COMP 472: Artificial Intelligence
Natural Language Processing part #5
Bag of Word Model Video #2

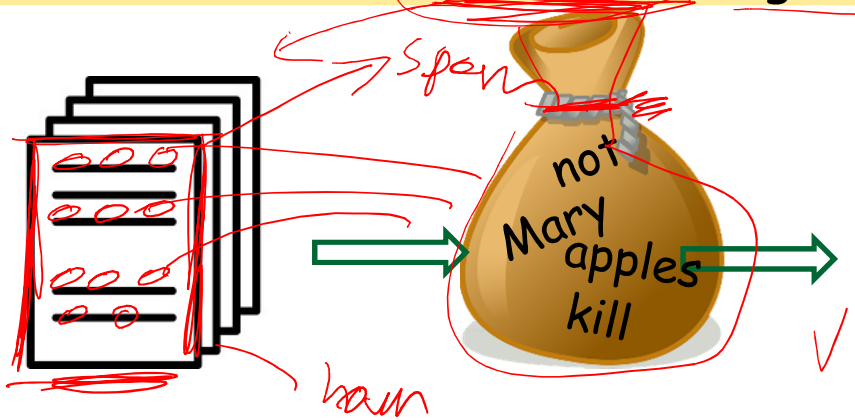
- Russell & Norvig: Section 23.1.1

Today

1. Introduction
2. Bag of word model
3. n-gram models
4. Deep Learning for NLP
    1. Word Embeddings
    2. Recurrent Neural Networks

Bag-of-word Model (BOW)

- A simple model where word order is ignored



Word	Value
Mary	
apples	
did	
eat	
John	
kill	
like	
not	
to	

- used in many applications:
  - NB spam filter seen in class a few weeks ago
  - Information Retrieval (eg. google search)
  - ...
- But has severe limits to understand meaning of text...
- Maybe we should take word order into account...

d1 Mary Killed John

d2 John Killed Mary

BOW – Document Representation

- Representation of a documents = vectors of pairs <word, value>
  - word: all word in the vocabulary (aka as a *term*)
  - value: a number associated with the word in the document
    - different possible schemes:
      1. binary (0, if term is absent ; 1, if term is present)
      2. term frequency
      3. some other weighting scheme (e.g. tf.idf)

Mary did kill John.
Mary did not like to eat apples.

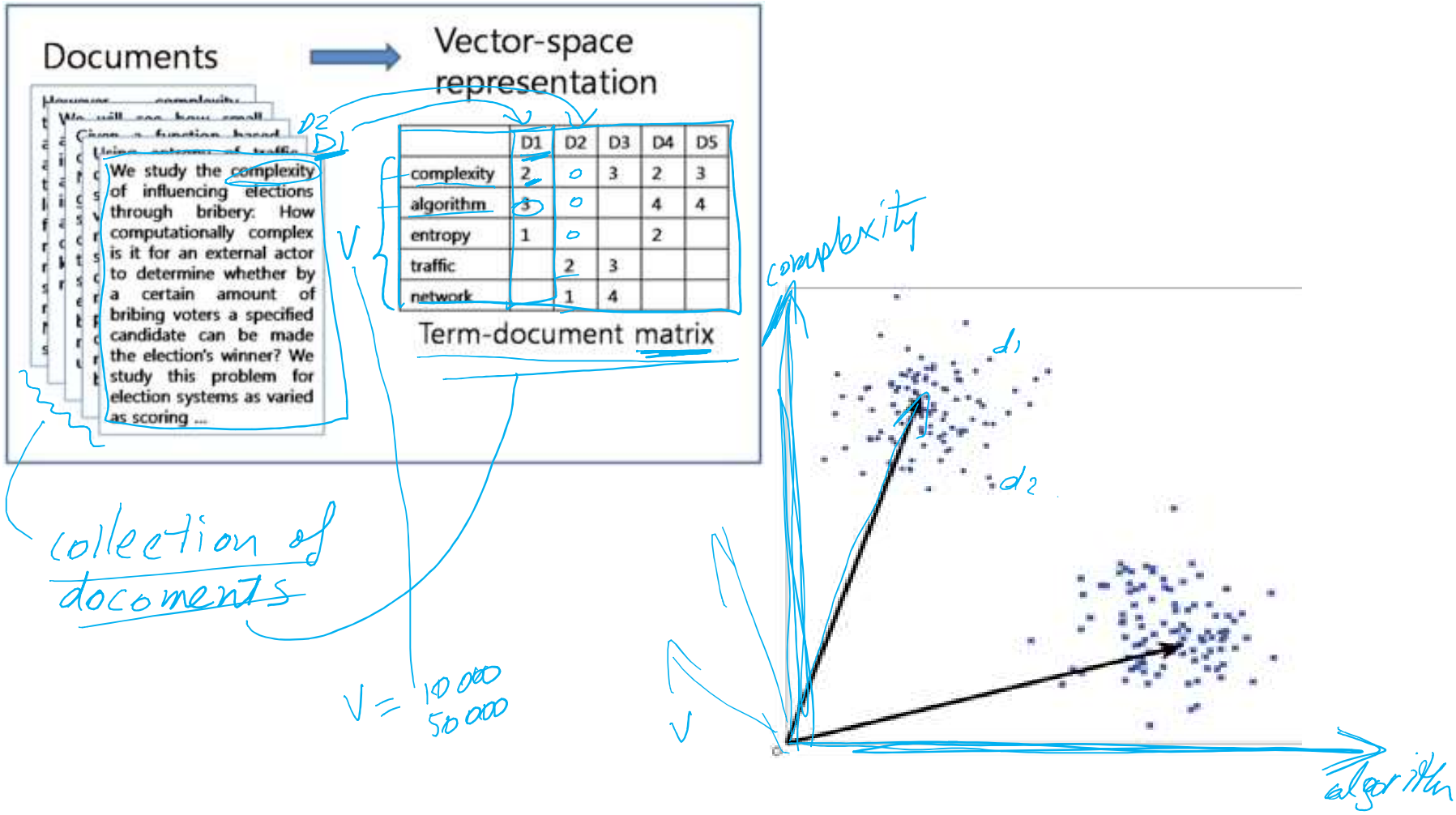
Word	Value
airplane	0
apples	1
banana	0
did	1
dinner	0
element	0
Mary	1
...	...
zoo	0

Word	freq
airplane	0
apples	1
banana	0
did	2
dinner	0
element	0
Mary	2
...	...
zoo	0

Word	other
airplane	?
apples	?
banana	?
did	?
dinner	?
element	?
Mary	?
...	...
zoo	?

V

BOW – Document Representation



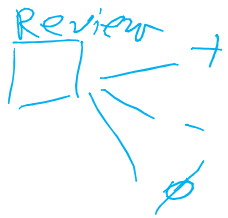
	D1	D2	D3	D4	D5
complexity	2	0	3	2	3
algorithm	3	0		4	4
entropy	1	0		2	
traffic		2	3		
network		1	4		

http://mlg.postech.ac.kr/research/nmf

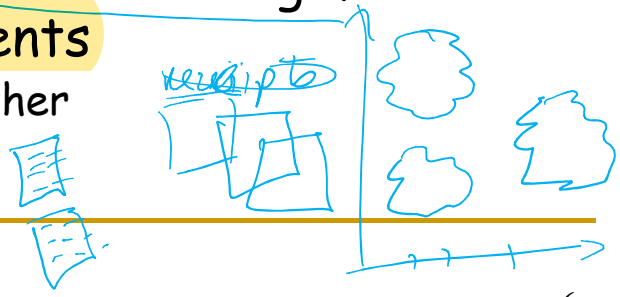
So what?

- once a document is represented as a long vector of numbers, we can:

- Do text categorization/classification
  - i.e. Use your favorite supervised machine learning model to classify a document into pre-defined classes
    - eg. Spam filtering, News routing, Sentiment Analysis
    - using: NB classifier, decision tree, neural networks...



- Do text clustering
  - i.e. use your favorite unsupervised machine learning model to compute the similarity between documents
    - eg. k-means to group similar documents together



Text Categorization

- Remember this slide?

Example

- Dataset
  - c1: SPAM
    doc1: "cheap meds for sale"
    doc2: "click here for the best meds"
    doc3: "book your trip"
  - c2: HAM
    doc4: "cheap book sale, not meds"
    doc5: "here is the book for you"
- Question:
  - doc6: "the cheap book"
  - should it be classified as HAM or SPAM?

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- Multinomial Naive Bayes Classification is a standard application

Text Clustering

- similar technique as used in information retrieval
- Assume we have 3 documents (Web pages)

d_1 = introduction knowledge in speech and language processing ambiguity models and algorithms language thought and understanding the state of the art and the near-term future some brief history summary

d_2 = hmms and speech recognition speech recognition architecture introduction knowledge in speech and language processing ambiguity models and algorithms language thought and understanding the state of the art and the near-term future some brief history summary
the hidden markov models the viterbi algorithm revisited advanced methods in decoding acoustic processing of speech computing acoustic probabilities training a speech recognizer waveform generation for speech synthesis human speech recognition summary}

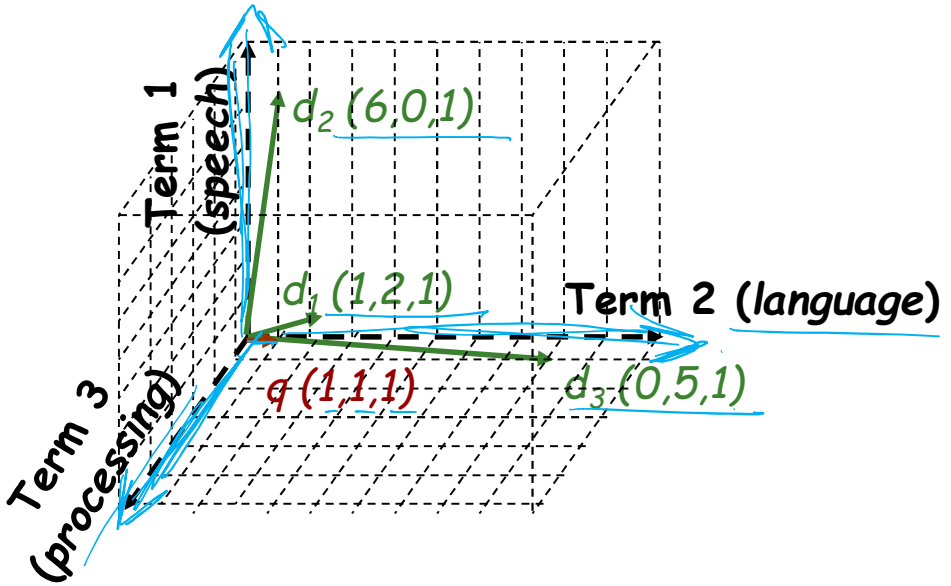
d_3 = language and complexity the chomsky hierarchy how to tell if a language isn't regular the pumping lemma are English and other language regular language ? is natural language context-free complexity and human processing summary

- a query Q = speech language processing

Example

- using term frequencies

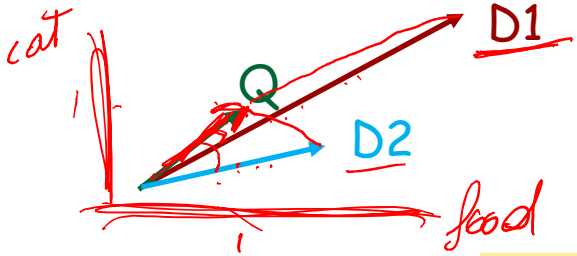
	d_1	d_2	d_3	Q
introduction	...	...	...	...
knowledge	...	...	...	...
...	...	...	...	...
speech	1	6	0	1
language	2	0	5	1
processing	1	1	1	1
...	...	...	...	...

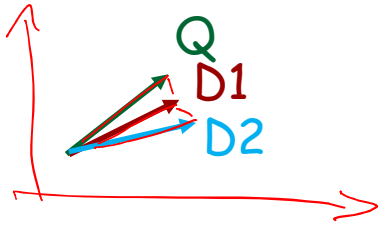


- the documents and the query can be seen as vectors in a multi-dimensional space
- In the case of IR
  - we compare all other documents to a single document (the quesry Q)
  - so only the terms of the query are relevant
  - so dimensions represent only the terms of the query

Distance Measure

- similarity between two documents (or doc & query) can be measured
  - using the Euclidian distance – as in k-means
  - but longer documents will have larger values and longer lengths
  - what we really care about is the relative distribution of the word values, not the exact values

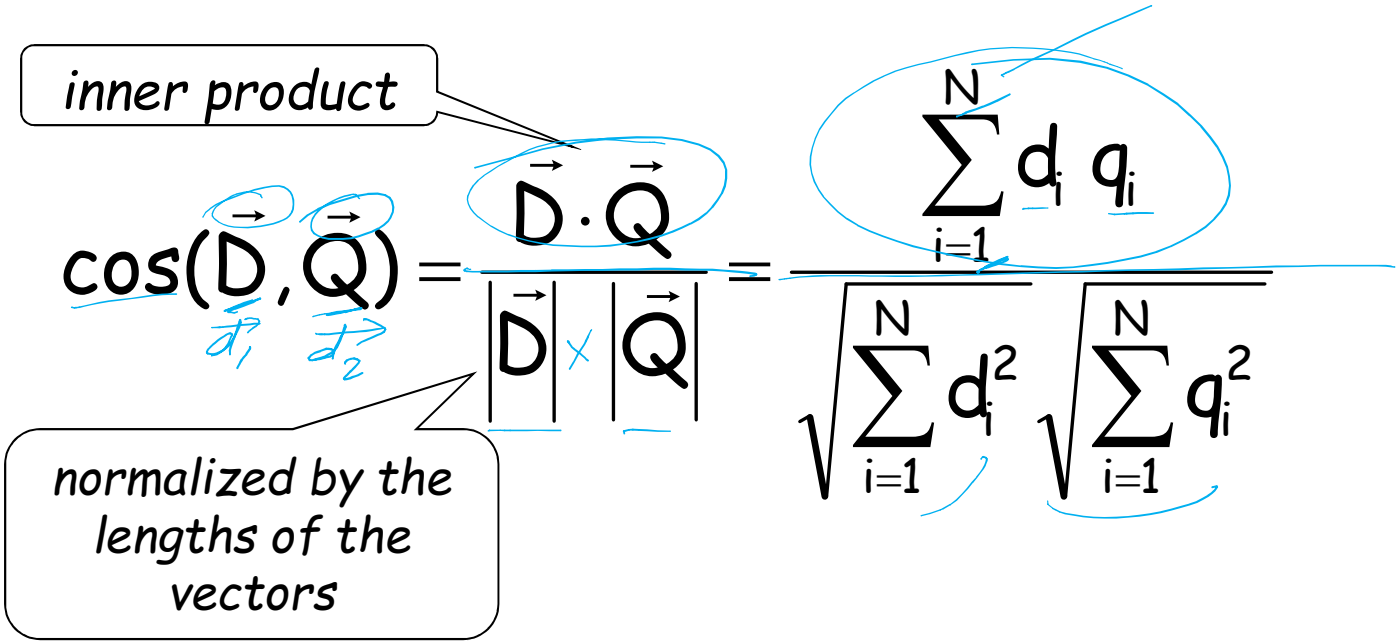




  - so other measures that normalize the length of the vectors are preferable
  - simplest/most popular measure is the cosine measure

The Cosine Measure

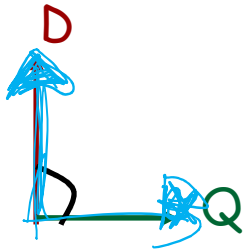
- The cosine of 2 vectors (in N dimensions)



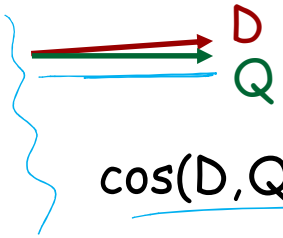
- as if all vectors had a length of 1

The Cosine Measure

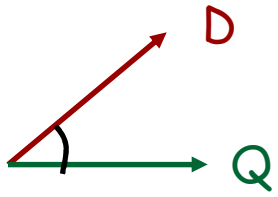
- cosine of the angle between the 2 vectors
  - if 2 document-vectors are identical
    - → they will have a cosine of 1
  - if 2 document-vectors are orthogonal (i.e. share no common term)
    - → they will have a cosine of 0



$\cos(D,Q) = 0$



$\cos(D,Q) \approx 1$



$\cos(D,Q) \approx 0.7$

The example again

	d_1	d_2	d_3	Q
introduction	1	0	0	0
knowledge	1	0	0	0
…				
speech	1	6	0	1
language	2	0	5	1
processing	1	1	1	1
…				

$$sim(D,Q) = \cos(\vec{D},\vec{Q}) = \frac{\vec{D}\cdot\vec{Q}}{|\vec{D}|\ |\vec{Q}|} = \frac{\sum_{i=1}^{N} d_i\, q_i}{\sqrt{\sum_{i=1}^{N} d_i^2}\ \sqrt{\sum_{i=1}^{N} q_i^2}}$$

if we only consider the words of the query {speech, language, processing}, then
query = (1,1,1)
d_1 = (1,2,1) d_2 = (6,0,1) d_3 = (0,5,1)

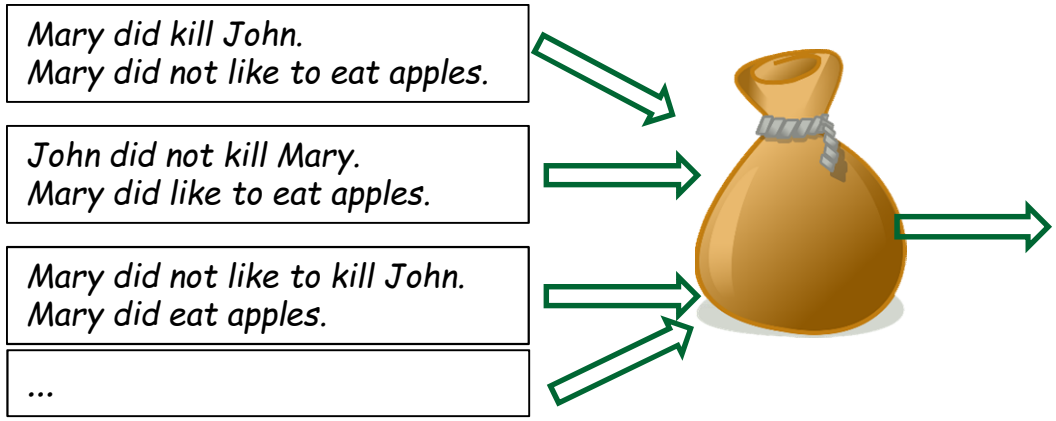
$$sim(d_1,Q) = \frac{(1x1) + (2x1) + (1x1)}{\sqrt{(1^2+2^2+1^2)} \times \sqrt{(1^2+1^2+1^2)}} = \frac{1+2+1}{\sqrt{6} \times \sqrt{3}} = 0.943$$

$$sim(d_2,Q) = \frac{(6x1) + (0x1) + (1x1)}{\sqrt{(6^2+0^2+1^2)} \times \sqrt{(1^2+1^2+1^2)}} = \frac{6+0+1}{\sqrt{37} \times \sqrt{3}} = 0.664$$

$$sim(d_3,Q) = \frac{(0x1) + (5x1) + (1x1)}{\sqrt{(0^2+5^2+1^2)} \times \sqrt{(1^2+1^2+1^2)}} = \frac{0+5+1}{\sqrt{26} \times \sqrt{3}} = 0.680$$

Pro/Cons of BOW Model

- pros:
  - simple model
  - efficient for large collections of documents
  - basis of many IR, and text categorization systems
- cons:
  - word order is ignored ==> meaning of text is lost.



Word	Freq.
Mary	2
apples	1
did	2
eat	1
John	1
kill	1
like	1
not	1
to	1

- Solution:
  - n-grams take [a bit of] word order into account

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Up Next

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