

## Unit 7: A multivariate approach to linguistic variation

Statistics for Linguists with R – A SIGIL Course

Stephanie Evert

Computational Corpus Linguistics Group  
FAU Erlangen-Nürnberg

## Linguistic variation

Variation of a quantitative linguistic feature

- frequency of passive, past perfect, split infinitive, ...
- frequency of expression, semantic field, topic, ...
- association strength, lexical density, productivity, ...

across

- languages and language varieties
- regions & social strata
- time (diachronic change)
- individual speakers & discourses

## Studying linguistic variation

- Univariate approach
  - compare single feature across two or more conditions
  - e.g. AmE vs. BrE vs. IndE vs. ... / male vs. female / etc.
  - **corpus frequency comparison**
- Regression approach
  - predict single quantity from multiple explanatory factors
- Multivariate approach
  - identify common patterns of variation across multiple different features → **correlation** analysis
  - inductive techniques don't require pre-defined conditions

Variation of a quantitative linguistic feature

- frequency of passive, past perfect, split infinitive, ...
- frequency of expression, semantic field, topic, ...
- association strength, lexical density, productivity, ...

across

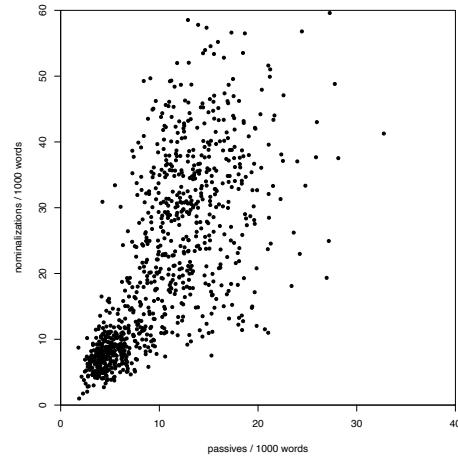
- languages and language varieties
- regions & social strata
- time (diachronic change)
- individual speakers & discourses

## Variation as a nuisance parameter

- Many aspects of linguistic variation are **nuisance parameters** in corpus linguistics
  - e.g. difference in frequency of passives between AmE and BrE, as well as development from 1960s to 1990s (Unit #2)
  - ignore other dimensions such as genre/register variation by **pooling** frequency data from all texts of each corpus
  - corpus is analyzed as a **random sample** of VP tokens
- Consequences
  - variation → non-randomness → overestimate significance
  - discussed in much more detail in Unit #8

## The multivariate approach

- Different linguistic features often show similar patterns of variation
- E.g. passives and nominalizations

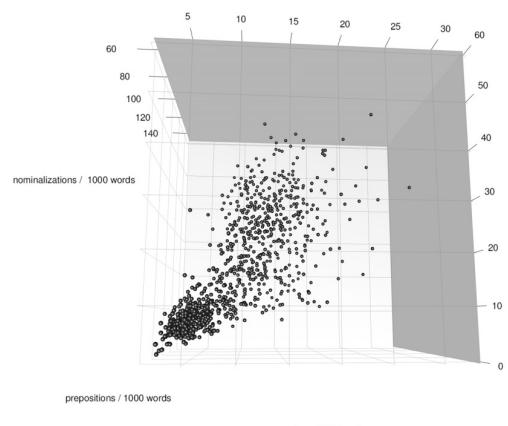


SIGIL Unit #7

[www.linguistik.fau.de](http://www.linguistik.fau.de) | [www.stephanie-evert.de](http://www.stephanie-evert.de)

5

## The multivariate approach



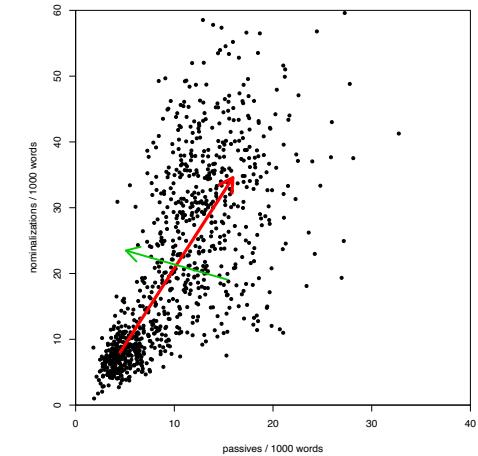
SIGIL Unit #7

[www.linguistik.fau.de](http://www.linguistik.fau.de) | [www.stephanie-evert.de](http://www.stephanie-evert.de)

7

## The multivariate approach

- Different linguistic features often show similar patterns of variation
- E.g. passives and nominalizations
- Such **correlations** can be exploited to determine major **dimensions of var.**



SIGIL Unit #7

[www.linguistik.fau.de](http://www.linguistik.fau.de) | [www.stephanie-evert.de](http://www.stephanie-evert.de)

6

## The multivariate approach

- Multivariate analysis exploits correlations between features in order to determine **latent dimensions**
  - interpreted as underlying “causes” of variation
- An inductive, data-driven approach
  - no theoretical assumptions about linguistic variation and categories / sub-corpora to be compared
- Pioneering work by Doug Biber (1988, 1993, 1995, ...)
- “multidimensional analysis” of register variation
- Related approaches: correspondence analysis, distributional semantics, topic modelling, ...

SIGIL Unit #7

[www.linguistik.fau.de](http://www.linguistik.fau.de) | [www.stephanie-evert.de](http://www.stephanie-evert.de)

8

# Biber's multidimensional analysis (MDA)

Table 5.7 Linguistic features used in the analysis of English

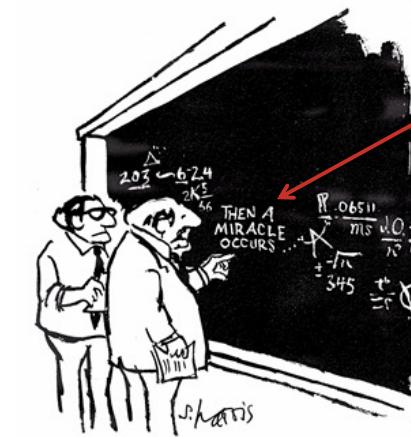
Table 5.7 (cont.)	
A.	Tense and aspect markers
1	Past tense
2	Perfect aspect
3	Present tense
B.	Place and time adverbials
4	Place adverbials (e.g., <i>above</i> , <i>beside</i> , <i>outdoor</i> )
5	Time adverbials (e.g., <i>early</i> , <i>instantly</i> , <i>soon</i> )
C.	Pronouns and pro-verbs
6	First-person pronouns
7	Second-person pronouns
8	Third-person personal pronouns (excluding <i>it</i> )
9	Pronoun <i>it</i>
10	Demonstrative pronouns ( <i>this</i> , <i>that</i> , <i>these</i> , <i>those</i> as pronouns)
11	Indefinite pronouns (e.g., <i>anybody</i> , <i>nothing</i> , <i>someone</i> )
12	Pro-verb <i>do</i>
D.	Questions
13	Direct wh-questions
E.	Nominal forms
14	Nominalizations (ending in <i>-ion</i> , <i>-ment</i> , <i>-ness</i> , <i>-ity</i> )
15	Gerunds (participial forms functioning as nouns)
16	Total other nouns
F.	Passives
17	Agentives passives
18	By-passives
G.	Stative forms
19	<i>be</i> as main verb
20	Existential <i>there</i>
H.	Subordination features
21	that verb complements (e.g., <i>I said that he went</i> )
22	that noun complements (e.g., <i>I'm glad that you like it</i> )
23	wh-clauses (e.g., <i>I believed what he told me</i> )
24	Infinitives
25	Present participle adverb clauses (e.g., <i>Stuffing his mouth with cookies, Joe ran out the door</i> )
26	Past participle adverb clauses (e.g., <i>Built in a single week, the house would stand for fifty years</i> )
27	Past participle postnominal (reduced relative) clauses (e.g., <i>the solution produced by this process</i> )
28	Predicative participles (reduced relative) clauses (e.g., <i>The event causing this define me</i> )
29	that relative clauses on subject position (e.g., <i>the dog that bit me</i> )
30	that relative clauses on object position (e.g., <i>the dog that I saw</i> )
31	wh relatives on subject position (e.g., <i>the man who likes popcorn</i> )
32	wh relatives on object position (e.g., <i>the man who Sally liked</i> )
33	Pred-piping relative clauses (e.g., <i>the manner in which he was told</i> )

SIGIL

9

# Biber's MDA

factor analysis  
(FA)



"I THINK YOU SHOULD BE MORE EXPLICIT HERE IN STEP TWO."

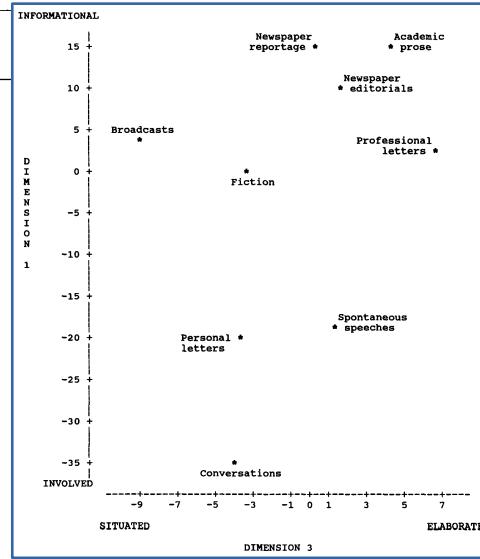
[www.linguistik.fau.de](http://www.linguistik.fau.de) | [www.stephanie-evert.de](http://www.stephanie-evert.de)

10

# Biber's MDA

TABLE 2  
Summary of the co-occurrence patterns underlying five major dimensions of English.

DIMENSION 1 (Informational vs. Involved)	DIMENSION 2 (Narrative versus Non-Narrative)
nouns	0.80
word length	0.58
prepositional phrases	0.54
type / token ratio	0.54
attributive adj.s	0.47
private verbs	-0.96
that deletions	-0.91
contractions	-0.90
present tense verbs	-0.86
2nd person pronouns	-0.86
do as pro-verb	-0.82
analytic negation	-0.78
demonstrative pronouns	-0.76
general emphatics	-0.74
first person pronouns	-0.74
pronoun <i>it</i>	-0.71
<i>be</i> as main verb	-0.71
causative subordination	-0.66
discourse particles	-0.66
indefinite pronouns	-0.62
general hedges	-0.58
amplifiers	-0.56
sentence relatives	-0.55
WH questions	-0.52
possibility modals	-0.50
non-phrasal coordination	-0.48
WH clauses	-0.47
final prepositions	-0.43



# Pitfalls

- Design bias: choice of quantitative features
- Design bias: selection of text samples
- Involves a miracle
  - not clear what quantitative patterns are captured by FA
  - magic number: how many factor dimensions?
- Interpretation bias
  - arbitrary cutoff for feature weights ("loadings")
  - risk of reading one's own expectations into features
- More subtle patterns of variation invisible
- Significance & reproducibility of results?

SIGIL Unit #7  
[www.linguistik.fau.de](http://www.linguistik.fau.de) | [www.stephanie-evert.de](http://www.stephanie-evert.de)

12

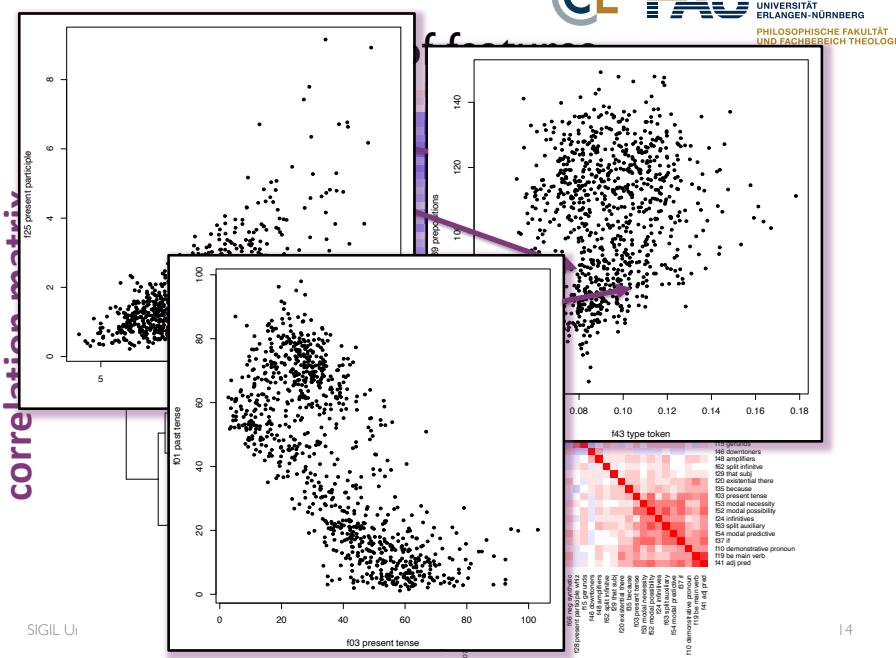
# Reproducing Biber's dimensions

- Sample of 923 medium-length published texts from written part of British National Corpus (BNC)
  - Covers 4 different text types + male/female authors
    - academic writing, non-academic prose, fiction, misc.
  - Biber features extracted automatically with Python script (Gasthaus 2007)
    - all frequencies normalized per 1000 words
    - data available in R package [corpora \(BNCbiber\)](#)
  - Factor analysis with 4 latent dimensions + varimax
    - seems to yield the most clearly structured analysis

SIGIL Unit #7

[www.linguistik.fau.de](http://www.linguistik.fau.de) | [www.stephanie-evert.de](http://www.stephanie-evert.de)

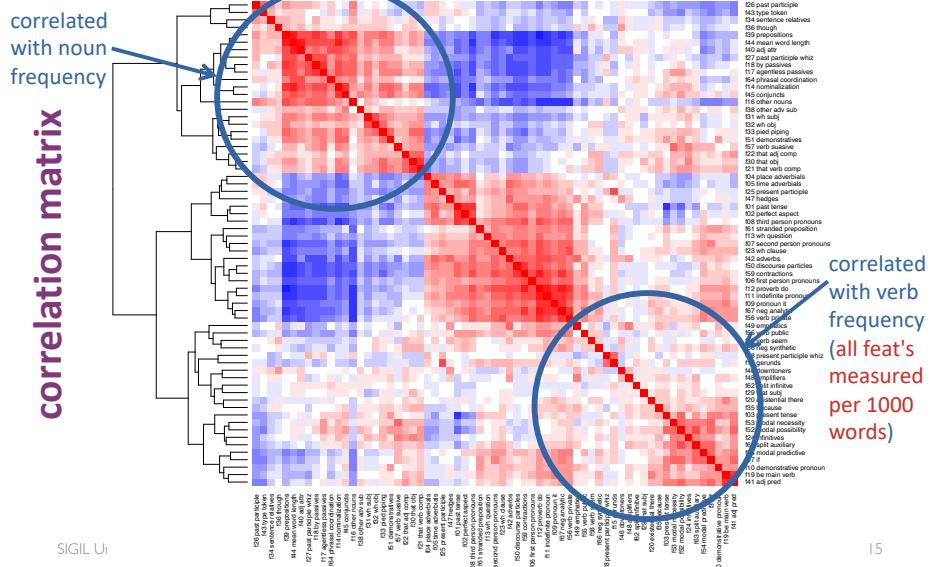
13



SIGIL U1

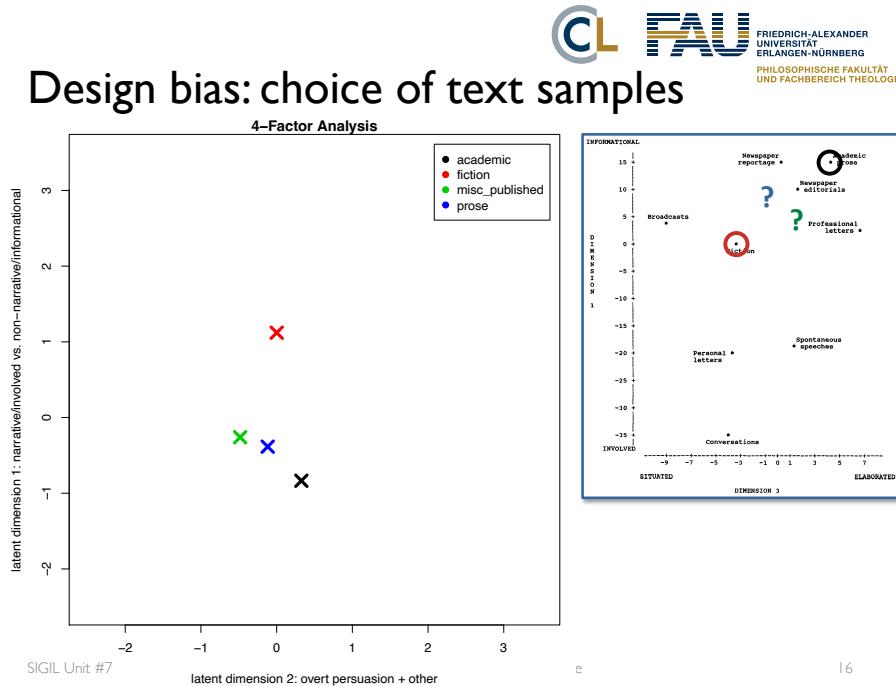
| 4

## Design bias: choice of features



SIGIL UI

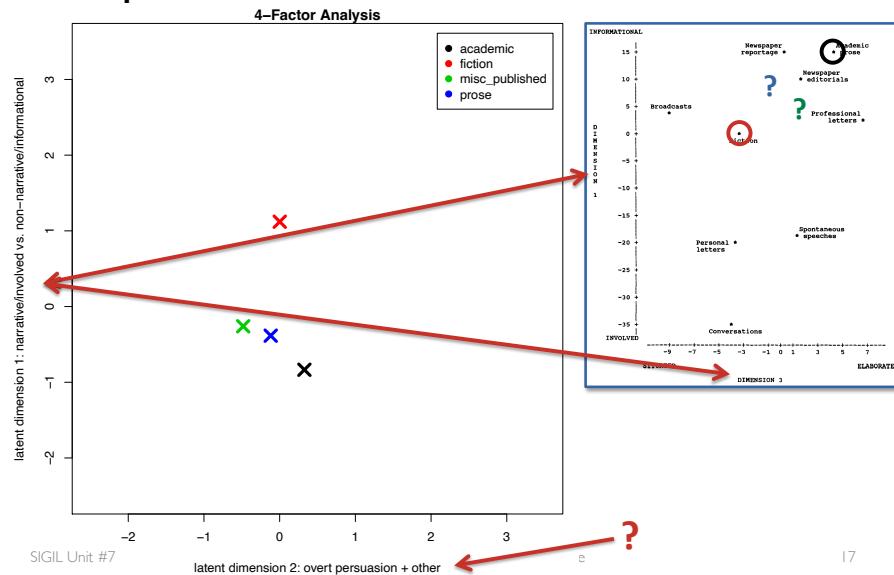
15



SIGIL Un

16

## Interpretation bias

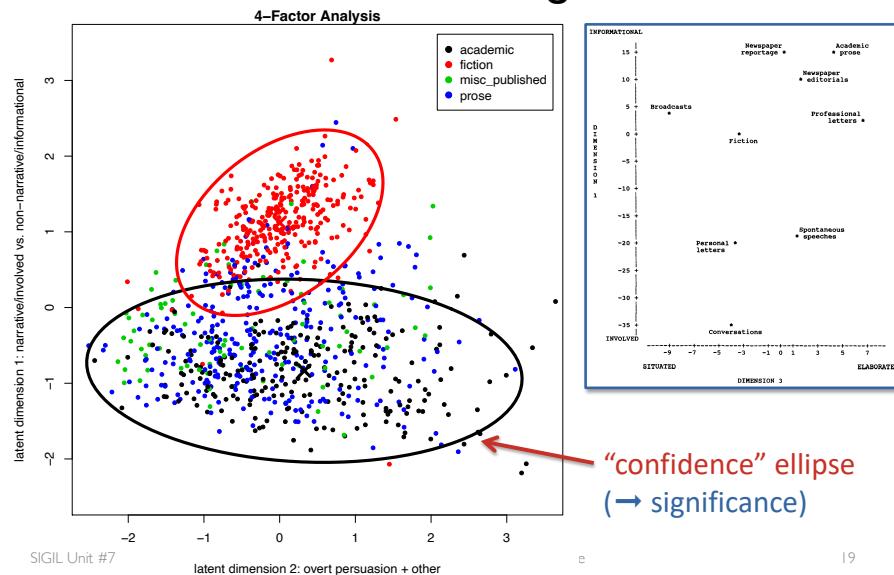


## Interpretation bias

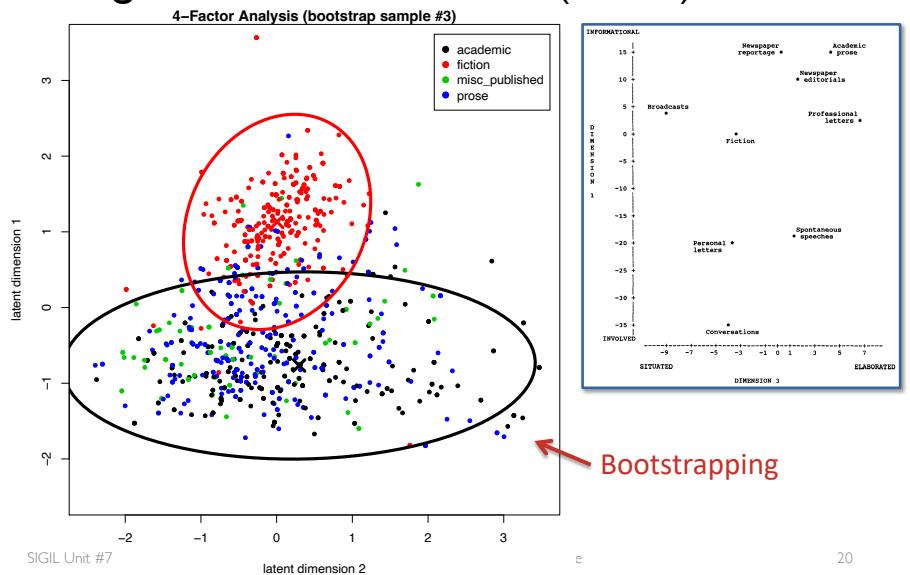
TABLE 2  
Summary of the co-occurrence patterns underlying five major dimensions of English.

DIMENSION 1 (Informational vs. Involved)	DIMENSION 2 (Narrative versus Non-Narrative)	DIMENSION 3 (Elaborated vs. Situated Reference)	DIMENSION 4 (Overt Expression of Persuasion)	DIM DIM Non-A	
nouns	0.80	past tense verbs	0.90	infinitives	0.76
word length	0.58	third person pronouns	0.73	prediction modals	0.54
prepositional phrases	0.54	perfect aspect verbs	0.48	agentive	0.49
type / token ratio	0.54	public verbs	0.43	past pa claus	0.43
attributive adj.	0.47	synthetic negation	0.40	conditional	0.47
private verbs	-0.96	WH relative clauses on present participial clauses	0.39	subordination	0.47
that deletions	-0.91	object positions	0.63	BY-pa BY-pa	0.46
contractions	-0.90	pied piping	0.61	necessity modals	0.46
present tense verbs	-0.86	constructions		split auxiliaries	0.44
2nd person pronouns	-0.86	WH relative clauses on subject position	0.45	possibility modals	0.37
do as pro-verb	-0.82	phrasal coordination	0.36	[No complementary features]	
analytic negation	-0.78	nominalizations	0.36	[No co	
demonstrative pronouns	-0.76	time adverbials	-0.60		
general emphatics	-0.74	place adverbials	-0.49		
first person pronouns	-0.74	other adverbs	-0.46		
pronoun <i>it</i>	-0.71				
<i>be</i> as main verb	-0.71				
causative					
subordination	-0.66				
discourse particles	-0.66				
indefinite pronouns	-0.62				
second hand	-0.62				

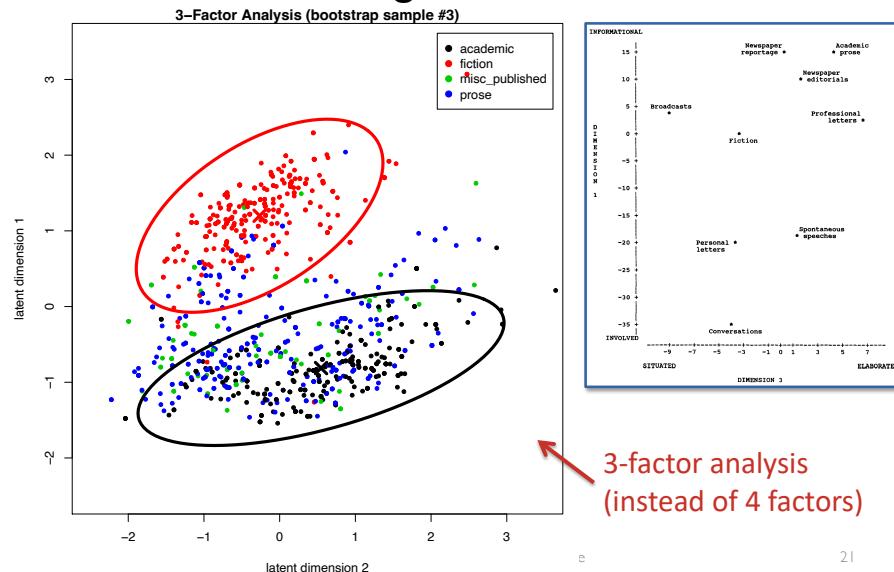
## Variation between texts is ignored



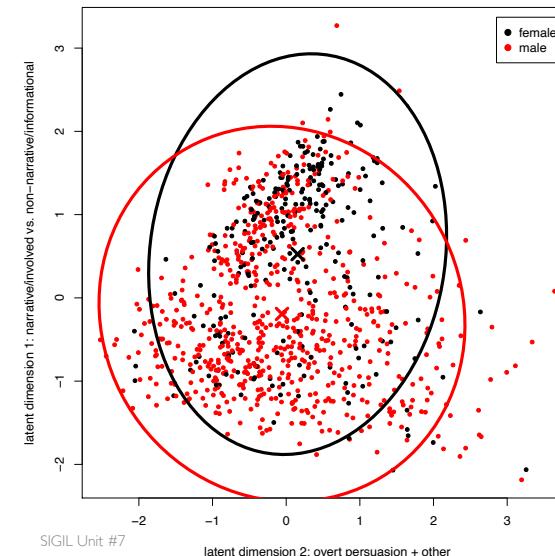
## Design bias: choice of texts (redux)



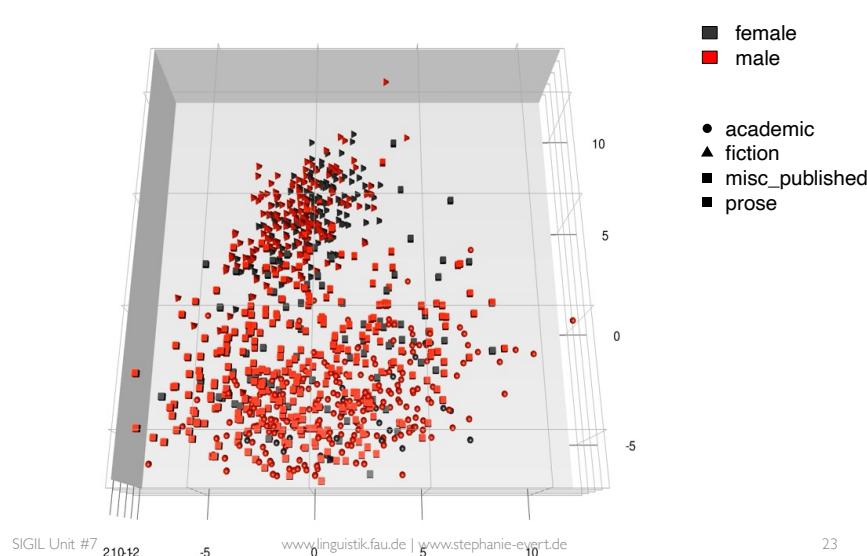
And there's the magic number ...



Blindness to subtle patterns



Blindness to subtle patterns



Geometric Multivariate Analysis

(Diwersy, Evert & Neumann 2014; Evert & Neumann 2017; Neumann & Evert 2021)



## Geometric Multivariate Analysis

(Diwersy, Evert & Neumann 2014; Evert & Neumann 2017; Neumann & Evert 2021)

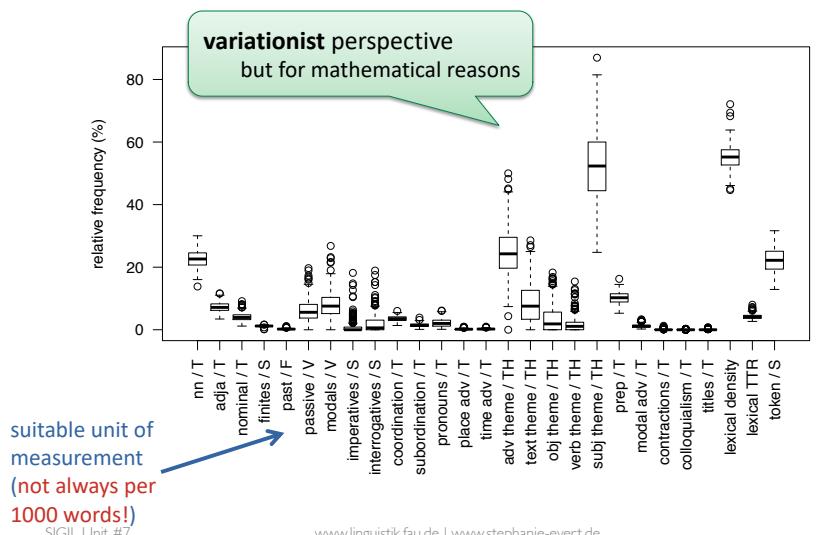
- Axiom: (Euclidean) distance = similarity of texts
  - depends crucially on theoretically motivated features
- Visualization → interpret geometric configuration
  - latent dimensions as geometric projections
  - orthogonal projection = perspective on data
  - method: principal component analysis (PCA)
- Minimally supervised intervention
  - based on externally observable, theory-neutral information
  - method: linear discriminant analysis (LDA)
- Bootstrapping / cross-validation to assess significance
- Cautious interpretation of feature weights

SIGIL Unit #7

[www.linguistik.fau.de](http://www.linguistik.fau.de) | [www.stephanie-evert.de](http://www.stephanie-evert.de)

25

## Feature design: avoid “obvious” correlations



SIGIL Unit #7

[www.linguistik.fau.de](http://www.linguistik.fau.de) | [www.stephanie-evert.de](http://www.stephanie-evert.de)

27

## Case study: CroCo

(Neumann 2013; Evert & Neumann 2017)

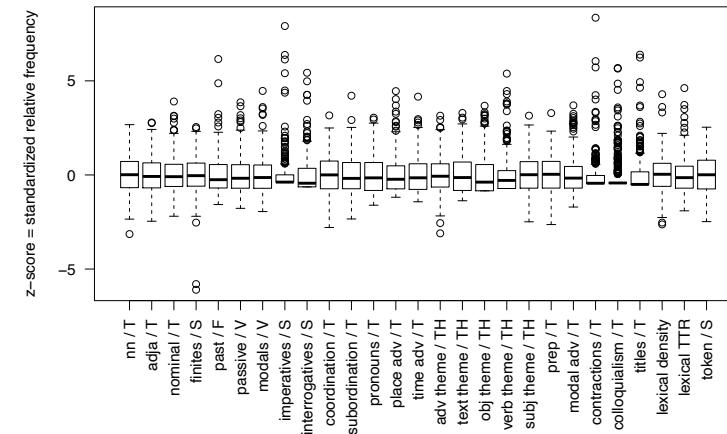
- CroCo: parallel corpus English/German
  - English-German and German-English translation pairs
  - we use 298 texts from 5 different genres
    - (excluded: instruction manuals, tourism, fiction)
- 28 lexico-grammatical features (Neumann 2013)
  - comparable between languages
  - inspired by SFL and translation studies
- Text = point in 28-dimensional feature space
- Research hypotheses: **shining through** (Teich 2003), **prestige effect** (Toury 2012)

SIGIL Unit #7

[www.linguistik.fau.de](http://www.linguistik.fau.de) | [www.stephanie-evert.de](http://www.stephanie-evert.de)

26

## Feature scaling: same contribution to Euclidean distances



SIGIL Unit #7

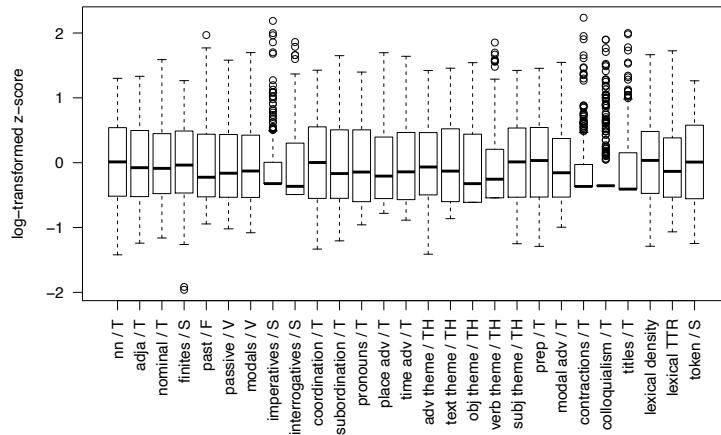
[www.linguistik.fau.de](http://www.linguistik.fau.de) | [www.stephanie-evert.de](http://www.stephanie-evert.de)

28

genre: language-external  
situation + purpose

register: language-internal  
co-occurrence patterns of  
linguistic features

## Feature scaling: optional signed log transformation

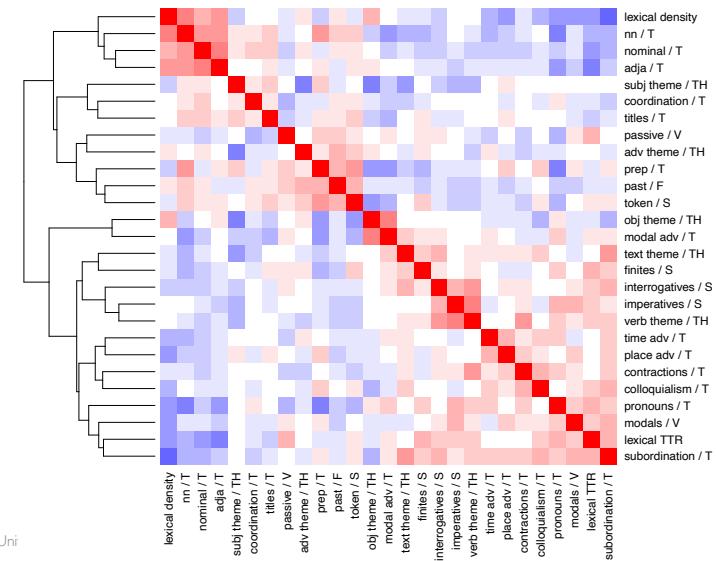


SIGIL Unit #7

[www.linguistik.fau.de](http://www.linguistik.fau.de) | [www.stephanie-evert.de](http://www.stephanie-evert.de)

29

## CroCo: correlation matrix



SIGIL Uni

30

## Latent dimensions as perspective on data configuration

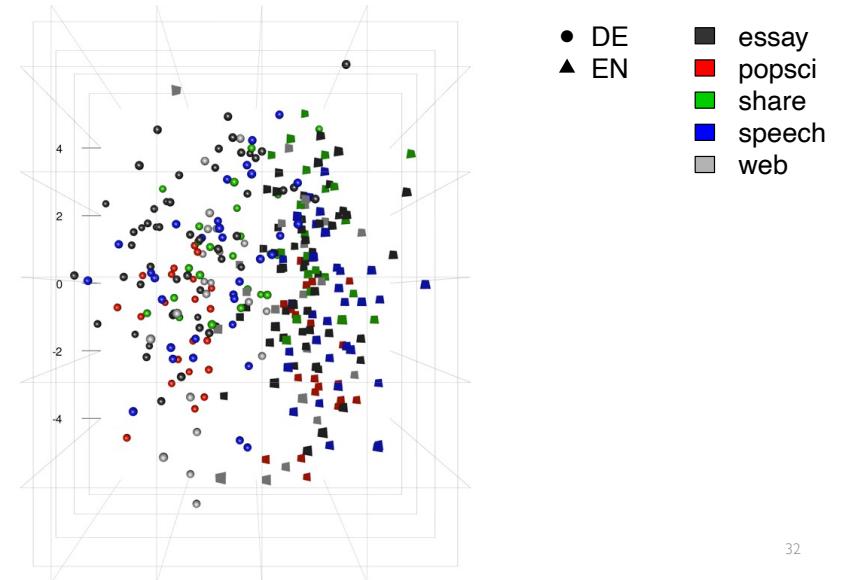
- Instead of “magical” latent dimensions we focus on **orthogonal projections** as perspectives on the data
  - cf. photograph as 2D perspective on 3D object
- Different perspectives highlight different aspects
- Multivariate analysis → choice of perspective
  - principal component analysis** (PCA) = perspective that reflects distances between texts as accurately as possible
  - should reveal major dimensions of variation
  - advantage over factor analysis (FA): dimensionality does not have to be fixed *a priori*

SIGIL Unit #7

[www.linguistik.fau.de](http://www.linguistik.fau.de) | [www.stephanie-evert.de](http://www.stephanie-evert.de)

31

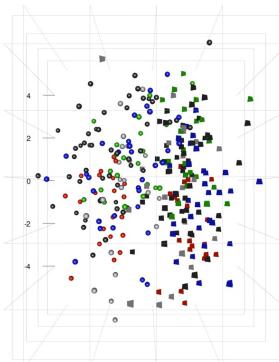
## CroCo: 3-dimensional projection



- DE
- ▲ EN
- essay
- popsci
- share
- speech
- web

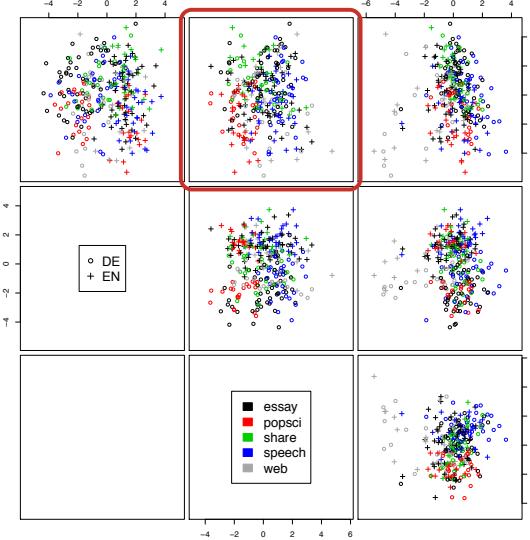
32

## CroCo: 4-dimensional projection



SIGIL Unit #7

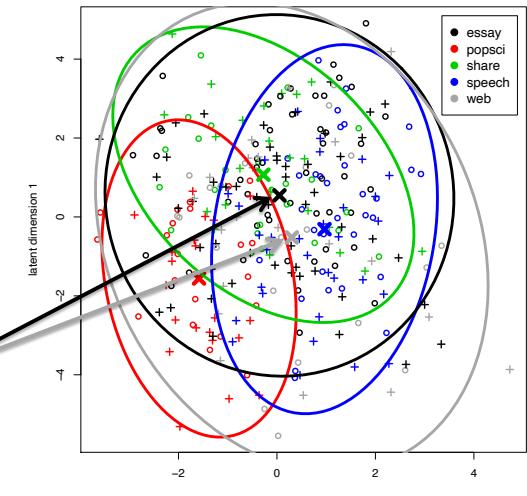
[www.linguistik.fau.de](http://www.linguistik.fau.de) | [www.stephanie-evert.de](http://www.stephanie-evert.de)



33

## CroCo: genre distribution

- Focus on latent dim's 1 and 3 (register variation)
- Describe genre by centroid + ellipse
- Comparison with Hotelling's  $t^2$  test
  - essays vs. Web
  - $t^2=4.21$ ,  $df=2/141$ ,
  - $p=.0167^*$



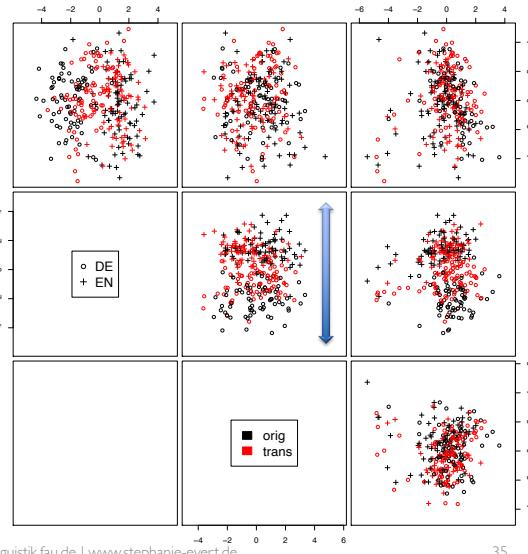
SIGIL Unit #7

[www.linguistik.fau.de](http://www.linguistik.fau.de) | [www.stephanie-evert.de](http://www.stephanie-evert.de)

34

## How about translationese?

- PCA dim's can't separate translations from original texts
  - 62.1% accuracy on first 3 PCA dim's
- But SVM machine learner can do this with >80% accuracy
  - RBF kernel
  - 10-fold c.v.
- Hints at **shining through**, but no clear-cut evidence



SIGIL Unit #7

[www.linguistik.fau.de](http://www.linguistik.fau.de) | [www.stephanie-evert.de](http://www.stephanie-evert.de)

35

## Minimally supervised LDA

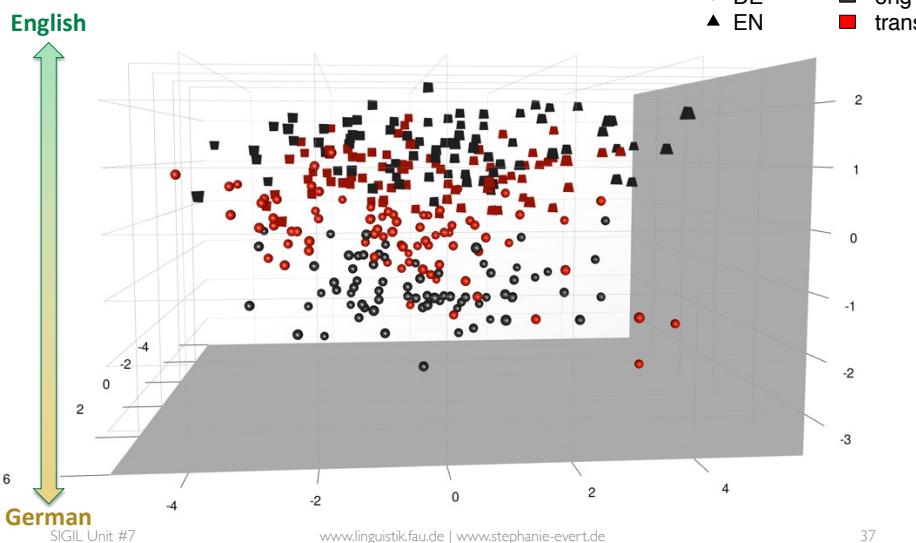
- Add minimal amount of supervised knowledge to find a more informative perspective
  - evidence for shining through hypothesis from dimension that corresponds to contrast German vs. English
  - supervised knowledge: language of **original texts** only
- Linear **discriminant analysis** (LDA)
  - maximize separation between German / English originals
  - minimize variability within each group
  - classical technique related to PCA and ANOVA
- Project *all* texts onto LDA discriminant
  - complemented by additional PCA dim's for visualization

SIGIL Unit #7

[www.linguistik.fau.de](http://www.linguistik.fau.de) | [www.stephanie-evert.de](http://www.stephanie-evert.de)

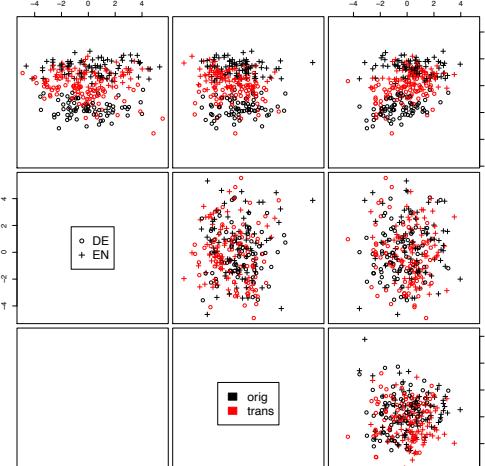
36

## CroCo: LDA perspective

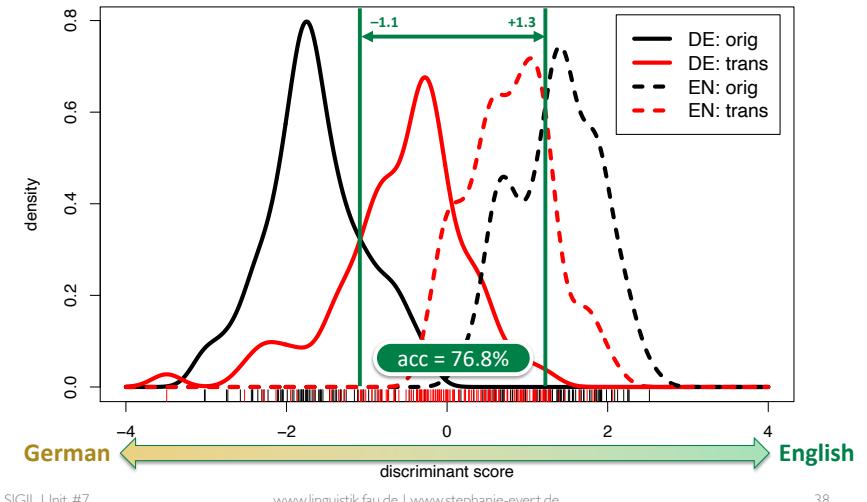


## LDA significance: bootstrapping / cross-validation

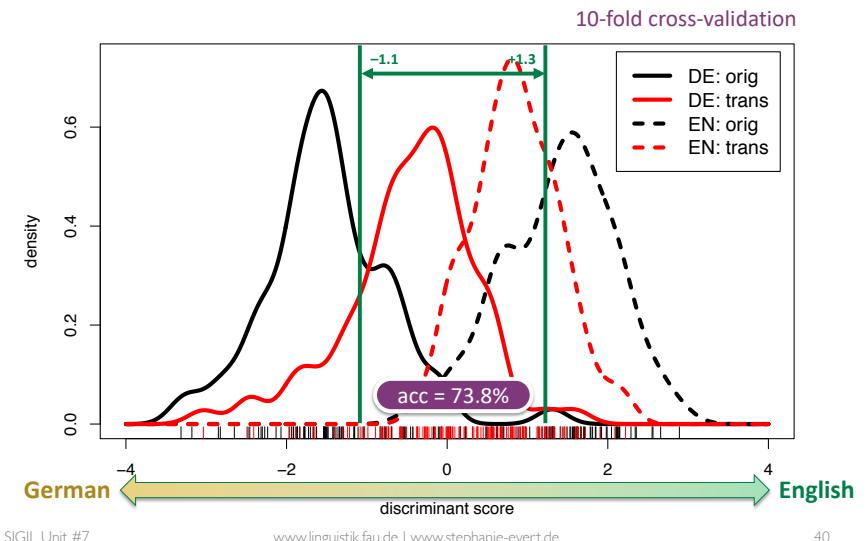
- LDA is a supervised ML technique → overtrained?
  - Would we find the same discriminant if we trained on a different set of texts?
- Verification with **bootstrap resampling** or **10-fold cross-validation**
  - LDA trained on 90% of data
  - discriminant axis shows “wobble” of approx. 10°
- Discriminant scores from c.v. (10% test data per fold)



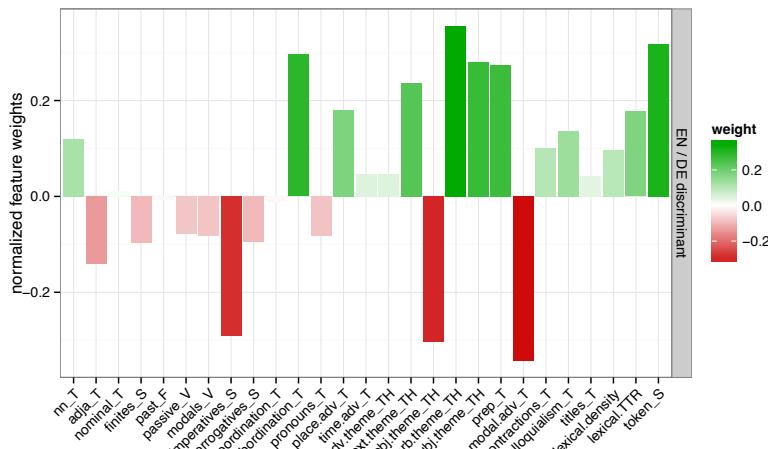
## Discriminant for DE vs. EN confirms shining through & prestige effect



## Cross-validated discriminant



## Interpreting discriminant features

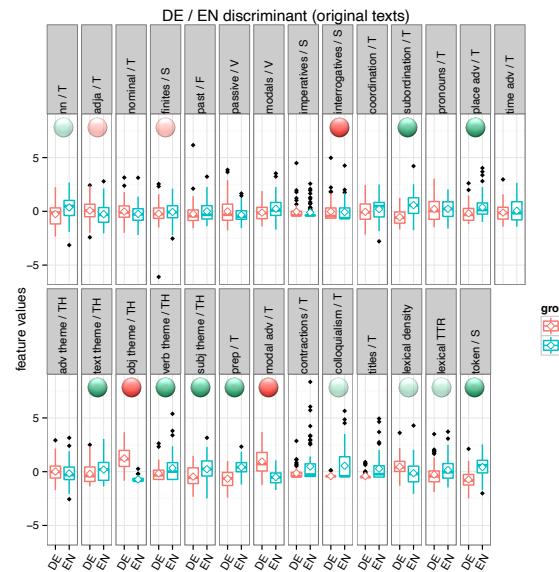


SIGIL Unit #7

[www.linguistik.fau.de](http://www.linguistik.fau.de) | [www.stephanie-evert.de](http://www.stephanie-evert.de)

41

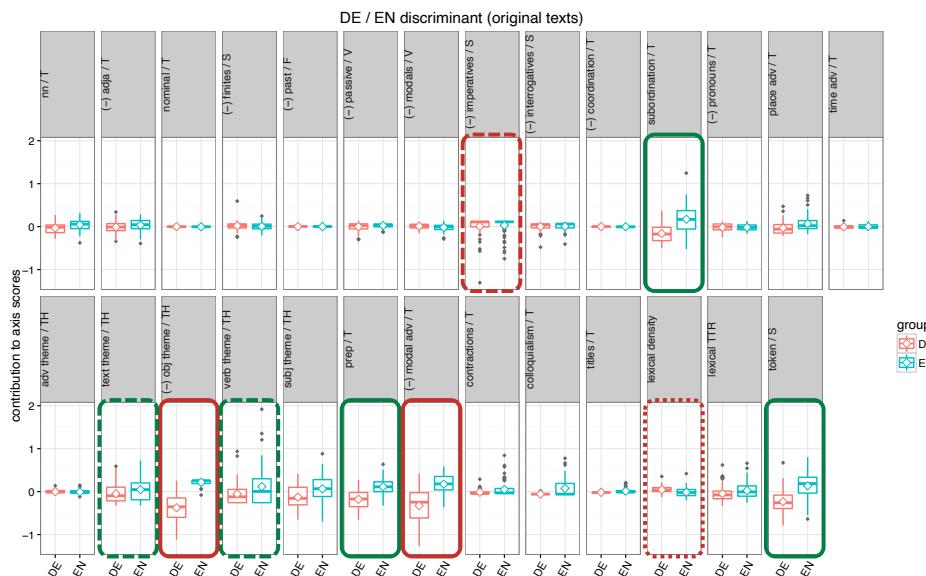
## Interpreting discriminant features



SIGIL Unit #7

42

## Interpreting discriminant features

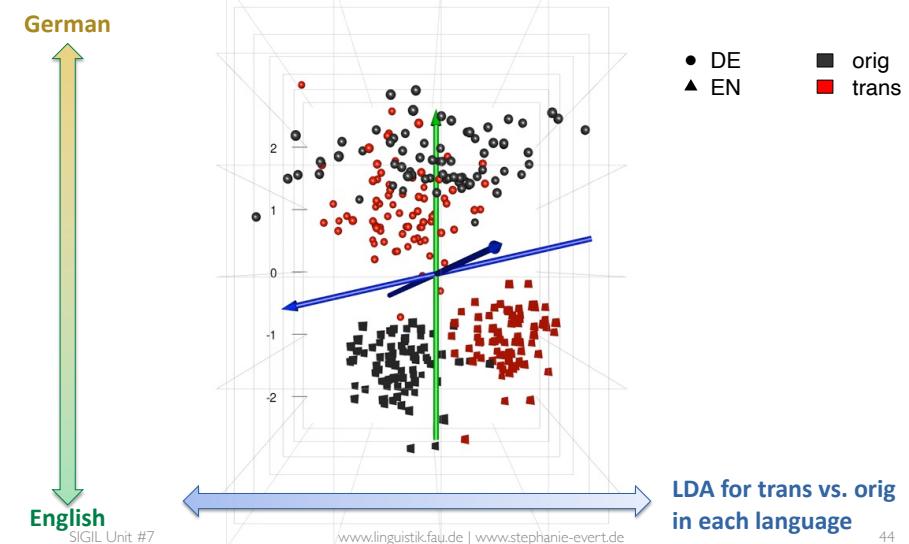


group

DE  
EN

DE / EN discriminant (original texts)

## Unravelling translationese



[www.linguistik.fau.de](http://www.linguistik.fau.de) | [www.stephanie-evert.de](http://www.stephanie-evert.de)

44

## Case study 2: French regional varieties

(Diwersy, Evert & Neumann 2014)

- Lexical differences in regional varieties of French
- Two nation-wide newspapers each from 6 countries
  - Cameroon, France, Ivory Coast, Morocco, Senegal, Tunisia
  - two consecutive volumes from each newspaper
  - total size approx. 14.5 million tokens
- Text samples = one week each
- Features: frequencies of shared colligations
  - colligation = lemma-function pairs
  - must occur in all subcorpora with  $f \geq 100$

SIGIL Unit #7

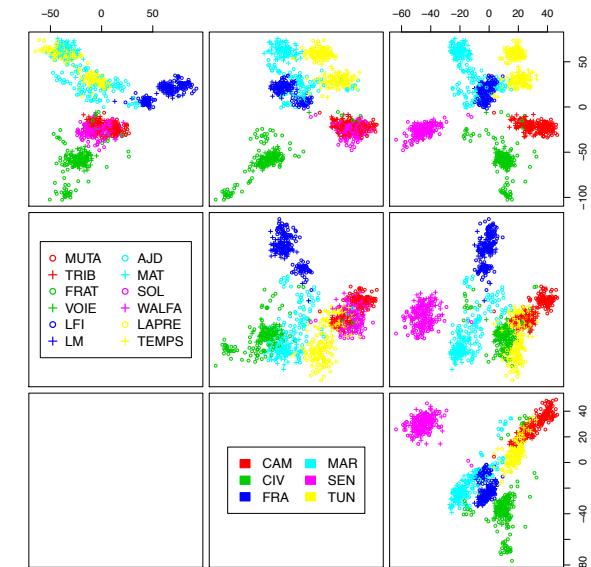
[www.linguistik.fau.de](http://www.linguistik.fau.de) | [www.stephanie-evert.de](http://www.stephanie-evert.de)

45

## FRV: poor choice of features

PCA not excluding country-specific words as features: perfect separation

Design bias results in a completely uninteresting model



FA not applicable:  
features >> texts

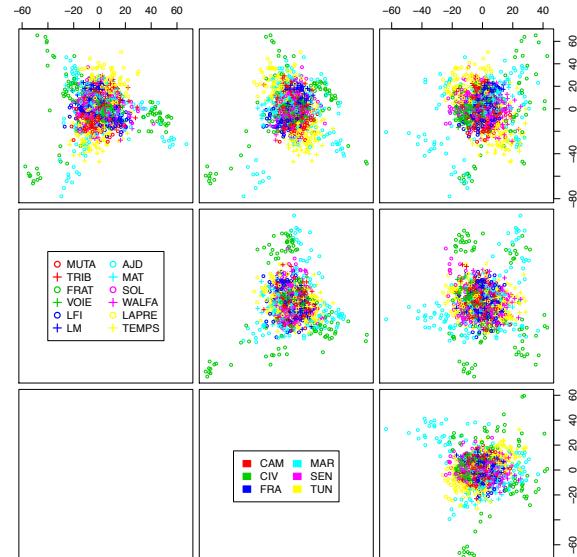
SIGIL Unit #7

## FRV: PCA dimensions

Using only shared words as features, PCA no longer reveals any patterns (just a few outliers)

Use LDA to find a meaningful perspective, based on newspaper source

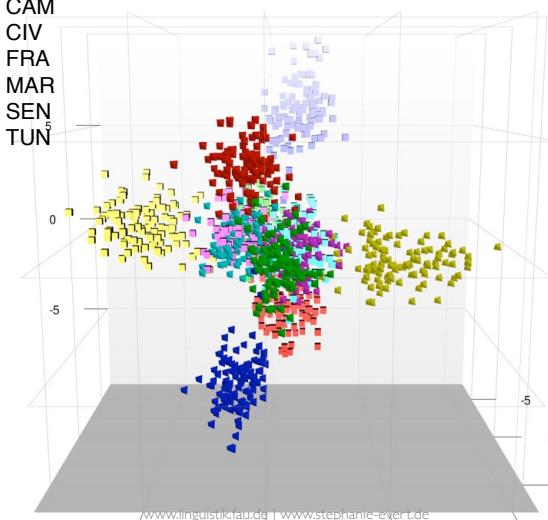
Country would presume regional varieties exist!



SIGIL Unit #7

## FRV: LDA dimensions (newspapers)

■ MUTA	■ CAM
▲ TRIB	■ CIV
■ FRAT	■ FRA
▲ VOIE	■ MAR
■ LFI	■ SEN
▲ LM	■ TUN
■ AJD	
▲ MAT	
■ SOL	
■ WALFA	
■ LAPRE	
▲ TEMPS	

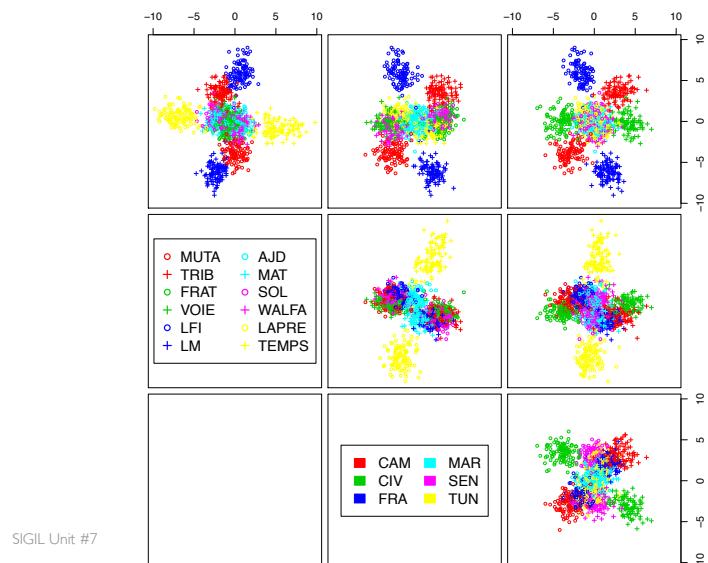


SIGIL Unit #7

48

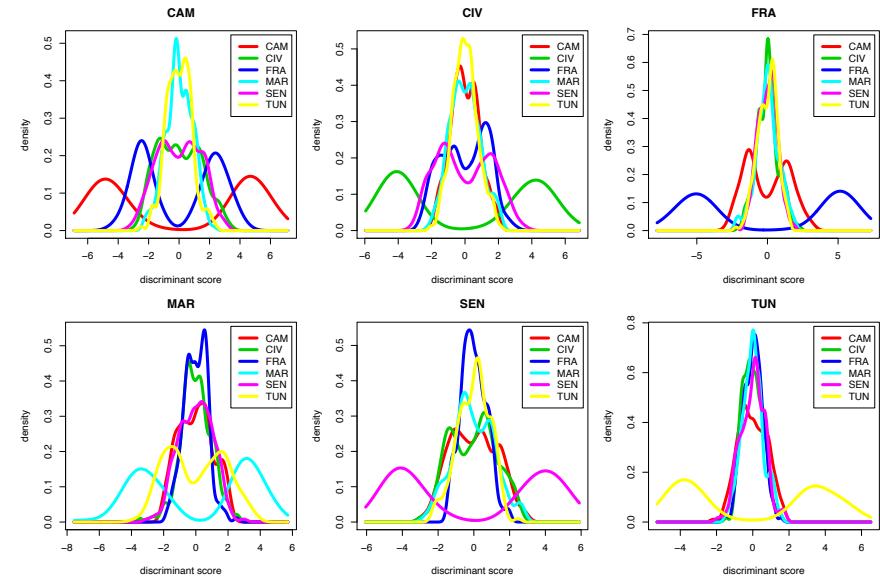
[www.linguistik.fau.de](http://www.linguistik.fau.de) | [www.stephanie-evert.de](http://www.stephanie-evert.de)

## FRV: LDA dimensions (newspapers)



49

## FRV: discriminant axes



## References

- Biber, D. (1988). *Variation Across Speech and Writing*. Cambridge University Press, Cambridge.
- Diwersy, S.; Evert, S.; Neumann, s. (2014). A weakly supervised multivariate approach to the study of language variation. In B. Szmrecsanyi & B. Wälchli (eds.), *Aggregating Dialectology, Typology, and Register Analysis. Linguistic Variation in Text and Speech*. De Gruyter, Berlin.
- Evert, S. & Neumann, S. (2017). The impact of translation direction on the characteristics of translated texts: a multivariate analysis for English and German. In G. De Sutter, M.-A. Lefer & I. Delaere (eds.), *Empirical Translation Studies. New Theoretical and Methodological Traditions* (TiLSM 300), pages 47–80. Mouton de Gruyter, Berlin.
- Gasthaus, J. (2007). *Prototype-Based Relevance Learning for Genre Classification*. B.Sc. thesis, Universität Osnabrück, Institute of Cognitive Science.
- Koppel, M.; Argamon, S.; Shimoni, A. R. (2003). Automatically categorizing written texts by author gender. *Literary and Linguistic Computing*, 17(4), 401–412.
- Neumann, S. (2013). *Contrastive Register Variation. A Quantitative Approach to the Comparison of English and German*. de Gruyter Mouton, Berlin.
- Neumann, S. & Evert, S. (2021). A register variation perspective on varieties of English. In E. Seoane & D. Biber (eds.), *Corpus based approaches to register variation*. Benjamins, Amsterdam.
- Teich, E. (2003). *Cross-linguistic variation in system and text. A methodology for the investigation of translations and comparable texts*. Berlin: Mouton de Gruyter.
- Toury, G. (2012). *Descriptive Translation Studies – and beyond: Revised edition*. 2nd ed. Amsterdam: John Benjamins.