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MULTICRITERIA MODELS FOR GROUP DECISION MAKING : COMPROMISE PROGRAMMING VS. THE ANALYTIC HIERARCHY PROCESS

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Abstract

This paper describes two contrasting approaches to group decision making involving multiple criteria. A compromise programming method and the analytic hierarchy process are analyzed and compared by using an illustrative example of a computer model selection problem to demonstrate their usefulness as a viable tool for group decision making. This paper further considers some extensions and modifications of these two methods for future study.

1. INTRODUCTION

In a competitive business society, there are many situations in which a decision must be made by a group of individuals. Each of these individuals may view the problem differently. They may differ on the importance attached to a particular factor in the decision or even on what factors are relevant in the decision. A committee or taskforce is often faced with the problem of summarizing concisely its findings or recommendations to a higher level in the organization. In the case of evaluating a set of mutuallyexclusive alternatives, a group's recommendations could take the form of a ranking or prioritization.

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Ideally, reasoned debate among group members will lead to consensus. In practice, however, it may be necessary to arrange for some sort of compromise. Zeleny [21] describes compromise solutions as solutions that are displaced from an "ideal" solution. That ideal solution is usually, in some sense, an unavailable, unattainable, or infeasible alternative. Because of these reasons, the "real-world" applications of the multicriteria decision-making (MCDM) models are rare.

This paper examines two contrasting approaches for group decision making involving multiple criteria: a compromise programming method and the analytic hierarchy process (AHP). Compromise programming for group decision making is a structured approach to seeking a consensus when the decision makers in the group settle their differences by making some concessions. The basic theme is to identify a compromise solution with minimal distance from the ideal solution. The method under consideration here was developed by Cook and Seiford [7] and classified by Zeleny as a compromise programming method. The AHP arrives at a group decision through a different approach. Discrete alternatives are prioritized as a result of a decomposition-synthesis process. The AHP was developed by Saaty [13] and has been applied to a very wide range of decision problems. These tow approaches are described and analyzed with an illustrative example to demonstrate their usefulness as a viable tool for managerial group decision making. Some extensions and modifications of these approaches are further considered in this paper.

2. MULTICRITERIA DECISION MAKING(MCDM)

Nature of MCDM

Chankong and Haimes [5] classify MCDM with regard to the underlying decision rule a decision maker uses for expressing priorities or ranking alternatives. The three classes indentified are:

1. methods based on global preference;
2. methods requiring elicitation of preference through weights, priorities, goals and ideals, and,
3. methods requiring elicitation of preference through trade-offs.

Utility models, for example, fall into the first class. The second class includes the variations of goal programming and compromise programming. The third includes the well-known Zionts-Wallenius method and the AHP among many others.

Interactive approaches in eliciting preferences are very common in MCDM. The Zionts-Wallenius method, among those mentioned above, uses an interactive approach to find a best-compormise solution. There are interactive versions of goal programming, compromise programming, and the AHP as well.

This articulation of preferences, whether interactive or not, is of great concern to MCDM analysts and researchers. Narasimhan and Vickery [12] investigated issues in elicitation of preferences for an experimental case study. They compared the decision maker's use of two MCDM methods: Zionts-Wallenius method and the HAP. To compare the two methods the following performance measures used were:

1. ease of use
2. time required for decision making
3. satisfaction with the solution
4. problem insight or understanding gained
5. ability of method to capture preferences, and
6. meaningfulness of the trade-offs preference judgments required.

They also investigated the effect of the complexity(number of criteria) of the problem in an analysis of variance test. Not unexpectedly, the number of objectives in a problem formulation degraded the ease-of-use and the meaningfulness measures. It is suggested that the MCDM analyst and researcher attempt to facilitate the articulation of preference judgments in such problems.

Cook et al. [6] divide MCDM models into two classes: (1) compensatory and 2) non-compensatory approaches. Compensatory models reduce the multiple attribute decision environment to a single objective through the use of trade-offs. Examples of compensatory approaches include multi-attribute utility theory models and economic cost-benefit analyses. The AHP also falls into this category. In these models, every factor, dimensions, or impact in the decision is expressed in a single measure(e. g., monetary value, utility, unitless ratio, etc.). This approach assumes that all trade-offs can be made; the decision maker is willing to trade one attribute for another at some marginal rate. The MCDM model then becomes similar to a single-objective optimization model.

If the decision environment contains qualitative factors, then these interattribute trade-offs may be difficult to express. Intangible or diverse criteria in these situations may lead decision makers to a non-compensatory approach. Examples of these include lexicographic and satisficing models, ordinal ranking models, various dominance approaches, and concordance analysis. In these models there is no need to express trade-offs among attributes which may not be comparable to the decision maker. Non-compensatory models also offer the advantage of involving the decision makers at various points in the decision process. This may provide the decision maker with some insights into the problem. Non-compensatory models also may avoid much of the "black-box" phenomenon of compensatory models. Saaty [15, 16] and Saaty and Vargas [17] have criticized the number crunching of these black box models on numerous occasions in arguing for the usefulness of the AHP.

Multicriteria Models for Group Decison Making

In a sense, having multiple decision makers for a problem is analogous to having multiple objectives for an individual decision maker. That is, each individual participating has an objective: to select the best alternative or to find an optimum. In multiple objective decision making, the best solution is found by compromising, subordinating some objectives, etc. The same occurs for multiple decision makers. The ideas of MCDM are applicable in either group or individual decision making.

Many MCDM models for groups have been developed. Kersten [9] describes an interactive procedure for group decision involving repeated iterations until consensus is reached. Cool and Seiford [7] show how individual priority rankings are combined in a non-interactive compromise programming model to form a group consensus. Saaty [14] and Aczel and Saaty [1] show the AHP may be applied in the case of group decision making. Basak [3] has studied the combining of group's judgments. Lockett et al. [11] illustrate the application of the AHP to three group MCDM problems: choice of daily newspaper, choice of country for international investment portfolio, and choice of a personal computer.

3. COMPROMISE PROGRAMMING vs. AHP

The main characteristic procedures of compromise programming and AHP methods are described below for comparison.

Compromise Programming

If the individual members of a group express their preferences for discrete alternatives in terms of ordinal rankings, then there exist a variety of approaches for combining their individual preferecnes into a group consensus. Some of these are described by Cook and Seiford.

Compromise programming method determines a consensus or compromise solution which minimizes he total absolute "distance" between the consensus ranking and the member's rankings. Assume there are m alternatives to be uniquely ranked; ties are not permitted. Absolute differences are calculated for each individual's ranking of an alternative, and these are summed to determine the distance measure:

$$d_{ik}=\sum_{j} | r_{ij}-k | , \quad \text{for } k=1, 2, \cdots, m \tag{1}$$

where d_{ik}=distance measure for product i for ranking k,

r_{ij}=the ranking of product i by individual j, and

k=consensus ranking value.

After calculating all the d_{ik}, the distance matrix is formed. Then, the problem can be expressed in the assignment problem from as:

$$\text{Minimize : } Z=\sum_{i=1}^{m} \sum_{k=1}^{m} d_{ik}\ x_{ik}$$

$$\text{Subject to : } \sum_{i=1}^{m} x_{ik}=\sum_{k=1}^{m} x_{ik}=1 \tag{2}$$

$$\text{and : } x_{ik}=x^2_{ik}(\text{i.e.}; x_{ik}=0 \text{ or } 1)$$

In the resulting assignment problem, it may be thought that we are assigning an alternative to a priority ranking in such a way as to minimize the total absolute "distance." The assignment problem may be solved with the Hungarian method or by using a software package, such as QSB+ [4]. It should be remembered with this compromise programming model that group members' preferences for the alternatives are expressed ordinally, not cardinally. That is, no degree of preference for one alternative over another is expressed. It is also required that the group members all carry equal weight in forming the consensus. Neither of these restrictions are necessary with other methods, such as the AHP.

The AHP Method

The AHP may also be used in determining prioritizations of alternatives, except that the group members′ preferences must be more explicit. The AHP may be viewed as consisting of a number of steps as indentified by Zahedi [20] :

1. development of hierarchical structure for a decision problem,
2. pairwise evaluation of decision hierarchy elements,
3. estimation of relative weights for the decision elements–the eigenvalue method is but one of these,
4. evaluation of decision alternatives.

The development of the hierarchical structure is very important in this process. At the top of the hierarchy is the overall objective of the problem. Proceeding downward one level, attributes(or factors or issues) relating to the overall objective are identified. The individuals must agree on the criteria to be included, perhaps in some sort of an iterative, interactive approach such as the Delphi method. Khorramshahgol and Steiner [10] have proposed for goal programming. Similarly, subsequent levels contain ever more detailed decision attributes, until the final level of the decision alternatives is reached. Saaty [14] suggests limiting the number of elements at any level to nine in order to avoid the excessive number of pairwise comparisons required. Clustering elements together in a form of hierarchical decomposition is suggested by Saaty and Vargas [17] as a means of reducing the number of pairwise comparisons.

The second step requires the group members to perform the pairwise comparisons referred to above. As data input to the problem, the participants compare two elements at a time in terms of those elements′ contribution toward the objectives of the next highest level. Saaty and Vargas argue for a scale limited to the range 1/9 to 9 with the following interpretation as shown in Table 1.

The individual group members separately perform the pairwise comparisons for the criteria and the alternatives in terms of the immediately higher level. If there are **n** elements to be compared, then an nth–order square matrix of relative comparisons, referred to as **A**, is generated. The elements of the main diagonal will always equal one, and the individual elements,

a_{ij}, will always equal $1/a_{ji}$. This reciprocal nature of the comparisons requires only that n(n−1)/2 comparisons be made. This process continues downward through the hierarchy until, finally, the decision alternatives are compared in terms of each immediately higher-level objective. The geometric mean of the individuals' pairwise comparisons is used for the a_{ij}. Aczel and Saaty [1] show that this function has the required property that the reciprocal of the geometric mean is the geometric mean of the reciprocals of the original values.

Table 1. A Scale of Intensity of Improtance

Intensity of Importance	Definition	Explanation
1	Equal importance	Two activitis contribute equally to the objective
3	Weak importance of one over another	Experience and judgment slightly favor one over another activity
5	Essential or strong importance	Experience and judgment strongly favor one over another activity
7	Demonstrated importance	An activity is strongly favored and its dominance is demonstrated in practice
9	Absolute importance	The evidence favoring one activity over another is of the highest possible order of offirmation
2,4,6,8	Intermediate values	Used when compromise is needed
Reciprocals of the above	See text explanation	
Rationals	Ratio values	Used for enforced consistency

For example, suppose that there are five group members evaluating a criterion relative to another criterion in terms of their importance to the overall objective. The five individuals give the following values:

5, 3, 5, 7, 3

The geometric mean of these is 4.3597, differing from the arith-metic mean value of 4.60. This is improtant for the reciprocal requirement of the AHP dominance matrix(i.e., $a_{ij}=1/a_{ji}$ for all i and j). The geometric mean of the reciprocal values(0.2., 0.333, 0.2, 0.143, and 0.333) is 0.2294, satisfying the required relationship. Note that 4.3597=1/0.2294.

The third step estimates the relative weights for each of the decision elements. If the participants making the pairwise comparisons actually knew the relative weights of the elements at a given level, then the a_{ij} would be estimated consistently. If these actual weights are unknown, as AHP presupposes, then they may be estimated from A since each $a_{ij}=w_i/w_j$. Then if the vector $W=[w_1, w_2, w_3, \cdots, w_n]^T$ represents the actual weights, these may be found by solving:

$$AW=nW,$$

where n is the eigenvalue of A. W is the (right) eigenvector of A. If W is unknown, then A will likely contain inconsistencies and is denoted A′ showing it to be based on observed pairwise comparisons. Similarly, W′ is the estimated weight vector and can be determined by:

$$A'W'=\lambda_{max}W,$$

where λ_{max} is the largest eigenvector of A′. The greater the inconsistencies in A′, the more λ_{max} will exceed n. Saaty [14] has developed a consistency ratio(CR):

$$CR=(\lambda_{max}-n)/(n-1)/(ACI),$$

where ACI is the average consistency index for a matrix of size n. Saaty has tabled values of ACI for matrices of size n. His rule of thumb suggests 0.10 as an upper limit for CR.

Finally, these weights are aggregated to produce the priority ratings for the decision alternatives. The method of aggregation is similar to that of expectation in a decision tree.

4. AN ILLUSTRATIVE EXAMPLE

The St. Louis University Computer Selection Committee is evaluating six different models for student use. Four important criteria have been identified: 1) Speed, 2) Memory, 3) Compatibility, and 4) Cost. Table 1 presents the qualitative evaluation of each of these computer models on each dimension; the asterisked designations are the most desirable for each dimention.

Preliminary review indicates Model Ⅳ to be dominated, and hence it is excluded from further consideration. Ten committee members, denoted A, B, C, ⋯, and J, are to evaluate five different computer models, Ⅰ, Ⅱ, Ⅲ, Ⅴ, and Ⅵ. Each member ranks the five models from highest to lowest and represents those proference rankings with the values 1 through 5, respectively. Tied rankings may be permitted but are not considered here. The resulting data is shown in Table 3. Individual members' rankings can serve as inputs to comittee's group decision making.

Table 2. **Qualitative Evaluations**

Alternative Model \ Criterion	Speed	Memory	Compatibility	Cost
Ⅰ	Very Good	Very Good*	Very Good	Very Good*
Ⅱ	Excellent*	Fair	Fair	Very Good*
Ⅲ	Excellent*	Fair	Fair	Very Good*
Ⅳ	Poor	Good	Good	Fair
Ⅴ	Good	Very Good*	Very Good	Good
Ⅵ	Good	Good	Excellent*	Good

Table 3.

Model \ Member	A	B	C	D	E	F	G	H	I	J
Ⅰ	2	5	2	2	2	3	5	1	5	3
Ⅱ	4	3	1	3	4	2	1	3	1	1
Ⅲ	3	4	4	1	1	5	4	2	3	4
Ⅴ	1	2	3	5	5	4	3	5	4	2
Ⅵ	5	1	5	4	3	1	2	4	2	5

Two alternate methods are analyzed and compared below.

Compromise Programming

Compromise programming is used to determine a group consensus or compromise solution which minimizes the total absolute "distance" between consensus ranking and the members' rankings. This provides an objective criterion for reaching a compromise.

By using eq. (1), absolute differences are calculated for each member's ranking of a computer model, and these are summed to determine the distance measure. For example, for $k=1$, the absolute distances and their sum, d_{11} are obtained as shown in Table 4.

Similarly, after claculating the remaining d_{lk} for $k=2$, 3, 4, and 5, the distance matrix is formed as shown in Table 5.

Table 4.

Model \ Member	A	B	C	D	E	F	G	H	I	J	d_{i1}
Ⅰ	1	4	1	1	1	2	4	0	4	2	20
Ⅱ	3	2	0	2	3	1	0	2	0	0	13
Ⅲ	2	3	3	0	0	4	3	1	2	3	21
Ⅴ	0	1	2	4	4	3	2	4	3	1	24
Ⅵ	4	0	4	3	2	0	1	3	1	4	22

Table 5.

Model \ k	1	2	3	4	5
Ⅰ	20	12	11	16	20
Ⅱ	13	11	11	17	27
Ⅲ	21	15	12	11	16
Ⅴ	24	16	14	12	18
Ⅵ	22	16	12	14	20

In this assignment problem format, we are assigning a computer to a priority ranking in such a way as to minimize the total absolute "distance." Four optimal assignment solutions are obtained, as shown in Table 6, all yiedlding a minimized total absolute distance of 66 ranking units.

Table 6 Optimal Solutions

Model	Solution 1		Solution 2		Solution 3		Solution 4	
	Ranking	d_{lk}	Ranking	d_{lk}	Ranking	d_{lk}	Ranking	d_{lk}
Ⅰ	2	11	2	12	2	12	2	12
Ⅱ	1	12	1	13	1	13	1	13
Ⅲ	3	18	3	16	4	11	4	11
Ⅴ	4	12	5	14	5	16	3	12
Ⅵ	5	13	4	12	3	14	5	18
$\sum d_{lk}$		66		66		66		66

In the above four solutions, the solution 4 has exactly the same ranking by member C. It is excluded from further consideration because it does not represent a compromise. The solutions 1, 2, and 3 may be presented as equally representing the compromise solution.

It should be remembered with this compromise programming model that committee members' preferences for the alternatives are expressed ordinally, not cardinally. That is, no degree of preference for one alternative over another is expressed. It is also required that the committee members all carry equal weight in forming the consensus. Neither of these restrctions are necessary with the AHP.

The AHP

The hierarchical structure of the computer selection problem is presented in Figure 1.

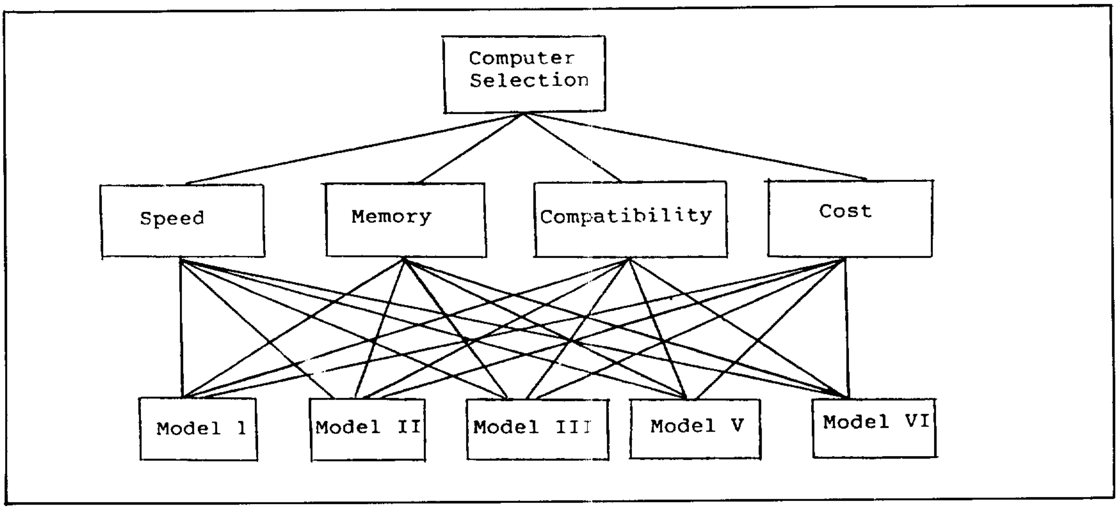

Figure 1. **Hierarchical Structure**

In using AHP, a decision maker must make pairwise comparisons for:

1. the criteria in terms of the overall objective, and
2. the alternatives in terms of each of the criteria.

For this example, these pairwise comparisons were prepared based on the qualitative evaluations given above.

This input data is shown in Table 7. Also shown for each matrix are the eigenvector and the normalized eigenvector(i, e., the estimated weights).

Table 7

(a) OVERALL	Speed	Memory	Compatibility	Cost		Eigenvector	Norm. eigenvector
Speed	1.00	0.33	0.20	2.00		0.179	0.109
Memory	3.00	1.00	0.50	7.00		0.545	0.332
Compatibility	5.00	2.00	1.00	5.00		0.812	0.494
Cost	0.50	0.14	0.20	1.00		0.106	0.065
(b) SPEED	Ⅰ	Ⅱ	Ⅲ	Ⅴ	Ⅵ	Eigenvector	Norm. eigenvector
Ⅰ	1.00	0.50	0.50	4.00	4.00	0.390	0.205
Ⅱ	2.00	1.00	1.00	5.00	5.00	0.641	0.336
Ⅲ	2.00	1.00	1.00	5.00	5.00	0.641	0.336
Ⅴ	0.25	0.20	0.20	1.00	1.00	0.117	0.061
Ⅵ	0.25	0.20	0.20	1.00	1.00	0.117	0.061
(c) MEMORY							
Ⅰ	1.00	7.00	7.00	1.00	3.00	0.668	0.370
Ⅱ	0.14	1.00	1.00	0.14	0.20	0.081	0.045
Ⅲ	0.14	1.00	1.00	0.14	0.20	0.081	0.045
Ⅴ	1.00	7.00	7.00	1.00	3.00	0.668	0.370
Ⅵ	0.33	5.00	5.00	0.33	1.00	0.308	0.170
(d) COMPATIBILITY							
Ⅰ	1.00	5.00	5.00	1.00	0.33	0.372	0.211
Ⅱ	0.20	1.00	1.00	0.20	0.14	0.087	0.049
Ⅲ	0.20	1.00	1.00	0.20	0.14	0.087	0.049
Ⅴ	1.00	5.00	5.00	1.00	0.33	0.372	0.211
Ⅵ	3.00	7.00	7.00	3.00	1.00	0.842	0.479
(e) COST							
Ⅰ	1.00	1.00	1.00	5.00	5.00	0.570	0.294
Ⅱ	1.00	1.00	1.00	5.00	5.00	0.570	0.294
Ⅲ	1.00	1.00	1.00	5.00	5.00	0.570	0.294
Ⅴ	0.20	0.20	0.20	1.00	1.00	0.114	0.059
Ⅵ	0.20	0.20	0.20	1.00	1.00	0.114	0.059

Table 8 presents the eigenvalue and consistency ratio for each of the five above tables. One notes that each of the consistency rations falls within the suggested guideline.

Table 8

Table	Eigenvalue	Consistency Ratio
a	4.101	0.04
b	5.035	0.01
c	5.441	0.10
d	5.090	0.02
e	5.000	0.00

Finally, the priority ratings are determined by the aggregation procedure. For example, for Model I, the rating value, 0.269, is determined by multiplying a criterion weight by the alternative's weight for that criterion and summing over the four criteria.

$$0.269 = 0.109(0.205) + 0.332(0.370) + 0.494(0.211) + 0.065(0.294)$$

Table 9 presents the final priority values(weights) and rankings.

Table 9

Computer Model	Final Weight	Rank
I	0.269	2
II	0.095	5
III	0.095	4
V	0.238	3
VI	0.304	1

A Comparison of Compromise Programming and the AHP

The two method, compromise programming and the AHP, are used to accomplish the same group task; rank order a set of alternatives. The differences are quite large however. Compromise programming does not require the explicit identification of criteria; this is done implicitly by each group member. This could be advantageous in terms of time and organizational conflict. The AHP would be more unwieldly to administer in practice. However, it is more likely that the AHP is closer to the "reasoned debate" referred to earlier. The acceptability of the solution, once reached, is likely to be greater with the AHP.

Referring again to the computer model selection example, note that the ideal solution would be to have a computer rated "Excellent" on speed, "Very Good" on memory, "Excellent" on compatibility, and "Very Good" for cost. Due to limitations of technology or some other reasons, none of the alternatives has this set of features. The AHP does not utilize directly the concepts of the ideal solution as compromise programming method does.

5. SOME MODIFICATIONS AND EXTENSIONS

Modifications and Extensions to Compromise Programming

After comparing the two methods here, it is apparent that many modifications of compromise programming method are possible. Armstrong et al. [2] extended the original problem to consider the case of tied rankings by individuals. Iyer [8] modified the original problem to take account of some concepts from concordance analysis.

Another possible modification would be to have the group members rank the alternatives on multiple dimensions. This would incorporate the explicit criteria approach of the AHP and other MCDM models. This modification would require a type of weighting or preference for the criteria, however. Maybe these could be ranked in importance as well. The resulting compromise programming problem would not be too different from the present one; it would be a multi-attribute ordinal distance minimization problem.

Application to Laboratory Instrument Selection Decisions

There are many possible application of these MCDM models. One example is in the selection of hospital laboratory instruments. Clearly, this is a group decision process; laboratory managers with different areas of expertise, medical directors, and hospital administration would typically be involved. Criteria are fairly well known in this case. For example, Shaikh [18] has developed a 13-criteria factor-scoring model for evaluating alternative instrumentation. Criteria include precision, accuracy, control requirements, training requirements, investment costs, etc. His weights are assigned a priori, but these are not necessarily the same for every organization. Like the AHP hierarchical structure, these criteria are grouped in three categories: analytic, operational, and financial. This appears to be an area for future research.

6. SUMMARY AND CONCLUSIONS

The two MCDM methods considered here differ considerably. Still they are used to accomplish the same task: ranking alternatives. This is probably typical of MCDM models; their differeneces lie in the differing forms of articulating managerial preferences. As noted in Narasimhan and Vickery, the MCDM world is rich with models but poor in real-life applications. Perhaps, application of simpler models, such as these two, would help to increase the acceptability of MCDM models in industry. Certainly, there is a growing acknowledgment of importance of multiple criteria in managerial decison making.

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