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Using Microcomputers and P/G% to Predict court Cases

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by

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The purpose of this article is to analyze a microcomputer program that can process a set of (1) prior cases, (2) predictive criteria for distinguishing among the cases, and (3) the relations between each prior case and each criterion in order to arrive at an accurate decision rule. Such a rule will enable all the prior cases to be predicted without inconsistencies, and thereby maximize the likelihood of accurately predicting future cases. To illustrate the program, this article uses five substantive fields, including the predicting of cases dealing with religion in the public schools, legislative redistricting, housing discrimination, international law, and criminal law.[1]

THE GENERAL METHODOLOGY

The predictive methodology on which the computer program is based involves six key elements:

1. Listing the cases or casetypes which are to be analyzed.
2. Listing the tentative criteria to aid in explaining why some cases were decided one way and other cases were decided differently. That listing might also involve indicating the relative importance of each criterion.
3. Listing how each case scores on each of those predictive criteria. That listing can use whatever measurement units seem comfortable, such as a yes-no dichotomy, a 1-5 scale, years, dollars, apples, etc.
4. Summing the scores for each case across the criteria in order to give each case an overall score. Doing so might involve transforming the raw scores into dimensionless part/whole percentages.
5. Relating the set of summation scores for the cases to the actual or presumed outcomes of those past cases or casetypes. One can thereby develop a decision rule indicating the summation scores that are associated with certain kinds of outcomes.
6. Doing a sensitivity analysis whereby one determines how the decision rule, the presence of inconsistencies, or a litigation strategy might be affected by changes in the cases, criteria, weights, relations, measurement units, or other inputs.

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[1]On traditional legal prediction, *see* H. JONES, J. KERNOCHAN & A. MURPHY, LEGAL METHOD (1980); K. LLEWELLYN, THE COMMON LAW TRADITION: DECIDING APPEALS (1960); W. STATSKY & J. WERNET, CASE ANALYSIS AND FUNDAMENTALS OF LEGAL WRITING (1977); and E. THODE, L. LEBOWITZ & L. MAZOR, INTRODUCTION TO THE STUDY OF LAW (1970). On behavioral statistical prediction as applied to court cases, *see* J. GROSSMAN & J. TANENHAUS, FRONTIERS OF JUDICIAL RESEARCH (1969); G. SCHUBERT, JUDICAL BEHAVIOR:

The program is called Policy/Goal Percentaging Analysis (P/G%) because it was originally designed to relate alternative legal policies to goals to be achieved. The program can be easily extended to relating prior cases to predictive criteria. The word "percentaging" is used in the title of the program, because the program uses part/whole percentages in order to handle the problem of goals or predictive criteria being measured on different dimensions. The measurement units are converted into a system of percentages showing the relative position of each case on each criterion, rather than work with a system of dollars, apples, years, miles, or other measurement scores.

Each set of substantive cases is designed to illustrate a different variation on the six key elements as follows:

1. The cases dealing with religion in the public schools involve casetypes, rather than actual cases. They also involve only one way of measuring the predictive criteria, namely a simple yes-no dichotomy.
2. The legislative redistricting cases involve specific cases, rather than casetypes. They especially illustrate resolving inconsistencies in how the cases were decided.
3. The housing discrimination cases illustrate how the program deals with multiple ways of measuring the predictive criteria.
4. The international law cases involve a continuum outcome like damages, sentences, or probabilities, rather than just winning or losing.
5. The criminal cases deal with multiple weights for the predictive criteria.

This article is designed to discuss a methodology that is helpful in arriving at accurate predictions of court cases. Making accurate predictions, however, depends on a number of factors in addition to having a good predictive methodology. Those factors include:

1. A knowledge of the subject matter.
2. Previous prediction experiences.
3. The stimulus of having a lot at stake, depending on the accuracy of the predictions.
4. Requiring written analysis justifying one's predictions.
5. Clarity as to what one is predicting.
6. Being a positive thinker with regard to one's ability to predict.
7. Being explicit about one's predictive criteria.
8. Having a relevant set of cases on which to base one's predictions.
9. Being accurate in how the cases are positioned on each of the predictive criteria.
10. Being capable of seeing relations and reasoning by analogy.

A READER IN THEORY AND RESEARCH (1964); H. SPAETH, SUPREME COURT POLICY MAKING: EXPLANATION AND PREDICTION (1979); and S. ULMER, COURTS, LAW AND JUDICIAL PROCESS (1981).

11. Having a knowledge of predictive methodologies, such as P/G%, multiple regression, and staircase prediction, which are compared in this article.[2]

CASETYPES, UNI-DIMENSIONALITY, AND RELIGION IN THE PUBLIC SCHOOLS

Table 1 contains data for predicting cases dealing with religion in the public schools. This simple example can serve well to illustrate the six key elements. They are referred to as elements, rather than steps, because they are developed in a cyclical way, rather than a sequential way. That means subsequent elements tend to lead to revising the previous elements in a series of repeated cycles. The process continues until one is satisfied that the elements make sense in light of the user's purposes and the overall criterion of 100 percent accuracy in predicting or post-dicting the cases on which the decision rule is based.

TABLE 1

Data for Predicting Cases Dealing with Religion in the Public Schools[3]

Criteria / *Casetypes*	*School Time*	*School Building*	*Purpose*	*Sum*[4]	*Outcome*[5]
1. Educational Purpose Off School Time Out of School Building	1	1	1	3	C
2. Educational Purpose Off School Time In School Building	1	2	1	4	C

[2]On the general methodology of policy/goal percentaging analysis as applied to both prescription and prediction, *see* S. NAGEL, PUBLIC POLICY: GOALS, MEANS, AND METHODS, 343-54 (1984); Nagel, *Part/Whole Percentaging as a Useful Tool in Policy/Program Evaluation,* 8 EVALUATION & PROGRAM PLANNING (1985); Nagel, *P/G% Analysis: An Evaluation-Aiding Tool Program,* 9 EVALUATION REV. 209 (1985); and Nagel, "Policy/Goal Percentaging Analysis: A Decision-Aiding Tool" (microcomputer manual available from the author on request, 1984). The cases to be listed can be found through manual legal search methods or through accessing the microcomputer data bases of such systems as LEXIS or WESTLAW. Listing predictive criteria generally requires a knowledge of the cases, the subject matter, and other factors mentioned above. Experiments are now being conducted on the extent to which microcomputer data bases can be used to help generate predictive criteria.

[3]The above data comes from Nagel, *Case Prediction by Staircase Tables and Percentaging.* 25 JURIMETRICS 168 (1985).

[4]The decision rule which the above data generates is: (1) If a case dealing with religion in the public schools has a summation score of 5 or less, the arrangements will be found constitutional. (2) With a summation score of 6 or more, the arrangements will be found unconstitutional.

The leading case is Zorach v. Clauson, 343 U.S. 306 (1952). It involved a summation score of 5, and the arrangement was found constitutional. Therefore, one would expect constitutionality to be found with scores lower than 5.

[5]A "U" in the outcome column means the arrangement is found unconstitutional. A "C" means the arrangement is found constitutional. The *Zorach* case is Casetype 7, and the *McCullom* is Casetype 8.

TABLE 1 *(Continued)*

Data for Predicting Cases Dealing with Religion in the Public Schools

Casetypes	*Criteria* School Time	School Building	Purpose	Sum	Outcome
3. Educational Purpose On School Time Out of School Building	2	1	1	4	C
4. Religious Indoctrination Off School Time Out of the School Building	1	1	2	4	C[6]
5. Educational Purpose On School Time In School Building	2	2	1	5	C
6. Religious Indoctrination Off School Time In the School Building	1	2	2	5	C
7. Religious Indoctrination On School Time Out of the School Building	2	1	2	5	C
8. Religious Indoctrination On School Time In the School Building	2	2	2	6	U

The cases listed on the rows of Table 1 are not specific cases, except for Case 7 which is *Zorach v. Clauson*[7], and Case 8 which is *McCollum v. Board of Education*[8]. Instead the "cases" are casetypes formed by combining the categories on the three predictive criteria. The first predictive criterion is whether the religious activity was on school time. A "yes" scores 2, and a "no" scores 1. The second predictive criterion is whether the religious activity was within the school building, with a yes scoring 2 and a no scoring 1. The third criterion is whether the purpose of the religious activity is for indoctrination (i.e., instilling or strengthening religious beliefs) (scored 2), or is for education as in a course on comparative literature or cultural geography (scored 1). A high score or a 2 on each predictive criterion indicates a score in the direction of unconstitutionality for these cases. Thus with three predictive criteria, each

[6]The Outcome of Case 4 is known from the case of McCullom v. Board of Educ., 333 U.S. 203 (1948).

[7]343 U.S. 306 (1952).

[8]333 U.S. 203 (1948).

of which is a yes-no dichotomy, there can be eight casetypes or possible combinations of the categories. Those casetypes are listed in the first column in the order of the summation scores for each casetype. Where two casetypes have the same summation scores, they are listed alphabetically.

After clarifying the cases or casetypes and the predictive criteria, the third element involves showing the relations between each case/casetype and each predictive criterion. That is easy here since the definition of each casetype shows how it is positioned on each criterion. The fourth element involves summing the relation scores in order to obtain an overall score for each case. That is also easy here since the raw scores can be summed, because all the predictive criteria are measured on the same 1-2 scale. We therefore do not have a problem of multi-dimensionality which is present when we try to add apples to oranges, years to dollars, or a 1-2 scale to a 1-5 scale.

The fifth element involves relating the summation scores to the outcomes in the form of a decision rule. Predictive decison rules in this context have the form, "If a case has a summation score of ____ or more, then predict a decision of ____; and if a case has a summation score of ____ or less, then predict an opposite decision. To aid in developing decision rules, the computer program arranges the casetypes in the order of their summation scores with ties broken alphabetically. Before the computer calculates the summation scores, it asks the user for (1) the labels for the casetypes or the names for the specific cases, (2) the labels for the predictive criteria, (3) an indication whether the criteria are all measured the same way or differently, and (4) the relative importance or weights of the criteria. Here the criteria are weighted equally, meaning they each receive a weight of 1. Where differential weights are involved, those weights are used to multiply the relation scores in order to work with weighted relation scores and thus weighted summation scores.

A sixth and especially important piece of information is the outcome for each case or casetype. That is normally easy information to provide where specific cases are involved. Where casetypes are involved as here, deductive reasoning may be needed to indicate the outcomes for those casetypes that do not correspond to specific cases. For example, in *Zorach,*[9] the Supreme Court upheld religious indoctrination on school time although not in the school building. The Court would then surely uphold religious indoctrination not on school time and not in the school building which is Casetype 4. In other words, if a case wins with an unfavorable score on Criterion A and a favorable score on Criterion B, then it is even more likely to win with a favorable score on Criterion A if all other variables are held constant. This is known as *a fortiori* reasoning. One can similarly deduce Casetype 1 where all three variables are favorable, and Casetype 3 where two variables are favorable rather than just one, and the one unfavorable variable has not changed. Another form of *a for-*

[9] 343 U.S. 306 (1952).

tiori reasoning which is not present here is to say if a case loses with a favorable score on Criterion A, then it will lose even more with an unfavorable score on Criterion A if everything else is held constant.

Likewise, if the Court explicitly says or implies that being on or off school time and in or out of the school building are of approximately equal importance, then one can deduce Casetype 2 and Casetype 6 since they interchange the scores on those two variables as compared to the *Zorach*[10] Casetype 7. Also if the Court explicitly says or implies that an educational purpose provides an exemption from unconstitutionality, then we can deduce that Casetype 5 will be found constitutional, as well as Casetypes 1, 2, and 3. Casetype 8 does not have to be deduced since it corresponds to the specific case of *McCullom v. Board of Education.*[11] If that case had not been decided, one would predict unconstitutionality from language that implies being in an unfavorable position on all three variables, crossing the threshold of unconstitutionality. When the outcome column has been completed, one should have no trouble seeing that the data generates a decision rule saying that if a case has a summation score of 6 or more, then predict a decision of unconstitutionality; and if a case has a summation score of 5 or less, then predict a decision of constitutionality.

As an example of sensitivity analysis in this substantive context, one could add a fourth variable such as whether or not the program is voluntary. We would then have 16 casetypes since we would have four dichotomous variables which lend themselves to 2 x 2 x 2 x 2 or 16 casetypes. The relations would still be determined by the definitions of the casetypes. Adding that fourth variable brings in the concept of violating a constitutional constraint, in the sense that all eight casetypes where the program is not voluntary would be unconstitutional. In other words, having a compulsory religious program is enough to generate an unconstitutionality decision, regardless of how the casetype is scored on the other three variables, even if the program is educational rather than doctrinal. A sensitivity analysis, however, is subject to change when the new inputs actually occur in a future case. Those new cases can then become part of the dataset that is used to develop and revise the decision rules.[12]

SPECIFIC CASES, RESOLVING INCONSISTENCIES, AND LEGISLATIVE REDISTRICTING

A. *Analyzing the Specific Cases*

Table 2 contains data for predicting legislative redistricting cases. The cases listed on the rows are all specific cases, rather than casetypes. They are

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[10]*Id.*

[11]333 U.S. 203 (1948).

[12]Cases dealing with religion in the public schools are discussed in N. DORSEN, P. BENDER, & B. NEUBOINE, POLITICAL AND CIVIL RIGHTS IN THE UNITED STATES, (1976), [hereinafter cited as N. DORSEN], H. PRITCHETT, CONSTITUTIONAL CIVIL LIBERTIES 150-54 (1984). For further details on predicting civil liberties cases quantitatively, *see* Nagel, *Predicting Court Cases Quantitively*, 63 MICH. L. REV. 1411 (1965).

the most important legislative redistricting cases decided in the United States by various courts from *Colegrove v. Green,*[13] through *Baker v. Carr*[14]. The cases are arranged in the order of their summation scores. That happens to be roughly the same as the chronological order of the cases, which shows that the cases became more favorable toward ordering redistricting as one moved from *Colegrove* to *Baker.*

TABLE 2

Data for Predicting Redistricting Cases[15]

Criteria[17] / *Casetypes*[18]	*Equality Requirement*	*State Legislature*	*Equality Violation*	*Federal Court*	*Sum*[16]	*Outcome*
1. *Colegrove*[19]	1	1	1	2	5	D
2. *Grills*[20]	2	2	1	1	6	A
3. *Maryland*[21]	1	2	2	1	6	D
4. *Scholle*[22]	1	2	2	1	6	D
5. *WMCA*[23]	1	2	1	2	6	D
6. *Asbury*[24]	2	2	2	1	7	A
7. *Dyer*[25]	2	1	2	2	7	A
8. *Baker*[26]	2	2	2	2	8	A
9. *Magraw*[27]	2	2	2	2	8	A

[13] 328 U.S. 549 (1946).

[14] 369 U.S. 186 (1962).

[15] The above date comes from Nagel, *Applying Correlation Analysis to Case Prediction,* 42 TEX. L. REV. 1006-17 (1964).

[16] The decision rule which the above data generates is: (1) If a redistricting case during the time period covered has a summation score of 7 or above, the attacker wins. (2) With a summation score of 6 or below, the defender wins. That decision rule generates one inconsistent case. The inconsistency can be eliminated by: (1) Changing the decision rule to say a summation score of 6 leads to an unclear outcome. (2) Giving the first variable a weight of 2, which would be consistent with the importance of requiring equality. (3) Adding a fifth variable called "Decided After the Maryland Case." (4) Eliminating the *Grills* case, but that does not seem justifiable. (5) Changing the measurement on the first variable from no-yes to a 1-3 scale and giving *Grills* a score of 3. (6) Finding that *Grills* really deserves a 2 on the third or fourth variables.

[17] A one in columns one through four equals no. A two in columns one through four equals yes. An "A" in the outcome column means the attacker wins. A "D" means the defender wins.

[18] When working with cases, rather than casetypes, inconsistencies are likely to occur that need resolving.

[19] Colegrove v. Green, 328 U.S. 549 (1946).

[20] Grills v. Anderson, 29 U.S.L.W. 2443 (Ind. 1961).

[21] Maryland Comm. for Fair Representation v. Towes, 377 U.S. 656 (1964).

[22] Scholle v. Hare, 360 Mich. 1, 104 N.W.2d 63 (1960), *vacated,* 369 U.S. 429 (1962) *reh'g denied,* 370 U.S. 906 (1962), on remand, 367 Mich. 176, 116 N.W.2d 350 (1962), *cert denied,* Beadle v. Scholle, 377 U.S. 990 (1964).

[23] W.M.C.A., Inc. v. Simon, 196 F. Supp. 758 (S.D.N.Y. 1961).

[24] Asbury Park Press v. Woolley, 33 N.J. 1, 161 A.2d 705 (1960).

[25] Dyer v. Abe, 138 F. Supp. 220 (D. Hawaii, 1956).

[26] Baker v. Carr, 369 U.S. 186 (1962).

[27] Magraw v. Donovan, 163 F. Supp. 184 (D. Minn. 1958).

There are four predictive criteria. As with the cases dealing with religion in the public schools, all four criteria are measured using a yes-no dichotomy. The first variable asks whether the relevant constitution expressly requires districts of equal population per representative. The *Colegrove* case, for example, involved Congressional redistricting.[28] The federal Constitution does not expressly require equality.[29] On the contrary, it expressly requires that each state have at least one representative, no matter how small the state might be.[30] Equality for Congressional districting has been read into the federal Constitution by way of finding it implicit in the due process clause of the fifth amendment and the equal protection clause of the fourteenth amendment. The *Baker* case, on the other hand, involved Tennessee state legislative-redistricting.[31] The Tennessee Constitution does explicitly require equality, which had been ignored for years by the refusal of the state legislature to redistrict.[32]

The second variable asks whether a state or federal legislature is involved. A state legislature is scored 2, and the federal legislature is scored 1. State legislatures are more likely to be ordered to redistrict because the courts (at least in those early years) seemed to show more respect for not upsetting Congress. Oliver Wendell Holmes had said the federal system could survive if Congress violated the Constitution, but not if the states did so. The third variable refers to the degree of equality violation. If less than 35% of the state's population can choose more than 50% of the state legislature, then the equality violation is high (scored 2). If more than 35% of the state's population is required to choose more than 50% of the state legislature, then the equality violation is relatively low (scored 1). The fourth variable asks whether a federal or state court is deciding the case. One would expect a federal court to be more likely to decide in favor of redistricting in view of the lifetime appointment of federal judges, which makes them less susceptible to pressure from the dominant political party.

With nine cases and four predictive criteria, there are 36 relations. They are shown in the cells of Table 2. Those relation scores can be objectively determined, as are the relation scores in most court case prediction. The fourth key element in the predictive analysis involves summing the relation scores for each case and arranging the cases in the order of their summation scores. The minimum summation score is 4 for a case that scores 1 on all four variables. There was no such case which is a further indication that we are dealing with actual cases, rather than casetypes. The *Colegrove* case comes closest with a score of 5. The maximum score possible is 8 for a case that scores 2 on all four variables. *Baker* is an example of that casetype.

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[28] 328 U.S. 549 (1946).

[29] *Id.* at 551.

[30] *Id.* at 556.

[31] 369 U.S. 186 (1962).

[32] *Id.* at 207-08.

With actual specific cases, the prior outcomes are generally easy to determine. Of these nine cases, five were decided in favor of the party attacking the existing apportionment, and four in favor of the party defending it. The decision rule which the data generates is that if a redistricting case during the time period covered has a summation score of 7 or above, the attacker wins. With a summation score of 6 or below, the defender wins. That decision rule, however, results in at least one inconsistency. This is so because four cases received scores of 6 apiece, and one of the four resulted in a victory for the attacker when the other three were won by the defender of the existing redistricting.

B. *Resolving the Inconsistencies*

The P/G% system provides methods whereby the system can guarantee 100% accuracy in predicting the past cases on which the decision rule is based. This is the equivalent in statistical regression analysis of guaranteeing there will be no residuals or differences between predicted scores and actual scores where one is predicting winning or losing. It is possible that there are some real inconsistencies across cases, judges, places, or time periods. The philosophy of the P/G% approach, however, assumes that the inconsistencies are only on the surface, and that if one does a better analysis of the cases, criteria, relations, weights, measures, and other inputs, then the inconsistencies will disappear. The P/G% approach facilitates such an analysis by enabling the user to easily determine the effects of changes in those inputs and by allowing for variables that refer to when, where, and by whom the cases were decided.

There are at least six ways of resolving what otherwise would be inconsistencies or residuals. Taking them in random order as applied to Table 2, one can change the decision rule to say a summation score of 7 or above leads to the attacker winning; a summation score of 5 or below leads to the defender winning; and a summation score of 6 leads to an unclear result. There would then be no inconsistencies since a summation score of 6 could then accommodate both an A and a D for its outcome. That approach, is, however, undesirable, because it may declare too many cases to be unpredictable. In this example, an undesirable four out of the nine cases would become unpredictable.

A more meaningful approach is to give the first criterion a weight of 2. That would have the effect of doubling all the numbers in that column before the summing is done. Doing so would mean the new summation scores would be 6, 8, 7, 7, 7, 9, 9, 10, and 10 respectively. The new decision rule would then be that a summation score of 8 or above leads to a redistricting order and a summation score of 7 or below leads to such an order being denied. In other words, each case that scored 1 on the equality requirement would move up one extra point on the summation score, and each case that scored 2 on the equality requirement would move up two extra points on the summation score. That means the *Grills*[33] case would move up from a 6 to an 8, and the other three cases that started at 6 would move up to a 7, because only *Grills* of the four cases received a 2 on the equality requirement. Giving the requirement of equality a weight of 2 when the other criteria receive a weight of 1 is substantively reasonable, since whether equality is required should be especially fundamental in determining whether a redistricting is ordered for lack of equality. The other criteria are less fundamental in that sense.

Instead of or in addition to changing the weights of the criteria, one could add an additional criterion. For example, the inconsistency would be resolved if we added a time variable which asks whether the case was decided after the *Maryland* case.[34] There were only two cases decided after the *Maryland case, namely Grills*[35] and *Baker.*[36] Thus they would be the only cases receiving a 2 on this new variable. All the others would receive a 1. That would mean the new set of nine summation scores would be 6, 8, 7, 7, 7, 8, 8, 9, and 8. Unlike the differential weighting, however, adding that variable is not so substantively reasonable. That time point was not a watershed in any sense, but rather just an arbitrary way of separating *Grills* from the other three cases. That time variable would have been more meaningful if there had been years rather than months separating the *Maryland* case from the *Grills* case, or if the *Maryland* case had established an important new precedent favoring redistricting which was applicable to *Grills.*

Another alternative might be to eliminate the *Grills* case. That does eliminate the inconsistency. It would be justifiable if the *Grills* case really did not belong by virtue of its being a foreign redistricting case, a redistricting of fire stations rather than legislative districts, or some other substantively meaningful reason. There is no such reason here. Any approach to eliminate inconsistencies must also be substantively meaningful. Approaches which do not work with Table 2 might, however, work with other sets of cases.

Another approach is to change the measurement on one or more predictive criteria. For example, perhaps the requirement of equality could be measured in three categories, rather than just yes-no. The three categories might be strongly yes, mildly yes, and no. If the constitution in the *Grills* case strongly requires equality, then that case would receive a 3 on the first variable, and the other three cases would remain at 1. The new summation scores would then be 7, 6, 6, and 6 for those four cases, which would separate *Grills* from the other three cases without creating any new inconsistencies. Another example might involve noting that the equality violation is rather crudely measured with a yes-no dichotomy. A more sophisticated measure-

[33]Grills v. Anderson, 29 U.S.L.W. 2443 (Ind. 1961).

[34]377 U.S. 656 (1964).

[35]29 U.S.L.W. 2443 (Ind. 1961).

[36]369 U.S. 186 (1962).

ment might ask what is the minimum percentage of the population needed to elect 51% of the legislature. The answer could range from a low of about 10% to a high of 51%. The *Grills* case, however, would not receive a substantially higher score on the degree of equality violation than those other three cases, since it received a no on the yes-no dichotomy when two of the other three received a yes.

Another alternative relates to finding an error in how the cases have been scored on each criterion. If, for example, *Grills* really deserves a 2 on the third or fourth variables, then the inconsistency would be resolved. That approach is more likely where there is more subjectivity in scoring the relations. An error could also occur in calculating the summation scores if they were calculated by hand or with a calculator. The microcomputer, however, is not likely to err in summing the relation scores even if they are multi-dimensional and weighted. The program also shows intermediate values between the raw scores and the summation scores to enable the user to check that the summation was done properly. The intermediate scores show the corresponding part/whole percentages for each raw score to consider multi-dimensionality (which will be discussed shortly), and weighted raw scores or weighted part/whole percentage scores to consider differential weighting.

All these changes are directed toward improving predictive decision rules by (1) having them make more substantive sense and by (2) reducing inconsistencies. The changes can be summarized in the form of a checklist in which each item refers to an input element that is subject to change as follows:

1. Cases or Casetypes
   (1) Adding or subtracting
   (2) Consolidating or subdividing
   (3) Specifying a maximum or minimum on a characteristic of a casetype

2. Predictive Criteria
   (1) Adding or subtracting
   (2) Consolidating or subdividing
   (3) Specifying a maximum or a minimum on a predictive criterion

3. Relations between Cases and Criteria
   (1) More refined or less refined measurement
   (2) Alternative units of measurement
   (3) Different scoring for some of the relations

4. Drawing a Conclusion as to the Predictive Decision-Rule
   (1) Expanding or contracting the indeterminate area
   (2) Changing the upper or lower cut-off
   (3) Predicting degrees, rather than a dichotomy or vice versa
   (4) Predicting degrees with a non-linear, rather than a linear equation or a different kind of non-linear equation
   (5) Recognizing a constraint such that if it is present, all cases will be decided positively, or all cases will be decided negatively, regardless how they score on the predictive criteria.

C. *Sensitivity Threshold Analysis*

The computer program aids the user in determining which alternative is best for eliminating inconsistencies. The program does so in various ways. One way is to inform the user what it would take to move the *Grills* case up to a tie with the lowest scoring case in which the attacker won. That kind of threshold analysis shows how each of the four relation scores or their weights would have to change. Another way is to inform the user what it would take to move the other three cases down to a tie with the highest scoring case beneath them in which the defender won. Probably the best way in which the sensitivity aspects of the program are helpful here is by enabling one to experiment quickly and accurately with different weights, variables, sets of cases, measurement units, and relation scores to see what their effects are in terms of new summation scores and the elimination of previous inconsistencies without introducing new ones.

A special form of sensitivity or threshold analysis in this substantive context could involve asking what would have enabled *Colegrove* to be decided in favor of the attacker the way *Baker* was. The answer is that it would have taken a combination of changes great enough to make up the 3-point gap between the score of 5 which *Colegrove* received and the score of 8 for *Baker*. The gap could be made up if *Colegrove* could receive a score of 4 on the equality requirement or *Baker* a score of -1. Neither change, however, is possible since that criterion only provides for scores of 1 and 2. The same thing is true of all the other criteria in that no change on any of them is possible that will make up the 3-point gap. The threshold analysis also informs us that the gap could be made up if any one of the first three criterion were to be given a weight of -2. Then *Colegrove* would receive weighted relation scores of $-2+1+1+2$ which sum to $+2$, and *Baker* would receive scores of $-4+2+2+2$ adding to $+2$ just like *Colegrove*. A -2 weight, however, makes no substantive sense for any of the first three variables. No weight will help *Colegrove* for the fourth variable. Both *Colegrove* and *Baker* receive the same raw score on that variable, since they were both decided in federal courts.

TABLE 3

An Example of the Computer Display: Threshold Analysis[37]

	Threshold Analysis Colegrove vs Baker			
	Eq. Requ	*Legis. S*	*Eq. Viol*	*Court Fe*
Coleg	4.00	4.00	4.00	5.00
Baker	-1.00	-1.00	-1.00	-1.00
Weight	-2.000	-2.000	-2.000	????

The threshold analysis is summarized in Table 3. The first row indicates the threshold values for the *Colegrove* case on each of the four variables. The second row indicates the threshold values for the *Baker* case. The third row indicates the threshold weights for each of the four predictive criteria. This analysis informs us that it would have been virtually impossible for *Colegrove* to have been decided any other way in view of the validity and meaning of these predictive variables, plus other variables that also disfavored *Colegrove.*

To apply the decision rule of Table 2, one needs a new case that is not included in the data set from which the decision rule was generated. If the next case after *Baker* involves no equality requirement, a state legislature, a severe equality violation, and a federal court, then the case would have 7 unweighted points. We would then predict victory for the attacker, since 6.5 is the cutoff summation score. If we weight the equality requirement by 2, then the new case would have a weighted summation score of 8. We would still predict victory, since the cutoff score with the weights is 7.5. We could test the predictive power of the methodology by predicting Case 3 from the first two, Case 4 from the first three, and so on. If we do that, we will predict accurately each time, provided that we use the weighting system whereby scores on the equality requirement are doubled, while the other scores remain unchanged.[38]

[37]The object here is to determine what it would take to bring *Colegrove* up to the same summation score as *Baker,* or to bring *Baker* down to the same summation score as *Colegrove.*

Each cell shows the threshold value of a relation or a weight. If an actual cell value in Table 1 were to change to its above threshold value, then there would be a tie between *Colegrove* and *Baker,* assuming all the other inputs are held constant.

No one threshold value can equalize *Colegrove* and *Baker* given the four criteria. All the threshold values are above or below the measurement range of 1-2. There is also no substantive sense for the weights of any of those predictive variables to be negative rather than positive.

[38]The cases dealing with legislative redistricting are discussed in R. DIXON, DEMOCRATIC REPRESENTATION: REAPPORTIONMENT IN LAW AND POLITICS (1968) and REAPPORTIONMENT IN THE 1970's (Polsby ed., 1971). For further detail on this predictive example, *see* Nagel, *Applying Correlation Analysis to Case Prediction,* 42 TEX. L. REV. 1006 (1964). Other variables that also disfavored *Colegrove* include (1) the intervening case of Gomillion v. Lightfoot, 364 U.S. 339 (1960), which ordered redistricting where blacks were being districted out of the city limits of Tuskegge, Alabama, (2) the partial reliance in the *Colegrove* case on the clause that guarantees a republican form of government, rather than the equal protection clause, (3) the increased public sensitivity to denials of equality between 1946 and 1962, (4) the increased malapportionment between 1946 and 1962, especially as a result of increased urban and suburban growth with virtually no new redistricting, and (5) the request in *Colegrove* for redistricting in time for the next congressional election which was only a few months away. The threshold weight of -2 is calculated by the computer by solving for

MULTI-DIMENSIONALITY AND HOUSING DISCRIMINATION CASES

Table 4 contains data for predicting housing discrimination cases in light of *Shelley v. Kraemer*[39]. That case held that covenants in deeds are unenforceable which prohibit the owner from selling to a black buyer, at least where a neighbor is seeking an injunction against a willing seller as a matter of the neighbors' property rights.[40] To predict related housing discrimination cases, it is useful to know how each case is positioned on the four predictive criteria of (1) whether the seller is willing to sell, (2) whether there is an interfering neighbor seeking to enjoin the sale, (3) whether the buyer is abusive in some way so that the seller would be legally right in not selling regardless of the racial matter, and (4) whether the claim of the plaintiff is based on a constitutional violation, a breach of contract, a personal injury, or a property violation. The sale is more likely to be upheld if the seller is willing, the plaintiff is an interfering neighbor, and the buyer is not abusive. The sale is also more likely to be upheld if the claim is based on a violation of constitutional law, contract law, tort law, or property law in that order.

W (or the threshold weight) in the equation, $W1+1+1+2 = W2+2+2+2$. That equation simplifies to $W1+4 = W2+6$, which in turn simplifies to $2W-1W = 4-6$. Thus $1W = -2$.

[39] 334 U.S. 1 (1948).

[40] *Id.* at 20.

TABLE 4

Data for Predicting Housing Discrimination Cases[41]

Criteria[42] / *Casetypes*	*(1)* *Is Seller Willing*	*(2)* *Part/Whole % (Weight = 2)*	*(3)* *Claim*	*(4)* *Part/Whole % (Weight = 1)*	*(5)* *Unweighted Sum*	*(6)* *Outcome*[43]	*(7)* *Sum of Unweighted Part/Whole %'s (2)+(4)*	*(8)* *Sum of Weighted Part/Whole %'s 2(2)+1(4)*
1. Unwilling Seller and Property Claim	1	8%	1	5%	2	?	13%	21%
2. Unwilling Seller and Injury Claim	1	8	2	10	3	?	18	26
3. Unwilling Seller and Contract Claim	1	8	3	15	4	?	23	31
4. Unwilling Seller and Constitutional Claim	1	8	4	20	5	?	28	36
5. Willing Seller and Property Claim	2	17	1	5	3	W	22	39
6. Willing Seller and Injury Claim	2	17	2	10	4	W	27	44
7. Willing Seller and Contract Claim	2	17	3	15	5	W	32	49
8. Willing Seller and Constitutional Claim	2	17	4	20	6	W	37	54
WHOLE	12	100%	20	100%	32		200%	300%

[41]The above data comes from Nagel, *Case Prediction by Staircase Tables and Percentaging*, 25 JURIMETRICS 168 (1985).

[42]The first variable is whether or not the seller is willing to sell. The second variable is the alleged violation which can be a constitutional violation, breach of contract, personal injury, or a property rights violation.

Part/whole percentages are added to give a summation score, rather than just adding the raw scores. The raw scores do not take into consideration that there are four categories on the second variable and only two categories on the first variable.

If we look to the sum of the raw scores, then we have three inconsistencies out of eight casetypes. If we look to the sum of the unweighted p/w%'s, then we have two inconsistencies, since there are two question-mark cases with higher scores than the lowest winning case.

It makes sense to give the variable of being a willing seller more weight than the variable of the alleged violation in cases like these involving restrictive racial covenants.

[43]A "W" in the outcome column means the sale is allowed. A "?" in the outcome column means the outcome is unclear. Shelly v. Kraemer, 334 U.S. 1 (1948), is Casetype 5. The above data generates the following decision rule: (1) If a casetype has a sum of weighted p/w%'s of .39 or higher, then the willing seller wins and the sale is allowed. (2) If a casetype has a sum or weighted p/w%'s of .36 or lower, then the unwilling seller may be allowed to get out of the sale depending on whether or not the buyer is abusive.

To illustrate the problem of multi-dimensionality in predictive criteria, Table 4 only uses criteria 1 and 4 which relate to the willingness of the seller and the nature of the claim. The multi-dimensionality problem involves the fact that the willingness of the seller is measured in terms of a yes-no dichotomy, whereas the nature of the claim is measured in terms of four categories. With two categories on one criterion and four on the other, there are eight casetypes, as listed at the left of Table 4. Column 1 shows how the eight casetypes score on the willingness variable, and column 3 shows how they score on the claim variable. Column 5 adds those raw relation-scores together to obtain an unweighted raw sum. Column 6 shows that the sale will be allowed if the seller is willing. If the seller is unwilling, the outcome depends partly on the other variables which are not included in Table 4.

Where the predictive variables are measured differently, merely summing the raw scores produces distorted results. That would be more obvious if one predictive criterion were measured in miles, and a second predictive criterion were measured in pounds. The results are also distorted if a case receives 4 points for being in the best category on the claim variable, while a case receives only 2 points for being in the best category on the willingness variable. That is due to the coincidence that the claim variable has four categories, and the willingness variable has only two categories. Partly to remedy that situation, the relation scores are transformed into part/whole percentages which are not influenced by whether a variable is measured in miles, pounds, a yes-no dichotomy, or a 1-4 scale.

To transform the relation scores on a given criterion or column, one merely sums the numbers in the column to obtain a total or whole. For example, the sum of the first column is 12. One then divides each number or part in the column by the whole in order to obtain a part/whole percentage for each relation score. For example, the part/whole percentage corresponding to the first relation score in column 1 is 1/12 or 8%. Now instead of adding the raw scores of column 1 to those of column 3 in order to obtain the unweighted raw sum of column 5, one adds the part/whole percentages of column 2 to the part/whole percentages of column 4 to obtain the sum of the unweighted part/whole percentages of column 7. For example, adding 8% in column 2 to 5% in column 3 gives 13% in column 7.

Notice that by working with just the unweighted raw sum there are three inconsistencies out of eight cases. The three inconsistencies are cases 2, 3, and 4. They have unweighted sums that are as high as cases 5, 6, and 7. Cases 2, 3, and 4, however, have unclear outcomes, whereas cases 5, 6, and 7 resulted in the sale being allowed. By working with the sum of the unweighted part/whole percentages, there are only two inconsistencies. They are cases 3 and 4. They have unweighted part/whole percentages larger than cases 5 and 6. Cases 3 and 4, however, have unclear outcomes, whereas cases 5 and 6 resulted in the sale being allowed. All the inconsistencies can be eliminated by recognizing that the willingness of the seller is more important than the nature of the claim. If willingness is given a weight of 2, then the sum of the weighted p/w%'s for the first casetype is twice 8% plus 5% for a total of 21%. If one does likewise for each of the eight casetypes, one obtains the sums of weighted p/w%'s shown in column 8. The percents in that column are in perfect ascending order, such that there are no inconsistencies. If a casetype has a sum of weighted p/w%'s of .39 or higher, then the willing seller wins and the sale is allowed. If a casetype has a sum of weighted p/w%'s of .36 or lower, then the unwilling seller may be allowed to get out of the sale depending on whether or not the buyer is abusive.[44]

OUTCOME RANGES AND INTERNATIONAL LAW CASES

Table 5 contains data for predicting international law cases where the United States is a party. The object is to predict the probability that the United States will win from at least two predictive criteria. The predictive criteria are the source of law and the industrial power of the U.S. opponent. They are two criteria from a larger list of seven, which also includes (1) the international law subject matter and the U.S. position on it, (2) the decision-making tribunal, (3) the economic interests that may be involved and the U.S. position on them, (4) the civil liberty interests that may be involved and the U.S. position on them, and (5) the nature of the plaintiff as a legal entity.

[44]Cases dealing with housing discrimination are discussed in J. KUSHNER, FAIR HOUSING: DISCRIMINATION IN REAL ESTATE, COMMUNITY DEVELOPMENT AND REVITALIZATION (1983); R. SCHWEMM, HOUSING DISCRIMINATION LAW (1983), and N DORSEN, *supra* note 12, at 940-46. For further details on this predictive example, *see* Nagel, *Case Prediction by Staircase Tables and Percentaging*, 25 *JURIMETRICS* 168 (1985).

TABLE 5

Data for Predicting International Law Cases with the U.S. as a Party[45]

Criteria / Casetypes	Source of Law	U.S. Opponent	Sum[46]	Outcome[47]
1. Foreign Law and Less Industrial Opponent	1	1	2	40%
2. Foreign Law and Non-Country Opponent	1	2	3	48
3. Treaty and Less Industrial Opponent	2	1	3	51
4. Foreign Law and Equal Opponent	1	3	4	62
5. International Law and Less Industrial Opponent	3	1	4	56
6. Treaty and Non-Country Opponent	2	2	4	58
7. International Law and Non-Country Opponent	3	2	5	63
8. Treaty and Equal Opponent	2	3	5	73
9. U.S. Law and Less Industrial Opponent	4	1	5	70
10. International Law and Equal Opponent	3	3	6	78
11. U.S. Law and Non-Country Opponent	4	2	6	78
12. U.S. Law and Equal Opponent	4	3	7	92

[45]Table 5 only deals with two of the seven variables in the international law cases. The two are the main source of law and the industrial power of the United States opponent. The source of law includes United States law, international law, a treaty, and foreign law. The United States opponent can be equal to the United States, not a country, or less than the United States in industrial power. Only two variables are used in Table 4 rather than seven, partly because of the temporary limitation to 15 alternatives. One can handle all seven variables through multiple runs with 15 casetypes per run. The number of casetypes, however, is 163,800 since the number of categories per variable of 4, 13, 6, 5, 5, 3, and 7 respectively. Under those circumstances, one would not want to list all the casetypes. Instead, one would want to know what the probability of United States victory is for any combination of seven categories. To estimate that, simply average the seven probabilities of United States victory. The above data comes from Nagel, *Judicial Prediction Analysis from Empirical Probability Tables,* 41 IND. L. J. 403-19 (1966).

[46]The decision rule which the above data generates is Y = .20 + .10(x), where Y is the probability of the United States winning and X is the summation score. The decision rule could also be expressed as a series of if-then statements like (1) if X is 1, then Y is .30; (2) If X is 2, Y is .40; (3) If X is 3, Y is .50; (4) If X is 4, Y is .60; (5) If X is 5, Y is .70; (6) If X is 6, Y is .80; and (7) If X is 7, Y is .90. The above prediction equation comes from observing the relation between the summation scores and the outcome probabilities in Table 5. One can determine the prediction equation more accurately by using a statistical calculation that can easily arrive at such an equation for 12 pairs of inputs. One can also think in terms of six pairs of input for the summation scores from 2 to 7. Thus a score of 4 had an average outcome of .57 since Casetype 6 had an outcome of .56 and Casetype 8 had an outcome of .58.

[47]The outcome figures shown above come from averaging the two probabilities from the two variables used for each casetype. Thus, the combination of United States law and equal power has a .92 probability because

The source of the law refers to the four categories of (1) domestic law of another country (the U.S. is victorious in only 25% of such cases), (2) an international treaty (47% victorious), (3) international law/custom (56%), and (4) U.S. domestic law (85%). The industrial power of the U.S. opponent refers to the three categories of (1) less industrial power than the U.S. (the U.S. is victorious in only 56% of such cases), (2) non-countries (70% victorious), and (3) about the same in industrial power (100% victorious although that sub-sample is small). The victory probabilities are based on an analysis of the 137 cases contained in four leading international law casebooks.

With four categories on one criterion and three categories on the second criterion, there are 12 casetypes, as shown at the left side of Table 5. The summation column sums the raw scores for each casetype across the variables. Technically speaking, part/whole percentages should be used since the predictive variables are measured differently via a 1-4 scale and a 1-3 scale. The scales, however, are close enough to justify working with raw scores at least for this methodological illustration.

Each probability in the outcome column is arrived at by averaging the probabilities for the relevant categories on each predictive variable. Thus, Casetype 1 involves foreign law (25% U.S. victory rate) and a less industrial U.S. opponent (56% U.S. victory rate). The average between 25% and 56% is 40% rounded to the nearest even number. There are more sophisticated ways of combining probabilities in accordance with Bayesian probability analysis. They are, however, highly complicated, especially when more than two predictive variables are involved. The information for a Bayesian analysis is almost never available since it requires knowing various details on how the predictive variables relate to each other. Simply averaging the basic probabilities should provide a sufficient approximation to an overall probability, especially if each predictive criterion is worded in the direction of winning and does not greatly overlap the other criteria. Even if the criteria do overlap, the weights can take that into consideration. Two duplicative criteria, for example, can each be given about half the weight they would otherwise receive if the other criterion in the pair were not also being used.

After determining the criteria, casetypes, relations, summation scores, and outcomes, one should develop a decision rule indicating for various summation scores what outcomes are likely to occur. This example, however, differs from the previous examples in that the outcome is a range between 40% and 92% rather than just a dichotomy of winning versus losing. Having an

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United States law has a .85 probability and equal power has a 1.00 probability. This gives an approximation to a Bayesian conditional, especially where we only have the main probabilities with which to work. Table 5 provides a good illustration of an outcome that is not a dichotomy of win or lose but rather a continuum outcome of 0 to 1.00.

outcome range is common in most court cases as well as a win-lose dichotomy. In damage cases, the dichotomous liability-decision is followed by a continuum damages-decision when liability is established. Damages can range from a low of $1 in some libel cases to millions of dollars in treble damage antitrust suits. In criminal cases, the conviction decision is followed by a sentencing decision when there is a conviction. Sentences can range from a low of no jail time to life imprisonment or the death penalty.

In Tables 1 through 5, one could bypass the summation score and formulate a decision rule that specifies for each casetype or case what the outcome is likely to be. That approach is likely to lead to inconsistencies, as was shown with the redistricting cases and the housing discrimination cases. It is also much more clumsy to have to specify how each case or casetype will be decided, especially if there are many casetypes. With a win-lose dichotomy, the decision rule simply specifies what summation score separates the winners from the losers. In predicting a range outcome, there is no such threshold summation score. Instead, one would like to know the likely outcome at a base summation score of 0 or 1, and how much the outcome is likely to increase for each 1-unit increase or 1% increase in the summation score.

Looking at the last two columns of Table 5 tends to generate a decision rule that Y = .20 + .10(X), where Y is the probability of the U.S. winning, and X is the summation score. One can see that the two casetypes with summation scores of 3 average about a .50 probability; the three casetypes that score 4, average about .60; and the three casetypes that score 5 average about .70. Extending those relations downward implies or extrapolates that a summation score of zero would have a probability of about .20. One cannot, however, score less than a 2 on the two predictive criteria together. At the other end, that eyeballing approach implies that a summation score of 8 would have a probability of about 1.00. One cannot, however, score more than 7 on the predictive criteria. Thus, the eyeballed or linear relation is not subject to the criticism that it leads to probabilities below zero or above 1.00 since all the possible summation scores lead to reasonable probabilities when using the decision rule Y = .20 + .10(X).

Greater precision may sometimes be required than the eyeballing approach provides. Under those circumstances, one can insert into a statistical calculator the 12 pairs of numbers, consisting of 2 and .40, 3 and .48, and so on. After keying in those 24 numbers, one can read out the value of the constant which is .19 rather than .20, and the value of the slope which is slightly more than .10. The computer program will do that kind of statistical regression analysis directly when the P/G% program is further developed.

One can also obtain a decision rule which reflects diminishing returns of the form $Y = .24(X)^{.65}$ by inserting the same 24 numbers and asking for diminishing returns output. With that equation, a summation score of 1 predicts a probability of .24, and a summation score of 2 predicts a probability of .38. Each successive increment on the summation score increases the probability, but at a diminishing rate. The .65 means that if the summation score doubles (i.e., increases by 100%), then the probability will increase by about 65%. For example if the summation scores doubles from 1 to 2, then the predicted probability goes up from .24 to .38. The .14 difference is about 65% of the .24 base. Diminishing returns is a fact of life in the relation between most inputs and most outputs, but linear relations often give good enough predictability. With the aid of the microcomputer program, one can request how one wants the summation scores related to the range outcomes with equal ease, regardless whether one chooses constant returns, diminishing returns, or other available options.[48]

MULTIPLE WEIGHTS FOR PREDICTIVE CRITERIA AND CRIMINAL CASES

Table 6 contains data for predicting criminal cases. The data is purely hypothetical, unlike any of the previous five tables. For methodological purposes, however, hypothetical data should be just as usable as real data. This data is not only hypothetical, it is also symbolic data, meaning the cases and criteria only have letters not names. The advantage of such data is that it enables one to see the methodology more clearly without substance getting in the way. Another advantage is that this particular set of hypothetical data is the first court-case prediction problem with which this author dealt back in 1960. This example thus illustrates some important changes over the past 25 years in systematic quantitative judicial prediction.

[48]The international law casebooks which provide the data base for this example are W. BISHOP, INTERNATIONAL LAW (1953); M. HUDSON, INTERNATIONAL LAW (1951); M. KATZ & K. BREWSTER, INTERNATIONAL TRANSACTIONS & RELATIONS (1960); L. ORFIELD & E. RE, INTERNATIONAL LAW (1955). For further details on this predictive example, *see* Nagel, *Judicial Prediction and Analysis from Empirical Probability Tables*, 41 IND. L.J. 403 (1966). Working with probabilities of victory and average damages under various circumstances can be facilitated by such loose-leaf services as those published by the Jury Verdict Research Service.

TABLE 6

Data for Predicting Hypothetical Criminal Cases[49]

Criteria[50] / *Casetypes*	*P Criterion (W = +.75)*	*Q Criterion (W = −.67)*	*R Criterion (W = +1.00)*	*S Criterion (W = +.67)*	*Unweighted Sum*	*Outcome*[51]	*Weighted Sum*[52]
1. A	1	2	1	1	5	P	1.09
2. C	2	2	1	1	6	P	2.09
3. B	2	2	2	2	8	D	3.50
4. D	2	1	2	1	6	D	3.50
5. E	2	1	2	2	7	D	4.16

There are five criminal cases called A, B, C, D, and E, although the data is general enough to be any kind of case. There are four predictive criteria called P, Q, R, and S. There are thus 20 relations. Each relation is a yes-no dichotomy. The criteria are worded in such a way that a yes answer favors the defense, and a no answer favors the prosecution. If one adds the unweighted raw relation scores across each case, one obtains unweighted sums of 5, 8, 6, 6, and 7 for cases A, B, C, D, and E, respectively. Those raw scores generate one inconsistency out of five opportunities, since both case C and D have 6 points, but C was decided in favor of the prosecution and D in the favor of the defense.

The best way to eliminate inconsistencies is generally by giving the predictive criteria different weights, rather than having the same weight for all the criteria. The best way to determine those weights is generally in terms of the relative substantive importance of the variables as known to reasonably knowledgeable people. That is what was once done (1) in the cases dealing with religion in the public schools, in saying educational purpose is an exemption variable and compulsory participation is a constraint variable, (2) in the redistricting cases, in saying the presence of an equality requirement is more

[49]The above data comes from Nagel, *Using Simple Calculations to Predict Judicial Decisions*, 7 PRAC. LAW. 68-74 (1961).

[50]There are various ways in which one can assign weights to predictive criteria. The method used here is to determine the correlation coefficient of each predictive variable with whether the prosecution or defendant wins. In other words, outcome can be considered a dichotomous Y variable to be correlated with the X1, X2, X3, and X4 predictive criteria.

This is a good example of the use of weights for the predictive variables.

[51]A "P" in the outcome column means the prosecution wins. A "D" means the defense wins.

[52]The decision rule which the above data generates is: (1) If the weighted summation score is 3.50 or above, the defendant wins. (2) With a summation score of 2.09 or below, the prosecution wins. (3) If the weighted summation score is between 2.09 and 3.50 the result is unclear. The weighted summation scores are calculated by multiplying the raw scores on each predictive criterion by the weight of the criterion. Those products are then added across each case. There is one inconsistency with the unweighted summation scores, but no inconsistencies with the weighted summation scores.

important than the other variables, and (3) in the housing discrimination cases, in saying the willingness of the seller is more important than the field of law. The best tests of how well the cases have been weighted are whether the weighting makes substantive sense, and whether the weighting results in a perfect separation of the winning cases from the losing cases.

An alternative weighting method is to weight the criteria in terms of their association with the outcome that one is trying to predict. That is what is done in Table 7. That table shows how the weights for Table 6 were determined. For example, criterion P has a weight of +.75 because 75% of the cases that had P present resulted in victory for the defense, whereas 0% of the cases that had P absent resulted in victory for the defense. By subtracting those two percentages, one obtains a constant of zero and a slope of .75 in an equation of the form $Y = 0 + .75(X)$. Y is the case outcome (with 0 for P and 1 for D), and X is the general predictive criterion (with 0 for absent and 1 for present). Thus if the predictive criterion moves from 0 to 1, the outcome then moves from a probability of 0% for the defense winning on up to 75%. The other four sub-tables of Table 7 can be interpreted the same way to yield equations of the form $Y = 1.00 - .67(Q)$; $Y = 0 + 1.00(R)$; and $Y = .33 + .67(S)$.

TABLE 7

Weighting Predictive Criteria by Association with Outcome[53]

P Criterion

	No	Yes	
Defense Wins	0 0%	3 75%	+.75
Prosecutor Wins	1 100%	1 25%	
Totals	1 100%	4 100%	5

Q Criterion

	No	Yes	
Defense Wins	2 100%	1 33%	-.67
Prosecutor Wins	0 0%	2 67%	
Totals	2 100%	3 100%	5

[53]There are always five cases regardless of the predictive variable that one is relating to outcome.

Each sub-table shows how the five cases are positioned on absence or presence of the variable and whether the defense or prosecution won.

Each sub-table has four cells because there are two categories on each variable being related. It is purely coincidental that there happen to be four variables.

TABLE 7 *(Continued)*
Weighting Predictive Criteria by Association with Outcome

	R Criterion No	R Criterion Yes	
Defense Wins	0 0%	3 100%	+1.00
Prosecutor Wins	2 100%	0 0%	
Totals	2 100%	3 100%	5

	S Criterion No	S Criterion Yes	
Defense Wins	1 33%	2 100%	+.67
Prosecutor Wins	2 67%	0 0%	
Totals	3 100%	2 100%	5

Those four slopes or weights can be used to weight the predictive criteria especially if those variables are independent of each other. If their lack of independence is great enough to produce inconsistencies, then the weights can be adjusted in light of the known overlap among the variables until the inconsistencies are eliminated. The weights can also be adjusted in light of the relative substantive importance of the variables. Those weights may not have been adequately measured by the kind of relational analysis shown in Table 7 due to problems of (1) reciprocal causation whereby prior case outcomes influence what evidence variables are subsequently introduced, (2) spurious causation whereby both the case outcome and the presence of an evidence variable are influenced by other common factors, and (3) multicolinearity whereby the predictive criteria influence each other in terms of overlap, interaction, and interference.

Notice that with the weights from Table 7 introduced into Table 6, the weighted sums for the cases proceed in perfect ascending order. All the defense cases now have higher weighted summation scores than any of the prosecution cases which was not so with the unweighted sums. The decision rule is that the defendant wins with a weighted summation score of at least 3.50, and the prosecution wins with a weighted summation score of at most 2.09. Between 2.09 and 3.50 is a gray area that requires more cases to resolve.[54]

[54]Cases dealing with criminal law prediction are discussed in W. LAFAVE & A. SCOTT, CRIMINAL LAW (1972). For the forerunner of this predictive example, *see* Nagel, *Using Simple Calculations to Predict Judicial Decisions*, 7 PRAC. LAW. 68 (1961).

Comparing Table 7 with Tables 1 through 6 indicates that there are two major ways of using a matrix for prediction purposes. One way is the essence of P/G% prediction. It involves cases or casetypes on the rows and predictive criteria on the columns. The other way is the essence of statistical prediction. It involves categories of the outcome variable shown on the rows, and categories of one predictive criterion shown on the columns. The first kind of matrix is a data matrix, and the second kind is a cross-tabulation matrix. Cross-tabulation is generally preceded by the preparation of a data matrix. P/G% prediction uses a data matrix to make predictions without the matrix being preliminary to a subsequent matrix, although P/G% prediction may rearrange the cases to put them in the order of their summation scores in order to see more clearly the optimum predictive decision-rule.

P/G% data-matrix prediction has advantages over cross-tabulation prediction. A data matrix can show any kind of measurement for the predictive criteria or the outcome variable. Cross tabulation tends to be confined to dichotomies or a limited number of categories on each variable. Along related lines, a data matrix works with raw data that is not likely to have been subjected to distorting transformations. A data matrix can show any number of predictive variables, but a cross-tabulation table is generally confined to only one predictive variable. A data matrix in the P/G% context is a working tool for suggesting predictive decision-rules and action strategies, whereas a cross-tabulation table tends to be a visual aid for showing results that have already been determined. One might note that some of the defects of a cross-tabulation table are not present in statistical regression analysis, such as arbitrary categorizing and being confined to one predictive variable at a time. Regression analysis may, however, have other even more serious disadvantages to which we now turn.

MULTIPLE REGRESSION, STAIRCASE PREDICTION, AND P/G% PREDICTION

One might ask why not do a multivariate regression analysis from the start, instead of doing a set of bivariate regression analyses like those shown in Table 7, in order to obtain the weights for a P/G% prediction analysis. Such a multivariate analysis would have the form $Y = a + b_1P + b_2Q + b_3R + b_4S$. Each b represents a regression weight which statistically controls for multi-dimensionality and overlap. The main advantage of that approach is its mechanical objectivity once the data table has been determined. Multiple regression analysis, however, is more complicated to do and present, although it has recently been made less complicated by the availability of microcomputer floppy discs which can quickly process a set of data like that shown in Tables 1-6 in order to generate the constant and the regression weights for the variables.

Disadvantages of a multiple regression approach are:

1. It cannot guarantee perfect prediction of the past cases on which the equation is based unless one uses the same substantive-reasoning methods for eliminating inconsistencies as the methods associated with P/G% prediction.
2. The same above problems of invalidity occur with multivariate regression as with bivariate regression (including reciprocal causation, spurious causation, and multicolinearity) since both approaches use the same relatively mechanical methods to arrive at weights, as contrasted to using knowledgeable insiders who can separate out those problems.
3. Regression analysis cannot meaningfully relate summation scores to winning or losing the way a threshold decision rule can, because a regression equation requires that as the predictor variable increases, the predicted variable must also change. A threshold decision rule recognizes that the same low scores may all lead to losing, and the same high scores may all lead to winning.
4. Weighting the predictive criteria substantively as was done with Tables 1, 2, and 4 is much easier methodologically than arranging for a multivariate regression analysis. Likewise, the bivariate analysis of Table 6 is much easier than a multivariate analysis even if the criteria are not all measured in yes-no dichotomies. One can then determine a bivariate regression weight with a statistical calculator, as mentioned in discussing Table 5, rather than with a four-cell cross-tabulation table.
5. One could express the idea of summing the unweighted raw scores as a regression equation of the form $Y = a + b_1P + b_2Q + b_3R + b_4S$, where "a" equals zero, and each "b" equals 1. That only complicates the summation rule, and provides no information as to what Y score leads to winning and what Y score leads to losing.
6. Regression analysis, like statistical techniques in general, requires a lot of random cases to be meaningful. That means at least 30 cases if one wants to have a representative sample randomly drawn from a larger data set. Sample size is important because regression analysis involves inductively arriving at generalizations. P/G% mainly involves deductively reasoning that (1) if a certain case is decided positively, then it would be decided even more positively with additional favorable variables; (2) if a certain case is decided negatively, then it will be decided even more negatively with fewer favorable variables; (3) if a certain case is decided positively or negatively with variable X_1 present, then it will also be similarly decided with variable X_2 substituted where X_2 is analogous or similar to X_1.
7. One cannot legitimately change the weights in regression analysis. They are locked in by the requirement that the weights must minimize

the sum of the squared deviations of the predicted scores from the actual scores. One can legitimately change the weights in P/G% prediction if doing so makes substantive sense and reduces inconsistencies. Making substantive sense and reducing inconsistencies is a more meaningful criterion than the least squares criterion.

8. Multivariate regression analysis may be the most sophisticated and widely used statistical method for predicting incidents or cases from variables. In light of the five points above, however, the method is (1) too imperfect in its predictive power, (2) too invalid in its attempt to describe empirical realities, (3) too irrelevant for predicting what is essentially a kinked or threshold relationship rather than a smooth straight or curved line, (4) too complicated, (5) too incomplete in expressing summation relations, (6) too demanding of large samples, and (7) too inflexible in not allowing one to change the predictive weights.

At the opposite extreme from the mechanical quantification of multivariate statistical regression analysis is the method of staircase prediction. It can be done with no quantification at all. It basically involves showing one predictive criterion along the horizontal axis of a two-dimensional matrix, with its categories shown as columns in ascending order toward winning. A second predictive criteria is shown along the vertical axis, with its categories shown as rows also in ascending order toward winning. The actual or presumed outcomes are then shown in the cells for each combination of categories expressing the outcomes in words or symbols, but not necessarily numbers. One can then see that as one moves from the southwest corner of the matrix toward the northeast, losing changes to winning. One can section off the losing cells from the winning cells with a thick kinked line that looks like a staircase.

That kind of staircase analysis, like P/G% prediction, does stimulate more careful thinking than multivariate regression analysis about the order of the categories on the variables and what the key variables are. It is also capable of working with a sample size of a few, one, or even no key cases by deducing outcomes for casetypes, as contrasted to multivariate regression analysis which needs many diverse cases with actual outcomes. Such an empirical sample may often be nonexistent. Staircase analysis is also a useful visual aid, like drawing indifference curves in economics or probability analysis.

On the other hand, staircase prediction is limited almost completely to situations where there are only two predictive variables because it is virtually impossible or at least quite difficult to use the two-dimensional matrix approach when adding a third or fourth variable. The staircase approach is also incapable of handling the assigning of different weights to the variables without introducing quantitative methods, especially if the variables are measured on different scales.

Multiple regression, staircase prediction, and P/G% prediction all have in common that they are systematic approaches to arriving at predictive decision-rules from a set of cases, criteria for distinguishing the cases, and the relations between the cases and the criteria. Those methods can be contrasted with unsystematic methods which involve relying on a holistic gestalt approach that does not disaggregate the decision-rule components into specific cases criteria, and relations. A holistic approach tends to lack precision, validity, objectivity and transferability. Its main advantage is that it requires little thinking, and the quality of results may therefore suffer substantially, although a combination holistic and disaggregated approach may be better than either alone.[55]

In conclusion, P/G% prediction can be considered more meaningful than multiple regression since P/G% has the advantages of quantitative regression without the above disadvantages. It can also be considered more meaningful than staircase prediction since P/G% has the qualitative and verbal advantages of staircase prediction without its limiting disadvantages. In addition, the P/G% approach has the simplicity of being usable via the kind of analysis shown in this article, or via the readily available P/G% microcomputer program.[56]

APPENDIX 1: FURTHER EXAMPLES OF P/G% PREDICTION

Data for Predicting Welfare Cases

Criteria / *Casetypes*	*Substance Severity*	*Procedural Severity*	*Sum*	*Outcome*
1. Eligibility Denied and No Attorney Appointed	1.00	0.99	1.99	L
2. Benefits Reduced and No Attorney Appointed	2.00	0.99	2.99	L
3. Eligibility Denied and No Hearing	1.00	2.00	3.00	L

[55]On multiple regression analysis at an introductory level, see A. EDWARDS, AN INTRODUCTION TO LINEAR REGRESSION AND CORRELATION (1976), and E. TUFTE, DATA ANALYSIS FOR POLITICS AND POLICY (1974). On staircase prediction, *see* Nagel, *Case Prediction by Staircase Tables and Percentaging*, 25 JURIMETRICS 168 (1985).

[56]For additional examples and aspects of P/G% prediction and evaluation, *see* NAGEL, MICROCOMPUTERS AS DECISION-MAKING AIDS IN LAW PRACTICE (1985). This book of materials will be used in a course on that title, offered by the Committee on Continuing Professional Education of the American Law Institute and the American Bar Association on May 10-11, 1985. The microcomputer program is available from the author on request for $20 to cover the cost of an IBM floppy disk, the manual, postage, and handling. The program was written with John Long of the University of Illinois.

APPENDIX 1: FURTHER EXAMPLES OF P/G% PREDICTION *(Continued)*

Data for Predicting Welfare Cases

Criteria / *Casetypes*	*Substance Severity*	*Procedural Severity*	*Sum*	*Outcome*
4. Termination and No Attorney Appointed	3.00	0.99	3.99	L
5. Benefits Reduced and No Hearing	2.00	2.00	4.00	?
6. Eligibility Denied and No Reasons	1.00	3.01	4.01	W
7. Criminal Prosecution and No Attorney Appointed	4.00	0.99	4.99	W
8. Termination and No Hearing	3.00	2.00	5.00	W
9. Benefits Reduced and No Reasons	2.00	3.01	5.01	W
10. Criminal Prosecution and No Hearing	4.00	2.00	6.00	W
11. Termination and No Reasons	3.00	3.01	6.01	W
12. Criminal Prosecution and No Reasons	4.00	3.01	7.01	W

NOTES:

1. A "W" in the outcome column means the welfare recipient wins. An "L" means the welfare recipient loses. The Goldberg case is Casetype 7, and the Argersinger case in Casetype 12.
2. The decision rule which the above data generates is:
   (1) If a welfare case involves a summation score of 4.01 or above, the welfare recipient wins.
   (2) With a summation score of 3.99 or below, the welfare recipient loses.
   (3) With a score of 4.00, the outcome is unclear.
3. The leading case is Goldberg v. Kelly, 397 U.S. 254 (1970). It involved a summation score of 5.00, and the welfare recipient won. Therefore, one would expect the welfare recipient to win even more with scores higher than 5.00. That covers Casetypes 2, 3, 4, and 8.
4. The outcome of Case 12 is known from Argersinger v. Hamlin, 407 U.S. 25 (1972).
5. The outcomes of Cases 1, 5, 9, 10 and 11 are known from things said in the Goldberg case, not from an *a fortiori* deduction.

6. The above data comes from Nagel, *Case Prediction by Staircase Tables and Percentaging,* 25 JURIMETRICS 168 (1985).

Data for Predicting Equal Protection Cases

Criteria / *Casetypes*	*Score On Rights*	*Score On Groups*	*Sum*	*Outcome*
1. Consumers/Region	1	1	2	D
2. Consumers/Economic Class	1	2	3	D
3. Employment/Region	2	1	3	D
4. Consumers/Sex	1	3	4	D
5. Employment/Economic Class	2	2	4	D
6. Housing/Region	3	1	4	D
7. Employment/Sex	2	3	5	D
8. Housing/Economic Class	3	2	5	D
9. Schools/Region	4	1	5	D
10. Housing/Sex	3	3	6	D
11. Schools/Economic Class	4	2	6	D
12. Consumers/Race	1	6	7	P
13. Criminal Justice/Region	6	1	7	?
14. Schools/Sex	4	3	7	?
15. Criminal Justice/Economic Class	6	2	8	P
16. Employment/Race	2	6	8	P
17. Voting/Region	7	1	8	P
18. Criminal Justice/Sex	6	3	9	P
19. Housing/Race	2	6	9	P
20. Voting/Economic Class	7	2	9	P
21. Schools/Race	4	6	10	P
22. Voting/Sex	7	3	10	P
23. Criminal Justice/Race	6	6	12	P
24. Voting/Race	7	6	13	P

NOTES:

1. The above data can generate two compatible *decision rules.* One rule is:
   (1) If an equal protection case has a summation score of 7 or higher, then the plaintiff will win.
   (2) If the case has a score of 6 or lower, then the defendant will win.

2. The alternative decision rule is:
   (1) If an equal protection case has a summation score greater than 7, then the plaintiff will win.
   (2) If the case has a score of exactly 7, then the outcome is questionable.
   (3) If the case has a score of 6 or lower, then the defendant will win.
3. Each *casetype* is defined in terms of:
   (1) The rights that are allegedly being denied which can relate to voting, criminal justice, schools, housing, employment, or consumer rights in that order of importance.
   (2) The group that is allegedly being given unequal treatment, which can relate to race (which generally means being black), sex (which generally means being female), economic class (which generally means being poor), or region (which generally means being urban or inner city) in that order of importance.
4. To determine the score of each casetype on the *rights,* the six rights are arranged in rank order with the most important right receiving a score of 6. Slight adjustments are then made to recognize there is more distance between the top two rights and the bottom four than there is between the other rights.
5. To determine the score of each casetype on the *groups,* the four groups are arranged in rank order with the most important group receiving a score of 4. Slight adjustments are then made to recognize there is more distance between the top group and the bottom three than there is between the other groups.
6. The first decision rule *implies* that the court would decide in favor of the plaintiff if the state provided grossly unequal right to counsel from one county to another, or if women were denied admission to an all-male public school, although the court has not yet done so.
7. The second decision rule implies that being black scores slightly higher than a 6. That causes 12 to score slightly higher than 7, and thus to be distinguishable from the questionable cases.
8. Landmark cases or Constitutional amendments that correspond to the casetypes include Gomillio v. Lightfoot, 364 U.S. 339 (1960) (casetype 24); Powell v. Alabama, 287 U.S. 45 (1932) (casetype 23); U.S. CONST. amend XIX (casetype 22); Brown v. Bd. of Educ., 347 U.S. 483 (1954) (casetype 21); Harper v. Virginia Bd. of Elections, 383 U.S. 663 (1966) (casetype 20); Shelley v. Kraemer, 334 U.S. 1 (1948) (casetype 19); Taylor v. Louisiana, 419 U.S. 522 (1975) (casetype 18); Reynolds v. Sims, 377 U.S. 533 (1964) (casetype 17); Jones v. Alfred H. Mayer Co., 392 U.S. 409 (1968) (casetypes 12 and 16); Gideon v. Wainwright, 372 U.S. 335 (1963) (casetype 15); and San Antonio Ind. School Dist. v. Rodriguez, 411 U.S. 1 (1973), *reh'g denied,* 411 U.S. 959 (1973).
9. The data for this table comes from Nagel, *Case Prediction by Staircase Tables and Percentaging, 25 JURIMETRICS 168 (1985).*

Using the P/G% Approach to Synthesize Case Facts

Criteria / *Alternatives*	*(1) Defense Statement (Alibi) W = 2*		*(2) Prosecution Statement (Scene of Crime) W = 1*	*(3) SUM (1)+(2)*	*(4) SUM/N (3)/2*	*(5) Weighted Sum (1.5)+(2)*	*(6) Weighted Sum/Sum of Weights (5)/3*
Defendant is Guilty	.20	(.40)	.70	.90	.45	1.10	.37
Defendant is not Guilty	.80	(1.60)	.30	1.10	.55	1.90	.63
	1.00	(2.00)	1.00	2.00	1.00	3.00	1.00

NOTES:

1. The numbers in columns 1 and 2 are probabilities. They indicate the degree of accuracy or truth associated with the statements in the direction of establishing the defendant's guilt. Thus, the .20 probability means that there is a .80 probability that the defense statement is true, and the .20 complement is in the direction of establishing the defendant's guilt. These are probabilities of truth, not probabilities of guilt.
2. The weights indicate the degree of importance of the evidence items. Thus an alibi statement is quite important (if true) in establishing innocence. A statement saying the defendant was at the scene of the crime is less important because even if it is true, it does not establish the defendant's guilt. The numbers in parentheses in column 1 are weighted probabilities.
3. The numbers in column 3 are the sum of the two unweighted probabilities. The numbers in column 5 are the sums of the two weighted probabilities.
4. The numbers in column 4 are unweighted average probabilities. The numbers in column 5 are weighted average probabilities. The numbers in column 6 are an approximation of Bayesian conditional probabilities especially when one only has probabilities of truthfulness and degrees of importance with which to work.
5. If the probability in the upper right hand corner is greater than .90, then the judge, juror, or other perceiver of these two items of evidence should vote to convict assuming (1) .90 is accepted as the threshold probability interpretation of beyond a reasonable doubt, and (2) these are the only items of evidence. If the starred probability is .90 or less, then one should vote to acquit.
6. With two alibi witnesses, each might receive a weight of 1.5 if one witness receives a 2. They do not both receive a 2 because they partly reinforce each other.
7. No set of weights will cause the weighted average to exceed .90 with probabilities of .20 and .70. Thus, there is no threshold value for either W1 or W2.
8. The difficulty of obtaining a set of evidence items across the prosecution and the defense that average better than a .90 probability may indicate that jurors and judges generally operate below the .90 threshold, even though judges and commentators say that .90 is roughly the probability translation of "beyond a reasonable doubt."

APPENDIX 2. THE COMPUTER OUTPUT FOR GOING FROM CASES, CRITERIA, AND SCORES TO A PREDICTIVE CONCLUSION

The Nine Redistricting Cases and How They Were Decided

Alternative	*Previous Outcome*
1. Colegrove	D Wins
2. Grills	A
3. Maryland	D
4. Scholle	D
5. WMCA	D
6. Asbury	A
7. Dyer	A
8. Baker	A
9. Magraw	A

NOTE:

1. These are nine key cases on the subject of legislative redistricting decided between Colegrove v. Green, 328 U.S. 549 (1946) and Baker v. Carr, 369 U.S. 186 (1962).

The Four Predictive Criteria and How They Are Measured and Weighted

Criterion	*Meas. Unit*	*Weight*
1. = Required	Yes/2 No/1	1.00
2. State Legis.	"	1.00
3. = Violated	"	1.00
4. Fed. Court	"	1.00

NOTES:

1. The first criterion is whether or not the relevant constitution required equal population per legislative district.
2. The second criterion is whether the legislature in question was a state legislature or the federal Congress.
3. The third criterion is whether the degree of equality violation is great enough that less than 35% of the state's population could choose more than 50% of the legislative body or congressional delegation.
4. The fourth criterion is whether the court deciding the case was a federal or state court.
5. All the criteria are worded so that a yes answer is favorable to a victory for the side attacking the prevailing redistricting.

The Scores of the Cases on the Criteria

Alternative/Criteria Scoring

	= Requi	*State Le*	*= Viola*	*Fed. Cour*
Colegrove	1.00	1.00	1.00	2.00
Grills	2.00	2.00	1.00	1.00
Maryland	1.00	2.00	2.00	1.00
Scholle	1.00	2.00	2.00	1.00
WMCA	1.00	2.00	1.00	2.00
Asbury	2.00	2.00	2.00	1.00
Dyer	2.00	1.00	2.00	2.00
Baker	2.00	2.00	2.00	2.00
Magraw	2.00	2.00	2.00	2.00

The Initial Predictive Conclusion with Equal Weights for the Criteria

Alternative	*Combined Rawscores*	*Previous Outcome*
1. Colegrove	5.00	D Wins
2. Grills	6.00	A
3. Maryland	6.00	D
4. Scholle	6.00	D
5. WMCA	6.00	D
6. Asbury	7.00	A
7. Dyer	7.00	A
8. Baker	8.00	A
9. Magraw	8.00	A

NOTE:

1. The decision rule for the above table is that if the combined raw scores for a case equal 7 or above, the attacker wins. If the combined raw scores equal 6 or below, the defender wins, but with one inconsistency, namely the Grills case where the attacker won.

The Predictive Conclusion with Double Weight for the Most Important Criteria

Alternative	*Combined Rawscores*	*Previous Outcome*
1. Colegrove	6.00	D Wins
2. Grills	8.00	A
3. Maryland	7.00	D
4. Scholle	7.00	D
5. WMCA	7.00	D
6. Asbury	9.00	A
7. Dyer	9.00	A
8. Baker	10.00	A
9. Magraw	10.00	A

NOTE:

1. Note that as the result of giving the equality requirement a weight of 2 in the Scores of the Cases Table the inconsistency is removed in the Initial Predictive Conclusion Table whereby the Grills case received only 6 points, but yet the attacker won.
2. The decision rule for the above table is that if the combined raw scores for a case equal 8 or above, the attacker wins. If the combined raw scores equal 7 or below, the defender wins, with no inconsistencies.