

# Splitting Lips

## Polarization through Parliamentary Speech

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### Polarization

Definitions of polarization vary (see Palonen 2009; Goet, 2019) and are commonly referred to:

- a state of political division in society
- the act of creating political division through discourse

We focus on **polarization as a state of affairs in parliament**. While individual methods cannot grasp the whole phenomenon, they can illuminate various aspects.

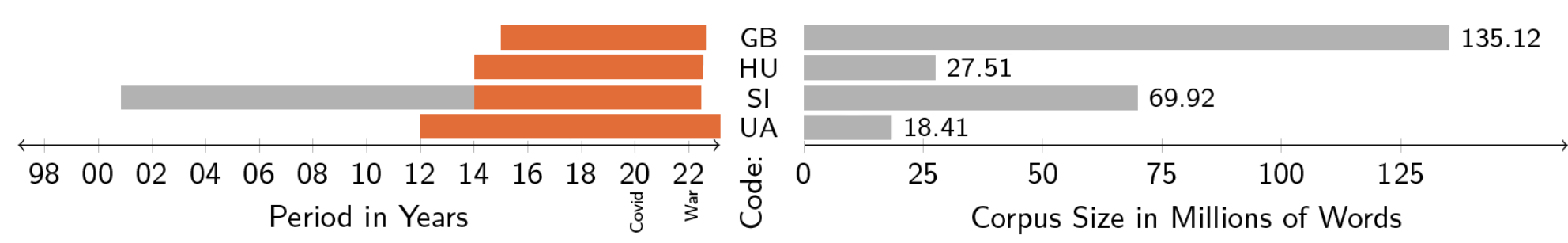
Manifestations	Approaches
groups do not talk about the same topics	sentence embeddings, TF-IDF
groups value the same topics differently	sentiment analysis
groups use alternative terms to set the agenda	close reading

### Research questions

- How do specific topics polarize parliaments?
- How does polarization manifest over time?
- How can polarization be measured with computational methods?

### Data

The research is based on the data set **Multilingual comparable corpora of parliamentary debates ParlaMint 3.0** (beta version) pre-released by CLARIN ERIC. We focused on **Great Britain, Hungary, Ukraine, and Slovenia** in the periods highlighted below.



### Methods

- Extract three thematic subcorpora using LDA and corpus keyword methods: **European Union, War, and Healthcare**.
- Calculate speech representations and sentiment with multilingual LLMs.
- Calculate and visualize SBERT embeddings for finding thematic differences between political parties.
- Conduct **in-depth reading** of relevant speeches and refine information from the visualizations into interpretations.

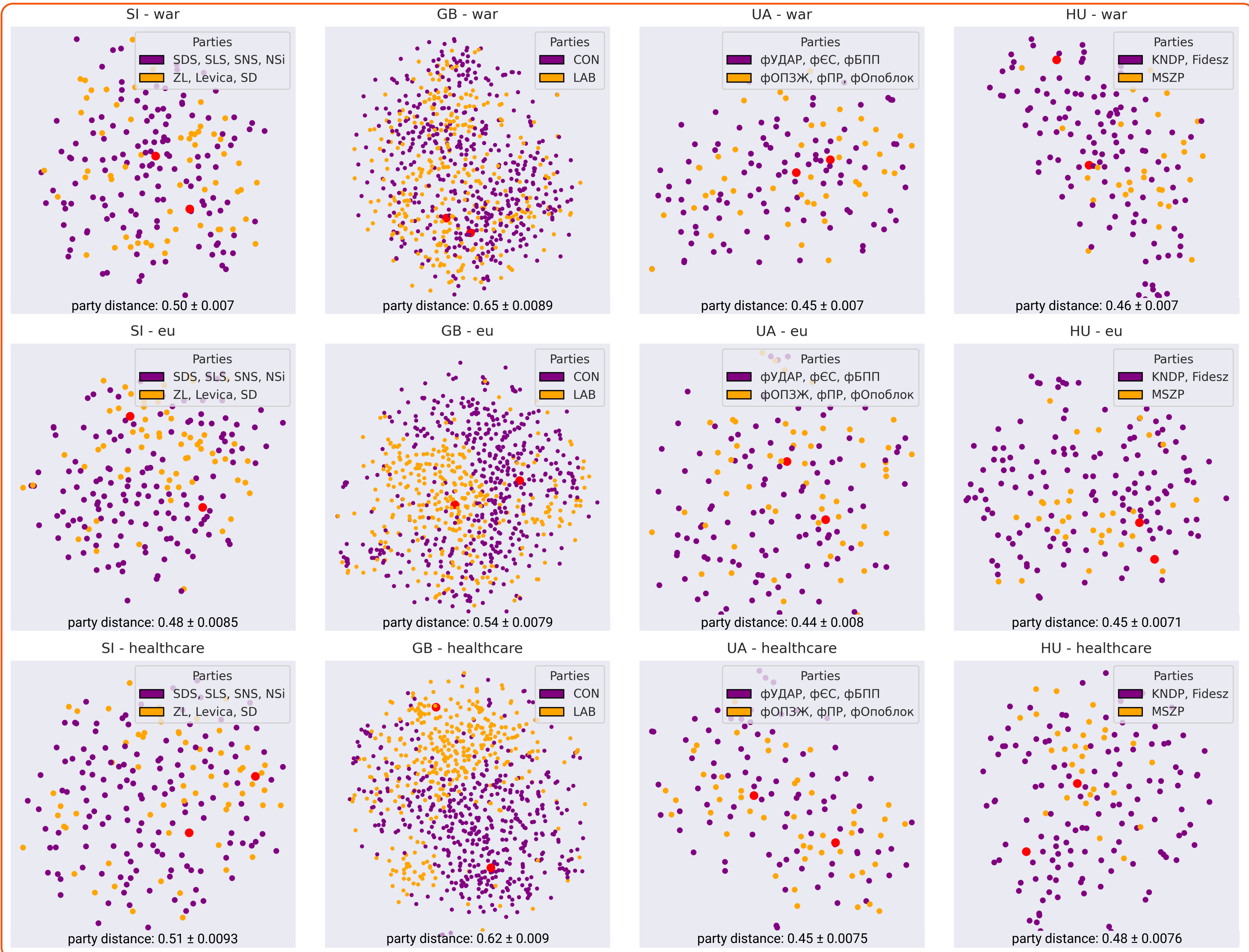


Figure 1:

#### Visualizing Embeddings

Scatterplots are showcasing parliamentarians from opposing groups of each parliament across the four thematic subcorpora.

Figure 2:

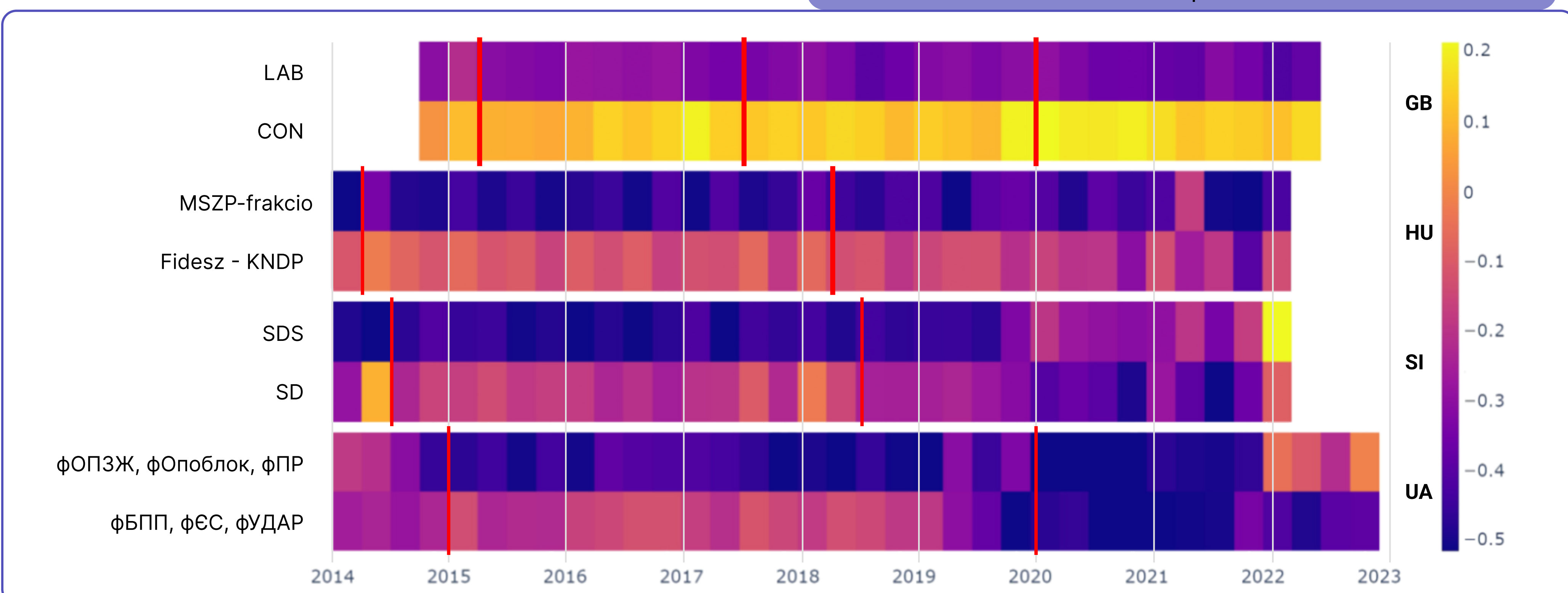
#### Temporal Sentiment Analysis

Heatmaps comparing opposing groups across the four parliaments. Vertical red lines represent elections.

Theme	Topic	Great Britain	
		Focus % (CON / LAB)	Sentiment (CON / LAB)
EU	Brexit Referendum	11.1 / 17.6	0.10 / -0.08
	Ukraine-Russia War	13.4 / 10.6	-0.08 / -0.30
Healthcare	Covid	30.1 / 22.5	0.17 / -0.35
		Ukraine	
		Focus % (Pro-UA* / Pro-RU*)	Sentiment (Pro-UA* / Pro-RU*)
EU	Language Policy	10.30 / 47.50	-0.34 / -0.55
	Legislations in War	9.60 / 22.40	-0.41 / -0.58
Healthcare	Organ Transplantation	16.80 / 1.10	0.03 / -0.88
		Hungary	
		Focus % (Fidesz-KNDP / MSZP)	Sentiment (Fidesz-KNDP / MSZP)
EU	Corruption Charges	16.70 / 30.9	-0.38 / -0.48
	Constitution Defense	13.4 / 29.5	-0.32 / -0.52
Healthcare	Covid	24.3 / 9.5	-0.13 / -0.52
		Slovenia	
		Focus % (SDS / SD)	Sentiment (SDS / SD)
EU	Tax Coffers	6.90 / 10.8	-0.04 / 0.02
	Veteran Pensions	2.2 / 5.0	-0.30 / -0.32
Healthcare	Healthcare System	14.2 / 8.0	-0.26 / -0.48

Pro-Ukraine\* - фБПП, фЕС, фУДАР  
Pro-Russia\* - фОПЗЖ, фОпоблок, фПР

Selected BERTopic subtopics highlighting the contrasting focuses between opposing political groups.



### Challenges

- **Data** – the different volumes of the thematic subcorpora limit the interpretability of the results and likely affect the generalizability of the sentiment model and reproducibility of the topic modeling.
- **Methods** – The LLM-based approaches offer suggestive insights into polarization. However, variations in topic interpretability hindered the qualitative analysis of detected topics within themes.
- **Qualitative Analysis** – A principled revision of the qualitative post-analysis framework would increase confidence in the validity of our methods. Having only one language expert for Hungarian and Ukrainian slowed down this analysis.

### Future research

- **Ontology** – crafting a more concrete definition of polarization to aid meaningful feature selection/identification and post-analysis.
- **Qualitative post-analysis for unsupervised methods** – the principled incorporation of corpus-based approaches in post-analysis could positively impact reliability.
- **Standardization of computational methodology.**
- **LLMs and Human readability** – Inclusion of explainable AI and white-box methods to aid interpretation and post-analysis.

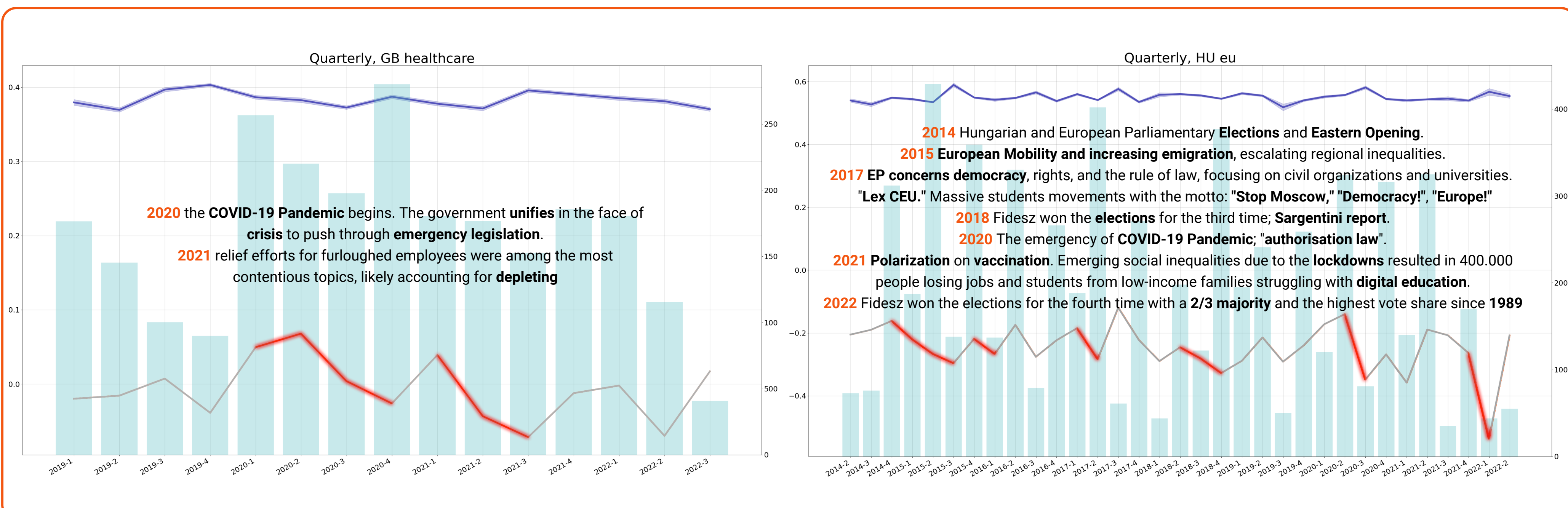


Figure 3:

#### Cosine Differences and Sentiments

Numerical difference of embedded opposition and coalition speeches (blue); average sentiment (red); and quarterly volume of speeches.