Spreadsheet Modeling for Insight

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Abstract

It is widely recognized that spreadsheets are error-filled, their creators are over-confident, and the process by which they are developed is chaotic. It is less well-understood that spreadsheet users generally lack the skills needed to derive practical insights from their models. Modeling for insight requires skills in establishing a base case, performing sensitivity analysis, using back-solving, and (when necessary) carrying out optimization and simulation. Some of these tasks are made possible only with specialized add-ins to Excel. In this paper we present an overview of the skills and software tools needed to model for insight.

Key words: sensitivity analysis, software engineering, spreadsheet engineering

1 Introduction

There is ample evidence that spreadsheets as actually used in industry are highly problematic [1]. Many, if not most, spreadsheets harbor serious bugs. The end-users who typically design and use spreadsheets are under-trained and overconfident in the accuracy of their models. The process that most spreadsheet developers use is chaotic, leading to time wasted in rework and in high error rates. Few spreadsheets are tested in any formal manner. Finally, many organizations fail to follow standard procedures for documentation or version control, which leads to errors in use even if the spreadsheets themselves are correct. While these problems are well known to a few researchers, and widely suspected by many managers, few companies recognize the risks that spreadsheet errors pose.

This paper is concerned with a much less well understood problem, involving missed opportunities to extract useful business insights from spreadsheet

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models. Many spreadsheet developers have extensive skills in Excel itself but far fewer have a disciplined approach to using a model to inform a decision or shed light on a business problem. We advocate an engineering approach to the process of designing and building a spreadsheet. In the same spirit, the analysis process itself can be improved by providing structure and specific software tools. We will discuss in particular four analytic tools that are contained in the Sensitivity Toolkit, a publicly-available Excel add-in we built.

2 Elements of Spreadsheet Engineering

Spreadsheet modeling is a form of computer programming, although it is usually carried out by people who do not think of themselves as programmers. Moreover, few spreadsheet developers are trained in software engineering. In order to improve this situation we have undertaken the task of translating the principles of software engineering into a form that end-users in business can actually use. We call the resulting discipline spreadsheet engineering. Our motivation is to improve both the efficiency and the effectiveness with which spreadsheets are created. An efficient design process uses the minimum time and effort to achieve results. An effective process achieves results that meet the users’ requirements. Although spreadsheet modeling is a creative process, and thus cannot be reduced to a simple recipe, every spreadsheet passes through a predictable series of four stages: designing, building, testing, and analysis. Some of the principles in each of the first three phases are given below:

- **designing**
  - sketch the spreadsheet
  - organize the spreadsheet into modules
  - start small
  - isolate input parameters
  - design for use
  - keep it simple
  - design for understanding
  - document important data and formulas

- **building**
  - follow a plan
  - build one module at a time
  - predict the outcome of each formula
  - Copy and Paste formulas carefully
  - use relative and absolute addresses to simplify copying
  - use the Function Wizard to ensure correct syntax
  - use range names to make formulas easy to read

- **testing**
  - check that numerical results look plausible
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- check that formulas are correct
- test that model performance is plausible

Since the focus of this paper is on improving the analysis phase, we will not discuss the first three phases of spreadsheet engineering further in this paper. These are described in more detail in [2].

3 Insight: The Goal of Spreadsheet Modeling

In many business applications, the ultimate goal of a spreadsheet modeling effort is not numerical at all; rather, it is an *insight* into a problem or situation, often a decision facing the organization. In our minds, an insight is never a number but can be expressed in natural language that managers understand, often in the form of a graph. Insights often arise from surprises. For example, Option A looks better than Option B on first glance, but our analysis shows why B actually is a better choice. Many insights involve trade-offs. For example, as we add capacity we find at first that service improves faster than cost increases, but eventually increasing costs swamp improvements in service.

If we accept the notion that the purpose of many spreadsheet models is to identify insights, it follows that the spreadsheet itself is not a particularly good vehicle for this purpose. As convenient as the spreadsheet format is, it does not display the *relationships* involved in a model, but hides them behind a mass of numbers. Nor does it show how changes in inputs affect outputs, which is where insight begins. Users of spreadsheets need to be taught how to make the row-and-column format work for them to generate insights. There are several powerful but obscure features built into Excel (like Goal Seek and Data Table) that can assist in this process. To augment these tools we have built a Visual Basic add-in called the Sensitivity Toolkit that automates some of the most powerful sensitivity analysis tools. (This add-in is publicly available at [http://mba.tuck.dartmouth.edu/toolkit/](http://mba.tuck.dartmouth.edu/toolkit/))

Although Excel itself has thousands of features, most of the analysis done with spreadsheets falls into one of the following five categories:

- base-case analysis
- what-if analysis
- breakeven analysis
- optimization analysis
- risk analysis

Within each of these categories, there are specific Excel tools, such as the Goal Seek tool, and add-ins, such as Solver [3] and Crystal Ball [4], which can be used either to automate tedious calculations or to find powerful business insights that cannot be found any other way. Some of these tools, such as Solver, are quite complex and can be given only a cursory treatment here. By contrast, some of the other tools we describe are extremely simple, yet are
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underutilized by the majority of spreadsheet users.

We will use the spreadsheet model Advertising Budget (see Figure 1) to illustrate each of these five categories of analysis. This model takes various inputs, including the price and unit costs of a product, and calculates revenues, total costs, and profit over the coming year by quarters. The essential relationship in the model is a sales response to advertising function characterized by diminishing returns. The fundamental question the model will be used to answer is how we should allocate a fixed advertising budget across quarters.

3.1 Base-case analysis

Almost every spreadsheet analysis involves measuring outcomes relative to some common point of comparison, or base case. Therefore, it is worth giving some thought to how the base case is chosen. A base case is often drawn from current policy or common practice, but there are many other alternatives. Where there is considerable uncertainty in the decision problem, it may be appropriate for the base case to depict the most likely scenario; in other circumstances, the worst case or the best case might be a good choice.

Sometimes, several base cases are used. For example, we might start the analysis with a version of the model that takes last year’s results as the base case. Later in the analysis, we might develop another base case using a proposed plan for the coming year. At either stage, the base case is the starting point from which an analyst can explore the model using the tools described in this paper, and thereby gain insights into the corresponding business situation.

In the Advertising Budget example, most of the input parameters such as price and cost are forecasts for the coming year. These inputs would typically be based on previous experience, modified by our hunches as to what will be different in the coming year. But what values should we assume for the decision variables, the four quarterly advertising allocations, in the base case? Our ultimate goal is to find the best values for these decisions, but that is premature at this point. A natural alternative is to take last year’s advertising expenditures ($10,000 in each quarter) as the base-case decisions, both because this is a simple plan and because initial indications point to a repeat for this year’s decisions.

3.2 What-if analysis

Once a base case has been specified, the next step in analysis often involves nothing more sophisticated than varying one of the inputs to determine how the key outputs change. Assessing the change in outputs associated with a given change in inputs is called what-if analysis. The inputs may be parameters, in which case we are asking how sensitive our base-case results are to forecasting errors or other changes in those values. Alternatively, the inputs we vary may be decision variables, in which case we are exploring whether changes in our decisions might improve our results, for a given set
of input parameters. Finally, there is another type of what-if analysis, in which we test the effect on the results of changing some aspect of our model’s structure. For example, we might replace a linear relationship between price and sales with a nonlinear one. In all three of these forms of analysis, the general idea is to alter an assumption and then trace the effect on the model’s outputs.

We use the term sensitivity analysis interchangeably with the term what-if analysis. However, we are aware that sensitivity analysis sometimes conveys a distinct meaning. In optimization models, where optimal decision variables themselves depend on parameters, we use the term sensitivity analysis specifically to mean the effect of changing a parameter on the optimal outcome. (In optimization models, the term what-if analysis is seldom used.)

When we vary a parameter, we are implicitly asking what would happen if the given information were different. That is, what if we had made a different numerical assumption at the outset, but everything else remained unchanged? This kind of questioning is important because the parameters of our model represent assumptions or forecasts about the environment for decision making. If the environment turns out to be different than we had assumed, then it stands to reason that the results will also be different. What-if analysis measures that difference and helps us appreciate the potential importance of each numerical assumption.

In the Advertising Budget example, if unit cost rises to $26 from $25, then annual profit drops to $53,700. In other words, an increase of 4 percent in the unit cost will reduce profit by nearly 23 percent. Thus, it would appear that profits are quite sensitive to unit cost, and, in light of this insight, we may decide we should monitor the market conditions that influence the material and labor components of cost.

When we vary a decision variable, we are exploring outcomes that we can influence. First, we’d like to know whether changing the value of a decision variable would lead to an improvement in the results. If we locate an improvement, we can then try to determine what value of the decision variable would result in the best improvement. This kind of questioning is a little different from asking about a parameter, because we can act directly on what we learn. What-if analysis can thus lead us to better decisions.

In the Advertising Budget example, if we spend an additional $1,000 on advertising in the first quarter, then annual profit rises to $69,882. In other words, an increase of 10 percent in the advertising expenditure during Q1 will translate into an increase of roughly 0.3 percent in annual profit. Thus, profits do not seem very sensitive to small changes in advertising expenditures in Q1, all else being equal. Nevertheless, we have identified a way to increase profits. We might guess that the small percentage change in profit reflects the fact that expenditures in the neighborhood of $10,000 are close to optimal, but we will have to gather more information before we are ready to draw conclusions about optimality.
In addition to testing the sensitivity of results to parameters and decision variables, there are situations in which we want to test the impact of some element of model structure. For example, we may have assumed that there is a linear relationship between price and sales. As part of what-if analysis, we might then ask whether a nonlinear demand-price relationship would materially alter our conclusions. As another example, we may have assumed that our competitors will not change their prices in the coming year. If we then determine that our own prices should increase substantially over that time, we might ask how our results would change if our competitors were to react to our pricing decisions by matching our price increases. These what-if questions are more complex than simple changes to a parameter or a decision variable because they involve alterations in the underlying structure of the model. Nonetheless, an important aspect of successful modeling is testing the sensitivity of results to key assumptions in the structure of the model.

In the Advertising Budget example, the relationship between advertising and sales is given by the nonlinear function:

\[ \text{Sales} = 35 \times \text{Seasonal Factor} \times \sqrt{\text{Advertising}} + 3000. \]  

(1)

In the spirit of structural sensitivity analysis, we can ask how different our results would be if we were to replace this relationship with a linear one. For example, the linear relationship

\[ \text{Sales} = 3,000 + 0.1(\text{Advertising} \times \text{Seasonal Factor}) \]  

(2)

lies close to the nonlinear curve for advertising levels around $10,000. When we substitute this relationship into the base-case model, holding advertising constant at $10,000 each quarter, we find that profit changes only slightly, to $70,000. But in this model, if we then increase Q1 advertising by $1,000, we find that profit decreases, while in the base-case model it increases. Evidently, this structural assumption does have a significant impact on the desired levels of advertising.

We have illustrated what we might call a “one-at-a-time” form of what-if analysis, where we vary one input at a time, keeping other inputs unchanged. We could, of course, vary two or more inputs simultaneously, but these more complex experiments become increasingly difficult to interpret. In many cases, we can gain the necessary insights by varying the inputs one at a time.

It is important not to underestimate the power of this first step in analysis. Simple what-if exploration is one of the most effective ways to develop a deeper understanding of the model and the system it represents. It is also part of the debugging process. When what-if analysis reveals something unexpected, we have either found a useful insight or perhaps discovered a bug.

Predicting the outcome of a what-if test is an important part of the learning process. For example, in the Advertising Budget example, what would be the result of doubling the selling price? Would profits double as well? In the base
case, with a price of $40, profits total $69,662. If we double the price, we find that profits increase to $612,386. Profits increase by much more than a factor of two when prices double. After a little thought, we should see the reasons. For one, costs do not increase in proportion to volume; for another, demand is not influenced by price in this model. Thus, the sensitivity test helps us to understand the nature of the cost structure — that it’s not proportional — as well as one limitation of the model — that no link exists between demand and price.

3.2.1 Data Sensitivity
The Data Sensitivity tool automates certain kinds of what-if analysis. It simply recalculates the spreadsheet for a series of values of an input cell and tabulates the resulting values of an output cell. This allows the analyst to perform several related what-if tests in one pass rather than entering each input value and recording each corresponding output.

The Data Sensitivity tool is one module in the Sensitivity Toolkit, which is an add-in to Excel (available at http://mba.tuck.dartmouth.edu/toolkit). Once the Toolkit is installed, the Sensitivity Toolkit option will appear on the far right of the menu bar (see Figure 1). Data Sensitivity and the other modules can be accessed from this menu. (An equivalent tool called Data Table is built into Excel.)

We illustrate the use of the Data Sensitivity tool in the Advertising Budget model by showing how variations in unit cost from a low of $20 to a high of $30 affect profit. (Note: we will not describe the specific steps required to run any of the tools in the Toolkit in this paper: details can be found in [2] or in the Help Facility in the Toolkit itself).

Figure 2 shows the output generated by the Data Sensitivity tool. A worksheet has been added to the workbook, and the first two columns on the sheet contain the table of what-if values. In effect, the what-if test has been repeated for each unit-cost value from $20 to $30 in steps of $1, and the results have been recorded in the table. In addition, the table is automatically converted to a graph. As the table and graph both show, annual profits drop as the unit cost increases, and the cost-profit relationship is linear. We can also see that the breakeven value of the unit cost falls between $29 and $30, since profits cross from positive values to negative values somewhere in this interval.

Note that the Data Sensitivity tool requires that we provide a single cell address to reference the input being varied in a one-way table. The tool will work correctly only if the input has been placed in a single location. By contrast, if an input parameter had been embedded in several cells, the tool would have given incorrect answers when we tried to vary the input. Thus, the use of single and separate locations for parameters (or for decisions), which is a fundamental principle of spreadsheet engineering, makes it possible to take advantage of the tool’s capability.
We can also use the Data Sensitivity tool to analyze the sensitivity of an output to two inputs. This option gives rise to a two-way table, in contrast to the one-way sensitivity table illustrated above. To demonstrate this feature, we can build a table showing how profits are affected by both $Q_1$ advertising and $Q_2$ advertising. By studying the results in Figure 3, we can make a quick comparison between the effect of additional spending in $Q_1$ and the effect of the same spending in $Q_2$. As we can observe in the table, moving across a row generates more profit than moving the same distance down a column. This pattern tells us that we can gain more from spending additional dollars in $Q_2$ than from the same additional dollars in $Q_1$. This observation suggests that, starting with the base case, we could improve profits by shifting dollars from $Q_1$ to $Q_2$. We can also note from the table, or from the three-dimensional chart that automatically accompanies it, that the relationship between profits and advertising expenditures is not linear. Instead, profits show diminishing returns to advertising.

3.2.2 Tornado charts
Another useful tool for sensitivity analysis is the tornado chart. In contrast to the information produced by the Data Sensitivity tool, which shows how sensitive an output is to one or perhaps two inputs, a tornado chart shows how sensitive the output is to several different inputs. Consequently, it shows us which parameters have a major impact on the results and which have minor impact.

Tornado charts are created by changing input values one at a time and recording the variations in the output. The simplest approach is to vary each input by a fixed percentage, such as $\pm 10$ percent, of its base-case value. For each parameter in turn, we increase the base-case value by 10 percent and record the output, then decrease the base-case value by 10 percent and record the output. Next, we calculate the absolute difference between these two outcomes and depict the results in the order of these differences.

The Sensitivity Toolkit contains a tool for generating tornado charts. The Tornado Chart tool provides a choice of three options:

- Constant Percentage
- Variable Percentage
- Percentiles

We will illustrate the Constant Percentage case first. The tornado chart appears on a newly inserted worksheet, as shown in Figure 4. The horizontal axis at the top of the chart shows profits; the bars in the chart show the changes in profit resulting from $\pm 10$ percent changes in each input. After calculating the values (which are recorded in the accompanying table on the same worksheet), the bars are sorted from largest to smallest for display in the diagram. Thus, the most sensitive inputs appear at the top, with the largest horizontal spans. The least sensitive inputs appear toward the bottom, with
the smallest horizontal spans. Drawing the chart using horizontal bars, with the largest span at the top and the smallest at the bottom, suggests the shape of a tornado, hence the name. If some of the information in the chart seems unclear, details can usually be found in the accompanying table, which is constructed on the same worksheet by the Tornado Chart tool. In our example, we can see in the table that price has the biggest impact (a range of more than $108,000), with unit cost next (a range of nearly $80,000), and the other inputs far behind in impact on profit.

The standardization achieved by using a common percentage for the change in inputs (10 percent in our example) makes it easy to compare the results from one input to another, but it may also be misleading. A 10 percent range may be realistic for one parameter, while 20 percent is realistic for another, and 5 percent for a third. The critical factor is the size of the forecast error for each parameter. If these ranges are significantly different, we should assign different percentages to different inputs. This can be accomplished using the Variable Percentage option in the Tornado Chart tool.

To illustrate the Variable Percentage option in the Advertising Budget example, suppose we limit ourselves to seven parameters: price, cost, four seasonal factors, and overhead rate. Suppose that, based on a detailed assessment of the uncertainty in these parameters, we choose to vary price by 5 percent, cost by 12 percent, seasonal factors by 8 percent, and overhead rate by 3 percent. The resulting tornado chart is shown in Figure 5. As the results show, cost now has the biggest impact on profits, partly because it has a larger range of uncertainty than price.

3.3 Breakeven analysis

Many managers and analysts throw up their hands in the face of uncertainty about critical parameters. If we ask a manager to directly estimate market share for a new product, the reply may be: “I have no idea what market share we’ll capture”. A powerful strategy in this situation is to reverse the sense of the question and ask not, “What will our market share be?” but rather, “How high does our market share have to get before we turn a profit?” The trick here is to look for a breakeven, or cutoff, level for a parameter — that is, a target value of the parameter at which some particularly interesting event occurs, such as reaching zero profits or making a 15 percent return on invested assets. Managers who cannot predict market share can often determine whether a particular breakeven share is likely to occur. This is why breakeven analysis is so powerful.

Even if we have no idea of the market share for the new product, we should be able to build a model that calculates profit given some assumption about market share. Once market share takes the role of a parameter in our model, we can use the Data Sensitivity tool to construct a graph of profit as a function of market share. Then, from the graph, we can find the breakeven
market share quite accurately.

New capital investments are usually evaluated in terms of their net present value, but the appropriate discount rate to use is not always obvious. Rather than attempting to determine the appropriate discount rate precisely, we can take the breakeven approach and ask how high would the discount rate have to be in order for this project to have an NPV of zero? (The answer to this question is generally known as the internal rate of return.) If the answer is 28 percent, we can be confident that the project is a good investment. On the other hand, if breakeven occurs at 9 percent, we may want to do further research to establish whether the appropriate discount rate is clearly below this level.

Breakeven values for parameters can be determined manually, by repeatedly changing input values until the output reaches the desired target. This can often be done fairly quickly by an intelligent trial-and-error search in Excel. In the Advertising Budget example, suppose we want to find the breakeven cost to the nearest penny. Recall our example earlier, where we noted that profit goes to zero between a unit cost of $29 and a unit cost of $30. By repeating the search between these two costs in steps of $0.10, we can find the breakeven cost to the nearest dime. If we repeat the search once more, in steps of $0.01, we will obtain the value at the precision we seek.

However, Excel also provides a specialized tool called Goal Seek (in the Tools menu) for performing this type of search. The tool locates the desired unit cost as $29.36, and the corresponding calculations will be displayed on the spreadsheet.

Note that the Goal Seek tool searches for a prescribed level in the relation between a single output and a single input. Thus, it requires the parameter or decision being varied to reside in a single location, reinforcing one of our design principles.

3.4 Optimization analysis

Another fundamental type of managerial question takes the form of finding a set of decision variables that achieves the best possible value of an output. In fact, we might claim that the fundamental management task is to make choices that result in optimal outputs. Solver is an important tool for this purpose. Solver is an add-in for Excel that makes it possible to optimize models with multiple decision variables and possibly constraints on the choice of decision variables. Optimization is a complex subject, and we can only provide a glimpse of its power here by demonstrating a simple application in the Advertising Budget example.

Suppose we wish to maximize total profits with an advertising budget of $40,000. We already know that, with equal expenditures in every quarter, annual profits come to $69,662. The question now is whether we can achieve a higher level of annual profits. The answer is that a higher level is, in fact,
attainable. An optimal reallocation of the budget produces annual profits of $71,447. The chart in Figure 6 compares the allocation of the budget in the base case with the optimal allocation. As we can see, the optimal allocation calls for greater expenditures in quarters $Q_2$ and $Q_4$ and for smaller expenditures in $Q_1$ and $Q_3$.

This is just one illustration of Solver’s power. Among the many questions we could answer with Solver in the Advertising Budget example are these:

- What would be the impact of a requirement to spend at least $8,000 each quarter?
- What would be the marginal impact of increasing the budget?
- What is the optimal budget size?

One way to answer this last question would be to run Solver with increasing budgets and trace out the impact on profit. We could do this manually, one run at a time, but it would be more convenient to be able to accomplish this task in one step. The Sensitivity Toolkit contains a tool called **Solver Sensitivity** that does just this: it runs Solver in a loop while varying one (or two) input parameters. Figure 7 shows the results of running Solver for advertising budgets from $40,000 to $100,000 in increments of $5,000. The table shows that profit increases at a decreasing rate as the budget increases, and beyond about $90,000 there is no discernible impact from additional budget. It also shows how the four decision variables ($Q_1$–$Q_4$ advertising) change as the budget changes.

### 3.5 Simulation and risk analysis

Uncertainty often plays an important role in analyzing a decision, because with uncertainty comes risk. Until now, we have been exploring the relationship between the inputs and outputs of a spreadsheet model as if uncertainty were not an issue. However, risk is an inherent feature of all managerial decisions, so it is frequently an important aspect of spreadsheet models. In particular, we might want to recognize that some of the inputs are subject to uncertainty. In other words, we might want to associate probability models with some of the parameters. When we take that step, it makes sense to look at outputs the same way — with probability models. The use of probability models in this context is known as **risk analysis**.

One tool for risk analysis in spreadsheets is Crystal Ball, an add-in for Monte Carlo simulation (another is @Risk [5]). This tool allows us to generate a probability distribution for any output cell in a spreadsheet, given probability assumptions about some of the input cells. Simulation and risk analysis are complex subjects. Here, we simply illustrate how Crystal Ball can help us answer an important question about risk.

In the Advertising Budget example, we return to the base case, with equal expenditures of $10,000 on advertising each quarter. Our base-case analysis,
which assumed that all parameters are known exactly, showed an annual profit of $69,662. However, we might wonder about the distribution of profits if there is uncertainty about the unit price and the unit cost. Future prices depend on the number of competitors in our market, and future costs depend on the availability of raw materials. Since both level of competition and raw material supply are uncertain, so, too, are the parameters for our price and cost. Suppose we assume that price is normally distributed with a mean of $40 and a standard deviation of $10, and that unit cost is equally likely to fall anywhere between $20 and $30. Given these assumptions, what is the probability distribution of annual profits? And how likely is it that profits will be negative?

Figure 8 shows the probability distribution for profits in the form of a histogram, derived from the assumptions we made about price and cost. The graph shows us that the estimated average profit is $69,721 under our assumptions. It also shows that the probability is about 30 percent that we will lose money. This exposure may cause us to reevaluate the desirability of the base-case plan.

Once again, we often wish to know how sensitive our simulation results are to one or more input parameters. This suggests running Crystal Ball in a loop while we vary the inputs, and to do so we have included the appropriate tool, called CB Sensitivity, in the Sensitivity Toolkit. Figure 9 shows the results of running Crystal Ball while we vary the budget from $40,000 to $100,000 in increments of $5,000, keeping advertising spending equal across the quarters. We plot here not only the mean profit, but the maximum and minimum values from each of the simulations, to give an idea of the range of outcomes likely at each step.

4 Research Issues

In contrast to software engineering, which has seen decades of development, spreadsheet engineering is in its infancy. Most of the ideas in this paper have been adapted from software engineering and tested informally in various instructional settings. However, there is little laboratory or field research to support claims that one or another spreadsheet engineering principle is effective in actual practice.

Spreadsheet engineers are fundamentally different from software engineers. Most of them would not describe themselves as programmers and most are not aware that they are under-trained for the spreadsheet design and analysis tasks they perform. Few recognize the risks they and their companies run when they use chaotic development processes or fail to use the powerful analytic tools described here.

The research needs are clear, although how best to carry out this kind of research is not. We need to know much more than we do about how spreadsheets are designed and used in industry. We also need to test various interventions,
including training programs and software add-ins, to see which really improve practice and which do not. We also need to study how corporate standards for training and use of spreadsheets influence the culture and performance of end-users. While spreadsheet programming has little cache in the computer science profession, it is likely that more computer programs are written by the millions of spreadsheet end-users than all professional programmers combined. The positive impacts of improving this aspect of programming practice are correspondingly high.

References


Fig. 1. The advertising budget spreadsheet.
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