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MUTUAL ADAPTIVENESS OF MAN AND MACHINE IN INFORMATION ACQUISITION TASKS

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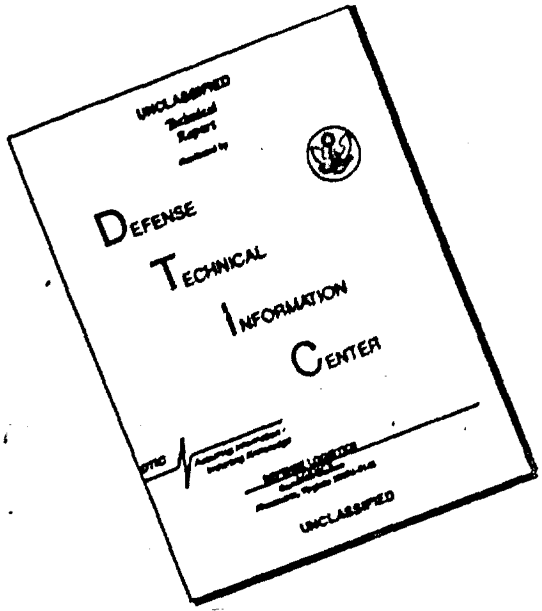

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20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

This report covers the period 12/15/80-12/15/81, during which period our efforts were directed toward the following tasks: (a) Survey and organize a list of analytic feature evaluation functions for use in information acquisition tasks; (b) Formulate military situation assessment tasks as hierarchical multiperspective pattern classification problems, and develop an approach for a decision support system for situation assessment; (c) Design, develop, and test the INFOACQ software by which computer-based simulation of behavioral and analytic information acquisition strategies may be investigated; → over

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INFORMATION ACQUISITION

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(d) Design, develop, and test the INFOACQ. EXP software which tracks information acquisition strategies employed by human decision maker in sequential classification tasks. Section 2 lists three publications which cover tasks (a) and (b). All three of them were submitted as part of our earlier progress reports. Section 3 describes our work under task (d), and Appendix I describes our work under task (c). This appendix contains a major part of a new article which is currently under preparation.

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MUTUAL ADAPTIVENESS OF MAN AND MACHINE IN INFORMATION ACQUISITION TASKS

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Basic Research

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1. SUMMARY

This report covers our work for the period 12/15/80 - 12/15/81 under contract number DAJA37-81-C-0065. During this period our efforts were directed toward the following tasks:

(a) Survey and organize a list of analytic feature evaluation functions for use in information acquisition tasks.

(b) Formulate military situation assessment tasks as hierarchical multiperspective pattern classification problems, and develop an approach for a decision support system for situation assessment.

(c) Design, develop, and test the INFOACQ software by which computer-based simulation of behavioral and analytic information acquisition strategies may be investigated.

(d) Design, develop, and test the INFOACQ.EXP software which tracks information acquisition strategies employed by human decision makers in sequential classification tasks.

Section 2 lists three publications which cover tasks (a) and (b). All three of them were submitted as part of our earlier progress reports. Section 3 describes our work under task (d), and Appendix I describes our work under task (c). This appendix contains a major part of a new article which is currently under preparation.

2. PUBLICATIONS

1. Ben-Bassat M. Use of distance measures, information measures, and error bounds in feature evaluation, In Krishnaiah and Kanal L.N. (Eds.) The Handbook of Statistics, Vol II, North Holland Publishers, 1981.

2. Ben-Bassat M., Shaket E. and Freedy A. Research into an intelligent decision support system for (military) situation assessment, DSS-81 Transactions, pp. 143-151, First International Conference on Decision Support Systems, Atlanta, Georgia, June 1981.

3. Ben-Bassat M. and Freedy A. Knowledge requirements and management in expert decision support systems for (military) situation assessment, IEEE Trans. on Systems Man and Cybernetics, 1982 (In Press).

3. HYPOTHESES CONCERNING INFORMATION ACQUISITION

Our hypothesis states: During sequential information acquisition, a decision maker (DM) tends to concentrate on a limited aspect of the problem. In pattern classification problems, such behavior is manifested by:

(a) When the number of classes is larger than a certain threshold (3 -.5), DM acquires information directed toward the verification/elimination of a subset of the complete set of classes.

(b) When the number of available sources of information is larger than a certain threshold (5 - 7), DM evaluates only a subset from which he selects the best one.

(c) When the number of classes and the number of features is large, DM focuses his attention on a subset of the class/feature matrix.

The first step in our plan is to test these hypotheses. The data which will be obtained from the experiments to test these hypotheses will be used to formulate additional hypotheses concerning behavioral strategies for selecting the subsets of classes and features. Discovering such strategies will greatly assist designers of decision support systems in creating better human-oriented systems. (See our original proposal, January 1979).

The basic hypotheses will be tested by interactive sessions in which subjects will be requested to solve a situation assessment problem which is formulated as a sequential Bayesian diagnosis problem. At any given stage, the subject will have access to any component of the problem including current probabilities of the possible classes and the conditional probabilities of the features (information scources) which have not yet been tested. By tracing the information and decision aids that he requests, we will be able to confirm or disconfirm our basic hypotheses, and will attempt to discover his information acquisition strategy(ies) for solving the situation assessment problem.

Four groups, each consisting of 10 subjects, will take part in the experiments. In each group the order of classes -and hence the order of prior probabilities- will be selected randomly. This will permit identifying effects which are not related to the basic hypothesis, but rather to other factors such as the order in which the classes are displayed or the location of high and low probabilities.

The problem will he presented to the subject as a medical diagnosis problem in which he plays the doctor's role. No knowledge of Bayesian statistics is required, however, since the probability updates will be performed by the computer. The subject's main task is to inform the system whether he wishes information for the entire problem or for a limited aspect of it. The subject's specific tasks will vary over the various experiments. Each subject will be requested to solve five problems.

A tape recorder will be used to present the problem and technical instructions to each group of subjects. During the experiments, only technical questions related to the operation of the software will be asnwered. A subject who will not comprehend the situation assessment problem will be eliminated.

The key data which will be collected at each stage of the sequential situation asse ment ocess consists of the following:

1) Classes being considered.

2) Posterior probabilities requested for display.

3) Entropy of posterior probabilities

4) Probability of error if a decision is made at this stage.

5) Time between consecutive user's inputs.

For the overall process, we will consider:

1) Average and standard deviation of the number of steps before a final classification is made.

2) Average and standard deviation of the number of classes (and/or features) considered at each stage.

3) Average and standard deviation of the sum of probabilities over the selected classes.

4) Characteristics of classes in selected subsets.

In addition, each subject will be requested to verbalize the reasons for each of his decisions. These protocols will be analyzed to gain better insight into the subject's strategy.

A special version of the INFOACQ software was implemented to examine behavioral information acquisition strategies. Named INFOACQ.EXP, and written in FORTRAN, this software operates on a microcomputer PDT 11/151 made by Digital under RT11 operating system. (Such a system, with 64K core memory, two diskette drives each for 256K bytes, and VT100 terminal, costs today $5000). This software is now being used to run the experiments described in section 3. The present version interacts with the user either in Hebrew or in English.

Many of the experiments have already been performed and we are now in the process of analyzing them.

APPENDIX I

Human-Oriented Information Acquisition in Sequential Pattern Classification

by

M. Ben-Bassat and D. Teeni

1. INTRODUCTION

Pattern classification constitutes a major component of a wide variety of decision making problems in military, medicine, management and other areas. These include battlefield reading, target detection, situation assessment, medical diagnosis, and the recognition of management and mismanagement styles. Real time classification proceeds in a sequential manner. Features(i.e. attributes, characteristics) are observed one or more at a time, the information gain is assessed by modifying the probabilities of the relevant alternatives (the classes), and a decision whether testing is to be continued or terminated is made. If a final decision cannot be made, the next feature is selected for testing.

A key module in a decision support system for pattern classification tasks generates recommendations for the next feature(s) to be tested in order to converge effectively to a final decision. Algorithms for such a module have been widely proposed in the literature (see Section 2). The recommendations suggested by such algorithms, however, are quite frequently, and particularly for problems with tens of classes and features, far from being natural. That is, the sequence of feature testing proposed by the system seems weird to a human decision maker working in this field who fails to see the logic behind it. The purpose of this paper is to identify some of the reasons for this lack of naturalness of the existing algorithms, to propose modified human-oriented algorithms and to evaluate their effectiveness relative to the existing algorithms.

2. PROBLEM FORMULATION

The basic pattern classification problem is concerned with the assignment of a given object to one of m known classes. Adopting the Bayesian approach, the true class is considered as a random variable C taking values in the set {1, 2, ... m}, where C=i represents class i. The initial uncertainty regarding the true class is expressed by the prior probability vector $A = (a_1, a_2, \ldots, a_m)$ where $a_i > 0, \sum_i a_i = 1$. This uncertainty can be modified by observing features (i.e., attributes, characteristics) of the given object. Let X_j, denote a feature j and let $P_i(x_j)$ denote the conditional probability function of feature j under class i for the value $X_j = x_j$. Once $X_1, X_2, \ldots X_n$ are observed, the prior probability of class i is replaced by its posterior probability which is given by Bayes' theorem:

$$a_i(x_1, x_2, \ldots, x_n) = \frac{a_i P_i(x_1, \ldots, x_n)}{\sum_{k=1}^{n} a_k P_k(x_1, \ldots x_n)} \qquad (1)$$

Example 1

Consider the pattern classification problem faced by an intelligent officer in situation assessment tasks. The aggressor's course of action may be classified into seven classes such as various types of attack, defend, delay or withdraw. To predict the aggressor's intention, the intelligent officer collects features (indicators) regarding the aggressor's activities. For instance, X_1 = Extensive artillery preparation, X_2 = Increased activity in rear areas, and so on. These features are binary features which may attain only two possible values, say 0 for negative and 1 for positive. The probability for a positive and a negative response for each feature changes under each course of action. Table 1 shows an example with seven classes and six features. The entries of the table represent the respective conditional probabilities for a positive response. If, for instance, X_3 is observed to be positive, the prior probabilities change from (0.30, 0.25, 0.15, 0.15, 0.07, 0.07, 0.01) to (0.12, 0.26, 0.24, 0.16, 0.17, 0.02, 0.03).

In sequential classification, e.g., Fu(1968), the features are tested one at a time, the posterior probabilities are computed, and a decision whether testing is to be continued or terminated is made. If testing is to be continued, the next feature is then selected for testing. Otherwise, a classification decision is made. When all types of errors are of equal cost and all types of correct decisions are of equal importance, the optimal Bayes decision rule assigns the pattern to the class with the highest a posteriori probability, and the Bayes risk reduces to the probability of error. Hence, if at

Table 1: An Example of 7 Classes and Six Features

Prior Probability		Conditional Probability					
Results:		1	1	1	0	1	0
.30	1	.15	.80	.15	.55	.43	.65
.25	2	.20	.90	.40	.60	.44	.80
.15	3	.11	.95	.60	.35	.37	.75
.15	4	.30	.55	.40	.99	.42	.55
.07	5	.95	.21	.95	.31	.80	.11
.07	6	.34	.50	.10	.75	.39	.98
.01	7	.25	.55	.99	.05	.45	.21

Table 2: Feature Values by Shannon's Entropy and Probability of Error

Evaluation Function \ Feature	x_1	x_2	x_3	x_4	x_5	x_6
H	.021	.028	.033	.023	.003	.016
P	.678	.691	.640	.700	.700	.695

the end of stage j, $j > 1$, a classification decision is made, the resulting probability of error P_e, is given by:

$$P_e = 1 - \{\max a_1^{(j)}, a_2^{(j)}, \ldots, a_M^{(j)}\} \tag{2}$$

where $a_i^{(j)}$ is the probability of class i at the end of stage j.

Dynamic programming formulation of the sequential classification problem provides, in principle, a method for obtaining an optimal strategy regarding the stopping decision and the feature selection decision, e.g., Cardilo and Fu (1967). Computationally, however, dynamic programming procedures are usually impractical, even for problems of moderate size and large scale computers, (see Bradt and Karlin (1956), Raiffa (1961), and Fu (1968) p. 67). Another drawback of a dynamic programming solution is due to the fact that the sequence of testing generated by the algorithm is often not natural. That is, although mathematically this sequence is the best, it is difficult for a human decision maker to see the reasoning behind it. This, of course, causes some reluctancy to use that solution.

One often used method to avoid the difficulties inherent in a dynamic programming solution is to use suboptimal myopic policies, i.e., policies which look only one or a few steps ahead. By this approach, a stopping decision is reached when the current probability of error is less than a predetermined tolerance value. If this stopping rule is not satisfied, the next feature is selected for testing according to a rule which optimizes an objective function for a one step look ahead. Assuming that the cost of testing for all the features is the same, this objective function represents, in fact, the information gain expected from the various features.

A frequently used feature evaluation function is derived from Shannon's entropy by which a feature X is preferred to Y if the expected posterior uncertainty resulting from X:

$$H(X) = E - [- \sum_i a_i(x) \log a_i(x)]. \tag{3}$$

is lower than that for Y. In (3) and throughout this paper Σ is from 1 to m and expectation is taken with respect to the mixed distribution of X

$$P(x) = \Sigma\, a_i P_i(x) \tag{4}$$

Alternatively, the features may be ranked by their expected probability of error

$$P(X) = E[\,1 - \max(a_i(X), \ldots, a_i(X))] \tag{3}$$

Example 2

Table 2 shows the feature ranking induced by the H functions and the P_e evaluation for the problem presented in

Example 1. From this table we learn that by both functions X_3 is the most promising feature for the next stage.

Ben-Bassat (1978) explores the efficiency of thirteen (13) feature evaluation functions in a myopic strategy for solving Bayesian pattern classification problems with conditionally independent binary features. Using an extensive set of experiments he demonstrates that none of these functions is consistently superior to the others. On the average, they all reach a final classification in about the same number of steps, although the sequence of features may be somewhat different for different strategies.

Myopic strategies seem to be closer to strategies used by human decision makers. (Humans have to adopt this approach simply because human limitations, in terms of computational and memory resources, do not leave them without any better choice.) See Teeni et al. (1982) for literature and evidence confirming this claim. Nevertheless, the sequence of testing generated by the myopic strategies is described above occasionally does not correspond well to a sequence which would be generated by a human decision maker. The reasons are identified and analyzed in the next sections where feature selection strategies which are based on mathematical functions will be referred to as <u>analytic</u> as opposed to <u>behavioral</u> strategies, which refer to strategies used by a human decision maker (DM).

3. HUMAN ORIENTED STRATEGIES

Behavioral strategies differ from the analytic myopic strategy described above -to be named henceforth strategy O- in two key aspects:

1) While strategy O always considers all of the m possible classes, human decision makers tend to limit themselves to a subset of the classes and to select features oriented toward this subset only. The subset on which a decision maker focuses attention depends on his personal style, as well as on the specific stage of the classification process. For example, in advanced stages DM may constrain his view to the current most probable classes and look for features which contribute mainly to their recognition. His objective is to obtain the final piece of evidence which is required to verify that the true class is indeed one the current most probable classes. In early stages, his objective may be to select features which are directed at the elimination of alternatives with low probability so that they do not "bother" him in the next stages.

2) At a given stage, strategy O ignores altogether the history of the process since its feature evaluation function considers the current class probabilities only (and the expected posterior probabilities). Human decision makers typically employ considerations related to

the class probabilities in earlier stages. Assume, for instance, that in the above example features X_3 and X_4 observed to be positive. This changes the class probabilities from (0.30, 0.25, 0.15, 0.15, 0.07, 0.07, 0.01) to (0.11, 0.22, 0.33, 0.003, 0.26, 0.00, 0.05). Considering only the posterior class probabilities to determine the next best feature, overlook the fact that the probability of class 5 has increased markedly from 0.07 to 0.26. Typically, such a significant change* in class probabilities triggers a *human decision maker* to invest in features aimed at the verification/elimination of this class.

In what follows we devise and investigate several analytic strategies which incorporate *human heuristics*.

<u>Strategy 1</u>: Dynamic Subset

At each stage a subset of classes S is selected according to the following procedure:

<u>Step 1</u> Rank the classes by their triggering ratio T defined as $T_i = a_i^{(n)} / a_i^{(0)}$. If for the most triggered class g $T_g > G$ (e.g. G = 2.0) *and* $a_g^{(n)} > F$ (e.g. F = 0.05), then include class g in S. Otherwise, S remains empty.

<u>Step 2</u> Take into S every class i for which $a_i^{(n)} > L$ (e.g. for L = 0.30 there are three at the most).

<u>Step 3</u> If S contains less than two classes, reduce the value of L by 0.05 and go back to Step 2.

Once a subset S has been established, the probabilities of the classes in S are normalized to sum up to 1, i.e. $a_k \leftarrow a_k / \sum_{i \in S} a_i$ for $k \in S$. The next feature to be tested is determined by applying strategy 0 to the reduced Bayesian classification problem defined by S and the non-tested features. Namely, a feature evaluation function such as H ranks the features which have not yet been tested, and the top ranked feature is selected.

Strategy 2: Stable Subset

The mechanism of the dynamic subset is carried over with one key difference: once a subset S is selected we continue exploring it as long as there is a good reason to believe that the true class is within the current subset. Mathematically, at stage n we test whether

$$\sum_{i\ S} a_i^{(n)} > D \qquad (6)$$

where D is a predetermined value, say D = 0.5. If the sum of the current probabilities exceeds D, the subset is maintained If the sum falls short, a new subset is generated as described in strategy 1.

Strategy 3: Most Probable Class (MPCL)

A subset of two classes is generated, one is the most probable class (MPCL), the other is the union of the rest of the classes considered as a collective alternative to MPCL. The subset remains unchanged as long as the MPCL remains the same.

The feature selection rule is as in strategy 0 applied to the classification problem defined as follows.

Assuming that the MPCL is k, the class probabilities and the conditional probabilities are defined as follows:

$$A' = (a_k, 1 - a_k)$$

$$P'_{1j} = P_{1j} \qquad \text{for all } j \qquad (7)$$

$$P'_{2j} = (\sum_{i \in k} a_i P_{ij}) / (1 - a_k)$$

Strategy 4: Most Triggered Class (MTCL) vs. the Rest

This strategy is the same as strategy 3, except that the selected class is determined as the most triggered class (MTCL), provided that $T_g > G$ and $a_g^{(n)} > F$. Otherwise MPCL is selected.

Comment The notion of one against the rest employed in strategies 3 and 4 has also been considered by Kanal and Kulkarni ( ).

Table 3 summarizes the parameters used in the various strategies.

Example

Table 4 illustrates the four strategies for the classification problem of example 1. The process stopping threshold V is set at 0.85.

5. EXPERIMENTS

A simulation computer program was written to evaluate and compare the various myopic feature selection strategies. For given problem dimensions and a myopic feature selection strategy, the program flow consists of four main loops as shown

Table 3: List of Parameters and Their Values in the Experiments

Value	Parameter	Definition
0.5	D	A threshold to determine whether a given subset is likely to include the true class. (Defined in strategy 2)
0.05	F	A minimal value for class probability to be eligible for inclusion in a subset. (Defined in strategy 1)
2.00	G	A threshold for the triggering ratio. (Defined in strategy 1)
0.30 (or less)	L	A lower bound for class probability above which the class is included in the selected subset regardless of its probability in earlier stages. (Defined in strategy 1)
0.85	V	A threshold used to terminate feature acquisition once the probability of a class is above V.

Table 4: Comparison of Strategies

\ Stage STRATEGY \	1	2	3	4	5
0-Classic Myopic					
Subset	All	All	All	All	All
Selected Feature	3	1	6	2	4
MPCL	2	5	5	5	5
MPCL Probability	.26	.51	.75	.46	.62
1-Dynamic Subset					
Subset	1,2,7,4	2,7	4,5	4,5	
Selected Feature	3	6	1	4	
MPCL	2	5	5	5	
MPCL Probability	.26	.39	.75	.86	
2-Stable Subset					
Subset	1,2,3,4	1,2,3,4	1,2,3,4	1,2,3,4	1,2,3,4
Selected Feature	3	4	2	1	6
4- One vs. All					
Selected Class	1	2	5	2	5
Selected Feature	3	1	2	6	5
MPCL	2	5	2	5	5
MPCL Probability	.26	.51	.31	.47	.62

in Figure 1. In the outer loop IV a probability matrix P and a prior probability vector are either randomly generated or read in from an input device. In loop III we specify the stopping threshold for terminating feature selection and classifying the object to the most probable class. At this the end of loop III we have a complete definition of a Bayesian classification problem.

In loop II a set of cases to be classified is generated by the following procedure. First, a random class i is selected according to the prior probabilities, and then an n dimensional 0-1 record is generated according to representing a possible pattern from class i.

In loop I a feature evaluation function is specified such as Shannon's entropy or the Probability of Error. Fourteen such functions may be selected (See Ben-Bassat (1978)).

For a given case the program proceeds as follows. By the myopic strategy and the feature evaluation function it ranks and selectes a feature to be tested. The result of this feature (either negative (0) or positive (1)) is retrieved from the record of the case under consideration, and the posterior probabilities are calculated. If the stopping rule is not satisfied, we go back to feature evaluation and selection. Otherwise we stop testing and classify the case to the most probable class. The output consists of a detailed description of the classification process for each case and a summary data as shown in Table 5. These data may be retained on a storage

Table 5: Summary Data Collected at the End of Proble

record 1

a. Number of features tested.

b. Probability of error (P) when process stopp

c. Difference between initial and final P .

d. Difference between initial and final entropy

e. Number of active classes when the process st

f. Number of times the Trigger mechanism was em if any.

g. Power index of descrimination.

record 2

a. Sequence of chosen features.

device for further statistical analysis.

It should be noted that using the same seed for the simulation tasks we are able to generate exactly the same classification problem and cases so that comparisons between strategies are made under the same conditions.

Using this program we are experimenting with the various strategies in an attempt to learn their efficiency and characteristics.