Unit 4: Measuring Keyness

Statistics for Linguistics with R – a SIGIL course

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What are Donald Trump's favourite words?

https://www.thetrumparchive.com/

	Trump tweets (target)	other tweets (reference)
crooked	p = 340 pmw TTA: $f = 453$	p = 6.4 pmw
everyone	p = 404 pmw TTA: $f = 538$	p = 404 pmw

→ **keywords** "occur with unusual frequency in a given text" or text collection (Scott 1997: 236)

→ basis: frequency comparison with reference corpus

Keywords in corpus linguistics

- Aboutness of a text → key keywords (Scott 1997)
- Technical/genre terminology (Paquot & Bestgen 2009)
- Literary style (Culpeper 2009)
- Linguistic & cultural differences (Oakes & Farrow 2006)
- Historical perspectives (Fidler & Cvrcek 2015)
- Similarity of text collections (Rayson & Garside 2000)
- Corpus-based discourse analysis (Baker 2006)
  - also know as corpus-assisted discourse studies (CADS)
  - clusters of keywords represent central topics, actors, metaphors, and framings (e.g. McEnery et al. 2015)

Keyness

- More generally, **keyness** is one of the most fundamental concepts in corpus linguistics
- Frequency comparison between corpora **A** and **B** (representative of underlying linguistic populations)
- For different kinds of lexico-grammatical items
  - word forms, lemmas, n-grams, multiword expressions
  - morphemes, grammatical constructions, n-grams of tags
- Wide range of applications depending on choice of lexico-grammatical items and of corpora **A** and **B**

Applications of keyness

Bibliographic keywords

- **A** = text, **B** = collection ➞ aboutness of text
- also: key keywords (that are key in many texts)

Target corpus vs. reference

- **A** = domain, **B** = general language ➞ terminology
- items = n-grams / MWE ➞ multiword terms (SkE)
- **A** = thematic corpus, **B** = reference ➞ discourse (CADS)

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Applications of keyness

Symmetric keyword analysis

- **A**, **B** similar but “opposite” ➞ contrastive framings (e.g. liberal vs. conservative newspaper)

Collocation identification

- **A** = contexts of node word, **B** = rest of corpus ➞ collocations of node word

Corpus comparison

- **A**, **B** = comparable corpora, items = grammatical constructions ➞ language variation

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Keywords in CQPweb

No.	Word	In whole “German COVID-19 tweets (v2)”:		In corpus “German Reference Tweets (2018/2019)”:		+/-	Conservative LR
		Frequency (absolute)	Frequency (per mill)	Frequency (absolute)	Frequency (per mill)		
1	Corona	2,114,391	9,453.42	42	0.37	+	13.14
2	#Corona	1,048,731	4,688.87	5	0.04	+	12.34
3	paNdEMIe	167,967	750.98	20	0.18	+	9.88
4	lockDown	143,748	642.70	25	0.22	+	9.56
5	#Lockdown	113,326	506.68	5	0.04	+	9.13
6	NeuINFEKTIONEN	70,034	313.12	5	0.04	+	8.44
7	rki	63,840	285.43	23	0.20	+	8.43
8	#Pandemie	55,078	246.25	5	0.04	+	8.09
9	impfstoff	82,550	369.08	69	0.61	+	8.07
10	Quaräntäne	71,280	318.69	58	0.51	+	8
27	@BAG_OFSP_UFSP	23,571	105.39	34	0.30	+	6.78
28	Infektion	39,620	177.14	90	0.80	+	6.77
29	fAlLzAhLeN	25,385	113.50	46	0.41	+	6.69
30	Biontech	20,703	92.56	5	0.04	+	6.68
31	#querdenker	16,895	75.54	18	0.16	+	6.6
32	infiziert	58,135	259.92	192	1.70	+	6.56
33	IntensivstationeN	16,277	72.77	18	0.16	+	6.54

The IMS Open Corpus Workbench

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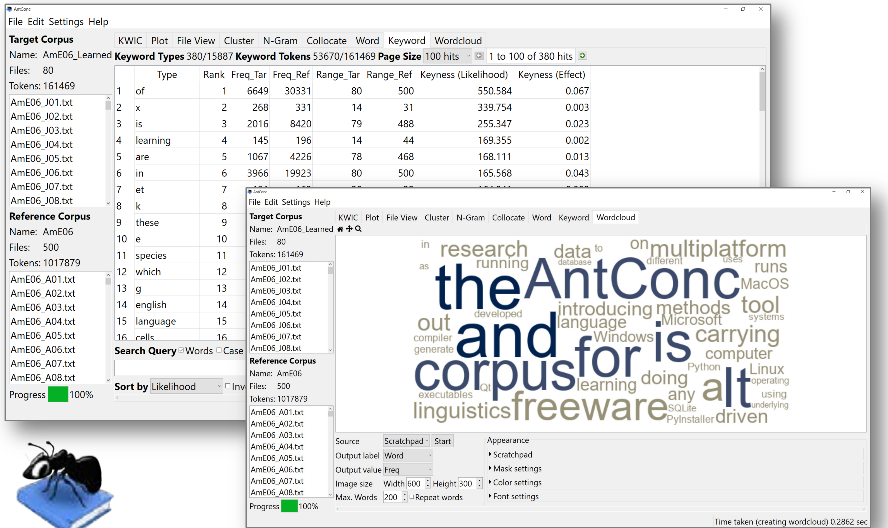
Keywords in AntConc



But what is happening behind the scenes when you use such software?

INSIDE THE BLACK BOX

Measuring keyness

- Compare frequency in **A** with frequency in **B** separately for each candidate term $w \in C$

Frequency data for *w*

- f_1 = freq. in corpus **A**
- n_1 = sample size of **A**
- f_2 = freq. in corpus **B**
- n_2 = sample size of **B**

	A	B
w	f_1	f_2
$\neg w$	$n_1 - f_1$	$n_2 - f_2$
	$= n_1$	$= n_2$

Measuring keyness

- Recent studies: document frequency more robust than term frequency (e.g. Egbert & Biber 2019)

Frequency data for *w*

- f_1 = df in corpus **A**
- n_1 = no. of texts in **A**
- f_2 = df in corpus **B**
- n_2 = no. of texts in **B**

	A	B
w	f_1	f_2
$\neg w$	$n_1 - f_1$	$n_2 - f_2$
	$= n_1$	$= n_2$

Measuring keyness

- Goal: compare frequencies π_1 and π_2 of candidate item in sublanguages represented by corpora **A** and **B**
  - statisticians speak of "populations"
- Best sample estimates (MLE)

$$\hat{\pi}_1 = \frac{f_1}{n_1}, \qquad \hat{\pi}_2 = \frac{f_2}{n_2}$$

- positive keyword if $\pi_1 >> \pi_2$
- negative keyword if $\pi_1 << \pi_2$

	A	B
w	f_1	f_2
$\neg w$	$n_1 - f_1$	$n_2 - f_2$
	$= n_1$	$= n_2$

Keyness measures: significance

- Inference about frequency in population **A** vs. **B**

$$H_0 : \pi_1 = \pi_2$$

- Observed contingency table

$O_{11} = f_1$	$O_{12} = f_2$
$O_{21} = n_1 - f_1$	$O_{22} = n_2 - f_2$

- Contingency table of expected frequencies

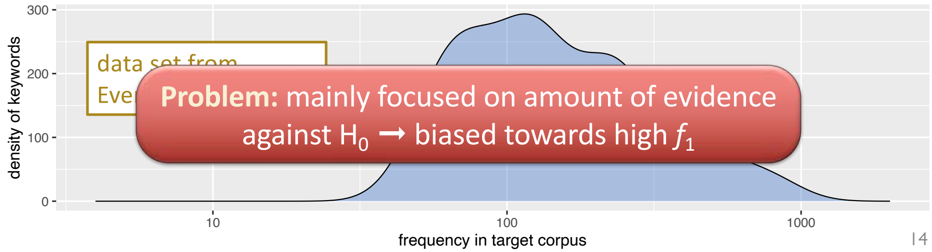
$E_{11} = n_1 \cdot \left(\frac{f_1 + f_2}{n_1 + n_2} \right)$	$E_{12} = n_2 \cdot \left(\frac{f_1 + f_2}{n_1 + n_2} \right)$
$E_{21} = n_1 - E_{11}$	$E_{22} = n_2 - E_{22}$

Keyness measures: significance

Statistical hypothesis tests for H_0 in contingency table:

- **log-likelihood** G^2 (Rayson & Garside 2000)
- chi-squared test X^2 (Scott 1997)
- Fisher's exact test (Lafon 1980)

$$G^2 = 2 \sum_{i=1}^{2} \sum_{j=1}^{2} O_{ij} \log \frac{O_{ij}}{E_{ij}}$$



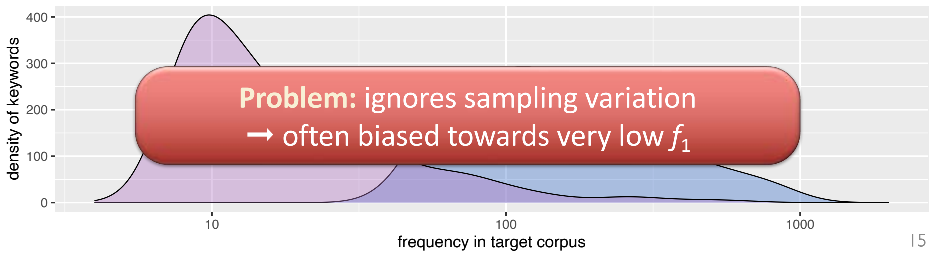
Keyness measures: effect size

Focus on magnitude of difference between π_1 and π_2:

- **LogRatio** (Hardie 2014) = log relative risk r
  - a better version (Walter 1975)

$$\text{LR} = \log_2 \frac{f_1 + \frac{1}{2}}{n_1 + \frac{1}{2}} - \log_2 \frac{f_2 + \frac{1}{2}}{n_2 + \frac{1}{2}}$$

- closely related measures: %DIFF (Gabrielatos & Marchi 2012), RRF, odds ratio, ΔP



Keyness measures: significance filter

- Effect-size measures combined with **significance filter**: set score = 0 if not significant according to G^2
- Hardie (2014): control family-wise error rate (FWER) in data set by using **adjusted significance level**

$$\alpha' = 1 - (1 - \alpha)^{\frac{1}{m}} \qquad \text{or} \qquad \alpha' = \frac{\alpha}{m}$$

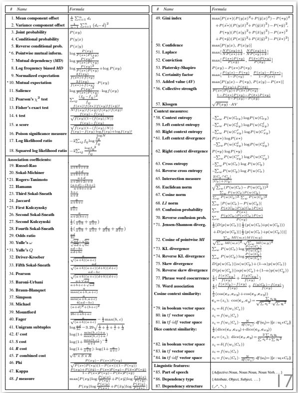
- Heuristic alternative: frequency **threshold**
  - typically $f_1 \geq 5, 10, 100, \ldots$
  - often also requirement $f_2 > 0$ in reference corpus

Keyness measures: heuristics

- Another heuristic: **SimpleMaths** (Kilgarriff 2009)

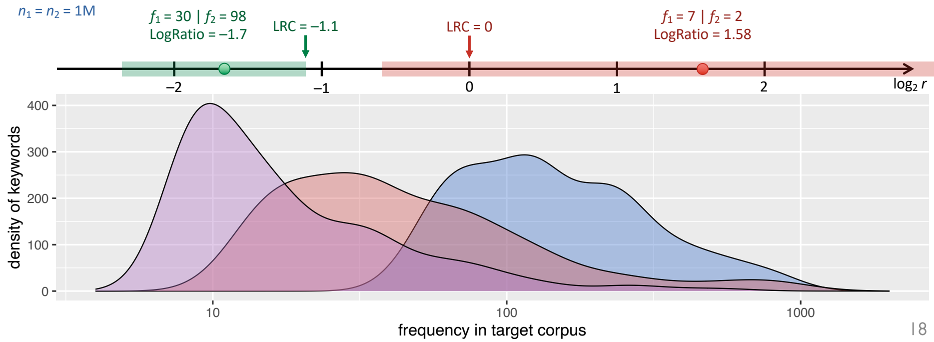
$$\mathrm{SM} = \frac{10^6 \cdot \frac{f_1}{n_1} + \lambda}{10^6 \cdot \frac{f_2}{n_2} + \lambda} \qquad (\lambda > 0)$$

- Mathematician: no comment!
- Many other (often heuristic) **association measures** have been suggested for collocation extraction (e.g. Pecina 2005)
- Hardie (2014) includes AM in his list of keyness measures



My measure: LRC (Evert 2022)

- Combine effect-size and significance aspects: confidence interval $[\log_2 r_-, \log_2 r_+]$ for relative risk
- Conservative estimate **LRC** (conservative LogRatio)
  - use value closest to 0 (not significant if 0 in interval ➞ LRC = 0)



The maths behind LRC

Be careful with approximations such as the one used by CQPweb

- Exact inference for relative risk in contingency table with conditional Poisson test (Fay 2010: 55)

$$\mathbb{P}(f_1 | f_1 + f_2) = \binom{f_1 + f_2}{f_1} \left(\frac{\lambda_1}{\lambda_1 + \lambda_2} \right)^{f_1} \left(1 - \frac{\lambda_1}{\lambda_1 + \lambda_2} \right)^{f_2}$$

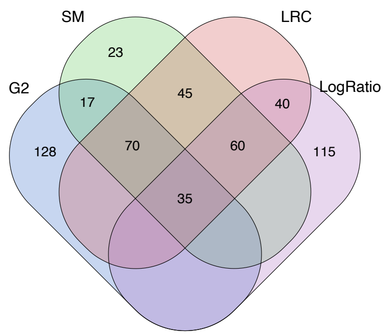
$$\lambda_1 = n_1 \pi_1, \quad \lambda_2 = n_2 \pi_2$$

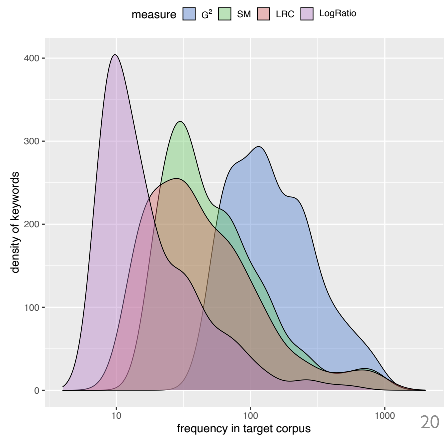
- Two-sided confidence interval
  - with Bonferroni correction
  - LRC = 0 if not significant
  - LRC > 0 ➞ significant pos. KW
  - LRC < 0 ➞ significant neg. KW

	A	B
w	f_1	f_2
$\neg w$	$n_1 - f_1$	$n_2 - f_2$
	$= n_1$	$= n_2$

Comparison

- Based on candidate data from Evert et al. (2018)
- Top-250 keywords from each measure





How well does it work in practice?

EVALUATION

Evaluating keywords

- Key challenge: many different applications of keyness
  ➞ different requirements and evaluation goals
- Evaluation always wrt. a specific goal (e.g. CADS)
- What to evaluate? – measures, reference corpora, …
- Primarily manual validation of KW candidates
  - occasionally evaluation against gold standard possible (e.g. for identification of domain terminology)
  - special case: keyness measures for corpus comparison (Rayson & Garside 2000) can be evaluated with known similiarity corpora (Kilgarriff & Rose 1998)

Evaluation: a case study

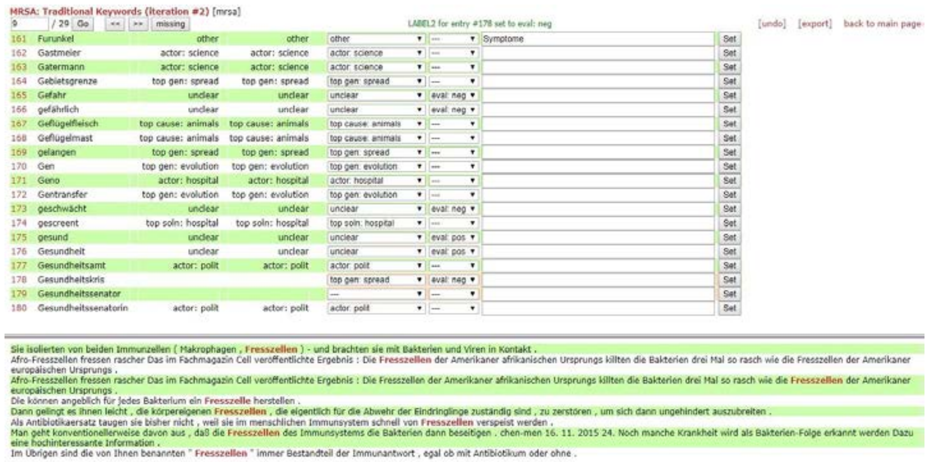
- 14.3M token corpus on German web data about multi-resistant pathogens (MRO) collected with BootCat (Baroni & Bernardini 2004)
  - 9,750 texts of varying genres and lengths
- Target corpus: 1.3M tokens (1,177 texts) of mass media texts and reader comments from MRO corpus
- Evaluation of different keyword extraction techniques for CADS analysis of MRO discourses (Evert et al. 2018)

Evaluation: a case study

- Three keyness measures: G^2, LogRatio, LRC
- Two comparable reference corpora: *Süddeutsche* (SZ) vs. *Frankfurter Allgemeine* (FAZ)
- Keywords based on raw frequency (classic) vs. document frequency (df-based)

- Extract top-200 keywords for each technique
  - frequency threshold $f \geq 5$ in reference corpus, because we are not interested in terminology extraction
- Manual annotation of TPs (categories, evaluative)
  - pre-determined category scheme from qualitative study

Annotation procedure

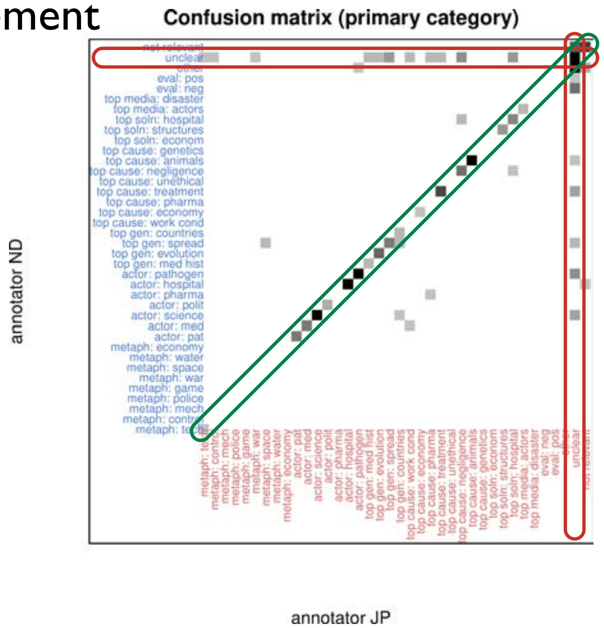


Web-based annotation platform MiniMarker

Agreement

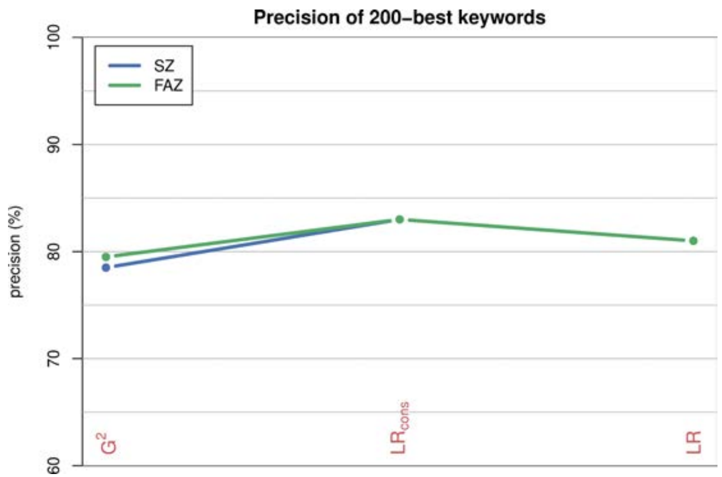
- Two independent annotators
- Agreement of 82.2% on distinction TP vs. FP (but Cohen κ = .566 fairly low)
- Domain-specific, highly frequent words often marked "unclear" (FP) by one annotator and TP by the other
- Disagreements between TP categories less frequent; mostly due to overlap between discourse levels
  - metaphors as part of topoi
  - intertwined argumentational levels
- Final gold standard jointly reconciled by annotators

Agreement



Precision = #TP / 200 candidates

TP = assigned to category and/or evaluative



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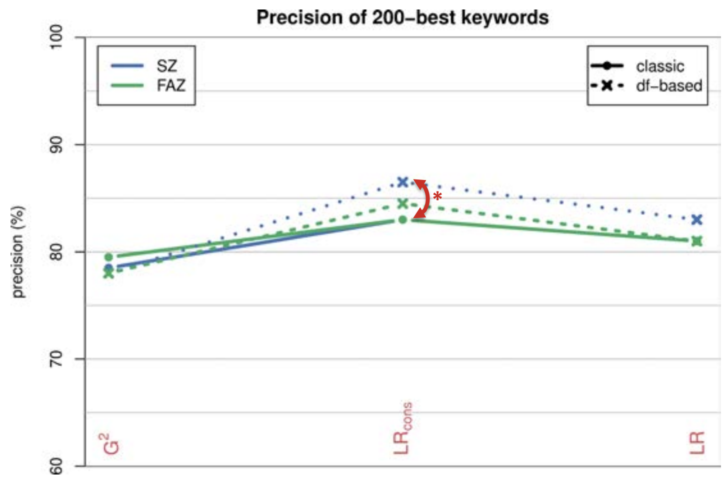
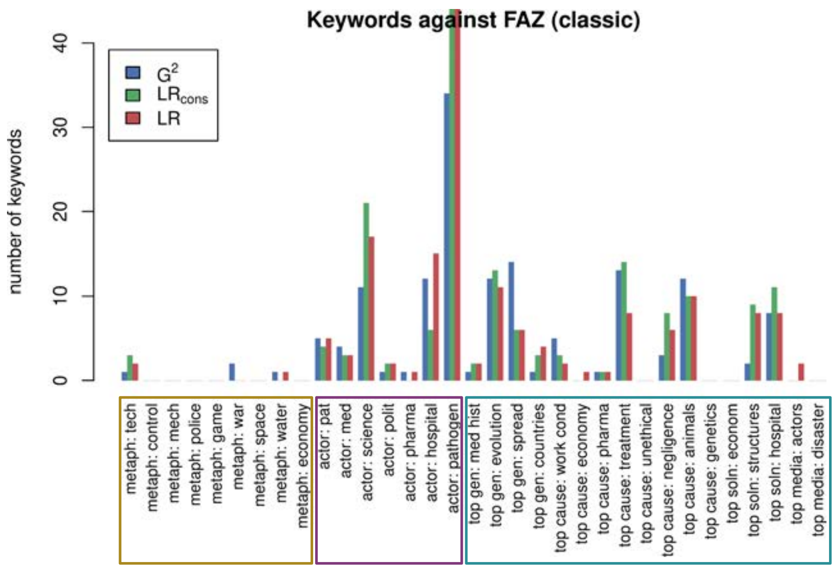
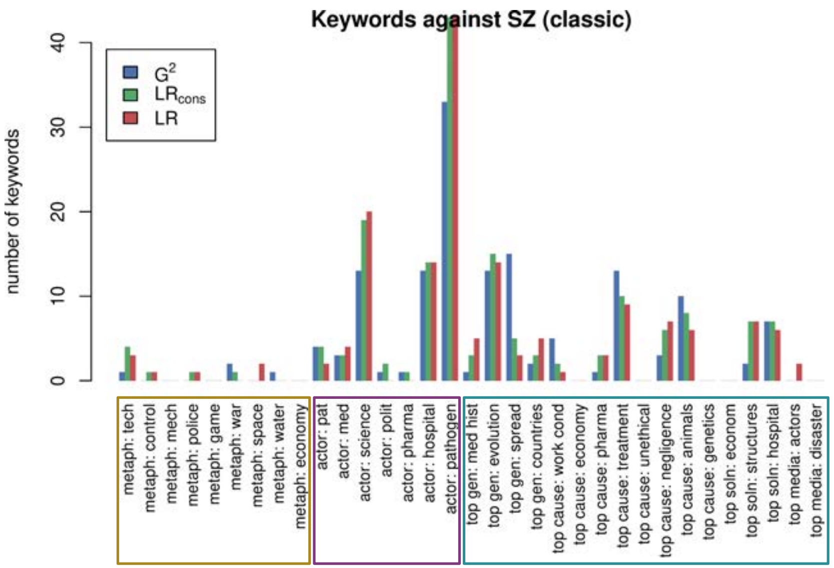


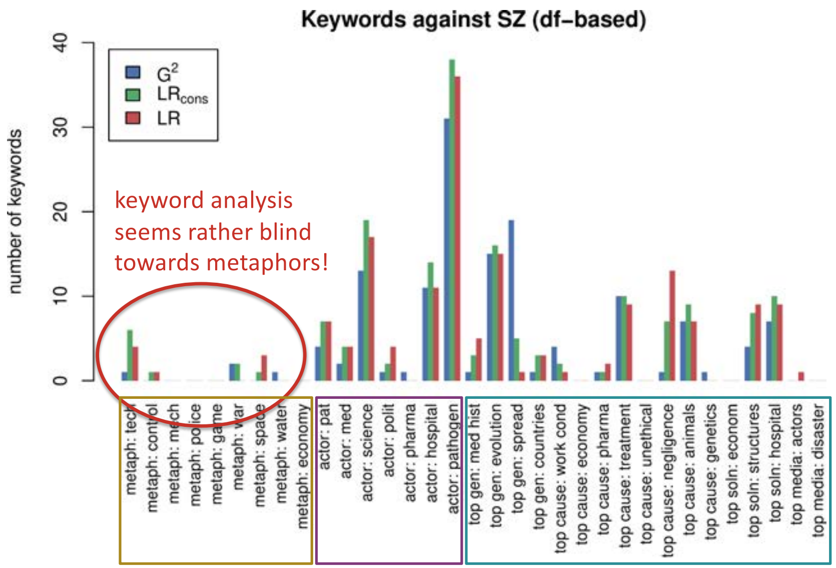
Recall = #KW for each category



Recall = #KW for each category



Recall = #KW for each category



A few quiz questions

- Which is the best keyness measure?
- What impact has the choice of reference corpus?
- How many keywords should you look at?
- Should you only consider significant keywords? Why?
- What's the best way of reading a keyword list?
  Ranked by keyness? Alphabetical? Word cloud? …
- What is "keyness" really?
- What are limitations of keyword analysis?

NB: None of these questions has a clear-cut answer!

Interactive session

COMPUTING KEYWORDS WITH R

What you will need

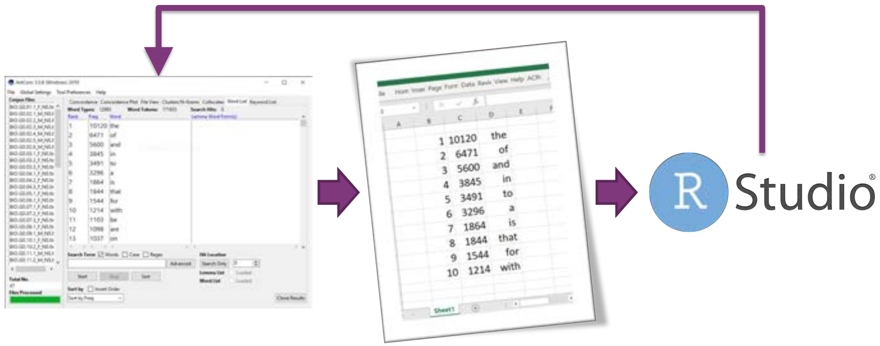
- R from https://cran.r-project.org
- RStudio from https://posit.co/downloads/
- R packages (install via RStudio)
  - `tidyverse` (to manipulate frequency lists)
  - `corpora` version 0.6 (or newer)
  - `Rtsne`, `ggrepel` (for a really cool visualisation)
  - `fastTextR` (to apply this visualisation to your own data)
- RStudio project with data sets & worked example
  - provided as ZIP archive `04_keyness_hands_on.zip`

Interoperability

- At least three steps in a keyword analysis
  - pre-processing & linguistic annotation of corpora **A** and **B**
  - extraction of frequency data (optionally with filters, df counts, dispersion-adjusted frequencies, etc.)
  - statistical analysis ➞ keyness measures & beyond
  - optional 4th step: visualisation (scattertext, semantic map, …)
- Many end-user tools integrate all three steps (CQPweb, AntConc, WordSmith)
- … but better to use specialised state-of-the art tools for each step (in particular, R for statistical analysis)

Interoperability with tabular data

- Tabular data in MTSV format (Anthony & Evert 2019)
  - data set = collection of TAB-delimited tables
    - word frequencies, positional data (for dispersion), kwic, …
  - important: link back from statistical analysis to corpus



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MTSV for keywords

target

freqlist

type	frequency	_reference
the	2	{"corpus": "xyz", "search": "the", "case": "0", …}
cat	1	{"corpus": "xyz", "search": "cat", "case": "0", …}
mat	1	{"corpus": "xyz", "search": "mat", "case": "0", …}
on	1	{"corpus": "xyz", "search": "on", "case": "0", …}
sat	1	{"corpus": "xyz", "search": "sat", "case": "0", …}

meta

_semantic_model	size	types	case	kind	threshold	comments
type_frequency_list	7	6	lower	token_counts	1	Target corpus frequency list

reference

freqlist

type	frequency	_reference
the	23383	{"corpus": "xyz", "search": "the", "case": "0", …}
cat	0	{"corpus": "xyz", "search": "cat", "case": "0", …}
mat	282	{"corpus": "xyz", "search": "mat", "case": "0", …}
on	2582	{"corpus": "xyz", "search": "on", "case": "0", …}
sat	7892	{"corpus": "xyz", "search": "sat", "case": "0", …}

meta

_semantic_model	size	types	case	kind	threshold	comments
type_frequency_list	19238145	8293	lower	token_counts	1	Reference corpus frequency list

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Tabular data in practice

- Little support for MTSV yet, except for AntConc
- How to obtain MTSV word frequency lists:
  - open desired corpus as *Target Corpus*
  - create word frequency list (in *Word* tab)
  - select *Save Current Tab Database Tables* from menu
  - creates ZIP archive with several CSV tables
- But most tools can easily read/write tabular files: CQPweb, WordSmith, CWB, Python, R, Excel, …
  - we'll look at examples from AntConc, CWB and CQPweb

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Tabular data in practice

- CSV = comma-separated values (RFC 4180)
  - https://datatracker.ietf.org/doc/html/rfc4180
  - comma-separated columns (usually), values double-quoted if necessary, data types of columns inferred from values
- TSV = TAB-delimited text files
  - columns delimited by TAB characters (ASCII 0x09, `"\t"`)
  - no quotes (values must not contain TABs or line breaks)
- Strategy: export frequency lists for corpora **A** and **B** from favourite corpus tool + note down sample sizes
  - some corpus tools create "tidier" tabular data than others

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And finally …

Hands on!

- LRC reference implementation, example data and mathematical details at https://osf.io/cy6mw/
- Implementation for end users: `keyness()` function in `corpora` package v0.6
- Unpack ZIP archive `keyness_hands_on.zip` then double-click the `.Rproj` file to open RStudio

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Interactive session

VISUALISING KEYWORDS

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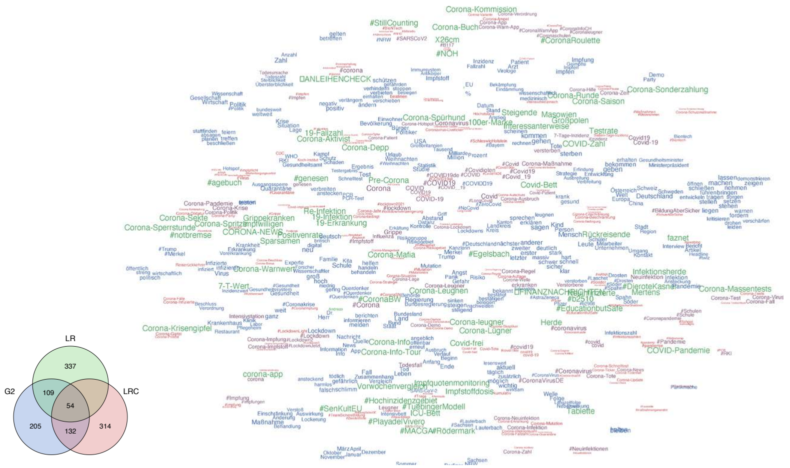
Visualisation as semantic map



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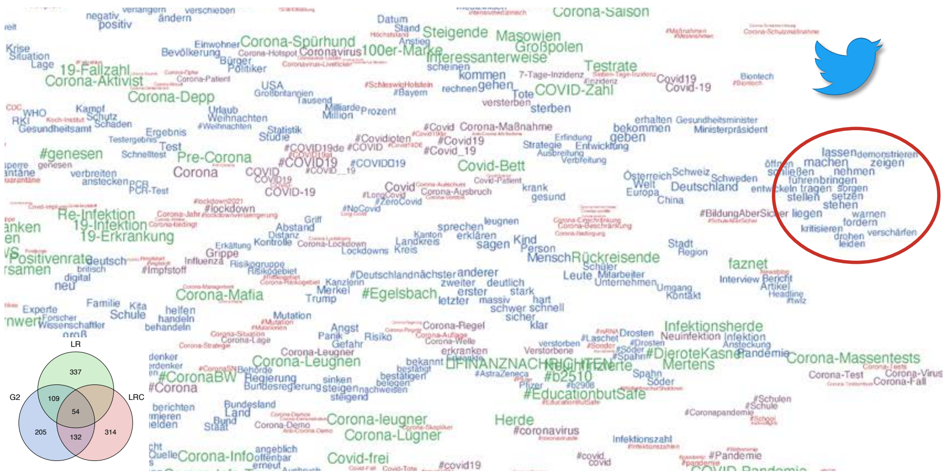
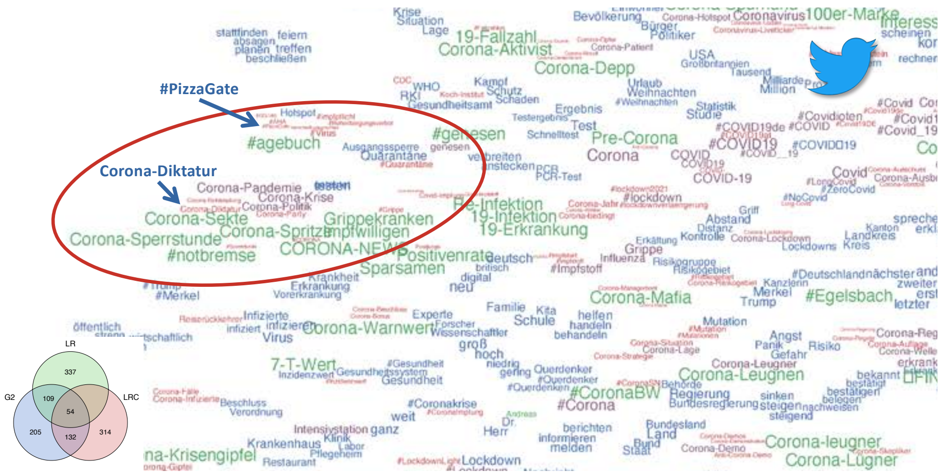
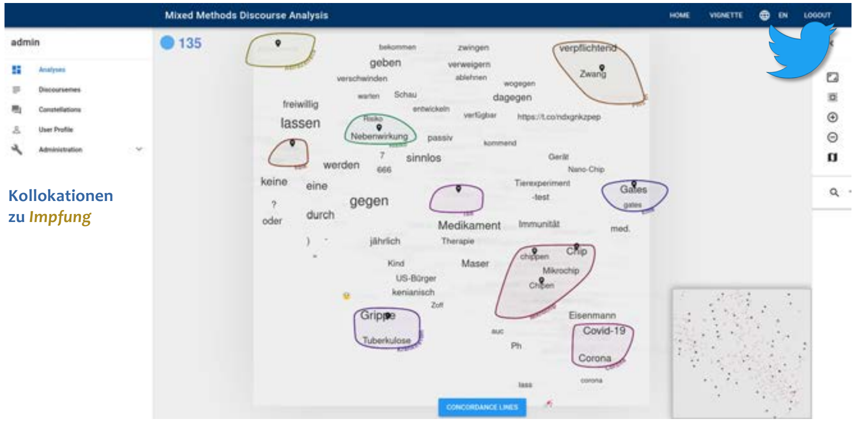
Visualisation as semantic map



Visualisation as semantic map



Interactive grouping with MMDA



https://www.linguistik.phil.fau.de/projects/efe/mmda-toolkit/

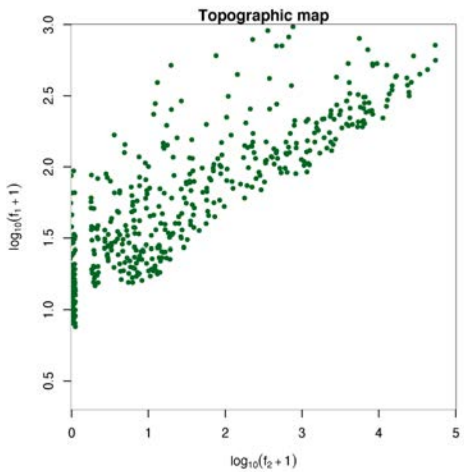
EMERGING FIELDS INITIATIVE

Exploring the Fukushima Effect

Interactive session

WHAT IS KEYNESS?

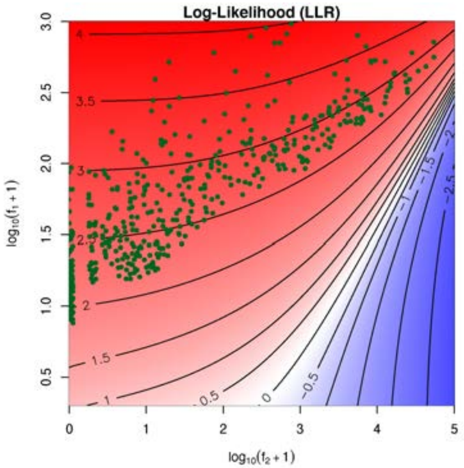
Understanding keyness measures



Candidates from data set of Evert et al. (2018) that are among top-250 keywords for any of several keyness measures

Topographic map visualises f_1 vs. f_2 (sufficient since n_1 and n_2 are fixed for data set) on a logarithmic scale
➞ similar to ScatterText
https://spacy.io/universe/project/scattertext

Topographic maps



Topographic map visualises f_1 vs. f_2 (sufficient since n_1 and n_2 are fixed for data set) on a logarithmic scale

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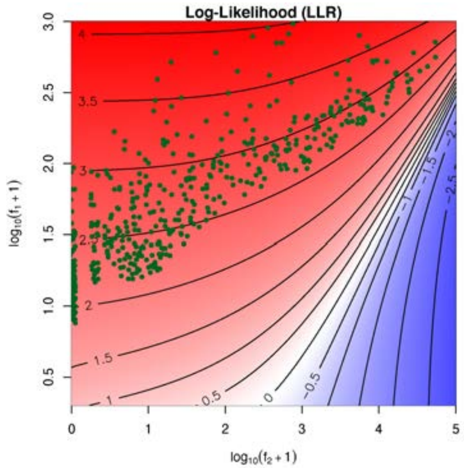
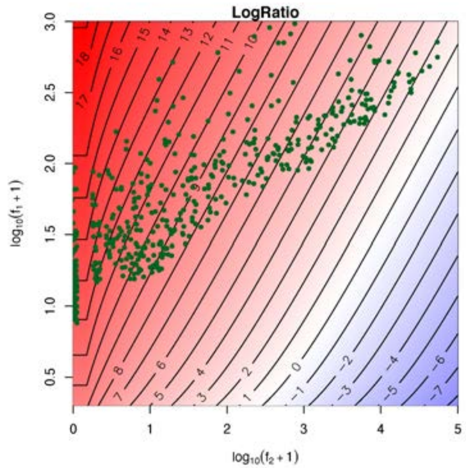
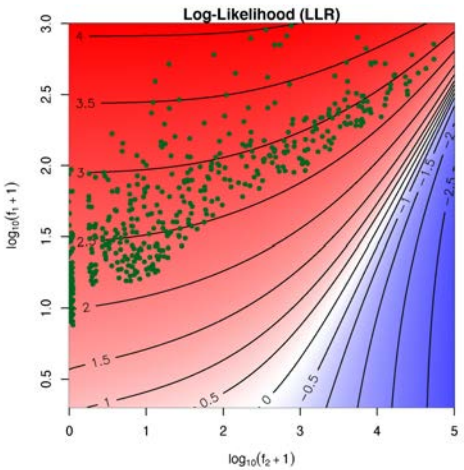
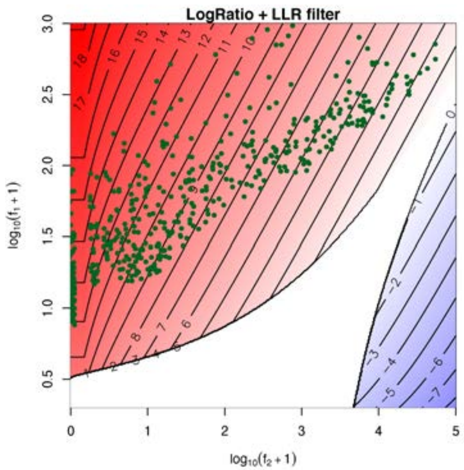
Topographic maps





Topographic maps





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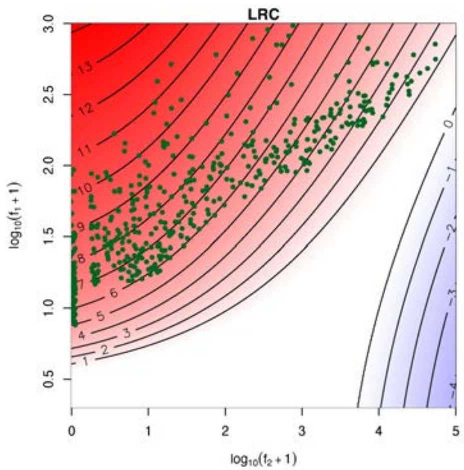
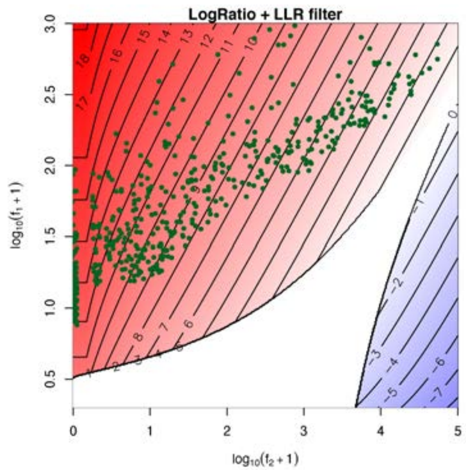
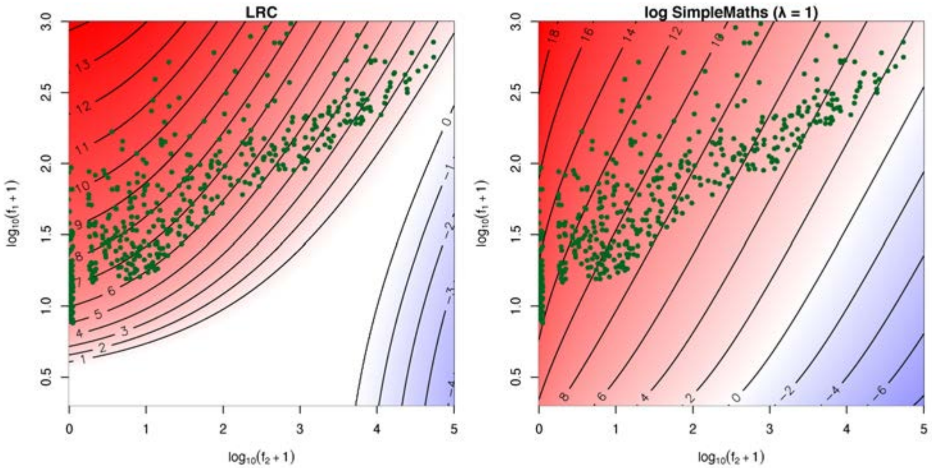




Topographic maps



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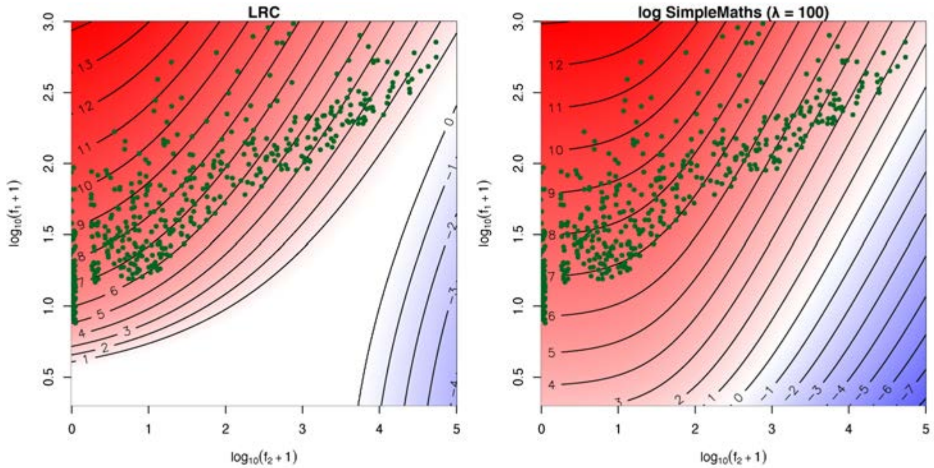
Topographic maps



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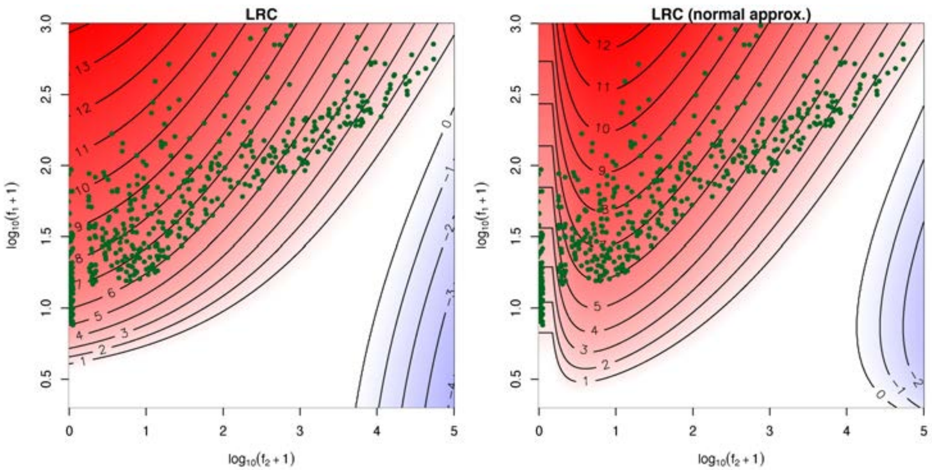

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Interactive session

FINDING METAPHORS

Finding better keywords

- Keyness as simple frequency comparison very limited
- But more sophisticated approaches often share its limitations ➞ still based on surface frequencies

- Certain types of keywords (terminology, topics) are easy to detect, other seem to be very challenging
- Perhaps more knowledge-rich approaches needed!
- Let's get back to case study from Evert et al. (2018)

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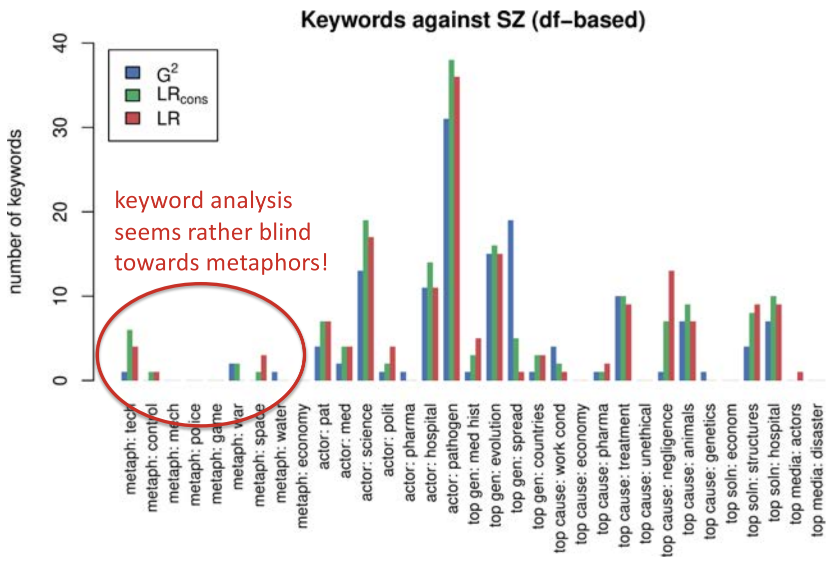
Recall = #KW for each category



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Why so few metaphor keywords?

Possible causes:

- No metaphors in online media discourse (unlikely)
- Cannot be reduced to single words
- Keywords occur, but are too infrequent

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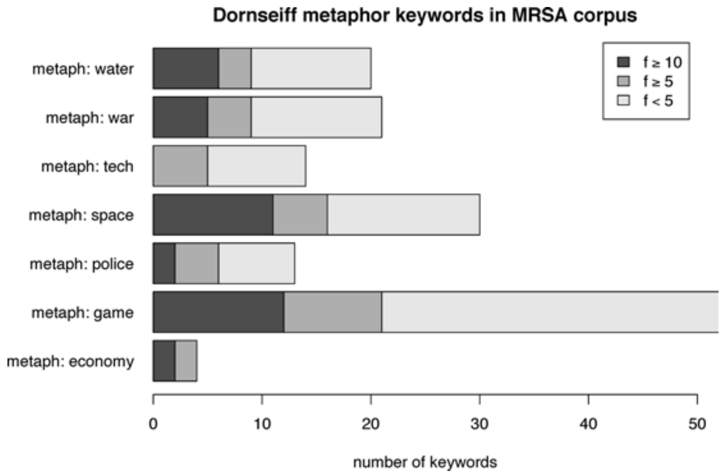
A case study

- List of plausible keywords for each metaphor category from thesaurus (Dornseiff 2004)
  - e.g. POLICE: *Indiz* clue, *Killer* killer, *Mord* murder, *Täter* culprit, *fahnden* search, *heimtückisch* insidious, …
  - manually validated against concordance in target corpus

- Comparison with full set of keyword candidates
  - frequency in target corpus
  - removed because of reference corpus threshold?
  - keyness score and rank in candidate set

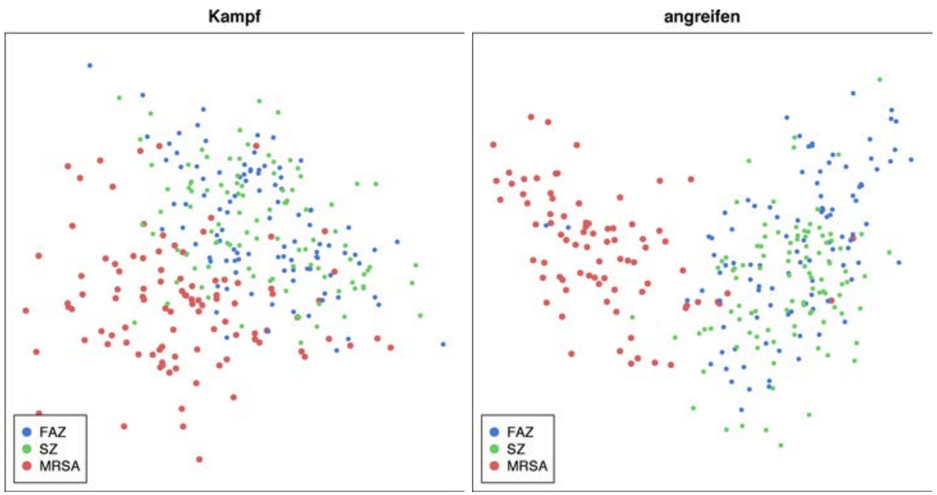
A case study



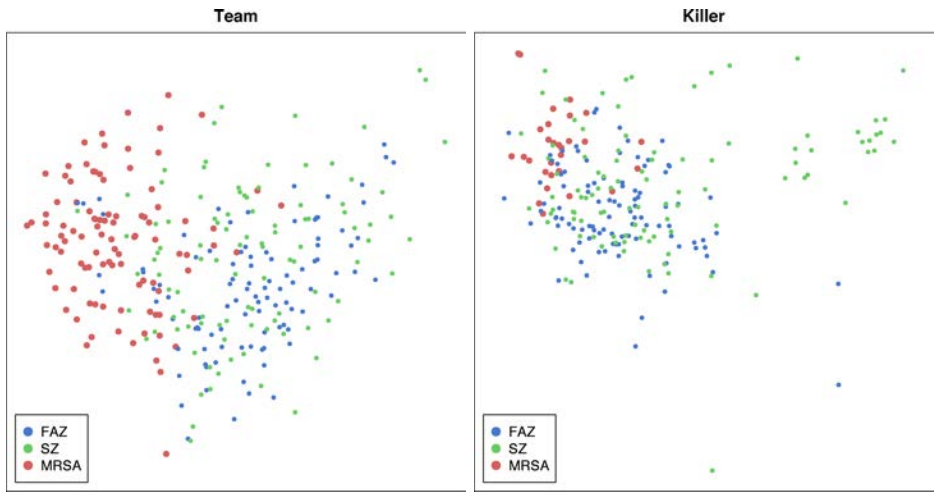
Finding metaphor keywords

- Substantial number of plausible keywords for all metaphor categories except ECONOMY
  - frequent in target corpus & pass threshold in reference
  - but very low ranks (> 1000) from all keyness measures
- Reason: literal senses very frequent in reference
  - aggregating all keywords from category doesn't help
- Approximate semantics with distributional context vectors (Schütze 1998)
  - three-sentence context around each potential keyword
  - bag-of-words centroids of word embeddings
  - MRSA contexts clearly separated from reference contexts?

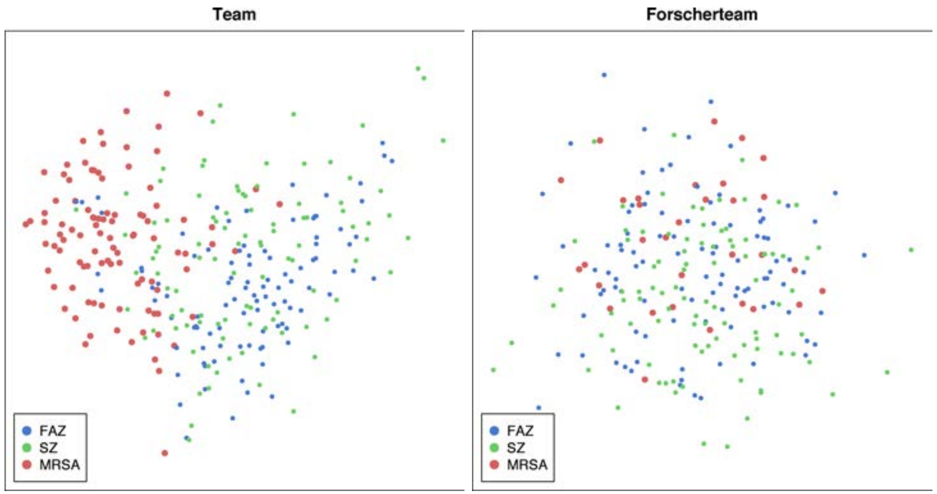
Finding metaphor keywords



Finding metaphor keywords



Finding metaphor keywords



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