The Evaluation of Automatic Retrieval Procedures—Selected Test Results Using the SMART System*

The generation of effective methods for the evaluation of information retrieval systems and techniques is becoming increasingly important as more and more systems are designed and implemented. The present report deals with the evaluation of a variety of automatic indexing and retrieval procedures incorporated into the SMART automatic document retrieval system. The design of the SMART system is first briefly reviewed. The document file, search requests, and other parameters affecting the evaluation system are then examined in detail, and the measures used to assess the effectiveness of the retrieval performance are described. The main test results are given and tentative conclusions are reached concerning the design of fully automatic information systems.

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• Introduction

The evaluation of information retrieval systems and of techniques for indexing, storing, searching and retrieving information has become of increasing importance in recent years. The interest in evaluation procedures stems from two main causes: first, more and more retrieval systems are being designed, thus raising an immediate question concerning performance and efficacy of these systems; and, second, evaluation methods are of interest in themselves, in that they lead to many complicated problems in test design and performance, and in the interpretation of test results.

The present study differs from other reports on systems evaluation in that it deals with the evaluation of automatic rather than conventional information retrieval. More specifically, it is desired to compare the effectiveness of a large variety of fully automatic procedures for information analysis (indexing) and retrieval. Since such an evaluation must of necessity take place in an experimental situation rather than in an operational environment, it becomes possible to eliminate from consideration such important system parameters as cost of retrieval, response time, influence of physical lay-out, personnel problems and so on, and to concentrate fully on the evaluation of *retrieval techniques*. Furthermore, a number of human problems which complicate matters in a conventional evaluation procedure, including, for example, the difficulties due to inconsistency among indexers or to the presence of search errors, need not be considered. Other problems, including those which have to do with the identification of information relevant to a given search request, and those concerning themselves with the interpretation of test results, must, of course, be faced in an automatic system just as in a conventional one.

The design of the SMART automatic document retrieval system is first briefly reviewed. The test environment is then described in detail, including in particular a description of the document file and of the search requests used. Parameters are introduced to measure the effectiveness of the retrieval performance; these parameters are similar to the standard recall and precision measures, but do not require that a distinction be made between retrieved and nonretrieved documents. The main test results are then given, and some tentative conclusions are reached concerning the design of fully automatic retrieval systems.

• The SMART Retrieval System

SMART is a fully automatic document retrieval system operating on the IBM 7094. Unlike other computer-based retrieval systems, the SMART system does

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not rely on manually assigned keywords or index terms for the identification of documents and search requests, nor does it use primarily the frequency of occurrence of certain words or phrases included in the texts of documents. Instead, an attempt is made to go beyond simple word-matching procedures by using a variety of intellectual aids in the form of synonym dictionaries, hierarchical arrangements of subject identifiers, statistical and syntactic phrase-generating methods and the like, in order to obtain the content identifications useful for the retrieval process.

Stored documents and search requests are then processed *without any prior manual analysis* by one of several hundred automatic content analysis methods, and those documents which most nearly match a given search request are extracted from the document file in answer to the request. The system may be controlled by the user in that a search request can be processed first in a standard mode; the user can then analyze the output obtained and, depending on his further requirements, order a reprocessing of the request under new conditions. The new output can again be examined and the process iterated until the right kind and amount of information are retrieved.

SMART is thus designed to correct many of the shortcomings of presently available automatic retrieval systems, and it may serve as a reasonable prototype for fully automatic document retrieval. The following facilities incorporated into the SMART system for purposes of document analysis may be of principal interest*:

(a) a system for separating English words into *stems* and *affixes* (the so-called "null thesaurus" method) which can be used to construct document identifications consisting of the word stems contained in the documents;

(b) a synonym dictionary, or *thesaurus*, which can be used to recognize synonyms by replacing each word stem by one or more "concept" numbers (the thesaurus is a manually constructed dictionary including about 600 concepts in the computer literature, corresponding to about 3000 English word stems); these concept numbers can serve as content identifiers instead of the original word stems;

(c) a *hierarchical arrangement* of the concepts included in the thesaurus which makes it possible, given any concept number, to find its "parent" in the hierarchy, its "sons," its "brothers," and any of a set of possible cross-references; the hierarchy can be used to obtain more general content identifiers than the ones originally given by going "up" in the hierarchy, more specific ones by going "down" in the structure, and a set of related ones by picking up brothers and cross-references;

(d) *statistical procedures* to compute similarity coefficients based on co-occurrences of concepts within the sentences of a given document, or within the documents of a given collection; association factors between documents can also be determined, as can clusters (rather than only pairs) of related documents, or related concepts; the related concepts, determined by statistical association, can then be added to the originally available concepts to identify the various documents;

(e) *syntactic analysis* and matching methods which make it possible to compare the syntactically analyzed sentences of documents and search requests with a pre-coded dictionary of "criterion" phrases in such a way that the same concept number is assigned to a large number of semantically equivalent, but syntactically quite different constructions (e.g. "information retrieval," "the retrieval of information," "the retrieval of documents," "text processing," and so on);

(f) *statistical phrase* matching methods which operate like the preceding syntactic phrase procedures, that is, by using a preconstructed dictionary to identify phrases used as content identifiers; however, no syntactic analysis is performed in this case, and phrases are defined as equivalent if the concept numbers of all components match, regardless of the syntactic relationships between components;

(g) a *dictionary updating* system, designed to revise the five principal dictionaries included in the system (stem thesaurus, suffix dictionary, concept hierarchy, statistical phrases, and syntactic "criterion" phrases).

The operations of the system are built around a supervisory system which decodes the input instructions and arranges the processing sequence in accordance with the instructions received. At the present time, about 35 different processing options are available, in addition to a number of variable parameter settings. The latter are used to specify the type of correlation function which measures the similarity between documents and search requests, the cut-off value which determines the number of documents to be extracted as answers to search requests, and the thesaurus size.

The SMART systems organization makes it possible to evaluate the effectiveness of the various processing methods by comparing the outputs obtained from a variety of different runs. This is achieved by processing the same search requests against the same document collection several times, and making judicious changes in the analysis procedures between runs. It is this use of the SMART system, as an evaluation tool, which is of particular interest in the present context, and is therefore treated in more detail in the remaining parts of the present report.

*More detailed descriptions of the systems organization are included in Refs. 1 and 2. Programming aspects and complete flowcharts are presented in Ref. 3.

Characteristic	Comment	Count
Number of documents in collection.	Document abstracts in the computer field.	405
Number of search requests (a) specific (b) general.	 0 – 9 relevant documents 10 – 30 relevant documents	 10 7
User population (requester also makes relevance judgments).	Technical people and students	about 10
Number of indexing and search programs used.	All search and indexing operations are automatic.	15
Number of index terms per document.	Varies greatly depending on indexing procedure and document.	(average) 35
Number of relevant documents per request (a) specific (b) general.		 (average) 5 (average) 15
Number of retrieved documents per request.	No cut-off is used to separate retrieved from nonretrieved.	405

FIG. 1. Test Environment.

• The Test Environment

The parameters which control the testing procedures about to be described are summarized in Fig. 1. The data collection used consists of a set of 405 *abstracts** of documents in the computer literature published during 1959 in the *IRE Transactions on Electronic Computers*. The results reported are based on the processing of about 20 search requests, each of which is analyzed by approximately 15 different indexing procedures. The search requests are somewhat arbitrarily separated into two groups, called respectively "general" and "specific" requests, depending on whether the number of documents believed to be relevant to each request is equal to at least ten (for the general requests) or is less than ten (for the specific ones). Results are reported separately for each of these two request groups; cumulative results are also reported for the complete set of requests.

The user population responsible for the search requests consists of about ten technical people with background in the computer field. Requests are formulated without study of the document collection, and no document already included in the collection is normally used as a source for any given search request. On the other hand, in view of the experimental nature of the system it cannot be stated unequivocally that an actual user need in fact exists which requires fulfilment.

An excerpt from the document collection, as it is originally introduced into computer storage, is reproduced in Fig. 2. It may be noted that the full abstracts are stored together with the bibliographic citations. A typical search request, dealing with the numerical solution of differential equations, is shown at the top of Fig. 3. Any search request expressed in English words is acceptable, and no particular format restrictions exist. Also shown in Fig. 3 is a set of documents found in answer to the request on differential equations by using one of the available processing methods. The documents are listed in decreasing order of the correlation coefficient with the search request; a short 12-character identifier is shown for each document under the heading "answer," and full bibliographic citations are shown under "identification."

The average number of index terms used to identify each document is sometimes believed to be an important factor affecting retrieval performance. In the SMART system, this parameter is a difficult one to present and interpret, since the many procedures which exist for analyzing the documents and search requests generate indexing products with widely differing characteristics. A typical example is shown in Fig. 4, consisting of the index "vectors" generated by three different processing methods for the request on differential equations (short form "DIFFERNTL EQ"), and for document number 1 of the collection (short form "1A COMPUTER").

It may be seen from Fig. 4 that the number of terms identifying a document can change drastically from one method to another: for example, document number 1 is identified by 35 different word stems using the word stem analysis (labelled "null thesaurus" in Fig. 4); these 35 stems, however, give rise to 50 different concept numbers using the regular thesaurus, and to 55 concepts for the statistical phrase method. The number of index terms per document shown in the summary of Fig. 1 (35) must therefore be taken as an indication at best, and does not properly reflect the true situation.

In Fig. 4, each concept number is followed by some mnemonic characters to identify the concept and by a

* Practical considerations dictated the use of abstracts rather than full documents; the SMART system as such is not restricted to the manipulation of abstracts only.

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*TEXT 2MICRO-PROGRAMMING .

$MICRO-PROGRAMMING
$R. J. MERCER (UNIVERSITY OF CALIFORNIA)
$U.S. GOV. RES. REPTS. VOL 30 PP 71-72(A) (AUGUST 15, 1958) PB 126893

MICRO-PROGRAMMING . THE MICRO-PROGRAMMING TECHNIQUE OF DESIGNING THE
CONTROL CIRCUITS OF AN ELECTRONIC DIGITAL COMPUTER TO FORMALLY INTERPRET
AND EXECUTE A GIVEN SET OF MACHINE OPERATIONS AS AN EQUIVALENT SET
OF SEQUENCES OF ELEMENTARY OPERATIONS THAT CAN BE EXECUTED IN ONE
PULSE TIME IS DESCRIBED .


*TEXT 3THE ROLE OF LARGE MEMORIES IN SCIENTIFIC COMMUNICATIONS

$THE ROLE OF LARGE MEMORIES IN SCIENTIFIC COMMUNICATIONS
$M. M. ASTRAHAN (IBM CORP.)
$IBM J. RES. AND DEV. VOL 2 PP 310-313 (OCTOBER 1958)

THE ROLE OF LARGE MEMORIES IN SCIENTIFIC COMMUNICATIONS . THE ROLE
OF LARGE MEMORIES IN SCIENTIFIC COMMUNICATIONS IS DISCUSSED . LARGE
MEMORIES PROVIDE AUTOMATIC REFERENCE TO MILLIONS OF WORDS OF MACHINE-RE-
ADABLE CODED INFORMATION OR TO MILLIONS OF IMAGES OF DOCUMENT PAGES
. HIGHER DENSITIES OF STORAGE WILL MAKE POSSIBLE LOW-COST MEMORIES
OF BILLIONS OF WORDS WITH ACCESS TO ANY PART IN A FEW SECONDS OR COMPLE-
TE SEARCHES IN MINUTES . THESE MEMORIES WILL SERVE AS INDEXES TO THE
DELUGE OF TECHNICAL LITERATURE WHEN THE PROBLEMS OF INPUT AND OF THE
AUTOMATIC GENERATION OF CLASSIFICATION INFORMATION ARE SOLVED . DOCUMENT
FILES WILL MAKE THE INDEXED LITERATURE RAPIDLY AVAILABLE TO THE SEARCHER
. MACHINE TRANSLATION OF LANGUAGE AND RECOGNITION OF SPOKEN INFORMATION
ARE TWO OTHER AREAS WHICH WILL REQUIRE FAST, LARGE MEMORIES .
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FIG. 2. Typical Document Prints.

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ANSWERS TO REQUESTS FOR DOCUMENTS ON SPECIFIED TOPICS          SEPTEMBER 28, 1964    PAGE 83

                CURRENT REQUEST - *LIST DIFFERNTL EQ NUMERICAL DIGITAL SOLN OF DIFFERENTIAL EQUATIONS

REQUEST   *LIST DIFFERNTL EQ NUMERICAL DIGITAL SOLN OF DIFFERENTIAL EQUATIONS
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          GIVE ALGORITHMS USEFUL FOR THE NUMERICAL SOLUTION OF ORDINARY
          DIFFERENTIAL EQUATIONS AND PARTIAL DIFFERENTIAL EQUATIONS ON DIGITAL
          COMPUTERS . EVALUATE THE VARIOUS INTEGRATION PROCEDURES (E.G. RUNGE--
          KUTTA, MILNE-S METHOD) WITH RESPECT TO ACCURACY, STABILITY, AND SPEED


ANSWER        CORRELATION          IDENTIFICATION
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384STABILITY   0.6675       STABILITY OF NUMERICAL SOLUTION OF DIFFERENTIAL EQUATIONS
                            W. E. MILNE AND R. R. REYNOLDS (OREGON STATE COLLEGE)
                            J. ASSOC. FOR COMPUTING MACH. VOL 6 PP 196-203 (APRIL, 1959)

ANSWER        CORRELATION          IDENTIFICATION
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360SIMULATIN   0.5758       SIMULATING SECOND-ORDER EQUATIONS
                            D. G. CHADWICK (UTAH STATE UNIV.)
                            ELECTRONICS VOL 32 P 64 (MARCH 6, 1959)

ANSWER        CORRELATION          IDENTIFICATION
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200SOLUTION    0.5663       SOLUTION OF ALGEBRAIC AND TRANSCENDENTAL EQUATIONS ON AN AUTOMATIC
                            DIGITAL COMPUTER
                            G.N. LANCE (UNIV. OF SOUTHAMPTON)
                            J. ASSOC. FOR COMPUTING MACH., VOL 6, PP 97-101, JAN., 1959

ANSWER        CORRELATION          IDENTIFICATION
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392ON COMPUT   0.5508       ON COMPUTING RADIATION INTEGRALS
                            R. C. HANSEN (HUGHES AIRCRAFT CO.), L. L. BAILIN (UNIV. OF SOUTHERN
                            CALIFORNIA, AND R. W. RUTISHAUSER (LITTON INDUSTRIES, INC.)
                            COMMMUN. ASSOC) FOR COMPUTING MACH. VOL 2 PP 28-31 (FEBRUARY, 1959)

ANSWER        CORRELATION          IDENTIFICATION
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386ELIMINATI   0.5483       ELIMINATION OF SPECIAL FUNCTIONS FROM DIFFERENTIAL EQUATIONS
                            J. E. POWERS (UNIV. OF OKLAHOMA)
                            COMMUN. ASSOC. FOR COMPTING MACH. VOL 2 PP 3-4 (MARCH, 1959)
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FIG. 3. Typical Search Request and Corresponding Answers.

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OCCURRENCES OF CONCEPTS.AND PHRASES IN DOCUMENTS          SEPTEMBER 28, 1964
DOCUMENT       CONCEPT,OCCURS                             PAGE 17

DIFFERNTL EQ   4EXACT 12  8ALGOR 12  13CALC 18  71EVAL  6  92DIGI 12
               110AUT 12  143UTI 12  176SOL 12  179STD 12  181QUA 24
               269ELI  4  274DIF 36  356VEL 12  357YAW  4  384TEG 12
               428STB  4  505APP 24

1A COMPUTER    2INPUT  4  9LOCAT 12  10ALPH 12  15BASE  6  168ASC  6
               318IT   3  32REQU  3  41MCHO  8  47CHNG  6  53DATA  6   REGULAR
               57DSCB 15  59AMNT 24  72EXEC  6  77LIST  4  83MAP   6   THESAURUS
               87ENBL 12  93ORDR 10  106NQU  6  107DGN 30  108LOO 12
               110AUT 36  112OPE  6  119AUT  8  121MEM  4  130MEA  4
               143UTI 12  146JOB 18  147SYS 12  149POG 36  158REL 12
               162ROF  6  163EAS 12  168ORD  4  176SOL 12  178SYM 18
               182SAV  4  187DIR 12  210OUT  4  212SIZ 12  216DOM 12
               276GEM 18  327AST 12  332SEE 12  338MCH  8  340LET  3
               346JET  6  350IFO  6  419GEM  6  501ORD  4  508ACT  6

DIFFERNTL EQ   ACCUR  12  ALGORI 12  COMPUT 12  DIFFER 24  DIGIT  12
               EQU    24  EVALU  12  GIVE   12  INTEGR 12  METHOD 12
               NUMER  12  ORDIN  12  PARTI  12  PROCED 12  RUNGE- 12
               SOLUT  12  SPEED  12  STABIL 12  USE    12  VARIE  12
                                                                       NULL
1A COMPUTER    BAS    12  CHARAC 12  COMPUT 36  DESCRI 12  DESIGN 12   THESAURUS
               DIRECT 12  ENABLE 12  ESTIM  12  EXPLAI 12  FORM   12
               GIVE   12  HANDLE 12  ILLUST 12  INDEPE 12  INFORM 12
               MACHIN 24  OPER   12  ORD    12  ORIENT 12  PLANE  12
               POS    12  POSS   12  PROBLE 36  PROGRA 36  RECOGN 12
               SCANN  12  SIMPLE 12  SIZE   24  STORE  12  STRUCT 12
               TECHNI 12  TOWARD 12  TRANSF 12  USING  12  WRITT  12

DIFFERNTL EQ   4EXACT 12  8ALGOR 12  13CALC 18  71EVAL  6  92DIGI 12
               110AUT 12  143UTI 12  176SOL 12  179STD 12  181QUA 24
               269ELI  4  274DIF 36  356VEL 12  357YAW  4  375NUM 36
               379DIF 72  384TEG 12  428STB  4  505APP 24

1A COMPUTER    2INPUT  4  5LOCAT 12  10ALPH 12  14CODR 72  15BASE  6  STAT.      STAT.
               168ASC  6  318IT   3  32REQU  3  41MCHO  8  47CHNG  6  PHRASES    PHRASE
               53DATA  6  57DSCB 15  59AMNT 24  72EXEC  6  77LIST  4             LOOK-UP
               83MAP   6  87ENBL 12  93ORDR 10  106NQU  6  107DGN 30
               108LOO 12  110AUT 36  112OPE  6  119AUT  8  121MEM  4
               130MEA  4  143UTI 12  146JOB 18  147SYS 12  149POG 36
               158REL 12  162ROF  6  163EAS 12  168ORD  4  176SOL 12
               178SYM 18  182SAV  4  187DIR 12  200DA- 72  210OUT  4
               212SIZ 12  216DOM 12  219POG 36  276GEM 18  292THK 36
               302LOO 72  327AST 12  332SEF 48  338MCH  8  340LET  3
               346JET  6  350IFO  6  419GEM  6  501ORD  4  508ACT  6
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FIG. 4. Typical Indexing Products for Three Analysis Procedures.

weight. The weights assigned to the concept numbers also change from method to method. Since no distinction is made in the evaluation procedure between retrieved and nonretrieved documents, the last indicator included in Fig. 1 (the number of retrieved documents per request) must also be put into the proper perspective. A discussion of this point is postponed until after the evaluation measures are introduced in the next few paragraphs.

• Evaluation Measures

1. *Recall and Precision*

One of the most crucial tasks in the evaluation of retrieval systems is the choice of measures which reflect systems performance. In the present context, such a measurement must of necessity depend primarily on the system's ability to retrieve wanted information and to reject nonwanted material, to the exclusion of operational criteria such as retrieval cost, waiting time, input preparation time, and so on. The last mentioned factors may be of great practical importance in an operational situation, but do not enter, at least initially, into the evaluation of experimental procedures.

A large number of measures have been proposed in the past for the evaluation of retrieval performance.[4] Perhaps the best known of these are, respectively, *recall* and *precision; recall* is defined as the proportion of relevant material actually retrieved, and *precision* as the proportion of retrieved material actually relevant.* A system with high recall is one which rejects very little that is relevant but may also retrieve a large proportion of irrelevant material, thereby depressing precision. High precision, on the other hand, implies that very little irrelevant information is produced but much relevant information may be missed at the same time, thus depressing recall. Ideally, one would of course hope for both high recall and high precision.†

Measures such as recall and precision are particularly attractive when it comes to evaluating *automatic* retrieval procedures, because a large number of extraneous factors which cause uncertainty in the evaluation of conventional (manual) systems are automatically absent. The following characteristics of the present system are particularly important in this connection:

(a) input errors in the conventional sense, due to faulty indexing or encoding, are eliminated since all indexing operations are automatic;

* Precision has also been called "relevance," notably in the literature of the ASLIB–Cranfield project.[5]

† It has, however, been conjectured that an inverse relationship exists between recall and precision, such that high recall automatically implies low precision and vice versa.

(b) for the same reason, conventional search errors arising from the absence of needed search terms are also excluded;
(c) errors cannot be introduced in any transition between original search request and final machine query, since this transition is now handled automatically and becomes indistinguishable from the main analysis operation;
(d) inconsistencies introduced by a large number of different indexers and by the passage of time in the course of an experiment cannot arise; and
(e) the role of human memory as a disturbance in the generation of retrieval measurements is eliminated (this factor can be particularly troublesome when source documents are to be retrieved in a conventional system by persons who originally perform the indexing task).

In order to calculate the *standard* recall and precision measures the following important tasks must be undertaken:

(a) relevance judgments must be made by hand in order to decide, for each document and for each search request, whether the given document is relevant to the given request;
(b) the relevance judgments are usually all or nothing decisions so that a given document is assumed either wholly relevant or wholly irrelevant (in case of doubt relevance is assumed); and
(c) a cut-off in the correlation between documents and search requests is normally chosen, such that documents whose correlation exceeds the cut-off value are retrieved, while the others are not retrieved.

2. The Generation of Relevance Judgments

A great deal has been written concerning the difficulties and the appropriateness of the various operations listed in part 1.[5-8] The first task, in particular, which may require the performance of hundreds of thousands of human relevance judgments for document collections of reasonable size, is extremely difficult to satisfy and to control.

Two solutions have been suggested, each of which would base the relevance decisions on less than the whole document collection. The first one consists in using sampling techniques to isolate a suitable document subset, and in making relevance judgments only for documents included in that subset. If the results obtained for the subset, however, are to be applicable to the total collection, it becomes necessary to choose a sample representative of the whole. For most document collections, this turns out to be a difficult task.

The other solution consists in formulating search requests based on specific source documents included in the collection, and in measuring retrieval performance for a given search request as a function of the retrieval of the respective source documents. This procedure suffers from the fact that search requests based on source documents are often claimed to be nontypical, thus introducing a bias into the measurements which does not exist for requests reflecting actual user needs.

Since the document collection used in connection with the present experiments is small enough to permit an exhaustive determination of relevance, the possible pitfalls inherent in the sampling procedure and in the use of source documents were avoided to a great extent. Many of the problems connected with the rendering of relevance judgments are, however, unresolved for general document collections.

3. The Cut-off Problem

The other major problem is caused by the requirement to pick a correlation cut-off value to distinguish retrieved documents from those not retrieved. Such a cut-off introduces a new variable which seems to be extraneous to the principal task of measuring retrieval performance. Furthermore, in the SMART system, a different cut-off would have to be picked for each of the many processing methods if it were desired to retrieve approximately the same number of documents in each case.

Because of these added complications, it was felt that the standard recall and precision measures should be redefined so as to remove the necessary distinction between retrieved and nonretrieved information. Fortunately, this is not difficult in computer-based information systems, because in such systems numeric coefficients expressing the similarity between each document and each search request are obtained as output of the search process. Documents may then be arranged in decreasing order of these similarity coefficients, as shown, for example, for the previously used request on differential equations in the center section of Fig. 5. It may be seen in the figure that document 384 exhibits the largest correlation with the search request, followed by documents 360, 200, 392, and so on.

An ordered document list of the kind shown in Fig. 5 suggests that a suitable criterion for recall and precision measures would be the set of *rank-orders* of the *relevant* documents, when these documents are arranged in decreasing correlation order. A function of the rank-order list which penalizes high ranks for relevant documents (and therefore low correlation coefficients) can be used to express recall, while a function penalizing low ranks of nonrelevant documents is indicative of precision.

*4. Normalized Recall and Normalized Precision**

It is desired to use as a measure of retrieval effectiveness a set of parameters which reflects the standard recall and the standard precision, and does not depend on a distinction between retrieved and nonretrieved documents. This suggests that one might take the average of the recall and the average of the precision obtained for

* The measures described in this part were suggested by J. Rocchio.[9]

ROW CORRELATIONS OF PHRASE-DOCUMENT MATRIX SEPTEMBER 28, 1964 PAGE 73

DIFFERNTL EQ 1A COMPUTER	0.1234	DIFFERNTL EQ 384STABILITY	0.6675	0.9800	0
DIFFERNTL EQ 2MICRO-PROGR	0.0875	DIFFERNTL EQ 360SIMULATIN	0.5758	0.9600	0
DIFFERNTL EQ 3THE ROLE OF	0.0293	DIFFERNTL EQ 200SOLUTION	0.5663	0.9400	0
DIFFERNTL EQ 4A NEW CLASS	0.0844	DIFFERNTL EQ 392ON COMPUT	0.5508	0.9200	0
DIFFERNTL EQ 5ANALYSIS OF	0.0658	DIFFERNTL EQ 386ELIMINATI	0.5483	0.9000	0
DIFFERNTL EQ 6GENERALIZED	0.0741	DIFFERNTL EQ 103RUNGE-KUT	0.5444	0.8800	0
DIFFERNTL EQ 7AN IMPROVED	0.2090	DIFFERNTL EQ 85NOTE ON AN	0.4510	0.8600	0
DIFFERNTL EQ 8SHORT-CUT M	0.0861	DIFFERNTL EQ 192SOLVING E	0.4106	0.8400	0
DIFFERNTL EQ 9OPERATION A	0.0611	DIFFERNTL EQ 358STABILIZA	0.3986	0.8200	0
DIFFERNTL EQ 10ACCURATE T	0.1102	DIFFERNTL EQ 102ON THE SO	0.3986	0.8000	0
DIFFERNTL EQ 12DIGITAL CO	0.0883	DIFFERNTL EQ 387BOUNDARY	0.3968	0.7800	0
DIFFERNTL EQ 13HALF-ADDER	0.0548	DIFFERNTL EQ 202STABLE PR	0.3906	0.7600	0
DIFFERNTL EQ 16CONTROL AP	0.0336	DIFFERNTL EQ 229MATRIX PR	0.3505	0.7400	0
DIFFERNTL EQ 17THE FUNCTI	0.0583	DIFFERNTL EQ 88PROPOSED M	0.3451	0.7200	0
DIFFERNTL EQ 18AN ACCURAT	0.1397	DIFFERNTL EQ 251ERROR EST	0.3329	0.7000	0
DIFFERNTL EQ 19RESISTANCE	0.0177	DIFFERNTL EQ 234ANALOGUE	0.3176	0.6800	0
DIFFERNTL EQ 20DIFFERENTI	0.2123	DIFFERNTL EQ 253ROUND-OFF	0.3152	0.6600	1
DIFFERNTL EQ 21AN ERROR-C	0.0105	DIFFERNTL EQ 186ALGORITHM	0.3144	0.6400	1
DIFFERNTL EQ 22LATCHING C	0.0057	DIFFERNTL EQ 169THEORETIC	0.3136	0.6200	1
DIFFERNTL EQ 23MINIATURE	0.0307	DIFFERNTL EQ 128COMPUTER	0.3034	0.6000	1
DIFFERNTL EQ 24SOME NOVEL	0.0199	DIFFERNTL EQ 226+DEPI ..	0.3028	0.5800	1
DIFFERNTL EQ 25A NEW TRAN	0.1068	DIFFERNTL EQ 45A CALCULAT	0.2958	0.5600	3
DIFFERNTL EQ 26SEMICONDUC	0.0653	DIFFERNTL EQ 390MONTE CAR	0.2866	0.5400	6
DIFFERNTL EQ 27TEN MEGAPU	0.1004	DIFFERNTL EQ 388A METHOD	0.2787	0.5200	6
DIFFERNTL EQ 28DESIGN OF	0.1375	DIFFERNTL EQ 173AUTOMATIC	0.2753	0.5000	6
DIFFERNTL EQ 29INVESTIGAT	0.0879	DIFFERNTL EQ 306ELECTRONI	0.2750	0.4800	6
DIFFERNTL EQ 30A TRANSIST	0.0736	DIFFERNTL EQ 318FROM FORM	0.2741	0.4600	6
DIFFERNTL EQ 31MAGNETIC C	0.0575	DIFFERNTL EQ 249MATHEMATI	0.2683	0.4400	7
DIFFERNTL EQ 32ANALOGUE I	0.2283	DIFFERNTL EQ 266UNIFYING	0.2682	0.4200	7
DIFFERNTL EQ 33THE USE OF	0.0802	DIFFERNTL EQ 217SIMULATIO	0.2665	0.4000	8
DIFFERNTL EQ 34END-FIRED	0.0456	DIFFERNTL EQ 367ON EXPONE	0.2661	0.3800	12
DIFFERNTL EQ 35A LOAD-SHA	0.0331	DIFFERNTL EQ 213PREDICTIO	0.2630	0.3600	12
DIFFERNTL EQ 36FUNDAMENTA	0.0392	DIFFERNTL EQ 108SECANT MO	0.2620	0.3400	14
DIFFERNTL EQ 37A HIGH-SPE	0.0364	DIFFERNTL EQ 383A NOTE ON	0.2580	0.3200	15
DIFFERNTL EQ 38AUTOMATIC	0.1043	DIFFERNTL EQ 191DIGITAL C	0.2370	0.3000	21
DIFFERNTL EQ 41COMMUNICAT	0.1185	DIFFERNTL EQ 171SMALL COM	0.2325	0.2800	23
DIFFERNTL EQ 42A DIRECT R	0.0439	DIFFERNTL EQ 248METHOD FO	0.2319	0.2600	33
DIFFERNTL EQ 43THE DATA C	0.0333	DIFFERNTL EQ 283BINARY AR	0.2311	0.2400	34
DIFFERNTL EQ 44ACCURACY C	0.1399	DIFFERNTL EQ 252A CLASS O	0.2303	0.2200	47
DIFFERNTL EQ 45A CALCULAT	0.2958	DIFFERNTL EQ 385NUMERICAL	0.2300	0.2000	60
DIFFERNTL EQ 46RADIO DIRE	0.0980	DIFFERNTL EQ 210EVALUATIO	0.2285	0.1800	73
DIFFERNTL EQ 47SPECIAL PU	0.1268	DIFFERNTL EQ 220DATA PREP	0.2282	0.1600	87
DIFFERNTL EQ 48A BUSINESS	0.0086	DIFFERNTL EQ 32ANALOGUE I	0.2282	0.1400	106
DIFFERNTL EQ 49A DUAL MAS	0.0575	DIFFERNTL EQ 197TECHNICAL	0.2280	0.1200	135
DIFFERNTL EQ 50ACCURACY C	0.0668	DIFFERNTL EQ 355A ROUTINE	0.2272	0.1000	166
DIFFERNTL EQ 52+ATHENA ,	0.1030	DIFFERNTL EQ 215DIGITAL C	0.2259	0.0800	200
DIFFERNTL EQ 53A COMPUTER	0.1327	DIFFERNTL EQ 69COMPUTERS	0.2249	0.0600	257
DIFFERNTL EQ 54AN AUTOMAT	0.0763	DIFFERNTL EQ 201ITERATIVE	0.2198	0.0400	304
DIFFERNTL EQ 55AUTOMATIC	0.0746	DIFFERNTL EQ 193ARTIFICIA	0.2196	0.0200	348
DIFFERNTL EQ 56THE COMPUT	0.1513	DIFFERNTL EQ 361SAINT COM	0.2187		
DIFFERNTL EQ 57CASE STUDY	0.0950	DIFFERNTL EQ 257SURVEY OF	0.2181		
DIFFERNTL EQ 58THE LARGES	0.0256	DIFFERNTL EQ 236OPERATING	0.2180		
DIFFERNTL EQ 59DATA PROCE	0.0302	DIFFERNTL EQ 117COMPUTATI	0.2170		
DIFFERNTL EQ 60INTELLIGEN	0.0091	DIFFERNTL EQ 207AN APPLIC	0.2162		
DIFFERNTL EQ 61AN INPUT R	0.0404	DIFFERNTL EQ 20DIFFERENTI	0.2122		
DIFFERNTL EQ 62ON PROGRAM	0.1181	DIFFERNTL EQ 235FREEZING	0.2093		

a) INCREASING DOCUMENT ORDER   b) DECREASING CORRELATION ORDER   c) HISTOGRAM

FIG. 5. Correlations Between Search Request and Document Collection.

all possible retrieval levels to define a new pair of measures, termed respectively *normalized* recall and *normalized* precision. Specifically, if $R_{(j)}$ is the standard recall after retrieving j documents from the collection (that is, if $R_{(j)}$ is equal to the number of relevant documents retrieved divided by the total relevant in the collection, assuming j documents retrieved in all), then the normalized recall can be defined as

$$R_{\text{norm}} = \frac{1}{N} \sum_{j=1}^{N} R_{(j)}$$

where N is the total number of documents in the collection.

Similarly, if $P_{(j)}$ is the standard precision after retrieving j documents from the collection, then a normalized precision measure is defined as

$$P_{\text{norm}} = \frac{1}{N} \sum_{j=1}^{N} P_{(j)} \ .$$

R_{norm} and P_{norm} may thus be obtained mechanically by first retrieving one document and calculating recall and precision, then retrieving another document, and again calculating R and P, and repeating the process one document at a time until all documents in the whole collection have been retrieved. Finally, all R's and P's are averaged to obtain the normalized measures.

In practice, this manner of proceeding would be extremely tedious for large document collections, even if the calculations were done by computer. It may, however, be shown by reasonably straightforward algebra that the normalized recall and normalized precision may be rewritten, respectively, as

$$R_{\text{norm}} = \frac{1}{N} \sum_{j=1}^{N} R_{(j)} = 1 - \frac{\sum_{i=1}^{n} r_i - \sum_{i=1}^{n} i}{n(N-n)} \qquad (1)$$

and

$$P_{\text{norm}} = \frac{1}{N} \sum_{j=1}^{N} P_{(j)} = 1 - \frac{\sum_{i=1}^{n} ln\, r_i - \sum_{i=1}^{n} ln\, i}{ln \dfrac{N!}{n!(N-n)!}} \qquad (2)$$

where r_i is the rank (in decreasing correlation order with the search request) of the ith relevant document in the collection,

n is the total number of relevant documents in the collection, and N is the total number of documents in all.

The expressions in the right-hand side are suitable for automatic computation and are in fact used in the SMART system. All basic definitions are summarized in Fig. 6.

	STANDARD DEFINITIONS (BASED ON THRESHOLD TO DISTINGUISH DOCUMENTS RETRIEVED FROM DOCUMENTS NOT RETRIEVED)	DEFINITIONS BASED ON RANKS OF RELEVANT DOCUMENTS (DOCUMENTS ARRANGED IN ORDER BY DECREASING CORRELATION WITH SEARCH REQUESTS)
RECALL	PROPORTION OF RELEVANT MATERIAL ACTUALLY RETRIEVED (LOW RECALL IMPLIES THAT SOME RELEVANT DOCUMENTS HAVE LOW CORRELATION WITH SEARCH REQUEST AND ARE THUS NOT RETRIEVED)	$1 - \frac{\sum_{i=1}^{n} r_i - \sum_{i=1}^{n} i}{n(N-n)}$ n: NUMBER OF RELEVANT DOCUMENTS N: NUMBER OF DOCUMENTS IN COLLECTION r_i: RANK ORDER OF i^{th} RELEVANT DOCUMENT
PRECISION	PROPORTION OF RETRIEVED MATERIAL ACTUALLY RELEVANT (LOW PRECISION IMPLIES THAT SOME NON-RELEVANT DOCUMENTS HAVE A HIGH CORRELATION WITH SEARCH REQUEST AND ARE THUS RETRIEVED)	$1 - \frac{\sum_{i=1}^{n} \ln r_i - \sum_{i=1}^{n} \ln i}{\ln \frac{N!}{n!(N-n)!}}$

FIG. 6. Basic Definitions of Recall and Precision.

• Test Results

1. *Output Formats*

The normalized recall and precision measures are a function only of the ranks of the relevant documents. If those measures are to be evaluated automatically as part of the retrieval process, it is necessary to introduce for each search request processed a list of the corresponding relevant document identifications. To this effect the requester is given a copy of the full document collection *after* his request is received, and he is asked to list those documents which he believes should be considered relevant to his request. It is important to note that these relevance judgments are *a priori* judgments, based on the document texts only, and not on any retrieval results produced by the computer.

The type of output obtained from the evaluation process is illustrated in Fig. 7. The top part of the figure represents the output from the regular thesaurus procedure for the request on differential equations previously used, while the bottom part is produced by the statistical phrase method. On the right side of the figure appears the list of all 16 relevant document numbers, as originally submitted by the user, together with the respective correlation coefficients and the ranks assigned by the computer during the retrieval process. It may be noticed that the relevant document which exhibits the lowest correlation with the search request is ranked 40th out of 405 by the regular thesaurus procedure, but only 25th out of 405 by the statistical phrase search.

The document ranks are used by the program to produce a variety of measures reflecting recall and precision, including the normalized recall and normalized precision measures previously introduced. Also calculated are simplified expressions, termed respectively *rank recall* and *log precision*, and defined as follows:

```
                                                  SEPTEMBER 28, 1964   PAGE 86
EVALUATION OF REQUEST DIFFERNTL EQ WITH  16 RELEVANT DOCUMENTS

    THE TOP FIFTEEN DOCUMENTS            RELEVANT DOCUMENT RANKS

     1 X 384STABILITY 0.6676              1 384STABILITY 0.6676
     2 X 360SIMULATIN 0.5758              2 360SIMULATIN 0.5758
     3 X 200SOLUTION  0.5664              3 200SOLUTION  0.5664
     4 X 392ON COMPUT 0.5508              4 392ON COMPUT 0.5508
     5 X 386ELIMINATI 0.5484              5 386ELIMINATI 0.5484
     6 X 103RUNGE-KUT 0.5445              6 103RUNGE-KUT 0.5445     REGULAR
     7 X 85NOTE ON AN 0.4511              7 85NOTE ON AN 0.4511     THESAURUS
     8   192SOLVING E 0.4106              9 102ON THE SO 0.3987
     9 X 102ON THE SO 0.3987             10 358STABILIZA 0.3986
    10 X 358STABILIZA 0.3986             11 387BOUNDARY  0.3968
    11 X 387BOUNDARY  0.3968             12 202STABLE PR 0.3907
    12 X 202STABLE PR 0.3907             15 251ERROR EST 0.3329
    13   229MATRIX PR 0.3506             17 253ROUND-OFF 0.3152
    14   88PROPOSED M 0.3452             23 390MONTE CAR 0.2866
    15 X 251ERROR EST 0.3329             24 388A METHOD  0.2788
                                         40 385NUMERICAL 0.2301

RANK RECALL= 0.7196 LOG PRECISION= 0.9169
NORMALIZED RECALL=0.9914626 NORMALIZED PRECISION=0.9572
RNK REC + LOG PRE=1.6365 WEIGHTED NORMED RECALL + NORMED PREC=1.9146

    THE TOP FIFTEEN DOCUMENTS            RELEVANT DOCUMENT RANKS

     1 X 384STABILITY 0.8576              1 384STABILITY 0.8576
     2 X 360SIMULATIN 0.7741              2 360SIMULATIN 0.7741
     3 X 386ELIMINATI 0.7408              3 386ELIMINATI 0.7408
     4 X 392ON COMPUT 0.6571              4 392ON COMPUT 0.6571
     5 X 200SOLUTION  0.6444              5 200SOLUTION  0.6444
     6 X 85NOTE ON AN 0.6372              6 85NOTE ON AN 0.6372     STATISTICAL
     7 X 387BOUNDARY  0.6072              7 387BOUNDARY  0.6072     PHRASE SEARCH
     8 X 103RUNGE-KUT 0.5875              8 103RUNGE-KUT 0.5875
     9 X 102ON THE SO 0.5648              9 102ON THE SO 0.5648
    10 X 390MONTE CAR 0.5448             10 390MONTE CAR 0.5448
    11 X 358STABILIZA 0.5437             11 358STABILIZA 0.5437
    12 X 388A METHOD  0.5318             12 388A METHOD  0.5318
    13 X 202STABLE PR 0.5163             13 202STABLE PR 0.5163
    14 X 385NUMERICAL 0.4942             14 385NUMERICAL 0.4942
    15   169THEORETIC 0.4794             21 251ERROR EST 0.3444
                                         25 253ROUND-OFF 0.3157

RANK RECALL= 0.9007 LOG PRECISION= 0.9751
NORMALIZED RECALL=0.9975900 NORMALIZED PRECISION=0.9880
RNK REC + LOG PRE=1.8758 WEIGHTED NORMED RECALL + NORMED PREC=1.9759
```

FIG. 7. Automatic Evaluation.

$$\text{rank recall} = \frac{\sum_{i=1}^{n} i}{\sum_{i=1}^{n} r_i}$$

$$\text{log precision} = \frac{\sum_{i=1}^{n} \ln i}{\sum_{i=1}^{n} \ln r_i} .$$

These simple measures are analogous to the normalized recall and normalized precision but do not take into account the collection size N.

Finally, two composite measures are produced which include both recall and precision components. The first one consists simply of the sum of rank recall plus log precision. The other is a weighted sum of the normalized measures, as follows:

$$\text{normed overall measure} = 1 - 5\,(R_{\text{norm}}) + P_{\text{norm}}$$

The factor of 5 is so chosen as to give equal weight to the two component measures.

Also included on the left-hand side of Fig. 7 are lists of the 15 documents which exhibit the highest correlation coefficients with the search request. The relevant documents on that list are provided with a special marker (X). It may be seen for the example of Fig. 7 that the recall and precision values obtained by the statistical phrase process are larger than the corresponding values for the thesaurus lookup procedure.

2. Results Derived from the Normalized Measures

In order to obtain statistically useful measurements, the recall and precision values must be averaged over many different search requests. This is done in Fig. 8 for nine different processing methods and for a total of ten specific and seven general requests.

The following processing methods are included in Fig. 8:

1. Thesaurus—Titles only
   The word stems included in the titles of the documents are looked up in the regular thesaurus and replaced by weighted concept numbers. The remainder of the document abstracts is not used.
2. Thesaurus—Hierarchy (up and add)
   The complete document abstracts are used. All word stems are replaced by weighted concept numbers from the thesaurus; these concept numbers are then looked up in the hierarchy, and to each original concept the corresponding "parent" from the next higher hierarchy level is added.
3. Thesaurus—Logical Vectors
   Complete document abstracts are used. All word stems are replaced by concept numbers from the thesaurus, and each concept is given a weight of 1.
4. Word Stems—Full Text (Null Thesaurus)
   Complete document abstracts are used, and weighted word stems are generated by the suffix cut-off procedure. No further dictionary is used.
5. Thesaurus—Syntactic Phrases
   The weighted concepts obtained from the thesaurus are looked up in the phrase dictionary, and phrase concepts corresponding to available concept groupings are detected and used as document identifiers, provided that certain specified syntactic relationships hold between the phrase components.
6. Thesaurus—Hierarchy (down and add)
   Procedure identical with 2 except that the concepts added from the hierarchy are obtained by

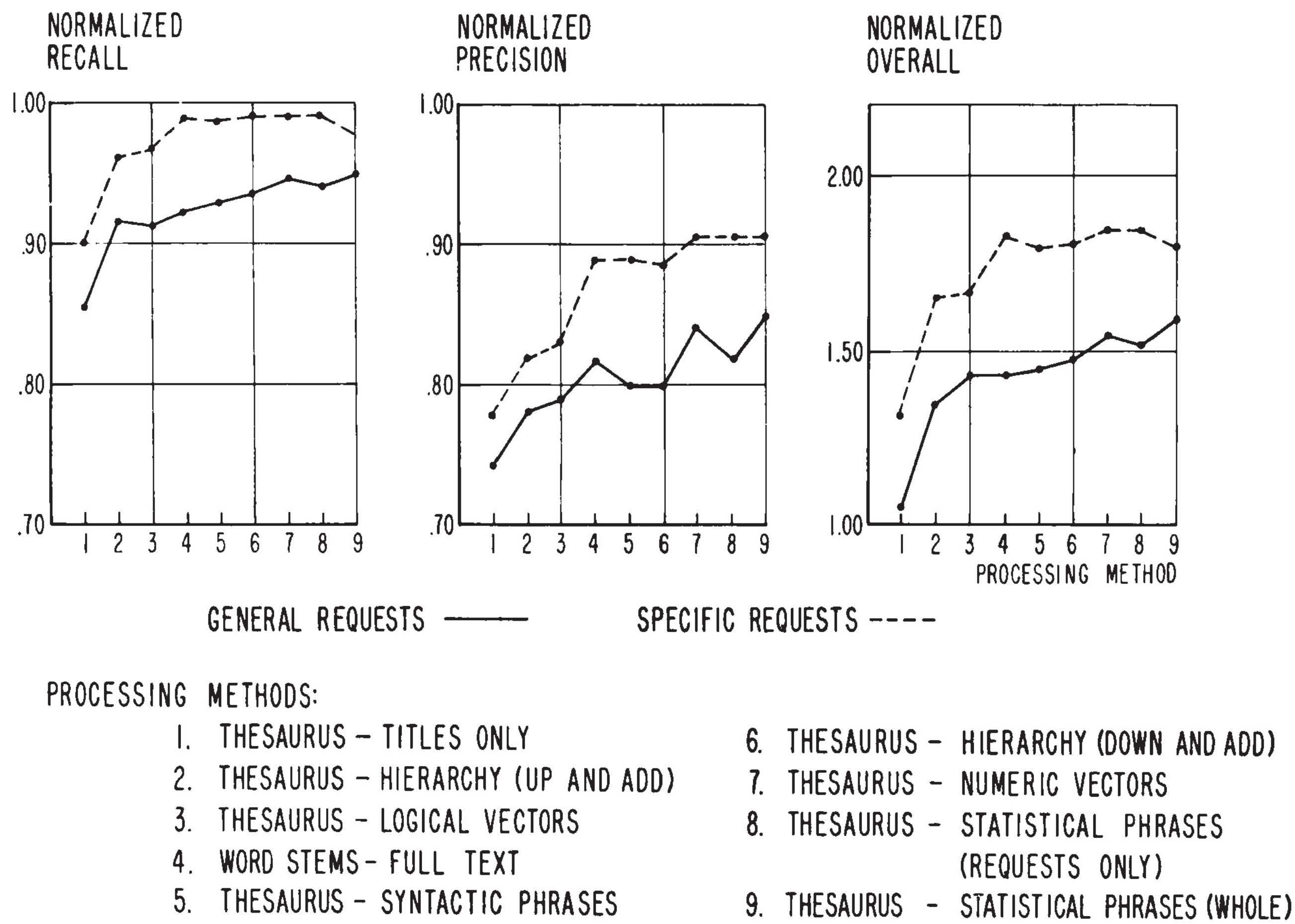


Fig. 8. Normalized Recall, Precision and Overall Measures (averaged over 10 specific and 7 general requests for several processing methods).

taking the "sons" of each original concept on the next lower level of the hierarchy.

7. Thesaurus—Numeric Vectors
Procedure identical with 3 except that the concepts obtained from the thesaurus are weighted in accordance with their frequency. This is the standard thesaurus method.

8. Thesaurus—Statistical Phrases (requests only)
Standard thesaurus method (7), to which are added phrases (concept groupings) occurring in the requests only. Syntactic relationships between phrase components are not used.

9. Thesaurus—Statistical Phrases (whole)
Standard thesaurus method (7) followed by the phrase procedure (5) for all documents without detection of syntactic relationships between phrase components.

The data of Fig. 8 give rise to the following observations:

(a) the normalized evaluation measures obtained for the various processing methods exhibit substantial differences;

(b) as one proceeds from one method to another, both recall and precision tend to vary in the same direction (either up or down);

(c) all the measures (recall, precision, and overall) obtained for the specific requests are larger than the corresponding values for the general requests, thus indicating a better systems performance for clearly specified topic classes*;

(d) methods one to four tend to produce relatively poorer recall than methods five to nine; these same methods also furnish relatively poor precision;

(e) the use of the regular thesaurus which provides vocabulary control (method seven) seems much more effective than the use of the original words included in document and search requests (method four)†;

(f) the most effective procedures seem to be those which use combinations of concepts (phrases), rather than individual concepts alone.

The data of Fig. 8 are of interest in themselves, since they do support the notion that more reasonable procedures (than mere word matching) can be generated to improve retrieval effectiveness in an automatic system. However, if full advantage is to be taken of the organization of the SMART system, then search requests are best processed iteratively by several different methods, and the respective outputs combined. In order to determine whether this juxtaposition of methods can in fact be used to improve the performance characteristics, average normalized recall and precision figures are given in Fig. 9 for six *combined methods* and for the 17 requests previously used in Fig. 8.

Figure 9 includes the normalized recall and precision values for the regular thesaurus run previously shown in Fig. 8, followed by the same measures for various combined methods. All of the combined runs include the regular thesaurus run (method 7 of Fig. 8) as a component. In fact, the following correspondences between Figs. 8 and 9 are apparent:

Method 1	of Fig. 9 corresponds to	method 7	of Fig. 8,
method 2	" " corresponds to	methods 7 + 4	" "
method 3	" " corresponds to	methods 7 + 9	" "
method 4	" " corresponds to	methods 7 + 6	" "
method 5	" " corresponds to	methods 7 + 2	" "
method 6	" " corresponds to	methods 7 + 4 + 9	" "

It may be seen that for three of the combined methods of Fig. 8 (methods 2, 3, and 6), the overall measures for both specific and general requests are larger than for any of the included methods alone. Method 6, consisting of a combination of regular thesaurus plus word stems plus statistical phrase runs, seems to be particularly effective.

The normalized recall and precision measures for the combined methods are computed by using the rank lists produced by the computer for the individual methods alone, and automatically generating a *combined rank list*. The combined rank of a given document depends on the individual ranks held by that document in the component methods. Specifically, documents are taken alternately from the component lists to form the new combined list, and a document already included on the combined list is rejected if an attempt is made to list it again. The final combined rank list is then used to compute normalized recall and precision measures for the combined methods, as specified in the previous section. The resulting measures are averaged over several search requests to produce the graphs of Fig. 9.

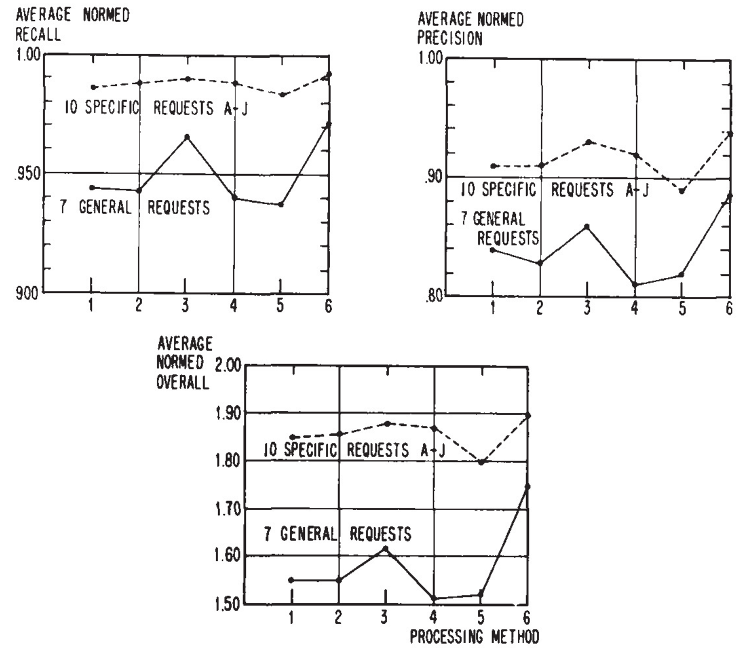
A combined rank list, generated for the two methods illustrated by the evaluation output of Fig. 7, is shown in Fig. 10 (only the first 15 documents are included for each component method). Documents previously specified as relevant are marked with an X, as in Fig. 7.

3. Results Using the Standard Measures

The performance characteristics of the SMART retrieval operations are reflected with reasonable accuracy in the data of Figs. 8 and 9. In particular, these figures

*These results would seem to indicate that Cleverdon's observations reported by Swet[4], that specific requests will have high precision and low recall and vice versa for general requests, need not necessarily hold in all circumstances.

† This observation has of course been made many times before, particularly by librarians and documentalists, but still requires emphasis in computer circles.



PROCESSING METHODS:

1. REGULAR THESAURUS
2. REGULAR THESAURUS + WORD STEMS
3. REGULAR THESAURUS + STATISTICAL PHRASES
4. REGULAR THESAURUS + HIERARCHY (DOWN)
5. REGULAR THESAURUS + HIERARCHY (UP)
6. REGULAR THESAURUS + WORD STEMS + STATISTICAL PHRASES

FIG. 9. Normalized Recall, Precision and Overall Measures for Several Merged Methods.

can be used to obtain an idea of the *relative* effectiveness of one method compared with another. The data are, however, difficult to interpret in absolute terms, particularly since the measures used are new ones, and no comparable output is available elsewhere in the literature.

In order to furnish some indication of systems performance which could lend itself more easily to a comparison with previously published data, the *standard* recall and precision measures, reflecting respectively the proportion of relevant material retrieved and the proportion of retrieved material relevant, are also computed for the search requests previously used. To generate these functions, it becomes necessary to choose appropriate threshold values which separate the retrieved information from that not retrieved. The procedure adopted for this purpose is as follows:

(a) a specified standard recall value is picked (say, 0.1);

(b) the number of documents which must be retrieved for a given search request in order to produce the specified recall is determined;

(c) using the cut-off value calculated under (b) for the number of retrieved documents, the precision measure (corresponding to the specified recall) is generated;

(d) the precision values obtained for a given recall level are averaged over a number of search requests, and the corresponding point is plotted on a precision versus recall plot;

(e) the complete procedure is repeated for a new recall level (say, 0.2, and 0.3, and so on) to produce a curve of the type shown in Fig. 11.

Figure 11 displays the standard precision versus standard recall graphs obtained for six processing methods, averaged over the 17 search requests previously used in Figs. 8 and 9. Figure 11 is in the exact form introduced by Cleverdon,[5,6] using the standard precision and recall measures, rather than the normalized measures based on rank lists. The procedure described above to generate the average precision over several requests is, however, different from Cleverdon's, since he combines requests not by computing separate recall-precision points for each request which are then averaged, but rather by treating sets of requests with $i,j,...,k$ relevant documents, respectively, as a single request with $i + j + ... + k$ relevant documents in all. Although the actual measurements are thus conducted from a somewhat different point of view, the output plots presented here should, nevertheless, lend themselves to a comparison with the published Cranfield material.*

* Recall versus precision plots have been criticized, because important information reflected in separate plots of recall and precision is obscured in the combined presentation (notably the number of documents both retrieved and relevant.)[10]

Ranks		Document Numbers	Ranks		Document Numbers	Ranks		Document Numbers
1	X	384	1	X	384	1	X	~~384~~
2	X	360	2	X	360	2	X	~~360~~
3	X	200	3	X	200	3	X	386
4	X	392	4	X	386	4	X	~~392~~
5	X	~~386~~	5	X	392	5	X	~~200~~
6	X	103	6	X	103	6	X	85
7	X	~~85~~	7	X	85	7	X	387
8		192	8	X	387	8	X	~~103~~
9	X	102	9		192	9	X	~~102~~
10	X	358	10	X	102	10	X	390
11	X	~~387~~	11	X	358	11	X	~~358~~
12	X	202	12	X	390	12	X	388
13		229	13	X	202	13	X	~~202~~
14		88	14	X	388	14	X	385
15	X	251	15		229	15		169
	⋮		16		88		⋮	
			17	X	385			
			18	X	251			
			19		169			
				⋮				

(a) Regular Thesaurus (b) Combined Rank List (c) Statistical Phrases

FIG. 10. Merging of Rank-order Lists.

The data of Fig. 11 confirm those previously shown in Fig. 8 in that the statistical phrase run again seems to give the best performance. Furthermore, word stem comparisons are again inferior to the regular thesaurus runs, and "titles only" analysis is generally inferior. The differences in systems performance previously noted for the output of Figs. 8 and 9 are again in evidence, since, for a given recall level, average precision can vary by over 30 percent from one method to another. The same is true of the average recall differences for a given level of precision.

Figure 12 shows standard precision versus standard recall figures averaged separately over the specific and the general requests for three processing methods. A comparison with Fig. 9 again indicates that both recall and precision measures are substantially higher for the specific requests than for the general requests.

• Conclusions

The evaluation procedures and results included in the present study are based on the manipulation of one relatively small collection of document abstracts, and a set of about 20 search requests. Only about 15 different processing methods are used. Under the circumstances, it is not possible to make claims of general validity, or to prove many assertions with finality.

Nevertheless, it is believed that the data presented here can be used as indications of the kind of performance to be expected of automatic retrieval systems. In particular, the data which point to the existence of considerable discrepancies in performance characteristics between processing methods may be expected to be confirmed by new experiments with different document collections and larger numbers of search requests. Of special interest, in this connection, is the fact that certain processing methods exhibit *both* high recall and high precision, thus indicating good overall performance.

The other principal piece of evidence tends to support the notion that the juxtaposition of a variety of processing methods provides improved retrieval performance over and above the performance of the individual component methods. The design philosophy of the SMART system, which is based on an iterative search procedure with a variety of analysis methods to retrieve relevant information, should therefore prove useful in practice. (A similar conclusion, pointing to the joint use of UDC (Universal Decimal Classification) coupled to a Uniterm system, has previously been reached in a conventional retrieval situation.[11])

Additional experiments remain to be carried out with different document collections not previously used with the available dictionaries, and with additional search requests. A careful analysis of systems failures is also mandatory, in order to determine more precisely the

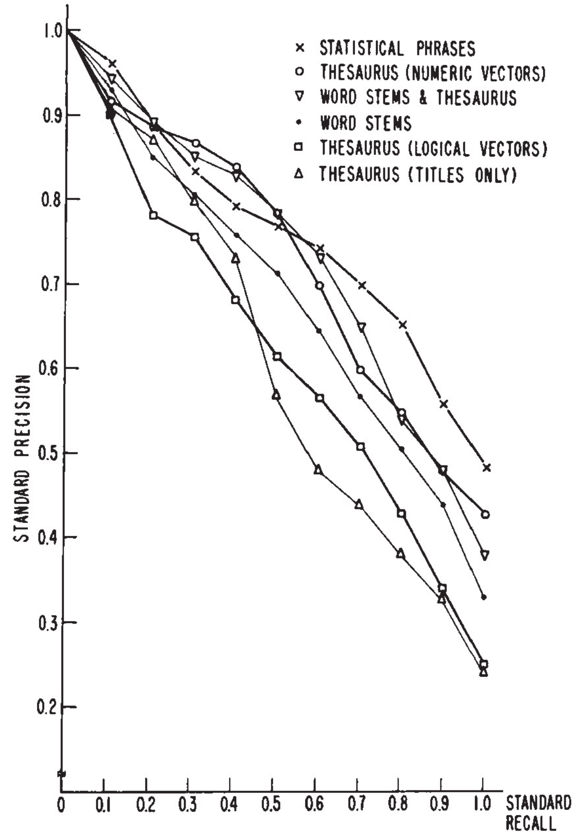


Fig. 11. Standard Precision vs. Standard Recall (average values over 17 requests).

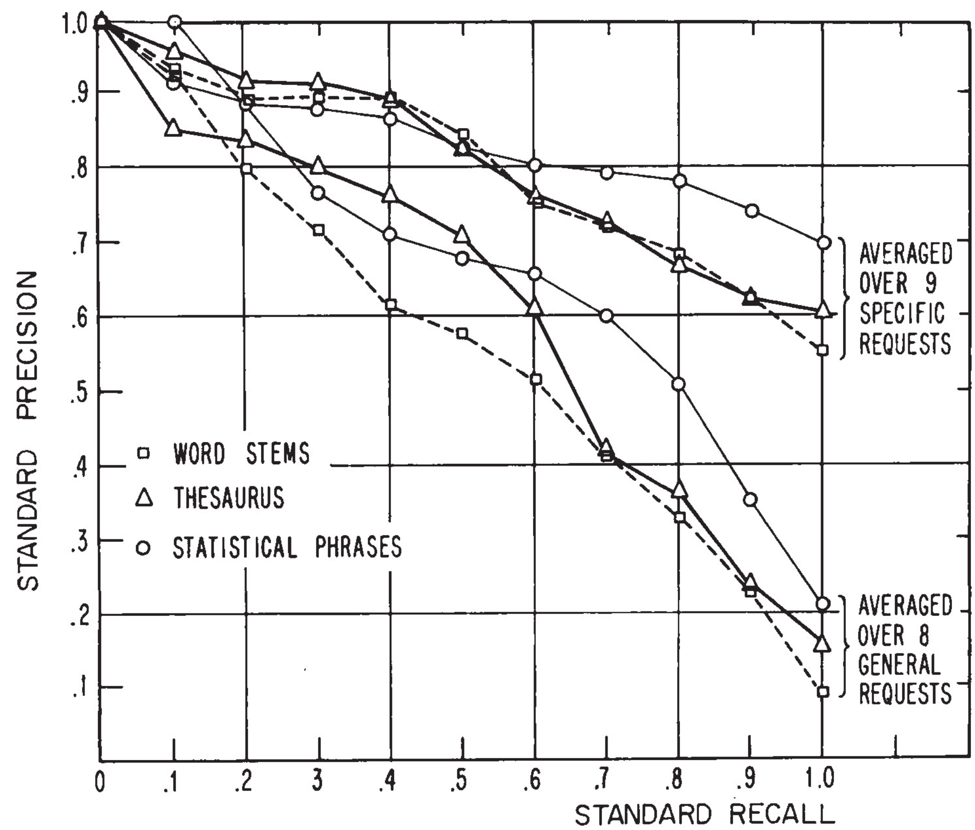


Fig. 12. Standard Precision vs. Standard Recall
Comparison of General and Specific Requests.

strengths and weaknesses of the individual methods, and the circumstances under which relevant documents are not recognized and receive therefore a low correlation on the output lists. Additional processing sequences must also be analyzed, and useful sequences identified in order to maximize system performance and retrieval effectiveness.

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