Multi-National Topics Maps for Parliamentary Debate Analysis

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2. Design Science As Our Methodology
3. Multi-national Political Topic Modeling
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Motivation

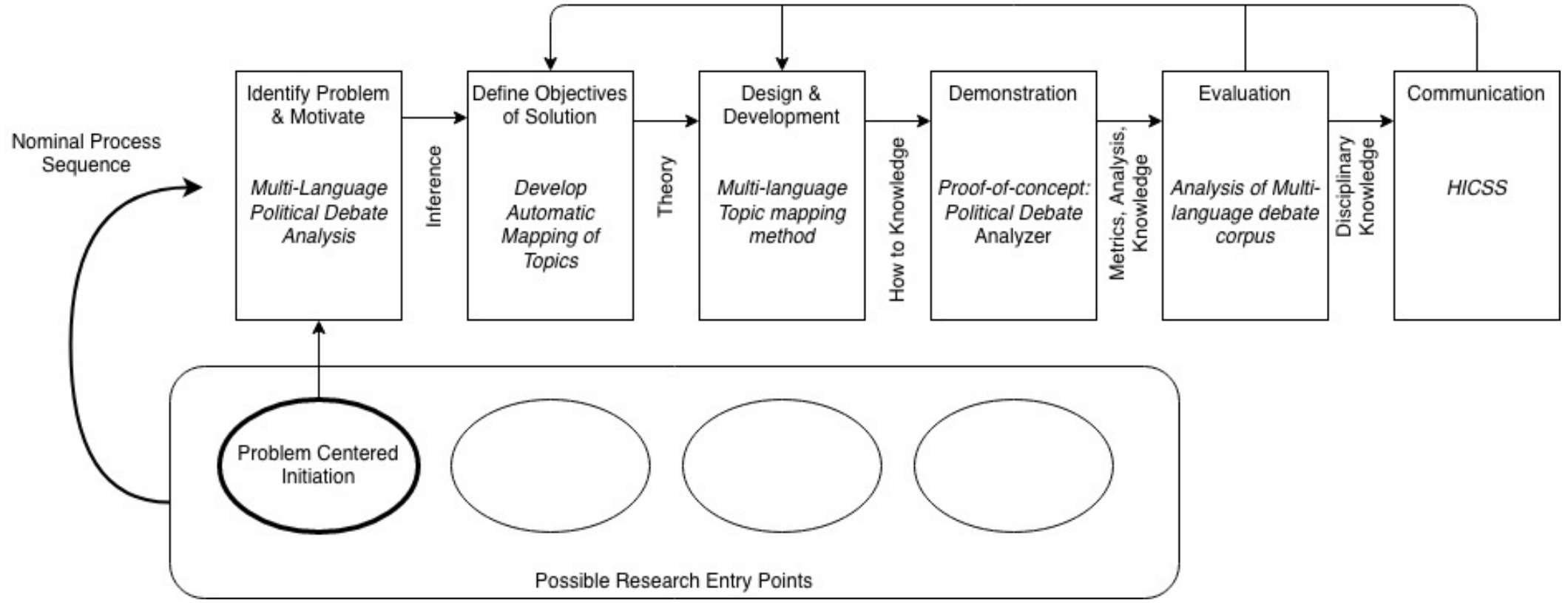
Linking parliamentary speech topics cross-nationally

Challenge:

- *different concepts in different languages*
- *addressed by latent topic models*
- *but linking unclear*

Design Science As Our Methodology

Research Methodology (DSRM)



c.f., Pfeffers, et al. 2007

Guidelines for Design Science Research

Guidelines		Our Application
Design as an Artifact	→	Towards multi-language political debate analysis
Problem Relevance	→	Political debates are important for democracy
Design Evaluation	→	Coherence score to evaluate topic alignment
Research Contribution	→	How to use LDA for cross-national transparency
Research Rigor	→	**Few and clear guidelines for design decisions**
Design as Search Process	→	Multiple alternatives are compared
Communication of Research	→	**This paper**

c.f., Hevner, et al. 2004

Multi-national Political Topic Modeling

ParlSpeechV2

– *"Full-text corpora of 6.3 million parliamentary speeches"*

c.f., Rauh and Schwalbach 2020

– Germany, United Kingdom, Spain
– Period: 1996-03-27 to 2018-12-14

  – Germany: 167943 Speeches
  – United Kingdom: 1381804 Speeches
  – Spain: 108214 Speeches

Multi-national Political Topic Modeling

Latent Dirchilet Allocation & Coherence Score

Latent Dirichlet Allocation (LDA):

Iterative procedure to find the best possible clusterings and probability distribution,

c.f., Blei et al. 2003

Coherence Score:

c-v as a novel coherence measure with the highest correlation with human ratings,

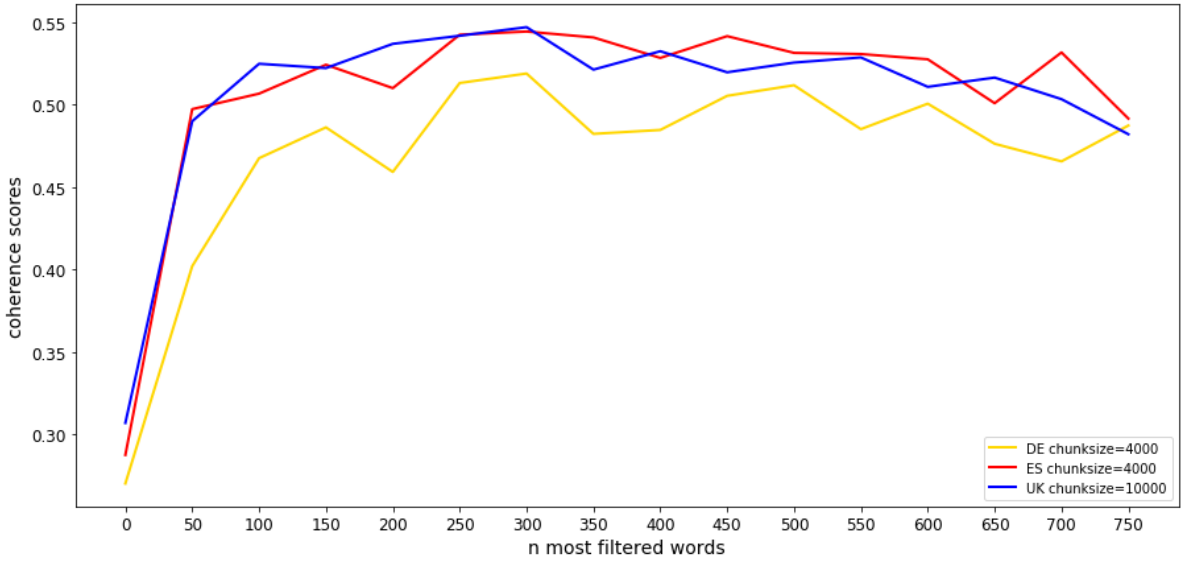
c.f., Röder et al. 2015

Preprocessing

1. Remove all text between brackets („(*text*)“)
   – Data set specifica
2. Remove punctuations
3. Remove numbers (digits 0-9)
4. Apply a Lemmatizer
5. Remove single-letter literals
6. Everything lowercase

Pass Ia: Frequency Cap Optimization

1. *filter_n_most_frequent(remove n)* method of Gensim (c.f., Radim Řehůřek and Peter Sojka 2010)
   - Frequency = #Documents in which a term occurs
2. Apply LDA with a standard (50 Topics)
3. Evaluate with **c-v** coherence score
4. using the maximum (average) coherence per national corpus



→ absolute maximum for all three national corpora is 300

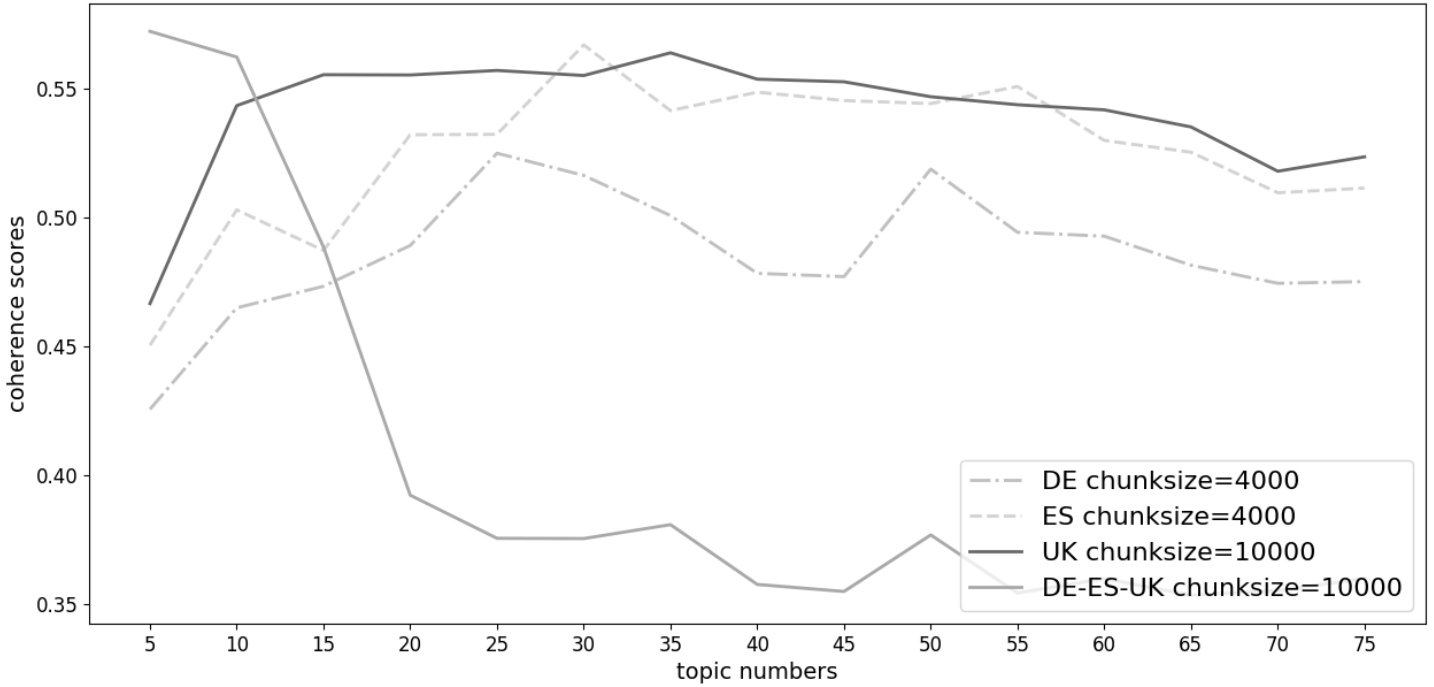
Pass Ib: Topic Number Optimization

Best Topic Models:

Germany: 25

Spain: 30

United Kingdom: 35



Multi-national Political Topic Modeling

Results: National Model - Germany

#	Topic terms	c-v
7	energie, klimaschutz, energiewende	0.738
EN	*energy, climate protection, energy transition*	
15	pflege, arzt, versorgung	0.736
EN	*care, doctor, supply*	
6	bundeswehr, einsatz, soldat	0.719
EN	*armed forces, use, soldier*	
11	türkei, syrien, menschenrechte	0.709
EN	*turkey, syria, human rights*	
19	projekt, infrastruktur, straße	0.665
EN	*project, infrastructure, street*	

Top-5 (out of 25) topics for Germany

Results: National Model - Spain

#	Topic terms	c-v
3	fiscal, imponer, impuesto	0.752
EN	*prosecutor, impose, tax*	
0	educativo, educación, formación	0.681
EN	*educational, education, training*	
8	aguar, andalucía, valenciano	0.673
EN	*water, andalusia, valencian*	
11	crecimiento, crisis, déficit	0.661
EN	*growth, crisis, deficit*	
9	justicia, judical, civil	0.652
EN	*justice, judical, civil*	

Top-5 (out of 30) topics for Spain

Results: National Model – United Kingdom

#	Topic terms	c-v
15	defence, armed, war	0.776
5	crime, prison, victim	0.731
0	care, nhs, hospital	0.727
6	international, security, foreign	0.725
33	rail, transport, train	0.721

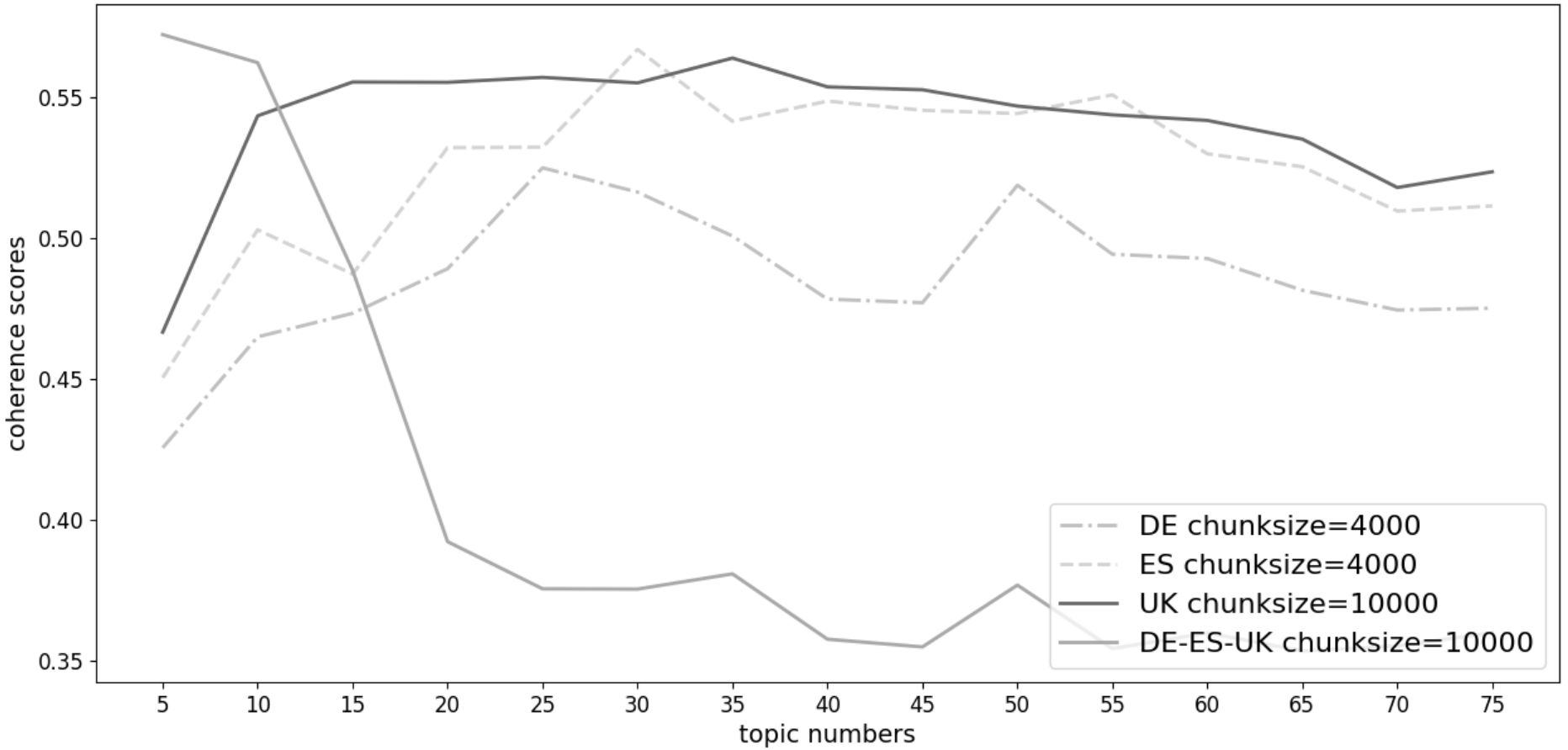
Top-5 (out of 35) topics for United Kingdom

Pass II: Unified Multi-National Corpus

1. Translate top 20 words non-englisch terms per topic
2. For each translation assign an ID
3. Multiple Translations (same source) → Keep most important
4. Multiple Translations (same target) → Unify ID
5. Multi-Term translations → Single token
6. Filter stop words
7. Replace terms in each corpus by their ID
8. Combine all corpora

Multi-national Political Topic Modeling

Pass II: Unified Multi-National Corpus



Linking the Topics

1. Only national topics with min 0.5 **c-v**
2. Cosine similarity between all possible topic pairs
3. Sort descending and cut off at 0.1 similarity
4. Highest similarity pair is a link

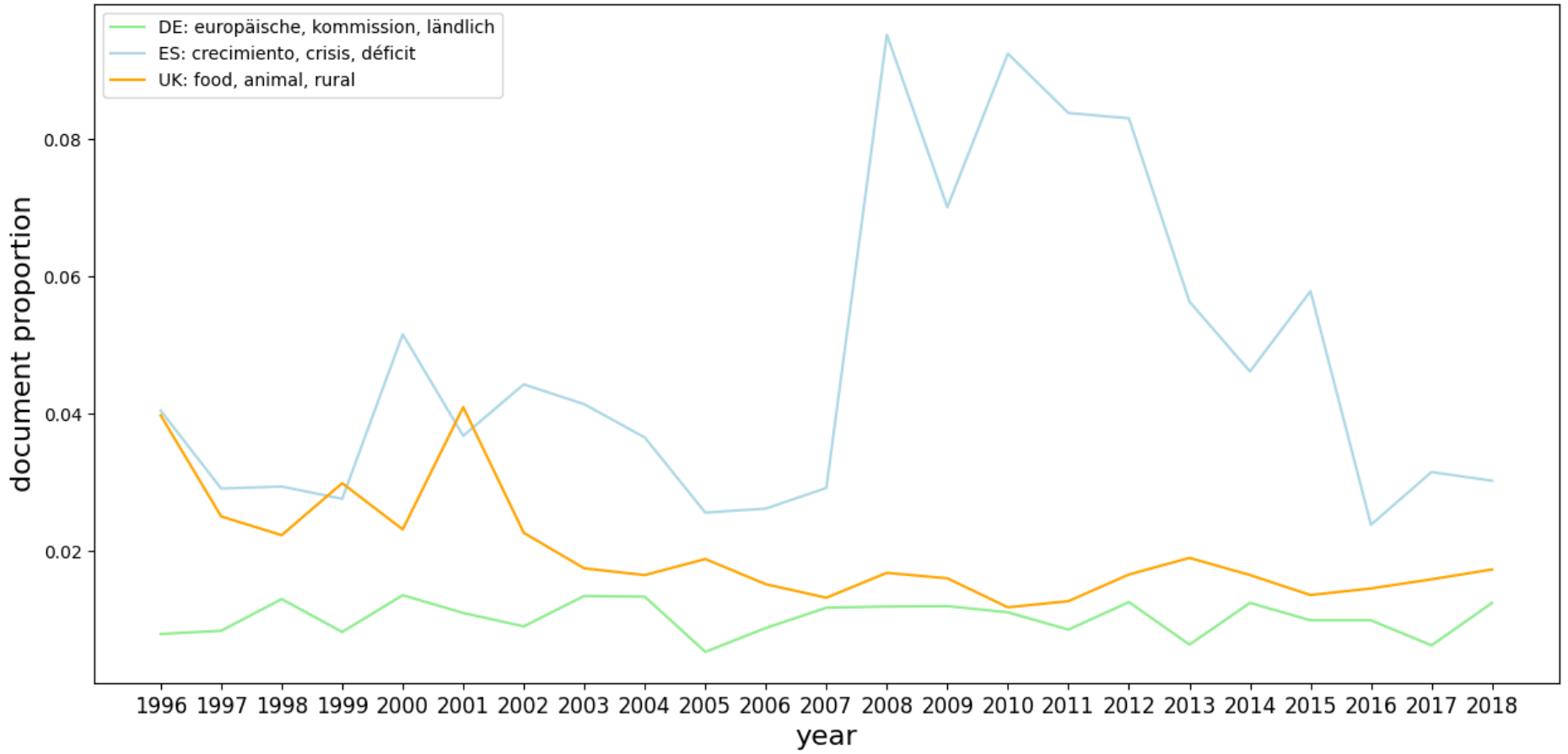
Multi-national Political Topic Modeling

Results: Reference Model

#	Germany	Spain	United Kingdom	Reference	c-v
2	zahlen, steuer, haushalt	fiscal, imponer, impeusto	tax, credit, universial	tax, bank, investment	0.357
	pay, tax, budget	*prosecuter, impose, tax*			
8		trabajador, laboral, formación	company, market, consumer	worker, contract, employer	0.36
		worker, labor, training			
11	projekt, infrastruktur, straße	inversión, sostenibilidad, obrar	rail, transport, train	investment, infrastructure, energy	0.344
	project, infrastructure, street	*investment, sustainability, work*			

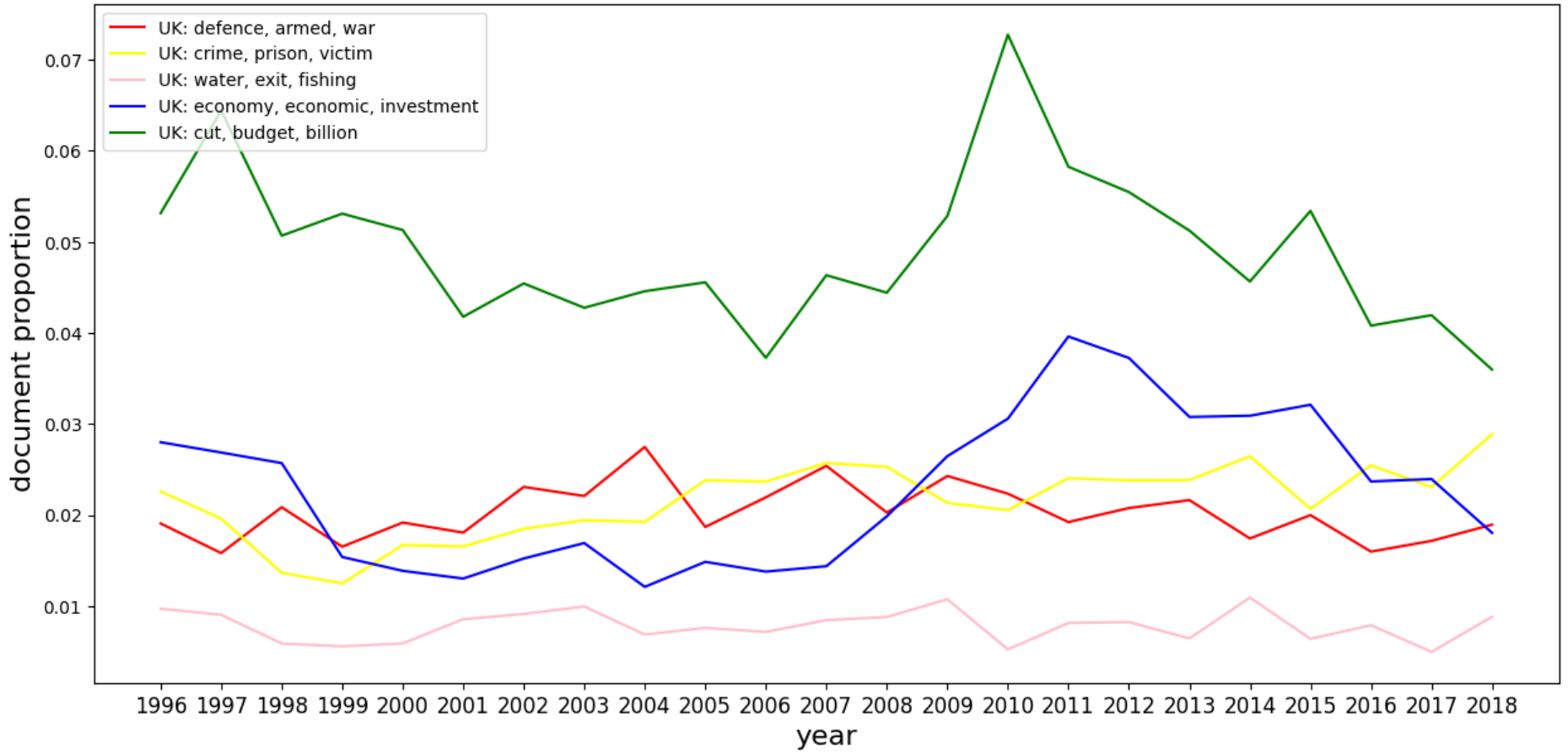
Multi-national Political Topic Modeling

Results: Reference Model



Multi-national Political Topic Modeling

Results: National Model



Conclusions

Our LDA-based process to create multi-national topics models …

1. Data-driven general approach for filtering stop words with LDA
2. Method to join multi-language corpora for probabilistic topic modeling
3. Method for topic linking

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