I. The Cornell Implementation of the SMART System
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#### Abstract

The systems organization of the SMART programs is discussed as implemented for operation in a batch processing mode on the IBM 360/65. Covered in particular are the basic input and text analysis routines, the document clustering programs, the search routines and the feedback operations. Sample computer output is shown in each case to illustrate the operations.


## 1. Introduction

The SMART system is designed for the exploration, testing and measurement of proposed algorithms for document retrieval. The system takes documents and search requests in English, performs a fully-automatic content analysis of the texts, matches analyzed documents with analyzed search requests, and retrieves those stored items believed to be most similar to the queries. The request authors (users) can submit information to improve their queries (relevance feedback), and this information is used by several experimental procedures to improve search results. The time required to match large collections of documents to requests can be reduced by grouping these documents (clustering) and matching requests against a representative of the entire group. Finally, exhaustive evaluation procedures can be used to ascertain the effectiveness of various methods used in searching.

Several important criteria are incorporated in the implementation
of the SMART system. [l] The requirement for mixing different processing methods, such as clustering, relevance feedback, and searching, implies that the programming system should be written in terms of many small blocks, in such a way that any one process would be synthesized by assembling several. blocks into one unit. In this manner, not only can a process be carried out using many different combinations of methods, but a change in any part: of the system does not require major alterations of the other parts of the system. The fast processing speed necessary to process large collections is gained by making it possible to process several queries in parallel.

## 2. Basic System Organization

The SMART information retrieval process can be divided into five basic sections: the input of printed text, the grouping of documents for searching purposes (clustering), the selection of a group of documents to be searched, the searching of the document group, and the evaluation of the search.

The printed text specifying the queries and documents must be con-verted into a form more easily handled by a computer. For this purpose various automatic language analysis devices can be used which reduce each query and document to "concept" vector form.

To produce fast searching algorithms, documents can be grouped into classes of similar documents. The grouping (clustering) is done by placing documents containing similar concepts together, into the same group; a representative central item is then constructed for each group.

The search of a document group (cluster) is done by first matching requests against clusters. Certain clusters are picked as most likely to
contain documents of interest. These documents are then searched in the normal manner, one item at a time. After seeing some retrieved documents, the requestor can modify his request, either by physically changing it, or using the requestor's relevance assessments to automatically modify the query.

Several measures of retrieval performance are computed to evaluate each search. The sign test, $T$ test, and Wilcoxon Rank Sum test are also used to determine the significance of the evaluation measurements.
A) Input of Printed Text

The first section involves the reading of text (e.g., abstracts, queries) and the conversion of a given text into numeric concept vectors with weights. The conversion process may involve the use of suitable dictionaries, thesaurus, and other language normalization aids. At present, a relatively simple $\mathrm{PL} / 1$ program is used to implement this section. A more flexible Fortran IV program is planned for later implementation as described in report ISR-14 [2] and included in the system flowcharts, part 4 of the report.

The presently available text-handling program, LOOKUP, is a procedure which performs dictionary lookups on a large IBM 360-series computer. It accepts a dictionary, suffix list, and texts and produces "concept vectors" for the texts. Words missing from the dictionary are also processed. The algorithm is essentially that of Sussenguth [3] although the tree structure storage format is not used. LOOKUP is designed primarily for ease of programming, and is coded entirely in PL/l.

The overall operation of LOOKUP is divided into three parts. First, the dictionary and suffix list are read into memory, sorted alphabetically and necessary initialization is performed. Secondly, text is read in, divi-
ded into words, and the words looked up in the dictionary and suffix lists. Third, the concept numbers derived from the words in each document are sorted and condensed into a properly weighted vector. The vector can be printed and/or stored in machine-readable form. The lookup program finds a match between an input word and a dictionary entry under the following conditions:
l) the word exactly matches a dictionary entry; or
2) it matches a dictionary entry with a final "e" dropped and a suffix beginning with a vowel added; or
3) it matches a dictionary entry plus a suffix; or
4) it matches a dictionary entry with a final "y" changed to "i" and a suffix added; or
5) it matches a dictionary entry, with a final consonant doubled and a suffix added.

When several possible matches are found the match involving the longest stem is preferred; within stems of the same length, preference is in numerical order as above. Thus, if "cop", "cope", and "copy" are all stems in the dictionary, and all normal Engiish suffixes are included in the suffix list, "cops" is found from "cop" under rule 3; "copes" or "coping" is found from "cope" under rule 2; "copying" from "copy" under rule 3; "copies" from "copy" under rule 4; and "copper" from "cop" under rule 5. Other morphological features of Engiish are not recognized; such word pairs as "mouse" and "mice", "sing" and "sung", "fight" and "fought", or "court-martial" and "courts-martial" must be entered explicitly in the dictionary if both members are tc be recognized. Special rules exist which specify that all stems must be at least three letters long (to avoid, for example, finding "wing"
from "we" under rule 2 or "inning" from "in" under rule 5); furthermore, all words are truncated at 24 characters.

The program can distinguish titles from the body of the text, if asked; and it may either split the weight of an ambiguous word among its concept numbers, or weight all concept occurrences equally. The suffix list may be omitted from the lookup, in which case only words that exactly match a dictionary entry can be found; and the programmer may choose whether hyphenated words are to be considered as a unit or as separate words. As in the previous SMART implementations, concept numbers of zero or concept numbers of 32000 or more are considered to be nonsignificant and are dropped from the vector.

Fig. l shows a typical output of LOOKUP. First the title is given, and then the text of the document (or query in this case). The resulting numeric concept vector is next printed, consisting of pairs of concept numbers followed by the respective concept weights (for example, concept 927 with weight 12, 2574 with weight 12, etc.). Concepts are listed in the vector in increasing numeric order.
B) Document Clustering for Search Purposes

At present two clustering algorithms are in operation at Cornell CLUSTR, which uses Rocchio's clustering algorithm [4], and DCLSTR, a variation of Doyle's clustering algorithm. [5]

Rocchio's clustering algorithm is based on the following methodology: an unclustered document is selected as a possible cluster center. Then, all of the other unclustered documents are correlated with it, and the document is subjected to a density test to see if a cluster should be formed around it. The density test specifies that at least $N_{l}$ documents should have corre-

*FIND QAIOGROUP

lations higher than a specified parameter $\mathrm{P}_{1}$ with the document in question, and that at least $\mathrm{N}_{2}$ documents should have correlations higher than $\mathrm{P}_{2}$ $\left(\mathrm{P}_{2}\right.$ is generally larger than $\mathrm{P}_{1}$ ). This test ensures that documents on the edge of large groups do not become cluster centers. If the document passes the density test, thus becoming a cluster center, a cutoff correlation, $P_{\min }$, is determined from the cluster size limits and the distribution of correlation values. The cutoff correlation becomes $\mathrm{P}_{1}$ if fewer documents than the minimum cluster size $\left(M_{1}\right)$ have correlations above $P_{\perp}$. If more such documents exist, the cutoff correlation is chosen at the greatest correlation difference between $M_{2}$ adjacent documents, where $M_{2}$ is the maximum cluster size.

A classification vector is then formed by taking the centroid of all the document vectors having correlations above $\mathrm{P}_{\mathrm{min}}$. This centroid vector is matched against the entire collection, and the cutoff parameters for cluster size are recalculated to create an altered cluster.

As a result of this process, some documents may appear in more than one cluster; and some which were in a cluster when the centroid was originally formed may not remain in any cluster. These documents, as well as those which failed the density test, are termed "loose", and those within the cluster are termed "clustered".

This entire procedure is repeated with all unclustered documents, the first pass terminating when all items are either clustered or loose. Figs. 2, 3, and 4 illustrate the formation of a cluster. Document 2 is first correlated with all previously unclustered documents in the collection ( 9 documents of the 82 documents in the collection had previously been clustered around document l). The correlations are ranked, and the ranks, docu-


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0 \sim 0 \\
0
\end{array}\right)
$$

$$
2 \quad W \exists 11
$$

ment numbers, and correlation coefficients are listed in Fig. 2. In the example, at least 10 documents $\left(N_{1}\right)$ must have a correlation greater than $0.15\left(\mathrm{p}_{1}\right)$, and at least 5 documents $\left(\mathrm{N}_{2}\right)$ must have a correlation greater than 0.25 . The correlation of document 2 is larger than 0.15 for 19 other documents, and for 5 other documents the correlation exceeds 0.25 . Document 2 therefore passes the density test. $M_{1}$ in this example is 5, and therefore $P_{\text {min }}$ is calculated by finding the greatest correlation difference between adjacent documents, starting with the document of rank 5 (at least $M_{1}$ documents must be included) and checking differences up to $M_{2}$ documents (in this case 15 documents). The largest gap occurs between ranks 7 and 8 - therefore $\mathrm{P}_{\min }$ is taken to be 0.2475 .

The classification vector (called the centroid) is formed by merging the document vectors of documents having correlations above $\mathrm{p}_{\min }(0.2475)$. The centroid, composed of concepts and weights, is shown in Fig. 4. This centroid is then correlated with all previously unclustered documents (Fig. 3). A second cutoff correlation $\mathrm{P}_{\mathrm{min}}$ is calculated to determine which documents belong in cluster 2. Here the greatest correlation difference (starting at $M_{1}$ and checking until $M_{2}$ ) occurs between the documents ranked 11 and 12 . Therefore $\mathrm{P}_{\mathrm{min}}$ becomes 0.3859 , and the top 11 documents are included in cluster 2. These documents are listed as the "ll Relevant" in Fig. 4. DCLSTR uses a variation of Doyle's Algorithm. The following description of the algorithm covers the main points. [5] Assume that the document set is arbitrarily partitioned into $m$ clusters, where $S_{j}$ is the set of documents in cluster $j$. Associated with each set $S_{j}$ is a corresponding concept vector $C_{j}$ and frequency vector $F_{j}$. The concept vector consists of all the concepts occurring in the documents of $S_{j}$, and the frequency vector specifies the number of documents in $S_{j}$ in which each concept occurs.

Every concept in $C_{j}$ is assigned a rank according to its frequency; i.e., concepts with the highest frequency have a rank of $l$, concepts with the next highest frequency receive a rank of 2 , etc. Given an integer b (base value), every concept in $D_{j}$ is assigned a rank value equal to the base value minus the rank of that concept. The vector of rank values is called the profile $P_{j}$ of the set $S_{j}$. Fig. 5 illustrates the concept and frequency vectors, and the corresponding profiles for a sample document collection.

Starting from a partition of the document set into $m$ clusters, the profiles are generated as described. Every document $d_{i}$ in the document space is now scored against each of the $m$ profiles by a scoring function $g$, where $g\left(d_{i}, P_{j}\right)$ equals the sum of the rank values of all the concepts from $d_{i}$ which occur in $C_{j}$. Fig. 5 shows the results of scoring the documents in the sample collection against the profiles from Fig. 5.

A new partition of the document set into $m+l$ clusters is then made by the following formula:

$$
\begin{aligned}
& S_{j}=\left\{d_{i} \mid g\left(d_{i}, P_{j}\right) \geq T_{i}\right\} \quad l \leq j \leq m \\
& T_{i}= \begin{cases}H_{i}-\left[a \cdot\left(H_{i}-T\right)\right] \quad \text { if } H_{i}>T \\
T \text { otherwise }\end{cases}
\end{aligned}
$$

where

$$
\begin{aligned}
H_{i} & =\max \left(g\left(d_{i}, P_{j}\right)\right) \\
0 & \leq a \leq l \\
T & =a \text { is the given cutoff value. }
\end{aligned}
$$

Those documents which do not fall into any of the $m$ clusters $S_{j}$ are called loose documents, and they are assigned to a special class L . The process is

| $d_{1}$ | $\frac{d_{2}}{c_{1}}$ | $\frac{d_{3}}{c_{1}}$ | $\frac{d_{4}}{c_{1}}$ | $\frac{d_{5}}{c_{1}}$ | $\frac{d_{6}}{c_{1}}$ | $\frac{d_{7}}{c_{3}}$ |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| $c_{2}$ | $c_{2}$ | $c_{6}$ |  |  |  |  |
| $c_{2}$ | $c_{2}$ | $c_{8}$ |  | $c_{8}$ |  |  |
| $c_{5}$ | $c_{4}$ | $c_{8}$ | $c_{3}$ |  |  |  |
|  | $c_{5}$ |  | $c_{5}$ |  |  |  |

a) Documents

b) Initial Clusters, Profiles, and Frequencies
Construction of Profiles from Documents
(base value $=6$ )

| Document | Profile of <br> Highest Score | Score |
| :---: | :---: | :---: |
| $\mathrm{d}_{1}$ | 2 | 15 |
| $\mathrm{~d}_{2}$ | 2 | 19 |
| $\mathrm{~d}_{3}$ | 1 | 12 |
| $\mathrm{~d}_{4}$ | 2 | 19 |
| $\mathrm{~d}_{5}$ | 1 | 9 |
| $\mathrm{~d}_{6}$ | 3 | 5 |
| $\mathrm{~d}_{7}$ | 3 | 10 |

$$
\begin{array}{cccc}
\frac{\mathrm{S}_{1}^{\prime}}{\mathrm{d}_{3}} \frac{\mathrm{~S}_{2}^{\prime}}{\mathrm{d}_{1}} & \frac{\mathrm{~S}_{3}^{\prime}}{\mathrm{d}_{7}} & \frac{\mathrm{~L}}{\mathrm{~d}_{5}} \\
& \mathrm{~d}_{2} & & \mathrm{~d}_{6} \\
& d_{4} & &
\end{array}
$$

b) Resulting Clusters

One Iteration of Doyle's Classification Algorithm (cutoff $=10$ )

Fig. 5
now repeated after replacing $P_{j}$ by $P_{j}^{\prime}$. The iteration continues until $S_{j}$ satisfies the termination condition that $S_{j}^{\prime}=S_{j}$ (actually $S_{j}^{* \prime}=S_{j}^{*}$, where $S_{j}^{*}$ is the subset of $S_{j}$ consisting of all those documents that score highest against profile $P_{j}$ ).

Basically, this algorithm matches documents to existing clusters by computing a document-cluster score for each document with respect to each cluster, and placing a document into those clusters for which a sufficiently high score is obtained. The clusters are then updated to include the new documents. In each iteration all the documents are correlated with all the clusters, and the clusters are updated until further updating does not alter the group of documents in each cluster. This updating is shown in list form in Figs. 6 and 7. The 12 profiles (clusters) of Fig. 6 are matched against the documents, and updated to become the profiles of Fig. 7 .

It should be noted that the document clustering process can be extended to the clustering of clusters. That is, if one of the two clustering algorithms generates $m$ groups of documents, these $m$ groups could be grouped together, as if they were documents, into $n$ clusters, where $l \leq n \leq m$. These $n$ clusters could then be grouped together, and so on, until a hierarchical cluster tree is formed as shown in Fig. 8. At present no routines for automatically constructing such multi-level cluster trees exist in the SMART system, although such an algorithm is planned for implementation in the near future. Both CLUSTR and DCLUSTR generate the first level of the cluster trees, thus representing special cases of more general tree construction routines.
C) The Selection of Documents to be Searched

The search process consists of four steps. First a search query is



## $\square$ cluster root <br> 人 centroid <br> d document



Fig. 8
defined, either using the author's original query, or a modification of the original query, in numeric concept vector form. One important modification consists in using documents judged relevant by the author to modify the original query vector. This process is known as relevance feedback and is discussed in part $D$ of this section.

Once a search query is defined, the set of documents to be correlated with the query is selected. SMART provides two options; either a full search or a tree search may be made. In a full search every document in the retrieval base is correlated with the query. In this case the selection of the documents to be searched is trivial - all documents in the collection are searched.

In the tree search [6], a set of documents is selected by a cyclic: process, using a tree such as that pictured in Fig. 9. At any one time, a set of active nodes exists in the tree; initially this is the set of roots (the highest level of clusters). Each node in the active set is compared with the search query. The "goodness" of each node is defined from the relatedness of a query to a node, and from other information about the structure of a tree; the nodes of the "active" set are then ordered by this value of a "goodness". A subset of active nodes is selected as being most. promising. The corresponding nodes are deleted from the active set, and the sons of these nodes (if centroids) are correlated with the query and become a part of the active set. Those sons which represent documents are then entered onto a list of documents to be used in subsequent correlations with the query. The active set is cyclically reordered and another group of nodes is selected to have its sons examined until some desired number of documents are located. The process used to obtain a list of specific docu-


Searching a Hypothetical Tree
Fig. 9
ments to be directly compared to a query is represented in Fig. 9 .
The listing reproduced in Fig. 10 shows an example of input to the cluster searching routine. The first iteration (Iteration 0) uses a full search instead of a tree search. The second iteration (Iteration l) represents a tree search on the cluster collection "CENTROID NO MORE" using the "COSINE" correlation. The desired number of documents to be selected for correlation with the query is given by "WANTED", where "WANTED" is defined as:

$$
\begin{aligned}
\text { WANTED }= & \text { "CORDOC" }+ \text { "TIMALL" } * \text { "ALLOF" } \\
& + \text { "TIMREL" * (the number of relevant } \\
& \text { documents not yet retrieved })+ \text { "TIMNMR" } \\
& * \text { "NOMOR" }
\end{aligned}
$$

where

| CORDOC | implies that at least "CORDOC" documents will be <br> Correlated in this iteration; |
| :--- | :--- |
| TIMALL | "TIMALL" times "ALLOF" (for this iteration) documents |
| are additionally correlated in this iteration; |  |

"ALLOF" and "NOMOR" are user-supplied constants indicating how many documents are used in relevance feedback. Therefore the second and fourth terms of the parameter "WANTED" are constants, like "CORDOC", for a given iteration. These constants are expressed by three parameters (rather than

-
Fig. 10
Iteratiun
iteratiun
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selection
rejection
a full search rather ihan a tref search is beding dune.

$$
\begin{array}{cc}
\text { CENTRUIU } & \text { NU MURE } \\
2 & \text { TIMALL } \\
1.00 & \text { PCN } \\
0.0 & \text { PALLUF } \\
0.0 & \text { PFFCCN } \\
0.0 & \text { PNCNLV } \\
\hline 0.0 & \text { PFCFLV } \\
\hline 1 & \text { MAXNOUD } \\
0.10 & \text { MNCŌRR }
\end{array}
$$


Selection and Expansion of Third Set of Nodes
for Query 34
being lumped into one) for user convenience; most users will set "TIMALL" and "TIMNMR" to zero. The parameter "TIMREL" allows the number of documents searched to be related to the number of relevant documents previously not found.

The "goodness" of each node (the parameter value used to rank the nodes) may also be controlled by the user through 17 parameters as follows.

$$
\begin{aligned}
\text { "GOODNESS" } & =" C O E F " ~+~ " M C N " ~ x ~ " C R O W N " ~ " P C N " ~+~ " M L V " ~+~ " L E V E L " " P L V " ~ \\
& + \text { "MCFCN" x "COEF" "PFCFCN" x "CROWN""PNCFCN" } \\
& + \text { "MCNLV" x "CROWN" "PNCNLV" x "LEVEL""PVCNLV" } \\
& + \text { "MCFLV" x "COEF" "PFCFLV" x "LEVEL""PVCFLV" } \\
& + \text { "MALL" x "COEF" "PALLCF" x "CROWN""PALLCN" x "LEVEL" "PALLLV" }
\end{aligned}
$$

where "COEF" is the correlation value (usually cosine) between the node and the query, "CROWN" is the number of nodes that are the sons of the node, and "LEVEL" is the level of the node. For example, the node in Fig. 9 with a "goodness" of 0.9 , has a "CROWN" of 11 and a "LEVEL" of 3.

It should be noted that the formula for "GOODNESS" contains many combinations of "CROWN" and "LEVEL", making the formula extremely flexible for experimental purposes. It is expected that most users will use only two or three terms, most parameters in "GOODNESS" being usually set to zero.

The size of the subset of active nodes to be expanded (after all active nodes are ranked by "goodness") is determined by additional parameters specified by the user, as printed in the listing (Fig. l0) under "SELECTION" and "REJECTION".

| MINNOD MAXNOD | At least 'MINNOD" nodes and not more than "MAXNOD" |
| :---: | :---: |
|  | nodes are to be expanded for this iteration; |
| GAP | If there ekist two nodes between "MINNOD" and |
|  | "MAXNOD" which have a difference greater than |
|  | "GAP", all nodes above that gap are expanded; |
| EPSLON | Any nodes within "EPSLON" of the last node |
|  | selected for expansion are also to be expanded; |
| MNGOOD | Any node with a "GOODNESS" of less than "MNGOOD" |
|  | is not to be retained for expansion; |
| MNCORR | Any node with a correlation less than "MNCORR" |
|  | with the query is not retained for expansion; |
| PERCOL | Only nodes whose combined "CROWN" is greater than |
|  | "PERCOL" percent of the size of the collection |
|  | being searched need be retained for expansion. |
| TIMWAN | Only nodes whose combined "CROWN" is greater than |
|  | "TIMWAN" times the number of documents to be corre- |
|  | lated with are retained for expansion. |

The selection of the documents using the parameters from Fig. 10 is shown in Figs. ll, 12, and 13. The queries are processed as a batch, and queries $31,32,33$, and 34 are shown as examples. The queries are first matched against the "roots" of the centroid tree consisting of centroids l, 2, and 3. The results of the matching and other useful statistics are shown in Fig. ll. The query number, iteration number, number of documents wanted and found, centroid used to match, "goodness" of the matching, statistics of the centroid, and the cosine correlation are given for each query match against all the roots. The "REJECTION" parameters are used here to eliminate centroids before any ranking is done on "goodness". A "MNGOOD" of 0.10 causes centroid 2 to be dropped from the active set of query 33, and centroid 3 to be dropped
tret searching -- selfciang the cccunents witt which 17 oueries hili ae correlated.

| $\begin{aligned} & \bar{\alpha} \\ & \underset{\sim}{c} \\ & \underset{z}{2} \end{aligned}$ | $\begin{aligned} & \bar{O} \\ & 0 \\ & 0 \\ & \text { Z } \\ & \text { 2 } \end{aligned}$ |  |
| :---: | :---: | :---: |
| $\stackrel{\searrow}{\propto}$ | $\underset{\sim}{x}$ |  |
| $\begin{aligned} & \text { c } \\ & 0 \\ & 0 \\ & 0 \\ & 0 \\ & 0 \end{aligned}$ | $\begin{aligned} & 0 \\ & 0 \\ & 0 \\ & 0 \\ & 0 \\ & 0 \\ & 0 \end{aligned}$ |  |
| $\underset{\sim}{\underset{\sim}{u}}$ | - | ¢ |
| $\bigcirc$ | 은 | 은 |





from the active set of queries 31 and 32. Similarly, a "MNCORR" of 0.05 causes centroid 1 and centroid 3 to be dropped from the active set of nery 33. The centroids remaining in the active set of each query are the ked and the "SELECTION" parameters used to select nodes to be expanded (Fi I). Note that query 33 has no active set remaining and therefore is dropped from further searching (a more careful set of paramecers for "goodness" would have eliminated this problem).

The "SELECTION" parameters indicate that at least 1 centroid should be expanded, and up to 3 centroids may be expanded until a gap of 0.10 in "goodness" occurs. Query 34 exhibits such a gap between centroids 3 and 2; hence only centroid 3 is selected for expansion.

The expansion of centroids is shown in Fig. 12. Query 31 and 32 both now have an active set of 6 centroids; query 34 has 3 centroids in its active set. Again the active sets are matched against their respective queries and the "REJECTION" parameters are applied. This time one centroid (centroid 4 ) is dropped from the active set of query 31,4 centroids (centroids 5, 6, 7, and 9) are dropped from the active set of query 32, and no centroids are dropped from the active set of query 34.

Fig. 13 shows the selection of centroids to be expanded from among the active sets. Again applying the "SELECTION" parameters, no gap greater than 0.1 occurs within the first 3 centroids (centroids 7, 9, and 5) for query 3l; furthermore, centroids 6 and 10 have a goodness within the "EPSLON" of 0.05 , and hence are also selected for expansion. A gap greater than 0.1 occurs between the first and second centroids (centroids 10 and 4) for query 32 ; therefore only centroid 10 is to be expanded. Query 34 has a gap in goodness greater than 0.1 between centroids 2 and 8 ; thus only centroids

11 and 12 are expanded.
The expansion for query 31 produces 43 document sons, easily satisfying the need for 12 documents. Query 32 finds 14 document sons during expansion, and the need for 12 documents is again satisfied. Query 34 , however, finds only 8 document sons and 3 centroid sons on expansion; it thus becomes necessary to search further to find the additional four documents. The selection and expansion of a third set of nodes for query 34 is shown in Fig. 14. Here, expansion of centroid 5 produces 21 document sons for query 34 , thus filling the total requirement of 12 documents.

It should be noted that the selection of documents to be searched is not equivalent to final searching. For example, query $3 l$ must be processed in a regular search against the 43 documents selected (instead of performing a full search using the entire document collection). The averaged results of the searching runs are shown in section $E$.
D) The Searching of the Document Groups

Once the documents to be searched in a given iteration are selected, the query used in the search process is constructed. The search query is generated using concept numbers from four distinct sources: the author's original query, documents which the author considers relevant before the search is started, specific concepts and weights which the author would like to add to the query, and relevance feedback information from previous search iterations (if any exists). Information from the first three sources is contained for iteration 0 (first search hence no feedback information) in Fig. 15. The following information is given for each query: the authors, the query number, the iteration number, the sources of the query and the corresponding document numbers, multipliers for these documents (all weights of



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| $\text { ORIG MULT }_{1}$ | PKEV MULI | $\begin{aligned} & \text { MIN LORKK } \\ & 0.0150 \end{aligned}$ | Iypt Letrk COSINE | NCKNAL AONOKMAL |  | $\begin{aligned} & \text { ITEMSEMULTS } \\ & \text { YES } \end{aligned}$ | $\begin{aligned} & \text { CJinsemghts } \\ & \text { YLS } \end{aligned}$ | $\begin{aligned} & \text { FREELE/FLUID } \\ & \text { FLUIO } \end{aligned}$ |  | unitve <br> BY WURD | nGHTS CRPFE puS.AVE. | PER JRPED |
| POS MULT | NEG MULT | pos rank Lut | $\underset{0}{\text { NEG RANK }}$ | cut pos | $\begin{gathered} \text { PCS } \\ 1 . \end{gathered}$ | curr cut <br> . 0000 | $\begin{aligned} & \text { IVEG CORK CUT } \\ & 1.0000 \end{aligned}$ | POS ATLEST | NEG | $\begin{aligned} & \text { ATLEST } \\ & 0 \end{aligned}$ | $\begin{gathered} \text { PCS NOMCRE } \\ \text { o } \end{gathered}$ | NEG NUMORE |
| $\underset{\text { C }}{\substack{\text { UNLESS }}}$ | stupall nu | prec cuitiff 0.0 | $\text { F PUEFIN } \begin{aligned} \text { ILS } \end{aligned}$ |  |  |  |  |  |  |  |  |  |
| CPTIONS FOR SEARCF EHM 1 ARE: |  |  |  |  |  |  |  |  |  |  |  |  |
| $\mathrm{ORIG}_{0} \text { MULT }$ | $\underset{1}{\text { PREV MULT }}$ | $\begin{aligned} & \text { MIN CORR } \\ & 0.0 \end{aligned}$ | TYPE CORR cosine | NURMAL ABNORMAL |  | $\begin{aligned} & \text { ITEMSEMULTS } \\ & \text { NO } \end{aligned}$ | CONSEWGHTS NU | freEle/fluid FLUID | unitvc <br> BY WORD |  | $\begin{aligned} & \text { WGHTS DRPED } \\ & \text { POS.NON. } \end{aligned}$ | $\begin{gathered} \text { PER DRPED } \\ 0.0 \end{gathered}$ |
| pos mult | NEG MULT | POS RANK CUT | NEG RANK | Cut PO | pos | corr cut | NEG CORK CUT | POS ATLEST | NEG | ATLESI | POS NOMURE |  |
| 1 | -1 | 5 |  |  |  | . 0000 | 1.00 .0 | pos a Tlest |  | 0 | POS 5 | NEG NOMORE |
| $\underset{2}{\text { UNLESS }}$ | $\begin{aligned} & \text { STOPALL } \\ & \text { YES } \end{aligned}$ | prec cutuff $0.0$ |  |  |  |  |  |  |  |  |  |  |

concepts in a given document are multiplied by the specified multiplier), and the query concept numbers and their weights. For example, query one uses the concepts from the original query (with all weights multiplied by one), plus all the concepts from documents 3 and 10 (all weights in both documents being multiplied by 2), plus concept 12 with a weight of 14. Query 1 is then defined by the combination of all these concepts and their weights.

Following the initial search query set-up, further modifications can be made before the search is started. The user specifies the type of modification to be made by introducing parameters as shown in Fig. 16. The options for the query modification are listed in Fig. 16, one section being devoted to each iteration. The parameters are defined as follows:

ORIG MULT Multiplier of original query.
PREV MULT Multiplier of query used for previous iteration.
MIN CORR Parameter controlling retrieval. Any document with a correlation less than (or equal to) "MINCOR" is not shown to the user and is deleted from the recovered list prior to sorting into correlation order. The higher this value, the faster the system can answer a query. If punched, the field must include a decimal point. As usual, a blank field is equivalent to zero. The type of correlation to be used. If blank, the correlation of the previous iteration is used. If blank for the zeroth iteration, 'COSINE' is substituted. At present, "COSINE" is the only available correlation.

| NORMAL | If this field contains the word 'NORMAL' for each definition, "RMULT" is divided by the number of relevant used in that definition. "NMULT" is likewise divided by the number of nonrelevant used in feedback. |
| :---: | :---: |
| ITEMS \& MULTS | This field contains 'YES' if specific items and multipliers are given for each and every query in this iteration. |
| CONS E WGHTS | This field contains 'YES' if a specific vector of concepts and weights is supplied for each and every query in this iteration. |
| FREEZE/ <br> FLUID | If this field contains 'FREEZE', the items seen by the user defining the query are frozen in the order seen. Otherwise, all rank positions are available and all documents are correlated. |
| UNITVC | If this field contains the words "BY WORD", the weights of a given vector are not normalized. If this field contains the word 'COSINE' all weights in a given vector are normalized according to the cosine correlation prior to being added to the composite for the new query. This produces the same weight for all documents, regardless of length. This is accomplished by multiplying each weight by the suitable multiplier and dividing by the square root of the sum of squared weights of the vector being added. To prevent weights from disappearing (due to integer arithmetic), the multipliers must be set at a high value when using this feature. If this field contains the word 'LINEAR', normalization is accomplished by dividing by the sum of absolute values of all weights in the vector being added. |

WGHTS DRPED This field is of the form 'XXXXYYYY'. If 'XXXX' is 'NEG.' negative weights are permitted; otherwise only positive weights will be kept after definition. 'YYYY' can be either ' ', 'ABS.', or 'AVE.'. If 'YYYY' is blank, only concepts with weight zero are deleted from the new query. (This obviously does not change correlations.) If 'YYYY' is 'ABS.' then all concepts with weight less than "PERDRP" are deleted. If 'YYYY' is 'AVE.' then all concepts with absolute weight less than ("PERDRP"\% the sum of absolute weights)/(100* the number of unique concepts) are deleted. The former method is used to delete weights less than a specific value, say 12. The latter method permits dropping all weights less than a certain percentage of the average weight. For example, if all concepts less than $90 \%$ of the average weight ane dropped from normal composites, $75 \%$ of the concepts are deleted, but only $40 \%$ of the weight of the composite is lost.

PER DRPED (See above. This is a floating point number and must be punched with a decimal point.)

The second line of Fig. 16 covers parameters used for relevance feedback, and not for the initial iteration, although the values are printed. Definitions for the second and third lines are covered in the discussion for the second iteration.

For query l, the user-supplied parameters call for a multiplier of the query of $l$, nonnormalized vectors, additional items and multipliers, additional concepts and weights, no normalizing of weights ("UNITVC" = "BY WORD"), and dropping of all concepts whose absolute weight is less than
(99.9 * sum of the absolute weights) / (100.0 * the number of unique concepts).
$=\frac{93.4 \times 962}{1000 \times 23}$
In query l, concepts with a weight smaller than 40 are dropped in accordance with the specifications of Fig. 16. The display of Fig. 17 for query $l$ shows that the original 23 concepts (formed by combining the concept vectors of the orignal query plus author-supplied documents and author-supplied concepts and weights ) are reduced to the six concepts shown in the figure.

These modified queries are then correlated with every document in the group previously selected (in this case a full search of the entire collection is made). After the queries are correlated with all the documents, documents having a correlation greater than 0.015 ("MIN CORR" for this iteration) are ranked. The top 30 documents retrieved are listed in Fig. 18. The first two lines of the listing contain the titles for the iteration, the query title and the relevant items for the query. (At present, the document relevance is pre-judged and held constant for all runs using a given query collection.) The major section of the page contains the correlation and rank of the documents retrieved for each iteration. The recall and precision values (defined in section E) obtained after retrieval of the given document are also given. For example, document 69 is the first document retrieved for query one in the first iteration (iteration 0 ). The correlation coefficient of this document with the query is 0.3924 , and the recall and precision values after the retrieval of document 3 are 0.0 and 0.0 respectively. Similarly, document 17 , a relevant document, is retrieved with rank 2, and its correlation with the query is 0.3430 . The recall and precision values after retrieval of document 17 are 0.333 and 0.333 respectively.

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$$
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$$

$$
0
$$

KUN $2-\mathrm{SCH}_{3}$
$C$ C
0
0.3924
0.3430
0.3087
0.2858
0.2654
0.2259
0.2146
0.2123
0.1945
0.1788
0.1778
0.1742
0.1742
0.1617
0.1358
0.1345
0.1324
0.1286
0.1213
0.1196
0.1180
0.1151
0.1078
0.0990
0.0980
0.0947
0.0857
0.0835
0.0808
0.0797

$$
\text { PAGE } \quad 55
$$

$$
\begin{aligned}
& 04 / 17 / 6904: 43: 21.51 \quad 33.4300 \\
& \text { RUN } 3-\text { SCH4 }
\end{aligned}
$$

$$
\begin{aligned}
& \text { RUN } 3- \\
& \text { REING }
\end{aligned}
$$

$$
46
$$


LEVANT ITEMS

$$
\left.\begin{array}{ccccccc}
17 & 46 & 62 & & \\
P_{0} & K & E_{1} & C & I & S_{2} & O
\end{array}\right]
$$



$$
-
$$



The last section of Fig. 18 contains various statistics for the run. These are defined as follows:

| DOC. CORR | The total number of document-query correlations performed in the given iteration. |
| :---: | :---: |
| CENT. CORR | The total number of centroid-query correlations performed in the given iteration. |
| DROP DOC | The number of documents with a query-document correlation of less than "MIN CORR". |
| CORR. RANK | The number of documents with a query-document correlation of greater than or equal to "MIN CORR". |
| OLD. DOC | The total number of documents previously seen by the user. |
| OLD RELDOC | The total number of relevant documents previously seen by the user. |
| NEW DOC | The total number of documents (relevant and nonrelevant) shown to the user in this iteration. |
| POS. FEED | The number of items in the definition of the query with a positive multiplier for feedback. |
| NEG FEED | The number of items in the definition of the query with a negative multiplier for feedback. |
| QUERY CORR | The correlation of the query used in the present iteration with the original user query. |
| REC. CEIL | The recall ceiling seen by the user. |

The listing of the retrieved relevant documents completes the first iteration of the search. At this point, the user makes relevance judgments, or, alternatively, prejudged relevance decisions are registered, and a new
search query is constructed using information about the retrieved documents. The user-supplied instructions specifying what information is to be used, and how the new query is to be constructed are taken from the input parameters (shown in Fig. 16 in the second two lines under options for SEARCH l). The definitions of the parameters are as follows:

| POS MULT | All weights of the relevant documents used in feedback are multiplied by this number. |
| :---: | :---: |
| NEG MULT | All weights of the nonrelevant documents used in feedback are multiplied by this number. To signify that negative feedback is not desired "NEG MULT" is blank or zero. |
| POS RANK CUT | All relevant items with iteration ranks above "POS RANK CUT" according to the ordering of the previous iteration are used in defining the new query. |
| NEG RANK CUT | All nonrelevant items with iteration ranks above "NEG RANK CUT" according to the ordering of the previous iteration are used in defining the new query. |
| POS CORR CUT | All relevant items with a correlation above this value are also used. (This value must include a decimal point.) If "POS CORR CUT" is zero or blank, no relevant are selected due to this parameter. |
| NEG CORR CUT | All nonrelevant items with a correlation above this value are also used. |
| POS ATLEST | At least "POS ATLEST" relevant will be fed back <br> (if they exist - i.e., more remain to be found) |
| NEG ATLEST | At least "NEG ATLEST" nonrelevant will be fed back. |

POS NOMOR

UNLESS

STOPALL

PREC CUTOFF

POEFIN

However, no more than "POS NOMOR" items will be searched to provide the "POS ATLEST" relevant documents.

However, not more than "NEG NOMOR" nonrelevant will be used. Note that only documents scanned in an attempt to locate relevant documents for positive feedback are used in attempting to find nonrelevant for negative feedback.

Negative feedback is done except when "UNLESS" relevant documents are found. If "UNLESS" are found, no negative feedback at all is done. To signify that no negative fcedback is desired, "NEG MULT" should contain blanks or a zero. Should 'UNLESS' be left blank or set to zero, negative feedback is attempted regardless of the number of relevant actually used in positive feedback.
"STOPALL" is set to 'YES' if the user wishes to stop considering documents for feedback once all the relevant documents have been found. If set to 'NO', documents will be considered until the specifications of the other feedback parameters have been satisfied. The default is 'NO'.

If the precision after "POS RANK CUT" documents is over "PREC CUTOFF", and if the precision after more items are judged drops below "PREC CUTOFF", the judging of documents ceases.
'SILENT' if search queries are not to be printed; 'STANDARD' if search queries are to be printed; 'DETAILS' if details of the search query definition process are to be printed (used only for debugging).

Using iteration 2 as an example, the new search query $Q_{i+1}$ is defined by the following equation:

$$
Q_{i+1}=(1) Q_{i}+(1) \sum_{j=1}^{n_{n}}\left(r_{i}\right)_{j}-(1) \sum_{j=1}^{n_{s}}\left(s_{i}\right)_{j}
$$

where $\left(r_{i}\right)_{j}$ designates the concepts and weights of relevant document $\left(r_{i}\right)_{j} ;\left(s_{i}\right){ }_{j}$ designates the concepts and weights of nonrelevant document $\left(s_{i}\right){ }_{j} ; Q_{i}$ is the previous query (for iteration $i$ ), and $n_{r}$ and $n_{s}$ are defined by the number of relevant documents retrieved and the number of nonrelevant documents retrieved, respectively.

In iteration 2, $n_{r} \leq 5$; therefore, only the top five documents are retrieved, and not all of them will be relevant (in most cases). If at least two relevant documents are retrieved among the top five documents, no negative feedback will be done $\left(n_{s}=0\right)$. If fewer than two relevant documents are found, any nonrelevant retrieved among the top two documents will be used for feedback ( $n_{s} \leq 2$ ). This condition is stipulated by an "UNLESS" of 2 and a "NEG RANK CUT" of 2 .

The newly defined search queries are shown in Fig. 19. For query l, one relevant and four nonrelevant documents are retrieved in the top 5 . The relevant document (17) and the only nonrelevant in the top two retrieved (69) are used to construct the new query. Query 2 retrieves 1 relevant, but the top 2 retrieved are both nonrelevant, so both (27 and 33) are used, together with the one relevant found during feedback. Query 3 finds 3 relevant in the top five retrieved; hence no negative feedback is used. The new query vectors (Fig. 20) are used for searching, and the results are shown in Fig. 18, second iteration.


Redefinition of Search Query
Fig. 19
ITEA 1 AOI TITLES PROB IN MAKING DESCRIPT - DIFF IN AUTO RETR R

E) Search Evaluation

Several different evaluation measures are used in the SMART system, all based on the concepts of recall and precision. The definitions of these measures are the following:

$$
\begin{aligned}
& \text { Recall }=\frac{a}{b} \\
& \text { Precision }=\frac{a}{c}
\end{aligned}
$$

where
$a=$ the number of relevant documents retrieved $b=$ the number of relevant documents in the collection $c=$ the number of documents retrieved.

These measures are usually computed at a specified point during retrieval, usually either after a given number of documents have been retrieved, or after a given recall has been obtained.

Two types of averaging graphs, and four types of overall recall and precision averages are generated by the SMART system and listed in Figs. 2l, 22, 24 , and 25. Fig. 21 shows one type of graph and all four overall averages. At the top of the listing the runs being evaluated are identified (in this case a full search run (run 0 ) and a centroid search run (run l)). Below are listed the recall levels being used, and the precision achieved at each recall level. The number of queries used in the averaging at each point is also given. For example, at recall level 0.10 , run 0 shows a precision of 0.4948 , but for only 2 queries a relevant document had been retrieved at that recall level.

$$
R E C A L L-L E V E L A V E A \text { L } L \text { U } E
$$

LEGEND: KUN $0-$ S 3 UUERIES (PLUS 0 NULLS) -- SMART FULL SCH DUCUMENTAIIUN KUN
RUN 1 - 35 UUERIES (PLUS 0 NULLS) - SMART CENT SCH DOCUMENTAIION RUN

|  |  | RUN |  | RUN |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | RECALL | Nou | PKECISION | NQ | PRECISIUN |
|  | 0.0 | $u$ | 0.4948 | 0 | 0.4813 |
|  | 0.05 | 1 | U.4448 | 1 | 0.4813 |
|  | 0.10 | 2 | U.4448 | 1 | 0.4803 |
|  | 0.15 | 5 | 0.4734 | 4 | 0.4620 |
|  | 0.20 | 13 | $0.4<82$ | 11 | 0.4197 |
|  | 0.25 | 18 | $0.4 \ll 2$ | 12 | 0.4148 |
|  | 0.30 | 18 | 0.4179 | 12 | 0.4073 |
|  | 0.35 | 24 | 0.3012 | 16 | 0.3797 |
|  | 0.40 | 24 | 0.3741 | 13 | 0.3680 |
|  | 0.45 | 24 | 0.3090 | 15 | 0.3599 |
|  | 0.50 | 31 | 0.3006 | 19 | 0.3599 |
|  | 0.55 | 31 | 0.2901 | 15 | 0.2900 |
|  | 0.60 | 31 | U. 2876 | 15 | 0.2895 |
|  | 0.65 | 31 | 0.2061 | 15 | 0.2800 |
|  | 0.70 | 30 | 0.1401 | 13 | U. 2154 |
|  | 0.75 | 29 | U. 1946 | 13 | 0.2154 |
|  | 0.80 | 29 | 0.1919 | 13 | 0.2102 |
|  | 0.85 | 25 | 0.11 - | 13 | 0.2102 |
|  | 0.90 | 24 | 0.1036 | 13 | ט. 2034 |
|  | $0.95$ | $<4$ | 0.1030 | 13 | 0.2034 |
|  | 1.00 | 28 | 0.1030 | 14 | 0.2034 |
| NURM | RECALL |  | U.7J<4 |  | 0.4920 |
| NORM | PRECISIUN |  | 1.0U00 |  | 1.0000 |
| RANK | RECALL |  | 0.2014 |  | 0.2208 |
| LUG | PRECISIUN |  | U.3435 |  | 0.3458 |

```
SYMBUL KEYS: NQ = NUMBER OF QUERIES USED IN THF AVERAGE NUT DEPENJENT ON ANY EXTKAPULATIUN. NORM = NLKMALIZEU.
```

Below the recall-level averages the four overall averages are listed. These are described more extensively in reference [3] (chapter 8) and are briefly defined below: [7]

$$
\begin{aligned}
& \text { Normalized Recall }=1-\frac{\sum_{i=1}^{n} r_{i}-\sum_{i=1}^{n} i}{n(N-n)} \\
& \text { Normalized Precision }=1-\frac{\sum_{i=1}^{n} \log r_{i}-\sum_{i=1}^{n} \log i}{\log \frac{N}{(N-n)!n!}} \\
& \text { Rank Recall }=\frac{\sum_{i=1}^{n} i}{\sum_{i=1}^{n} r_{i}^{n}} \\
& \text { Log Precision }=\frac{\sum_{i=1}^{n} \log i}{\sum_{i=1}^{n} \log r i}
\end{aligned}
$$

where

$$
\begin{aligned}
& n=\text { number of relevant documents } \\
& N=\text { number of documents in collection } \\
& r_{i}=\text { rank of } i^{\text {th }} \text { relevant document } \\
& i=\text { ideal rank positions for the } i^{\text {th }} \text { relevant item. }
\end{aligned}
$$

Fig. 22 shows a computer-generated graph of the recall and precision averages previously given in Fig. 21.

In this type of graph, the precision is recorded for a given recall level.


| 1.0000 |
| :--- |
| 0.9000 |
| 0.8000 |
| 0.7000 |
| 0.6000 |
| 0.5000 |
| 0.4000 |
| 0.1000 |
| 0.3000 |
| 0.2000 |
| 0000 |

For example, at a recall of 0.10 ( 10 percent of the relevant documents retrieved) run 0 shows a precision of 0.4948 , and run 1 a precision of 0.4803 . These precision values are the averages of the precision, at a given recall level, for all the queries searched. It should be noted that interpolation methods are needed to produce the averages, since all queries do not possess an exact precision value at each given recall level.

The graph of Fig. 23 shows the necessary interpolation for a hypothetical query with four relevant items. The relevant documents are assumed to be retrieved with ranks of $4,6,12$ and 20 . Thus, at 25 percent recall, the precision is 0.25 ; at 50 percent recall, the precision is 0.33 , and so on. However, these values correspond actually to the highest possible precision points, since they are calculated just after a relevant document is retrieved. In this example, after 3 documents are retrieved, the precision is 0 , after 5 documents, the precision is 0.20 , and so on. This range of precision for each recall level is indicated by the top and bottom points in Fig. 23 at $25 \%, 50 \%, 75 \%$, and $100 \%$ recall. The solid sawtooth line connecting these points is not used for interpolation; it is intended to indicate the drop in precision between the actual recall levels for this query, as more nonrelevant documents are retrieved.

The interpolation method actually used by the SMART system is based on the dashed lines shown in Fig. 23 where a horizontal line is led leftward from each peak point of precision, up to a point where a higher point of precision is encountered. This new curve (the dashed line in Fig. 23) does not lie above the sawtooth curve at all points. When the precision drops from one recall level actually achieved to the next, an immediate drop in precision after the first point to the level of the next point is


An Illustration of the Interpolation Method Used by the "Neo-Cleverdon" Recall-Precision Averages

Fig. 23
indicated. For example, in Fig. 23 the precision value at 0.50 recall is 0.33 ; but at 0.55 recall, the interpolated value used for the new averages is 0.25 precision. When the precision rises from one recall level to the next, however, the first precision point actually achieved is ignored for purposes of interpolation. The achieved precision of 0.25 at 0.25 recall in the example of Fig. 23 is ignored, and an interpolated precision of 0.33 is used for the averages for all recall levels from 0 to 0.50 .

The second kind of average graph also generated is shown in Figs. 24 and 25. In this graph, the recall and precision are recorded and averaged after the retrieval of a given number of documents. For example, after one document has been retrieved in run 0 , the average recall (over all the queries) is 0.0903 , and the average precision is 0.3714 . The recall and precision are averaged for 24 different cutoff points, and for 6 different percentage points, such as after 10 percent of the collection has been retrieved, etc. Three other statistics (besides the recall and precision) are measured and listed for each cutoff point. The first (NR) is the number of relevant documents retrieved at the given cutoff, and the second (CNP) is the cumulative number of relevant documents retrieved by this point. These values are included to aid in the proper evaluation of runs, since the document-level averages are not plotted at equal levels of recall for each query (as are the recall-level graphs). Also listed is the number of queries used to obtain the average at each point.

The final part of the evaluation process consists of tests of the significance of the differences between runs. Three basic statistical tests, the sign test, the T-test, and the Wilcoxon signed rank test, are calculated for each pair of search runs. All three statistical tests indicate whether


LEGEND: RUN U -- S QUERIES (PLUS 0 NULLS) -- SMART FUIL SCF:
RUN 1 - 35 QUERIES (PLUS 0 NULLS) -- SBART CEINT SCH
ducumelvatilin ruiv

|  |  |  | ruve 0 |  |  |  |  | KUN |  | Precelolua |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| kaivk | NK | CNK | No | KECALL | PRECISICN | NK | Civk | NQ | recall |  |
| 1 | 13 | 13 | 35 | 0.0903 | 0.3714 | 13 | 13 | 24 | 0.0903 | 0.3714 |
| 2 | 11 | 24 | 35 | 0.1927 | 0.3429 | 11 | 24 | 24 | 0.1927 | 0.3424 |
| 3 | 7 | 31 | 33 | 0.2265 | 0.3095 | 7 | 31 | 21 | $0.220{ }^{\circ}$ | 0.319 H |
| 4 | 4 | 35 | 33 | 0.2389 | 0.2714 | 4 | 35 | 21 | 0.2300 | 0.2714 |
| 5 | 7 | 42 | 33 | 0.2831 | 0.2657 | 7 | 42 | $\angle 1$ | 0.2831 | 0.20,1 |
| 6 | 4 | 40 | 33 | 0.2977 | 0.2476 | 5 | 47 | 19 | U. 29.6 | 0.2524 |
| 7 | 4 | bo | 33 | 0.3170 | 0.2347 | 5 | 52 | $1{ }^{18}$ | 0.3230 | 0.2424 |
| 8 | 3 | 53 | 33 | U.3258 | $0.2<14$ | 2 | 54 | 11 | 0.3315 | 0.2270 |
| 9 | 1 | 54 | 33 | 0.3315 | 0.2048 | 3 | 57 | 17 | 0.3417 | 0.2183 |
| 10 | 1 | 55 | 33 | 0.3324 | 0.1914 | 2 | 54 | 17 | 0.3457 | U.2390 |
| 11 | 6 | 61 | 33 | 0.3074 | 0.1935 | 7 | -0 | 17 | 0.30 ¢7 | 0.2139 |
| 12 | 1 | 62 | 32 | 0.3710 | 0.1853 | 3 | 4 O | 13 | 0.4080 | 0.2117 |
| 13 | 2 | 64 | 32 | 0.3703 | 0.1805 | 3 | 72 | 11 | $0.42+7$ | 0.2103 |
| 14 | 5 | 69 | 32 | 0.4018 | 0.1820 | 4 | 76 | 11 | 0.4397 | 0.2111 |
| 15 | 4 | 73 | 31 | 0.4336 | 0.1824 | 4 | 80 | 10 | 0.45 ¢0 | $0.212+$ |
| 16 | 2 | 75 | 31 | 0.4717 | 0.1741 | 4 | 84 | 9 | 0.4092 | 0.2141 |
| 17 | 4 | 79 | 30 | 0.4950 | 0.1796 | 1 | 85 | 7 | 0.4739 | (). 210 |
| 18 | 2 | 81 | 29 | 0.5015 | 0.1774 | 3 | 8 c | 6 | 0.4910 | 0.2105 |
| 19 | 4 | 85 | 29 | U.5238 | 0.1784 | 0 | 88 | 4 | 0.4918 | 0.2009 |
| 20 | 1 | 86 | 28 | 0.5280 | 0.1752 | 2 | 40 | 4 | 0.4907 | 0.2000 |
| 30 | 20 | 100 | 24 | 0.6571 | 0.1657 | 3 | 43 | 0 | 0.5243 | 0.1953 |
| 50 | 28 | 134 | 13 | 0.8120 | 0.1020 | 0 | 93 | - | 0.5243 | 0.135 |
| 75 | 21 | 155 | く | 0.9430 | 0.1603 | 16 | lus | $\bigcirc$ | 0.3434 | 0.1237 |
| 100 | 15 | 170 | u | 1.0000 | 0.1636 | 61 | 170 | $\cup$ | 1.0000 | U.2134 |
|  | 0 | 170 |  |  |  | 0 | 170 |  |  |  |
| $10.0 \%$ | 53 | 53 | 33 | 0.3258 | 0.2214 | ら+ | 54 | 17 | 0.3317 | 0.2270 |
| 25.06 | 33 | 86 | 28 | 0.5280 | 0.1752 | 30 | 90 | '+ | 0.4977 | 0.2006 |
| 30.06 | 38 | 124 | 16 | 0.7576 | 0.1643 | 3 | 03 | $\checkmark$ | 0.5243 | 0.1874 |
| 75.0\% | 22 | 140 | 0 | 0.8802 | 0.1019 | 0 | 93 | $1)$ | 10.5243 | 0.1373 |
| 90.06 | 7 | 153 | 2 | 0.9145 | 0.1601 | 12 | 105 | i) | 0.5364 | 1.1220 |
| 100.0\% | 17 | 170 | ט | 1.0000 | 0.1036 | 65 | 170 | v | 1.0000 | 0.2034 |

SYMBOL KEYS: NR = NUMUER OF RELEVANT.
CNR = CUMULATiVE NUMBER UF RELEVANI.
NQ = Number uf qutries ustu iv the avekarg nut dependent un aivy extrafolatiliv.
6 = ptrcent uf tutal nuibter or items in uillegidov.

a given difference in two averages is likely to have occurred by chance.

A one-sided test is designed to compare a supposedly better sample B, with a given standard sample A. Specifically, one proposes two hypotheses $H_{0}$ and $H_{1} \cdot H_{0}$ states that two samples $A$ and $B$ are produced by the same distribution; $H_{1}$ states that sample $B$ is statistically better than sample A. $H_{l}$ is accepted if it is unlikely, under $H_{0}$, that a difference between samples as great as, or greater than, that observed would occur by chance.

A two-sided test similarly compares two samples under the same $H_{D}$, but with the alternate hypothesis $H_{l}$ being that samples $A$ and $B$ are from different distributions. Here again $H_{l}$ is accepted if the probability, under $H_{0}$, is low that a difference between two samples is as great as, or greater than, that observed would occur by chance.

The T-test assumes that the differences $d_{i}$ between the two measures, $a_{i}$ and $b_{i}$, are distributed normally. Explicitly, it is assumed that $d_{i}$ has mean $\bar{d}$, and standard deviation $\sigma_{d}$. Note that $\bar{d}$ and $\sigma_{d}$ are computable for any distribution, including also the normal distribution. In particular, it is known that many sets of differences are not normally distributed. (For further discussion of the $T$-test and sign test, see reference [7], page 12, also [3] chapter 8).

The sign test assumes that a result is equally likely to favor either sample $A$ or sample B. Thus, it measures the probability of a more extreme distribution favorins $B$, or favoring either $A$ or $B$.

The Wilcoxon signed rank test postulates that a greater difference between paired samples is more significant, but only as the numbers affect the ranking of the differences. For example, differences of $-1,2,-3,4$, and 20 are equivalent to differences of $-1,2,-3,4$, and 5 since only the rank
of the ordered differences favoring a sample is important (not the actual values of the differences). The Wilcoxon test assumes that the two samples come from thesame family of distributions, i.e., either two normal distributions, or two binomials, etc.

The three tests are performed for eleven points of the recall-
level averages, and for the four overall measures of recall and precision of the document level averages; in addition, the tests are also performed for the 17 cost statistics. The three listings for the three different test procedures (Fig. $26-28$ ) cover only the first option (eleven points of the recall-level averages plus the four overall measures).

For the T-test (Fig. 26), the following values are given for each of the fifteen statistics: the mean and standard deviation of the statistic for each of the two searches (A and B); the mean and standard deviation of the differences between the statistics for $A$ and $B$; and a value $T$, which is defined as

$$
T=\frac{(\bar{A}-\bar{B}) * \sqrt{N}}{\sigma_{A-B}}
$$

where N is the number of degrees of freedom (which is one less than the number of queries being tested). The one-sided and two-sided probabilities (indicating whether a difference between the two samples as great as, or greater than, that observed would occur by chance) is also listed. Finally, the fifteen one-sided tests are statistically combined into a single measure also listed.

The sign test (Fig. 27) gives the number of queries favoring search A, favoring search $B$, and tied; the normal deviate ignoring ties (computed by using the binomial normal approximation) ; and the one-sided and two-sided
SMART--FEEDBACK SEARCHES ON CRANFIELD 200 WORUFURM
87.0200

ON OPIION 1, 15 MEASUKES -- RANK RECALL, LOG PRECISION, NORMALILEU RECALL, NORMALILED PRECISION, AND RECALL LEVEL AVERAGES 1-SIDED 2-SIDED




SO A-

MEAN A-B

-0.0526
-0.0343 0.0343
-0.0343
-0.0135 -0.0135
-0.0135 -0.0199
-0.0325
-0.0361

0.0499
-0.0401
-0.0521 -0.0521
-0.0530


NOIIVIAGO OVVONVIS -- OS : SABX TOBHAS

> Test

Fig. 26
SMART--FEEDBACK SEARCHES ON CRANFIELD 200 WORDFORM
PAGE 66 09/10/69 23:53:16.10 87.1600 PAGE 66 ( thesaurus
thesaurus
ON OPTION 1, 15 MEASURES -- RANK RECALL, LOG PRECISION, NORMALILEO RECALL, NORMALIZED PRECISIUN, AND RECALL LEVEL AVERAGES

$\begin{array}{ll}-0.6172 & 0.7800 \\ -0.9258 & 0.8598 \\ -0.6172 & 0.7800 \\ -0.9258 & 0.8598 \\ -4.3205 & 1.0000 \\ -4.3205 & 1.0000 \\ -4.0119 & 1.0000 \\ -2.4689 & 0.9955 \\ -1.8516 & 0.9778 \\ -1.2344 & 0.9174 \\ -0.3086 & 0.6784 \\ -1.5430 & 0.9552 \\ -1.2344 & 0.9174 \\ -0.9258 & 0.8598 \\ -0.9258 & 0.8598\end{array}$
$-6.7730 \quad 1.0000$

| IGNORING TIES -- THE PROBABILITY OF A CHI SQUARE LARGER THAN THE OBSERVED |
| :--- |
| USING TIES |
| U- THE PROBABILITY OF A CHI SQUARE LARGER THAN THE OBSERVED |
| 3.4126 |

SYMBOL KEYS: NORA DEV IGN TIES -- STANDARD NORMAL DEVIATE CALCULATED IGNORING TIES
Sign Test
probabilities for the test ignoring ties. The normal deviate and the onesided probability using ties (based on a method developed by Cathy May [8]) are also computed and listed. The one-sided tests are again statistically combined into overall figures.

The Wilcoxon signed rank test (Fig. 28) gives the sum of ranks favoring search A and favoring search B; the number of degrees of freedom (specifically, the number of untied pairs); the normal deviate (computed using the Wilcoxon-normal approximation) ; and the resulting one-sided and two-sided probabilities. A statistically combined significance value is also listed.
3. Access to the SMART System

The SMART system exists at Cornell as a private library system, located on a disk, which is accessible by reading in sets of control cards. When the SMART programs are loaded, a routine called EXEC receives control. This routine interrogates control cards in the data stream to ascertain which routines are desired and transfers control of those routines in the sequence requested.

A typical deck setup for the system is reproduced as follows:

```
initiates SMART [ //JOB . . . . . . (parameters). . . . . .
routines
sets up
document
groups for a
collection already
on file
performs retrieval
runs using methods
called for by the
parameter cards
```


ON UPTIUN 1. 15 MEASURES -- RANK KECALL, LOG PRECISIUN, NORMALIZEO RECALL, NORMALIZED PRECISION, AND RECALL IFVEL AVERAGES
 1
fon
STATISTICS

$$
\begin{aligned}
& \text { RANK } R \\
& \text { LOG } P
\end{aligned}
$$

RANK R

$$
\begin{aligned}
& \text { K } \\
& A .0 \\
& 0.0 \\
& 0.2 \\
& 0.2 \\
& 0.3 \\
& 0.4 \\
& 0.5 \\
& 0.6 \\
& 0.7 \\
& 0.8 \\
& 0.9 \\
& 1.0
\end{aligned}
$$

$$
\begin{aligned}
& \text { NORMAL } \\
& \text { OFVIATF }
\end{aligned}
$$

$$
\begin{aligned}
& 1-S I D E D \\
& \text { PROB }
\end{aligned}
$$

2-SIDED
0.0019
0.0019
0.0026
0.0091
0.0030
0.0685
0.0685
0.0378
0.0086
0.0045
0.0044
0.00022
0.1066
0.0888
0.0157
0.0157

$\begin{array}{ll}3.1494 & 0.0009 \\ 3.0605 & 0.0013 \\ 2.6287 & 0.0045 \\ 3.0097 & 0.0015 \\ 1.8904 & 0.0342 \\ 1.8904 & 0.0342 \\ 2.1325 & 0.0189 \\ 2.6680 & 0.0043 \\ 2.8957 & 0.0022 \\ 2.8974 & 0.0022 \\ 3.4977 & 0.0001 \\ 1.6286 & 0.0533 \\ 1.7144 & 0.0444 \\ 2.4255 & 0.0079 \\ 2.4255 & 0.0079\end{array}$
COMBINED SIGNIFICANLE -- TOTAL CHI SQUARE WITH 30 DEGREES OF FREEDOM
THE PROBABILITY UF A CHI SQUARE LARGER THAN THE OBSERVED 157.3448 IS 0.0000
THE PKOBABILITY UF A CHI SQUARE LARGER THAN THE OBSERVED 157.3448 IS 0.0000
SYMBOL KEYS: NUF-- NUMBER OF DEGREES OF FREEDOM NORMAL




$$
\begin{aligned}
& \text { G ONIYOAVJ YNIHOAVJ } \\
& \text { SXNVY GO WNS SXNVY GO WNS }
\end{aligned}
$$

SMART--HEEDBACK SEARCHES ON CRANFIELC 200 WURDPURM

## $$
\begin{aligned} & \text { A (FILE O), } 42 \text { QUEKIES: CRN2ST } \\ & \text { B (FILE I), } 42 \text { QUERIES: CRN2ST } \end{aligned}
$$ <br> FEE



4. Basic SMART System Flowchart

The SMART routines fall into two categories: routines that can be called with control cards, and routines that can only be called by other routines. The latter set in interconnected by means of complex internal vectors, designed to make the most efficient use of in-core storage. A flowchart is produced in Figs. 29-33. The routines which can be called by control cards are enclosed by boxes.

SMART Systems Chart

$$
\text { Fig. } 29
$$


SMART System Chart - Text Input Routines

## Fig. 30



SMART Systems Chart - Vector Handling Routines

Fig. 31


Fig. 32

SMART Systems Chart - Clustering Routines

## References

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[8] Cathy May, Evaluation of Search Methods in an Information Retrieval System, Term Report written for Computer Science 435, Cornell University, May 1968.

