COMP4901K/Math4824B
Machine Learning for Natural Language Processing

Lecture 4: Vector Space Model

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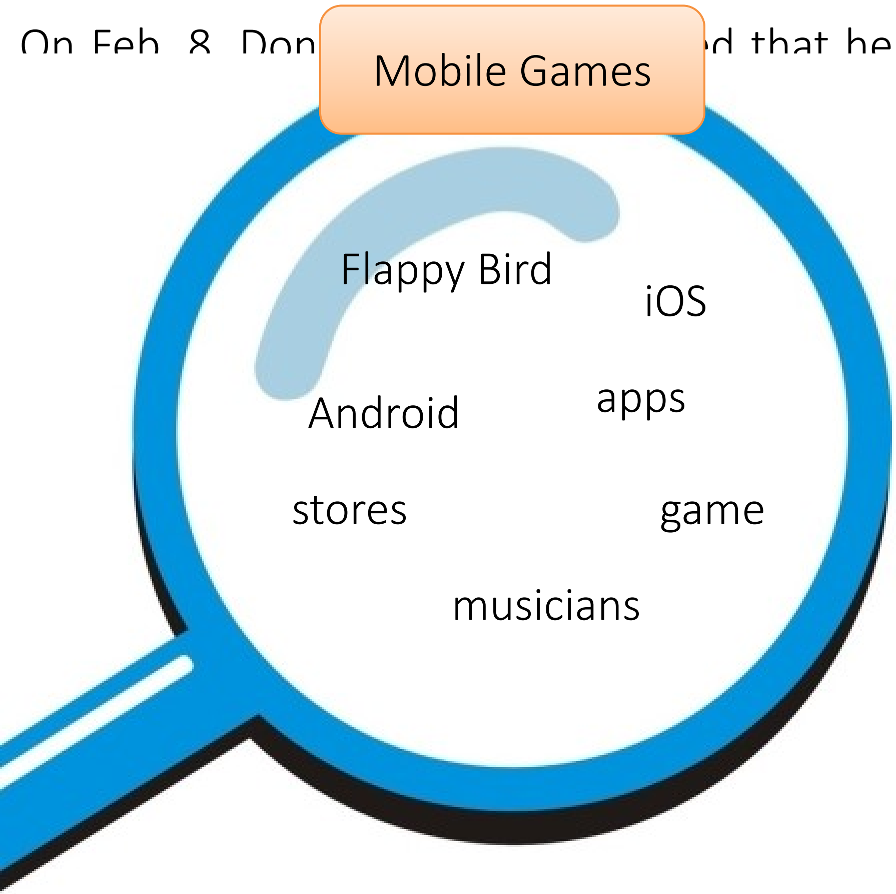
Frequency Distributions

- How can we identify the words of a text that are most informative about the topic and genre of the text?
  - You might go about finding the 50 most frequent words of a book



Corpus based Approach

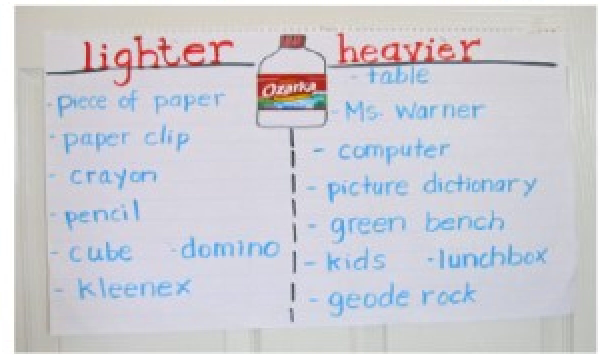
- Distributional semantics
  - The distributional hypothesis in linguistics is derived from the semantic theory of language usage, i.e. words that are used and occur in the same contexts tend to purport similar meanings.
  - The basic idea of distributional semantics can be summed up in the so-called Distributional hypothesis: *linguistic items with similar distributions have similar meanings*.

We will mention distributed representation based neural language models in later classes

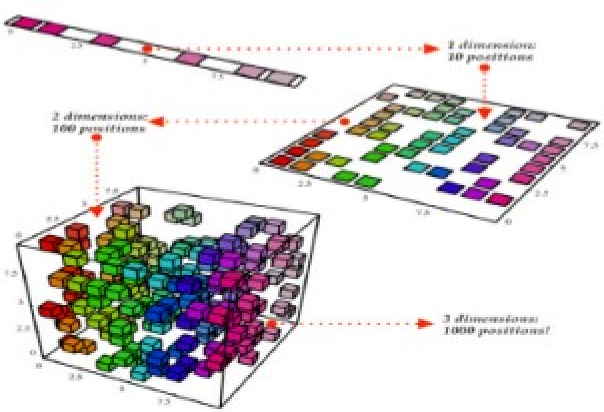
Corpus based Approach

1) Corpus

2) Preprocessing



3) Dimensionality Reduction



4) Post Processing

Context of Words

- Let's try to keep the kitchen ______ .

- We used WordNet to ______ the synset of *cat*.

What does ____ mean?

Let's try to keep the kitchen _______ .

- Observation: context can tell us a lot about word meaning
- Context: local window around a word occurrence (for now)

- Roots in linguistics:
  - Distributional hypothesis [Harris, 1954]:
    - Semantically similar words occur in similar contexts
    - “If A and B have almost identical environments we say that they are synonyms.”
  - "You shall know a word by the company it keeps." [Firth, 1957]

- Pros: data-driven, easy to implement
- Cons: ambiguity

Intuition of distributional word similarity

- Nida example:

    `A bottle of` ***tesgüino*** `is on the table`
    `Everybody likes` ***tesgüino***
    Tesgüino `makes you drunk`
    `We make` ***tesgüino*** `out of corn.`

- From context words humans can guess ***tesgüino*** means
  - an alcoholic beverage like **beer**

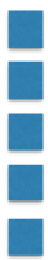
- Intuition for algorithm:
  - Two words are similar if they have similar word contexts.

Different Kinds of Vector Models

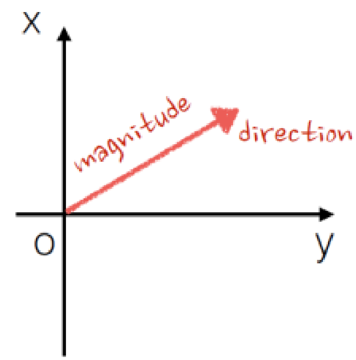
- Sparse vector representations
  - Weighted word co-occurrence matrices
- Dense vector representations:
  - Singular value decomposition (and Latent Semantic Analysis)
  - Neural-network-inspired models (word embeddings)

A Little Linear Algebra

- Scalar: A number: length, area, density, pressure, temperature
  - Magnitude only! a, b, c
- Vector: A collection of scalars



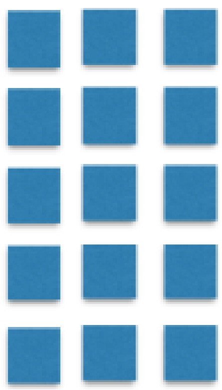
$$\mathbf{a} = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_d \end{bmatrix} \quad \mathbf{a}^\top = [a_1, a_2, \cdots, a_d]$$



  - d is called dimensionality of vector a
  - Scalar is one-dimensional vector

A Little Linear Algebra

- Matrix: A collection of vectors



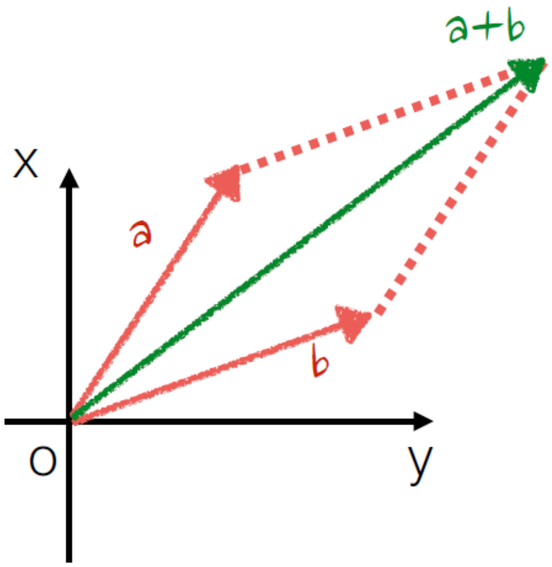
$$\mathbf{A} = [\mathbf{a}_1, \mathbf{a}_2, \cdots, \mathbf{a}_n] = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ A_{d1} & A_{d2} & \cdots & A_{dn} \end{bmatrix}$$

$$\mathbf{A}^\top = \begin{bmatrix} A_{11} & A_{21} & \cdots & A_{n1} \\ A_{12} & A_{22} & \cdots & A_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ A_{1d} & A_{2d} & \cdots & A_{nd} \end{bmatrix}$$

Vector Operations

- Addition

$$\mathbf{a}+\mathbf{b}=\begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_d \end{bmatrix}+\begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_d \end{bmatrix}=\begin{bmatrix} a_1+b_1 \\ a_2+b_2 \\ \vdots \\ a_d+b_d \end{bmatrix}$$



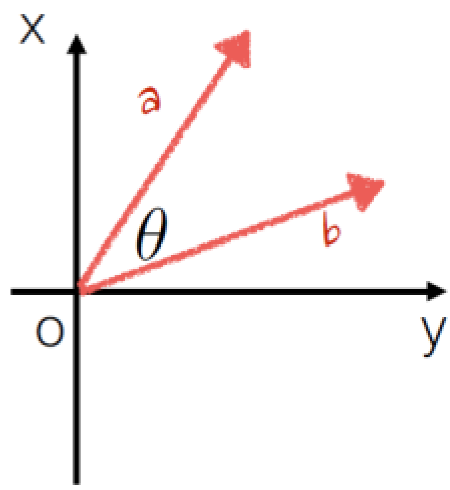
- Can vectors with different dimensionalities be added together?

- The resultant thing is a vector or a scalar?

Vector Operations

- Inner product

$$\langle \mathbf{a}, \mathbf{b} \rangle = \mathbf{a}^\top \mathbf{b} = \sum_{i=1}^{d} a_i b_i$$
$$= \|\mathbf{a}\|_2 \|\mathbf{b}\|_2 cos(\theta)$$



- Can inner product be operated on vectors with different dimensionalities?

$$cos\theta = \frac{\mathbf{a}^\top \mathbf{b}}{\|\mathbf{a}\|_2 \|\mathbf{b}\|_2}$$

- The resultant thing is a vector or a scalar?

Vector Norm

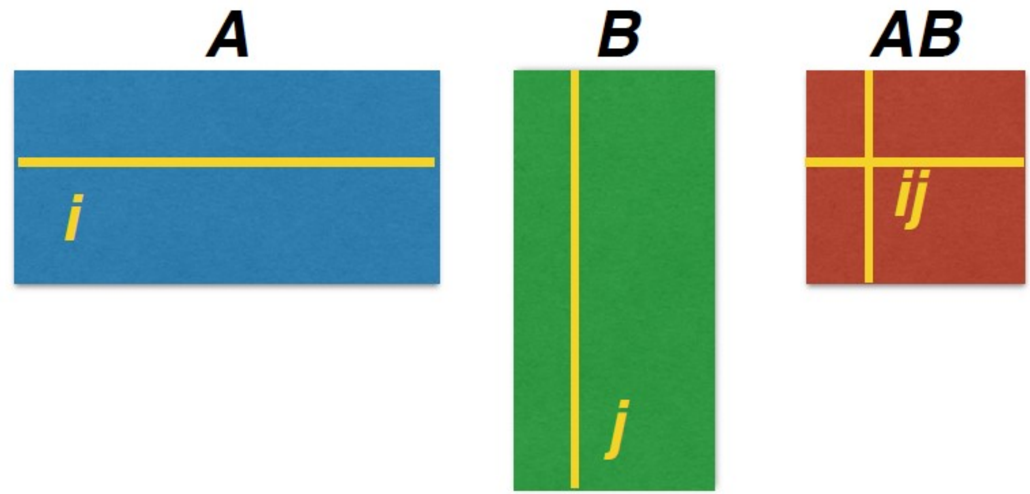
$$\text{1-norm: } \|\mathbf{a}\|_1 = \sum_{i=1}^{d} |a_i|$$

$$\text{2-norm: } \|a\|_2 = \sqrt{\mathbf{a}^\top \mathbf{a}}$$

- The resultant thing is a vector or a scalar?
- Can vector norms be negative?

Matrix Multiplication

$$(\mathbf{AB})_{ij} = \sum_k A_{ik} B_{ik}$$

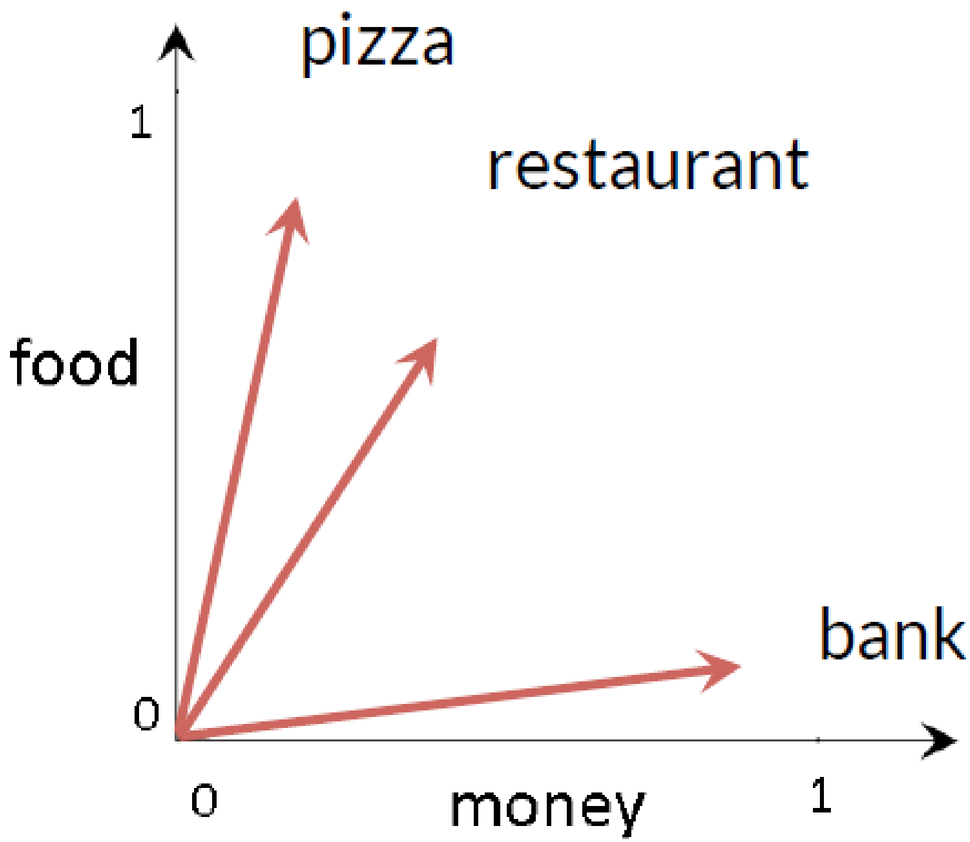


- What is the dimensionality requirement for matrix multiplication?

- What is the dimensionality of the resultant matrix?

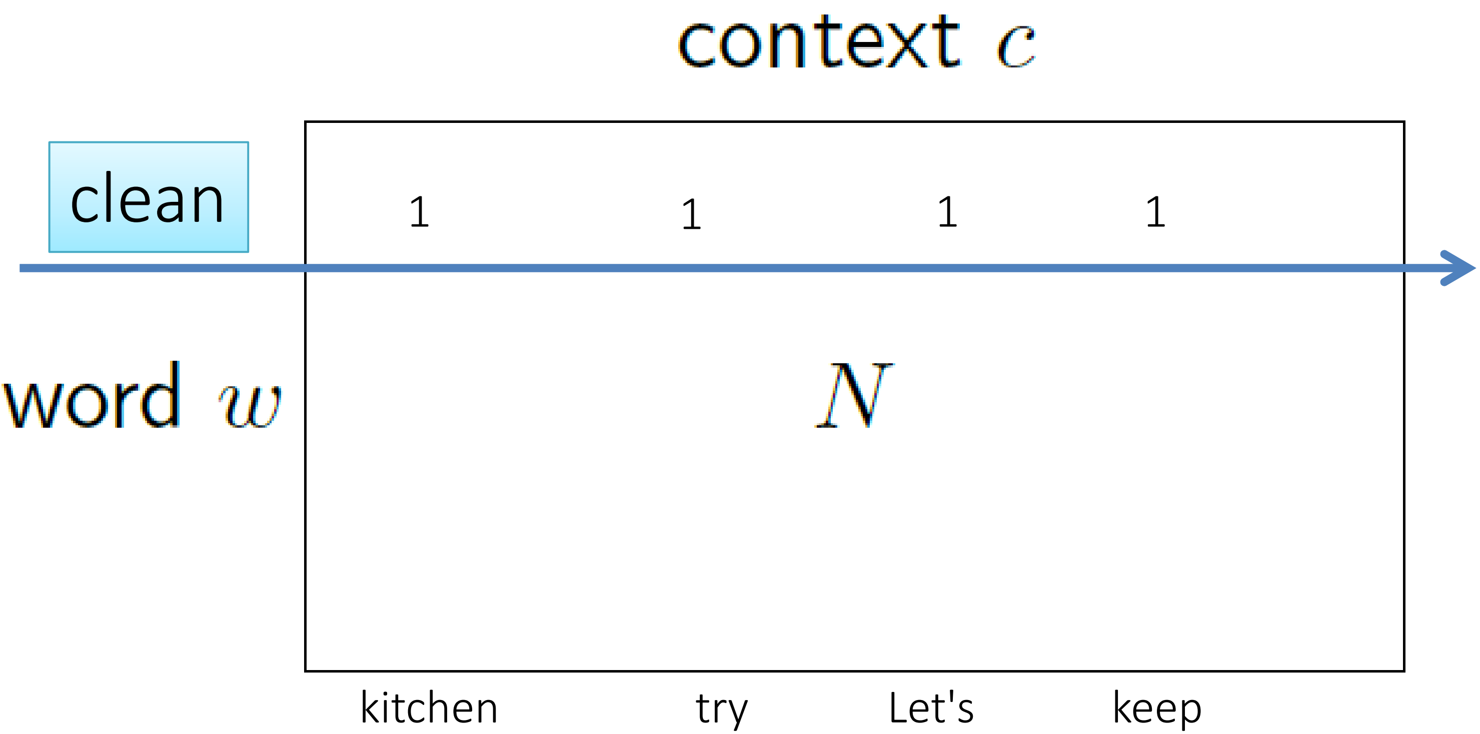
Back to Distributional Representation

- Vector Space Model (VSM)
  - Represent each word with its context words



Context Vector Construction

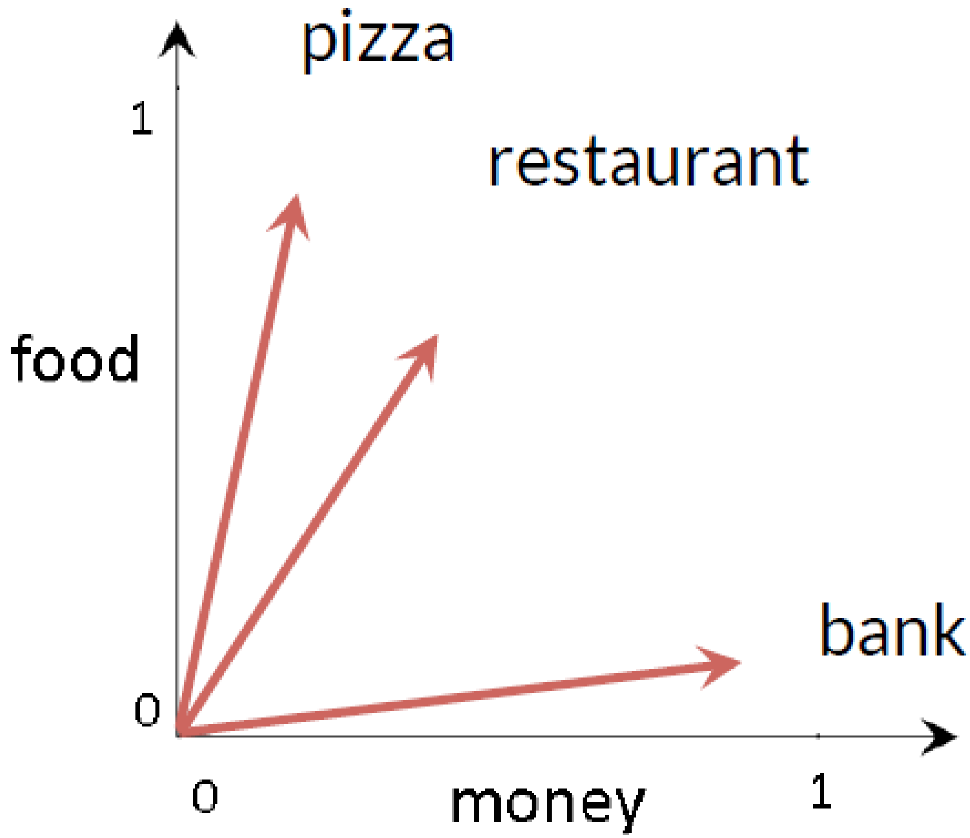
- Form a word-context matrix of counts (data)



Let's try to keep the kitchen clean.

Similarity between Words

$$cos\theta = \frac{\mathbf{a}^\top \mathbf{b}}{\|\mathbf{a}\|_2 \|\mathbf{b}\|_2}$$



Features for Part-of-speech Induction

- Matrix: **contexts (2)** = words on left, words on right

Doc1: Cats have tails.

Doc2: Dogs have tails.

	cats_L	dogs_L	tails_R	have_L	have_R
cats	0	0	0	0	1
dogs	0	0	0	0	1
have	1	1	1	0	0
tails	0	0	0	1	0

Document Representation

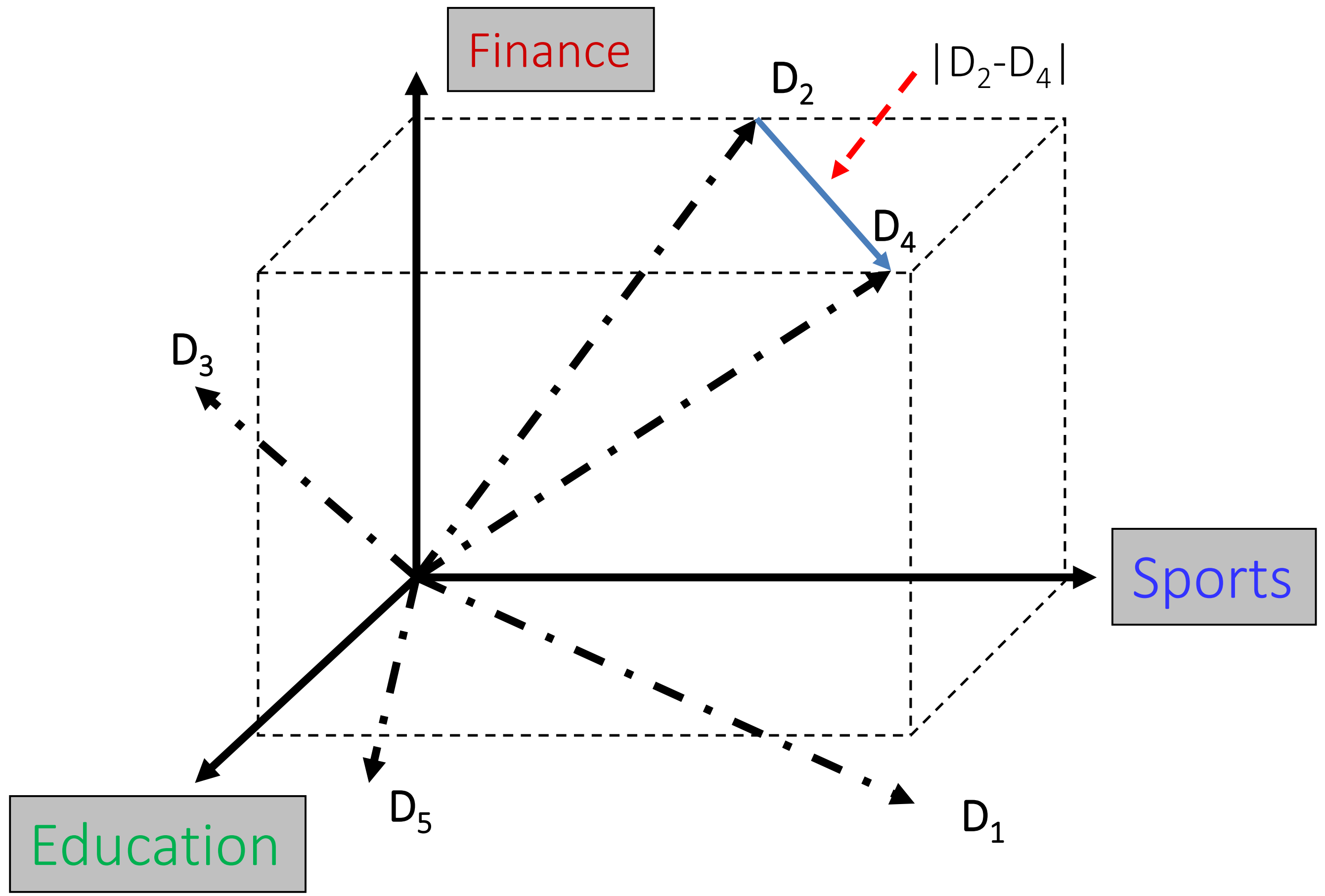
- Matrix: contexts = documents that word appear in

Doc1: Cats have tails.
Doc2: Dogs have tails.

	Doc1	Doc2
cats	1	0
dogs	0	1
have	1	1
tails	1	1

Document Vector Space Model

- All documents are projected into this concept space



Is This Just as Simple as Counting?

What if I give you a raw document?

Let’s take a look at a document

- On Feb. 8, Dong Nguyen announced that he would be removing his hit game Flappy Bird from both the iOS and Android app stores, saying that the success of the game is something he never wanted. Some fans of the game took it personally, replying that they would either kill Nguyen or kill themselves if he followed through with his decision.

- Frank Lantz, the director of the New York University Game Center, said that Nguyen's meltdown resembles how some actors or musicians behave. "People like that can go a little bonkers after being exposed to this kind of interest and attention," he told ABC News. "Especially when there's a healthy dose of Internet trolls."

Document Tokenization

- Regular expressions
  - \\w+: so-called -> ‘so’, ‘called’
  - \\s+: It’s -> ‘It’s’ instead of ‘It’, ‘’s’
- Statistical methods
  - Explore rich features to decide where the boundary of a word is
    - Apache OpenNLP (http://opennlp.apache.org/)
    - Stanford NLP Parser (http://nlp.stanford.edu/software/lex-parser.shtml)
  - Online Demo
    - Stanford (http://corenlp.run/)
    - UIUC/UPenn (http://cogcomp.org/curator/demo/index.html)

Bag-of-words Representation

- Term as the basis for vector space
  - Doc1: Text mining is to identify useful information.
  - Doc2: Useful information is mined from text.
  - Doc3: Apple is delicious.

	text	information	identify	mining	mined	is	useful	to	from	apple	delicious
Doc1	1	1	1	1	0	1	1	1	0	0	0
Doc2	1	1	0	0	1	1	1	0	1	0	0
Doc3	0	0	0	0	0	1	0	0	0	1	1

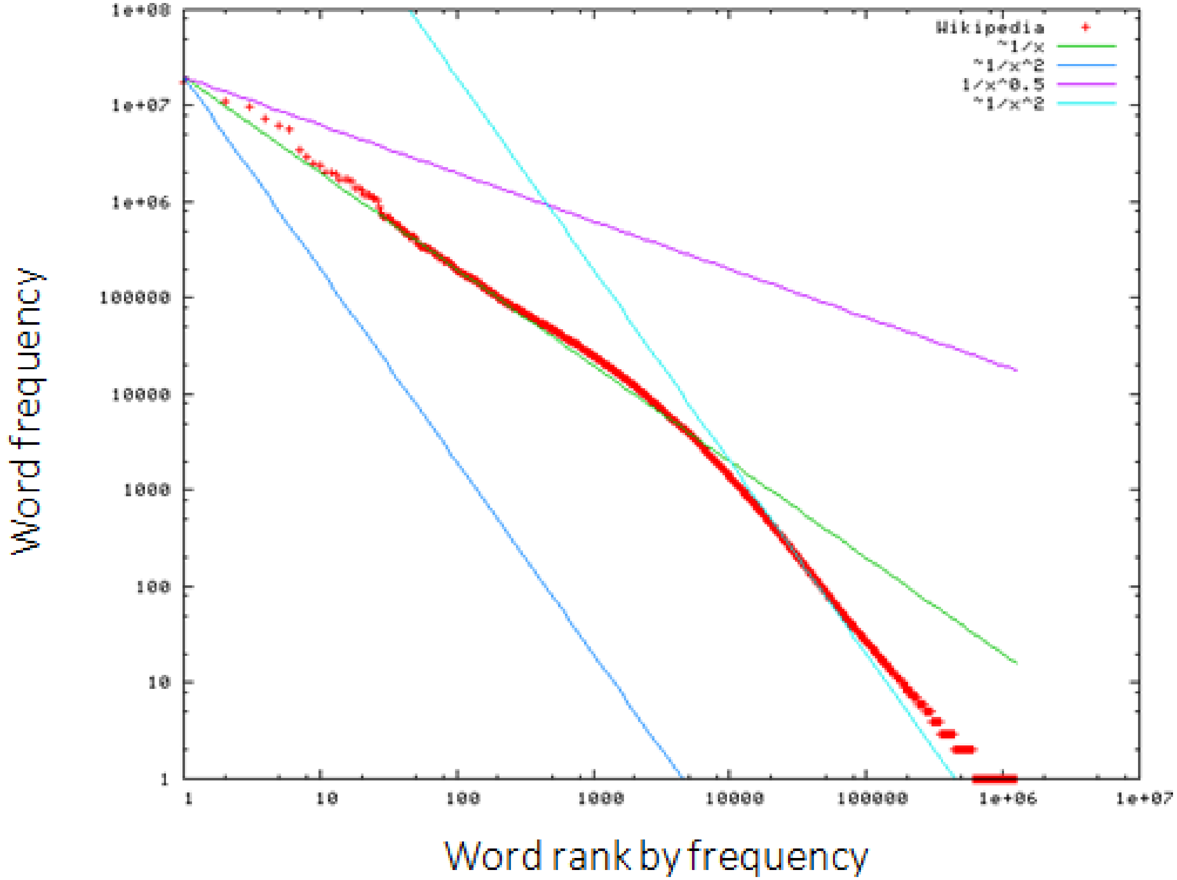
- Assumption
  - Words are independent from each other
- Pros
  - Simple
- Cons
  - Basis vectors are clearly not linearly independent!
  - Grammar and order are missing

Bag-of-Words with N-grams

- N-grams: a contiguous sequence of n tokens from a given text
  - "Text mining is to identify useful information."
  - Bi-grams: "text_mining", "mining_is", "is_to", "to_identify" , "identify_useful", "useful_information", "information_."
- Pros: capture local dependency and order
- Cons: increase the vocabulary size

Statistics of Words in Corpus

- Zipf's law
  - Frequency of a word is inversely proportional to its rank in the frequency table



A plot of word frequency in Wikipedia (Nov 27, 2006)

Zipf’s Law Tells Us

- Head words take large portion of occurrences, but they are semantically meaningless
  - E.g., the, a, an, we, do, to
- Tail words take major portion of vocabulary, but they rarely occur in documents
  - E.g., dextrosinistral
- The rest is most representative
  - To be included in the controlled vocabulary

*In the Brown Corpus of American English text, the word "the" is the most frequently occurring word, and by itself accounts for nearly **7%** of all word occurrences; the second-place word "of" accounts for slightly over **3.5%** of words.*

Better Document Representation

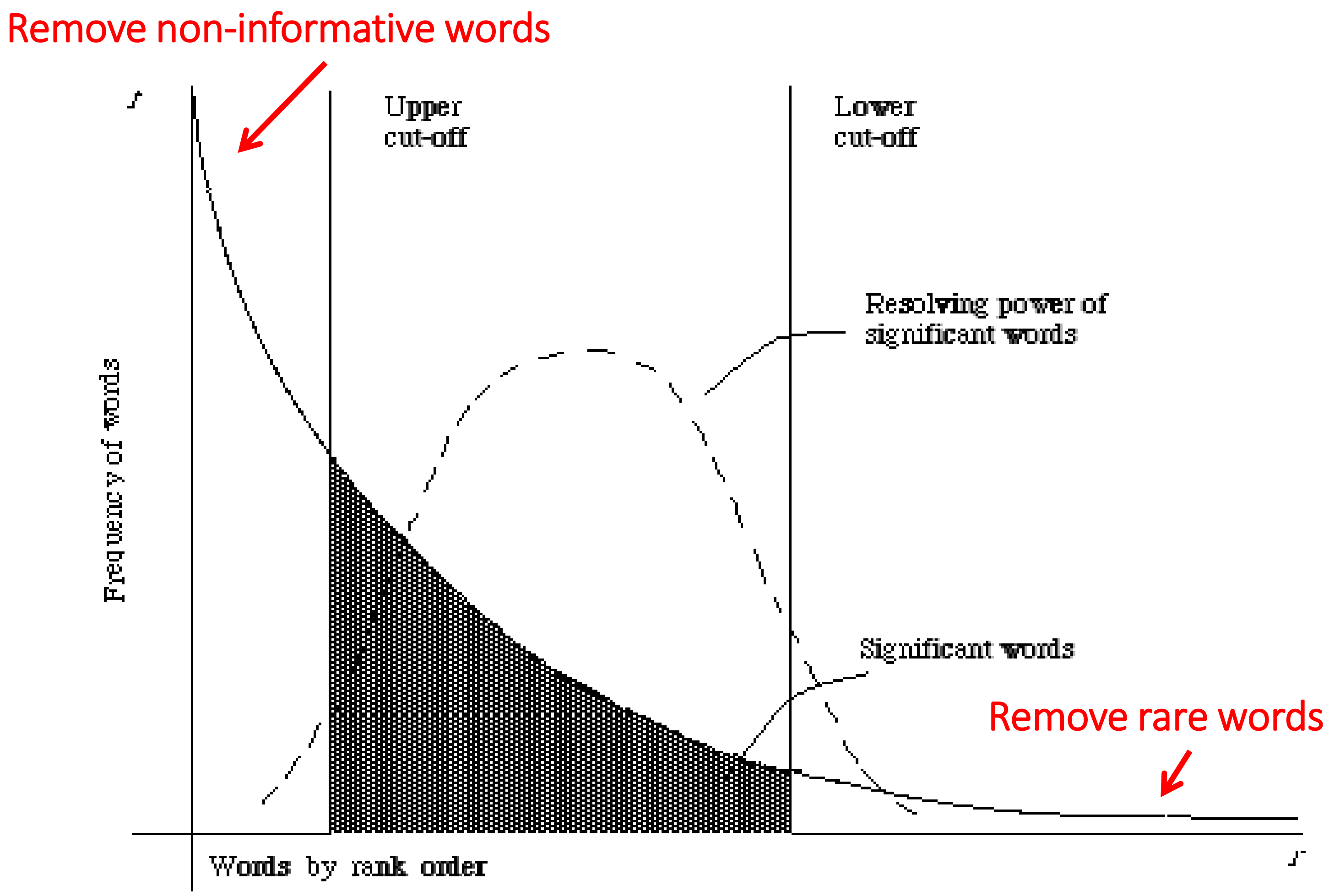


Figure 2.1. A plot of the hyperbolic curve relating f, the frequency of occurrence and r, the rank order (Adaped from Schultz[44] page 120)

Stopwords

- Useless words for document analysis
  - Not all words are informative
  - Remove such words to reduce vocabulary size
  - No universal definition
  - Risk: break the original meaning and structure of text
    - E.g., this is not a good option -> option

      to be or not to be -> null

Nouns	Verbs	Adjectives	Prepositions	Others
1. time	1. be	1. good	1. to	1. the
2. person	2. have	2. new	2. of	2. and
3. year	3. do	3. first	3. in	3. a
4. way	4. say	4. last	4. for	4. that
5. day	5. get	5. long	5. on	5. I
6. thing	6. make	6. great	6. with	6. it
7. man	7. go	7. little	7. at	7. not
8. world	8. know	8. own	8. by	8. he
9. life	9. take	9. other	9. from	9. as
10. hand	10. see	10. old	10. up	10. you
11. part	11. come	11. right	11. about	11. this
12. child	12. think	12. big	12. into	12. but
13. eye	13. look	13. high	13. over	13. his
14. woman	14. want	14. different	14. after	14. they
15. place	15. give	15. small	15. beneath	15. her
16. work	16. use	16. large	16. under	16. she
17. week	17. find	17. next	17. above	17. or
18. case	18. tell	18. early		18. an
19. point	19. ask	19. young		19. will
20. government	20. work	20. important		20. my
21. company	21. seem	21. few		21. one
22. number	22. feel	22. public		22. all
23. group	23. try	23. bad		23. would
24. problem	24. leave	24. same		24. there
25. fact	25. call	25. able		25. their

The OEC: Facts about the language

Stemming

- Reduce inflected or derived words to their root form
  - Plurals, adverbs, inflected word forms
    - E.g., ladies -> lady, referring -> refer, forgotten -> forget
  - Solutions (for English)
    - **Porter stemmer**: patterns of vowel-consonant sequence
    - **Krovetz stemmer**: morphological rules
  - Risk: lose precise meaning of the word
    - E.g., lay -> lie (a false statement? or be in a horizontal position?)

Summary of Preprocessing

Example: *'Text mining is to identify useful information.'*

- **Tokenization**:
  - D1: *'Text', 'mining', 'is', 'to', 'identify', 'useful', 'information', '.'*

Optional

- **Stemming/normalization**:
  - D1: *'text', 'mine', 'is', 'to', 'identify', 'use', 'inform', '.'*
- **N-gram construction**:
  - D1: *'text-mine', 'mine-is', 'is-to', 'to-identify', 'identify-use', 'use-inform', 'inform-.'*

- **Stopword/controlled vocabulary filtering**:
  - D1: *'text-mine', 'to-identify', 'identify-use', 'use-inform'*

Term Weighting

- Term as the basis for vector space
  - Doc1: Text mining is to identify useful information.
  - Doc2: Useful information is mined from text.
  - Doc3: Apple is delicious.

	text	information	identify	mining	mined	is	useful	to	from	apple	delicious
Doc1	1	1	1	1	0	1	1	1	0	0	0
Doc2	1	1	0	0	1	1	1	0	1	0	0
Doc3	0	0	0	0	0	1	0	0	0	1	1

- "Repeated occurrences" are less informative than the "first occurrence"
- Information about semantic does not increase proportionally with number of term occurrence

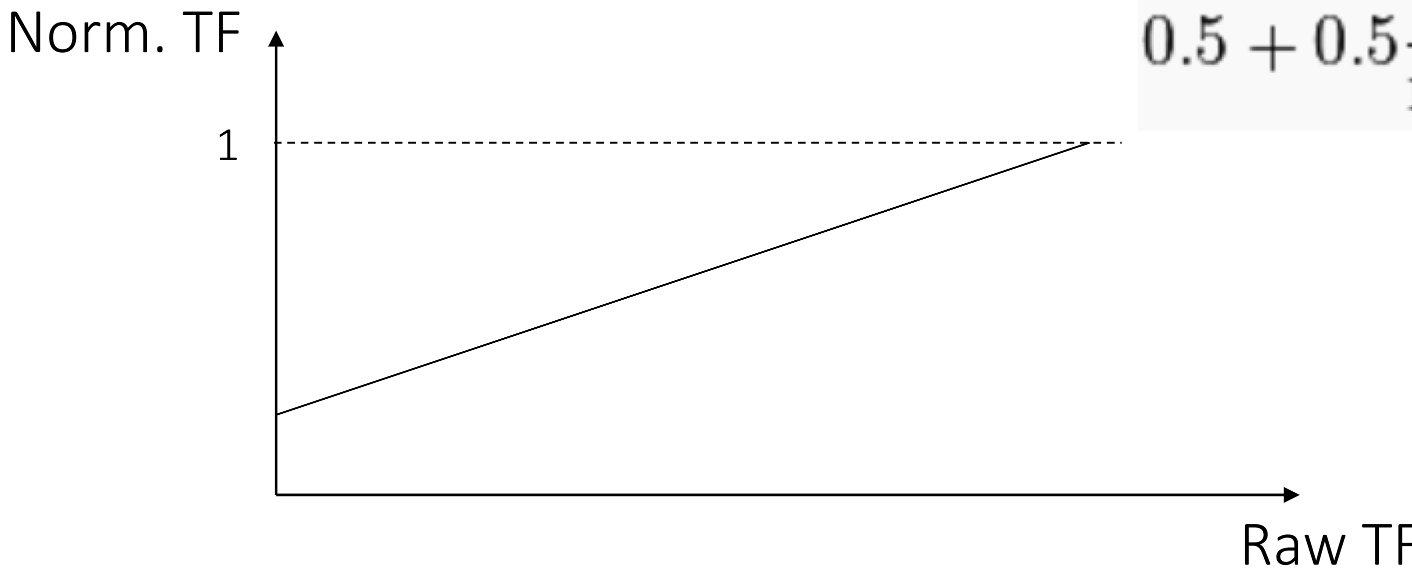
Term Frequency Weights

- Examples of weighting terms

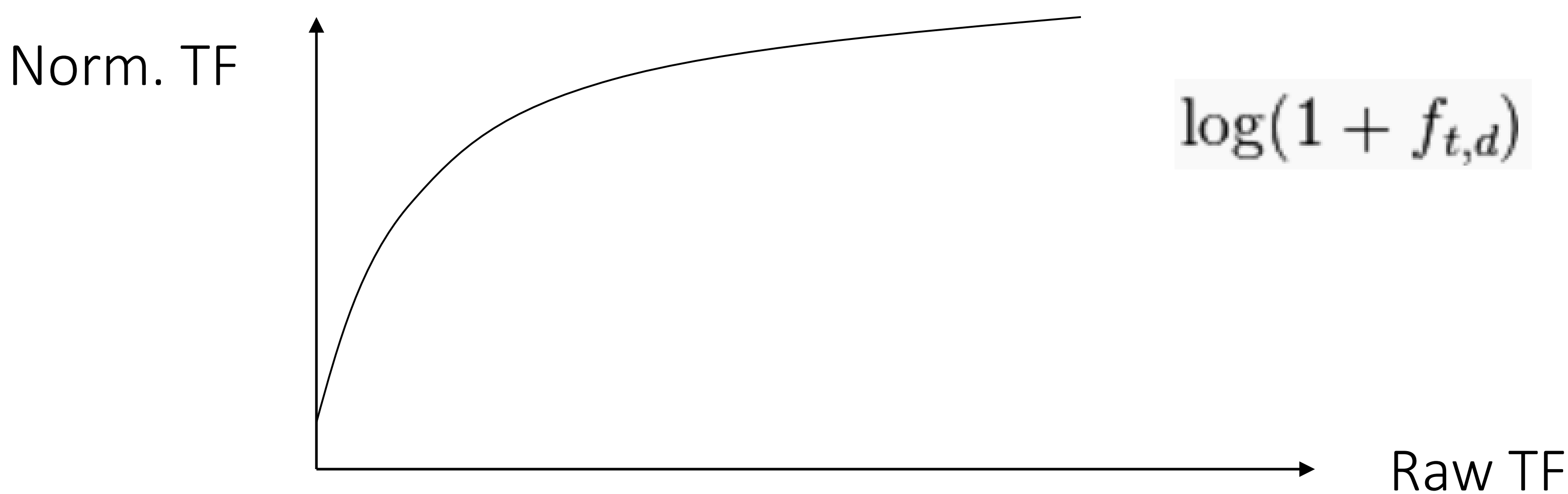
Variants of TF weight

weighting scheme	TF weight
binary	$0, 1$
raw frequency	$f_{t,d}$
log normalization	$\log(1 + f_{t,d})$
double normalization 0.5	$0.5 + 0.5 \frac{f_{t,d}}{\max f_{t,d}}$
double normalization K	$K + (1 - K) \frac{f_{t,d}}{\max f_{t,d}}$

Number of times term *t* appearing in document *d*



$$0.5 + 0.5\frac{f_{t,d}}{\max f_{t,d}}$$



$$\log(1 + f_{t,d})$$

Document Frequency Weighting

- Idea: a term is more discriminative if it occurs only in fewer documents

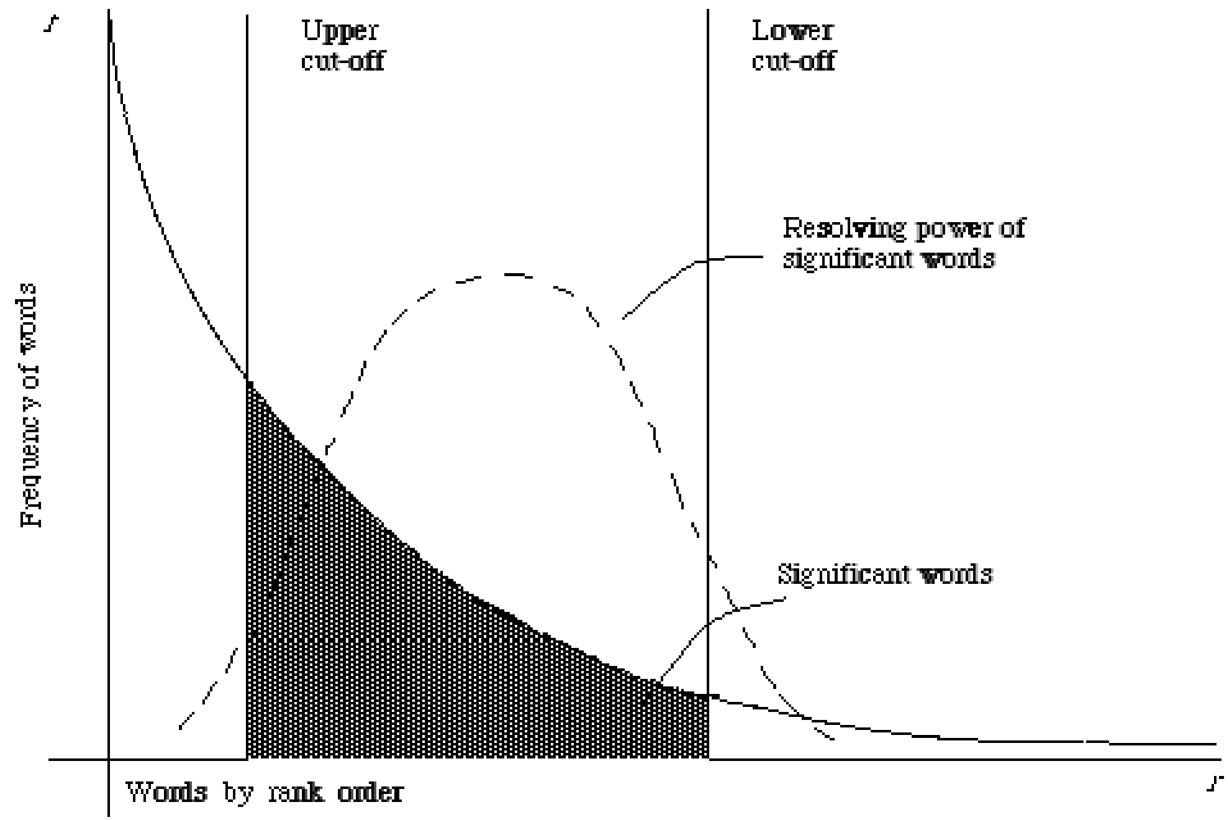


Figure 2.1. A plot of the hyperbolic curve relating f, the frequency of occurrence and r, the rank order (Adaped from Schultz[44] page 120)

Inverse Document Frequency

- Examples of IDF

Variants of IDF weight

weighting scheme	IDF weight
unary	1
inverse frequency	$\log \frac{N}{n_t}$
inverse frequency smooth	$\log(1 + \frac{N}{n_t})$
inverse frequency max	$\log\left(1 + \frac{\max_t n_t}{n_t}\right)$
probabilistic inverse frequency	$\log \frac{N - n_t}{n_t}$

Non-linear scaling

Total number of docs in collection

Number of docs containing term *t*

TFIDF

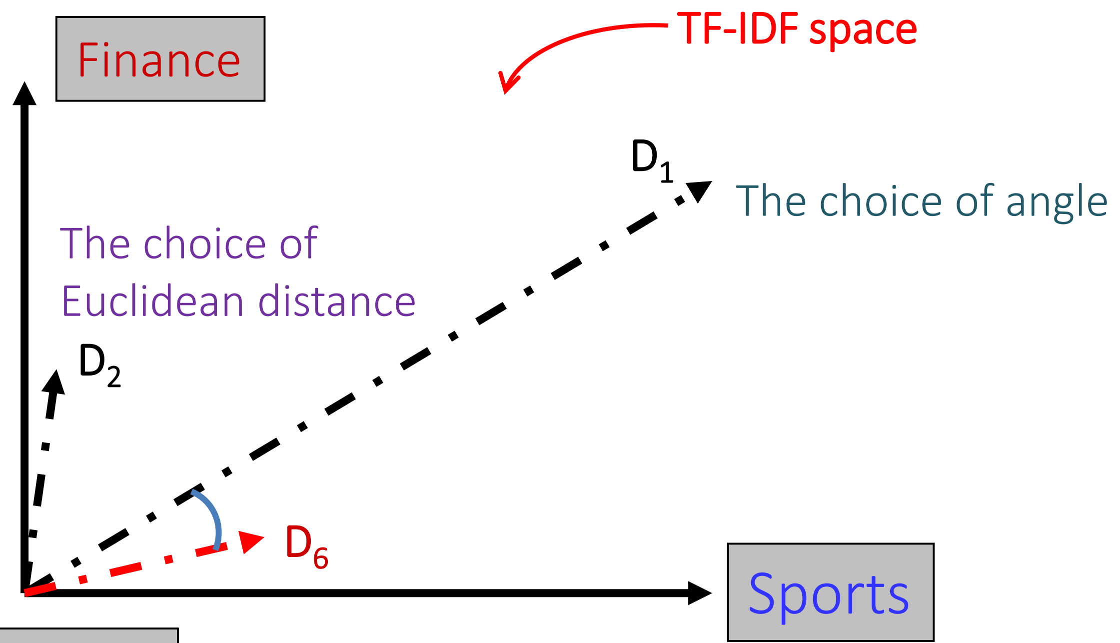
- **Term frequency–Inverse document frequency**
  - Higher tf: more frequently a word appearing in a document
  - Higher idf: less frequently a word appearing in a corpus

Recommended TF-IDF weighting schemes

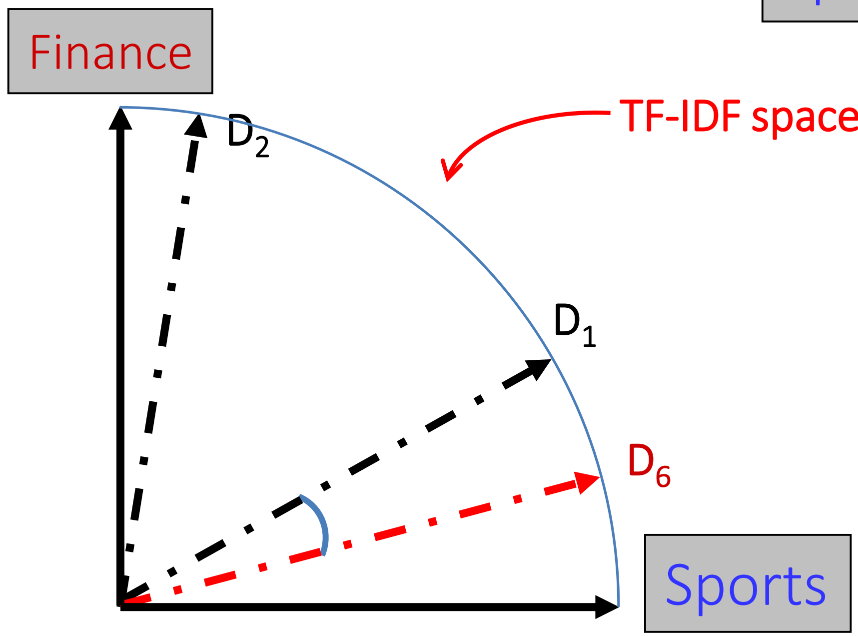
weighting scheme	document term weight	query term weight
1	$f_{t,d} \times \log \frac{N}{n_t}$	$\left(0.5 + 0.5 \frac{f_{t,q}}{\max_t f_{t,q}}\right) \times \log \frac{N}{n_t}$
2	$1 + \log f_{t,d}$	$\log(1 + \frac{N}{n_t})$
3	$(1 + \log f_{t,d}) \times \log \frac{N}{n_t}$	$(1 + \log f_{t,q}) \times \log \frac{N}{n_t}$

Document Similarity

- Euclidean Distance

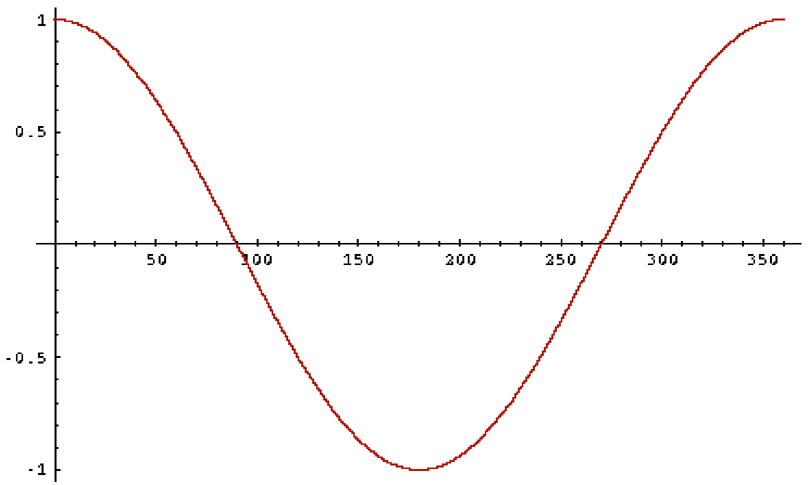


- Cosine Similarity



Cosine as a Similarity Metric

- -1: vectors point in opposite directions
- +1: vectors point in same directions
- 0: vectors are orthogonal



Summary of Vector Space Model

- Pros:
  - Empirically effective!
  - Intuitive
  - Easy to implement
  - Well-studied/mostly evaluated
  - Warning: many variants of TF-IDF!
- Cons
  - Assume term independence
  - Lack of “predictive adequacy”
    - Arbitrary term weighting
    - Arbitrary similarity measure
  - Lots of parameter tuning!
- Any improvements?