# Multilingual Ideology and Power Identification in Parliamentary Debates
## Touché'25 Task 2
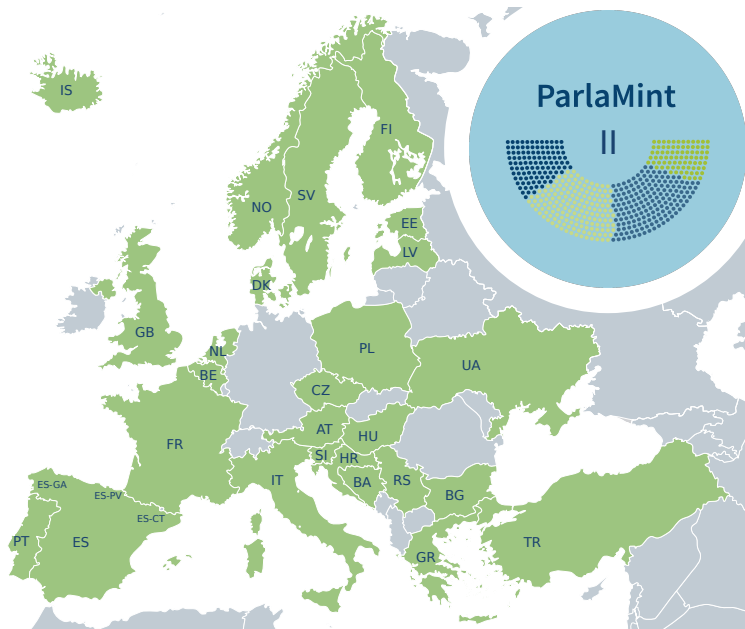
# Multilingual Ideology and Power Identification in Parliamentary Debates
## Introduction

❑ 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

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## 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)

# Multilingual Ideology and Power Identification in Parliamentary Debates

## Results - orientation

| Rank | Team | Approach | Precision | Recall | F$_1$-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[2]IN | Event Extraction + Logistic Regression | 0.727 | 0.724 | 0.719 |

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## Results - populsim

| Rank | Team | Approach | Precision | Recall | F$_1$-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[2]IN | Event Extraction + Logistic Regression | 0.560 | 0.556 | 0.558 |
|  | Baseline | Logistic Regression + Char n-grams | 0.717 | 0.517 | 0.501 |

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## Results - populsim

| Rank | Team | Approach | Precision | Recall | $F_1$-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$^2$IN | Event Extraction + Logistic Regression | 0.737 | 0.727 | 0.729 |

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## Results: observations

- Similar approaches to last year (with slightly reduced participant nunbers)
- 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
- 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