A Decision Support Software on Bidding for Job Interviews in College Placement Offices

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Many university placement offices employ a bidding system to allocate on-campus recruiter interview slots to students. Typically, a student is given (say) 700 points each week to bid on the firms visiting that week. Interview slots for each firm are assigned beginning with the highest bidder until all slots are filled. This paper describes the mathematical modeling behind a decision support system for helping students to bid in such a system. It has three components. The first component elicits a student's utilities of getting an interview with the various firms. The second component estimates the probability of getting an interview with a particular firm for a given bid amount. The final component considers our bidding problem as the maximization of a student's expected utility, which can be formulated as a nonlinear integer programming (IP) problem. It is shown that this IP problem can be transformed into a number of nonlinear programming problems without integer requirements, which can then be solved very rapidly to give on-line bidding recommendations to a large number of students.
(*Decision Support System; Bidding; Mixed Integer Programming*)

1. Introduction

Many college placement offices operate a bidding system to allocate limited on-campus job interview slots to students. However, students often do not understand the basic principles of bidding; they often "waste" their bidding points and become upset with the outcomes and then the system. Also, the interview slots of some recruiting firms are not filled up and the firms get offended, although this embarrassment arises not because the firms are unattractive employers, but because the students have wasted their points elsewhere and/or are unaware of these "bargain" slots. This paper describes the mathematical/statistical bases of a decision support system (DSS) developed to help students in deciding how they should bid (i.e., allocate their bidding points to firms).

1.1 Description of the Bidding System

Each week, a student is given a list of N_T firms recruiting on campus next week and H points to bid on no more than n of these firms (for example, on our campus each senior is given $H = 700$ points, he can bid on no more than $n = 5$ firms, while N_T varies from week to week in the range of 5 to 40 firms). Bids are collected on Wednesdays and results are announced on Fridays. The process repeats every week during the interviewing seasons. For a given student in a given week, let:

N = number of firms the student has at least some interest in ($N \le N_T$);

x_i = number of bid points allocated to firm i (the decision variables of our problem);

U_i = the vonNeumann-Morgenstern utility to the student for getting an interview with firm i;

$P_i(x)$ = probability of winning an interviewing slot with firm i if one bids x points on firm i.

Our purpose is to solve the student's problem of maximizing his expected utility, which can be formulated as a mixed-integer nonlinear program P1:

$$\textbf{P1:} \quad \text{Max} \quad \sum_{i=1}^{N} U_i P_i(x_i) \tag{1a}$$

$$\text{s.t.} \quad \sum_{i=1}^{N} x_i \le H \tag{1b}$$

0025-1909/94/4007/0842$01.25

$$\sum_{i=1}^{N} y_i \leq n \quad (1c)$$

$$(x_i/H) - y_i \leq 0 \quad \text{for } i = 1 \text{ to } N \quad (1d)$$

$$y_i = 0 \text{ or } 1 \quad \text{for } i = 1 \text{ to } N \quad (1e)$$

$$x_i \geq 0 \quad \text{for } i = 1 \text{ to } N \quad (1f)$$

where

y_i = 0 if the student does not bid on firm i,

= 1 if the student bids on firm i.

Inequalities (1b) and (1c) respectively ensure that the student does not bid more than H points and on more than n firms. (1d) to (1f) are standard integer programming mechanisms.

Sections 2, 3, and 4 will describe, respectively, our approach in: (i) estimating the U_is; (ii) computing the $P_i(x)$s; and (iii) solving the integer programming problem P1.

In the initial stage of implementing our DSS, a student gives relevant information written on a standardized form to an "operator," who will run the software on a mainframe computer and obtain a bid recommendation for the student. However, the software can be easily modified to enable a student to run it himself on either a mainframe or microcomputer to obtain multiple bidding recommendations interactively.

2. Estimating the Utilities U_is

It is apparent from such reviews as Hull et al. (1973) and Schoemaker (1982) that the literature on eliciting subjective utilities is vast, and that human subjects often do not behave in accordance with the vonNeumann-Morgenstern model used in our study (see, e.g., Tversky and Kahneman 1991, Tversky et al. 1990). The simple procedure suggested below makes no attempt to incorporate the many refinements and exceptions considered in the literature; it is but one example of how utilities can be practically elicited from hundreds of students over many weeks with minimal guidance. However, this simple procedure under our interactive version of the DSS does allow a student to easily revise repeatedly his expressed preferences and determine immediately the effects of these revisions, thus alleviating much of the problem of initially inaccurate utility elicitation.

Given the list of N_T firms recruiting next week, a student is asked to put the firms he is interested in into 5 ranked categories A to E, with category A containing the most-interested firms. An example of a student's categorized preference is:

category	A	B	C	D	E
Index # of firms	(27)	(4, 7)	(1, 2, 3)	(6, 9, 13, 24)	(8, 5, 15, 17, 18, 23)

(2)

To estimate the student's perceived utility of a firm in each category, he is asked: "Assume that, instead of the current point system, everybody will have to pay cash for a ticket to each interview. As long as you are willing to pay the asking price, you can always get the interview you want. What is the highest cash price you are willing to pay for a ticket that admits you to an interview with firm 27 (a category-A firm)?" Similar questions are asked with respect to a firm in each of the remaining categories. An example of the answers is:

category	A	B	C	D	E
price ($)	20	10	5	2	1

(3)

These prices will be used as the utilities.

Note, however, that it will be apparent in §4 that our DSS is not restricted to this five-category approach; the user can specify his utilities in any way he likes.

3. Computing the Probabilities $P_i(x)$s

3.1 A Direct Approach for Estimating $P_i(x)$

Define $G_i(x)$ as the probability that the lowest winning bid for an interviewing slot with firm i is x or less. Clearly $G_i(x)$ is equivalent to $P_i(x)$. Therefore, taking the actual lowest winning bid in each of the previous S semesters gives S empirical observations from $G_i(x)$; if S is reasonably large, a functional form of $G_i(x)$ (hence $P_i(x)$)

can be estimated using one of the many standard methods. For brevity's sake, this is the approach assumed in subsequent discussions.

3.2 An Alternative Approach When "S" Is Small

The preceding approach, though simple, is very wasteful because it uses only one data point (the lowest winning bid) from each semester of data. When the proposed DSS is first set up, a university may have retained only a very small number of semesters of past data, and one needs an alternative method that makes full use of the limited data. Lau and Kletke (1992) present the details of such an alternative, whose basic steps are: (A) construct a distribution function describing the generation process of all submitted bids; (B) use historical data and subjective judgment to estimate the number of bids that will be submitted and the number of available interview slots in the current semester; (C) use order statistics to combine the information obtained in steps A and B to compute the values of $P_i(x)$ for a series of x-values. These $P_i(x)$'s values are then stored in a vector, from which the $P_i(x)$-value for any given x-value can be obtained rapidly by interpolation.

4. Solving the Nonlinear Program to Maximize Expected Utility

4.1 Transforming P1 to Many Tractable Sub-Problems P2s

The objective function in the mixed-integer program P1 is a very complicated nonlinear function of the decision variables x_is, therefore P1 cannot be solved directly by any currently available mathematical programming algorithm. Since a student can only bid on n out of the N firms he is interested in, a simpler problem can be considered: "Given a *specific* set $\{S\}$ of n firms, what is the optimal bid and expected utility obtainable from bidding on these n firms?" After this question is answered for each of all possible combinations of n out of N firms, the combination $\{S^*\}$ of n firms (and the associated bids) that generates the highest expected utility is the solution to P1. In other words, we will transform one very difficult problem (P1) into ${}_NC_n$ much simpler nonlinear programming problems P2 that have *no* integer restriction (the integer restriction in P1 is the major cause of computational and solution difficulties). Each P2-problem considers only a set $\{S\}$ of n firms; i.e.:

P2:

$$\text{Max} \quad \sum_{i \in \{S\}} U_i P_i(x_i) \tag{4a}$$

$$\text{s.t.} \quad \sum_{i \in \{S\}} x_i \leq H \tag{4b}$$

$$x_i \geq 0 \quad \text{for all } i \in \{S\}. \tag{4c}$$

Among the solutions to the ${}_NC_n$ P2-problems (each with a different $\{S\}$), the one with the highest objective function is the solution to P1. We found that problem P2 can be rapidly solved with the IMSL (1987) subroutine BCPOL.

The final difficulty is: ${}_NC_n$ different P2 problems have to be solved. Although in most cases N is probably not much larger than n and therefore ${}_NC_n$ is not large, theoretically there could be (say) $N_T = 40$ firms visiting during the week and the student is interested in (say) $N = 30$ of them; giving ${}_{30}C_5 = 142506$ for $n = 5$. One way to reduce the number of P2-problems to be solved in such a situation is to solve P2 only for "promising" sets of n firms. Various heuristics for selecting "promising" $\{S\}$s were tested, the following procedure performs well.

4.2 Identifying a Promising Subset of the P2s to Solve

First, we want to identify "good" firms whose inclusion into $\{S\}$ will likely lead to high optimal expected utilities from the resultant P2-problems. Clearly, firms with large U_i are desirable. However, including a firm of large U_i into $\{S\}$ may not lead to a high optimal expected utility for the resultant P2-problem if the probability of getting an interview with the firm is very low, perhaps because (say) there are many H-point bids on this firm. Alternatively, including a firm with a relatively low U_i into $\{S\}$ may lead to a high optimum for the resultant P2-problem if a very low bid will ensure an interview with the firm. Therefore, a "good" firm is one with a high ratio between U_i and some measure of the competitiveness (or difficulty) of actually getting an interview with the firm.

A given $G_i(x)$ (see §3.1) has a corresponding mean value μ_i and standard deviation σ_i. A low μ_i (or σ_i) implies that bids required to win an interview with firm i has a low mean (or standard deviation). Therefore, a reasonable measure of difficulty of actually getting a firm is $(\mu_i + 2\sigma_i)$, and a "good" firm is one with a high value of R_i, where

$$R_i = U_i / (\mu_i + 2\sigma_i) \qquad (5)$$

In our computer procedure, the N firms of a given student are ranked according to their R_is, and combinations of n firms are formed by moving from the top to the bottom of the list. For example, if $N = 30$ and the identity numbers of the ranked firms happen to be $\{1, 2, 3 \cdots 30\}$, then for $n = 3$ the sequence of combinations (i.e., $\{S\}$) formed will be: $\{1, 2, 3\}$, $\{1, 2, 4\} \cdots \{1, 2, 30\}$, $\{1, 3, 4\}$, $\cdots \{28, 29, 30\}$. It is obvious that the earlier $\{S\}$s in the sequence are more likely to generate higher optima to P2 than the later $\{S\}$s. Depending on the CPU time an institution wants to spend on each student, the sequence can be truncated at a suitable point.

In our institution where $n = 5$, solving 10 P2-problems (i.e., with 10 different $\{S\}$s each containing 5 firms) takes less than 1 CPU second in our IBM 3090–200S. Therefore, our DSS can be practically implemented on any campus with a mainframe computer. This small CPU requirement also means that the very simple utility-elicitation procedure described in §2 can be safely used, because even if a student is initially unable to express his own utilities consistently (a common behavior) with the procedure, this can be resolved by allowing a student to repeatedly revise and submit his utilities after looking at the recommendations generated from his most recent utilities-statement.

5. Conclusion

We presented a computerized DSS that helps college students to bid for interview slots with campus recruiters. The computation requirement is quite small, and the system can be easily implemented for a campus with thousands of students and thousands of recruiting firms.

A common question from the users is: "Since this DSS is available to all students, how can it be advantageous to me?" Our DSS should be useful to each individual student for two reasons. Firstly, just as it is known from the "efficient market theory" that the dissemination of public information makes financial markets more "efficient" and benefits "society" (and hence "everyone"), our DSS provides everybody with the population bidding data and makes the bidding process more "efficient" for both the students and the recruiters. Secondly, given the market information, although one may assume that financial-market investors can choose their own sophisticated decision tools, most college students bidding for interview slots are less equipped to perform the logical decision analyses offered by our DSS.

References

Hull, J., P. Moore and H. Thomas, "Utility and Its Measurement," *J. Royal Statistical Society A*, 136 (1973), 226–247.

IMSL, *User's Manual, MATH/LIBRARY*, IMSL, Houston, TX 1987.

Lau, H. and M. Kletke, "A Mathematical/Statistical Decision Model for Bidding Interview Slots in College Placement Offices," working paper, College of Business, Oklahoma State University, 1992.

Schoemaker, P., "The Expected Utility Model: Its Variants, Purposes, Evidence and Limitation," *J. Economic Literature*, 20 (1982), 529–563.

Tversky, A. and D. Kahneman, "Loss Aversion in Riskless Choice: A Reference-Dependent Model," *Quarterly J. Economics*, 106 (1991), 1039–1061.

——, P. Slovic and D. Kahneman, "The Causes of Preference Reversal," *American Economic Review*, 80 (1990), 204–217.

Accepted by Arnold Barnett, former Departmental Editor; received February 1991. *This paper has been with the authors 7 months for 1 revision.*