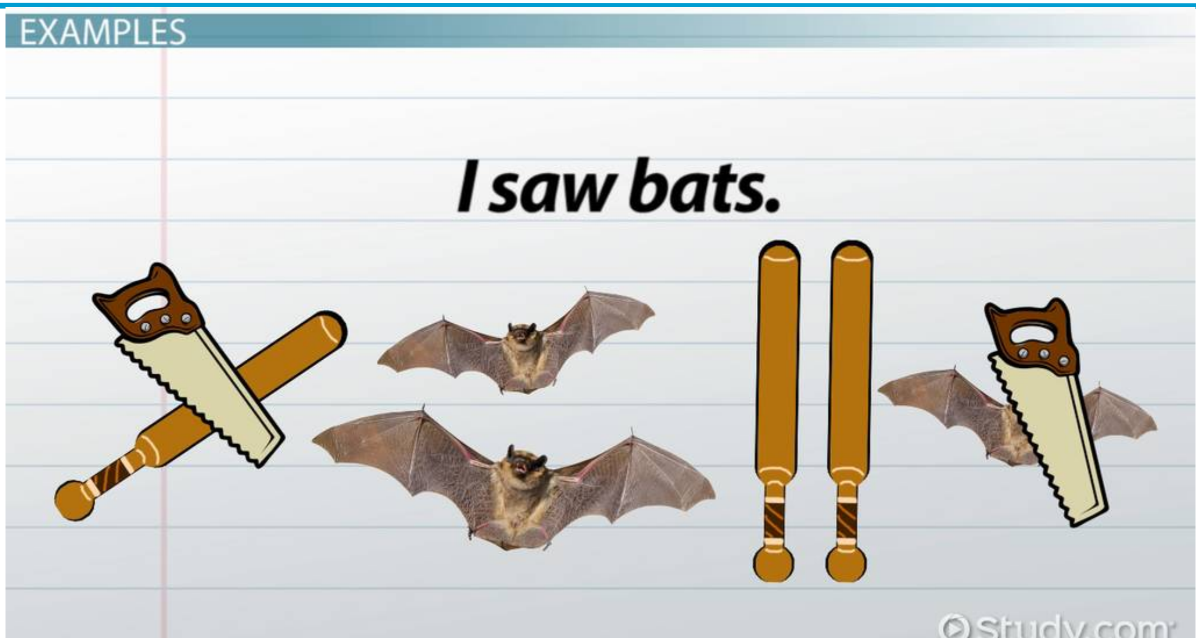
- Jurafsky, D. and Martin, J. H. (2009): Speech and Language Processing. An Introduction to Natural Language Processing, Computational Linguistics and Speech Recognition. Second Edition. Pearson: New Jersey: Chapter 20
- Agirre, E., Edmonds, P. (2006): Word Sense Disambiguation: Algorithms and Applications (Text, Speech and Language Technology). Springer, Heidelberg

knowledge-based, supervised, word sense induction, substitution

WORD SENSE AND MEANING

MOTIVATING EXAMPLE



http://study.com/academy/lesson/lexical-ambiguity-definition-examples.html

- ambiguous words have multiple senses
- Word Sense Disambiguation assigns a single (out of multiple) sense in a given context
- Semantic disambiguities: assume that syntactic disambiguation has already been performed

WHY LANGUAGE IS HARD ..

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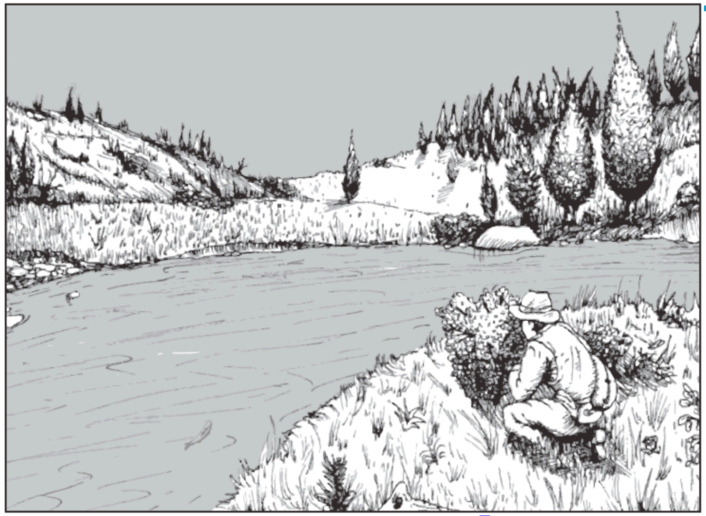

Image © dero

polysemous

synonymous

Concept Layer

Lexical Layer

He sat on the river bank and counted his dough.

She went to the bank and took out some money.

TYPES OF AMBIGUITY

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- Homonymy: two or more meanings happen to be expressed with the same string
  - withdrawing money from the **bank**
  - embark on a boat from the river **bank**

- Polysemy: the same string has different, but related senses, stemming from the same origin
  - the **bank** was robbed by Billy the Kid
  - the **bank** was constructed by a famous architect

APPROACHES TO WSD

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- Knowledge Based Approaches ('unsupervised')
  - Rely on knowledge resources like WordNet, Thesaurus etc.
  - May use grammar rules for disambiguation.
  - May use hand coded rules for disambiguation.
- Machine Learning Based Approaches ('supervised')
  - Rely on corpus evidence.
  - Train a model using tagged or untagged corpus.
  - Probabilistic/Statistical models.
- Hybrid Approaches
  - Use corpus evidence as well as semantic relations from WordNet.
- Unsupervised, knowledge-free Approaches
  - induce sense inventory
  - disambiguate in context

WSD USING SELECTIONAL PREFERENCES AND ARGUMENTS

Sense 1

This airline ***serves*** dinner in the evening flight.

- serve (Verb)
  - agent
  - object – edible

Sense 2

This airline ***serves*** the sector between Munich and Rome.

- serve (Verb)
  - agent
  - object – sector

Requires exhaustive enumeration of:

- Argument-structure of verbs.
- Selectional preferences of arguments.
- Description of properties of words such that meeting the selectional preference criteria can be decided.

  E.g. This flight serves the “region” between Paris and Warsaw.

  How do you decide if “region” is compatible with “sector”

OVERLAP-BASED APPROACHES

- Requires a Machine Readable Dictionary (MRD).
- Find the overlap between the features of different senses of an ambiguous word (sense bag) and the features of the words in its context.
- These features could be sense definitions, example sentences, etc.
- The sense which has the maximum overlap is selected as the contextually appropriate sense.

> **Concise Oxford English Dictionary**
>
> • **dance**
>
> ■ verb
>
> 1 ▶ move rhythmically to music, typically following a set sequence of steps. ▶ perform (a particular dance or a role in a ballet).
>
> 2 ▶ move in a quick and light or lively way. ▶ (of someone's eyes) sparkle with pleasure or excitement.
>
> ■ noun
>
> 1 ▶ a series of steps and movements that match the speed and rhythm of a piece of music. ▶ an act or period of dancing.
>
> 2 ▶ a social gathering at which people dance.
>
> 3 ▶ (also **dance music**) music for dancing to, especially in a nightclub.

LESK (1986) ALGORITHM

- Identify senses of words in context using definition overlap
- Can do this either between gloss and context or between all sense combinations
- Main problem: zero overlap for most contexts

```
function SimplifiedLesk(word, sentence) {
 bestSense= mostFrequentSense(word);
 maxOverlap =0;
 context = allWords(sentence);

 foreach sense in allSenses(word) {
    signature=signature(sense);
    overlap = overlap(signature, context);
    if (overlap > maxOverlap) {
         maxOverlap = overlap;
         bestSense - sense
 }}
 return bestSense;
}
```

Dictionary functions

- `mostFrequentSense`: returns most frequent / first sense identifier from dictionary
- `allSenses`: returns all sense identifiers for a word from dictionary
- `signature`: returns set of words from sense definition in dictionary

Lesk, M. (1986). Automatic sense disambiguation using machine readable dictionaries: how to tell a pine cone from an ice cream cone. In SIGDOC '86: Proceedings of the 5th annual international conference on Systems documentation, pages 24-26, New York, NY, USA. ACM.

SIMPLIFIED LESK ALGORITM

- Lesk algorithm relies on definitions of context words to disambiguate the senses of a target word
- Simplified Lesk:
  - Measure the overlap between the (sentence) context of the target, and the definition of its senses
  - If no overlap, use most frequent sense (MFS)

■ noun

1 ▶ a series of steps and movements that match the speed and rhythm of a piece of music. ▶ an act or period of dancing.

2 ▶ a social gathering at which people dance.

3 ▶ (also **dance music**) music for dancing to, especially in a nightclub.

1, 2 or 3 ?

"With the music, the **dance** started with slow movements."

WORDNET – AN ONLINE LEXICAL DATABASE

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HTTP://WORDNET.PRINCETON.EDU/ - CURRENT VERSION: 3.1

- High coverage lexical-semantic network built by psychologists

POS	Monosemous Words and Senses	Polysemous Words	Polysemous Senses
Noun	101863	15935	44449
Verb	6277	5252	18770
Adjective	16503	4976	14399
Adverb	3748	733	1832
Totals	**128391**	**26896**	**79450**

- Relations:
  - ISA-relation (hyponom - hypernym, taxonomic backbone)
  - Part-of (meronym - holonym)
  - Type-instance (e.g. Obama is an instance of President)
  - Opposite-of (antonym), mostly for adjectives
  - Derivative (pertainym), e.g. crime – criminal
  - some semantic roles between verbs and nouns, e.g. AGENT, INSTRUMENT …

SYNSETS FOR "MAGAZINE#N"

WordNet Search - 3.0 - WordNet home page - Glossary - Help

Word to search for: magazine [Search WordNet]

Display Options: (Select option to change) [Change]

Key: "S:" = Show Synset (semantic) relations, "W:" = Show Word (lexical) relations

Noun

Synset

sample use

- (13)S: (n) **magazine#1**, mag#1 (a periodic publication containing pictures and stories and articles of interest to those who purchase it or subscribe to it) *"it takes several years before a magazine starts to break even or make money"*
- (2)S: (n) **magazine#2** (product consisting of a paperback periodic publication as a physical object) *"tripped over a pile of magazines"*
- (1)S: (n) **magazine#3**, magazine publisher#1 (a business firm that publishes magazines) *"he wo[...] for a magazine"*
- S: (n) **magazine#4**, cartridge#2 (a light-tight supply chamber holding the film and supplying it for exposure as required)
- S: (n) **magazine#5**, powder store#1, powder magazine#1 (a storehouse (as a compartment on a warship) where weapons and ammunition are stored)
- S: (n) cartridge holder#1, cartridge clip#1, clip#1, **magazine#6** (a metal frame or container holding cartridges; can be inserted into an automatic gun)

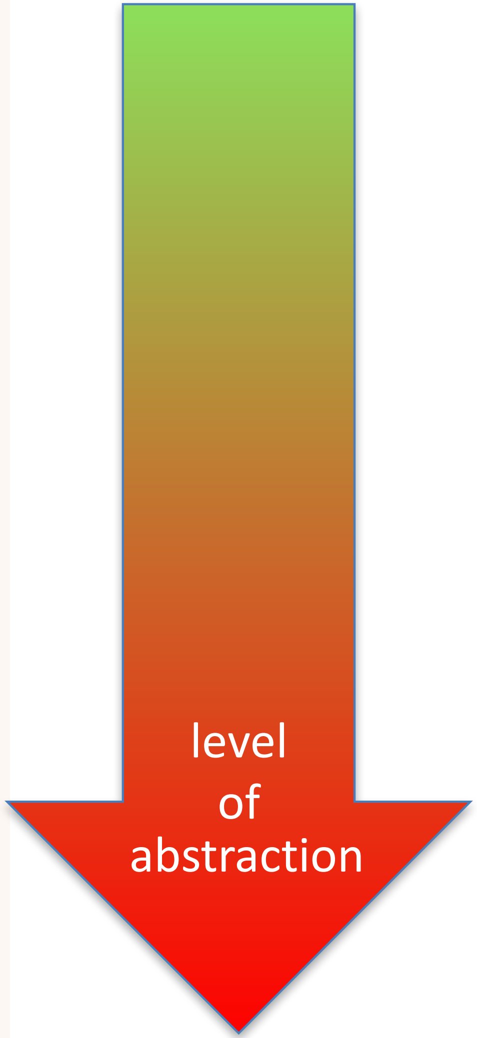
gloss

Lexical members

SemCor count

WORDNET HYPERNYM CHAIN

- (2)S: (n) **magazine#2** (product consisting of a paperback periodic publication as a physical object) *"tripped over a pile of magazines"*
  - *direct hypernym* | *inherited hypernym* | *sister term*
    - S: (n) product#2, production#3 (an artifact that has been created by someone or some process) *"they improve their product every year"; "they export most of their agricultural production"*
      - S: (n) creation#2 (an artifact that has been brought into existence by someone)
        - S: (n) artifact#1, artefact#1 (a man-made object taken as a whole)
          - S: (n) whole#2, unit#6 (an assemblage of parts that is regarded as a single entity) *"how big is that part compared to the whole?"; "the team is a unit"*
            - S: (n) object#1, physical object#1 (a tangible and visible entity; an entity that can cast a shadow) *"it was full of rackets, balls and other objects"*
              - S: (n) physical entity#1 (an entity that has physical existence)
                - S: (n) entity#1 (that which is perceived or known or inferred to have its own distinct existence (living or nonliving))



GLOSS OVERLAPS ≈ RELATEDNESS

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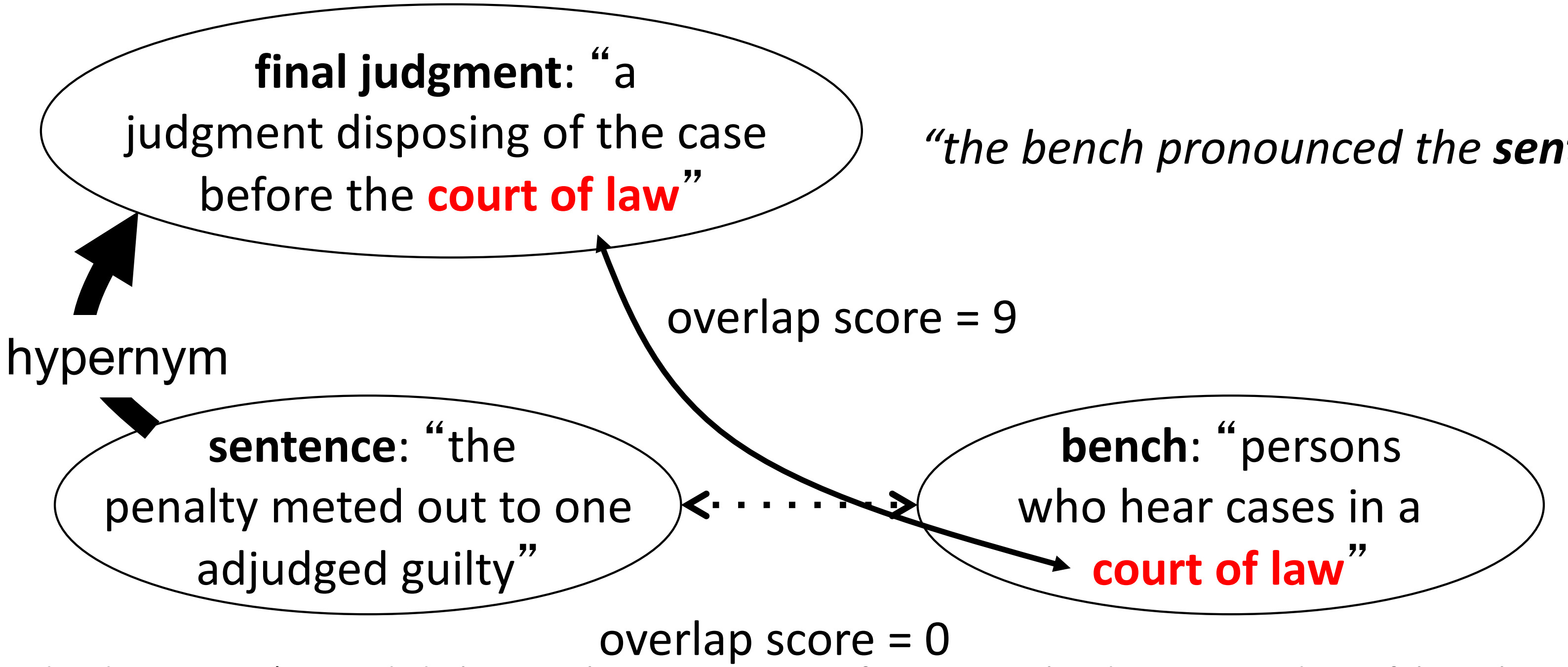
- Lesk' s (1986) idea: Related word senses are (often) defined *using the same words.* E.g:
  - bank(1): "a financial institution"
  - bank(2): "sloping land beside a body of water"
  - lake: "a body of water surrounded by land"
- Gloss overlaps = # content words common to two glosses ≈ relatedness
  - relatedness (bank(2), lake) = 3
  - relatedness (bank(1), lake) = 0

Problem: "lexical gap": Same or similar meaning can be expressed with a large variety of words from the vocabulary. For most pairs of glosses, overlap = 0 .

EXTENDED LESK (BANERJEE AND PEDERSEN, 2002)

- Utilize link structure of WordNet to pull in related glosses for overlap computation
- Addresses the overlap sparseness issue
- do this for one ambiguous word at-a-time
- Reweighting: For n-gram overlaps, add a score of n^2



*"the bench pronounced the **sentence**"*

(Banerjee and Pedersen, 2002). Extended Gloss Overlaps as a Measure of Semantic Relatedness. Proceedings of the Eighteenth International Joint Conference on Artificial Intelligence, pp. 805-810, August 9-15, 2003, Acapulco, Mexico.

ONE-SENSE-PER-DISCOURSE HYPOTHESIS

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- Idea: When a word is used several times in a document, it probably has the same meaning in all occurrences.
- This means that we can gather evidence from all contexts per document, which reduces sparseness
- holds for homonymous, not polysemous nouns, does not hold for verbs and adjectives as much
- Measuring the validity of the hypothesis (Small study on 12 nouns)
- Applicability: How often do we in fact observe an ambiguous word more than once in a document?
- Accuracy: If we observe an ambiguous word more than once per document, how often do these occurrences have the same meaning?

The one-sense-per-discourse hypothesis:

Word	Senses	Accuracy	Applicblty
plant	living/factory	99.8 %	72.8 %
tank	vehicle/contnr	99.6 %	50.5 %
poach	steal/boil	100.0 %	44.4 %
palm	tree/hand	99.8 %	38.5 %
axes	grid/tools	100.0 %	35.5 %
sake	benefit/drink	100.0 %	33.7 %
bass	fish/music	100.0 %	58.8 %
space	volume/outer	99.2 %	67.7 %
motion	legal/physical	99.9 %	49.8 %
crane	bird/machine	100.0 %	49.1 %
Average		99.8 %	50.1 %

Gale William, Kenneth Church, and David Yarowsky, “One Sense Per Discourse”, in Proceedings of the ARPA Workshop on Speech and Natural Language Processing, pp. 233– 237, 1992.

SEMEVAL: SHARED TASK FOR SEMANTIC EVALUATIONS

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- Shared task initiative since 2001, currently preparing 2018 edition
- Increasing number of tasks and systems
- Core WSD tasks (for many languages):
  - lexical sample task: for a small set of ambiguous target words, a large number of labeled examples
  - all word task: every word in a short text is labeled with the appropriate sense
- Other tasks include:
  - (cross-lingual) lexical substitution
  - word sense induction
  - semantic role annotation
  - Sentiment analysis
  - temporal relation identification
  - semantic text similarity
  - …

e.g. Semeval-2 English lex. sample

Algorithm	Precision	Recall	F1
Sval-1st	0.402	0.401	0.401
Ext Lesk	**0.351**	**0.342**	**0.346**
Sval-2nd	0.293	0.293	0.293
Lesk	**0.183**	**0.183**	**0.183**
Random	0.141	0.141	0.141

SENSEVAL/SEMEVAL ALL-WORD TASK

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Example annotation

Homeless
<head id="d00.s08.t01">people</head>
not
only
<head id="d00.s08.t04">lack</head>
safety
,
privacy
and
<head id="d00.s08.t09">shelter</head>
,
they
also
<head id="d00.s08.t13">lack</head>
the
elementary
<head id="d00.s08.t16">necessities</head>
of
nutrition
,
cleanliness
and
basic
health
care
.

- No training data, can only use lexical resources (‘knowledge-based, unsupervised’) and sense-labeled corpora
- all ambiguous words are marked and need to be assigned a sense
- Fine-grained scoring: upper bound is inter-annotator-agreement, which is at about 75%
- Coarse-grained scoring: inter-annotator-agreement at around 90%
- Top system performances: 65% (fine-grained), 82% (coarse-grained); MFS baseline: 78% (coarse-grained)

SENSEVAL/SEMEVAL LEXICAL SAMPLE TASK

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Example annotation

<instance id="11:0@2@wsj/14/wsj_1404@wsj" corpus="wsj">
<answer lemma="**double**" pos="v" on="1" wn="1" wn-version="2.1"/>
Groupe AG 's chairman said 0 the Belgian insurer is prepared *-1 to give up some of its independence to a white knight if * necessary * to repel a raider . Amid heavy buying of shares in Belgium 's largest insurer , Maurice Lippens also warned in an interview that a white knight , in *-1 buying out a raider , could leave speculators with big losses on their AG stock . Since the beginning of the year , the stock has nearly **<head> doubled </head>** , * giving AG a market value of about 105 billion Belgian francs -LRB- $ 2.7 billion *U* -RRB- . The most likely white knight would be Societe Generale de Belgique S.A. , which *T*-2 already owns 18 % of AG and which *T*-3 itself is controlled *-1 by Cie . Financiere de Suez , the acquisitive French financial conglomerate . But Mr. Lippens said 0 a rescue also could involve Asahi Mutual Life Insurance Co. , which *T*-1 owns 5 % of AG .
</instance>

<instance id="8:0@37@wsj/14/wsj_1432@wsj" corpus="wsj">
<answer lemma="**double**" pos="v" on="1" wn="1" wn-version="2.1"/>
We 'll coordinate on this end to places like Bangkok , Singapore and Manila . '' Asian traffic , which *T*-1 currently accounts for 65 % of Cathay 's business , is expected *-2 to continue as the carrier 's mainstay . Cathay has long stated its desire * to **<head> double </head>** its weekly flights into China to 14 , and it is applying *-1 to restart long-canceled flights into Vietnam . Further expansion into southern Europe is also possible , says 0 *T*-1 Mr. Bell , the spokesman . While a large number of Hong Kong companies have reincorporated offshore ahead of 1997 , such a move is n't an option for Cathay because it would jeopardize its landing rights in Hong Kong .
</instance>

- Training and test data: can use a supervised system in a Machine learning setup
- can also use knowledge-based systems
- supervised systems show about 5-7% better performance in evaluations
- Performance: about 87% (coarse-grained)
- variations
  - ML learning algorithm
  - features computed on the context
  - features computed through analysis of large background corpora

LOCAL CONTEXT FEATURES FOR WORD SENSE DISAMBIGUATION

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Standard features for WSD

- word window
- lemma/baseform/stem window
- morphological information, e.g. gender, number, tense
- open class words in proximity, e.g. closest adjectives to target
- POS of target and context
- syntactic relations, e.g. headwords

Knowledge-based features (in hybrid systems)

- WordNet similarity with context - "Lesk"
- WordNet hypernym chains

TOPICAL FEATURES FOR WSD

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- Topical features are computed from the global context: statistics over a corpus as a whole
- Structure discovered on the corpus level can be used to characterize individual instance
- Topical features aim at bridging the “lexical gap”
- some of the methods presented here have not been developed as WSD features, but we can treat them as such

Selection of Methods

- Topic Signatures
- Word Sense Induction features
- Latent Semantic Analysis vector space similarity
- Topic Models
- Lexical Expansion

TOPIC SIGNATURES

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- Idea: Get more ‘training data per word sense
- if people issue an ambiguous query in a search, they add more words to narrow down the meaning of the query
- can do this automatically using WordNet:

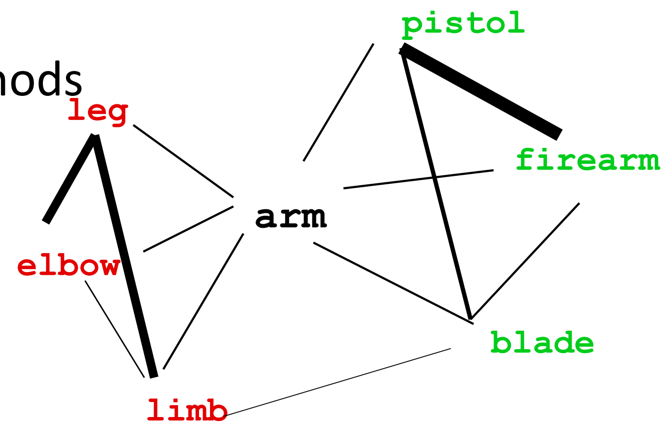
```
TopicSignatures(ambiguous word w):
senses=findWNConcepts(w);
foreach sense s {
  query=w + findRelatedWNwords(s);
  resultSet = issueQuery(query, contextCollection);
  topicSignature_s= getRepresentation(resultSet); }
```

Strategies:

- findRelatedWords: only monosemous vs. all, synset-only vs. neighborhood, number of related words, …
- contextCollection: Sentences from Corpus vs. WWW
- getRepresentation: Sig(w, resultWord), LSA vectors, …

WORD SENSE INDUCTION AS FEATURES

- Unsupervised, knowledge-free sense discovery
  - compute similarities of words using corpus-based methods
  - cluster local neighborhood of similarity graph per word
  - collect typical features of clusters
  - use these for disambiguation
- Example: similarities by comparing dependencies

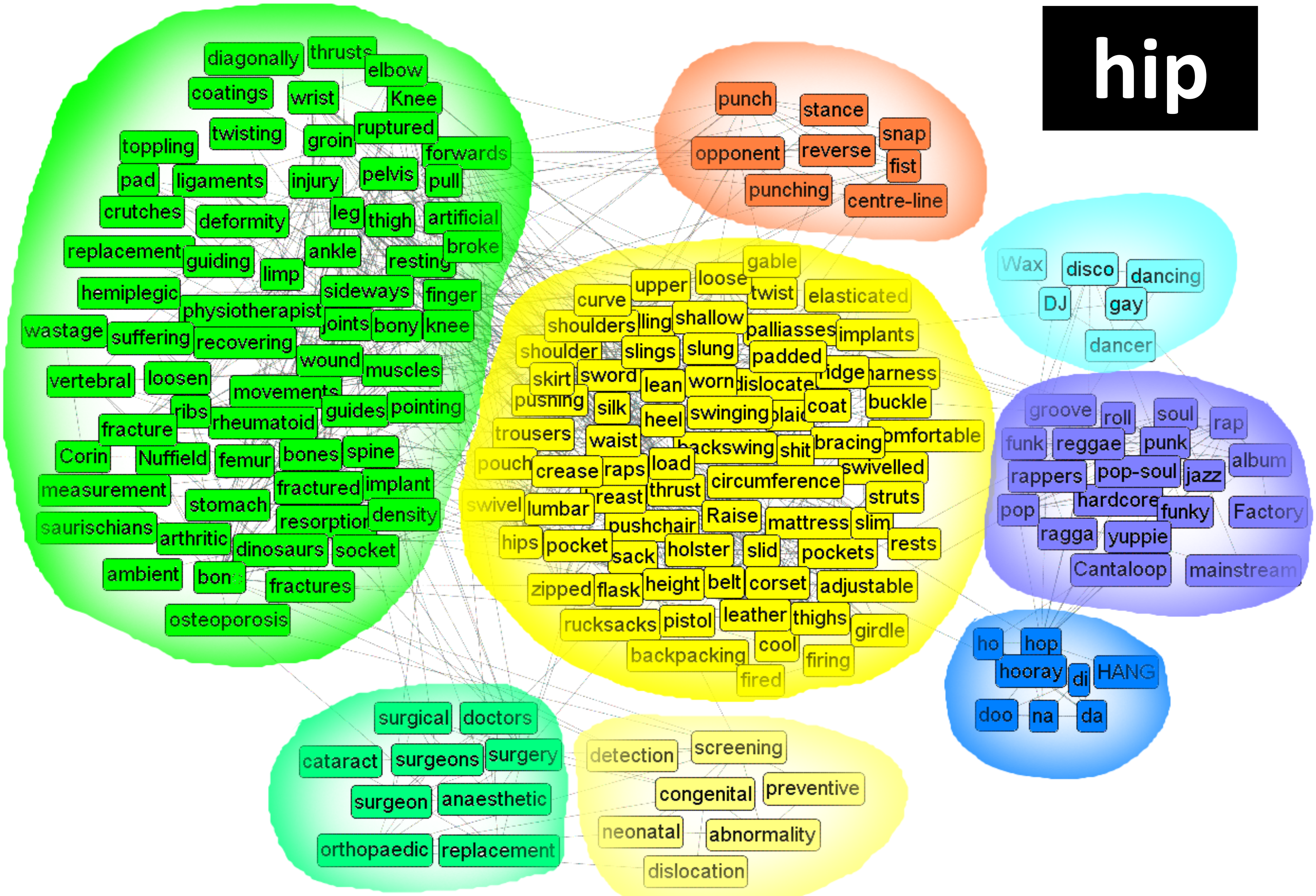


arm@0: *thigh, spear, crest, stick, wrist, rack, throat, tip, beak, eye, mouth, mount, trunk, leg, edge, piece, fin, shoulder, back, motor, jaw, abdomen, paw, pair, face, belly, chair, claw, shaft, elbow, rib, vertebra, collar, skull, hand, blade, wing, stem, hammer, end, handle, roof, forehead, pole, neck, ankle, ton, axle, frame, cord, foot, shield, needle, fracture, knee, nose, penis, bottom, turret, slide, hook, limb, lever, chest, ear, bay, sword, head, flag, tail, half, banner, hip, joint, beam, breast, bone, backward, horn, spine, forearm, bow, badge, finger, toe, thumb, mirror (87)*

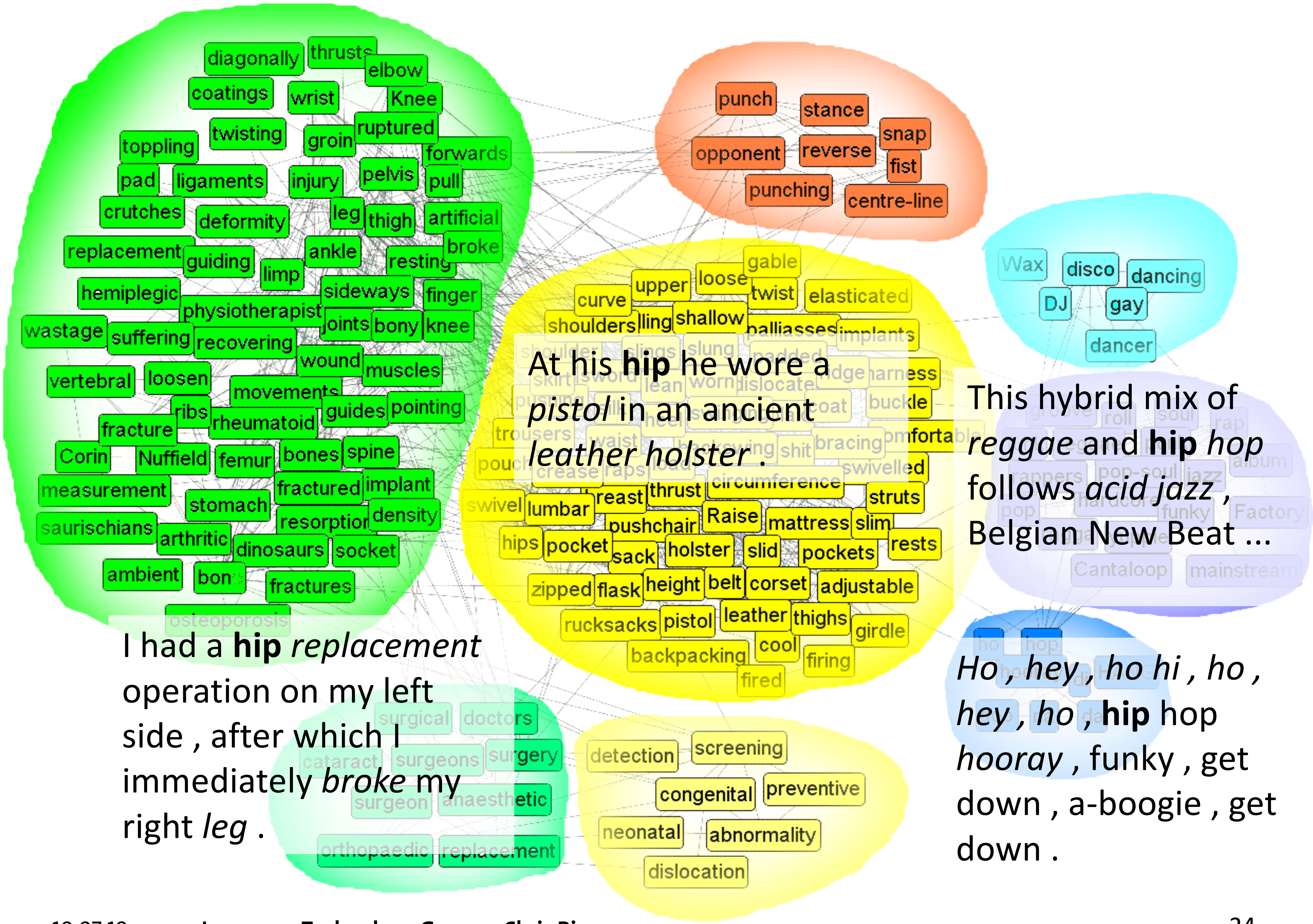
arm@1: *pistol, saber, grenade, firearm, launcher, weapon, rifle, ammunition, shotgun, mortar (10)*

arm@2: *venture, fund, boom (3)*

hip



punch
stance
snap
opponent
reverse
fist
punching
centre-line
diagonally
thrusts
elbow
coatings
wrist
Knee
toppling
twisting
groin
ruptured
forwards
pad
ligaments
injury
pelvis
pull
crutches
deformity
leg
thigh
artificial
replacement
guiding
ankle
broke
limp
resting
hemiplegic
sideways
finger
physiotherapist
joints
bony
knee
wastage
suffering
recovering
wound
muscles
vertebral
loosen
movements
ribs
guides
pointing
fracture
rheumatoid
Corin
Nuffield
femur
bones
spine
measurement
fractured
implant
stomach
density
saurischians
resorption
arthritic
dinosaurs
socket
ambient
bon
fractures
osteoporosis
gable
upper
loose
curve
twist
elasticated
shoulders
ling
shallow
balliasses
implants
shoulder
slings
slung
padded
skirt
sword
lean
worn
dislocate
ridge
harness
pushing
silk
heel
swinging
plaid
coat
buckle
trousers
waist
backswing
shit
bracing
omfortable
pouch
crease
raps
load
swivelled
swivel
reast
thrust
circumference
struts
lumbar
pushchair
Raise
mattress
slim
hips
pocket
sack
holster
slid
pockets
rests
zipped
flask
height
belt
corset
adjustable
rucksacks
pistol
leather
thighs
girdle
backpacking
cool
firing
fired
Wax
disco
dancing
DJ
gay
dancer
groove
roll
soul
rap
funk
reggae
punk
album
rappers
pop-soul
jazz
pop
hardcore
funky
Factory
ragga
yuppie
Cantaloop
mainstream
ho
hop
hooray
di
HANG
doo
na
da
surgical
doctors
cataract
surgeons
surgery
surgeon
anaesthetic
orthopaedic
replacement
detection
screening
congenital
preventive
neonatal
abnormality
dislocation



At his **hip** he wore a *pistol* in an ancient *leather holster* .

This hybrid mix of *reggae* and **hip** *hop* follows *acid jazz* , Belgian New Beat ...

I had a **hip** *replacement* operation on my left side , after which I immediately *broke* my right *leg* .

Ho , *hey* , *ho hi* , *ho* , *hey* , *ho* , **hip** hop *hooray* , funky , get down , a-boogie , get down .

NOTORIOUS BANK EXAMPLE: DIFFERENT CLUSTERING PARAMETERS

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1. Clustering

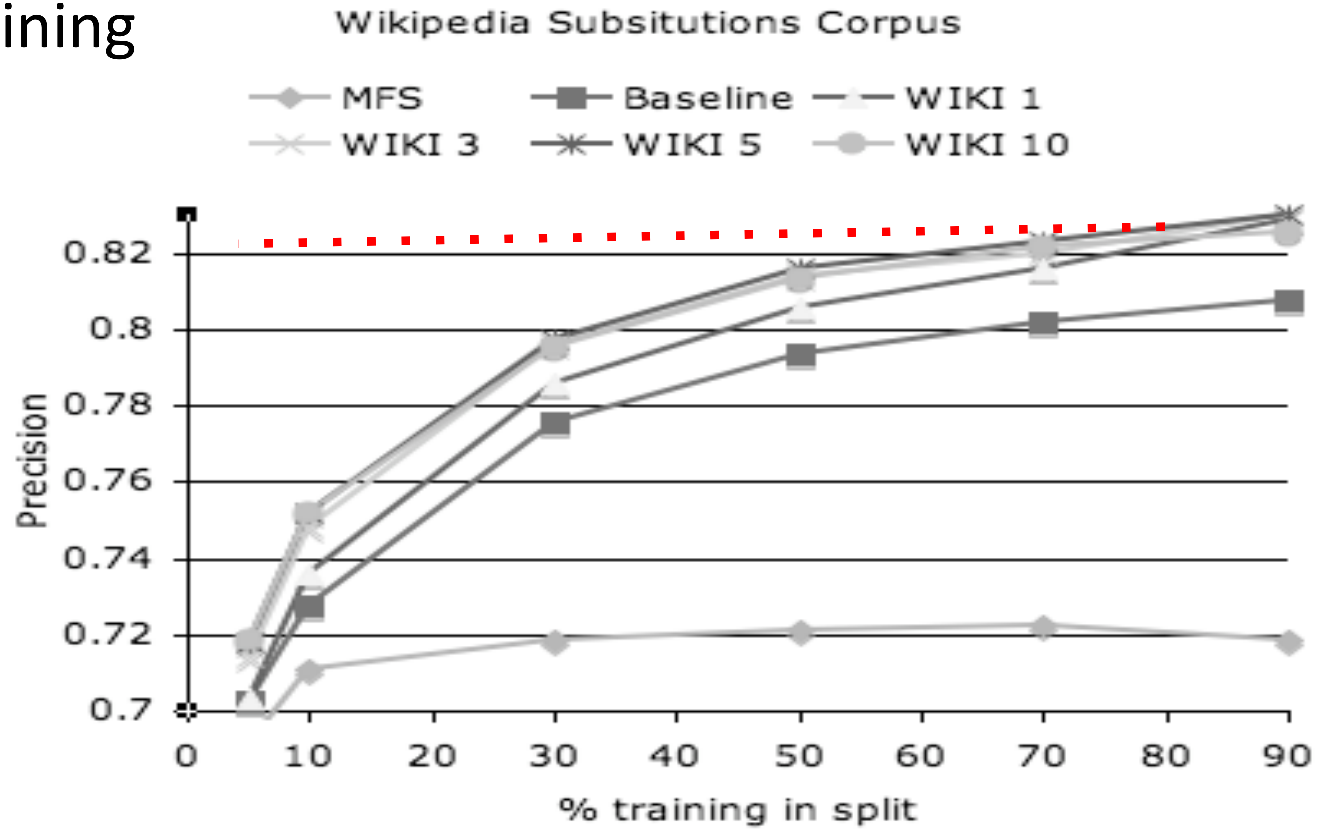
- **bank0**: largest, north, branches, eastern, opposite, km, east, west, branch, Thames, banks, located, Danube, town, south, situated, River, Rhine, river, western, commercial, central, southern
- **bank1**: right, left
- **bank2**: money, robbers, deposit, robberies, cash, currency, account, deposits, Bank, robbery, funds, financial, banking, loans, notes, robber, rob, accounts, credit, assets, teller, Banco, loan, investment, savings

2. Clustering

- **bank0**: eastern, banks, central, river, km, western, south, southern, located, largest, east, deposits, commercial, Thames, north, west, Danube, town, situated, Rhine, River
- **bank1**: branches, branch
- **bank2**: robberies, robbers, robbery, robber
- **bank3**: right, left, opposite
- **bank4**: loans, cash, investment, teller, account, financial, loan, deposit, credit, funds, accounts, assets, savings, banking, money, rob
- **bank5**: Banco, currency, notes, Bank

COMBINATION OF SEVERAL CLUSTER FEATURES

- Learning curve
  - X axis: amount of training
  - Y axis: performance
- Several cluster features improve performance, especially for small amounts of training



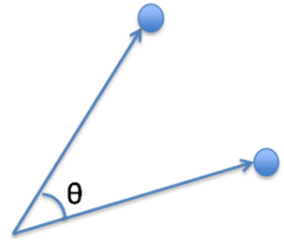
LATENT SEMANTIC ANALYSIS AND OTHER DENSE VECTORS

- Vector Space Model (VSM): represent words as vector of contexts (cf. document term matrix in Information Retrieval)
- Problems with VSM
  – sparsity: Power law distribution of frequencies: many words occur only in few contexts
  – high dimensionality: large storage space, slow processing
  – synonymy: synonyms are represented as different words, but should be the same "concept"
- LSA addresses these problems by
  – mapping the VSM data into an orthogonal space where different dimensions denote different concepts
  – reducing the space to a fixed number of dimensions to keep only the "most important" concepts
- The hope is to map synonyms to the same dimensions, at this creating an abstraction level to latent concepts

LSA FOR WSD

- in VSM: compare aggregated vector of contexts per sense with vector of instance, e.g. with cosine similarity

$$sim(A,B) = \cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|}$$



- in LSA, we have to project the context vector into the reduced space
- comparison of instance vector and aggregated vectors per sense serve as a feature in the ML setup
- Building the LSA matrices is typically done using a large background corpus, with k=100 – 1000, depending on the task

Why this works:

- LSA can generalize over similar words
- LSA serves as a noise reduction technique
- LSA can fold in knowledge about lexical similarities beyond what is in the labeled training data

CURRENT TOPICS

- word embeddings vs. sense embeddings: whenever context is too dis-similar, spawn an new sense in word2vec-like architectures

- use contextualized language models: e.g. in lexical sample task, use closest BERT embedding for target word from training to predict test label

SUMMARY ON WORD SENSES AND MEANING

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- Formalization is less clear than in syntactic methods
- Extensive semantic resources (WordNet, BabelNet), still lack of connection to text
- Meaning has many facets and manifests itself in context
- Sense-inventory–based WSD vs. Lexical Substitution
- More semantic tasks: Semantic Role Labeling, Frame-Semantic Parsing

KLAUSUR / EXAM

Universität Hamburg
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Exam 1: Th, 25. Jul. 2019 09:30-11:30
Room: **ESA C**

Exam 2: Tue, 17. Sep. 2019 09:30-11:30
Room: **Hörs Pharmazie (gr) Bu 45, Pharm**

Content:

- Lecture
- Exercises
- Reading

No materials, just bring a pen.

MASTER STUDIES INFORMATICS
UNIVERSITÄT HAMBURG, SS 2017

Universität Hamburg
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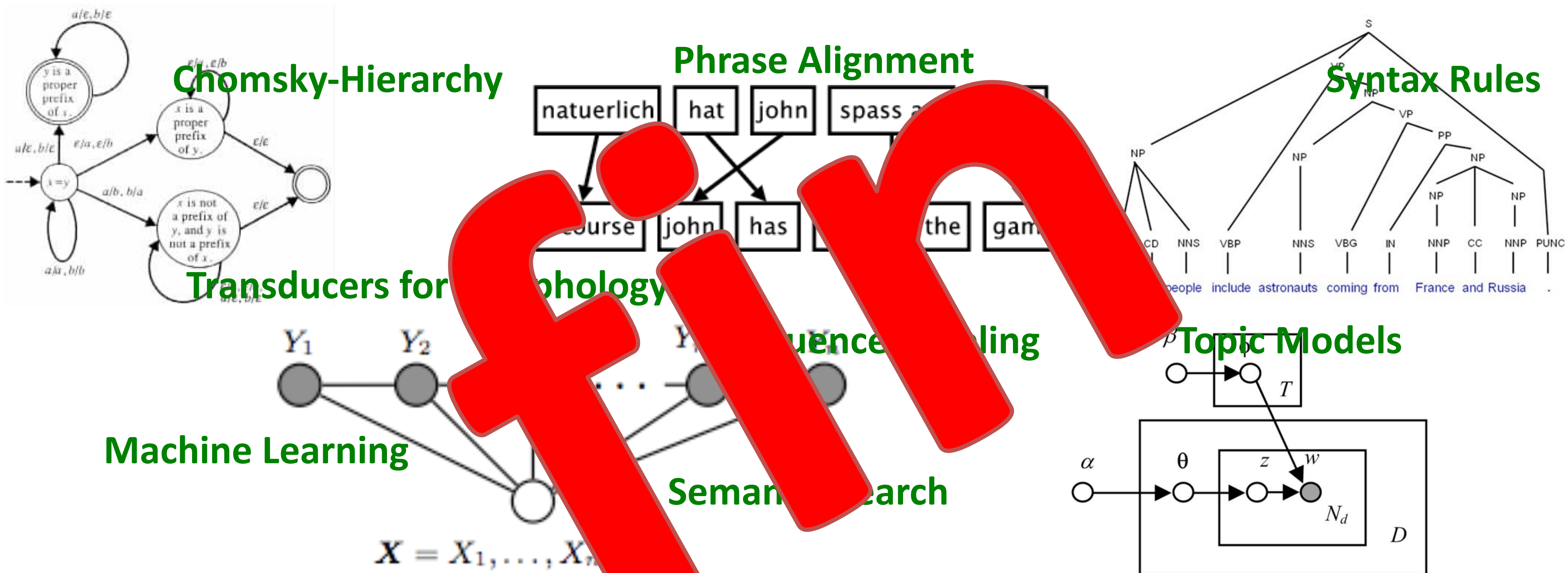


CHRIS BIEMANN, EUGEN RUPPERT

STATISTICAL METHODS OF LANGUAGE TECHNOLOGY

TEACHING EVALUATION (SUMMARY)

Aggregated grades:

- content: ~2.3
- course material: ~2.1
- lecturer: ~1.9
- practice class: ~2.0

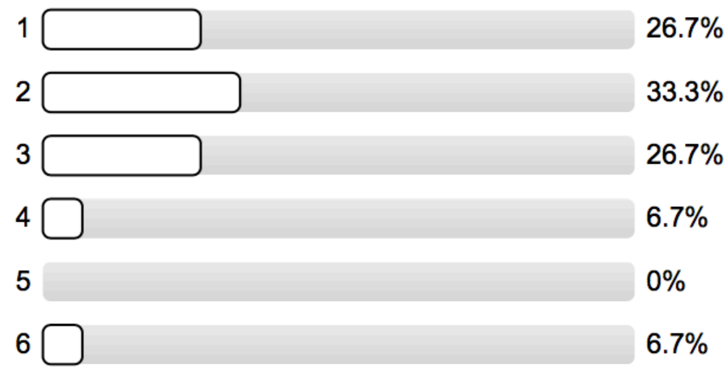
Positive:

- feedback mechanisms
- recording
- interesting topics
- exercises well alignend with lecture, variety of tools

Negative:

- not interactive enough
- too theoretical, need for more practical applications
- too many tools
- not always ending on time
- balance of old and new methods

overall grade



one extremely negative feedback

Only 15 participants!

SPEAKING OF WHICH ..

- More courses?
  - NLP4Web
  - Master Project
- Hiwi Jobs / MA Theses?
  - sense change over time
  - language and structure of law
  - web-scale argument mining
  - meeting minute bot