Lecture 4:
Retrieval Models

01204453 Web Information Retrieval and Mining

Department of Computer Engineering
Faculty of Engineering, Kasetsart University
Bangkok, Thailand.

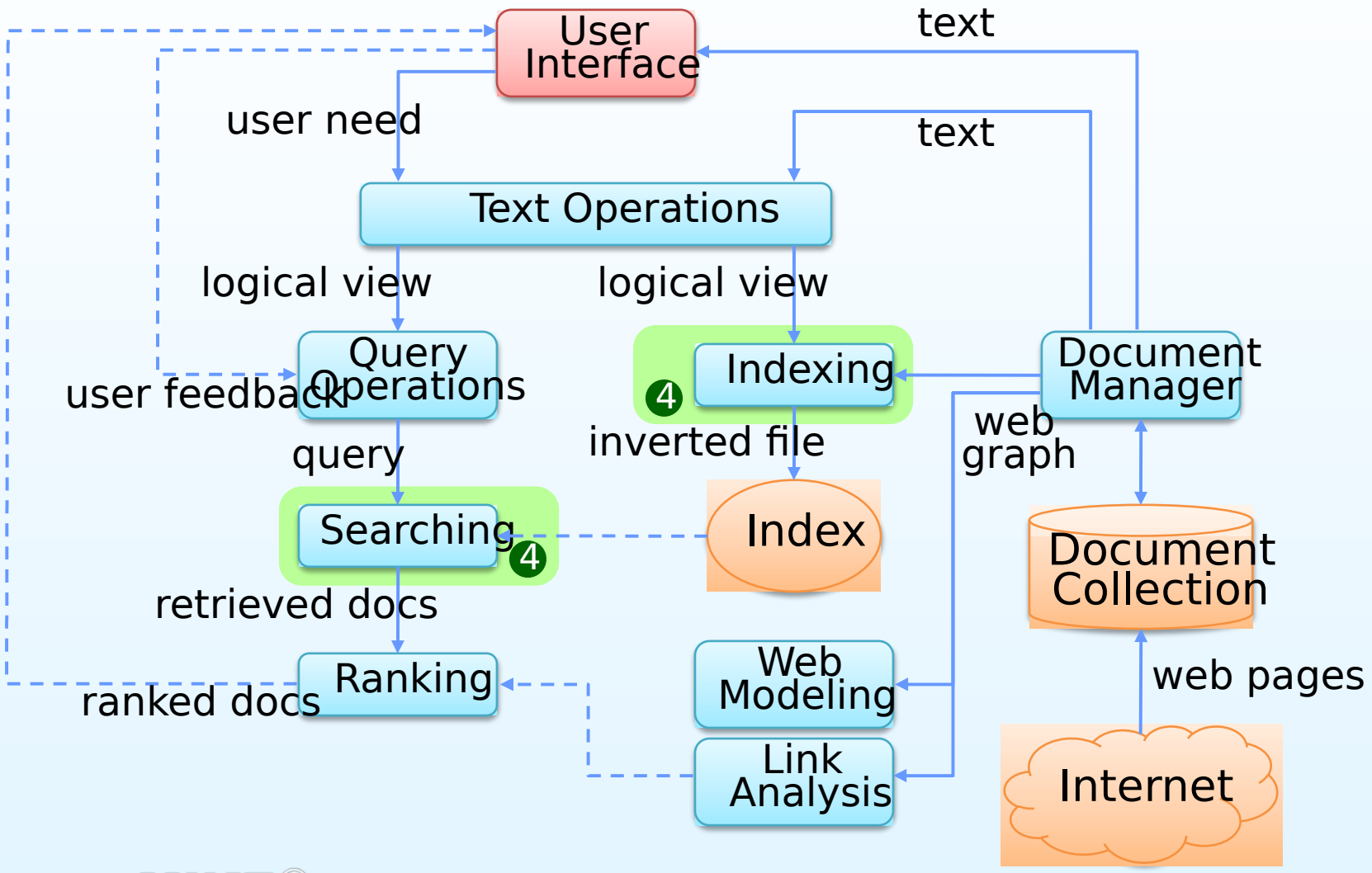
Department of Computer Engineering
Computer Engineering
Kasetsart University

MIKE LABORATORY

Outline

- Introduction to IR Models
- Basic Concepts
- Classical IR Models
  - Boolean Model
  - Vector Model
  - Probabilistic Model

Review: Search Engine Architecture



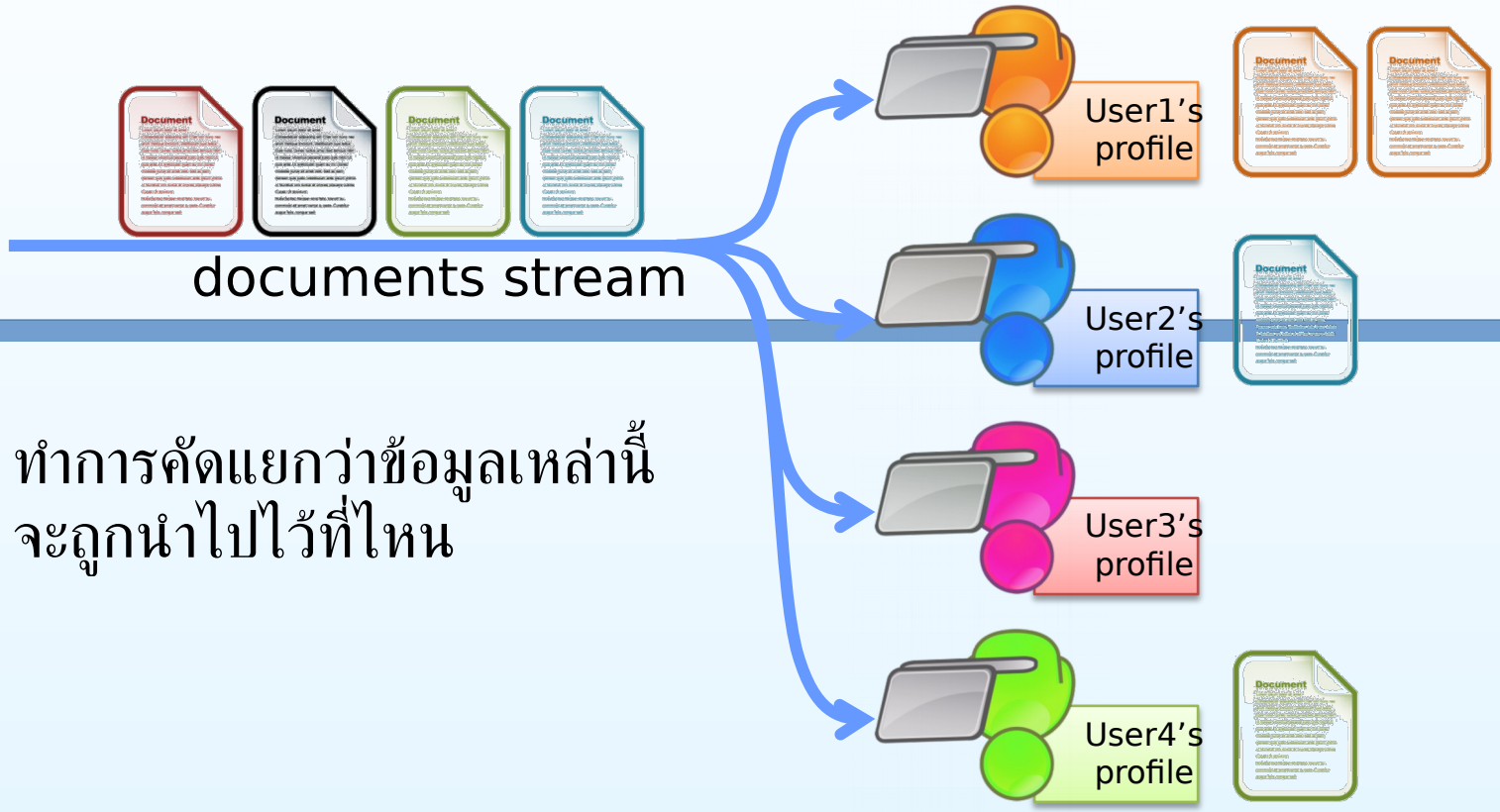
Retrieval: Ad Hoc VS. Filtering

- Ad hoc retrieval

Ad hoc คือเกิดขึ้นมา ณ ตอนนั้นใช้เสร็จก็หายไป

Retrieval: Ad Hoc VS. Filtering

- Filtering



ทำการคัดแยกว่าข้อมูลเหล่านี้จะถูกนำไปไว้ที่ไหน

IR Models

- What is a model?
  - A representation of a system that allows for investigation of t properties of the system.

เป็ยตัวแทนของระบบแทนที่จะไปศึกษาระบบโดยตรงให้ได้มา ซึ่งคุณสมบัติอะไรบางอย่าง

- 2 main components of modeling in IR:
  - A logical framework for representing documents and queries
  - A ranking function for quantifying similarities among documer and queries

องค์ประกอบหลักมี2อย่าง
Logical คือตัวแทนเอกสาร Rankingคือการจัดเรียงลำดับผลลัพธ์

- What is representative in indexing documents?
  - Assumption: the semantics of the documents and of the user information need can be naturally expressed through sets of index terms.

คำที่ปรากฏในตัวDocนั้นๆจะเป็นตัวแทนในDocนั้นๆจะต้องเป็นคำที่สื่อไปในความหมายที่เขาต้องการ **เป็นตัวแทนของ Docนั้นๆ เป็น index terms.**

Index Terms นำมาใช้ในการทำดรรชนี

- Adopt to index and retrieve documents

  เลือกคำนามเป็น index terms.
- Usually play the role of noun—meaning on its own

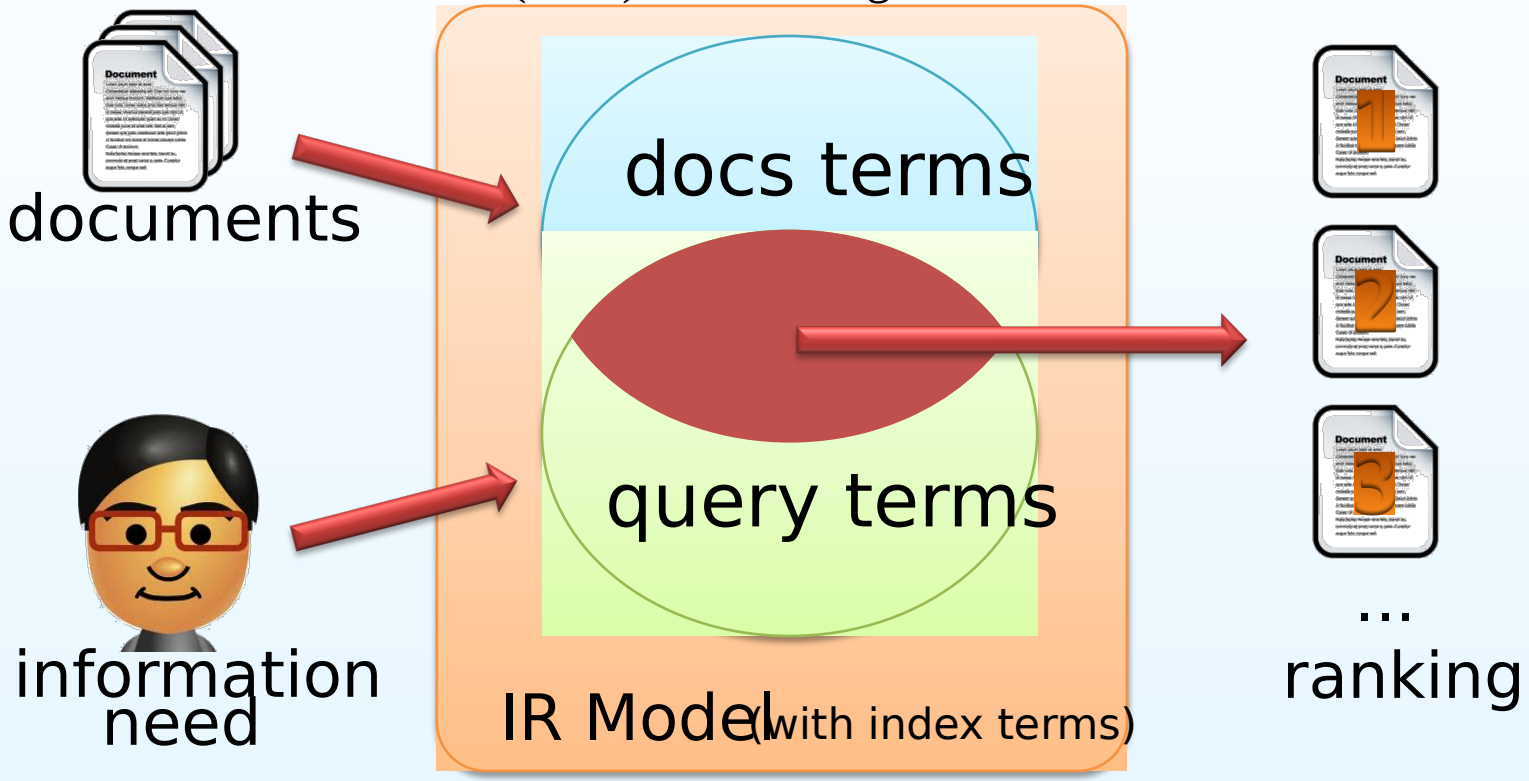
  เลือกคำที่อยู่ในDoc
- Appear in a document of a collection

- Also, simply refer to in a query

นำคำมาใช้ใน
การSearchในฐานข้อมูล
ในการทำ ดรรชนี

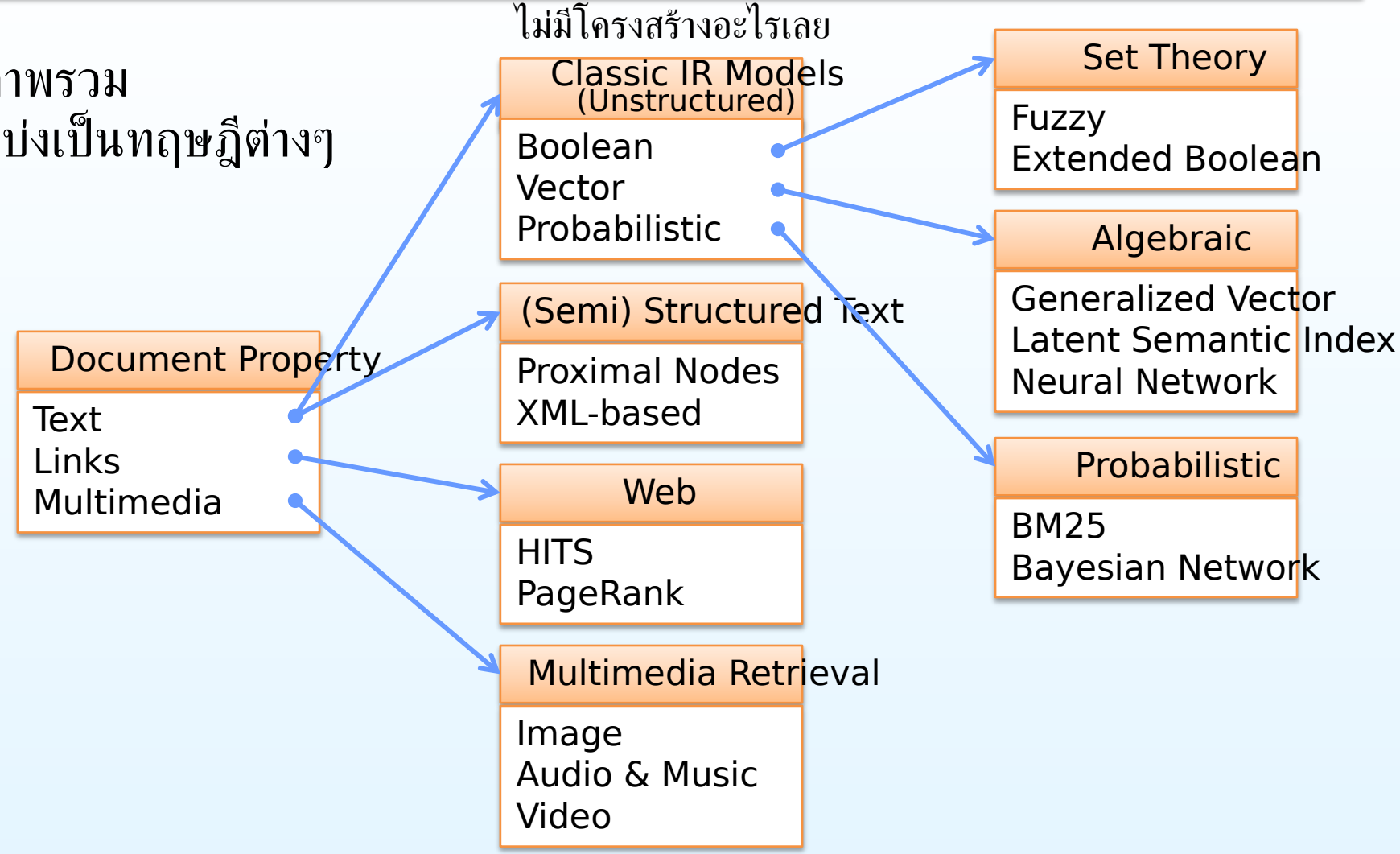
IR Process

Docเอามาทำเป็น docs term
User เรียกหาinformationจึงเอามาใช้เป็น query terms แล้วเลือกคำซ้ำที่เหมือนกัน(สีแดง)มาทำ ranking



A Taxonomy of IR Models

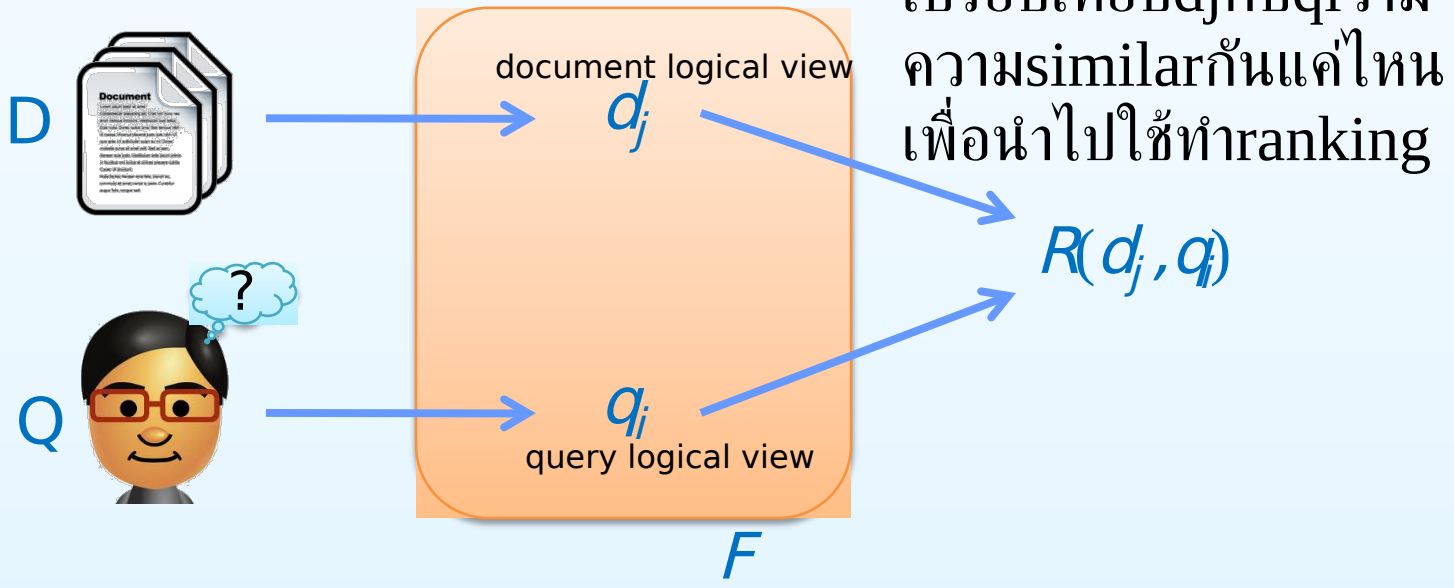
ภาพรวม
แบ่งเป็นทฤษฎีต่างๆ



Formal Characterization of IR Models

An IR model is a quadruple [D, Q, F, $R(d_j, q_i)$] where

- D is a set of logical views for the documents in the collection.
- Q is a set of logical views for the user queries.
- F is a framework for modeling documents and queries.
- $R(d_j, q_i)$ is a ranking function.



Basic Concepts: Logical Views

- Each document is represented by a set of representati index terms (or keywords).

Index terms อาจเป็นคำๆ เดียวหรือกลุ่มคำก็ได้I

- An index term is a word or group of consecutive words in a document.

- It might assume that all word are index terms (full tex representation).

Basic Concepts

- Let
  - t be the number of distinct index terms in the document collection.
  - k_i be a generic index term.

- Then,
  - the vocabulary $V = \{k_1, k_2, ..., k_t\}$ is the set of all distinct index terms in the collection.

vocab=set index termที่เป็นไปได้

Basic Concepts

สำหรับDocหนึ่งๆมีเทอมไรบ้างที่ปรากฏอยู่แล้วเอามาทำกดรรชนีเรียก term co-occurrences

- Documents and queries can be represented by patterns of term co-occurrences.
- Each of these patterns of term co-occurrence is called a term conjunctive component.
- For each document d_j (or query q), we associate a unique term conjunctive component $c(d_j)$ (or $c(q)$).
- Example:

$V =$ | k_1 | k_2 | k_3 | … | k_t |

Term ที่ปรากฏอยู่ก็คือ term conjunctive component

$c(d_j) =$ | 1 | 1 | 0 | … | 1 |

$c(q) =$ | 0 | 1 | 0 | … | 0 |

c(dj) term conjunctive component เทียบการปรากฏในDocของCo-ocเทียบVocabเจอคือ1ไม่ปรากฏอยู่คือ0

Term Conjunctive Component: Exampl

		term co-occurrences	term conjunctive component
			$V = ($ A, B, C, D, E
d_1	A B D	A, B, D	$c(d_1) = (1, 1, 0, 1, 0)$
d_2	E C A	A, C, E	$c(d_2) = (1, 0, 1, 0, 1)$
q	C D B	B, C, D	$c(q) = (0, 1, 1, 1, 0)$

The Term-Document Matrix

- The occurrence of a term k_i in a document d_j establishes a relation between k_i and d_j.
- A term-document relation between k_i and d_j can be quantified by the frequency of them in the document.
- In a matrix form, this can written as:

$$
\begin{array}{c} \\ k_1 \\ k_2 \\ \ldots \\ k_t \end{array}
\begin{array}{c}
\begin{array}{cccc} d_1 & d_2 & \ldots & d_N \end{array} \\
\begin{bmatrix}
freq_{1,1} & freq_{1,2} & \ldots & freq_{1,N} \\
freq_{2,1} & freq_{2,2} & \ldots & freq_{2,N} \\
 & & & \\
freq_{t,1} & freq_{t,2} & \ldots & freq_{t,N}
\end{bmatrix}
\end{array}
$$

where each $freq_{i,j}$ element stands for the frequency of term k_i in document d_j.

Boolean Model

Boolean Model

- Simple model based on set theory and boolean algebr
- Queries specified as boolean expressions
  - Intuitive and precise semantics
  - Example: $q = k_a \wedge (k_b \quad k_c)$
- Frequencies in the term-document matrix are all binar
  - $w_{i,j} \in \{0,1\}$: weight associated with pair (k_i, d_j)
  - $w_{i,q} \in \{0,1\}$: weight associated with pair (k_i, q)

Boolean Model

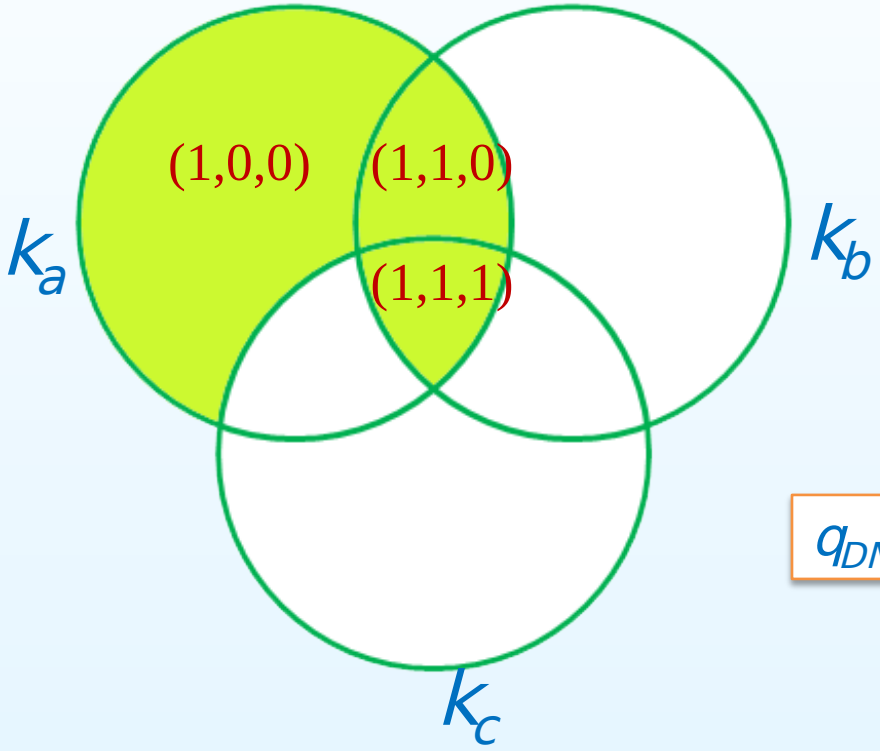
- A term conjunctive component that satisfies a query q is called a query conjunctive component c ($c \in q$).
- A query q rewritten as a disjunction of those components is called the disjunctive normal form q_{DNF}.

- Let
  - the vocabulary $= V\{k_a, k_b, k_c\}$
  - a query $q = k_a \wedge (k_b \vee \neg k_c)$
- So that there are 3 query conjunctive components:
  - $(1,1,1)$, $(1,1,0)$, and $(1,0,0)$
- Then,
  - the disjunctive normal form $q_{DNF} = (1,1,1) \vee (1,1,0) \vee (1,0,0)$

Boolean Model

- The three conjunctive components for the query

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



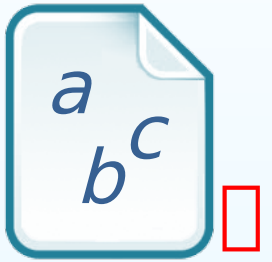
$$q_{DNF} = (1,1,1) \vee (1,1,0) \vee (1,0,0)$$

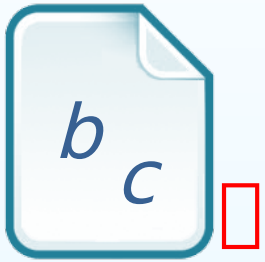
Boolean Model: Examples

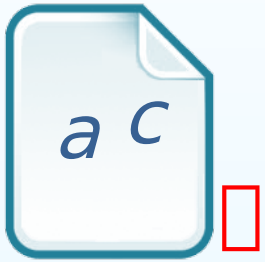
- Which ones are the answers for $q = k_a \wedge (k_b \vee \neg k_c)$?

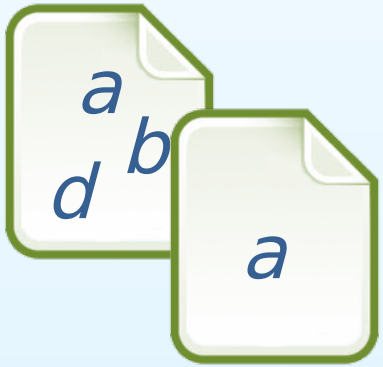
$V = \{k_a, k_b, k_c\}$ → $q_{DNF} = (1,1,1) \vee (1,1,0) \vee (1,0,0)$

เป็นคำตอบมั้ย ตอบเป็นเพราะมันตรงกับ conditionที่1 คือเอาVไป
เทียบกับ qDNF ว่าตรงมั้ย









$V = \{k_a, k_b, k_c, k_d\}$

↓

$q_{DNF} = ?$

Vเปลี่ยนเพราะมีDอยู่ทำให้
ไม่สามารถใช้ร่วมกันได้
qDNFจะต้องเปลี่ยนไป

Boolean Model

- The similarity of the document d_j to the query q is defined as

$$sim(d_j, q) = \begin{cases} 1 & \text{if } \exists c(q) \in q_{DNF} \mid c(d_j) = c(q) \\ 0 & \text{otherwise} \end{cases}$$

- The boolean model predicts that each document is eit relevant or non-relevant (irrelevant).

การทำแบบ booleanตอบได้แค่relevantหรือnon (เกี่ยวข้องหรือไม่เกี่ยงข้อง)

Drawbacks of the Boolean Model

- Information need has to be translated into a boolean expression.

- Retrieval is based on binary decision criteria with no partial matching.

ไม่สามารถบอกได้ถูกกี่%

- No ranking (grading scale) of the documents is provid

Rankไม่ได้เพราะเป็น $1 \| 0$

- The model frequently return either too few or too man documents in response to a user query.

Vector Model

Vector Model

- Boolean matching and binary weights are too limiting.
- The vector model proposes a framework in which part matching is possible.
- This is accomplished by assigning non-binary weights index terms in queries and in documents.
- Term weights are used to compute a degree of similar between a query and each document.
- The documents are ranked in decreasing order of thei degree of similarity.

Vector Model

- For the vector model,
  - The weight $w_{i,j} > 0$ is associated to quantify the importance of the index term k_i in the documents d_j.
    - if k_i does not appear in d_j, then $w_{i,j} = 0$.

termที่ปรากฏอยู่ในdjจะให้ค่าwij>0

  - The index terms are assumed to be all mutually independent.

การเกิดคำๆนี้ไม่เกี่ยวข้องกับคำอื่นๆใดเลย

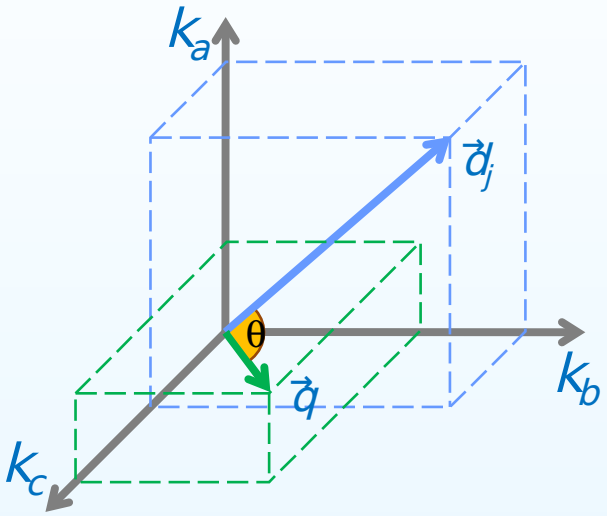
  - They are represented as unit vectors of a t-dimensional space where t is the total number of index terms.
  - The representations of document d_j and query q are given by

$$\vec{d}_j = (w_{1,j}, w_{2,j}, \ldots, w_{t,j})$$

$$\vec{q} = (w_{1,q}, w_{2,q}, \ldots, w_{t,q})$$

Vector Model หลุด

- Similarity between a document d_j and a query q

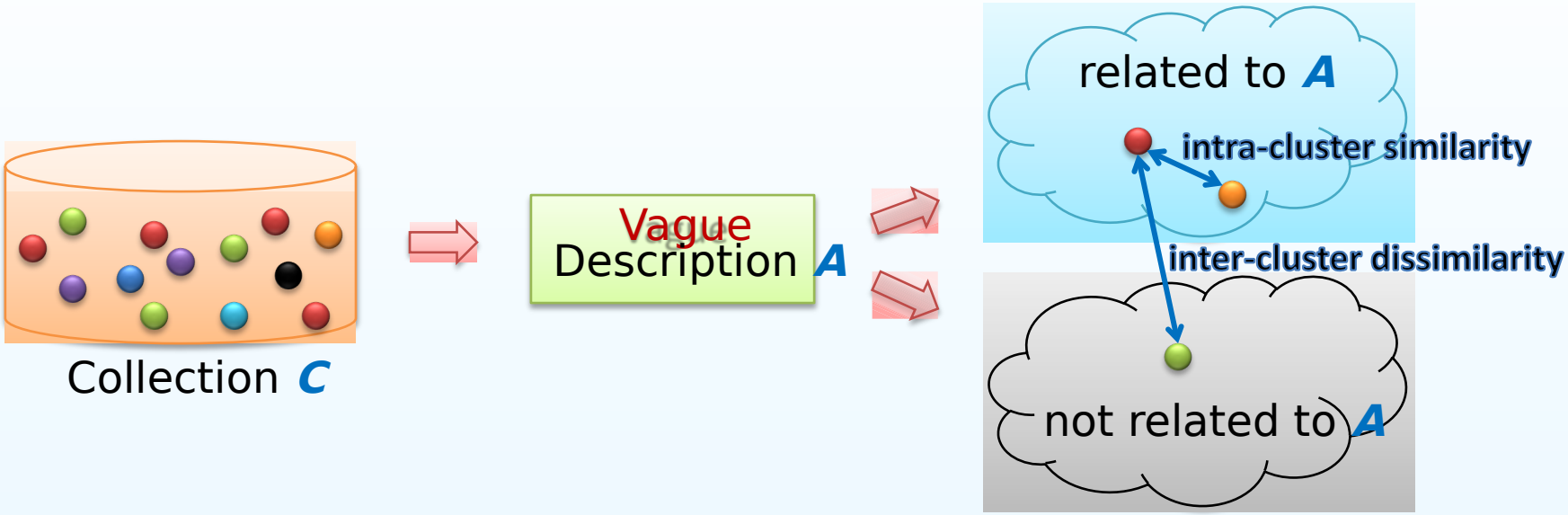


$$\cos(\theta) = \frac{\vec{d}_j \cdot \vec{q}}{|\vec{d}_j| \times |\vec{q}|}$$

$$sim(d_j, q) = \frac{\sum_{i=1}^{t} w_{i,j} \times w_{i,q}}{\sqrt{\sum_{i=1}^{t} w_{i,j}^2} \times \sqrt{\sum_{i=1}^{t} w_{i,q}^2}}$$

Since $w_{i,j} \geq 0$ and $w_{i,q} \geq 0$, we have $0 \leq sim(d_j, q) \leq 1$.

IR Problem as a Clustering



- For the IR,
  - intra-cluster similarity is quantified by term frequency (*tf*)
  - inter-cluster dissimilarity is quantified by inverse document frequenc

The *tf-idf* Weight

- Let
  - N be the total number of documents in the collection.
  - n_i be the number of documents in which the term k_i appears.
  - $freq_{i,j}$ be the raw frequency of term k_i in the document d_j.
- Then,
  - the normalized frequency of k_i in d_j is given by

$$tf_{i,j} = \frac{freq_{i,j}}{\max_l freq_{l,j}}$$

  - the inverse document frequency for k_i is given by

$$idf_i = \log_2 \frac{N}{n_i}$$

The *tf-idf* Weight

- The best known term-weighting schemes are

$$w_{i,j} = tf_{i,j} \times idf_i = \frac{freq_{i,j}}{\max_l freq_{l,j}} \times \log_2 \frac{N}{n_i}$$

- The query term weights

$$w_{i,q} = \left(0.5 + \frac{0.5\ freq_{i,q}}{\max_l freq_{l,q}}\right) \times \log_2 \frac{N}{n_i}$$

Example: The *tf* Weights

$$tf_{i,j} = \frac{freq_{i,j}}{\max_l freq_{l,j}}$$

d_1: To do is to be. To be is to do.

d_2: To be or not to be. I am what I am.

d_3: I think therefore I ar Do be do be do.

d_4: Do do do, da da da Let it be, let it be.

	Vocabulary	$tf_{i,1}$	$tf_{i,2}$	$tf_{i,3}$	$tf_{i,4}$
1	to	1	1	-	-
2	do	0.5	-	1	1
3	is	0.5	-	-	-
4	be	0.5	1	0.667	0.667
5	or	-	0.5	-	-
6	not	-	0.5	-	-
7	I	-	1	0.667	-
8	am	-	1	0.333	-
9	what	-	0.5	-	-
10	think	-	-	0.333	-
11	therefore	-	-	0.333	-
12	da	-	-	-	1
13	let	-	-	-	0.667
14	it	-	-	-	0.667

Example: The *idf* Weights

$$idf_i = \log_2 \frac{N}{n_i}$$

d_1: To do is to be. To be is to do.

d_2: To be or not to be. I am what I am.

d_3: I think therefore I ar Do be do be do.

d_4: Do do do, da da da Let it be, let it be.

	Vocabulary	n_i	*idf*
1	to	2	1
2	do	3	0.415
3	is	1	2
4	be	4	0
5	or	1	2
6	not	1	2
7	I	2	1
8	am	2	1
9	what	1	2
10	think	1	2
11	therefore	1	2
12	da	1	2
13	let	1	2
14	it	1	2

Example: The *tf-idf* Weights

$w_{i,j} = tf_{i,j} \times idf_i$

d_1: To do is to be. To be is to do.

d_2: To be or not to be. I am what I am.

d_3: I think therefore I ar Do be do be do.

d_4: Do do do, da da da Let it be, let it be.

	Vocabulary	$w_{i,1}$	$w_{i,2}$	$w_{i,3}$	$w_{i,4}$
1	to	1	1	-	-
2	do	0.208	-	0.415	0.415
3	is	1	-	-	-
4	be	-	-	-	-
5	or	-	1	-	-
6	not	-	1	-	-
7	I	-	1	0.667	-
8	am	-	1	0.333	-
9	what	-	1	-	-
10	think	-	-	0.667	-
11	therefore	-	-	0.667	-
12	da	-	-	-	2
13	let	-	-	-	1.333
14	it	-	-	-	1.333

Example: The Vector Model

d_1: To do is to be. To be is to do.

d_2: To be or not to be. I am what I am.

d_3: I think therefore I am. Do be do be do.

d_4: Do do do, da da da. Let it be, let it be.

Consider a query "to do":

$q = (1, 0.415, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0)$

Doc.	Computation	Similarity
d_1	$\frac{(1\times1)+(0.208\times0.415)}{\sqrt{1+0.208^2+1}\times\sqrt{1+0.415^2}}$	0.702
d_2	$\frac{(1\times1)+(0\times0.415)}{\sqrt{6}\times\sqrt{1+0.415^2}}$	0.377
d_3	$\frac{(0\times1)+(0.415\times0.415)}{\sqrt{0.415^2+3\cdot0.667^2+0.333^2}\times\sqrt{1+0.415^2}}$	0.125
d_4	$\frac{(0\times1)+(0.415\times0.415)}{\sqrt{0.415^2+2^2+2\cdot1.333^2}\times\sqrt{1+0.415^2}}$	0.057

Document & Query Weighting Scheme

- SMART notation for *tf-idf* variants

Term Frequency		Inverse Document Frequency		Normalization	
n (natural)	$freq_{i,j}$	n (no)	1	n (none)	1
l (logarithm)	$1+\log_2(freq_{i,j})$	t (idf)	$\log_2\left(\frac{N}{n_i}\right)$	c (cosine)	$\frac{1}{\sqrt{\sum_{i=1}^{t} w_i^2}}$
a (augmented)	$0.5+\frac{0.5\times freq_{i,j}}{\max_l freq_{i,j}}$	p (prob. idf)	$\max\left(0,\log_2\left(\frac{N-n_i}{n_i}\right)\right)$	b (byte size)	$\frac{1}{CharLength^{\alpha}}$, $\alpha<1$
b (boolean)	$\begin{cases}1 & \text{if } freq_{i,j}>0\\ 0 & \text{otherwise}\end{cases}$				
L (log avg.)	$\frac{1+\log_2(freq_{i,j})}{1+\log_2(\text{avg}(freq_{i,j}))}$				

Advantage & Disadvantage

- Advantages
  - Term-weighting improves quality of the answer set.
  - Partial matching allows retrieval of documents that approxima the query conditions.
  - Cosine ranking formula sorts documents according to a degre of similarity to the query.
  - Document length normalization is naturally built-in into the ranking.

- Disadvantage
  - The model assumes independence of index terms.

ข้อดี การกำหนดweightให้กับtermจะทำให้ได้ระบบ weight ที่smartและมีค่าsimilarกี่%ทำให้ทำrankได้ด้วย
ข้อเสียคือแต่ละเทอมมันไม่เกี่ยงข้องกันซึ่งตามปกติแล้วไม่จริง เช่นcomputer engineering มักจะมีengตามมาด้วย

Any Question?