**Appendix A. Teaching and Learning Principles**

Source: Eberly Center for Teaching Excellence & Educational Innovation, Carnegie-Mellon University, 2014

**Learning Principles**

 The following list presents the basic principles that underlie effective learning. These principles are distilled from research from a variety of disciplines.

1. Students’ prior knowledge can help or hinder learning.

 Students come into our courses with knowledge, beliefs, and attitudes gained in other courses and through daily life. As students bring this knowledge to bear in our classrooms, it influences how they filter and interpret what they are learning. If students’ prior knowledge is robust and accurate *and activated at the appropriate time*, it provides a strong foundation for building new knowledge. However, when knowledge is inert, insufficient for the task, activated inappropriately, or inaccurate, it can interfere with or impede new learning.

2. How students organize knowledge influences how they learn and apply what they know.

 Students naturally make connections between pieces of knowledge. When those connections form knowledge structures that are accurately and meaningfully organized, students are better able to retrieve and apply their knowledge effectively and efficiently. In contrast, when knowledge is connected in inaccurate or random ways, students can fail to retrieve or apply it appropriately.

3. Students’ motivation determines, directs, and sustains what they do to learn.

 As students enter college and gain greater autonomy over what, when, and how they study and learn, motivation plays a critical role in guiding the direction, intensity, persistence, and quality of the learning behaviors in which they engage. When students find positive value in a learning goal or activity, expect to successfully achieve a desired learning outcome, and perceive support from their environment, they are likely to be strongly motivated to learn.

4. To develop mastery, students must acquire component skills, practice integrating them, and know when to apply what they have learned.

 Students must develop not only the component skills and knowledge necessary to perform complex tasks, they must also practice combining and integrating them to develop greater fluency and automaticity. Finally, students must learn when and how to apply the skills and knowledge they learn. As instructors, it is important that we develop conscious awareness of these elements of mastery so as to help our students learn more effectively.

5. Goal-directed practice coupled with targeted feedback enhances the quality of students’ learning.

 Learning and performance are best fostered when students engage in practice that focuses on a specific goal or criterion, targets an appropriate level of challenge, and is of sufficient quantity and frequency to meet the performance criteria. Practice must be coupled with feedback that explicitly communicates about some aspect(s) of students’ performance relative to specific target criteria, provides information to help students progress in meeting those criteria, and is given at a time and frequency that allows it to be useful.

6. Students’ current level of development interacts with the social, emotional, and intellectual climate of the course to impact learning.

 Students are not only intellectual but also social and emotional beings, and they are still developing the full range of intellectual, social, and emotional skills. While we cannot control the developmental process, we can shape the intellectual, social, emotional, and physical aspects of classroom climate in developmentally appropriate ways. In fact, many studies have shown that the climate we create has implications for our students. A negative climate may impede learning and performance, but a positive climate can energize students’ learning.

7. To become self-directed learners, students must learn to monitor and adjust their approaches to learning.

 Learners may engage in a variety of metacognitive processes to monitor and control their learning--assessing the task at hand, evaluating their own strengths and weaknesses, planning their approach, applying and monitoring various strategies, and reflecting on the degree to which their current approach is working.  Unfortunately, students tend not to engage in these processes naturally. When students develop the skills to engage these processes, they gain intellectual habits that not only improve their performance but also their effectiveness as learners.

**Teaching Principles**

 Teaching is a complex, multifaceted activity, often requiring us as instructors to juggle multiple tasks and goals simultaneously and flexibly. The following small but powerful set of principles can make teaching both more effective and more efficient, by helping us create the conditions that support student learning and minimize the need for revising materials, content, and policies. While implementing these principles requires a commitment in time and effort, it often saves time and energy later on.

1. Effective teaching involves acquiring relevant knowledge about students and using that knowledge to inform our course design and classroom teaching.

 When we teach, we do not just teach the content, we teach students the content. A variety of student characteristics can affect learning. For example, students’ cultural and generational backgrounds influence how they see the world; disciplinary backgrounds lead students to approach problems in different ways; and students’ prior knowledge (both accurate and inaccurate aspects) shapes new learning. Although we cannot adequately measure all of these characteristics, gathering the most relevant information as early as possible in course planning and continuing to do so during the semester can (a) inform course design (e.g., decisions about objectives, pacing, examples, format), (b) help explain student difficulties (e.g., identification of common misconceptions), and (c) guide instructional adaptations (e.g., recognition of the need for additional practice).

2. Effective teaching involves aligning the three major components of instruction: learning objectives, assessments, and instructional activities.

 Taking the time to do this upfront saves time in the end and leads to a better course. Teaching is more effective and student learning is enhanced when (a) we, as instructors, articulate a clear set of learning objectives (i.e., the knowledge and skills that we expect students to demonstrate by the end of a course); (b) the instructional activities (e.g., case studies, labs, discussions, readings) support these learning objectives by providing goal-oriented practice; and (c) the assessments (e.g., tests, papers, problem sets, performances) provide opportunities for students to demonstrate and practice the knowledge and skills articulated in the objectives, and for instructors to offer targeted feedback that can guide further learning.

3. Effective teaching involves articulating explicit expectations regarding learning objectives and policies.

 There is amazing variation in what is expected of students across American classrooms and even within a given discipline. For example, what constitutes evidence may differ greatly across courses; what is permissible collaboration in one course could be considered cheating in another. As a result, students’ expectations may not match ours. Thus, being clear about our expectations and communicating them explicitly helps students learn more and perform better. Articulating our learning objectives (i.e., the knowledge and skills that we expect students to demonstrate by the end of a course) gives students a clear target to aim for and enables them to monitor their progress along the way. Similarly, being explicit about course policies (e.g., on class participation, laptop use, and late assignment) in the syllabus and in class allows us to resolve differences early and tends to reduce conflicts and tensions that may arise. Altogether, being explicit leads to a more productive learning environment for all students.

4. Effective teaching involves prioritizing the knowledge and skills we choose to focus on.

 Coverage is the enemy: Don’t try to do too much in a single course. Too many topics work against student learning, so it is necessary for us to make decisions – sometimes difficult ones – about what we will and will not include in a course. This involves (a) recognizing the parameters of the course (e.g., class size, students’ backgrounds and experiences, course position in the curriculum sequence, number of course units), (b) setting our priorities for student learning, and (c) determining a set of objectives that can be reasonably accomplished.

5. Effective teaching involves recognizing and overcoming our expert blind spots.

 We are not our students! As experts, we tend to access and apply knowledge automatically and unconsciously (e.g., make connections, draw on relevant bodies of knowledge, and choose appropriate strategies) and so we often skip or combine critical steps when we teach. Students, on the other hand, don’t yet have sufficient background and experience to make these leaps and can become confused, draw incorrect conclusions, or fail to develop important skills. They need instructors to break tasks into component steps, explain connections explicitly, and model processes in detail. Though it is difficult for experts to do this, we need to identify and explicitly communicate to students the knowledge and skills we take for granted, so that students can see expert thinking in action and practice applying it themselves.

6. Effective teaching involves adopting appropriate teaching roles to support our learning goals.

 Even though students are ultimately responsible for their own learning, the roles we assume as instructors are critical in guiding students’ thinking and behavior. We can take on a variety of roles in our teaching (e.g., synthesizer, moderator, challenger, commentator). These roles should be chosen in service of the learning objectives and in support of the instructional activities.  For example, if the objective is for students to be able to analyze arguments from a case or written text, the most productive instructor role might be to frame, guide and moderate a discussion.  If the objective is to help students learn to defend their positions or creative choices as they present their work, our role might be to challenge them to explain their decisions and consider alternative perspectives. Such roles may be constant or variable across the semester depending on the learning objectives.

7. Effective teaching involves progressively refining our courses based on reflection and feedback.

 Teaching requires adapting. We need to continually reflect on our teaching and be ready to make changes when appropriate (e.g., something is not working, we want to try something new, the student population has changed, or there are emerging issues in our fields).  Knowing what and how to change requires us to examine relevant information on our own teaching effectiveness.  Much of this information already exists (e.g., student work, previous semesters’ course evaluations, dynamics of class participation), or we may need to seek additional feedback with help from the university teaching center (e.g., interpreting early course evaluations, conducting focus groups, designing pre- and posttests). Based on such data, we might modify the learning objectives, content, structure, or format of a course, or otherwise adjust our teaching. Small, purposeful changes driven by feedback and our priorities are most likely to be manageable and effective.

**Appendix B: Course-Based ABC**

 Imagine that a small group of faculty, or even a single professor, has decided to dig deeply into the question of teaching cost--perhaps, but not necessarily, as part of a course redesign project. Working with an analyst from the dean's office, the group begins by focusing its attention on a single course. How should the analysis proceed? The steps are straightforward, albeit unfamiliar to anyone who has not previously been involved in course redesign. This Appendix offers a template for building the course based ABC model.

 To set ideas let's assume the goal is to describe a large science course--though the approach works for any size and subject. The basic approach is "historical" in nature: it documents what’s being done now so as to better understand how teaching costs are incurred. I'll describe the modifications needed to produce a "predictive" model, one that can be used to test new designs and do the what-if analyses needed for planning, as we go along.

Characterization of Activities

 Deciding what activities to consider is the first step in building a course-based ABC model. This is a sensitive issue because defining activities at too high a level limits the model's usefulness while defining them in too much detail makes the model difficult to construct and understand. There are three basic types of categories as shown below:

1. *Contact Activities* (*organized classes and other group work)*. Class sections appearing in the Registrar's timetable provide the classic example of contact activity. They are characterized by class size, frequency and duration of meetings, the number of sections offered, and whether the offering is face-to-face or synchronous online. This basic structure also applies to certain kinds of asynchronous group work: for example, where teams are organized in advance (and thus are controlled for size) and advised by a teacher who may attend some but not all the group meetings.
2. *Directly Variable Activities (ones that vary directly with enrollment)*. The classic examples here are students’ reading before class and doing problem sets afterwards. They are characterized by the time students spend doing assignments and the time faculty and TA's use to grade and provide feedback on the work.
3. *Fixed Activities: (ones that don’t depend on enrollment)*. These are primarily administrative in nature: for example, organizational work before the semester begins, management during the semester, and wrap-up after the semester. Preparation for in-class teaching is included in Category 1 because it depends on the numbers and durations of classes.

 The three represent a refinement of the *Synchronous activities*, *Asynchronous activities: students*, and *Asynchronous activities: teachers* categories in text Figure 3-1 of Chapter 3. Notice that categories 1 and 2 depend on enrollment: the first through the relation between class size and section counts and the second through the “minutes per student” construct.

 Suppose the analysis team has decided to model the six activities listed on the rows of Table B-1. They are primary class sections (lectures), two kinds of secondary sections (discussion sessions and labs), two homework activities (reading and doing problem sets), and an undifferentiated course administration activity. The columns in Part A of the Table characterize these contact activities. *Average meetings per* week (for the whole semester), *Minutes per meeting*, and *Section count* can be observed directly. Average class size is calculated dividing section count into a predetermined enrollment figure, and faculty and Student contact hours (not displayed) are calculated from the section counts and numbers and durations of classes. (Student time is not always considered, but it definitely represents an input to the teaching and learning process.) The *Other Faculty Effort* and *Other Expenditures* variables are:

TABLE B-1 ABOUT HERE.

* *Preparation*: time spent by faculty preparing for class, per hour of contact time (used in connection with Table B-2, below);
* *Office*: faculty office hours, per assigned section per week
* *Other*: faculty time used for other purposes (e.g., supervising TAs), per hour of section per week;
* *Operations*: expenditures on supplies, etc., per section per week; and
* *Facilities*: pro-rata cost facilities usage, per section per week (depends room size and type, the amount of time utilized, and cost per hour as estimated by the Finance Office).

 Estimates of student and faculty effort on homework assignments and faculty fixed effort, needed in Part B of the Table, are obtained by talking with faculty who currently teach the course or have done so in the recent past. While these variables are less easily quantified than the ones in Part A, experience shows that people who are familiar with a given course can estimate them in a reasonable way. But while these data are relatively easy to collect, it’s not all that common to do so. That, of course, is precisely the reason for using a spreadsheet template. In addition to pulling the data together, the spreadsheet can calculate the linkages between activity and enrollment that are embodied in the activity characterizations.

 Switching from a historical to a predictive model requires some changes in perspective. The first is that users must choose whether to control for class size or section counts when making their projections. Controlling on class size lets the number of sections, and hence resourcing requirements, vary with enrollment. The user sets a target class size and the model calculates the number of sections needed to accommodate the enrolled students without exceeding the target. Controlling on sections lets class size, and hence (other things being equal) learning quality, vary with enrollment. Class size equals the chosen section count divided by enrollment. Which approach is better depends on the circumstances, as discussed in Chapter 4.

 One usually builds more detail into models used for designing courses (a special kind of predictive modeling) that is typical for analyzing existing courses. The extra detail may elaborate the time dimension or provide a finer set of category definitions. The time dimension is important because the incidences and durations of activities may vary from week to week during the semester. Courses should be designed “brick by brick,” one week at a time, rather than by assuming all activities proceed in lockstep or averaging activities over time in ways that obscure important design details. This is particularly important when novel technology applications are being considered. Extending the template to allow week-to-week variation facilitates this endeavor.

Resources and Unit Costs

 Modeling resources and unit costs is easier than characterizing activities. Again, the first step is to decide on the amount of detail to be considered. The *Percent of Effort* columns of Table B-2 list the human resource types that have been important in a number of my modeling projects. There are two levels of regular faculty, (paid) adjunct faculty, TAs, and an “Other” polyglot category that includes administrators and unpaid adjuncts. The *Dual Preparation* column estimates the percentage of sections where a teacher is assigned to teach multiple sections of the same type, which can influence the cost of teaching in a significant way. The last column gives the *Support Staff* hours (the time of technicians and other non-teaching personnel) needed per section per week.

TABLE B-2 ABOUT HERE.

 The *Percent of Effort* figures show how each resource type contributes to the teaching tasks for each activity. For contact hours, the figures refer to percent of sections: e.g., 10% of primary sections are taught by senior faculty, 50% by junior faculty, 30% by adjuncts, and 10% by other. For non-contact activities, they are percentages of the estimated total minutes required to perform the task. The percentages sum to more than one when team teaching or other needs put multiple instructors on a task at the same time. The table assumes that a TA will be present along with faculty in all primary class sessions, and that junior faculty supervise the grading work of TAs.

 The faculty effort figures can encompass more innovation than meets the eye. It’s usual to think of an instructor as taking a given discussion section for the whole semester, but this is by no means necessary. Suppose that some “lectures” are conducted virtually--e.g., by means of videos--and that the freed-up professorial time is applied to team-teach discussion sections on a rotating basis along with the regular TA. This would give both students and TAs more intimate contact with the professor, to the benefit of both. I recently had occasion to talk with my granddaughter (an undergraduate at a state flagship university) who had just experienced a discussion-section “drop-in” by her literature professor. She said it made a huge difference.

 The bottom row of Table B-2 gives the unit costs ($ per hour) of the various resources. Preparation of these data is more technical than we've seen up to this point. It falls in the province of university cost accountants, but departmental and school model builders would do well to provide the accountants with the following instructions: (1) personnel costs should include salaries, benefits, and perhaps an allocated share of departmental support like secretaries, supplies, and travel; (2) overheads above the level of the department should not be allocated to personnel or other operating costs; and (3) both organized and departmental research should be excluded from the faculty salary data for reasons that will be discussed later.[[1]](#endnote-1) (The treatment of overhead stems from the need to estimate the direct cost of teaching--overheads can be allocated later if desired.) With the unit costs in hand, it is a simple matter to calculate a blended cost per section or cost per minute or hour for each activity--which then can be applied to the activity requirements provided back in Table B-1.

 The activity and resourcing data are all that's necessary to build a rich bottom-up ABC model for a particular course. Sample results for the model are shown in Table B-3. The first two columns represent the *Overall Hours* associated with each activity. *Student* hours reflect time spent per person, based only on actual contact time. *Staff* hours reflect the total hours, including preparation time and office hours where applicable, needed to execute the activities for the prespecified enrollment level. Staff time and cost can be separated by staff type if desired. *Facilities* hours represent classroom and laboratory time; these are the same as student hours for contact activities and zero for non-contact activities. The *Total Cost: $* figures reflect the sum of hours for each staff type times its hourly rate, plus the *Other Expenditures* figures in Table B-1, and the *% Acad* figures show the percentage represented by faculty, TA, and other teaching. *Average Cost* figures are calculated by dividing total cost by section count and enrollment--or other measures like SCH if desired.

TABLE B-3 ABOUT HERE.

**Appendix C: Computer Aided Course Design**

 It doesn't take much experience with spreadsheet templates like the one shown back in Tables B-1 and B-2 to know these tools become unwieldy as course designs become more complex. This manifests itself in two ways: (i) the activities on the rows of the table proliferate; and (ii) the assignments of activities to time periods (on the columns of the Table) become much more variegated. (An example of the latter is that an activity may occur in some weeks but not in others or have different durations from week to week.) All this could be handled on a spreadsheet, but the sheet would become unwieldy and the formulas difficult to maintain.

 About fifteen years ago I envisioned a computer-aided course design tool (“Course-CAD”) that could facilitate and automate the work currently being done on spreadsheet templates. The idea was for users to configure a custom list of activities, drag and drop them on an appropriate timeline, assign resources, and then push a button to perform the ABC calculations. My design concept is presented here. Lack of time and development tools, coupled with doubts about whether the tool would be adopted in the then-prevailing environment, led me to set the idea aside--but now its pursuit seems eminently worthwhile.

 The scale of the programming task makes such an application amenable to distributed open-source development under a Creative Commons license.[[2]](#endnote-2) Indeed, today's development tools might make the work feasible as a student Computer Science project. It seems to me that this kind of grassroots development would maximize the possibilities for getting a good product and, very importantly, getting it adopted by faculty.

FIGURE C-1 ABOUT HERE.

 My design concept for Course-CAD is illustrated in Figure C-1. The illustration is based loosely on the five-week multi-method module outlined in Appendix B, but the ideas are easily generalized. I'll explain the elements in the order most users would encounter them.

1. *Teaching and Learning Activities* (Part A). The module is assumed to involve six basic learning activities, each represented by a different “smart” shape (i.e., one containing customizable attributes that can be read from external code). Users customize the basic activities into specific ones like *Contact activity: Lecture* and *Contact activity: Seminar* that appear in Part B of the Figure. Double-clicking a customized shapeopens a dialog box where one can enter the activity’s name and general attributes. (The attributes are patterned after the ones in text Appendix B.) The basic activities have slightly different attribute sets, as follows.
	1. *Contact Activity*: can represent primary or secondary lecture-discussion classes, seminars, labs, and other class types. The attributes are duration, target and maximum class size, teacher preparation time as a percentage of contact time, and supplementary resources like technicians and TA's who help the main teacher conduct the class. The distribution of teachers by type (e.g. adjunct vs. regular faculty) may be specified at this point or deferred for later designation as discussed below.
	2. *Student Group Activity*: non-contact work that’s done in organized groups. The attributes are target and maximum group size, total hours required for students over the course of the assignment (not per week), and total fixed and variable hours required for teachers and other resources. Variable time includes teachers’ periodic visits to group meetings, and emails and office hours specifically related to the assignment.
	3. *Student Individual Activity*: non-contact work done by students on an individual basis and/or in informal groups. The attributes are the same as those for group activity except there is no group size.
	4. *Computer Mediated Activity*: work by students with software learning objects and similar resources as described in Chapter 3. Attributes are the same as above, plus any special resource requirements like lab time and software licenses.
	5. *Early Exit Arrows*: curved arrows that show the fraction of students who leave an assignment early. *Straight arrows* represent precedence relations that apply to all students who exit in the normal way. Dropout and failure percentages also can be represented if desired.
	6. *Supplementary Material and Teacher Interaction*: access to syllabus materials (e.g. via a course management system) and to teachers through email and general office hours. Attributes are the same as for computer-mediated activities.
2. *Design Canvas* (Part B). The user drags activity shapes to the appropriate time slot(s) and connects the needed precedent arrows. The following features also can be activated.
	1. *Further customization*: double-clicking a shape situated on the design canvas allows the general attributes to be overridden or new ones added: e.g., to amend an activity’s duration or the fraction of students exiting in a particular week.
	2. *Set durations for non-contact activities*: done by stretching a shape to span a desired time interval. Resource requirements are prorated over whatever interval is chosen.
	3. *Teacher specification*: invokes a procedure (not shown) that specifies teacher type for activities where this decision has been deferred. The idea is to allow users to make global changes in estimated teacher type distributions for specified activities and/or time periods.
3. *"Go" Button* (on the Design Canvas). Pushing this button activates an engine for totaling up resource requirements and costs, based on an assumed student throughput. This is analogous to preparing a bill of materials and costs in a conventional computer aided design application.

 Among other things, the engine will determine the number of sections and groups required to meet size objectives, and the number of students that leave each applicable assignment early. (Recall from the Chapter 3 that students can move from computer-mediated work to special individual projects as soon as they demonstrate competence.)

 A Course-CAD developer will need to test the above against local requirements, and also add detail is needed to reduce the design concept to practice. I believe, however, that the material in this Appendix will provide sufficient guidance and motivation to get development off the ground.

**Appendix D: Incremental Cost of Enrollment**

 Table 4 of Chapter 5 presented sample results for the incremental cost of enrollment, but the method of calculation was described only in general terms. This Appendix presents the method of calculation.

 Accommodating a few students in a section with unused capacity incurs per-student costs like grading, but adding more students will at some point require extra sections--with the extra cost that entails." This formulation leads to two questions: (i) how should the number of extra students be characterized; and (ii) how should one determine the number of new sections that will be required? Adding the “new section cost” to the per-student cost (if any) will produce the overall incremental cost. (The prototype model did not include per-student cost, so text Table 4-4 reported only the “new section cost.”)

 It’s possible to assume a series of specific values for the extra students and calculate the incremental cost associated with each, but this would be very tedious. A better approach is to assume a probability distribution for the number of extra students and calculate the resulting expected value for incremental cost. An "exponential distribution" offers simplicity, and it also appears to reflect the kinds of situations usually encountered--for example, that small enrollment changes are considerably more probable than larger ones. The distribution is characterized by a single parameter: E[*x*], where *x* is the expected number of extra students.

 When the first extra section must be added depends either on (i) the total number of unused seats in the current sections, or (ii) the department’s policy for maximum class size. We'll call the unused capacity *Slack*. An additional section will need to be added when the extra enrollment exceeds *Slack* plus the *Maximum* section size.

 Figure D-1 depicts the scheme as it appears for positive enrollment changes. The solid curve shows an exponential probability density with mean E[*x*]=1/** (shown on the x-axis to denote the scale). The formulas for the density function and distribution (cumulative density) function are:

$$f\left[x\right]=λe^{-λx}; F\left[x\right]=1-e^{-λx}$$

 The dotted steps in the Figure denote the extra sections that must be added to accommodate the new enrollments: none until the *Slack* has been used up, and then one additional section when each *Max class size* is reached.

FIGURE D-1 ABOUT HERE.

 We want to calculate the expected cost (*C*) per incremental student (*x*), which is obtained as follows:

$$E\left[{C}/{x}\right]=\sum\_{n=0,1,2…}^{}n∙CpS×E\left[ \frac{1}{x}|n\right]∙Pr\left[n\right],$$

where $E\left[\frac{1}{x}|n\right]$ is the expectation of 1/*x* for the range of *x* included in *n*, Pr[*n*] = F[*x*n]−F[*x*n−1], and *CpS* is the cost of one section. (Notice that the expression for *n*=0 is zero.) E[1/*x*] for an exponential distribution has no closed-form solution, and the series solution converges very slowly due to the alternating signs of its successive terms. Therefore, we get the solution by calculating E[1/*x*] for many small intervals of *x*. It has proven practical to use a step size of one student, which, given that the solution must be integer, produces an exact result. A Visual Basic Function is presented below for readers who want to do the calculation in Excel.

TEXT BOX FOR APPENDIX D (IN TABLES FILE) ABOUT HERE

 The cost saved by reducing enrollments is obtained by applying a negative sign to the above calculation. In this case ”slack” means the amount by which classes can be made smaller without triggering the policy response of closing a section. While not discussed in the text, it’s very likely that the incremental costs for adding and subtracting students will differ because of these differing interpretations of slack. For example, a class that’s almost full will have little upside slack but potentially a lot of downside slack. This requires that calculation to take account of current class size as well as the upper and lower policy limits.

**Appendix E. Smart What-ifs in the Course-Based ABC Model**

 This appendix describes the “smart what-if” model in general terms, but hopefully in enough detail for a management science professional to be able to re-create the model. I prototyped the model as part of my research but for technical reasons did not include it in the software used for the pilot test described in Chapter 4.

 Step one is to decide which variables should be used as criteria and controls for the optimization. There are many possibilities, but the model as prototyped works well with only these:

 Criterion Variables

* 1. *Percentage of sections* in each course category
	2. *Average class size* for each category
	3. Percentage of adjunct sections for each category
	4. Faculty teaching load for the department

 Control Variables

1. *Number of sections* offered in each activity category
2. Number of adjunct sections in each category

 The enrollment forecast for each instructional category and the total number of sections that can be taught by the department’s regular faculty are taken as given (“exogenous”).

 The procedure adjusts the control variables to meet the criteria as closely as possible, based on the target and exception reporting thresholds presented in text Figure 4-7. A variable’s *Target* is the figure the department wants to achieve, but it would be a miracle if the exogenous factors allowed the targets for all criterion variables and course categories to be hit exactly. Hence we model the degree of discomfort (“regret”) associated with deviations from the targets--a quantity its assumed the department wants to minimize. Reasonable assumptions are that: (i) regret rises at an increasing rate as a variable gets further from its target; and (ii) the effect is inversely proportional to the size of the variable’s normal range.

 This leads to what’s called a "Quadratic Ideal Point Model" as shown below.

$$Minimize Regret=\sum\_{i}^{}w\_{i}\left(x\_{i}- x\_{i}^{T}\right)^{2},$$

where the control index *i* runs over the control variables, $x\_{i}$ are the criterion variables, $x\_{i}^{T}$ are the targets, and $w\_{i}$ are the weights described under (b) above.

 Minimization will be facilitated if the variables are transformed so the criteria are linear functions of the control variables. The linearity requirement is violated for some of the criteria described in the text but this is remedied by approximations like the one illustrated below for the first criterion: $\%Sects\_{i}$=$Sects\_{i}$/*Sects*.

 $\left( \frac{Sects\_{i}}{Sects}-\%Sects\_{i}^{T}\right)\rightarrow \left( \frac{Sects\_{i}-\%Sects\_{i}^{T}×Sects}{Sects}\right)\rightarrow \left( \frac{Sects\_{i}-\%Sects\_{i}^{T}×\sum\_{}^{}Sects\_{1}}{\sum\_{}^{}Sects\_{i}^{T}}\right)$

The transformation introduces only small errors while producing a strictly quadratic objective function.

 It’s possible to limit the amount a department can pay to hire adjuncts. First determine the average cost per adjunct section, which may vary by course category. The minimization algorithm then constrains *average compensation* × *number of adjunct sections* to stay within the available funds. Such adjunct budgets are common in today's universities.

 So far the unacceptability thresholds have not entered the picture, but that can be taken care of by adding additional constraints that require each variable to come in above its minimum acceptability threshold and below its maximum threshold. The resulting model, a quadratic objective function with linear constraints, is easy to minimize using a standard quadratic programing algorithm.

 To summarize, the smart forecasting procedure minimizes regret with respect to the control variables for each year in the planning period, subject to the budget and policy constraints. The optimizer can be run in either of two modes: (i) where the control variables must be integer, which of course is a condition of the real world; or (ii) as a non-integer approximation. The second mode runs much more quickly and may be acceptable for routine forecasting, though it might be risky to rely on it in some situations.

**Appendix F. Margin Equivalents for Start-up Programs**

 This appendix presents my proposed method for handling margins that are expected to vary over time when applying the mission-margin trade-off model discussed in Chapter 7. The method applies the trade-off model once and for all, during initial consideration of the project. Later adjustments involve only positive budget increments, which means the approach introduces a slightly conservative element into the budgeting process.

 Figure F-1 presents time series of cash flows for a hypothetical startup program that will be used to illustrate the solution. Panel A shows a situation where the expected steady-state margin is negative; Panel B shows one where the expected steady state is profitable. Years 1 through 5 depict outcomes during the project's introductory period and the bars labeled “SS” show the steady states. The sum of the bars (which is the same in both cases) represents what I'll call the project's "startup capital requirement"--i.e., shortfalls that will need to be funded before reaching the steady state.

 FIGURE F-1 ABOUT HERE

 Two basic approaches are available for handling the startup capital requirement: “equity funding” and “loan funding.” Their strengths and weaknesses are as follows.

1. *Equity Funding*. The university considers the funding to be an equity investment that does not have to be paid back. (Creation of equity funds represents an example of the "sustainability" allocations discussed in Chapter 5.) The trade-off analysis should use the project's expected steady-state margin, shown in the Figure as dotted lines, because that is the only figure that impacts the operating budget.

The above might be reasonable when the expected steady-state margin is negative (Part A of the Figure) but there is a serious problem when the anticipated margin is positive. This situation would have the Equity Fund pay the annual surplus (the distance between SS and zero) to the operating budget during each startup year. Such a procedure would invite a financially hard-pressed administration to "raid" the Equity Fund by putting forward plausibly profitable but highly risky new ventures--a loss of financial discipline that should not be tolerated.

1. *Loan Funding*. The startup capital requirement is handled by advances from a revolving fund that needs to be paid back, possibly with interest. The “once-and-for-all” requirement introduced above means the operating budget should provide a flat payment during the startup period that is sufficient to cover the shortfalls and amortize the loan. The annual payments required for a zero interest rate are shown by the dashed lines labeled “Avg” (average).

 The budget should be adjusted to reflect the steady-state margin once the debt has been extinguished, shown by the "Bump-up" increment from the Average to the steady state. The bump-up will be positive unless the financial projections have been seriously wrong. Showing the bump-up as a horizontal bar to the right of the relevant icon on the tradeoff Options Chart (e.g., text Figure 5-9) would remind users of the eventual upside potential, which may prove helpful as they make their Choice-group selections.

 There is merit in requiring the operating budget to have some "skin in the game" with respect to startup capital requirements, but not so much as to stifle innovation. This can be accomplished by blending the two funding approaches. Getting the right balance is of course of matter of judgment, but so is virtually everything connected with a university’s resource allocation.

**Appendix G. Extensions to the Mission-Margin Model**

 This Appendix performs four tasks: (i) to provide the mathematical and conceptual underpinnings for the economic theory of not-for-profit enterprises discussed in Chapter 2; (ii) to show how to quantify the Frontier Curve (“mission contribution function” described at the end of Chapter 5; (iii) to describe the budget optimization tool also described also described at the end of Chapter 5; and (iv) to justify the assertions of Chapter 2 about the relation between financial affluence and the ability to further mission-related values. I won't repeat those descriptions here, so readers should read the material in conjunction with the respective chapters.

Not-for-Profit Enterprise Theory

 The for-profit decision rule is derived by maximizing the entity’s profit function, *Profit* (***x***), where *x* is the vector of activities that might be undertaken. Let R(***x***) represent the revenue produced by the activities (“demand function”) and C(***x***) the costs incurred by them (“cost function”). Then:

 Maximize: *Profit* (***x***) = R(***x***) – C(***x***) with respect to ***x***.

The maximum occurs where the partial derivatives of the profit function vanish: i.e., where *Marginal Profit* (*x*i) = 0 for every acivity *x*i. This requires the derivatives of the revenue and cost functions to equal one another, or in more familiar terminology:

 MR(*x*i) = MC(*x*i), for all *i*

which is *Marginal revenue* = *Marginal cost* as used in the text.

 Not-for-profit entities like traditional universities maximize an *Institutional value function* rather than profits, while requiring revenues equal to costs (“budget balance”). Let V(***x***) be the value function. Then the maximization is:

 Maximize: V(***x***) with respect to ***x***.
 subject to
 R(***x***) – C(***x***) = 0.

We proceed by adding the product of the constraint (which equals zero at the maximum but is non-zero elsewhere) and a “Lagrangian undetermined multiplier” (*λ*) to the objective function to the objective:

 Maximize: *Value* (***x***) + *λ* {R(***x***) – C(***x***)} with respect to ***x***.

Setting the derivatives with respect to both ***x*** and *λ* to zero yields the following system of equations:

 MV(***x***) + *λ* {MR(*x*i) – MC(*x*i)} =0 for each *i* R(***x***) – C(***x***) = 0,

The Lagrangian, *λ*, can be interpreted as the *Marginal value of money* because it is the extra value created by an extra dollar of margin. The last step is to divide the first part of the above by *λ* to obtain:

 MV(*x*i)/*λ* + MR(*x*i) = MC(*x*i)} for each *i.*

This is the equation given in the text forthe not-for-profit decision rule:

 *Value added* + *Incremental revenue* = *Incremental cost.*

An alternative’s contribution to mission now is revealed as the ratio of the *slope of the* *value function* for each activity to the *marginal value of money*.

Quantifying a Budget Alternative's Mission Contribution

 Text Figure 5-10 introduced two elements that were not a part of the previous results:

* Feasible alternatives that were “on the cusp” of being selected (i.e., were just in the money) are indicated by larger icons than the others. They are called *Frontier Points*.
* A curve that lies slightly *below and to the left* of the points that were selected, and slightly *above and to the right* of the ones that were feasible but not selected at the end of the exercise (the “chosen path” mentioned below). This is called the “*Frontier Curve*.” Points that lie above and to the right of the Curve are included in the budget and conversely.

The Frontier Curve can be viewed as estimating an alternative’s “Mission Contribution” (heretofore referred to as “Value”) as a function of its Rank. Hence it also may be referred to as the “Mission Contribution Function.”

 The *Frontier Curve* is estimated from the *Frontier Points* using a special least squares procedure. The procedure forces the curve into the chosen path and prevents it from “bending backward.” (Bending backward means travel in a northeasterly rather than southwesterly direction, which would violate the principle of dominance.) The estimation can be performed using Excel’s Visual Basic capability but, as with the tradeoff analysis, it would be better to create a specialized app.

 The procedure’s first step is to postulate a mathematical form for the Frontier Curve. Let this function be denoted by V[*R*], where *R* stands for rank. The simplest possible function is a linear one, where each change in ranking contributes the same amount to the institution's mission. If one starts the metric at 100 and sets the increment to –4, say, then V[*R*] = 100 – 4 (*R*–1) so that V[1] = 100, V[2] = 96, and so on down to V[26] = 0. (Larger numerical ranks produce lower contributions.) A bigger increment allows for negative mission contributions as discussed earlier. For example, V[*R*] = 100 –5.5 (*R*–1) makes V[*R*] negative for all ranks greater than 22.

 While good for illustration, the linear function is too restrictive to be used in practice. For example, there may be very little difference among the top-ranked packages and/or very large differences among the low-ranked ones. Such variations can be accommodated by a high-order polynomial.

 V[*R*] = *b*0 + *b*1 *R* + *b*2 *R*2 + *b*3 *R*3+ *b*4 *R*4+ *b*5 *R*5 + …

The data points in the illustrative problem required terms to the 13th power to give an adequate fit. (There are thirteen data points, so this leaves zero degrees of freedom; however, that’s not a problem given the nature of the problem.) The usual desiderata for defining a preference function (e.g. that it be convex) do not apply because: (i) the best fit to the dataset may involve one or more inflection points; and (ii) the knapsack optimization algorithm does not require convexity.

 We’re interested in the decision alternatives that define the chosen path. Alternatives not close to the frontier do figure in the optimization to be described later, but they are not relevant for estimating the mission contribution function. The thirteen frontier points in the example proved sufficient to estimate function, although more points would have added power to the analysis.

 The next step is to substitute the polynomial, for V[*R*], in place of the *Mission contribution* term of the “Not-for-profit Decision Rule” given earlier. The result is:

 *Margin* = *b*0 + *b*1 *R* + *b*2 *R*2 + *b*3 *R*3+ *b*4 *R*4+ *b*5 *R*5 + …,

where *Margin* has been placed on the left-hand-side and given a positive sign to reflect its role as the dependent variable in what amounts to a multiple regression. This formulation defines the *Contribution* metric in the same units as –*Margin*, but the units can be changed through multiplication by any positive constant. Notice that all the variables are readily available in text Table 5-7.

 The unknown parameters (*b*-values) are estimated from the frontier points by minimizing the sum of squared deviations between the equation's left-and right-hand sides. Two constraints are added to the minimization in order handle the following requirements.

1. The contribution function should be monotonic with respect to *R*: that is, it should not bend backward. Violation of this condition would mean an alternative further down on the ranking scale would have a larger contribution metric than one higher up, which is not acceptable. The estimator prevents this condition by minimizing the sum of squared deviations subject to the condition that the slope of the contribution function be non-negative for every decision package. That is:

 dV[*R*]/d*R* = *b*1 + 2 *b*2 *R*+ 3 *b*3 *R*2+ 4 *b*4 *R*3+ 5 *b*5 *R*4 + …≥ 0,

The constraint does not bind in the case of zero derivatives, which indicate tied rankings and thus pose no problem.

1. The contribution function must lie to the left of the funded points and to the right of the unfunded ones. That is:

 V[*R*] ≤ *Margin* – *k* for the Funded (green) frontier points

 V[*R*] ≥ *Margin* + *k* for the Unfunded (yellow) frontier points,

 where *k* is a small non-negative “buffer constant” to be discussed later.[[3]](#endnote-3) (The results presented in the text are based on *k*=−300.)

The constrained minimization problem can be solved using a quadratic programming procedure of the kind included in Excel’s Solver tool.

 The coefficients for the preference function illustrated in the text are shown in Table G-1. (Term 0 in the polynomial’s constant term, Term 1 the linear term, etc..) The *Rank* value used with these coefficients has been transformed to the interval between 1.0 (best) and 2.0 (worst) in order to reduce rounding errors. Contribution is expressed in “margin-equivalent” terms, with negative contributions being better than positive ones. The coefficients’ alternating signs would be worrisome in many studies, but that’s not a problem here because the objective is simply to interpolate between the frontier points without trying to infer anything about structure. As noted in the text, the above can be used to calculate V[*R*] for a new decision package once it has been slotted it into the list of ranks.

 TABLE G-1 ABOUT HERE

 The *Mission contribution* equation allows one to plug in an alternative’s *Rank* and estimate its *Contribution*. The previous paragraph explained why this is so for the frontier points, but how about the other points? Consider two frontier points with rank *X* and *X*+2 and one non-frontier point with rank *X*+1. The equation gives estimated values for *X* and *X*+2, and we know that *Value* for *X*+1 must lie between *X* and *X*+2. Hence it is sensible to interpolate between these two numbers.[[4]](#endnote-4) The equation converts the rank-order information about direction of preference into quantitative information about degree of preference or dislike. For example, it shows that the higher-ranked points produce considerably greater mission contribution than the lower-ranked ones. This is not a necessary outcome, however. An economist would say that the original tradeoff analysis, used to estimate the *mission contribution* curve, has “revealed” the university’s underlying preferences.[[5]](#endnote-5)

A Budget Optimization Tool

 The estimated contribution function enables construction of a Budget Optimization Tool for finding the budget alternatives that produce the largest possible contribution given the university’s available funds. The procedure maximizes the sum of the estimated mission contributions of the chosen alternatives subject to the budget limit. Management scientists call this a "knapsack problem": one wants the total contribution of chosen items as large as possible without exceeding the knapsack's capacity. Our problem differs from the classic knapsack one because some contribution and/or margins can be negative, but that poses no difficulty. Implementation proceeds by defining each decision alternative as a binary variable that equals 1 if it is chosen and 0 if it's not, and then maximizing the sum of the included mission contributions subject to the prespecified budget limit and any precedence relations. The optimization can be performed using Excel but, as with the previous analyses, a user-friendly app that decision-makers could use hands-on would pay dividends.

 The optimization can be formulated as the following integer programming problem. Define:

 *I:* the *index* of the decision package

 *X*i: the package's *decision variable*: *X*i = 1 if the it is included in the
 optimized budget and *X*i = 0 if not

 *v*i:the package's *mission contribution* as determined by V[*R*]

 *m*i *:*the package's *margin*

 *p*ithe package's *precedence variable*, if any: *P*i = *X*j, where *X*j refers

 to the package pointed to by *i*'s precedence relation and

 *P*i = 0 if *i* has no precedence relation.

 *B* the budget limit

 Now the problem can be stated as:

 Maximize

 ∑*i* { *v*i × *X*i} with respect to the Xi

 Subject to the constraints

 *Xi is Integer To prevent fractional choices*

 *0 ≤ Xi ≤ 1 (all i) Upper and lower limits for the
 integer definitions*

 *Xi ≤ pi (all i) Precedence requirements*

 *∑I* {*–mi × Xi*} *≤ B Budget limit*

This maximizes the sum-product of the decision variables (*X*i) times their contributions (*V*i), subject to the four constraints. The first two constraints enforce the variable definitions. The third keeps *Xi* at 0 unless (i) the package preceding it already has been selected or (ii) it has no precedence relation. (*Pi* = 1 in either of these cases, whereas *Pi* = 0 if there is a precedence relation and it's not in the budget.) The fourth constraint ensures that the sum of the margins for the chosen alternatives does not exceed the available budget. This is a variation on the classic knapsack problem in that some *v* and *m* may be negative and there is an extra constraint, but integer programming can still obtain a solution.

 Optimization is faster and more powerful than the tradeoff app discussed in the text, although it also is more demanding analytically. The algorithm always gets the right answer for the data fed into it, but one must be aware that the estimated mission contribution function is just that--an estimate. Hence the tool may not quite replicate the list of selected alternatives obtained in the underlying dominance-based analysis. (The difference in total mission contribution achieved will be minor, however.) But while users lose the “hands-on control” that characterizes the tradeoff app, the optimization tool offers the huge advantage of performing sensitivity analysis at the push of a button--which gives users a much better opportunity to envision the consequences of changes in the dataset. Importantly, the tool allows one to change the budget limit as well as other elements of the dataset.

 Users can overcome the loss of hands-on control by considering the optimization app’s calculated budget as being only a recommendation: the penultimate rather than the ultimate step in the process. The results should be entered on a new Options Chart, and changes made as desired. (The frontier curve isn’t needed for this purpose, so changes in the budget limit are perfectly admissible.) Combining the optimizing and dominance methods provides a great deal of power without the loss of hands-on control.

 As mentioned above, the optimization result may not quite replicate the selected alternatives from the underlying dominance-based analysis. This is to be expected given that it works on an *approximation* to the decision-maker's subjective contribution function. It may be possible to improve the approximation by adding terms to the function’s polynomial and/or adjusting the "buffer constant” (*b*) in subparagraph 2 of the estimator description. (It's also possible that the subjective analysis itself lacked perfect consistency.) But while the two lists of selected alternatives may vary, the differences in contributions attained are likely to be quite small. This suggests that the fine structure of choices may not make a lot of difference. Large errors caused by making choices piecemeal are the real value killers, and these are avoided in both the integer programming and subjective procedures.

Effects of Financial Affluence and Stringency

 I asserted in Chapter 1 that the traditional university's ability to support money-losing programs--to exert its values over those of the marketplace--is directly proportional to its degree of budget flexibility. How this works is illustrated by the five scenarios described below. Figure G-1 shows the *Frontier Curve* associated with each scenario, along with the final results of the *Base Case* analysis. The divisors used in the Relaxed Budget and Stringent Budget scenarios represent the “Marginal Value of Money,” for the indicated budget limits, which were discussed above. They were obtained by running the Optimization App for various budget limits, fitting a smooth curve to the results (the curve is convex from above), and calculating the slopes of the curve at the indicated points.

* *Base Case* (the result shown in text Figure 5-10). The budget limit is $6,500, which is sufficient to fund a goodly fraction of the proposed items but by no means all of them.
* *Very Loose Budget*. Money is so easy that all alternatives with positive *mission contribution* can be funded, and there is no need to fund any with negative contributions. The frontier curve is a horizontal line, at the point where the curve crosses the zero-margin line. It is obtained by dividing the base-case curve by a number very close to zero: so that any upward shift on the *Rank* scale translates to a very large *Mission Contribution*.
* *Relaxed Budget* (compared to the Base Case). Money is easy but it’s not unlimited. In this case $15,000 thousand is available for distribution (as opposed to the $6,500 thousand in the base case), which produces a divisor of 0.27. The curve, which has been rotated downward so that small changes in rank produce big changes in mission contribution, permits more alternatives to be funded than in the base case.
* *Stringent Budget*. The limit assumed for this case is to require a profit of $1,500 thousand. The divisor is 1.85, which rotates the curve upward, so fewer alternatives can be funded.
* *Very Tight Budget.* The university wants to harvest all possible positive margins and incur no liabilities--perhaps because it is threatened with bankruptcy. This requires a vertical frontier that coincides with the zero-margin axis (in effect dividing by a number close to infinity). All alternatives to the right of the line are accepted and none of those to the left, which amounts to profit maximization.

 FIGURE G-1 ABOUT HERE

 The *Frontier Curves* in Figure G-1 were generated through division of the base case curve by a constant called the “incremental value of money”: in principle, the amount of extra mission contribution attainable by adding to the budget limit.[[6]](#endnote-6) The incremental value of money approaches zero when funds are very loose (the university already is doing all it can) and infinity when funds are very tight (the university teeters on the brink of bankruptcy). For purposes of the Figure, the figures for incremental value of money were approximated from the final objective function values achieved by running the optimization tool for the indicated budget limits.

1. Organized Research is identified in the general ledger and thus can easily be excluded. Departmental research can be excluded by means of a notional or survey-based allocation scheme. See Anguiano (2014) and the top-down allocation section of this Chapter. [↑](#endnote-ref-1)
2. http://creativecommons.org. The automation tools of Microsoft Visio might be used to advantage. [↑](#endnote-ref-2)
3. Some non-linear programming algorithms have trouble finding a feasible solution. If that happens, try eliminating this constraint *except* for the dominant points that have not been selected (i.e., the ones for which Mission Contribution must be negative); this produces a considerably simpler problem. [↑](#endnote-ref-3)
4. The non-for-profit decision rule for discreet alternatives is an inequality rather than an equality, so the non-frontier points conform to the rule just as the frontier ones do. [↑](#endnote-ref-4)
5. Nobelist Paul Samuelson introduced this notion of “revealed preference” in his Foundations of Economic Analysis (Samuelson, 1947). [↑](#endnote-ref-5)
6. I say “in principle” because the concept relates to a continuous model rather than the discreet one used here. The difference is not important for present purposes, however. [↑](#endnote-ref-6)