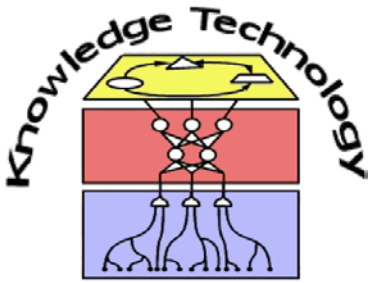
Data Mining

Lecture 12
Text Mining



http://www.informatik.uni-hamburg.de/WTM/

Overview

- Structure, grammar and meaning; ambiguity in language
  - Parsing & part-of-speech tagging
  - Semantic role labeling
- Information retrieval
  - Vector space model, TF-IDF weighting
  - Stop words; Stemming
  - Latent semantic indexing, Word2Vec
- Text classification
- Ontologies

Word Mining for Language Acquisition

Video from BBC documentary with Prof. Deb Roy
http://www.media.mit.edu/people/dkroy

Goal and Definition of Text Mining

- Text mining is the process of compiling, organizing, and ***analyzing large document*** collections
- Goal is to support the delivery of ***targeted types of information*** to analysts and decision makers
- ***Discovery of relationships*** between related facts that span wide domains of inquiry

Mining Text Data Comes with Different Names

- Data mining from text, text mining
- Natural language processing
- Information extraction
- Information retrieval from text
- Text categorization methods
- Material based on book by Han and Kamber, 2006 and additional slides from Cheng Xiang Zhai, Mooney, Volinsky

Free Text versus Structured Data

Data Mining / Knowledge Discovery

Structured Data

HomeLoan (
Loanee: *Frank Rizzo*
Lender: *MWF*
Agency: *Lake View*
Amount: *$200,000*
Term: *15 years*
)

Multimedia

Loans(*$200K*,[*map*],...)

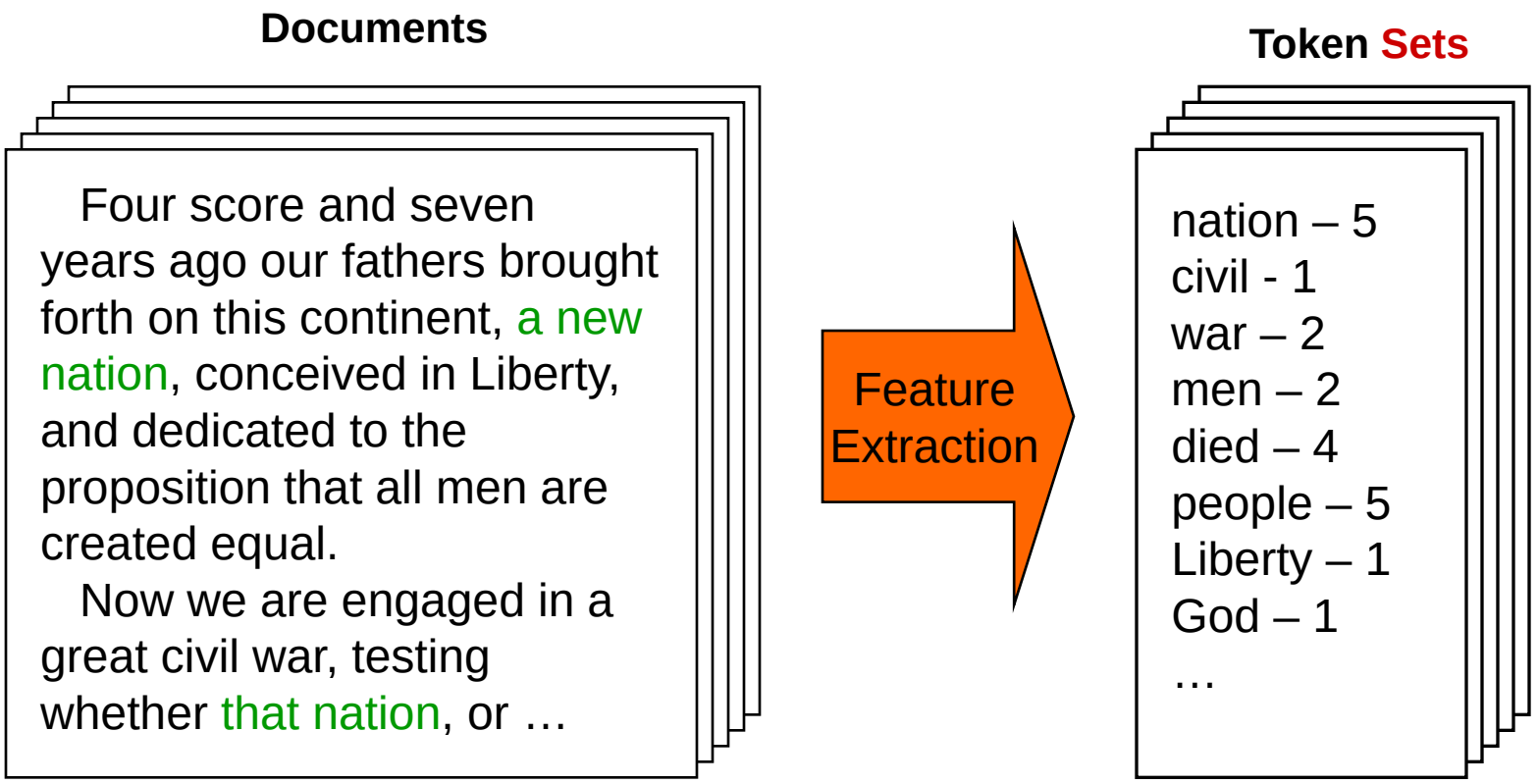
Free Text

Frank Rizzo bought his home from Lake View Real Estate in 1992.
He paid $200,000 under a 15-year loan from MW Financial.

Hypertext

<a href>Frank Rizzo bought <a hef>this home from <a href>Lake View Real Estate In 1992. <p>...

Bag-of-Tokens Approaches



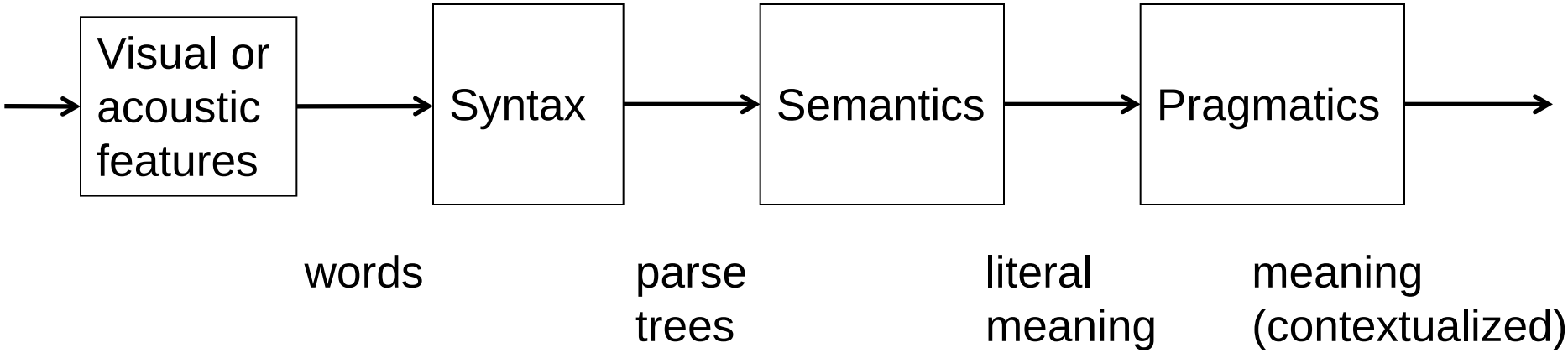
Looses all order-specific information!
Reduces context information.

a.k.a. “bag of words”

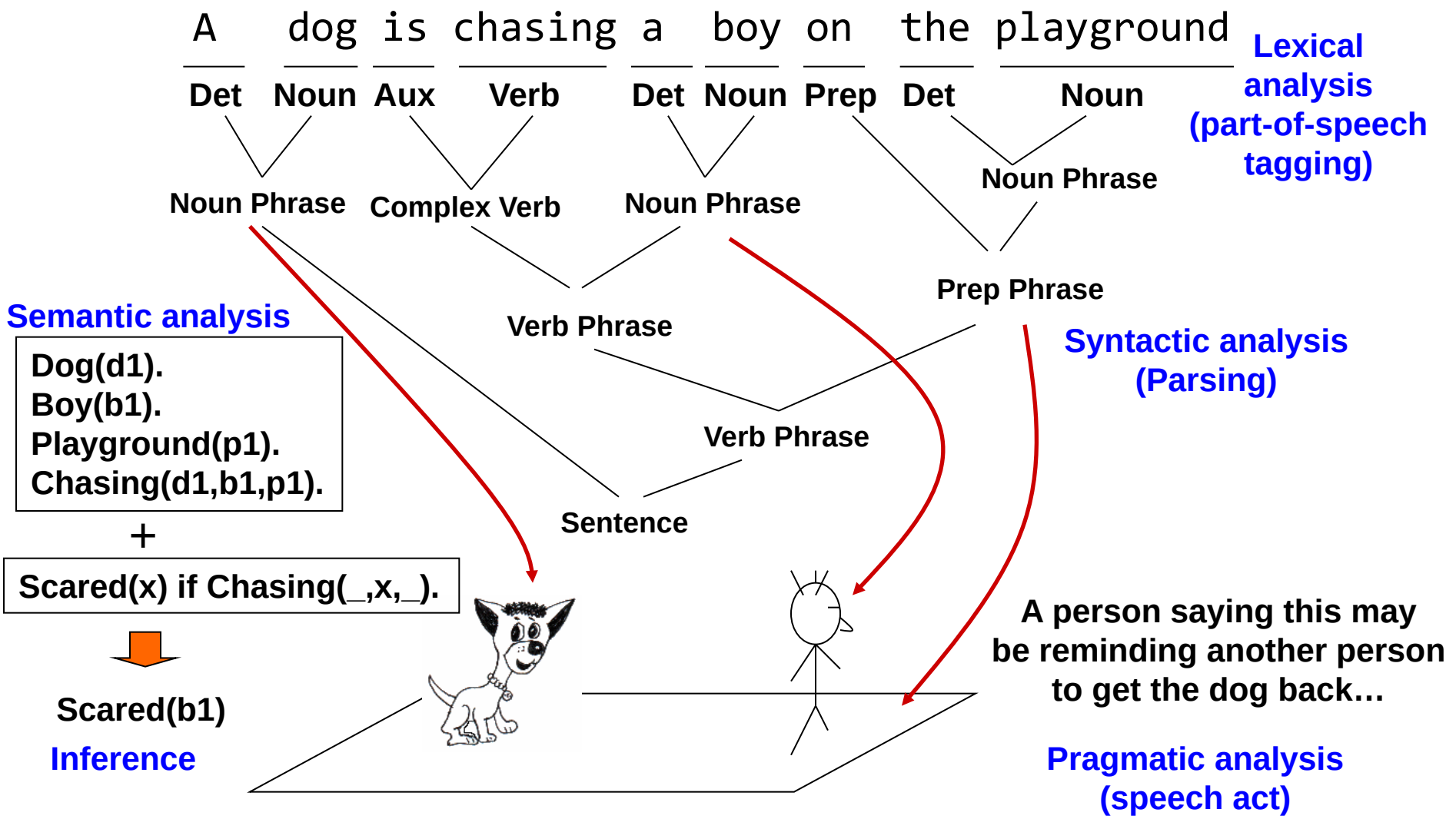
Syntax, Semantic, Pragmatics

- ***Syntax***: ordering of words and its possible effect on meaning.
  - `The dog bit the boy.`
  - `The boy bit the dog.`
  - `* Bit boy dog the the.`
  - `* Colorless green ideas sleep furiously.`
- ***Semantics:*** concerns the (literal) meaning of words, phrases, and sentences.
  - `“plant” as a photosynthetic organism`
  - `“plant” as a manufacturing facility`
  - `“plant” as an act of sowing`
- ***Pragmatics:*** concerns the overall communicative and social context and its effect on interpretation.
  - `The ham sandwich wants another beer.`
  - `John thinks vanilla.`

Comprehension as a Simplified Sequential Model



From Flat Text to Structure and Meaning



Formal Grammars

- A grammar is a set of *production rules* which generates a set of strings (a language) by *rewriting* the top symbol S.
- *Nonterminal* symbols are intermediate results that are not contained in strings of the language.
  - S -> NP VP
  - NP -> Det N
  - VP -> V NP
- *Terminal* symbols are the final symbols (words) that compose the strings in the language.
- Production rules for generating words from part of speech categories constitute the lexicon.
  - N -> boy
  - V -> eat

Context-Free Grammars

- A context-free grammar only has productions with a single symbol on the left-hand side.
- CFG:
  - S -> NP V
  - NP -> Det N
  - VP -> V NP
- not CFG:
  - A B -> C
  - B C -> F G

Language is full of Ambiguities

- Word-level ambiguity
  - “design” can be a noun or a verb (Ambiguous Part of Speech)
  - “root” has multiple meanings (Ambiguous semantic sense)
- Syntactic ambiguity
  - “natural language processing” (Modification/Bracketing)
  - “`A man saw a boy with a telescope.`” (Prepositional Phrase Attachment)
- Semantics and Anaphora resolution
  - “`John persuaded Bill to buy a TV for himself.`”
    (himself = John or Bill?)
- Presupposition and pragmatic inferences
  - “`He has quit smoking.`”
  - implies that he smoked before.

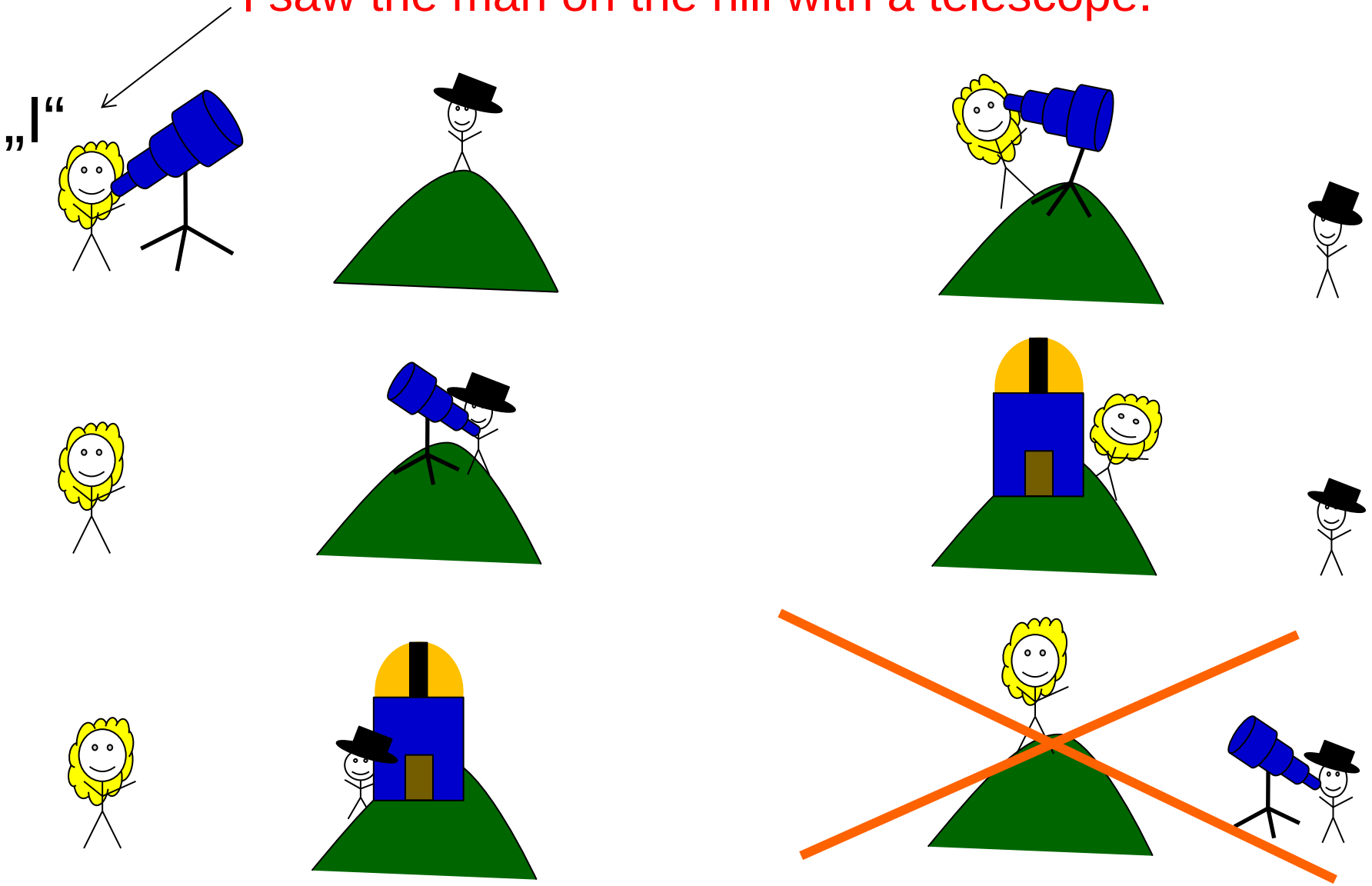
Humans rely on *context* to interpret (when possible).
This context may extend beyond a given document!

Ambiguity: Different Interpretations?

- Natural language can be highly ambiguous
- Can you find ambiguities?
  - `I saw the Grand Canyon flying to LA.`
  - `Time flies like an arrow.`
  - `I saw the man on the hill with a telescope.`

Ambiguity

I saw the man on the hill with a telescope.



Ambiguity is Ubiquitous but we may not Notice

- Speech Recognition
  - "recognize speech" vs. "wreck a nice beach"
- Syntactic Analysis
  - "I ate spaghetti with chopsticks" vs. "I ate spaghetti with meatballs."
- Semantic Analysis
  - "I put the plant in the window" vs. "Ford put the plant in Mexico"
- Pragmatic Analysis
  - **Example** from "The Pink Panther Strikes Again":

Clouseau: Does your dog bite?
Hotel Clerk: No.
Clouseau: [*bowing down to pet the dog*] Nice doggie.
[*Dog barks and bites Clouseau in the hand*]
Clouseau: I thought you said your dog did not bite!
Hotel Clerk: That is not my dog.

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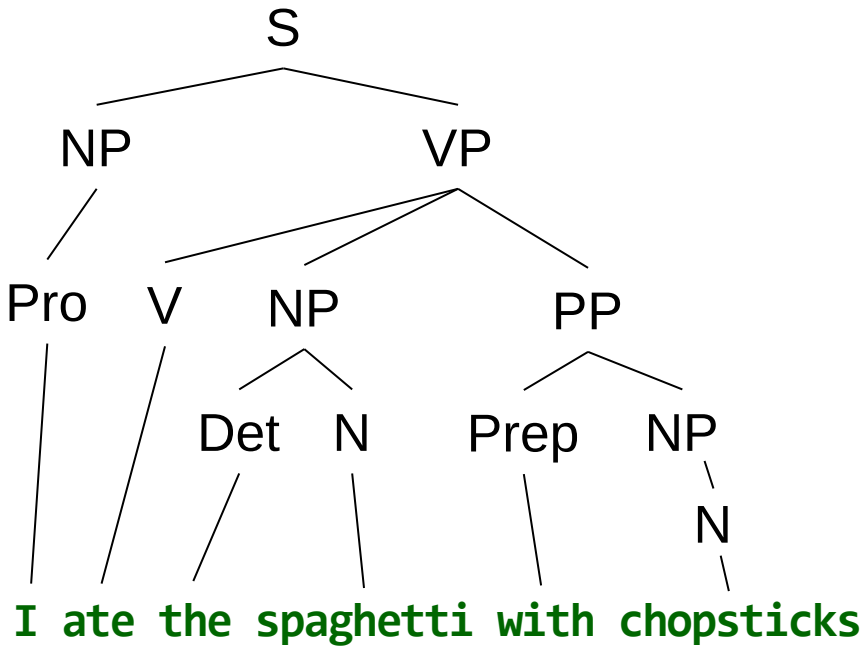
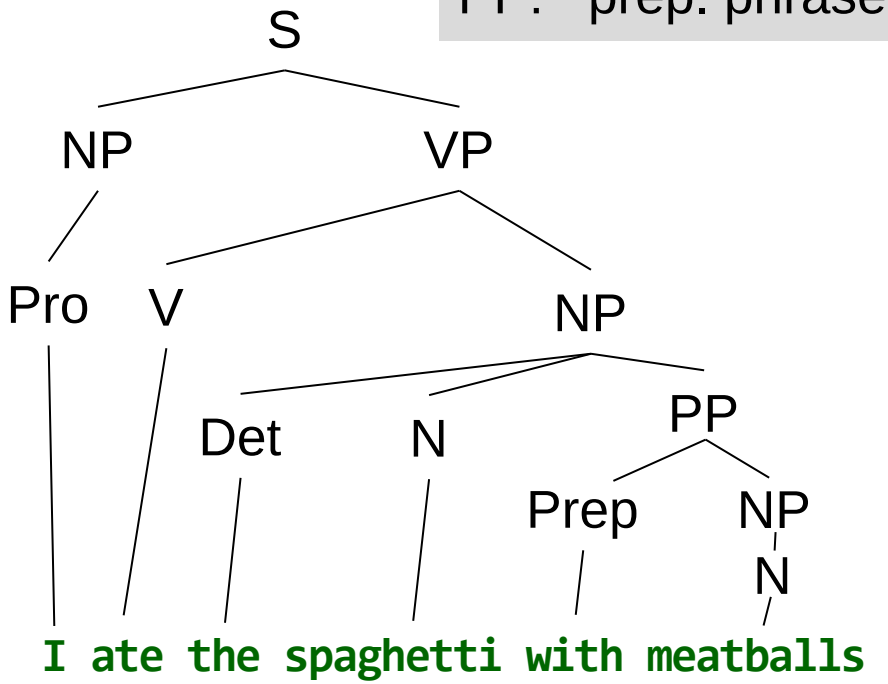
Syntactic Parsing

- Produce the correct syntactic parse tree for a sentence

S: sentence
NP: noun phrase
VP: verb phrase
N: noun
V: verb
Pro: pronoun
Det: determinant
Prep: preposition
PP: prep. phrase





Ambiguity is Explosive

- Ambiguities compound to generate enormous numbers of possible interpretations.
- In English, a sentence ending in *n* prepositional phrases has *over* 2^n syntactic interpretations.
  - "I saw the man with the telescope.": 2 parses
  - "I saw the man on the hill with the telescope.": 5 parses
  - "I saw the man on the hill in Texas with the telescope.": 14 parses
  - "I saw the man on the hill in Texas with the telescope at noon.": 42 parses
  - "I saw the man on the hill in Texas with the telescope at noon on Monday." 132 parses

Mining Language in Complex Environments (Knowledge Technology Lab, WTM)

How can we Deal with Mining from Text at all? Shallow Natural Language Processing

- Progress on useful ***Sub-Goals***:
  - English Lexicon
  - Part-of-Speech Tagging
  - Word Sense Disambiguation
  - Phrase Detection / Parsing

Morphological Analysis

- ***Morphology*** is the field of linguistics that studies the internal structure of words.
- A ***morpheme*** is the smallest linguistic unit that has semantic meaning
  - **E.g.** “carry”, “pre”, “ed”, “ly”, “s”
- Morphological analysis is the task of segmenting a word into its morphemes:
  - carried $\Rightarrow$ carry + ed (past tense)
  - independently $\Rightarrow$ in + (depend + ent) + ly
  - Googlers $\Rightarrow$ (Google + er) + s (plural)
  - unlockable $\Rightarrow$ un + (lock + able) ?

    $\Rightarrow$ (un + lock) + able ?

Part-of-Speech (POS) Tagging

Training data (Annotated text)

This	*sentence*	*serves*	*as*	*an*	*example*	*of*	*annotated*	*text…*
Det	N	V1	P	Det	N	P	V2	N

"This is a new sentence." → POS Tagger → *This is a new sentence.*
Det Aux Det Adj N

Pick the *most likely* tag sequence.

$$p(w_1,\ldots,w_k,t_1,\ldots,t_k) = \begin{cases} p(t_1 \mid w_1)\ldots p(t_k \mid w_k)\, p(w_1)\ldots p(w_k) \\ \prod_{i=1}^{k} p(w_i \mid t_i)\, p(t_i \mid t_{i-1}) \end{cases}$$

Independent assignment
Most common tag

Partial dependency
(HMM)

Phrase Chunking rather than Full Parsing

- Find all non-recursive noun phrases (**NPs**) and verb phrases (**VPs**) in a sentence.
  - [NP I] [VP ate] [NP the spaghetti] [PP with] [NP meatballs].
  - [NP He] [VP reckons] [NP the current account deficit] [VP will narrow] [PP to] [NP only $ 1.8 billion] [PP in] [NP September]

Probabilistic Structure Parsing to Reduce Ambiguity

Choose *most likely* parse tree…

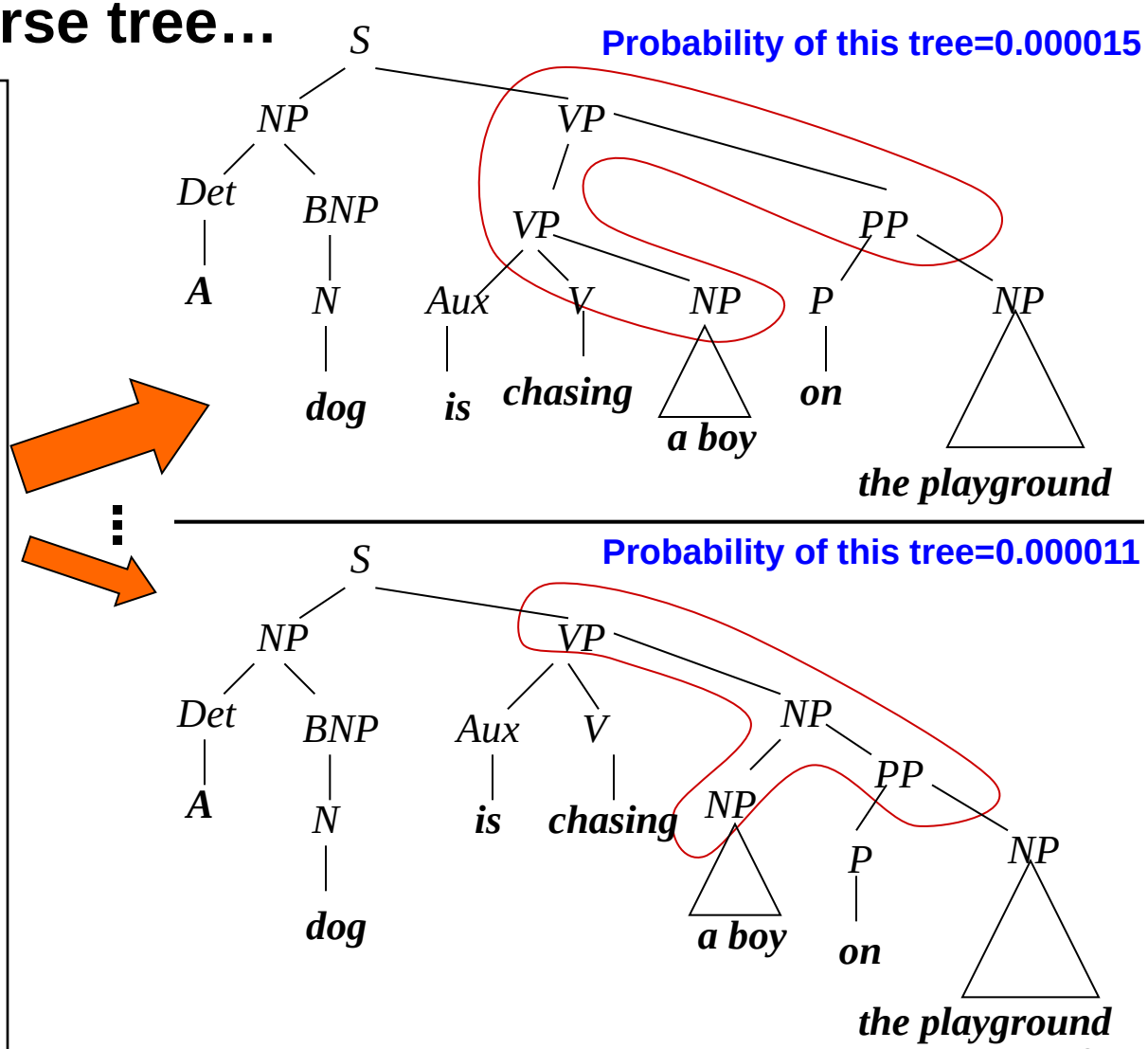
Probabilistic CFG

Grammar

$S \rightarrow NP\ VP$	1.0
$NP \rightarrow Det\ BNP$	0.3
$NP \rightarrow BNP$	0.4
$NP \rightarrow NP\ PP$	0.3
$BNP \rightarrow N$	…
$VP \rightarrow V$	
$VP \rightarrow Aux\ V\ NP$	
$VP \rightarrow VP\ PP$	…
$PP \rightarrow P\ NP$	1.0

Lexicon

$V \rightarrow chasing$	0.01
$Aux \rightarrow is$	
$N \rightarrow dog$	0.003
$N \rightarrow boy$	
$N \rightarrow playground$	…
$Det \rightarrow the$	
$Det \rightarrow a$	…
$P \rightarrow on$	



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From Structure to Semantics: Word Sense Disambiguation (WSD)

- Words in natural language usually have a fair number of different possible meanings.
  - `Ellen has a strong interest in computational linguistics.`
  - `Ellen pays a large amount of interest on her credit card.`

- For many tasks (question answering, translation), the proper sense of each ambiguous word in a sentence must be determined.

Semantic Role Labeling (SRL)

- For each clause, determine the semantic role played by each noun phrase that is an argument to the verb.

  agent patient source destination instrument

  - John drove Mary from Austin to Dallas in his Toyota Prius.
  - The hammer broke the window.

- Also referred to as "***case role analysis***", "***thematic analysis***", and "***shallow semantic parsing***"

Semantic Information Extraction (IE)

- Identify phrases in language that refer to specific types of entities and relations in text.
- ***Named entity recognition*** for identifying names of people, places, organizations, etc. in text.

people organizations places

- Michael Dell is the CEO of Dell Computer Corporation and lives in Austin Texas.

- ***Relation extraction*** identifies specific relations between entities.

Question Answering

- Directly answer natural language questions based on information presented in a corpus of textual documents (e.g. the web).
  - When was Barack Obama born? (***factoid***)
    - ⇨ August 4, 1961
  - Who was president when Barack Obama was born?
    - ⇨ John F. Kennedy
  - How many presidents have there been since Barack Obama was born? (***towards more inferences***)
    - ⇨ 9

⇨ Much but not all information may be directly available

Text Summarization

- Produce a short summary of a longer document or article.
  - ***Article***: With a split decision in the final two primaries and a flurry of super-delegate endorsements, Sen. Barack Obama sealed the Democratic presidential nomination last night after a grueling and history-making campaign against Sen. Hillary Rodham Clinton that will make him the first African American to head a major-party ticket. Before a chanting and cheering audience in St. Paul, Minn., the first-term senator from Illinois savored what once seemed an unlikely outcome to the Democratic race with a nod to the marathon that was ending and to what will be another hard-fought battle, against Sen. John McCain, the presumptive Republican nominee….
  - ***Summary***: Senator Barack Obama was declared the presumptive Democratic presidential nominee.

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Mining Text Data in Internet (Video)

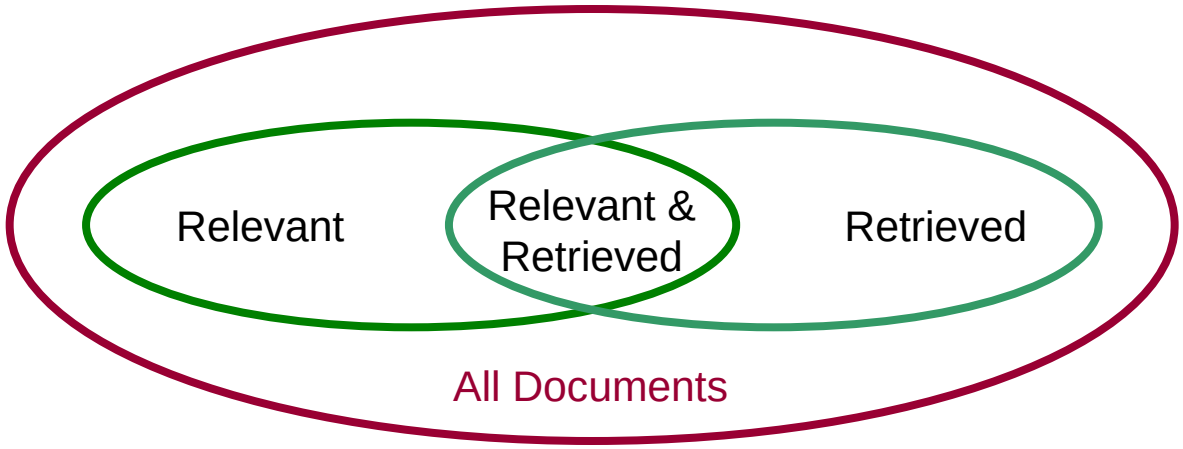
Information Retrieval as Start for Text Mining

- Typical traditional IR systems
  - Online library catalogs
  - Online document management systems
- Information retrieval vs. database systems
  - Some IR problems are not addressed well in DBMS
    - **E.g.**, unstructured documents, approximate search using keywords and relevance
  - Some DB problems are not present in IR
    - **E.g.**, update, transaction management, complex objects

Information Retrieval vs Information Extraction

- ***Information Retrieval***
  - Given a set of query terms and a set of document terms select only
    - the most relevant documents [***precision***], and
    - preferably all the relevant [***recall***].
- ***Information Extraction***
  - Extract what the document contains from the text
- IR systems can FIND documents but do not need to "understand" them

Basic Measures for Text Retrieval



- ***Precision***: the percentage of retrieved documents that are in fact relevant to the query (i.e., "correct" responses)

$$precision = \frac{|\{Relevant\} \cap \{Retrieved\}|}{|\{Retrieved\}|}$$

- ***Recall***: the percentage of documents that are relevant to the query and were, in fact, retrieved

$$recall = \frac{|\{Relevant\} \cap \{Retrieved\}|}{|\{Relevant\}|}$$

Precision vs. Recall

- In other words (we have been here before!)
  - Precision = TP/(TP+FP)
  - Recall = TP/(TP+FN)

	Truth:Relevant	Truth:Not Relevant
Algorithm:Relevant	TP	FP
Algorithm: Not Relevant	FN	TN

  - Trade off:
    - If algorithm is ‘picky’: precision high, recall low
    - If algorithm is ‘relaxed’: precision low, recall high
  - BUT: recall often hard if not impossible to calculate

Information Retrieval Techniques

- Basic Concepts
  - A document can be described by a set of representative keywords called ***index terms***.
  - Different index terms have varying relevance when used to describe document contents.
  - This effect is captured through the ***assignment of numerical weights to each index term*** of a document. (e.g.: frequency, tf-idf: term frequency-inverse document frequency)
- DBMS Analogy
  - Index terms → ***Attributes***
  - Weights → ***Attribute Values***

Information Retrieval Techniques

- ***Effective Index Terms (Attribute) Selection***
  - Stop list (words to ignore)
  - Word stem (reduce #terms)
  - Index terms weighting methods
    - Terms × Documents Frequency Matrices
- ***Information Retrieval Models***
  - Boolean Model
  - Vector Model
  - Probabilistic Model

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Boolean Model

- Consider that ***index terms are either present or absent*** in a document

  → the index term weights are assumed to be all ***binaries***

- A query is composed of index terms linked by three connectives: *not*, *and*, and *or*
  - **E.g.**: car *and* repair, plane *or* airplane
- The Boolean model predicts that ***each document is either relevant or non-relevant*** based on the match of a document to the query
- Think about the advantages / disadvantages …

Vector Space Model

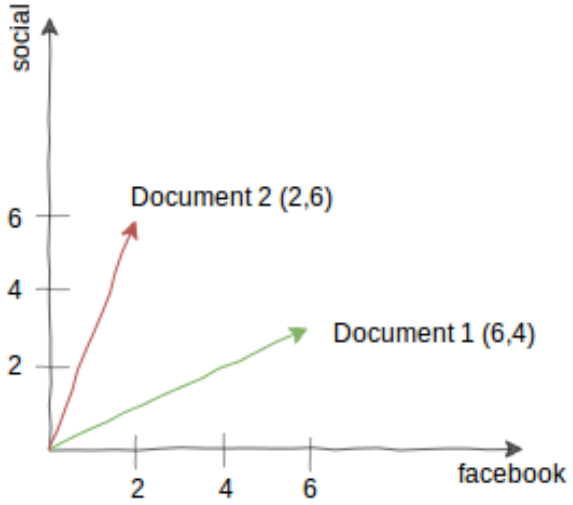
- ***Represent a document by a term vector***
  - Term: basic concept, e.g., word or phrase
  - Each term defines one dimension
  - N terms define a N-dimensional space
  - Element of vector corresponds to term weight
  - E.g., d = (x_1,…,x_N), x_i is ***importance*** of term i

- New document is assigned to the most likely category based on ***vector similarity***.

Vector Space Model

- Documents & user queries represented as N-dimensional vectors
  - N = # index terms in document collection

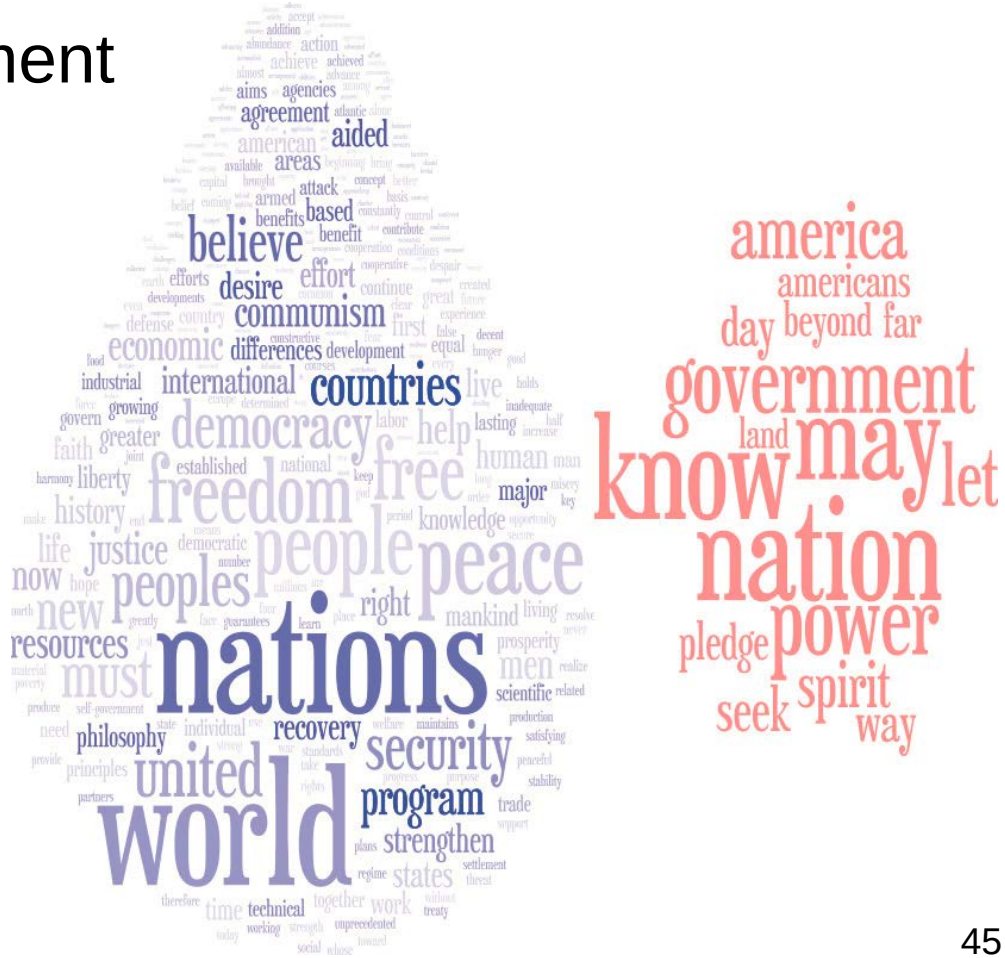
	doc1	doc2
facebook	6	2
social	3	6



- Degree of ***similarity*** of the document d with regard to the query q:
  - Calculated as the ***correlation*** between the vectors that represent them
  - Using measures such as the *Euclidian distance* or the *cosine* of the angle between these two vectors

Word Clouds

- Find most frequent/interesting words in text, and display them graphically
  - Summarize a document
  - Blogs do this
  - → wordle.net



blue: Harry Truman's 1948 inaugural address

red: words absent from Truman's speech, but in those of his contemporaries

What VS Model does not Specify

- How to ***select terms*** to capture "basic concepts"
  - Stop words
    - **E.g.** "a", "the", "always", "along"
  - Word stemming
    - **E.g.** "computer", "computing", "computerize" => "compute"
- How to ***assign weights***
  - Not all words are equally important: Some are more indicative than others
    - **E.g.** "algebra" vs. "science"
- How to measure the similarity?

How to assign Weights

- Two-fold heuristics based on frequency
  - TF (Term frequency)
    - More frequent ***within*** a document → more relevant to semantics
    - e.g., “algebra” vs. “trigonometry” in literature on maths
  - IDF (Inverse document frequency)
    - Less frequent ***among*** documents → more discriminative
    - e.g. “algebra” vs. “science”

TF Weighting

- ***Weighting***:
  - More frequent ⇨ more relevant to topic
    - Raw TF= *f*(*t*,*d*): how many times term *t* appears in doc *d*
- ***Normalization***:
  - Document length varies ⇨ relative frequency preferred
    - **E.g.**, Maximum frequency normalization

$$\mathrm{TF}(t,d) = 0.5 + \frac{0.5 \cdot f(t,d)}{Length(d)}$$

  - After normalization: values between 0.5 and 1
  - Augmented frequency to prevent bias for longer documents

IDF Weighting

- Ideas:
  - Measure of how much information the word provides
  - Less frequent ***among*** documents → more discriminative

- Formula:

$$\mathrm{IDF}(t) = \log\left(\frac{n}{1+k}\right)$$

n — total number of docs

k — number of docs with term t appearing
(the DF document frequency)

1 — avoid division by 0

TF-IDF Weighting

- Ideas:
  - Combine term frequency and inverse document frequency

- Formula:

$$\mathrm{TF\,IDF}(t,d,D) = \mathrm{TF}(t,d)\ \mathrm{x}\ IDF(t,D)$$

- High weighting values for

  1) high term frequency in a document, and

  2) a low document frequency of term t in all documents D

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Similarity-based Retrieval in Text Data

- Finds similar documents based on a set of common keywords
- Answer should be based on the ***degree of relevance*** based on the nearness of the keywords, relative frequency of the keywords, etc.
- ***Stop list***
  - Set of words that are deemed ***irrelevant***, even though they may appear frequently
  - **E.g.**, `a, the, of, for, to, with,` etc.
  - Stop lists may vary when document set varies

Stop Words

- Many of the most frequently used words in English are almost worthless in retrieval and text mining – these words are called ***stop words***
  - the, of, and, to, ….
  - Typically up to about 400 to 500 such words
  - For an application or domain specific stop words list may be constructed
- ***Why do we need to remove stop words***?
  - Reduce indexing (or data) file size
    - stopwords accounts 20-30% of total word counts.
  - Improve efficiency
    - stop words are not useful for searching or text mining
    - stop words always have a large number of hits

Stemming: additional examples

- Techniques used to find the root/stem of a word:
  - E.g.,

▪	user	engineering
▪	users	engineered
▪	used	engineer
▪	using	
• stem:	use	engineer

- ***Usefulness***:
  - improving effectiveness of retrieval and text mining
    - matching similar words
  - reducing indexing size
    - combing words with same roots may reduce indexing size as much as 40-50%.

Basic stemming algorithms (e.g. Porter Algorithm)

- remove ending
  - if a word ends with a **consonant** other than **s**,

    followed by an **s**, then delete **s**.
  - if a word ends in **es**, drop the **s**.
  - if a word ends in **ing**, delete the **ing** unless the remaining word consists only of one letter or of **th**.
  - If a word ends with **ed**, preceded by a consonant, delete the **ed** unless this leaves only a single letter.
  - ……
- transform words
  - if a word ends with “ies” but not “eies” or “aies” then “ies --> y.”

Better than Stemmers: Lemmatizers

- Find the base of a word based on intended meaning
  - E.g. ``saw´´

    → see (verb)

    → saw (noun)
- Requires context, e.g. by using a POS tagger
- Open area of research

- NLTK Python toolkit has both, stemmer and lemmatizer
  http//www.nltk.org

Term / Document Matrix

- Most common form of representation in text mining is the ***term - document*** matrix
  - Term: typically a single word, but could be a word phrase like “data mining”
  - Document: a generic term meaning a collection of text to be retrieved
  - Can be large - terms are often 50k or larger, documents can be in the billions (www).
  - Can be binary or use counts

Term / Document Matrix Example (1)

Example: 10 documents: 6 terms

	Database	SQL	Index	Regression	Likelihood	linear
D1	24	21	9	0	0	3
D2	32	10	5	0	3	0
D3	12	16	5	0	0	0
D4	6	7	2	0	0	0
D5	43	31	20	0	3	0
D6	2	0	0	18	7	6
D7	0	0	1	32	12	0
D8	3	0	0	22	4	4
D9	1	0	0	34	27	25
D10	6	0	0	17	4	23

$$D_1 = (d_{i1}, d_{i2}, \ldots, d_{it})$$

- Each document now is just a vector of terms, sometimes boolean

Distances in TD Matrices

- Given a term doc matrix representation, now we can define distances between documents (or terms!)
- Elements of matrix can be 0,1 or term frequencies (sometimes normalized)
- Can use Euclidean or cosine distance
- Cosine distance proven to work well:

$$d_c(D_i, D_j) = \frac{\sum_{k=1}^{T} d_{ik} d_{jk}}{\sqrt{\sum_{k=1}^{T} d_{ik}^2 \sum_{k=1}^{T} d_{jk}^2}} = \frac{D_i \cdot D_j}{|D_i||D_j|}$$

- If docs are the same, d_c =1, if nothing in common d_c=0

Term / Document Matrix Example (2)

Example: 10 documents: 6 terms

$$D_1 = (d_{i1}, d_{i2}, \ldots, d_{it})$$

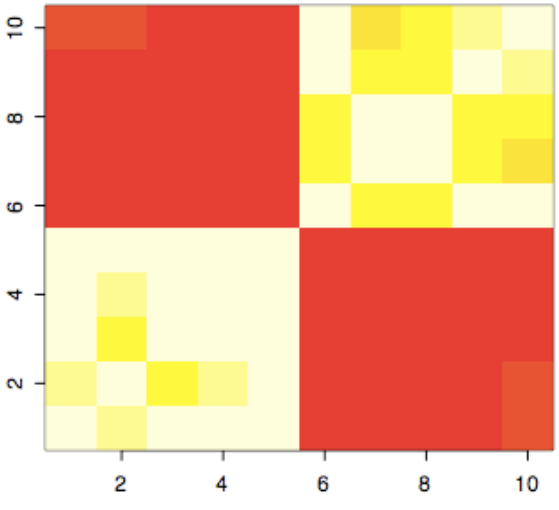
	Database	SQL	Index	Regression	Likelihood	linear
D1	24	21	9	0	0	3
D2	32	10	5	0	3	0
D3	12	16	5	0	0	0
D4	6	7	2	0	0	0
D5	43	31	20	0	3	0
D6	2	0	0	18	7	6
D7	0	0	1	32	12	0
D8	3	0	0	22	4	4
D9	1	0	0	34	27	25
D10	6	0	0	17	4	23

- We can calculate cosine and Euclidean distance for this matrix
- What would you want the distances to look like?

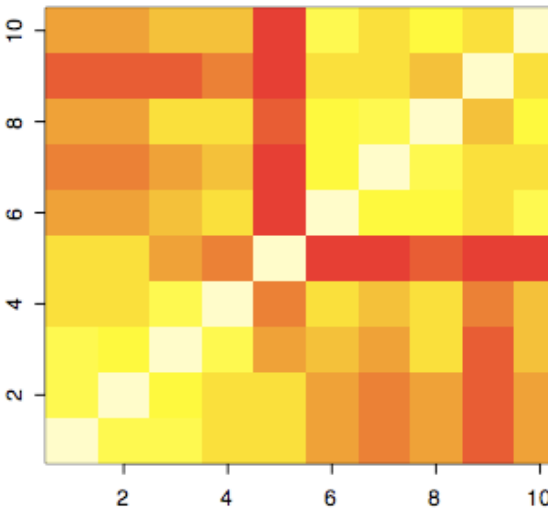
Visualisation of Document distance

- Images plot pairwise distances between documents

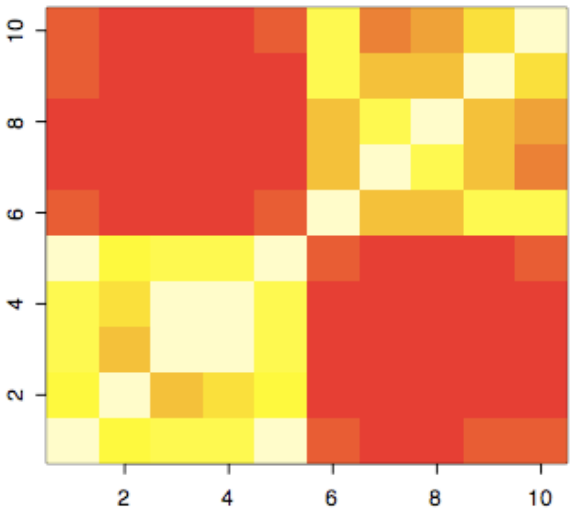
cosine distance



Euclidean



scaled Euclidean



white: small distance
dark: large distance

R function: ‘image’

Overview

- Structure, grammar and meaning; ambiguity in language
  - Parsing & part-of-speech tagging
  - Semantic role labeling
- Information retrieval
  - Vector space model, TF-IDF weighting
  - Stop words; Stemming
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Queries and towards Latent Semantic Indexing

- A query is a representation of the user's information needs
  - Normally a list of words.
- Once we have a TD matrix, queries can be represented as a vector in the same space
  - "Database Index" = (1,0,1,0,0,0)
- Query can be a simple question in natural language

- Calculate cosine distance between query and documents
  - Returns a ranked vector of documents

Latent Semantic Indexing (1)

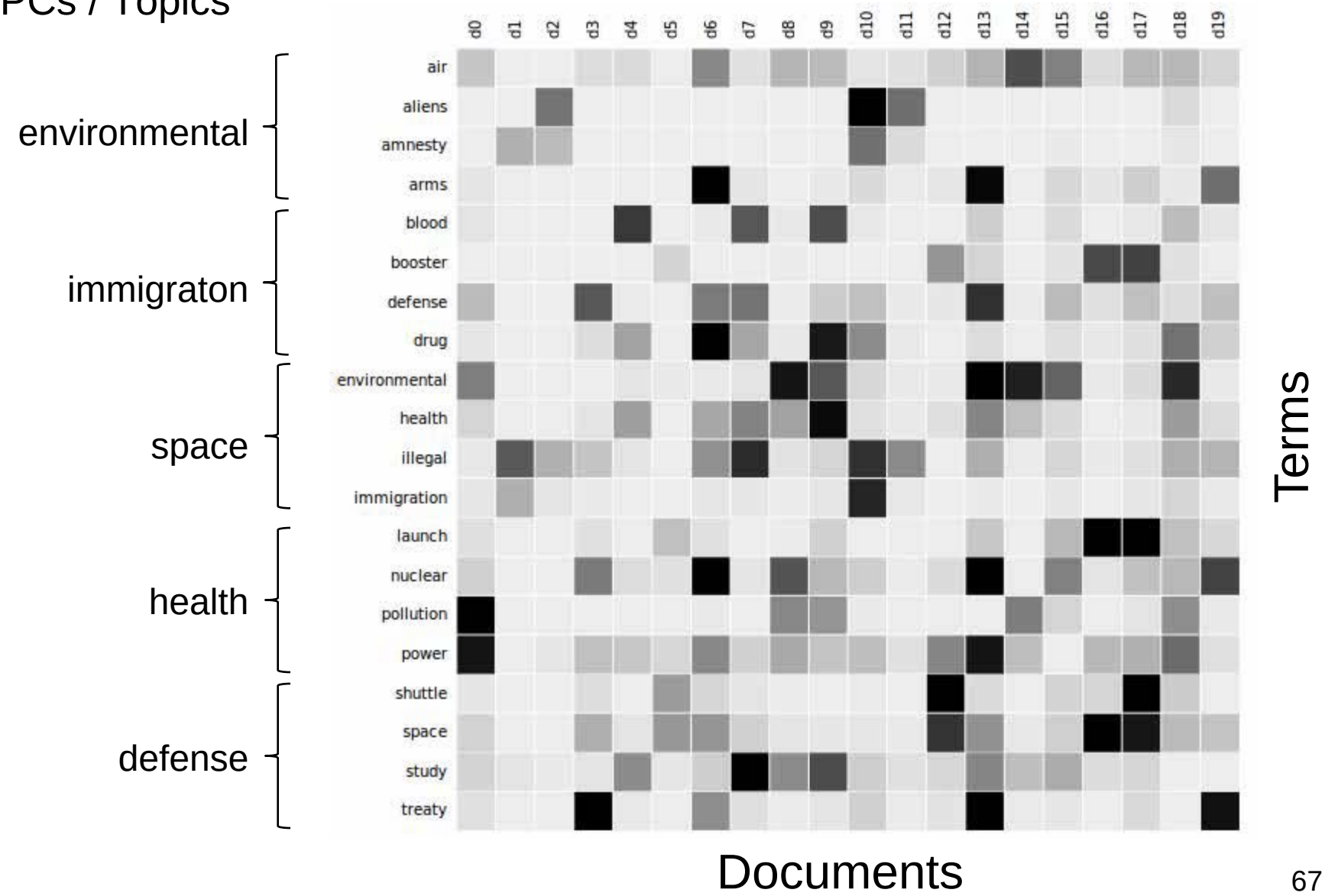
- Criticism: queries can be posed in many ways, but still mean the same
  - Data mining *or* knowledge discovery; car *or* automobile; beetroot *or* beet; …
- ***Semantically***, these are (almost) the same, and documents with either term are relevant.
- Possibilities to address the problem:
  - Synonym lists or Thesauri ← imperfect and difficult to maintain
  - Latent Semantic Indexing (LSI), aka Latent Semantic Analysis
    - tries to ***extract latent semantic structure*** in the documents
  - Word2Vec
- Search what I meant, not what I said!

Latent Semantic Indexing (2)

- Approximate the T-dimensional term space using principal components calculated from the TD matrix
- The first k ***Principal Components*** (PCA) directions provide the best set of k orthogonal basis vectors - these explain the most variance in the data.
  - Data is reduced to an N x k matrix, without much loss of information (N number of documents)
- Each ***direction*** is a linear combination of the input terms, and define a clustering of “topics” in the data.

LSI Example (1)

- PCs / Topics



Ex.: Eigenvectors to a block-diagonal Matrix

$$\begin{pmatrix}1&1&0\\1&1&0\\0&0&1\end{pmatrix}\cdot\begin{pmatrix}1\\0\\0\end{pmatrix}=\begin{pmatrix}1\\1\\0\end{pmatrix}$$

← No eigenvector
(vector gets rotated)

$$\begin{pmatrix}1&1&0\\1&1&0\\0&0&1\end{pmatrix}\cdot\begin{pmatrix}1\\1\\0\end{pmatrix}=\begin{pmatrix}2\\2\\0\end{pmatrix}$$

← Eigenvector!
(vector gets stretched only)

$$\begin{pmatrix}1&1&0\\1&1&0\\0&0&1\end{pmatrix}\cdot\begin{pmatrix}1\\1\\1\end{pmatrix}=\begin{pmatrix}2\\2\\1\end{pmatrix}$$

← No eigenvector
(vector gets rotated)

$$\begin{pmatrix}1&1&0\\1&1&0\\0&0&1\end{pmatrix}\cdot\begin{pmatrix}0\\0\\1\end{pmatrix}=\begin{pmatrix}0\\0\\1\end{pmatrix}$$

← Eigenvector!

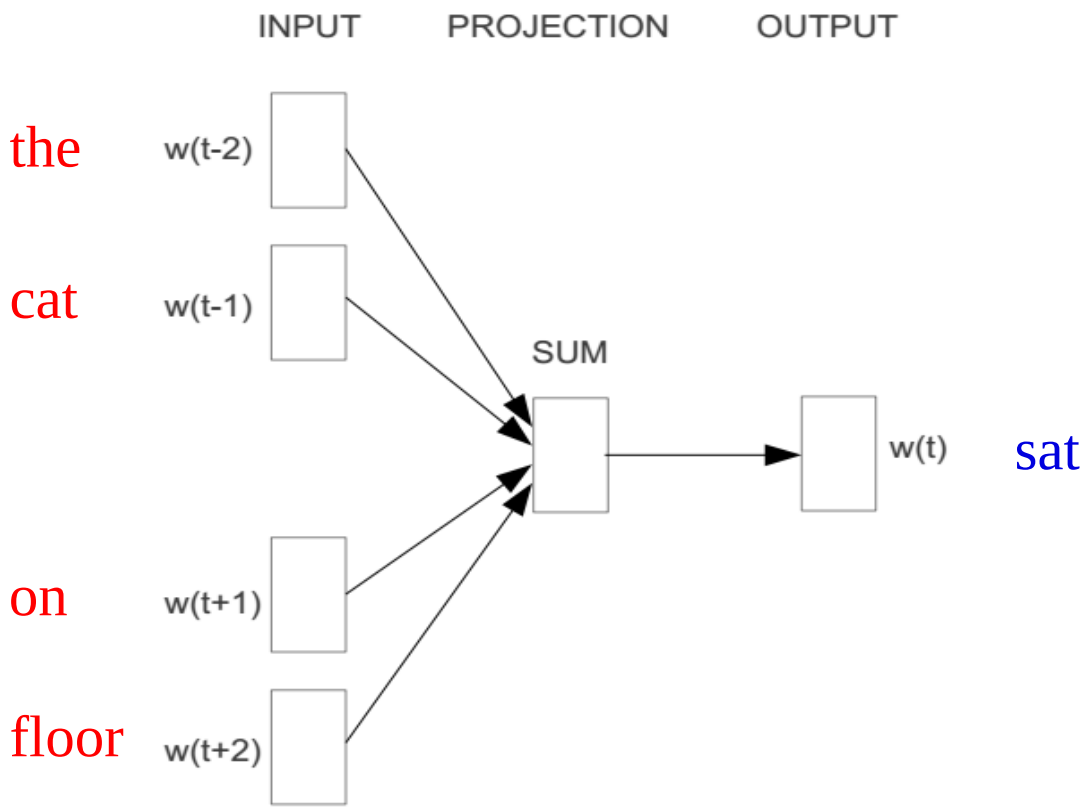
Word2vec

Another approach to represent the meaning of a word

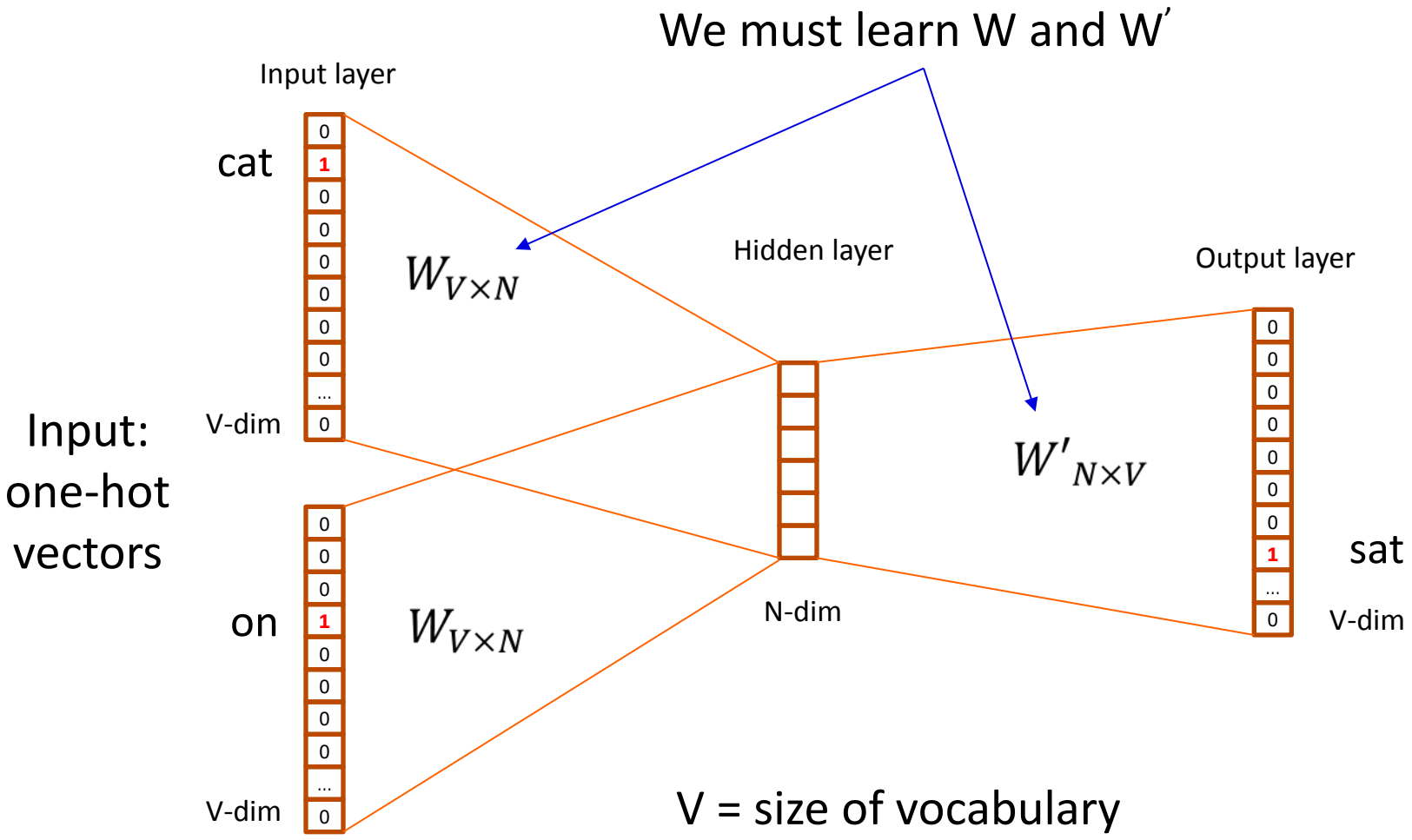
- Represent each word with a low-dimensional vector
- Word similarity = vector similarity
- Key ideas:
  - Predict surrounding words of every word
  - Using a multi-layer perceptron (MLP) with 1 hidden layer
  - Small number of linear hidden units → compression
  - Large-scale training using all domains / topics at once

Word2vec – Continuous Bag-of-Words

- E.g. “The cat sat on floor”
  - window size = 2



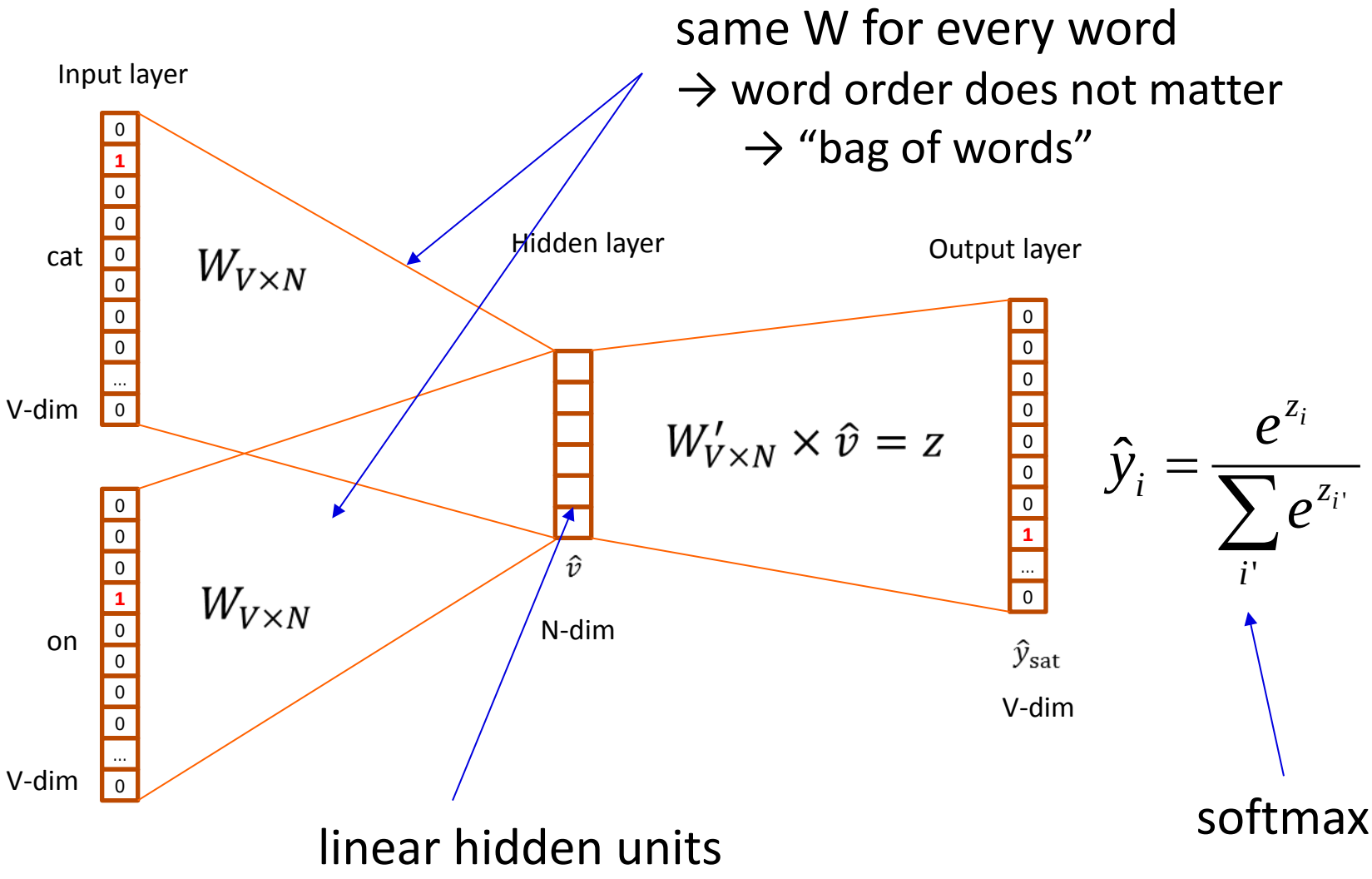
Word2vec – CBOW



V = size of vocabulary

N = size of word vector

Word2vec – CBOW

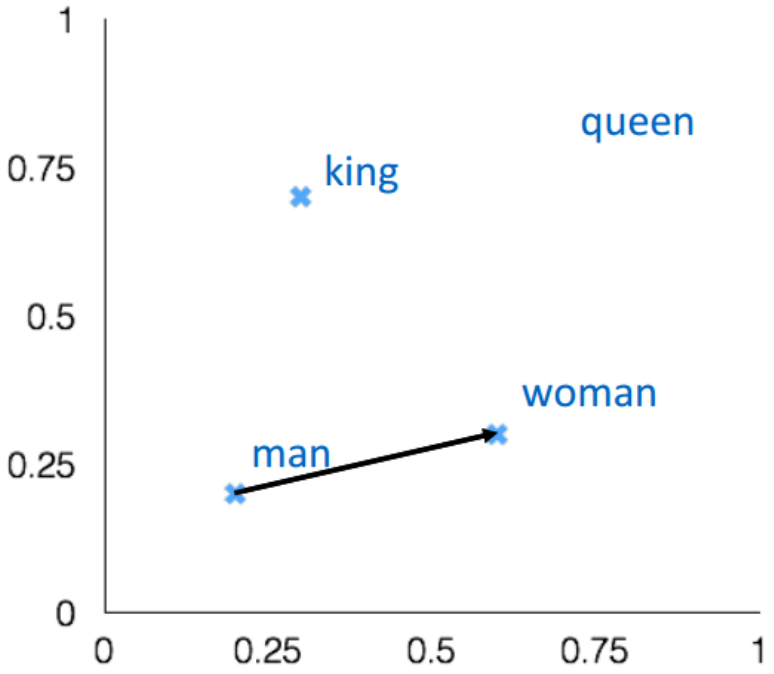


Word2vec – Some Interesting Results

- Word analogies – test for linear relationships (Mikolov, 2014)

man:woman :: king:?

+	king	[0.30 0.70]
-	man	[0.20 0.20]
+	woman	[0.60 0.30]
	queen	[0.70 0.80]



Word2vec - links

- Implementations (google original and Python/gensim)
  - https://code.google.com/archive/p/word2vec/
  - https://rare-technologies.com/deep-learning-with-word2vec-and-gensim/

- Pretrained word vectors
  - Trained on 100 billion words from a Google News dataset
  - 3 million words, 300 features (* 4bytes/feature = 3.35 GB)
  - http://mccormickml.com/2016/04/12/googles-pretrained-word2vec-model-in-python/

Applications of Word Vectors

- Word Similarity
  - Synonyms (plane, aircraft)
  - Stemming, inflections/tense forms (thought -> think)
  - Clustering
- Machine translation
- POS tagging and named entity recognition
- Relation extraction
- Sentiment analysis (e.g. words nearby “happy” or “sad”)

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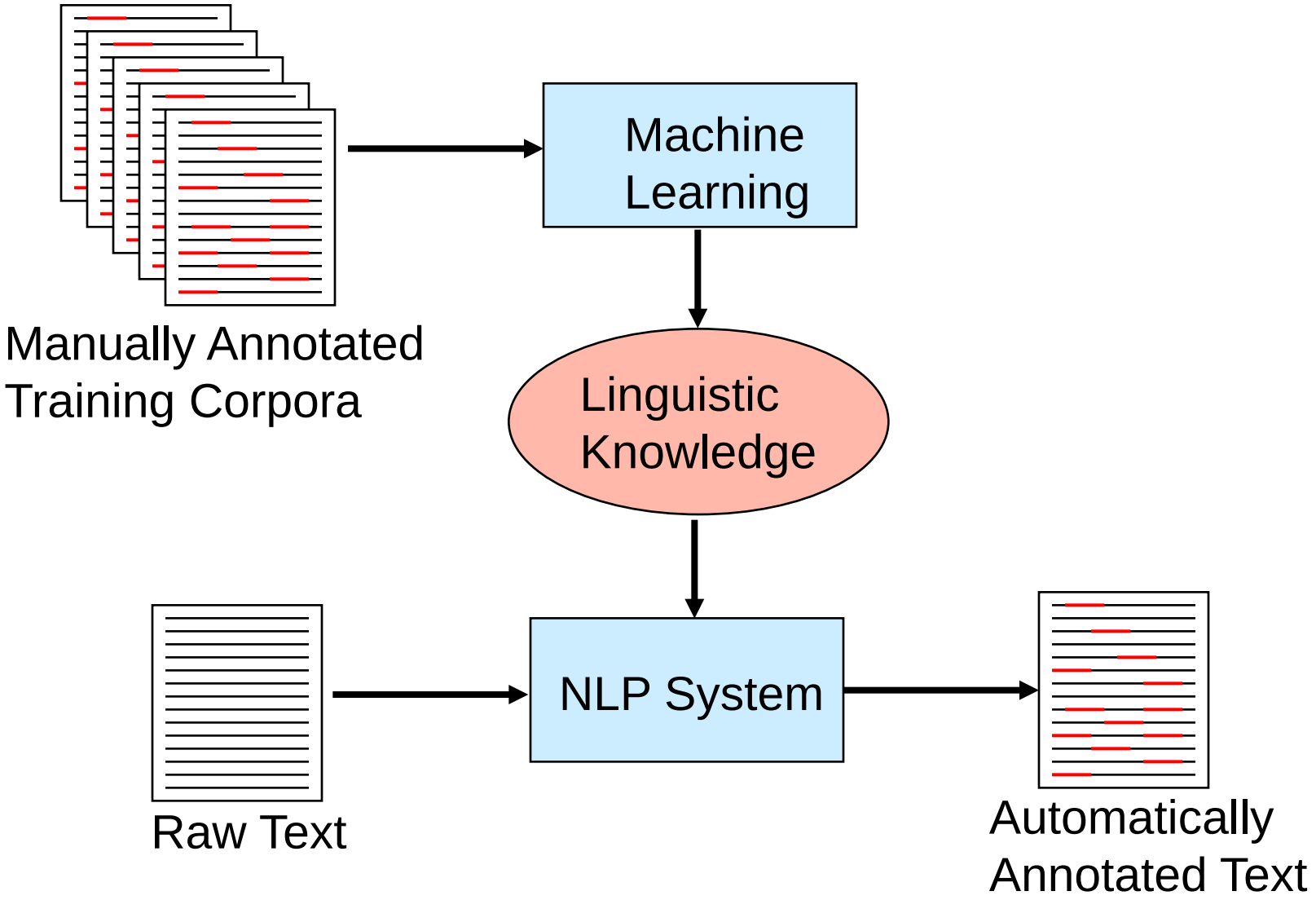
Manual Knowledge Acquisition

- Traditional, ***rationalist***, approaches to language processing require human specialists to specify and formalize the required knowledge.
- ***Rules*** in language have numerous exceptions and irregularities.
  - "`All grammars leak.`" Edward Sapir (1921)
- Manually developed systems were expensive to develop and their abilities were limited and "brittle" (***not robust***).

Automatic Learning Approach

- Use machine learning methods to automatically acquire the required knowledge from appropriately annotated text corpora.
- ***``corpus based´´***, ***``statistical´´***, or ***``empirical´´*** approach
- Statistical learning methods widely used in NLP and Speech processing

Learning Approach

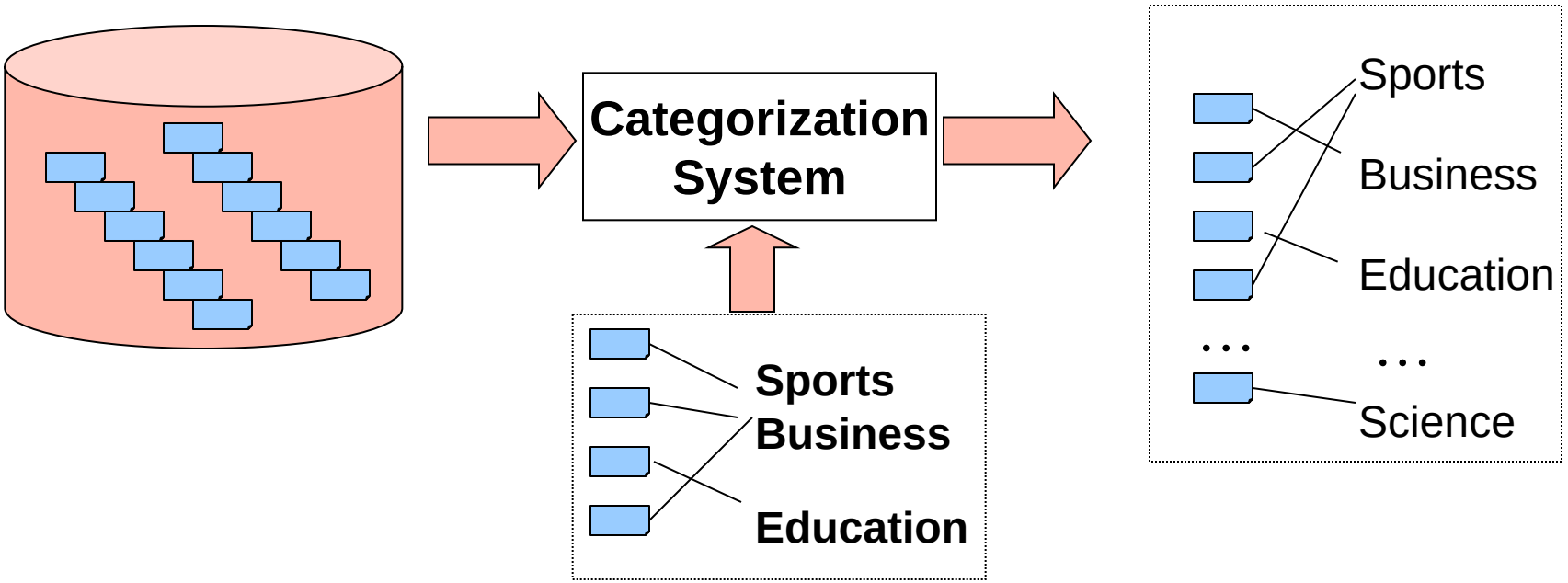


Advantages of the Learning Approach

- ***Large amounts*** of electronic text are now available.
- Annotating/labeling corpora is easier and requires less expertise than manual knowledge engineering.
- Learning algorithms today can handle large amounts of data and acquire accurate ***probabilistic knowledge***.
- This knowledge allows ***robust*** processing, handling linguistic regularities as well as exceptions.

Text Classification

- Pre-given categories and labeled document examples (categories may form hierarchy)
- A standard classification (supervised) learning problem



Text Classification (1)

- Motivation
  - Automatic classification for the large number of on-line text documents (Web pages, e-mails, corporate intranets, etc.)
- Classification Process
  - Data preprocessing
  - Define training- and test set
  - Create the classification model using a classification algorithm
  - Validate the model
  - Classify new text documents

Text Classification (2)

- Classification algorithms: classes usually known
  - K-Nearest Neighbors
  - Neural Networks
  - Decision Trees
  - Association rule-based
  - Boosting
  - Naïve Bayes
  - Support Vector Machines

(Text) Classification with Tools

- Classification Algorithms, e.g. Weka: http://www.cs.waikato.ac.nz/ml/weka/

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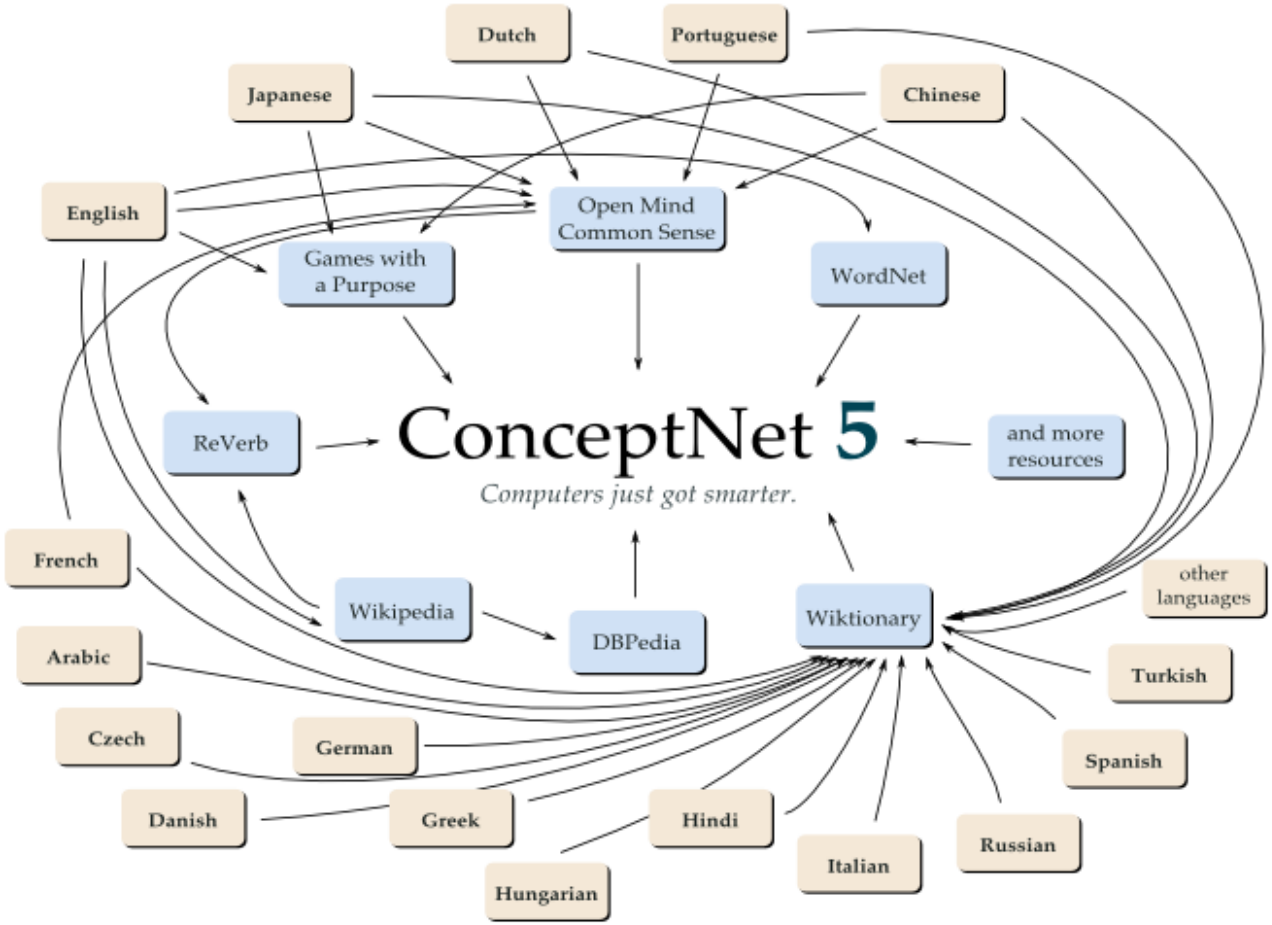
Ontologies

- Early forms: a ***thesaurus*** groups words according to similarity of meaning
- An ***ontology*** defines types, properties and ***interrelationships*** of entities
- Examples and extensions:
  - ConceptNet
  - WordNet
  - Meaning Bank
  - BabelNet
  - CyC
  - Watson

ConceptNet – an Ontology with Rich Semantic Relationships



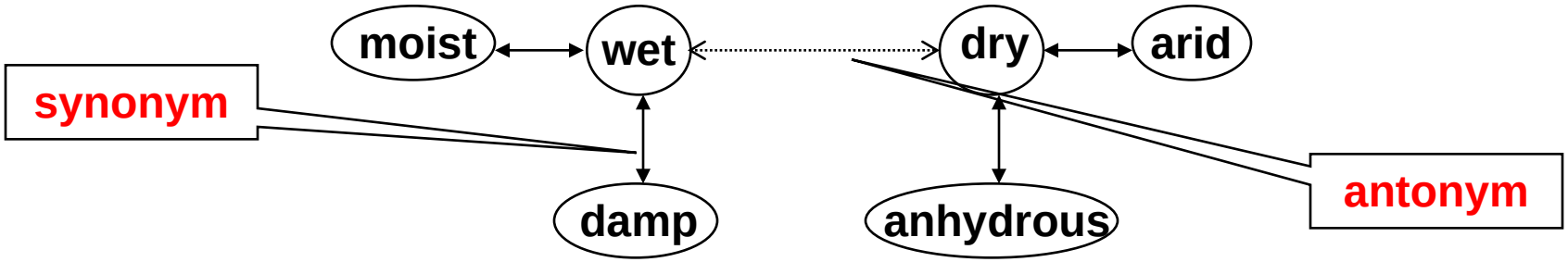
replace "toast" with any other word!

Play around: http://conceptnet5.media.mit.edu/data/5.4/c/en/toast

WordNet Lexicon

An extensive ***lexical network*** for the English language

- Contains over ***138,838 words***.
- Several graphs, one for each ***part-of-speech***.
- ***Synsets*** (sets of cognitive synonyms), each defining a semantic sense.
- ***Relationship*** information (antonym, hyponym, …)
- *Encodes some of the lexicon that humans carry with them when interpreting text.*
- → wordnet.princeton.edu



WordNet Lexicon

- Nouns:
  - > 90,000 forms
  - 116,000 senses
  - Relations →

hypernym	breakfast -> meal
hyponym	meal -> lunch
has-member	faculty -> professor
member-of	copilot -> crew
has-part	table -> leg
part-of	course -> meal
antonym	leader -> follower

- Verbs
  - >10,000 forms
  - 20,000 senses

Hypernym	fly-> travel
Troponym	walk -> stroll
Entails	snore -> sleep
Antonym	increase -> decrease

Meaning Bank

GMB online Explorer

Downloads

Documentation

Publications

People

Groningen Meaning Bank

A free semantically annotated corpus that anyone can edit!

The current (development) version of the GMB is accessible via the GMB Explorer, and comprises thousands of texts in raw and tokenised format, tags for part of speech, named entities and lexical categories, and discourse representation structures compatible with first-order logic.

http://gmb.let.rug.nl/

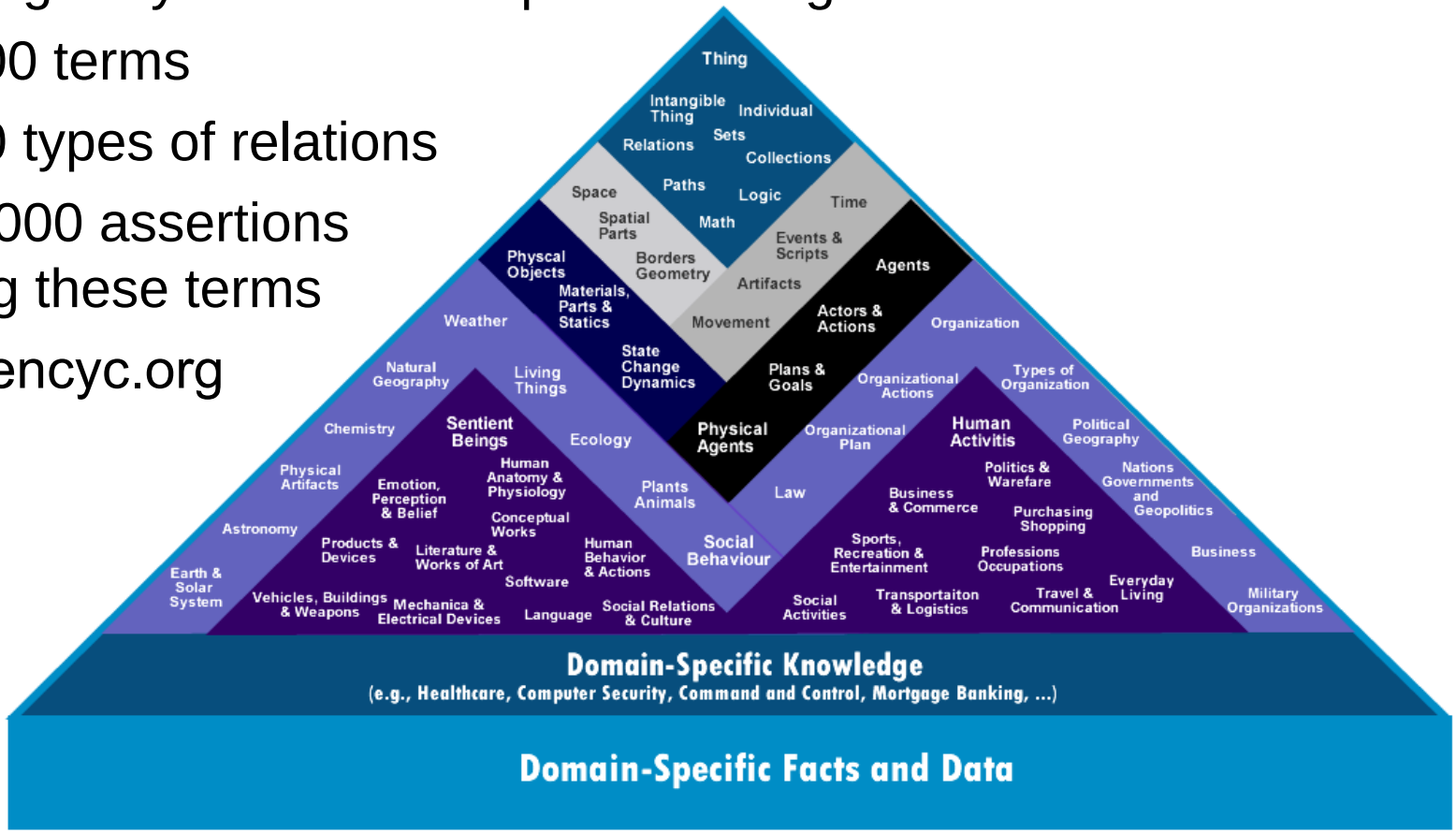
BabelNet – a new Multilingual Ontology

A **very large multilingual ontology** with **5.5 millions** of concepts • A wide-coverage **"encyclopedic dictionary"** • Obtained from the automatic integration of **WordNet** and **Wikipedia** • Enriched with **automatic translations** of its concepts • Connected to the **Linguistic Linked Open Data** cloud!

http://www.babelnet.org/

CyC

- CyC: Knowledge base and ontology framework
- Q&A system in the 80s; can reason things never directly told
- Built originally on first-order predicate logic
- 500,000 terms
- 17,000 types of relations
- 7,000,000 assertions relating these terms
- → opencyc.org



Watson and the DeepQA Text Mining project

Watson: computer system to compete in real time with expert humans in the *Jeopardy* Quiz

- Content acquisition: ***Domain analysis***, automatic corpus expansion, leveraging of the content
- Question analysis: Parsing, lexical answer type detection, ***semantic role labelling***, co-referencing, syntactic and semantic reasoning, decomposition
- Hypothesis generation: Get best candidates based on ***search*** and ***constraint satisfaction***,
- Filtering, scoring and ranking: Machine learning and much more to estimate confidence.

Watson on Jeopardy!

Further reading:

- IBM's Watson/DeepQA: http://dl.acm.org/citation.cfm?id=2019525
- In the news: http://www.bbc.co.uk/news/technology-20159531

Summary

- Much available information is stored in text databases
  - Growing collections of documents from various sources
- Data in most text databases is ***semi-structured***
- Todays tools become increasingly essential
  - ***Compare*** different documents
  - ***Rank*** importance
  - ***Find patterns*** and trends
- Information retrieval tools for everybody`s taste
  - Simple count-based (bag of words)
  - Analysing grammar
  - Statistical learning methods

Examinations

- Written Exams:
  - Tue 18. July 2017; 9:30am; ESA B, ESA C
  - Tue 12. September 2017; 9:30am; Phil A
- You need to register before deadline to take part
- Info:
  https://www.inf.uni-hamburg.de/studies/orga/dates/2017-suse-written-exams.html

Finish with some fun?
(built by our team some time ago ….)