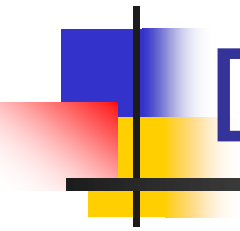
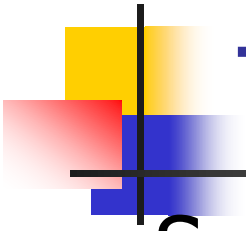


Data Mining
-- Text Mining

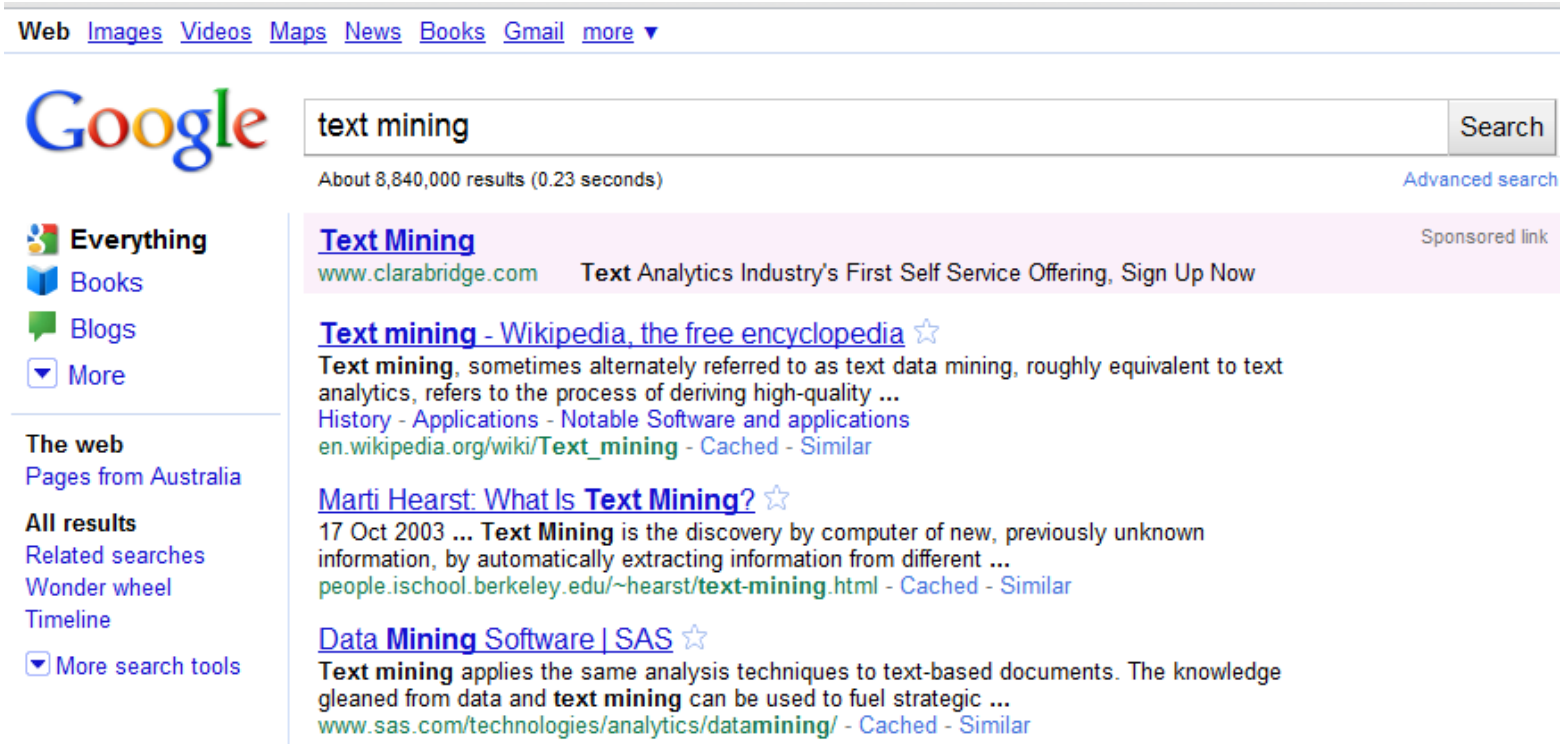


Text Mining

Synthesis of …

- Information Retrieval
  - the science of searching for documents, for information within documents, and for metadata about documents, as well as that of searching relational databases and the World Wide Web.
- Natural Language Processing
  - Part of Speech Tagging
  - Phrase Chunking
  - Deep Parsing
  - Named Entity Recognition
  - Information Extraction

Information Retrieval



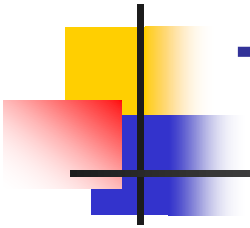
Natural Language Processing

An example of part-of-speech tagging:

This	sentence	serves	as	an	example.
Det	Noun	Verb	P	Det	Noun

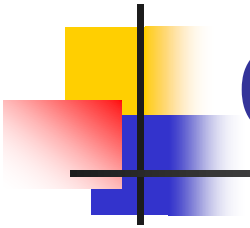
An example of entity recognition:

The University of Queensland,	St. Lucia	Brisbane
University	Suburb	City



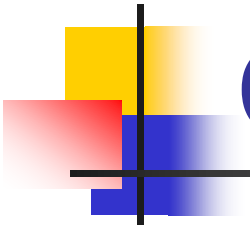
Text Mining Tasks

- Text Classification
  - Assigning a document to one of several pre-specified classes
- Text Clustering
  - Unsupervised learning
- Text Summarization
  - Extracting a summary for a document
  - Based on syntax and semantics
- … …



Challenge of Text Mining

- In traditional data mining, all data are "structured".
  - We usually store the data into database.
    - Table structure. Very clear.
  - Every attribute is well defined.
  - We understand the record very well.
    - Each record is defined by a set of attributes
    - We can measure the similarity between any pair.



Challenge of Text Mining

- However, in text mining, data are "unstructured"!
  - Example:
    - Given two documents, how can you compute their similarity? Base on what?
- So, what we need to do…
  - Unstructured => Structured
- In other words…
  - How to represent a document "structurally"???
  - Document representation problem.

Document Representation

- Document
- Word (term)
- "This is a data mining course. Data mining is important."

term →

frequency →

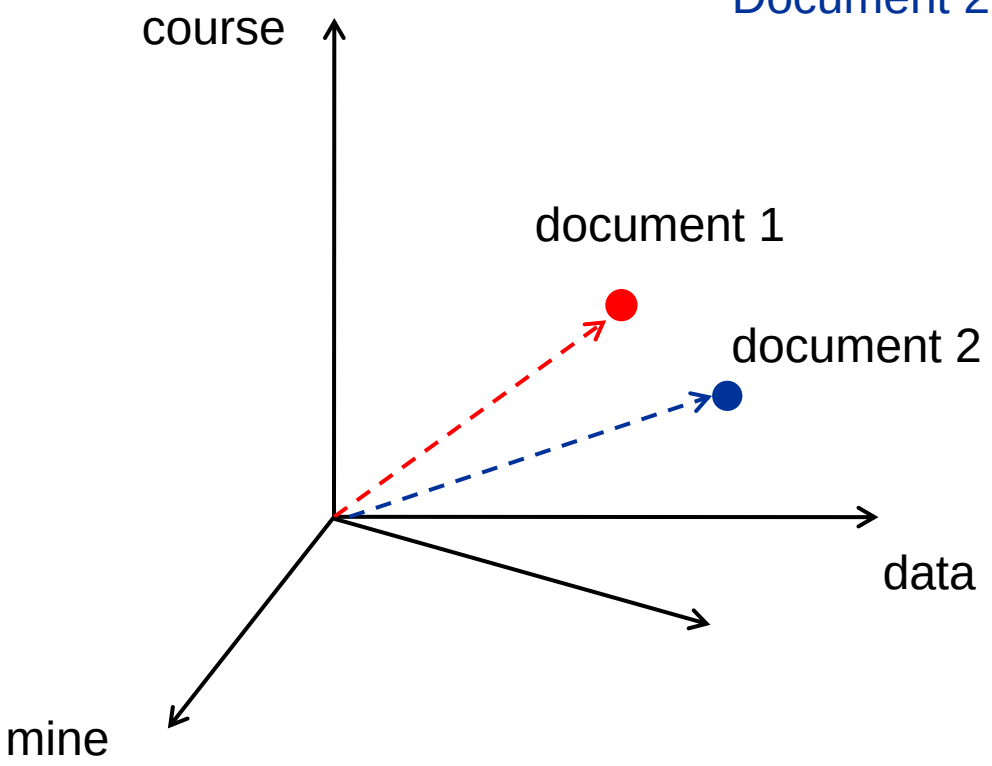
This	is	a	data	mining	course	important
1	1	1	1	1	1	
	1		1	1		1
1	2	1	2	2	1	1

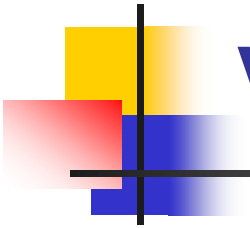
Vector Space Model

- Each word is a dimension
  - If we have M different words. Then, we have a M-dimensional vector space.
- Each document is regarded as a point in this vector space.
  - $d = \{w_1, w_2, \ldots w_m\}$
    In term of geometry, w_i is the coordinate of dimension i in d.
    Yet, conceptually, w_i denotes the importance of word i in d.

An Example of VSM

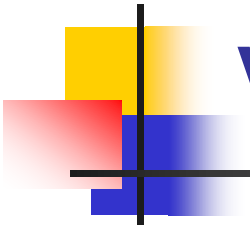
Document 1: (0.938, 0.346, 0, 0, 0, 0, 0)
Document 2: (0, 0.225 0, 0, 0.611, 0.611, 0.450)





Vector Space Model

- Problems:
  1. There are soooooooooooooo many English words!
  2. How to determine the "importance of the words"?



Vector Space Model

- The first problem: too many words
- We solve the first problem by:
  - Remove stop words
    - A, the, this, that …
  - Stemming
    - study
    - study, studying, studied

Vector Space Model

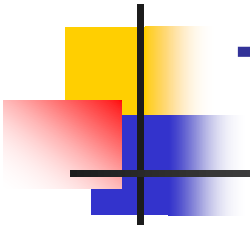
- The second problem: how to determine the importance of the terms
- We solve the second problem by:
  - Using a weighting schema, the TF-IDF schema:

$$w(word_i) = TF(word_i) \times IDF(word_i)$$

$$TF(word_i) = \text{number of times } word_i \text{ appears in the document}$$

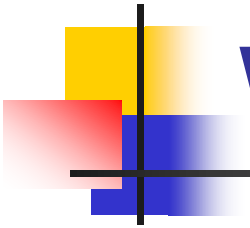
$$IDF(word_i) = \log \frac{\text{total documents}}{\text{document frequency}}$$

  - Normalize the document into unit length



TF-IDF

- TF-IDF
  - Term frequency-inverse document frequency
  - Evaluate how important a word is to a document in a collection
  - the number of times a term occurs in a document is called its term frequency.
  - the number of documents a term occurs in is called its document frequency.



Why TF-IDF

- Can we simply use term frequency?
  - diminish the weight of terms that occur very frequently in the collection
  - increase the weight of terms that occur rarely in the collection
  - Example, the, a, …
  - Example, UQ

TF-IDF Calculation

Term Importance:

$$w(word_i) = TF(word_i) \times IDF(word_i)$$

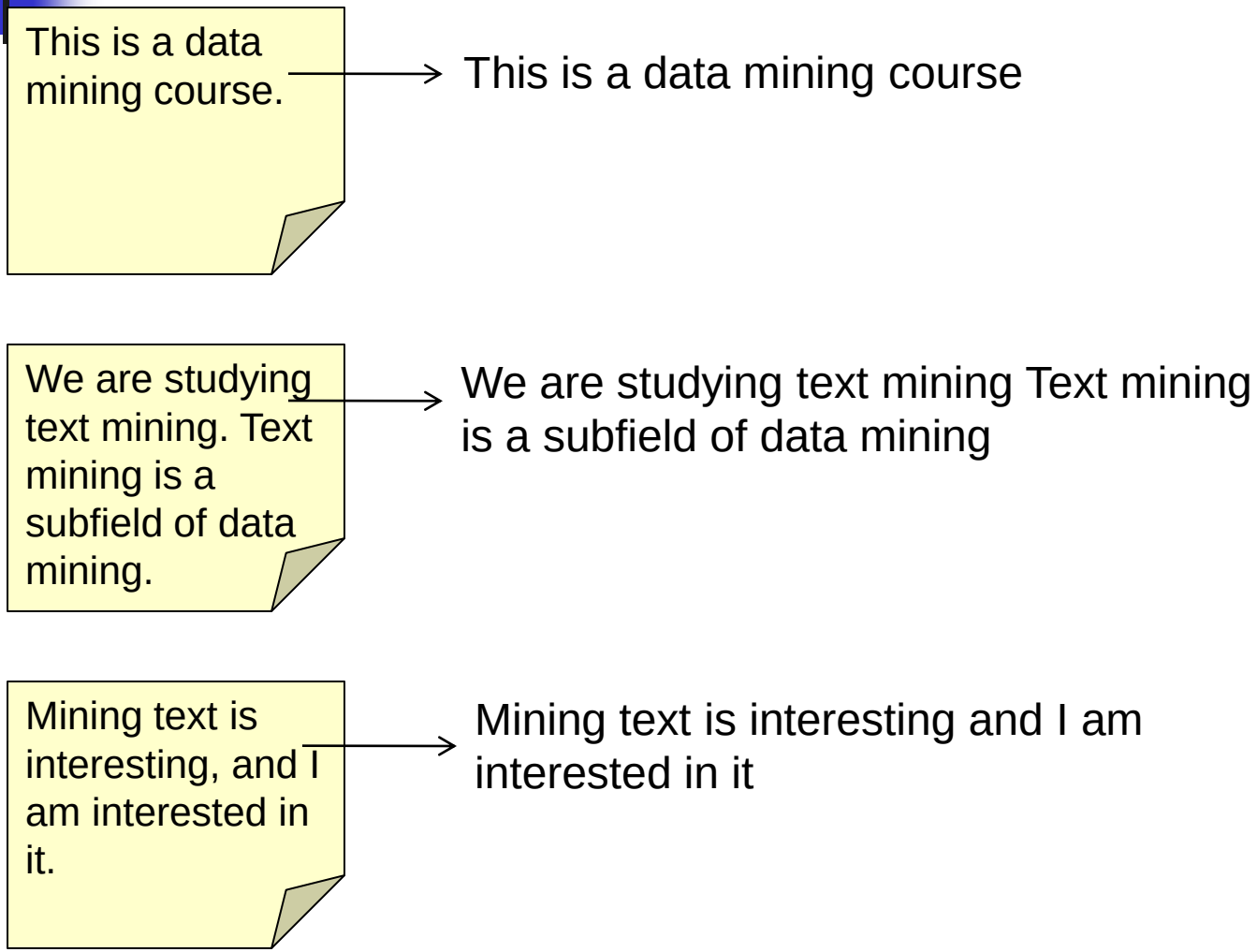
Term Frequency :

$$TF(word_i) = \text{number of times } word_i \text{ appears in the document}$$

Inverse Document Frequency :

$$IDF(word_i) = \log \frac{\text{total documents}}{\text{document frequency}}$$

A Running Example
Step 1 – Extract text



A Running Example
Step 2 – Remove stopwords

This is a data mining course.

~~This is a~~ data mining course

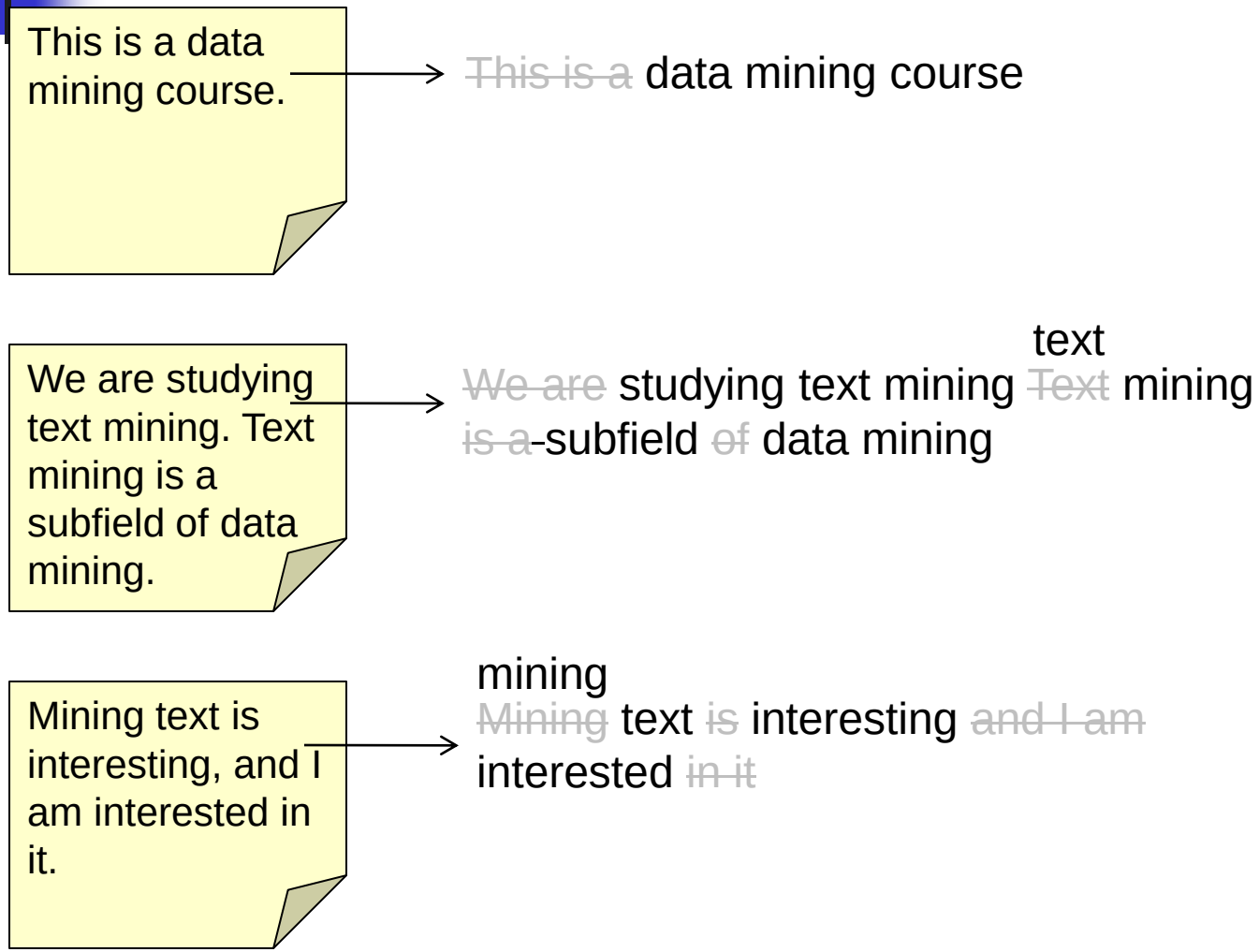
We are studying text mining. Text mining is a subfield of data mining.

~~We are~~ studying text mining Text mining ~~is a~~-subfield ~~of~~ data mining

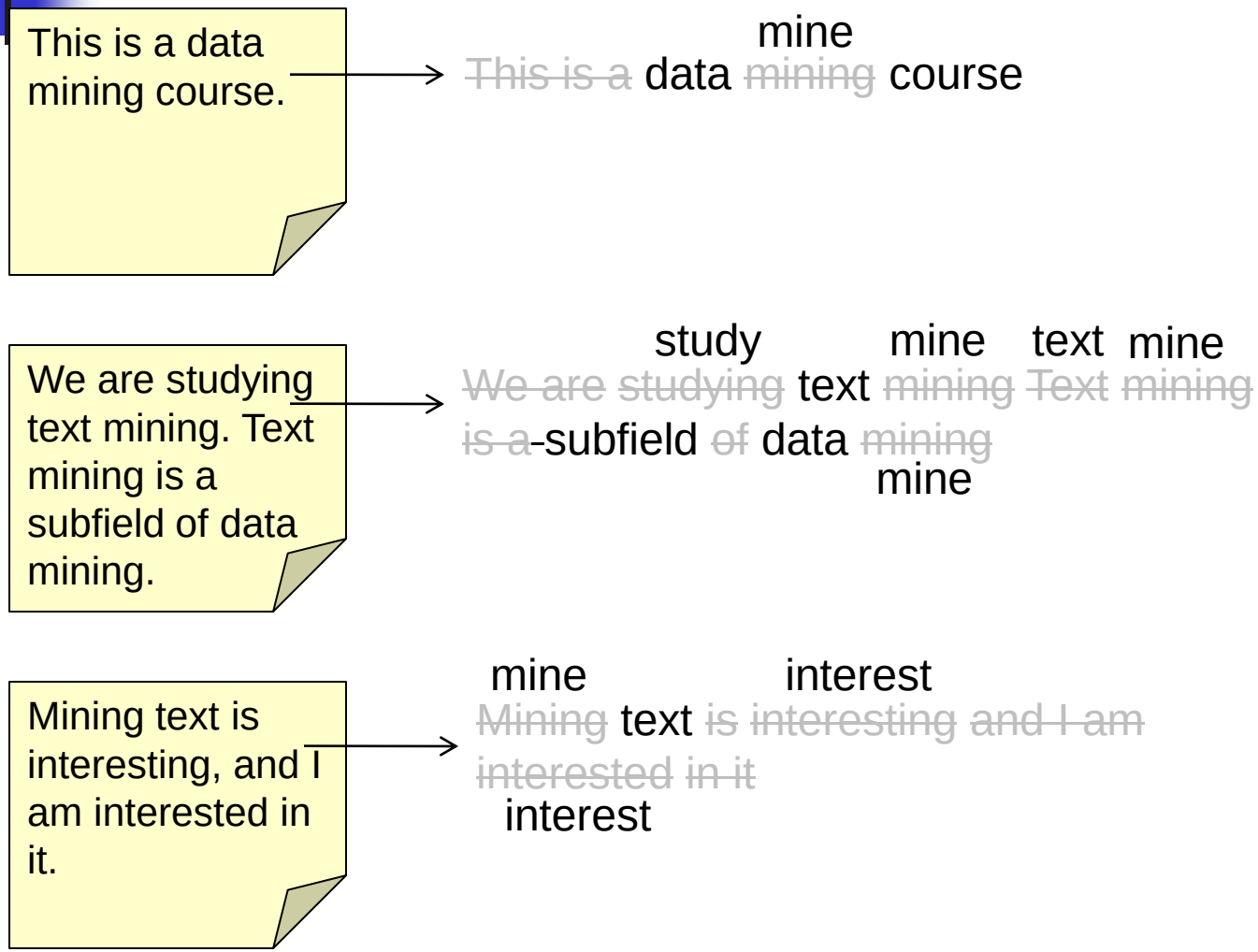
Mining text is interesting, and I am interested in it.

Mining text ~~is~~ interesting ~~and I am~~ interested ~~in it~~

A Running Example
Step 3 – Convert all words to lowercase



A Running Example
Step 4 – Stemming



A Running Example
Step 5 – Count the word frequencies

This is a data mining course.

mine

~~This is a~~ data ~~mining~~ course

course:1, data:1, mine:1

We are studying text mining. Text mining is a subfield of data mining.

study mine text mine

~~We are~~ ~~studying~~ text ~~mining~~ ~~Text~~ ~~mining~~ ~~is a~~-subfield ~~of~~ data ~~mining~~

mine

data:1, mine:2, study:1, subfield:1, text:2

Mining text is interesting, and I am interested in it.

mine interest

~~Mining~~ text ~~is interesting~~ ~~and I am interested~~ ~~in it~~

interest

Interest:2, mine:1, text:1

A Running Example
Step 6 – Create an indexing file

This is a data mining course.

mine
~~This is a~~ data ~~mining~~ course

course:1, data:1, mine:1

We are studying text mining. Text mining is a subfield of data mining.

study mine text mine
~~We are~~ ~~studying~~ text ~~mining~~ ~~Text~~ ~~mining~~
~~is a~~-subfield ~~of~~ data ~~mining~~
mine

data:1, mine:2, study:1, subfield:1, text:2

Mining text is interesting, and I am interested in it.

mine interest
~~Mining~~ text ~~is~~ ~~interesting~~ ~~and I am~~ ~~interested~~ ~~in it~~
interest

interest:2, mine:1, text:1

ID	word	document frequency
1	course	1
2	data	2
3	interest	1
4	mine	3
5	study	1
6	subfield	1
7	text	2

A Running Example
Step 7 – Create the vector space model

This is a data mining course.

mine
~~This is a~~ data ~~mining~~ course

course:1, data:1, mine:1

(1, 1, 0, 1, 0, 0, 0)

We are studying text mining. Text mining is a subfield of data mining.

study mine text mine
~~We are studying~~ text ~~mining Text minin~~
~~is a~~-subfield ~~of~~ data ~~mining~~
mine

data:1, mine:3, study:1, subfield:1, text:2

(0, 1, 0, 3, 1, 1, 2)

Mining text is interesting, and I am interested in it.

mine interest
~~Mining~~ text ~~is interesting and I am interested in it~~
interest

interest:2, mine:1, text:1

(0, 0, 2, 1, 0, 0, 1)

ID	word	document frequency
1	course	1
2	data	2
3	interest	1
4	mine	3
5	study	1
6	subfield	1
7	text	2

A Running Example
Step 8 – Compute the inverse document frequency

This is a data mining course. → (1, 1, 0, 1, 0, 0, 0)

We are studying text mining. Text mining is a subfield of data mining. → (0, 1, 0, 3, 1, 1, 2)

Mining text is interesting, and I am interested in it. → (0, 0, 2, 1, 0, 0, 1)

$$IDF(word) = \log \frac{\text{total documents}}{\text{document frequency}}$$

ID	word	document frequency	IDF
1	course	1	0.477
2	data	2	0.176
3	interest	1	0.477
4	mine	3	0
5	study	1	0.477
6	subfield	1	0.477
7	text	2	0.176

A Running Example
Step 9 – Compute the weights of the words

This is a data mining course.

(1, 1, 0, 1, 0, 0, 0)

(0.477, 0.176, 0, 0, 0, 0, 0)

We are studying text mining. Text mining is a subfield of data mining.

(0, 1, 0, 3, 1, 1, 2)

(0, 0.176, 0, 0, 0.477, 0.477, 0.352)

Mining text is interesting, and I am interested in it.

(0, 0, 2, 1, 0, 0, 1)

(0, 0, 0.954, 0, 0, 0, 0.176)

ID	word	document frequency	IDF
1	course	1	0.477
2	data	2	0.176
3	interest	1	0.477
4	mine	3	0
5	study	1	0.477
6	subfield	1	0.477
7	text	2	0.176

$$w(word_i) = TF(word_i) \times IDF(word_i)$$

$$TF(word_i) = \text{number of times } word_i \text{ appears in the document}$$

A Running Example
Step 10 – Normalize all documents to unit length

This is a data mining course.

(1, 1, 0, 1, 0, 0, 0)

(0.938, 0.346, 0, 0, 0, 0, 0)

We are studying text mining. Text mining is a subfield of data mining.

(0, 1, 0, 3, 1, 1, 2)

(0, 0.225 0, 0, 0.611, 0.611, 0.450)

Mining text is interesting, and I am interested in it.

(0, 0, 2, 1, 0, 0, 1)

(0, 0, 0.983, 0, 0, 0, 0.181)

ID	word	document frequency	IDF
1	course	1	0.477
2	data	2	0.176
3	interest	1	0.477
4	mine	3	0
5	study	1	0.477
6	subfield	1	0.477
7	text	2	0.176

$$w(word_i) = \frac{w(word_i)}{\sqrt{w^2(word_1) + w^2(word_2) + \cdots + w^2(word_n)}}$$

Normalization

This is a data mining course.

(1, 1, 0, 1, 0, 0, 0)

(0.477, 0.176, 0, 0, 0, 0, 0)

$$w(\text{course}) = \frac{0.477}{\sqrt{0.477^2 + 0.176^2 + 0 + 0 + 0 + 0 + 0}} = 0.938$$

(0.938, 0.346, 0, 0, 0, 0, 0)

A Running Example

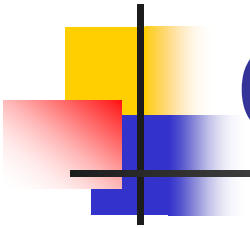
- Everything become structural!
  - We can perform classification, clustering, etc!!!!

This is a data mining course. → (0.938, 0.346, 0, 0, 0, 0, 0)

We are studying text mining. Text mining is a subfield of data mining. → (0, 0.225 0, 0, 0.611, 0.611, 0.450)

Mining text is interesting, and I am interested in it. → (0, 0, 0.983, 0, 0, 0, 0.181)

ID	word	document frequency	IDF
1	course	1	0.477
2	data	2	0.176
3	interest	1	0.477
4	mine	3	0
5	study	1	0.477
6	subfield	1	0.477
7	text	2	0.176



Query A Document

- How can we query the document?
  - Simple! Just similar to the previous steps:
    1. Remove stopwords.
    2. Stem every word of the query string.
    3. Transform the query string into a vector space model (VSM) by using TD-IDF schema.
    4. Normalize the VSM into unit length.

A Running Example
Q = {interested in interesting data and text}

Original Query:
(interested in interesting data and text)

Step 1: Remove stop word:
(interested interesting data text)

Step 2: Stemming:
(interest interest data text)

Step 3: Remove duplication:
(interest data text)

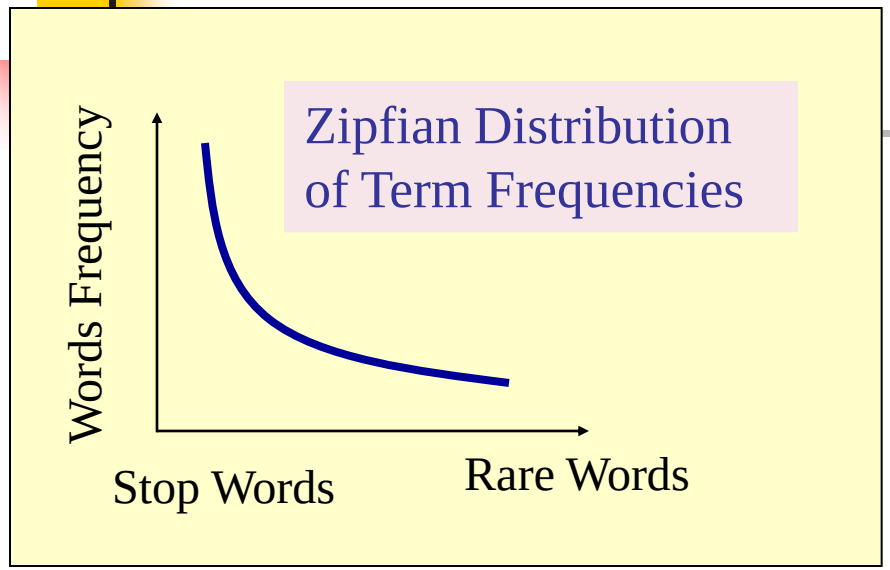
Step 4: Construct a vector space model:
(0, 1, 1, 0, 0, 0, 1)

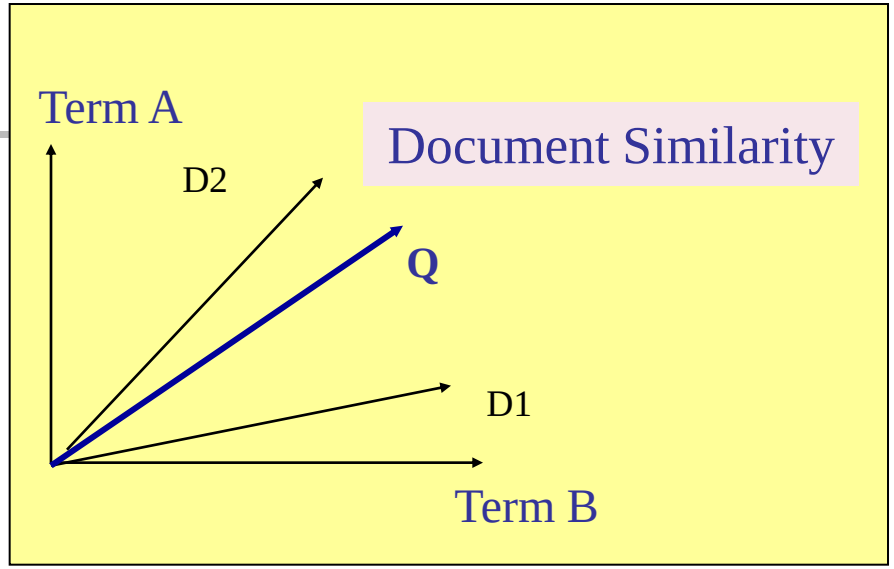
Step 5: Compute the weight of each word:
(0, 0, 0.477, 0, 0, 0, 0.176)

Step 5: Normalize the vector space model:
(0, 0, 0.938, 0, 0, 0, 0.346)

ID	word	document frequency	IDF
1	course	1	0.477
2	data	2	0.176
3	interest	1	0.477
4	mine	3	0
5	study	1	0.477
6	subfield	1	0.477
7	text	2	0.176

Ranking Document by Similarity





Vector similarity (dot product):

$$sim\ (Q, D) = \sum_{k=1}^{t} w_{qk} \cdot w_{dk}$$

Cosine vector similarity:

$$sim(Q, D) = \frac{\sum_{k=1}^{t} w_{qk} \bullet w_{dk}}{\sqrt{\sum_{k=1}^{t} (w_{qk})^2 \bullet \sum_{k=1}^{t} (w_{dk})^2}}$$

A Running Example – The Result

Q: (0, 0, 0.938, 0, 0, 0, 0.346)

Document 1: (0.938, 0.346, 0, 0, 0, 0, 0)
Document 2: (0, 0.225 0, 0, 0.611, 0.611, 0.450)
Document 3: (0, 0, 0.983, 0, 0, 0, 0.181)

ID	word	document frequency	IDF
1	course	1	0.477
2	data	2	0.176
3	interest	1	0.477
4	mine	3	0
5	study	1	0.477
6	subfield	1	0.477
7	text	2	0.176

$$\text{cosine}(P,Q) = \frac{\sum p_i \cdot q_i}{\sqrt{\sum p_i^2 \times \sum q_i^2}}$$

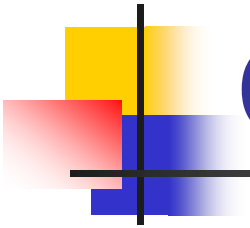
$$\text{cosine}(D1,Q) = 0$$

$$\text{cosine}(D2,Q) = \frac{0.346 \times 0.450}{\sqrt{(0.938^2 + 0.346^2) \times (0.225^2 + 0.611^2 + 0.611^2 + 0.450^2)}} = 0.156$$

$$\text{cosine}(D3,Q) = \frac{0.938 \times 0.983 + 0.346 \times 0.181}{\sqrt{(0.938^2 + 0.346^2) \times (0.983^2 + 0.181^2)}} = 0.985$$

1

Conclusion: Return Document 3



QUIZ!

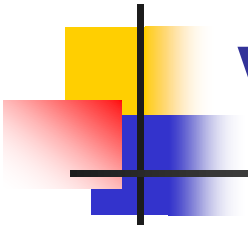
- Given a query of "W4 W5" and a collection of the following three documents:

- Document 1: <W1 W2 W3 W4 W5 >
- Document 2: <W6 W7 W4 W5>
- Document 3: <W8 W3 W9 W4 W10>

- Use the Vector Space Model, TF/IDF weighting scheme, and Cosine vector similarity measure to find the most relevant document(s) to the query.

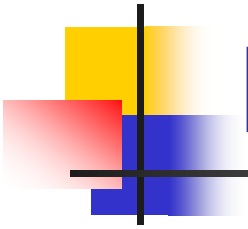
IDF

Word list	DF	IDF
W1	1	0.477
W2	1	0.477
W3	2	0.176
W4	3	0
W5	2	0.176
W6	1	0.477
W7	1	0.477
W8	1	0.477
W9	1	0.477
W10	1	0.477



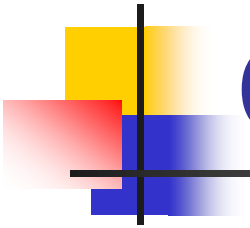
VSM

- D1=(1,1,1,1,1,0,0,0,0,0)
  (0.477,0.477,0.176,0,0.176,0,0,0,0,0)
- D2=(0,0,0,1,1,1,1,0,0,0)
  (0,0,0,0,0.176,0.477,0.477, 0,0,0)
- D3=(0,0,1,1,0,0,0,1,1,1)
  (0,0,0.176,0,0,0,0,0.477,0.477, 0.477)



Normalization

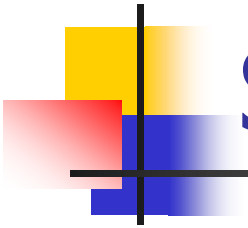
- D1= [0.6634 0.6634 0.2448 0 0.2448 0 0 0 0 0]
- D2= [0 0 0 0 0.2525 0.6842 0.6842 0 0 0]
- D3= [0 0 0.2084 0 0 0 0 0.5647 0.5647 0.5647]



Query

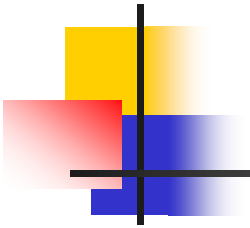
- Q=(0,0,0,0,0.176,0,0,0,0,0)
  (0,0,0,0,1,0,0,0,0,0)

- Cosine_sim(Q,D1)=0.2448
- Cosine_sim(Q,D2)=0.2525
- Cosine_sim(Q,D3)=0



Simple? Well…

- What we have discussed so far is a general framework only.
- There are still a lot of issues:
  - How to define stopword?
    - "A" is usually regarded as a stopword. However, "Vitamin A" may be an important term in an article.
  - How to perform stemming?
    - What to stem and what not to stem?
      - Should "booking" be converted to "book"?
    - How to stem? There are many new words everyday!



- Spelling error?
  - Spelling error always appears in documents! Should we consider two similar word as a same word?
    - Are they the same: “classification” and “classificatiam”?
    - But then, how about “Information” and “informatics”?

IR Evaluation: Recall and Precision

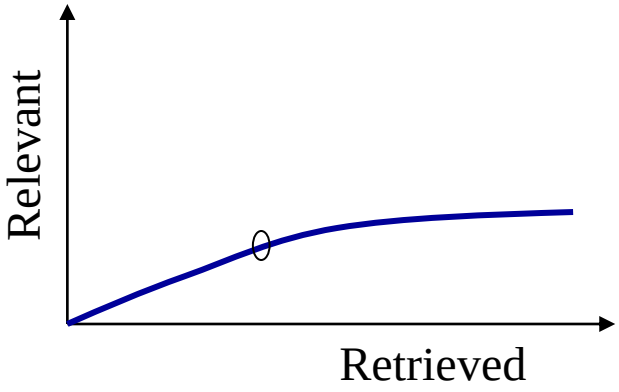
	Retrieved	Not-Retrieved
Relevant	A	B
Non-Relevant	C	D

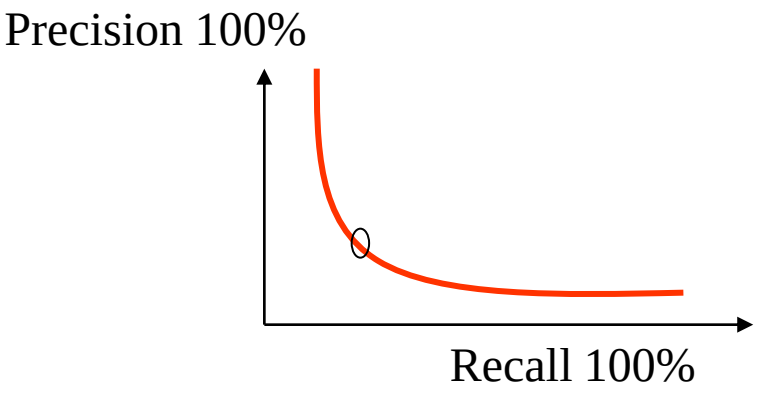
Precision = A/(A+C)

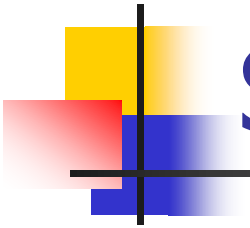
Recall = A/(A+B)

Fallout = C/(C+D)

$N_{database}$ = A+B+C+D







Summary

- Information Retrieval Concepts
  - VSM Model
  - Similarity Measure
  - IR Evaluations

- Next Week:
  - **Web Mining**