UNIT-IV

User Search Techniques: Search statements and binding, Similarity measures and ranking, Relevance feedback, Selective dissemination of information search, weighted searches of Boolean systems, Searching the Internet and hypertext. **Information Visualization:** Introduction, Cognition and perception, Information visualization technologies.

Search Statements and Binding

Search statements are the statements of an information need generated by users to specify the concepts they are trying to locate in items. In generation of the search statement, the user may have the ability to weight (assign an importance) to different concepts in the statement. At this point the binding is to the vocabulary and past experiences of the user. Binding in this sense is when a more abstract form is redefined into a more specific form. The search statement is the user's attempt to specify the conditions needed to subset logically the total item space to that cluster of items that contains the information needed by the user.

The next level of binding comes when the search statement is parsed for use by a specific search system. The final level of binding comes as the search is applied to a specific database. This binding is based upon the statistics of the processing tokens in the database and the semantics used in the database. This is especially true in statistical and concept indexing systems.

INPUT	Binding
"Find me information on the impact of the oil spills in Alaska on the price of oil"	User search statement using vocabulary of user
impact, oil (petroleum), spills (accidents), Alaska, price (cost, value)	Statistical system binding extracts processing tokens
impact (.308), oil (.606), petroleum (.65), spills (.12), accidents (.23), Alaska (.45), price (.16), cost (.25), value (.10)	Weights assigned to search terms based upon inverse document frequency algorithm and database

Figure 7.1 Examples of Query Binding

Similarity Measures and Ranking A variety of different similarity measures can be used to calculate the similarity between the item and the search statement. A characteristic of a similarity formula is that the results of the formula increase as the items become more similar. The value is zero if the items are totally dissimilar. An example of a simple "sum of the products" similarity measure from the examples in Chapter 6 to determine the similarity between documents for clustering purposes is:

$$\text{SIM (Item i, Item j)} = \sum \text{(Term i, k) (Term j, k)}$$

This formula uses the summation of the product of the various terms of two items when treating the index as a vector. If is replaced with then the same formula generates the similarity between every Item and Theproblemwiththissimplemeasureisinthenormalizationneededtoaccountfor variances in the length of items. Additional normalization is also used to have the final results come between zero and+1(some formulas use the range-1 to+1) This assumption of the availability of relevance information in the weighting process was later relaxed by Croft and Harper (Croft-79). Croft expanded this original concept, taking into a count the frequency of occurrence of terms with in an item producing the following similarity formula (Croft-83):

$$\text{SIM}(\text{DOC}_i, \text{QUERY}_j) = \sum_{i=1}^{Q} (C + IDF_i) * f_{i,j})$$

where C is a constant used in tuning, $\mathbf{IDF_i}$ is the inverse document frequency for term "i" in the collection and

$$f_{i,j} = K + (K - 1)\, TF_{i,j}/\text{maxfreq}_j$$

Where K is a tuning constant, is the frequency of "i" and is the maximum frequency of any term in item "j." The best values for K seemed to range between 0.3 and 0.5. Another early similarity formula was used by Salton in the SMART system (Salton-83). To determine the "weight" an item has with respect to the search statement, the Cosine formula is used to calculate the distance between the vector for the it demands the vector for the query:

$$SIM(DOC_i, QUERY_j) = \frac{\sum_{k=1}^{n} (DOC_{i,k} * QTERM_{j,k})}{\sqrt{\sum_{k=1}^{n} (DOC_{i,k})^2 * \sum_{k=1}^{n} (QTERM_{j,k})^2}}$$

where is the kth term in the weighted vector for Item "i" and is the kth term in query "j." The Cosine formula calculates the Cosine of the angle between the two vectors. As the Cosine approaches "1," the two vectors become coincident (i.e., the term and the query represent the same concept). If the two are totally unrelated, then they will be orthogonal and the value of the Cosine is "0." What is not taken into account is the length of the vectors for example, if the following vectors are in a three-dimensional (three term) system: Item = (4,8,0) Query 1 = (1,2,0)

Query 2 = (3,6,0)

$$QTERM_{j,k} = (0.5 + (0.5\ TF_{i,k}/maxfreq_k)) * IDF_i$$

Where K is a tuning constant, is the frequency of "i" and is the maximum frequency of any term in item "j." The best values for K seemed to range between 0.3 and 0.5. Another early similarity formula was used by Salton in the SMART system (Salton-83). To determine the "weight" an item has with respect to the search statement, the Cosine formula is used to calculate the distance between the vector for the it demands the vector for the query:

$$SIM(DOC_i, QUERY_j) = \frac{\sum_{k=1}^{n} (DOC_{i,k} * QTERM_{j,k})}{\sum_{k=1}^{n} DOC_{i,k} + \sum_{k=1}^{n} QTERM_{j,k} - \sum_{k=1}^{n} (DOC_{i,k} * QTERM_{j,k})}$$

The Dice measure simplifies the denominator from the Jaccard measure and introduces a factor of 2 in the numerator. The normalization in the Dice formula is also invariant to the number of terms in common.

$$SIM(DOC_i, QUERY_j) = \frac{2 * \sum_{k=1}^{n} (DOC_{i,k} * QTERM_{j,k})}{\sum_{k=1}^{n} DOC_{i,k} + \sum_{k=1}^{n} QTERM_{j,k}}$$

QUERY = (2, 2, 0, 0, 4)
DOC1 = (0, 2, 6, 4, 0)
DOC2 = (2, 6, 0, 0, 4)

	Cosine	Jaccard	Dice
DOC1	36.66	16	20
DOC2	36.66	−12	20

Figure 7.2 Normalizing Factors for Similarity Measures

similarityformulaisusedtocalculatesimilaritybetweenthequeryandeachdocument.Ifnothresholdisspecified, all three documents are considered hits. If a threshold of 4 is selected, then only DOC1 isreturned.

Onespecialareaofconcernarisesfromsearchofclustersoftermsthatarestoredina hierarchicalscheme

Vector:	American, geography, lake, Mexico, painter, oil, reserve, subject
DOC1	geography *of* Mexico *suggests* oil reserves *are available* vector (0, 1, 0, 2, 0, 3, 1, 0)
DOC2	American geography *has* lakes *available everywhere* vector (1, 3, 2, 0, 0, 0, 0, 0)
DOC3	painters *suggest* Mexico lakes *as* subjects vector (0, 0, 1, 3, 3, 0, 0, 2)
QUERY	oil reserves *in* Mexico vector (0, 0, 0, 1, 0, 1, 1, 0)

SIM(Q, DOC1) = 6, SIM (Q, DOC2) = 0, SIM(Q, DOC3) = 3

Figure 7.3 Query Threshold Process

The items are stored in clusters that are represented by the centroid for each cluster.

showsaclusterrepresentationofanitemspace.Eachletterattheleaf(bottomnodes)representanitem(i.e.,K, L, M, N, D, E, F, G, H, P, Q, R, J). The letters at the higher nodes (A, C, B, I) represent the centroid oftheir immediate children nodes. The hierarchy is used in search by performing a top-down process. Thequery is compared to the centroids "A" and "B." If the results of the similarity measure are above thethreshold, the query is then applied to the nodes‟ children. If not, then that part of the tree is pruned and notsearched

The problem comes from the nature of a centroid which is an average of a collection of items (in Physics,the center of gravity). The risk is that the average may not be similar enough to the query for continuedsearch,butspecificitemsusedtocalculatethecentroidmaybecloseenoughtosatisfythesearch.Ther isksof missing items and thus reducing recall increases as the standard deviation increases. Use of centroidsreduces the similarity computations but could cause a decrease in recall. It should have no effect onprecisionsincethat isbaseduponthesimilaritycalculationsat theleaf(item)level.

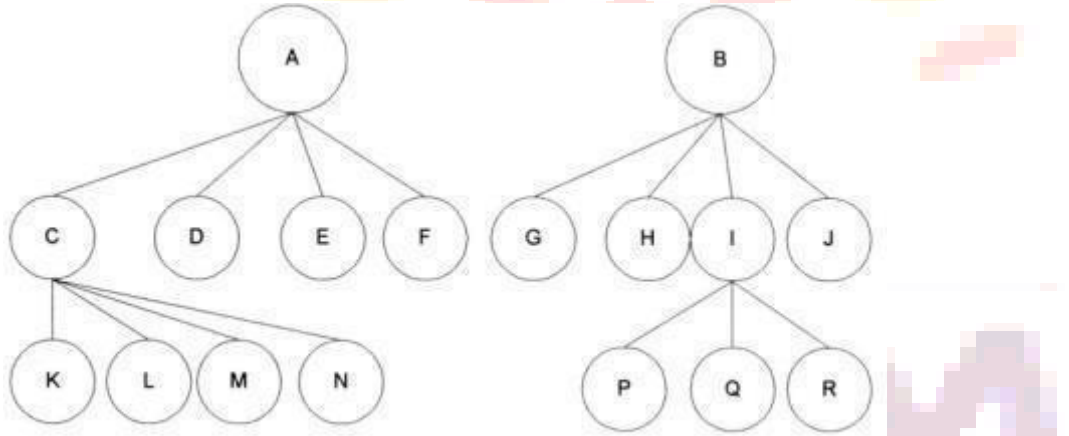

Figure 7.4 Item Cluster Hierarchy

HiddenMarkovModelsTechniques

Use of HiddenMarkovModels forsearching textualcorporahas introduceda new paradigm forsearch. Inmostof thepreviussearch techniques, thequeryis thoughtof as another"document"and thesystem triestofindotherdocumentssimilartoit.InHMMsthedocumentsareconsideredunknownstatisticalprocesses that can generate output that is equivalent to the set of queries that would consider the document relevant.Another way to look at it is by taking the general definition that a HMM is defined by output that isproducedbypassingsomeunknownkeyvia statetransitionsthrougha noisychannel.Theobservedoutputisthequery,andtheunknownkeysaretherelevantdocuments.Thenoisych annelisthe mismatchbetweenthe author's way of expressing ideas and the user's ability to specify his query. Leek, Miller and Schwartz(Leek-99)computedforeachdocumenttheprobabilitythatDwastherelevantdocumentintheusersmindgiventhatQ

$$P(D \text{ is } R/Q) = P(Q/D \text{ is } R) * P(D \text{ is } R) / P(Q)$$

wasthequeryproduced,i.e.,P(DisR/Q).ThedevelopmentforaHMMapproachbeginswithapplyingBayesrul etotheconditionalprobability

Thebiggestprobleminusingthisapproachistoestimatethetransitionprobabilitymatrixandtheoutput(queriest hatcouldcausehits)foreverydocumentinthecorpus.

RankingAlgorithms

Aby-productofuseofsimilaritymeasuresforselectingHititemsisavaluethatcanbeusedinrankingtheoutput.Rankingthe outputimpliesorderingtheoutputfrommostlikelyitemsthatsatisfythequerytoleastlikely items. This reduces the user overhead by allowing the user to display the most likely relevant itemsfirst. The original Boolean systems returned items ordered by date of entry into the system versus bylikelihood of relevance to the user‟s search statement. With the inclusion of statistical similarity techniquesintocommercialsystemsandthelargenumberofhitsthatoriginatefromsearchingdiversecorpora,su chasthe Internet, ranking has become a common feature of modern systems. A summary of ranking algorithmsfromtheresearchcommunityisfoundinanarticlewrittenbyBelkinandCroft(Belkin-87)

RelevanceFeedback

The first major work on relevance feedback was published in 1965 by Rocchio (republished in 1971:Rocchio-71). Rocchio was documenting experiments on reweighting query terms and query expansionbased upon a vector representation of queries and items. The concepts are also found in the probabilisticmodelpresentedbyRobertsonandSparckJones(Robertson-76).Therelevancefeedbackconceptwasthatthenewqueryshouldbebasedontheoldquerymodifiedtoincrease theweightof

$$Q_n = Q_o + \frac{1}{r}\sum_{i=1}^{r} DR_i - \frac{1}{nr}\sum_{j=1}^{nr} DNR_j$$

where

Q_n	= the revised vector for the new query
Q_o	= the original query
r	= number of relevant items
DR_i	= the vectors for the relevant items
nr	= number of non-relevant items
DNR_j	= the vectors for the non-relevant items.

The factors r and nr were later modified to be constants that account for the number of items along with the importance of that particular factor in the equation. Additionally a constant was added to Q_o to allow adjustments to the importance of the weight assigned to the original query. This led to the revised version of the formula:

$$Q_n = \alpha Q_o + \beta\sum_{i=1}^{r} DR_i - \gamma\sum_{j=1}^{nr} DNR_j$$

Termsinrelevantitemsanddecreasetheweightoftermsthatareinnon-relevantitems.Thistechniquenotonly modified the terms in the original query but also allowed expansion of new terms from the relevantitems.Theformulaused is:

Whereandaretheconstantsassociatedwitheachfactor(usually1/nor1/nrtimesaconstant).The factorisreferred to as positive feedback because it is using the user judgments on relevant items to

increase thevaluesoftermsforthenextiterationofsearching.

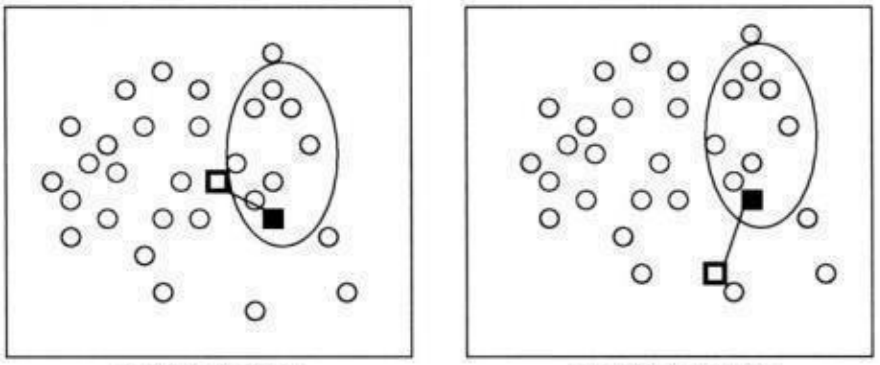

Figure 7.6 Impact of Relevance Feedback

Thefactorisreferredtoasnegative

Relevancefeedback,inparticularpositivefeedback,hasbeenproventobeofsignificantvalueinproducingbetter queries. Some of the early experiments on the SMART system (Ide-69, Ide-71, Salton-83) indicatedthe possible improvements that would be gained by the process. But the small collection sizes andevaluationtechniquesputintoquestiontheactual gainsbyusingrelevancefeedback.

Oneoftheearlyproblemsaddressedinrelevancefeedbackishowtotreatquerytermsthatarenotfoundinany retrieved relevant items. Just applying the algorithm would have the effect of reducing the relativeweightofthosetermswithrespecttootherqueryterms.Fromtheuser‟sperspective,thismaynotbedesiredbe cause the term may still have significant value to the user if found in the future iterations of the searchprocess.

Harper and van Rijisbergen addressed this issue in their proposed EMIM weighting scheme (Harper-78,Harper-80). Relevance feedback has become a common feature in most information systems. When
theoriginalqueryismodifiedbaseduponrelevancefeedback,thesystemsensurethattheoriginalquerytermsa re in the modified query, even if negative feedback would have eliminated them. In some systems themodified query is presented to the user to allow the user to readjust the weights and review the new termsadded.

SelectiveDisseminationofInformationSearch

Selective Dissemination of Information, frequently called dissemination systems, are becoming moreprevalent with the growth of the Internet. A dissemination system is sometimes labeled a “push” systemwhile a search system is called a “pull” system. The differences are that in a search system the userproactivelymakesadecisionthatheneedsinformationanddirectsthequerytotheinformationsystemtosear ch. In a dissemination system, the user defines a profile (similar to a stored query) and as newinformationisaddedtothesystemitisautomaticallycomparedtotheuser‟sprofile.

WeightedSearchesofBooleanSystems

ThetwomajorapproachestogeneratingqueriesareBooleanandnaturallanguage.Naturallanguagequeriesare easily represented within statistical models and are usable by the similarity measures discussed. Issuesarise whenBooleanqueries are associatedwithweightedindexsystems.Some of the issues are

associatedwith how the logic (AND, OR, NOT) operators function with weighted values and how weights areassociatedwiththequeryterms.

Iftheoperatorsareinterpretedintheirnormalinterpretation,theyacttoorestrictiveortoogeneral(i.e.,ANDandOROperatorsrespectively).Salton,FoxandWushowedthatusingthestrictdefinitionoftheoperators will sub optimize the retrieval expected by the user (Salton-83a). Closely related to the strictdefinitionproblemisthelackofrankingthatismissingfromapureBooleanprocess.

Some of the early work addressing this problem recognized the fuzziness associated with mixing Booleanand weighted systems (Brookstein-78, Brookstein-80) To integrate the Boolean and weighted systemsmodel,FoxandSharatproposedafuzzysetapproach(Fox-86).Fuzzysetsintroducetheconceptofdegreeofmembershiptoaset(Zadeh-65).ThedegreeofmembershipforANDandOROperationsaredefinedas:

TheMMMtechniquewasexpandedbyPaice(Paice-84)consideringallitemweightsversusthemaximum/minimumapproach.Thesimilaritymeasureiscalculatedas:

$$DEG_{A\cap B} = \min(DEG_A, DEG_B)$$

$$DEG_{A\cup B} = \max(DEG_A, DEG_B)$$

$$SIM(QUERY_{OR}, DOC) = C_{OR1} * \max(DOC1_1, DOC_2, \ldots, DOC_n) + C_{OR2} * \min(DOC_1, DOC_2, \ldots, DOC_n)$$

$$SIM(QUERY_{AND}, DOC) = C_{AND1} * \min(DOC_1, DOC_2, \ldots, DOC_n) + C_{AND2} * \max(DOC1_1, DOC_2, \ldots, DOC_n)$$

$$SIM(QUERY\ DOC) = \sum_{i=1}^{n} r^{i-1} d_i \ / \ \sum_{i=1}^{n} r^{i-1}$$

$$Q_{OR} = (A_1, a_1)\ OR\ (A_2, a_2)\ OR\ \ldots OR\ (A_n, a_n)$$

$$Q_{AND} = (A_1, a_1)\ AND\ (A_2, a_2)\ AND\ \ldots\ AND\ (A_n, a_n)$$

SearchingtheINTERNETandHypertext

The Internet has multiple different mechanisms that are the basis for search of items. The primarytechniquesareassociatedwithserversontheInternetthatcreateindexesofitemsontheInternetandallowsearchofthem.SomeofthemostcommonlyusednodesareYAHOO,AltaVistaandLycos.Inallofthesesystems there are active processes thatvisita large numberof Internetsitesandretrieve textual datawhichthey index. The primary design decisions are on the level to which they retrieve data and their generalphilosophyonuseraccess.

LYCOS (http://www.lycos.com) and AltaVista automatically go out to other Internet sites and return thetextatthesitesforautomaticindexing(http://www.altavista.digital.com).Lycosreturnshomepagesfromeach site for automatic indexing while Altavista indexes all of the text at a site. The retrieved text is thenusedtocreateanindextothesourceitemsstoringthe

UniversalResourceLocator(URL)toprovidetotheuser to retrieve an item. All of the systems use some form of ranking algorithm to assist in display of theretrieved items. The algorithm is kept relatively simple using statistical information on the occurrence ofwordswithin theretrievedtext

Closelyassociatedwiththecreationoftheindexesisthetechnique

foraccessingnodesonTherearesixkeycharacteristicsofintelligentagents(Heilmann-96):

1. Autonomy - the search agent must be able to operate without interaction with a human agent. It musthavecontroloveritsowninternalstatesandmakeindependentdecisions.Thisimpliesasearchcapabilitytotraverseinformationsitesbaseduponpre-establishedcriteriacollectingpotentiallyrelevantinformation.
2. Communications Ability - the agent must be able to communicate with the information sites as ittraversesthem.Thisimpliesauniversallyacceptedlanguagedefiningtheexternalinterfaces(e.g.,Z39.50).
3. CapacityforCooperation-
thisconceptsuggeststhatintelligentagentsneedtocooperatetoperformmutuallybeneficialtasks.
4. Capacity for Reasoning - There are three types of reasoning scenarios (Roseler-94): Rule-based - whereuserhasdefinedasetofconditionsandactionstobetakenKnowledge-based-
wheretheintelligentagentshave stored previous conditions and actions taken which are used to deduce future actions Artificialevolution based - where intelligent agents spawn new agents with higher logic capability to perform itsobjectives.
5. AdaptiveBehavior-
closelytiedto1and4,adaptivebehaviorpermitstheintelligentagenttoassessitscurrentstateandmakedecisionsontheactionsitshouldtake
6. Trustworthiness-
theusermusttrustthattheintelligentagentwillactontheuser"sbehalftolocateinformationthattheuserhasaccesstoand isrelevanttotheuser.

InformationVisualization
Functionsthatareavailablewithelectronicdisplayandvisualizationofdatathatwerenotpreviouslyprovided are:

- modifyrepresentationsofdataandinformationorthedisplaycondition(e.g.,changingcolorscales)
- usethesamerepresentationwhileshowingchangesindata(e.g.,movingbetweenclustersofitemsshowingnewlinkages)
- animatethedisplaytoshowchangesinspaceandtime
- Createhyperlinksunderusercontroltoestablishrelationshipsbetweendata

Information Visualization addresses how the results of a search may be optimally displayed to the users tofacilitate their understanding of what the search has provided and their selection of most likely items ofinteresttoread.Cognitive(themental actionorprocessof acquiringknowledge and understanding throughthought,experience, and thesenses)engineeringderives designprinciplesfor visualization techniquesfromwhatweknowabouttheneuralprocessesinvolved

withattention,memory,imageryandinformationprocessingofthehumanvisualsystem.
Cognitive engineering results can be applied to methods of reviewing the concepts contained in itemsselected by search of an information system. Visualization can be divided into two broad

classes: linkvisualizationand attribute(concept)visualization.Linkvisualizationdisplays relationships among items.Attributevisualizationrevealscontent relationshipsacrosslargenumbersofitems. Therearemanyareasthatinformationvisualizationandpresentationcanhelptheuser:

a. reducetheamountoftimetounderstandtheresultsofasearchandlikelyclustersofrelevantinformation

b. yieldinformationthatcomes fromtherelationshipsbetweenitemsversustreatingeachitemasindependent

c. performsimpleactionsthatproducesophisticatedinformationsearchfunctions

Visualizationisthetransformationofinformationintoavisualformwhichenablestheusertoobserveandunderstandtheinformation.

Cognition (themental actionorprocessof acquiringknowledge andunderstanding through thought,experience,and thesenses)

Perception (the ability to see, hear, or become aware of something through the senses)Proximity -nearbyfiguresaregroupedtogetherSimilarity-similarfiguresaregroupedtogether
Continuity-figuresareinterpretedassmoothcontinuouspatternsratherthandiscontinuousconcatenationsof shapes (e.g., a circle with its diameter drawn is perceived as two continuous shapes, a circle and a line,versustwo halfcirclesconcatenated together)

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Closure - gaps within a figure are filled in to create a whole (e.g., using dashed lines to represent a squaredoesnotpreventunderstandingitasasquare)Connectedness-uniformandlinked spots,linesorareasareperceivedasasingleunit.

AspectsoftheVisualizationProcess

Oneof thefirst-levelcognitiveprocesses is preattention,thatis,taking thesignificantvisual informationfrom the photoreceptors and forming primitives. In Figure 8.1 the visual system detects the difference inorientations between the left and middle portion of the figure and determines the logical border betweenthem.Anexampleofusingtheconsciousprocessingcapabilitiesofthebrainisthedetectionofthedifferents hapedobjectsandtheborderbetweenthemshownbetweentheleftsideandmiddleoftheFigure8.1.Thereadercanlik elydetectthedifferencesinthetimeittakestovisualizethetwodifferentboundaries. Thepreattentiveprocesscandetecttheboundariesbetweenorientationgroupsofthesameobject.Aharderprocess is to identify the equivalence of rotated objects. For example, a rotated square requires more effortto recognize it as a square. As we migrate into characters, the problem of identification of the character isaffectedbyrotatingthecharacterinadirectionnotnormallyencountered.It iseasiertodetectthesymmetrywhentheaxisisvertical.Figure8.2demonstratestheseeffects.

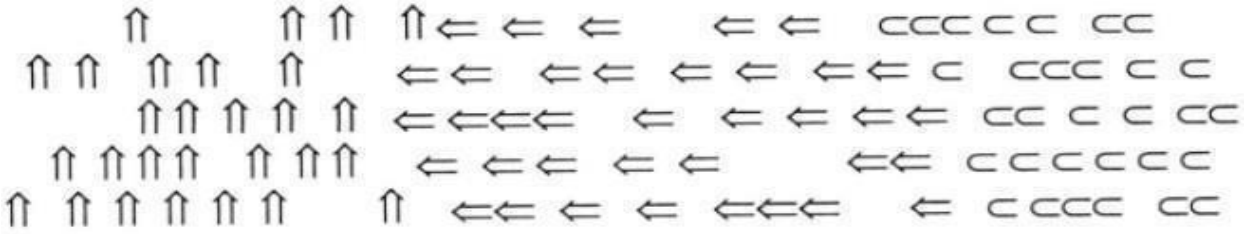

Figure 8.1 Preattentive Detection Mechanism

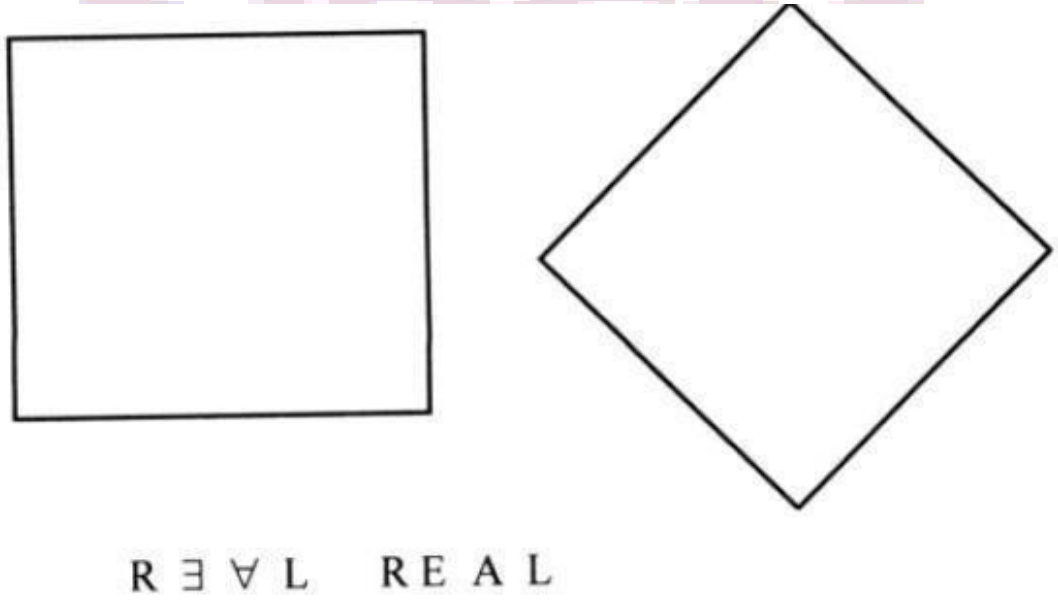

Figure 8.2 Rotating a Square and Reversing Letters in "REAL"

Colorisoneofthemostfrequentlyusedvisualizationtechniquestoorganize,classify,andenhancefeatures.Theg

oalsfordisplayingtheresult fromsearchesfallintotwomajorclasses:documentclusteringandsearchstatementanalysis.Thegoalofdocumentclusteringistopresenttheuserwithavisualrepresentationofthedocumentspaceconstrainedbythesearchcriteria.Withinthisconstrainedspacethereexistclustersof documentsdefinedbythedocumentcontent.Visualizationtoolsinthisareaattempttodisplaytheclusters,withanindicationoftheirsizeandtopic,asabasisforuserstonavigatetoitemsofinterest.The second goal is to assist the user in understanding why items were retrieved, thereby providinginformationneededtorefinethequery.Visualizationtechniquesapproachthisproblembydisplayingthetotalsetof terms,including additionalterms from relevance feedback orthesaurus expansion, alongwithdocumentsretrievedandindicatetheimportanceofthetermtotheretrieval andrankingprocess. Link analysis is also important because it provides aggregate-level information within an informationsystem.Onewayoforganizinginformationishierarchical.Atwo-dimensionalrepresentationbecomesdifficultforausertounderstand as

The hierarchy becomes large. One of the earliest experiments in information visualization was theInformationVisualizerdevelopedbyXEROXPARC.Itincorporatesvariousvisualizationformatssuchas DataMap,

InfoGrid, ConeTree, and the Perspective wall. The Cone-Tree is a 3-Dimensional representation of data,whereonenodeofthetreeisrepresentedattheapexandaltheinformationsubordinatetoitisarrangedinacircularstructureatitsbase.

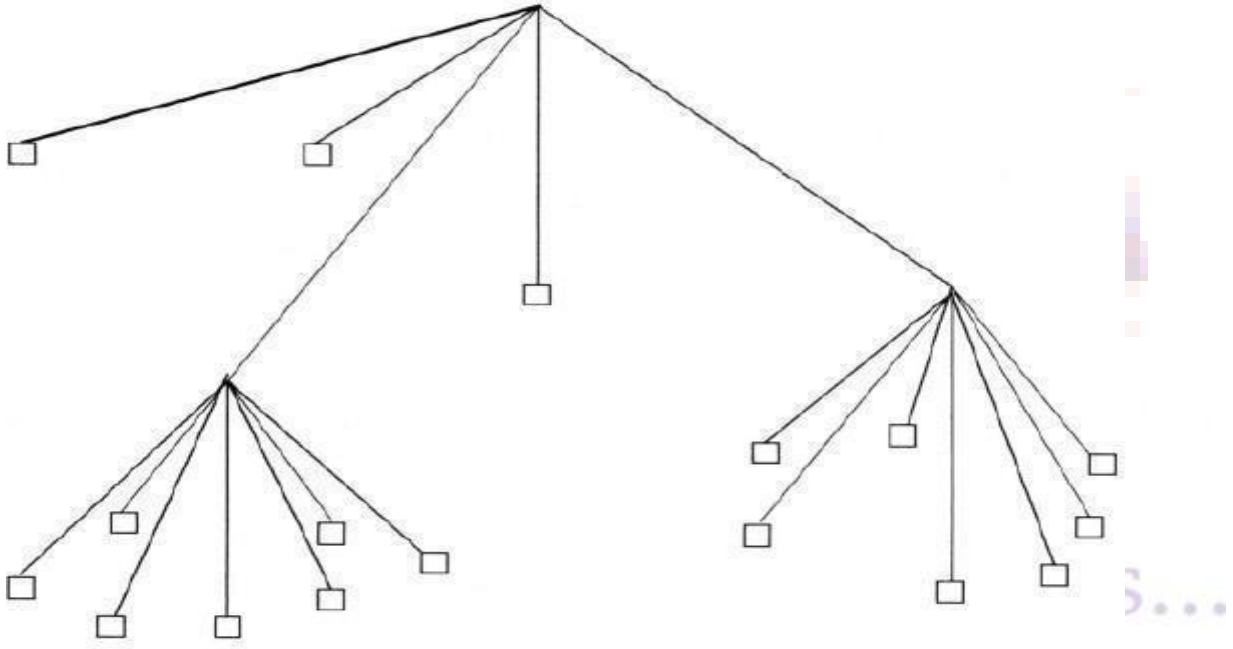

Figure 8.4 Cone Tree

Thusasix-dimensionalcoordinatespacemayhavethreeofthecoordinatesdefinedasasubspacewithintheotherthreecoordinatespaces.ThishasbeencalledFeiner‟s“worldswithinworlds”approach

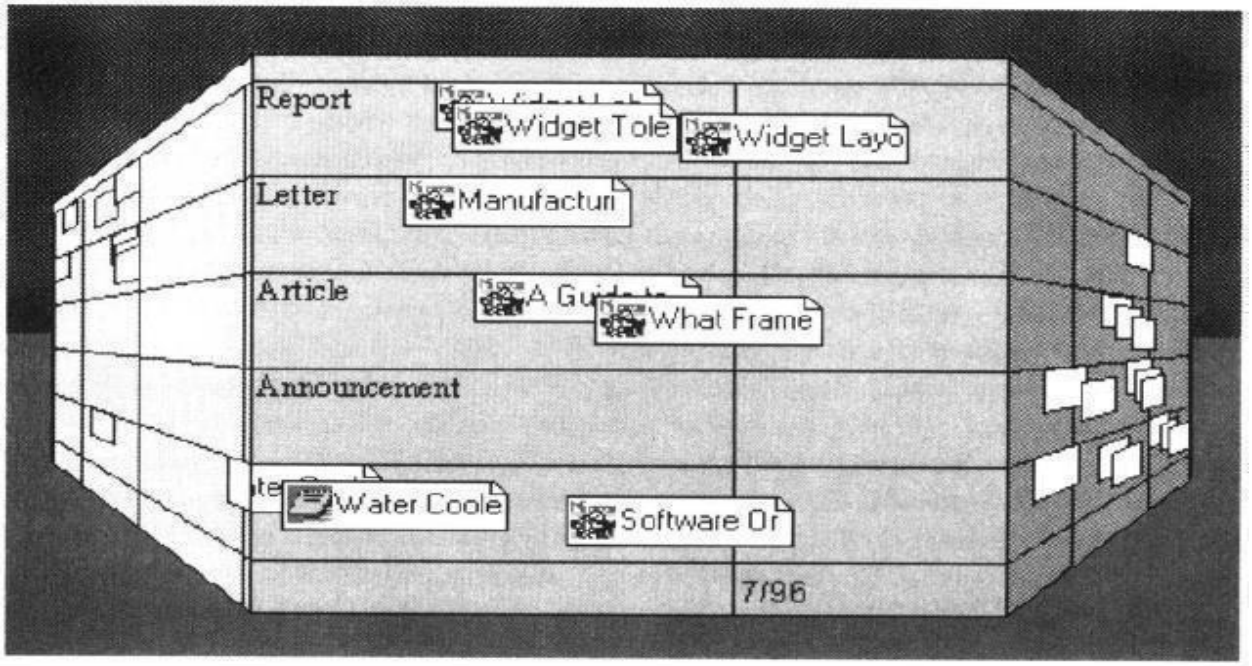

Figure 8.5 Perspective Wall
From inXight web site - www.inxight.com

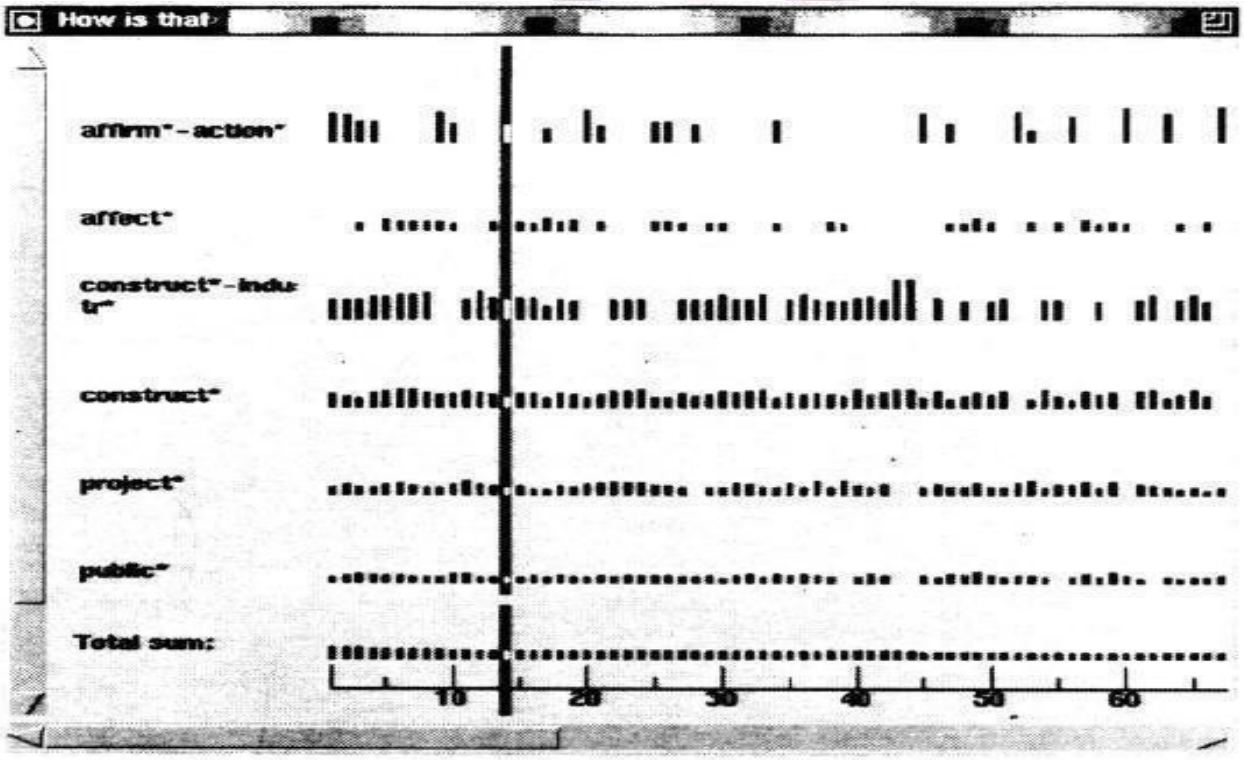

Figure 8.8 Visualization of Results
(from SIGIR 96, page 88)

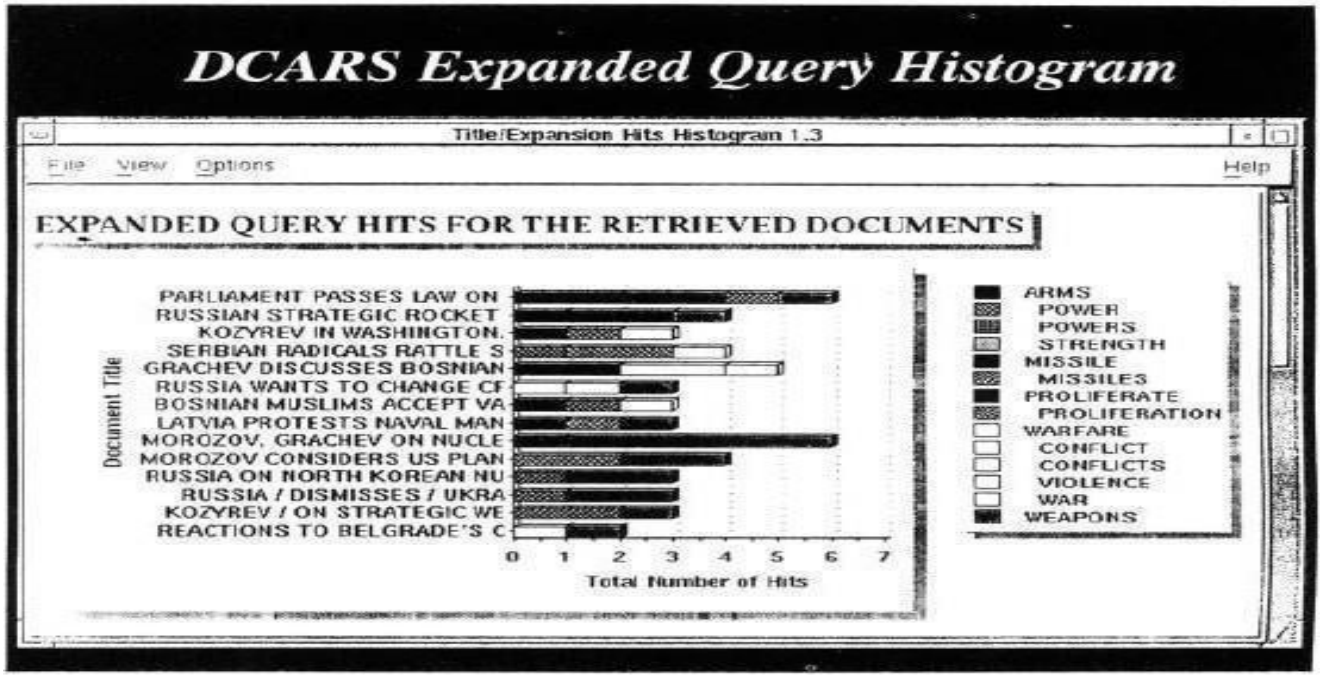

Figure 8.9 Example of DCARS Query Histogram (from briefing by CALSPAN)

A slightly different commercial version having properties similar to the systems above is theDocument Content Analysis and Retrieval System (DCARS) being developed by CalspanAdvanced Technology Center.Theirsystem isdesigned to augmenttheRetrievalWaresearchproduct.Theydisplaythequeryresultsasahistogramwiththeitems asrowsandeachterm‟scontributiontotheselectionindicatedbythewidthofatilebarontherow(seeFigure8.9).

DCARSprovidesafriendlyuserinterfacethatindicateswhyaparticularitemwasfound,butitismuchharder tousetheinformationindeterminghowtomodifysearchstatementstoimprovethem.

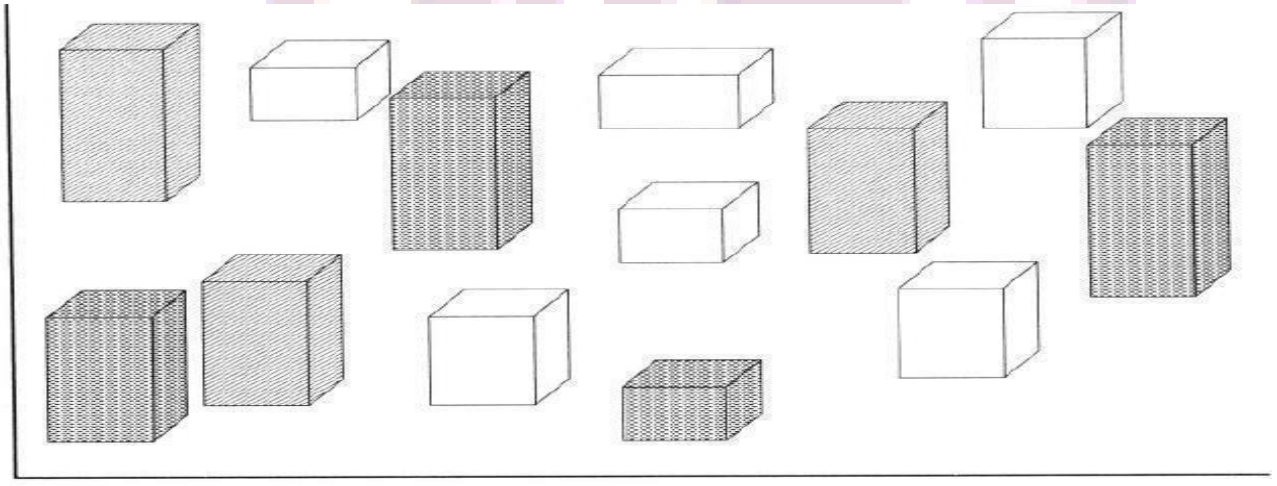

Figure 8.10 CityScape Example

Questions:

1. Write about Search Statements and Binding ?
2. Write about similarity Measures and Ranking?
3. What is Relevance Feedback? Explain with example?
4. Explain about Information Visualization?
5. Explain about Cognition and Perception? Information Visualization Technologies?

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