Auto-IA Workshop HMTM Hannover

Automatische Sprachverarbeitung

LEIBNIZ-INSTITUT
FÜR MEDIENFORSCHUNG
HANS-BREDOW-INSTITUT

Automatic Content Analysis

Introduction

Gregor Wiedemann | g.wiedemann@leibniz-hbi.de
Media Research Methods Lab
Leibniz-Institute for Media Research | Hans-Bredow-Institut

Andreas Niekler | aniekler@informatik.uni-leipzig.de
Abteilung Automatische Sprachverarbeitung, Institut für Informatik
Universität Leipzig

Course plan

- Lectures
  - Text as data / pre-processing
  - Lexicometrics: Frequency, Keyness, Co-occurrence
  - Topic Modelling
    - Berechnung
    - Evaluierung / Modell-Selektion
- Tutorials: 3+ work sheets
- Hands-On: Corona News Coverage

1. Text processing

Text Mining

- Text Mining (TM) is a set of *"computer based methods for a semantic analysis of text that help to automatically, or semi-automatically, structure text, particular very large amounts of text"*

  (Heyer 2009, p.2)

- TM combines
  - linguistic knowledge
  - statistical knowledge

Text as data

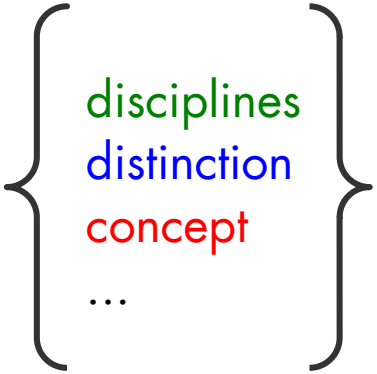
- **symbol** ← meaning
  - character: linguistic unit (meaning representation)
    - 豊 δ A ♣ ...
  - glyph: graphical representation of a symbol
    - a ← {a 𝐚 a a A A A A}
- **alphabet:** fixed set of characters
  - {a, b, c, d, e, …}
- **encoding**
  - unambigous assignment of characters from an alphabet to {bit patterns, octets, …}
  - standards („a"): ASCII (61), ISO-8859-1 (61), UTF-8 (U+0061), …

Text as data

- **String:** concatenation of alphabet elements
  - „Hello world!“, „“, „0001011111000101 01“, „To be or not to be…“
  - essential, elementary data type in computer linguistics
  - common operations: e.g.
    - concatenation: „Hello“ + „World“ + „!“ → „Hello World!“
    - splitting: split(„Hello World!“, „ “) → {„Hello“, „World!“}
    - case conversion: uppercase(„Hello“) → „HELLO“
    - substring: substr(„Hello“, start = 0, length = 4) → „Hell“
- **Document:** compound data type
  - (collection of) strings (e.g. title, body) [+ Metadata]
- **Corpus:** collection of documents

Text as data

- **Type** (cp. class)
  - (abstract) string representing a meaningful concept, e.g. words
- **Token** (cp. object)
  - (concrete) string as instance of a meaningful concept

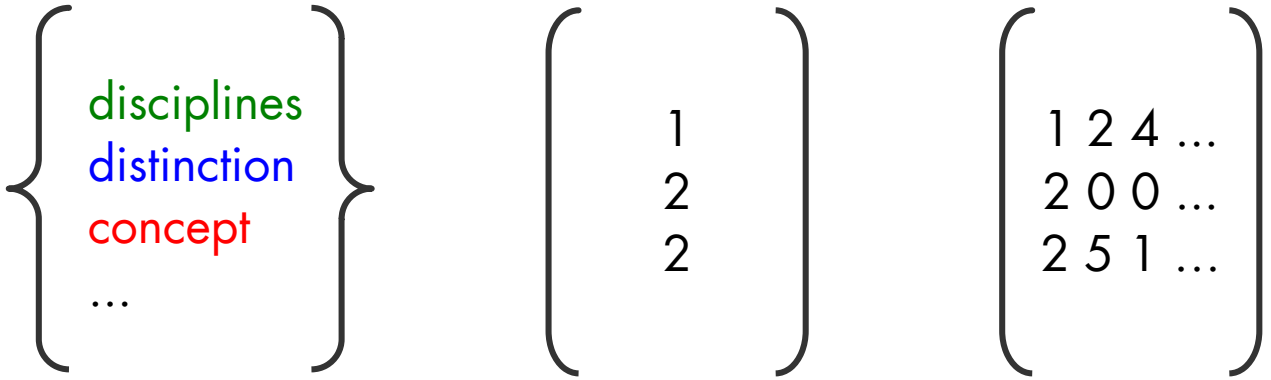


> In disciplines such as knowledge representation and philosophy, the type–token distinction is a distinction that separates a concept from the objects which are particular instances of the concept."
>
> *(Wikipedia → Type–token distinction)*

- **Vocabulary**
  - complete set of all types occuring in a [document | collection]

Text as data

- Transformation of text into numerical objects



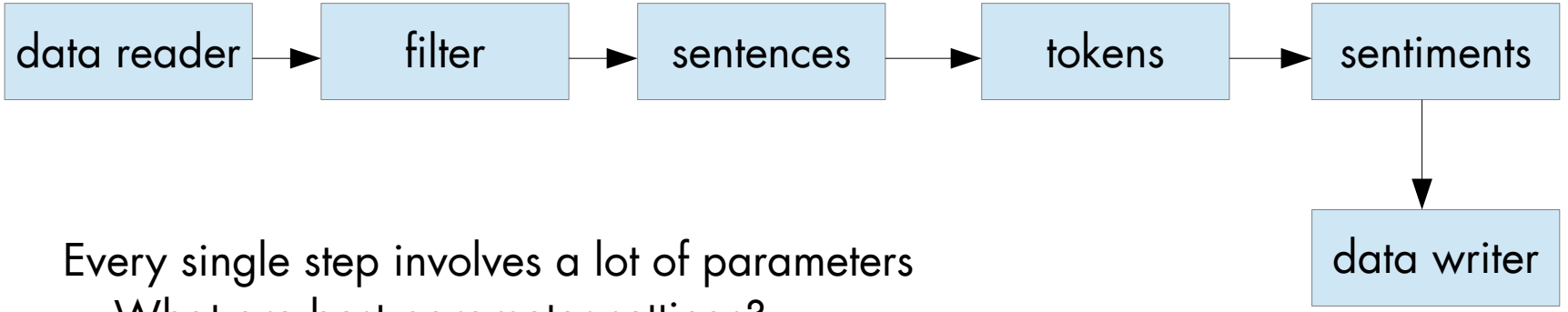
List of strings vector matrix

- Transformed objects → Data Mining
  - process of discovering patterns in large data sets

NLP piplines

- **PIPELINE**: application of different data manipulation procedures in row
  - preprocessing
  - actual analysis
  - output format

e.g.



Every single step involves a lot of parameters
→ What are best parameter settings?
→ Reproducibility?

7. TEXT MINING PROCEDURES

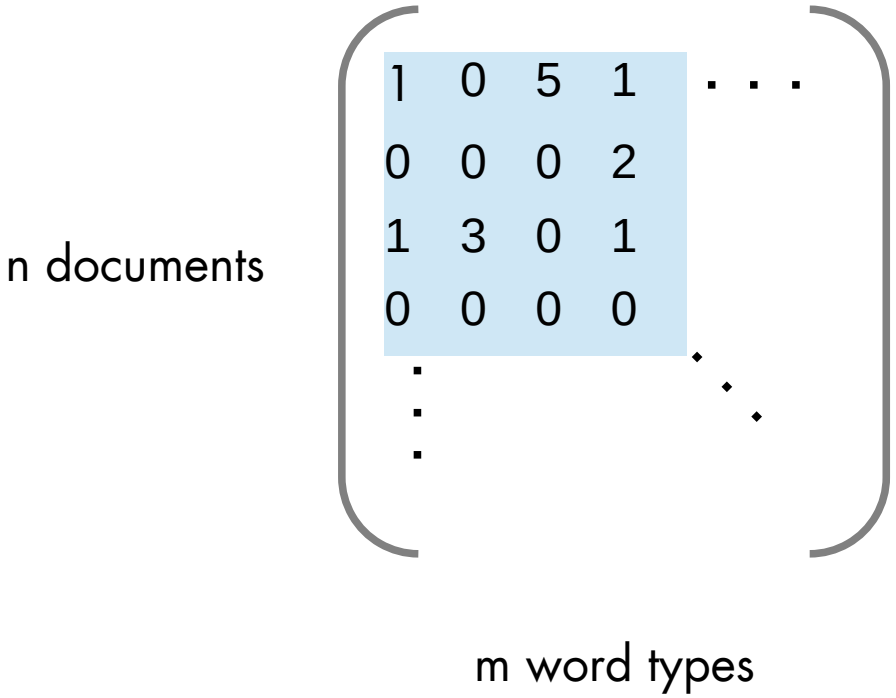
Vector Space Model

- Idea: Encode textual
  - documents in **vectors**
  - collections in **matrices**
- **data = event counts**
- dimensionality of vector space
  - |vocabulary of collection|

- D1: Kim is leaving home.
- D2: Kim is at home.
- D3: Karen is leaving.

Kim	is	leaving	home	.	at	Karen
1	1	1	1	1	0	0
1	1	0	0	1	1	0
0	1	1	0	1	0	1

Document-Term-Matrix



- may get very large!
- events: frequency counts of word types in each document
- bag of words
- very sparse (contains mostly zeros)
- variations:
  - binary event counts
  - paragraphs as documents
  - sentences as documents
  - additional n-grams (n > 1) as events
  - ...

n – size of collection
m – size of vocabulary

Stop words

- stop words = list of words considered as no meaningful for specific NLP task
- → can be filtered out of global vocabulary to reduce data / improve performance
- example:
  - $DTM^{50x2103}$, 6198 tokens
  - remove 78 sw (– 4%) →
  - $DTM^{50x2027}$, 4801 tokens (– 22%)

- am
- among
- amongst
- amoungst
- amount
- an
- and
- another
- any
- anyhow
- anyone
- anything
- anyway
- anywhere
- are
- around
- as
- at
- back
- be
- became
- because
- become
- becomes
- becoming
- been
- before
- beforehand
- behind
- ...

N between ~100 … ~1000

Stop words

Nach den Ungarn hatten auch die Comecon-Behörden bereits die Hand nach Kapitalisten-Dollars ausgestreckt. Vor wenigen Monaten hatte die Internationale Bank für Wirtschaftliche Zusammenarbeit in Moskau, das Finanzzentrum des Comecon, bei einer europäischen Bankengruppe elf Millionen Dollar ausgeliehen.

In Wall Street werden indes noch Anleihen gehandelt, die eine russische Schuld aus dem Jahre 1916 verbürgen. Damals lieh sich Zar Nikolaus II 75 Millionen Dollar. Doch nach der Revolution verweigerten die Kommunisten die Rückzahlung der Schuld. Heute sind 1000 Dollar von 1916 in Wall Street nur noch um 40 Dollar wert. Zur Zeit der Konferenz von Jalta im Jahre 1945 hatte dagegen die späte Hoffnung auf eine Erstattung der Russenschulden die Papiere immerhin auf einen Kurs von 230 Dollar hinaufgetrieben. smi

Stop words

Automatische Sprachverarbeitung

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Pruning

- Pruning = filtering the vocabulary of a collection by minimum / maximum thresholds of occurrence
- very useful preprocessing step to reduce vocabulary size:
  - Count occurrence of types in the complete collection
  - keep only those terms which occur above / below a defined threshold
- Caution: distribution of language data → see chapter *„frequency analysis“*

- term frequency:
  - sum all term occurrences in all documents
  - filter terms which occur e.g. count(term) > 1 AND count(term) < 100
- document frequency:
  - for each term count number of documents in which it is contained
  - allows for filters like: terms which occur e.g. in more than 99% AND less than 1%

    of documents

Unification: Stem vs. Lemma

Automatische Sprachverarbeitung

- Unification:
  - observation: similar semantic types share similar orthographic forms
  - connect -ion, -ions, -ive, -ed, -ing
  - Idea: map variants to reduced form
    - → reduce vocabulary
    - → reduce data sparsity

- Two methods:
  - Stemming: cut of endings by language specific rules
  - Lemmatization: mapping of types to linguistic its lemma by dictionary lookup (external resource)

Stemming

- Standard appraoch: Porter Stemmer (1980) / Snowball
- separation of suffixes by rules, e.g.
  - SSES → SS caresses → caress
    IES → I ponies → poni
  - (if m>1) EED → EE feed → feed
    agreed → agree

    m = number of syllables
- Problems:
  - overstemming: artificial ambiguity
    - {organization, organ} → organ
  - understemming: unification fails
    - European → european, Europe → europ

Lemmatization

Automatische Sprachverarbeitung

- Lookup of canonical / dictionary form
- usually retrieved by long dictionary files which contain
  - inflected_type lemma_type
    European Europe
    Europe Europe
    Organizations Organization
- Problems:
  - getting external resources (e.g. ASV Leipzig list of > 600.000 type-lemma-relations for German)
  - incomplete lists

Example

McLean Industries Inc's United
States Lines Inc subsidiary said it has agreed in principle to transfer its South American service by arranging for the transfer of certain charters and assets to <Crowley Mariotime Corp>'s American Transport Lines Inc subsidiary.
U.S. Lines said negotiations on the contract are expected to be completed within the next week. Terms and conditions of the contract would be subject to approval of various regulatory bodies, including the U.S. Bankruptcy Court.

PREPROCESSING

mclean industri inc united
st line inc subsidiari said agre principl
transfer south american servic arrang
transfer certain charter asset crowley mariotime
corp american transport line inc subsidiary
line said negoti contract expected
complet within next week term condit
contract subject approv various regulatory
bodies includ bankruptci court

- lowercase
- remove punctuation
- remove stop words
- stemming
- strip white spaces

Sentence detection / Tokenization

Automatische Sprachverarbeitung

- → Essential preprocessing step!
  Badly tokenized text data may lead to bad results
- frequent errors:
  - intra-word dashes: 'front-end' → 'front end' OR 'front-end'
  - quotation marks '„Hello“' → '„ Hello “' OR '„Hello“'
  - dots for abbreviation: 'Mr.' → 'Mr .' OR 'Mr.'
  - colon / semicolon: 'Monday' → 'Monday:' OR 'Monday :'
  - apostrophe:

    „O'Neill“ → „Neill“ OR „ONeill“ OR „O'Neill“ OR „O ' Neill“ OR „O' Neill“
    „aren't“ → „aren t“ OR „aren't“ or „arent“ or „are n't“

Part-of-Speech

- Task PoS-Tagging = Assign a word type label to each token in a sentence
  - The cat barks at the dog .
  - DET NN VF PRE DET NN $
- Ideal task for machine learning classifiers on annotated training data!
  - e.g. Conditional Random Field classifier: most probable sequence of outcome labels to an input sequence
- label sets are called „tag sets“ → different sets for different languages / tasks
  - English: Penn Treebank POS tags (36 labels)
  - German: STTS Stuttgart/Tübingen Tagset (57 labels)
  - Translingual: Universal POS tags (17 labels)

Summary

- Linguistic Preprocessing
  - shall reduce / unify data for application specific purpose
  - may contain various steps in row
    - Encoding
    - Spelling correction
    - Removing uninformative data: noise, duplicates, stopwords, low/high frequent terms (pruning), dictionaries
    - Sentence detection, tokenization, Part-of-Speech tagging
    - Unification: punctuation, capitalization, stemming, lemmatization
  - best setup usually has to be identified experimentally (or by experience)
  - caution: order of steps may influence result!

2. Machine Learning

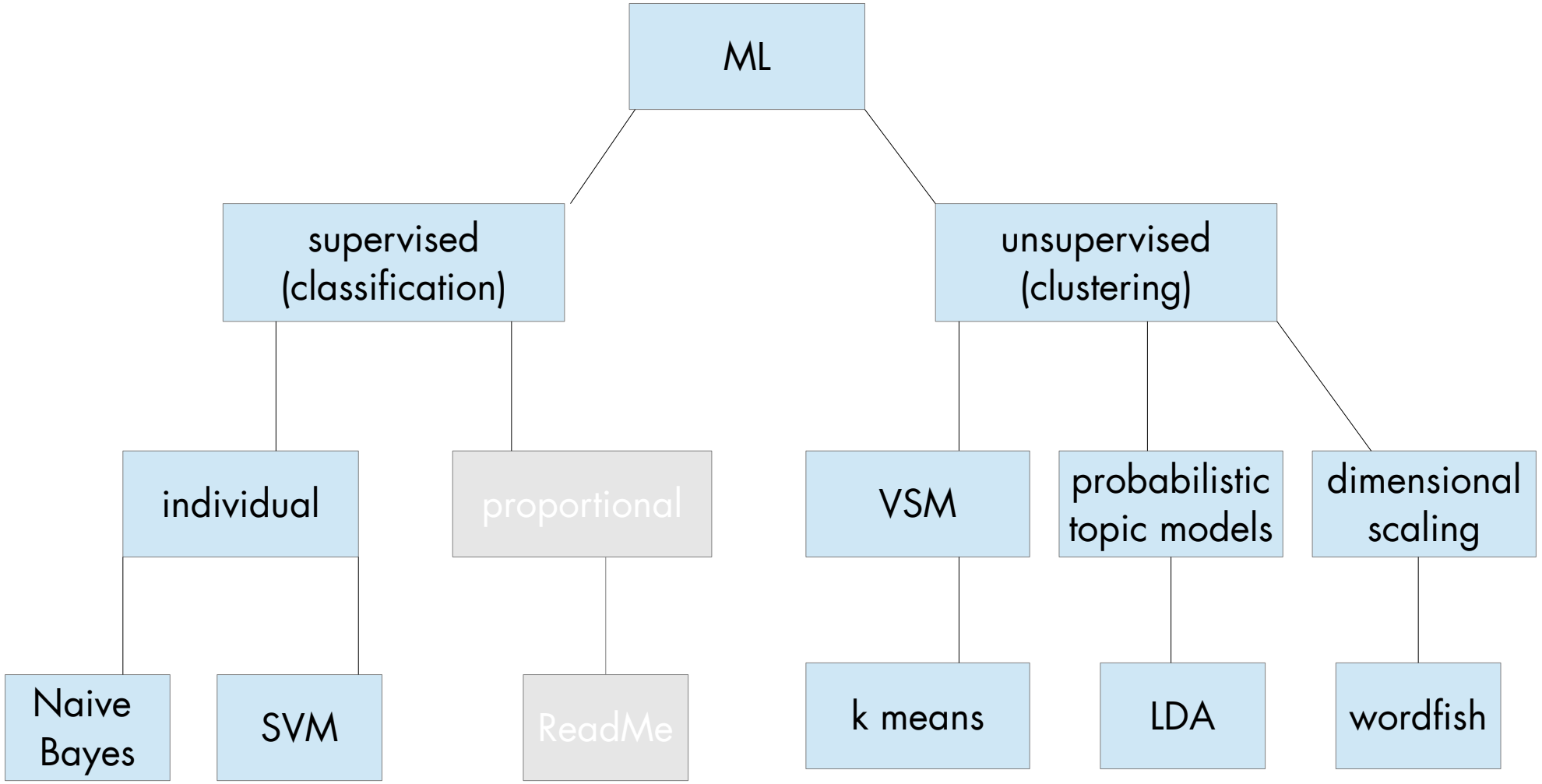
Machine Learning

- Definitions
  - "[Giving] computers the ability to learn without being explicitly programmed" – Arthur Samuel
  - "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E" – Tom M. Mitchell
- Common foundations
  - Probability Theory
  - Decision Theory (making "good" decisions based on data)
  - Optimization (optimize model of data based on decision objective)
- independent of application domain

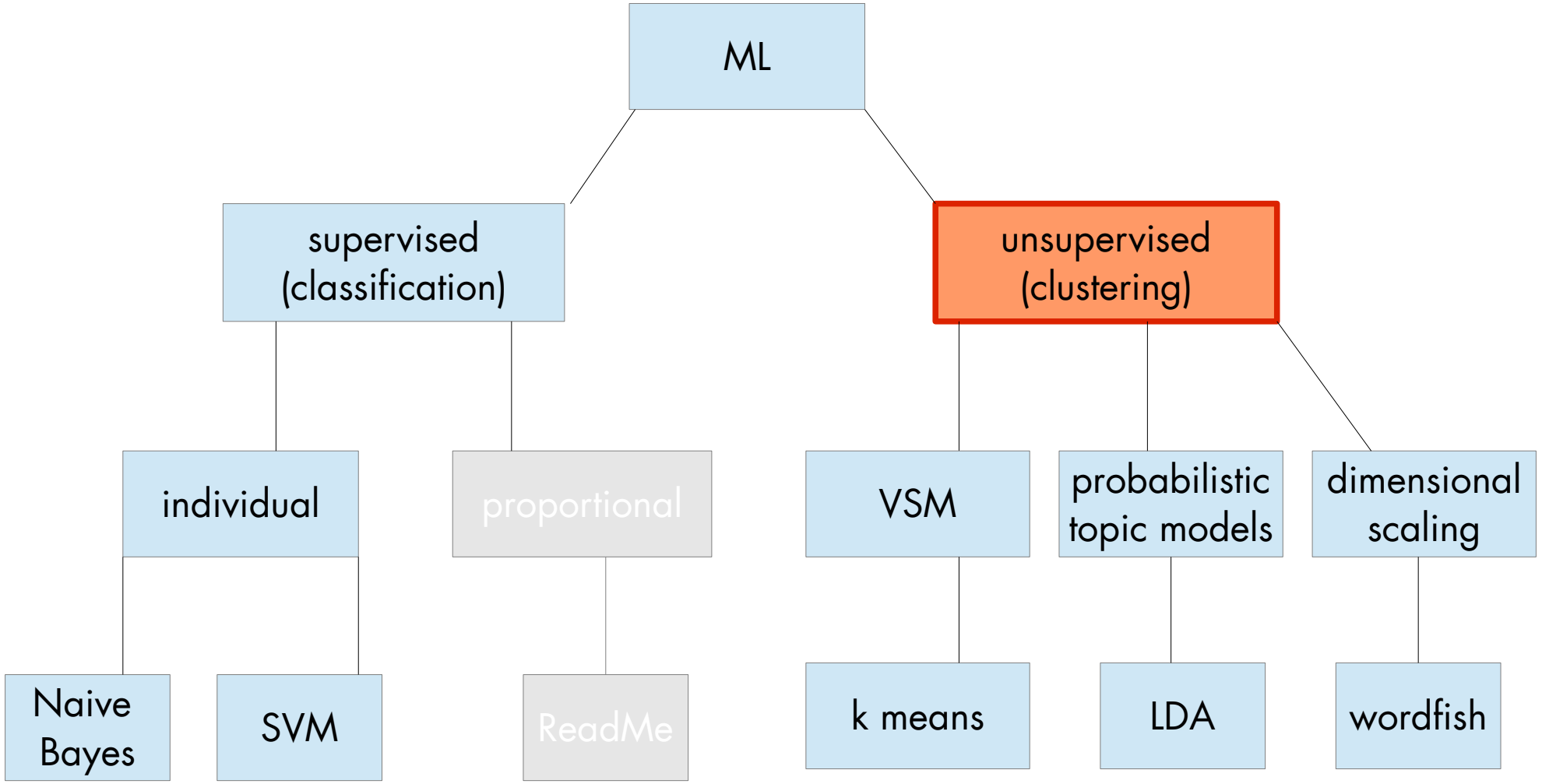
Application domains of ML

- Autonomous driving
- Medical diagnosis
- Network security
- …
- Textmining and NLP:
  - Linguistic preprocessing: POS-Tagging, Parsing
  - Modelling Language Semantic
    - category classification
    - clusters of (latent) meaning

Machine learning for NLP



Machine learning for NLP



Clustering

- Cluster analysis:
  - „task of grouping a set of objects in such a way that objects in the same group (called a cluster) are more similar (in some sense or another) to each other than to those in other groups (clusters)“ [Wikipedia]
- Motivation in content analysis:
  - identifying similar / (quasi-)duplicate documents / parts of text
  - splitting a collection of documents into groups
    - thematic
    - time periods
  - identifying groups of related terms
  - placing documents on an ideological scale

Topic Models

Topic Models

- Class of probabilistic graphical models which infer semantic coherences from large text collections as latent variables
  - Latent variables = topics
- Background assumptions
  - Bag-of-words model
  - Generative process (1. document author, 2. draw topic mixture, 3. draw terms from topics → document)
- 2 posterior distributions
  - θ : Documents = mixtures of topics
  - β : Topics = probability distributions over terms

Variety of models (Blei 2012): e.g.

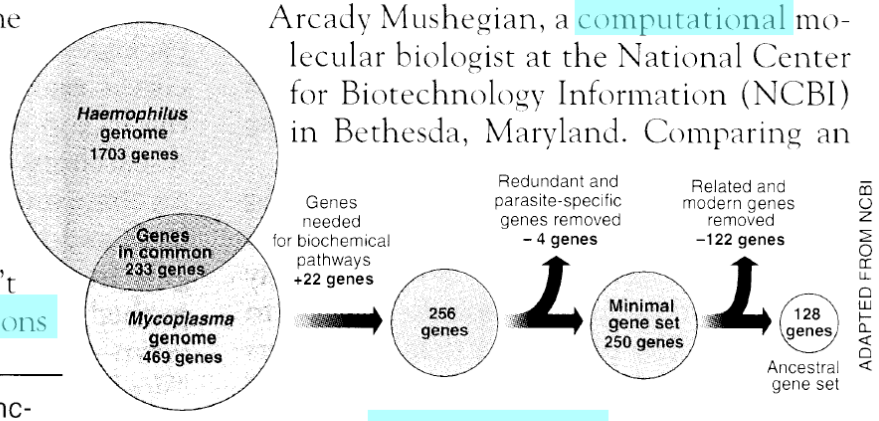
- Latent Dirichlet Allocation (Blei et al. 2003)
- Correlated Topic Models (Blei & Lafferty 2007)
- Hierarchical Dirichlet Process (Teh et al. 2006)
- Author-Topic Model (Rosen-Zvi et al. 2004)
- …

Latent Dirichlet Allocation (LDA)

Seeking Life's Bare (Genetic) Necessities

COLD SPRING HARBOR, NEW YORK—How many genes does an organism need to survive? Last week at the genome meeting here,* two genome researchers with radically different approaches presented complementary views of the basic genes needed for life. One research team, using computer analyses to compare known genomes, concluded that today's organisms can be sustained with just 250 genes, and that the earliest life forms required a mere 128 genes. The other researcher mapped genes in a simple parasite and estimated that for this organism, 800 genes are plenty to do the job—but that anything short of 100 wouldn't be enough.

Although the numbers don't match precisely, those predictions "are not all that far apart," especially in comparison to the 75,000 genes in the human genome, notes Siv Andersson of Uppsala University in Sweden, who arrived at the 800 number. But coming up with a consensus answer may be more than just a genetic numbers game, particularly as more and more genomes are completely mapped and sequenced. "It may be a way of organizing any newly sequenced genome," explains Arcady Mushegian, a computational molecular biologist at the National Center for Biotechnology Information (NCBI) in Bethesda, Maryland. Comparing an



Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes.

* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.

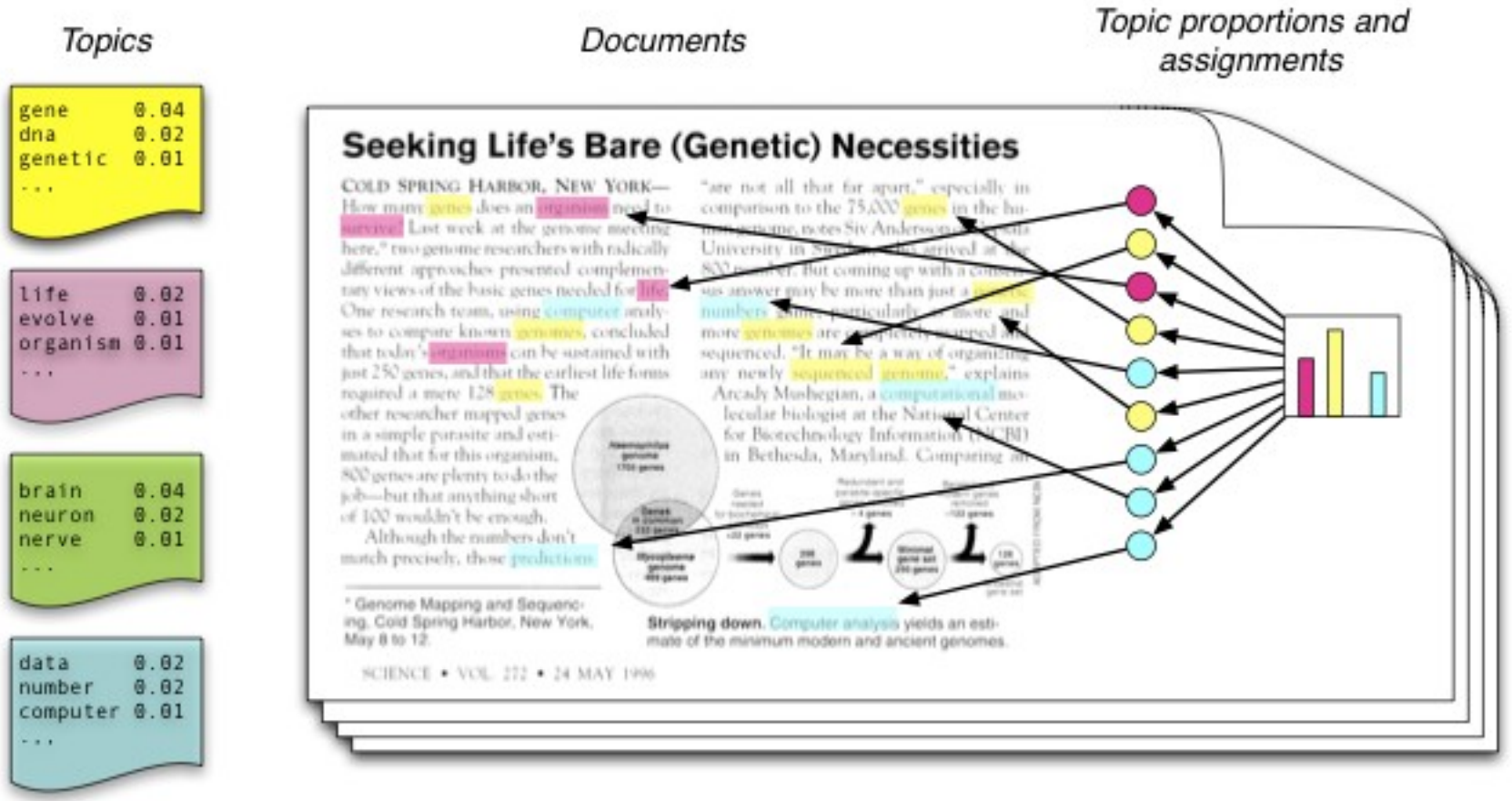
SCIENCE • VOL. 272 • 24 MAY 1996

Assumptions:

1. Documents are mixtures of topics

2. Topics are distributions over terms

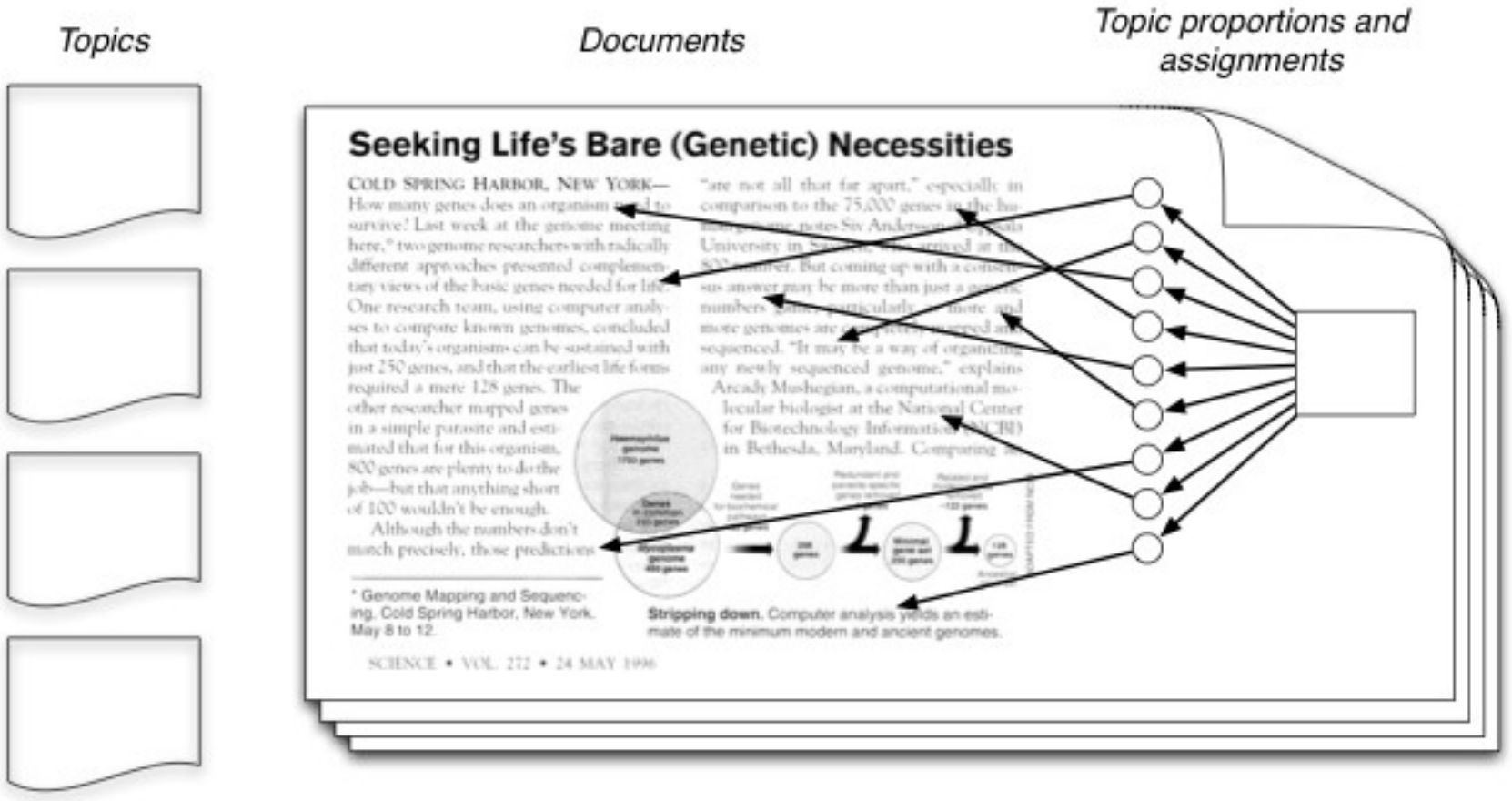
Latent Dirichlet Allocation (LDA)



Model assumptions

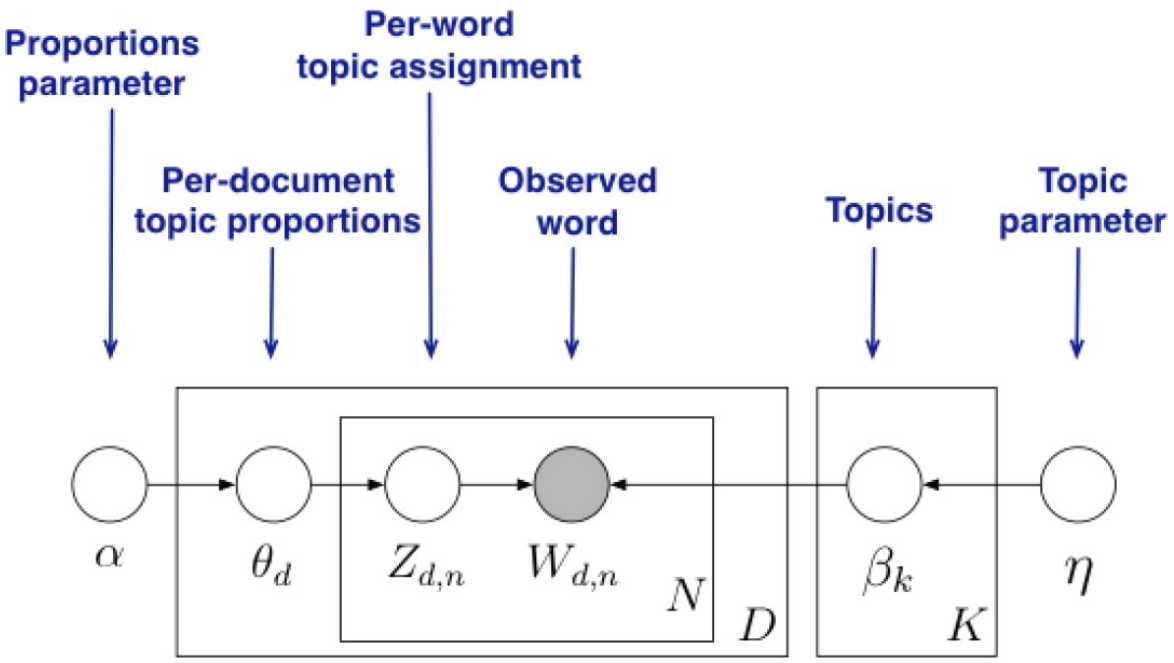
- every topic is represented by a distribution over terms
- every document is represented by a distribution over topics
- generative process: for every document → draw a topic distribution → for each topic → draw a term

Latent Dirichlet Allocation (LDA)



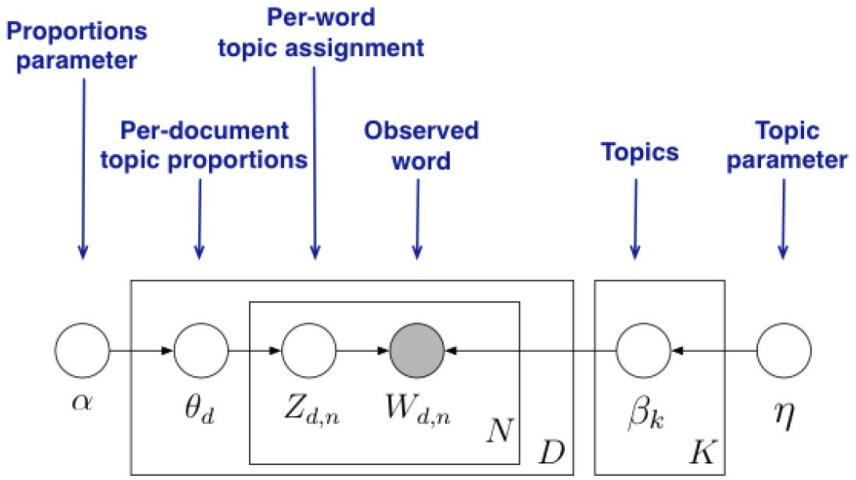
- in reality we see only the documents
- topics as latent variables have to be inferred from the observations (terms in documents)
- → calculate the distribution: *p(topics, proportions, assignments | document)*

LDA as graphical model



$$p(\beta, \theta, \mathbf{z}, \mathbf{w}) = \left(\prod_{i=1}^{K} p(\beta_i|\eta) \right) \left(\prod_{d=1}^{D} p(\theta_d|\alpha) \prod_{n=1}^{N} p(z_{d,n}|\theta_d) p(w_{d,n}|\beta_{1:K}, z_{d,n}) \right)$$

LDA as graphical model



- from joint distribution P(β,θ,**z**,**w**), posterior distribution can be inferred: P(β,θ,**z**|**w**)
- i.e. Topic model inference resulting in
  - assignments $z_{d,n}$ of topics to all words in each document
  - distribution of topics θ_d in each document
  - distribution of terms β_k in each of the K topics
- results can be used for information retrieval, time series, collection filtering, …

Inference

$$p(\beta, \theta, \mathbf{z}, \mathbf{w}) = \left(\prod_{i=1}^{K} p(\beta_i|\eta) \right) \left(\prod_{d=1}^{D} p(\theta_d|\alpha) \prod_{n=1}^{N} p(z_{d,n}|\theta_d) p(w_{d,n}|\beta_{1:K}, z_{d,n}) \right)$$

- Analytically intractable → approximate solution needed
- Hard task in topic modeling: computationally tractable inference on model parameters; e.g.
  - Gibbs Sampling
  - Variational inference
- Good news: there are some fast and reliable implementations, that do the math for you :)

- Crucial parameters influencing model outcomes:
  - K – number of topics to be inferred
  - α – prior for topic–document distributions
  - η – prior for term–topic distributions
- Inference is based on sampling → results are not entirely deterministic

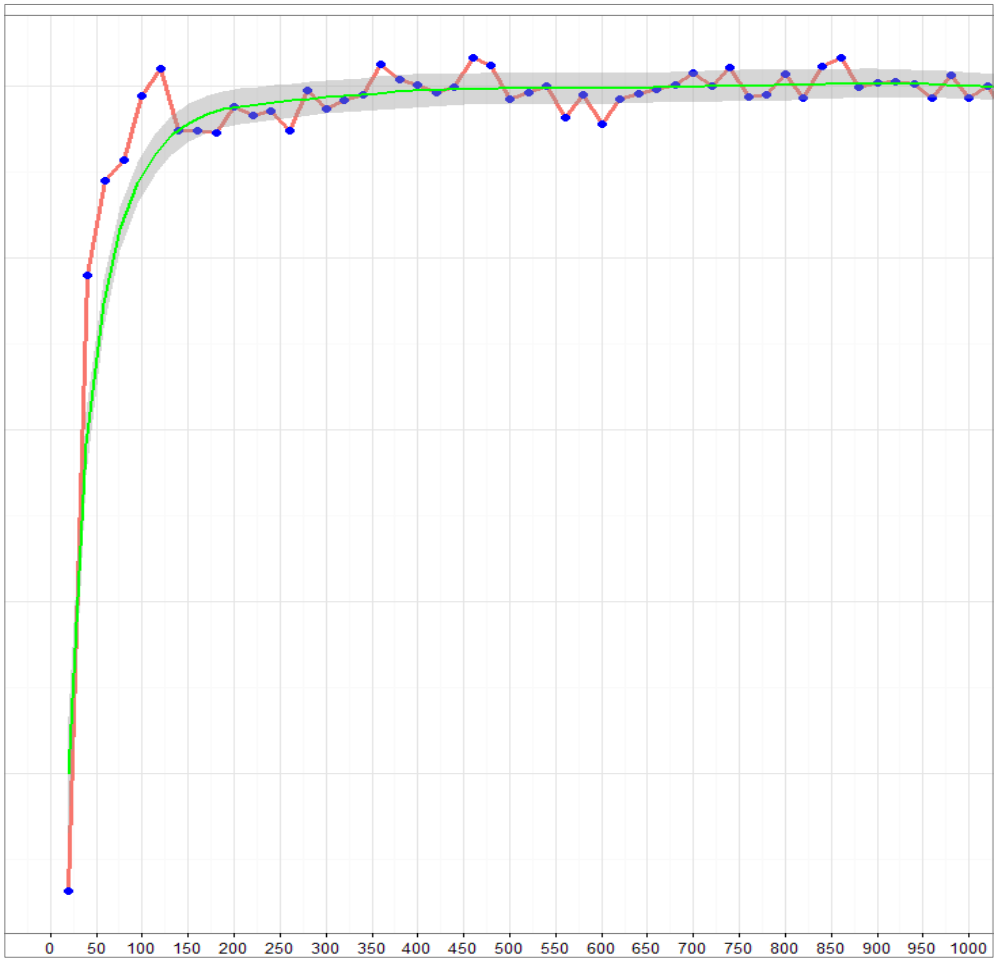
Inference – Gibbs Sampling

Automatische Sprachverarbeitung

Data: words $\mathbf{w} \in$ documents $\mathbf{d}$
Result: Topic assignments $\mathbf{z}$
initialize $\mathbf{z}$ randomly
foreach *iteration* **do**
  foreach *word* w **do**
    foreach *topic* k **do**
      $\theta_{d_w,k} \propto \frac{n^{(t)}_{k,\neg i} + \beta_t}{\sum_{t=1}^{V} n^{(t)}_{k,\neg i} + \beta_t} (n^{(k)}_{m,\neg i} + \alpha_k)$
    end
    topic $\leftarrow$ sample from $mult(\theta_{d_w})$
    z[w]$\leftarrow$ topic
    update counts according to new assignment
  end
end
return z

Inference – Gibbs Sampling

$$p(\beta, \theta, \mathbf{z}, \mathbf{w}) = \left(\prod_{i=1}^{K} p(\beta_i|\eta) \right) \left(\prod_{d=1}^{D} p(\theta_d|\alpha) \prod_{n=1}^{N} p(z_{d,n}|\theta_d) p(w_{d,n}|\beta_{1:K}, z_{d,n}) \right)$$



- More interations = better likelihood of the model
- Optimum almost reached at 200 – 300 iterations – This is called „burnin“ of the sampler
- Likelihood does implicate the quality of the model for your research – it is an optimum w.r.t. the model assumptions
- Rule of thumb: 1000 – 2000 iterations

Inference – Gibbs Sampling

$$\propto \frac{n_{k,\neg i}^{(t)} + \beta_t}{\sum_{t=1}^{V} n_{k,\neg i}^{(t)} + \beta_t} (n_{m,\neg i}^{(k)} + \alpha_k)$$

Gibbs algorithm samples assignments for each word

$$\varphi_{k,t} = \frac{n_k^{(t)} + \beta_t}{\sum_{t=1}^{V} n_k^{(t)} + \beta_t},$$

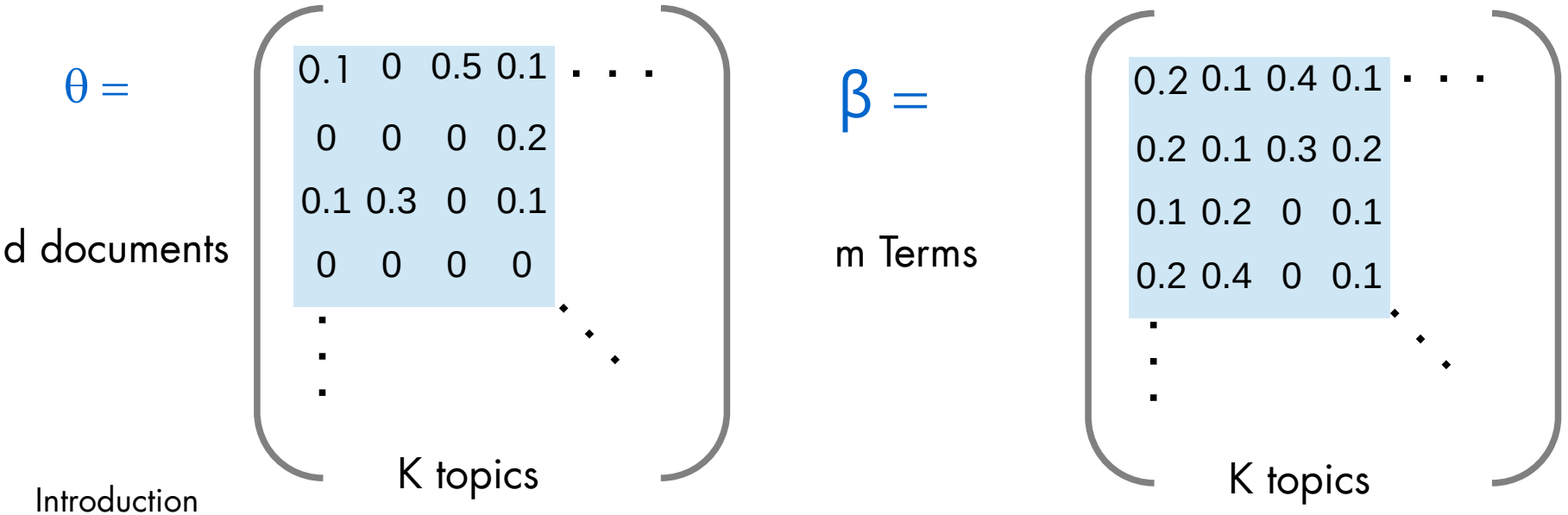
$$\vartheta_{m,k} = \frac{n_m^{(k)} + \alpha_k}{\sum_{k=1}^{K} n_m^{(k)} + \alpha_k}.$$

!!! Sometimes β is referenced as Φ because of the hyperparameters redundant name.

Samples must be converted to parameters θ and β by accuiring the statistics from the assigments.

Inference

- 2 mutually exclusive goals of inference process
  - assign terms to as little as possible topics in one document
  - assign high probability to as little as possible terms in one topic
- interdependency:
  - assign all terms in one document to one topic only → missing 2. goal
  - assigning high probability to few terms in each topic → missing 1. goal
- optimal alignment of these goals results in semantically coherent groups of terms and interpretable numbers of topics in documents



LDA examples

Example: Wortschatz data source, 100 million sentences in 2010

Topic 12
people
haiti
air
flight
day
hours
airport
weather
morning
port
night
earthquake
early
thursday
fire

[Jähnichen 2015]

LDA examples

Example: Wortschatz data source, 100 million sentences in 2010

Topic 23
oil
bp
gulf
spill
gas
company
coast
water
mexico
drilling
million
day
disaster
louisiana
barrels

[Jähnichen 2015]

LDA examples

Example: Wortschatz data source, 100 million sentences in 2010

Topic 48
space
nasa
station
shuttle
program
earth
planet
center
rocket
moon
international
mission
launch
mars
star
search

[Jähnichen 2015]

LDA examples

Topic 5	Topic 11	Topic 19	Topic 30	Topic 86
apple	food	fish	bank	summer
iphone	eat	river	financial	fall
phone	restaurant	water	banks	spring
mobile	fresh	animals	debt	year
google	meat	lake	crisis	early
users	wine	dog	market	winter
ipad	chicken	fishing	investment	late
company	add	dogs	capital	tourism
software	small	species	money	season
computer	water	boat	fund	trips
web	cheese	animal	billion	garden
video	vegetables	hunting	company	spirit
internet	rice	bass	investors	tour
access	lunch	waters	government	ll
devices	foods	forest	companies	travel
microsoft	menu	wildlife	based	families

[Jähnichen 2015]

Sorting Terms

Automatische Sprachverarbeitung

Standard Term Scoring

$$relevance(w|t) = sort(p(w|t))$$

Scoring by Chang, J., Chang, M.J.: Package “lda”. Citeseer (2010).

$$relevance(w|t) = p(w,t) \cdot \left(\log p(w|t) - \frac{1}{K} \sum_{t'} \log p(w|t') \right)$$

Scoring by Sievert, C., Shirley, K.E.: LDAvis: A method for visualizing and interpreting topics. In: Proceedings of the workshop on interactive language learning, visualization, and interfaces. pp. 63–70 (2014).

$$relevance(w|t) = \lambda \cdot \log p(w|t) + (1-\lambda) \cdot \log \frac{p(w|t)}{p(w)}.$$

Sorting Topics

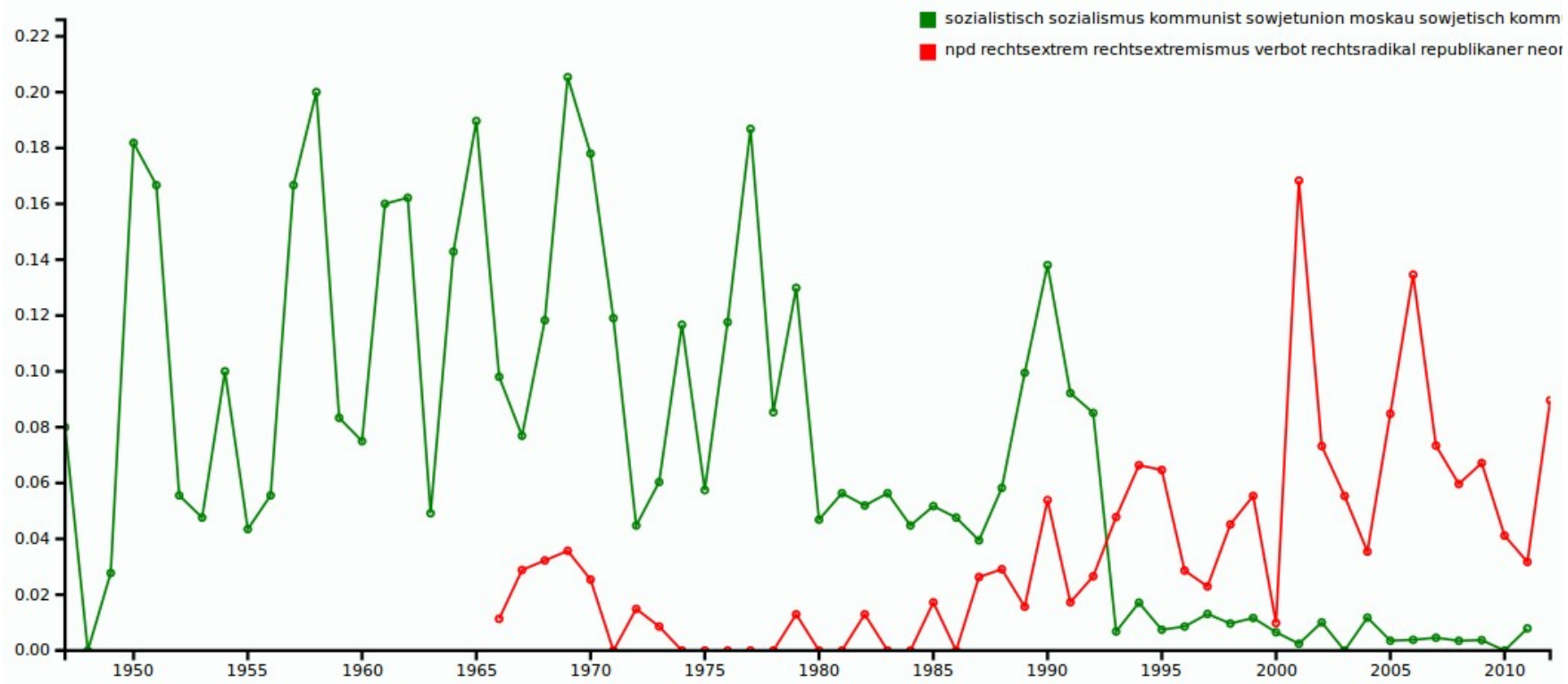
1. Approach: We sort the topics by their probability among the whole collection:

$$p(z) = \frac{\sum_D p(z|d)}{\sum_D \sum_{z=1}^{K} p(z|d)}$$

2. Approach: We count how often a topic appears as the primary topic within the documents. This method is called Rank-1.

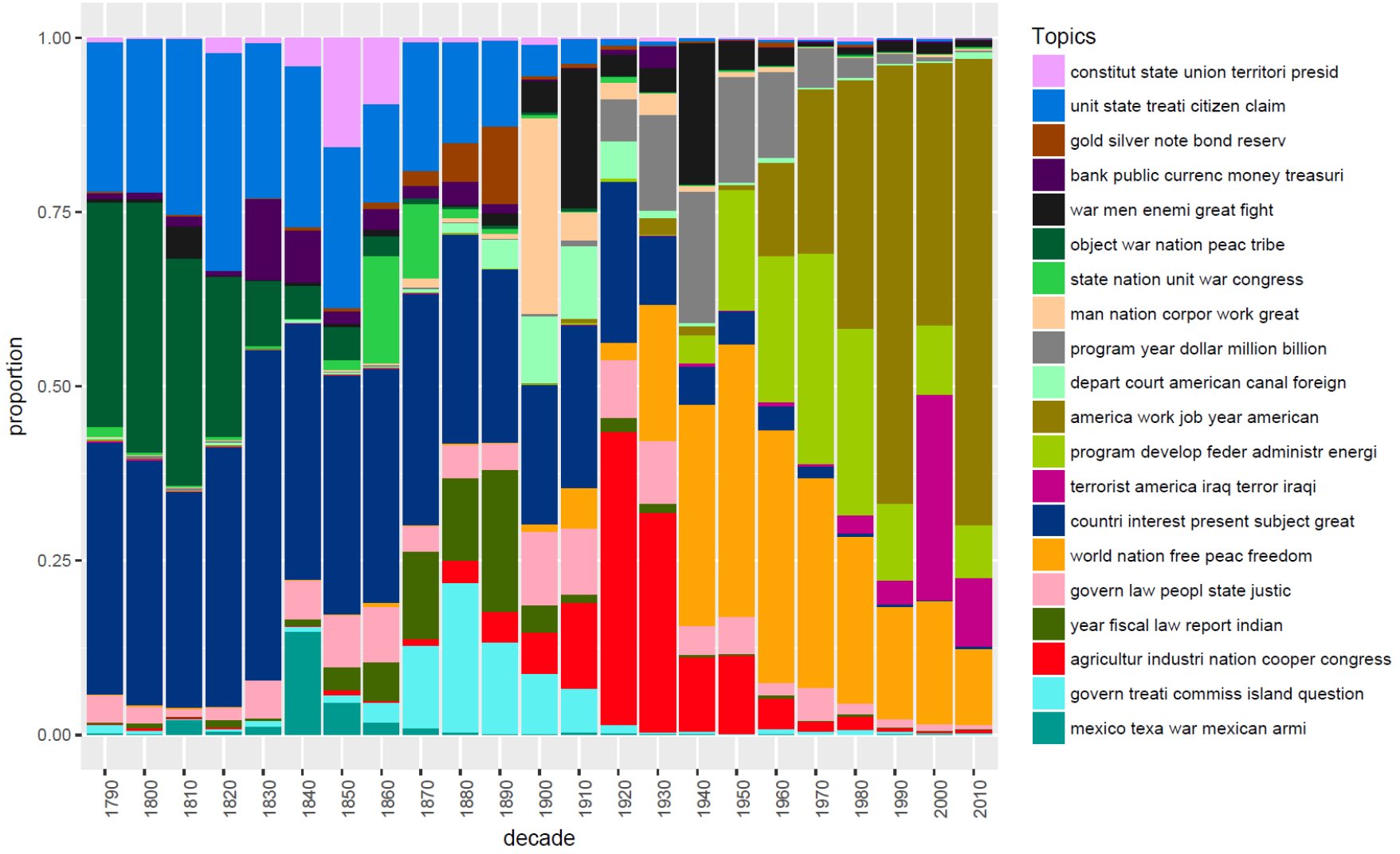
$$count(z) = \sum_{d=1}^{D} \arg\max_{z' \in K} p(z'|d) \begin{cases} 1, & \text{if } z' = z, \\ 0, & \text{otherwise.} \end{cases}$$

LDA examples



Time series: frequencies (relative to collection size) of documents containing minimum 25% share of topic k ($\theta_{d,k} > 0.25$)

LDA examples



Applying topic models in CA

Automatische Sprachverarbeitung

- Topic models can be employed to
  - split collections into thematic clusters
  - identify documents related to certain topics
  - track topic quantities over time (aggregation of document topic probabilities)
  - identify similar documents based on similarity of topic distributions rather than term frequencies (cp. k-means on DTM)
  - identify relevant vocabulary within a collection
- Analysts need to
  - choose appropriate K
  - interprete resulting topics
  - eventually optimize mode parameters (α, η priors)
  - incorporate result data into their workflows

Possible alterations

- Filter POS-Types: Concentrate on NN(S) / NNP(S)
- Add extra vocabulary
  - time stamps, categories, dictionary terms, onthology categoritzation
- Initialize to predefined assignments – forced topic id's for words
  - seeded initialization
  - initialization by co-occurrence clusters of words
- Problem: Inner document statistics are dependent on empirical data within the document - Short documents cannot be modelled very well
  - Twitter: Try to concat tweets of the same user or hashtag to longer artificial documents – depends on the intendet topical structures