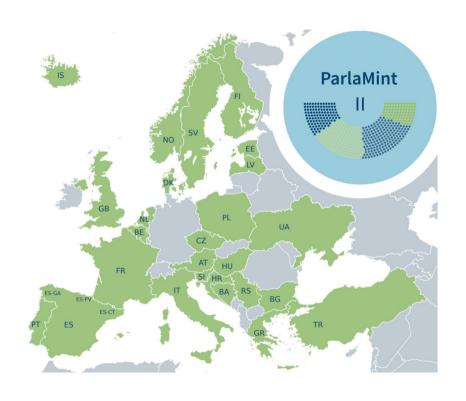
Touché'25 Task 2





Çağrı Çöltekin



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- Parliamentary debates result in decisions with high societal impact
- Political/parliamentary language is difficult to analyze
  - highly conventionalized
  - strategies like evasion, circumlocution or the use of metaphors are common
- This task is about identifying three fundamental aspects in political discourse
  - Political orientation: the 'classic' left-right spectrum
  - Populism index: another 'popular' dimension of recent political discourse
  - Power role: central in discourse analysis, virtually no computational studies

Task Description

Scenario: Identify the political orientation and the power role of the speaker from their speeches in parliamentary debates.

Task: Given a transcribed speech delivered in a parliament

Subtask 1: identify political orientation of the speaker (left-right)

Subtask 2: identify the position of the speaker's party in populsit—pluralist scale (4 values)

Subtask 3: identify power role of the speaker (coalition-opposition)

Data: - A subset of the ParlaMint version 4.1

- 29 national and regional parliaments (some available only for one of the tasks)
- 30 languages (also automatic translation to English)
- Date range varies by parliament, but includes at least from 2015 to 2022
- Typically long texts (approx. 600 words on average)

Results - orientation

Rank	Team	Approach	Precision	Recall	F <sub>1</sub> -score		
1	Munibuc	SVM + NV-Embed-v2	0.680	0.665	0.660		
2	GIL_UNAM_Iztacala	SVM/RF/LR/NB + n-grams	0.664	0.655	0.652		
3	TüNLP	XLM-RoBERTa	0.684	0.660	0.648		
	Baseline	Logistic Regression + Char n-grams	0.661	0.597	0.570		
Only on GB							
1	Munibuc	SVM + NV-Embed-v2	0.826	0.828	0.827		
2	GIL_UNAM_Iztacala	SVM/RF/LR/NB + n-grams	0.801	0.802	0.801		
3	TüNLP	XLM-RoBERTa	0.805	0.802	0.797		
	Baseline	Logistic Regression + Char n-grams	0.770	0.771	0.770		
4	DEMA <sup>2</sup> IN	Event Extraction + Logistic Regression	0.727	0.724	0.719		

Results - populsim

Rank	Team	Approach	Precision	Recall	F <sub>1</sub> -score
1	GIL_UNAM_Iztacala	SVM/RF/LR/NB + n-grams	0.533	0.522	0.512
2	Munibuc	SVM + NV-Embed-v2	0.559	0.496	0.497
	Baseline	Logistic Regression + Char n-grams	0.571	0.442	0.419
Only	on GB				
1	Munibuc	SVM + NV-Embed-v2	0.710	0.573	0.593
2	GIL_UNAM_Iztacala	SVM/RF/LR/NB + n-grams	0.570	0.565	0.565
3	DEMA <sup>2</sup> IN	Event Extraction + Logistic Regression	0.560	0.556	0.558
	Baseline	Logistic Regression + Char n-grams	0.717	0.517	0.501

Results - populsim

Rank	Team	Approach	Precision	Recall	F <sub>1</sub> -score
1	GIL_UNAM_Iztacala	SVM/RF/LR/NB + n-grams	0.709	0.707	0.703
	Baseline	Logistic Regression + Char n-grams	0.708	0.637	0.626
Only	on GB				
1	GIL_UNAM_Iztacala	SVM/RF/LR/NB + n-grams	0.801	0.788	0.729
	Baseline	Logistic Regression + Char n-grams	0.784	0.762	0.765
2	DEMA <sup>2</sup> IN	Event Extraction + Logistic Regression	0.737	0.727	0.729

Results: observations

- Similar approaches to last year (with slightly reduced participant numbers)
- □ Many teams used 'traditional' ML methods and (large) language models to extract features
  - likely the due to cost of processing long texts
- Finetuning a single multilingual model also seems promising
- $\Box$  Focused participation based on event extraction from one of the teams (DEMA $^2$ IN)
- Populism identification proves to be most difficult
- Scores on English are much better than the average performance