Query Operations

Berlin Chen 2005

Reference:

1. *Modern Information Retrieval*. chapter 5

Introduction

- Users have no detailed knowledge of
  - The collection makeup
  - The retrieval environment

Difficult to formulate queries

- Scenario of (Web) IR
  1. An initial (naive) query posed to retrieve relevant docs
  2. Docs retrieved are examined for relevance and a new improved query formulation is constructed and posed again

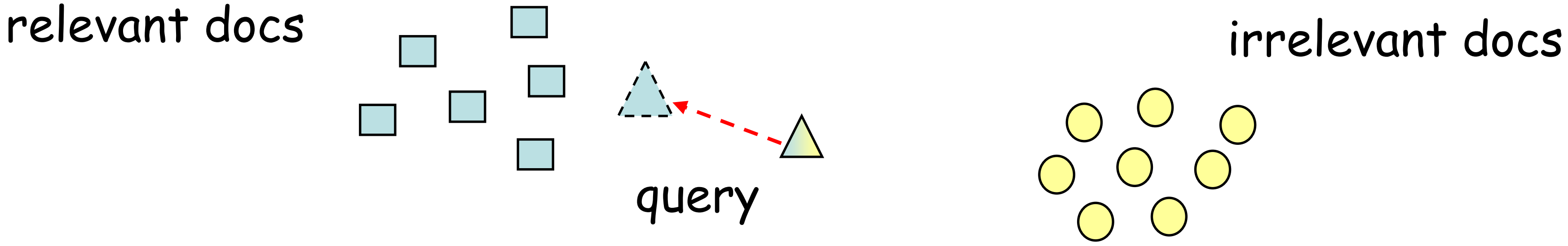
Expand the original query with new terms (**query expansion**) and rewight the terms in the expanded query (**term weighting**)

Query Reformulation

- Approaches through *query expansion* (QE) and *terming weighting*
  - Feedback information from the user
    - **Relevance feedback**
      - With vector, probabilistic models et al.
  - Information derived from the set of documents initially retrieved (called *local* set of documents)
    - **Local analysis**
      - Local clustering, local context analysis
  - Global information derived from document collection
    - **Global analysis**
      - Similar thesaurus or statistical thesaurus

Relevance Feedback

- User (or *Automatic*) Relevance Feedback
  - The most popular query reformation strategy
- Process for user relevance feedback
  - A list of retrieved docs is presented
  - User or system exam them (e.g. the top 10 or 20 docs) and marked the relevant ones
  - Important terms are selected from the docs marked as relevant, and the importance of them are enhanced in the new query formulation



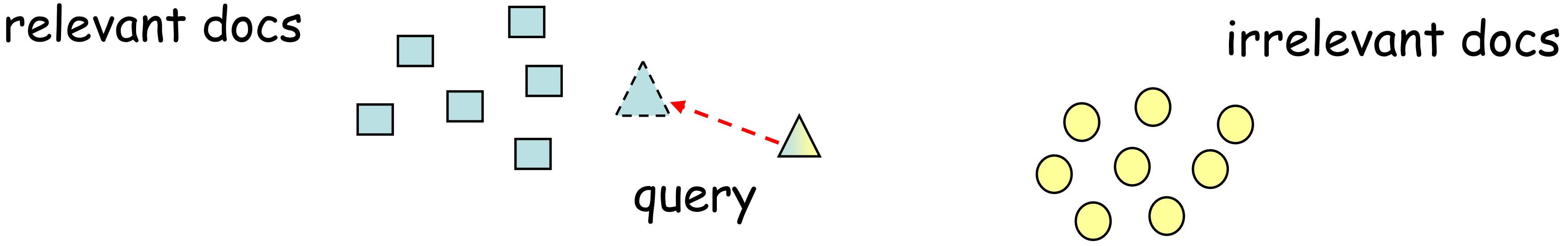
User Relevance Feedback

- Advantages
  - Shield users from details of query reformulation
    - User only have to provide a relevance judgment on docs
  - Break down the whole searching task into a sequence of small steps
  - Provide a controlled process designed to emphasize some terms (relevant ones) and de-emphasize others (non-relevant ones)

For **automatic relevance feedback**, the whole process is done in an implicit manner

Query Expansion and Term Reweighting for the Vector Model

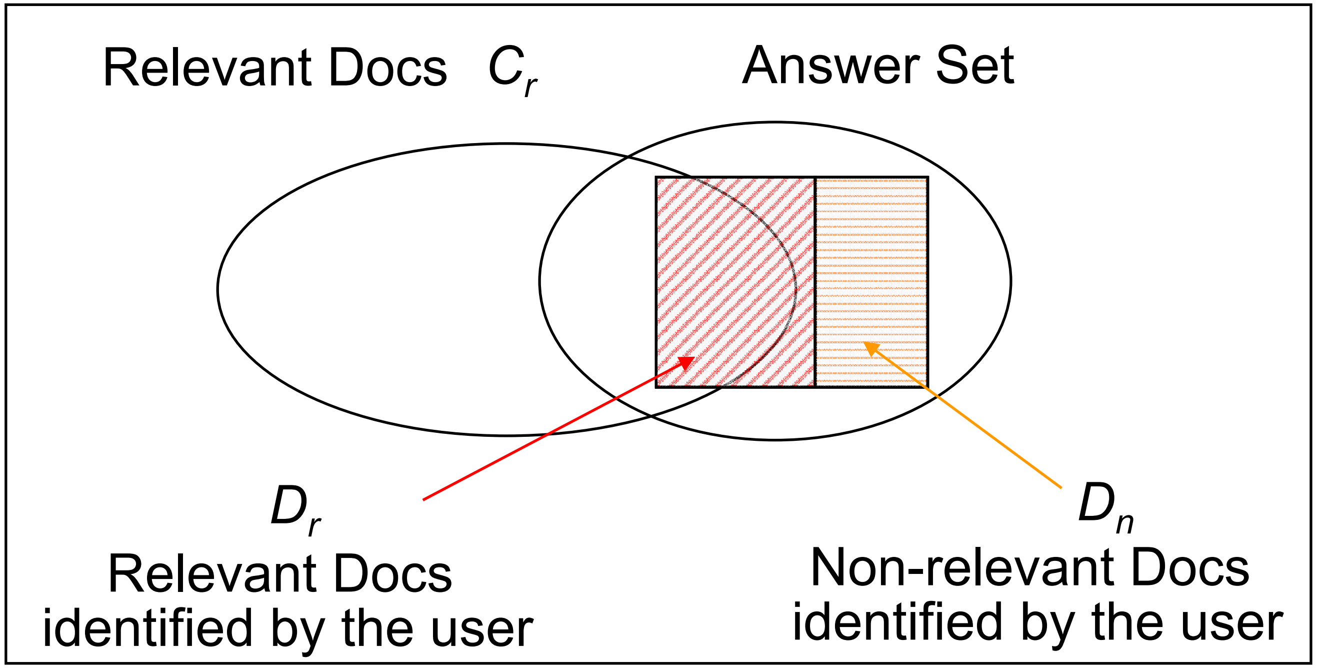
- ***Assumptions***
  - Relevant docs have term-weight vectors that resemble each other
  - Non-relevant docs have term-weight vectors which are dissimilar from the ones for the relevant docs
  - The reformulated query gets to closer to the term-weight vector space of relevant docs



term-weight vectors

Query Expansion and Term Reweighting for the Vector Model (cont.)

- **Terminology**


Relevant Docs C_r
Answer Set
D_r
Relevant Docs identified by the user
D_n
Non-relevant Docs identified by the user

Doc Collection with size N

Query Expansion and Term Reweighting for the Vector Model (cont.)

- **Optimal Condition**
  - The complete set of relevant docs C_r to a given query q is known in advance

$$\vec{q}_{opt} = \frac{1}{|C_r|} \sum_{\forall \vec{d}_i \in C_r} \vec{d}_i - \frac{1}{N - |C_r|} \sum_{\forall \vec{d}_j \notin C_r} \vec{d}_j$$

Elements in the final vector representation should be kept nonnegative

  - Problem: the complete set of relevant docs C_r are not known a priori
    - **Solution**: formulate an initial query and incrementally change the initial query vector based on the known relevant/non-relevant docs
      - User or automatic judgments

Query Expansion and Term Reweighting for the Vector Model (cont.)

- **In Practice**

1. Standard_Rocchio

Rocchio 1965

modified query

$$\vec{q}_m = \alpha \cdot \vec{q} + \frac{\beta}{|D_r|} \cdot \sum_{\forall \vec{d}_i \in Dr} \vec{d}_i - \frac{\gamma}{|D_n|} \cdot \sum_{\forall \vec{d}_j \in Dn} \vec{d}_j$$

initial/original query

2. Ide_Regular

$$\vec{q}_m = \alpha \cdot \vec{q} + \beta \cdot \sum_{\forall \vec{d}_i \in Dr} \vec{d}_i - \gamma \cdot \sum_{\forall \vec{d}_j \in Dn} \vec{d}_j$$

3. Ide_Dec_Hi

The highest ranked non-relevant doc

$$\vec{q}_m = \alpha \cdot \vec{q} + \beta \cdot \sum_{\forall \vec{d}_i \in Dr} \vec{d}_i - \gamma \cdot \boxed{\max_{non-relevant}\left(\vec{d}_j\right)}$$

Elements in the final vector representation should be kept nonnegative

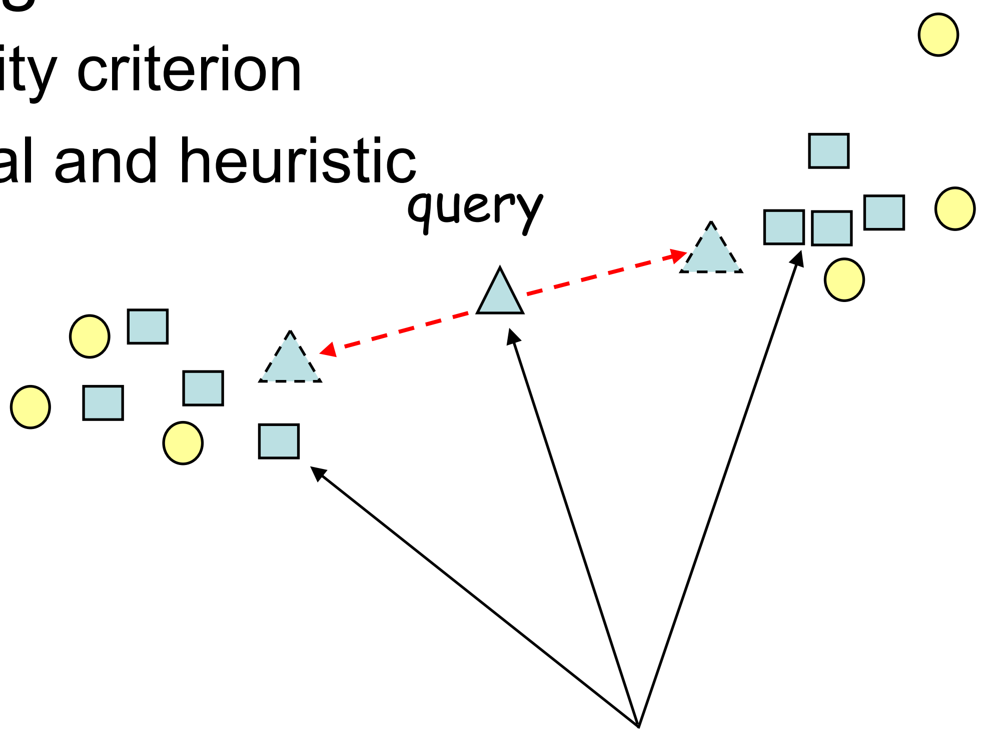
Query Expansion and Term Reweighting for the Vector Model (cont.)

- **Some Observations**
  - Similar results were achieved for the above three approach (Dec-Hi slightly better in the past)
  - Usually, constant β is bigger than γ (why?)

- **In Practice** (cont.)
  - More about the constants
    - Rocchio, 1971: α =1
    - Ide, 1971: $\alpha = \beta = \gamma$ =1
    - **Positive feedback strategy**: γ =0

Query Expansion and Term Reweighting for the Vector Model (cont.)

- Advantages
  - Simple, good results
    - Modified term weights are computed directly from the retrieved docs
- Disadvantages
  - No optimality criterion
    - Empirical and heuristic



Term Reweighting for the Probabilistic Model

Roberston & Sparck Jones 1976

- **Similarity Measure**

$$sim(d_j, q) \approx \sum_{i=1}^{t} w_{i,q} \times w_{i,j} \times \left[\log \frac{P(k_i \mid R)}{\boxed{1 - P(k_i \mid R)}} + \log \frac{1 - P(k_i \mid \overline{R})}{P(k_i \mid \overline{R})} \right]$$

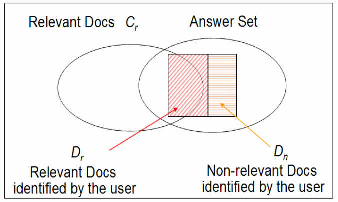
Binary weights (0 or 1) are used

prob. of observing term k_i in the set of relevant docs

- **Initial Search** (with some assumptions)
  - $P(k_i \mid R) = 0.5$:is constant for all indexing terms
  - $P(k_i \mid \overline{R}) = \frac{n_i}{N}$:approx. by doc freq. of index terms

$$\Rightarrow sim(d_j, q) \approx \sum_{i=1}^{t} w_{i,q} \times w_{i,j} \times \left[\log \frac{0.5}{1 - 0.5} + \log \frac{1 - \frac{n_i}{N}}{\frac{n_i}{N}} \right]$$

$$= \boxed{\sum_{i=1}^{t} w_{i,q} \times w_{i,j} \times \log \frac{N - n_i}{n_i}}$$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Non-relevant Docs identified by the user

Doc Collection with size N

Term Reweighting for the Probabilistic Model (cont.)

- **Relevance feedback** (term reweighting alone)

$$P(k_i \mid R) = \frac{|D_{r,i}|}{|D_r|}$$

← Relevant docs containing term k_i

← Relevant docs

$$P(k_i \mid \bar{R}) = \frac{n_i - |D_{r,i}|}{N - |D_r|}$$

Approach 1

$$P(k_i \mid R) = \frac{|D_{r,i}| + 0.5}{|D_r| + 1}$$

$$P(k_i \mid \bar{R}) = \frac{n_i - |D_{r,i}| + 0.5}{N - |D_r| + 1}$$

$$P(\bar{k}_i \mid R) = \frac{|D_r| - |D_{r,i}| + 0.5}{|D_r| + 1}$$

Approach 2

$$P(k_i \mid R) = \frac{|D_{r,i}| + \frac{n_i}{N}}{|D_r| + 1}$$

$$P(k_i \mid \bar{R}) = \frac{n_i - |D_{r,i}| + \frac{n_i}{N}}{N - |D_r| + 1}$$

Or $\dfrac{n_i - |D_{r,i}|}{N - |D_r|}$

$$sim(d_j, q) \approx \sum_{i=1}^{t} w_{i,q} \times w_{i,j} \times \left[\log \frac{\frac{|D_{r,i}|}{|D_r|}}{1 - \frac{|D_{r,i}|}{|D_r|}} + \log \frac{1 - \frac{n_i - |D_{r,i}|}{N - |D_r|}}{\frac{n_i - |D_{r,i}|}{N - |D_r|}} \right]$$

$$= \sum_{i=1}^{t} w_{i,q} \times w_{i,j} \times \log \left[\frac{|D_{r,i}|}{|D_r| - |D_{r,i}|} \cdot \frac{N - |D_r| - n_i + |D_{r,i}|}{n_i - |D_{r,i}|} \right]$$

Term Reweighting for the Probabilistic Model (cont.)

- Advantages
  - Feedback process is directly related to the derivation of new weights for query terms
  - The term reweighting is optimal under the assumptions of term independence and binary doc indexing
- Disadvantages
  - Document term weights are not taken into account
  - Weights of terms in previous query formulations are disregarded
  - No query expansion is used
    - The same set of index terms in the original query is reweighted over and over again

A Variant of Probabilistic Term Reweighting

Croft 1983

http://ciir.cs.umass.edu/

- **Differences**
  - Distinct initial search assumptions
  - Within-document frequency weight included
- **Initial search** (assumptions)

$$sim(d_j, q) \propto \sum_{i=1}^{t} w_{i,q} w_{i,j} F_{i,j,q}$$

$$F_{i,j,q} = (C + idf_i)\,\bar{f}_{i,j} \qquad \bar{f}_{i,j} = K + (1+K)\frac{f_{i,j}}{\max(f_{i,j})}$$

~ Inversed document frequency

~ Term frequency
(normalized with the maximum
within-document frequency)

- *C* and *K* are adjusted with respect to the doc collection

A Variant of Probabilistic Term Reweighting (cont.)

- **Relevance feedback**

$$F_{i,j,q} = (C + \log \frac{P(k_i \mid R)}{1 - P(k_i \mid R)} + \log \frac{1 - P(k_i \mid \overline{R})}{P(k_i \mid \overline{R})}) \bar{f}_{i,j}$$

$$P(k_i \mid R) = \frac{|D_{r,i}| + 0.5}{|D_r| + 1}$$

$$P(k_i \mid \overline{R}) = \frac{n_i - |D_{r,i}| + 0.5}{N - |D_r| + 1}$$

A Variant of Probabilistic Term Reweighting (cont.)

- Advantages
  - The *within-doc frequencies* are considered
  - A normalized version of these frequencies is adopted
  - Constants *C* and *K* are introduced for greater flexibility

- Disadvantages
  - More complex formulation
  - No query expansion (just reweighting of index terms)

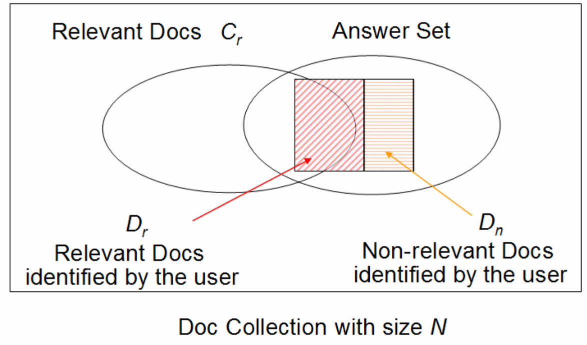
Evaluation of Relevance Feedback Strategies

- Recall-precision figures of user reference feedback is unrealistic
  - Since the user has seen the docs during reference feedback
    - A significant part of the improvement results from the higher ranks assigned to the set *R* of docs

$$\vec{q}_m = \alpha \cdot \vec{q} + \frac{\beta}{|D_r|} \cdot \sum_{\forall \vec{d}_j \in Dr} \vec{d}_i - \frac{\gamma}{|D_n|} \cdot \sum_{\forall \vec{d}_j \in Dn} \vec{d}_j$$

modified query

original query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Doc Collection with size *N*

  - The real gains in retrieval performance should be measured based on the docs not seen by the user yet

Evaluation of Relevance Feedback Strategies (cont.)

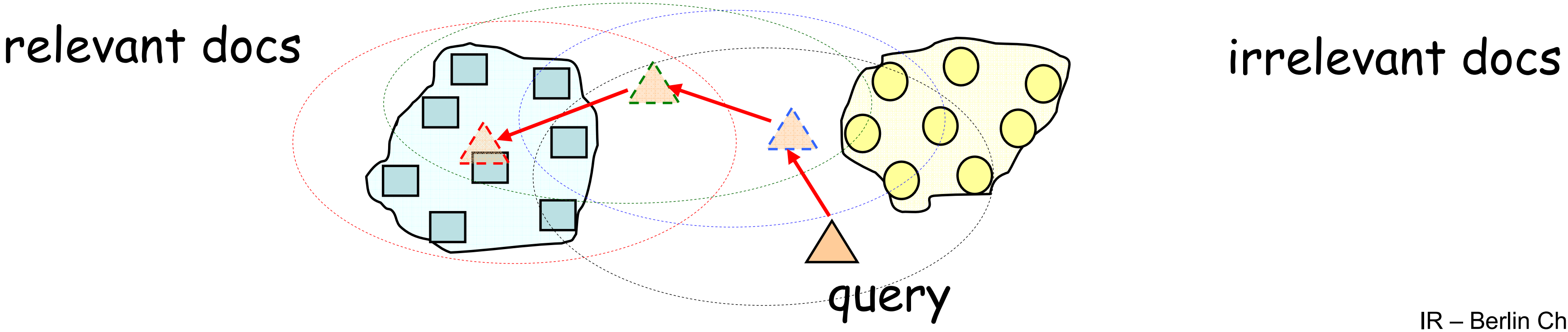
- Recall-precision figures relative to the residual collection
  - Residual collection
    - The set of all docs minus the set of feedback docs provided by the user
  - Evaluate the retrieval performance of the modified query $\vec{q}_m$ considering only the residual collection
  - The recall-precision figures for $\vec{q}_m$ tend to be lower than the figures for the original query $\vec{q}$
    - It's OK ! If we just want to compare the performance of different relevance feedback strategies

Automatic Local/Global Analysis

- **Recall** - in user relevance feedback cycles
  - Top ranked docs separated into two classes
    - Relevant docs
    - Non-relevant docs
  - Terms in known relevant docs help describe a larger cluster of relevant docs
    - From a "**clustering**" perspective

Attar and Fraenkel 1977

  - Description of larger cluster of relevant docs is built iteratively **with assistance from the user**



Automatic Local/Global Analysis (cont.)

- *Alternative approach*: automatically obtain the description for a large cluster of relevant docs
  - Identify terms which are related to the query terms
    - Synonyms
    - Stemming variations
    - Terms are close each other in context

陳水扁 總統 李登輝 總統府 秘書長 陳師孟 一邊一國…

連戰 宋楚瑜 國民黨 一個中國 …

Automatic Local/Global Analysis (cont.)

- Two strategies
  - Global analysis
    - All docs in collection are used to determine a global thesaurus-like structure for QE
  - Local analysis
    - Similar to relevance feedback but without user interference
    - Docs retrieved at query time are used to determine terms for QE
    - Local clustering, local context analysis

QE through Local Clustering

- QE through **Clustering**
  - Build **global structures** such as **association matrices** to quantify term correlations
  - Use the correlated terms for QE
  - But not always effective in general collections

    陳水扁 總統 呂秀蓮 綠色矽島 勇哥 吳淑珍 …

    陳水扁 視察 阿里山 小火車
- QE through **Local Clustering**
  - Operate solely on the docs retrieved for the query
  - Not suitable for Web search: time consuming
  - Suitable for intranets
    - Especially, as the assistance for search information in specialized doc collections like medical doc collections

QE through Local Clustering (cont.)

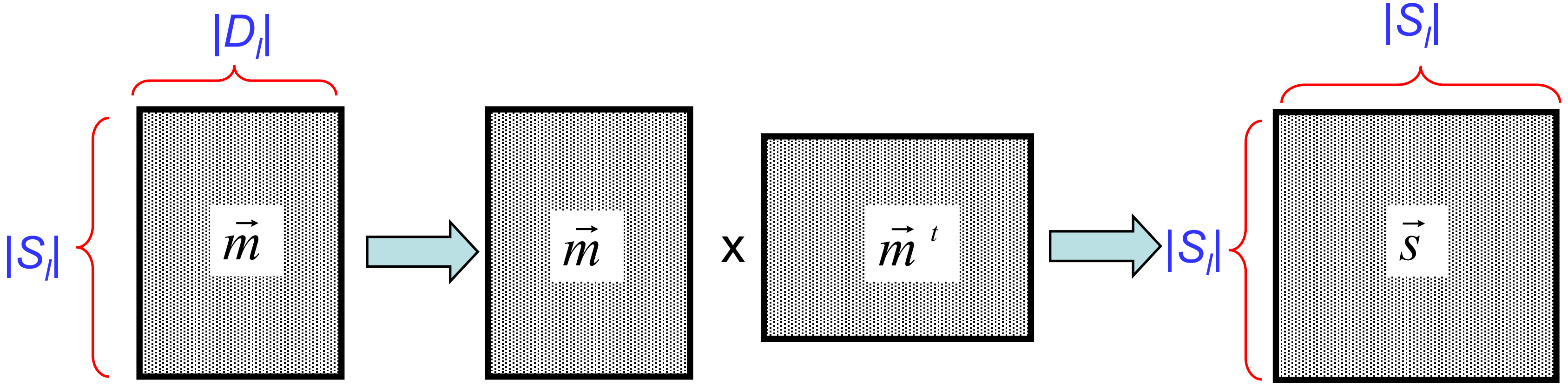
- Definition
  - Stem
    - *V*(*s*): a non-empty subset of words which are grammatical variants of each other
      - E.g. {polish, polishing, polished}
    - A canonical form s of *V*(*s*) is called a **stem**
      - e.g., *s*= polish
  - For a given query
    - Local doc set D_l : the set of documents retrieved
    - local vocabulary V_l : the set of all distinct words (stems) in the local document set
    - $S_{l:}$ the set of all distinct stem derived from V_l

Strategies for Building Local Clusters

- **Association clusters**
  - Consider the co-occurrence of stems (terms) inside docs
- **Metric Clusters**
  - Consider the distance between two terms in a doc
- **Scalar Clusters**
  - Consider the neighborhoods of two terms
    - Do they have similar neighborhoods?

Strategies for Building Local Clusters (cont.)

- ***Association clusters***
  - Based on the **co-occurrence** of stems (terms) inside docs
    - Assumption: stems co-occurring frequently inside docs have a *synonymity* association
  - An association matrix with $|S_l|$ rows and $|D_l|$ columns
    - Each entry $f_{s_i,j}$ the frequency of a stem s_i in a doc d_j



stem-doc matrix

stem-stem association matrix

Strategies for Building Local Clusters (cont.)

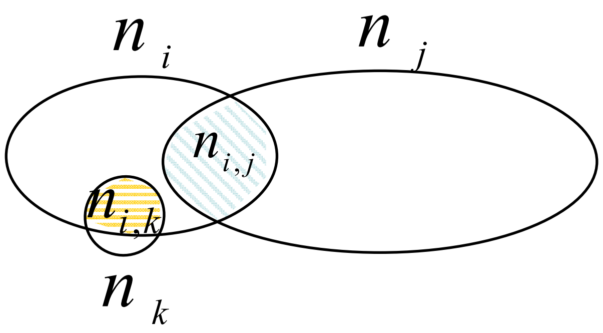
- ***Association clusters***
  - Each entry in the stem-stem association matrix stands for ***the correlation factor*** between two stems

$$c_{u,v} = \sum_{d_j \in D_l} f_{s_u,j} \times f_{s_v,j}$$

  - The unnormalized form

$$s_{u,v} = c_{u,v}$$

    - Prefer terms with high frequency



  - The normalized form (ranged from 0 to 1)

$$s_{u,v} = \frac{c_{u,v}}{c_{u,u} + c_{v,v} - c_{u,v}}$$

Tanimoto coefficient

    - Prefer terms with low frequency

Strategies for Building Local Clusters (cont.)

- **Association clusters**
  - The *u*-th row in the association matrix stands all the associations for the stem s_u
  - A **local association cluster** $S_u(m)$
    - Defined as a set of stems s_v ($v \neq u$) with their respective values $s_{u,v}$ being the top *m* ones in the *u*-th row of the association matrix
  - Given a query, only the association clusters of query terms are calculated
    - The stems (terms) belong to the association clusters are selected and added the query formulation

Strategies for Building Local Clusters (cont.)

- ***Association clusters***
  - Other measures for term association
    - Dice coefficient

$$s_{u,v} = \frac{2 \times c_{u,v}}{c_{u,u} + c_{v,v}}$$

    - Mutual information

$$s_{u,v} = MI\left(k_u, k_v\right) = \log \frac{P\left(k_u, k_v\right)}{P\left(k_u\right)P\left(k_v\right)} = \log \frac{\frac{n_{u,v}}{N}}{\frac{n_u}{N} \times \frac{n_v}{N}}$$

Strategies for Building Local Clusters (cont.)

- **Metric Clusters**
  - Take into consideration the distance between two terms in a doc while computing their correlation factor

$$c_{u,v} = \sum_{k_i \in V(s_u)} \sum_{k_j \in V(s_v)} \frac{1}{\boxed{r(k_i, k_j)}}$$

no. of words between k_i and k_j in the same doc

$r(k_i,k_j)=\infty$ if k_i and k_j are in distinct docs

  - The entry of **local stem-stem metric correlation** matrix $\vec{s}$ can be expressed as
    - The unnormalized form

$$s_{u,v} = c_{u,v}$$

    - The normalized form

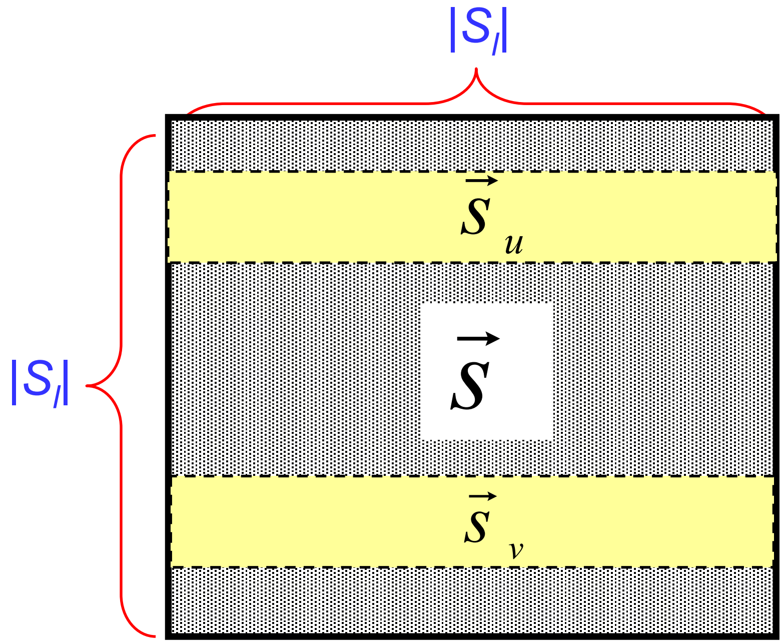
$$s_{u,v} = \frac{c_{u,v}}{|V(s_u)| \times |V(s_v)|}$$

ranged from 0 to 1

The local association clusters of stems can be similarly defined

Strategies for Building Local Clusters (cont.)

- **Scalar Clusters**
  - **Idea**: two stems (terms) with similar neighborhoods have some synonymity relationship
  - Derive the synonymity relationship between two stems by comparing the sets $S_u(m)$ and $S_v(m)$



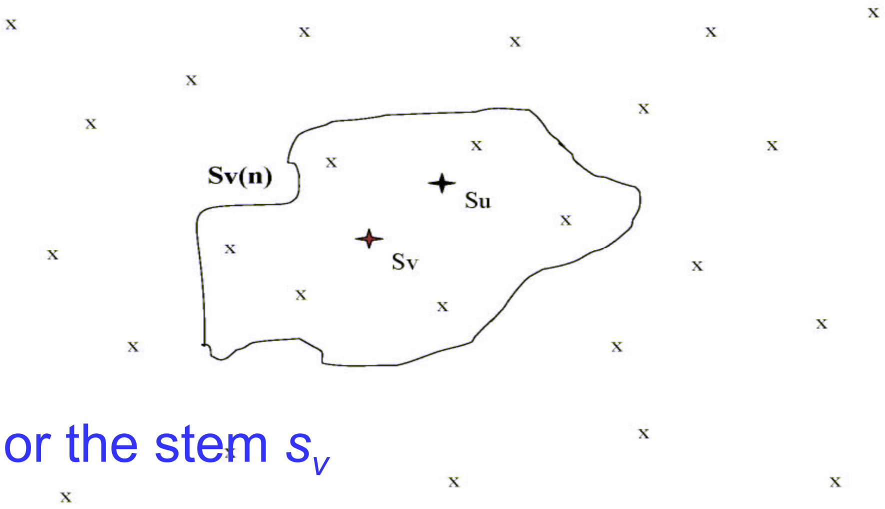
$$s_{u,v} = \frac{\vec{s}_u \cdot \vec{s}_v}{\left|\vec{s}_u\right| \times \left|\vec{s}_u\right|}$$

Use Cosine measure to derive a new scalar association matrix

The stem-stem association matrix achieved before

QE through Local Clustering (cont.)

- Iterative Search Formulation
  - "**neighbor**": a stem s_u belongs to a cluster associated to another term s_v is said to be a neighbor of s_v
    - Not necessarily synonyms in the grammatrical sense
  - Stems belonging to clusters associated to the query stems (terms) can be used to expand the original query



stems s_u as a neighbor or the stem s_v

QE through Local Clustering (cont.)

- Iterative Search Formulation

$$\text{e.g,}\quad s_{u,v} = \frac{c_{u,v}}{c_{u,u} + c_{v,v} - c_{u,v}}$$

  - Query expansion
    - For each stem $s_v \in q$, select *m* neighbors stems from the cluster $S_v(m)$ and add them to the query
    - The additional neighbor stems will retrieve new relevant docs
  - The impact of normalized or unnormalized clusters
    - Unnormalized: group stems with high frequency
    - Normalized: group rare stems
    - Union of them provides a better representation of stem (term) correlations

Local Context Analysis

- Local Analysis
  - Based on the set of docs retrieved for the original query
  - Based on term (stem) correlation inside docs
  - Terms are neighbors of **each query terms** are used to expand the query
- Global Analysis
  - Based on the whole doc collection
  - The thesaurus for term relationships are built by considering small contexts (e.g. passages) and phrase structures instead of the context of the whole doc
  - Terms closest to **the whole query** are selected for query expansion

Calculation of term correlations at query time

Pre-calculation of term correlations

Local context analysis combines features from both

Local Context Analysis (cont.)

Xu and Croft 1996

- Operations of local context analysis
  - **Document concepts**: Noun groups from retrieved docs as the units for QE instead of single keywords
  - **Concepts** selected from the top ranked passages (instead of docs) based on their co-occurrence with the whole set of query terms (no stemming)

QE through Local Context Analysis

- The operations can be further described in three steps
  - Retrieve the top *n* ranked passages using the original query (a doc is segmented into several passages)
  - For each concept *c* in the top ranked passages, the similarity *sim*(*q,c*) between the whole query q and the concept *c* is computed using a variant of *tf-idf* ranking
  - The top *m* ranked concepts are added to the original query *q and* appropriately weighted, e.g.
    - Each concept is assigned a weight
      1-0.9x *i*/*m* (*i*: the position in rank)
    - Original query terms are stressed by a weight of 2

QE through Local Context Analysis (cont.)

- The similarity between a concept and a query

$$sim(q,c)=\prod_{k_i \in q}\left(\delta+\frac{\log\left(f(c,k_i)\times idf_c\right)}{\log n}\right)^{idf_i}$$

emphasize the infrequent terms

Set to 0.1 to avoid zero

the no. of top ranked passages considered

$$f(c,k_i)=\sum_{j=1}^{n} pf_{i,j}\times pf_{c,j}$$

the no. of passages in the collection

$$idf_c=\max\left(1,\frac{\log_{10} N/np_c}{5}\right)$$

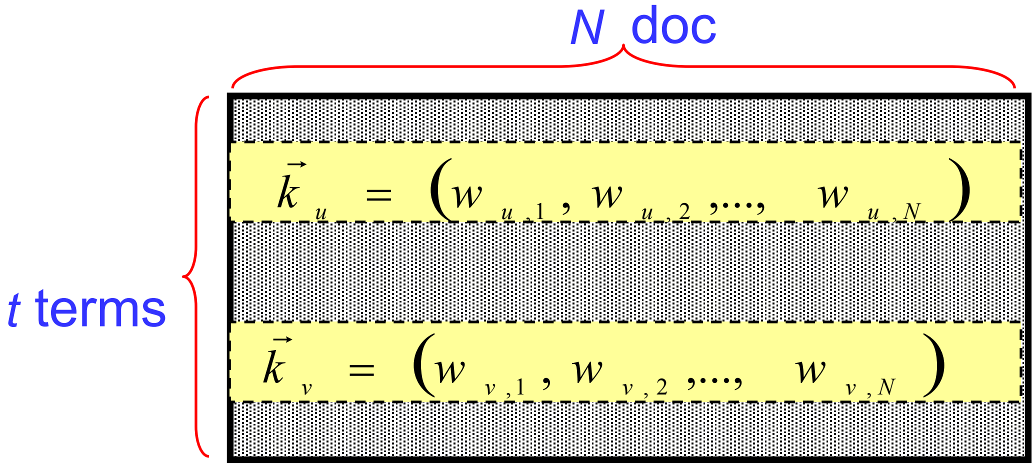
the no. of passages containing concept c

$$idf_i=\max\left(1,\frac{\log_{10} N/np_i}{5}\right)$$

QE based on a Similarity Thesaurus

Qiu and Frei 1993

- Belongs to Global Analysis
- How to construct the similarity thesaurus
  - Term to term relationships rather than term co-occurrences are considered
- How to select term for query expansion
  - Terms for query expansion are selected based on their similarity to the whole query rather the similarities to individual terms



$$\vec{k}_u = (w_{u,1}, w_{u,2}, \ldots, w_{u,N})$$

$$\vec{k}_v = (w_{v,1}, w_{v,2}, \ldots, w_{v,N})$$

term-doc matrix

Docs are interpreted as indexing elements here

- Doc frequency within the term vector
- Inverse term frequency

QE based on a Similarity Thesaurus (cont.)

- Definition
  - $f_{u,j}$: the frequency of term k_u in document d_j
  - t_j : the number of distinct index terms in document d_j
  - Inverse term frequency

$$itf_j = \log \frac{t}{t_j}$$

(doc containing more distinct terms is less important)

- The weight associated with each entry in the term-doc matrix

$$w_{u,j} = \frac{\left(0.5 + 0.5 \frac{f_{u,j}}{\max_j f_{u,j}}\right) \times itf_j}{\sqrt{\sum_{l=1}^{N} \left[\left(0.5 + 0.5 \frac{f_{u,l}}{\max_l f_{u,l}}\right) \times itf_l\right]^2}}$$

The importance of the doc d_j to a term k_u

Let term vector have a unit norm

QE based on a Similarity Thesaurus (cont.)

- The relationship between two terms k_u and k_v

is just a cosine measure?

$$c_{u,v} = \vec{k}_u \cdot \vec{k}_v = \sum_{\forall d_j} w_{u,j} \times w_{v,j}$$

ranged from 0 to 1

  - The vector representations are normalized
  - The computation is computationally expensive
    - There may be several hundred thousands of docs

QE based on a Similarity Thesaurus (cont.)

Concept-based QE

- Steps for QE based on a similarity thesaurus

1. Represent the query in the term-concept space

$$\vec{q} = \sum_{k_u \in q} w_{u,q} \times \vec{k}_u$$

2.Based on the global thesaurus, compute a similarity between the each term k_v and the whole query q

$$sim(q, k_v) = \left(\sum_{k_u \in q} w_{u,q} \times \vec{k}_u \right) \cdot \vec{k}_v = \sum_{k_u \in q} w_{u,q} \times c_{u,v}$$

3. Expand the query with the top r ranked terms according to $sim(q,k_v)$

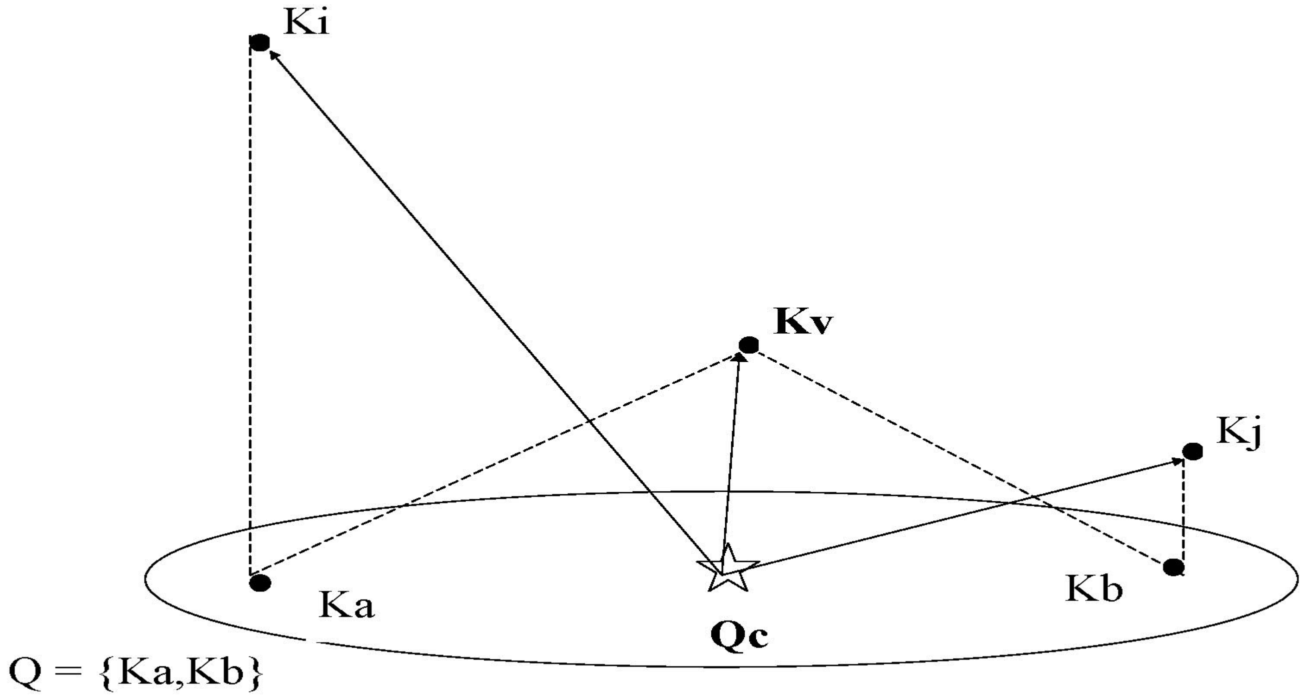
   - The weight assigned to the expansion term

$$w_{v,q'} = \frac{sim(q, k_v)}{\sum_{k_u \in q} w_{u,q}} = \frac{\sum_{k_u \in q} w_{u,q} \times c_{u,v}}{\sum_{k_u \in q} w_{u,q}}$$

ranged from 0 to 1 ?

QE based on a Similarity Thesaurus (cont.)

- The term k_v selected for query expansion might be quite close to the whole query while its distances to individual query terms are larger



QE based on a Similarity Thesaurus (cont.)

- The similarity between query and doc measured in the term-concept space
  - Doc is first represented in the term-concept space

$$\vec{d}_j = \sum_{k_v \in d_j} w_{v,j} \times \vec{k}_v$$

  - Similarity measure

$$sim(q, d_j) \propto \sum_{k_v \in d_j} \sum_{k_u \in q} w_{v,j} \times w_{u,q} \times c_{u,v}$$

    - Analogous to the formula for query-doc similarity in the generalized vector space model
      - Differences
        - » Weight computation
        - » Only the top *r* ranked terms are used here

QE based on a Statistical Thesaurus

- Belongs to Global Analysis

- Global thesaurus is composed of classes which group correlated terms in the context of the whole collection

- Such correlated terms can then be used to expand the original user query
  - The terms selected must be **low frequency terms**
    - With high discrimination values

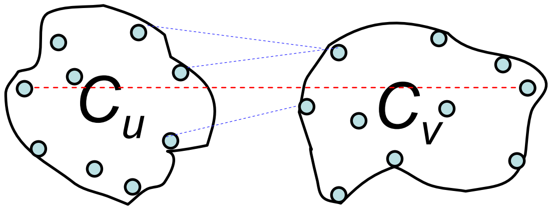
QE based on a Statistical Thesaurus (cont.)

- However, it is difficult to cluster **low frequency terms**
  - To circumvent this problem, we cluster docs into classes instead and use the low frequency terms in these docs to define our thesaurus classes
  - This algorithm must produce small and tight clusters
    - Depend on the cluster algorithm

QE based on a Statistical Thesaurus (cont.)

- Complete Link Algorithm
  - Place each doc in a distinct cluster
  - Compute the similarity between all pairs of clusters
  - Determine the pair of clusters $[C_u, C_v]$ with the highest inter-cluster similarity (using the cosine formula)
  - Merge the clusters C_u and C_v
  - Verify a stop criterion. If this criterion is not met then go back to step 2
  - Return a hierarchy of clusters

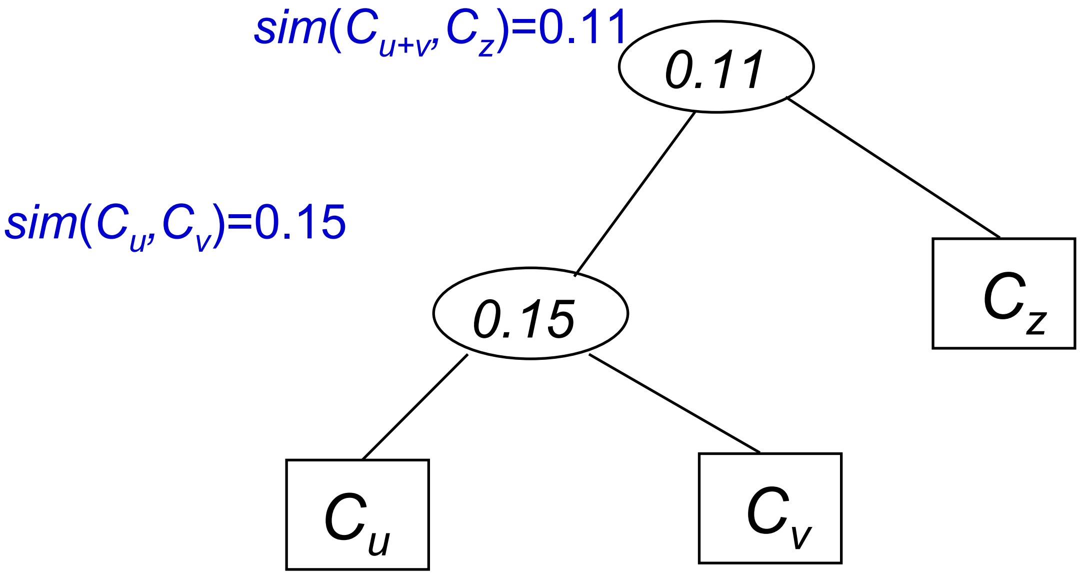
- Similarity between two clusters is defined as
  - The minimum of similarities between all pairs of inter-cluster docs



Cosine formula of the vector model is used

QE based on a Statistical Thesaurus (cont.)

- Example: hierarchy of three clusters



  – Higher level clusters represent a looser grouping
    - Similarities decrease as moving up in the hierarchy

QE based on a Statistical Thesaurus (cont.)

- Given the doc cluster hierarchy for the whole collection, the terms that compose each class of the global thesaurus are selected as follows
  - Three parameters obtained from the user
    - *TC*: Threshold class
    - *NDC*: Number of docs in class
    - *MIDF*: Minimum inverse doc frequency

QE based on a Statistical Thesaurus (cont.)

- Use the parameter *TC* as threshold value for determining the doc clusters that will be used to generate thesaurus classes
  - It has to be surpassed by sim(C_u,C_v) if the docs in the clusters C_u and C_v are to be selected as sources of terms for a thesaurus class

- Use the parameter *NDC* as a limit on the size of clusters (number of docs) to be considered
  - A low value of *NDC* might restrict the selection to the smaller clusters

QE based on a Statistical Thesaurus (cont.)

- Consider the set of docs in each doc cluster pre-selected above
  - Only the lower frequency terms are used as sources of terms for the thesaurus classes
  - The parameter *MIDF* defines the minimum value of inverse doc frequency for any term which is selected to participate in a thesaurus class

- Given the thesaurus classes have been built, they can be to query expansion

QE based on a Statistical Thesaurus (cont.)

- Example

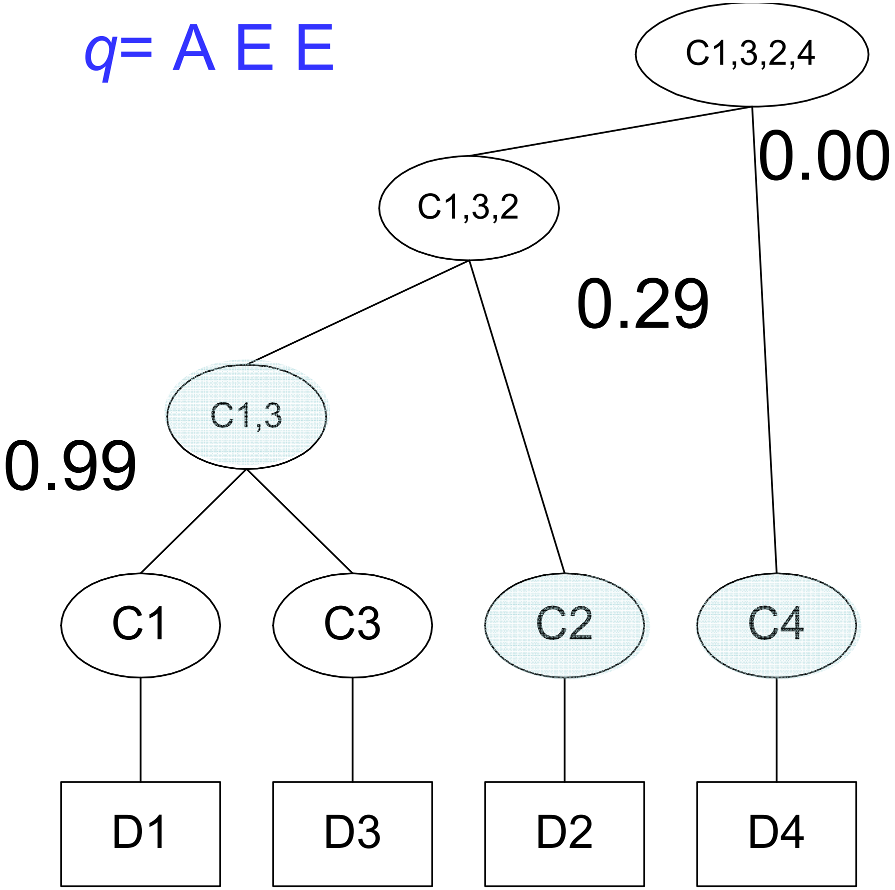
Doc1 = D, D, A, B, C, A, B, C
Doc2 = E, C, E, A, A, D
Doc3 = D, C, B, B, D, A, B, C, A
Doc4 = A

sim(1,3) = 0.99
sim(1,2) = 0.40
sim(2,3) = 0.29
sim(4,1) = 0.00
sim(4,2) = 0.00
sim(4,3) = 0.00

cosine formula with *tf-idf* weighting

idf A = 0.0
idf B = 0.3
idf C = 0.12
idf D = 0.12
idf E = 0.60

q= A E E



- *TC* = 0.90 *NDC* = 2.00 *MIDF* = 0.2

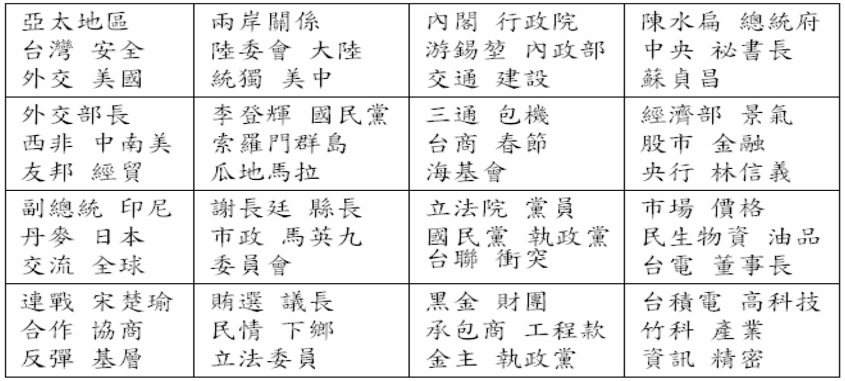
q'=A B E E

QE based on a Statistical Thesaurus (cont.)

- Problems
  - Initialization of parameters *TC*, *NDC* and *MIDF*
  - *TC* depends on the collection
  - Inspection of the cluster hierarchy is almost always necessary for assisting with the setting of *TC*
  - A high value of *TC* might yield classes with too few terms
    - While a low value of *TC* yields too few classes

Trends and Research Issues

- Visual display
  - Graphical interfaces (2D or 3D) for relevance feedback
    - Quickly identify relationships among doc in the answer set



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Adapted from Prof. Lin-shan Lee

The 16 Blocks for major semantic concepts or topics in the category of "local political news."

- Utilization of local and global analysis techniques to the Web environments
  - Alleviate the computational burden imposed on the search engine