

Models for Retrieval and Browsing

- Fuzzy Set, Extended Boolean,
Generalized Vector Space Models



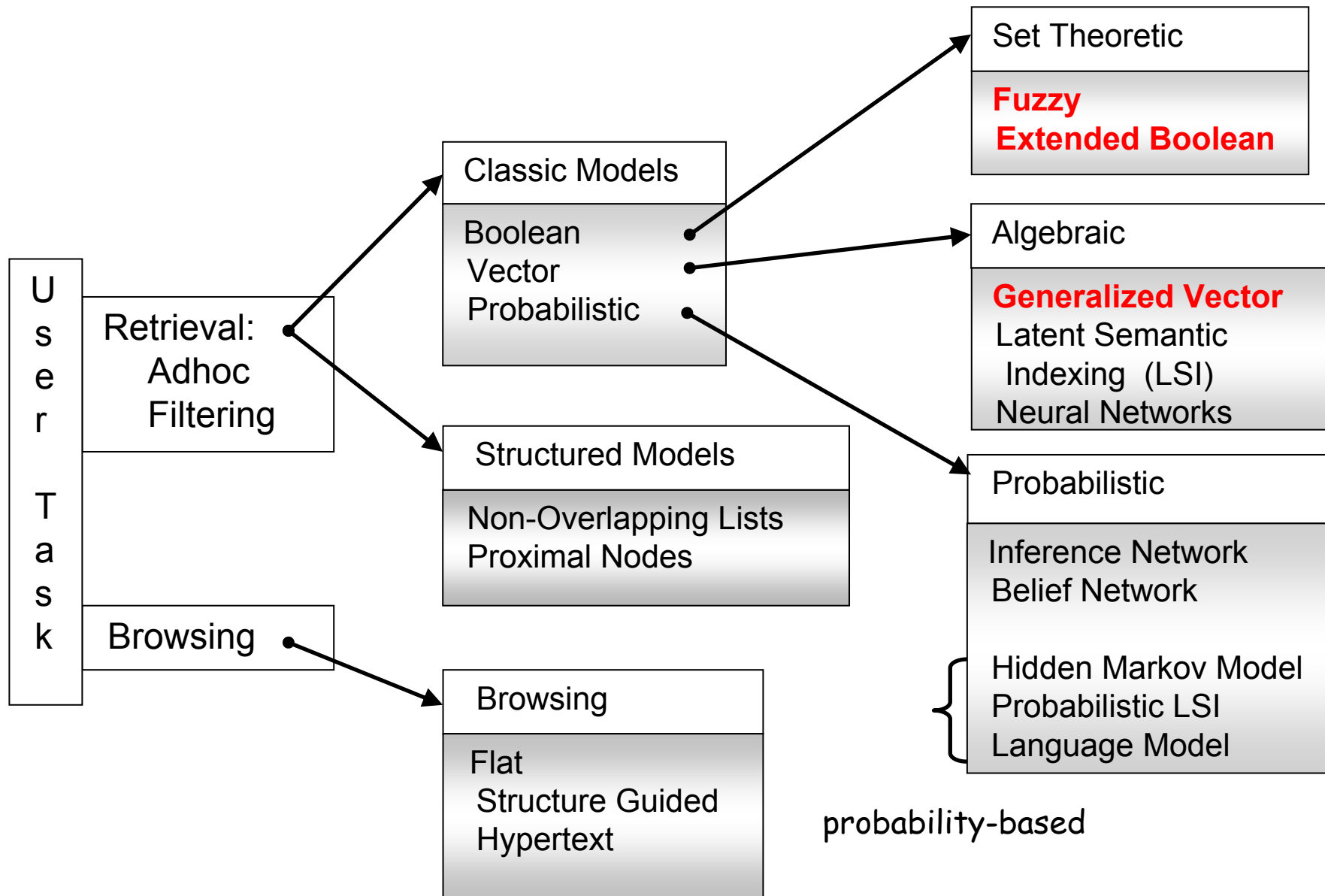
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Reference:

1. *Modern Information Retrieval*. Chapter 2

Taxonomy of Classic IR Models



Outline

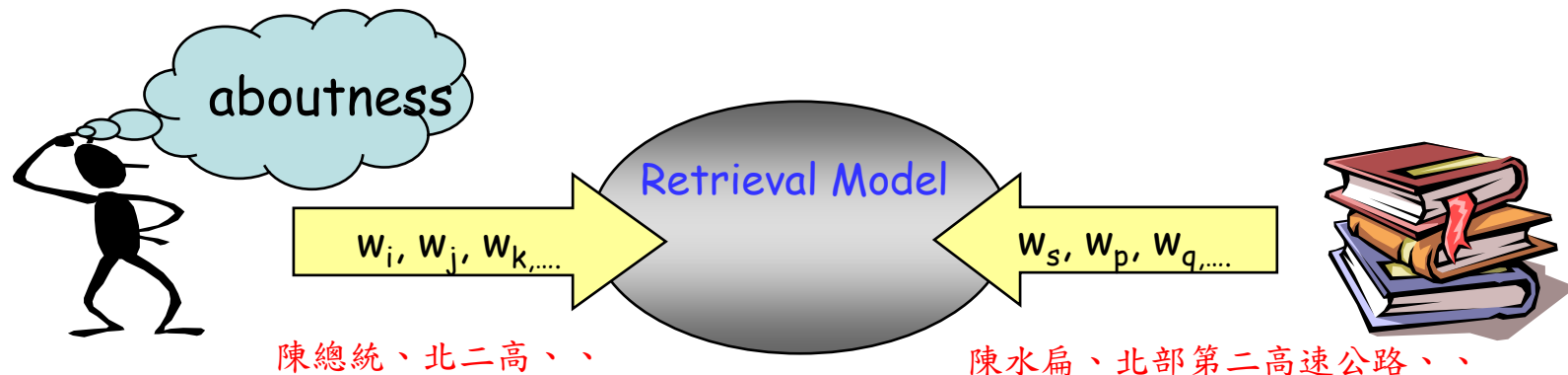
- **Alternative Set Theoretic Models**
 - Fuzzy Set Model (Fuzzy Information Retrieval)
 - Extended Boolean Model
- **Alternative Algebraic Models**
 - Generalized Vector Space Model

Fuzzy Set Model

- Premises

- Docs and queries are represented through sets of keywords, therefore the matching between them is vague

- Keywords cannot completely describe the user's information need and the doc's main theme



- For each query term (keyword)

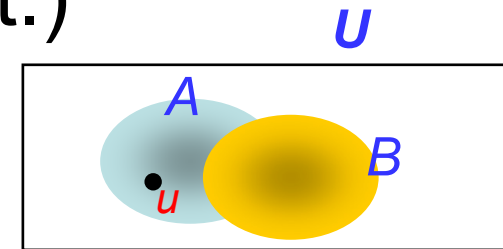
- Define a fuzzy set and that each doc has a degree of membership (0~1) in the set

Fuzzy Set Model (cont.)

- Fuzzy Set Theory
 - Framework for representing classes (sets) whose boundaries are not well defined
 - Key idea is to introduce the notion of a *degree of membership* associated with the elements of a set
 - This degree of membership varies from 0 to 1 and allows modeling the notion of *marginal membership*
 - 0 → no membership
 - 1 → full membership
 - Thus, membership is now a gradual instead of abrupt
 - Not as conventional Boolean logic

Here we will define a fuzzy set for each query (or index) term, thus each doc has a degree of membership in this set.

Fuzzy Set Model (cont.)



- Definition

- A fuzzy subset A of a universal of discourse U is characterized by a membership function

$$\mu_A: U \rightarrow [0,1]$$

- Which associates with each element u of U a number $\mu_A(u)$ in the interval $[0,1]$

- Let A and B be two fuzzy subsets of U . Also, let \bar{A} be the complement of A . Then,

- Complement $\mu_{\bar{A}}(u) = 1 - \mu_A(u)$
- Union $\mu_{A \cup B}(u) = \max(\mu_A(u), \mu_B(u))$
- Intersection $\mu_{A \cap B}(u) = \min(\mu_A(u), \mu_B(u))$

Fuzzy Set Model (cont.)

- Fuzzy information retrieval

Defining term relationship

- Fuzzy sets are modeled based on a **thesaurus**
- This thesaurus can be constructed by a **term-term correlation matrix** (or called keyword connection matrix)

- \vec{c} : a term-term correlation matrix
- $C_{i,l}$: a normalized correlation factor for terms k_i and k_l

$$C_{i,l} = \frac{n_{i,l}}{n_i + n_l - n_{i,l}}$$

| |
|--|
| n_i : no of docs that contain k_i |
| $n_{i,l}$: no of docs that contain both k_i and k_l |

ranged from 0 to 1

docs, paragraphs, sentences, ..

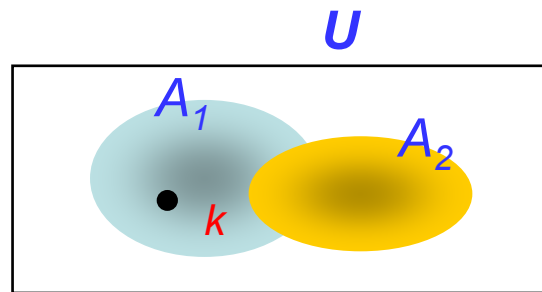
- We now have the notion of proximity among index terms

- The relationship is symmetric !

$$\mu_{k_i}(k_l) = c_{i,l} = c_{l,i} = \mu_{k_l}(k_i)$$

Fuzzy Set Model (cont.)

- The **union** and **intersection** operations are modified here



$$\begin{aligned}
 & ab + \bar{a}b + a\bar{b} \\
 &= ab + (1-a)b + a(1-b) \\
 &= ab + b - ab + a - ab \\
 &= 1 - (1-a-b+ab) \\
 &= 1 - (1-a)(1-b)
 \end{aligned}$$

- **Union**: algebraic sum (instead of max)

$$\begin{aligned}
 \mu_{A_1 \cup A_2}(k) &= \mu_{A_1}(k)\mu_{A_2}(k) + \mu_{\bar{A}_1}(k)\mu_{A_2}(k) + \mu_{A_1}(k)\mu_{\bar{A}_2}(k) \\
 &= 1 - \prod_{j=1}^2 (1 - \mu_{A_j}(k)) \quad \text{a negative algebraic product}
 \end{aligned}
 \Rightarrow
 \begin{aligned}
 \mu_{A_1 \cup A_2 \dots \cup A_n}(k) &= \mu_{\cup_j A_j}(k) \\
 &= 1 - \prod_{j=1}^n (1 - \mu_{A_j}(k))
 \end{aligned}$$

- **Intersection**: algebraic product (instead of min)

$$\mu_{A_1 \cap A_2}(k) = \mu_{A_1}(k)\mu_{A_2}(k) \Rightarrow \mu_{A_1 \cap A_2 \dots \cap A_n}(k) = \prod_{j=1}^n \mu_{A_j}(k)$$

Fuzzy Set Model (cont.)

- The degree of membership between a doc d_j and an index term k_i algebraic sum (a doc is a union of index terms)

$$\mu_{k_i}(d_j) = \mu_{d_j}(k_i) = \mu_{\cup_{k_l \in d_j} k_l}(k_i)$$

$$= 1 - \prod_{k_l \in d_j} (1 - \mu_{k_l}(k_i)) = 1 - \prod_{k_l \in d_j} (1 - c_{i,l})$$

| | | |
|-------|---------------|---------------|
| | k_a | k_b |
| k_i | $c_{i,a}$ | $c_{i,b}$ |
| | $1 - c_{i,a}$ | $1 - c_{i,b}$ |

- Computes an **algebraic sum** over all terms in the doc d_j
 - Implemented as the complement of a negative algebraic product
 - A doc d_j belongs to the fuzzy set associated to the term k_i if its own terms are related to k_i
- If there is at least one index term k_l of d_j which is strongly related to the index k_i ($c_{i,l} \sim 1$) then $\mu_{k_i,d_j} \sim 1$
 - k_i is a good fuzzy index for doc d_j
 - And vice versa

Fuzzy Set Model (cont.)

- Example:

- Query $q = k_a \wedge (k_b \vee \neg k_c)$

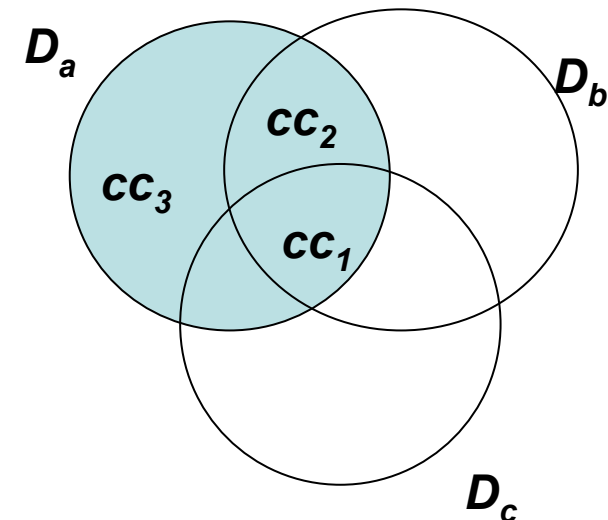
disjunctive normal form

$$\vec{q}_{dnf} = (k_a \wedge k_b \wedge k_c) \vee (k_a \wedge k_b \wedge \neg k_c) \vee (k_a \wedge \neg k_b \wedge \neg k_c)$$

$$= CC_1 + CC_2 + CC_3 \leftarrow \text{conjunctive component}$$

- D_a is the fuzzy set of docs associated to the term k_a

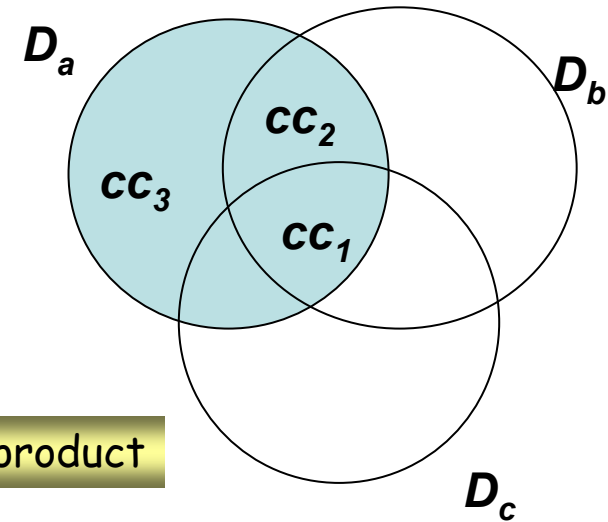
- Degree of membership ?



Fuzzy Set Model (cont.)

- Degree of membership

algebraic sum



$$\mu_q(d_j) = \mu_{CC_1 \cup CC_2 \cup CC_3}(d_j)$$

for a doc d_j in
the fuzzy answer
set D_q

negative algebraic product

$$= 1 - \prod_{i=1}^3 (1 - \mu_{CC_i}(d_j))$$

$$= 1 - (1 - \mu_{a \cap b \cap c}(d_j)) (1 - \mu_{a \cap b \cap \bar{c}}(d_j)) (1 - \mu_{a \cap \bar{b} \cap \bar{c}}(d_j))$$

algebraic product

$$= 1 - (1 - \mu_a(d_j) \mu_b(d_j) \mu_c(d_j))$$

$$\times (1 - \mu_a(d_j) \mu_b(d_j) (1 - \mu_c(d_j))) \times (1 - \mu_a(d_j) (1 - \mu_b(d_j)) (1 - \mu_c(d_j)))$$

Fuzzy Set Model (cont.)

- Advantages
 - The correlations among index terms are considered
 - Degree of relevance between queries and docs can be achieved
- Disadvantages
 - Fuzzy IR models have been discussed mainly in the literature associated with fuzzy theory
 - Experiments with standard test collections are not available

Extended Boolean Model

Salton et al., 1983

- Motive

- Extend the Boolean model with the functionality of partial matching and term weighting

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- E.g.: in Boolean model, for the query $q=k_x \wedge k_y$, a doc contains either k_x or k_y is as irrelevant as another doc which contains neither of them

- How about the disjunctive query $q=k_x \vee k_y$

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- Combine Boolean query formulations with characteristics of the vector model

- Term weighting

- Algebraic distances for similarity measures

} a ranking can be obtained

Extended Boolean Model (cont.)

- Term weighting

- The weight for the term k_x in a doc d_j is

$$w_{x,j} = \underset{\substack{\text{normalized frequency} \\ \nearrow}}{tf_{x,j}} \times \frac{\overset{\text{ranged from 0 to 1}}{idf_x}}{\underset{\text{Normalized idf}}{\max_i idf_i}}$$

- $w_{x,j}$ is normalized to lay between 0 and 1

- Assume two index terms k_x and k_y were used

- Let x denote the weight $w_{x,j}$ of term k_x on doc d_j

- Let y denote the weight $w_{y,j}$ of term k_y on doc d_j

- The doc vector $\vec{d}_j = (w_{x,j}, w_{y,j})$ is represented as $d_j = (x, y)$

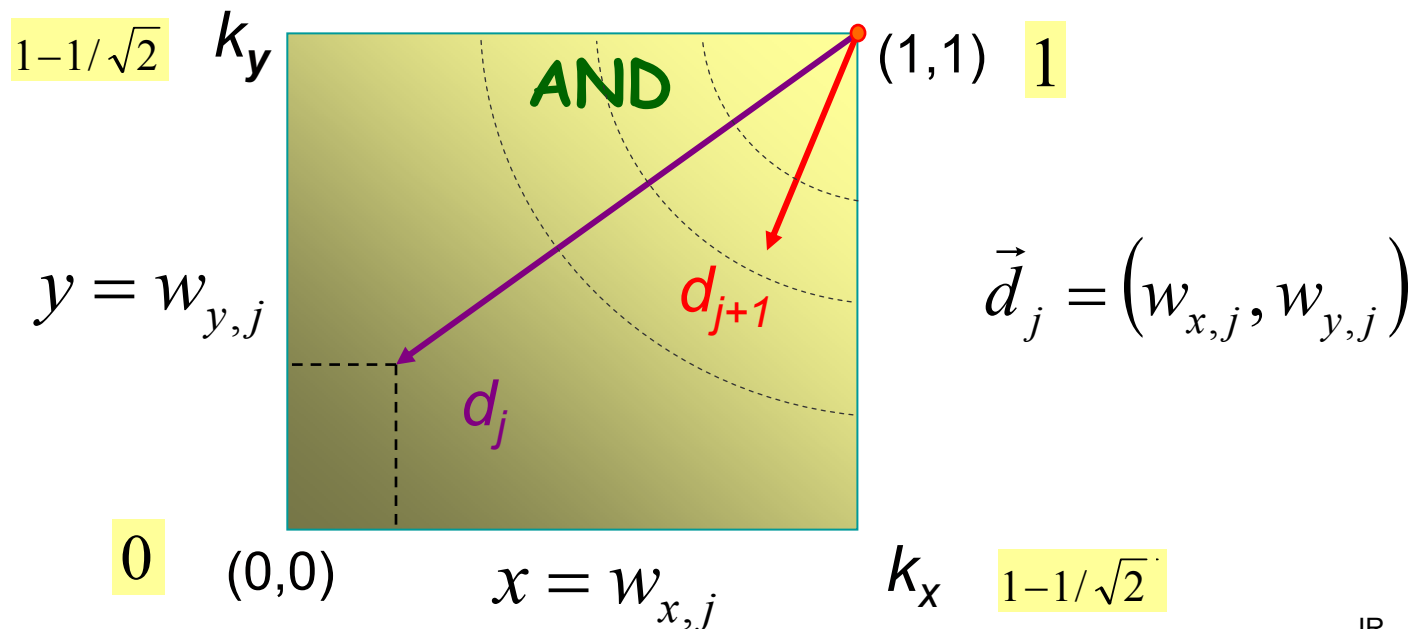
- Queries and docs can be plotted in a two-dimensional map

Extended Boolean Model (cont.)

- If the query is $q = k_x \wedge k_y$ (conjunctive query)
 - The docs near the point (1,1) are preferred
 - The similarity measure is defined as

$$\text{sim}(q_{\text{and}}, d) = 1 - \sqrt{\frac{(1-x)^2 + (1-y)^2}{2}}$$

2-norm model
(Euclidean distance)

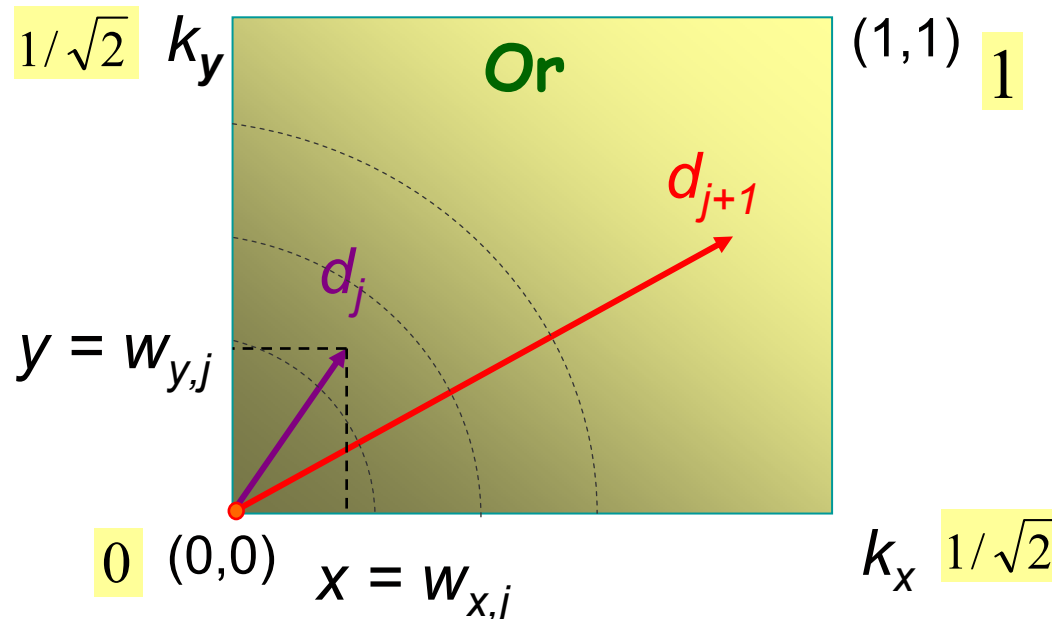


Extended Boolean Model (cont.)

- If the query is $q = k_x \vee k_y$ (disjunctive query)
 - The docs far from the point (0,0) are preferred
 - The similarity measure is defined as

$$\text{sim}(q_{or}, d) = \sqrt{\frac{x^2 + y^2}{2}}$$

2-norm model
(Euclidean distance)



Extended Boolean Model (cont.)

- The similarity measures $\text{sim}(q_{or}, d)$ and $\text{sim}(q_{and}, d)$ also lay between 0 and 1

Extended Boolean Model (cont.)

- Generalization

- t index terms are used \rightarrow t -dimensional space

- p -norm model, $1 \leq p \leq \infty$

$$q_{and} = k_1 \wedge^p k_2 \wedge^p \dots \wedge^p k_m \quad \Rightarrow \quad sim(q_{and}, d) = 1 - \left(\frac{(1-x_1)^p + (1-x_2)^p + \dots + (1-x_m)^p}{m} \right)^{\frac{1}{p}}$$

$$q_{or} = k_1 \vee^p k_2 \vee^p \dots \vee^p k_m \quad \Rightarrow \quad sim(q_{or}, d) = \left(\frac{x_1^p + x_2^p + \dots + x_m^p}{m} \right)^{\frac{1}{p}}$$

- Some interesting properties

- $p=1 \Rightarrow sim(q_{and}, d) = sim(q_{or}, d) = \frac{x_1 + x_2 + \dots + x_m}{m}$

- $p=\infty \Rightarrow sim(q_{and}, d) \approx \min(x_i)$

- $sim(q_{or}, d) \approx \max(x_i)$

just like the
formula of fuzzy logic

Extended Boolean Model (cont.)

- Example query 1: $q = (k_1 \wedge^p k_2) \vee^p k_3$
 - Processed by grouping the operators in a predefined order

$$sim(q, d) = \left(\frac{\left(1 - \left(\frac{(1 - x_1)^p + (1 - x_2)^p}{2} \right)^{\frac{1}{p}} \right)^p + x_3^p}{2} \right)^{\frac{1}{p}}$$

- Example query 2: $q = (k_1 \vee^2 k_2) \wedge^\infty k_3$
 - Combination of different algebraic distances

$$sim(q, d) = \min \left(\left(\frac{x_1^2 + x_2^2}{2} \right)^{\frac{1}{2}}, x_3 \right)$$

Extended Boolean Model (cont.)

- Advantages

- A hybrid model including properties of both the set theoretic models and the algebraic models

- Relax the Boolean algebra by interpreting Boolean operations in terms of algebraic distances

- Disadvantages

- Distributive operation does not hold for ranking computation

- E.g.: $q_1 = (k_1 \wedge^2 k_2) \vee^2 k_3, q_2 = (k_1 \vee^2 k_3) \wedge^2 (k_2 \vee^2 k_3)$

$$\left(\frac{\left(1 - \left(\frac{(1-x_1)^2 + (1-x_2)^2}{2} \right)^{\frac{1}{2}} \right)^2 + x_3^2}{2} \right)^{\frac{1}{2}}$$

$$\text{sim} (q_1, d) \neq \text{sim} (q_2, d)$$

$$1 - \left(\frac{\left(1 - \left(\frac{x_1^2 + x_2^2}{2} \right) \right)^2 + \left(1 - \left(\frac{x_2^2 + x_3^2}{2} \right) \right)^2}{2} \right)^{\frac{1}{2}}$$

- Assumes mutual independence of index terms

Generalized Vector Model

Wong et al., 1985

- Premise
 - Classic models enforce independence of index terms
 - For the **Vector model**
 - Set of term vectors $\{\vec{k}_1, \vec{k}_1, \dots, \vec{k}_t\}$ are linearly independent and form a basis for the subspace of interest
 - Frequently, it means pairwise orthogonality
 $\forall i, j \Rightarrow \vec{k}_i \bullet \vec{k}_j = \vec{0}$ (in a more restrictive sense)
- Wong et al. proposed an interpretation
 - The index term vectors are linearly independent, but not pairwise orthogonal
 - Generalized Vector Model

Generalized Vector Model (cont.)

- **Key idea**

- Index term vectors form the basis of the space are not orthogonal and are represented in terms of smaller components (**minterms**)

- **Notations**

- $\{k_1, k_2, \dots, k_t\}$: the set of all terms
- $w_{i,j}$: the weight associated with $[k_i, d_j]$
- **Minterms**: binary indicators (0 or 1) of all patterns of occurrence of terms within documents
 - Each represent one kind of co-occurrence of index terms in a specific document

Generalized Vector Model (cont.)

- Representations of **minterms**

$$m_1=(0,0,\dots,0)$$

$$m_2=(1,0,\dots,0)$$

$$m_3=(0,1,\dots,0)$$

$$m_4=(1,1,\dots,0)$$

$$m_5=(0,0,1,\dots,0)$$

...

$$m_{2^t}=(1,1,1,\dots,1)$$

2^t minterms

Points to the docs where only index terms k_1 and k_2 co-occur and the other index terms disappear

Point to the docs containing all the index terms



$$\vec{m}_1=(1,0,0,0,0,\dots,0)$$

$$\vec{m}_2=(0,1,0,0,0,\dots,0)$$

$$\vec{m}_3=(0,0,1,0,0,\dots,0)$$

$$\vec{m}_4=(0,0,0,1,0,\dots,0)$$

$$\vec{m}_5=(0,0,0,0,1,\dots,0)$$

...

$$\vec{m}_{2^t}=(0,0,0,0,0,\dots,1)$$

2^t minterm vectors

Pairwise orthogonal vectors \vec{m}_i associated with minterms m_i as the **basis** for the **generalized vector space**

Generalized Vector Model (cont.)

- Minterm vectors are pairwise orthogonal. But, this does not mean that the index terms are independent
 - Each minterm specifies a kind of dependence among index terms
 - That is, the co-occurrence of index terms inside docs in the collection induces dependencies among these index terms

Generalized Vector Model (cont.)

- The vector associated with the term k_i is represented by **summing** up all minterms containing it and **normalizing**

$$\vec{k}_i = \frac{\sum_{\forall r, g_i(m_r)=1} c_{i,r} \vec{m}_r}{\sqrt{\sum_{\forall r, g_i(m_r)=1} c_{i,r}^2}} = \sum_{\forall r, g_i(m_r)=1} \hat{c}_{i,r} \vec{m}_r$$

where $\hat{c}_{i,r} = \frac{c_{i,r}}{\sqrt{\sum_{\forall r, g_i(m_r)=1} c_{i,r}^2}}$

$$c_{i,r} = \sum_{d_j | g_l(\vec{d}_j) = g_l(m_r), \text{ for all } l} w_{i,j}$$

- The weight associated with the pair $[k_i, m_r]$ sums up the weights of the term k_i in all the docs which have a term occurrence pattern given by m_r
- Notice that for a collection of size N , only N minterms affect the ranking (and not 2^N)

All the docs whose term co-occurrence relation (pattern) can be represented as (exactly coincide with that of) minterm m_r

$g_i(m_r)$ Indicates the index term k_i is in the minterm m_r

Generalized Vector Model (cont.)

- The similarity between the query and doc is calculated in the space of minterm vectors

$$\vec{d}_j = \sum_i w_{i,j} \vec{k}_i \quad \Rightarrow \quad = \sum_r s_{j,r} \vec{m}_r$$

$$\vec{q}_j = \sum_i w_{i,q} \vec{k}_i \quad \Rightarrow \quad = \sum_r s_{q,r} \vec{m}_r$$

t-dimensional

2^{*t*}-dimensional



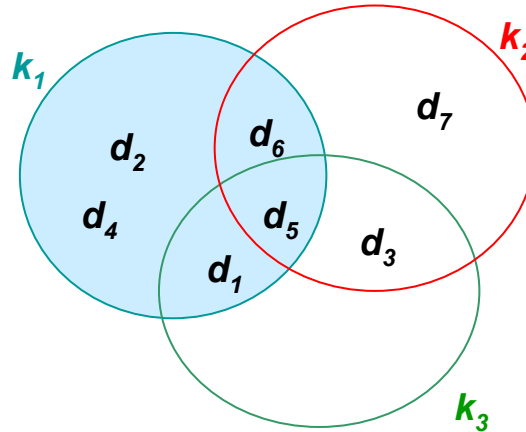
$$\text{sim}(\vec{q}_j, \vec{d}_j) = \frac{\sum_i w_{i,q} \cdot w_{i,j}}{\sqrt{\sum_i w_{i,q}} \sqrt{\sum_i w_{i,j}}}$$

$$\text{sim}(\vec{q}_j, \vec{d}_j) = \frac{\sum_r s_{q,r} \cdot s_{d,r}}{\sqrt{\sum_r s_{q,r}} \sqrt{\sum_r s_{d,r}}}$$

Generalized Vector Model (cont.)

- Example** (a system with three index terms)

| minterm | k_1 | k_2 | k_3 |
|---------|-------|-------|-------|
| m_1 | 0 | 0 | 0 |
| m_2 | 1 | 0 | 0 |
| m_3 | 0 | 1 | 0 |
| m_4 | 1 | 1 | 0 |
| m_5 | 0 | 0 | 1 |
| m_6 | 1 | 0 | 1 |
| m_7 | 0 | 1 | 1 |
| m_8 | 1 | 1 | 1 |



$$\vec{k}_1 = \frac{c_{1,2}\vec{m}_2 + c_{1,4}\vec{m}_4 + c_{1,6}\vec{m}_6 + c_{1,8}\vec{m}_8}{\sqrt{c_{1,2}^2 + c_{1,4}^2 + c_{1,6}^2 + c_{1,8}^2}}$$

$$\vec{k}_2 = \frac{c_{2,3}\vec{m}_3 + c_{2,4}\vec{m}_4 + c_{2,7}\vec{m}_7 + c_{2,8}\vec{m}_8}{\sqrt{c_{2,3}^2 + c_{2,4}^2 + c_{2,7}^2 + c_{2,8}^2}}$$

$$\vec{k}_3 = \frac{c_{3,5}\vec{m}_5 + c_{3,6}\vec{m}_6 + c_{3,7}\vec{m}_7 + c_{3,8}\vec{m}_8}{\sqrt{c_{3,5}^2 + c_{3,6}^2 + c_{3,7}^2 + c_{3,8}^2}}$$

| | k_1 | k_2 | k_3 | minterm |
|-------|-------|-------|-------|---------|
| d_1 | 2 | 0 | 1 | m_6 |
| d_2 | 1 | 0 | 0 | m_2 |
| d_3 | 0 | 1 | 3 | m_7 |
| d_4 | 2 | 0 | 0 | m_2 |
| d_5 | 1 | 2 | 4 | m_8 |
| d_6 | 1 | 2 | 0 | m_4 |
| d_7 | 0 | 5 | 0 | m_3 |
| q | 1 | 2 | 3 | |

$$c_{1,2} = w_{1,2} + w_{1,4} = 1 + 2 = 3 \quad \vec{k}_1 = \frac{3\vec{m}_2 + 1\vec{m}_4 + 2\vec{m}_6 + 1\vec{m}_8}{\sqrt{3^2 + 1^2 + 2^2 + 1^2}}$$

$$c_{1,4} = w_{1,6} = 1$$

$$c_{1,6} = w_{1,1} = 2$$

$$c_{1,8} = w_{1,5} = 1$$

$$c_{3,5} = 0$$

$$c_{3,6} = w_{3,1} = 1$$

$$c_{3,7} = w_{3,3} = 3$$

$$c_{3,8} = w_{3,5} = 4$$

$$c_{2,3} = w_{2,7} = 5$$

$$c_{2,4} = w_{2,6} = 2$$

$$c_{2,7} = w_{2,3} = 1$$

$$c_{2,8} = w_{2,5} = 2$$

$$\vec{k}_2 = \frac{5\vec{m}_3 + 2\vec{m}_4 + 1\vec{m}_7 + 2\vec{m}_8}{\sqrt{5^2 + 2^2 + 1^2 + 2^2}}$$

$$\vec{k}_3 = \frac{0\vec{m}_5 + 1\vec{m}_6 + 3\vec{m}_7 + 4\vec{m}_8}{\sqrt{0^2 + 1^2 + 3^2 + 4^2}}$$

Generalized Vector Model (cont.)

- Example: Ranking**

$$\vec{k}_1 = \frac{3\vec{m}_2 + 1\vec{m}_4 + 2\vec{m}_6 + 1\vec{m}_8}{\sqrt{3^2 + 1^2 + 2^2 + 1^2}} = \frac{3\vec{m}_2 + 1\vec{m}_4 + 2\vec{m}_6 + 1\vec{m}_8}{\sqrt{15}}$$

$$\vec{k}_2 = \frac{5\vec{m}_3 + 2\vec{m}_4 + 1\vec{m}_7 + 2\vec{m}_8}{\sqrt{5^2 + 2^2 + 1^2 + 2^2}} = \frac{5\vec{m}_3 + 2\vec{m}_4 + 1\vec{m}_7 + 2\vec{m}_8}{\sqrt{34}}$$

$$\vec{k}_3 = \frac{0\vec{m}_5 + 1\vec{m}_6 + 3\vec{m}_7 + 4\vec{m}_8}{\sqrt{0^2 + 1^2 + 3^2 + 4^2}} = \frac{1\vec{m}_6 + 3\vec{m}_7 + 4\vec{m}_8}{\sqrt{26}}$$

$$\vec{d}_1 = 2\vec{k}_1 + 1\vec{k}_3$$

$$= \frac{2 \cdot 3}{\sqrt{15}} \overset{S_{d1,2}}{\vec{m}_2} + \frac{2 \cdot 1}{\sqrt{15}} \overset{S_{d1,4}}{\vec{m}_4} + \left(\frac{2 \cdot 2}{\sqrt{15}} + \frac{1 \cdot 1}{\sqrt{26}} \right) \overset{S_{d1,6}}{\vec{m}_6} + \frac{1 \cdot 3}{\sqrt{26}} \overset{S_{d1,7}}{\vec{m}_7} + \left(\frac{2 \cdot 1}{\sqrt{15}} + \frac{1 \cdot 4}{\sqrt{26}} \right) \overset{S_{d1,8}}{\vec{m}_8}$$

$$\vec{q} = 1\vec{k}_1 + 2\vec{k}_2 + 3\vec{k}_3$$

$$= \frac{1 \cdot 3}{\sqrt{15}} \overset{S_{q,2}}{\vec{m}_2} + \frac{2 \cdot 5}{\sqrt{34}} \overset{S_{q,3}}{\vec{m}_3} + \left(\frac{1 \cdot 1}{\sqrt{15}} + \frac{2 \cdot 2}{\sqrt{34}} \right) \overset{S_{q,4}}{\vec{m}_4} + \left(\frac{1 \cdot 2}{\sqrt{15}} + \frac{3 \cdot 1}{\sqrt{26}} \right) \overset{S_{q,6}}{\vec{m}_6} + \left(\frac{2 \cdot 1}{\sqrt{34}} + \frac{3 \cdot 3}{\sqrt{26}} \right) \overset{S_{q,7}}{\vec{m}_7} + \left(\frac{1 \cdot 1}{\sqrt{15}} + \frac{2 \cdot 2}{\sqrt{34}} + \frac{3 \cdot 4}{\sqrt{26}} \right) \overset{S_{q,8}}{\vec{m}_8}$$

$$sim(q, d) = \text{consine}(q, d) = \frac{\sum_{r | S_{q,r} \neq 0 \wedge S_{d,r} \neq 0} S_{q,r} \cdot S_{d,r}}{\sqrt{\sum_{r | S_{q,r} \neq 0 \wedge S_{d,r} \neq 0} S_{q,r}^2} \sqrt{\sum_{r | S_{q,r} \neq 0 \wedge S_{d,r} \neq 0} S_{d,r}^2}}$$

The similarity between the query and doc is calculated in the space of minterm vectors

$$sim(q, d_1) = \frac{S_{q,2}S_{d1,2} + S_{q,4}S_{d1,4} + S_{q,6}S_{d1,6} + S_{q,7}S_{d1,7} + S_{q,8}S_{d1,8}}{\sqrt{S_{q,2}^2 + S_{q,3}^2 + S_{q,4}^2 + S_{q,6}^2 + S_{q,7}^2 + S_{q,8}^2} \sqrt{S_{d1,2}^2 + S_{d1,4}^2 + S_{d1,6}^2 + S_{d1,7}^2 + S_{d1,8}^2}}$$

Generalized Vector Model (cont.)

- Term Correlation

- The degree of correlation between the terms k_i and k_j can now be computed as

$$\vec{k}_i \bullet \vec{k}_j = \sum_{\forall r | g_i(m_r)=1 \wedge g_j(m_r)=1} \hat{c}_{i,r} \times \hat{c}_{j,r}$$

- Do not need to be normalized? (because we have done it before! See p25)

Generalized Vector Model (cont.)

- Advantages
 - Model considers correlations among index terms
 - Model does introduce interesting new ideas
- Disadvantages
 - Not clear in which situations it is superior to the standard vector model
 - Computation costs are higher