, usually being defined as specialists in a narrow area. Therefore, the quality of an individual faculty member's productivity must be judged using outside peer review, which is usually only done for tenure and promotion, not for annual reviews. Therefore practical considerations force a review to focus on the amount of productivity rather than on the quality of productivity. It must be acknowledged that there is a difference. It should also be acknowledged that different disciplines have different standards to evaluate research productivity (Clark, 1997). Those standards do not always translate to other disciplines. Therefore, a department should be very cautious when evaluating interdisciplinary productivity.

However, the amount of effort directed towards professional activity can differ dramatically between faculty members since some faculty will have buyout from teaching from external grants (Figure 4). It seems reasonable that faculty with a higher research percentage should have a higher rate of research productivity.

Figure 4. Probability Distribution of Research Percentages on Workload

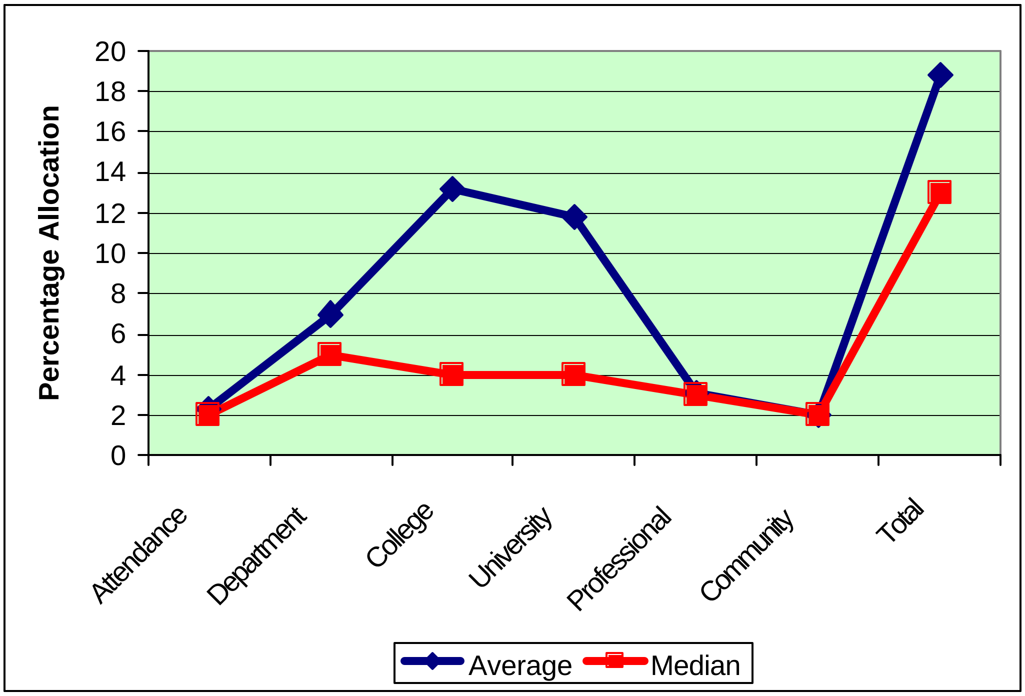


The peak occurs at 30% of faculty time, with a smaller peak at 100%. Those with 100% allocations are usually on a sabbatical year, which is defined by research. Clearly, those with 100% research time should have a high expectation of productivity.

Service

Most of the service assignments are selected by individual faculty members; the assignments may include a variety of responsibilities. Faculty involved in administrative positions can have a very high service allocation (Figure 5). Generally, service counts for no more than 15% of a faculty member's workload. However, for faculty with administrative responsibilities (currently seven members of the faculty), this workload percentage could reach as high as 70%. Because those with administrative responsibilities were assigned those responsibilities for the general well-being of the department, these faculty should be asked to identify initiatives that would advance the department's mission.

Figure 5. Mean and Median Values for Types of Service



To evaluate service, faculty may be asked to provide information on the outcomes of the activity, time involved in completing the activity, letters of assessment from other faculty members involved in the activity. However, the faculty usually do not keep a time log of their daily activities and the number of hours reportedly spent on certain service activities may not be reliable. Therefore, the focus of service evaluation should also be on the products of the service activity. This is particularly true of service activities conducted outside of the university in the profession, and in the community at large.

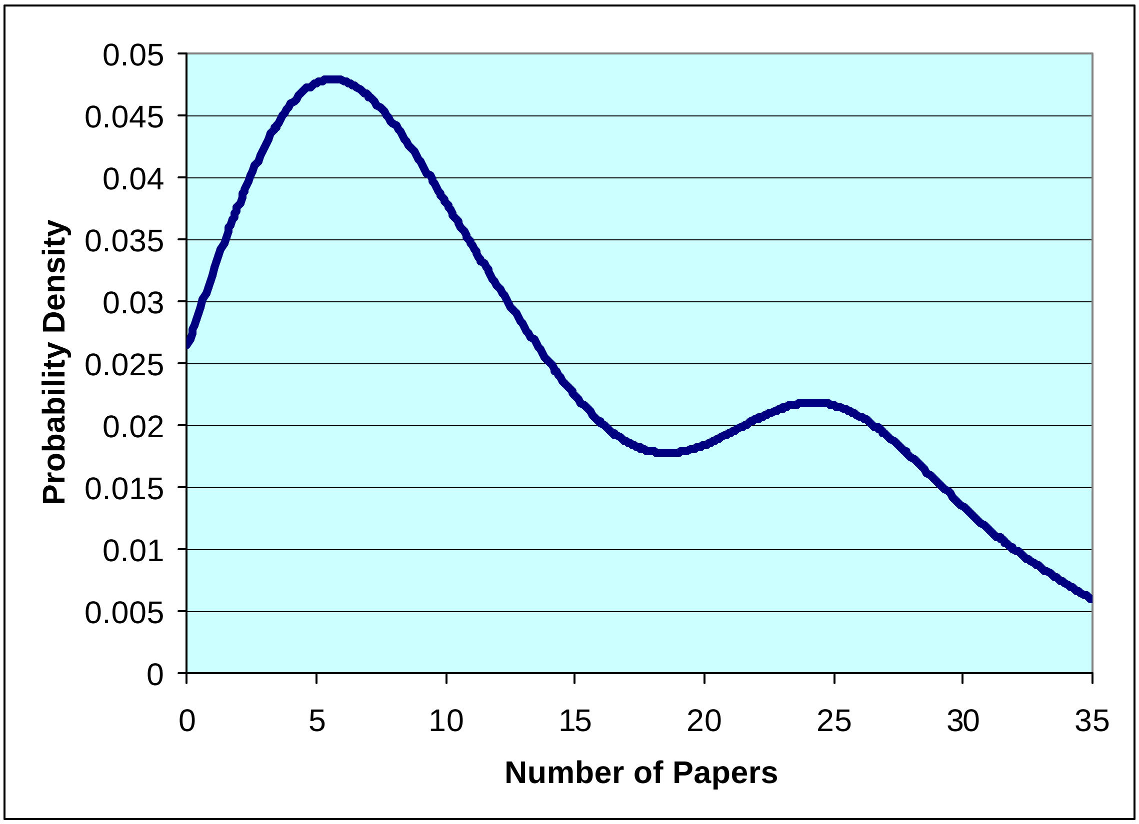
Yearly Productivity

Research

Although acknowledged as inadequate, the chief measure of faculty productivity in research remains the number of journal articles that have been submitted, accepted, or published (Teodorescu, 2000; Seaman, Krismann, and Hamilton, 1999; Huettner and Clark, 1997; Vinsonhaler, Vinsonhaler, and Bartholome, 1995). Michael Middaugh (2000) from the University of Delaware recently published a book on benchmarks to evaluate faculty productivity. However, the emphasis remained on teaching with little discussion of research productivity. In some schools, productivity is measured more in grants funded (Glazer, 1999), although this policy, “made revenue generation the principal function of faculty and demeaned the importance of teaching and service.” Middaugh takes this approach, measuring research productivity more in the number of research dollars generated. However, some research activities require major purchases of equipment and will generate more research dollars compared to other activities.

Faculty may have 80%-100% allocations for professional activity due to external funding and sabbaticals. Other faculty members may have 0-20% professional activity commitments. Therefore, output alone is not sufficient to evaluate faculty performance; it should be viewed in the light of percentage of time allocated for the activity. There is the additional problem of comparing single-author papers to multiple-author papers. Papers can be published in mathematics journals while other application papers are published in a variety of fields including medicine, biology, and engineering. Conference presentations can be extremely competitive in one discipline while relatively routine in another. One statistical measure that may be used is to standardize productivity by the equation (number of papers) / (% research allocation) x 100% (Figure 6). This measure is not entirely satisfactory since it provides an incentive to faculty to write a number of shorter papers, as well as to cut the FTE allocation for research to a minimal amount while not changing responsibilities in the areas of teaching and service.

Figure 6. Standardized Measure of Number of Papers Submitted

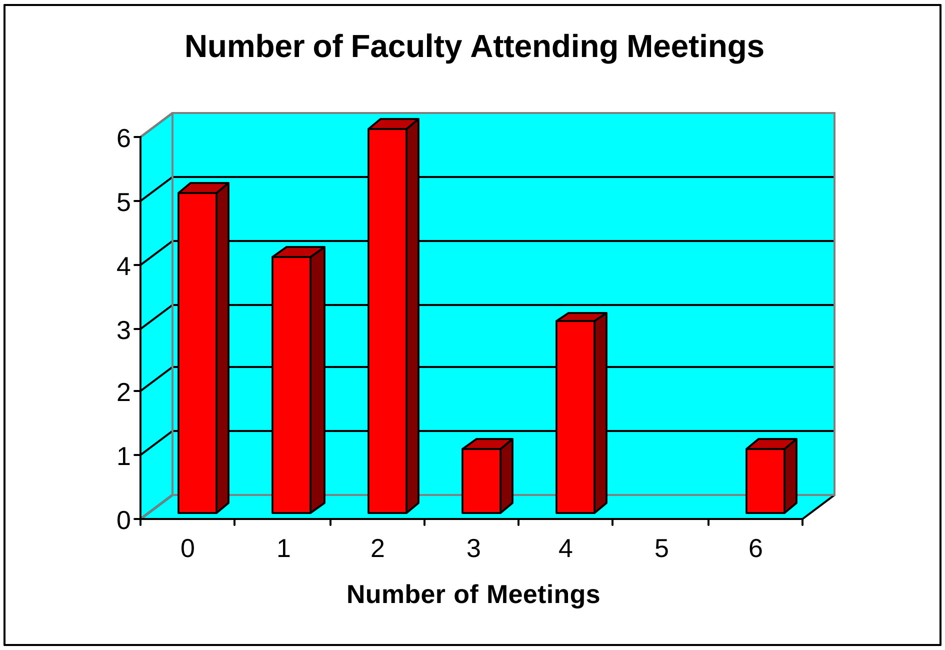


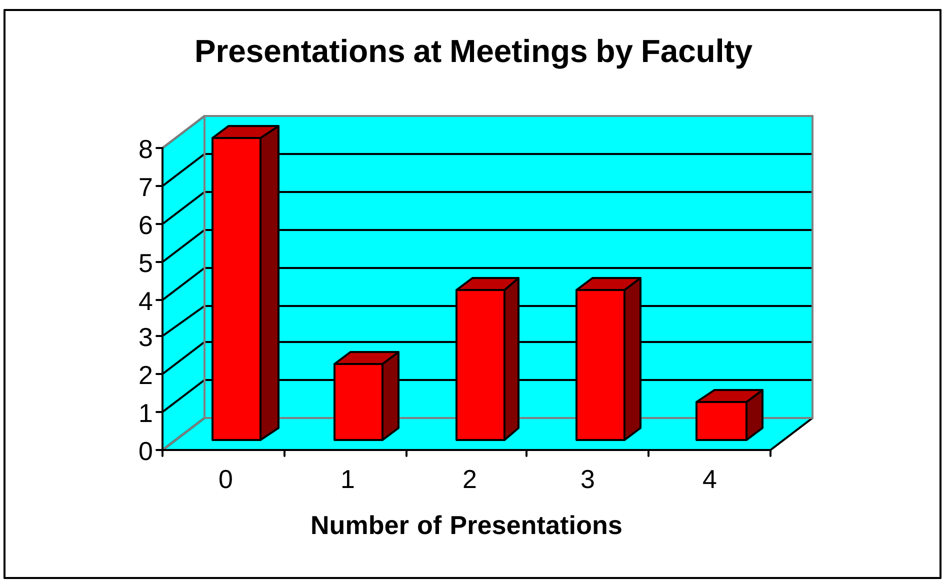
The standardized measure does not take into consideration the number of pages in each paper since there are too many "fuzzy" factors involved. Is a page defined by the number of words? How should the formulas count? Should a page be single or double spaced? Multiple authorship represents another "fuzzy" factor. While it is possible to divide a paper by the number of authors, such division assumes that each author makes a relatively equal contribution. Mathematics is one of the few disciplines where author's names are listed alphabetically regardless of contribution. Other disciplines are very careful in assigning the order of authorship. Moreover, one may argue about the desirability of collaboration and joint work, as it may bring on results that would be unattainable for any of the single authors. The whole may be greater than the sum of its parts.

The standardized measure provides some means for assessing the level of professional productivity (Figure 6), primarily to accomplish the goal of determining if the faculty member was activity engaged in research given the amount of work time allocated. It can also measure the level of engagement. In Figure 6, it should be noted that there is a clear split in the distribution around the point 18. Therefore, the use of this measure could distinguish between “high” productivity versus more “moderate” productivity.

Other activities that enhance an individual faculty member’s professional standing include conference and workshop participation, and grant submission. The number of conferences attended, and the number of presentations made are considered (Figure 7). Most faculty attended multiple meetings but only about half of the faculty made presentations. Caution should be exercised in using conference participation as a professional performance measure, since such participation may be limited by availability of travel funds.

Figure 7. Involvement of Faculty in Meetings to Advance Research





Only a small proportion of the faculty generally receives external funding. There can be no external funding without grant submissions. However, grant submissions require substantial effort. They often have to be resubmitted to receive funding. For example, NSF limits the narrative of a grant proposal to

15 pages and NIH limits it to 25 pages. However, 15 and 25 pages of text represent substantial scholarly activity. Hence it may be desirable to view a full grant submission as being equivalent to a paper submission. This will encourage faculty to write grant submissions.

Teaching

Virtually all faculty teach their courses and meet at the designated times. They have office hours to be accessible to students outside of the classroom. Because of the continued need to quantify, the review of teaching is focused almost exclusively on student teaching evaluations. However, there are some indications that this focus can lead to a reduction in expectations of student effort in the classroom.

Pre- and post- testing of students can quantify the amount of learning that has taken place in the classroom. However, such testing is not usually performed. In addition, faculty have a great deal of autonomy in deciding what should be taught in the classroom in all but the most basic of general education classes. Standardized testing without input as to course content may be problematic.

For this reason, some have suggested the use of teaching portfolios that can be evaluated qualitatively by teaching peers. Faculty should be encouraged to assemble a portfolio on their contributions to the profession of teaching. Faculty who have done some course development, or who can demonstrate innovative teaching techniques can be acknowledged through the portfolio. Publications on pedagogy can be encouraged as an additional measure of teaching productivity. Research on students and instruction can also be included when measuring performance.

Cost of Instruction

The Department of Mathematics at the University of Louisville has 25 full time Tenured and Tenure-Track faculty. Each is responsible for teaching 2 courses per semester. However, an examination of the last four years indicates that the faculty members teach approximately 2/3 of this potential number of courses (Table 4).

Table 4. Number of Course Sections Taught by Tenured Faculty

Semester	Number of Sections	Semester	Number of Sections	Total for Year
Fall, 2000	31	Spring, 2000	38	69
Fall, 2001	35	Spring, 2001	31	66
Fall, 2002	35	Spring, 2002	34	69
Fall, 2003	34	Spring, 2003	34	68

The additional 30 courses that potentially could be taught by faculty must be taught by part-time and term faculty. Therefore, it is worth examining the reasons that those courses are not taught (Table 5).

Table 5. Reasons Faculty Have Lower Teaching Requirements

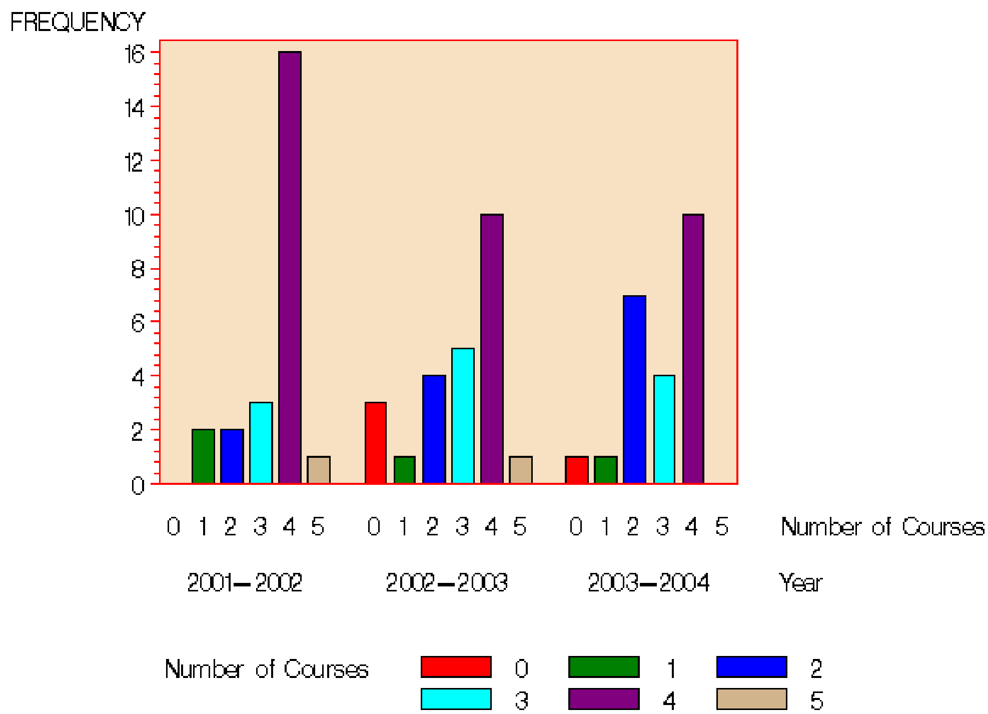
Course Sections	Explanation	Reimbursement to College
68	Taught by full-time faculty	Salary base
9	Reductions for Administration	None
4	Grant buyout	90% salary base
3	Reduction for assistant professors	None
12	Unpaid leave	100% salary base
8	Paid leave	50% one salary base
2	Emergency medical leave	50% one salary base

The paid leaves and grant buyouts provide the department with an estimated $182,000 in salary dollars (based upon average salary figures), and this amount tends to be fairly consistent from year to year. This money can be used to pay for term and part-time instruction, including post-doc positions. One term faculty member can teach 10 course sections per year of general education while 2.5 term positions can cover the courses not taught by faculty. Therefore, the paid leave results in a net gain for the department of almost $100,000 so that paid reductions in teaching yield a net gain to the department because of salary differentials between full-time and part-time and term faculty.

A total of 9 courses for administrative buyout is the equivalent of 2+ faculty positions. Define $Ratio_1$=#courses taught by faculty/#administrative buyout courses=68/9=7.5. For every 7.5 courses taught by full-time faculty, there is a loss of one course to administration. Assuming an average of $5000 cost of faculty time to teach a course, administrative overhead is equal to a 19% overhead rate for instructional purposes.

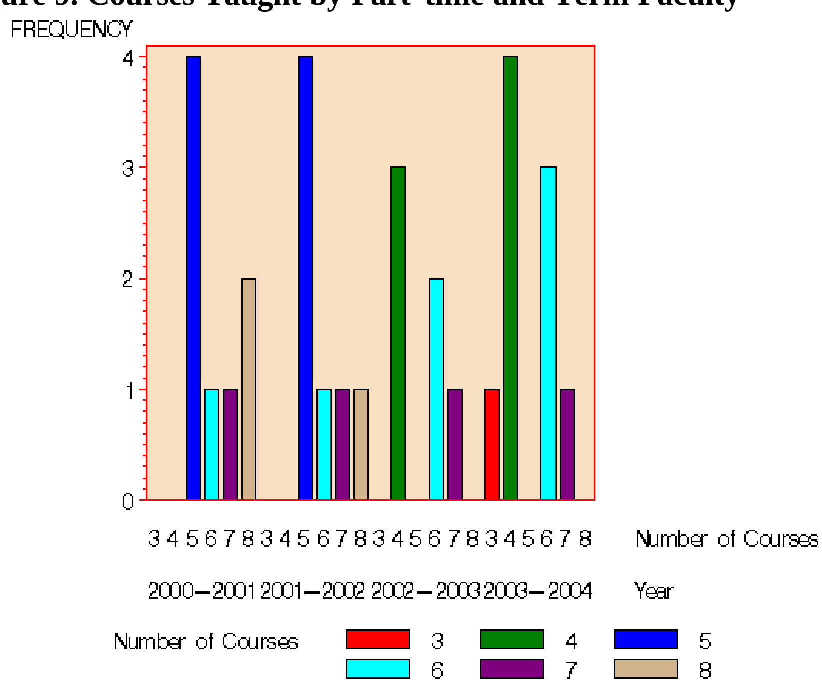
The number of faculty teaching the standard 4 courses has declined from 16 to 10 while the number of faculty on reduced loads of 2 has increased from 2 to 7, and reduced loads of 3 from 3 to 4. Therefore, 10 members of the faculty teach a full load; 11 teach a reduced load. The total number of courses taught by faculty has declined from 77 to 68 (Figure 8).

Figure 8. Number of Courses by Faculty Members



The number taught by full-time faculty was contrasted to the number taught by part-time and term faculty (Figure 9).

Figure 9. Courses Taught by Part-time and Term Faculty



In 2000-2001, term instructors taught a total of 49 sections. This declined to 44 sections in 2003-2004. In 2000-2001, term and full-time faculty taught a total of 126 courses; this declined to 102 in 2003-

3004. Table 6 gives a breakdown for the cost of a 3-hour credit course by faculty rank. It is based upon average salaries.

Table 6 Estimated Cost Per Course by Faculty Rank

Faculty	Cost
Term and Part-Time	$3500
Assistant Professor	$6000
Associate Professor	$7500
Professor	$9000

Given the cost of instruction, the average enrollment provides information concerning the revenue per course. Graduate courses have a higher cost; out-of-state tuition is a higher rate compared to in-state tuition (Table 7).

Table 7. Average Enrollment by Course Level

Course Level	Average Enrollment	Median Enrollment
General Education	25.87	26.06
Freshman Majors	24.05	25.00
Undergraduate Majors	19.74	19.25
Graduate/UG	13.73	14.00
Graduate	9.05	8.00

Table 8. Average Revenue Assuming In-State Tuition

Course Level	Average Enrollment	Average In-State Tuition
General Education	25.87	$14,358
Freshman Majors	24.05	$17,796
Undergraduate	19.74	$10,956
Graduate/UG	13.73	$7620
Graduate	9.05	$7303

The courses for freshmen majors have a higher in-state tuition since they are 4-credit hours courses while the general education are 3-credit hour courses. The average in-state tuition is based upon a credit hour rate. Even though graduate courses have a higher tuition, there are fewer students enrolled so that they generate fewer tuition dollars. These courses are also more likely to be taught by senior faculty while term faculty will teach general education courses. There is no question that cost-shifting is occurring, with the lower-level courses paying for the graduate courses.

Another way of generating revenue is to teach courses on-line. The tuition is 125% of the in-state rate (Table 9). However, since faculty are required to teach on-line outside of their regular teaching responsibilities, some financial incentives need to be provided since the development of an on-line course is very time-consuming. For this reason, some Departments have developed many on-line courses, and are starting to provide on-line degrees while other departments have no on-line courses.

Table 9. Comparison to On-line Tuition Rates

Course Level	Average In-State Tuition	On-line Tuition
General Education	$14,358	$17,948
Freshman Majors	$17,796	$22,245
Undergraduate	$10,956	$13,695
Graduate/UG	$7620	$9525
Graduate	$7303	$9129

Discussion

Cost and accountability are important for any business. University faculty are not immune to these requirements. Legislators and students will insist upon accountability to determine whether a university education is cost-effective. This will be particularly true as students get more options, especially the ready availability of on-line degrees.

In order to determine the direction of this accountability, it is important for universities and faculty to investigate the means of determine productivity levels, and to determine the true costs of course instruction. While it is cost-effective to use part-time and term faculty while senior faculty can buyout teaching through grants, at what point does this trend reduce the quality of the education? Should senior faculty teach College Algebra, or can term faculty with a Master's level education teach general education courses as well, or better compared to senior faculty?

To what extent should general education support graduate education? Can the University document the benefits of graduate education? Since state taxes support public state universities, the University should be prepared to document the return on the taxpayer dollar.