

# **Does Data Mining Really Work for Higher Education Fundraising?**

## **A Study of the Results of Predictive Models Built for 5 Higher Education Institutions**

By Peter B. Wylie and John Sammis

By the year 2000 it was not uncommon to hear the terms data mining and predictive modeling bandied about in higher education advancement. Even though most of us would struggle if asked to give an explanation of these terms, it was becoming clear that a new era of data-driven decisionmaking was dawning for people who raise money for secondary schools, colleges and universities.

Fast forward to 2008. Things have progressed quite a bit. Now it's common for many advancement professionals to have a good conceptual grasp of data mining and how they can use it both for the annual fund and major giving. There is at least one listserv devoted solely to fundraisers interested in the concept. Both the Council for Advancement and Support of Education (CASE) and the Association of Professional Researchers for Advancement (APRA) offer seminars on data mining and modeling at their regional and national meetings. More and more schools are at least considering the hiring of a full-time data mining professional. A "Data Mining Summit" for fundraisers was held in Nashville in April 2008; some 150 people endured budget battles and the exigencies of air travel to attend it.

Bottom line, data mining has arrived. And that's great. But there's a question on the minds of all who either do data mining or pay someone in house (or a vendor) to do it for our institutions: Does it work? More specifically, does it help save money on appeals and generate more revenue from those appeals than would have been raised without data mining?

We recently tried to answer this question using data we've collected for five schools over the past few years, and we thought you'd like to see what we've found.

### **Why Straightforward Answers Aren't Easy**

If you've had a bit of training in experimental science and research methodology, you know that the question of "Does Data Mining Work?" might seem simple and straightforward, but it's not.

Take for instance a study of whether traffic light cameras reduce accidents. On the face of it, this question seems fairly easy to answer. You measure the number of accidents at traffic light intersections before you install cameras and start mailing out tickets to the owners of offending vehicles. Then, after a reasonable period of time, you measure the number of accidents at those intersections after you put the cameras in place. If there is a substantial difference with respect to these counts, then you have an answer to your question, yea or nay. But not so fast. We would encourage you to read the Executive Summary of the report *Safety Evaluation of Red-Light Cameras*, FHWA-HRT-05-048, published by the Federal Highway Administration in April 2005. In this study of seven jurisdictions and 132 sites, the investigators found that the cameras reduced the number of right angle crashes but *increased* the number of rear end crashes.

Since we knew next to nothing about this kind of research before reading the summary, we were surprised. Why would that be? But as we thought about it, the results made a lot of sense. Many drivers will be cautious about speeding through a yellow light knowing they are being photographed. That would naturally cut down on the collisions with other vehicles going through the intersection at right angles. However, how about those tailgaters we've all come to know and hate? Bang! Right into us because they're not slowing down, right?

So ... answering questions with scientific rigor is not easy. And that fact has at least two implications for our question of whether or not data mining really works.

**We need more than anecdotal evidence that data mining helps reduce fundraising costs and generates more donor dollars.** Right now, anecdotal evidence is mostly what we've got. For example, we often hear comments like these from folks who are using data mining in their institutions:

- “The scores we're using helped us get a big bump in our annual fund participation this past fiscal year.”
- “Our alums with the top scores are much easier to reach by phone than the ones with the lower scores. And they're also much more likely to give us a pledge.”
- “We've found a lot of good major giving prospects that we wouldn't have otherwise uncovered.”

Claims like these are encouraging, no question about that. But that's all they are — claims. What we need is empirical evidence to verify them. And the only way we're going to get such evidence is if we start gathering it and reporting it to the rest of the field. That will take some time.

**No one study is going to definitively answer the question.** All the textbooks we've read on applied science and research methodology assert this. Solid scientific knowledge is acquired slowly, study by study. And what we're reporting here is just one study.

That said, here's an outline of what we'll cover in the rest of this paper:

- Some background on how the study got launched
- The results we got from the data
- Some conclusions we arrived at

### **Some Background**

For over ten years we have been gathering data from over 200 North American colleges and universities of all types and sizes for three basic reasons:

1. To show them that data mining and predictive modeling may well help them with both the annual fund and/or major giving
2. To teach some of their staff how to do data mining and modeling for themselves
3. To do the data mining and the modeling for them

Regardless of the reason we gathered the data, we generated a predictive score for each of thousands of records from each institution's alumni database using standard statistical techniques. Sometimes the score was based on only a few fields such as:

- The presence or absence of a home phone listed for a record in the database
- The presence or absence of an e-mail address listed for a record in the database
- The codes listed for each record in the marital status field
- The preferred year of graduation for each record

And sometimes the score was based on more than 25 fields such as:

- Number of class reunions attended
- Number of volunteer activities after graduation
- Spouse name present in the database (yes/no)
- Member of dues paying alumni association (yes/no)
- Zip + 4 listed (yes/no)
- Member of Greek organization as an undergraduate (yes/no)
- Number of e-mails opened

In a number of the institutions the scores were not used right away to help segment alums for any kind of an appeal. Not for snail mail, not for the call center, not for identifying new major giving prospects. Not for anything. The scores just slumbered comfortably in their cyberspace beds.

On the one hand, you could say this was a shame. For if these scores had been used as part of the appeals process, they might have helped the schools save money and generate a lot more gifts. On the other hand, the fact that the scores were not used provided a special opportunity to test their predictive power.

### **How We Evaluated the Scores**

In the next several pages you'll see the results of an analysis for five higher education institutions. For each we collected our data before the scores were used to inform their targeting, so we know that the scores did not influence the results. Here's how we did the data mining:

- For each school we requested the amount of lifetime hard credit dollars received *since* the time the score had been developed, for each alum who had been scored. (Sometimes this time interval was only a few months; sometimes it was several years.)

- We computed (a) whether the alum had contributed anything during this period and (b) how much they had contributed.
- For each score level we computed (a) the percentage of alums at that score level who had made any kind of gift and (b) the mean (average) dollars they had contributed.

Here's a brief description of each of the schools whose data we analyzed:

- **Institution A:** A large western public higher education institution where the time interval between score development and analysis was more than four years.
- **Institution B:** A prestigious east coast private higher education institution where the time interval was less than a year.
- **Institution C:** A large eastern public higher education institution where the time interval was about three and a half years.
- **Institution D:** A medium-sized private higher education institution in the southeast where the time interval was almost five years.
- **Institution E:** A faith-based higher education institution where the time interval was about ten months.

## Results

The charts and corresponding tables that follow are pretty straightforward once you understand how we've recorded our results.

- For each school we converted all scores to a scale from 1 to 20 where each score represented about five percent of the sample we looked at. (Not one of these samples was fewer than ten thousand records.)
- Partly for reasons of confidentiality and partly for reasons of simplicity, we've reported only percentages of giving by score level.

For starters, let's go through Figure 1 and Table 1 to make sure our system is clear. Figure 1 graphically conveys the information you see in Table 1: The percentage of alums at each score level who gave anything at all to the school over (in this case) a four-year period. For us at least two things stand out in both the figure and the table:

- As the scores go up, the percentage of alums who gave during the four years *generally* goes up, but there are some exceptions. Notice, for example, that the percentage participation rate for score

9 is lower than score 8. The percentage participation rate for score 11 is lower than score 10. (This is the world of real data and these kinds of inconsistencies are common.)

- There is a striking difference in the participation rate between scores 1-5 and scores 16-20. Scores 1-5 represent the lowest fifth of scored alums for the sample for this school; scores 16-20 represent the highest fifth. The *biggest* percentage participation rate for the lower fifth is 14.9% at score 5; the *smallest* percentage participation rate for the upper fifth is 32.4% at score 17.

Now take some time to look through Figures and Tables 2-5. Once you do that, we'll tell you some conclusions we've come to regarding this study.

**Results for Institution A:** A large western public higher education institution where the time interval between score development and analysis was more than four years.

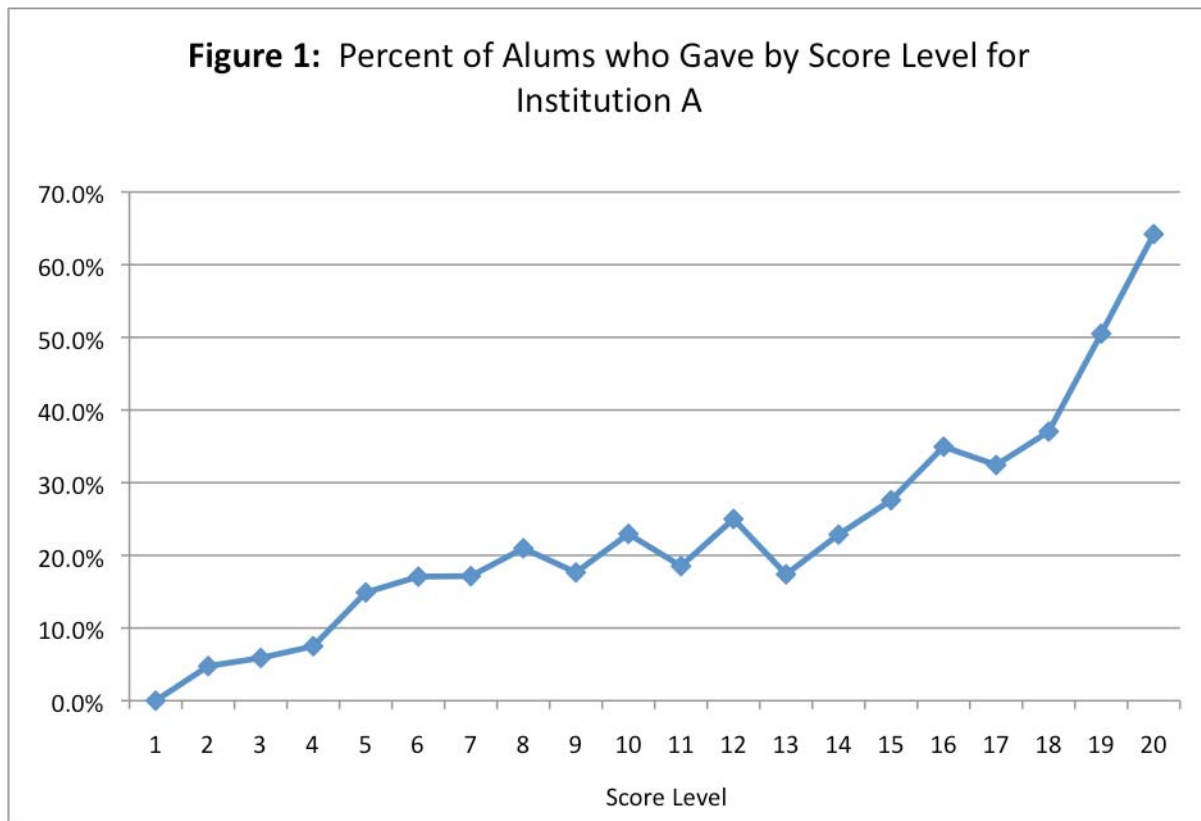


Table of Giving Percentage by Score Level for Institution A:

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
0	4.8	5.9	7.5	14.9	17.1	17.1	21	17.6	23	18.5	25	17.4	22.9	27.6	35	32,4	37	50.5	64.2

**Results for Institution B:** A prestigious east coast private higher education institution where the time interval was less than a year.

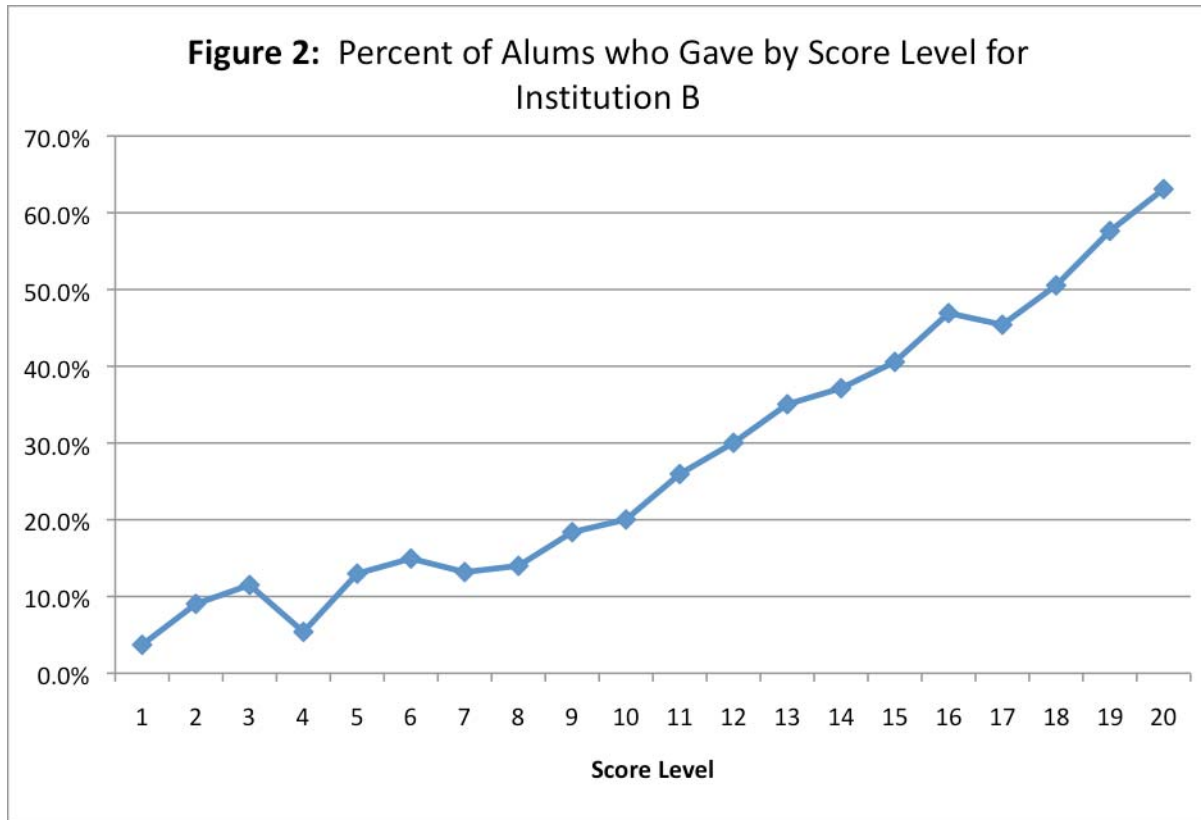


Table of Giving Percentage by Score Level for Institution B:

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
3.7	9	11.5	5.4	13	14.9	13.2	14	18.4	20	26	30	35	37.1	40.6	46.9	45.4	50.5	57.6	63.1

**Results for Institution C:** A large eastern public higher education institution where the time interval was about three and a half years.

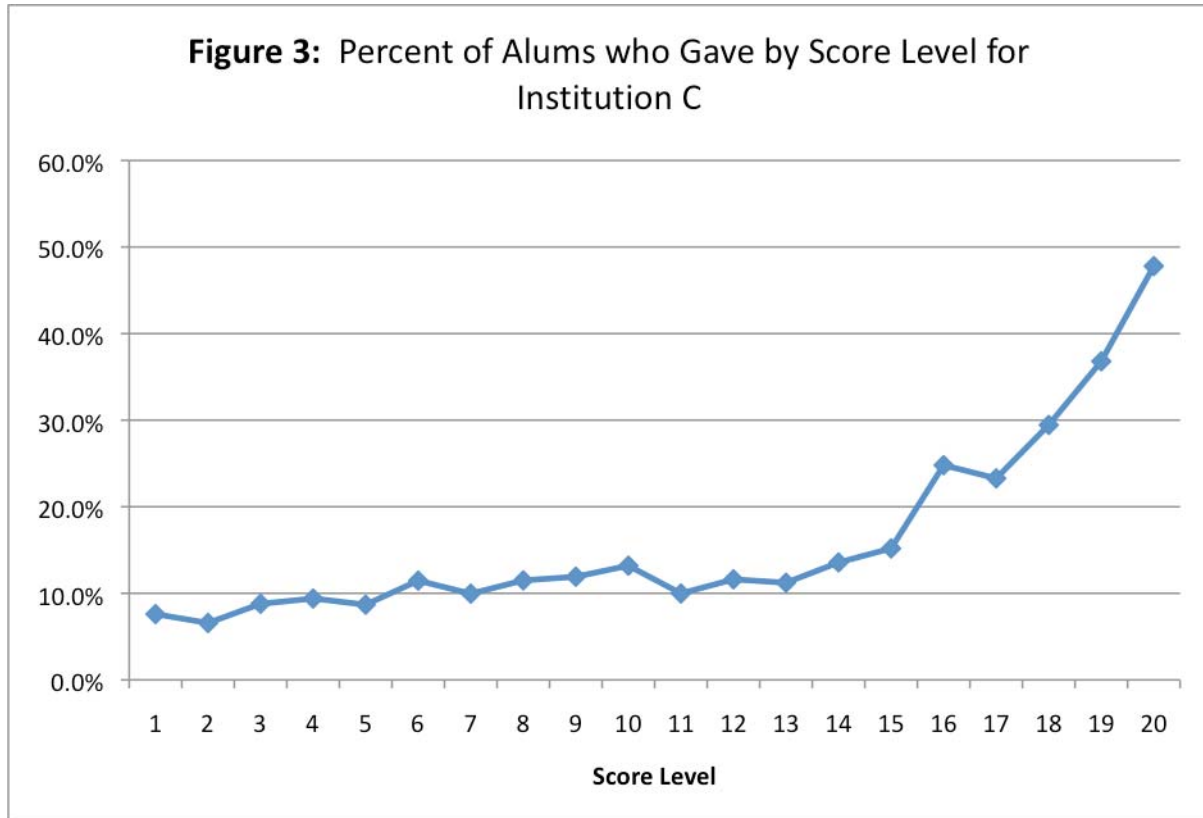


Table of Giving Percentage by Score Level for Institution C:

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
7.6	6.6	8.8	9.4	8.7	11.5	10	11.5	11.9	13.2	10	11.6	11.2	13.6	15.2	24.8	23.3	29.4	36.8	47.8

**Results for Institution D:** A medium-sized private higher education institution in the southeast where the time interval was almost five years.

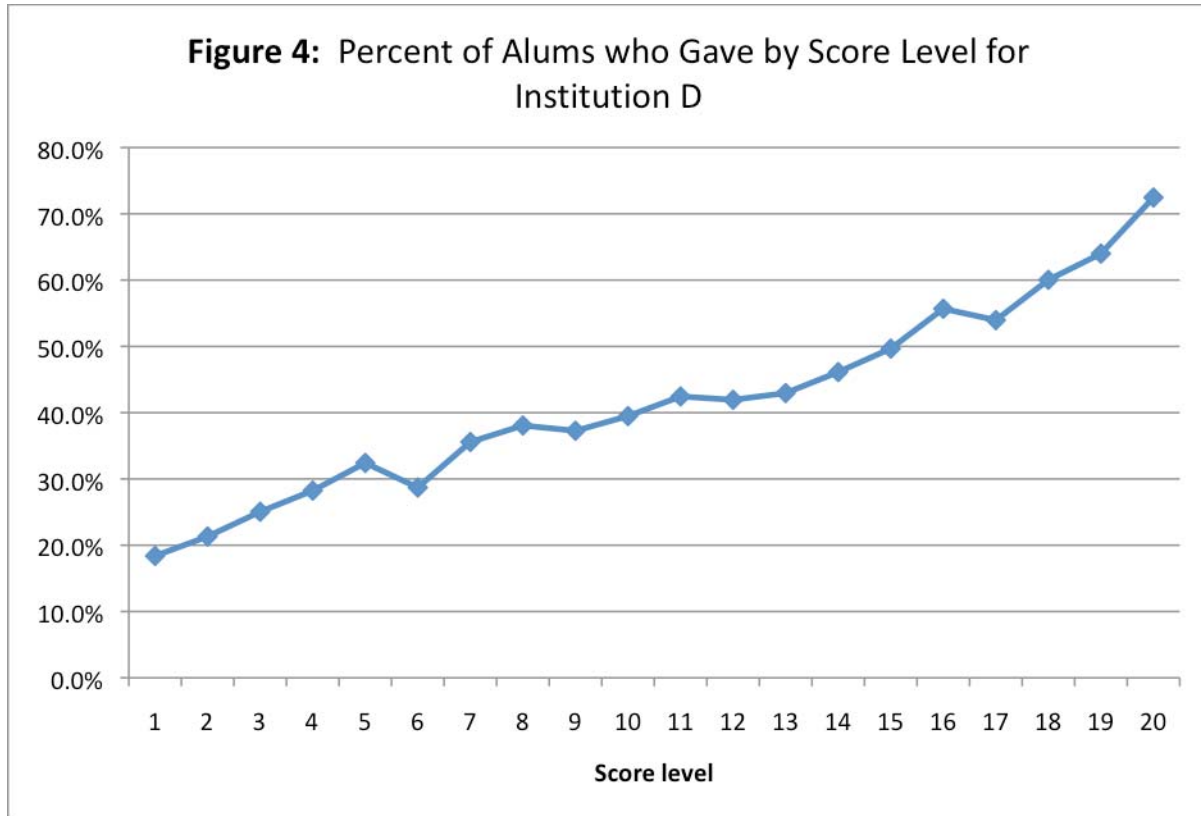


Table of Giving Percentage by Score Level for Institution D:

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
18.4	21.3	25	28.2	32.4	28.7	35.6	38.1	37.3	39.5	42.4	41.9	43	46.1	49.7	55.7	54	60	64	72.5

**Results for Institution E:** A faith-based higher education institution where the time interval was about ten months.

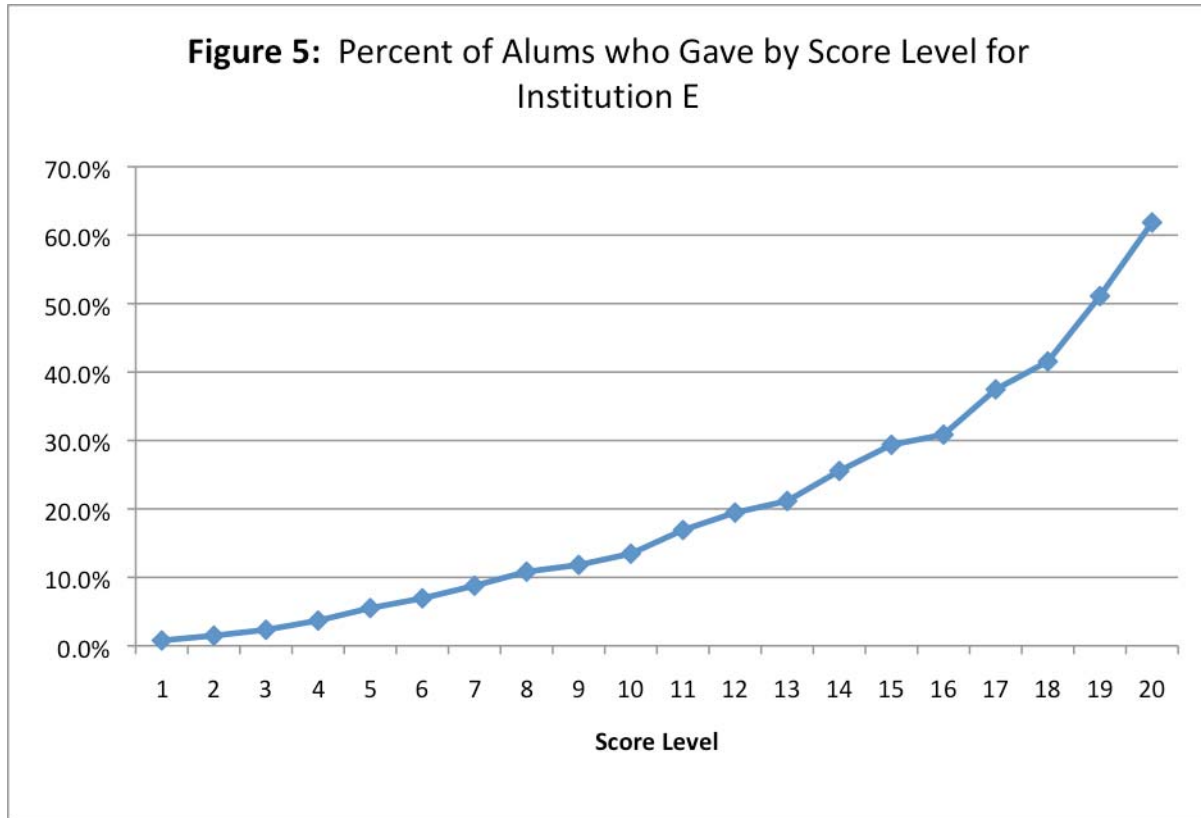


Table of Giving Percentage by Score Level for Institution E:

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
0.8	1.5	2.3	3.7	5.5	6.9	8.8	10.8	11.8	13.5	16.9	19.5	21.2	25.5	29.4	30.9	37.5	41.5	51.1	61.9

### Conclusions

Here are a couple of conclusions we've made about this study:

- There is no question whatsoever that the scores created for this study worked. With good (but far from perfect) accuracy the scores predicted which alums would be more likely to give over the time interval — whether that interval was just a few months or several years.

- Let's assume each of these five schools had been using the scores to segment their appeals (at least for annual fund efforts such as mailings and calling). If they had, they would have been able to focus their resources and efforts on the higher scorers. And we have every confidence that they would have saved money on the appeals process and gotten much higher participation rates as well as higher dollar donation totals; in other words, they would have increased their return on investment.

### **What's Next?**

In terms of the big picture of answering the question of whether data mining and predictive modeling work in higher education, we'd like to see both schools and data mining vendors doing studies like this. If they do, we think good things will happen:

- Lively discussions and disagreements over conflicting results will occur. They always do when people engage in this kind of applied science.
- High level administrators who now tend to know little about data mining will have to start paying more attention to its utility in raising badly needed funds.
- As a field we'll move much more in the direction of making decisions on data-based facts and less on widely held beliefs, many of which are at best misleading and at worst downright wrong.

So what are you waiting for? There are a number of things you can do to get started.

- Read any number of different books on the topic. The CASE bookstore has several them. For example, Josh Birkholz has released a book recently, Peter has two books on this topic, and John and Peter collaborated on a multimedia training product called KeyDonor.
- Join a listserv. One we recommend is [prospect-dmm@mit.edu](mailto:prospect-dmm@mit.edu).
- Attend a conference. Many CASE and APRA meetings have sessions on data mining.
- Do some simple analyses with the tools that you have now. Try pulling some data from the donor database and putting it into Excel and use Excel's charting tools to learn more about your data.
- Introduce yourself to the institutional research staff or a friendly statistics professor and ask if they would be willing to help.